FLIGHT BASED RELATIONAL CARBON EMISSION PERFORMANCE ANALYSIS USING DEA: A CASE STUDY

(VZA KULLANARAK UÇUŞ BAZINDA İLİŞKİSEL KARBON EMİSYON PERFORMANS ANALİZİ: BİR VAKA ÇALIŞMASI)

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LIST OF SYMBOLS

AHP : Analytic Hierarchical Process
ANP : Analytic Network Process
APU : Auxiliary Power Unit
BCC : Banker, Charnes, and Cooper DEA Model
CCR : Charnes, Cooper, and Rhodes DEA Model
CNG2020 : Carbon Neutral Growth from 2020
CORSIA : Carbon Offsetting and Reduction Scheme for International Aviation
CRS : Constant Return to Scale
DEA : Data Envelopment Analysis
EU : European Union
EIA : US Energy Information Administration
ETS : Emissions Trading System
FANP : Fuzzy Analytical Network Process
GCD95 : Great Circular Distance
ICAO : International Civil Aviation Organization
MCPI : Malmquist Carbon Emission Performance Index
VRS : Variable Return to Scale

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ABSTRACT

Governments and international organizations act for global warming prevention, greenhouse gases emissions reduction, and to impose penal sanctions on companies that are polluting above the allowed limits with protocols, programs, and systems. In aviation environmental actions gained speed with the inclusion of aviation industry into the European Union’s Emission Trading System (EU ETS) in 2012.

According to the European Union’s Environment Commission, aviation industry is responsible for more than 2% of global emissions by itself. In civil aviation operations, main cause of carbon emission may be seen as jet fuel combustion in engines. Therefore, civil aviation companies carry out researches on some popular subjects such as using sustainable alternative fuel types, making efficient use of fuel in their flight operations.

Release of International Civil Aviation Organization (ICAO)’s Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) in 2018 and European Union’s Emissions Trading System (ETS) pushed civil aviation companies to review and improve their flights’ carbon emission amounts. Both of these regulations use a single indicator to track and evaluate carbon emission performance, which is carbon emission amount per ton-kilometer. Therefore, most of the civil aviation companies adapted this performance indicator formula to determine the carbon emission performance improvement potentials on their flights. However, aviation companies will not be able to minimize the effects of fixed assumptions from aviation regulation on carbon emission performance with this performance indicator. This causes civil aviation companies to choose wrong flight for improvement with limited improvement potential, which cause small improvements on carbon emission performance with great effort.

The model, which we introduced in this study, we aim to provide a method for aviation companies to evaluate carbon emission performance and to detect improvement potentials on flights with reducing the effects of fixed regulatory obligation on carbon emission performance. Our goal is to provide a useful model to calculate flight based carbon emission performance and to determine possible improvement potentials on flights for civil aviation companies.

In this study, introduction and outline of this study is given in first section. In second section, background information about regulators and their applications for aviation industry. In the third section, literature review and recent studies on global warming and carbon emission, emission performance measurement, aviation and carbon emission and we analyze the previous studies and papers about carbon emission efficiency, efficiency measurement and calculation methodologies. In the fourth section, methodology, which we use in this study, is explained in detail. In the fifth section, application principles for our study given in detail. In the last two section, the application results, discussion, conclusion and further research suggestions are given.

First, we define the inner and outer main and sub factors, which have effect on emission performance of a flight. In this part of our study, we meet with 12 experts from one private held Turkish civil aviation company personnel. These experts are from technical maintenance, piloting, and sustainability departments, which are selected among more than 5 years of experienced personnel. This group of experts suggested four main and thirteen sub-factor, which affect the emission performance of a flight. Main factors are technology, distance, load, and piloting. Sub factors are flight time, average speed, flight distance (GCD95), ground time, fuel weight, cargo weight, zero-fuel weight, aircraft type, passenger weight, cruising altitude, fuel type, airport (arrival), airport (departure). Experts asked to rank these factors with a given linguistic scale, which is weighted from one to nine. After ranking process, we converted the answers to fuzzy scales, then constructed matrices for FANP, and calculated relative weights for factors. These weights are used for estimating main factor values via multiplying sub factors with corresponding weight value. To test our model, we prepared a randomly selected 10.000 flight history data from flight dataset in 2017, main factors as inputs and emission amount as output. To solve and get results we constructed model based on constant returns to scale (CRS) and variable returns to scale (VRS) Data Envelopment Analysis (DEA) models. Then, we use R software's benchmarking library to compute the results.

In this thesis, the conducted empirical dataset study indicates that CRS model has more distinctive properties than VRS model. This result shows us CRS model usage for flight based carbon emission performance score calculation has more advantages in detail analysis for performance improvement potentials of flight carbon emission. In addition, results show us that the current accepted performance indicator, carbon emission amount per ton-kilometer, does not correlate with our result in favor.

The results of this study are showing similarity with literature and provide new approach for leg based flight emission efficiency tracking and ranking for global civil aviation. Global aviation companies to assess their flights' carbon emission performance and potential on improvement can use this approach.

ÖZET

Hükümetler ve uluslararası organizasyonlar küresel ısınmayı, sera gazı salınımını azaltmaya ve izin verilen değerlerin üzerinde kirlilik oluşturan firmalara cezai müeyyideler uygulamaya yönelik protokoller, programlar ve sistemler yayınlamaktadır. Birçok sektörü kapsayan bu regülasyonlara 2012 yılında sivil havacılık sektörünün Avrupa Birliği tarafından Karbon Ticaret Sistemine (EU ETS) dâhil edilmesiyle birlikte, havacılıkta çevresel aksiyonların alınmasına hız verildi.

Avrupa Birliği Çevre Komisyonuna göre sivil havacılık sektörü küresel karbon emisyonun %2'sinden sorumludur. Sivil havacılık operasyonlarında karbon emisyonu salınımının büyük bölümü uçaklarda kullanılan jet yakıtlarının yanmasıyla oluşmaktadır. Bu nedenle sivil havacılık firmaları sürdürülebilir alternatif yakıt seçenekleri, uçuş operasyonlarında daha verimli yakıt kullanımı sağlayacak uygulamalar üzerine çalışmalar yürütmektedir.

Uluslararası Sivil Havacılık Organizasyonu (ICAO) tarafından 2018 yılı içerisinde taslağı yayınlanan Uluslararası Havacılıkta Karbon Ofset ve Azaltma Programı (CORSIA) ve Avrupa Birliği tarafından 2012 yılında havacılığın dâhil edildiği Avrupa Birliği Karbon Ticaret Sistemi (EU ETS) ile birlikte sivil havacılık firmalarını uçuşlarından kaynaklanan karbon emisyonunu gözden geçirmeye ve iyileştirmeye yönelmiştir. Bahsi geçen her iki uygulama da karbon emisyon performansını takip etmek ve değerlendirmek için ton-kilometre başına düşen karbon emisyon miktarını performans göstergesi olarak kabul etmiştir. Bu nedenle sivil havacılık firmalarının çoğunluğu kabul verilen bu performans göstergesini takip ederek karbon emisyon performansında iyileştirme potansiyellerini bu gösterge üzerinden belirlemeye çalışmaktadır. Fakat bu göstergenin uçuş ile ilişkili sadece iki faktöre odaklanmasından ötürü havacılık regülasyonları ve uygulamalarından kaynaklı, değiştirilmesi mümkün olmayan, etmenlerin karbon emisyon performansına olan etkisinin en aza indirgenmesi mümkün olmamaktadır. Bu durum sivil havacılık firmalarının iyileştirmek için seçtiği kötü performansa sahip uçuşlarının çoğunlukla yanlış seçilmesi ve ufak iyileştirme potansiyellerinin tespitine yol açmaktadır.

Bu tez çalışması içerisinde oluşturduğumuz model ile değiştirilmesi mümkün olmayan faktörlerden kaynaklı karbon emisyon performans kaybını odağımızdan uzaklaştırarak sivil havacılık firmaları için daha etkili bir karbon emisyon performansı hesaplama ve derecelendirme metodu sunmayı hedeflemekteyiz. Sunduğumuz modelin sivil havacılık firmaları tarafından kullanılarak karbon emisyon performans takibi ve iyileştirmeye açık alanların belirlenebilmesi amacıyla kullanılmasını da hedeflemekteyiz.

Bu tez çalışması içeriğinde, hükümetlerin ve uluslararası organizasyonların havacılık sektörünü hedef alan regülasyonlarının tanıtımı hakkında bir bölüm bulunmaktadır. Küresel ısınma, karbon emisyon performansı ölçümü, havacılık alanında karbon emisyonu alanlarında yapılan çalışmalara literatür araştırması bölümünde yer verilmiştir. Kullanılacak metotlara ve uygulama esaslarına ilişkin bilgiler yöntem bölümünde verilmiştir. Oluşturulan modelin deneysel bir veri seti üzerinde uygulaması ve bu uygulama sonuçlarına uygulama bölümünde yer verilmiştir. Son bölümde uygulamanın literatüre olan katkısı, vaka çalışması sonuçları ve önceden yapılan çalışmalar ile bu çalışma sonuçlarının yorumlarına yer verilmiştir.

Bu tez çalışması için ilk olarak uçuşların karbon emisyon miktarına etki eden içsel ve dışsal faktörlerin belirlenmiştir. Bu süreçte Türkiye'nin önde gelen özel sermayeli bir sivil havacılık firmasından alanlarında uzman 12 personel ile görüşülmüştür. Bu personeller teknik bakım, pilot, çevre alanlarında 5 yıldan fazla süredir görev yapmakta olan kişilerden seçilmiştir. Görüşmeler sonucunda dört ana faktör altında 13 alt faktör belirlenmiştir. Ana faktörler; teknoloji, mesafe, ağırlık ve sürüş olarak, alt faktörler; uçuş süresi, yer süresi, ortalama hız, dairesel mesafe, uçak ağırlığı, yolcu ağırlığı, yakıt ağırlığı, kargo ağırlığı, ortalama irtifa, yakıt türü, uçak türü, kalkış havalimanı ve varış havalimanı olarak belirlenmiştir. Belirlenen bu faktörler bir ila dokuz arasında puanlanan nitel bir yelpaze kullanılarak puanlandırılmıştır. Sonrasında puanlandırma bulanık ölçeğe uyarlanarak faktörlerin göreceli ağırlıklarını belirmek üzere bulanık analitik ağ süreci yönetimine aktarılarak sonuçlar elde edilmiştir. Elde edilen bu sonuçlar daha sonra alt faktörlerin ana faktörlere çevrilmesinde kullanılmıştır. Uçuşların karbon emisyon performans derecelerinin belirlenmesi için 2017 yılı içerisinde gerçekleştirilen 178.000 uçuş arasından rassal olarak seçilen 10.000 uçuşa ait veri seti dört girdi, ana faktörler, ve bir çıktı olacak şekilde düzenlenmiştir. Düzenlenen bu veri seti veri zarflama metodunun (VZA) ölçeğe sabit dönen (CRS) ve ölçeğe değişken dönen (VRS) modelleri temel alınarak oluşturulan modeller için çözülmüştür.

Bu çalışmada yapılan deneysel veri seti çözümü CRS VZA modellinin VRS VZA modeline göre daha ayırt edici sonuçlar verdiğini göstermektedir. Mevcutta havayolu firmaları tarafından kullanılmakta olan ton-kilometre başına emisyon miktarı göstergesinin kıyaslanması ile çalışma sonuçları dört ana faktörün ilişkisini ortaya çıkartmakta daha başarılı olduğu gözlemlenmiştir.

Sonuçlarımız literatür ile örtüşmekte ve uçuş bazında karbon emisyon performans takibi ve sıralaması için yeni bir yaklaşım ortaya koymaktadır. Bu yaklaşım küresel sivil havacılık firmaları tarafından kullanılabilir.

1. INTRODUCTION

Today's fully industrialized world requires energy to operate and develop. Most of this energy requirement supplied from energy production resources such as natural gases, fossil fuels, coal, and traditional bio-fuels. All of these energy production resources emit carbon dioxide and other greenhouse gases into the atmosphere, while they are burning. Greenhouse gases, especially carbon dioxide, make our atmosphere more inner reflective for heat energy, which causes average global temperature to rise. This harsh processed named as global warming or climate change.

Global warming, one of the emerging environmental topics for the last century, is the long-term rise in the world's average temperature, which is caused by excessive amount of greenhouse gases emissions.

Aviation industry responsible for 2% of annual global carbon emission. In last 10 years, fuel consumption of aviation industry increased by more than 45%.[1] These developments make governments and aviation authorities to act for reduction of aviation carbon emission. In aviation industry, jet engines burn fossil and bio fuels and the result of this process creates two major outputs trust and carbon dioxide. Burning 1 liter of jet fuel emits approximately 2.53 kg of carbon dioxide into the atmosphere according to US Energy Information Administration (EIA).[2] All of these facts and recent attention of governments to limit aviation's carbon emission with lack of decision support system studies in this field make carbon emission performance scoring in aviation ideal subject to study for improvement and sustainability.

[1] https://ec.europa.eu/clima/policies/transport/aviation_en

[2] CO2 Emissions Coefficients, https://www.eia.gov/environment/emissions/co2_vol_mass.php

In this study, we aim to provide a new method for aviation companies to evaluate carbon emission performance and to detect improvement potentials on their flights relatively with reducing the effects of regulatory obligation on carbon emission performance. Our goal is to provide a factor based two step model to calculate flight based relational carbon emission performance and to determine possible improvement potentials on flights for civil aviation companies. By providing this indicator, we aim to improve the current indicator (CO2 per tone*km) significantly, and make aviation companies aware about their potential to improve different factors like ground time, average speed, fuel weight, cargo weight etc.

Scope of this study consist factors, which affect aviation industry's carbon emission amount, and methodology for evaluating efficiency scores of flights' carbon emission. In this thesis, explanation of carbon emission significance to aviation industry, expert opinions on factors that affect emission performance of a flight, generic usage of FANP and DEA methodologies, proposed model for scoring carbon emission efficiencies of flight, and a case study to assess proposed model.

In order to give insight about flight performances of an aviation company, we need a model to assess vast amount of data and correlates some factors. In the literature, there are useful methods on MCDM and efficiency analysis such as analytical hierarchical process (AHP), analytical network process (ANP), data envelopment analysis (DEA), and Malmquist index introduced by researchers. Fuzzy usage of ANP is ideal for linguistically scaled factors with empirical data. Therefore, we started our study with this method and calculated relative weights for factors affecting carbon emission performance of flight. On the other hand, aviation companies have hundreds of thousands flights each year even a sessional analysis will have vast amount of data. Therefore, we need a method to calculate efficiency scores faster with better computational power usage. The method, which provides this kind of ability, is Data Envelopment Analysis (DEA). At the end, we constructed our work on DEA models.

Our approach provides a new model to evaluate flights based carbon efficiency scoring for aviation companies using their historic flight data and criteria defined in this study. An aviation company will be able to find its best and worst performed flights with these efficiency calculation results, and it will be able to determine which criteria caused the flight operated efficiently or inefficiently.

In the literature there are some studies, which share similar goals such that to measure relative performance of carbon emission for countries, several firms by using different techniques. However, there is no significant study focuses on relative performance of flight emission efficiency for aviation companies to assess their flights' sustainability and to determine improvement potential in the literature. This thesis provides a new model to calculate and measure relative of flight carbon emission efficiency scores for aviation companies, and put a brick on wall for filling the gap in literature to relative flight carbon emission efficiency score calculation.

Outline of this study, introduction and outline of this study is presented in first chapter. In second chapter, background information about regulators and their applications for aviation industry is presented. In the third chapter, literature review and recent studies on global warming, carbon emission, emission performance measurement, aviation and carbon emission and we analyze the previous studies and papers about carbon emission efficiency, efficiency measurement and calculation methodologies. In the fourth chapter, methodology, which we use in this study, is explained in detail. In the fifth chapter, application principles for our study given in detail. In the last two chapter, the application results, discussion, conclusion and further research suggestions are given.

2. BACKGROUND

Greenhouse gases are carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and fluorinated gases (F-gases). These greenhouse gases share on global emission amount are shown in Figure 2.1, carbon dioxide has 76% share on global emission, and the most polluting greenhouse gas.

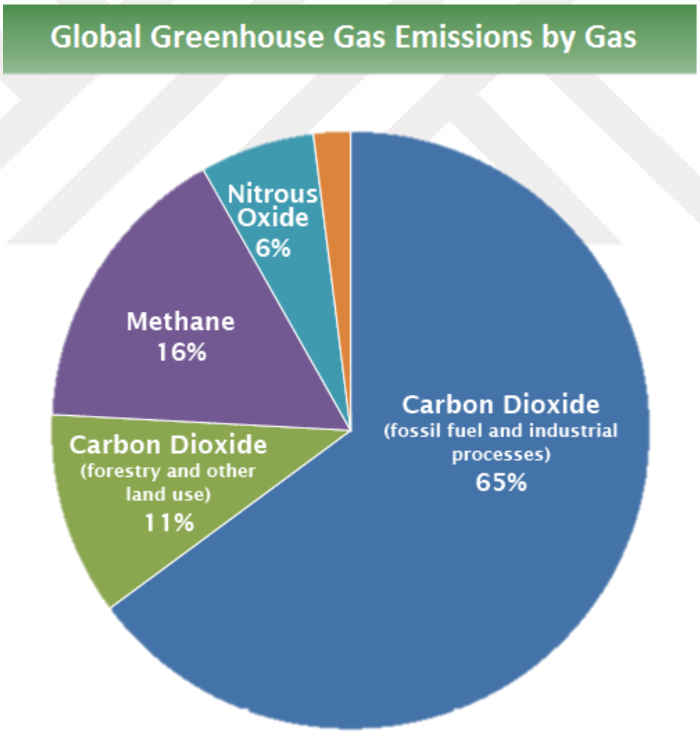

Figure 2.1: Greenhouse gases shares on global emissions[3]

To prevent global warming's catastrophic event, governments, organizations and charities are putting great effort.

[3] https://www.ipcc.ch/report/ar5/syr/

European Union Emission Trading System (EU ETS) developed by EU in 2005 as the first emission trading system in world. It aims to fight global warming via strict policy to polluting industries. In EU ETS, every company have limitation on annual emission and firms can use it, buy additional carbon credit or sell excessive carbon credit in market. In addition, allowances reduce every year. In 2012, aviation activities area (flights with departure and arrival has to be in EU borders) are included into EU ETS. EU ETS allowance prices for last 5 years shown in Figure 2.2. EU ETS CO2 allowance prices increased more than 350% in last 5 years.[4]

Figure 2.2: CO2 European emission allowances prices[5]

International Civil Aviation Organization (ICAO) released a strategy for its 2020 vision on carbon neutral growth, which is named as Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). CORSIA is based on voluntariness of aviation companies and governments, there is no obligation, but it offers economically and socially sustainable future for most of the aviation companies. CORSIA's preparatory actions were in 2018 and baseline period still ongoing (2019-2020), and it has more 3

[4] [4] https://markets.businessinsider.com/commodities/co2-emissionsrechte

phases in future as; pilot phase in 2021-2023, first phase 2024-2026, and second phase 2027-2035.[6]

In recent studies, the subject of carbon emission performance considered for transportation industry, energy production, and aviation industry. Some of these studies are; Country based total factor carbon emission performance (Zhou et al., 2009), China's regional energy and emission performance's undesired output elimination method (Wang et al., 2012), Fossil fueled power plants emission performance (Zhang & Choi, 2013), Carbon emission performance of transportation industry in China (Zhang et al., 2015), Countries' regional energy and carbon emission performance (Yao et al., 2015).

[6] https://www.icao.int/environmental-protection/CORSIA/Pages/default.aspx

3. LITERATURE REVIEW

In this chapter, we presented the studies on carbon emission efficiency and factors affecting this efficiency with aviation in three sub-topics. These sub-topics are presented in following paragraphs.

3.1 Carbon Emission Efficiency

The term efficiency described as doing something well and effectively without wasting time, money or energy. In scientific terms described as the ratio of outputs to inputs.[7]

Most of the studies on environmental efficiency performance exhibits constant returns to scale (CRS). Discussion of output oriented DEA technologies placed in the study. Non-increasing return to scale (NIRS) and variant returns to scale (CRS) DEA technologies are used to benchmark input and output oriented methodologies. The results show that the output oriented DEA methodologies have higher discriminating power for efficiency benchmarking (Zhou et al., 2008).

As an alternative to fossil fuels, bio-fuels are more environmental friendly and renewable fuel type. In their study, Wu et al. (2009) experimented on biodiesel fuel alternatives emission performance via measuring released greenhouse gases such as: nitrogen oxide, unburned hydrocarbon, and carbon monoxide. The results show that the all alternative fuels have lower carbon monoxide release than current diesel fuel, and efficiency saving may vary up to 35%.

In their study, Zhou et al. (2010) introduced a Malmquist CO2 emission performance index (MCPI) to measure deviation in gross carbon emission performance along the time.

[7] Longman Dictionary : https://www.ldoceonline.com/dictionary/efficiency

They construct their model on the environmental DEA technology with inputs as capital stock, labor force, and energy, outputs as domestic product (desirable output) and CO2 emissions (undesirable output). The result of this study showed that 1997 to 2004 these 18 top emitting countries carbon emission performance improved by 24%.

China is one the top emitters in the world. So, pollutant emissions reduction and environment protection subjects very important for China. In their recent study, Wang et al. (2012) studied China's regional energy and emission performance to find the best way to deal with undesired outputs such as greenhouse gases. They used three different DEA models: (1) Energy performance evaluation model, (2) Performance evaluation model for energy and emission, and (3) DEA window analysis and rank sum test to analyze and measure emission and energy performances. They grouped 30 selected regions as east, central, and west areas, then they analyze the period of 2000-2009 for regional and areal energy and emission performance indices. The results show to treat emission as desirable output provides higher discriminating power, but for China's case treatment as undesirable output provides higher accuracy on results.

A non-radial directional function approach used to measure energy and carbon dioxide emission performance for calculating 129 countries' electricity production efficiency. To calculate an aggregate index for energy and carbon, optimally produced energy over half of optimally consumed fuel and produced carbon used. The result shows that for energy production usage energy-carbon performance index provides better insides for countries to develop their sustainable energy production (Zhou et al., 2012).

In their recent study, Zhang & Choi (2013) studied total-carbon factor emission performance of fossil fuel usage in power plants in China using a non-radial Malmquist index analysis. They consider inputs as capital, labor and fuel, and output as electricity and carbon emission. Data gathered by two groups such as central group and local group. Results of their study indicate that total-factor CO2 emission performance increased by 0.38% for the same period results in Zhou et al. (2010).

3.2 Factors Affecting Carbon Emission in Aviation

In her article, Rypdal (2000) gives emission performances of aircraft model for same landing and take-off (LTO) cycles and cruising. This study indicates that aircraft model, which is considered as new and old technologies, is an effecting for carbon emission of a flight.

In their recent study, Buttress & Morris (2005) indicate that the ground movements of an aircraft also emit carbon dioxide. An aircraft run on idle power for taxi-in or taxi-out, uses thrust power around 7% for control before take-off, movement on taxiways, and general lighting, air-conditioning, etc. power requirements. If the airport's taxiways longer and the airport is crowded, then aircrafts will take more time on ground.

In their recent work, Blakey et al. (2011) consolidate the test on alternative fuel types, such as: Jet A1, JP-8, SPK from Camelina, S8 and GTL, for aviation industry usage and result shows that Fischer–Tropsch (FT) processed fuels have positive effect on emission performance.

In their recent study, Masiol & Harrison (2014) show that the fuel flow to engines is directly related with emission performance. As an airplane needs more thrust for load, speed, or take-off it pulls more fuel from depot and this process releases more carbon dioxide into the atmosphere.

3.3 Measuring Carbon Emission Efficiency in Aviation

In their recent study, Meleo et al. (2016) study Italian aviation sector's adaptation of EU ETS. General findings of this study highlight that direct costs are connected with EU ETS and impact of these costs on both aviation companies and passengers or cargo clients are currently quite small in amount. The increment in these costs tends to increase because of two main reasons. First, the excessive amount of allowance was recorded for the aviation industry in 2012 will be assimilated; second, the increase on greenhouse gases emissions expected once the economy recovers ends. Figure 2.5 shows the EUA prices for 12-month between Dec 2017 – Dec 2018.

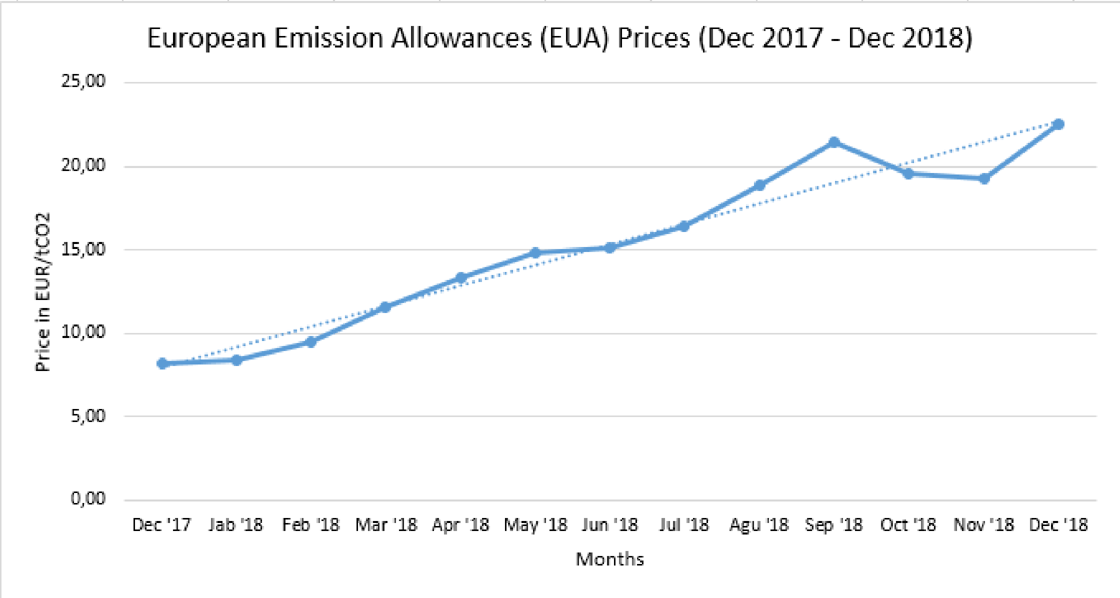

Figure 3.1 – EUA prices between Dec 2017 and Dec 2018[8]

Seven variables and a method to calculate total fuel usage of a flight studied in two parts: fuel usage per available seats miles, and delay related fuel usage. To calculate fuel usage per available seats miles some variables such as, an indicator for aircraft fuel efficiency, average seats on an aircraft, aircraft body length, total variable load amount, and fuel & conservation effort have been used. By computing connection between fuel use and fuel value they gave important bits of knowledge about air ship measure choice, fuel utilization and outflow decrease, deferred flights impact on fuel use and discharge. (Brueckner & Abreu, 2017)

In their recent study, Li & Cui (2017) examined the Carbon Neutral Growth from 2020 (CNG2020) as a roadmap in aviation environmental efficiency gap based on a forecasted dataset. They used back propagation neural network technique to forecast the data that they use for analysis, and then they introduced a new model, which they called network ranged adjusted environmental data envelopment analysis, to show the difference with CNG2020 roadmap for aviation. They presented their results in three parts, as follows; overall and body efficiency gaps for 29 aviation companies' datasets in 2021-2023 period. CNG2020 roadmap's beneficial outcome on environmental efficiency of most aviation

[8] https://sandbag.org.uk

companies. Operational expenses in aviation industry and operational efficiency gap are two correlated subjects, feasible expansion of total revenue and sales are showed as efficiency gaps, which are correlated.

Malmquist carbon emission performance index (MCPI) may be used to evaluate the changes in total-factor carbon emissions efficiency over period using a production frontier framework. In their recent study, Liu et al. (2017) used MCPI to measure the carbon emission performance of 12 Chinese civil aviation companies in the period of 2007 to 2013; this study also introduced a bootstrapping MCPI to try statistical usage of the MCPI results. They presented three significant findings, which are as follows, first the additive MCPI of 12 Chinese civil aviation improved by more than 11% over 2007 to 2013 period. The decomposition analysis that they us to show us this development in Chinese civil aviation was majorly because of technical improvements change index, with total effect of more than 20%. Other factors influenced developments included the change index of scale efficiency up to 3%. Among the aviation companies studied, Hebei Airlines developed the most with more than 43%. Hence, Sichuan Airlines had approximately -2.5% and China Postal Airlines had less than -10% are the occurred deteriorations in CO2 emission performance. Second, convergence in CO2 emission performance while there were differences in CO2 emission performance among three aviation companies. Private and joint venture aviation companies developed the most, at a speed of nearly 15% annually. Aviation companies in central and local distinct done similar developments in efficiency, at approximately 10% for each aviation companies. The least developed aviation companies started to change with an effect called catch-up effect that makes these aviation companies to approach developed aviation companies. In this research, the higher MCPI increase indicates the least developed aviation companies, which had higher improvement compared to those with higher MCPI values at the beginning. Third, a cross-carrier relational examination demonstrated that civil aviation CO2 emission efficiency is the most affected by course conveyance, trailed by fuel utilization rate, airplane usage rate, and movements on the ground (Liu et al., 2017).

In their recent study, Fukui et al. (2017) examined the effects of increases in aviation's fuel tax for reducing fuel consumption and carbon emissions based on the data from the US aviation industry. Results showed that the long-run price elasticities caused by an increase in fuel prices via additive fuel taxes have larger impact on smaller aviation companies than on larger aviation companies. In this study, they study the highest fuel tax increase in 2012 for US (4.3-cent), and the result showed this type of increase has no significant effect on CO2 emission decrease. The short-run reduction in CO2 emissions in the US resulting from a 4.3-cent increase in aviation fuel tax is only around 0.15%. In the long run, the presence of a positive rebound effect would reduce the impact of an increase in aviation fuel tax on fuel consumption and CO2 emissions. A 4.3-cent increase in aviation fuel tax would reduce annual jet fuel consumption and CO2 emissions in the US by approximately average on 0.45 million metric tons, respectively. For the next 3 years from 2012, a perpetual 4.3-penny increment on the price of jet fuel by taxes would add to the decrease of CO2 outflows in the US by just up to 0.01%. The long-run emanation decrease impact coming about because of a changeless 4.3-penny fuel charge increment is just about a 0.2– 0.3% decrease of CO2 outflows in the US aeronautics segment. This implies over the long haul, on the off chance that we are to accomplish a 1% decrease of CO2 emanations in the US avionics part, the flight fuel charge should be about 3– multiple times higher than the present dimension. In addition, the go through rate of aeronautics fuel duty to transporters is by all accounts under 1: the assessed normal go through rate was roughly 54.3 – 62.3% in 2000. This recommends flight fuel charges have not been passed completely to bearers, and subsequently, the real measure of decreases could be a lot littler than the present appraisals.

Arjomandi et al. (2017) extend previous approaches to a premature efficiency indicator by facilitates frontiers like using desired output, undesired output and production of efficiencies to compare European and Asian airlines. They additionally analyze whether the heterogeneity in natural administrative measures between these districts has encouraged Asian aircrafts to be less eco-accommodating as well as more piece of the pie chasing. They exhibited a mechanical hole proportion evaluates likewise point to some Asian carriers beating every single other aircraft on innovative measures, showing they work in an increasingly good business condition. Largely, the technique that they introduced adds to the methodological improvement of data envelopment analysis (DEA) and permits further bits of knowledge into firm tasks as a rule, and natural proficiency examination of European and Asian carriers specifically. The technique has enabled us to get increasingly nitty gritty and modern experiences into the effectiveness of European and Asian aircrafts contrasted and those of past examinations. The discoveries recommend that European carriers have put an expanding center around ecological productivity (and maybe the greening) of their flight exercises following the danger to incorporate aircrafts in the EU ETS in 2009. The deterioration of effectiveness factors gives a reasonable picture of EU aircrafts consistently improving their natural proficiency, with some EU carriers driving inside their own gathering and in contrast with the gathering of Asian aircrafts. Such airlines can be seen as setting a performance benchmark for those that need to improve their performance by emulating peer airlines, though, they may be lacking a learning curve to emulate (Wanke et al., 2016; Arjomandi et al., 2018).

Ma et al. (2018) presented a least squares compromise model to the airline fleet assignment problem. The model tested on real world data and the results showed better controllability is possible by facilitating the compromise method than the linear-weighted sum in terms of risk. Compared with the prevalent assignment strategy of China S Airline, our model performed much better in terms of both profit and emission. Further tests on replacing A320s with B737s and B757s showed better emission-reduction efficiency and profitability for B7** types aircrafts.

3.4 Original Contributions of This Thesis

Previous studies only focuses on one or some the factors, which effect carbon emission performance of flights. Also, there are studies on airline companies' carbon emission benchmarks and effects of agencies policies on airline companies.

We consider most of the proposed factors and some additional factors together and propose a new two step model (using Fuzzy ANP and DEA) for any airline company to benchmark its own flights and find out improvement potential on its worst performed flights.

We also test our model with real world data to give insights about results and how to interpret these results for aviation industries improvement.

4. PROPOSED METHODOLOGY

Our main goal is to provide a model for airline companies to evaluate carbon emission performance with respect to the flights that they have done in a specific period. In order to provide such a model, we first need factors, which effect a flight's carbon emission amount. Then, we need weights of this factors to interpret the relationship of emission performances of flights.

Therefore, we develop a framework, which is shown in Figure 4.1, to make our case easier to understand.

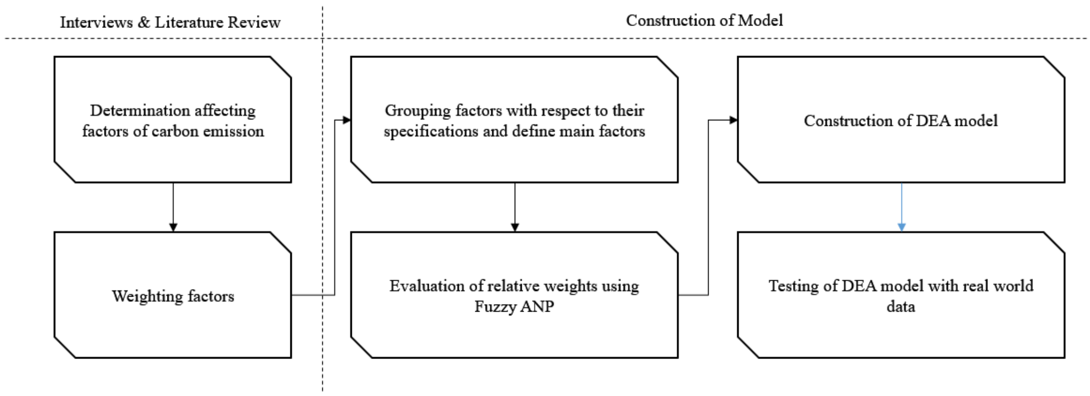

Figure 4.1: Framework of the proposed methodology

4.1 Determination and Weighting of Factors Effecting Carbon Emission

We first check literature for factors and find limited amount of studies, which focus on carbon emission in airline industry. Therefore, we take what we find from literature and ask aviation experts from a Turkish airline company, if they have any additional factors that affect carbon emission of a flight.

In the literature review, we find some studies proposing factors, which effect carbon emission of a flight. Nowacki & Olejniczak, (2018) A flight's fuel consumption and carbon emission amount is directly related with the fuel flow to engines. Brueckner & Abreu, (2017) use a regression model on a set historical flight data to determine the factors, which affects fuel consumption and carbon emission, and they give some of these factors as total load (in tons), flight distance (in kilometers), aircraft type (by construction year), and flight delays (in minutes). According to UK Civil Aviation Authority the factors, which affect carbon emission of a flight, are: aircraft type, cruising altitude, take-off and landing efficiency, flight distance, and total take-off load, operational procedures, fuel type and weather condition[9]. In their recent study, Hassan et al., (2018) three factors are considered to assess airline companies' carbon emission. These factors are aircraft technology, operational improvements and sustainable biofuel.

For further analysis of factors, we interviewed 12-expert from one of private held Turkish civil aviation company personnel. These experts are from technical maintenance, piloting, and sustainability departments, which are selected among more than 5 years of experienced personnel. We defined 13 factors and their relations, which are shown in Figure 4.2, which affect the emission performance of a flight with the help this group of experts' opinions.

We define the main factors as: (1) technology factor, (2) piloting factor, (3) distance factor, and (4) load factor.

- Technology factor: contains aircraft and fuel sub-factors for weighting the difference between new and old types of them according to better or worse emission performance.
    - Aircraft type: New aircraft technologies provides less emission, up to 15%, comparing to the old aircrafts. To comply with this improvement, we consider aircraft type as one of our sub-factors, which affects emission performance of a flight. This sub-factor also has an effect on zero-fuel weight via aircraft weight.
    - Fuel type: Besides widely used jet fuel, Jet A1, there are new and sustainable fuel alternatives with less emission amounts. To comply with this type of usage on flights we consider fuel type as one of our sub-factors, which affects emission performance of a flight.

[9] https://publicapps.caa.co.uk/docs /33/cap1524environmentalinformation29032017.pdf

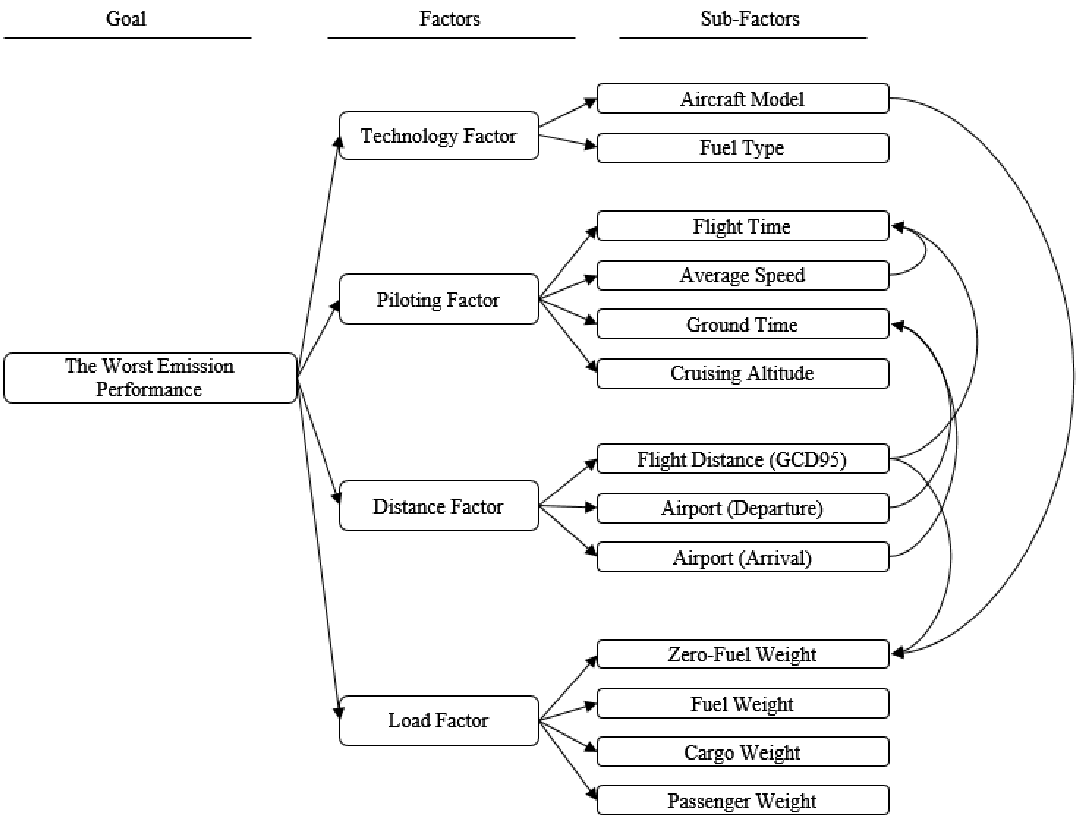

Figure 4.2: Analytical network for the worst emission performance goal

- Piloting factor: contains flight time, ground time, average speed, and cruising altitude sub-factors for weighting the varying specifications of every flight. These sub-factors may vary for numerous reasons such as; delays, slot filling, slot specs etc.
    - Flight time: May vary because of tardiness on air or distance travelled, and it causes vast amount of emission increase. This sub-factor is affected by flight distance and average speed.
    - Ground time: May vary because of delays, emergencies etc. also the origin and target airport sizes have an effect on this sub-factor.
    - Average speed: May vary limitedly because commercial aircraft’s top speed limited up to 850 km per hour. However, slower travel may cause less emission release.
    - Cruising altitude: Typically, a commercial flight occurs between 33,000 to 42,000 feet high, the friction on thin air is less so the thrust needed will be less causes less emission.
- Distance factor: contains flight distance, origin airport and target airport sub-factors for weighting the distance related factors.

  - Flight distance: Measured from take-off to landing as the distance travelled in air. It is the higher emitting part of a flight.
  - Origin airport: airport size is one of the parameters that we cannot change or improve as an airline company. However, it has huge effect on ground time and emission released on ground. Therefore, we must consider this parameter to calculate the emission efficiency.
  - Target airport: same as origin airport this one also has effect on ground time and emission amount.
- Load factor: contains all load to be travelled such as zero-fuel weight, fuel weight, passenger weight, and cargo weight.
  - Zero-fuel weight: Simply we can think it as aircraft sole weight. It is a fixed weight but if you have different types of aircrafts in your fleet, you should consider this sub-factor as emission changer.
  - Fuel weight: Authorities are forcing to carry fuel based on a flights length but some airline companies are taking much more than they need. Therefore, fuel weight must include into the calculation in order to compare relative emission efficiency of flights.
  - Passenger weight: distributed quite equally on an airplane. This differs passenger weight from cargo weight.
  - Cargo weight: even if this load distributed equally it is most of the time higher on front side of the plane.

Besides these factors, there are geographic (wind, mountain, lake etc.) and extreme measure (such as; route change, manual maneuver etc.) factors as well. However, in this study we omitted due to lack of sufficient data and we assumed that they have very small effect percentage on carbon emission.

4.2 Fuzzy ANP

The Analytic Network Process (ANP) first proposed by Saaty (1996). ANP is considered as a general form of AHP, which focuses on dependencies between the hierarchical elements. Both the ANP and AHP contains a goal, multiple criteria in clusters, but ANP has multiple sub-criteria in clusters, and alternatives in clusters. AHP is a hierarchical process with no feedbacks or internal relationships while ANP is a network process with at least one or multiple feedbacks or internal relationships. Differences between AHP and ANP shown in Figure 4.3.

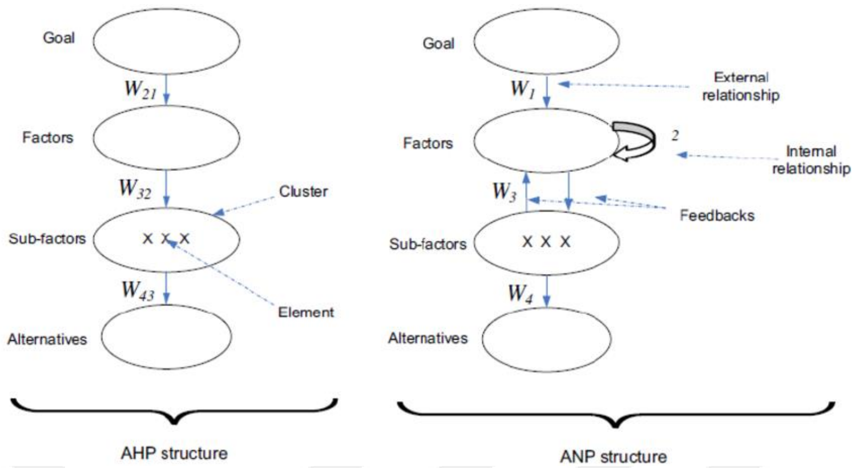

Figure 4.3: Comparison of AHP and ANP methods[10]

A person needs a goal, factors, sub-factors and alternatives, besides these elements also needs relationships (both importance scales and directions), dependencies in order to use ANP to find best match for the goal. Therefore, importance scales of each element has to be considered while using ANP. If the importance can be evaluated using some mathematical formulas, it will be a certain value with no doubt, but most of the relationship importance scales in our study are linguistic with a person's judgement. Therefore, we use fuzzy triangular numbers to make personal judgements more certain.

Buckley (1985) uses calculation of criteria weights geometric mean on fuzzy triangular number. The geometric mean *r* for fuzzy triangular numbers as shown in (4.1). A fuzzy triangular number defined as shown in (4.2).

$$\tilde{A}_i = (l_i, m_i, u_i) \tag{4.1}$$

$$r = (\prod_{i=1}^{n} l_i , \prod_{i=1}^{n} m_i , \prod_{i=1}^{n} u_i) \tag{4.2}$$

$\tilde{A}$ is a triangular fuzzy number and r is geometric mean for fuzzy triangular numbers.

[10] https://www.researchgate.net/figure/Comparison-of-AHP-and-ANP-methods-17_fig1_285550168

We used an importance scale table introduced by Parkash (2003) shown in Table 4.1 to evaluate importance scales of factors.

Table 4.1: Linguistic variables for pairwise comparisons.

Linguistic variable	Importance intensity	Fuzzy numbers
Equal importance	1	(1,1,1)
Moderate importance	3	(2,3,4)
Strong importance	5	(4,5,6)
Very strong importance	7	(6,7,8)
Extreme importance	9	(9,9,9)
Intermediate values	2	(1,2,3)
	4	(3,4,5)
	6	(5,6,7)
	8	(7,8,9)

The fuzzy ANP analysis in this study reviewed through 6 steps according to proposed methodology by Saaty (2013) and Buckley (1985), which are given as follows.

Step 1. *Network model construction and problem structuring*. At first, we construct a network model for evaluation. Network model construction needs all the relationships and importance scales, which are gathered by using Table 4.1, between goal, factors, and sub-factors. Also a figure given in below as Figure 4.4.

Step 2. *Fuzzified comparison matrices creation*. These comparison matrices are constructed by using fuzzy number concepts introduced by Buckley (1985) and network model, which is created in Step 1.

Step 3. *Calculating fuzzy weights for each sub-factor*. After creations of fuzzified comparison matrices, we need to calculate fuzzy weights for each sub-factor to weight external and internal relationships. We use the formulas given in (4.3), (4.4), (4.5), and (4.6) to calculate fuzzy weights from fuzzified importance of each factor pair.

$$Fuzzy\ Weight = \tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \tilde{r}_3 \ldots \oplus \tilde{r}_n)^{-1} \quad (4.3)$$

$$A_1 \oplus A_2 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (4.4)$$

$$A_1 \otimes A_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 * l_2, m_1 * m_2, u_1 * u_2) \quad (4.5)$$

$$A^{-1} = (l_1, m_1, u_1)^{-1} = (\frac{1}{u}, \frac{1}{m}, \frac{1}{l}) \quad (4.6)$$

Step 4. *Calculating normalized weights for ANP*. We construct fuzzified comparison matrices and fuzzy weights of each factor but in order to make ANP analysis we need certain numbers to put them inside ANP software (such as SuperDecisions). Therefore, at this step we calculate the normalized weights from fuzzy weights of each sub-factor using the formula given in (4.7) and (4.8). We must use the formula in (4.8) to make the total of factor weights equal to 1.

$$Centre\ of\ Area\ (COA) = w_i = \frac{(l, m, u)}{3} \quad (4.7)$$

$$Normalized\ Weight = \hat{w}_i = \frac{w_i}{\sum w_i} \quad (4.8)$$

Step 5. *Calculating inconsistency for factors*. After we calculate the normalized weights for each sub-factor. In this step, we calculate the consistency index (CI) and the consistency ratio (CR) (which calculated by using random index table provided by Saaty (1980)) using formulas given in (4.9), (4.10), and (4.11). For a model to be considered reasonably consistent CR value must be less than 0.10 value.

$$\lambda_{max} = \frac{\sum_j^n (\frac{\sum_i^n (w_{ij} * r_{ij})}{n})}{3} \quad (4.9)$$

$$Consistency\ Index = CI = \frac{\lambda_{max} - n}{n - 1} \quad (4.10)$$

$$Consistency\ Ratio = CR = \frac{CI}{Random\ Index\ (RI)} \quad (4.11)$$

Step 6. *Selection of alternatives and result interpretation*. After we calculate the normalized weights for each sub-factor and there is no inconsistency. In this step, we randomly choose flights from a specific period and we solve our network model for these randomly chosen flight alternatives to calculate factor weights with the internal relationship impacts.

By applying fuzzy ANP to our first model, we have weights for sub-factor and corresponding sum of sub-factor weights for factor weights. We have factors with weights and without any internal loops or feedbacks, which makes us be able to apply DEA method easily without any error caused from internal relationship of factors or feedback from factors.

4.3 Data Envelopment Analysis

After defining and weighting factors, we are able to use these data to evaluate relative flight carbon emission performance for airline companies. To assess efficiency and define the optimum (the best) performed flight(s), we decided to use Data Envelopment Analysis (DEA) method, because of it is widely used and accepted by most of the researchers.

Data envelopment analysis (DEA) first introduced by Charnes et al. (1978). Now their model is also known as CCR model with orientation of constant return to scale (CRS) DEA developed for measuring decision making efficiency with concentrating on decision making units (DMU), which have common input and outputs. Charnes et al. (1978) defined their model based on maximum ratio of weighted outputs to weighted inputs for each DMUs considered to be calculated. In more mathematical form,

$$\max h_0 = \sum_{r=1}^{s} u_r y_{r0} \,/ \sum_{i=1}^{m} v_i x_{i0} \tag{4.12}$$

Subject to:

$$\left(\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}\right) \leq 1 \;\; ; \quad j = 1,2,\dots,n \tag{4.13}$$

$$u_r, v_i \geq 0;\ \ r = 1,2, \dots, s;\ \ j = 1,2, \dots, n \tag{4.14}$$

Where y_{rj}, x_{ij} are positive and known as outputs and inputs of DMU_j, and u_r, v_i are variable weights, which will be calculated by solving the model given in formulation (4.12), (4.13), and (4.14).

Model given in formulations (4.12), (4.13), and (4.14) is nonlinear programming formulation of an ordinary fractional formulation of decision-making efficiency. This formulation can be reduced to linear programming formulation in order to work with large set of DMUs easily. Therefore, Charnes et al. (1978) provides a linear form of DEA, shown in formulations (4.15), (4.16), (4.17), and (4.18).

$$\max f_0 = \sum_{k=1}^{s} v_k y_{kp} \tag{4.15}$$

Subject to:

$$\sum_{j=1}^{m} u_j x_{jp} = 1\ \ ;\ \ \ j = 1,2, \dots, m \tag{4.16}$$

$$\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji}\ \leq 0\ \ ;\ \ \ i = 1,2, \dots, s \tag{4.17}$$

$$v_k, u_j \geq 0;\ \ k = 1,2, \dots, s;\ \ j = 1,2, \dots, n \tag{4.18}$$

Where *p* is the DMU currently calculated, *s* and *m* are the number of outputs and inputs respectively, y_{ki} is the amount of output provided for k^{th} output for DMU_i, and x_{ji} is the amount of input provided for i^{th} input for DMU_j, v_k, u_j are the weight for k^{th} output and i^{th} input respectively.

This model converted to dual form to provide insides about the improvement potential through the efficiency frontier on output inequalities. The dual form of CCR model for input formulation (4.19), (4.20), (4.21), and (4.22) and output formulations (4.23), (4.24), (4.25), and (4.26) orientations given below.

$$\min \theta \tag{4.19}$$

Subject to:

$$\sum_i \lambda_i x_{ji} \leq \theta x_{jp} \;;\quad \forall j \tag{4.20}$$

$$\sum_i \lambda_i y_{ki} \geq y_{kp} \;;\quad \forall k \tag{4.21}$$

$$\lambda_i \geq 0;\ \forall i \tag{4.22}$$

Where θ represents the efficiency value for DMU_p and λ_i is the dual slack variable, which represents the comparative value for inefficiency on outputs.

$$\min \theta \tag{4.23}$$

Subject to:

$$\sum_i \lambda_i x_{ji} \leq x_{jp} \;;\quad \forall j \tag{4.24}$$

$$\sum_i \lambda_i y_{ki} \geq \theta y_{kp} \;;\quad \forall k \tag{4.25}$$

$$\lambda_i \geq 0;\ \forall i \tag{4.26}$$

Where the efficiency calculated by $1/\theta$ because of output orientation.

In their study, Banker et al. (1984) introduced a new DEA model, which later called BCC model. BCC model is, unlike CCR model's constant return to scale (CRS), variable returns to scale (VRS). They proposed more advanced model for CCR model by replacing CCR's concave efficiency frontier with convex efficiency frontier. This change in the model provides precise differences on DMUs efficiency values. BCC also has output and input oriented models.

$$\max \theta \tag{4.27}$$

Subject to:

$$\sum_i \lambda_i x_{ji} \leq x_{jp} \;\; ; \;\; \forall j \tag{4.28}$$

$$\sum_i \lambda_i y_{ki} \geq \theta y_{kp} \;\; ; \;\; \forall k \tag{4.29}$$

$$\sum_i \lambda_i = 1 \tag{4.30}$$

$$\lambda_i \geq 0; \; \forall i \tag{4.31}$$

Where a new constraint for convexity added on formulation (4.30). This model shows output oriented BCC model. The input oriented BCC model given below.

$$\max \theta \tag{4.32}$$

Subject to:

$$\sum_i \lambda_i x_{ji} \leq \theta x_{jp} \;\; ; \;\; \forall j \tag{4.33}$$

$$\sum_i \lambda_i y_{ki} \geq y_{kp} \;\; ; \;\; \forall k \tag{4.34}$$

$$\sum_{i} \lambda_i = 1 \tag{4.35}$$

$$\lambda_i \geq 0;\ \forall i \tag{4.36}$$

Where only theta moved from formulation (4.34) to formulation (4.35) and the efficiency is $1/\theta$.

There is one more model, which is widely used in recent studies, called additive DEA model. The additive DEA model introduced by Charnes et al. (1985) for calculating efficiency based on the calculation of simultaneous distance of input and outputs. The models general form given by Cooper et al. (2007) shown below.

$$\text{Max } Z = es^{-} + es^{+} \tag{4.37}$$

Subject to:

$$\sum_{i} \lambda_i x_{ji} + s_i^{-} = x_{jp} \ ; \quad \forall j \tag{4.38}$$

$$\sum_{i} \lambda_i y_{ki} + s_i^{+} = y_{kp} \ ; \quad \forall k \tag{4.39}$$

$$\sum_{i} \lambda_i = 1 \tag{4.40}$$

$$\lambda_i \geq 0;\ s_i^{-} \geq 0;\ s_i^{+} \geq 0; \quad \forall i \tag{4.41}$$

Where the main goal is to maximize output by minimizing the values of s_i^{-} and s_i^{+} on efficiency frontier.

There are also new DEA models published such as super efficiency model, DEA models with weight restrictions, cross efficiency DEA models, etc. but the usage and coverage of models, which we give above, considered for study because of only these models are suitable for our case.

5. APPLICATION

5.1 Factor Weight Evaluation Using Fuzzy ANP

Using the network model, we give in section 4.2, we constructed our model with linguistic importance scales from our interviews with 12-expert from one of private held Turkish civil aviation company personnel. These experts are from technical maintenance, piloting, and sustainability departments, which are selected among more than 5 years of experienced personnel. Model structure, which we will use in model, is shown in Figure 5.1.

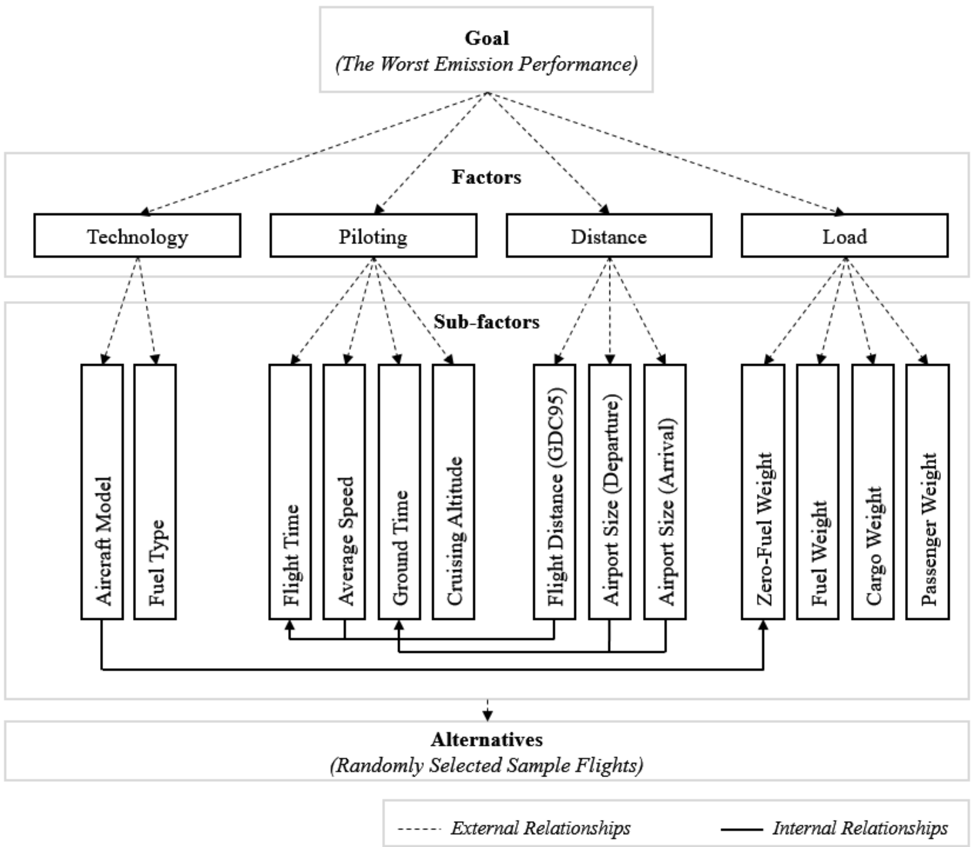

Figure 5.1: Network model of fuzzy ANP for flight emission performance

Using fuzzy triangular numbers and corresponding values in Table 4.1, we have converted expert opinions into numbers. Then, we construct fuzzy comparison matrices for each main factor. These comparison matrices are given in Table 5.2, Table 5.2, Table 5.3, and Table 5.4. Also, the corresponding weights are given under each table.

Table 5.1: Fuzzy pairwise comparisons matrix for main factors.

Factors	Technology			Piloting			Distance			Load		
Technology	1	1	1	0.167	0.2	0.25	0.25	0.33	0.5	0.33	0.5	1
Piloting	4	5	6	1	1	1	3	4	5	5	6	7
Distance	2	3	4	0.2	0.25	0.33	1	1	1	1	2	3
Load	1	2	3	0.143	0.167	0.2	0.33	0.5	1	1	1	1

W = {0.0816; 0.6023; 0.198; 0.1181}

Table 5.2: Fuzzy pairwise comparisons matrix for technology sub-factors.

Factors	Aircraft Type			Fuel Type		
Aircraft Type	1	1	1	3	4	5
Fuel Type	0.2	0.25	0.33	1	1	1

W = {0.664; 0.336}

Table 5.3: Fuzzy pairwise comparisons matrix for piloting sub-factors.

Factors	Flight Time			Average Speed			Ground Time			Altitude		
Flight Time	1	1	1	2	3	4	6	7	8	7	8	9
Average Speed	0.25	0.33	0.5	1	1	1	3	4	5	4	5	6
Ground Time	0.13	0.14	0.17	0.2	0.25	0.33	1	1	1	2	3	4
Cr. Altitude	0.11	0.13	0.14	0.17	0.2	0.25	0.25	0.33	0.5	1	1	1

W = {0,589; 0,266; 0,094; 0,051}

Table 5.4: Fuzzy pairwise comparisons matrix for load sub-factors.

Factors	Zero-Fuel W.			Fuel W.			Cargo Weight			Passenger W.		
Zero-Fuel W.	1	1	1	2	3	4	0.33	0.5	1	0.33	0.5	1
Fuel Weight	0.25	0.33	0.5	1	1	1	0.2	0.25	0.33	0.2	0.25	0.33
Cargo Weight	1	2	3	3	4	5	1	1	1	1	1	1
Passenger W.	1	2	3	3	4	5	1	1	1	1	1	1

W = {0.210; 0.084; 0.353; 0.353}

Inconsistency reports based on four main-factor given in Appendix B., these factors show no inconsistency, as their inconsistency indexes are all 0.00.

These weights evaluated from only insights and we need to check their consistency with real world data. Therefore, we decide to use The Analytic Network Process (ANP) to assess the weights consistency with randomly selected flight data. Our weightings are all in fuzzy and this makes our first model Fuzzy ANP.

Using the fuzzy pairwise comparisons matrices, which we prepared. We construct a model with respect to the given network in Figure 5.1. Solving our network in SuperDecision software we get final weighting matrix of our sub-factors, which is shown in Table 5.5.

Table 5.5: Sub-factor priorities calculated on Super Decision.

Sub-factors	Priorities
Flight Time	0.408
Average Speed	0.110
Flight Distance (GCD95)	0.109
Ground Time	0.066
Fuel Weight	0.061
Cargo Weight	0.057
Zero-Fuel Weight	0.054
Aircraft Type	0.037
Passenger Weight	0.029
Cruising Altitude	0.021

Fuel Type	0.019
Airport (Arrival)	0.014
Airport (Departure)	0.014

5.2 Data Preparation for Efficiency Analysis with DEA

A flight contains six parts, which are taxi, takeoff, climb, cruise, descent, and landing. Taxi is the part, which a plane disconnected from auxiliary power unit (APU) to take off. Take off is the part, which plane cut off its connection with ground. Climb is the part, which plane gains altitude. Cruise is the part, which plane carry on its path with fixed altitude. Descent is the part, which plane loses altitude and eventually reach the runway, the part, which starts with reaching the runway to park position named landing. These phases of a flight are visualized in Figure 5.2.

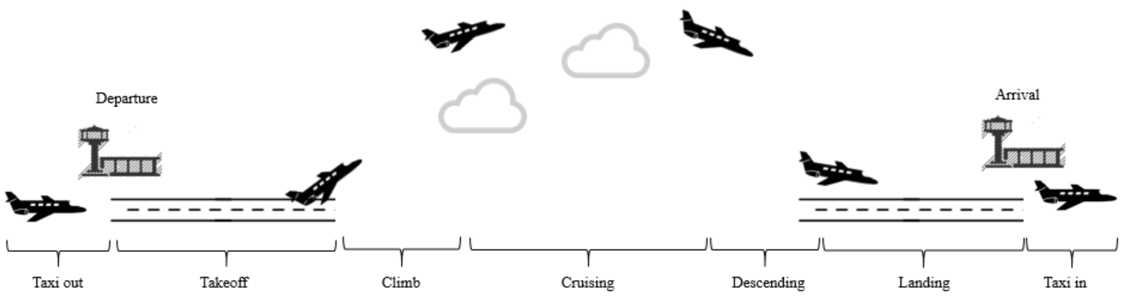

Figure 5.2: Phases of a flight

The purpose of a flight is to transport matter from a place to a place. Therefore, the desired output is the tons*km and undesired outputs are emission, noise, heat. The inputs of a flight, to achieve desired transportation, are fuel, piloting and load. However, there are factors affecting the amount of undesired outputs. We define these factors as aircraft technology, fuel type, cruising altitude, average speed, ground time and flight time. An airline company needs to detect emission performance abnormalities in their flights to make its flights more fuel and emission efficient. Therefore, an airline company needs to evaluate all of its flights for a period and decide flights' performance with respect to the factors mentioned in previous paragraph.

In this part of our study, we use a dataset of randomly selected 10,000 flights from a list of 178,000 flights, which occurred in year 2017, of a Turkish privately held commercial airline company. In the dataset, we have flight number, departure airport, arrival airport, fuel type, aircraft type, fuel load, total fuel burned, passenger load, cargo load, flight distance, ground time, flight time, and projected emission amount.

First, we have to gather some of missing data such as cruising altitude, airport sizes. Therefore, we extracted these data from flight tracking websites and airport websites. We used the flight number to find out the average cruising altitudes, and then we find annual passenger traffic and number of active runways of each airport in our study to rank airports for their business. To calculate the airport numerical values, which shown in Appendix A., we use the ratio of total number of annual passengers to number of runways, and then we take the maximum value and divide all other values to this maximum to find the percentage of weight.
After we construct our dataset with numerical values, we normalized our raw data columns in order to work with consistent data. Normalizer value X_i for each column (i indicates the column index) calculated using formulation (5.1). For each element of raw data set, c_{ij}^* normalized value calculated using formulation (5.2).

$$X_i = \sqrt{\sum_j c_{ij}^2} \tag{5.1}$$

$$c_{ij}^* = \left(\frac{c_{ij}}{x_i}\right); \quad \forall i; \quad \forall j \tag{5.2}$$

5.3 Calculating Carbon Efficiency Scores for Flights Using DEA

We give factors affecting a flight's emission performance in Figure 5.1 and factor weights in Table 5.5. Because of computational limitations and coverage of main factors consistent on sub-factors. In our model, we consider 4 main factors as inputs and carbon emission as output. Using weights of thirteen sub-factors, which are given in Table 5.5, we calculate the numerical values of four main factors shown in Table 5.6 as relative weights.

Table 5.6: Main factor relative weights based on sub-factor priorities

Main Factors	Relative Weights	Sub-factors	Priorities
Technology (X_1)	0.056	Aircraft Type	0.037
		Fuel Type	0.019
Piloting (X_2)	0.605	Flight Time	0.408
		Ground Time	0.066
		Average Speed	0.110
		Cruising Altitude	0.021
Distance (X_3)	0.137	Flight Distance (GCD95)	0.109
		Airport (Arrival)	0.014
		Airport (Departure)	0.014
Load (X_4)	0.201	Fuel Weight	0.061
		Cargo Weight	0.057
		Zero-Fuel Weight	0.054
		Passenger Weight	0.029

Using only four main factors provides us faster results with less computational power. However, it might cause small errors, which will not affect the overall results, for our efficiency results.

According to Table 5.6, the result of fuzzy ANP study, emission performance inputs X_i weights are as follows 60.5% piloting, 20.1% load, 13.7% distance, and 5.6% technology factors related. These values considered as DEA weight limitations in this study. The output for our DEA model is total released carbon emission in kilograms Y. Our DEA model for relative carbon emission performance of flights has four input and one output.

We construct an input oriented CCR, an output oriented BCC and an additive DEA model for this study and tested our models with empirical data, which we created from a real flight dataset. The results and details of this application are given in section 5.4.

Randomly selected 10,000 flights data among a Turkish commercial airline company's more than 178,000 flights, which occurred in 2017. The raw data has 13 sub-factors, total estimated emission amount with, and a unique identifier as flight numbers. Two of these 13 sub-factors, which are short codes airports, are linguistic. Therefore, we used the weights in Table 5.6 to calculate the aggregate factors.

After provide the numeric values for all sub-factors and main factors. We put data into a *.csv file and upload it on R Software. The benchmarking library of R Software provides functions for solving CCR, BCC, and additive models with respect to input or output orientation.
R benchmarking library's *dea()* function, which is shown in formulation (5.3), estimates the DEA efficiency frontier and calculates efficiency measures for all DMUs. This functions usage given below.[11]

```
dea(X, Y, RTS="vrs", ORIENTATION="in", XREF=NULL, YREF=NULL, FRONT.IDX=NULL,
SLACK=FALSE, DUAL=FALSE, DIRECT=NULL, param=NULL, TRANSPOSE=FALSE,
FAST=FALSE, LP=FALSE, CONTROL=NULL, LPK=NULL)
```
(5.3)

Where *X* is the inputs. *Y* is the outputs. *RTS* is the selection for returns to scale type. *ORIENTATION* is solution orientation it can be input (in), output (out), or graph efficiency (graph). *XREF* and *YREF* are defaults to *X* and *Y*. *FRONT.IDX* is the index to determine methodology. *SLACK* activates the slack calculations. *DUAL* calculates the dual variables and *DIRECT* is the directional efficiency. The *param* parameter used for additional parameters and the other parameters used for debugging purposes.

[11] https://cran.r-project.org/web/packages/Benchmarking/Benchmarking.pdf

5.4 Results and Discussions

Using R software, we tested our models with 10,000 rows of data. Some remarks from the results of input oriented CCR DEA model given in Table 5.8, Table 5.9, and Figure 5.3. Some remarks from the results of output oriented BCC DEA model given in Table 5.10, Table 5.11, and Figure 5.4. The results of additive DEA model do not show any indicator of efficiency performance because all the efficiency score are calculated 100%, for this reason we are not including additive DEA model into our case study.

The results for top and bottom 10 showed in tables below, also distribution of efficiency scores shown as scatter diagram. The quartiles for CCR and BCC models computational results given in Table 5.7.

Table 5.7: Quartiles for CCR and BCC models' computational results

Quartile	CCR (Input)	BCC (Output)
Q1	64%	74%
Q2	69%	79%
Q3	75%	83%

In Table 5.7, the quartiles for BCC model are approximately 10% higher than quartiles for CCR model and in the efficiency results for 10,000 rows; we have 68 rows of flights, which have less than 50% efficiency score, for CCR model and 3 rows of flights for BCC model. These results indicate that the BCC model tends to give higher efficiency scores than the CCR model.

The biggest differences on efficiency scores between CCR and BCC models computational results given in Table 5.7, and more than 75% percent of the efficiency score results have less than 15% difference.

Computational results in Table 5.8, Table 5.9, Table 5.10 and Table 5.11 indicates that CCR and BCC models to find relative efficiency scores on sub-factors and each other are better ways to measure carbon emission performance.

In Table 5.8 and Table 5.10, computational results for top ten best-performed flights for input oriented CCR and output oriented BCC models shown. Results similar with last three flights different on the list, these differences occurred because BCC model's lack of sensitivity on slight differences. BCC model's results are always tending to be higher than CCR model's results.

In Table 5.9 and Table 5.11, computational results for top ten worst performed flights for input oriented CCR and output oriented BCC models shown. Only three of the results different, when we compare the results of BCC and CCR models' computational results.

Both of the results discussed above have 70% similarity on selection of best and worst performed flights. However, CCR model's results are tend to be in more detail for detecting improvement potential. In the computational results, relationship of main factors calculated and used as inputs. Hence, the result is dependent with these four main factors. In our case, technology factor only changes for aircraft type new or old technology. Other three factors mostly fluctuated, and this makes us hard to see the potential cause of worst emission performance. Another situation for our case is BCC model fails when one or more factors are equal or near zero value. Because of this fail, we seen some big differences such as shown in Table 5.12.

Table 5.8: Top 10 best performed flights efficiency scores in CCR results

Plane Type	Fuel Type	Flight Time (min.)	Average Speed (kmh)	Ground Time (min.)	Cruising Altitude (km)	Flight Distance (GCD95) (km)	Airport Dep.	Airport Arrv.	Zero Fuel Weight (Kg)	Fuel Weight (Kg)	Cargo Weight (Kg)	Passenger Weight (Kg)	Emission (Kg)	Emis. Per Ton*Km	Efficiency (CCR - CRS)	Efficiency (BCC - VRS)
B737	A1	197	802	13	12019	2635	2.20	0.65	41145	11760	1583	11870	25704	0.147	100.00%	100.00%
A320	A1	156	816	17	10737	2124	10.3	2.25	42600	9740	3044	11115	21105	0.149	100.00%	100.00%
B737	A1	204	739	14	11178	2515	0.65	10.32	41145	12310	2600	10660	27216	0.162	100.00%	100.00%
B737	A1	59	783	12	10293	770	2.25	0.42	41145	9180	1646	12720	9292	0.186	100.00%	100.00%
B737	A1	93	774	14	11168	1201	10.25	2.25	41145	8370	2072	12405	14710	0.191	100.00%	100.00%
A320	A1	47	667	27	12470	523	2.25	0.07	42600	7140	1179	10385	6867	0.214	100.00%	100.00%
B737	A1	72	629	22	10831	755	0.65	10.25	41145	5810	0	13385	10458	0.229	100.00%	100.00%
A320	A1	69	669	11	12422	770	0.42	2.25	42600	7520	1168	11880	9828	0.202	99.86%	99.86%
A320	A1	57	461	47	10729	438	2.25	0.89	42600	5420	1430	11660	8442	0.315	99.81%	99.81%
A320	A1	177	793	16	12074	2340	57.09	2.25	42600	10420	4501	12615	21105	0.128	99.66%	99.66%

Table 5.9: Bottom 10 worst performed flights efficiency scores in CCR results

Plane Type	Fuel Type	Flight Time (min.)	Average Speed (kmh)	Ground Time (min.)	Cruising Altitude (km)	Flight Distance (GCD95) (km)	Airport Dep.	Airport Arrv.	Zero Fuel Weight (Kg)	Fuel Weight (Kg)	Cargo Weight (Kg)	Passenger Weight (Kg)	Emission (Kg)	Emis. Per Ton*Km	Efficiency (CCR - CRS)	Efficiency (BCC - VRS)
B737	A1	202	775	10	10948	2612	21.58	2.25	41145	11740	3463	13735	27688	0.151	30.56%	44.86%
B737	A1	74	750	12	12628	926	2.25	0.20	41145	10500	945	13235	11277	0.185	35.03%	48.52%
B737	A1	47	559	12	10728	438	0.89	2.25	41145	7800	822	13775	7686	0.276	36.74%	49.63%
B737	A1	42	597	14	11258	418	1.29	2.25	41145	4620	1337	13035	5922	0.235	38.39%	56.36%
B737	A1	49	682	14	10993	557	2.25	0.65	41145	5330	0	0	7087	0.273	40.32%	74.21%
A320	A1	47	711	14	12648	557	2.25	0.65	42600	4700	1612	12030	7245	0.213	42.87%	55.89%
A320	A1	225	696	28	10345	2612	2.25	21.58	42600	12300	1275	6480	28413	0.173	43.88%	55.65%
B737	A1	65	766	9	12503	830	2.25	0.41	41145	8550	2791	12530	9670	0.179	44.18%	57.67%
B737	A1	86	850	13	11163	1219	0.89	0.26	41145	8400	1512	13865	12379	0.156	44.52%	51.09%
B737	A1	77	893	16	11408	1147	2.25	6.85	41145	7440	4822	10755	11497	0.156	44.72%	55.99%

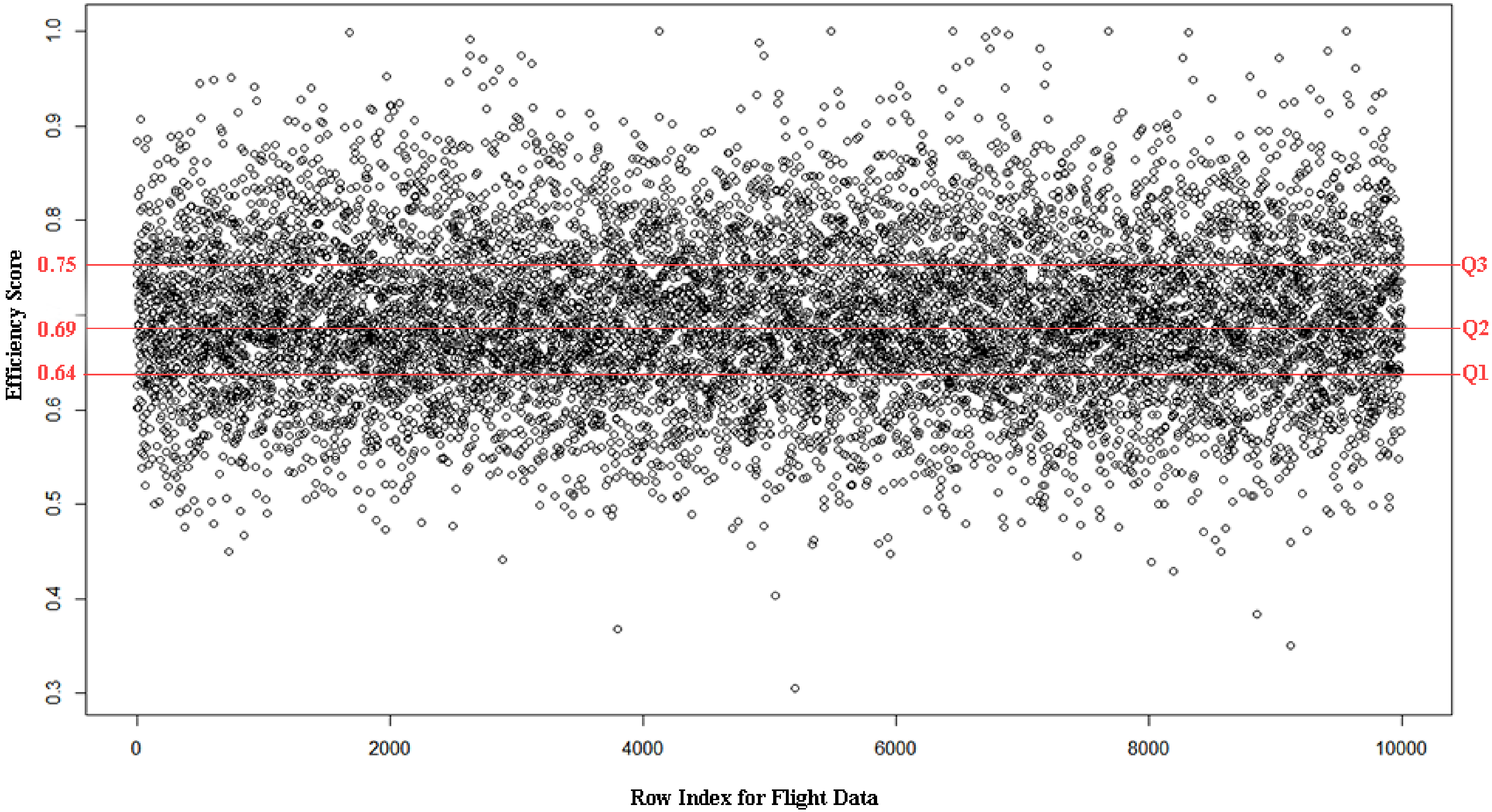

Figure 5.3: Input oriented CCR (CRS) model efficiency score results for 10,000 flights on scatter diagram

Table 5.10: Top 10 best performed flights efficiency scores in BCC results

Plane Type	Fuel Type	Flight Time (min.)	Average Speed (kmh)	Ground Time (min.)	Cruising Altitude (km)	Flight Distance (GCD95) (km)	Airport Dep.	Airport Arrv.	Zero Fuel Weight (Kg)	Fuel Weight (Kg)	Cargo Weight (Kg)	Passenger Weight (Kg)	Emission (Kg)	Emis. Per Ton*Km	Efficiency (CCR - CRS)	Efficiency (BCC - VRS)
B737	A1	197	802	13	12019	2635	2.20	0.65	41145	11760	1583	11870	25704	0.147	100.00%	100.00%
A320	A1	156	816	17	10737	2124	10.3	2.25	42600	9740	3044	11115	21105	0.149	100.00%	100.00%
B737	A1	204	739	14	11178	2515	0.65	10.32	41145	12310	2600	10660	27216	0.162	100.00%	100.00%
B737	A1	59	783	12	10293	770	2.25	0.42	41145	9180	1646	12720	9292	0.186	100.00%	100.00%
B737	A1	93	774	14	11168	1201	10.25	2.25	41145	8370	2072	12405	14710	0.191	100.00%	100.00%
A320	A1	47	667	27	12470	523	2.25	0.07	42600	7140	1179	10385	6867	0.214	100.00%	100.00%
B737	A1	72	629	22	10831	755	0.65	10.25	41145	5810	0	13385	10458	0.229	100.00%	100.00%
B737	A1	52	642	15	11347	557	0.65	2.25	41145	6200	1400	12965	7969	0.231	99.33%	100.00%
B737	A1	53	734	14	11996	649	1.29	0.41	41145	6030	0	0	7654	0.250	94.73%	100.00%
B737	A1	45	700	10	11182	525	0.09	2.25	41145	5230	1820	11830	6741	0.213	93.61%	100.00%

Table 5.11: Bottom 10 worst performed flights efficiency scores in BCC results

Plane Type	Fuel Type	Flight Time (min.)	Average Speed (kmh)	Ground Time (min.)	Cruising Altitude (km)	Flight Distance (GCD95) (km)	Airport Dep.	Airport Arrv.	Zero Fuel Weight (Kg)	Fuel Weight (Kg)	Cargo Weight (Kg)	Passenger Weight (Kg)	Emission (Kg)	Emis. Per Ton*Km	Efficiency (CCR - CRS)	Efficiency (BCC - VRS)
B737	A1	202	775	10	10948	2612	21.58	2.25	41145	11740	3463	13735	27688	0.151	30.56%	44.86%
B737	A1	74	750	12	12628	926	2.25	0.20	41145	10500	945	13235	11277	0.185	35.03%	48.52%
B737	A1	47	559	12	10728	438	0.89	2.25	41145	7800	822	13775	7686	0.276	36.74%	49.63%
B737	A1	86	850	13	11163	1219	0.89	0.26	41145	8400	1512	13865	12379	0.156	44.52%	51.09%
B737	A1	64	717	18	11093	765	0.15	1.29	41145	5520	1089	10715	9576	0.214	47.55%	51.98%
B737	A1	67	743	11	10652	830	2.25	0.41	41145	6920	1408	12675	9355	0.181	50.32%	52.04%
B737	A1	200	783	24	11627	2612	21.58	2.25	41145	11240	1318	9200	25483	0.155	47.05%	53.60%
A320	A1	225	696	28	10345	2612	2.25	21.58	42600	12300	1275	6480	28413	0.173	43.88%	55.65%
A320	A1	47	711	14	12648	557	2.25	0.65	42600	4700	1612	12030	7245	0.213	42.87%	55.89%
B737	A1	77	893	16	11408	1147	2.25	6.85	41145	7440	4822	10755	11497	0.156	44.72%	55.99%

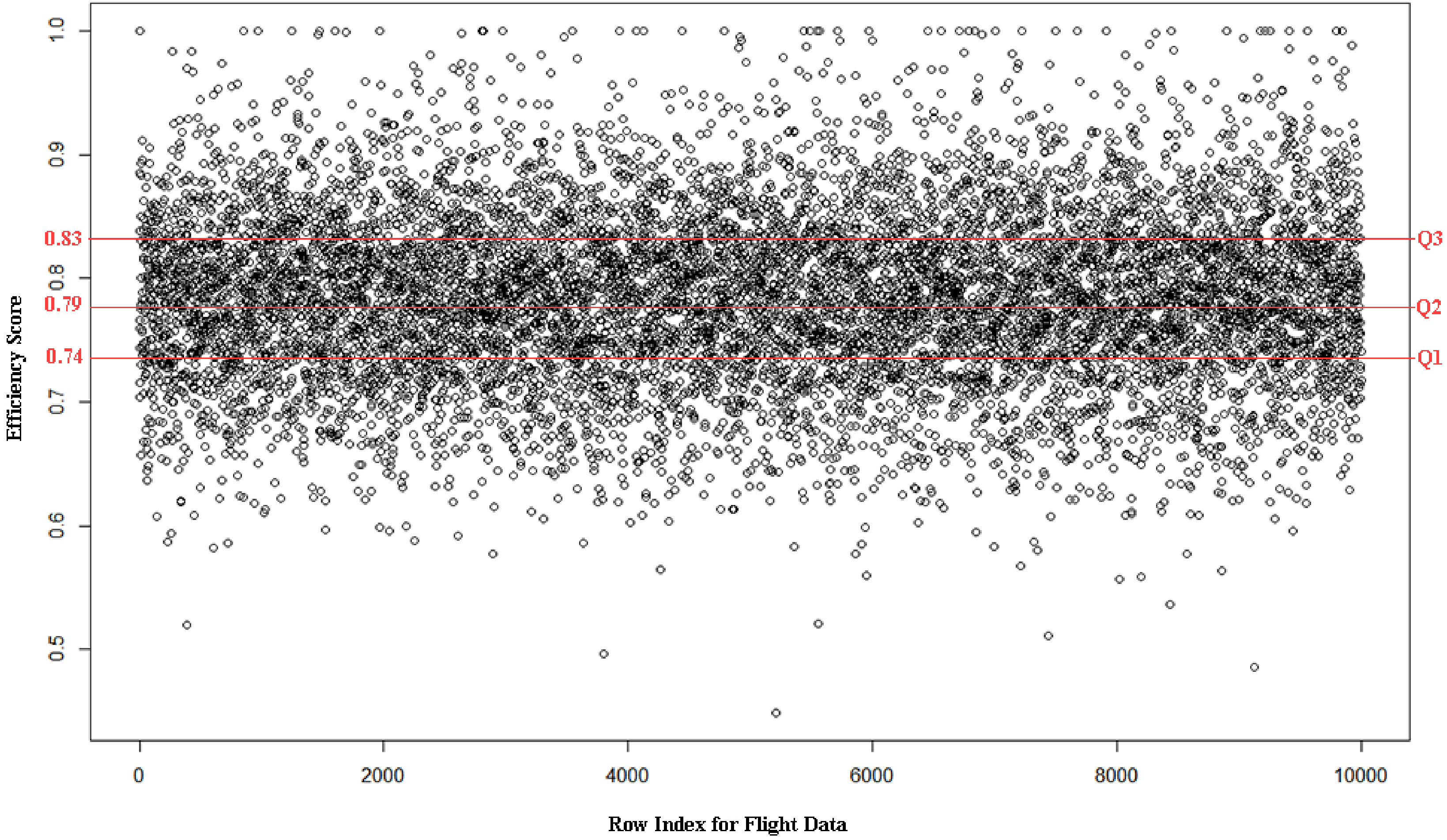

Figure 5.4: Output oriented BCC (VRS) model efficiency score results for 10,000 flights on scatter diagram

Table 5.12: The most differentiated 10 flights on CCR and BCC efficiency score computational results

Plane Type	Fuel Type	Flight Time (min.)	Average Speed (kmh)	Ground Time (min.)	Cruising Altitude (km)	Flight Distance (GCD95) (km)	Airport Dep.	Airport Arrv.	Zero Fuel Weight (Kg)	Fuel Weight (Kg)	Cargo Weight (Kg)	Passenger Weight (Kg)	Emission (Kg)	Emis. Per Ton*Km	Efficiency (CCR - CRS)	Efficiency (BCC - VRS)	CCR-BCC Difference
B737	A1	66	688	10	12097	757	0.41	0.89	41145	6280	0	0	8631	0.240	46.69%	100.00%	53.31%
B737	A1	47	688	15	12111	539	1.29	0.00	41145	7220	778	11240	7024	0.215	51.07%	100.00%	48.93%
A320	A1	40	787	13	12570	525	0.09	2.25	42600	7080	0	0	4977	0.190	53.34%	100.00%	46.66%
B737	A1	147	772	21	11236	1892	2.25	9.13	41145	9780	3237	13035	21105	0.166	54.10%	99.20%	45.10%
B737	A1	178	784	27	11149	2326	2.25	22.1	41145	11890	3582	12615	27058	0.168	55.86%	100.00%	44.14%
B737	A1	87	762	24	10959	1106	2.25	0.11	41145	7530	1317	12425	12537	0.181	56.14%	100.00%	43.86%
A320	A1	136	713	17	11867	1617	2.25	6.83	42600	7220	2639	9725	15435	0.153	56.26%	100.00%	43.74%
B737	A1	59	533	9	10451	525	0.09	2.25	41145	5200	1254	13730	8694	0.270	54.49%	96.56%	42.07%
B737	A1	41	623	18	11913	426	0.89	4.37	41145	7000	0	0	6394	0.311	53.65%	94.87%	41.22%
B737	A1	67	737	10	10208	824	0.89	0.42	41145	8900	952	11135	10174	0.198	58.86%	100.00%	41.14%

6. MANAGERIAL INSIGHTS

6.1 Current State of Agencies and Governments on Carbon Emission Mitigation

Direct emissions caused by aviation industry is 3% of the European Union's total greenhouse gases emissions and more than 2% of total global greenhouse gases emissions[12]. According to ICAO's latest reports forecasted international aviation CO2 emissions value will increase by 250% to 450% reference to year 2018. [13]

Since The Kyoto Protocol entered into force in 2005, governments and authorities are developing new systems to mitigate GHG emissions in their territories. European Union launched EU Emission Trading System (EU ETS) in 2005 and included aviation into this system in 2012. International Civil Aviation Organization (ICAO) introduced a new system Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) in January 2018. The main objective of these systems are to mitigate GHG emission.

In 2017, civil aviation, as a whole, emitted around 859 million tons of CO2, which is roughly 2% of fabricated carbon emission in whole the world. ICAO forecasted commercial aviation growth for the next 10-year, 20-year, and 30-year as 4.4%, 4.3%, and 4.2% for yearly average.[14] Figure 6.1 shows the forecasts made by ICAO.[15]

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[12] European Commission, https://ec.europa.eu/clima/policies/transport/aviation_en

[13] [11] [12] https://www.icao.int/Meetings/EnvironmentalWorkshops/Documents/Env-Seminars-Lima-Mexico/Mexico/08_UnitedStates_EnvironmentTrends.pdf

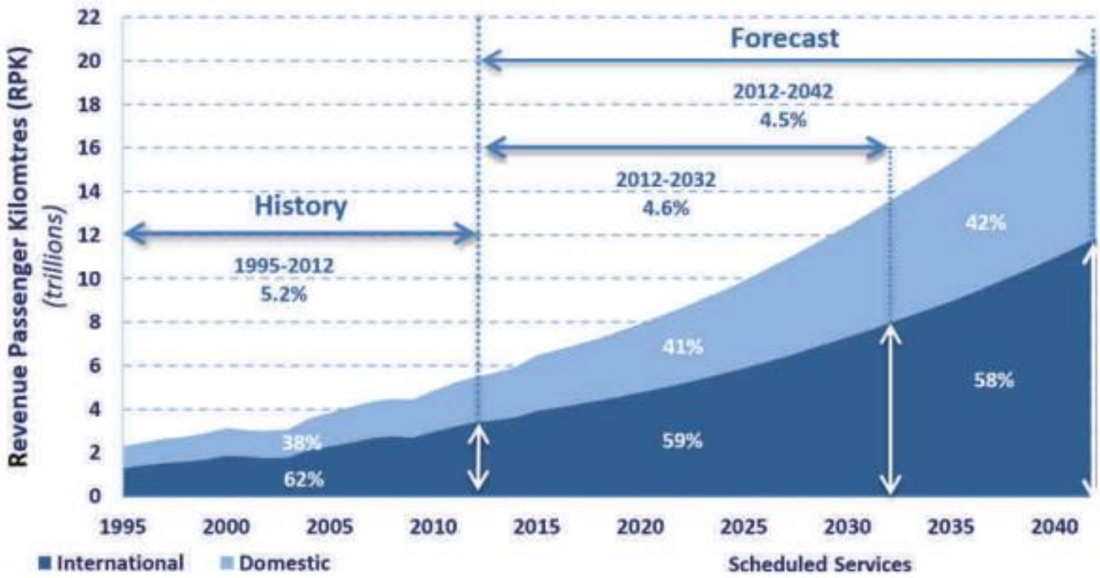

Figure 6.1: Total passenger traffic: history and forecasts[16]

The EU Emissions Trading System (EU ETS) is a ‘cap and trade’ system. It caps the total volume of greenhouse gases emissions from installations and aircraft operators responsible for around 50% of EU greenhouse gases emissions. The system allows trading of emission allowances so that the total emissions of the installations and aircraft operators stays within the cap and the least-cost measures can be taken up to reduce emissions[17] as shown in Figure 6.2.

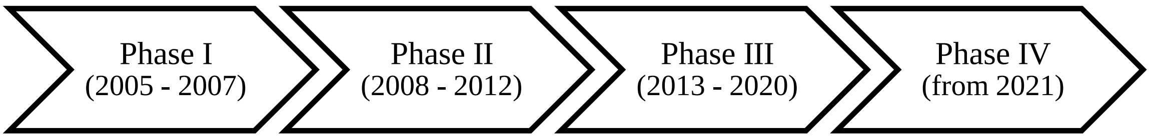

Figure 6.2: Phases of EU ETS Development

In the first phase, commission constructed the price formation in the emission trading market and monitoring, reporting and verification of emissions models. In the second

[16] *www.icao.int/Meetings/aviationdataseminar/Documents/ICAO-Long-Term-Traffic-Forecasts-July-2016.pdf*

[17] *https://ec.europa.eu/clima/sites/clima/files/docs/ets_handbook_en.pdf*

phase, commission apply the rules and limitations to comply with Kyoto promised emission reduction numbers. In the phase three, four, and beyond, commission will extend the coverage of ETS into different industries and its foreign suppliers.

ICAO's Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) covers more than 87% of international aviation operations with 73 states/countries to participate in the pilot phase as June 2018[18] as shown in Figure 6.3.

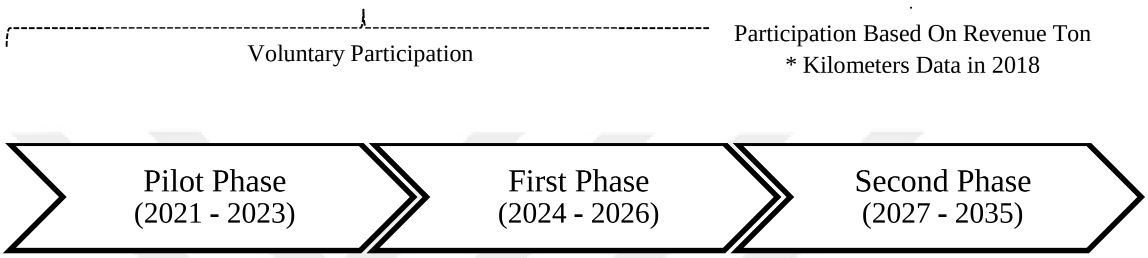

Figure 6.3: Phases of CORSIA Development[19]

Considering accelerating climate change and increasing global effort to reduce emissions towards net-zero levels in the second half of this century, it is likely that future carbon emissions will be subject to some form of 'penalty' (Becken & Shuker, 2019).

CORSIA and EU ETS use constants to convert burned fuel into carbon emission such as ICAO accepts this constant as 3.16 kg CO2 per a kg of Jet A1 fuel. They also use CO2 emission per carrying a ton of load for a kilometer as main performance indicator. EU ETS only concerned with emitted CO2 amount rather than reduction actions or improvement operation, they just give annual limited amount and charge the excessive amount. On the other hand, CORSIA includes sustainable fuel usage, and improvement activities into their CO2 emission calculator.[20]

[18] [16] Introduction to CORSIA, https://www.icao.int

[20] https://blog.openairlines.com/corsia-how-to-monitoring-reporting

6.2 Recommendation to Agencies and Governments for Improving Their Carbon Emission Mitigation Activities

Most of the aviation companies started their carbon emission mitigation activities just after regulations, such as; EU ETS and CORSIA published. Therefore, at first governments and local aviation agencies should prepare plans to mitigate their territories carbon emission.

In our case we only studied aviation as a pollutant industry and propose a model for aviation companies to assess their flights emission performance indoor, but this study might be used in other areas with different factors.

Currently most of the airline companies using carbon emission amount per each tone * kilometer for their emission performance measurement, but this indicator only shows them how much they are polluting the air and there is no insight about what to improve or which factor they should focus on. Our model considers 4 main- and 13 sub-factors when it is used to evaluate emission performance. Due to the nature of DEA method it also gives improvement potential on each factor.

Using our model any organization can easily set a strategic goal and follow up this goal. For example, in our case study with 10,000 rows of data we found that there are opportunities on average speed optimization, taxi process improvement, and cargo weight optimization improvements.

7. CONCLUSION

Governments and international agencies are working to enact for preventing global warming. Aviation is one the major players of global air polluters. Therefore, aviation companies need to act quickly to adapt these early released of programs and systems such as EU ETS, CORSIA, etc.

The subject such as carbon emission, carbon footprint, etc. are quite new to aviation sector, it come to the aviation's agenda with EU ETS started to charge excessive amount of carbon emission in 2012. Some researchers introduced the emission limitation activities, which have been carried out by governments and global agencies, and others studied on overall aviation carbon emission performance for countries or aviation companies.

Besides all these improvements on aviation and carbon emission, no one studied carbon emission for aviation companies to decide 'what to improve?' and 'where to focus?' Our approach provides a solution to assessing flights for carbon emission improvement. Therefore, with the help of aviation industry factors in this study can be improved and adapted by an improvement assessment tool.

In this thesis, the relationship in aviation industry and carbon emission subjects is discussed. Expert opinions gathered for determining factors, which affects carbon emission of a flight. Thirteen sub and four main factors found and ranked by 12 aviation experts to find weights of factors using fuzzy ANP. After this study, models for calculation of relational flight emission performance scores, constructed via CCR and BCC models from literature.

Computation results from R Software of these models given in section 5 show significant difference from emission performance index accepted by global aviation, which is commonly used as carbon emission amount per a ton through a kilometer. This index tells us how much a flight emits to carry a ton of load for just a kilometer. However, calculation such as this one will not directly give us where we have a potential to improve our carbon emission performance. Therefore, we need to use advanced methods to describe improvement opportunities for sustainable flights.

Using thirteen sub-factors to calculate four main factors as technology, piloting, load and distance factors makes our computation faster, but if one wants to test our weight results, which we used to calculate main factors values, may use sub-factors as inputs to this model.

In computational results, one may find out the emission performance improvement potentials, which emission performance calculation with input oriented CCR (CRS) and output oriented BCC (VRS) models. In detail, quartile analysis and computation details indicates that BCC model has lower significance level and worse than CCR model on showing slight differences.

In Table 5.8 and Table 5.10, computational results for top ten best-performed flights for input oriented CCR and output oriented BCC models shown. Results similar with last three flights different on the list, these differences occurred because BCC model's lack of sensitivity on slight differences. BCC model's results are always tending to be higher than CCR model's results.

This thesis contributes to the literature by filling gap on flight based carbon emission performance calculation for decision makers using inner and outer flight related factors such as airport sizes, ground time, cargo weight, etc. Data preparation and model usage methods are useful for aviation companies' environmental responsible personnel to define improvement potential for a past flight or a route and investigate detected flights in detail to find abnormalities.

There are parameters like average tail wind, taxi distance travelled, and time for idle run of engines that could be considered in this study however we did not use because the lack of data on these matters. This issue is the main limitation of this study.

Further researches should focus on expanding factors and their data gathering methods, and should use other DEA methods like super-efficient DEA model to handle vast amount data and provide insights for big aviation companies or multiple year data of mid-range aviation companies.

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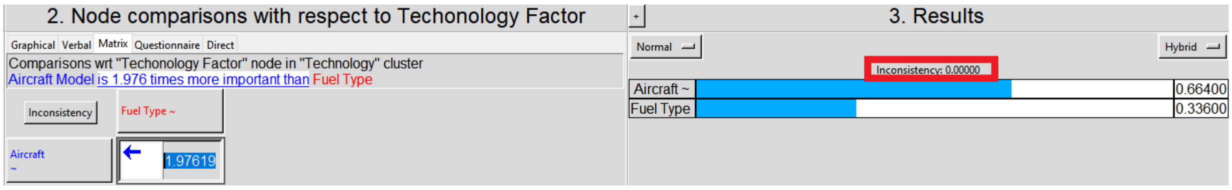
APPENDICES

Appendix A. Relative weights of airports for ground delay effects

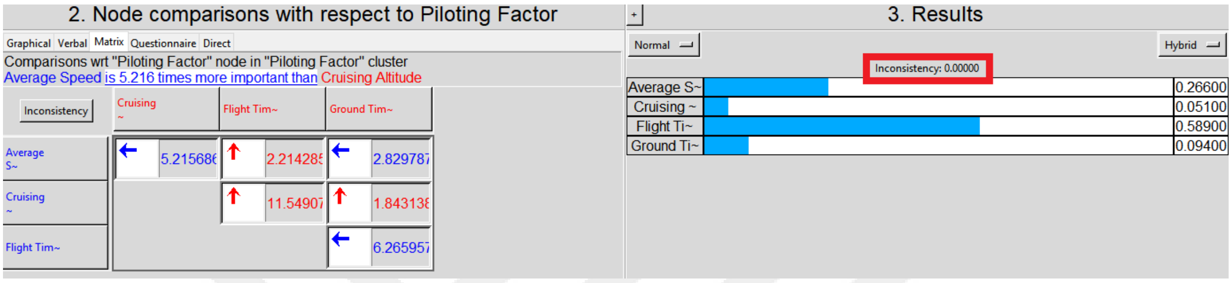
Code	Weight	Code	Weight	Code	Weight	Code	Weight	Code	Weight	Code	Weight
DOH	100,00	VIE	20,33	BAH	7,31	KUF	2,21	AYT	0,66	EZS	0,08
NAP	82,78	ATH	18,11	BEY	6,86	TLL	2,21	SYZ	0,64	KYA	0,07
DXB	73,50	GVA	14,75	BLQ	6,83	LEJ	2,14	LWO	0,50	GNY	0,07
AMS	57,10	HAM	14,69	AMM	6,60	BRE	2,12	ADA	0,42	MLX	0,07
FRA	53,75	XFW	14,36	CDG	6,58	EBL	1,75	ECN	0,42	DLM	0,06
MED	53,08	CAI	13,30	BSL	6,57	MRV	1,63	KZR	0,42	MQM	0,05
MAD	44,50	PRG	12,85	CRL	6,42	TBZ	1,62	GRV	0,42	BAL	0,05
LGW	37,96	BGW	12,50	KHI	5,58	LIL	1,59	PAD	0,42	DNZ	0,05
MUC	37,15	KWI	11,42	SOF	5,41	PRN	1,57	ERF	0,42	KSY	0,05
FCO	34,14	BUD	10,91	HAJ	4,89	SKP	1,56	EBU	0,42	MSR	0,04
JED	28,33	HRG	10,83	ALA	4,70	RTM	1,54	BCM	0,37	VAS	0,04
ORY	26,70	SXF	10,72	NTE	4,57	SSH	1,46	SCN	0,33	ERC	0,03
BCN	26,67	OTP	10,67	BEG	4,45	DRS	1,42	OZH	0,29	GZP	0,03
DME	25,58	KBP	10,50	IST	4,37	ESB	1,29	TZX	0,27	ADF	0,02
ZRH	24,50	CGN	10,32	VNO	4,33	FRU	1,28	GZT	0,21	KCM	0,02
CPH	24,31	BGY	10,28	OVB	4,17	VAN	1,10	DIY	0,16	EDO	0,02
MAN	23,14	TLV	10,25	TSE	3,58	SNN	1,09	ASR	0,14	YEI	0,02
OSL	22,90	SHJ	9,50	NUE	3,49	ODS	1,03	SZF	0,12	NAV	0,02
ARN	22,19	LYS	9,20	KRR	2,92	ADB	0,90	IEV	0,12	MZH	0,02
STN	21,59	STR	9,14	TBS	2,54	VOG	0,83	ERZ	0,12	BGG	0,02
BRU	20,65	VCE	8,64	TIA	2,46	GOJ	0,81	CLJ	0,10	NOP	0,01
MXP	20,60	TLS	7,72	ABA	2,34	FMO	0,80	HTY	0,09	TEQ	0,01
DUS	20,53	MRS	7,50	IFN	2,32	SJJ	0,80	BJV	0,09	ISE	0,01
AUH	20,40	IKA	7,38	SAW	2,25	HRK	0,67	OGU	0,08	KFS	0,01

Appendix B.

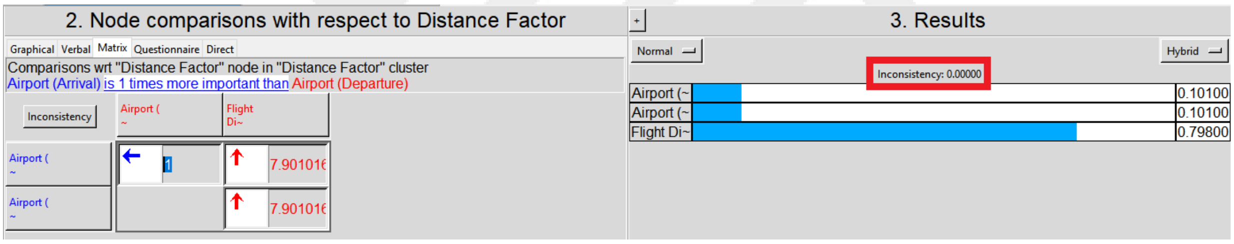
Technology main factor inconsistency report



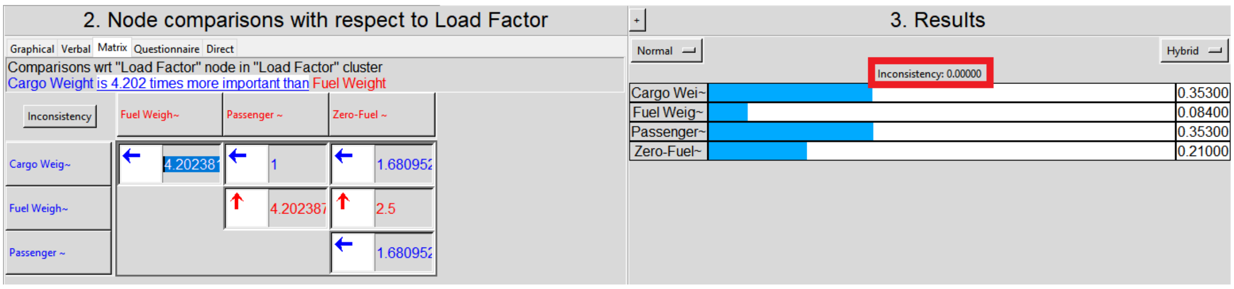
Piloting main factor inconsistency report



Distance main factor inconsistency report



Load main factor inconsistency report



BIOGRAPHICAL SKETCH

Furkan AYDOGAN was born in Istanbul on November 7, 1987. He graduated from University of Gaziantep with Industrial Engineering Bachelor Degree in August 2012. He worked as Quality and Process Development Engineer at Metro Istanbul between 2013 and 2016. He worked as Management Consultant at Consulta Management Consultancy between 2016 and 2018. He worked Business Excellence Senior Engineer at Pegasus Airlines in 2018. He is working as Process Management Senior Specialist at Vodafone Turkey since November 2018. He is studying master's degree on Logistics and Financial Management field, and writing this graduation thesis under supervision of Assist. Prof. Dr. İlke Bereketli ZAFEİRAKOPOULOS at Institute of Science and Engineering Galatasaray University. He and Assist. Prof. Dr. İlke Bereketli ZAFEİRAKOPOULOS prepared a paper with the title of '*Leg Base Airline Flight Carbon Emission Performance Assessment Using Fuzzy ANP*', which they receive an acceptance from INFUS 2019 conference.