IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF AIR TRANSPORT MANAGEMENT

MASTER THESIS

FORECASTING GLOBAL CIVIL AIRCRAFT IN-SERVICE AND OTHER PARAMETERS IN COMMERCIAL AEROSPACE

YUSUF YÖRELİ

THESIS SUPERVISOR

PROF. MUSTAFA KEMAL YILMAZ

ISTANBUL, 2021

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by
YUSUF YÖRELİ

A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of Master of Science in Air Transport Management

THESIS SUPERVISOR

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ISTANBUL, 2021

APPROVAL PAGE

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science in Air Transport Management.

Thesis Jury Members

Title - Name Surname	Opinion	Signature

This is to confirm that this thesis complies with all the standards set by the School of Graduate Studies of Ibn Haldun University.

Date of Submission Seal/Signature

ACADEMIC HONESTY ATTESTATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ÖZ

SİVİL HAVACILIKTA UÇAK SAYILARININ VE DİĞER PARAMETRELERİN TAHMİNİ

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Eylül 2021, 47 sayfa

Bu çalışmada, havacılık ekosisteminde yer alan şirketlerin uzun vadede stratejik olarak pozisyon alabilmeleri için sivil yolcu uçağı sayıları ile arz edilen koltuk kilometre (ASK) ve ücretli yolcu kilometre (RPK) parametrelerine ilişkin 20 yıllık tahminler yapılmıştır. Bu tahminler için geçmişe dönük 20 yıllık veriler kullanılmış ve Tableau Software yazılımının tahmin özelliği ile elde edilen sonuçlar Boeing, Airbus gibi şirketlerin tahminleri ile karşılaştırılmıştır. Ayrıca çalışmada, tahmin edilen parametreler üzerinde Gayri Safi Yurt İçi Hasıla (GSYİH), enflasyon ve ham petrol fiyatlarının etkileri de incelenmiştir. Çalışmada uzun vadeli tahminlerde üstel düzleştirme (exponential smoothing) ve tahminlere etkisi olduğu değerlendirilen indikatörler için ise çoklu doğrusal regresyon analizi yöntemleri kullanılmıştır.

Çalışma sonuçları, Tableau yazılımının özellikle sivil yolcu uçağı sayılarında Boeing ve Airbus gibi firmaların tahminlerine oldukça yakın sayılabilecek tek haneli sapma ile sonuçlar verdiğini göstermiştir. Çalışmada ayrıca, GSYİH'nın RPK ve ASK parametrelerine pozitif ve anlamlı bir biçimde etki ettiği, enflasyonun ise sivil yolcu uçağı sayısına negatif ve anlamlı etkisinin olduğu tespit edilmiştir. Çalışma sadece havacılık sektörü ve bu ekosistem içerisinde yer alan şirketler için değil, aynı zamanda ilgili sivil otoriteler, havacılık sektörü ile ilgilenen yatırımcılar için de özellikle sivil uçak sayılarının tahmininde Tableau yazılımından faydalanabileceğini ortaya koymaktadır.

Anahtar Kelimeler: Arz Edilen Koltuk Kilometre (ASK), Sivil Havacılık, Sivil Yolcu Uçağı Sayısı, Tahminleme, Ücretli Yolcu Kilometre (RPK)

ABSTRACT

FORECASTING GLOBAL CIVIL AIRCRAFT IN-SERVICE AND OTHER PARAMETERS IN COMMERCIAL AEROSPACE

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This study examines the forecast of commercial aerospace paramaters, i.e., Aircraft in-Service Fleet, Available Seat Kilometer (ASK) and Revenue Passanger Kilometer (RPK) for the next 20 years for airlines and other market players in the aerospace ecosystem regarding their long-term strategies. The forecasts are run with the previous 20 years data via Tableau Software by employing exponential smoothing and multilinear regression analysis. The results are then compared with Boeing and Airbus figures. The study also explores the effects of Gross Domestic Product, inflation, and crude oil prices on the forecasts figures.

The findings suggests that Tableau Software forecasting tool has accurate and promising results, particularly in Aircraft in-Service fleet forecast compared to Boeing and Airbus estimations. The results also show that Gross Domestic Product has a significant and positive effect on ASK and RPK, while inflation rate has a negative and significant effect on Aircraft in-Service fleet. The study provides valuable insights on long term aircraft fleet forecast outputs for the civil aviation industry, policymakers, and investment professionals that are interested in civil aviation.

Keywords: Aircraft in-Service Fleet, Available Seat Kilometer, Commercial Aerospace, Forecasting, Revenue Passanger Kilometer

DEDICATION

I would like to dedicate this thesis to my beloved family.

ACKNOWLEDGEMENT

I am grateful for the valuable inputs of my respected supervisor Prof. Mustafa Kemal YILMAZ, for his guidance and support throughout my master thesis journey. I am thankful for his promptness in responding to my emails and messages concerning reviewing this study.

I would also like to thank my family, especially my parents, for their unconditional love and support.

YUSUF YÖRELİ

ISTANBUL, 2021

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LIST OF ABBREVIATIONS

A&D	: Aerospace and Defense
ASK/ASM	: Available Seat Kilometers / Miles
ATAG	: Air Transport Action Group
EASA	: European Aviation Safety Agency
FAA	: Federal Aviation Administration
GDP	: Gross Domestic Product
IATA	: International Air Transport Association
ICAO	: International Civil Aviation Organization
IMF	: International Monetary Fund
INR	: Indian Rupee
JADC	: Japan Aircraft Development Corporation
LCC	: Low-Cost Carriers
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MASE	: Mean Absolute Scaled Error
MTBF	: Mean Time Between Failure
OEM	: Original Equipment Manufacturer
RMSE	: Root Mean Square Error
RPK/RPM	: Revenue Passenger Kilometers / Miles
US	: United States
USD	: United States Dollar

CHAPTER I

INTRODUCTION

1.1. Overview of Commercial Aviation Industry

Commercial aviation industry is one of the major business arms that contribute to global economic prosperity with its wide range of ecosystems, including air carriers, airports, aerospace manufacturers and affiliates as depicted in Figure 1.1 (ICAO, 2005). While the production of aircraft itself directly sustains production environment, transportation function (passenger/cargo) stimulates tourism and economic growth, facilitates business and international trade, and generates jobs as shown in Figure 1.2.

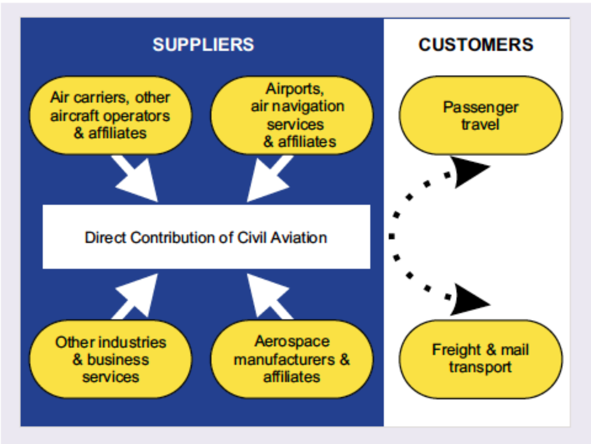

Figure 1.1. Air Transport Ecosystem

Source: International Civil Aviation Organization (ICAO, 2005)

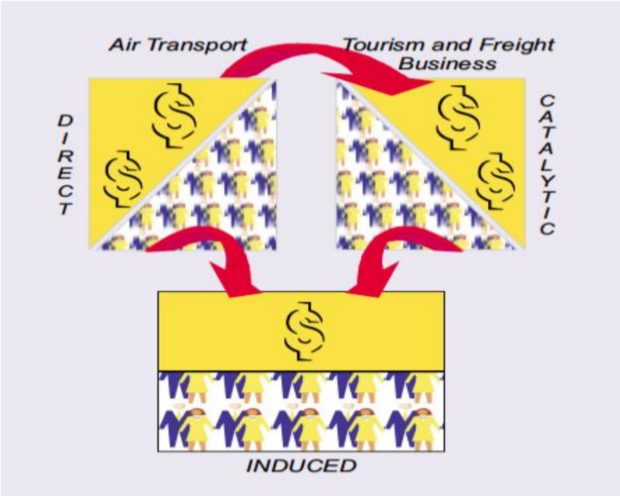

Figure 1.2. Air Transport Catalytic Effect

Source: International Civil Aviation Organization (ICAO, 2015)

Figure 1.3 shows that according to the International Air Transport Association (IATA) estimations, a direct economic contribution of USD 2.7 trillion has been created for the year 2019 (ATAG, 2018). When we look at the total jobs created in 2019 aerospace is supported by 10.2 million jobs with the break-down of air carries, other aircraft operators and affiliates for 6.1 million jobs at airports, 2.7 million in airlines and 1.2 million in commercial aerospace manufacturing. Furthermore, other sectors such as tourism also benefit from the stimulation via aviation with the creation of jobs for 36.7 million people. About 57% of global tourists fly by air in 2019 and for air transportation of every million passengers around 1,000 staff have been employed on airports to provide goods and services for air transportation (ATAG, 2018).

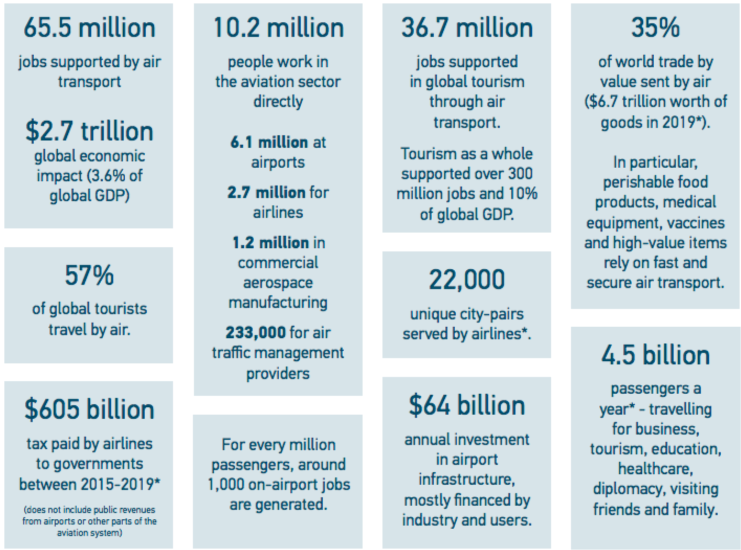

Figure 1.3. Aviation Supporting the Global Economy

Source: Air Transport Action Group (ATAG, 2018)

According to the ATAG, employed workforce directly and indirectly produced USD 2.7 trillion economic benefit to global economy in 2018, while aviation contributes almost 3% of the world Gross Domestic Product (GDP), i.e., USD 86 trillion in 2018 (ATAG, 2018) (Figure 1.4).

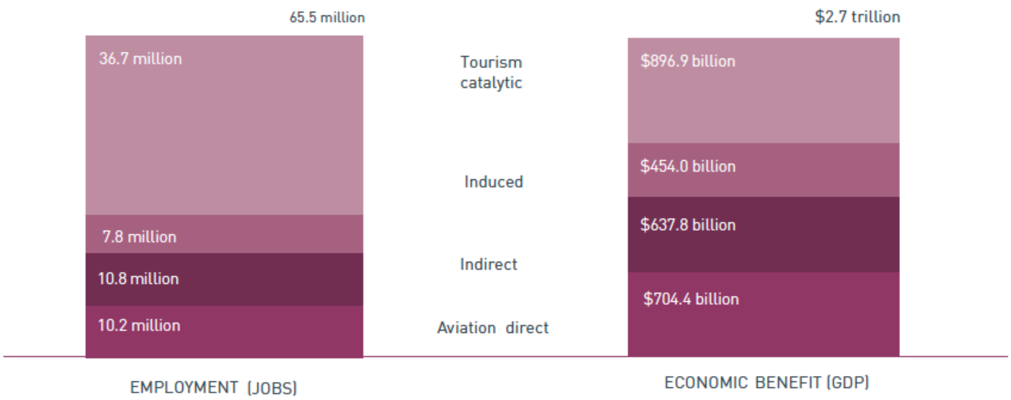

Figure 1.4. Global Contribution of Aviation to GDP and Employment

Source: Air Transport Action Group (ATAG, 2018)

1.2. Aim and Scope of the Study

The aviation industry contributes to social and economic growth across countries although its growth rate has been highly affected by crises and external shocks. Thus, companies in commercial aerospace industry should position themselves to manage the challenges in the competitive business environment. Forecasting is key in aerospace due to the complex nature of the industry and market interruptions. Since the lead-time for the delivery of an airplane is approximately five years, and the investments are large, making accurate forecasts is essential to take right decisions, i.e., how much to produce, how to plan resources, capacity, how to improve production. Thus, each supplier in the aerospace ecosystem should manage its own challenges and navigate its company for the future.

Therefore, accurate forecasts offer airline companies the opportunity to improve their operating margins. There are some publications on market outlook for the upcoming 20 years by the main airplane manufacturers, i.e., Boeing, Airbus, authorities (Federal Aviation Administration - FAA, European Aviation Safety Agency - EASA) and industry organizations (IATA, ICAO). Figure 1.5 shows a high-level forecast published and renewed annually by Boeing (Boeing, 2020). These publications, however, do not provide the details of their forecasting methods due to confidentiality.

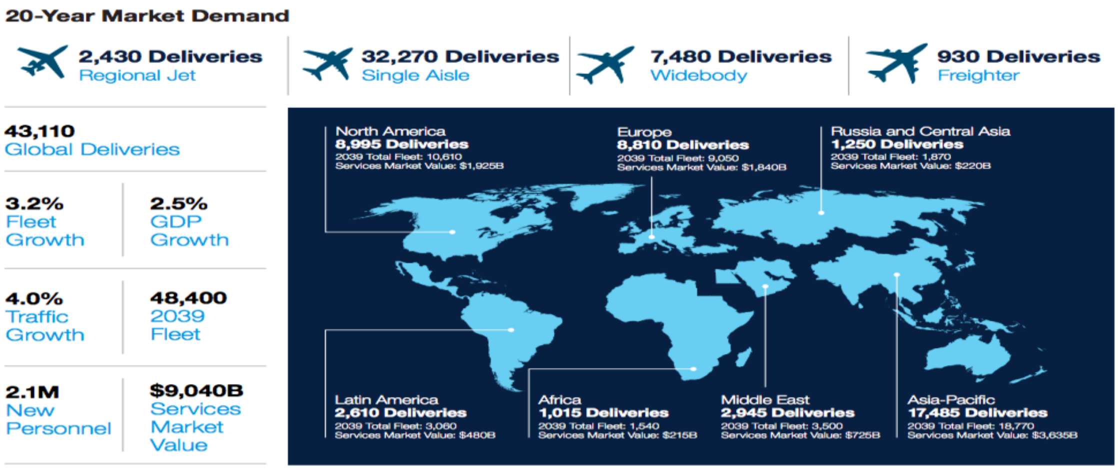

Figure 1.5. Commercial Market Outlook (2020–2039)

Source: Boeing

This thesis aims to make a prediction of global commercial aircraft fleet figures, global Revenue Passenger Kilometers/Miles (RPKs/RPMs) growth rates and global Available Seat Kilometers/Miles (ASKs/ASMs) growth rates for the next 20 years by using exponential smoothing models with trend/seasonality components (Tableau Software) forecasting technique and employing the parameter within Tableau Software quality metrics of forecast such as forecast errors, scale-dependent errors, percentage errors, smoothing coefficients. We use global aircraft fleet data from Aviation Week, global RPKs/RPMs growth rates, global ASKs/ASMs growth rates from IATA and GDP data from International Monetary Foundation (IMF). The study also compares the results with the forecasting figures of the major market players i.e., Boeing, Airbus and Japan Aircraft Development Corporation (JADC).

1.3. Contribution of the Study

This study aims to provide proof on how effective the usage of Tableau Software forecasting technique is to make comparison with the forecasted figures of the main Original Equipment Manufacturers (OEMs) (Boeing, Airbus, Japan Aircraft Development Corporation) off the shelf published reports i.e., Boeing Current Market Outlook, Airbus Global Market Forecast and JADC Worldwide Market Forecast. It also contributes to the literature by presenting the accuracy and applicability of the exponential smoothing model in forecasting for the commercial aerspace industry.

1.4. Organization of the Thesis

The thesis is organized as follows:

Chapter 1 gives an overview of global commercial aviation industry, aim, scope and contribution of the study and research question.

Chapter 2 provides the interaction of the facts for forecasting in commercial aviation industry such as global aircraft fleet figures, RPKs/RPMs and ASKs/ASMs growth rates.

Chapter 3 reviews the literature on aerospace forecasting.

Chapter 4 presents data, the variables, and methodology. We run Tableau Software tool on forecasting key parameters to measure supply and demand in commercial aerospace such as RPKs/RPMs and ASKs/ASMs growth rates for the upcoming 20 years and we compare the accuracy of the model to the forecasted figures published by the main OEMs.

Chapter 5 discusses empirical results.

Chapter 6 concludes and discusses the implications of the study.

CHAPTER II

FORECASTING IN COMMERIAL AVIATION

2.1. The Effects of Performance Parameters in Aviation

The performance of commercial aerospace industry is usually measured by two parameters: Revenue Passenger Kilometers/Miles (RPKs/RPMs) (passenger demand) and Available Seat Kilometers/Miles (ASKs/ASMs) (capacity or supply side). Figure 2.1 shows the growth rate in both parameters during the years 2012-2019. There has been a positive growth in commercial aerospace industry driven by supply and demand and the growth rate change has never been lower than 3% during the last decade.

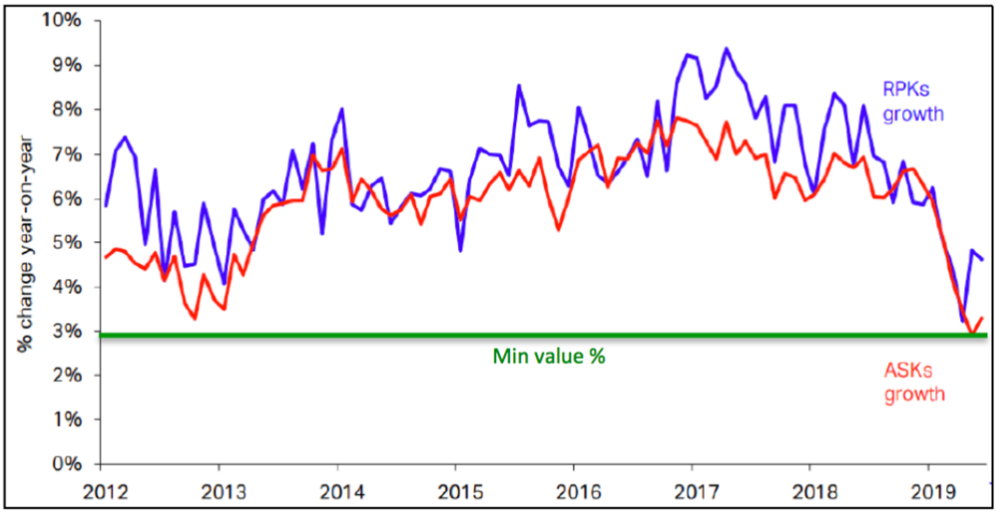

Figure 2.1. Growth in Global RPKs and ASKs (2012-2019)

Source: ICAO (2019)

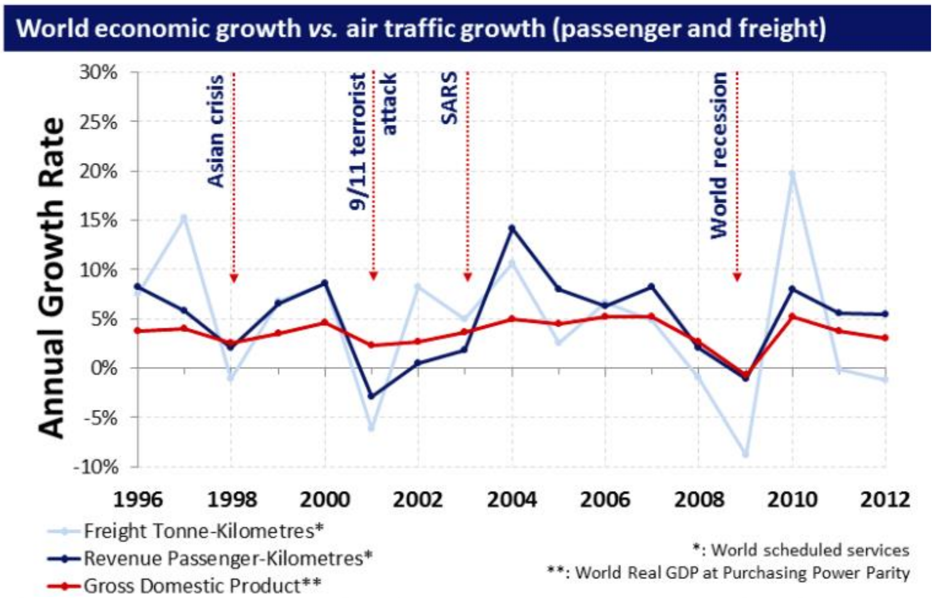

Figure 2.2. World Aviation and the World Economy

Source: ICAO (2019) Facts and Figures

Global passenger demand has also grown throughout the years except in crises periods and external shocks such as 1991 Iraq War, 2001 terrorist attack, 2009 Global Financial Crisis, SARS, MERS, H1N1 pandemic crisis. As shown in Figure 2.2, average growth rate for the last decade is almost 6.6% (ICAO, 2019). In fact, there is a strong relationship between economic growth and air travel. The correlation between air traffic (in RPKs) and GDP growth is calculated as follows:

$$\text{Air traffic growth} = \text{Multiplier} \times \text{GDP Growth}$$

The estimate for the multiplier varies. As given in Figure 2.3, it is typically around 2.0-2.2 over the period of 1991-2018 (Corrodi, Hildbrand and Steiner, 2019).

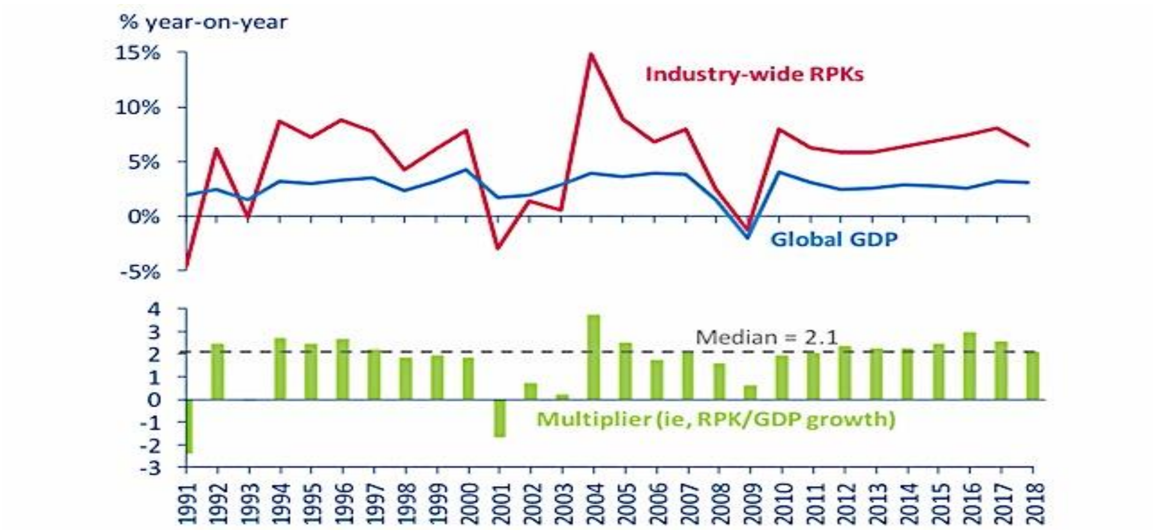

Figure 2.3. Industry Wide RPK Growth and Global GDP Growth

Source: IATA Monthly Statistics, IMF

2.2. Importance of Forecasting

Although the famous strategy guru Peter Drucker (1973, p. 124) says that "…forecasting is not a respectable human activity and not worthwhile beyond the shortest of periods" there has been key business decisions that should be taken by companies on long term strategic planning by forecasting (Armstrong 1988; Drucker, 1973). They should forecast how demand will be, how much to produce, how much capacity and resources to use, what products to develop, and how much financing to get in the short and long term.

Forecasts help to analyze factors that may drive market movements, and to review alternative scenarios and potential outcomes (Lester, 2011). However, forecasting activities may neglect some extreme events that may have detrimental effects on companies in risk management. This uncertainty can take a variety of forms, including financial, operational, strategic, compliance, and other risks. Although many companies make attempts to consider these risks in forecasting and planning, they tend to do it on an informal, and qualitative way, without strong interaction of financial and strategic planning (Ittner & Michels, 2017). Forecasting activity aids reducing this uncertainty and mitigate risk. It also reduces unnecessary spending, schedules optimum production level and staffing, avoids missing potential opportunities and manages cash flow efficiently. Generally, managers prefer to benefit from the ‘‘naive’’ forecasting approach claiming that the future will be the same as it is in the past. This approach is simplistic due to its deficiency in recovering the market turmoil around the globe.

Forecasting is a key business tool that helps companies on decision taking. For instance, accurate weather forecasting is critical in aviation. It can have a major impact on the flight – both economically and physical safety, especially for commercial airlines. Each weather turbulence-related incident costs airlines on average USD 150,000. Total cost of the weather changes exceeds USD 100 million to the industry per year as claimed by Honeywell IntuVue Weather Radar White Paper (Honeywell Aerospace, 2015). Each airlines benefit from weather forecasting tools to optimize the flight routes and manage risky weather conditions. As a success story, Exelon’s wind forecasting accuracy enabled higher energy capturing of USD 2 million per year in 2016. The success of the project contributed to Exelon’s decision to sign a long-term enterprise agreement with General Electric (GE Digital, 2016). Another example may be Walmart, a retail giant with over USD 330 billion annual sales in 2019. Walmart improved its forecasting accuracy with NVIDIA company and perfectly forecasted 52-week sales. The system also helped Walmart in inventory management by reducing overall forecast error by ~ 1.7 percentage points (Walmart, 2019).

2.3. Forecasting in Aviation

In the aerospace industry, many factors contribute to the variations in commercial aerospace demand and supply. Since forecasting is tough and confidential none of the companies discloses their forecasting methods. However, the main OEMs such as Boeing, Airbus, Embraer publish the figures and opinions in their annual commercial aerospace market outlook reports as shown in Figure 1.5 (Boeing, 2020). These reports are perceived as a reference book by many Tier-1, 2 and other suppliers in commercial aerospace business environment. There are many drivers in market outlook reports on forecasting such as GDP, crude oil prices, ASK/ASM (supply in aviation) and RPK/RPM (demand in aviation).

For airlines, jet fuel is one the main expense item (approximately up to 30 to 40% of the airlines' cost arises from fuel charges) that resides in the balance sheet. Therefore, forecasting fuel prices is quite important. However, hedging ratio used by airline companies to manage fuel price risk varies at different levels, affecting their profitability. For instance, in the last quarter of 2000, US Airways, which did not hedge its position, estimated that its USD 88 million exact loss would have been a profit of USD 38 million if the fuel costs had not increased (Carter, Rogers, & Simkins, 2004). Thus, if airlines could control fuel cost, they may more accurately estimate their earnings and budgets.

For instance, Southwest Airlines, not following the traditional wisdom of the airline industry, ran a successful hedging program throughout the years. The program saved the company USD 171 million in jet fuel cost in 2003. The company protected itself in 2004 and 2005 with over 80% and 70% of the anticipated fuel requirements hedged with prices capped at approximately USD 24 per barrel of crude oil. This hedging activity also saved the company USD 240 million in 2004 (Westbrooks, 2005). Similarly, during 2015-2016 Air India's hedging of 2 million barrels of jet fuel annually at USD 75 per barrel helped the company to save INR 20 billion by March 31, 2016. On October 14, 2016, The Hindu Business Line in 2016 reported that Air India reported an operating profit of INR 1.50 billion for 2015–2016 for the first time in 10 years period (Kar & Khandelwal, 2020).

Revenue management is one of the hot topics for airlines to generate maximum revenue with different demand forecasting scenarios. The challenging part is to balance supply and demand with variable pricing for the Economy, Business and First Classes. Supply represents the ticket demand by air traveler and demand forecasts give critical information and insights on customer analytics during the ticket purchasing process. Revenue management uses forecasting to match pricing and demand by opening and closing a variety of fare classes. Amadeus that provides revenue management infrastructure to airlines, indicated that even a 10% escalation in forecast accuracy can lead to a 1% gain in revenue (Fiig, 2020).

Another study shows that revenue management adds USD 500 million and USD 100 million a year to the incomes of American Airline and United Airlines respectively. This is directly related to the demand and fare-forecasting algorithm executed by these airlines. In fact, airlines raise additional income of 1% to 10% by good revenue management and forecasting accuracy plays a vital role on this issue. Hossam (2000) showed that a 10% decrease in forecast error increases revenue by 0.5%. This positive impact is observed by some airlines. American Airline made USD 80 million additional revenue, while America West reported that a 25% reduction in the forecasting error increased its revenue by 1.4% (Hossam, 2000).

CHAPTER III

LITERATURE REVIEW

There are different parameters for forecasting in commercial aerospace. Although Boeing, Airbus and JADC publish their forecasts annually no information is available on the forecasting model in the reports due to confidentiality. In this section, we review studies held on forecasting in the field of aviation.

Verleger (1962) investigated models of demand for air transport. He used gravity model for demand analysis and claimed that travel or communication between two cities would decrease as the distance between the cities increases. He also highlighted that travel should be a function of price, income, and other variables related to changes in the availability of other modes of travel.

Brown and Watkins (1968) held a study about the effect of fares on demand for air travel addressing to the following question: How will fare changes affect growth of traffic? They employed time-series data of air travel in 300 domestic city-pairs and cross-sectional analysis under the gravity model. They argued that Marshallian law applies to air travel demand: people buy more at lower prices and less at higher prices. However, other variables i.e., incomes, population, and tastes, do often change. During this study trips were divided into three groups; first group covers short trips of 300 miles or less, second group covers trips between 301 to 1,100 miles and last group includes trips over 1,100 miles. The findings confirmed the hypothesis that fare elasticities are low or insignificant for the first and third group which means that demand has no or less effect due to the changes in fares, while in the second group, fare elasticities are high and then decline to insignificant level at the longest distances. Elasticities with respect to categorized trips time appear to increase (numerically) fairly steadily, as the length of trip increases (Samuel and Watkins, 1968).

Vitek and Taneja (1975) investigated the bounce of inflation on the interest for domestic air passenger transportation with the help of time-series information and linear and non-linear least squares regressions with Revenue Passenger Miles as the dependent variable, and calculations of cost, income, and inflation as the explanatory variables. The forecasts are performed for 15 years covering both linear and non-linear secular trends. The findings showed that the cost is the most permanent and significant determinant of demand. The non-linear trend model gave the best results and fitted 96% of the variation in appeal.

The report prepared by the US Congress (1984) focused on how the trends may affect the future needs of airports based on Aviation Demand Forecasting. It claimed that forecaster should consider two basic types of input data to project future activity: aviation activity and historical performance trends. Alternatively, researchers may prefer data related to economic, social, and technological factors that has a direct or indirect effect on aviation and use time trends, econometric models, gravity models, and other models for forecasting. Table 3.1 shows that the prepared models that were presented to the US Congress in 1984.

Table 3.1. Summary of FAA Forecasts (1959-1983)

Periods in which forecasts made	Method	Performance 5 years ahead	Market environment
1959-65	Trend forecasting: unspecified links to economy, business cycle, population, fares, competition from other modes	Average error – 18.7 percent Worst year –32.5 percent	Expanding, prosperous economy. Rapidly growing population. Declining first-class and coach fares, (declining unit costs because of increasing use of jets).
1966-73	Trend forecasting: unspecified links to economy, business cycle, population, fares, competition from other modes	Average error +32.5 percent Worst year +58.4 percent	Softening trends in aviation activity. Increasing ticket taxes, rising fares. Forecasts made in 1969 (published January 1970) assumed 4.25 percent growth rate in 1973, to continue at that rate through decade. Inflation 2 percent per year from 1973.
From 1974	Linear econometric models	Average error +21.2 percent Worst year +34.7 percent	Airline deregulation, economic recession, fare wars, and depressed airline revenues.

Source: US Government: Airport System Development (1984)

Ghobbar and Friend (2003) employed a general linear based model for predicting spare parts demand for airline fleets for scheduled and unscheduled maintenance, repair, and overhaul of the aircraft intervals between flights. They examined the experimental results of 13 forecasting methods used by aviation companies. They used the general linear model approach to clarify the variation attributable to different experimental factors and their interactions. The results with linear model approach provided accurate estimates in predicting spare parts demand for airline fleets for scheduled and unscheduled maintenance, repair, and overhaul of the aircrafts. The authors also suggested that linear model can be applied for predicting spare parts demand in other industrial sectors since the latter have similar demand patterns.

Besides commercial aerospace, it is also vital to forecast the inventory and keep some minimum equipment ready off the shelf for military aircrafts. Yoon and Sohn (2007) used the random-effects regression models to forecast the mean time between failure (MTBF) of modules of fighter aircraft. They showed that random-effects regression model could be applied to find seasonal and annual demand of minor parts.

Muhammad and Manarvi (2009) stated that the production is highly complex in terms of inventory, cost, and production planning in aviation. Data driven decision making for procurement and demand forecasting is required based on historical information through mining data from related databases. They focused on mining supplier performance measurement data and by using it for forecasting they claimed that to preserve the competitiveness of a company in aerospace data mining techniques must be used to save cash, achieve better operational performance, and mitigate risk.

The operational side of commercial airlines is also challenging to manage demand derived by passengers. The demand fluctuates in summer and winter season. Xie, Wang, and Lai (2014) investigated short-term forecasting of air passenger by using combinational seasonal decomposition and least squares support vector regression models approaches. By using time series of air passengers at Hong Kong International Airport, they made an empirical analysis to illustrate the proposed hybrid model. The results suggested that seasonal decomposition is an effective way to air passenger forecasting. Hence, seasonal characteristic and nonlinear nature of air passenger should be considered for better forecasting. Finally, hybrid model is used for short-term forecasting of passengers.

Other studies have employed similar approaches. Zhang (2017) developed a hypothesis on the long-term production planning decision with appropriate demand forecasting model and decision-making theory. He compared probabilistic models i.e., Geometric Brownian motion and Autoregressive Integrated Moving Average to make accurate decisions. The results showed that capacity-planning problem could occur when improper models are chosen. Thus, studies should also be held on macroeconomic variables, and fuel prices. Boonekamp, Zuidberg and Burghouwt (2018) conducted a study similar to Xie et al. (2014) and investigated long-term forecasting of air passengers and air transport movements at German airports with a new direct demand model. Gelhausen, Berster and Wilken (2018) claimed that the German Aerospace Center developed and executed a "classical" four-step model for forecasting passenger and German airports flight volume. The model is used for simulating and forecasting traffic. Unfortunately, the model becomes increasingly difficult to update and verify due to lack of data. The new demand model showed that simulating and forecasting traffic could be executed with lower number of input variables compared to the classical model. Moreover, the forecast values for the input variables are easier to implement for the new direct demand model due to the less complexity and easy access.

Monahan (2016) investigated aircraft demand forecasting and highlighted that forecasting aircraft demand depends particularly on aircraft orders and deliveries in the aerospace and defense industry. Moreover, orders are given by airlines to aircraft manufacturers in advance with long lead times i.e., on some point three-years. Due to the uncertainty of the air transport environment, sudden crises such as terrorist attacks, should be aligned with forecasting plans. Time series and multiple regression forecasting methods are applied to past trends. According to Theil's U Naïve No-Change forecast, the results reveal bad performance in terms of the forecast accuracy.

Küçükönal and Sedefoğlu (2017) developed another model to examine the effects of macroeconomic parameters i.e., GDP as a leading indicator for RPK, unemployment and others on air transport. They used Granger causality analysis to investigate the existence of a causal relationship (unidirectional or bidirectional) among air transport, tourism, GDP, and employment. They found the highest correlation between tourism and air transport and the lowest correlation between employment and air transport. Their results also showed that there is a unidirectional causal relationship in the short run running from GDP, employment, tourism to air transport. Similarly, Boonekamp et al. (2018) investigated the determinants of air travel demand in the scope of the role of low-cost carriers (LCC) ethnic links and aviation-dependent employment. They used a comprehensive gravity model in which the most important determinants for air travel demand, including GDP, population, and tourism, domestic traffic, LCC activity and public service obligations have been identified. Also, a two-stage least squares technique is used. The results showed that the LCCs provide incremental market stimulation through increase in passenger demand.

Alsalous (2015) analyzed the global demand model with the capability to predict future demand in air transportation and highlighted that for aviation planning and policy making demand forecasting is a core matter. An econometric regression model is used for forecasting the number of air passenger seats by employing GDP, population, and airlines market shares. The model is conducted through an algorithm that uses the R Square as the measure of Goodness-of-Fit in addition to a sanity check for the generated forecasts. The results showed that R square is an imperfect measure of model performance. Moreover, prediction error can be used in model assignment for further studies. Burgos (2017) analyzed aviation global demand forecast model development i.e., air transportation demand distribution and aircraft fleet evolution to enhance the global demand capabilities found by Alsalous (2015). A Fratar model is applied for the distribution of the forecast demand. The results estimate a worldwide aircraft fleet size of 17,616 aircraft by 2016, 7% lower than the Airbus's prediction for the same year, worldwide aircraft fleet size of 35,119 aircraft by 2036, 14% and 16% lower than the prediction of Airbus and Boeing for the same year, respectively.

Time series analysis has also been widely applied to perform forecasting in air transport. It is easy to use in terms of accessibility of historical data and macroeconomic variables i.e., GDP, inflation rate, crude oil prices. Macroeconomic parameters may have either positive or negative impact on air transport, and this will be investigated as a holistic approach in this thesis. In this frame, we investigate forecasting with exponential smoothing method under the umbrella of trend model. We also measure the quality metrics of the forecasts with forecast errors, scale-dependent errors, percentage errors and smoothing coefficients.

CHAPTER IV

DATA AND METHODOLOGY

4.1. Data Sample

In this study, we employed different forecasting models by using a variety of aerospace parameters i.e., Aircraft in-Service, Revenue Passenger Kilometer / Mile (RPK/RPM) and Available Seat Kilometer / Mile (ASK/ASM). We use time-series data regarding the Aircraft in-Service for the years 2000-2019 for global active aircraft fleet. The latter represents the number of aircrafts in operation at the end of each year. Aircraft in-Service figures represents the actual data gathered by service provider. Global aircraft fleet figures are the sum of aircraft fleet of 10 different regional breakdowns, including Africa, Australia, Canada, Caribbean, Central America, Europe, Far East, Middle East, South America, and US. We use Aviation Week Network Fleet and Data Services that provides solutions to many aerospace companies. We obtained GDP growth rate and inflation rate from the IMF Data Mapper and crude oil prices from Bloomberg.

4.2. Variables

To estimate commercial Aircraft in-Service fleet forecasts, we used GDP annual growth rate, inflation rate, and crude oil prices as independent variables, and RPK/RPM, Available ASK/ASM, Aircraft Fleet and Aircraft in-Service as dependent variables.

4.2.1. Independent Variables

Aircraft orders are the output of airline companies, and they help airlines generate revenues and serve better to their passengers. Airlines try to balance passenger demand (RPK/RPM) and supply (ASK/ASM) with the number of aircrafts.

Purchasing or leasing aircrafts is also called fleet management. Besides having new aircrafts, timing is also important since airlines should be ready to respond to demand in the forthcoming periods. GDP growth, inflation and crude oil prices trigger purchasing power of passengers and affect demand in commercial aerospace ecosystem. Figure 4.1 shows the interaction between macroeconomic variables and commercial aerospace industry, while Table 4.1 gives the measurement and description of the independent variables.

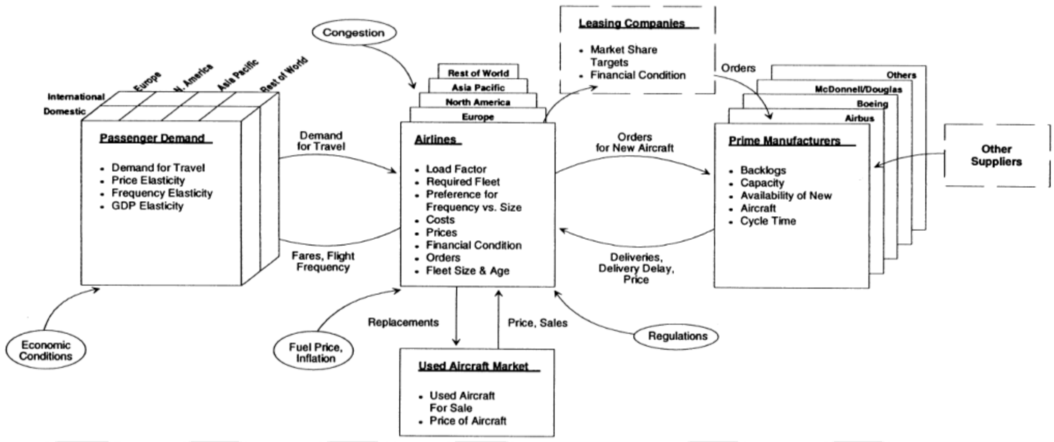

Figure 4.1. Structure of Commercial Aviation Industry as a Supply Chain

Source: Lyneis (2000)

Table 4.1. Measurements and Descriptions of Independent Variables

Category	Proxy	Measurement	Description
Gross Domestic Product (%)	GDP	Goods & Services × Prices	Yearly change in monetary value of goods and services
Inflation rate (%)	-	Level of prices for Goods & Services	General level of prices for goods and services from year to year
Crude oil prices (USD)	-	Barrel × Price	West Texas Intermediate price per barrel

4.2.2. Dependent Variables

Dependent variables are the key indicators to monitor the performance of commercial aerospace industry. RPK/RPM and ASK/ASM are the backbone metrics of transportation. Airlines try to match the supply (ASKs) and demand (RPKs). Shortage of seats often result in higher airfare, and excess capacity and may lead to lower margin due to higher fixed costs. Thus, an increase in capacity is positive only if it is supported by an adequate rise in demand for air travel.

In this study, we use secondary data sources. To elaborate on the impact of commercial aircraft forecast, we look at key variables i.e., RPK/RPM, ASK/ASM, Aircraft in-Service forecasts published by markets players, i.e, Boeing, Airbus, and international authorities i.e., IATA. Table 4.2 shows the measurement and descriptions of independent variables.

Table 4.2. Measurements and Descriptions of Dependent Variables

Category	**Proxy**	**Measurement**	**Description**
Revenue Passenger Kilometer / Mile	RPK / RPM	Total number of revenue passengers × Flight distance in Kilometers / Mile	RPK / RPM reflects demand in aviation.
Available Seat Kilometer / Mile	ASK / ASM	Number of seats per aircraft× Flight distance in Kilometers / Mile	ASK / ASM reflects the supply in aviation.
Aircraft in-Service	-	Number of the total aircraft	Number of aircraft to fly and generate revenue

4.3. Methodology

Forecasting can be executed in three different time-zones: short-term, mid-term and long-term (Hyndman & Athanasopoulos, 2018). Companies make short term forecasting for scheduling of personnel, production, and transportation. For scheduling, demand forecasting is often required. Companies execute mid-term forecasting to determine future resource demands and to buy raw materials, employ personnel, or buy machinery and equipment. Finally, long-term forecasting is used for strategic planning. It should consider market opportunities, environmental factors, and internal resources.

On the other hand, there are two types of forecasting methods: qualitative and quantitative (Hyndman & Athanasopoulos, 2016). The appropriate method depends on available data. If no input is available, or the input is not relevant, qualitative forecasting may be the right choice. One may use quantitative forecasting when there is available data, and it is reasonable to assume that some aspects of the past patterns will continue in the future. In aviation, quantitative forecasting methods are usually employed.

4.3.1. Time Series Method

Data is usually tracked in time series. Time-series forecasting include the following process:

1. Economic planning
2. Sales forecasting
3. Inventory control
4. Production and capacity planning
5. Evaluation of alternative economic strategies
6. Budgeting
7. Financial risk management
8. Model evaluation

We investigate time series data by using average method, naïve method, and exponential smoothing method. Average method and naïve method are simple and effective in forecasting with historical data and single variable (Hyndman & Athanasopoulos, 2018).

4.3.1.1. Average Method

The forecast of all future values is equal to the average (or "mean") of the historical data. If the historical data is denoted as $"y_1"$, … , $"y_T"$, then the forecast can be written as follows.

$$"\hat{y}_{T+h|T}" = ("y_1" + \cdots + "y_{t-1}") \, / \, T. \quad (1)$$

The following notation will be used for both average and naïve approach methods:

t: Time

y_t: Observed value at time "t" and used data to be forecasted (based on the historical data)

$\hat{y}_t$: Forecasted value of "y_t"

$y_t|$: Random variable of "y_t"

$\hat{y}_{t|t-1}$: Mean forecast of "y_t" based on the observations of "y_1", … , "y_{t-1}"

h: Number of the forecast steps based on time "T"

T: Time interval for the "h"

$\hat{y}_{T+h|T}$: Mean forecast of "y_{T+h}" based on the observations of "y_1", … , "y_T"

Estimate of "y_{T+h}" based on the data "y_1", … , "y_T, "$\hat{y}_{T+h|T}$" is a short-hand notation of "y_{T+h}".

4.3.1.2. Naïve Approach Method

In the naïve approach, the forecasting is performed based on the value of the last period of the actuals. There is also no adjustment for the value of the last period of the actuals. The following notation is used for forecasting:

$$"\hat{y}_{T+h|T}" = "y_T" \qquad (2)$$

4.3.1.3. Exponential Smoothing Models with Trend / Seasonality Components (with Tableau Software)

Tableau Software forecasting method gives more exhaustive statistics and smoothing coefficient data for the exponential smoothing model regarding the forecasts (Tableau Software, 2020). Tableau analyzes the raw data to forecast itself and understands the nature of the data in terms of the level, trend or season based on the following parameters.

4.3.1.3.1. Forecast Parameters

Initial: The value and the prediction interval of the initial forecast period.

Change from initial: The variance among the first and the last forecast prediction points. The interval for these points is given in error bars for each forecasting. It is optional to show values as percentages or actual value for the difference.

Seasonal effect: Seasonality determines the characteristic of the forecast. There exist displayed columns for models regarding seasonality. Seasonality can be called as a repeating pattern of variation over time.

Contribution: Contribution can extend the trend and seasonality and adds up to the forecast. Contribution values are shown as percentages and can reach up to 100% of the forecast.

Quality: It indicates the performance of the forecast compared to actual data. The combination and length of the actual data (number of the observation) have a direct effect to the quality of forecast. Tableau Software classifies the forecast into three categories: “GOOD”, “OK”, and “POOR”. When the forecast result is displayed as OK, the quality expresses that the result is relative to a naïve forecast, however it includes less error than naïve forecast. GOOD is the case when the error value for the forecast is 50% less than the naïve forecast error. POOR means that the forecast has more errors than a naïve forecast.

4.3.1.3.2. Quality Metrics of Forecast

There exists four major metrics to determine the quality of the forecast.

Forecast errors: A forecast “error” is the difference between the forecast based on the observed value and observed value itself. Although it is called “error” it should not be accepted as a real mistake. It represents the safety factor or the unpredictable part of an observation. It can be written as follow:

$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T}$$
(3)

where the data is given by "y_1", …, "y_T", and the test data is given by "y_{T+1}", "y_{T+2}",…

Before the forecasting, the right model should be determined. This is the initial step that affects the accuracy of the forecast. In general, the data set to be forecasted splits into the two sections: test data and training data. Training data is a tool to estimate closer assumptions with the variety of the tests regarding the test data. Tableau Software has internal algorithm to determine optimum test and training data.

Scale-dependent errors: Accuracy may be measured depending only on "e_t", therefore it is scale-dependent. It is not possible to compare it with the series, which includes different units. There exist two widely employed scale-dependent measures depending on the absolute errors or squared errors as shown below:

Mean absolute error: MAE = mean ("$|e_t|$"), (4)

Root mean square error: RMSE = √mean ("e^2_t") (5)

MAE indicates the size of the error from the average forecast value. Lower MAE increases the accuracy of the forecast. RMSE is another indication for the quality. It is the standard deviation of prediction errors. Lower RMSE values are more acceptable.

Percentage errors: The percentage error is calculated as follows:

$$"p_t" = "100e_t/y_t"$$
(6)

Percentage errors are unit-free and give flexibility to make comparison between data sets. The most widely used measure is the following one:

Mean absolute percentage error: MAPE = mean("$|p_t|$")

(7)

MAPE is a measure of prediction accuracy for the forecasting method. The smaller the value of MAPE is the better the forecast. Table 4.3 gives the quality metrics of forecast summary table for the scale-dependent errors and percentage errors value and definition.

Table 4.3. Quality Metrics of Forecast Summary Table Scale-Dependent Errors and Percentage Errors Value and Definition

Value	**Definition**
RMSE: Root mean squared error	$\sqrt{\left(\frac{1}{n}\right) \sum e\ (t))^2}$
MAE: Mean absolute error	$\left(\frac{1}{n}\right) \sum \lvert e\ (t)\ \rvert$
MASE: Mean absolute scaled error MASE measures the magnitude of the error compared to the magnitude of the error of a naive one-step ahead forecast as a ratio. A naive forecast predicts that whatever the value is today will be similar tomorrow. So, a MASE of 0.5 means that your forecast probably has half as much error as a naive forecast, which is better than a MASE of 1.0, which is no better than a naive forecast. Since this is a normalized statistic that is defined for all values and weighs errors evenly, it is an excellent metric for comparing the quality of various forecast methods. The advantage of MASE over the MAPE metric is that MASE is defined for time series that contain zero, while MAPE is not. MASE weights errors equally, whereas MAPE weights positive and/or extreme errors more heavily.	$\frac{\left(\frac{1}{n}\right) \sum \lvert e\ (t)\rvert}{\left(\frac{1}{n-1}\right) \sum_n^2 \lvert Y(t))-Y(t-1)1)\rvert}$
MAPE: Mean absolute percentage error. MAPE measures the magnitude of the error compared to the magnitude of the value as a percentage. So, a MAPE of 20% is better than a MAPE of 60%. Errors are the differences among the response values, that the model estimates, and the real response values for all explanatory value in the data. Since this is a normalized statistic, it can be used to compare the quality of various models computed in Tableau. But it is unreliable for some comparisons because it weights some kinds of error more heavily than others. It is also undefined for data with values of zero.	$100 \left(\frac{1}{n}\right) \sum \lvert\frac{e(t)}{A(t)}\rvert$

Source: Tableau Software Forecast Descriptions (www.help.tableau.com)

The following notations are used for variables in Tableau Software forecast descriptions.

t : Index of a period in time series

n : Time series length

m : Number of periods in a season/cycle

$A(t)$: Actual value of the time series at period "t"

$F(t)$: Fitted or forecast value at period "t"

Residuals are: $e(t) = F(t) - A(t)$
(8)

Smoothing coefficients: Smoothing coefficients are used for the optimization of the data set in terms of the dependence of the observation period with regards to forecast. Alpha "α" is the level smoothing coefficient, beta "β" is the trend-smoothing coefficient, and gamma "γ"is the seasonal smoothing coefficient for the forecast. Each parameter is a value between $0.00 < \alpha, \beta, \gamma < 1.00$. It is better to have lower α, β, γ values. It is a sign that the forecast has less reliance to the latest observations and lower smoothing is applied to the forecast.

4.3.2. Time Series Regression Models

As shown in Figure 2.2, there is a strong relationship between GDP growth and air travel. Besides the forecasting methods, we also conduct a separate analysis by using regression models to measure the interaction of dependent and independent variables (highlighted in section 4.3.1 as "y_1", … , "y_T"). The statistics show that air traffic (in RPKs) is 2.0-2.2 times of GDP growth over the period of 1991-2018 (Corrodi et al., 2019). Thus, when GDP grows by 1 unit RPK grows 2.0-2.2 times and GDP has a multiplier effect on RPK growth. Beside GDP growth, inflation, and crude oil prices have impacts on dependent variables.

4.3.2.1. Simple Linear Regression

Simple linear regression measures the relationships between the predictor variable denoted as "x", and the forecast denoted as "y" (The Pennsylvania State University, 2018). The forecast formula is denoted as follows:

$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

(9)

"β_0" and "β_1" are the coefficients, "$\beta_0 + \beta_1 x_1$" is the slope of the line and "ε_t" is the "random error".

4.3.2.2. Multiple Linear Regression

We also apply multiple linear regression, where there exist more than two predictors. The forecast formula is denoted as follows:

$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_k x_{k,t} + \varepsilon_t$

(10)

"β_0", ... , "β_k" are the coefficients, "k" is the predictor variable and "y" is the variable for the forecast.

CHAPTER V

EMPIRICAL FINDINGS

To make forecasts for the period of 2020 to 2039 for Aircraft in-Service, RPK/RPM and ASK/ASM we used actual data from 1999 to 2019. Since the Covid-19 and Boeing 737 Max crisis had detrimental effect on commercial aerospace ecosystem due to the grounding of the global aircraft fleet we did not take 2020 figures into consideration.

5.1. Aircraft in-Service Fleet Forecast

Figure 5.1 shows the forecast results. In Figure 5.1, the dark blue line represents the forecast of by Boeing (50,660) for the years 2019-2038, while the purple line shows the forecast of aircraft fleets by Airbus (47,680) for the same period. The forecast values include the specific values, upper and lower prediction interval values per year for Aircraft in-Service fleet from 2020 to 2039. Table 5.1 presents the forecast results.

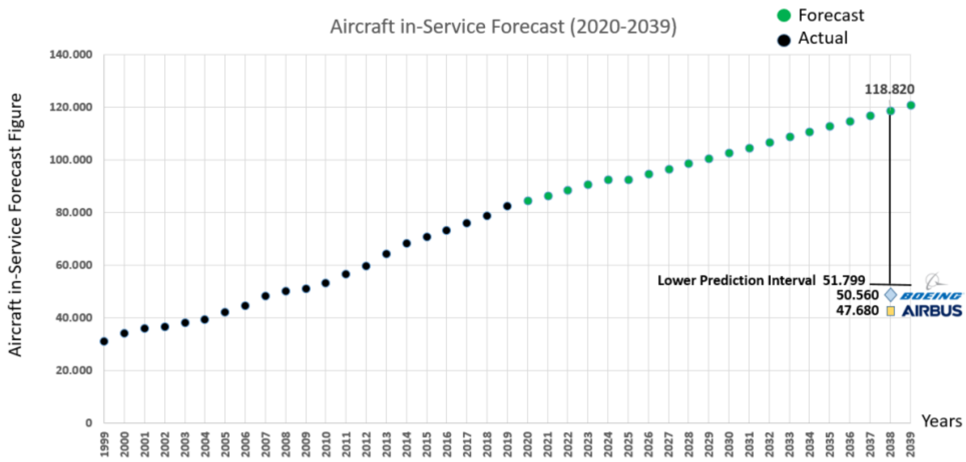

Figure 5.1. Commercial Aircraft in-Service Fleet Figures

Table 5.1. Commercial Aircraft in-Service Fleet Forecast Estimate (2020-2039)

Aircraft in-Service Fleet Forecast	Lower Prediction Interval for Aircraft Fleet	Upper Prediction Interval for Aircraft Fleet	Aircraft Fleet
2039	48,872	192,807	120,840
2038	51,799	185,841	118,820
2037	54,606	178,995	116,800
2036	57,288	172,272	114,780
2035	59,844	165,677	112.761
2034	62,268	159,213	110,741
2033	64,557	152,885	108,721
2032	66,706	146,697	106,701
2031	68,708	140,655	104,682
2030	70,559	134,764	102,662
2029	72,251	129,033	100,642
2028	73,775	123,470	98,622
2027	75,120	118,085	96,603
2026	76,274	112,891	94,583
2025	77,219	107,907	92,563
2024	77,933	103,154	90,543
2023	78,379	98,668	88,524
2022	78,509	94,499	86,504
2021	78,241	90,727	84,484
2020	77,470	87,459	82,464

5.1.2. Quality Metrics of Forecast

Quality metrics display performance results, types, and parameters of the forecast. It also provides ability to measure reliability of the forecast compared to other OEM forecasts. There exist two metrics to measure the quality: forecast method and results and forecast quality metrics.

5.1.2.1. Forecast Method and Results

The forecast is run by using exponential smoothing method. Table 5.2 shows that the compound annual growth rate for aircraft fleet per year is 6.1%. This annual growth rate brings the compounded growth from 2020 to 2039 to 46.5%. No repeating pattern is observed over time. Thus, there is no seasonal effect. The contribution converges to trend. Finally, the performance of the forecast that is explained in section 4.3.1.3.1 is displayed as “Ok”. The result is acceptable compared to the basic forecasting technique, i.e., naïve forecast and is more accurate. This is important since naïve forecast is the baseline compared to more complex forecasting methods such as applied exponential smoothing.

Table 5.2. Commercial Aircraft Fleet Forecast Results

Initial	Change From Initial	Seasonal Effect		Contribution		
2020	**2020 – 2039**	**High**	**Low**	**Trend**	**Season**	**Quality**
82,464 ± 6.1%	46.5%	None		100%	0%	Ok

5.1.2.2. Forecast Quality Metrics

There also exists metrics to investigate the quality of the forecast. Table 5.3 gives the results for the forecast quality metrics. The forecast quality metrics is meaningful when it is compared to ASK and RPK forecasts. Further comparison will be given in Section 5.4.

Table 5.3. Commercial Aircraft Fleet Forecast Quality Metrics Results

Model			Quality Metrics				Smoothing Coefficients		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**Alpha**	**Beta**	**Gamma**
Additive	Additive	None	1,939	1,473	0.62	3.0%	0.500	0.500	0.000

Based on the forecast run in Tableau Software with exponential smoothing method, lower prediction interval for Aircraft in-Service Fleet is determined as 51,799. Table 5.4 compares this value with Boeing current market outlook for 2019-2039 (50,660) and Airbus Global Market Forecast (47,680). The variation (delta) of the forecast changes from 2.24% to 8.64% compared to Boeing and Airbus figures.

Table 5.4. Commercial Aircraft Fleet Forecast (2020-2039 Estimate)

Forecast Comparison	**Aircraft in-Service Fleet**	**Tableau 2038 Delta (%)**
Boeing CMO 2019-2039	50,660	+2.24
Airbus GMF 2019-2039	47,680	+8.64
Tableau Software 2039	51,799 (Lower Prediction Interval for Aircraft Fleet)	-

5.2. Available Seat Kilometer (ASK) Forecast

Figure 5.2 gives the forecast results for ASK growth rate. The dark purple line represents ASK forecast held by JADC. The forecast values include the value itself, upper and lower prediction intervals values per year for ASK from 2020 to 2039. Table 5.5 presents the forecast results.

In Table 5.6, Tableau Software exponential smoothing method predicts the compounded annual average growth rate as 12.27% until 2039. However, JADC estimates that ASK forecast value as 4.3%. Tableau forecast is 185% higher than JADC prediction.

Figure 5.2. ASK in Tableau Forecast and Outputs (1999-2019 Actual, 2020-2039 Estimate)

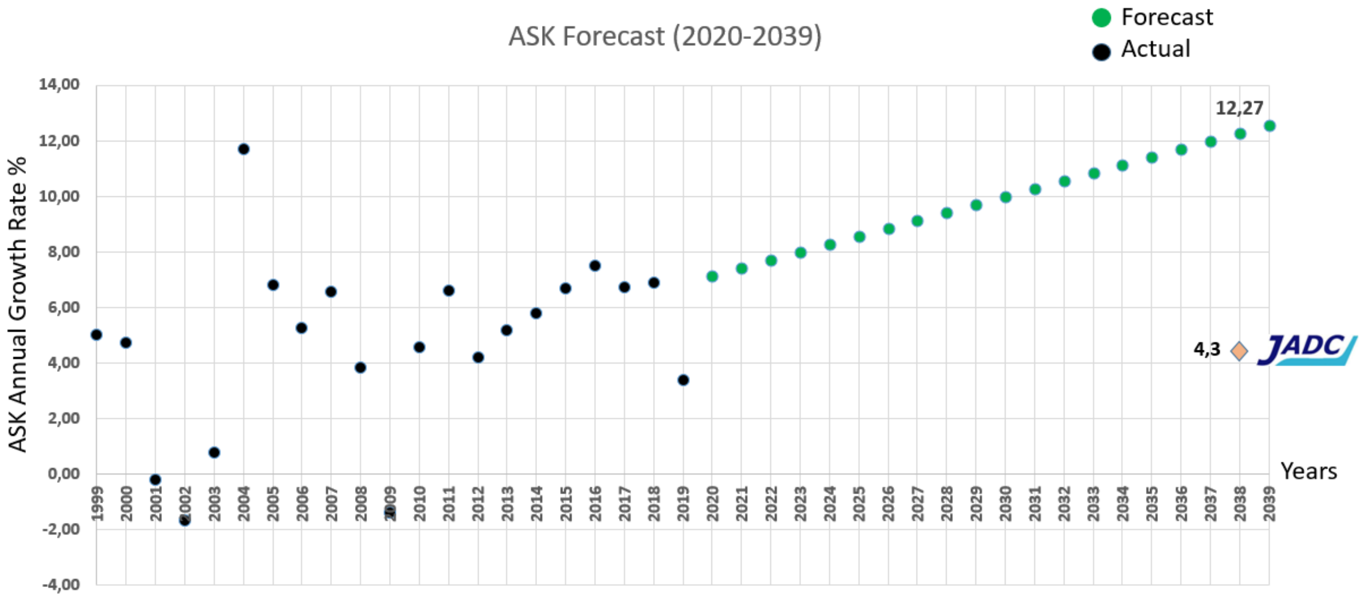

Table 5.5. ASK Figures

Years	Year-on-Year Growth (%)
2039	12.55
2038	12.27
2037	11.99
2036	11.70
2035	11.42
2034	11.13
2033	10.85
2032	10.56
2031	10.28
2030	9.99

Table 5.5 (Continued)

2029	9.71
2028	9.42
2027	9.14
2026	8.85
2025	8.57
2024	8.28
2023	8.00
2022	7.71
2021	7.43
2020	7.15

Table 5.6. ASK Forecast Findings (1999-2019 Actual, 2020-2039 Estimate)

Forecast Comparison	Compound Annual Average Growth %	Tableau 2038 Delta (%)
JADC	4.30%	+185
Tableau Software 2039	12.27%	-

5.2.1. Quality Metrics of Forecast

The quality metrics display the performance results, types, and parameters of forecast. It also provides ability to measure reliability of the forecast compared to other OEM forecasts. There exist two metrics to measure the quality: forecast method and results and forecast quality metrics.

5.2.1.1 Forecast Method and Results

The forecast is run by using exponential smoothing method. Table 5.7 shows that the compounded annual growth rate for ASK per year is 9.85%. This annual growth rate brings the compounded growth to 75.7% from 2020 to 2039. No repeating pattern is observed over time. Thus, there is no seasonal effect. The contribution converges to trend. Finally, the performance of the forecast that is explained in section 4.3.1.3.1 is displayed as “Poor”. The result is unacceptable compared to the basic forecasting technique, i.e., naïve forecast and is less accurate than it. This is important since naïve forecast is the baseline compared to the more complex forecasting methods such as applied exponential smoothing.

Table 5.7. ASK Growth Rate Forecast Results

Initial	Change From Initial	Seasonal Effect		Contribution		
2020	**2020 – 2039**	**High**	**Low**	**Trend**	**Season**	**Quality**
7.15 ± 91.2%	75.7%	None		100.0%	0.0%	Poor

5.2.1.2 Forecast Quality Metrics

There also exists major metrics to investigate and determine the quality of the forecast. Table 5.8 gives the results for the forecast quality metrics. The latter is meaningful when it is compared to Aircraft in-Service, and RPK forecasts. Further comparison will be given in Section 5.4.

Table 5.8. ASK Growth Rate Forecast Quality Metrics Results

Model			Quality Metrics				Smoothing Coefficients		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**Alpha**	**Beta**	**Gamma**
Additive	Additive	None	3.32	2.41	0.90	120.6%	0.058	0.367	0.000

5.3. Revenue Passenger Kilometer (RPK) Forecast

Figure 5.3 gives the forecast results for RPK growth rate. In Figure 5.3, the dark blue line represents the forecast of by Boeing (4.6%) for the years 2019-2038, while the purple line shows the forecast of aircraft fleets by Airbus (4.3%) for the same period. The forecast values include the specific values per year for RPK from 2020 to 2039. Table 5.9 presents the forecast results.

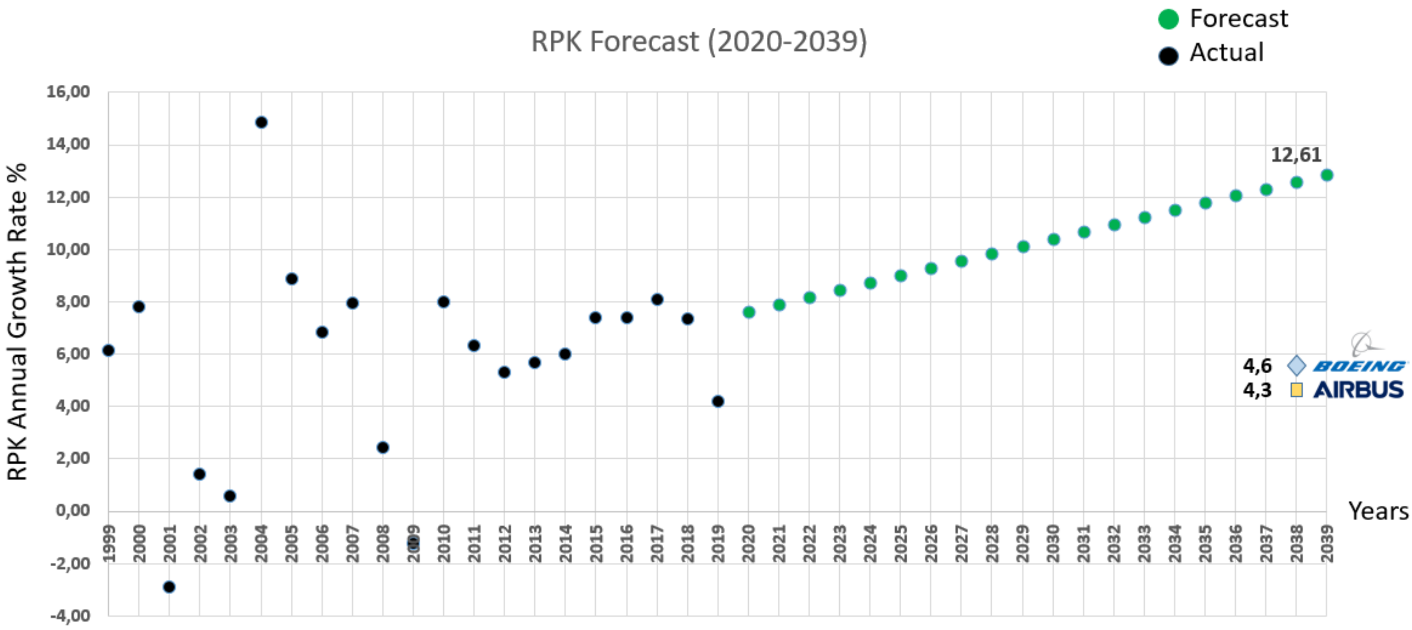

Figure 5.3. RPK in Tableau Forecast and Outputs (1999-2019 Actual, 2020-2039 Estimate)

Table 5.9. RPK Figures

Years	Year-on-Year Growth %
2039	12.88
2038	12.61
2037	12.33
2036	12.06
2035	11.78
2034	11.50
2033	11.23
2032	10.95
2031	10.67
2030	10.40
2029	10.12
2028	9.85
2027	9.57
2026	9.29
2025	9.02
2024	8.74

Table 5.9. (Continued)

2023	8.47
2022	8.19
2021	7.91
2020	7.64

In Table 5.10, Tableau Software exponential smoothing method predicts the compound annual average growth rate as 12.61% until 2039. However, Boeing and Airbus estimates that RPK forecast value is 4.6% and 4.3%, respectively. Tableau forecast is 174% higher than Boeing prediction and 193% higher than Airbus prediction.

Table 5.10. RPK Forecast Findings (2020-2039 Estimate)

Forecast Comparison	**Compound Annual Average Growth %**	**Tableau 2039 Delta (%)**
Boeing CMO 2019-2039	4.6 %	+174
Airbus GMF 2019-2038	4.3 %	+193
Tableau Software 2039	12.61 %	-

5.3.1. Quality Metrics of Forecast

Quality metrics display the performance results, types, and parameters of the forecast. It also provides ability to measure reliability of the forecast compared to other OEM forecasts. There exist two metrics to measure the quality: forecast method and results and forecast quality metrics.

5.3.2. Forecast Method and Results

The forecast is run by using exponential smoothing method. Table 5.11 shows that the compounded annual growth rate for RPK per year is 12.88%. This annual growth rate brings the compounded growth to 68.7% from 2020 to 2039. No repeating pattern is observed over time. Thus, there is no seasonal effect. The contribution converges to trend. Finally, the performance of the forecast that is explained in section 4.3.1.3.1 is displayed as “Poor”. The result is unacceptable compared to the basic forecasting technique, i.e., naïve forecast and is less accurate than it. This is important since naïve forecast is the baseline compared to the more complex forecasting methods such as applied exponential smoothing.

Table 5.11. RPK Growth Rate Forecast Results

Initial	Change From Initial	Seasonal Effect		Contribution		
2020	**2020 – 2039**	**High**	**Low**	**Trend**	**Season**	**Quality**
7.64 ± 105.4%	68.7%	None		100.0%	0.0%	Poor

5.3.2.1 Forecast Quality Metrics

There also exists major metrics to investigate and determine the quality of the forecast. Table 5.12 gives the results for the forecast quality metrics. The latter is meaningful when it is compared to Aircraft in-Service, and ASK forecasts. Further comparison will be provided in Section 5.4.

Table 5.12. RPK Growth Rate Forecast Quality Metrics Results

Model			Quality Metrics				Smoothing Coefficients		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**Alpha**	**Beta**	**Gamma**
Additive	Additive	None	4.10	3.01	0.88	87.1%	0.040	0.453	0.000

5.4. Comparison of Forecast Quality Metrics

The comparison of quality metrics results for commercial Aircraft in-Service Fleet, ASK and RPK forecasts are presented in Table 5.13. We observe that exponential smoothing model with the level and trend is applied as additive. The smoothing coefficients of alpha, beta and gamma indicate the level, trend, and seasonality for the model, respectively. All values for commercial Aircraft in-Service Fleet, ASK and RPK prove that there is no seasonality for the forecasts. The result from the forecast quality metrics show that commercial Aircraft in-Service Fleet has the most accurate result with a minimal MAPE and MASE values compared to the ASK and RPK forecasts. However, the forecast accuracy for RPK is medium due to the difference in MAPE values (ASK MAPE: 120.60% and RPK MAPE: 87.10%) compared to that of ASK. Regarding the ASK quality metrics, it is the worst performer for the forecast. Table 5.14 also proves that Aircraft in-Service Fleet is the top performer in terms of forecast quality.

Table 5.13. Comparison of Forecast Quality Metrics Results

	Model			**Quality Metrics**				**Smoothing Coefficients**		
Forecast	**Level**	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**Alpha**	**Beta**	**Gamma**
Aircraft In-Service Fleet	Additive	Additive	None	1,939	1,473	0.62	3.00%	0.500	0.500	0.000
ASK	Additive	Additive	None	3.32	2.41	0.9	120.60%	0.058	0.367	0.000
RPK	Additive	Additive	None	4.1	3.01	0.88	87.10%	0.040	0.453	0.000

Table 5.14. Comparison of Forecast Results

	Initial			Change From Initial	Seasonal Effect		Contribution		
Forecast	**2020**			**2020 – 2039**	**High**	**Low**	**Trend**	**Season**	**Quality**
Aircraft In-Service Fleet	82,464	±	6.10%	46.50%	None		100.00%	0.00%	Ok
ASK	7.15	±	91.20%	75.70%	None		100.00%	0.00%	Poor
RPK	7.64	±	105.40%	68.70%	None		100.00%	0.00%	Poor

5.5. Regression Analysis

5.5.1. Regression Analysis for Aircraft in-Service Fleet

We run multilinear regression by using the dependent variables of jet fuel price per barrel, GDP growth rate, and inflation rate. Table 5.15 show that adjusted R square of the model is 0.486 with the $R^2 = .563$, meaning that the linear regression explains 56.3% of the variance in the data. The results in Table 5.16 presents that inflation has a negative and significant effect on Aircraft in-Service fleet because the passengers will be reluctant to prefer travelling by air during the inflationary periods. Hence, the total volume of the Aircraft in-Service Fleet decreases due to the lack of demand. We observe positive but insignificant effects for GDP growth rate and jet fuel prices.

Table 5.15. Regression Model Summary for Aircraft in-Service Fleet

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	.751	.563	.486	11361.534

Table 5.16. Regression Analysis Coefficients for Aircraft in-Service Fleet

Model	Unstandardized Coefficients		Standardized Coefficients	
	B	Std. Error	Beta	Significance
(Constant)	87494.611	15417.805		<.001
GDP Growth Rate	539.716	2183.973	.044	.808
Inflation Rate	-13014.622	3923.389	-.592	.004
Jet fuel price (Per Barrel)	206.363	72.870	.455	.012

5.5.2. Regression Analysis for ASK

We run the same multilinear regression for ASK. Table 5.17 show that adjusted R square of the model is 0.401 with the $R^2 = .491$, meaning that the linear regression explains 49.1% of the variance in the data. The results in Table 5.18 presents that the GDP growth rate has a positive and significant effect on ASK since GDP growth creates wealth effect and this leads airlines to increase the capacity of seats. We observe no significant effects for inflation rate and jet fuel prices.

Table 5.17. Regression Model Summary for ASK

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	.701	.491	.401	2.46326%

Table 5.18. Regression Analysis Coefficients for ASK

Model		Unstandardized Coefficients		Standardized Coefficients	Significance
		B	Std. Error	Beta	
	(Constant)	.973	3.343		.774
	GDP Growth Rate	1.791	.474	.728	.001
	Inflation Rate	-1.134	.851	-.257	.200
	Jet fuel price (Per Barrel)	.018	.016	.202	.261

5.5.3. Regression Analysis for RPK

We run the same multilinear regression for RPK. Table 5.19 show that adjusted R square of the model is 0.478 with the $R^2 = .556$, meaning that the linear regression explains 55.6% of the variance in the data. The results in Table 5.20 presents that the GDP growth rate has a positive and significant effect on RPK since GDP growth stimulates consumer appetite for more air travel, leading to an increase in demand. We observe no significant effects for inflation rate and jet fuel prices.

Table 5.19. Regression Model Summary for RPK

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	.746	.556	.478	2.81850%

Table 5.20. Regression Analysis Coefficients for RPK

Model		Unstandardized Coefficients		Standardized Coefficients	Significance
		B	Std. Error	Beta	
	(Constant)	.354	3.825		.927
	GDP Growth Rate	2.425	.542	.805	<.001
	Inflation Rate	-1.182	.973	-.218	.241
	Jet fuel price (Per Barrel)	.009	.018	.083	.613

In summary, we observe no significant effect for jet fuel prices in none of the regression models because the jet fuel prices do not have a direct effect on passenger demand and seat capacity. However, it has a direct effect for the operations of the airlines.

CHAPTER VI

CONCLUSION

Commercial aviation industry highly contributes to global economy. Likewise, there is close interaction between global economic parameters such as GDP, inflation rate, and fuel prices and commercial aviation ecosystem, affecting the demand and supply in the industry. Forecasting comes into play due to the uncertainty raised in the aviation industry. In fact, recent unfortunate incidences such as 737-Max grounding, and COVID-19 have shown the importance of forecasting. Original Equipment Manufacturers, airlines, and airports have been deeply affected from these crises. However, these events are no longer Black Swan. They should be forecasted and managed by all parties in commercial aerospace ecosystem. Thus, "accurate forecasting" becomes much more critical than ever before to keep a sustainable business environment.

This study analyses three significant parameters of the airline industry, namely, Aircraft in-Service, RPK, and ASK, via Tableau Software exponential smoothing forecasting method. Multilinear regression analysis demonstrates that global economic parameters have an impact on the Aircraft in-Service, RPK and ASK. GDP has a positive and significant effect on RPK and ASK, while inflation rate has a negative and significant effect on the Aircraft in-Service. The delta of the Aircraft in-Service forecast varies from 2.24% to 8.64% compared to Boeing and Airbus figures. However, RPK forecast in Tableau is 174% higher than Boeing prediction and 193% higher than Airbus prediction, while ASK forecast is 185% higher than Japan Aircraft Development Corporation prediction.

6.1. Implications of the Study

The results have important implications on different parties in commercial aviation business. Airlines and Original Equipment Manufacturers may employ the Tableau Software to make accurate forecasts for metrics in defining and fine-tuning their long-run strategies. The findings also provide insights to financial institutions and institutional investors that are interested in giving loans and making long-term investments based on the forecasted figures since the latter would affect cash flows derived by these companies. Last but not least the results influence policy makers and government authorities in deciding on the size of investment that would be made in airlines and airports to identify the break-even point and return on investment depending on the forecasted figures.

6.2. Limitations of the Study and Future Research

We acknowledge that the study has some limitations. The figures may be more accurately forecasted if a longer period database i.e., longer than 20 years, could be used. Although Tableau Software is a promising candidate for Aircraft in-Service forecast, and other parameters further studies may be held to support the findings of this study by employing other methods such as SAS, Qlik Sense, MicroStrategy, and Oracle Analytics.

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