Fuel Efficiency in Saudi Arabia’s Aviation Sector: Progress and Future Implications

Andres Felipe Guzman, Juan Nicolas Gonzalez, and Abdulrahaman Alwosheel

June 2023

Doi: 10.30573/KS--2023-DP16
Acknowledgments

The authors are very grateful to our colleagues at the King Abdullah Petroleum Studies and Research Center (KAPSARC) for their constructive and valuable comments.

About KAPSARC

KAPSARC is an advisory think tank within global energy economics and sustainability providing advisory services to entities and authorities in the Saudi energy sector to advance Saudi Arabia’s energy sector and inform global policies through evidence-based advice and applied research.

This publication is also available in Arabic.

Legal Notice

© Copyright 2023 King Abdullah Petroleum Studies and Research Center (“KAPSARC”). This Document (and any information, data or materials contained therein) (the “Document”) shall not be used without the proper attribution to KAPSARC. The Document shall not be reproduced, in whole or in part, without the written permission of KAPSARC. KAPSARC makes no warranty, representation or undertaking whether expressed or implied, nor does it assume any legal liability, whether direct or indirect, or responsibility for the accuracy, completeness, or usefulness of any information that is contained in the Document. Nothing in the Document constitutes or shall be implied to constitute advice, recommendation or option. The views and opinions expressed in this publication are those of the authors and do not necessarily reflect the official views or position of KAPSARC.
Despite the fast global expansion of the aviation industry, due to its sustainability issues, the industry’s concerns about energy efficiency and emissions are still very important. Studying the changing energy consumption patterns in Saudi Arabia is crucial, as the country is expected to see significant changes in the coming years with new infrastructure, an increase in tourism, and new airlines. As a result, the energy efficiency performance of the aviation sector will have a key role in achieving global targets and commitments related to the environment. This paper considers time series models of 20 airports in Saudi Arabia and determines, on a fleet-wide basis, how fuel was efficiently utilized by aviation from 2017 to 2021, including during the outbreak of the COVID-19 pandemic. This research assesses fuel efficiency by considering historical trends, the situation that would have happened if the COVID-19 pandemic had not occurred, and the situation that effectively occurred in the aviation sector to contribute to the ongoing debate about energy in aviation. The findings, supported by abrupt fluctuations centered on a few days, show significant increases in airport efficiency explained by the segment of religious travelers. Additionally, by contrasting the predicted and anticipated situation and what occurred, the results show that aviation has improved by considering fuel efficiency regardless of disruptive events. In other words, airports that previously decreased fuel efficiency have started to improve significantly, while the other airports are maintaining a steady growth pattern to recover their previous fuel efficiency. Energy concerns and emissions in this sector continue to be a topic of research because the outcomes can support the promotion of new policies and measures to encourage this sector to overcome the challenges affecting energy and the environment in the short and medium terms in a sector in which abatement is difficult.
Since the twentieth century, air transport development has become an essential issue of world transport because numerous travel possibilities worldwide have been opened up, shortening distances, reducing travel times, and supporting tourism and local businesses. Therefore, the aviation sector has witnessed significant growth worldwide in recent decades. Additionally, it has been an essential stimulus for economic development because of worldwide connectivity (e.g., job creation, global trade, gross domestic product, and gross value-added growth). Although aviation has been resilient to external events, the sector continues to receive attention regarding concerns about its energy performance and environmental impact caused by the greenhouse gas (GHG) emissions emerging from this transport mode.

In addition, aviation is one of the most important intensively energy-demanding sectors in transportation, just behind road transportation, which is historically the most demanding sector worldwide. The numbers provided by the Organization of the Petroleum Exporting Countries (OPEC) (2021) show that oil demand in aviation worldwide was approximately 6.7 million barrels per day (MMb/d) in 2019 (i.e., 12% of the global total) and decreased to 3.5 MMb/d in 2020 due to measures to contain and prevent the spread of the COVID-19 pandemic. However, people dealt with the virus, and over time, governments have gradually lifted restrictions. Domestic flights were steadily resumed in each country, while international flights took longer because the restrictions were more substantial at the international level.

The energy performance of aviation can be understood interchangeably as a measure of energy intensity and/or efficiency. Indeed, energy is a significant concern today, not only for the depletion of nonrenewable resources (for their use in generating fossil-based fuels) but also for rising related emissions. The introduction of new technology, more efficient aircraft designs, the use of low-carbon aviation fuels (LCAFs), new alternative fuels (such as hydrogen, sustainable aviation fuels (SAFs), and electrical power), new airline carriers, and changes in passenger load factors are just a few of the energy-related issues that the aviation sector is currently facing. Therefore, stakeholders, including aircraft manufacturers, airports, governments, and airline carriers, are pushing for new initiatives aimed at improving a sector that is highly dependent on fossil-based fuels. Thus, the energy performance of the aviation sector is crucial for its future development since aviation is expected to continue to grow despite the situation worldwide evidenced during the COVID-19 pandemic. Although aviation is likely to fully recover to a prepandemic (i.e., 2019) level in the following months or years, depending on each country’s factors and the global situation, the demand for air transportation will continue to grow in the years to come, resulting in a rise in fuel consumption and emissions. Consequently, energy performance or efficiency will be crucial for understanding whether the growth percentage in energy differs as the aviation sector grows.

At the global level, the aviation sector in the Middle East and North Africa (MENA) has experienced rapid growth over recent decades, mainly driven by the global expansion of Emirates and other carriers from the Persian Gulf region (Joshan and Maertens 2020). In this sense, remarkably, aviation in Saudi Arabia has been one of the fastest growing transport sectors in the country. According to the General Authority of Civil Aviation (GACA) (2022), aviation demand peaked in 2019 with more than 103 million passengers that year, including international and domestic flights. Furthermore, considering both departures and arrivals, traffic in Saudi Arabia rose rapidly at a composite annual
growth rate (CAGR) of 9.8% per year from 2010 to 2019, showing a definite upward trend. Moreover, the historical trends of aviation in Saudi Arabia from 1971 to 1994 reported by Ba-fail et al. (2000) stress an average annual growth rate of 15%, which confirms the considerable development in this sector in recent decades. Indeed, aviation in the Kingdom has increased tremendously since the early 1980s, when only three international airports existed in Saudi Arabia (Al-Jarallah 1983) compared to the 27 operating airports registered in 2022 (13 with international and domestic services and 14 with domestic services exclusively). Thus, the expected growth in aviation in Saudi Arabia could soon be larger than the growth in the country’s GDP. In addition, the International Air Transport Association (IATA) (2022) has prompted attention to global aviation growth from 2019 to 2040, with an average annual rate of 3.3%.

Although the total passenger demand in Saudi Arabia led to higher growth from 2010 to 2019, with a CAGR of approximately 10%, the COVID-19 pandemic created a significant disruption in 2020. The COVID-19 pandemic led to a 65% reduction in total demand in 2020 (losing approximately 66 million passengers). This reduction was entirely the result of the preventive measures taken in the country and worldwide to prevent the spread of the virus. The measures taken by the government regarding the aviation sector started before the first COVID-19 case was reported, as it suspended flights between Saudi Arabia and China as well as the entry of all international pilgrims and tourists and banned inbound travel from affected countries (including Gulf Cooperation Council (GCC) citizens). Additionally, after the first COVID-19 case was reported on March 2, all international and domestic air travel was suspended by March 15 (Algaissi et al., 2020).

The objective of this study is to provide a broad understanding of the recent trends and patterns in the fuel efficiency of the aviation sector of Saudi Arabia, given the plans to invest in this sector and the significant expected growing demand due to economic activity and tourism. Additionally, Saudi Arabia is located at the crossroads of three continents, making it a strategically important hub and gateway for air travel. Therefore, the factors mentioned above concerning Saudi Arabia make its selection for this research meaningful and helpful in developing effective energy policies. This paper develops a comprehensive analysis of the energy efficiency of the aviation sector of Saudi Arabia by considering its progress in the prepandemic period (2017 to 2019) and the current evolution in the recovery timeframe of the COVID-19 pandemic (2020 to 2021). The assessment compares the situation that would have happened to the historical trends, and finally, this study provides the short-term perspective to assess the evolution of energy efficiency. In addition, the impacts of the COVID-19 pandemic on the energy efficiency of the aviation sector of Saudi Arabia have not yet been documented. The results show that the regional lockdowns and gradual introduction of travel restrictions have considerably affected domestic and international passengers. Nevertheless, domestic air transportation exhibits more resilience than international air transportation. The policy implications for the region hold significance for policymakers and transport-related parties.

The remainder of this paper is organized as follows. Section 2 presents the previous literature related to energy in the aviation sector. Section 3 includes the data source used, as well as the description of the methodology, the estimation of fuel efficiency, and the limitations. This section is the basis of the results presented in Section 4. Finally, Section 5 summarizes the main results and policy suggestions derived from this research.
Energy in aviation is a critical issue worldwide due to the impact of fossil-based fuels on climate change. As an end-use sector, aviation has a long tradition of consuming significant amounts of fossil-based fuels compared to the residential, industrial, and commercial sectors. Indeed, in recent decades, energy demand has increased as the demand for transport has increased. According to the International Energy Agency (IEA) (2021), transport has the highest level of reliance on fossil fuels of any end-use sector and accounted for 37% of carbon dioxide (CO₂) emissions in 2020 (7.1 gigatonnes [Gt]). Specifically, in the aviation sector, the energy demand will increase by more than 5 MMb/d by 2030, reaching just over 14 MMb/d (Cozzi et al. 2021). Therefore, despite the efficiency improvements in aviation, energy will continue to increase due to the higher expected growth rate worldwide.

Causal relations with economic growth and population have traditionally been considered in demand forecasts. Different models and approaches have been developed to assess energy demand in many previous types of research to derive energy usage. For example, one of the most widely used methods is based on applying econometric models to forecast aviation demand to derive energy demand. However, as Perifanis (2021) mentioned, econometric models are criticized because they are based on past data to forecast future values. In addition, some researchers have fully implemented econometrics, while others use it as a component of their forecasting methodology (Perifanis 2021).

In addition to econometric models, other accounting methods have been used to assess and predict energy consumption as well as GHG emissions by including bottom-up and top-down accounting methods. The bottom-up approach considers the assessment of energy consumption from a technological perspective since it uses the technical parameters of transport activity, energy intensity, and emission factors for evaluation (J. Liu et al. 2019). On the other hand, the top-down method allocates the energy consumption in end-use sectors, namely, the industrial, residential, power, and transportation sectors. The application of these methodologies is well known in previous assessments of transport (see more details in Hao et al. [2015], He et al. [2005], Bahn et al. [2013], J. Liu et al. [2019], L. Liu et al. [2018]), reflecting the energy consumption in the road transport system sector. Importantly, these accounting methods have prompted the need for various considerations in the
method (i.e., the vehicle fleet, the average vehicle mileage traveled, and fuel economy, among other variables).

On the other hand, fuel demand estimation and emissions—principally GHGs—in aviation are of the utmost importance since this transport mode is highly dependent on fossil fuels and it is a sector in which abatement is difficult. Globally, aviation is responsible for 12% of transport-related GHG emissions and 2%-3% of all anthropogenic emissions (Kadyk et al. 2018). The general process of obtaining fuel consists of applying a fuel estimation model to convert aviation data into quantities of fuel using aircraft type information and route profiles. In the literature, two approaches are commonly used for this purpose. Low-fidelity models rely on simplified assumptions about the flight mission, while high-fidelity models depend on detailed flight mission data. For instance, Yanto and Liem (2018) defined low-fidelity physics-based models by considering aircraft operations and performance data for 40 different aircraft types, considering the mission payload and the range as inputs. On the other hand, reduced-order fuel consumption based on a high-fidelity flight profile simulator model was developed by Seymour et al. (2020). These model inputs are the great circle distance (GCD) between the origin and destination airports and the aircraft type. The model relies on ordinary least squares (OLS) regression for the specific parametrizations of each aircraft type. The different approaches show that fuel consumption (energy) in the aviation sector can be derived through mathematical models as an alternative to high-fidelity models such as flight planning software or historical fuel consumption obtained from airlines.

In addition to the methodologies above for estimating fuel consumption, other assessments consider the productivity gained per unit of fuel consumed. In this sense, the research carried out by Hileman et al.(2008) used payload fuel energy efficiency (PFEE) to compare its performance in the US, considering the total payload carried per kilometer over the fuel energy consumed. The findings show that for cargo and passengers overall operational efficiency improved by 51% between 1991 and 2007. Similarly, Dobruszkes & Ibrahim (2021) researched changes in fuel efficiency by considering nine European airports from 1996 to 2018, demonstrating an approximately 30% improvement. However, they found that the absolute fuel burned was multiplied by 2.5 during the same period.

In addition to previous research, there are crucial ongoing debates on the COVID-19 pandemic. It is receiving more attention due to the unexpected drop in worldwide demand in 2020, including its related consequences, with significant differences between domestic and international flights. Notably, the speed of recovery in the aviation sector in 2021 was also uneven due to the vaccination rollout and the individual measures taken by each country. Recent research by Wang et al. (2023) has prompted attention to the recovery process, showing that the passenger flow follows similar progressive rules and that the recovery rate increases over time, providing a reference for the expected restoration of air traffic. On the other hand, the impact of the energy consumption and CO₂ emissions of the aviation sector during the COVID-19 pandemic was analyzed by Bazzo Vieira et al. (2022). They used a fuel efficiency estimation involving passengers, distance, and the fuel consumed. The findings show that compared to the pre-post period of the pandemic outbreak, CO₂ emissions and the average fuel efficiency decreased due to the decrease in the number of passengers and passengers/flight regardless of the aircraft seat capacity. In
conclusion, fuel efficiency improvement has come to perform three main functions in the aviation sector: the change in the technology of aircraft, the increase in seat density, and the upward trend in the passenger load factor (PLF).

As described above, the aviation assessments related to energy (fuel) consumption, intensity, and efficiency have considered different approaches: a. forecasting demand using different econometric models as part of the methodology; b. assessment through either mathematical models, high-fidelity models, or historical data; and c. fuel efficiency methods that consider the payload, distance, and the fuel consumed. Despite the efforts to forecast aviation growth and demand, other factors, such as technology, the aircraft type, load management, and seat capacity, affect the industry's intensity or efficiency. In this regard, it is crucial to highlight fuel efficiency in this intensive end-user sector, including its GHG emissions, which are receiving more interest from policymakers, to provide a technical reference for implementing policies to improve energy efficiency and reduce the related $\text{CO}_2$ emissions.
Data description

To assess the fuel energy efficiency of the aviation sector of Saudi Arabia, we used the daily historical data available from the GACA (2022) at the airport level, exclusively considering domestic and international departures from Saudi Arabia to avoid double counting aircraft movements (flights) by also considering arrivals. Moreover, military flights, general aviation flights, and flights with zero passengers were excluded from the dataset because these flights are beyond the purview of this study. A total of 20 airports were selected for modeling purposes. In comparison, 6 airports were not included in the dataset to simplify the analysis, considering the different characteristics of the airports, the variation in the records due to unexpected closures due to the conflict with Yemen, regional heterogeneity, and their small reasonable traffic share – below 5% – participation in the Saudi market (within the study period 2017-2021). Additionally, one airport (Neom Bay Airport (NUM)) that started operation in 2019 was excluded due to unavailable information for the study period.

Regarding fuel efficiency, we estimated it on a daily fleet-wide basis considering the following expression:

\[
FE_{day}^j = \sum_{i=1}^{m} \frac{PAX_i \times D_i}{FK_i}
\]

where
- \(FE_{day}^j\) is the fuel efficiency per day of airport \(j\) (passenger kilometers [pax-km]/barrel) considering the number of daily flights \((i \text{ to } m)\)
- \(PAX_i\) is the total number of passengers carried on flight \(i\) (pax)
- \(D_i\) is the distance traveled by the passengers traveling in flight \(i\) (km)
- \(FK_i\) is the total fuel burned considering the specific aircraft \(FK\) used for flight \(i\) traveling distance \(i\) and expressed as barrels of oil equivalent (barrels)

We assume that the flight requires Arabian jet fuel (jet A-1 fuel). The distances were obtained considering all the daily flights registered by the airport from 2017 to 2021 using the GCD between all the origin-destination airport pairs and considering the route used for connecting the different domestic and international flight services registered during the day. Finally, we accounted for the different types of aircraft, considering the historical data in the analysis to estimate the fuel burned through the reduced models included in Seymour et al. (Seymour et al. 2020), regardless of either the payload or the number of passengers carried and expressed as the amount of energy contained in a barrel of crude oil (barrel of oil equivalent -BOE).

**Figure 1** shows the daily changes in the fuel efficiency of 20 airports in the aviation sector of Saudi Arabia. The magnitude of fuel efficiency in each airport is quite varied because the aviation sector seemed to have important fluctuations during the days of the years analyzed due to the seasonality of religious travel and the services offered. However, some airports showed that before the COVID-19 pandemic, they had a declining trend (ABT, AQI, URY, HAS, ELQ, HOF, RAH, TUI, URY), while other airports showed a constant trend (AJF, BHH, MED, RAE, SHW, TIF, TUU, YNB), and still others seemed to have a steadily increasing trend (GIZ, DMM, JED, RUH). Thus, these trends show that the aviation sector in Saudi Arabia has evolved significantly over the last few years.
Materials and Methods

Figure 1. Fuel efficiency in the aviation sector of Saudi Arabia (domestic and international services per day and airport, 2017-2021).

Note: ABT – King Saud Bin Abdulaziz Airport (Al-Bahah province); AJF – Al-Jawf Airport (Al-Jawf province); AQI – Al-Qaisumah Airport (Eastern province); BHH – Bisha Airport (Asir province); DMM – King Fahd International Airport (Eastern province); ELQ – Prince Naif Bin Abdulaziz Airport (Al Qassim province); GIZ – King Abdullah Bin Abdulaziz Airport (Jizan province); HAS – Ha’il Airport (Ha’il province); HOF – Al Ahsa Airport (Eastern province); JED – King Abdul Aziz International Airport (Makkah province); MED – Prince Mohammed bin Abdulaziz (Al Madinah province); RAE – Arar Airport (Northern Borders province); RAH – Rafha Airport (Northern Borders province); RUH – King Khalid International Airport (Riyadh province); SHW – Sharurah Airport (Najran province); TIF – Taif International Airport (Makkah province); TUI – Turafif Airport (Northern Borders province); TUU – Prince Sultan Bin Abdulaziz Airport (Tabuk province); URY – Gurayat Airport (Al-Jawf province); YNB – Prince Abdulmohsin Bin Abdulaziz Airport (Al Madinah province).

Source: KAPSARC analysis based on GACA (2022) information.

Method – Time Series Modeling

Time series analysis is a fascinating research field with numerous applications in business, economics, finance, transport, energy, and computer science. Time series analysis aims to investigate the path observations of time series, develop a model to describe the data structure, and then predict future time series values. Because time series forecasting is essential in many branches of applied science, an increment of effective models to improve forecasting accuracy has been developed. As noted by Papastefanopoulos et al. (2020), time series are useful in two situations: first, when there is little or no knowledge about the underlying data-generating distribution/process and, second, when there is no explanatory model that can adequately relate the prediction variable to other explanatory variables.
Additionally, a time series consists of four main components: (i) the level, i.e., the baseline; (ii) the trend, which increases or decreases over time; (iii) seasonality, which denotes a pattern or cycles over time; and (iv) noise, which represents variation in the data observed. The interactions of these components are typically classified as additive or multiplicative (Washington, Karlaftis, and Mannering 2010; Silveira-Santos et al. 2022).

Predictive accuracy must be evaluated because forecasting is frequently the primary goal of time series analysis (Gonzalez et al. 2022; Silveira-Santos et al. 2022). In most cases, accuracy refers to how well the model replicates traditionally collected data. Forecasting error (the difference between actual and predicted values) is a standard measure of accuracy. The root mean square error (RMSE) is an error validation metric that compares actual and predicted values. Therefore, the difference is referred to as the residual and is calculated using the standard deviation of the prediction errors. The same dependent unit is used in this metric.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Actual_i - Predicted_i)^2}{n}}
\]  

where

- RMSE is the root mean square error
- Actual \(_i\) is the actual value in a specific period of time \(i\)
- Predicted \(_i\) is the predicted value in a specific period of time \(i\)
- \(n\) is the total number of values considered

The last several decades have seen significant efforts and research output focused on developing and improving time series forecasting models. Time series modeling considers several factors, such as stationarity, autocorrelation, seasonality, unit roots, and structural breaks, that must be tested and can affect the accuracy and validity of the results. For this reason, six of the most commonly used and recent models were chosen and are described below.

**Prophet model**

Prophet is a time series forecasting model developed by Facebook that is designed to make forecasting easy and accessible to many users (Taylor and Letham 2018). The model decomposes the time series model into three main components: the trend, seasonality, and holidays. As noted by Taylor & Letham (2018), Prophet uses a Bayesian framework to model the trend component and a Fourier series to model the seasonality component. Prophet incorporates an additional component to account for the effect of holidays on the time series. It can handle missing data and other time-varying factors that may impact the forecasted values. One advantage of using Prophet is that it requires few parameter adjustments, making it easy even for those with little or no experience with time series forecasting.

**ETS model**

The ETS model is a time series forecasting model that decomposes a time series into its underlying components: the error, the trend, and seasonality. It uses a combination of exponential smoothing and the Box–Jenkins methodology to model these components, allowing it to handle a wide range of time series patterns (Hyndman and Athanasopoulos 2018; Hyndman and Khandakar 2008). The ETS model has three different configurations (Naim and Mahara 2018) i.e., ETS(A, N, N), ETS(A, A, N), and ETS(M, A, N), which vary based on the type of component: A for additive, M for multiplicative, and N for none. The first variant assumes that the error component is additive, and the second assumes that
both the trend and error components are additive. The third variant assumes that the trend component is multiplicative and that the error component is additive. The ETS model can handle missing values and data with trend or seasonality components. Adjusting its parameters can improve its forecasting accuracy.

**Seasonal autoregressive integrated moving average (SARIMA) model**

The seasonal autoregressive integrated moving average (SARIMA) model is a variation of the classical ARIMA model. It was introduced by Box et al. (2016), and in this model, the seasonal effect of the attribute is considered. In general, it is denoted as $SARIMA(p,d,q) (P,D,Q)_s$, where $p$, $d$, $q$ and $P$, $D$, $Q$ are nonnegative integers that refer to the polynomial order of the autoregressive (AR), integrated (I), and moving average (MA) parts of the nonseasonal and seasonal components, respectively. In other words, this model is very similar to the ARIMA model, except for an additional set of AR and MA components. The frequency of seasonality offsets the additional lags. SARIMA models allow differencing data by seasonal frequency and nonseasonal differencing.

**Bagged model**

A bagged model is a technique for improving the performance of time series forecasting models by training multiple models on different subsets of data and then averaging their predictions to make a final prediction. As noted by Bergmeir et al. (2016), a bagged model is an ensemble technique that involves training multiple models on different data subsets and then combines the predictions of all the models to make a final prediction. Bagging can be applied by training multiple models on different subsets of time series data, with each subset being created by randomly resampling the original data with replacement data. The final prediction is then made by averaging the predictions of all the models. Bagging can reduce the variance in the model’s predictions, making them more robust and less prone to overfitting (Petropoulos, Hyndman, and Bergmeir 2018).

**BATS and TBATS models**

The Bayesian additive trends and seasonality (BATS) model and the exponential smoothing state-space model with Box–Cox transformation, autoregressive moving average (ARMA) errors, and trend and seasonal components (TBATS) are two time series forecasting models designed to handle data with both additive and multiplicative trends and seasonality, and they are helpful in handling complex data (de Livera, Hyndman, and Snyder 2011). BATS is a Bayesian state-space model that can handle multiple seasonal patterns and changes in the intensity of seasonality. On the other hand, TBATS is a combination of exponential smoothing and a state-space approach that includes a Box–Cox transformation and ARMA errors. It can handle additive and multiplicative trends and seasonality as well as multiple seasonal patterns and changes in the intensity of seasonality (Webel 2022).

**STLM**

The structural time series model (STLM) is a time series forecasting model that can handle both linear and nonlinear data patterns. It is a state-space model that captures the underlying structure of data using a set of latent variables (Harvey and Shephard 1993). It can manage various time series patterns, including trends, seasonality, and irregular components. The STLM divides a time series into three components: a linear trend, a seasonal component, and an irregular component. According to Harvey (1990), a Kalman filter is used...
to model the linear trend, and a hidden Markov model is used to model the seasonal and irregular components. The model also includes a noise component to account for measurement error. The STLM helps address time series data with multiple seasonalities, and it helps in modeling data with nonlinear patterns. It can be used for various forecasting applications, including demand forecasting and energy consumption forecasting. However, it necessitates a thorough understanding of the underlying data structure, and it may be necessary to tune the model parameters for optimal performance.

For time series estimation, the R package autoTS was used (Roussez 2022). It provides a simple and efficient way to forecast time series data automatically. The function uses a combination of different time series forecasting models and evaluation metrics to find the best model for the data.
This paper studies the evolution of fuel efficiency over time using time series models. The data used in the analysis cover a significant period and were carefully selected to ensure that the results represent the overall fuel efficiency trends. Importantly, the period covers daily data comprising five years, and previous or more recent data were not available with the same detail. The analysis results clearly and concisely highlight the study’s key findings on the evolution of fuel efficiency in Saudi Arabia. The results also provide valuable insights into the evolution of fuel efficiency and will contribute to the ongoing discussion surrounding energy policies and the role of alternative fuels in meeting energy demands and global environmental targets and commitments.

Some patterns are identified as a preliminary analysis for each airport. Figure 2 shows the variability of fuel efficiency values among airports for each year and the

**Figure 2.** Boxplot of the average daily fuel efficiency in the aviation sector of Saudi Arabia (domestic and international services per year and airport, 2017–2021).

Note: ABT – King Saud Bin Abdulaziz Airport (Al-Bahah province); AJF – Al-Jawf Airport (Al-Jawf province); AQI – Al-Qaisumah Airport (Eastern province); BHH – Bisha Airport (Asir province); DMM – King Fahd International Airport (Eastern province); ELQ – Prince Naif Bin Abdulaziz Airport (Al Qassim province); GIZ – King Abdullah Bin Abdulaziz Airport (Jizan province); HAS – Ha’il Airport (Ha’il province); HOF – Al Ahsa Airport (Eastern province); JED – King Abdul Aziz International Airport (Makkah province); MED – Prince Mohammed bin Abdulaziz (Al Madinah province); RAE – Arar Airport (Northern Borders province); RAH – Rafha Airport (Northern Borders province); RUH – King Khalid International Airport (Riyadh province); SHW – Sharurah Airport (Najran province); TIF – Taif International Airport (Makkah province); TUI – Turailf Airport (Northern Borders province); TUU – Prince Sultan Bin Abdulaziz Airport (Tabuk province); URY – Gurayat Airport (Al-Jawf province); YNB – Prince Abdulmohsin Bin Abdulaziz Airport (Al Madinah province).

Source: KAPSARC analysis based on GACA (2022) information.
differences in distribution between years (2017-2021). Outliers are visible on the plots, allowing additional investigation into the causes of the extreme values explained mainly by the dynamics of the country. Multiple findings are revealed. First, it is clear that the distribution of fuel efficiency values varied greatly among airports, with some airports consistently performing better than others because of their domestic and international services and the aircraft used (see JED, DMM, RUH). Second, the variability of fuel efficiency values in nine airports increased over time before the COVID-19 pandemic may indicate that the efficiency of air transportation was increasing. Third, unsurprisingly, fuel efficiency decreased considerably in 2020 due to the measures taken worldwide to stop the spread of the virus. However, as an initial preview, some airports have started recovering their fuel efficiency, showing a steady upward trend.

For each airport, the performance of multiple time series models was evaluated. The models were trained on fuel efficiency data from each airport before the period of the COVID-19 pandemic. The forecast values were compared to the fuel efficiency

Table 1. Root mean square error (RMSE) metric for all models and airports (best models in bold).

<table>
<thead>
<tr>
<th>Airport</th>
<th>Prophet Model</th>
<th>ETS Model</th>
<th>SARIMA Model</th>
<th>TBATS Model</th>
<th>BATS Model</th>
<th>STLM Model</th>
<th>Bagged Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABT</td>
<td>5,606</td>
<td>3,168</td>
<td>3,781</td>
<td>3,812</td>
<td>3,812</td>
<td>3,682</td>
<td>3,591</td>
</tr>
<tr>
<td>AJF</td>
<td>6,118</td>
<td>6,848</td>
<td>5,068</td>
<td>5,397</td>
<td>5,255</td>
<td>5,633</td>
<td>5,454</td>
</tr>
<tr>
<td>AQI</td>
<td>6,139</td>
<td>3,551</td>
<td>3,508</td>
<td>3,542</td>
<td>3,532</td>
<td>3,787</td>
<td>3,779</td>
</tr>
<tr>
<td>BHH</td>
<td>3,623</td>
<td>3,080</td>
<td>3,093</td>
<td>3,409</td>
<td>3,072</td>
<td>3,040</td>
<td>3,035</td>
</tr>
<tr>
<td>DMM</td>
<td>57,634</td>
<td>60,676</td>
<td>66,510</td>
<td>62,830</td>
<td>60,500</td>
<td>61,936</td>
<td>57,139</td>
</tr>
<tr>
<td>EJH</td>
<td>1,059</td>
<td>1,038</td>
<td>1,019</td>
<td>1,000</td>
<td>1,005</td>
<td>1,073</td>
<td>1,012</td>
</tr>
<tr>
<td>ELQ</td>
<td>15,138</td>
<td>18,098</td>
<td>16,659</td>
<td>17,408</td>
<td>16,652</td>
<td>17,635</td>
<td>15,977</td>
</tr>
<tr>
<td>GIZ</td>
<td>26,936</td>
<td>20,925</td>
<td>20,666</td>
<td>21,316</td>
<td>21,458</td>
<td>21,148</td>
<td>18,484</td>
</tr>
<tr>
<td>HAS</td>
<td>27,733</td>
<td>27,582</td>
<td>53,416</td>
<td>27,683</td>
<td>23,347</td>
<td>124,978</td>
<td>46,471</td>
</tr>
<tr>
<td>HOF</td>
<td>6,328</td>
<td>3,005</td>
<td>5,220</td>
<td>2,792</td>
<td>3,006</td>
<td>3,698</td>
<td>3,054</td>
</tr>
<tr>
<td>JED</td>
<td>285,815</td>
<td>401,109</td>
<td>249,339</td>
<td>259,380</td>
<td>399,247</td>
<td>357,197</td>
<td>299,634</td>
</tr>
<tr>
<td>MED</td>
<td>140,444</td>
<td>126,995</td>
<td>121,044</td>
<td>123,708</td>
<td>135,214</td>
<td>141,968</td>
<td>121,735</td>
</tr>
<tr>
<td>RAJ</td>
<td>3,533</td>
<td>3,282</td>
<td>2,813</td>
<td>3,225</td>
<td>3,336</td>
<td>3,226</td>
<td>3,030</td>
</tr>
<tr>
<td>RAH</td>
<td>1,764</td>
<td>1,619</td>
<td>1,540</td>
<td>1,477</td>
<td>1,503</td>
<td>1,700</td>
<td>1,546</td>
</tr>
<tr>
<td>RUH</td>
<td>117,600</td>
<td>126,810</td>
<td>130,683</td>
<td>122,368</td>
<td>122,152</td>
<td>124,976</td>
<td>115,410</td>
</tr>
<tr>
<td>SHW</td>
<td>3,671</td>
<td>2,866</td>
<td>2,467</td>
<td>2,814</td>
<td>2,730</td>
<td>2,994</td>
<td>2,858</td>
</tr>
<tr>
<td>TIF</td>
<td>10,803</td>
<td>15,038</td>
<td>12,830</td>
<td>12,635</td>
<td>13,399</td>
<td>15,332</td>
<td>12,876</td>
</tr>
<tr>
<td>TUI</td>
<td>1,905</td>
<td>1,949</td>
<td>1,833</td>
<td>5,134</td>
<td>1,872</td>
<td>1,922</td>
<td>2,065</td>
</tr>
<tr>
<td>TUU</td>
<td>20,073</td>
<td>15,134</td>
<td>13,560</td>
<td>34,500</td>
<td>14,224</td>
<td>20,355</td>
<td>14,958</td>
</tr>
<tr>
<td>ULH</td>
<td>2,306</td>
<td>2,480</td>
<td>2,505</td>
<td>2,487</td>
<td>2,526</td>
<td>2,611</td>
<td>2,470</td>
</tr>
<tr>
<td>URY</td>
<td>7,796</td>
<td>5,376</td>
<td>3,679</td>
<td>3,701</td>
<td>4,205</td>
<td>4,005</td>
<td>4,616</td>
</tr>
<tr>
<td>WAE</td>
<td>1,555</td>
<td>1,098</td>
<td>1,031</td>
<td>1,006</td>
<td>1,212</td>
<td>1,144</td>
<td>1,132</td>
</tr>
<tr>
<td>YNB</td>
<td><strong>11,311</strong></td>
<td>17,182</td>
<td>14,313</td>
<td>13,421</td>
<td>14,372</td>
<td>12,143</td>
<td>13,001</td>
</tr>
</tbody>
</table>

Source: KAPSARC analysis based on GACA (2022) information.
values, and the results were analyzed using various statistical metrics, including the mean absolute error (MAE), mean square error (MSE), and root mean squared error (RMSE). Table 1 shows the RMSE estimated for each airport and model tested. The best model selected corresponds to the model with the lowest RMSE. Importantly, the RMSE orders of magnitude presented vary depending on the fuel efficiency of each airport. For this reason, it is not possible to compare models between airports.

As shown in Table 1, depending on the airport, the model that best fits the behavior of the data may vary. This variability occurs because the different models used have different strengths, as mentioned previously in the Methods section. The Prophet, SARIMA, and bagged models are the models with the best accuracy for the majority of the airports.

After selecting the best model for each airport, predictions for each airport are generated for the period of the COVID-19 pandemic (2020 and 2021). The aforementioned analysis allows us to see the fuel efficiency behavior if the pandemic had not occurred. Figure 3 shows graphical model predictions for the period in question. In general,

Figure 3. Forecast models for the period of the COVID-19 pandemic for the aviation sector of Saudi Arabia (2020-2021) (historical data in black, predicted data in blue).

Note: ABT – King Saud Bin Abdulaziz Airport (Al-Bahah province); AJF – Al-Jawf Airport (Al-Jawf province); AQI – Al-Qaisumah Airport (Eastern province); BHH – Bisha Airport (Asir province); DMM – King Fahd International Airport (Eastern province); ELQ – Prince Naif Bin Abdulaziz Airport (Al Qassim province); GIZ – King Abdullah Bin Abdulaziz Airport (Jizan province); HAS – Ha’il Airport (Ha’il province); HOF – Al Ahsa Airport (Eastern province); JED – King Abdul Aziz International Airport (Makkah province); MED – Prince Mohammed bin Abdulaziz (Al Madinah province); RAE – Arar Airport (Northern Borders province); RAH – Rafha Airport (Northern Borders province); RUH – King Khalid International Airport (Riyadh province); SHW – Sharurah Airport (Najran province); TIF – Taif International Airport (Makkah province); TUI – Turaif Airport (Northern Borders province); TUU – Prince Sultan Bin Abdulaziz Airport (Tabuk province); URY – Gurayat Airport (Al-Jawf province); YNB – Prince Abdulmohsin Bin Abdulaziz Airport (Al Madinah province).

Source: KAPSARC analysis based on GACA (2022) information.
the different models follow the trends (increasing or decreasing) of the previous data. Moreover, in cases where seasonality was notorious, this behavior was reproduced. As shown in Figure 3, for some airports, the forecast was that they would continue decreasing their fuel efficiency. However, the COVID-19 pandemic has functioned as a wake-up call for increasing fuel efficiency. To illustrate this point, the effect of the COVID-19 pandemic on fuel efficiency was evaluated by comparing what really occurred and what was predicted to have occurred. Figure 4 shows the change in fuel efficiency during the period of the COVID-19 pandemic. The findings reveal that the COVID-19 pandemic significantly impacted fuel efficiency at all airports (values less than 0). This decrease in fuel efficiency can be attributed to the pandemic’s decreased air travel demand and occupancy rates and even changes in flight patterns or airline management practices. An exciting result is that several airports have been recovering and reaching fuel efficiency levels similar to what they would have been (values higher than 0). This happens mainly at the lower level of efficient airports. Although the most efficient airports have not yet recovered, the trend shows that they will do so in the future.

Figure 4. Change in fuel efficiency during the period of the COVID-19 pandemic for the aviation sector of Saudi Arabia.
Based on historical data and calibrating multiple time series models, this paper explores the recent trends and patterns in the fuel efficiency of the aviation sector of Saudi Arabia. The aviation sector has started to recover, with some airports improving their fuel efficiency or reaching the fuel efficiency that they had in the years before the COVID-19 pandemic. However, the COVID-19 pandemic has brought attention to this energy-intensive sector and its rising concerns about energy. The findings of this research raise three policy issues: (i) COVID-19 has been a wake-up call for improving fuel efficiency in the aviation sector; (ii) further research is necessary to determine the impact of technology, fleet rollover, and modernization on fuel efficiency; and (iii) the aviation sector in Saudi Arabia has the potential for improvement through better management practices.

The COVID-19 pandemic has been a wake-up call for improving fuel efficiency in the aviation sector. The air services (domestic and international routes when available) of some airports did not consistently improve fuel efficiency in the period before the COVID-19 pandemic. The trends suggest that either those airports had been operating with a significantly greater aircraft frequency, increasing the amount of fuel used per passenger kilometer (pax-km), or that aircrafts were being flown with a lower occupancy factor (PLF) as a result of a lack of demand and the existence of alternative transport modes. However, as we found in the results, even if those airports registered poor fuel efficiency, the COVID-19 period has acted as a wake-up call to improve fuel efficiency. In addition, the seasonal trends over the years evidenced in most airports demonstrate significant gains in fuel efficiency on a specific number of days. Therefore, religious tourism and general tourism can help to promote efficiency.

Further research is necessary to determine the impact of technology, fleet rollover, and modernization on fuel efficiency. In countries such as Saudi Arabia, the aviation sector has experienced significant growth in passengers and services in recent years. However, no conclusive results demonstrate how changes in technology, fleet rollover, or fleet modernization during the study period modified fuel efficiency since their effects were not covered in this research. Similarly, we did not include the impact of fuel prices on fuel efficiency or fare prices in our research due to the daily time period covered because of data unavailability and the research objective. For this reason, further research could focus on analyzing how technology, fares, and fuel prices have progressed in the different airports of the country to provide more policy-relevant insights into the fuel efficiency gained by these factors.

The aviation sector in Saudi Arabia has the potential for improvement through better management practices. The results show that there is room for improvement in the aviation sector of Saudi Arabia. To illustrate this point, for most airports, the trends in fuel efficiency evidenced gains in their efficiency related to the management practices imposed through strict measures to avoid the spread of the virus. Therefore, airlines must adopt better management practices to improve their fuel efficiency performance, which will also complement their operational cost and environmental performance (CO₂ emissions).

Finally, as data for 2022 and 2023 become available, more research on the development of the Saudi aviation sector may be conducted to confirm the trends identified in this study regarding the increase in energy efficiency.
Endnotes

1 Energy intensity refers to the amount of energy required to produce output (for example, revenue tonne-km, kg-fuel/ revenue passenger kilometers (RPK)).

2 Fuel efficiency refers to the amount of fuel a unit of transport consumes per unit of distance traveled (for example, RPK/kf-fuel).

3 Located in Jeddah, Riyadh, and Dharan.

4 The Gulf Cooperation Council comprises Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

5 Religious tourism activities concentrated in the holy cities, Makkah and Madinah, and the opening of tourist visas in 2019.

6 AHB – Abha Airport (Asir province); DWD – Aldwadmi Airport (Riyadh province); EAM – Najran Airport (Najran province); EJH – Al Wajh Airport (Tabuk province); ULH – Prince Abdulmajeed Bin Abdulaziz Airport (Al Madinah province); and WAE – Wadi al-Dawasir Airport (Riyadh province).

7 A total of 1,825 days for 20 different airports, with approximately more than 2.5 million records.

8 DMM, ELQ, GIZ, JED, MED, RAH, RUH, TIF, and YNB.
References


About the Authors

Andres Felipe Guzman
Andres Felipe is a Fellow at KAPSARC working on the future of aviation energy demand. He has previously worked as a professor, researcher, and consultant. His research interests include assessing the economic impact of transport policies/economics, the macroeconomic impact of transport policies, and the development of transport- and energy-related models for energy-related decision support.

Juan Nicolas Gonzalez
Juan Nicolas Gonzalez is a researcher at the Transport Research Centre (TRANSyT) of the Universidad Politécnica de Madrid. His research interests include assessing the impact of transport policies, modeling, and economics.

Abdulrahman Alwosheel
Abdulrahman is a research associate at KAPSARC. He worked as a lecturer at the College of Engineering at Muhammed Ibn Saud University and as a traffic engineer in the Riyadh Metro project. His interests lie in transport demand, choice modeling, transport economics, and energy demand modeling.
About the Project

The objective of the KAPSCARC Aviation Model project is to analyze the main drivers of aviation demand and to assess energy concerns by considering the current and future use of fossil- and non-fossil-based fuels. Aviation is a key transport mode worldwide. It is essential for connecting the world and generating economic growth in many other related sectors. Therefore, a better understanding of aviation in countries such as Saudi Arabia is necessary to illustrate how policy decisions are framed so that they continue to be a catalyst for national development. This project explores current and future aviation and energy demand scenarios to generate policy-relevant insights. The ever-increasing needs related to aviation performance, energy demand, and consumption necessitate the development of better information management tools and methodologies, models, and technologies, which this project aims to provide.