IOSR Journal Of Humanities And Social Science (IOSR-JHSS)
Volume 29, Issue 1, Series 7 (January, 2024) 51-68
e-ISSN: 2279-0837, p-ISSN: 2279-0845.
www.iosrjournals.org

Passenger volume dynamics at Juazeiro do Norte Airport (CE): reflections on significant events and econometric approaches

Wellington Ribeiro Justo[1]
[1]*(Economy, Regional University of Cariri, Federal University of Pernambuco, Brazil)*

Maria Jennefer Pereira da Silva[2]
[2]*(Economy, Regional University of Cariri)*

Anderson Oliveira Brito[3]
[3]*(Economy, Regional University of Cariri)*

José Eduardo Carvalho Batista de Lima[4]
[4]*(Economy, Regional University of Cariri)*

Antonio José Ferreira Marinho[5]
[5]*(Economy, Regional University of Cariri)*

Abstract:
Background*: Orlando Bezerra Airport in Juazeiro do Norte plays a key role as a regional aviation hub in northeastern Brazil due to its strategic location, which places it equidistant from the region's main capitals and commercial centers. The main objective of this work is to thoroughly analyze the temporal evolution of passenger demand at Juazeiro do Norte Airport, located in Ceará, covering the period from January 2004 to March 2023.*
Materials and Methods *Using a combination of classical and contemporary time series econometric techniques, several models were meticulously designed, including ARIMA, SARIMA, SARIMA with an exogenous variable, ETS, Holt-Winters, Bats and Tbats, along with an in-depth exploration of possible structural changes.*
Results*: Through the careful application of model selection criteria, such as AIC, BIC, efficiency and accuracy metrics, convergence occurred elegantly towards the specific configuration of the SARIMA (2,1,1) (2,0,0) model [12].*
Conclusion: *With this basis established, a foray was made into the predictive horizons orchestrated by the refined model was made. An extensive evaluation of the model's assumptions, combined with cross-validation analysis, collectively attested to the resilience of the forecasts, echoing a coherent upturn in passenger volumes. Notably, these forecasts advocate an upward trajectory in passenger demand post-pandemic, unveiling a myriad of benefits that inform strategic investments and guide airport management. Among these achievements, the landscape of prospective inquiries remains expansive, particularly in elucidating long-term demand forecasts, thus providing a wealth of opportunities for further exploration.*
Key Word*: Regional aviation; Time series; Juazeiro do Norte Airport.*

Date of Submission: 15-01-2024 Date of Acceptance: 25-01-2024

I. Introduction

Time series analysis is an essential tool for understanding and predicting the behavior of phenomena over time. In the context of civil aviation, the study of passenger demand at airports plays a key role, providing valuable insights for managers and authorities in the sector and enabling more efficient planning and better management of available resources.

The main objective of this article is to analyze the temporal evolution of passenger demand at Juazeiro do Norte airport, located in the state of Ceará, over the period from January 2004 to March 2023. To achieve this goal, we will use time series econometric models, with special attention to relevant events that may have impacted the series, especially the COVID-19 pandemic.

The dynamics of passenger demand at airports are influenced by various factors, such as the regional economy, seasonal events, holidays, cultural events and, more recently, exceptional events such as the COVID-19 pandemic. This last event had significant effects on the entire air transport sector, causing abrupt fluctuations in passenger demand.

Thus, in addition to investigating the presence of trends and seasonality in the passenger time series, we will also examine the existence of structural breaks that could indicate significant changes in the dynamics of demand, especially related to the COVID-19 pandemic. To achieve our objectives, we will use econometric techniques, such as ARIMA *(*Autoregressive Integrated Moving Average*)* models, which will allow a detailed analysis of the time evolution of the series, identifying trends, seasonality, and randomness. Based on the data obtained from Infraero, covering almost two decades, including the period of the pandemic in 2020, we will process and pre-process the data to ensure the quality and consistency of the results obtained.

The temporal analysis of the number of passengers at Juazeiro do Norte airport is of great relevance, considering the airport's strategic role as a point of entry and exit for people in the region, contributing to the region's economic and social development. With the COVID-19 pandemic drastically affecting the air transportation sector worldwide, this analysis will also provide valuable information on the effects of the event on passenger demand in the region, helping to understand the factors that influence air transportation in Juazeiro do Norte. Carson, Cenesizoglu, Parker (2011) points out the advantages of analyzing passenger demand individually by airport, rather than aggregated data at a national level.

On the northeastern regional aviation scene, Juazeiro do Norte Airport has assumed a prominent position as a crucial connectivity hub. Strategically located in the south of Ceará and in the heart of the Northeast, this airport has witnessed remarkable growth over the last few years, becoming an important entry point for tourism and business in the region. With its strategic proximity to the northeastern capitals, serving as a vital link for the flow of regional industrial production and the provision of services, Juazeiro do Norte plays a central economic role. Recent figures indicate a consistent increase in passenger volumes. This upward performance reflects the airport's growing role as a driver of intra- and inter-regional connectivity, boosting not only the air transport sector, but also indirectly impacting the socio-economic development of the Northeast region of Brazil.

It is hoped that the results obtained from this time series analysis will provide relevant *insights* for airport managers and civil aviation authorities, making it possible to formulate demand planning and management strategies that consider seasonal factors, trends and exceptional events that influence passenger demand behavior. The aim is to contribute to the more efficient and effective management of Juazeiro do Norte airport, improve the air transport sector in the region, and promote the sustainable development of air transport in Ceará.

Several papers have dealt with this issue, with a special focus on the effects of the pandemic. Xiaoqian, Wandelt and Zhang (2022) reviewed more than 200 articles on the subject. Several studies have used econometric techniques, such as ARIMA and SARIMA models, to understand how the pandemic has affected passenger demand at airports over time. These models make it possible to analyze the evolution of the time series in terms of trend, seasonality, and randomness. For example, Kanavos, Hounelis, Makris (2021) discuss the development of empirical air travel demand models using time series techniques and deep learning. The authors developed air demand estimation and forecasting models using classical autoregressive integrated moving average (ARIMA) methods, seasonal approaches (SARIMA), and deep learning neural networks (DLNN). Mattera, Athanasopoulos, Hyndman (2023) highlight the importance of the ARIMA model for forecasting time series and have used this type of model to estimate the weights in infinite autoregressive models to define hierarchical structure and improve the forecasting of financial series.

In Brazil, there has also been research into the evolution of passenger demand at airports, using ARIMA models. These studies have revealed significant growth trends at some airports, such as Guarulhos and Galeão, and marked seasonality at others, such as Recife and Brasília. In addition to the use of ARIMA models, other econometric models, such as GARCH (Generalized Autoregressive Conditional Heteroscedasticity), were used to analyze the volatility of passenger demand at airports such as Shanghai, identifying relevant patterns of volatility over the period analyzed.

The contribution of this work lies in the approach to the dynamics of regional aviation with the application of classic and contemporary methodologies that have contributed to the identification of the behavioral pattern of passenger demand at one of the main regional airports in northeastern Brazil, allowing forecasts to be made that point to a considerable resumption of demand for this service after the pandemic.

In addition to this introduction, the second section of the paper contains a literature review. The third section presents the data sources and the methodology used. The fourth section presents and discusses the results. Finally, the last section summarizes the conclusions.

II. Literature Review

In the context of the pandemic, it is essential to understand the impact on the aviation sector and on passenger demand. Although there are still no specific studies on Juazeiro do Norte-CE Airport, we turn to the economic literature, which has offered valuable *insights into* how the pandemic has affected demand for air transportation at a global level. This theoretical framework explores the main analyses and perspectives, providing a solid basis for understanding the current scenario and its possible implications for Juazeiro do Norte-CE Airport.

Examining the Dynamics of Passenger Demand at Airports in the Pandemic: Perspectives and Approaches

According to Sun, Wandelt and Zhang (2022), the impacts caused by the COVID-19 pandemic have had significant effects on the aviation sector and passenger movement. During the first months of the pandemic, there was a drastic reduction in the number of flights operated by airlines, resulting in a sharp decrease in the volume of passengers transported. This reduction was a direct result of travel restrictions imposed by governments around the world, along with passengers' own concerns about safety during the pandemic. The drop in demand for air travel led to the cancellation of flights and the suspension of routes that were no longer financially viable, directly impacting connectivity between different cities and countries and making it difficult for people to move around.

To cope with the economic difficulties caused by the pandemic, Sun, Wandelt and Zhang (2022) point out that several airlines have adopted drastic measures, such as laying off employees and granting unpaid leave to their staff. These decisions led to financial and emotional challenges for thousands of aviation professionals, who saw their professional activities and sources of income compromised during the period of uncertainty.

In addition, to ensure the safety of both passengers and employees, airlines and airports have had to adopt strict sanitary protocols. These measures included the mandatory use of face masks, health checks, social distancing, and the frequent disinfection of common areas in airports (SUN; WANDELT; ZHANG, 2022).

Li et al. (2022) examines the impact of COVID-19 and the control measures adopted on domestic air transport in China, using a hybrid model of temporal and spatial effects. The results show that the number of new confirmed cases and control measures have a significant negative effect on the number of flights operated, both in the temporal and spatial dimensions. The article also shows that the control measures adopted in the initial phase of the pandemic had a positive effect on the recovery of the aviation industry and other industries in the later phase. The article contributes to the literature on the determinants of air traffic demand and volume, as well as to the understanding of the effects of COVID-19 and related policies on air transportation.

As the pandemic evolved, some countries began to require health certificates or proof of vaccination as a requirement to allow passengers to enter. This new requirement created an additional logistical challenge for both airlines and passengers, as each destination could have different requirements. As the pandemic situation stabilized in some regions, there was a gradual resumption of aviation operations. However, the recovery was slow, and passenger numbers remained low compared to pre-pandemic times.

The aviation industry has faced unprecedented financial challenges, and many airlines have struggled to survive during the pandemic. To avoid mass bankruptcies, several governments had to intervene with financial aid packages. According to Sun, Wandelt and Zhang (2022), the drastic reduction in passenger movements has also had a significant impact on the tourism chain, negatively affecting hotels, travel agencies, restaurants and other businesses related to the sector.

The study by Tang et al. (2022) focused on the relationship between trends in the COVID-19 pandemic and passenger traffic in an airport terminal in China in a daily context. The article identified three distinct differences in passenger changes during the pandemic, highlighting a pattern of "sharp drops and gradual recovery". In addition, a Light GBM model was developed that incorporated pandemic variables to predict passenger traffic in the short term, demonstrating a significant reduction in error compared to a base model. The study also highlighted the importance of the cumulative numbers of COVID-19 cases in previous weeks as stronger predictors of future traffic than recent daily cases.

In this sense, the impacts of COVID-19 on aviation and passenger movement have been profound and widespread, resulting in a significant reduction in flights, passengers, jobs, routes and company profitability. The industry's full recovery will require a concerted effort and adaptation to a new scenario with a greater emphasis on health and safety. In addition to the general context, several studies analyze the specific impact of this health crisis on passenger demand at airports around the world as observed in empirical evidence. For example, researchers examined the situation in the United States, identifying a drastic reduction in passenger demand, reaching more than 90% in some cases (SUN; WANDELT; ZHANG, 2022).

Xiaoqian, Wandelt, Zhang (2022), using a categorization framework, address the unprecedented impact of the COVID-19 pandemic on the aviation industry, considering it an unparalleled disruption to the sector in the last century. Starting with an unimaginable reduction in the number of flights between March and May 2020, the airline industry has experienced challenges in recovering from the crisis. This process has been accompanied by an extensive number of scientific studies exploring the direct and indirect impacts of the pandemic on aviation, as well as their reciprocal influences. The article offers a systematic review of the impacts present in recent literature, based on almost 200 publications from 2021/2022. The studies are organized into eight categories, covering aspects such as airlines, airports, passengers, workforce, markets, contagion, sustainability and economics.

For Velu, Iver (2021), the COVID-19 pandemic was anything but a near miss, it was a total blow to society. Aviation, by definition, is prone to taking on huge but ambiguous roles in the evolution of pandemics, being one of the main victims, but also allowing the effective spread of a contagion through a highly efficient global transportation system. Without changes in the way we live and travel, the COVID-19 pandemic will not be the last to hit our society (Chansuk et al., 2022, Tsvetkova et al., 2022, Rahman Fatmi et al., 2022).

These studies highlight the magnitude of the challenge faced by the aviation industry on a global scale. The consequences of the pandemic have affected not only the health of airlines but also the economy, causing impacts at different levels of the sector's value chain. The need for a safe and sustainable resumption of operations is a crucial priority to restore passenger confidence and ensure the gradual recovery of the sector.

Faced with this scenario, the aviation industry will need to adapt to a new paradigm, implementing strict health and safety protocols and adopting innovative strategies to rebuild traveler confidence. Only with a joint effort between governments, companies and regulatory bodies will it be possible to overcome the challenges posed by the pandemic and chart a sustainable path towards the full recovery of aviation and air transport.

In summary, although there are still no specific studies on passenger demand at Juazeiro do Norte-CE Airport during the pandemic, it is possible to infer from international and national research, which will be cited below, that the health crisis has had a significant impact on demand for air transportation around the world, affecting both supply and demand for flights. The impacts have been profound and widespread, resulting in drastic reductions in flights, passengers, jobs, routes, and profitability for the aviation industry. Although the situation is challenging, the use of econometric models can play a key role in understanding these impacts and identifying relevant trends and patterns in the dynamics of passenger demand at airports during this challenging period. With the help of accurate analysis and data, it will be possible to base effective strategies for the recovery of the aviation industry and air transport on, seeking to guarantee passenger safety and the sustainability of the sector in the face of an ever-changing scenario.

It is therefore crucial that researchers, airlines, government authorities and other stakeholders work together to address the challenges and chart a solid and resilient recovery path for aviation and airports, seeking a promising future amid the complexity imposed by the COVID-19 pandemic.

Examining the Dynamics of Passenger Demand at Airports in the Pandemic: Perspectives and Approaches

According to Sun, Wandelt and Zhang (2022), the impacts caused by the COVID-19 pandemic have had significant effects on the aviation sector and passenger movement. During the first months of the pandemic, there was a drastic reduction in the number of flights operated by airlines, resulting in a sharp decrease in the volume of passengers transported. This reduction was a direct result of travel restrictions imposed by governments around the world, along with passengers' own concerns about safety during the pandemic. The drop in demand for air travel led to the cancellation of flights and the suspension of routes that were no longer financially viable, directly impacting connectivity between different cities and countries and making it difficult for people to move around.

To cope with the economic difficulties caused by the pandemic, Sun, Wandelt and Zhang (2022) point out that several airlines have adopted drastic measures, such as laying off employees and granting unpaid leave to their staff. These decisions led to financial and emotional challenges for thousands of aviation professionals, who saw their professional activities and sources of income compromised during the period of uncertainty.

In addition, to ensure the safety of both passengers and employees, airlines and airports have had to adopt strict sanitary protocols. These measures included the mandatory use of face masks, health checks, social distancing, and the frequent disinfection of common areas in airports (SUN; WANDELT; ZHANG, 2022).

Li et al. (2022) examines the impact of COVID-19 and the control measures adopted on domestic air transport in China, using a hybrid model of temporal and spatial effects. The results show that the number of new confirmed cases and control measures have a significant negative effect on the number of flights operated, both in the temporal and spatial dimensions. The article also shows that the control measures adopted in the initial phase of the pandemic had a positive effect on the recovery of the aviation industry and other industries in the later phase. The article contributes to the literature on the determinants of air traffic demand and volume, as well as to the understanding of the effects of COVID-19 and related policies on air transportation.

As the pandemic evolved, some countries began to require health certificates or proof of vaccination as a requirement to allow passengers to enter. This new requirement created an additional logistical challenge for both airlines and passengers, as each destination could have different requirements. As the pandemic situation stabilized in some regions, there was a gradual resumption of aviation operations. However, the recovery was slow, and passenger numbers remained low compared to pre-pandemic times.

The aviation industry has faced unprecedented financial challenges, and many airlines have struggled to survive during the pandemic. To avoid mass bankruptcies, several governments had to intervene with financial aid packages. According to Sun, Wandelt and Zhang (2022), the drastic reduction in passenger movements has also had a significant impact on the tourism chain, negatively affecting hotels, travel agencies, restaurants and other businesses related to the sector.

The study by Tang et al. (2022) focused on the relationship between trends in the COVID-19 pandemic and passenger traffic in an airport terminal in China in a daily context. The article identified three distinct differences in passenger changes during the pandemic, highlighting a pattern of "sharp drops and gradual recovery". In addition, a Light GBM model was developed that incorporated pandemic variables to predict passenger traffic in the short term, demonstrating a significant reduction in error compared to a base model. The study also highlighted the importance of the cumulative numbers of COVID-19 cases in previous weeks as stronger predictors of future traffic than recent daily cases.

In this sense, the impacts of COVID-19 on aviation and passenger movement have been profound and widespread, resulting in a significant reduction in flights, passengers, jobs, routes and company profitability. The industry's full recovery will require a concerted effort and adaptation to a new scenario with a greater emphasis on health and safety. In addition to the general context, several studies analyze the specific impact of this health crisis on passenger demand at airports around the world as observed in empirical evidence. For example, researchers examined the situation in the United States, identifying a drastic reduction in passenger demand, reaching more than 90% in some cases (SUN; WANDELT; ZHANG, 2022).

Xiaoqian, Wandelt, Zhang (2022), using a categorization framework, address the unprecedented impact of the COVID-19 pandemic on the aviation industry, considering it an unparalleled disruption to the sector in the last century. Starting with an unimaginable reduction in the number of flights between March and May 2020, the airline industry has experienced challenges in recovering from the crisis. This process has been accompanied by an extensive number of scientific studies exploring the direct and indirect impacts of the pandemic on aviation, as well as their reciprocal influences. The article offers a systematic review of the impacts present in recent literature, based on almost 200 publications from 2021/2022. The studies are organized into eight categories, covering aspects such as airlines, airports, passengers, workforce, markets, contagion, sustainability, and economics.

For Velu, Iver (2021), the COVID-19 pandemic was anything but a near miss, it was a total blow to society. Aviation, by definition, is prone to taking on huge but ambiguous roles in the evolution of pandemics, being one of the main victims, but also allowing the effective spread of a contagion through a highly efficient global transportation system. Without changes in the way we live and travel, the COVID-19 pandemic will not be the last to hit our society (Chansuk et al., 2022, Tsvetkova et al., 2022, Rahman Fatmi et al., 2022).

These studies highlight the magnitude of the challenge faced by the aviation industry on a global scale. The consequences of the pandemic have affected not only the health of airlines but also the economy, causing impacts at different levels of the sector's value chain. The need for a safe and sustainable resumption of operations is a crucial priority to restore passenger confidence and ensure the gradual recovery of the sector.

Faced with this scenario, the aviation industry will need to adapt to a new paradigm, implementing strict health and safety protocols and adopting innovative strategies to rebuild traveler confidence. Only with a joint effort between governments, companies and regulatory bodies will it be possible to overcome the challenges posed by the pandemic and chart a sustainable path towards the full recovery of aviation and air transport.

In summary, although there are still no specific studies on passenger demand at Juazeiro do Norte-CE Airport during the pandemic, it is possible to infer from international and national research, which will be cited below, that the health crisis has had a significant impact on demand for air transportation around the world, affecting both supply and demand for flights. The impacts have been profound and widespread, resulting in drastic reductions in flights, passengers, jobs, routes, and profitability for the aviation industry. Although the situation is challenging, the use of econometric models can play a key role in understanding these impacts and identifying relevant trends and patterns in the dynamics of passenger demand at airports during this challenging period. With the help of accurate analysis and data, it will be possible to base effective strategies for the recovery of the aviation industry and air transport on, seeking to guarantee passenger safety and the sustainability of the sector in the face of an ever-changing scenario.

It is therefore crucial that researchers, airlines, government authorities and other stakeholders work together to address the challenges and chart a solid and resilient recovery path for aviation and airports, seeking a promising future amid the complexity imposed by the COVID-19 pandemic.

Empirical Evidence

The study by Li, Wang, Huang and Chen (2022) thoroughly investigated the impact of the COVID-19 pandemic on China's domestic air transportation. By analyzing data covering the period from January to April 2022, the researchers examined how the COVID-19 outbreak and the control measures adopted significantly affected the aviation industry. The results revealed significant negative effects on the number of flights operated, with a significant reduction during the lockdown phases and the imposition of social distancing measures. In addition, the study addressed the gradual recovery process of the aviation industry as restrictions were relaxed, and control policies were adjusted. Relevantly, this research contributes significantly to an in-depth understanding of the impacts of COVID-19 on China's domestic air transport industry, providing valuable insights to guide future decision-making in dealing with similar crises.

Following on from this line of research into the impact of the COVID-19 pandemic on the aviation industry, another relevant study by Sun, Wandelt and Zhang (2022) was also dedicated to analyzing this issue in depth. This research aimed to cover both the direct and indirect implications of the pandemic on the airline industry, providing a holistic view of several areas of interest. They investigated not only the impact on airlines and airports but also how passengers were affected, how the aviation workforce had to adapt, the functioning of markets during the crisis, contagion and health patterns, as well as sustainability and economic considerations.

By carrying out a comprehensive review of the available literature on the subject, the authors identified important findings that could be instrumental in guiding future research and policy formulation. Based on their conclusions, they sought to direct efforts towards making the aviation sector more resilient in situations of pandemics or similar crises. This approach allowed for a more complete understanding of the challenges faced by the aviation sector during the pandemic, as well as providing valuable guidance for developing more effective coping strategies in future crisis scenarios.

The study conducted by Tang et al. (2022) provided a valuable perspective by investigating passenger forecasting at airport terminals during COVID-19 outbreaks, focusing on a case study in China. Throughout their analysis, the researchers identified three distinct phases of change in passenger flow in response to the outbreaks, encompassing a decline phase, a stabilization phase and finally a recovery phase. This characterization highlighted the recurring pattern of "sudden drop and slow recovery" observed in passenger traffic during periods of crisis.

To improve the prediction of daily passenger traffic in the short term, the researchers developed a model based on Light GBM that incorporated variables related to the pandemic. The incorporation of these variables proved to be significant, resulting in a 27.7% reduction in model error when compared to a reference model. This advanced modeling approach proved effective in understanding and predicting passenger behavior amid the pandemic scenario, providing useful information to improve airport terminal operations in response to the ongoing COVID-19 pandemic. Another important finding of this study was the relevance of the cumulative number of COVID-19 cases in previous weeks as a stronger predictor for future passenger traffic compared to the most recent daily cases. This finding underscores the importance of considering the cumulative effects of the pandemic when making forecasts and strategic decisions related to airport operations.

In summary, this empirical evidence presented by Tang et al. (2022) provides crucial information for managing airport terminal operations in the face of the ongoing COVID-19 pandemic. By understanding the changing patterns in passenger flows and adopting advanced modeling that incorporates relevant pandemic variables, airport authorities can prepare and adapt more efficiently amid this challenging situation.

Karuppiah, Sankaranarayanan, and Ali (2022) carried out a study to identify the interconnections between the impacts of COVID-19 on supply chain activities, particularly those supplied by air. Through an approach that combined exploratory factor analysis and gray evaluation, the causal relationships between these impacts were revealed. The results highlighted disruption management, relationship management and production management as critical areas during a crisis. Supply disruption and its effects on supply chain operations had significant effects. The analysis contributes to guiding supply chain management policies and strategies, although it is limited to India. Extending these findings to other developing countries could offer broader generalizations.

In short, the impact of the COVID-19 pandemic on the aviation industry has been widely recognized and the subject of in-depth research. The study carried out by Hudáková (2021) added an important understanding of the initiatives adopted by the aviation industry in response to the crisis as well as passengers' intentions to travel by air during this challenging period. Using an approach that combined a literature review and an online empirical experiment, the research examined the effects of security measures implemented by airlines on customer satisfaction, value for money, perceived health risk and intention to travel. The results revealed that security measures adopted by airlines can indeed have a positive impact on anticipated customer satisfaction. However, these measures do not seem to significantly influence the perception of health risk and do not increase the cost-benefit ratio perceived by passengers.

It is important to note that customer satisfaction and value for money were identified as determining factors in an individual's intention to travel, while a higher perception of health risk was associated with a lower propensity to travel by air. This empirical evidence reinforces the importance of airlines and those involved in the sector in meeting passengers' needs and expectations during the pandemic.

Given these results, the aviation industry needs to consider additional strategies to minimize the perception of health risk while creating value for customers during this challenging period. By focusing on the well-being and safety of passengers, and aligning its initiatives with public expectations, the industry will be able to adapt in a more resilient and promising way to the circumstances imposed by the COVID-19 pandemic.

Thus, Hudáková (2021) offers a significant contribution to understanding the impact of the COVID-19 pandemic on the aviation industry. Her empirical evidence emphasizes the need for a customer-centric approach and innovative strategies to respond to the challenges posed by the pandemic, which will allow the airline industry to thrive even in uncertain times. This in-depth understanding is essential to inform future decisions and actions, ensuring the resilience and success of the aviation industry amid the ongoing COVID-19 pandemic.

For Hudácová (2021), the COVID-19 pandemic has had a significant impact on the aviation industry, resulting in movement restrictions, a drop in travel demand, and negative economic effects. In this context, it has become crucial to rethink airport processes and operations, seeking sustainable strategies to meet current and future challenges. In order to better understand patterns of behavior and identify the causes of phenomena, an explanatory research approach was adopted, with an inductive approach and an action research methodology. This approach made it possible to collect data and carry out practical activities to solve specific organizational problems. One of the main conclusions was the need to implement contactless technologies, such as biometric solutions, to reduce human contact and ensure passenger safety. In addition, it is essential to re-evaluate airport infrastructure in line with new demand and make financial decisions to optimize operating costs and increase revenues. When it comes to post-pandemic recovery, the financial sustainability of airports plays an essential role. It is recommended to postpone non-essential expenses, look for cost-saving solutions, and diversify revenue sources. In addition, it is important to adapt airport operations to social distancing guidelines and promote cooperation between aviation and tourism stakeholders. In short, resilient airports that adopt sustainable strategies and incorporate technological innovations will have a better chance of facing current and future challenges.

Kanavos, Hounelis, Makris (2021) review recent literature on deep learning architectures, neural networks, aviation problems and ARIMA and SARIMA models. The article also cites previous work that used hybrid models, combining linear and non-linear models for time series forecasting. They present the popular ARIMA and SARIMA models, along with Deep Learning Neural Networks, in detail, showing their potential in time series forecasting problems. Experimental results have shown that the proposed approaches can provide significant assistance in forecasting air travel demand, producing accurate and robust results.

Li (2021) proposes a combined forecasting method based on ARIMA-REGRESSION to estimate the volume of civil aviation passengers in China. The article also presents an analysis of the factors that influence the demand for air transportation, such as the number of scheduled routes, the number of tourists, gross national income, gross domestic product, and rail passenger traffic. The article compares the performance of the proposed method with the individual methods and shows that the combined method has higher accuracy and lower forecasting risk.

Kumar, Singh, and Singh (2023) carry out a systematic review of studies on passenger demand forecasting in the aviation industry, addressing the different levels, methods, variables, and performance measures used in forecasting. The article also identifies the factors that influence demand for air transportation, such as economic, social, political, and environmental, and evaluates the advantages and disadvantages of each forecasting technique, from econometric and statistical models to machine learning models and deep neural networks. The article also discusses the application areas, challenges, and future potential of passenger demand forecasting in aviation.

Finally, Zachariah, Sharma, Kumar (2023) also present a systematic review of recent studies on forecasting demand for air transportation and evaluate the various forecasting techniques used, as well as the advantages and disadvantages of each one. The article investigates various forecasting techniques for passenger demand, emphasizing the multiple factors that influence aviation demand. The article examines the benefits and challenges of various models ranging from economic and statistical to machine learning and deep neural networks, and the latest hybrid models. The article also discusses various application areas where passenger demand forecasting is used effectively. In addition to the benefits, the challenges and future potential of passenger demand forecasting are discussed.

For the Brazilian case and prior to the pandemic, we highlight the contribution of Bandinelli and Oliveira (2015), who modeled passenger demand at Confins airport in Minas Gerais. The authors concluded that the future of the airport concession is dependent on the country's economic growth. Estimating the model using instrumental variables and sensitivity tests made it possible to find the GDP and price elasticity of demand, with the former being elastic and the latter inelastic, respectively. Another relevant contribution is the work by Marcos and Ferreira (2015). The authors used a dynamic model with data on air passenger demand, average number of passengers per flight, peak hour demand, passenger terminal service level, and average aircraft parking time to analyze the situation at thirteen Brazilian airports. The results showed which subsystems present bottlenecks in meeting a demand growth rate of around 5% per year.

Finally, Santos; Oliveira; Aldrighi (2021) point out that the economic crisis and the drop in air travel due to the coronavirus pandemic threaten a new class of consumers in emerging economies, such as Brazil. Using regression analysis, they identified airline markets with higher social inclusion and then examined the factors behind the drop in demand. In the results, they highlight that short and low-density routes are the most supported, especially those aimed at businesses. They found that more inclusive markets face a sharper decline in demand, indicating greater vulnerability to the current crisis.

III. Material And Methods

This study adopts a methodological approach aimed at analyzing the temporal dynamics of passenger demand at Juazeiro do Norte Airport, located in the state of Ceará. The main aim is to identify and explore trends, seasonality and possible structural discontinuities that may have influenced the time series in question. To achieve these objectives, a set of time series econometric models is used, notably the ARIMA, Ets, Holt-Winters, Bats and Tbats models, integrated with specialized structural change analysis techniques.

The Autoregressive Integrated Moving Average (ARIMA) model is a statistical structure that combines autoregressive (AR), moving average (MA) and differentiation (I) components to characterize and anticipate patterns in time series. Preference is given to using the AUTO-ARIMA model, which automates the selection of these components based on statistical criteria. This choice is because, when conducting the analysis in the RStudio environment, the model was indicated as the most appropriate choice for this study.

The selection of these models is based on their widespread use in the literature for analyzing airport time series, as discussed in the literature review section. By modeling with ARIMA models, the evolution of the time series can be identified and represented in relation to its trend, seasonality, and randomness components. Structural break analysis techniques will be used to detect possible significant changes in the dynamics of passenger demand.

The evaluation of the results will be enriched by referencing the literature previously discussed, which illustrates examples of research that has scrutinized passenger demand at airports using time series econometric models. This comparison will make it possible to identify agreements and divergences between the outcomes of this study and those found in the literature, while outlining the restrictions and possible contributions that this research could make to the field in question.

After applying the models and analysis techniques, the results will be discussed in depth, pointing out their practical implications and relevance to the context of Juazeiro do Norte Airport. The combination of econometric methods and references to the literature will provide a solid and well-founded approach to analyzing the evolution of passenger demand over time, contributing to an understanding of the behavior of this variable at the airport in question.

Autoregressive model (AR(p))

The *Autoregressive Model* (AR) is a statistical tool used to analyze time series. It is based on the premise that the past values of the series itself have an influence on the current value, i.e., the series is autocorrelated. This autocorrelation is captured through the parameters $\boldsymbol{\phi i}$, which represent the contribution of past values to predicting the present value. In this sense, the p-order AR model, denoted as AR(p), considers p past values to forecast the current value. The AR(p) model equation is given by Equation 1:

$$\boldsymbol{X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t} \quad (\mathbf{1})$$

In equation (1), $\boldsymbol{X_t}$ represents the current value of the series, and the terms $\boldsymbol{X_{t-1}}$, $\boldsymbol{X_{t-2}}$,..., $\boldsymbol{X_{t-p}}$ represent the p past values that influence $\boldsymbol{X_t}$. The term $\boldsymbol{\varepsilon_t}$ is white noise, which represents the error or the part of the series that is not explained by the contributions of the past values. With this approach, the AR model can identify patterns and trends over time, providing a solid basis for forecasting and time series analysis.

An important characteristic of many time series is that their value in the current period depends strongly on the value in the immediately preceding period, reflecting the fact that the observations are not independent, but autocorrelated. In other words, the series has some degree of persistence. This case can be described by an autoregressive process of order 1, for example, given by:

$$\boldsymbol{y_t = \phi\, y_{t-1} + \varepsilon_t} \quad (2)$$

In other words, the value of $\boldsymbol{y}$ is related to its value at t - 1 plus a random error, which we assume to be white noise:

$$\boldsymbol{\varepsilon_t \sim i.i.d.N(0, \sigma^2)}. \quad (3)$$

A time series $\boldsymbol{\varepsilon_t}$ is considered white noise if $\{\boldsymbol{\varepsilon_t}\}$ has mean 0 and constant variance $\boldsymbol{\sigma^2}$i.e:

$\boldsymbol{E}\,(\boldsymbol{\varepsilon_t}) = \mathbf{0}\ \boldsymbol{E}(\in^2) = \mathbf{0}$ $\boldsymbol{t}$

(4)

Where $\boldsymbol{\varepsilon_t}$ is not temporally correlated, $\boldsymbol{E}\,(\boldsymbol{\varepsilon_t \varepsilon_{t-1}}) = \mathbf{0}\ \boldsymbol{para}\ \mathbf{1} \neq \mathbf{0}$.

Now, with a basic understanding of the AR model and its contributions to time series analysis, we will explore the next model, the Moving Average (MA) model. While the AR model is based on the influence of the past values of the series itself, the MA model approaches the series $\boldsymbol{X_t}$ as a combination of white noise ε from the current period and previous periods. Thus, the MA(q) model is expressed by Equation 5:

Moving average model - MA(q)

The moving average model consists of a linear combination of the white noise errors. The MA (1) can be written as follows:

$$\boldsymbol{y_t} = \mu + \boldsymbol{\varepsilon_t} + \boldsymbol{\theta \varepsilon_{t-1}} (\mathbf{5})$$

Where:

- y_t = represents the vector of the time series at time t.
- μ = is the average value of the time series over time
- s_t = represents the forecast error in the current period.
- s_{t-1}= represents the random error at the previous time.
- θ = is a parameter that multiplies the past error $s_{\boldsymbol{t-1}}$

Here, the value $\boldsymbol{y_t}$ is calculated by adding the overall average (μ) with the current error ($s_{\boldsymbol{t}}$) and the previous error ($\boldsymbol{\theta} s_{\boldsymbol{t-1}}$), where $\boldsymbol{\theta}$ is a number that determines how much the past error affects the current forecast. The random error $s_{\boldsymbol{t}}$ follows a normal distribution with zero mean and variance σ^2. In summary, the MA (1) is a way of predicting future values using only the current error and the previous error, weighted by the parameter θ and added to an overall average. It is important to note that the MA model requires the time series to be stationary so that its statistical properties can be properly estimated.

Autoregressive moving average model - ARMA (p, q)

In addition to the AR (Autoregressive Model) and MA (Moving Average Model) models, there is a model that combines elements of these two approaches: the Autoregressive Moving Average Model (ARMA). An ARMA (p, q) model can be described by the following equation (6)

$$y_t = c + \sum_{j=1}^{P} \phi_J \boldsymbol{y_{t-1}} + \sum_{j=0}^{q} \theta_i s_{t-1} \quad (6)$$

Where:

- y_t = represents the vector of the time series at time t.
- c = is a constant.
- P = is the order of the AR component, representing how many past values of the time series are considered.
- ϕ_J = is the AR coefficient associated with the value $\boldsymbol{y_{t-1}}$where "j" ranges from 1 to "p".
- q = is the order of the MA component, representing how many past forecast errors are considered.
- θ_i = is the MA coefficient associated with the error s_{t-1} where "j" ranges from 1 to "q".
- s_t = represents the forecast error over the period.

The idea behind the ARMA model is to use the past values of the time series to capture autocorrelation patterns (AR component) and incorporate past forecast errors to capture moving average patterns (MA component). These two components together can help to better explain the time dependency structure present in the series and thus improve future forecasts. It is worth noting that the ARMA model also assumes that the time series is stationary, which means that its statistical properties (such as mean and variance) remain constant over time.

Autoregressive integrated moving average model - ARIMA (p, d, q)

The combination of the differencing methods and the autoregression and moving average models results in a non-seasonal ARIMA model, which can be described mathematically as:

$$y_t = c + \phi_1 \acute{y}_{t-1} + \phi_p \acute{y}_{t-p} + \theta_1 + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-1} + s_t \quad (7)$$

Where $\acute{y}_t$ is the differentiated series. Equation (7) describes the **ARIMA** model **(p, d, q),** where: p is the order of the autoregressive model, d is the degree of differentiation and q is the order of the moving average model. Explaining equation (7) in parts to make it more understandable**,** we have that:

- y_t = the current value of the series at time "t".
- c = constant or intercept.
- ϕ_i = autoregression coefficient for the previous value $\acute{y}_{t-1}$.
- ϕ_p = autoregression coefficient for the value in the previous step $\acute{y}_{t-p}$.
- $\theta_1, \theta_2, \ldots, \theta_q$ = moving average coefficients for past errors e_{t-1}.
- s_t = error term at time "t".

This combination of models was used to analyze the time series of paid passengers in Juazeiro do Norte - CE, bringing significant applications in forecasting and modeling phenomena that evolve over time. The precise selection of the appropriate model rests on a thorough analysis of the data and the stationarity of the specific time series.

In addition to these models, different methods have also been used for modeling and forecasting time series: Holt-Winters, Bats and Tbats.

The Holt-Winters method is a widely used approach for modeling time series with trends and seasonality. It consists of three main components: level, trend and seasonal. This technique is particularly useful for capturing patterns in data with linear growth behavior over time (Hyndman; Athanasopoulos, 2021).

The Bats method, or Bayesian Structural Time Series, is a statistical approach that models time series considering different components, such as trends, seasonality, and special events. The Bayesian approach allows uncertainties to be incorporated into the model's parameters, making it flexible enough to adapt to different data patterns (Livera; Hyndman; Snyder, 2011).

Finally, the Tbats method is an extension of Bats that effectively handles time series with multiple seasonalities, such as daily, weekly, or annual seasonality. It incorporates trigonometric components to model complex seasonality. This approach is particularly useful for time series that have non-linear seasonal patterns (HONG, 2020)

The use of these methods makes it possible to explore different aspects of the time series, considering trends, seasonality, and specific characteristics, to obtain more accurate and meaningful forecasts for the total number of passengers at Juazeiro do Norte Airport, Ceará.

We will also adopt an approach that includes the investigation of structural breaks in the passenger time series at Juazeiro do Norte Airport. To identify possible points of significant change in the trajectory of the series, we will employ a multiple structural break test analysis. This method will allow us to detect periods or events in which there have been substantial changes in the behavior of the series, providing a deeper understanding of the factors that have influenced the evolution of passenger numbers over time. The inclusion of tests for multiple structural breaks will improve the evaluation of the trends and patterns observed, considering internal and external influences that have shaped the dynamics of the time series. To support this approach, we refer to the methodology proposed by Bai and Perron (2003), which provides a solid framework for detecting structural breaks in time series.

Cross-validation tests will also be incorporated to assess the performance of forecasting models in situations of unobserved data. To this end, we will use the cross-validation technique proposed by Hyndman and Athanasopoulos (2021), which will allow us to estimate the models' ability to make accurate forecasts in future periods. Cross-validation is a technique used to assess the performance of a predictive model and estimate its test error. The aim of cross-validation is to divide the data set into several partitions, called validation sets, and use each of these partitions to evaluate the model's performance.

This approach will provide a more robust assessment of the models' performance, considering the forecasts' ability to generalize beyond the training data. The analysis includes the comparison of metrics such as ME (mean error), RMSE (root mean square error), MAE (mean absolute error), MPE (mean percentage error), MAPE: (mean absolute percentage error), MASE (scaled mean absolute error), and ACF1(first order autocorrelation of forecast residuals) (Bayle, et al, 2020).

Database

To carry out this study, we used data made available by the National Civil Aviation Agency (ANAC), referring to the number of passengers paid in air operations in Juazeiro do Norte - CE. This data was used to shape the composition of the distribution spectrum applied during the time series analysis. It should be noted that the passenger movement data was extracted specifically for Juazeiro do Norte airport, obtained from Infraero, and covers the extensive period from January 2004 to December 2022. The comprehensive time frame provides the opportunity to dissect the evolution of passenger demand over almost two decades, including analysis of the implications resulting from the Covid-19 pandemic, which has intensified since 2020.

Before proceeding with the modeling, the data went through a careful treatment and pre- processing process. This stage was carried out to guarantee the quality and consistency of the data, reducing any possible noise or discrepancies that could affect the accuracy of the analysis. With the database duly prepared and organized, the forecast model was applied to carry out temporal observations and analyses. The information obtained from this modeling will provide valuable *insights* into passenger demand trends over time, contributing to an understanding of seasonal variations and the effects of the pandemic on the aviation sector in Juazeiro do Norte - CE.

In addition to the information mentioned above, Table 1 shows the descriptive statistics of the variables used in the study. The statistics included are minimum (Min.), 1st quartile (1st Qu.), median (Median), mean (Mean), 3rd quartile (3rd Qu.) and maximum (Max.). Each statistic represents different measures of the central tendency and dispersion of the data over the period.

Table 1: Descriptive statistics

Variable	Min	1st Qu	Median	Mean	3rd Qu	Max
Year	2004	2008	2013	2013	2018	2022
PAID PASSENGERS	119	6.749	15.567	13.467	19.034	30.136

Source: Own elaboration based on ANAC data.

The series shows a low of 119 paid passengers in January 2004 and a high of 30,136 paid passengers in July 2019. This indicates a wide variation in the number of passengers over the period, reflecting fluctuations in demand for air travel in the region. The average, however, is 13,467 passengers, with a median of 15,567 paid passengers. This means that, on average, the airport received around 13,000 passengers per month, but that half of the months had more than 15,000 passengers. This suggests that the series has an asymmetrical distribution, with some months showing very high or very low values in relation to the average.

In the first quartile, there are 6,749 paid passengers, and in the third quartile, there are 19,034 paid passengers. This means that 25% of the months had fewer than 6,749 passengers, and 25% of the months had more than 19,034 passengers. This shows that the series has considerable dispersion, with a difference of more than 12,000 passengers between the quartiles. A sharp drop was observed in 2020, because of the COVID-19 pandemic.

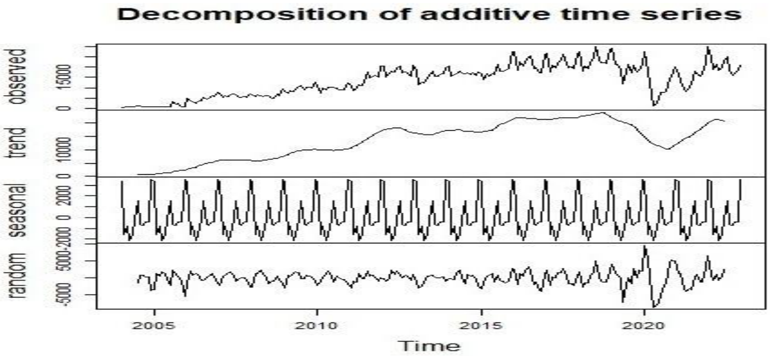
To visualize the evolution of the main variable over the period of analysis, Figure 1 not only illustrates the graphical pattern of the series of passengers paid overtime, but also provides a Time Series Decomposition. This graph encompasses the different components of the series, including the original series, the trend, seasonality, and residuals. This graphical analysis complements the descriptive statistics presented in Table 1, providing a more holistic understanding of the behavior of the series over the period. In addition, this visualization enriches the interpretation of the results derived from the econometric model.

Figure 1 shows the decomposition of the time series of the total number of passengers at Juazeiro do Norte Airport - CE, from January 2004 to December 2022. Decomposition is a way of separating the series into four components: the original series, the trend, seasonality, and residuals.

The original series is the line in the upper frame, representing the observed values of the variable over time. It shows the monthly variations in the number of passengers at the airport.

The trend is the line in the second quadrant, representing the general pattern of the series, ignoring short-term fluctuations. It shows that the series has an upward trend, indicating an increase in demand for air travel in the region over the years.

Figure 1: Time series decomposition



Source: Own elaboration based on ANAC data.

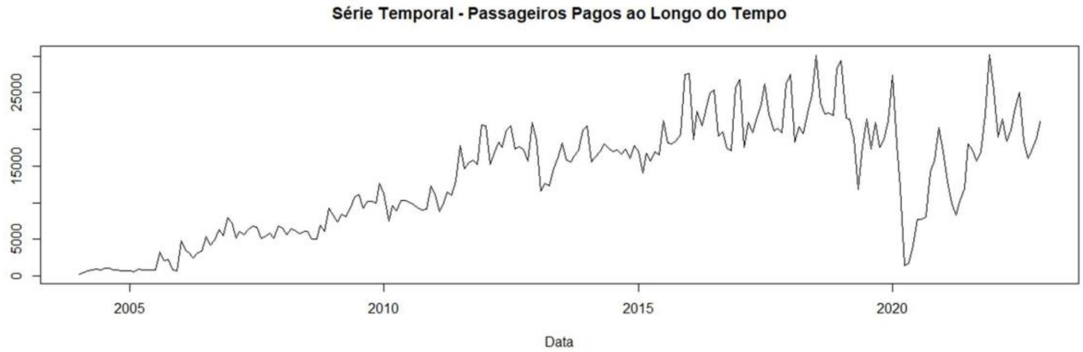
Seasonality, the third box in the figure, represents cyclical patterns that recur at regular intervals. It shows that the series has an annual seasonality, with peaks in January and July, and valleys in April and October. This may be related to school vacation periods and religious vacations in the region.

The residuals, in the lower frame of the figure, represent the part of the series that is not explained by the trend and seasonality. They show the random or irregular variations in the series, which can be caused by external or unpredictable factors. One example is the impact of the Covid- 19 pandemic, which caused a sharp drop in the number of passengers in 2020.

The decomposition of the time series serves to better understand the behavior of the variable and its determining factors. It also helps in choosing and applying suitable econometric models to analyze and forecast the series.

Figure 2, on the other hand, focuses exclusively on the representation of the isolated series, providing a more detailed view of the evolution of the variable over time without the decomposition components overlapping. This allows for a more focused analysis of the underlying trend and variations over the period.

Figure 2: Temporal Behavior of the "Paid Passengers" Variable



Source: Own elaboration based on ANAC data.

Figure 2 shows the graphical behavior of the variable passengers paid at Juazeiro do Norte Airport - CE, from January 2004 to December 2022. From this figure, you can see some important characteristics of the time series mentioned above.

The series shows an upward trend over time, indicating an increase in demand for air travel in the region. This increase may be related to the economic and social development of the city and its region of influence, which attracts more visitors and businesses, or to the expansion of flights and routes offered by the airlines operating at the airport.

It also has an annual seasonality, with peaks in January and July, and valleys in April and October. These patterns may be associated with school vacation periods and religious vacations, which influence the flow of passengers at the airport.

The series fell sharply in 2020 because of the Covid-19 pandemic, which has drastically affected the air transport sector worldwide. The pandemic has caused travel restrictions, reduced flights and routes, and decreased passenger confidence in health safety. These factors have led to a significant reduction in demand for air travel in the region.

However, there was a partial recovery in 2021 and 2022, following the relaxation of pandemic control measures and the advance of vaccination. However, the figures have not yet returned to pre-pandemic levels, indicating that there are still challenges to the full recovery of the sector.

IV. Result and Discussion

Based on the analysis of the time series of the total number of passengers at Juazeiro do Norte Airport - CE, using the ARIMA model, some important interpretations and considerations were obtained. It was observed that the series of paid passengers shows a trend over time, with a gradual increase in the number of passengers. This pattern may indicate the growth in demand for air travel in the region or local economic development, which is a relevant point for the aviation sector.

An analysis of structural breaks was carried out to identify significant changes in the series over time. Identifying these breaks can help to better understand the relevant events that have affected passenger numbers, such as economic crises, special events or changes in airport infrastructure. In this context, a "pandemic" variable was added to the data set, representing the structural break that occurred in 2020. This inclusion makes it possible to assess the specific impact of the COVID-19 pandemic on the aviation sector and on the number of passengers at the airport.

In addition, stationarity tests (ADF, PP and KPSS) were carried out on both the original series and the differentiated series. Stationarity is essential to ensure that the ARIMA model is appropriate and capable of providing reliable forecasts.

Table 1 shows the results of the ADF, PP and KPSS tests to check whether the time series of the total number of passengers at Juazeiro do Norte Airport - CE has a unit root. A unit root means that the series is non-stationary, i.e. that its statistical properties vary over time. This can cause problems in modeling and forecasting the series if not handled properly.

Unit root tests consist of testing the null hypothesis that the series has a unit root against the alternative hypothesis that the series is stationary. To do this, the t-test values and the corresponding critical values are calculated for different significance levels. If the value of the t-test is less (in modulus) than the critical value, the null hypothesis cannot be rejected, and it is concluded that the series has a unit root. If the value of the t-test is greater (in module) than the critical value, the null hypothesis is rejected, and it is concluded that the series is stationary.

Table 1 shows the results of the ADF, PP and KPSS tests for three different specifications: without constant or trend, with constant but without trend and with constant and trend. These specifications reflect different ways of capturing the trend of the series. In addition, the table shows the number of lags used in the tests, chosen based on statistical criteria.

Looking at the results in the table, we can see that, in all specifications and for both tests, the t-test value is lower (in modulus) than the critical values for the significance levels of 1%, 5% and 10%. This means that the null hypothesis that the series has a unit root cannot be rejected in any of the cases. Therefore, it can be concluded that the original series of the total number of passengers at Juazeiro do Norte Airport - CE is non-stationary and has a unit root.

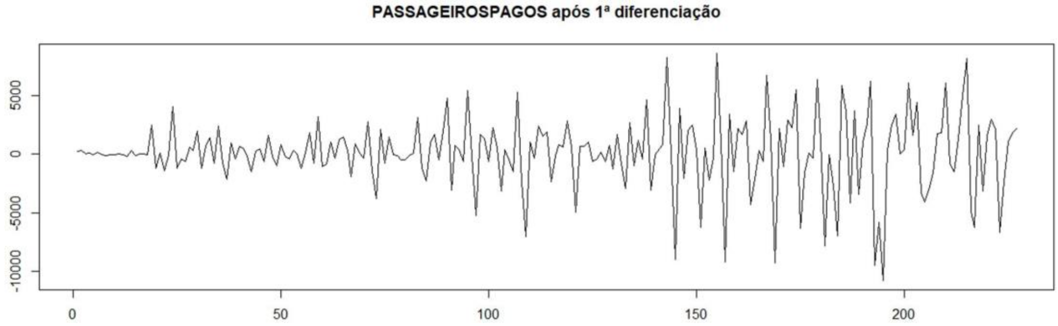
Considering the results of the tests carried out, concluding that the series is not stationary at level, the differentiation technique was applied to the series.

After applying the differentiation technique to the "PASSAGEIROSPAGOS" time series (resulting in the "diff_PASSAGEIROSPAGOS" series), the stationarity tests were performed again on the differentiated data, as shown in Table 3.

In addition, stationarity tests (ADF, PP and KPSS) were carried out on both the original series and the differentiated series. Stationarity is essential to ensure that the ARIMA model is appropriate and capable of providing reliable forecasts. Table 3 shows that the series after the first difference is stationary, which suggests that seasonal fluctuations have been removed, making the model more suitable for future forecasts.

As illustrated in Figure 3, this highlights an apparent stationarity in the series. This graphical inspection makes it possible to identify the absence of discernible patterns and trends in the data, supporting the notion of stationarity after applying the differentiation process.

Figure 3: Graphical behavior of the variable after the first difference



source: Own elaboration based on ANAC data.

Structural breaks

Tests were carried out for multiple structural breaks in the series using the package. Four breaks were identified (2006, 2011, 2015 and 2020). However, only the break referring to the pandemic (2020) was significant. Therefore, to incorporate this issue into the selection of the models, the pandemic dummy was created assuming a value of 1 from March 2020 and 0 before that date.

It is important to note that the analysis of structural breaks in the time series of the number of passengers at Juazeiro do Norte - CE airport must consider a combination of factors to obtain a complete understanding of the variations observed. The Bai-Perron test approach provides a valuable perspective by identifying critical points, such as the most significant break during the 2020 period, closely related to the impacts caused by the COVID-19 pandemic.

The global health crisis has caused travel restrictions, social isolation measures and significant changes in passenger behavior, drastically reflected in the demand for paying passengers at Juazeiro do Norte airport. Understanding these structural breaks is essential to understanding the context of the analysis and to providing relevant insights into the behavior of passenger demand in the region.

Selecting the Fitted Model Using the Autoarima Function

This section outlines the process of automated estimation of the ARIMA model using the "autoarima" function. The purpose is to identify the most suitable ARIMA model for estimation. Initially, the "autoarima" function was applied to the time series under examination in this study. This function incorporates an algorithmic exploration that aims to discern the ARIMA model that best harmonizes with the data, paying attention to a variety of model selection criteria, including the AIC (Akaike Information Criterion) and other measures of fit, such as the mean square error. The product of this function is shown in Table 4, which describes the optimal model identified as the "ARIMA (2,1,1) (2,0,0) model [12]".[4] The model was estimated with the variable in level, in logarithms and with the inclusion of the pandemic variable. The following models were also estimated: Holt-Winters, Bats and Tbats. According to both the AIC criterion and the other metrics, the model selected was the one shown in Table 4, which includes the pandemic dummy.

The first set of parameters (p, d, q) are the specifications of the non-seasonal ARIMA model. Where:

- p: refers to the order of the autoregressive (AR) term, which expresses the relationship between the time series and its own past observations. In this scenario, p=1, which means that the model only uses the last observation to project the next one.
- d: indicates the order of integrated differentiation (I) applied to achieve the stationarity of the time series, removing trends and non-constant patterns. In this context, d=1, revealing that a first- order differentiation was used to stationaries the series.
- q: represents the order of the moving average (MA) term, which denotes the relationship of the errors (or residuals) of the time series with its own past errors. In the current context, q=1, indicating that the model incorporates the previous error to predict the next value.

The second set of parameters (P, D, Q) refers to the seasonal components of the ARIMA model.

- P: reflects the order of the seasonal autoregressive (SAR) term, illustrating the seasonal dependence of the time series. In this context, P=2, meaning that the model uses observations of delay 12 (equivalent to one year) to predict the next value.
- D: reflects the order of seasonal differentiation used to achieve seasonal stationarity in the time series. In this scenario, D=0, indicating no seasonal differentiation.
- Q: indicates the order of the seasonal moving average (SMA) term, portraying the seasonal dependence of

the errors. In this situation, Q=0, which denotes the absence of a seasonal moving average term in the model.

In summary, the ARIMA (2,1,1) (2,0,0) model [12] with the pandemic dummy denotes an ARIMA model with an autoregressive component (AR) of order 1, an integrated differentiation (I) of order 1, a moving average component (MA) of order 1, and a seasonal autoregressive component (SAR) of order 2. This configuration was applied to the differentiated time series once to establish stationarity, with a 12-period seasonal pattern. This model was used to forecast the forecasts shown in Figure 3 for the next data points in the time series.

The estimated coefficients of the ARIMA (2,1,1) (2,0,0) model [12][5] are shown in Table 5. Each coefficient is associated with a specific component of the ARIMA model.

The coefficients represent the influence of the series' past values and forecast errors on the current value. For example, the ar1 coefficient means that the current value of the series depends on the value in the previous period, multiplied by this coefficient. The ma1 coefficient means that the current value of the series depends on the forecast error in the previous period, multiplied by this coefficient. The constant coefficient means that there is a fixed value added to the series in each period[6].

Table 5: Estimated coefficients

Coefficients	ar1	ar2	ma1	sar1	sar2	xreg
	0.6891***	0.1545	-0.9768***	0.4897***	0.2593***	-8136.21***
Standard Errors	0.0718	0.0712	0.0147	0.0658	0.0689	1902.31

Source: Own elaboration based on ANAC data. Note: *** significant at 1%.

Where:

- ar1: represents the coefficient of the non-seasonal autoregressive term (AR). In this case, ar1 is equal to 0.6891. This means that the ARIMA model uses the previous value in the series multiplied by 0.8601 as part of its forecast for the next value in the series.
- ar2: represents the coefficient of the non-seasonal autoregressive term (AR). In this case, ar2 is equal to 0.1545. This means that the ARIMA model uses the value of the second lag of the series multiplied by 0.1445 as part of its forecast for the next value in the series.
- ma1: represents the coefficient of the non-seasonal moving average (MA) term. In this case, ma1 is equal to 0.4897. This means that the ARIMA model uses the previous forecast error multiplied by 0.4897 as part of its forecast for the next value in the series. The moving average term helps to capture the error patterns in the time series.
- sar1: represents the coefficient of the seasonal autoregressive term (SAR) of lag 12. In this case, sar1 is equal to 0.4897. This means that the ARIMA model uses the observation that occurred 12 periods ago (12 months, corresponding to one year) multiplied by 0.4897 as part of its forecast for the next value in the series, considering the seasonality of one year.
- sar2: represents the coefficient of the second seasonal autoregressive term (SAR) of lag 24. In this case, sar2 is equal to 0.2593. This means that the ARIMA model uses the observation that occurred 24 periods ago (24 months, corresponding to two years) multiplied by 0.2593 as part of its forecast for the next value in the series. This coefficient captures the seasonal dependence of two years.
- xreg: represents the coefficient of the pandemic variable. In this case, xtereg is equal to - 8136.21. This means that the pandemic had a negative average impact of this magnitude on the number of passengers paid at Juazeiro do Norte airport.

The standard error values represent the standard discrepancies of the estimated coefficients. These values are used to derive confidence intervals for the coefficients and to perform statistical significance tests. In simple terms, the lower the value of the standard errors, the greater the accuracy of the estimated coefficients. In this case, all the coefficients are significant at 1%, as shown by the asterisks.

Based on the adjusted ARIMA model, forecasts were made for the coming periods, as shown in Figure 4. These forecasts are based on the patterns deciphered in the previous time series, providing valuable insights into the possible future trajectory of the number of passengers paid at the airport. However, it is important to emphasize that the impact of the COVID-19 pandemic can have a significant impact. In fact, it proved to be relevant, impacting the model selected. Therefore, to consider, the effect of the pandemic on the forecasts, cross-validation tests were carried out, as shown below.

Li et al. (2022) also found a strong negative impact on domestic flights in China, with a drop of up to 97% in the number of flights at the peak of the pandemic and a gradual recovery after the peak.

In summary, the analysis of the time series of the overall number of passengers at Juazeiro do Norte Airport provides relevant information about the trends and patterns associated with the demand for air travel at the regional airport. However, it is imperative to consider extrinsic variables, such as notable events (like the pandemic) and structural changes, which have exerted an influence on the behavioral evolution of the series over time. Such a holistic assessment will foster a more precise and functional interpretation of the results obtained, contributing to informed decision-making and forward planning in the context of the aviation sector in the region under analysis.

Table 6. Passenger volume forecast at Juazeiro do Norte Airport using the ARIMA (2,1,1) (2,0,0) model [12].

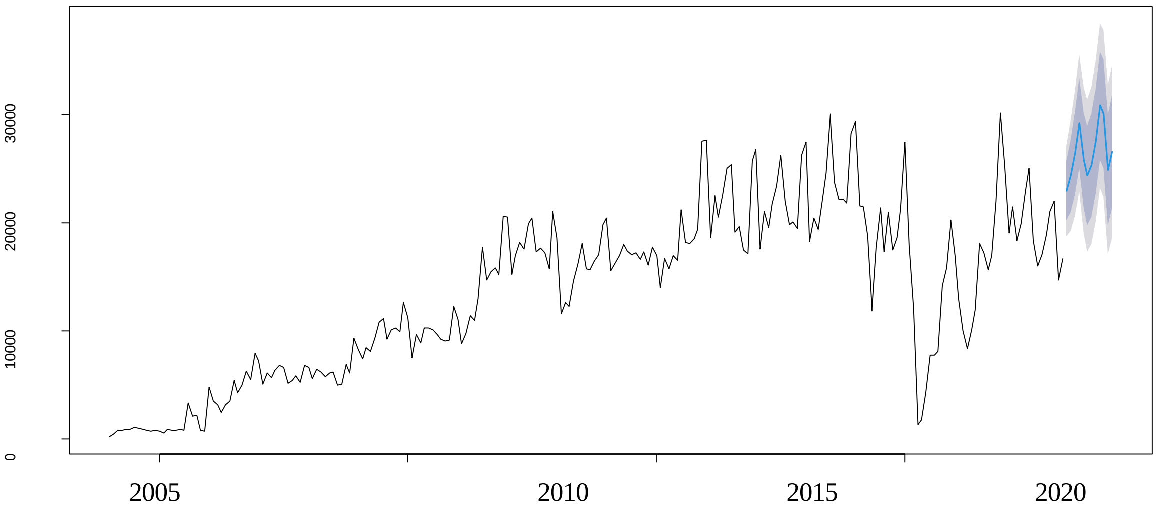
Period (2023/2024)	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
April	22878.04	20148.86	25607.22	18704.13	27051.95
May	24310.84	20960.17	27661.52	19186.43	29435.26
June	26411.58	22596.40	30226.76	20576.76	32246.40
July	29166.54	25021.34	33311.73	22827.00	35506.07
August	25779.15	21383.67	30174.63	19056.85	32501.46
September	24343.89	19754.15	28933.64	17324.49	31363.30
October	25271.70	20527.79	30015.61	18016.51	32526.89
November	27539.05	22670.62	32407.48	20093.43	34984.67
December	30799.58	25829.00	35770.15	23197.74	38401.41
January	30037.91	24982.35	35093.47	22306.10	37769.72
February	24879.88	19752.66	30007.11	17038.46	32721.30
March	26570.04	21381.61	31758.47	18635.02	34505.05

Source: own elaboration based on ANAC data.

The forecasts of the adjusted ARIMA (2.1.1) (2.0.0) model [12] can be seen in the form of a time series line graph as shown in figure 4. The recovery in the volume of passengers paid is evident. although seasonal effects characteristic of the original series can be seen.

Figure 4 Series of the volume of passengers paid at Juazeiro do Norte airport with the forecast via the adjusted ARIMA model (2.1.1) (2.0.0) [12].

Forecasts from Regression with ARIMA(2.1.1)(2.0.0)[12] errors



Source: Own elaboration based on ANPAC data.

Test to assess the quality of the adjusted ARIMA (2.1.1) (2.0.0) model [12]
Autocorrelation and normality test

The de test is a statistical test used to check whether a time series is autocorrelated. In this case. the test was applied to the residuals of the adjusted model. According to Table 7. the p-value of the test is 0.9032. indicating that there is not enough evidence to reject the null hypothesis that the residuals are not autocorrelated. This suggests that the fitted model can adequately capture the temporal dependency structure of the data and that the residuals are independent.

The normality test is an important tool for validating statistical assumptions and ensuring the proper use of parametric methods. It makes it possible to check whether the data follows a normal distribution. which is crucial for the application of parametric tests. According to Table 7. the p-value of the Shapiro-Wilk normality test is greater than 0.05. Therefore. the null hypothesis that the residuals of the adjusted model follow a normal distribution is not rejected.

Table 7 Testing the model's statistical assumptions

Box-Ljung test	X-squared = 0.01479	df = 1	p-value = 0.9032

Source: Own elaboration based on ANPAC data.

Cross-validation test

According to Bergmeir. Hyndman. Koo (2018) the cross-validation test is important after a model has been adjusted to make predictions. as it allows us to assess the model's ability to generalize to new data. This is done by dividing the data into training and test sets and evaluating the model's performance on both sets. Cross-validation testing is therefore an important step in ensuring the quality of the predictions generated by the fitted model.

Table 8 shows some of the error measures calculated to assess the quality of the ARIMA (2.1.1) (2.0.0) time series forecasting model [12] and its performance in cross-validation. Each error measure compares the values predicted by the model with the actual values observed in the training set and the validation set. The lower the error value. the better the model fits the data.

The first row of the table shows the error measures calculated for the training set. i.e.. the data set used to fit the model. The second row of the table shows the error measures calculated for the validation set. i.e. the data set used to evaluate the model's performance in cross-validation.

Comparing the error measures in the two rows of the table. you can see that the model performs similarly in the training set and the validation set. This indicates that the model is not suffering from overfitting or underfitting and has a good ability to generalize to new data.

Table 8 Cross-validation test

Error measures	ME	RMSE	MAE	MEP	MAPE	MASE	ACF1
Training set	200.03	2097.07	1391.92	-1.55	15.09	0.42	-0.01
Validation set	160.65	2181.01	1459.25	-2.17	16.16	0.43	-0.04

Source: Prepared by the authors with data from ANAC.

V. Conclusion

In the regional aviation scenario. Orlando Bezerra Airport in Juazeiro do Norte has emerged as an important hub. strategically placed in the northeastern transportation network. Exploring the time series of total passengers at Juazeiro do Norte Airport - CE. by applying the ARIMA model. provides valuable insights into the traits and trajectories underlying the demand for air travel in the region. This outlines a dynamic panorama in which the series of paid passengers shows a gradual upward trend over the period. possibly indicating an increase in demand for air travel or local economic development.

To gain a deeper understanding of the salient changes throughout the series. an analysis of structural breaks was incorporated. which revealed the turning point represented by the outbreak of the COVID-19 pandemic in 2020. The inclusion of the "pandemic" variable in the data set attested to the damaging impact of the health crisis on both the aviation sector and the airport's passenger contingent.

Stationarity tests previously carried out on the original and differentiated series corroborated the suitability of the ARIMA model. with the post-differentiation series showing stationarity. indicating the suppression of seasonal fluctuations.

The estimation of the ARIMA model crystallized in the identification of a SARIMA pattern (2.1.1) (2.0.0) [12]. indicating a strong interdependence between current and previous passenger volumes. Future passenger volume projections. based on the adjusted model. were made. prospectively revealing scenarios for the coming periods. It is important to note that these projections are derived from past patterns and can offer insights into general trends. but it is recommended to carefully consider the impact of the COVID-19 pandemic and other relevant exogenous factors when interpreting these forecasts.

In summary. the temporal analysis of Juazeiro do Norte Airport provides a comprehensive overview of the vectors and trajectories that guide the demand for air travel in the region. The structural disruptions identified. notably the pandemic. provide crucial information for understanding the events influencing the behavior of the series over time. However. when envisioning horizons. it is essential to consider the possible influence of other external catalysts. in addition to the intrinsic patterns of the national economy.

References

[1]. Adey, P. Airports, Mobility And The Calculative Architecture Of Affective Control, Georofum, 39(1), 9.438-451, 2008.

[2]. Anilkumar, V. Historical Research: A Qualitative Research Methodology. International Journal Of Science And Interdisciplinary Research, 3(4), P.175-181, 2014.

[3]. Bai, J.; Perron, B. Computation And Analysis Of Multiple Structural Change Models. Journal Of Applied Econometrics, 18(1), P. 1-22, 2002.
[4]. Bayle, P.; Baye, A.; Janson, L.; Mackey, L. Cross-Validation Confidence Intervals For Test Error. New England 34th Conference On Neural Information Processing Systems (Neurips), Vancouver, Canada, 2020.
[5]. Bendinelli, W. E., Oliveira, A. V. M. Econometric Modeling Of Demand At Privatized Airports: A Case Study Of Confins International Airport, Belo Horizonte. Journal Of Transport Literature, 9(2), 20-24, Apr. 2015. Doi: Https://Doi.Org/10.1590/2238-1031.Jtl.V9n2a4
[6]. Bergmeir, B.; Hyndman, R. J.; Koo, B. A Note On The Validity Of Cross-Validation For Evaluating Autoregre Ssive Time Series Prediction, Computational Statistics & Data Analysis, V. 120,P. 70-83, 2018.
[7]. Borgatta, E. F.; Lambert, W. W. Handbook Of Personality Theory And Research. Chicago: Rand Mcnally, 1968.
[8]. Box, G.E.P., Jenkins, G.M.Time Series Analysis: Forecasting And Control. Revised Edition, Holden Day, San Francisco, 1976.
[9]. Box, G.E., Jenkins, G.M., Reinsel, G.C. And Ljung, G.M. Time Series Analysis: Forecasting And Control. John Wiley & Sons, Hoboken, 2015.
[10]. Brixi, R, Et Al. (2012). Explaining System Behavior: On Overview Of Explanatory Research. The World Bank.
[11]. Camillo, G. I.; Ruy, M. Evaluation Of The Accuracy Of Arima Methods, Exponential Smoothing And Neural Networks In Forecasting Brazilian Annual Time Series. Journal Of Management And Business, 1, 1-10, 2019. Doi: 10.1007/S11042-023-15552-1.
[12]. Carson, R.; Cenesizoglu, T.; Parker, R. Forecasting (Aggregate) Demand For Us Commercial Air Travel, International Journal Of Forecasting, 27(3), P. 923-941, 2011. Doi: Https://Doi.Org/10.1016/J.Ijforecast.2010.02.010.
[13]. Chansuk, C.; Arreeras, T.; Chiangboon, C.; Phonmakham, K.; Chotikool, N.; Buddee, R.; Pumjampa, S.; Yanasoi, T.; Arreeras, S. Using Factor Analyses To Understand The Post-Pandemic Travel Behavior In Domestic Tourism Through A Questionnaire Survey. Transportation Research Interdisciplinary Perspectives, V. 16, P. 100691, 2022. Issn 2590-1982. Doi: Https://Doi.Org/10.1016/J.Trip.2022.100691
[14]. Fatmi, M. R.; Orvin, M. M.; Thirkell, C. E. The Future Of Telecommuting Post Covid-19 Pandemic. Transportation Research Interdisciplinary Perspectives, V. 16, P. 100685, 2022.Issn 2590-1982. Doi: Https://Doi.Org/10.1016/J.Trip.2022.100685
[15]. Gössling, S.; Scott, D.; Hall, C. M. Pandemics, Tourism And Global Change: A Rapid Assessment Of Covid-19. Journal Of Sustainable Tourism, 29(1), P.1-20, 2021.Doi: 10.1080/09669582.2020.1758708
[16]. Hyndman, Rob J.; Athanasopoulos, George. Forecasting: Principles And Practice. Otexts, 2018.