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DEVELOPMENT OF AVIATION INFRASTRUCTURE IN SELECTED EUROPEAN COUNTRIES: STATISTICAL ANALYSIS AND IMPLICATIONS

ROZWÓJ INFRASTRUKTURY LOTNICZEJ W WYBRANYCH KRAJACH EUROPEJSKICH: ANALIZA STATYSTYCZNA I IMPLIKACJE

Abstract

The main contribution of the article is the statistical analysis of the aviation infrastructure in selected European countries. Research explores various factors that contribute to aviation infrastructure and evaluates their impact on risk management. The paper presents a detailed description of the aviation infrastructure and its division, including graphs and data analysis. The study found disparities in the level of development of aviation infrastructure between selected countries, with Germany having significantly more hub airports compared to other countries. The results of the study provide information on the state of the aviation infrastructure and inform risk management strategies to improve the safety and quality of air transportation.

Keywords: statistical analysis, passenger modelling, infrastructure development

Streszczenie

Głównym celem artykułu jest analiza statystyczna infrastruktury lotniczej w wybranych krajach europejskich. Badania dotyczą różnych czynników, które składają się na infrastrukturę lotniczą i oceniają ich wpływ na zarządzanie ryzykiem. W artykule przedstawiono szczegółowy opis infrastruktury lotniczej i jej podział, w tym wykresy i analizę danych. Badanie wykazało rozbieżności w poziomie rozwoju infrastruktury lotniczej między wybranymi krajami o porównywalnej powierzchni, ale różnym stopniu rozwoju ekonomicznego. Jednym z wybranych krajów są Niemcy, które mają znacznie więcej lotnisk węzłowych w porównaniu z innymi krajami. Wyniki badania dostarczają informacji na temat stanu infrastruktury lotniczej i informują o strategiach zarządzania ryzykiem w celu poprawy bezpieczeństwa i jakości transportu lotniczego.

Słowa kluczowe: analiza statystyczna, modelowanie liczby pasażerów, rozwój infrastruktury

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1. INTRODUCTION

1.1. BACKGROUND AND CONTEXT FOR THE STUDY

Aviation is among one of the fastest growing transportation industries in the world. According to ICAO data, in 2019 more than 100 000 air operations were carried out each day during which nearly 12 million passengers and goods were transported for a total of about $18 bilion were transported. Such a large scale of operations underlines the key role of having powerful facilities in the form of properly prepared airport infrastructure. The aforementioned infrastructure is the pillar on which the global air transport system rests, and it is on its performance and resilience that the safety and efficiency of air operations performed around the world depend. Its development and proper functioning are indispensable in the context of increased global mobility and economic development.

The functioning of the aviation infrastructure in the global concept depends on the functionality of its components in individual countries. Depending on needs and financial possibilities, countries opt for different solutions; for example, Norway, due to its mountainous landscape rich in fjords, has many small local airports, and Germany, due to its location, has many transfer airports. In both cases cited, airport capacity is crucial to maintaining a smooth flow of people and goods. This is why it is so important to predict the number of people traveling over a given period of time. Knowing even the approximate number of passengers makes it possible to prepare the airport infrastructure in such a way that it provides a continuous flow of people and goods. The level of preparation of a given infrastructure can be determined by the level of its resistance to undesirable factors, such as a sudden drop in passenger numbers dictated by a pandemic or crisis. Therefore, it is very important to carry out research in this area, because of this research it is possible to track the impact of undesirable situations on infrastructure capacity and extract the characteristics that resilient aviation infrastructures possess.

Due to the indicated need for research on the state of aviation infrastructure, it was decided to expand the published results of the paper[1] with the implementation of the SARIMA model, which will allow a wider prediction of passenger flow, while highlighting the seasonality of data fluctuations. The analysis will continue to focus on the capacity aspect of airports, in the context of the free movement of people and goods. The countries considered are the following. Norway, Finland, Germany, Poland, and Italy. The results provided will allow future predictions of the airport infrastructure needs of each of the countries mentioned.

1.2. STATEMENT OF THE PROBLEM

The aviation industry plays a key role in shaping economic growth and global connectivity, and European countries contribute significantly to its development. This

1 Zieja et al., 'Risk Management in Aviation Infrastructure'.

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study aims to address the multifaceted challenge of understanding and assessing the development of aviation infrastructure in selected European countries. Particular attention has been paid to:

- differing degrees of economic development, political stability and geography;
- the discrepancies in the development of aviation infrastructure between European countries, resulting from the development of advanced airport facilities and transport networks;
- imbalances in the development of aviation infrastructure affecting economic growth and regional disparities in selected European countries;
- the availability and quality of data on aviation infrastructure across European countries;
- the number of passengers, at different periods of the year.

In light of these challenges, this study aims to provide a comprehensive statistical analysis of the current state of aviation infrastructure development in selected European countries over the period 2004 to 2023. By addressing these complex issues, this study seeks to shed light on the implications for regional development, global connectivity and environmental sustainability, offering valuable insights for policy makers, industry stakeholders and the wider public.

1.3. SIGNIFICANCE OF THE STUDY

This research delves into the intricate dynamics of aviation infrastructure within a select group of European countries. It undertakes an in-depth statistical analysis that extends far beyond the numbers, aiming to uncover the multifaceted implications for the regions under examination. The significance of this work is multi-fold, and can be summarized as follow:

- Bridging Knowledge Gaps: This study addresses existing knowledge gaps related to the development of aviation infrastructure in Europe. It amalgamates data from a variety of sources to offer a comprehensive overview of the current state of aviation infrastructure, thereby serving as a valuable resource for scholars, policymakers, and industry experts.
- Economic Impact: The aviation sector is a cornerstone of economic development. By analyzing the relationship between aviation infrastructure and economic growth in our selected European countries, this study provides insights into the industry's contribution to the Gross Domestic Product (GDP) of these nations.
- Regional Development: Beyond GDP, the research investigates how variations in aviation infrastructure impact regional development. This is crucial for understanding the disparities between regions with advanced airport facilities and those that still face infrastructure challenges.
- Global Connectivity: The study explores the implications of aviation infrastructure development on global connectivity. It highlights how robust infrastructure is essential for ensuring that these European countries remain connected to the world and competitive on the global stage.

- Environmental Sustainability: In an era marked by growing environmental awareness, the aviation industry faces significant pressure to address its carbon footprint. The work conducted here evaluates the environmental sustainability of aviation infrastructure and its alignment with global environmental goals.
- Policymaking and Planning: The research equips policymakers and stakeholders in the aviation industry with data-driven insights. These insights can inform strategic planning and investment decisions, thereby aiding in the development of more resilient and efficient aviation infrastructure.
- Implications for Future Research: By delving into these critical areas, this study lays the foundation for further research in the field of aviation infrastructure development. It identifies avenues for future investigations, both in Europe and beyond.

Concluding the main novelty of this work lies in its ability to offer a holistic understanding of aviation infrastructure in selected European countries and its implications for economies, regions, global connectivity, and environmental sustainability. The selection of European countries with similar area but different economic situation for analysis allows for a comparative assessment of aviation infrastructure development. The utilization of SARIMA for long-term passenger forecasting allows develop a methodology that can be adapted and applied to other regions or countries beyond Europe.

The paper is organized as follow: Literature review is presented in section 2. Section 3 describes the time stories. Section 4 presents chosen countries and the selection criteria. Section 5 describes the source of collected data. Results of the analysis are presented in section 6. Some concluding remarks are presented in Section 6.

2. LITERATURE REVIEW

2.1. REVIEW OF EXISTING RESEARCH ON PASSENGER BEHAVIOR AND INTERNATIONAL TRAVEL

Investigations into the efficiency of aviation infrastructure have been conducted by Gitto[2] on a sample of 28 Italian airports, which revealed that the productivity of airports is significantly impacted by their location, which is indirectly linked to the GDP of the local population. Additionally, the authors found that the form of airport ownership does not have a major effect on productivity, with airports managed by concessions having higher productivity scores than those with partial or temporary partial concessions[3]. This conclusion is also supported by the study of Merkert[4] based on data from Norwegian and Italian airports. Štimac[5] examined the influence of

2 Gitto and Mancuso, 'Bootstrapping the Malmquist Indexes for Italian Airports'.
3 Jacyna-Gołda et al., 'The Assessment of Supply Chain Effectiveness'.
4 Merkert and Mangia, 'Efficiency of Italian and Norwegian Airports'.
5 Štimac et al., 'Optimization of Airport Capacity Efficiency by Selecting Optimal Aircraft and Airline Business Model'.

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different airline business models on airport infrastructure and operational capacity[6], with particular attention paid to the need to adjust the airport infrastructure to the requirements imposed by the volume of air traffic[7,8]. As a solution to this problem, a model was proposed that could optimize the capacity of aviation infrastructure and operations while maintaining an acceptable level of service[9]. The article Pearce[10] also provides an analysis of business models. Most of the research on aviation infrastructure to date has been focused on increasing or optimizing airport capacity. However, the severe impact of the COVID-19 pandemic in 2020 on airport operations necessitated an examination of the airline market for new developments. This topic was addressed in the articles Magniszewski[11], which all agree that the reduced demand for transport in 2020 had a major impact on aviation infrastructure. The decrease in passenger numbers directly led to the loss of profitability of some airports, which may have been a direct cause of the closure of some of them. These changes indicate the need to analyze aviation infrastructure and adapt it to the changing market. This study aims to document and analyze, the transformation process taking place in the aviation infrastructure of countries in the European Union with an area similar to that of Poland. The countries and elements of the aviation infrastructure to be analyzed are identified and defined. The article mainly focuses on showing the changes that occurred between 2014 and 2021, and interpreting them from a statistical perspective. Trends and relationships are presented in this study, with parameterization of the indicated trends to be the subject of future research.

2.2. KEY CONCEPTS AND THEORIES

Passenger demand forecasting is a crucial aspect of transportation planning and management. The autoregressive integrated moving average (ARIMA) model has been widely used in the literature to forecast passenger demand in various transportation sectors. Borucka[12] applied mathematical modeling, including ARIMA, as an element of planning rail transport strategies. They observed that the investigated time series of passenger demand exhibited strong seasonality and an upward trend. The ARIMA model was used to capture these patterns and provide accurate short-term forecasts. In the context of air passenger traffic forecasting, Al-Sultan[13] evaluated different time series models, including ARIMA, for long-term forecasting of Kuwait air passenger data. They compared the performance of ARIMA with other models and found that ARIMA provided accurate forecasts for air passenger traffic volume.

6 Jacyna et al., 'Effectiveness of National Transport System According to Costs of Emission of Pollutants'.
7 Ziółkowski et al., 'Planning Supplies in the Enterprise in the Aspect of Reliability'.
8 Kowalski et al., 'Planning and Management of Aircraft Maintenance Using a Genetic Algorithm'.
9 Żak et al., 'Assessment of Airside Aerodrome Infrastructure by SAW Method with Weights from Shannon's Interval Entropy'.
10 Pearce, 'The State of Air Transport Markets and the Airline Industry after the Great Recession'.
11 Magniszewski, 'Economic analysis of passenger transport at polish airports before and during the Covid-19 pandemic'.
12 Borucka, Mazurkiewicz, and Łagowska, 'Mathematical Modelling as an Element of Planning Rail Transport Strategies'.
13 Al-Sultan et al., 'Forecasting air passenger traffic volume'.

Cyprich[14] focused on short-term passenger demand forecasting using univariate time series theory. They identified the ARIMA model as suitable for their analysis, as it fulfilled most statistical criteria. However, they noted that the normality assumption of the model residuals was not met. These studies demonstrate the applicability of the ARIMA model in passenger demand forecasting. The ARIMA model can effectively capture seasonality, trends, and other patterns in passenger data, making it a valuable tool for transportation planning and management.

2.2.1. ARIMA

ARIMA models have been widely used in various fields for time series forecasting and analysis. These models combine autoregressive (AR) and moving average (MA) components, and are particularly useful for analyzing and predicting data with temporal dependencies. For example, Vieira[15] applied an adapted ARIMA model to estimate excess mortality during the COVID-19 pandemic in Portugal, while Ma[16] used ARIMA models to predict the trend of variation in energy consumption in South Africa. ARIMA models have also been applied in the aviation industry for probabilistic and statistical analysis of aviation accidents[17]. In the field of renewable energy, Kushwah[18] discussed various statistical models to predict wind turbine performance, including ARIMA models. Additionally, Pan[19] combined the ARIMA model with a backpropagation neural network (BPNN) model to forecast the primary energy requirements of the territories. In the financial sector, Minhaj[20] conducted a comparative research study on stock price prediction using ARIMA models. Furthermore, Ighravwe[21] compared ARIMA models with artificial neural network (ANN) techniques to predict port productivity and berth effectiveness. Finally, Friedman[22] used ARIMA intervention time series models to evaluate the effect of raised speed limits on road fatalities and serious injuries. Lydia et al[23] also developed time series models for wind speed forecasting using linear and non-linear autoregressive models, with ARIMA models being used to forecast wind speed for day-ahead forecasting. Anastasiades[24] discussed the

14 Cyprich, Konečný, and Kiliánová, 'Short-Term Passenger Demand Forecasting Using Univariate Time Series Theory'.
15 Vieira et al., 'Rapid Estimation of Excess Mortality during the COVID-19 Pandemic in Portugal -Beyond Reported Deaths'.
16 Ma and Wang, 'Prediction of the Energy Consumption Variation Trend in South Africa Based on ARIMA, NGM and NGM-ARIMA Models'.
17 Amaral et al., 'Probabilistic and Statistical Analysis of Aviation Accidents'.
18 Kushwah and Wadhvani, 'Performance Monitoring of Wind Turbines Using Advanced Statistical Methods'.
19 Pan and Lv, 'Forecasting Primary Energy Requirements of Territories by Autoregressive Integrated Moving Average and Backpropagation Neural Network Models'.
20 Minhaj et al., 'A Comparative Research of Stock Price Prediction of Selected Stock Indexes and the Stock Market by Using Arima Model'.
21 Ighravwe and Anyaeche, 'A Comparison of ARIMA and ANN Techniques in Predicting Port Productivity and Berth Effectiveness'.
22 Friedman, Barach, and Richter, 'Raised Speed Limits, Case Fatality and Road Deaths'.
23 Lydia et al., 'Wind Resource Estimation Using Wind Speed and Power Curve Models'.
24 Anastasiades and McSharry, 'Quantile Forecasting of Wind Power Using Variability Indices'.

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limitations of ARIMA models in forecasting wind power due to the bounded nature of wind power series. They suggested that ARIMA models may not be suitable for wind power forecasting and proposed the use of other models. Radziukynas[25] reported the good performance of ARIMA models in the short-term forecast of loads and wind power for the Latvian power system. ARIMA models were among the time series models used in their study. Lališ[26] employed ARIMA models to predict the aviation safety performance index. ARIMA models were used to forecast safety occurrences related to traffic collision avoidance system (TCAS) issues. In general, ARIMA models have been extensively used in various fields for time series forecasting and analysis. They have been applied in epidemiology, the energy sector, the aviation industry, the financial sector, renewable energy, and other industries. ARIMA models combine autoregressive and moving average components, making them suitable for analyzing and predicting data with temporal dependencies.

2.2.2. SARIMA

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a popular time series model that has been successfully used to forecast air traffic volume in different regions. For example, Gultekin[27] applied SARIMA models to analyze air traffic data in Turkish airspace, and Abellana[28] utilized a SARIMASVR hybrid model to forecast statistical indicators in the aviation industry for capacity management and planning. Accurate forecasting of air traffic volume is essential for capacity management and planning in the aviation industry. The SARIMA model provides a useful tool for predicting future air traffic patterns, allowing airlines and airports to optimize their resources and infrastructure. By examining historical data and recognizing seasonal patterns, the SARIMA model can generate reliable forecasts for short-term and long-term planning. Despite its effectiveness in predicting air traffic patterns, the SARIMA model has certain limitations, such as its reliance on historical data that may not capture sudden changes or unprecedented events. To address these limitations, future research could explore the integration of external factors, such as economic indicators or travel restrictions, into the SARIMA model and the combination of SARIMA with other forecasting techniques, such as artificial neural networks (ANNs). The application of the SARIMA model in aviation contributes to efficient resource allocation, improved operational planning, and informed decision making in the industry.

[25] Radziukynas and Klementavičius, 'Short-Term Forecasting of Loads and Wind Power for Latvian Power System'.
[26] Lališ, 'Time-Series Analysis And Modelling To Predict Aviation Safety Performance Index'.
[27] Gultekin and Acik Kemaloglu, 'Evaluation of the Impact of Covid-19 on Air Traffic Volume in Turkish Airspace Using Artificial Neural Networks and Time Series'.
[28] Abellana et al., 'Hybrid SVR-SARIMA Model for Tourism Forecasting Using PROMETHEE II as a Selection Methodology'.

2.3. IDENTIFICATION OF GAPS IN THE LITERATURE

There is a gap in research on passenger forecasting and the return to trend development in the face of global health events or the geopolitical situation. There is also lack of the complex analysis of changes of airport infrastructure in Poland and their comparison with different countries.

3. METHODOLOGY

3.1. TIME SERIES

To model the passenger number of an airline using time series, various time series models can be applied. These models utilize historical data to forecast future passenger traffic. Some commonly used models for forecasting air passenger numbers include the autoregressive integrated moving average (ARIMA) model, exponential smoothing and Holt-Winters methods, bagging Holt-Winters method, and hybrid methods[29]. The ARIMA model is a popular choice for time series forecasting. It combines autoregressive (AR), moving average (MA), and differencing components to capture the underlying patterns and trends in the data. This model has been widely applied in forecasting air passenger traffic volume.

Exponential smoothing methods, such as the Holt-Winters method, are also commonly used for time series forecasting. These methods assign exponentially decreasing weights to past observations, giving more importance to recent data. The Holt-Winters method, in particular, incorporates seasonality and trend components in the forecasting process. Bagging Holt-Winters method is another approach that combines multiple Holt-Winters models to improve forecasting accuracy. This method generates an ensemble of models by bootstrapping the training data and aggregating the forecasts from each model. Hybrid methods combine different forecasting techniques to leverage the strengths of each model. For example, a hybrid seasonal decomposition and least squares support vector regression approach has been proposed for short-term forecasting of air passenger numbers[30]. In addition to these time series models, other factors can also influence air passenger numbers. Market segmentation analysis can help identify different passenger segments and their preferences, which can be incorporated into the forecasting models. Factors such as service quality, flight safety, travel cost, and time can also impact passenger demand. Furthermore, the impact of airline alliances on passenger numbers has been studied, with findings suggesting that alliances may not have a significant impact beyond changes in fares, aircraft types. It is worth noting that the COVID-19 pandemic has had a severe impact on the airline industry, leading to significant fluctuations in passenger numbers. Therefore, when modeling passenger numbers using time series, it

29 Al-Sultan et al., 'FORECASTING AIR PASSENGER TRAFFIC VOLUME'.

30 Xie, Wang, and Lai, 'Short-Term Forecasting of Air Passenger by Using Hybrid Seasonal Decomposition and Least Squares Support Vector Regression Approaches'.

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is important to consider the specific period and any external factors that may have influenced the data.

Overall, modeling the passenger number of an airline using time series involves selecting an appropriate forecasting model, considering factors such as market segmentation and service quality, and accounting for any external factors that may affect passenger demand. By incorporating these elements into the modeling process, accurate forecasts can be generated to support decision-making in the airline industry.

RIMA is an advanced time series model which combines three series – autoregressive order (p), integrated difference order (d) and moving average (q) in forecasting dependent parameter. Its ARIMA model to predict dependent parameters without much emphasis on historical data pattern is responsible for ARIMA model wide applications in literature especially in financial journals[31]. The formula for computing p is expressed as 1.

$$z_t = \beta_0 + \beta_1 z_{t-1} + \cdots + +\beta_p z_{t-p} + \epsilon_t \tag{1}$$

3.2. MODEL CONSTRUCTION

A diagram of passenger forecasting using SARIMA models is shown in Figure 1.

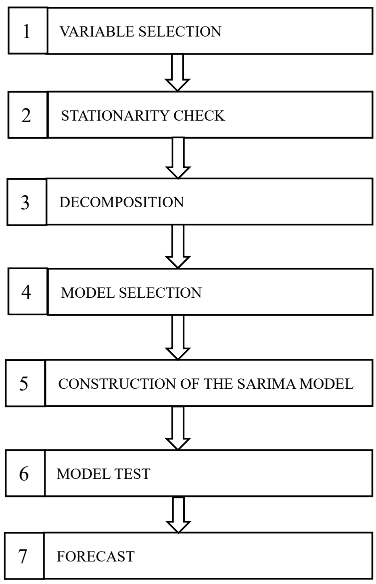

Fig. 1. Decision-making scheme using the SARIMA method [own study]

There are 7 steps in the SARIMA method to develop a model.

[31] Tse, 'An Application of the ARIMA Model to Real-estate Prices in Hong Kong'.

1. Variable selection

A mathematical model is not required at this stage, since the selection of variables is more related to data analysis and expert experience than to a specific mathematical model

2. Stationarity check

Mathematical model for ADF (Augmented Dickey-Fuller):

- H_0: The time series has a unit root and is not stationary.
- H_1: The time series is stationary.
- Model: $\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + _{\dots} + \delta_k \Delta y_{t-k} + \varepsilon_t$
- Accepting the hypothesis H_0 means that the time series is non-stationary.

3. Decomposition

Mathematical model for decomposition:

- $y_t = T_t + S_t + R_t$
- T_t – Trend
- S_t – Seasonality
- R_t – Random component
- Trend model, seasonality and the random component can be nonlinear and dependent on the data specification.

4. Model selection

No specific mathematical model at this stage. Model decisions are based on analysis of ACF charts, PACF, ADF test results and other diagnostic tools.

5. Construction of the SARIMA model

SARIMA mathematical model (p, d, q) (P, D, Q)m:

- $y'_t = \varphi_1 y'_{t-1} + \varphi_2 y'_{t-2} + _{\dots} + \varphi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + _{\dots} + \theta_q \varepsilon_{t-q} + \varepsilon_t$
- $y'_t = (1-B)^d (1-B^m)^D y_t$
- $Y_t = y_t - \mu_t$
- $Y_t = T_t + S_t + R_t$
- The model is linear with respect to the parameters φ and θ, but nonlinear due to d and D.

6. Model tests

Mathematical model for diagnostic tests:

- Error model: $\varepsilon_t = Y_t - \hat{Y}_t$
- Tests may include analysis of residuals, testing for normality, homoskedasticity, autocorrelation, etc.

7. Forecast

Model matematyczny dla prognozy w oparciu o SARIMA:

- $y'_{t+1} = \varphi_1 y'_{t-1} + \varphi_2 y'_{t-1} + _{\dots} + \varphi_p y'_{t-p+1} + \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-1} + _{\dots} + \theta_q \varepsilon_{t-q+1} + \ \varepsilon_{t+1}$
- $y'_t = (1-B)^d (1-B^m)^D y_{t+1}$
- $Y_{t+1} = T_{t+1} + S_{t+1} + R_{t+1}$
- Forecast includes prediction of trend, seasonality and random component for the next time period.

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4. COUNTY SELECTION

One of the determinants of aviation development is the size of the country, therefore countries of similar size were selected for further analysis. However, attention was paid to other factors such as GDP and population. Poland was selected as the main country of interest, with Norway, Finland, Germany, and Italy as countries of similar size. The area difference between the selected countries is no more than 16%, however, the number of inhabitants and GDP per capita differ significantly. In 2021, the population of Germany was approximately 15 times that of Norway. These are the two countries with the highest distinction in comparison in terms of population per km^2. In terms of GDP per capita in 2021, the largest disparity was observed between Poland and Norway. On average, Norwegians earned five times more than Poles. It should be noted that Norway is the only country in this ranking that is not a member of the European Union. The impact of these factors on the aviation infrastructure and the number of flight operations will be examined later in this article.

Table 1. Basic characteristics of countries selected for the analysis for year 2021

Country	Area (km^2)	Number of inhabitants	GDP Per capita (Euro)
Poland	312 679	37 840 001	13 760
Germany	357 376	83 155 031	35 480
Norway	324 220	5 391 369	71 150
Italy	302 073	59 236 213	26 780

4.1. POLAND

Poland has 14 functioning airports, which in 2019 served a record number of almost 47 million passengers. However, due to the COVID-19 pandemic in 2020, this number has decreased by 70%. Currently, the situation related to air transport in Poland is improving, as evidenced by the increase in the number of passengers served in Poland in 2021 by nearly 37% compared to the previous year.

4.2. GERMANY

Germany's aviation infrastructure is one of the most developed in Europe. In 2019, it included nearly 41 major airports and 567 aircraft, which allowed the transport of a record number of 226 million passengers. To ensure the safety and efficiency of air transport, Germany is constantly developing its infrastructure by modernizing airports and purchasing new aircraft. In 2021, German airlines acquired 171 new aircraft and carried 27% more passengers than in 2020.

4.3. NORWAY

According to Williams, Fewings, and Fuglum (2007), Norway has one of the highest air transport dependencies in Europe. In 2003, the country's domestic air trip rate was recorded at 1.87 per capita, which is three times higher than the average rate of other European nations. However, this trip rate is not uniformly distributed across the country, with varying rates observed in different regions. For example, as reported in Solvoll, Mathisen, and Welde (2020), the Helgeland district in Nordland county had a trip rate of 3.98, the second highest after Finnmark county, which had a rate of 5.81.

4.4. ITALY

In 2019, Italy recorded 160 million passengers carried, which, like the rest of the countries noted in the article, is a record Sergi, D'Aleo, Arbolino, Carlucci, Barilla, and Ioppolo (2020). In 2020, this Figure fell fourfold due to the pandemic. It is worth mentioning that Italy is the only country on the list cited to record an increase of nearly 47% in the number of passengers served in 2021. This high percentage was recorded despite a slight reduction in the number of airports and the

5. DATA ANALYSIS

5.1. DATA COLLECTION AND SOURCES

The primary data source for this study is Eurostat, a well-established authority for European statistical information. Eurostat provides data in various domains, including but not limited to economics, demographics, transportation, and environmental factors. The specific datasets and sources used in this study include:

- Transportation Data: Eurostat's transportation statistics, encompassing information about airports, road networks, railway systems, and other transportation-related metrics.
- Economic Data: Economic indicators, including GDP, employment, and trade statistics, which are vital for understanding the economic context.
- Demographic Data: Demographic data, such as population figures and migration statistics, which are essential for assessing the impact of these factors on infrastructure.
- Environmental Data: Data related to environmental factors, including emissions, energy consumption, and sustainability metrics.
- Infrastructure Data: Information on infrastructure facilities, such as the number of roads, airports, passenger facilities, parking places, and more.

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By utilizing these comprehensive datasets from Eurostat, we can provide a thorough analysis of the infrastructure and its relation to economic and demographic factors in the European Union.

6. RESULTS

6.1. TIME SERIES – ANALYSIS OF TRENDS

Analyzing data on, for example, passenger numbers for different modes of transport allows trends, patterns and insights crucial for informed decision-making to be observed. This subsection presents time series analysis in the field of transport. They are one of the predictive tools to understand not only long-term changes but also seasonal changes.

Fitting predictive models to real-world data will allow an understanding of the trends likely to be encountered in the future and how unexpected situations, such as a pandemic, change transport developments.

The Figures 2–5 shows the trends for Germany, Norway, Poland and Italy, respectively.

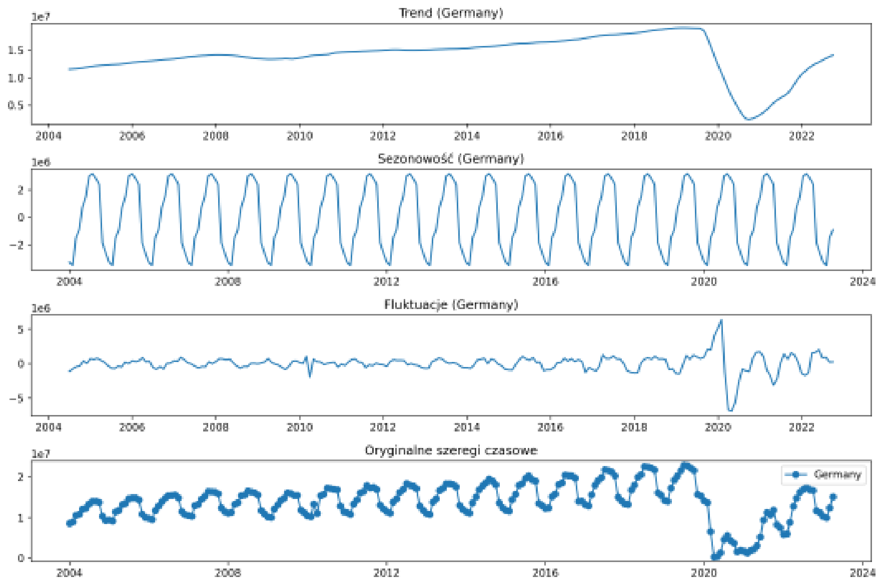

Fig. 2. Time Series – Germany

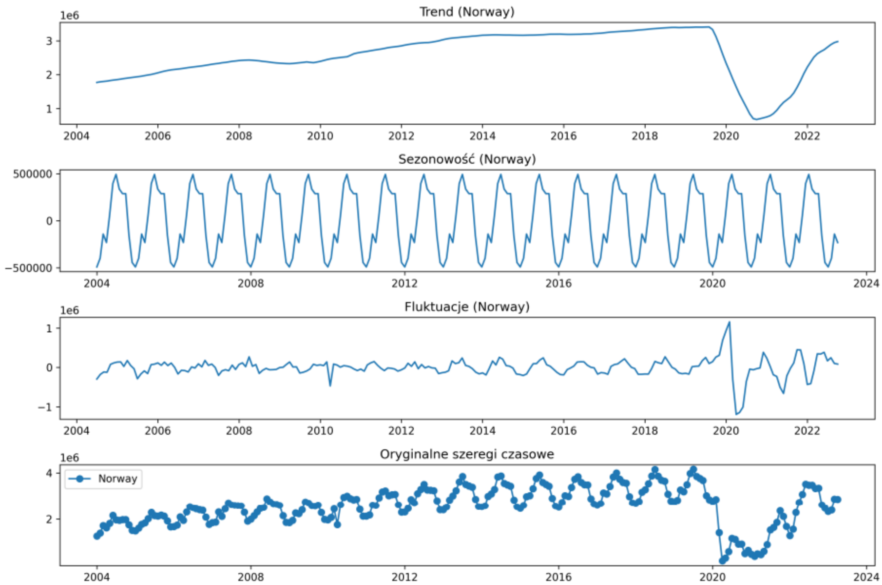

Fig. 3. Time series Norway

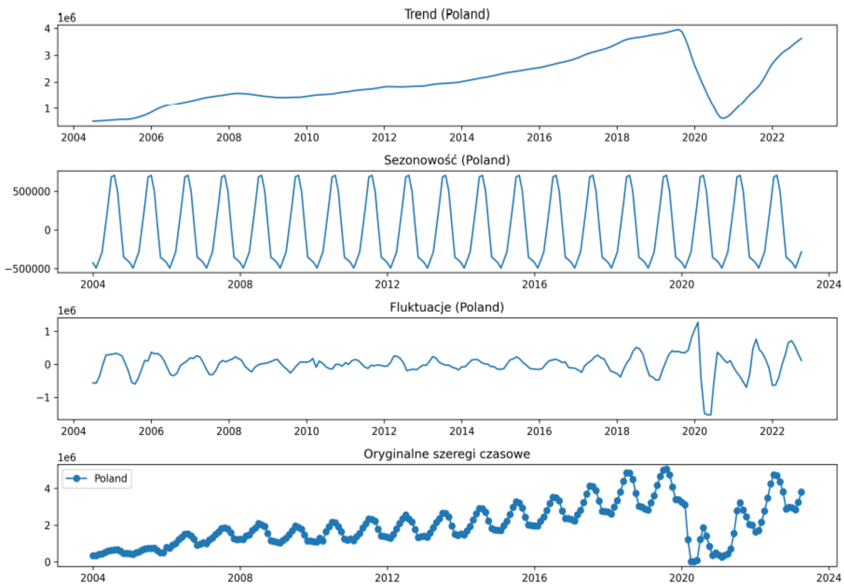

Fig. 4. Time series – Poland

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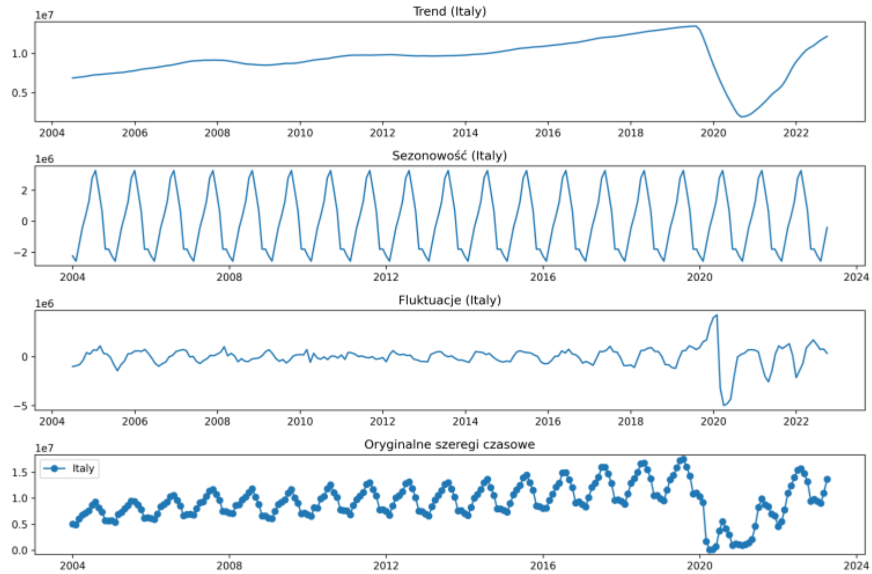

Fig. 5. Time Series – Italy

6.2. TIME SERIES – PREDICTION MODEL

This subsection delves into the realm of time series prediction models, employing rigorous scientific methodologies to unravel the underlying patterns within temporal data. Through meticulous analysis and advanced statistical techniques, this chapter navigates the complexities of forecasting future trends based on historical temporal information. The emphasis lies on the application of robust predictive models, meticulously calibrated to dissect the inherent structure of time series data, facilitating informed projections and enhancing our understanding of the intricate dynamics governing the observed phenomena.

A factor forcing the development of aviation infrastructure is the increase in passenger numbers. Increased interest in flying is forcing the development of airports, increasing their capacity, the number of people serving passengers, etc.

When comparing the two mentioned coefficients, long-term trends can be distinguished, such as the decrease in the number of passenger aircraft in Italy from 302 in 2001 to 77 in 2021, which began in 2008.

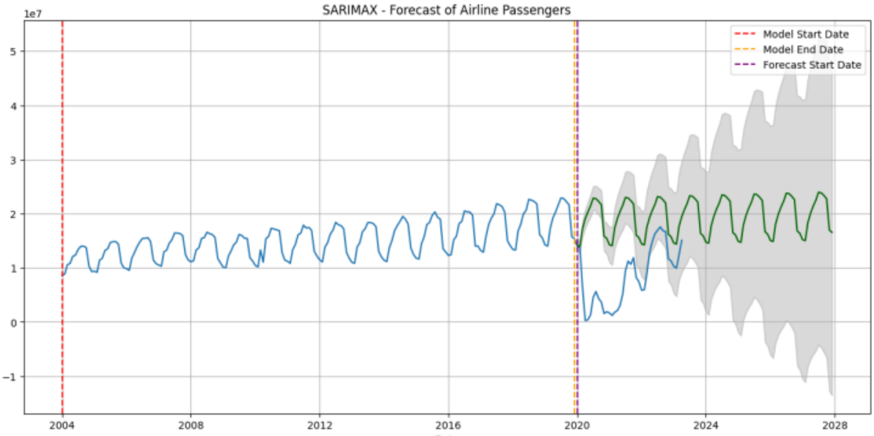

Fig. 6. Sarimax – Germany

Table 2. Parameters of SARIMA model

Parameters of SARIMA model	
P Value: 0.008634343749711143	Number of differencing needed: 0
Results of Dickey-Fuller Test:	
Test Statistic	-3.475671
p-value	0.008634
No. Lags Used	13.000000
Number of Observations Used	218.000000
Critical Value (1%)	-3.460708
Critical Value (5%)	-2.874891
Critical Value (10%)	-2.573886

The analysis on Germany's time series data (Table 2), employing an ARIMA(11, 2, 1) model. Firstly, the Dickey-Fuller test indicates that the series is stationary, substantiated by a negative Test Statistic and a p-value below 0.05. Moving on to the SARIMAX model, it comprises autoregressive (AR) and moving average (MA) components, with specific parameters. The model's coefficients exhibit significance, as denoted by low p-values. Model diagnostics, including the Ljung-Box and Jarque-Bera tests, unveil acceptable autocorrelation at lag 1 and non-normality in residuals. Heteroscedasticity is detected with a factor of 2.30, signifying varying residual variances. While the model provides a valuable framework for forecasting, addressing observed issues like heteroscedasticity could enhance its robustness. These findings underscore the importance of meticulous interpretation and potential refinement for a more accurate representation of the underlying patterns.

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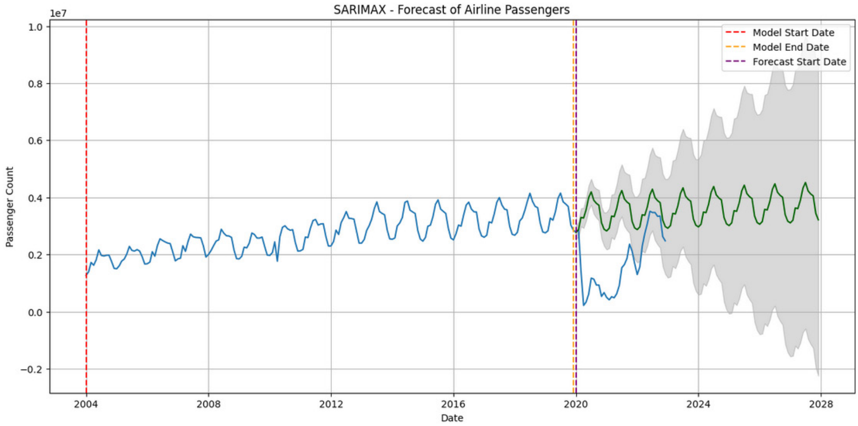

Fig. 7. Sarimax – Norway

Table 3. Parameters of SARIMA model – Norway

P Value: 0.019851314774895556	Number of differencing needed: 0
Results of Dickey-Fuller Test:	
Test Statistic	-3.202311
p-value	0.019851
#Lags Used	13.000000
Number of Observations Used	218.000000
Critical Value (1%)	-3.460708
Critical Value (5%)	-2.874891
Critical Value(10%)	-2.573886

The examination of Norway's time series data (Table 3) utilizes an ARIMA (11, 2, 1) model, providing valuable insights. The Dickey-Fuller test indicates stationarity with a p-value of 0.019851, corroborated by the negative Test Statistic. The SARIMAX model reveals a blend of autoregressive (AR) and moving average (MA) components, each contributing uniquely to the model. The coefficients demonstrate significance, emphasizing the robustness of the model. The Ljung-Box and Jarque-Bera tests suggest satisfactory autocorrelation and non-normality in residuals. However, a notable heteroskedasticity factor of 2.44 signifies varying residual variances. While the model successfully captures underlying patterns, addressing heteroskedasticity could enhance its precision. Additionally, caution is advised due to the near-singular covariance matrix, potentially impacting standard errors. These findings underscore the dynamic nature of Norway's aviation landscape, necessitating ongoing monitoring and potential adjustments to infrastructure as passenger volumes evolve.

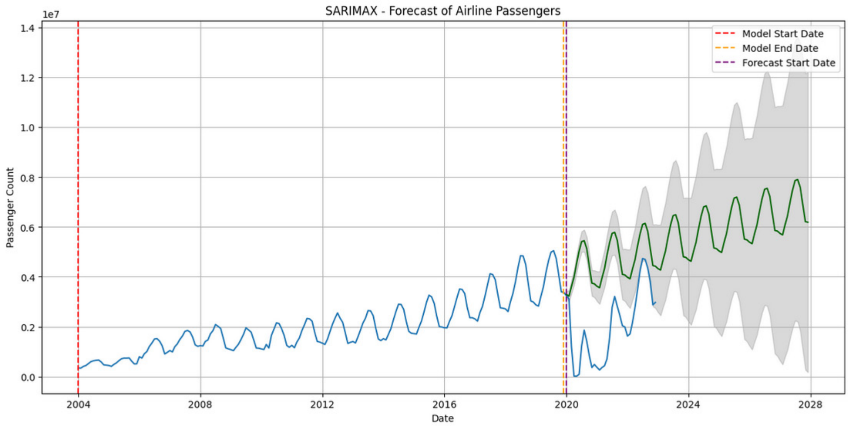

Fig. 8. Sarimax – Poland

Table 4. Parameters of SARIMA model – Poland

P Value: 0.002929994511063486	Number of differencing needed: 1
Results of Dickey-Fuller Test:	
Test Statistic	-2.208911
p-value	0.203027
#Lags Used	15.000000
Number of Observations Used	216.000000
Critical Value (1%)	-3.460992
Critical Value (5%)	-2.875016
Critical Value (10%)	-2.573952

The analysis of Poland's time series data (Table 4) employs an ARIMA model, offering valuable insights into the country's aviation trends. The Dickey-Fuller test results suggest stationarity, given the low p-value (0.00293) and a Test Statistic of -2.208911. However, differencing is necessary, as evidenced by the non-zero order of differencing. The SARIMAX model reveals a combination of autoregressive (AR) and moving average (MA) components contributing significantly to the model's efficacy. The model coefficients are statistically significant, indicating the robustness of the model. However, attention is warranted due to the heteroskedasticity factor of 7.39, implying varying residual variances. The Ljung-Box and Jarque-Bera tests underscore acceptable autocorrelation and deviations from normality in residuals, respectively. While the model effectively captures the underlying patterns in Poland's aviation data, addressing heteroskedasticity could enhance its precision. Furthermore, the pronounced kurtosis suggests heavy-tailed distribution, signaling extreme values. Consequently, continuous monitoring and potential refinements to the model are advised, reflecting the dynamic nature of Poland's aviation landscape.

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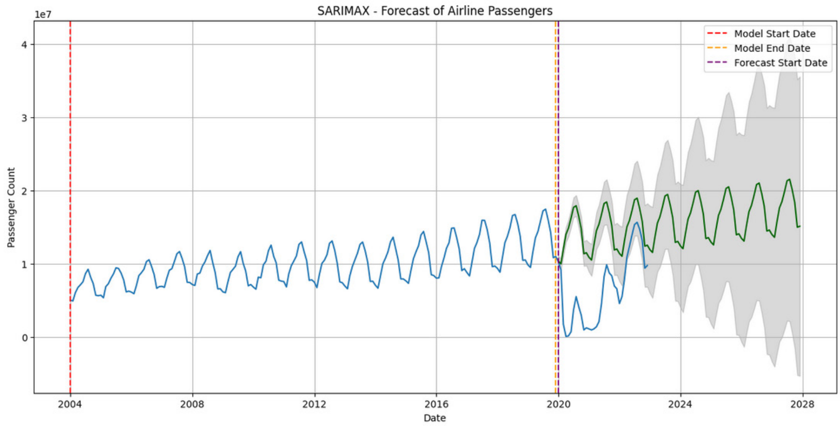

Fig. 9. Sarimax – Italy

Table 5. Parameters of SARIMA model – Italy

P Value: 0.002929994511063486	Number of differencing needed: 1
Results of Dickey-Fuller Test:	
P Value: 0.002278990788375654	Number of differencing needed: 0
Results of Dickey-Fuller Test:	
Test Statistic	-3.868537
p-value	0.002279
#Lags Used	13.000000
Number of Observations Used	218.000000
Critical Value (1%)	-3.460708
Critical Value (5%)	-2.874891
Critical Value (10%)	-2.573886

The examination of Italy's time series data (Table 5) employs an ARIMA model, revealing insightful insights. Beginning with the Dickey-Fuller test, the p-value of 0.002279 signifies stationarity, supported by the negative Test Statistic. The SARIMAX model showcases a mix of autoregressive (AR) and moving average (MA) components, each with distinct parameters. Coefficients exhibit significance, contributing to the model's robustness. Model diagnostics, including the Ljung-Box and Jarque-Bera tests, indicate acceptable autocorrelation and non-normality in residuals. A notable heteroskedasticity factor of 4.57 suggests varying residual variances. While the model successfully captures patterns, addressing heteroskedasticity could further refine its accuracy. These findings emphasize the dynamic nature of Italy's aviation landscape, calling for continuous monitoring and potential adjustments to infrastructure as passenger volumes evolve.

6.3. NUMBER OF AIRCRAFTS

In the airline industry, a comprehensive analysis of forecasting passenger growth requires at the same time an analysis of the number of aircraft serves as a key cornerstone. The number of aircraft has a direct impact on an airline's ability to accommodate passengers, shaping the overall operational landscape. Understanding the complex relationship between aircraft availability and passenger demand enables stakeholders to make informed decisions, optimise resource allocation and improve strategic planning.

Meticulously examining the changing aircraft landscape provides insight into fleet expansion, technological advances and industry competitiveness. By analysing historical data and identifying patterns of growth or reduction in aircraft fleets, analysts can discern the underlying drivers of aviation dynamics. This knowledge, in turn, forms the basis for constructing robust forecasting models that predict future trends in passenger demand.

The correlation between aircraft numbers and passenger forecasts is an integral part of mitigating operational challenges. As the airline industry is constantly evolving, an accurate passenger forecast depends heavily on a detailed understanding of relevant changes in the aircraft landscape. Airlines, regulators and industry analysts can use this information to optimise route planning, infrastructure development and fleet management strategies.

The composition of the aircraft fleet is an important factor in aviation infrastructure and risk management. The number of aircraft and their seating capacity can significantly impact operations and profitability.

By analyzing changes in the size of the air fleet and changes in the number of aircraft of different sizes (Figure 10–13) over time for selected countries, it is possible to understand which types of aircraft are added or removed from the fleet. For example, there is a large disparity in the number of aircraft assigned to each country. Norway stands out with a significant number of passenger aircraft with 50 seats or less, attributed to challenging terrain and the need for smaller aircraft. Italy has a high number of aircraft within the range of 51 to 150 seats, likely influenced by its geographical location as a transfer point in the Mediterranean. Germany, Poland, and Norway have a notable proportion of aircraft in the 150 to 250-seat range. Germany also leads in the number of aircraft with more than 250 seats, reflecting its well-developed economy and the high demand for intercontinental travel.

This information is valuable for risk management, as different types of aircraft can involve different operational, maintenance, and safety aspects. Additionally, changes in the fixed base index can provide information on the age profile of commercial aircraft fleets in different countries. Changes in fleet size over time can indicate fleet renewal or retirement patterns, which can impact risk management. Older aircraft may have different risk profiles compared to newer ones, and understanding the age distribution of the fleet can help identify potential safety concerns and guide maintenance and inspection programs. Furthermore, sudden changes in the number of aircraft can indicate a poor condition of a selected carrier in a particular country and may require a reassessment of associated risks. A statistical analysis of the composition of the fleet reveals interesting insights.

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The popularity of certain aircraft types is driven by factors such as cost-effectiveness and the demand for affordable airfares. The availability of different aircraft sizes allows airlines to cater to varying market demands and optimize profitability.

In general, analyzing the composition of the fleet provides valuable information for effective risk management in aviation infrastructure, allowing stakeholders to make informed decisions and allocate resources accordingly.

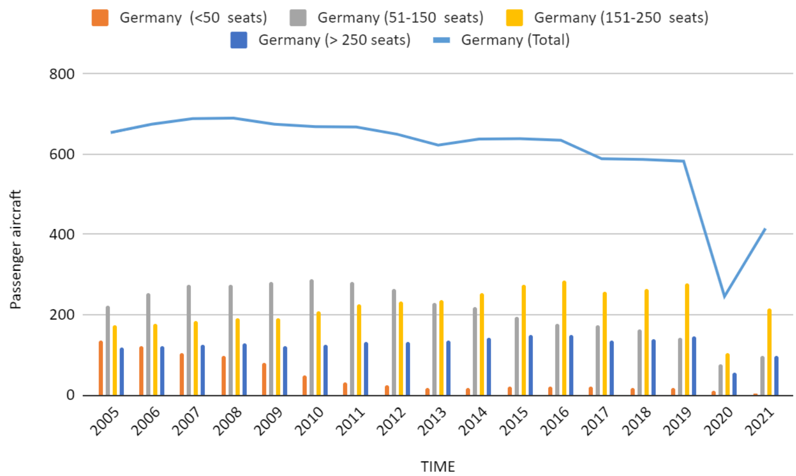

Fig. 10. Number of aircraft of different types – Germany

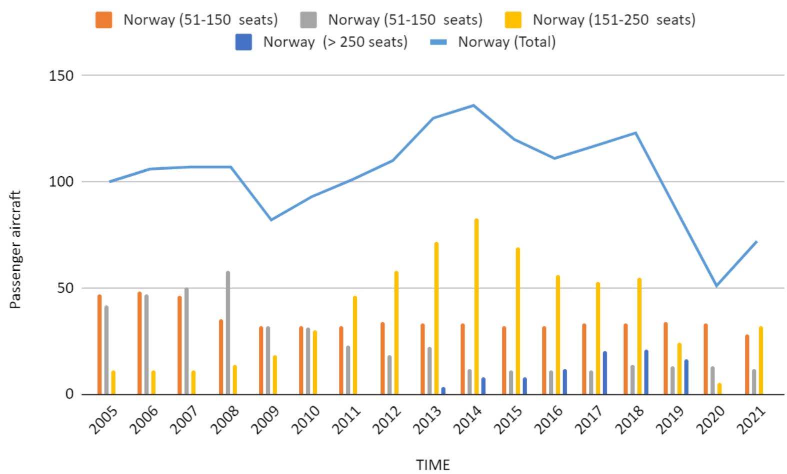

Fig. 11. Number of aircraft of different types – Norway

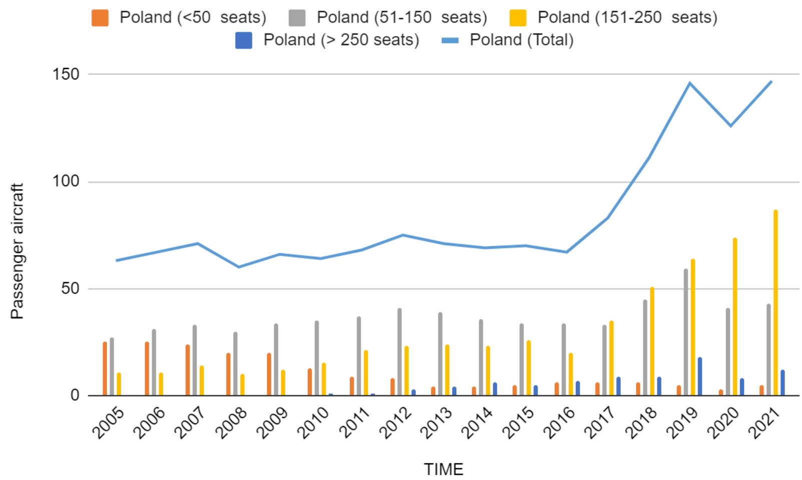

Fig. 12. Number of aircraft of different types – Poland

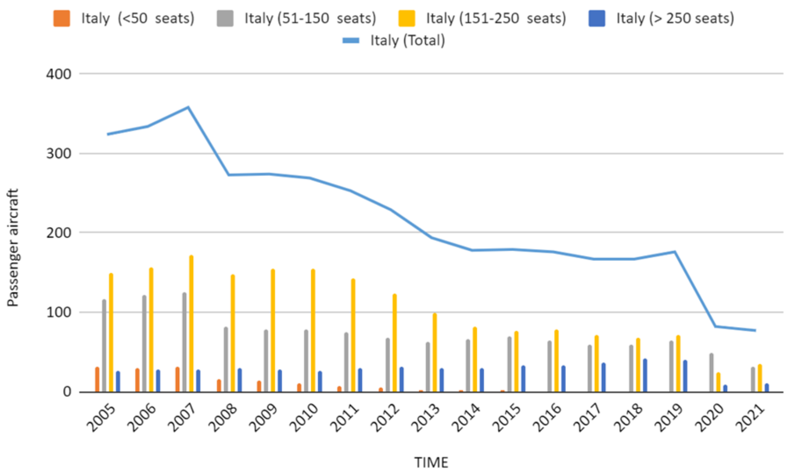

Fig. 13. Number of aircraft of different types – Italy

6.4. AIRPORTS

This subsection analyses the change in the number of airports in the countries studied. Through statistical analysis, the chapter aims to show the trends of change in the aviation infrastructure of the studied country. This study will provide a better understanding of the interaction between geographical, economic and logistical factors shaping the airport infrastructure landscape.

Number of airports is presented in Table 6.

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Table 6. Number of airports

	Germany	Italy	Poland	Norway
2005	33	37	10	42
2006	34	37	9	46
2007	33	38	10	47
2008	34	39	10	48
2009	34	38	10	48
2010	33	38	10	49
2011	41	38	10	50
2012	38	37	10	49
2013	39	37	10	50
2014	38	38	12	49
2015	42	37	12	47
2016	40	37	13	47
2017	136	35	14	42
2018	140	36	14	42
2019	182	36	14	42
2020	167	35	14	39
2021	171	35	14	37

The temporal evolution of aircraft counts across the surveyed European countries reveals discernible trends and dynamic shifts in their respective aviation landscapes. Germany's aviation sector demonstrates a consistent upward trend, marked by significant growth in aircraft numbers over the years, reaching its zenith in 2019. This trajectory underscores Germany's strategic positioning as a key player in European aviation. In contrast, Italy maintains a relatively stable fleet size, reflecting a resilient and balanced approach to its aeronautical infrastructure.

Poland exhibits a distinctive pattern characterized by a period of constancy from 2005 to 2014, followed by a substantial surge in 2015. This pronounced shift signifies a strategic development in Poland's aviation industry, potentially influenced by economic and geopolitical factors. Norway, initially witnessing a gradual increase in aircraft numbers until 2016, experiences a noteworthy decline in subsequent years. This shift may be attributed to evolving national priorities, economic considerations, or changes in air travel patterns.

These trends and changes underscore the dynamic nature of the aviation sector, influenced by a myriad of factors such as economic conditions, technological advancements, and geopolitical considerations. Analyzing these trends provides valuable insights for stakeholders, policymakers, and industry experts to adapt strategies, forecast future developments, and navigate the ever-changing landscape of aviation.

Number of airports is presented in Table 7.

Table 7. Number of main airports

	Germany	Italy	Poland	Norway
2005	24	30	6	15
2006	25	32	8	17
2007	26	32	10	17
2008	27	33	10	17
2009	26	32	10	18
2010	27	33	10	19
2011	27	34	10	19
2012	26	35	10	19
2013	26	33	10	21
2014	25	33	12	20
2015	25	33	12	18
2016	24	33	12	18
2017	24	33	12	17
2018	24	32	12	17
2019	23	33	12	17
2020	20	26	9	17
2021	18	26	9	14

Analyzing Table 7, which focuses on main airports, Germany consistently maintains a higher number than the other countries. The data reveal that Germany's main airports, though fewer in quantity compared to total airports, demonstrate a resilient and upward trend, showcasing strategic concentration and investment in major aviation hubs. On the other hand, Italy and Poland show incremental growth, while Norway experiences a decline.

In conclusion, the analysis underscores Germany's dominance in both total and main airports, portraying a robust and evolving aviation landscape. Italy and Poland exhibit more measured developments, while Norway's main airports witness a reduction, possibly reflecting strategic adjustments or shifts in air travel dynamics. These trends underscore the dynamic interplay between infrastructure planning, passenger demand, and regional priorities in shaping the aviation sector across these countries.

6.5. AGE OF AIRCRAFT

The examination of the age of aircraft is a critical facet in the comprehensive evaluation of aviation dynamics. Aircraft age serves as a pivotal determinant in assessing fleet efficiency, safety, and environmental impact. As aviation continually evolves, understanding the age distribution of aircraft within a fleet becomes instrumental for strategic planning, regulatory compliance, and technological adaptation. This analysis delves into the temporal dimensions of aircraft fleets, scrutinizing how the varying ages of aircraft in service contribute to overall operational effectiveness and sustainability. By exploring the age composition of aircraft, this study aims to unravel nuanced patterns that can inform decision-makers, industry stakeholders, and regulatory bodies, fostering a deeper comprehension of the aviation landscape and its trajectory.

The number of aircraft in the ages categories is presented in Figure 14–17.

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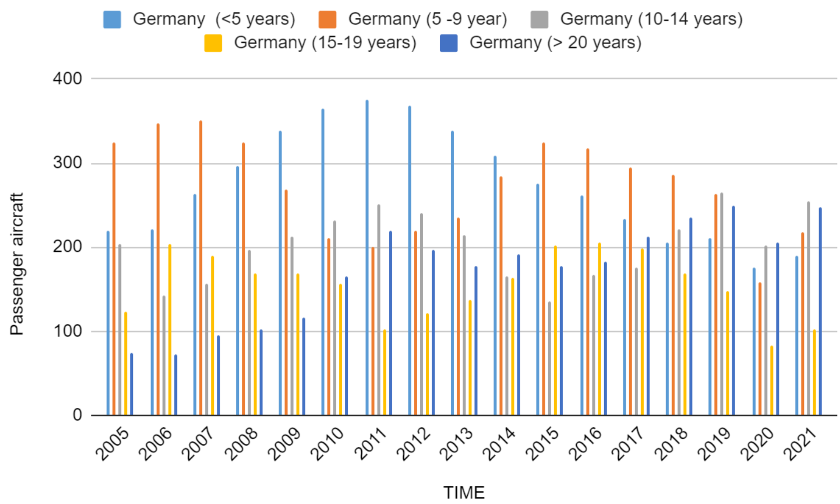

Fig. 14. Number of aircraft in the ages categories for Germany

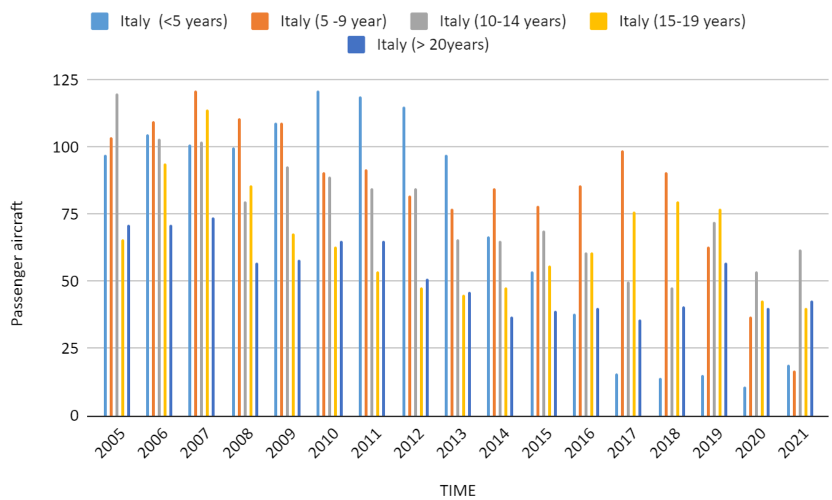

Fig. 15. Number of aircraft in the ages categories for Italy

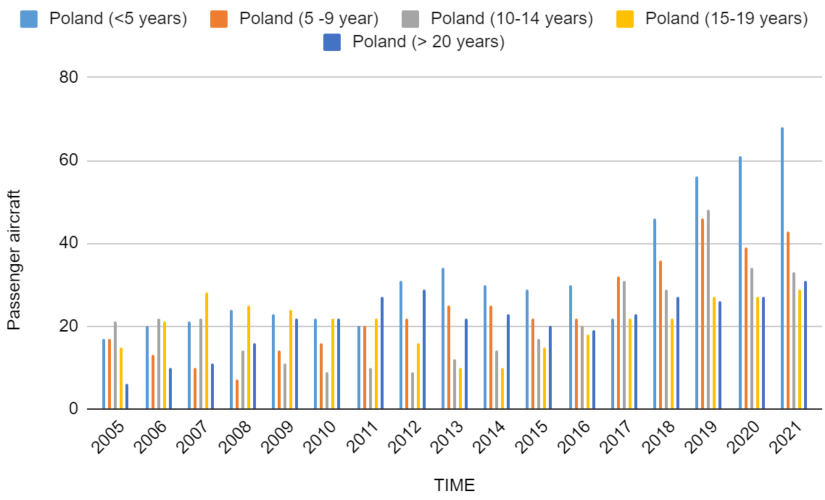

Fig. 16. Number of aircraft in the ages categories for Poland

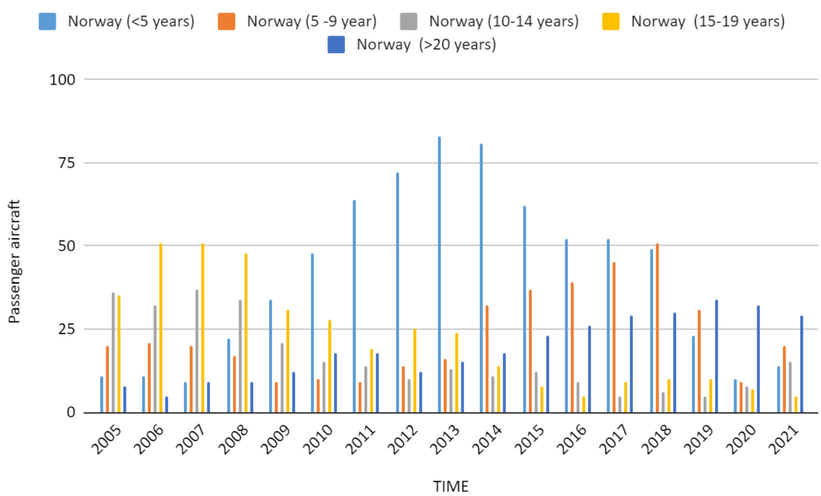

Fig. 17. Number of aircraft in the ages categories for Norway

The analysis of the age distribution of aircraft in Germany, Italy, Poland, and Norway over the years reveals intriguing patterns and shifts in the composition of their respective fleets. The total number of aircraft in each country has undergone fluctuations, mirroring the dynamic nature of the aviation industry. In 2005, Germany had the highest total number of aircraft at 944, followed by Italy (458), Poland (76), and Norway (110). Over the subsequent years, Germany experienced a steady increase,

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reaching 1.010 aircraft in 2021. Italy and Poland also demonstrated growth, albeit with variations in different periods, while Norway's total aircraft count fluctuated.

Examining the age categories provides further insights. The distribution into age brackets – less than 5 years, 5–9 years, 10–14 years, 15–19 years, and over 20 years – allows a nuanced understanding of fleet composition. In Germany, for instance, the proportion of aircraft in the over 20 years category decreased over the years, indicating potential modernization efforts. Italy witnessed a notable increase in the number of aircraft aged 10–14 years, suggesting a shift towards a mature fleet. Poland experienced growth across various age categories, reflecting a diverse fleet. Norway demonstrated a decrease in older aircraft, potentially aligning with efforts towards a more modern and sustainable fleet.

In conclusion, the analysis of the age distribution of aircraft in these countries offers valuable insights into the evolution of their aviation fleets. These trends hold significance for strategic planning, regulatory compliance, and environmental considerations within the dynamic landscape of the aviation industry.

6.6. OTHER FACTORS

The infrastructure at some airports faces challenges in meeting the growing needs of travelers, particularly in terms of limited taxiways and parking spaces. The number of taxiways on the biggest airports in selected countries varies at each airport: Warsaw 2, Rome 4, Oslo 2, and Frankfurt 3. In terms of passenger facilities, Frankfurt Airport offers the highest number of check-in counters (481), followed by Rome (425), Warsaw (137), and Oslo (145). When it comes to passenger gates, Frankfurt has 210 gates, Rome 83, Oslo 84, and Warsaw 45. The number of parking spaces significantly differs at these airports: Frankfurt provides up to 15.000 parking spaces, Rome 19.033, Warsaw 2.250, and Oslo 8.000. These data demonstrate the diversity of airport infrastructure at different locations, which can impact the comfort of travel and passenger service. It is important to monitor these indicators and adjust the infrastructure as needed, especially with the increasing number of passengers.

The number of parking spaces does not appear to be keeping up with the rise in passenger numbers, creating a difficulty in providing enough space for the increasing air traffic. To tackle this issue, it is essential to keep track of and adjust airport infrastructure to meet the expanding requirements of travelers.

7. CONCLUSION

7.1. SUMMARY OF KEY FINDINGS

Airports play a key role in global air travel, connecting people around the world. Understanding the nuances and trends of each country's aviation sector is essential to identifying risks and effectively managing infrastructure. For example, Germany's numerous airline hubs and extensive commercial aircraft fleet require robust risk management for operational safety and handling increased passenger numbers. Scandinavian countries, where air transport is concentrated around smaller airports, face challenges related to access, infrastructure maintenance and emergency response capabilities.

The research presented showed the projected growth in passenger numbers in the coming years. In addition, it can be seen that at this stage of air transport development, even disruptions such as an epidemic allow for a relatively quick return to the pre-pandemic situation.

The large number of aircraft accommodating between 151 and 250 passengers in Italy highlights the need to adapt risk management strategies to the unique operational requirements of larger aircraft. Incorporating these insights into aviation infrastructure management enhances stakeholders' ability to proactively mitigate risk, optimize planning and strengthen overall resilience.

The paper, similar to the work of Rodríguez-Sanz and Andrada[32], notes that with increasing passenger numbers, and the consequent need for more aircraft, there will be an increased demand for more taxiways or infrastructure such as check-in and parking facilities. To meet these expectations, airports will have to be rebuilt or new locations sought for larger airports.

To address these challenges, the importance of monitoring and adapting airport infrastructure is highlighted. The methodological framework developed by Mascio and Moretti[33] proposes an assessment of hourly capacity, applicable to different airport layouts. Regular convection is also an important element[34] .

In summary, the data presented make it possible to identify trends in changes in passenger numbers and elements of modern aviation. They also point to the need to continuously adapt aviation infrastructure to the dynamic growth in demand, which may require innovative approaches such as airport conversions or the search for new locations. Further research should focus on developing forecasts of air traffic growth, assessing the impact of disruptions, such as an epidemic, on long-term infrastructure and developing adaptation strategies for airports.

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