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Systematic review of passenger demand forecasting in aviation industry

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Abstract

Forecasting aviation demand is a significant challenge in the airline industry. The design of commercial aviation networks heavily relies on reliable travel demand predictions. It enables the aviation industry to plan ahead of time, evaluate whether an existing strategy needs to be revised, and prepare for new demands and challenges. This study examines recently published aviation demand studies and evaluates them in terms of the various forecasting techniques used, as well as the advantages and disadvantages of each. This study investigates numerous forecasting techniques for passenger demand, emphasizing the multiple factors that influence aviation demand. It examined the benefits and drawbacks of various models ranging from econometric to statistical, machine learning to deep neural networks, and the most recent hybrid models. This paper discusses multiple application areas where passenger demand forecasting is used effectively. In addition to the benefits, the challenges and potential future scope of passenger demand forecasting were discussed. This study will be helpful to future aviation researchers while also inspiring young researchers to pursue careers in this industry.

Keywords Aviation demand forecasting · Deep learning · Passenger throughput · Statistical approach

1 Introduction

The work of academic researchers and industry personnel has substantially aided aviation traffic forecasting in recent decades. They analyzed the need for air travel from several perspectives. Air transport demand studies span international, national, regional, and intercity

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levels and airports. The demand for air travel changes as different types of travelers and their preferred locations varies. Only some studies have specifically examined the various modes of air travel due to the range of traveler types and their desired destinations. Most individuals fly to get somewhere and do something; few fly just for fun, indicating that demand for air travel is mainly derived [77]. In other words, geographically fixed activities, especially those associated with business, pleasure, visiting friends and family, and other reasons, substantially impact air travel demand. Figure 1 depicts the diverse travel objectives by classifying travelers as business, leisure, or others.

Because of increased travel opportunities, the air transport industry has grown significantly during the past decades. Even though the industry has suffered due to the pandemic, political and market-driven events discourage passengers from traveling. Forecasting future demand for the aviation industry is critical, as is knowledge of determinants. The most standard predictive models used in aviation demand studies are econometric and time series models. Many forecasting models rely on aggregate demographic or economic factors such as total population, gross domestic product (GDP), or per capita income. Similarly, most airline cost estimates are based on highly aggregated characteristics such as average airline yield. However, as evident by the recent dramatic increase in oil prices and the eventual collapse of global markets owing to pandemics, passenger demand in the aviation industry plays a crucial role.

Based on the above facts, this study has three folds. The first step is to review the available air travel literature at various levels. The second step is to identify the primary factors influencing aviation demand and asses alternative forecasting passenger demand techniques based on their efficiency in dealing with the volatile nature of air travel. The third step entails presenting a detailed mapping of the existing challenges with aviation demand forecasts, which will be critical in the current unstable economy or post-pandemic era [46].

1.1 Motivation

The airline industry and the travel economy highly emphasize predicting the number of passengers per trip. It has attracted airline executives' interest in developing better predictive models to integrate into their business models. Mid-term and short-term
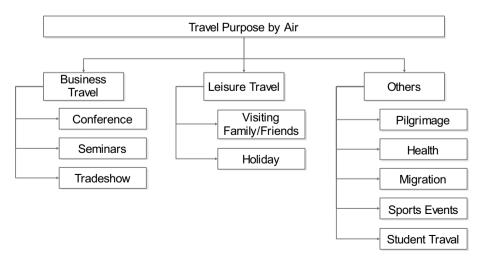

Fig. 1 Travel Purpose by Air

forecasts provide critical information for monthly operations and maintenance decisions, such as fleet scheduling, ticket fares, and the opening of airports or new business ventures, allowing time to market strategy implementation.

We were inspired to conduct this investigation for the reasons listed below:

1. There has yet to be a recent systematic review that considers all aspects of predicting aviation demand.
2. To draw attention to the various challenges in forecasting aviation demand.
3. To research various performance evaluation metrics.
4. To discuss applications and limitations in aviation demand forecasting.

1.2 Contribution

This work is motivated by substantial research surveys to identify the main factors that determine aviation demand [43] and forecast passenger demand techniques [43]. Because of recent global shifts, anticipating aviation demand has become increasingly important. Because of market uncertainty and volatility, most forecasting research has relied on deep learning techniques and statistical models. The purpose of this paper is to investigate the numerous aspects that influence aviation demand forecasting as well as the various forecasting approaches. The contributions of this study are as follows:

1. The impact of various factors on aviation demand is investigated.
2. Pros and cons of Artificial Intelligence techniques for aviation demand forecasting are discussed.
3. Commonly used performance metrics are discussed.
4. Different application areas of Aviation demand forecasting.
5. The current challenges associated with aviation demand forecasting techniques are also studied.

The word cloud depicts the top 100 Aviation demand forecast keywords (see Fig. 2). The keywords related to the aviation demand forecast algorithm, such as "Forecast," "demand," "airport," and "passenger," are widely used in this word cloud.

The remainder of this paper is organized as follows: Section 2 discusses the background of aviation demand. These variables drive aviation along with a Machine learning-based framework for passenger demand foresting. Section 3 presents the research methodology used in this study. Section 4 discusses various techniques used for forecasting aviation demand. The evaluation of forecasting techniques is in Section 5. Section 6 discusses the applications of aviation demand. Section 7 summarizes the current research challenges, followed by future research directions—section 8 presents the discussions, followed by the concluding remarks in Section 9.

2 Background

This section briefly describes drivers and machine learning models for passenger demand forecasting.

Fig. 2 Word cloud of passenger forecasting literature

2.1 Drivers of aviation demand

Aviation demand is affected by economic, geographical, service quality, airfare, and market factors. Service quality criteria include aircraft size, flight time, frequency of flights, and in-house service [104]. Market determinants include the hubbing strategy, year, and period of observation.

Figure 3 summarizes the various factors that influence passenger demand. Regional economic activity is controlled by commercial, industrial, and cultural factors [29]. The two most important economic factors are income and population size.

2.1.1 Economic growth

Most research was devoted to identifying and measuring economic factors influencing aviation demand. Financial elements include the gross domestic product (GDP), GDP per capita, income, and population size [91]. The rate of GDP growth is used to assess economic progress. Several studies have been conducted to forecast GDP growth based on passenger demand forecasting. Even though the study's findings show that GDP is a primary driver of aviation demand, Zhang et al. [118] investigated the genuine market demand in the Chinese market. A stochastic frontier analysis and model average technique is used to model the uncertainty component. With the advent of new technologies, the goal is to use scientific methods to determine the genuine demand (Table 1).

However, predicting the extent of changes in economic factors that may affect the aviation industry, particularly passenger volume, is challenging. Wang et al. [109] used Bayesian network analysis to bridge the gap. It is a probabilistic method for dealing with global uncertainty. Users can use a Bayesian network to make decisions. The Bayesian network's probabilistic output provides a more comprehensive view of global uncertainty. The Bayesian network was developed by combining airport-level data with city
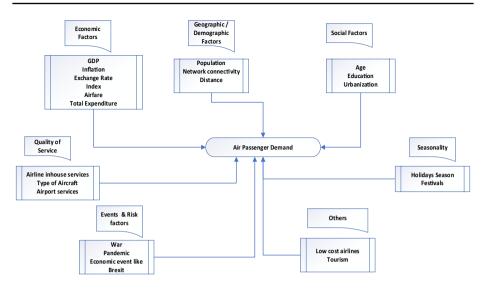
Fig. 3 Aviation Demand Drivers

or country-level. The data shows that the findings, GDP, and inflation have an impact on passenger demand, whereas fuel prices have a direct effect on cargo volume. This study's scope is limited to 45 cities in developed countries. This result may not be correct in the case of undeveloped countries.

The African study emphasizes the link between aviation demand and economic development in six African countries [2]. The study was conducted using three distinct income levels (i.e., low, middle, and high income). A one-way causal relationship exists between economic development and aviation demand in middle-income countries. Direct investment in other industries may help the growth of the aviation industry. The low-income region has a unidirectional causal relationship pattern because the country is a hub for the region's largest airline group. As a result, the region's economic strategy should focus on aviation growth and tourism facilitation. However, the elasticity of the interaction between economic growth and aviation demand varies across countries in the short and long run. The marginal contribution coefficient is higher in lower-income and middle-income countries. Economic development changes impact air passenger demand more than air freight demand.

Gallet and Doucouliagos [36] conducted a detailed study in Cyprus to quantify the income elasticity of air travel. The magnitude of income elasticity influences consumers, perceptions of air travel as a luxury and necessity. Kluge et al. [58] did this analysis to find passenger demand forecasting in the European market. They considered GDP per capita, urbanization level, geographical location, and the population's education level. The empirical studies proved that the factors mentioned above influence aviation demand.

Albayrak [54] investigated the factors influencing air traffic in developing economies. According to their findings, airport physical characteristics significantly impact air passenger traffic, tourism volume, and the number of foreign residents. The airport competition is positively correlated with the increased air passenger demand. The emerging economies' behavioral patterns are comparable to those of developed economies. The panel data estimation technique estimates the key drivers and their impact on aviation demand. GDP per

Table 1 Different predictor variables for forecasting passenger throughput

Reference	Predictor variable	Market	Purpose
[118]	GDP	Developed Countries	Explore the actual demand and GDP has a direct impact.
[101]	Income	6 African countries	Explore different Income ranges with a country that has different income ranges.
[54]	GDP per capita	Developing economy	Impact of GDP per capita on the developing economy.
[50]	Geographical Factors	Colombia	Complex geography, if well connected or good infrastructure, has a direct impact on passenger demand
[110]	GDP and Inflation	45 cities in developed countries	Bayesian network analysis to solve uncertainties issues due to Inflation and GDP
[81]	Quality of Service & Customer	Australia	Impact of Airport quality as well as customer choice for the airline and airport
[66]		China	Identifying customer travel preferences and the impact of personal intrinsic factors on aviation demand.
[88]		EU countries	Customer spending habits, as well as ticket prices, have an impact on aviation demand.
[31]	Tourism	Australia, New Zealand, United States, United Kingdom	An in-depth examination of the interdependence of international air travel and tourism.
[41]		Generic	An exclusive comparative study of different factors in tourism that helps aviation demand.
[65]		Cyprus	What role does aviation demand forecasting play in tourism growth in Cyprus?
[87]		70 different countries	International tourist data is being used to investigate the demand for aviation in various parts of the world.
[64]		China	Big data from a variety of sources and daily demand forecasting assist tourist operators in developing a dynamic pricing strategy.
[25]	Seasonality	Poland	In matured markets, seasonality impacts aviation demand
[14]		Wrocław	Representing seasonality indicator as a dummy variable to forecast aviation demand
[6]	Low-Cost Carrier (LCC)	Saudi Arabia	The study's objective is on Muslim holidays and LCC in Saudi Arabia.
[9]		Saudi Arabia	A comparison of LCCs and FSAs was conducted to the aviation demand growth.
[80]		The US and Europe	Impact of LCC entering saturated or developed countries.
[39]	Economic Event	Germany	Relation between Brexit and aviation demand. To predict how to forecast aviation during Brexit.
[19]	System Failure	UK	Aviation system outages and passenger demand.

Table 1 (continued)

Reference	Predictor variable	Market	Purpose
[111]	Pandemic Covid −19	China	Understanding the likelihood of an airline rebounding.
[74]		Global	Study to evaluate travel restriction frequent flight cancellation on aviation demand.
[60]		US	Study to evaluate passenger willingness to travel and the airline's level of safety on the impact on aviation demand during restriction.
[98]		Global	Evaluate the direct impact of Covid-19 on aviation demand.
[51]		Global	Socioeconomic impact due to the pandemic and that impact on Aviation demand.

capita, population, the position of a hub, distance to the closest airport, the number of beds, the number of foreign residents, and the academician ratio are all factors to consider.

2.1.2 Geographical location

Geographical location is an essential factor in influencing passenger demand. A well-connected and well-structured transportation system has an impact on travelers. International passengers prefer well-connected infrastructure. It is impossible to overestimate the importance of smooth transit and well-connected and comfortable terminals. Dubai, Singapore, and Heathrow are examples of well-known transit hubs. Visas on arrival in transit hubs are used by airlines to attract consumers. Tolga and GÖKMEN [102] identified the impact of geographical location and economic factors on aviation demand.

The use of airport transportation aids in overcoming geographical constraints. Hoyos and Olariaga [50] conducted research in the Colombian liberalized market. Colombia has a complicated landscape with multiple mountain ranges but inadequate regional connectivity. The domestic passenger could be identified and forecasted using system dynamics. Although the model correctly identified the peak traffic season, including the main geographic features influencing passenger demand would have been a better approach.

2.1.3 Quality of service

Service quality factors significantly influence passenger demand: seating comforts, legroom, meal service, in-flight entertainment, and modern aircraft quality. Passengers and airlines are more sensitive to these aspects in contemporary scenarios such as COVID-19.

Prentice and Kadan [81] found that airport service quality significantly impacted aviation demand. They assess check-in, ambiance, basic facilities, mobility, and security as airport service quality characteristics. A confirmatory factor analysis with maximum likelihood is performed to determine the reliability and validity of these factors. The environment plays a significant role in deciding aviation demand. Passengers at Heathrow Airport reported a strong connection between scents and their destination experience, prompting the installation of aroma dispensers.

2.1.4 Customer

Personalized travel is the new buzzword in the airline industry. One of the most recent drivers of aviation demand is customized travel. The airline customers' travel preferences and forecasting their travel demands are critical. In a competitive market, airlines can use customer travel preferences to improve services and optimize flight schedules based on need.

Understanding travel behavior is also essential in various aviation-related industries, such as airport design, supplier requirements, and tourism-related firms. Liu et al. [66] proposed a Multiple Factor Travel Prediction model for aviation demand. Various elements influence a customer's travel decision, including personal intrinsic factors such as travel preferences.

Another factor driving aviation demand is customer spending capacity. Secilmis and Koc [88] investigated the relationship between economic factors and aviation demand. The interaction between aviation demand and economic factors was estimated using

cross-sectional data analysis. According to their findings, rising per capita income and lower ticket prices significantly impacted aviation demand.

2.1.5 Impact of tourism

Transportation and tourism are inextricably intertwined industries. Good accessibility, as determined by available transportation services, is crucial for developing any tourist destination. Aviation is an essential mode of transportation for tourism markets. While long-distance travel and international tourism have traditionally been dominated by air travel, deregulation, particularly the emergence of the low-cost carrier sector, has increased aviation's importance for short and medium-distance tourism. More research is needed to study the growth of aviation and tourism. Furthermore, airports are becoming more proactive and experienced in generating leisure demand and providing an appealing service to leisure travelers.

Divisekera [31] investigated the relationship between international air travel demand and international tourism demand. The association was discovered by utilizing a consumer analysis method. The study's main finding is that the degree of substitutability varies between destination pairs, reflecting the diversity of tourist preferences among countries. The cross-price elasticities of transportation and tourism demand are similar. This study does not account for possible interactions between short-distance destinations because it is limited to long-distance intercontinental travel.

Ghalehkhondabi et al. [41] analyzed demand forecasting in passenger transportation. This study emphasized the logical dependency on passenger transportation. It prioritizes the accuracy of short-term and long-term forecasts, allowing the tourism industry to provide the necessary services at the right moment. Short-term forecasts might be helpful in daily or weekly activities such as determining the price of a seasonal cruise vacation. Long-term forecasts can aid in developing costly infrastructure and facilities, such as extending roads to meet increased visitor demand at a tourist attraction. Over a year (long-term), the expected number of visitors can help develop necessary infrastructures such as hotels and transportation terminals.

Liasidou [65] did qualitative research to address aviation's strategic influence on the tourism industry. They considered the tourist destinations such as Cyprus, the Maldives, and Lakshadweep. A questionnaire was created specifically for the study's location. Peeters et al. [78] analyzed that the aviation and tourism industries should work together to thrive. Overtourism is a relatively new term, yet it is an emerging concept. The impact of over-tourism on aviation demand prediction and its implications in the post-Covid era was investigated in this study [78].

Travel websites are a valuable source of information. The keywords tickets to or travel at a specific location were used to collect data on search query volume. Another critical feature for demand prediction is customer testimonials from a travel website. ARIMAX and naive models were used to forecast tourism demand. This novel approach emphasized the importance of multisource online big data. Tourism forecasting methods could be revolutionized in the long run by employing dynamic pricing strategies and proper staff scheduling. Tourist attraction operators can change daily demand predictions based on near real-time and high-frequency forecasting [64].

2.1.6 Impact of seasonality

Aviation demand for a variety of tourist destinations varies from season to season. When variability occurs regularly, the time series identifies it as having a seasonal component. Because the data's behavior is time-dependent, this seasonal component is inherently non-stationary [20]. Global traffic seasonality measures shed light on the dynamics of aviation demand. Airports can better plan for capacity and resource use during peak periods if they understand the market and its dynamics. Information about traffic seasonality also enables airlines to efficiently manage their fleets at various airports during peak periods. Aside from air travel, seasonality impacts businesses such as tourism. The seasonality ratio and the seasonality indicator are used to compute seasonality. The seasonality ratio is calculated by dividing the most significant monthly traffic by its median monthly traffic at an airport. The seasonality indicator calculates the percentage of annual traffic assigned to the peak month.

Chudy-Laskowska [25] discovered the seasonality component in the dataset using seasonality-based modeling techniques such as exponential smoothing, seasonal auto-regressive integrated moving average (SARIMA), support vector machines (SVM), and artificial neural networks (ANN). The paper's conclusion on the seasonality measure is ambiguous, although it does observe that dynamic growth is diminishing. Aviation demand is predictable due to its seasonality.

Seasonality is always a challenge in forecasting. Seasonality causes model variations. Samli et al. [87] used econometric models to examine seasonality in time series data, the seasonality method, and the history of similar periods. One of the model's most essential aspects is using dummy variables as a seasonality indicator. Although the research was limited to a single airport, the model's reliability might be evaluated in other markets.

2.1.7 Low-cost carriers

Flying used to be a luxurious experience, but with the emergence of Low-Cost Carriers (LCC), the glamour has disappeared. It has evolved into history's most practical mode of transportation. Most passengers thought that paying low fares for no-frills air travel was a good deal. The success of LCC is owing to the discounted fares. One of the most important competitive factors for airlines is ticket cost. Most airline passengers want to arrive at their destination as soon as possible and for the least amount of money possible. Another reason for LCC's success is technology, such as ticketless travel, which reduces reliance on Global Distribution System (GDS) booking and increases ticket fare transparency.

Alarfaj and AlGhowinem [6] researched to improve LCC passenger demand prediction by considering Islamic holidays in Saudi Arabia. During festival season, millions of people from all over the world go to these destinations. The impact of the holiday season on LCC airlines was investigated using genetic, artificial neural networks, and multiple linear regression. The results demonstrated that demand increased during this season. This study will aid in developing a new fleet for the upcoming season. However, the study was limited to Islamic holidays and did not consider other seasonal factors. It was feasible to change the face of aviation by introducing consumers.

Alsumairi and Tsui [9] investigated the impact of low-cost carriers on inbound Saudi passengers. Because of LCC's growing market presence, passengers now have a choice. LCCs generally serve budget-conscious passengers, contributing to converting

non-frequent flyers to frequent flyers. Short-term and long-term passenger demand has increased as aviation markets have been liberalized. According to the findings of this study, airline passenger capacity is steadily growing. The model, Box Jenkins Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and Seasonal Auto-Regressive Integrated Moving Average with eXogenous (SARIMAX) with explanatory variables that include LCC variables, reveals the importance of air passenger demand.

Boonekamp et al. [18] studied the impact of low-cost carriers (LCCs), ethnic ties, and aviation-related jobs as demand drivers for aviation. Strong ethnic relations between countries, as well as a large proportion of aviation-dependent work, accelerate demand. In contrast, a more significant presence of LCC on a route positively impacts the market. Pratt and Schuckert [80] analyzed the impact of low-cost carriers entering saturated or developed transportation markets such as the United States or Europe. The outcome indicated economic leakage, but it also demonstrated market implications. International tourists that travel on low-cost airlines significantly contribute to the economy.

2.1.8 System failures

The airline system is the backbone of the aviation industry. The system's expected availability is 99.99%. An outage in the air system can cause flight cancellations, delays, passengers missing connecting flights, inability to check-in, and other issues. If there is an outage, the airline will lose a lot of money, and passengers may be hesitant to travel again. Southwest Airlines lost $5 million to $10 million in ticket sales due to one of its recent outages. The airline must have a backup plan in place. Brause et al. [19] investigated the possibility of a backup decision support system in the case of a system failure. The decision support system will assist the operator in deciding which and how many passenger handling service stations can be distributed without disrupting flight operations. The failure points can be minimized as the legacy aviation system is phased out and new distributed cloud systems are introduced.

2.1.9 Economic events

Economic events have a significant impact on passenger demand. Air passenger demand in the United States has reached an all-time low due to the September 11 attacks. The Brexit vote is another economic event that directly influences the aviation industry [39]. Gelhausen et al. [38] improved the current direct demand model and applied it to the new model. The new model, which is based on co-integration theory, is more adaptable. It directly estimates passenger and flight volume at German airports. The model's estimated GDP elasticity was 1.31. The model was used to estimate the effects of Brexit on traffic volume at German airports from 2016 to 2018. This model handles two scenarios concerning the impact of Brexit on traffic volume.

2.1.10 Events

Natural disasters significantly impact the operations and passenger demand of the aviation sector. Airports and borders are closed. Flight paths are diverted during natural disasters such as hurricanes, tsunamis, and pandemics. It is necessary to assess both the passengers' eagerness to fly and the airline's potential to offer a high degree of safety. Lamb et al. [60] used a qualitative approach to better understand the social and emotional behavior of flight

passengers during the pandemic, emphasizing the importance of putting in place safety measures and a stress-free journey. The airline and airport authorities must make additional investments to accommodate this. Sun et al. [98] conducted an empirical study on the impact of a pandemic on the aviation industry. Researchers examined the actual effect at various scales, including domestic and international travelers and origin-destination pairs for large markets. The most affected is international travel. The results may not be accurate as the survey used simulated data.

Travel restrictions always impact passengers, and there are several factors to consider, such as planning a trip during a travel restriction. Passenger-centric metrics will be analyzed to understand better how people feel while traveling. If flights are frequently canceled or delayed, passenger demand may suffer. Passenger demand can also be forecasted using passenger-specific indicators. Monmousseau et al. [74] investigated how passengers in the US aviation industry feel during travel limitations. The data was taken from Twitter or sentiment analysis tools [79]. More complex analysis and quantitative methods are required for a more accurate result.

Travel restrictions will result in air traffic disruptions and a reduction in global mobility in the short term. It has a worldwide socioeconomic impact at the same time. Iacus et al. [51] gathered data on air passenger volume worldwide. It investigated how travel restrictions affect the number of air passengers as well as socioeconomic conditions. The non-homogeneous Poison process was used to forecast the aviation demand.

Forecasting aviation demand during the pandemic is critical because the return on investment is one of the factors used to justify their investment. The effect of COVID-19 on Chinese air passenger demand has been investigated [111]. The data is sourced from a central Global Distribution System (GDS) provider and is updated in real-time. The number of available seats and the passenger flown ratio for a specific route was studied throughout the time. According to the findings of this study, lesser lockdowns and travel restrictions may increase airline recovery chances. As a result, all Chinese airlines are unaffected. This study should be expanded into other markets to determine the actual impact.

Forecasting is difficult in these uncertain times. With the advent of neural networks and geospatial analysis, forecasting is now possible. The technologies should be used to help the aviation industry's rapid recovery [70]. According to studies, international travel is the most affected. However, aviation can focus on domestic travel to recover more rapidly.

2.2 General framework for passenger demand forecasting

Data is highly volatile as a result of market fluctuations and looming uncertainties. Machine learning-based demand forecasting is more adaptive and allows for faster new data integration into models than conventional approaches. As a result, machine learning-based frameworks are flexible and reliable enough to benefit researchers [76, 85, 86].

The forecasting framework for estimating passenger demand involves data collection, pre-processing, time series analysis, and forecasting [4]. Many tried to evaluate appropriate suitable methods for their research, and a common approach is not applicable in many scenarios [103]. The phases of aviation demand forecasting methods are depicted in Fig. 4. Data can be collected from various sources, including airport and airline official websites. Since aviation demand is nonlinear and is affected by a variety of external factors and it is necessary to forecast passenger demand more accurately. It is crucial to assess and choose the influencing factor in the forecast.
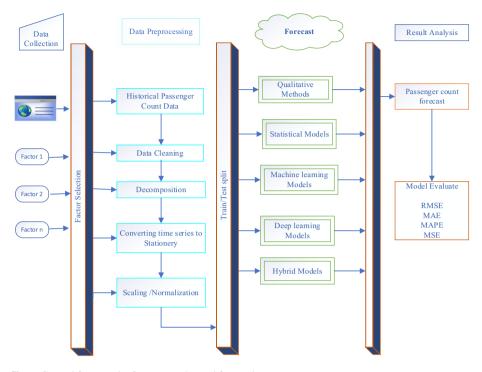
Fig. 4 General framework of passenger demand forecasting

Influencing factors can range from social causes, such as football events or exhibitions, to economic reasons, such as the country's GDP, population index, inflation, or travel restrictions. These variables can be introduced as an exogenous variable or as a multivariate into the model.

Data pre-processing is the next critical stage after data collection. The collected data may be susceptible. Data cleaning aids in the filling of the missing values, the treatment of outliers, and the removal of the noise if present. The Decomposition of time series data helps understand the data's inner dynamics. Time series analysis can be used to study seasonality and trends in time series data [106]. Before forecasting techniques can be used, time series must satisfy tests such as the stationarity tests [27]. Normalization of the data is required due to the varying dimensions of data. Data is divided into testing and training datasets. Forecasting is the next major step after the data pre-processing. Aviation demand forecasting techniques vary from qualitative to statistical methods to Artificial Neural Networks. Each forecasting model must be evaluated using the measures like metrics like Mean Square Error (MSE) and Mean Absolute Percentage Errors (MAPE) [73].

3 Research methodology

This section presents the survey papers related to aviation demand, followed by the paper selection and exclusion methodology used in this study.

3.1 Existing surveys

Wang and Song [109] assess 115 works in air transportation research written between 1950 and 2008 and examine several factors, including research advancement, publishing journals, demand determinants, estimation techniques, and demand elasticity. His study revealed that the demand for aviation in the US region increased significantly during uncertain incidents such as the terrorist attack and the Sars Pandemic outbreak in the US. Another review by Addepalli et al. [2] examines the effects of socioeconomic and demographic factors, which are crucial for maintaining the demand for the aviation industry and boosting manufacturing productivity. Gosling and Ballard [44] and Gosling et al. [45] provide a summary report of academic and commercial research that forecasts the variation in U.S. air travel demand using disaggregated socio-economic data. Wang and Gao [108] evaluate 87 studies on demand for air travel that were published between 2010 and 2020 and provide an overview of each one based on its input data and main analytical techniques.

Table 2 presents the highlights of the period and focus areas in aviation demand forecasting in the existing surveys compared to the proposed work.

3.2 Survey methodology

Figure 5 presents the search process for the articles for this survey highlighting the elimination and inclusion criteria. A comprehensive literature search was conducted using popular search engines, databases, and websites such as the social science citation index (SSCI), Google Scholar, ScienceDirect, and arXiv. The preliminary search string consists of "Aviation Demand," "air transport," "Passenger count," "forecasting," "drivers of aviation demand," and a combination of these keywords. Second, the identified articles' citations were tracked down—the scope of the articles to be reviewed.

The article identification phase presents the technique for identifying the articles based on a keyword search through the electronic databases and the manual search. Further, the second phase is the screening phase responsible for filtering out irrelevant articles. Phase three is the eligibility phase, responsible for shortlisting the articles based on their title and abstract. Final phase four is the inclusion phase, finalizing the article selection process for the quantitative and qualitative analysis.

4 Techniques

Air travel demand forecasting is a field of applied research. The choice of an appropriate forecasting model is influenced by the past, various environmental variables, time-series data, and other factors. Since the 1970s, Statistical methods, particularly those based on the Box-Jenkins Auto-Regressive Integrated Moving Average (ARIMA) methodology [47]. Since the emergence of machine learning and its powerful regression methods, many models have been proposed to outperform the former, which have remained baseline methods in most research works. Deep learning-based strategies outperform traditional methods, and new architectures are being developed [89, 94]. Figure 6 summarizes the different techniques used to forecast aviation demand.

Table 2 Comparison of state-of-the-art and proposed survey

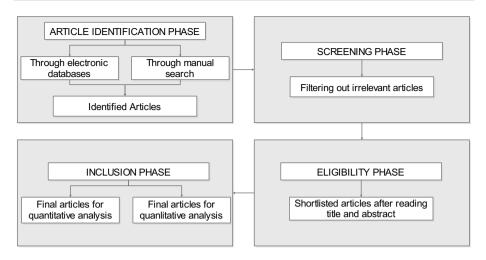| Survey Reference	Period	Focus Areas in Aviation demand forecasting
Wang and Song [109]	1950–2008	1. Examine Factors Impacting 2. Techniques used 3. Demand Elasticity
Addepalli et al. [2]	2018	Effects of socioeconomic and Demographic Factors
Gosling and Ballard [44] and Gosling et al. [45]	2019	Disaggregated socio-economic data to predict the variation in US air travel demand
Wang and Gao [108]	2010–2020	1. Input Data and Primary analytical Methods2. Citation Analysis to explore the relationship among the reviewed studies
Proposed Work	2007–2022	1. Determinants Impacting 2. Techniques Used 3. Evaluation Metrics 4. Application Area 5. Challenges

Fig. 5 Search process with elimination and inclusion criteria

4.1 Econometric models

Econometric models [8] are statistical models. The econometric forecasting model is a method for predicting future events based on discovering relationships between economic variables. Econometric models are used to determine which economic factors influence aviation demand. The airline has no control over economic determinants. GDP, interest rate, currency conversion rate, the standard of living, income per capita, population size, and exchange rate are all Common economic determinants used in modeling. Economic variables are explainable independent variables. They are used to increase demand for aviation. Long-term forecasting can be done by using econometric models. There are three models in econometric modeling: cross-sectional, time series, and panel data.

The vast majority of econometric models are country-specific. These models are limited to the country's major or minor airports. These studies help local governments determine whether to add a new hub to a specific airport. This model can help determine which economic factors influence passenger demand in a region, country, or city pair.
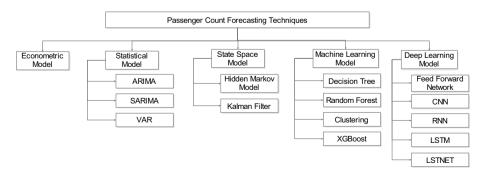

Fig. 6 Aviation Demand Forecasting Techniques

Suryan [99] researched to learn more about the economic factors influencing passenger demand in Indonesia. Indonesia's primary industry is tourism. The government must develop a well-structured aviation infrastructure to encourage more passengers. Traditional regression models and panel regression models were used in the study. In this particular study, the economic considerations were not taken into account. Bastola [15] conducted the research in Nepal. The econometric model employed the total number of passengers flown as an input variable to estimate air passengers' throughput. The number of passengers flown was the dependent variable, while the number of tourists who visited and the country's gross domestic product was the independent variables. Air Passenger Demand Model (APDM) used simple and multiple regression models to forecast air passenger demand. The main challenge in predicting short-term air traffic demand is that determinants that influence the current econometric forecasting models do not account for economic crises, pandemics, and fuel prices.

Carmona-Benítez et al. [21] proposed an econometric dynamic to better investigate the dynamic nature of economic factors to understand the economic determinants of passenger demand better. This study was conducted in the Mexican air transportation industry. They suggested that EDM be measured using the Arellano-Bover method and verified using the Sargan and Arellano-Bond Autocorrelation tests. The panel data identified the economic determinants that influence air passenger demand by location, and these determinants explain pax demand patterns. As an explanatory variable for passenger demand, the EDM uses the total number of flights or airline frequencies at the airport. The passenger demand forecast considered states with more frequent flights. Holt-Winters method is used to predict econometric determinants. The passenger demand per location was expected using these determinant models. Developing a database per city to analyze the dynamic econometric model is a constraint. The disadvantage is that airports must be classified as hubs based on market conditions.

Endogeneity, or reverse causality, is a significant flaw in econometric models. A common remedy is to use instrumental variables in two or three-staged least squares regression. Lagged explanatory variables can be instrumental in addressing issues in time series models [49]. The Table 3 presents below the comparative analysis of the various models in the literature.

In a nutshell, econometric analysis is a type of multivariate analysis that investigates the relationship between independent economic, demographic, and passenger demand variables (price, personal income, GDP, and population size).

4.2 Statistical models

Time series forecasting is a technique for predicting future events based on historical data. Data observed at regular intervals, such as monthly, yearly, quarterly, hourly, and so on, is called time-series data. Time series forecasting aims to forecast how data will change—simple time series forecasting methods to predict the future based on a single historical event. When only one variable changes over time, univariate forecasting is utilized. Multivariate time series forecasting is used when multiple variables and their values change over time.

Statistical models are used to forecast aviation demand. The data's stationarity must be checked before statistical modeling because statistical variables such as mean, variance, and autocorrelation should not change over time. Auto-Regressive Integrated Moving Average (ARIMA) and SARIMA [71] are state-of-the-art statistical models. Trend and seasonal factors are incorporated in aviation demand time series data.

Table 3 Comparative analysis of models in terms of data format, the method used, hardware/software and market

Year	Ref.	Data Format	Method	Hardware/Software	Market
2007	[16]	Time series Data	Holt-Winters	Public Domain Software- RLimited Memory-BFGS quasi-Newton	UK
2017	[99]	Time Series + Panel	Time series: linear regression. Panel: PLS + FE + RE	STATA software 2 GB RAM Multicore CPU	Indonesia
2017	[15]	Panel	Econometric Model: APDM	Statistical SoftwareRAM-2GBCPU	Nepal
2017	[21]	Panel	Econometric Dynamic Model	Ram- 2GBMulticore CPU	Mexico
2019	[97]	Time series Data	MIV +NVARNN	Open-source	Beijing, China
2019	[95]	Time series Data	Logistic Regression	Open-source statistical software	US commercial airports
2019	[116]	Time-series Data	SARIMA-SVR	R- with forecast function	China
2019	[62]	Time-series Data	ARIMA-REGRESSION	MATLAB's optimization toolbox	China
2020	[69]	Time series Data	ARIMA + BSTS	Public Domain Software- R	India
2020	[23]	Time series Data	K-Means + DT	Public Domain Software- R	China (Sanja to Beijing)
2020	[82]	Time series Data	ARIMA + ANN	Open-source	Indonesia
2020	[33]	Time series Data	LSTM + SARIMA	LSTM using TensorFlow	Incheon
2020	[63]	Time-series Data	PSO-SVR	Open-source	China
2020	[53]	Time-series Data	VMD-ARMA/KELM-KELM	Open-source	China
2021	[47]	Time Series	GVAR	GVAR Toolbox 2.0for Microsoft Excel and Matlab	Asia-Pacific + Latin America-Caribbean regions
2021	[87]	Time series Data	ANN+LR+RF+GB	Java with WEKA API	Turkey
2021	[56]	Time series Data	ARIMA+SARIMA +DLNN	Python, Pandas, Keras, Local Machine -4CPU 16gb Ram,488 GB storage	U.S. commercial airports

Holt-Winter [32] is a statistical model that can deal with univariate time when seasonality and trend are present. Bermúdez et al. [16] presented a formulation for an additive Holt-Winters forecasting technique that simplifies the computation of point predictions. It helps to predict intervals by obtaining maximum likelihood estimates of smoothing parameters and initial conditions. Additive, uncorrelated, homoscedastic, and average errors were used to introduce the stochastic component of the model. Data transformation was used to improve the model training. The point forecast technique fails to account for low demand during the Gulf War.

Madhavan et al. [69] attempted to forecast aviation demand throughput in the Indian aviation industry. The bayesian structural time series (BSTS) approach is used. The traditional models were effective for short-term forecasting of general air passenger demand. Both international and domestic throughputs were considered in this study. Recommendations and research directions for both medium- and long-term projections of the Indian airline sector were also summarized.

Time series-based forecasting is difficult due to the increased uncertainty and irregularity of air passenger movement. Sun et al. [97] proposed a nonlinear vector auto-regression neural network (NVARNN) method to predict passenger throughput. First, the input features were identified and extracted using the mean impact value (MIV) way. The second NVARNN method is used to forecast for modeling purposes. The model is evaluated on the passengers at Beijing International Airport. According to this study, multivariate forecasting approaches consistently outperformed univariate forecasting approaches. Neural networks were preferable to SARIMA models due to their complexity. The scope of this study was limited to six factors influencing air passenger flow.

4.3 Machine learning models

In the last ten years, machine learning models have established themselves as serious competitors to traditional statistical models in forecasting [17]. Machine learning models have grown in popularity over the last decade, and researchers have investigated using them to increase the precision of time-series forecasts. The data constraint aspect of the problem has been partially resolved, and researchers have started investigating thousands of characteristics and cutting-edge machine learning models capable of handling big data applied in time series data for prediction accuracy [3].

Uncertain economic conditions and planners' optimism or bias are the leading causes of forecasting errors. These mistakes may be responsible for ill-advised infrastructure and poor aviation management. Suh and Ryerson [95] developed forecasting models by combining prior prediction errors from similar airports, i.e., learning from a peer. The study also addressed concerns about a possible slowdown in passenger volume in the future. A binary Logistic Regression model was investigated to foretell the possibility of a drastic drop in passenger numbers. Regional socioeconomic changes can expect a sharp decline in airport demand. The forecast error is positive, implying that the predicted value is greater than the actual value [11].

Samli et al. [87] investigated passenger demand in the aviation industry using machine learning models such as Artificial Neural Networks, Linear Regression [30], Gradient Boosting [22], and Random Forest [7, 117]. World Bank dataset was used in the study. This study will help identify the factors influencing international travel demand and participation in different regions. As features and models become more complex, the overfitting nature of models becomes a significant concern. Machine models do not reveal the

temporal nature of the time series. The data for the Covid-19 pandemic was not considered due to the unique circumstances.

Time-series clustering techniques can be used for classification and forecasting. The relevant features were identified in a variety of ways and helped in the identification of common groups during training. Chen et al. [23] used K-means and decision trees to identify the factors influencing regional passenger demand. After identifying critical features, clustering can help to group airports and areas based on features. Identifying the feature was given more weight than the temporal nature of the time series.

4.4 Artificial intelligence models

Deep learning for time series prediction is a relatively new venture. It is a promising tool because of its flexibility. It helps in modeling highly complex and nonlinear temporal time series data without prior knowledge of the business's functional aspects. Deep learning models captured the time series data and predicted the events more accurately than the competitors. Brause et al. [19] forecasted future airline passenger values in Indonesia using ARIMA and ANN. The main aim was to find the best-fitting model among ARIMA and ANN. The overfitting problem occurs in neural network models when the dataset is small. ARIMA model outperformed the neural network on both domestic and international passenger traffic. Gelhausen et al. [38]investigated the efficacy and applicability of Long Short-Term Memory (LSTM), Deep Neural Networks, and SARIMA forecasting approaches at Incheon International Airport. The study considered both tried and proven procedures. The study focused on monthly and weekly forecasting. Both SARIMA and LSTM techniques provided accurate forecasting and improved predictive capabilities. The LSTM model outperformed the SARIMA model in terms of prediction.

Machine learning techniques can help aviation to improve prediction performance, which relies on traditional statistical models. Time series analysis and deep neural network modeling are becoming more critical in aviation maintenance and operation. When it comes to selecting a suitable model, model accuracy is essential. As a result, it is vital to improving decision-making accuracy in fields such as time series forecasting and industries such as aviation. Deep learning techniques have the potential to improve accuracy, and the study [56] emphasizes the importance of employing the most up-to-date methods in the aviation industry. Iacus et al. [51] demonstrated how aviation demand is analyzed and modeled using traditional statistical models and deep learning techniques. The experiments showed that deep learning might help estimate aviation travel demand. Evolutionary meta-heuristic algorithms have been implemented to improve the performance of ANNs. The findings demonstrate that applying these methods accelerates the neural network (NN) prediction rate with actual data adaptation [75].

4.5 Hybrid models

Combination models have outperformed individual models in recent years. Researchers attempted to incorporate the strengths of both unique model architectures. It is critical to forecasting statistical indicators. A hybrid technique was used to indicate passenger demand in the airline industry. Xu et al. [116] introduced a new forecasting model that combines SARIMA and Single Vector Regression (SVR) models. SARIMA began by analyzing the time series and identifying the control parameters. The SARIMA model eliminated the series' non-stationarity by employing seasonal differencing in proper order.

SARIMA was used to find SVR input determinants. SVM was used to capture linear and nonlinear patterns in time series data. To improve the forecasting accuracy, a hybrid model was used. The forecasting model was only tested on short-term demand. External factors influenced aviation demand that was not considered during model construction. This study used historical data on statistical determinants as its data source. They found that the incorporation of noise may improve forecasting accuracy.

The support vector regression model is up-and-coming due to its ability to capture data nonlinearity. Stavelin et al. [94] investigated the characteristics of air passenger demand using a hybrid model. A combination of support vector regressor and particle swarm optimization (PSO-SVR) was used to forecast air passenger demand. First, historical airport passenger throughput data was used to extract conditional and decision attributes. Second, the particle swarm optimization algorithm maximized the kernel function variables and penalty attributes. Finally, the SVR machine was used to forecast the airport passenger throughput. External factors or economic determinants were not considered in this hybrid model's forecast (Table 4).

Li [62] used a hybrid forecasting model that utilized ARIMA-Regression concepts and the IOWHA operator. Regression models were used to identify the independent variable that affects aviation demand. Independent variables such as inbound tourist count, gross national income, railway passenger count, and GDP are employed for multiple regression. ARIMA model was used to forecast the demand. ARIMA-based hybrid forecasting models outperformed the other models.

On the other hand, aviation demand exhibits significant nonlinearity and non-stationarity. Variable mode Decomposition (VMD) was used to simplify the original data by decomposing it into several mode functions. Using the unit root test, these modes were classified into stable and unstable series. Meanwhile, the ARMA and KELM models were used to forecast the stationary and non-stationary components. Finally, the result was integrated using a KELM model that incorporated all outcomes predicted. Passenger demands from Beijing, Guangzhou, and Pudong airports were used to evaluate the innovative model's system performance [53].

Based on a prior study, several additional significant social media aspects could be used as influencers to forecast airline passenger demand. For example, sentiment analysis of different Twitter hash tags may reveal the existence of a particular event in the city of origin or destination of a flight, enhancing demand predictions. This feature extraction includes searching for specific keywords or sets of keywords, calculating their frequency, understanding the time and place, context, and so on. The use of social media features can have an even more significant impact on projecting aviation demand than economic and social factors for short-term forecasting [1].

DNN models show good behavior when the time series data is not linear. Deep learning is computationally very complex, showing the model's tendency to overfit. A recent study found that hybrid models worked well and attempted to combine the best features of various models [115]. Complex deep neural networks are the future when time-series data contain uncertainty.

5 Performance evaluation

Goodness-of-Fit (GOF) tests compute the expected and actual value difference. These measures are used to compare the outcomes of different studies or competing models and to evaluate statistical hypotheses. GOFs are frequently used to assess the

Table 4 Pros and Cons of different forecasting techniques

References	Year	Methods	Pros	Cons
[16]	2007	• Holt-Winters	• The additive Holt-Winters forecasting technique is given a new formulation. • The time series' stochastic nature is investigated.	• Holt-Winters forecasting is based on the most recent data; if there is an anomaly in the most recent data, middle and long-term forecasting will be inaccurate.
[24]	2015	• Multinomial logit	• The study focuses on the impact of LCC on airport selection. • According to a study, the presence of LCCs reduces demand at competing airports.	• The study only looked at average route-specific fares, not passenger-specific fares. Due to a lack of data, the study did not consider frequent flyer information when making customer decisions.
[119]	2016	• Multivariate models involving macroeconomic variables	• The theory of partial adjustment is used in this study. • This study attempts to address the issue of endogeneity and serial correlation. • The model has been expanded to include rail, road, and ocean transportation.	• The study is limited to China
[105]	2016	• Gravity model	• This article focuses on changes in the Hong Kong International passenger network. • A study was conducted on nine important factors: economic factors such as GDP, cultural factors such as tourism, and speaking a common language.	• The approach fails to explain why some regions, such as Dubai or London, have seen a decrease in passenger numbers. • There is no route-based analysis.
[57]	2016	• Big Query	• Using big data from search engine queries to forecast passenger demand. • Short-term forecasting, as well as short-term big-query, aid in locating short-term fluctuations.	• The scope doesn't include long-term forecasting
[40]	2017	• Gravity model	• A gravity model for estimating international passenger origin-destination (OD) flows. • Airfare is considered in addition to economic factors for a better understanding.	• This proposed method is better suited for long-distance rather than short- to medium-distance flights.
[67]	2017	• SVM • Multivariable Regression • ARMA and RBF-based NN	• To predict the passenger count in China, a comparative study of machine learning techniques such as SVM, Multi-variable regression model, ARMA, and RBF-based neural network model was conducted. • Models claim to be extremely precise.	• For better performance and the nature of the input data, RNN and LSTM can be used.

Table 4 (continued)

References	Year	Methods	Pros	Cons
[28]	2017	• Bagging Holt-Winters method	• For forecasting, the Bagging Holt-Winters method, a novel model in the field of air transport, is used. • To predict future demand for air transportation, the study uses the Bootstrap aggregating (Bagging) method and the exponential smoothing method Holt-Winters.	• Variation in the aggregated forecasts is essential because it can affect the forecast error. This has not been given importance for the same.
[48]	2017	• Econometric models	• This research aims to determine the explanatory variable for economic models. • As a prerequisite to modeling In econometric models, the correlation between variables is taken into account for better accuracy.	• More factors, such as events and low-cost carrier market share, should be considered when developing an econometric model.
[59]	2018	• Multiple linear regression • Backpropagation neural networks • Gravity models • Multimodal models	• A comparative study with multiple linear regression, backpropagation neural networks, gravity models, multimode models, and time series models are used in forecasting passenger demand. • Cloud-based data analysis solutions such as AzureML are used.	• Seasonality can be taken into account.Training neural networks with a variety of neurons and a large amount of data
[39]	2018	• New Direct Demand Model	• The model incorporates external demand shocks such as 9/11 and the effects of Brexit. • It is more versatile than the classification algorithm.	• The scope was limited to German airports
[6]	2018	• Genetic Algorithms • Artificial Neural Networks • Classical linear regression	• Impact of the Islamic holiday on Saudi Arabia's Low-Cost Carrier passenger demand forecasting. • Different algorithms, such as Genetic Algorithms, Artificial Neural Networks, and classical linear regression, are compared and evaluated.	• The study was limited to Islamic holidays, but other seasonal trends could be included.More data, such as domestic and international, can be included for better accuracy.
[95]	2019	• Binary Logistic Regression	• Incorporate past forecasting errors of peers to improve forecasting efficiency. • The probability of passenger contraction is predicted using a model.	• The study faced challenges due to data unavailability
[97]	2019	• Nonlinear vector auto-regression neural network	• A hybrid approach called Nonlinear vector auto-regression neural network is proposed to solve air passenger flow forecasting. • This method was created to deal with the time series' irregularity and volatility.	• Only six factors affecting airport understudy were taken into account. • Optimal algorithms can improve the performance of a neural network.

Table 4 (continued)

References	Year	Methods	Pros	Cons
[5]	2019	• Econometric analysis followed by Granger causality framework	• Examines the link between domestic air passenger throughput and economic factors such as GDP per capita, agricultural production index, manufacturing production index, and consumer price index. • Forecasting is done for both short and long-term advantages.	• The study is limited to Nigeria
[62]	2019	• ARIMA-Regression	• A combined forecasting analysis method based on ARIMA-Regression is proposed to improve accuracy. • Forecasting risks can be reduced using a combination of methods.	• The research was limited to China's civil aviation industry.
[82]	2020	• ARIMA and ANN	• A comparison of the ANN model and ARIMA. • The forecast period is for the next 12 months or Short-term forecasting.	• The use of an automated method for parameter optimization is not considered. • For weekly and daily predictions, the data interval considered is too large.
[23]	2020	• K-means Clustering	• A practical methodology for investigating the relationships between air traffic volume and macroeconomic development. • The study uses data mining techniques such as K-means and clustering algorithms.	• The relationship between macroeconomic factors and air traffic demand is not quantified.
[69]	2020	• ARIMA and BSTS	• A comparison of the ARIMA and BSTS models shows how well they incorporate uncertainty in dynamic settings. • Both models under investigation are effective at forecasting in the short-term.	• The study's scope is limited to the Indian market. • Because the focus was solely on the short-term, medium, and long-term forecasting was overlooked.Seasonality and economic factors aren't considered.
[63]	2020	• Hybrid model (PSO-SVR)	• To improve the accuracy of long-term forecasting, a hybrid model was developed.	• External factors that influence air passenger throughput are not considered or accounted for.
[33]	2020	• LSTM and SARIMA	• Comparing the LSTM and SARIMA techniques for forecasting passenger throughput shows that the LSTM method is superior.	• The disadvantage of LSTM training is that it takes longer to build a model, and tuning the parameters is more complicated.
[83]	2020	• Dynamic Linear Models	• Dynamic Linear Models are used to forecast the medium term. • It detects the time series' stochastic nature. • It also detects structural changes, allowing for estimating the variable effect of exogenous shocks over time without adding more parameters.	• Scope for Long term forecasting

Table 4 (continued)

References	Year	Methods	Pros	Cons
[101]	2020	• Vector error correction • Vector auto-regressive models.	• A causal analysis is conducted to determine whether airport transportation boosts economic development or vice versa. • The researchers used vector error correction and vector auto-regressive models.	• Time series or other state-of-the-art models can be used to compare the results.
[113]	2020	• LSSVM	• A forecasting model based on LSSVM is used to correct the ARIMA error. • Included The PSO algorithm's inertia weight and acceleration coefficients	• The study is limited to Baiyun Airport
[92]	2020	• Elasticity, analogy, and transport model	• This study develops a generic strategy for decision-makers. • According to the findings, the airport project has a negative net present value when the lowest traffic forecasts are used. In contrast, when the highest traffic forecasts are used, the project has a positive net current worth.	• The study is particular to Norwegian airport
[110]	2021	• Bayesian network analysis	• The Bayesian network investigates how economic factors such as GDP and inflation affect passenger and cargo volumes. • Both passenger and cargo volumes are taken into account in this study.	• Since the study was limited to developed or large airports, the results may be accurate for small airports, as the factors that affect them are not included in the data. • More research is required to comprehend the causal relationship in the domain fully.
[37]	2021	• Panel Discussion	• The study takes into account the recent pandemic covid-19 impact. • Forecasts for how passenger preferences, booking curves, and fare product restrictions may change in the aftermath of the COVID-19 pandemic	• To make better decisions after Covid-19, it is necessary to delve deeper into dynamic and continuous pricing.
[56]	2021	• ARIMA, SARIMA, and DLNN	• ARIMA, SARIMA, and DLNN are all compared in depth. • External factors such as population and financial information for each airport's state were considered.	• Batch normalization, which is not included in this study, can improve the efficiency of DLNN models. • Hybrid models were not considered for better performance.
[87]	2021	• Random Forest • Gradient Boosting • ANN • Linear Regression.	• This study employs machine learning models such as Random Forest, Gradient Boosting, ANN, and Linear Regression to forecast passenger count. • The 1983 features are used to forecast passenger demand for the first time.	• Seasonal factors aren't taken into account. Extensive research on RF and ANN for passenger demand forecasting

performance of forecasting models [6]. Evaluation measures are necessary to determine the quality of the trained model. Several techniques and algorithms can be used to assess how closely a forecast matches the actual result. Most of these techniques can be divided into two categories. These are scale-dependent and percentage-dependent errors. While percentage errors are measured in percentages, scale-dependent errors are measured in the number of mistakes. Most studies use scale-dependent errors such as mean absolute error (MAE), mean squared error (MSE), root represent squared error (RMSE), and normalized root mean squared error (NRMSE). The disparity between actual and anticipated values is called forecasting errors [107]. Forecasting errors are classified into two types such as: random and systematic.

Table 5 summarizes the performance measures used to evaluate aviation demand forecasting techniques. The most important performance measures are Mean Absolute Error (MAE), mean absolute percentage error (MAPE), Mean Square Error (MSE), Sum-of-Squares-for-Error (SSE), Root Mean Square Error (RMSE), Symmetric mean absolute percentage error (SMAPE), Mean squared prediction error (MSPE), Mean Forecast Error (MFE) and R-square. In Table 5, ✗ means the mentioned evaluation measure is not used in the study, while ✓ means the mention evaluation metrics are used in the study.

5.1 Comparison of state-of-the-art methods

It is clear from Table 5 that the most widely used evaluation metric is MAPE. A comparison of various MAPE values is presented from the literature, including the name of the best model of that research work in Table 6.

Total absolute forecast errors divided by actual values over time yield the mean absolute percentage error (MAPE). It's a metric for assessing precision by looking at the percentage of mistakes made. Better forecasts can be made when the MAPE value is closer to zero.

6 Applications

The applications of passenger demand forecasting are tourism, revenue management, and infrastructure planning [96]. These are discussed in succeeding subsections.

6.1 Tourism industry

Tourism is an important industry that is inextricably linked to aviation. Tourism relies on air transportation to deliver visitors, and the air transportation industry relies on tourism to generate demand for its services. Estimating the volume of passenger transportation is an inseparable part of tourism demand forecasting and is an essential factor in the strategic planning of the tourism industry. Most air transport demand is derived; from tourism contributes to aviation demand [34]. Air travel and tourism are highly correlated and sensitive to economic, social, and political changes. The improvement in accessibility provided by modern airport infrastructure and the establishment of direct airline connections may attract tourists to a destination [77].

6.2 Revenue management

An airline's goal is to maximize revenue by effectively matching the limited supply of seats with different segments of demand. The demand in the airline business is stochastic. Forecasting the demand (Forecasting Module) and then allocating available seats at other fares (Optimization Module) is at the core of Revenue Management (RM) systems. The accuracy of demand forecasts is crucial to increase the performance of RM systems. Revenue is improved by optimizing the pricing of each flight seat to make as much money as possible. Effective revenue management necessitates external understanding elements such as rivals and worldwide events. It also requires a large amount of historical data. This paper studies the optimal seat capacity problem between the source and destination [87].

Another area of revenue management is optimizing the profit by dynamically pricing the seat based on demand. A ticket sale does not cease when the available seats are depleted. The airline decides to overbook in anticipation of a cancellation or no-show. Overbooking can be accomplished by predicting passenger demand (Table 7).

6.3 Infrastructure management

Strategic planning concerns infrastructure development, such as terminal capacity, new airports, or vehicle capacity. Long-term passenger demand necessitates a more detailed forecasting level in network resource planning and aims to optimize resource allocation across the network based on passenger loads in each area [13]. This is a complex problem to solve because resources must be carefully allocated according to demand on each route. The crew assignment problem is a part of network resource planning. Larger vehicles require more experienced crews and additional cabin crews [10]. The supply side, demand side, and market fluctuations have all been studied as influencing variables for the development of China's aviation industry. Research shows that the proportion of air passengers is relatively significant and growing.

7 Current limitations and future research directions

This section discusses the central issue in aviation demand forecasting and future research directions.

Short-term forecasts encompass day-to-day operations; medium-term forecasts cover up to five years and include route-planning decisions; long-term forecasts cover more than five years and have an airport and airline infrastructure planning decisions.

7.1 Challenges associated with forecasting

Various challenges associated with forecasting have been discussed in this sub-section.

7.1.1 Short-term forecasting challenges

Short-term passenger gives vital input into daily operations management, aircraft scheduling, maintenance planning, advertising and sales campaigns, and opening new sales offices [114]. Therefore, data will be highly seasonal and unpredictable. The main challenge is

Table 5 Evaluation of passenger demand forecasting in terms of performance measures

Ref.	Year	SMAPE	MAPE	MAE	SSE	MSE	MSPE	R2	RMSE	MFE	NRMSE	Other
[16]	2007	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[24]	2015	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[105]	2016	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[119]	2016	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[57]	2016	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[15]	2017	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗
[67]	2017	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[28]	2017	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
[67]	2017	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓
[38]	2017	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓
[48]	2017	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓	✗
[25]	2017	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗
[39]	2018	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗	✓
[6]	2018	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[59]	2018	✗	✓	✓	✗	✓	✗	✓	✓	✗	✗	✗
[116]	2019	✗	✓	✓	✗	✗	✗	✗	✓	✗	✗	✗
[62]	2019	✗	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗
[97]	2019	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✗
[95]	2019	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓
[5]	2019	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[23]	2020	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓
[82]	2020	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[69]	2020	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[63]	2020	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[33]	2020	✗	✓	✗	✗	✓	✗	✗	✓	✗	✗	✓
[83]	2020	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[101]	2020	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[113]	2020	✗	✗	✗	✗	✓	✗	✗	✓	✗	✗	✗
[92]	2020	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[110]	2021	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
[56]	2021	✗	✓	✓	✗	✓	✗	✓	✗	✗	✗	✗
[87]	2021	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
[37]	2021	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗

predicting with accuracy. Xie et al. [114] found that the hybrid seasonal decomposition and least squares support vector regression approaches were used to forecast short-term air passenger demand. The seasonal characteristic and nonlinear nature of air passengers were exploited to improve forecast effectiveness.

Most airports forecast their short-term passenger demand based on experience. Short-term forecasting involves multiple seasonality and external data that drive the business. Indian aviation industry focuses on the BSTS model to incorporate uncertainty and delivers better accuracy than the others. A machine learning approach is proposed based on time series models, feature extraction, and feature selection techniques

Table 6 Comparison of aviation demand model on MAPE

Reference	Model Description	MAPE
[87]	RF	6.76%
[56]	DNN	7.98%
[84]	Dynamic model with Operations, GDP per capita, population, TRM	0.25%
[63]	PSO-SVR FOR CAN	2.38%
[69]	ARIMA-HOLD OUT For International	1.45%
[82]	ANN CGK-JOG	1.29%
[25]	MLP Neural Net (12–2–1)	2.80%
[116]	SARIMA-SVR Passenger Traffic Volume	2.31%
[67]	Regression + SVM Model	5.07%
[62]	Regression prediction	2.30%
[33]	LSTM	4.00%
[72]	Holt-Winters SARIMA -Singapore	2.69%

to improve short-term air passenger forecasting. A particular emphasis was placed on developing the modified version of Principal Component Analysis (PCA) to drive additional characteristics [26].

7.1.2 Long-term forecasting challenges

Long-term forecasting is required for strategic planning to see the aviation industry in a profitable position. Long-term forecasting accuracy is critical because it involves budget and new investment initiatives. Most studies address issues such as the feasibility of constructing a new airport in the city or recent infrastructure upgrades. In general, time series models are always helpful for long-term forecasting. More than one variable can be used as a predictor in multivariate forecasting. The model becomes inconsistent and biased when these predictors are associated with the error term. Empirical analysis demonstrates that the proposed hybrid approaches outperform other time series models in long-term complex time series with high volatility and irregularity [91] (Table 8).

7.1.3 Forecasting challenges with pandemic

Economic forecasting has become more divergent. The pandemic has introduced a great deal of uncertainty in all aspects of life. Factors such as the financial speed of policy

Table 7 Applications of passenger demand forecasting

Broad Area	References
Tourism	[9, 25, 31, 41, 43, 65, 77, 93, 112]
Revenue Management	[61, 87]
Infrastructure Management	[10, 13, 42, 96, 100]

Table 8 Challenges associated with passenger forecasting

Broad Area	References
Short-term forecasting challenges	[12, 15, 41, 51, 53, 69]
Long-term forecasting challenges	[5, 63, 68]
Forecasting challenges with pandemic	[35, 74, 77, 87, 98]

changes in all sectors impact forecasting passenger demand directly or indirectly. Few studies have found that aviation recovered after the pandemic [52].

7.2 Future challenges

Aviation is driven by demand. It is vulnerable to shocks and fluctuations in the market. For example, a country's geopolitical situation or poor economic condition can impact aviation demand. The business environment is categorized into two parts, such as, internal and external environments. The main factors in the internal environment are man, money, marketing, machinery, and management structure. External factors primarily drive demand; nevertheless, how a company responds to the external environment affects whether or not it will be successful. Cutting-edge forecasting techniques such as deep learning and hybrid models address these highly volatile situations [55, 90].

Causality is commonly emphasized in forecasting studies. Models performed better in terms of reliability and accuracy when forecasting aviation demand. The economic, social, and natural disasters and airline service to airport services are all variables. However, most studies focused on economic factors. At the same time, the effect of financial shock or pandemic has received little attention. These challenges have been laid out for Aviation demand forecasting researchers.

7.3 Future research directions

Future research must take advantage of big data, and alternative modeling techniques should be explored to take advantage of big data. Numerous forecasting methods have been developed using emerging big data applications. But the use of those techniques should be extended to the aviation industry. A fascinating subject for future research might be the study of the creation of innovative demand forecasting techniques employing big data.

Critical social media features like sentiment analysis are another new influencer. Additionally, including dynamic data in forecasting techniques can improve forecast accuracy. If a model is accurate for a current system, it does not imply that it will be accurate for the same system in a year. Developing dynamic demand forecasting methods that can make decisions based on real-time data would assist airlines and related applications.

8 Discussions

This paper presents a comprehensive survey and considerable research for aviation demand forecasting. This survey has examined a wide range of the existing studies of air passenger demand by many researchers, as well as the methods generally used to forecast future markets and the external factors that influence future direction. Initially, the different factors

that impact aviation demand forecasting were discussed. The techniques employed for passenger demand forecasting have been discussed. The most recent quantitative forecasting techniques are econometric, statistical, machine learning, artificial intelligence, and hybrid models. Various model evaluation metrics that have been employed in research studies are discussed. The current and future challenges related to aviation demand in the real world have been discussed. Different application areas where passenger demand forecasting is widely used are discussed. A comparative study of quantitative forecasting methods and their performance metrics evaluation may be considered in future reviews.

The proper forecasting technique is selected based on the history of the time series data, environmental factors, and the responsibilities of the airline and airport. Accurate projection is a critical criterion when using models to identify the right independent variable or determinant factors. Short-term forecasts perform better than long-term forecasts in terms of tracking changes in seasonal patterns and business cycles; however, short-term forecasts are volatile due to non-linearity and irregularity in time series data. Another problem for econometric models is endogeneity or reverse causality. The solution is to use instrumental variables. Traditional statistical models are the best fit for linear time series forecasting. It does not require a large amount of computational power. It is simple to use, and statisticians can understand the behavior and nature of the data. Due to the limitations of many traditional forecasting models, forecasting economic time series is typically difficult, prompting academic researchers and business practitioners to develop more effective forecasting models.

9 Conclusions

This study is a helpful guide and handy reference for other researchers interested in carrying out similar research on aviation demand. This study provides an overview of the major demand-influencing factors and demand-forecasting approaches by examining previous studies on aviation demand. For other academics interested in this topic, this study integrates the many challenges of forecasting aviation demand and might be used as a reference.

The significance of forecasting method accuracy is one observable trait in the manuscripts reviewed. However, there is little research on the use of accurate data for forecasting. Future studies must focus on big data and sentiment analysis in aviation demand forecasting. Developing dynamic demand forecasting methods that can make decisions based on real-time data will assist airlines and related applications such as tourism plans effectively and save money.

Abbreviations ARIMA: Auto Regressive Integrated Moving Average; AR: Auto Regressive; ARMA: Auto Regressive Moving Average; ES: Exponential Smoothing; GRU: Gated Recurrent Unit; GDP: Gross Domestic Product; GDS: Global Distribution System; IATA: International Air Transport Association; IV: Instrumental Variable; KELM: Kernel Extreme Learning Machine; LCC: Low-Cost Carriers; LSTM: Long Short-Term Memory; MAE: Mean Average Error; MAPE: Mean Absolute Percentage Error; MA: Moving Average.; MSE: Mean Squared Error; NN: Neural Network.; PCA: Principal Component Analysis.; RMSE: Root Mean Square Error.; RNN: Recurrent Neural Network.; SARIMA: Seasonal Auto-Regressive Integrated Moving Average.; SES: Simple Exponential Smoothing.; SVR: Single Vector Regression.

Declarations

Conflict of interest The corresponding author states that there is no conflict of interest on behalf of all authors.

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