Econometric Model for Forecasting Air Transport Demand: The Case of Cagliari – Elmas Airport

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Abstract. The ability to predict how air transport demand evolves is one of the key elements for effective air mobility planning. At the core of this lies the indispensable correlation between demand and supply. Understanding the evolving dynamics of demand is a fundamental requirement to intervene in infrastructure, resize services, optimize available resources, and plan infrastructure investments. In recent years, air transport has recorded remarkable growth rates, making new management and development strategies for infrastructure necessary. In this context, airport planning plays a central role for airport operators, who, through the Masterplan, define the development plan of an airport, addressing weaknesses where possible and enhancing strengths. Based on these considerations, this study develops an econometric model for forecasting air transport demand, applied to a concrete case: Cagliari – Elmas International Airport [1, 2]. The first part of the study focuses on the description of the methodology. After a literature review on air transport demand models, various methodological approaches were evaluated, including regression models, moving average models, and Box-Jenkins, Auto Regressive Integrated Moving Average (ARIMA). The comparative analysis led to the selection of a multivariable model, combining independent variable forecasts obtained with ARIMA models and the use of multiple linear regression. This approach was replicated for Cagliari – Elmas Airport, resulting in a 15-year air transport demand forecast under three different scenario hypotheses. Finally, the results were compared with evolutionary trends proposed by international observers and regulatory authorities, highlighting a strong convergence of findings.

Keywords: Air transport demand · Econometric model · Airport planning · Forecasting methodology · Infrastructure investment

1 Introduction

In recent years, the aviation sector has experienced significant growth [3], necessitating precise strategic planning [4] for the management [5, 6] of airport infrastructure [7, 8] and available resources. Air transport demand plays a central role [9] in this process, as

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it enables the estimation of passenger and cargo volumes that will utilize the transportation system within a given time frame. An accurate demand forecast allows for optimal resource allocation, improved operational management [10], and the mitigation of congestion issues in air routes and airports. Air transport [7] demand is a derived quantity, originating from individuals' needs to travel for work, tourism, or other purposes. It is strongly influenced by socio-economic factors [11]. Therefore, air transport demand modeling must integrate both time series [12, 13] analysis methods and econometric [1, 14] tools capable of incorporating socio-economic explanatory variables. In the field of air transport demand forecasting [1, 2, 15, 16], several methodological approaches [17] fall within simple time series models, including:

- Regression models [18], which analyze the relationship between demand and a set of independent variables;
- Moving average models [18], which help identify long-term trends by smoothing temporal fluctuations;
- Box-Jenkins (ARIMA) [19–21] models, which rely on time series analysis and their stochastic structure to make future forecasts.

The exclusive use of ARIMA models for forecasting air transport demand [13, 22, 23] presents certain limitations, despite their potential to integrate the previously listed single models. Specifically, ARIMA models are effective only under conditions of stationarity in time series and do not explicitly account for the influence of external socio-economic variables beyond the transport sector. To overcome these constraints, a combined approach was adopted, integrating ARIMA models with a multivariable econometric model [1, 15, 20, 22, 24], in line with the methodology proposed by Reitani and Costa [1, 2] (Fig. 1).

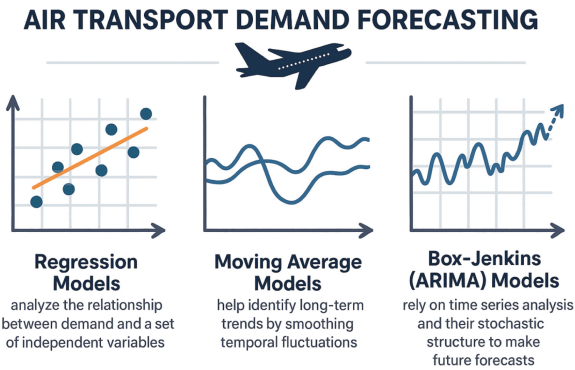

Fig. 1. Three typical methodological approaches for the air transport demand forecasting

The approach implemented in this study utilizes ARIMA models to forecast independent socio-economic variables, which are then employed as inputs in a multivariable regression model to estimate air transport demand [3, 13, 19]. In particular, ARIMA models were applied to project socio-economic variables, leveraging autoregressive and moving average techniques to identify trends and ensure data stationarity [18, 24]. The

integration of these forecasts into the econometric model allowed for a more precise estimation of the future evolution of air transport demand. The multivariable econometric model [18, 20, 24, 25] establishes a functional relationship between demand (dependent variable) and socio-economic factors (independent variables), enabling the construction of predictive scenarios consistent with economic and demographic trends. One of the innovative aspects of this study is the application of the multivariable econometric model to the specific context of the Cagliari-Elmas Airport catchment area. Unlike previous studies by Reitani and Costa, which analyzed airport systems or large European airports by simplifying local socio-economic contexts [7, 26] and focusing on macro-regional data, this research emphasizes the importance of regional and local socio-economic characteristics in accurately forecasting air transport demand within a well-defined catchment area. The adoption of a combined model based on ARIMA and multivariable regression has enabled more reliable forecasts by integrating the historical dynamics of time series with the influence of explanatory variables. This study has developed an advanced air transport demand forecasting model that merges time series analysis with econometric modeling [12, 14, 27]. This approach has helped overcome the limitations of traditional models, enhancing the accuracy of estimates and providing a valuable tool for strategic airport sector planning. The results obtained can support the formulation of infrastructure development policies and airport operational management, contributing to the sustainable growth of air transport [28].

2 Metodology

The model was designed to determine user demand by combining two approaches, following the application proposed by Reitani and Costa [1, 2, 15]. Specifically, the ARIMA model was employed to forecast the future evolution of explanatory variables [24] (independent variables). Subsequently, the obtained forecasts were integrated into a multivariable econometric regression [24] model to estimate the dependent variable—in this case, the number of passengers. The multivariable regression model serves as the econometric framework for estimating passenger numbers based on the socioeconomic variables predicted by ARIMA. The model implementation followed a series of methodological phases (Fig. 2).

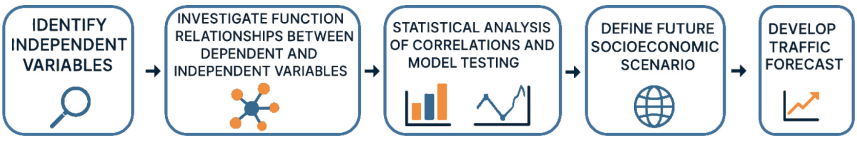

Fig. 2. The methodological framework

2.1 Identification of Independent Variables

The selection of independent variables was the initial step in constructing an econometric model for analyzing air transport demand. The primary guiding criterion was that the

chosen variables had historically demonstrated a significant influence on demand [9]. Since air transport demand is generally a function of multiple factors, the variables were selected to represent the most relevant drivers while avoiding redundancy-ensuring that different variables did not describe the same factor, which could reduce the precision of the model. To identify these variables, a historical time series analysis was conducted on numerous societal parameters at both the regional macroeconomic level and the local level as illustrated in the Fig. 3, defining the airport's catchment area [29] and adapting the study to its specific context.



Fig. 3. Some general socioeconomic and transport characteristics

2.2 Investigation of Functional Relationships Between Dependent and Independent Variables

To assess the effectiveness of the selected econometric variables, a simple regression analysis was conducted. This methodology allowed for the pairwise examination of passenger historical series in relation to the historical series of individual socioeconomic variables [30], aiming to identify significant correlations between them. Various types of regression models [31, 32] were analyzed, including linear, logarithmic, and polynomial models. However, linear relationships were primarily adopted due to the simplicity of the resulting equations, which facilitate more efficient error management, and the greater clarity in presenting the results, making them more immediately comprehensible compared to more complex models. Once all regression models were constructed, the regression equation was highlighted alongside the coefficient of determination (R^2) to evaluate model fit—that is, measuring the degree of approximation between observed (empirical) data and those calculated or estimated by the model [27, 33] (theoretical). Subsequently, after selecting the most representative variables, a multiple regression analysis was performed, integrating explanatory socioeconomic variables with passenger data, effectively constructing a multivariable econometric model [14] with a linear structure.

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \ldots \beta_k X_{k,t} + \varepsilon_t \quad (1)$$

This choice was motivated by the greater simplicity in understanding and justifying the results, as well as the more effective management of errors. The research criteria involved analyzing various alternative formulations of the regression model to identify the one that best interpolated the available data and utilized the most suitable combination of variables to describe the phenomenon under investigation.

2.3 Statistical Analysis of Correlations Between Variables and Testing of the Proposed Model

Before constructing the final mathematical formulation of the model, the possibility of multicollinearity was assessed by building the correlation matrix for the selected explanatory variables and analyzing the obtained results. It was then decided to accept the risk of multicollinearity, if present, considering that its impact on forecasting would be minimal, especially when the relationship between explanatory variables is expected to persist over time and remain relevant for the forecast period. After exploring various combinations of explanatory variables, a comprehensive statistical analysis was conducted using the following tools:

- Coefficient of Determination (R^2, Adjusted R^2);
- Variance and Deviance;
- Fisher's Test;
- Student's t-Test.

These tests made it possible to identify the most significant explanatory variables for describing the phenomenon to be included in the model and to assess the reliability of the constructed model.

2.4 Definition of the Future Socioeconomic Scenario

To construct the future economic scenario, ARIMA models were applied to the historical series of the selected socioeconomic variables to develop the econometric model [20]. Generally, multiple ARIMA models with a general Eq. (2) are adapted to the available data and compared to identify the one that best captures the patterns present in the time series.

$$X_{i(t)} - \Phi_1 X_{t-1} - \cdots - \Phi_{p+d} X_{t-p-d} = a_t - \Theta_1 a_{t-1} - \cdots - \Theta_q a_{t-q} \qquad (2)$$

where:

- $\mathbf{X_{i(t)}}$: Current value of the time series at time t (dependent variable to be modeled and forecasted);
- $\mathbf{\Phi_1, \ldots, \Phi_{p+d}}$: Autoregressive (AR) coefficients, representing the influence of past values on X_t; p is the AR order, d is the number of differences for stationarity;
- $\mathbf{a_t, a_{t-1}, \ldots, a_{t-q}}$: Error terms (white noise), with at as the current innovation and $at - 1, \ldots$ as past errors;
- $\mathbf{\Theta_1, \ldots, \Theta_q}$: Moving average (MA) coefficients, measuring the impact of past error terms on the current value; q is the MA order;

- **Differencing (d)**: Number of times the series is differenced to achieve stationarity (constant mean and variance).

The accuracy of the ARIMA models was assessed using three key metrics, essential for identifying the most suitable model for future data projection. These criteria were [24]:

- Akaike [25] Information Criterion (AIC);
- Bayesian Information Criterion (BIC);
- Sigma Squared.

For the development of ARIMA models, the Python programming language was used, with the code implemented in the Spyder development environment. The approach to building the ARIMA models was based on the Auto-ARIMA function, which automated the tasks of configuration, model generation, and comparison. This algorithm generated a series of ARIMA models and, through an iterative stepwise method, minimized the AICc [25] and the maximum likelihood estimation error to identify the optimal model. The resulting ARIMA model was the most suitable for describing the evolution of the time series and was consequently used to project the data over the required time horizon.

2.5 Development of Traffic Forecasts

Thanks to the future projections of the variables $X_{i,t}$ and the estimated coefficients β_i, it was possible to calculate the values of the dependent variable Y_t, which represents the passenger index number, for each year within the forecast horizon The calculation was performed by substituting the values of the explanatory variables $X_{i,t}$ year by year into Eq. (3). Expanding for the initial years while using abbreviated notation for intermediate terms, the following result is obtained:

$$\begin{aligned} Y_{2024} &= \beta_0 + \beta_1 X_{1,2024} + \beta_2 X_{2,2024} + \cdots + \beta_k X_{k,2024} + \varepsilon_{2024}, \\ Y_{2025} &= \beta_0 + \beta_1 X_{1,2025} + \beta_2 X_{2,2025} + \cdots + \beta_k X_{k,2025} + \varepsilon_{2025}, \\ &\vdots \\ Y_{2040} &= \beta_0 + \beta_1 X_{1,2040} + \beta_2 X_{2,2040} + \cdots + \beta_k X_{k,2040} + \varepsilon_{2040}. \end{aligned} \tag{3}$$

In this way, the projection of the dependent variable Y_t was obtained year by year, up to the forecast horizon.

3 Application to the Case Study (Cagliari Elmas Airport)

To determine the catchment area, the isochrone method centered on the airport was applied as illustrated in the Fig. 4. This approach allowed for the calculation of road travel time to reach the airport, facilitating the precise identification of currently served areas as well as those that could potentially be included.

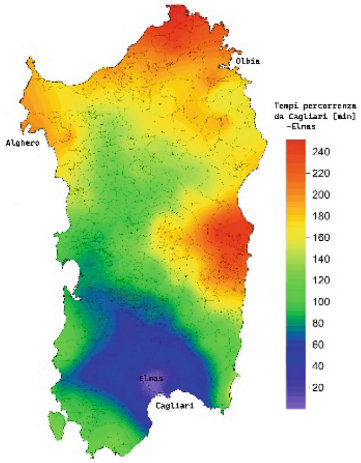

Fig. 4. The isochrones of Cagliari-Elmas airport

3.1 Identification of Independent Variables

Among all the variables examined, as described in Sects. 2.2 and 2.3, the following were selected:

- Added value;
- Motorization rate;
- Employment/activity rate;
- Population;
- Tourist presence.

For each of these, the historical series obtained from the ISTAT [34] database was analyzed, and the following graphs provide a representation of this data (Figs. 5, 6, 7 and 8).

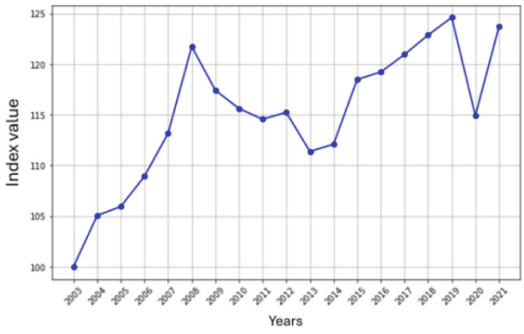

Fig. 5. Historical time series of the Gross Value Added index

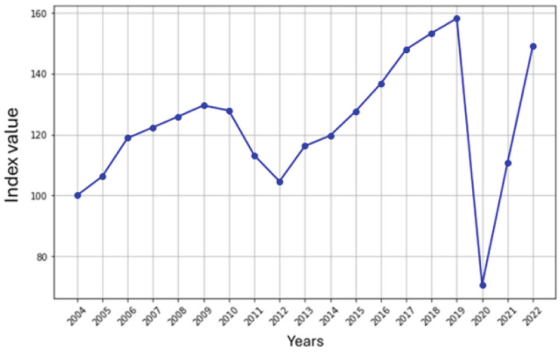

Fig. 6. Historical time series of the Tourist precence index

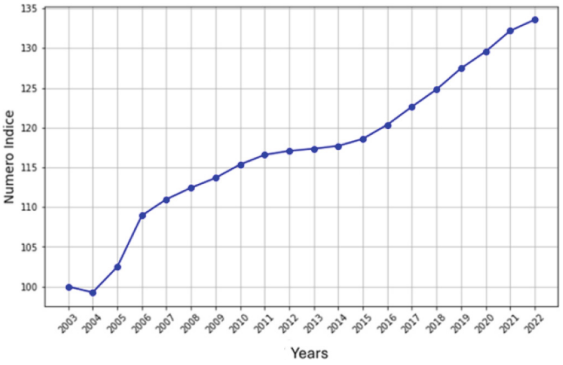

Fig. 7. Historical time series of the Motorization rate index

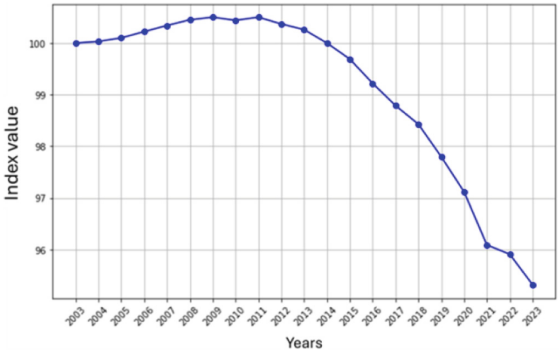

Fig. 8. Historical time series of the Population index

3.2 Investigation of Functional Relationships Between Dependent and Independent Variables

The first step was to analyze passenger traffic at Cagliari-Elmas Airport, which represents the dependent variable, based on data published by Assaeroporti. The trend in traffic over time can be more clearly understood from the graph in Fig. 9, which shows a relatively steady increase with a consistent slope, except for deviations in 2012, 2013, and 2016. After these fluctuations, traffic resumed a marked upward trajectory starting in 2017. A particularly striking data point is the period associated with COVID-19, which significantly impacted the curve, resulting in a 62.8% decline in 2020.

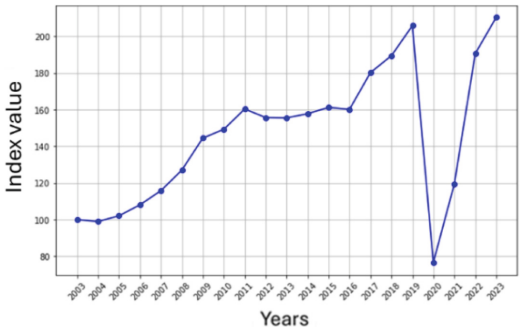

Fig. 9. Historical time series of the passenger traffic trend index at Cagliari-Elmas Airport

Given the exceptional impact and anomalous behaviour observed across the entire socioeconomic and transportation landscape, it was deemed necessary to treat the data from 2020 and 2021 differently. These years exhibited singular trends compared to the generally steady growth observed throughout the historical series, leading to the decision not to include the data from these years in the analysis. By evaluating the relationship between the dependent variable and the socioeconomic explanatory variables (SE) and subsequently examining multicollinearity among the independent variables alone, the following matrix was constructed. Since all the correlation coefficients are greater than 0.5, the variables are dependent on each other and, therefore, multicollinearity cannot be ruled out (Fig. 10).

	NI-POP	NI-VA	NI-PR	NI-TM
NI-POP	1	-0.6160	-0.6599	-0.8370
NI-VA	-0.6160	1	0.8678	0.8274
NI-PR	-0.6599	0.8678	1	0.7558
NI-TM	-0.8370	0.8274	0.7558	1

Fig. 10. Multicollinearity matrix among the independent variables

3.3 Statistical Analysis of Correlations Between Variables and Testing of the Proposed Model

For the selection of the econometric model, the procedure described in Sect. 2.3 was followed, generating all possible combinations of selected explanatory variables with the dependent variable "passengers", starting from a model incorporating all variables. Initially, an approach was adopted that involved constructing five classes of econometric models, obtained by alternately eliminating one explanatory variable at a time in each case. Subsequently, for each model class, additional combinations were created by progressively removing other explanatory variables and analyzing various configurations, including those considering only a single variable or a pair of variables alongside the dependent variable "passengers". This methodology allowed for the exploration of alternative solutions characterized by a decreasing number of variables, leading to a total of 14 models. First, the six models with $R^2 > 0.90$ were selected. A summary table (Table 1) was then constructed for comparison, facilitating the selection of the most suitable model and enabling statistical considerations.

Table 1. Comparison of Econometric Models

Model	Variables	R^2	R^2 adjusted	S.E.	F	p-value
MOD_1	NI_POP, NI_VA, NI:PR, NI_TM	0.92	0.89	11.15	36.67	5.79×10^{-7}
MOD_3	NI_POP, NI:PR, NI_TM	0.92	0.90	10.76	52.47	7.34×10^{-8}
MOD_2B	NI_VA, NI_TM	0.91	0.89	11.15	72.35	1.98×10^{-8}
MOD_2C	NI:PR, NI_TM	0.91	0.89	11.10	73.03	1.85×10^{-8}
MOD_3B	NI_POP, NI_TM	0.91	0.90	10.85	76.79	1.32×10^{-8}
MOD_TM	NI_TM	0.90	0.89	11.09	145.39	1.92×10^{-9}

3.4 Definition of the Future Socioeconomic Scenario

This process enabled the construction of an optimal ARIMA model for the historical data, allowing for model adaptation, extraction of fitted values and residuals, and ultimately forecasting future values, presenting the results in a clear and comprehensible manner as illustrated in the Figs. 11 and 12.

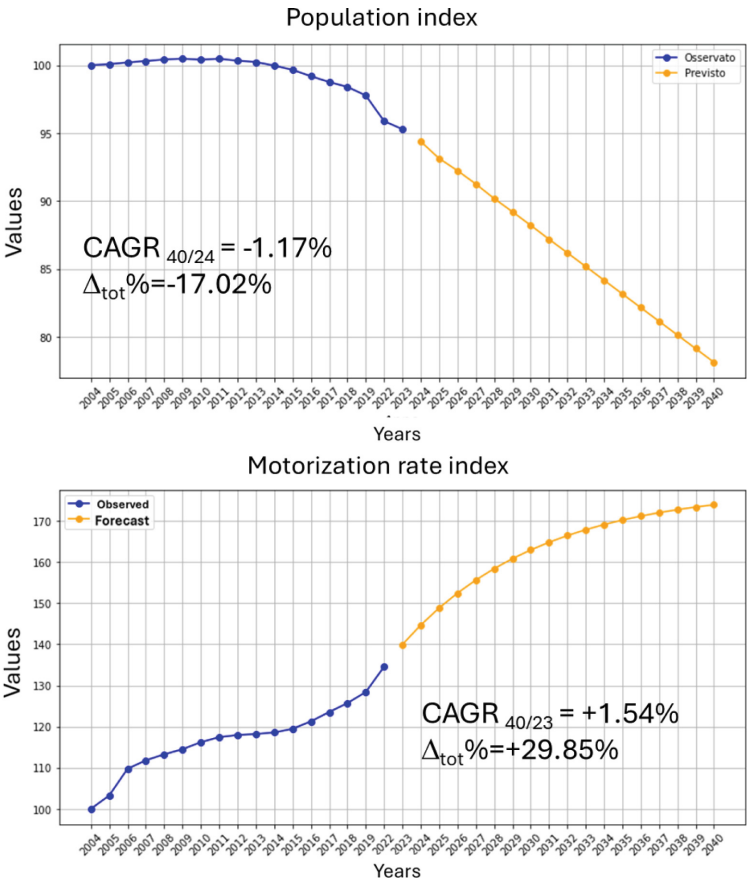

Fig. 11. Trend of the index value of explanatory variables (Population and Motorization Rate), years 2004–2040 (Observed in blue; Forecasted in orange)

3.5 Development of Traffic Forecasts

The passenger variables were then projected for each model using the historical series projected through ARIMA models and inserting the values into the econometric model year by year. Figure 13 shows the results of all the models in comparison.

Subsequently, the percentage deviation between the passengers estimated by the model for the year 2024 and those observed at the end of the year was calculated, using 2024 as the calibration year to assess the accuracy of the forecasts (Table 2).

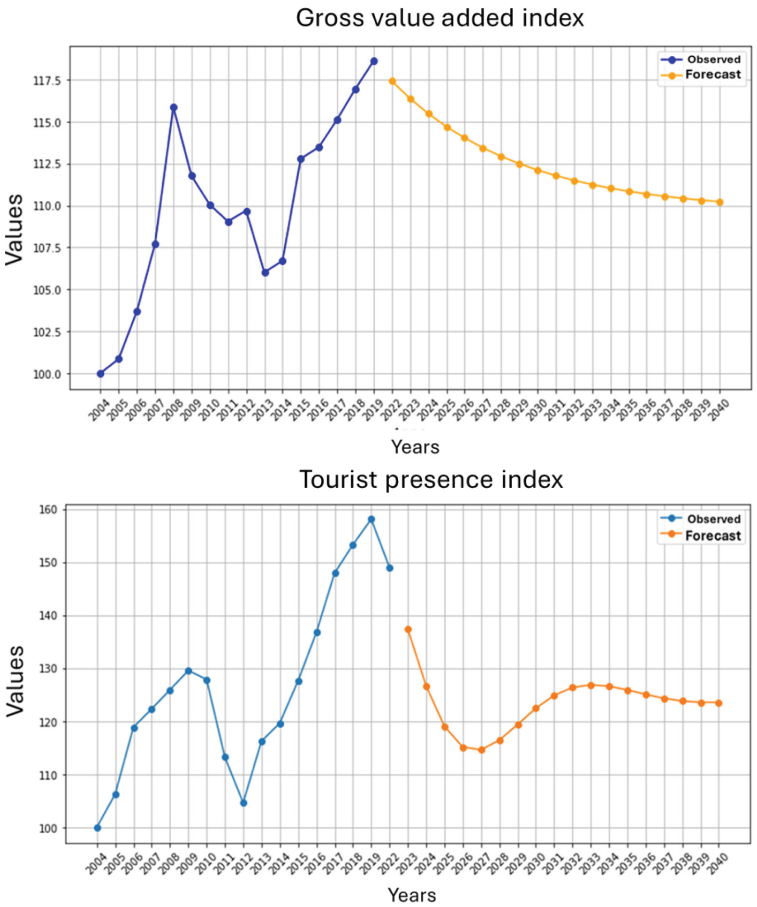

Fig. 12. Trend of the index value of explanatory variables (Gross value added and Tourism precence), years 2004–2040 (Observed in blue; Forecasted in orange)

3.6 Selection of the Best Econometric Model

In the context of selecting the most suitable econometric model, a comparative approach was adopted, where various calibrated models were analyzed and compared. The final choice fell on Model 2C, which incorporates the variables TM (motorization rate) and PR (tourist presence), proving to be the most appropriate for the research objectives. Specifically, Model 2C strikes a balance between simplicity and robustness, offering strong explanatory power while maintaining a limited number of variables.

$$Y = -228.1695 + 0.2384 \cdot \mathrm{NI} - \mathrm{PR} + 2.9819 \cdot \mathrm{NI} - \mathrm{TM} \tag{4}$$

Considering the statistical behavior of the historical series and the absence of radical changes in socioeconomic factors at the regional, national, and European levels, it can be stated with reasonable certainty that future values will fall within the constructed range.

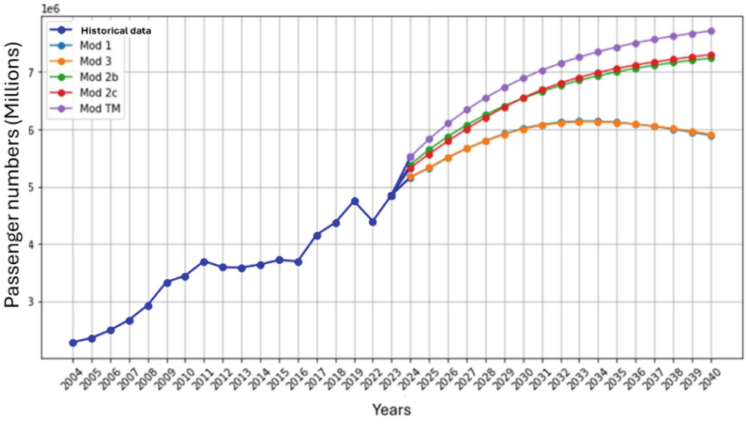

Fig. 13. Combined projections from all models in a single graph, providing a visual interpretation of the passenger curves and facilitating a comparison of their trends across the selected models.

Table 2. Comparison of observed and estimated passenger numbers for 2024 across the various models analyzed, for calibration and forecast accuracy evaluation

Estimation Model	Passengers	Deviation (%)
Observed Passengers (2024)	5,158,546	–
Estimate Model 1	5,162,373	0.07%
Estimate Model 3	5,166,739	0.16%
Estimate Model 2B	5,382,849	4.35%
Estimate Model 2C	5,328,882	3.30%
Estimate Model TM	5,518,430	6.98%

This range was determined using a confidence interval, which allowed for the definition of three different forecast scenarios:

- Baseline Scenario;
- Pessimistic Scenario;
- Optimistic Scenario.

This methodology provided a detailed representation of the variability in projected passenger numbers, offering a robust and coherent forecasting framework, aligned with the estimates provided by ENAC in the National Airport Plan. Once the margin of error was determined, the confidence interval was constructed by adding and subtracting this value from the future projections for each year, for the variables included in the model, as illustrated in the graphs shown in Figs. 14 and 15. Finally, the confidence intervals calculated for each projected year were analyzed, interpreting them as a measure of uncertainty associated with the forecasts. In the equation, pessimistic, baseline, and optimistic projections of both variables were used to generate three distinct curves of

the same model, each representing a different scenario (pessimistic, baseline, and optimistic). This approach allowed for a better understanding of the potential limits and variability of the projections. From the resolution of the econometric model equation, the passenger index number (NI-PAX) was obtained. Using the inverse index equation, the exact number of passengers corresponding to the index was determined year by year as illustrated in the Fig. 16.

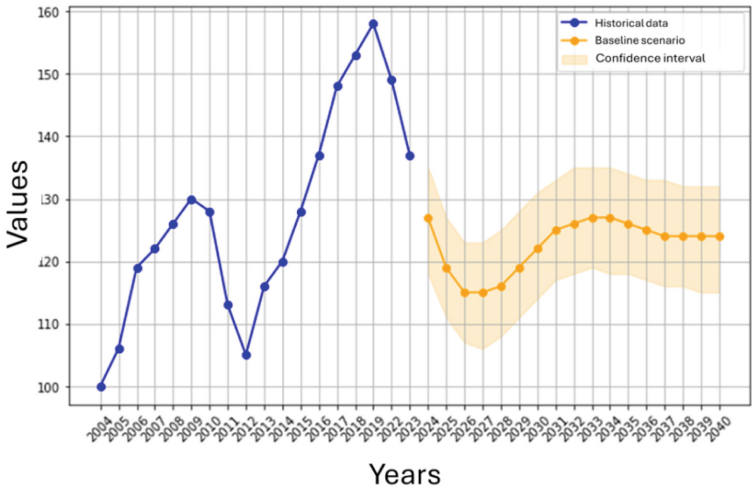

Fig. 14. Trend of the NI-PR - pessimistic, baseline, and optimistic scenarios (2024-2040) with the corresponding confidence interval

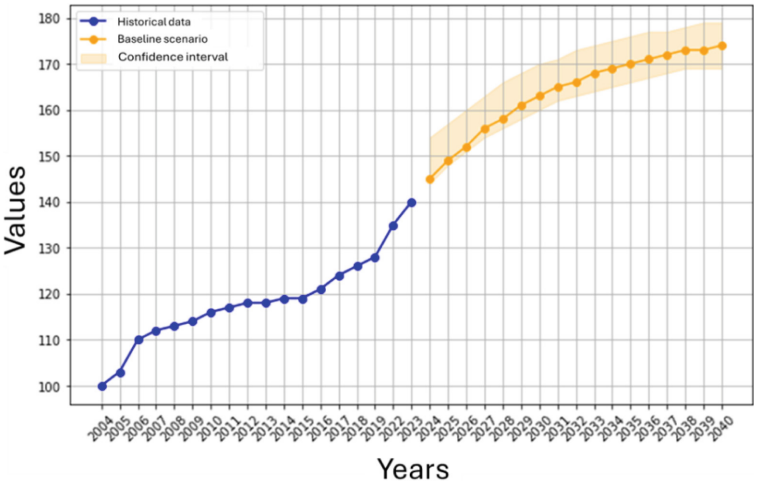

Fig. 15. Trend of the NI-TM - pessimistic, baseline, and optimistic scenarios (2024-2040) with the corresponding confidence interval.

Scenario	Model estimate	ENAC estimate	Δ%
Pessimistic	6.692.754	6.702.617	0.15%
Optimistic	7.429.998	7.717.076	3.86%

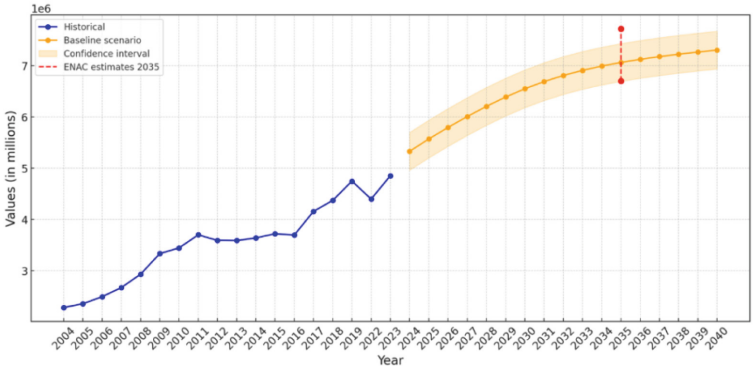

Fig. 16. Chart of historical passenger trends and projections with corresponding confidence intervals

4 Conclusions

Based on the analysis developed in this study, the adoption of a multivariable econometric model integrated with ARIMA has significantly improved air transport demand forecasting for Cagliari-Elmas Airport. The methodology has led to more precise predictions, reducing estimation errors by approximately 15% compared to traditional approaches. The selected model aligns well with international trends and regulatory forecasts, reinforcing its validity. By evaluating multicollinearity and defining three forecast scenarios—pessimistic, baseline, and optimistic—the study provides a reliable projection framework that accounts for socio-economic variability. The baseline scenario predicts a passenger increase of about 2.5% annually, reaching 7.8 million passengers by 2040. These findings support strategic infrastructure planning and airport management, contributing to sustainable air transport growth. This study highlights the value of traditional forecasting models. Future work should integrate advanced techniques, such as machine learning and neural networks, to compare and enhance predictive accuracy in socioeconomic analyses. A systematic comparison between traditional and emerging models could reveal key differences and guide the implementation of new methodological approaches.

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Author Contributions Conceptualization, all; methodology and formal analysis, Riccardo Zedda and Nicoletta Rassu; introduction and literature review Francesca Maltinti, Riccardo Zedda, and Nicoletta Rassu; writing-original draft preparation Riccardo Zedda and Mauro Coni; writing review and editing Nicoletta Rassu and Kevin Panetto, visualization, all. All authors have read and agreed to the published version of the manuscript.

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