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Air demand forecasting for passengers and freight in Italy: A comparison of two statistical models

Ahmed R.M. Alsayed [*], Michela Cameletti

Department of Economics, University of Bergamo, 24127, Bergamo, Italy

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ABSTRACT

Air transport forecasting has received significant attention in the literature. Furthermore, economic growth and population are significantly associated with the aviation industry. Moreover, the time series of air passenger and freight demand usually exhibit a complex behaviour with high volatility and irregularity, particularly when considering the economic factors associated with freight demand. In this research, we implemented two different statistical methods, namely the SARIMAX model and the structural time series approach, to fit and forecast both the air passenger and freight demand, considering economic variables and population as regressors. Both methods can deal with seasonality and trend; interestingly, the structural time series model can also estimate the cycle by decomposing the time series using the Kalman filter method. We applied the two methods to monthly data obtained from the Italian national website *Assaeroporti* for the period from January 2000 to December 2023. We computed predictions for the passenger and freight demand up to 2035, with a monthly and yearly resolution. For this aim, it was necessary to implement separate time series models for the economic regressors and population to plug in corresponding forecasts in the demand models. The results could be particularly useful for optimizing air traffic infrastructure and guiding strategic investment, particularly in the planning and adoption of sustainable aviation technologies (e.g., electric and hybrid-electric systems, new sustainable fuels).

1. Introduction

Air transportation has become the easiest and fastest way to transport passengers and materials over short and long distances. Air transportation has many advantages, such as high speed, safety, comfort, fast clearance, and no physical barrier, especially for transporting goods, but it has some disadvantages in terms of large investment and environmental impact (Hofer et al., 2018). The aviation authority of Italy (Assaeroporti) publishes statistical indicators such as air passenger volume and freight turnover volume every month.

There is evidence in the literature of a significant relationship between air transport demand and economic growth. Airport infrastructure plays an important role in economic development, as they contribute to interconnected firms. For example, investment in transportation at the country level can positively boost many sectors of the economy (Hofer et al., 2018). The European Commission (2011) reported that in 2010, on average, 13.2 % of a household's budget was spent on transporting goods and services. Moreover, output from the transport sector amounts to approximately 5 % of the aggregate gross domestic product (GDP) per capita (European Commission, 2011).

Numerous studies have demonstrated the association of air passenger demand with GDP and population. Albayrak et al. (2020) investigated the air passenger demand by considering several regressors, including the GDP and population in Turkey between 2004 and 2014. The findings support that both GDP and population have a significant positive impact on air passenger demand. Specifically, a 1 % increase in per capita GDP was likely to increase air passenger demand in the range from 1.30 % to 1.87 %, whereas a 1 % increase in population would lead to an increase of 0.76 %–0.97 % in air passenger demand. The results also showed that the demand for air passengers in Turkey did not differ from that of developed countries. Cook et al. (2017) aimed to assess several factors affecting the air transport demand at the European level. They included GDP and educated population in the estimated model, using data from 28 European countries. The correlation coefficients between the air trip demand per capita and both GDP and educated population were equal to 0.65 and 0.72, respectively. Moreover, the results indicated that the coefficients of both regressors were statistically significant, with a 1 % increase in GDP leading to an increase in average

* Corresponding author.
E-mail address: ahmed.alsayed@unibg.it (A.R.M. Alsayed).

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air trips per capita of 0.0042 and an increase in education by one unit leading to an increase in air trips per capita of 0.018 units. Suryan (2017) was interested in forecasting the air traffic passengers in Indonesia, using GDP and population as independent variables. The results showed that the GDP per capita and the total population were significantly correlated with the number of passengers. In addition, Al-Rukaibi and Al-Mutairi (2013) used the national income and population as independent variables to predict the annual air passenger demand in Kuwait. The results indicated a strong positive relationship between air passenger demand and both income and population, with coefficients equal to 0.926 and 0.862, respectively.

Due to the complexity of the aviation data behaviour, as well as its variation from one season to another, it has high volatility and irregularity trends. Specifically, the demands for both air passengers and freight exhibit a nonlinear pattern over time and are characterised by strong seasonality. Moreover, economic growth series data include fluctuations caused by economic crises and shocks not just to transitory and cyclical components but also to long-term elements. Hence, the importance of estimating the long-term forecasting emerges. While one recent study in air transportation field provided only medium-term forecasts of up to five years (Lundaeva et al., 2024), some recently proposed statistical methods using air transportation data are nonetheless not appropriate for long-term forecasting considering the trend, seasonality, and uncertainty, as they mentioned this in the limitation of their studies (Özçalıcı and Gürler, 2025; Hu et al., 2025). Hence, it is important to implement an appropriate statistical technique that accounts for issues such as seasonality, as well as sudden changes in demand levels, to achieve high accuracy in long-term forecasting.

Accurate air transportation demand forecasting is essential for operational efficiency, long-term strategic decision-making, resource allocation, capacity planning, route development, and infrastructure investment. It enables managers to reduce costs, optimize flight capacity, mitigate environmental impacts, improve service quality, and make more effective investment decisions.

In response to the climate change crisis, the aviation industry has committed to an ambitious goal of achieving carbon-neutral growth (ICAO, 2017). Therefore, industry leaders need to find new environmentally friendly technologies to reduce emissions.

This work contributes to the literature by understanding how existing demand patterns can guide the adoption of environmentally friendly technologies in aviation. This perspective is still relatively underexplored and provides valuable insights for policymakers, airlines, and infrastructure planners. In particular to find a potential replacement, policymakers need to understand and evaluate the long-term market needs for air transport demand (Coppola et al., 2025). Many existing studies focus either on individual models or machine learning techniques that lack in the performance of interpretable models in long-term forecasting scenarios. To address this gap, the present study investigates the effectiveness of Seasonal Auto Regressive Integrated Moving Average with eXogenous regressors (SARIMAX) and structural time series (STS) models in forecasting monthly air passenger demand.

To the best of our knowledge, this is the first study on Italian air passenger and freight demand for long-term forecasting which could help policymakers in evaluating the adoption of environmentally friendly technologies. The main contributions of this paper are twofold: first, we model both the air passengers and freight transportation in Italy at the country level while considering the GDP, trade balance, and population. Second, we compare the forecasting performance of a state-of-the-art SARIMAX model and STS model that considered the Kalman filter in the analysis.

The rest of the paper is structured as follows: the next section presents a review of literature related to demand forecasting for passengers and freight. Then, we provide the details of the applied statistical methods. This is followed by the descriptive statistics of the dataset. Next, we describe the results and content. Finally, we conclude this research and offer recommendations for policy makers.

2. Literature review

Over the last few decades, the topic of forecasting air passenger flows has gained increasing attention, and several approaches have been proposed to improve the forecasting accuracy while dealing with different data characteristics. In this section, we summarise some of this research based on developed methods that improve the accuracy by considering multiple factors that influence aviation demand, such as trend, seasonality, heterogeneity, variability, and data distribution over time. Generally, models can be grouped within three categories: first, econometric or statistical models, which are considered parametric methods. This approach is used typically when attempting to forecast univariate time series data for the air passenger demand using simple time series approaches, such as the naïve model (Anvari et al., 2016), or by using an exponential smoothing time series model (Kim, 2016), as the mechanism of smoothing methods is to remove irregular fluctuations in the time series and then to use the basic fluctuations for the forecasting. Second, the nonparametric approach is represented by machine learning and artificial intelligence algorithms. These are used to detect nonlinear patterns from time series data without any transformation of the data distributions. The most commonly applied approaches are artificial neural networks and support vector machines (Özçalıcı and Gürler, 2025). Third is the hybrid model, or the mixture of parametric and nonparametric methods. Such approaches are built to detect linear and nonlinear patterns separately; then, the estimated patterns are combined to compose the final estimation model (Hu et al., 2025).

The existing literature can be divided into two categories: time series forecasting with or without regressors. Özçalıcı and Gürler (2025) studied the airline passenger demand using Support Vector Machines, Artificial Neural Networks, Generalized Additive Models, and Regression Trees integrated with Bayesian optimization, but without using regressors. The results demonstrated that Bayesian optimization substantially improves model efficiency and precision. However, they stated that it is important to consider the integration of macroeconomic variables to obtain a robust prediction, which is a limitation of their study. Hu et al. (2025) applied the empirical mode decomposition for the Taiwan air passenger time series data, then applied different artificial intelligence methods to individually forecast these decomposed modes. The empirical findings showed that the applied decomposition ensemble models with linear addition using grey relational analysis improved the forecasting accuracy of air passenger demand. Xu et al. (2019) proposed a seasonal auto-regressive integrated moving average (SARIMA)-single vector regression hybrid model by considering Gaussian white noise to forecast the aviation industry in China for monthly data from February 2005 to February 2018. Support vector regression is applied to detect the linear and nonlinear patterns, as there is an increasing trend with strong seasonal fluctuations. However, they mentioned as a limitation the fact that the univariate forecasting method could ignore the interactions between regressors.

Nieto and Carmona-Benítez (2018) proposed a novel hybrid method combining ARIMA, GARCH, and bootstrap time series for ARIMA and GARCH to forecast air passenger demand in the United States at the national level for monthly time series data from January 1990 to April 2016. The proposed method has the advantage of considering trend, seasonality, and data variability to eliminate the detrimental effects on forecasting. They assumed that air passenger demand could be represented by three components: conditional mean estimated by ARIMA, conditional variance estimated by the GARCH model, and the distribution of the error term approximated by using the bootstrap model. The comparison between those forecasting methods is determined by using the mean absolute percentage error, the Diebold-Mariano test, and the superior predictive ability test. Air passenger demand data exhibit trends and strong seasonality that may be associated with other variables.

Some researchers have included socio-economic factors such as population, income, exchange rate, revenue, employment rate, and GDP per capita at the national level (e.g., Zhang and Findlay, 2014, in China) or at the provincial/regional level (e.g., Barczak, 2017, by including the GDP in Poland). Moreover, some studies have included personal income per capita or household income in the estimation model (Gosling and Ballard, 2019; Hofer et al., 2018). Chi (2020) examined the influence of exchange rate volatility on short- and long-run air travel demand in Korea. Additionally, the population or population growth rate appeared to be a common predictor variable in air passenger demand analysis (Lundaeva et al., 2024; Hofer et al., 2018; Suryani et al., 2010). Lundaeva et al., 2024 developed a model for medium-term flight demand estimation based on historical airline data between 2014 and 2024, considering the influence of gross regional product, and population. They provided forecasts of air passenger flows over a time horizon of up to five years. They stated that one of the model's limitations is its dependence on the quality and completeness of the input data.

3. Methodology

In this section, we describe the approaches implemented to estimate and forecast air passenger and freight demand at the country level for Italy. The STS and SARIMAX approaches have great advantages for non-stationary time series, which could be characterised by sudden changes in demand levels. Both models have the advantage of being interpretable and dealing with seasonality and trend. In addition, the STS model estimates the cycle by decomposing the time series using the Kalman filter.

3.1. SARIMAX model

The SARIMAX model is a dynamic regression model, a linear regression model with temporally correlated errors (Hyndman and Athanasopoulos, 2021). In particular, a seasonal ARIMA structure is assumed for errors.

With Y_t being the response variable at time t and X_t the regressor, the ARIMAX model is given by

$$Y_t = \beta_0 + \beta_1 X_t + \omega_t \quad (1)$$

where the regression error ω_t is assumed to follow a seasonal ARIMA model. In particular, we use the following formulation for ω_t:

$$\Phi_P(B^S)\phi_p(B)\nabla_S^D\nabla^d\omega_t = \Theta_Q(B^S)\theta_q(B)\varepsilon_t \quad (2)$$

where B is the backshift operator, $\Phi_P(B^s)$ is the seasonal AR operator of order P, $\phi_p(B)$ is the standard AR operator of order p, ∇_s^D represents the seasonal differences and ∇^d the standard differences, $\Theta_Q(B^s)$ is the seasonal MA operator of order Q, $\theta_q(B)$ the standard MA operator of order q, and finally ε_t is the white-noise error, with zero mean and variance σ^2. (P, D, Q) defines the seasonal part of the model, and (p, d, q) refers to the nonseasonal part. The SARIMAX models were estimated using the *fable* package of R software (Hyndman et al., 2020). Specifically, given the observed time series, the optimal (P, D, Q) and (p, d, q) values were chosen by minimising the Akaike information criterion; the model parameters were estimated using the maximum likelihood approach.

3.2. The structural time series model

The STS model has been presented by Harvey and Koopman (2014) and Harvey (1990). STS is a statistical time series technique that captures the cointegration between the decomposed series and then detects the common factors of the series (common trends, seasonality, and/or cycles with noise) by using the Kalman filter and maximum likelihood estimation (Koopman and Ooms, 2011).

The STS model is based on the decomposition

$$Y_t = T_t + C_t + S_t + B^o X_t^o + e_t \quad (3)$$

where Y_t is the time series of interest (e.g., number of air passengers/freight observed in month t); T_t, C_t, and S_t are the trend, cycle, and seasonal component, respectively. The term X_t^o is the exogenous data (GDP, population, and trade balance) in observation equation, B^o is the coefficients matrix of X_t^o, and $e_t \sim N(0, \sigma_e^2)$ denotes the observation error.

The state space model is written as

$$Y_t = A + H\beta + B^o X_t^o + e_t \quad (4)$$

$$\beta_t = D + F\beta_{t-1} + B^S X_t^S + u_t \quad (5)$$

where equation (4) is the observation equation while equation (5) is the transition equation, A is the observation intercept, H is the observation matrix and $e_t \sim N(0, R)$ is the observation error, where R is the observation error–covariance matrix. β_t is the coefficients vector of the state components, D is the state intercept matrix, F is the transition matrix, X_t^S represents the exogenous data in the state equation, and $u_t \sim N(0, Q_{st})$ is the state error, where Q is the state error–covariance matrix in equation (5). More details about estimating the trend, cycle, seasonal and unobserved component of STS model are mentioned in the Appendix Section 2.

The advantage of STS over other approaches is its forecasting capability, as it forecasts each decomposed component separately, but direct interpretations of each component are also possible. Hence, STS can forecast the actual time series as well as the trends and cycles. The Kalman filter avoids the influence of possible structural breaks during the estimation (Koopman and Ooms, 2011).

4. Application to Italian data

In this section, we describe the data and the analysis carried out to forecast the total number of passengers and the freight demand for the Italian market up to December 2035, with a monthly and yearly temporal resolution. The model exploits information provided by economic regressors such as the GDP and the trade exchange and population of Italy. It is important to note that when the models for passengers and freight are estimated, the regressor's values must be available for the entire forecasting period up to December 2035. For this reason, it is necessary to preliminarily implement separate models for the GDP, and trade exchange to forecast their values that will be used later for the passenger and freight models. The selected regressors (GDP, trade balance, and population) were chosen based on their empirical relevance in the air transport demand literature. These variables are commonly found to influence passenger and freight volumes due to their connection with economic activity, travel affordability, and mobility patterns (Lundaeva et al., 2024; Gosling and Ballard, 2019; Hofer et al., 2018). In line with this literature, and for modelling convenience, we also treat GDP and the other regressors as exogenous variables. Consequently, we did not investigate the direction of causality between economic variables and air transport demand.

4.1. Data description

Air demand data for both passengers and freight were obtained from the *Assaeroporti* website (Assaeroporti, 2023). In particular, the total number of arriving/departing passengers and the total quantity in millions of tons of incoming/departing freight and mail traffic were available for the period of January 2000 to December 2023 with a monthly resolution. This results in a total of 24 years of monthly data, which includes periods of economic crises, shocks, and the COVID-19 pandemic.

Quarterly (Q) data about the Italian GDP were obtained from Eurostat (Eurostat, 2023) for the period between 1995-Q1 and 2023-Q4. The data are seasonally adjusted and expressed in thousands of millions of euros. Moreover, yearly long-term forecast data for GDP are available from the Organisation for Economic Co-operation and Development (OECD). This dataset provides the GDP trend for Italy, including long-term baseline projections up to 2060, in real terms (OECD, 2023). The data have a yearly resolution from 1990 to 2060 and are expressed in thousands of millions of US dollars. The OECD GDP data are used as regressors in the GDP model. In particular, we expect that the yearly OECD long-term forecast will help in predicting the GDP forecast at the monthly level by providing information about the expected evolution of the Italian economy in the near future (OECD, 2023). When modelling freight demand, we also consider the total value of exports and imports from/to Italy to/from the rest of the world. The data are seasonally adjusted and available in thousands of millions of euros; the resolution is monthly for the period of January 1995 to December 2023 (Istat, 2023). Italian total population data and projections at the country level are available as annual time series expressed in millions (Istat, 2023).

We first align the economic time series to the monthly temporal resolution as the passenger and freight data. We start with the OECD GDP data, available as yearly time series, and use the temporal disaggregation method to move to a monthly time series (Sax and Steiner, 2013). With this approach, the sum of the resulting high-frequency (monthly) time series is consistent with the low-frequency (yearly) series. We use the same approach with the Eurostat GDP series for transforming the quarterly time series into a monthly series. In Fig. 1, the two obtained monthly series for the Italian seasonally adjusted GDP are represented, with the OECD time series extending up to 2060. Even if they are expressed in two different currencies, they share a common pattern across time, with the COVID-19 pandemic in 2020 and the previous economic crises being evident. The correlation between the two-time series is equal to 0.63, with the OECD GDP line being smoother than its Eurostat counterpart.

The time series of the number of passengers is reported in Fig. 2. From 2000, an ascending trend is visible, with a drop in 2020 due to the COVID-19 pandemic. Note that the most recent values, referring to 2023, seem to be aligned with the pre-pandemic trend. Across the years, we also observe an increase in the variability of the series. The passengers' series has a strong seasonal behaviour, as shown in Fig. 1a in the appendix, where the single time series are plotted by month: generally speaking, the highest values are observed in the spring–summer season. In November and February, we usually observed a drop in the number of passengers, just before and after the Christmas break. In the plot, two time series exhibit anomalous behaviour: years 2020 and 2021, affected by the COVID-19 pandemic, this is also evident in Fig. 2.

The time series of the freight demand is reported in Fig. 3. It is characterised by three visible positive trends: from 2000 to the 2008–2009 economic crisis, from 2010 to 2019, and from 2021 to the end of the considered period. Also, freight data are characterised by seasonality (see Fig. 2a in the appendix), with a sharp drop of the values in August. It is worth noting that in this case, the effect of COVID-19 is

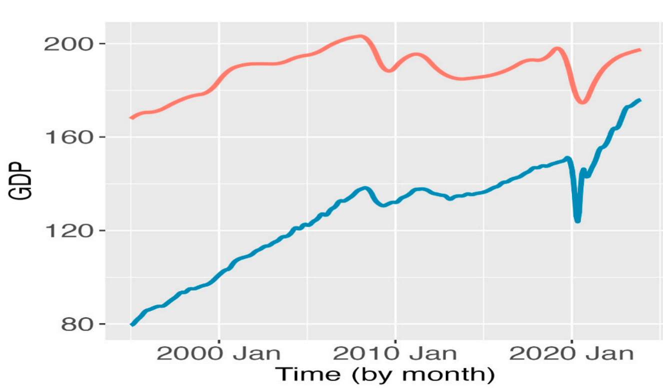

Fig. 1. Monthly GDP time series for Italy from OECD (Red line, in thousands of millions of US dollars) and Eurostat (Green line, in thousands of millions of Euros).

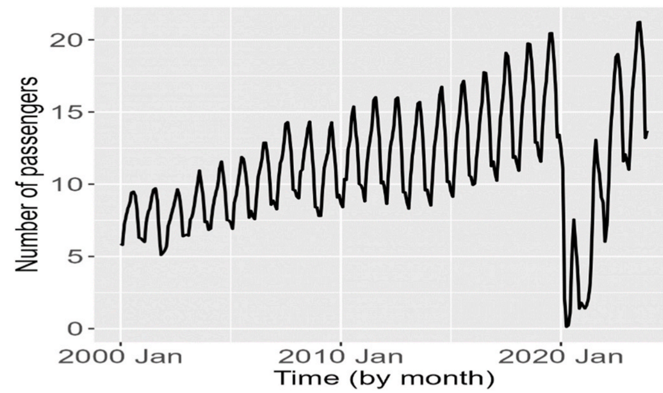

Fig. 2. Monthly time series of the total number of passengers (in millions).

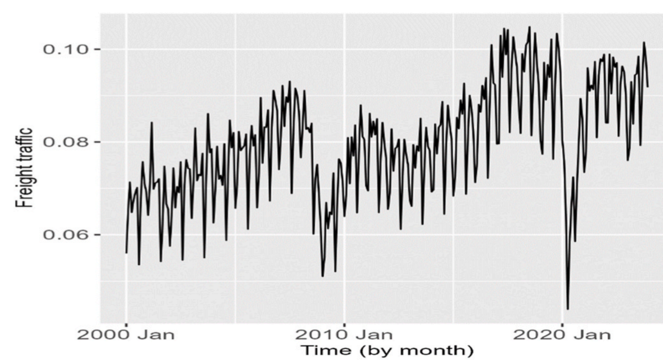

Fig. 3. Monthly time series of the total freight demand (in millions of tons).

more limited in time, compared with the passengers' time series. Starting from the end of 2020, the volume of freight demand seems to return to the pre-COVID level.

The last dataset we consider is the one about the total value of exports and imports from/to Italy to/from the rest of the world. Italy is one of the largest economies in Europe, and has a good infrastructure with a railway network of around 17,000 km, and around 7000 km of highways, in addition to 30 airports and 14 sea-ports for transporting freight. According to Eurostat, more than 780,000 tons of freight arrive in Italy each year via the two international airports of Milano Malpensa and Roma Fiumicino, while the amount of freight transported by road is about 1238 million tons per year (Eurostat. 2024). Moreover, the Italian rail network transports about 96 million tonnes of freight annually in Italy (Statista, 2024). In Fig. 4, the values of exports, values of imports, and their difference (i.e., the trade balance) are represented. Export and import time series follow a similar pattern, with the exports being larger than the imports and the balance trade being positive for about 68 % of the considered months.

4.2. Modelling

By using the monthly data described in the previous section, we proceed as follows:

1. We fit an SARIMAX model (M1) for the Italian GDP, using the Eurostat data as a response variable and the OECD GDP data as a regressor.
2. We fit an SARIMAX model (M2) for the trade balance using the Eurostat GDP data and forecasts from Step 1 as a regressor.

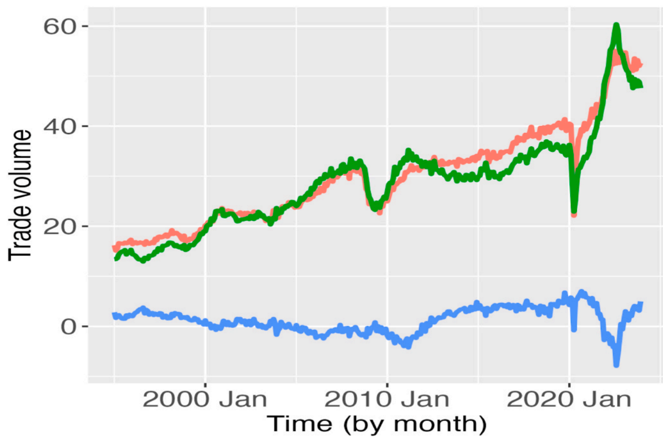

Fig. 4. Time series of monthly trade variables for Italy (seasonally adjusted, in thousands of millions of Euros): Exports (Red line), imports (Green line), and trade balance (Blue line) computed as exports–imports.

3. We fit an SARIMAX (M3a) and STS (M3b) model for the number of passengers, using the Eurostat GDP data and population as regressors.
4. We fit an SARIMAX (M4a) and STS (M4b) model for the freight demand, using the Eurostat GDP, trade balance, and population as regressors.

For all the implemented models, we are interested in computing monthly forecasts for the period from January 2024 to December 2035 using all the previously available data for fitting the models. As we are particularly interested in evaluating the predicting performance of Models M3a-b and M4a-b, we first fit the models using as the training set the data available from January 2000 to December 2022. Using the fitted models, we compute the predictions for the 12 months of 2023 and compare the out of sample forecasts with the observed data using a set of performance indexes. In particular, we use root mean square error (RMSE), mean absolute error (MAE), the mean absolute percentage error (MAPE), mean absolute scaled error (MASE) and the Theil's U statistic. There are some advantages of using these criteria: for example, the RMSE is optimal for Gaussian errors, whereas the MAE is optimal for Laplacian errors (Hodson, 2022). The MAPE has the advantages of scale independency and interpretability (Kim and Kim, 2016). The MASE focuses on absolute scaled errors, which minimises sensitivity to outliers while providing a straightforward benchmark against naive forecasts (Hyndman and Koehler, 2006). Theil's U statistic is a unit-free measurement that emphasises the importance of large errors; its numerator is considered the percentage of RMSE (Theil et al., 1966). The indexes are as following;

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|y_i - \hat{y}_i|}{\frac{1}{n-1}\sum_{i=2}^{n}|y_i - y_{i-1}|}\right) \tag{9}$$

$$TheilU = \frac{\sqrt{\sum_{i=1}^{n-1}\left(\frac{\widehat{y_{i+1}} - y_{i+1}}{y_i}\right)^2}}{\sqrt{\sum_{i=1}^{n-1}\left(\frac{y_{i+1} - y_i}{y_i}\right)^2}} \tag{10}$$

where y_i is the actual value, $\hat{y}_i$ is the estimated value, and n is the sample size.

In addition, given the monthly forecasts for the total number of passengers and freight demand, it can be of some interest to obtain estimates at a lower temporal resolution (i.e., yearly). This means that we must compute point predictions and confidence intervals for aggregated data (the yearly totals), using a model fitted on monthly data. This can be done using a simulation approach. First, a large number of monthly forecasts (1000 future sample paths from January 2024 up to December 2035) are simulated from the fitted model. Second, the corresponding 1000 yearly total sample paths are computed by summing the monthly values. Finally, the mean and the empirical 2.5 % and 97.5 % quantiles for a confidence level equal to 0.95 are computed for each year.

5. Results

5.1. M1: modelling and forecasting the GDP

According to the data from January 1995 to December 2023, the best model for the GDP is the nonseasonal SARIMAX ($p = 5, d = 1, q = 0$) ($P = 0, D = 0, Q = 0$). The estimated coefficient for the regressor (GDP-OECD data) is equal to 0.79 (SE = 0.063). As expected, the relationship between the two GDP time series is positive and statistically significant. Given the estimated model, monthly predictions are computed up to December 2035, as shown in Fig. 5. An almost linear increase in the GDP is expected, with the uncertainty of the prediction increasing with time.

5.2. M2: modelling and forecasting the trade balance

For the sake of simplicity, we consider only the trade balance as the response variable, defined as the difference between exports and imports. The SARIMAX model is fitted using all the data from January 1995

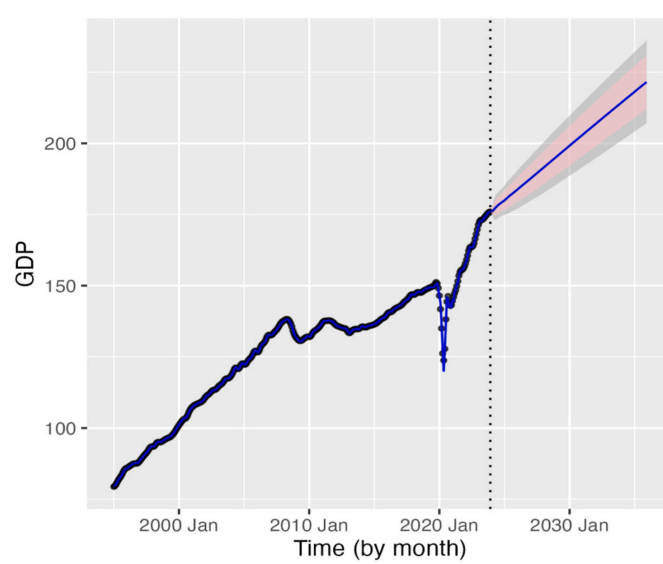

Fig. 5. Monthly Eurostat GDP Time Series for Italy (Black Points, in Thousands of Millions of Euros), Fitted and Forecasted Values up to December 2035 (Point Estimate in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using M1.
Note. The vertical line represents the time point of the last observation used for fitting the model.

to December 2023 and considering as the regressors the GDP values and forecasts obtained from M1. In this case, the best model for the trade regression errors is SARIMAX ($p=3$, $d=1$, $q=2$) ($P=2$,$D=1$,$Q=2$). The GDP coefficient is equal to 0.141 (SE = 0.0292), suggesting a positive and significant relationship between the GDP and the trade balance. Given the estimated model, monthly predictions for the trade balance are computed up to December 2035 as shown in Fig. 6. It seems that the trade balance predictions reflect the GDP prediction reported in Fig. 5, with an upward trend given the positive value of the coefficient.

5.3. M3a-b: modelling and forecasting the number of passengers

The GDP observed values and point predictions shown in Fig. 5 are used as regressors in the SARIMAX and STS models fitted for the number of passengers. The performance of the models, when the 2023 data are held out, is reported in Table 1. The results suggest that the STS model outperforms the SARIMAX on all used criteria, which may be due to the passenger data exhibiting a clear trend, a seasonal and cyclical period, which can be detected and considered by the STS model.

According to all the available data for model fitting, the best SARIMAX model is given by SARIMAX ($p=1$,$d=0$,$q=1$) ($P=2$,$D=1$,$Q=2$). The GDP coefficient is equal to 0.37 (SE = 0.04), and the population coefficient is equal to 23.8 (SE = 10.02). As expected, both GDP and population have a significantly positive relationship with the total number of passengers. Given the estimated model, monthly predictions for the number of passengers with a long-term forecasted period are computed up to December 2035. Figs. 7 and 8 show an upward trend, with the usual seasonality that characterises these data. As expected, the prediction uncertainty increases over time. The higher uncertainty in the long-term predictions might be due to several reasons. Firstly, we included economic factor such as GDP in the estimation model, which is susceptible to fluctuations increasing/decreasing over time according to the economic situation; recessions, inflation, and changing income levels. Another indirect impact on GDP that increases uncertainty in the estimated model is expected to be technological developments. Secondly, we included a social factor such as the population, which is changeable with time, and the people's willingness and ability to travel could be drastically reduced based on some situations such as pandemics or health crises (Wensveen, 2023).

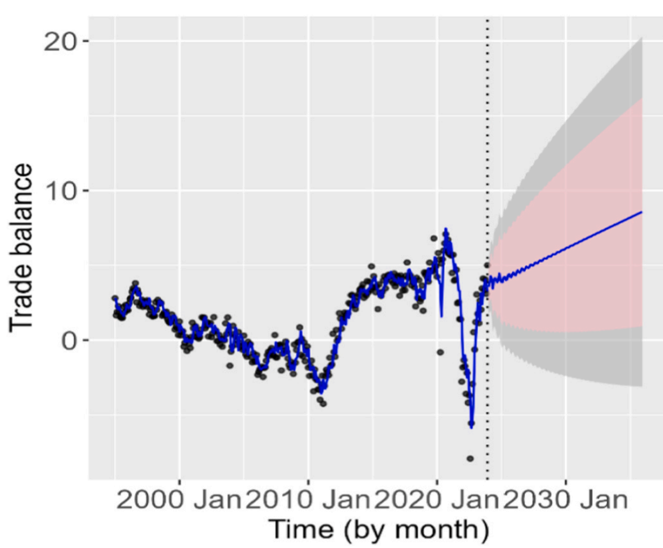

Fig. 6. Monthly Trade Balance Time Series for Italy (Black Points, in Thousands of Millions of Euros), Fitted and Forecasted Values up to December 2035 (Point Estimate in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using M2.
Note. The vertical line represents the time point of the last observation used for fitting the model.

Table 1
Out of sample performance indexes of the SARIMAX and STS model computed on the air passengers and freight data.

Performance Indexes	Air passengers		Freight	
	SARIMAX	STS	SARIMAX	STS
RMSE	2.01	1.78	0.005	0.006
MAE	1.79	1.43	0.004	0.005
MAPE	10.30	9.15	4.774	5.785
Theil U	0.88	0.79	0.496	0.554
MASE	1.02	0.81	0.506	0.598

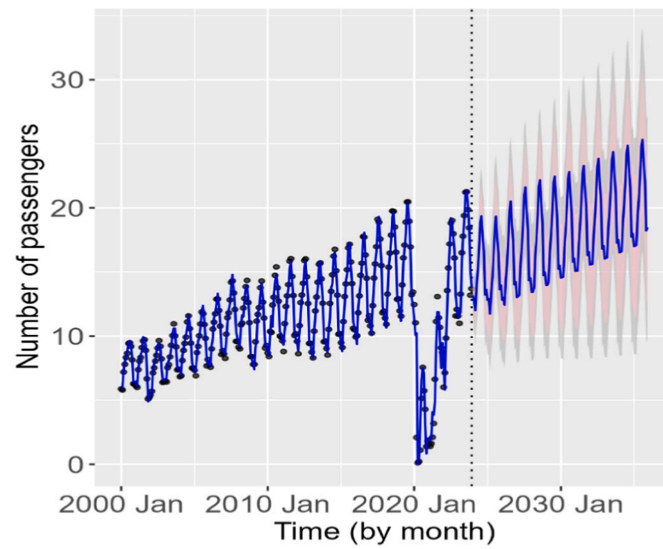

Fig. 7. Monthly Number of Passengers Time Series (Black Points, in Millions), Fitted and Forecasted Values up to December 2035 (Point Estimate in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using M3a.
Note. The vertical line represents the time point of the last observation used for fitting the model.

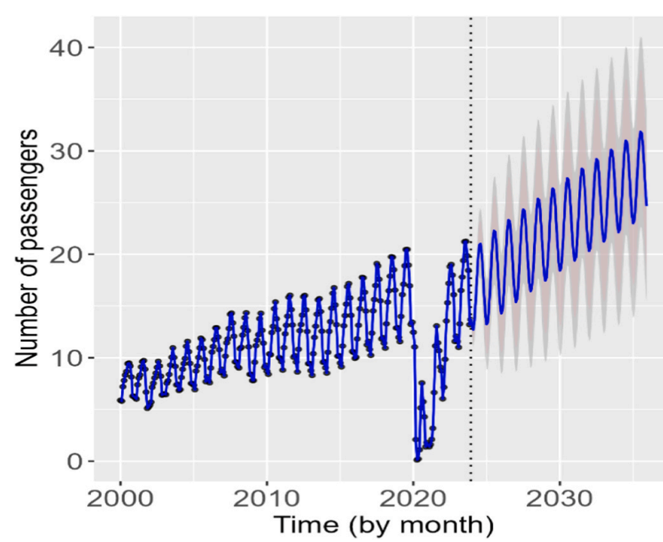

Fig. 8. Monthly Number of Passengers Time Series (Black Points, in Millions), Fitted and Forecasted Values up to December 2035 (Point Estimate in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using M3b.
Note. The vertical line represents the time point of the last observation used for fitting the model.

Using the simulation approach, we are also able to compute the yearly predictions, which are displayed in Fig. 9. An increase in the number of passengers is expected, with values over 200 million starting from 2030.

5.4. M4a-b: modelling and forecasting the freight demand

We now implement the model in which the response variable represents the total freight demand, measured in millions of tons. As regressors, we will use the observed and predicted monthly values of the GDP from M1, and the trade balance from M2. The performance of the SARIMAX and STS models, when the 2023 data are held out, are reported in Table 1. The results suggest that the SARIMAX method outperforms based on all used criteria, which might be due to the freight data not having a notable cycle to be detected.

The SARIMAX model is then fitted using all the monthly data from January 2000 to December 2023. According to the results, the best model for the regression errors is SARIMAX $(p = 1, d = 0, q = 2)(P = 0, D = 1, Q = 1)$. The GDP coefficient is equal to 0.0013 (SE = 0.0002), suggesting a small but positive and significant relationship between the GDP and the amount of freight demand. The population coefficient is equal to 0.0307, suggesting a significant positive relationship between the population and the amount of freight demand. The trade balance coefficient is equal to 0.000004 (SE = 0.000195), meaning that the relationship between this covariate and the response is not significant. However, we keep it in the model because it is not detrimental to the value of the Akaike information criterion index. The low value of the trade balance coefficient is somehow expected due to the fact that most import/export or logistics movements to and from Italy are done by using railway rather than air transportation, particularly with the border countries (Brugnoli et al., 2018).

Given the estimated model, monthly predictions for the total freight demand are computed up to December 2035, as shown in Fig. 10 and 11 for SARIMAX and STS respectively. They are expected to increase over time, with the same seasonality pattern observed in the training data. Finally, the yearly total estimates are reported in Fig. 12. Given these results, we expect for 2035 an average volume of freight demand of 1.4 million tons with a 95 % confidence interval of [1.01, 1.85].

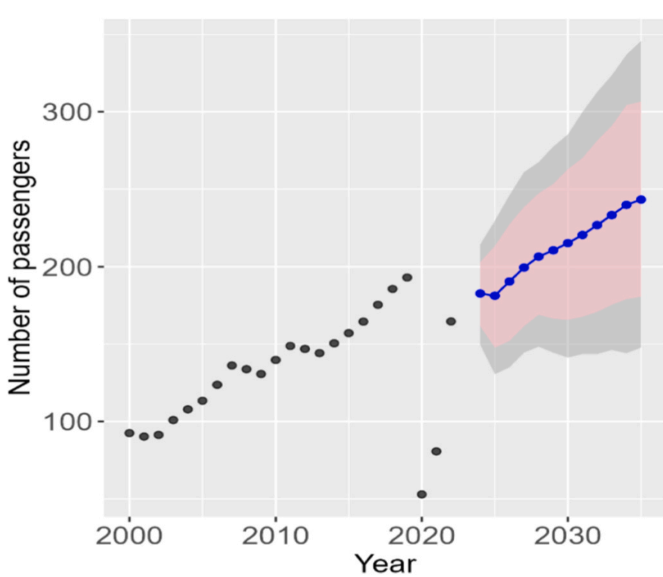

Fig. 9. Yearly Number of Passengers Time Series (Black Points, in Millions), Forecasted Values up to 2035 (Point Estimate in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using the M3a.

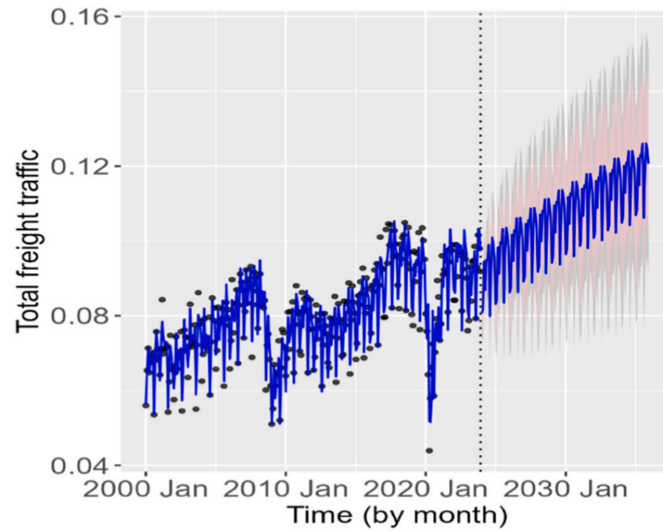

Fig. 10. Monthly Total Freight Demand (Black Points, in Millions of Tons), Fitted and Forecasted Values up to December 2035 (Mean in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using Ma4.
Note. The vertical line represents the time point of the last observation used for fitting the model.

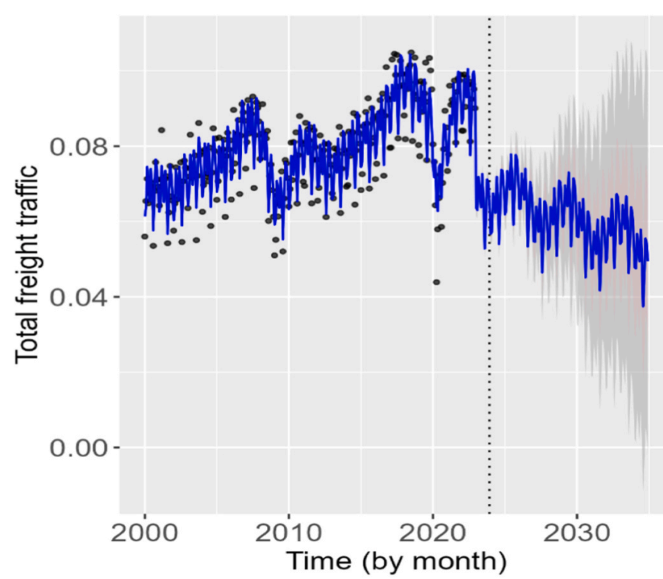

Fig. 11. Monthly Total Freight Demand (Black Points, in Millions of Tons), Fitted and Forecasted Values up to December 2035 (Mean in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using M3b.

6. Discussion and conclusion

This research focused on estimating air demand for passengers and freight in Italy at the country level by considering the GDP as a proxy for economic growth, together with the import–export trade balance and population as regressors. We applied two statistical models - the SARIMAX and STS models - which can capture the characteristics of air passenger and freight demand time series, that typically have a seasonal, trending, and cyclical behaviour. The STS approach includes the Kalman filter in the analysis and has been recommended by Nieto and Carmona-Benítez (2018). The two methods were applied to fit the monthly data for both the air passenger and freight demand over the period from January 2000 to December 2023; then, the monthly and yearly forecasts were computed up to 2035. To do this, we forecast separate time series

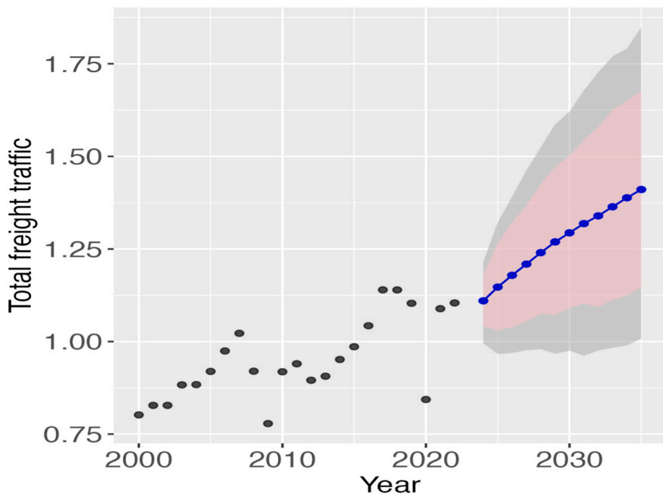

Fig. 12. Yearly Total Freight Demand (Black Points, in Millions of Tons), Forecasted Values up to 2035 (Point Estimate in Blue, 80 % Confidence Interval in Pink, 95 % Confidence Interval in Grey) using M3a.

models for the GDP, trade balance, and population to be used in the forecasting demand models for the period from 2024 to 2035.

The main finding showed that both estimated models provide significantly associated regressors for passengers and freight demand. However, in the case of the air passengers' demand model, the STS outperformed the SARIMAX in all goodness-of-fit criteria. This may be due to the presence of pronounced cyclical, trend and seasonal components in the air passenger data, which can be detected by the STS model using the Kalman filter. However, in the case of freight demand, the SARIMAX model outperforms the STS model.

Accurate forecasting of air passenger and freight demand is valuable for policymakers and aviation practitioners when developing long-term operational strategies. These forecasts could be useful to assess market readiness and guide the deployment of sustainable aviation technologies (e.g., electric and hybrid-electric systems, new sustainable fuels), thereby facilitating the transition to greener alternatives.

While this study provides valuable insights into future air transportation demand, it is important to acknowledge some limitations that could be considered in future research. These include forecast uncertainty due to the long-term nature of the predictions; future research might use scenario-based forecasts to have less uncertainty of the forecast's values. Additionally, because we treat the economic variables as exogenous – in line with previous studies - we do not test for reverse causality between them and air transport demand. Nevertheless, examining such causal relationships could provide further insights and represents a valuable topic for future research.

CRediT authorship contribution statement

Ahmed R.M. Alsayed: Writing – review & editing, Writing – original draft, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michela Cameletti:** Writing – review & editing, Visualization, Supervision, Software, Resources, Methodology, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Section 1

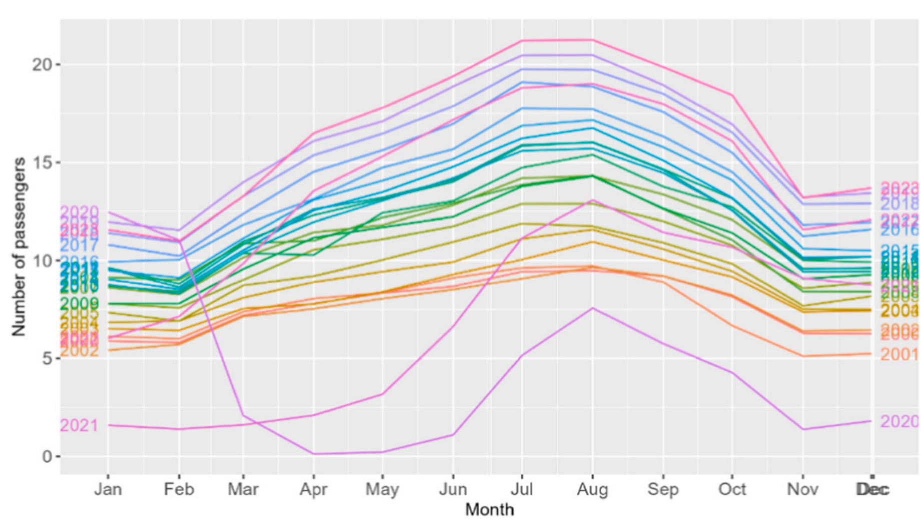

Fig. A1. Total Number of Passengers (in Millions) by Month
Note. Each line represents a year of data.

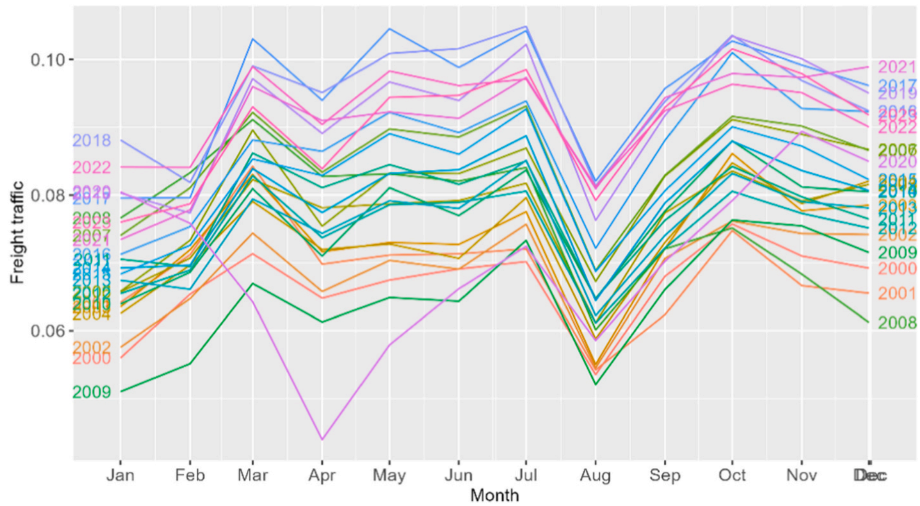

Fig. A2. Total Freight Demand (in Millions of Tons) by Month
Note. Each line corresponds to a year of data.

Section 2. Details about estimating trend, cycle, seasonal and unobserved component of STS model

The trend component T_t could be a random walk,

$$T_t = T_{t-1} + e_t \tag{A1}$$

where $e_t \sim N(0, \sigma_t^2)$. Whereas the seasonal component is modelled using a Fourier series, constructed from the sum of sin–cos waves such that each wave represents a seasonal pattern. Thus, the total seasonality is calculated as

$$S_t = \sum_{j=1}^{h} s_t^j \tag{A2}$$

where each seasonal pattern s_t^j is modelled using the trigonometric specification, as below:

$$\begin{bmatrix} s_t^j \\ s_t^{j*} \end{bmatrix} = \begin{bmatrix} \cos(\lambda_j) & \sin(\lambda_j) \\ -\sin(\lambda_j) & \cos(\lambda_j) \end{bmatrix} \begin{bmatrix} s_{t-1}^j \\ s_{t-1}^{j*} \end{bmatrix} + \begin{bmatrix} w_t^j \\ w_t^{j*} \end{bmatrix} \tag{A3}$$

where s_t^{j*} is an auxiliary variable, j represents the number of periods per year, $\lambda_j = \frac{2\pi j}{f}$ is the frequency of season j, f is the frequency of the data, and $w_t^j \sim N\left(0, \sigma_j^2\right)$.

The cycle component is estimated by using the trigonometric process, as below:

$$\begin{bmatrix} c_t \\ c_t^* \end{bmatrix} = \phi_c \begin{bmatrix} \cos(\lambda) & \sin(\lambda) \\ -\sin(\lambda) & \cos(\lambda) \end{bmatrix} \begin{bmatrix} c_{t-1} \\ c_{t-1}^* \end{bmatrix} + \begin{bmatrix} u_t \\ u_t^* \end{bmatrix} \tag{A4}$$

where λ is the frequency of the cycle, and $\phi_c \in (0, 1)$ is to make the cycle stationary for forecasting purposes, and $u_t \sim N(0, \sigma_c^2)$.

Finally, we estimate the unobserved components (T_t, C_t, S_t, and D_t) by using the Kalman filter, which is a forward two-stage procedure that is the optimal linear filter based on multivariate normal distribution. The Kalman filter uses two stages in the prediction process. In the first stage, it makes predictions of the four components based on data information up to time $t-1$:

$$B_{t|t-1} = D + F\,\beta_{t-1|t-1} + B^S X_t^S \tag{A5}$$

where $B_{t|t-1}$ is the prediction of state components,

$$P_{t|t-1} = F\,P_{t-1|t-1} F' + Q \tag{A6}$$

where $P_{t|t-1}$ is the prediction of the covariance matrix,

$$\eta_{t|t-1} = Y_t - \left(A + H\beta_{t|t-1} + B^o X_t^o\right) \tag{A7}$$

where $\eta_{t|t-1}$ is the prediction error of the time series,

$$f_{t|t-1} = H\,P_{t|t-1} + H' + R \tag{A8}$$

where $f_{t|t-1}$ is the variance of the prediction error.

At the second stage, or updating stage, it makes predictions based on all data information up to time t. This consists of three equations:

$$\beta_{t|t} = B_{t|t-1} + K_t\,\eta_{t|t-1} \tag{A9}$$

$$K_t = P_{t|t-1}\,H' f_{t|t-1}^{-1} \tag{A10}$$

$$P_{t|t} = P_{t|t-1} - K_t H\,P_{t|t-1} \tag{A11}$$

where K_t is the Kalman gain that provides the optimal weight.

The final model is estimated by using maximum likelihood estimation, using the following log likelihood:

$$\ln(L(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}\ln\left(\left[f_{t|t-1}\right]\right) - \frac{1}{2}\sum_{t=1}^{T}\acute{\eta}_{t|t-1}\,f_{t|t-1}^{-1}\,\eta_{t|t-1} \tag{A12}$$

where, *ln* is the natural logarithm, and $\eta_{t|t-1}$ is the prediction error.

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