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Air transportation demand forecast through Bagging Holt Winters methods

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ABSTRACT

This paper expands the fields of application of combined Bootstrap aggregating (Bagging) and Holt Winters methods to the air transportation industry, a novelty in literature, in order to obtain more accurate demand forecasts. The methodology involves decomposing the time series into three adding components: trend, seasonal and remainder. New series are generated by resampling the Remainder component and adding back the trend and seasonal ones. The Holt Winters method is used to modelling each time series and the final forecast is obtained by aggregating the forecasts set. The approach is tested using data series from 14 countries and the results are compared with five methodology benchmarks (SARIMA, Holt Winters, ETS, Bagged.BLD.MBB.ETS and Seasonal Naive) using Symmetric Mean Absolute Percentage Error (sMAPE). The empirical results obtained with Bagging Holt Winters methods consistently outperform the benchmarks by providing forecasts that are more accurate.

1. Introduction

The year of 2014 marked one hundred years after the creation of the world's first airline between St. Petersburg-Tampa operated by Percival Fansler. Since then, the air transportation business has grown massively improving people's mobility and boosting economy. Indeed, the air transportation segment is a driver of the economic and social development of a country (Singh et al., 2016). The numbers are expressive. According to the International Air Transportation Association, IATA, in an average year, the airline industry carries 3 billion people and 50 million tons of cargo, supporting 56.6 million jobs and $ 2.2 trillion of economic activity (IATA, 2014).

Though the relationship between air transport demand and economic development is consensual, the direction of causality is not straightforward as discussed by Green (2007). It may be found in literature evidences that the relationship may be unidirectional or bidirectional according to the context. Indeed, the spacial, economic, cultural and social characteristics of the region under study may derive in different results as these factors induce distinct travel motivations. Knowing each reality is of uttermost importance for planners, investors and policy makers. The reader is invited for a detailed discussion on this topic in Hakim and Merkert (2016) and Baker et al. (2015).

The growth of air transportation business places complex investment and managerial decision-making problems. Nowadays, the performance of the air transportation industry is the result of the application of complex and modern optimization techniques mostly based on operations research (OR) theories. Barnhart et al. (2003) published an overview about the application of OR techniques to the air transportation industry. The areas covered include aircraft and crew scheduling, revenue management, overbooking, leg-based seat inventory management and the planning and operations of aviation infrastructure. Regarding infrastructure there is a vast literature dealing with airport location and several papers deal with airport locations issues such as hub location (for a review on the topic see Farahani et al., 2013). In a scenery where most processes are already subjected to optimization methodologies, competitive advantages for the players may arise from more accurate and realistic input data. For that reason, forecast modelling still plays an essential role, despite its inherent uncertainty.

According to Marazzo et al. (2010), demand forecast is the basis for reaching efficient air transportation systems. The consequences for using erroneous forecasts are system congestion, excess infrastructure capacities, increased operators costs, public and private drainage of funds, among others. Forecast models assume an even more prominent role given the volatility of the air transportation

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market, for which contributes air transportation deregulation, the crescent competition (Graham, 1999) and the fact that airports are now viewed as commercial enterprises rather than public service organizations (Singh et al., 2016).

In this work we aim to generate a year ahead (short to medium term) forecasts for the air passenger demand. To do so, we use an approach that has never been referenced in the air transportation context. The general idea is to decompose time series of air transport demand into key components, simulate new series, forecast each of them and average all of the forecasts into one single output. Specifically, the approach combines Bootstrap aggregating (Bagging) and exponential smoothing methods and follows the approach recently proposed by Bergmeir et al. (2016) with small modifications.

In section 2, we briefly review the literature about air transportation forecasting. Section 3 reviews the methodologies along with the forecasting approach in details. Section 4 is dedicated to present data and the evaluation metrics used in the study. Section 5 is dedicated to present the results. Finally, the last section presents the conclusions and suggestions for future researches on the subject.

2. Literature review

Forecasting models may be classified according to different factors. In order to ground the problem presented in this paper, the literature review section focus on two classification factors: time horizon and method approach. Additionally, forecast can be performed for different elements and scales: for single routes, that is, between a given pair of origin and destination airports; for a single airport accounting for all movements based on the facility, or for a group of airports aggregated at a regional, national or international scale. The review identifies individually which element or scale was used by each author.

Forecast may be dealt with at different time-horizons according to the type of planning problem. Long and medium-term forecasts provide key inputs for airport infrastructure planning (terminal capacity, runway utilization, and expansion decisions), air navigation services, fleet ordering and design. Singh et al. (2016) forecasted long-term demand in India in order to evaluate the investment required to expand the capacity of the Indian airports for the following 20 years. Suryani et al. (2010) focused on long-term forecast models that can be used for infrastructure planning, namely: runway and terminal capacity expansion.

Short-term forecasts provide key inputs for daily operation management decisions. These include aircraft scheduling, crew scheduling, congestion delay occurrences, maintenance planning, revenue management, advertising and sales campaigns, among others. Scarpel (2013) built a short-term forecasting model for the number of monthly domestic passengers at São Paulo International Airport located in Brazil. Xie et al. (2014) focused on short-term forecasting of air passengers. Scarpel (2014) developed both, short and long-term forecast models that are useful for aviation policy makers to mitigate, respectively, congestion delay occurrences and optimize infrastructure planning.

Regarding forecasting methods, several approaches have been considered to predict air transport demand. Among the most commonly used approaches three are worth highlighting: causal econometric, time series and artificial intelligence. The econometric approach seeks to identify relationships between demand-related factors (e.g. total air passengers) and social, economic, and service-related factors. The time series approach relies on historical data series to generate forecasts making use of the correlation between present and past observations. The artificial intelligence approach are computationally intensive techniques that tries to learn and reproduce patterns that are not always obvious in order to make forecasts.

Regarding time series approaches, Grubb and Mason (2001) presented a modified version of the Holt Winters method called Holt Winters with damped trend. The authors considered monthly time series of total air passengers at UK airports to demonstrate that their approach improved forecasting performance for long lead times. One interesting feature of their method is that it allows generating low, medium and high scenarios by just varying the future trend. Another forecasting application was developed by Chin and Tay (2001). The application predicts the probability of survival for asian airlines using an adapted Markov model that take into account the relationship between airline growth and profitability. Forecast models have also been used to evaluate official forecasts. Samagaio and Wolters (2010) used auto-regressive and exponential smoothing methods to make independent forecasts for the total number of passengers at Lisbon airport. When compared to the forecasts made by the government they concluded the official ones were too optimistic.

Regarding causal and econometric modelling, an application presented by Njegovan (2005) uses leading indicators such as macroeconomic variables as input for a Probit model to predict short-term shifts in demand for business travels by air to and from the United Kingdom. The forecasts generated by his approach were shown to be more precise in comparison with the benchmark linear model. With regard to sensitive events, Lai and Lu (2005) analyzed the impact of September 11 on air travel demand in the United States. The authors developed an intervention model to show that there was a significant impact during 1 month, for domestic demand, and during 2 months, for international demand. The model was also used to make forecasts and then compared with the ones generated by an ARIMA model. The superiority of the intervention model was proved. Regarding specifically the United States, Carson et al. (2011) analyze whether it is better to forecast the air travel demand using aggregated data at a national level or to aggregate the resulting forecasts of individual airports.

Considering artificial intelligence approaches, Alekseev and Seixas (2009) recurred to artificial neural networks to develop a multivariate hybrid approach to forecast air transportation demand in Brazil and showed that their approach was better than an econometric approach. Specifically about city-pairs, Kotegawa et al. (2010) consider an Artificial Neural Network Model along with logistic regression algorithms to forecast the probability of unconnected city-pairs being connected in the future by an air route. Grosche et al. (2007), address the issue of forecasting air passenger volume between already connected city-pairs using gravity models. More recently, a combination of methods was proposed by Xiao et al. (2014). The authors put a high effort on developing a Neuro Fuzzy method based on Singular Spectral Analysis. The study uses data from the Hong Kong International Airport to show that the approach was capable of producing better forecasts when compared with several methods and models like ARIMA, Multi-Layer Perceptron, Wavelet Neural Network, Takagi-Sugeno-Kang Recurrent Fuzzy System, Classical Decomposition and Singular Spectral Analysis.

The literature review resulted in no evidence, as far as we are aware, of the application of a combined approach of Bootstrap aggregating (Bagging) and time series forecasting methods to predict air transport demand. It is our belief that this gap is worth pursuing, as the results of such combined approach were promising in other fields. See Zontul et al. (2013) and Hillebrand and Medeiros (2010) for examples. Thus, Section 3 describes the methodology we are proposing.

3. Methods

The Bootstrap aggregating (Bagging), is a well-known machine learning technique, proposed by Breiman (1996). The objective is to generate multiple versions of a predictor using Bootstrap and then use them to get an aggregated predictor. Despite the good results in the field of Machine Learning, there are just a few papers using Bagging to improve accuracy in time series forecasting. In most of them, the authors have demonstrated, majorly with econometric applications, that the combination of techniques produces large improvements in forecast accuracy.

The approaches adopted to combine Bagging and time series vary from author to author since the combination of techniques imposes a previous choice of methods. Considering Bagging and exponential smoothing, there are only two methods currently developed: The method created by Cordeiro and Neves (2009) and more recently, the one from Bergmeir et al. (2016). The later presented a new way to perform Bagging with time series that leads to better and more stable forecasting results than the former. Bergmeir et al. (2016) tested their approach on time series from the M3 competition, which has 3003 time series from many fields (eg. macroeconomics, demographics, industry etc), and is the main dataset to evaluate and compare time series forecasting methods, see Makridakis and Hibon, 2000. The authors' results are very impressive, since, considering monthly time series, their approach was able to beat all other contestants. That led us to believe that several industries may benefit from the same approach.

Next, we briefly describe a generic way of performing Bagging in time series. We also provide specific details about the methods combined in this paper. Our methodology is aligned with the work of Bergmeir et al. (2016) with some specific details. The approach is designated Bagging Holt Winters, as it combines Bootstrap aggregating with Holt Winters. The methodology involves 4 steps as described:

3.1. *Step 1 — decomposition*

–Decompose the time series into three components: seasonal, trend and remainder;

There are several methods to decompose time series. In this work, the Seasonal-Trend decomposition using Loess (STL decomposition) is adopted. The main idea of the method is to apply a sequence of smoothing operations based on Locally Weighted Regression - Loess (for details see Cleveland et al., 1990). According to Hyndman and Athanasopoulos (2013), the method has some interesting features, such as the possibility to not only change the seasonal component over time but also to control the rate of the changes and the smoothness of the trend-cycle component.

3.2. *Step 2 — simulation*

- Generate 100 new versions of the remainder;
- Add back the seasonal and trend components to each of the 100 new versions of the remainders;

New versions of the remainder component are generated using Bootstrap (for details see Efron, 1979). When applying the Bootstrap it is important to take into account that the Remainder component can still be serially correlated. When that happens, the classical procedure is to maintain the dependency structure of the data by breaking it into blocks and resample the blocks. Several methods make use of this idea. Among the most common we can cite Non Overlapping Block Bootstrap (Carlstein, 1986), Circular Block Bootstrap, Stationary Block Bootstrap (Politis and Romano, 1992, 1994) and the method used in this work, Moving Block Bootstrap - MBB (Kunsch, 1989).

3.3. *Step 3 — forecasting*

- Apply a forecasting method to generate forecasts for the 100 time series;

Although there are many predicting methods available to perform forecasts (e.g. SARIMA, Neural Nets etc.), due to strong seasonal patterns detected in the series, the Holt Winters method (Holt, 1957; Winters, 1960) is used. The method belongs to a class of exponential smoothing methods that aims to capture the behavior of the time series, separating it in trend, season and error terms. Hyndman et al. (2002) used the state space framework to demonstrate that the method has a solid theoretical background.

The Holt Winters Additive method can be defined as follows:

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{1}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{3}$$

$$\hat{y}_{t+h} = l_t + hb_t + s_{t-m+h} \tag{4}$$

The Holt Winters Multiplicative method can be defined as follows:

$$l_t = \alpha\frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{5}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{6}$$

$$s_t = \gamma\frac{y_t}{l_{t-1} - b_{t-1}} + (1-\gamma)s_{t-m} \tag{7}$$

$$\hat{y}_{t+h} = (l_t + hb_t)s_{t-m+h} \tag{8}$$

where l_t, b_t, s_t are, respectively, the level component, trend component and seasonal component at time t. m stands for the period of the seasonality and h denotes the forecast horizon. Constants α, β and γ are the smoothing parameters.

3.4. *Step 4 — aggregation*

- Aggregate the forecasts to generate the final result.

There are several possible aggregating measures, e.g. simple mean, median, weighted mean etc. It is important to have in mind that depending on the kind of forecasting distribution the results can vary a lot, especially in the presence of outliers. The median is the aggregating measure adopted as it is less sensitive to outliers.

The combination of specific techniques used in the generic framework is called Bagging Holt Winters, since it combines Bootstrap aggregating and Holt Winters. It is important to notice two differences from the original work of Bergmeir et al. (2016). The first one is related to the fact that we did not use Box Cox transformation. The second difference is in the use of Holt Winters instead of the entire class of exponential smoothing methods, called ETS by the authors. Although both were tested during the study, the results generated considering the transformation or ETS did not improve forecast accuracy. However, please note that the choices that we have made are particular cases of the original approach since one of the possible Box Cox transformations is the identity and Holt Winters is part of the ETS family of models. Fig. 1 shows a flowchart of the approach.

4. Data description

The datasets used in this study involve air passenger demand at national scale. In total, we considered datasets from 14 countries, of which 11 are in Europe - Belgium, Czech Republic, Denmark, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain and the United Kingdom - and the other three are Australia, Brazil and the United States of America. The period considered runs from January 2007 to December 2014, except for Ireland and the United Kingdom, for which we used data from January 2003 to December 2014. We considered data from January 2007 to December 2013 as training set (in-sample) and the observations from January 2014 to December 2014 as test set (out-of-sample).

For the European Countries, we used the monthly time series of total passengers carried. For Australia, it was considered the monthly time series of total passengers carried by international airlines to and from Australia. For Brazil, we considered the monthly time series of total passenger carried by brazilian airlines

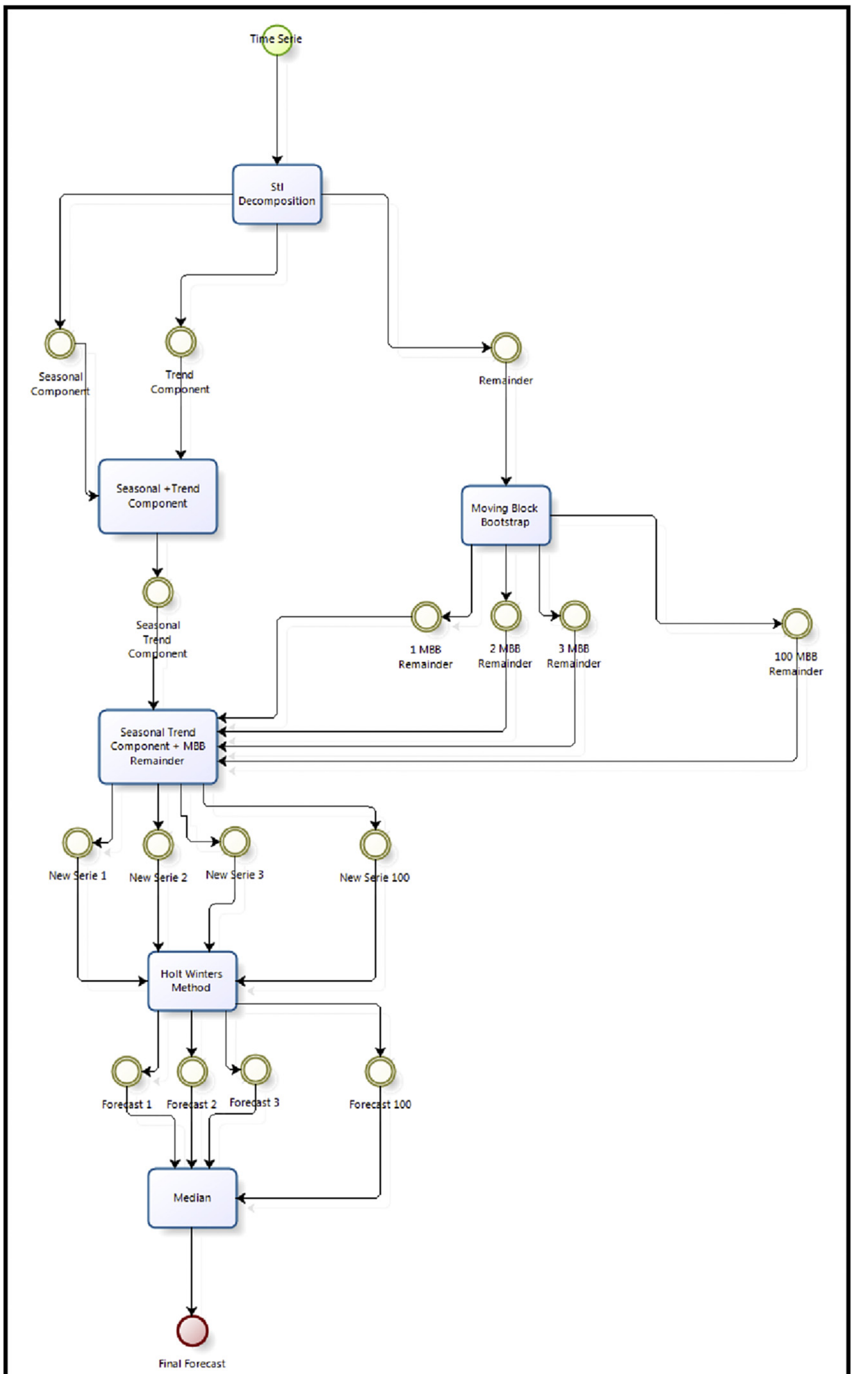

Fig. 1. Bagging Holt Winters flowchart.

and for the U.S.A. the monthly time series of total passenger enplanements.

The datasets were obtained online from EUROSTAT, for the European countries, from Bureau of Infrastructure, Transport and Regional Economics (BITRE) for Australia, from The National Civil Aviation Agency of Brazil (ANAC) for Brazil and from the Bureau of Transportation Statistics (BTS) for the USA.

Fig. 2 illustrates the 14 time series used in the study. Some comments are worth making at this point. There are perceived evolution trends among the 14 countries. While most countries exhibit demand growth during the analysis period, as it is confirmed by IATA, the growth rate is not homogeneous among all countries. Indeed, the growth is slower in developed markets as it is the case of Europe or USA. The latter, after a decrease in 2008, even exhibits stationary air passenger demand from 2011 onwards. The effects of the world economic crisis of 2008 in the air industry are visible in the time series. All countries exhibit a notorious passenger demand decrease between 2008 and 2010. In the following years, the crisis effects are still visible in the countries that were more affected by the crisis, Ireland, Spain, Greece, and U.K. Portugal, despite being one of the countries most affected by the economic crisis, managed to follow the northern Europe growth tendency with regard to air passengers' demand. The three non-European countries show different behaviors, as the economic reality felt in those countries was also different. The effect of the crisis in the USA lasted longer, which reflected in a stationary period for the air industry. Brazil lived a remarkable economic growth during the time period analyzed and consequently the air industry growth was above average. The effects of the crisis and other internalities only became visible in Brazil after 2014. Finally, Australia also followed the growth tendency of Brazil benefiting from the economic development lived in emerging economies located in the Asia-Pacific region. Despite the differences found in each country, it is clear that there is a strong seasonal pattern governing all time series.

The quality of the approach is evaluated using the Symmetric Mean Absolute Percentage Error (sMAPE), as defined by Makridakis (1993). The metric is largely used to evaluate time series forecasts

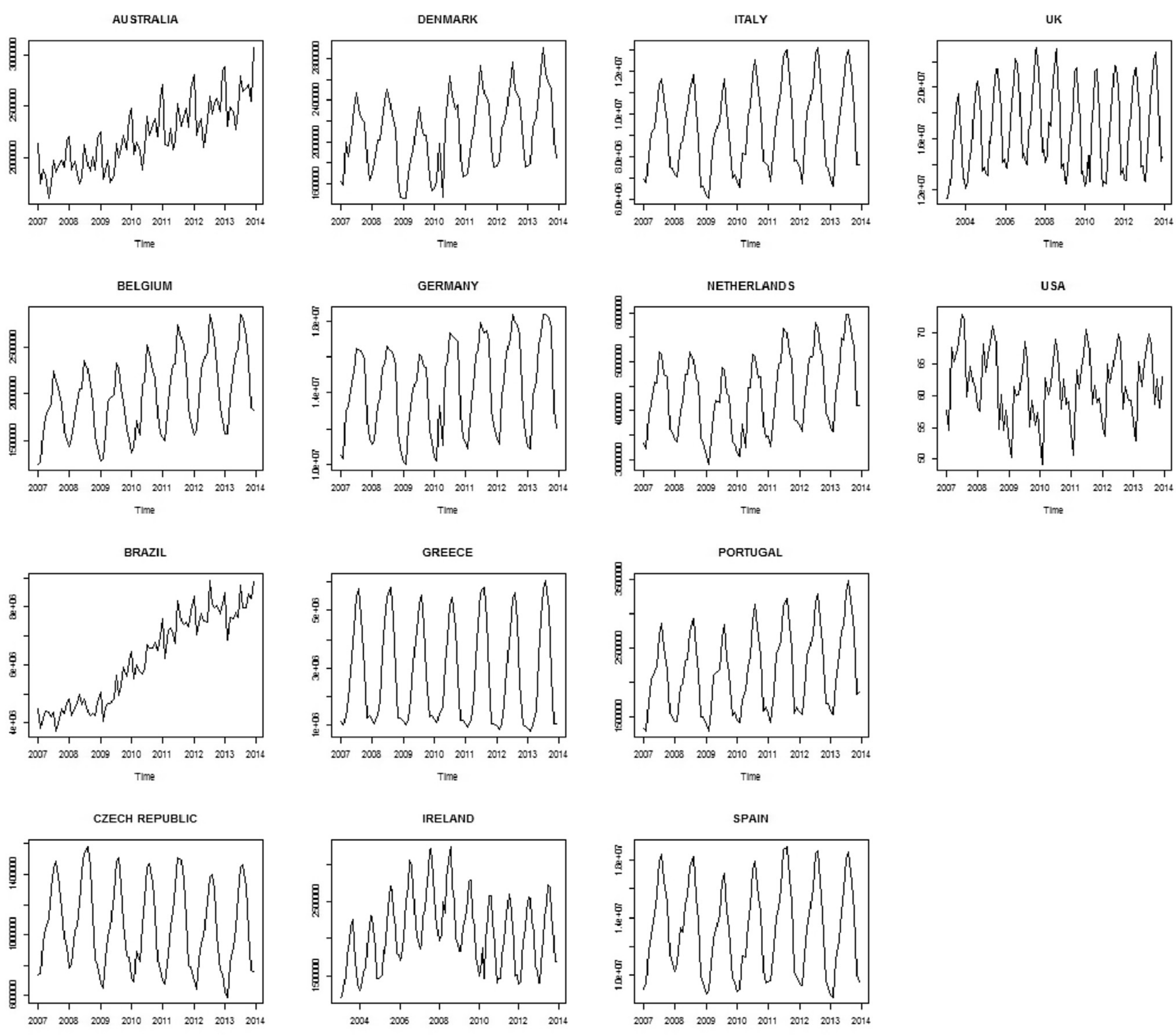

Fig. 2. Air Passenger demand by country.

and has as main advantages the fact that it gives symmetric penalties to negative and positive values and is a scale-free metric, making it possible to compare the results of time series with different scales, for further details see Makridakis, 1993, Makridakis and Hibon, 2000. The test set considered in the study covers data from January 2014 to December 2014. In total, 12 out of sample values were considered. The results were then compared to the forecasts obtained from traditional forecasting methods, SARIMA, Holt Winters, ETS, Seasonal Naive and the approach from Bergmeir et al. (2016), Bagged.BLD.MBB.ETS.

5. Forecasting results

The empirical results are summarized in Table 1. They evince that the combination of Bagging and Holt Winters (Bagging Holt Winters) substantially reduced sMAPE for all 14-country series when compared to the forecasts obtained with the three traditional methods. On average, Bagging Holt Winters reduced 31% of the Symmetric Mean Absolute Percentage Error in comparison with Bagged.BLD.MBB.ETS, 32% in comparison with Holt Winters, 37% in comparison with SARIMA, 38% in comparison with ETS and 43% in comparison with Seasonal Naive. It is important to note that the gain in accuracy was remarkably good in some countries, namely Brazil and USA where the sMAPE reductions reached more than 50% in comparison to Holt Winters alone. A visualization of the forecasts generated by Bagging Holt Winters plotted against the actual values can be seen in Fig. 3.

The gain in accuracy is remarkable as accurate forecasts are decisive for assertive profit/cost management and investment decisions and for the definition of aviation policies at a local or national scale. The time series used in this study are all at a national scale, but the same methodology can be applied for a single airport, for a group of airports or for a given route or set of routes. More accurate demand forecasts provide policy makers, both from public powers or private institutions, and airport operators better estimations of profit and cost and therefore less operating uncertainty.

The type of results obtained in this case study are of uttermost importance for identifying capacity need in the short term and therefore decide on national airport infrastructure and services provision strategies. These results are also very useful to reach an agreement between government, airport concessionaires and national regulation aviation institutes and create a common discussion platform to be presented in annual world forums such as World Routes, where all international leading airlines, airports and tourist authorities are present.

If forecast is applied locally, the benefits for private airports mean the maximization of profit, while for public airports a reduction of public expenses. It should be noted that both over and under predictions are noxious. The former makes operating unit costs higher (e.g., unnecessary staff, idle equipment) while the latter reduces the level of service (e.g., lack of staff, queues, higher waiting times). Benefits derive both from the airlines operation and from commercial concessions celebrated in the airport. The benefits regarding investment decisions are even higher as they are almost uniquely based on demand forecasts. The higher the accuracy the better the investments can be planned such that infrastructure does not strangle demand but also does not remain idle and commercial services offered at airports respond to travelers needs and provide adequate profit for the airport operator and service concessionaires.

6. Conclusion

Given the massive application of operation research techniques in the air industry, competitive advantage among players is sought in details. The optimization of processes and the corresponding costs are discussed at decimals scale. In this context, any contribution to reach more accurate demand forecasts is welcome.

This paper applies for the first time, as long as the authors are aware, a combination of the Bootstrap aggregating (Bagging) method with the exponential smoothing method Holt Winters to the air industry in order to predict future demand for air transportation. The combined methodology is designated as Bagging Holt Winters. The results obtained for prove that the methodology can improve forecast accuracy.

The empirical results show that the approach was capable of generating consistently highly accurate forecasts. When compared to forecasting benchmarks - SARIMA, Holt Winters, ETS, Bagged.BLD.MBB.ETS and Seasonal Naive - the Bagging Holt Winters method reduced sMAPE across 13 out of 14 time series considered in the study. It is our belief that equally satisfactory results may be reached to other countries and time series related to the air transport demand. Moreover, the methodology proposed has two important advantages, it is easy to implement and although Bagging can be slow depending on the number of replics generated by Bootstrap, the method can be easily parallelized, meaning that the approach takes just a few minutes to run. These results give us confidence to conclude that the Bagging Holt Winters methodology is an important forecast tool for the air industry, despite its gap in related literature.

Finally, as a methodological extension of this work, we plan to study the effects of the variance on the aggregated forecasts since it

Table 1
sMAPE out of sample. Best results for each country series are highlighted in bold.

Countries	Bagging Holt Winters		Holt Winters		Bagged.BLD.MBB.ETS	ETS	SARIMA	Seasonal Naive
	Multiplicative	Additive	Multiplicative	Additive				
Australia	1.71	2.28	2.01	2.22	1.63	**1.56**	1.94	5.55
Belgium	**3.73**	6.47	4.52	7.81	7.68	7.83	5.82	8.74
Brazil	**2.32**	2.76	4.80	4.30	2.54	3.21	3.89	6.06
Czech Republic	2.88	**1.74**	3.39	1.85	1.89	2.42	3.57	2.39
Denmark	**2.97**	4.85	4.39	6.20	5.22	5.97	4.49	5.80
Germany	**2.66**	3.40	3.68	4.53	3.63	3.74	3.36	3.11
Greece	**8.81**	13.63	19.76	17.63	14.05	18.63	16.90	14.51
Ireland	5.73	**4.98**	7.48	6.45	5.80	7.38	6.68	7.32
Italy	**2.54**	3.86	4.70	5.71	3.91	4.47	3.17	2.77
Netherlands	**1.63**	2.71	2.36	4.04	3.89	4.85	3.88	4.87
Portugal	**3.09**	6.83	5.01	8.98	6.59	6.67	4.98	8.98
Spain	**3.90**	4.65	5.19	5.36	4.83	5.75	4.56	4.58
United Kingdom	**2.55**	3.22	3.51	4.31	3.97	4.97	4.09	4.49
United States	**1.09**	1.75	2.25	1.23	2.16	1.37	8.22	2.54

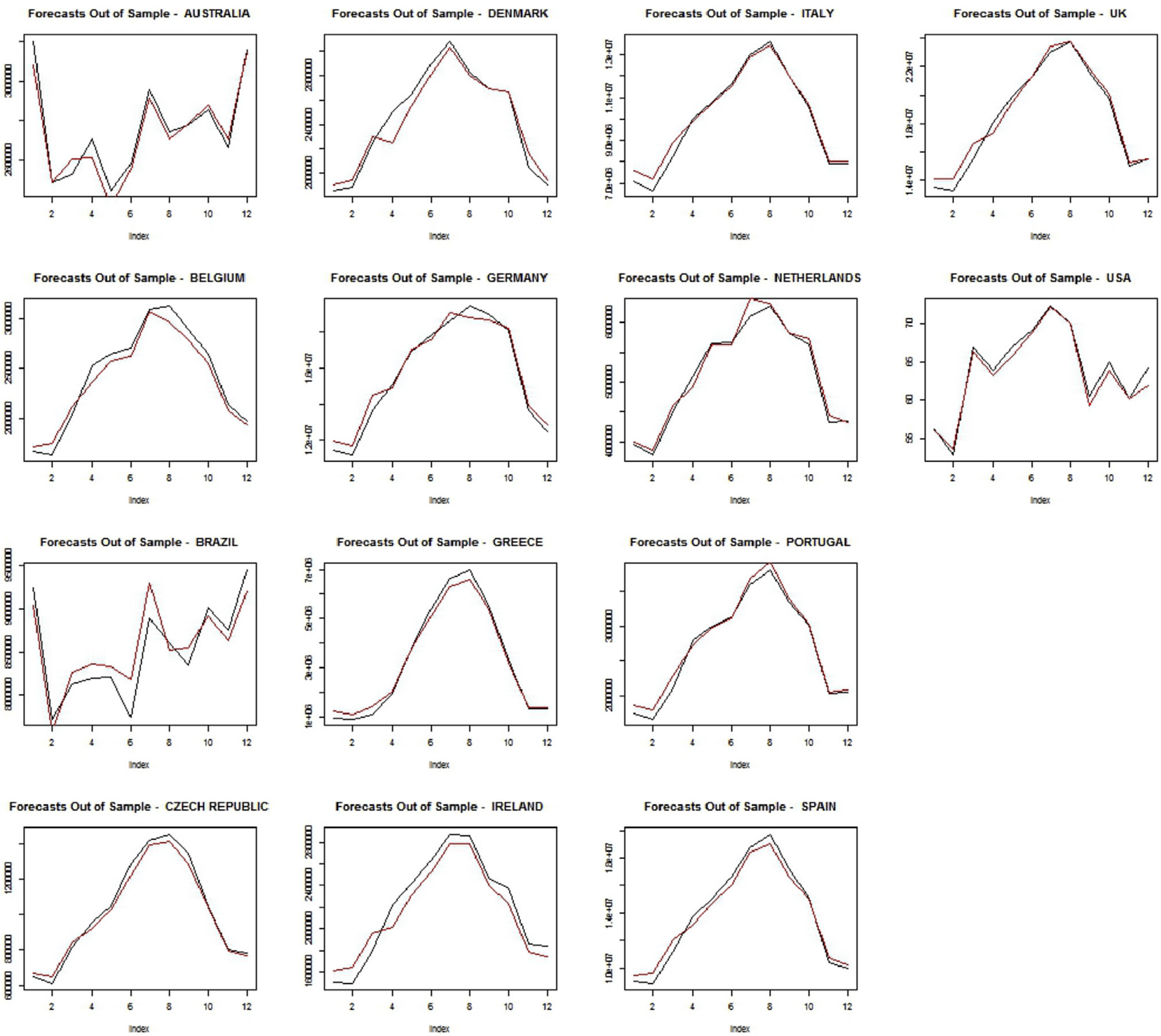

Fig. 3. Forecasts out of sample by country.

can potentially impact the forecast error. The study of other decomposition and forecasting methods to combine with Bagging is also a logical extension of this work.

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