Common Trends in International Tourism Demand: Are They Useful to Improve Tourism Predictions?

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ABSTRACT. This study evaluates whether modelling the existing common trends in tourist arrivals from all visitor markets to a specific destination can improve tourism predictions. While most tourism forecasting research focuses on univariate methods, we compare the performance of three different Artificial Neural Networks in a multivariate setting that takes into account the correlations in the evolution of inbound international tourism demand to Catalonia (Spain). We find that the multivariate multiple-output approach does not outperform the forecasting accuracy of the networks when applied country by country, but it significantly improves the forecasting performance for total tourist arrivals.

KEY WORDS: Tourism demand, forecasting, multivariate, multiple-input multiple-output (MIMO), artificial neural networks

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1. *Introduction*

Tourism demand forecasting has become essential in one of today's fastest growing economic activities. Song and Li (2008) have acknowledged the importance of applying new approaches to tourism demand forecasting in order to improve the accuracy and the performance of the methods of analysis. Whilst most research efforts focus on conventional tourism forecasting methods (Gounopoulos, Petmezas, & Santamaria, 2012) or a combination of them (Chan, Witt, Lee, & Song, 2010), in recent years the availability of more advanced forecasting techniques and the requirement for more accurate forecasts of tourism demand have led to a growing interest in Artificial Intelligence (AI) techniques (Wu, Law, & Xu, 2012; Cang, 2013; Pai, Hung, & Lin 2014). The suitability of AI models to handle nonlinear behaviour is one of the reasons why Artificial Neural Networks (ANNs) are increasingly used for forecasting purposes.

In spite of the increasing interest in AI methods for time series forecasting, very few studies compare the accuracy of different ANN architectures for tourism demand forecasting. This study seeks to break new ground by comparing the performance of three different ANN models in a multivariate setting that takes into account the common trends in inbound international tourism demand shared by all visitor markets to a specific destination. We use three ANNs: the multi-layer perceptron (MLP) network, the radial basis function (RBF) network and the Elman network. ANNs are able to learn from experience. Each ANN architecture handles information in a different manner, so by comparing the different models we can evaluate the impact of alternative ways of processing data on forecast accuracy.

Given that univariate specifications are limited and unable to capture dynamic interrelationships between different countries of origin, we analyse whether a multivariate approach, in which information about tourist arrivals from all origin countries is simultaneously used, provides useful for forecasting purposes. With this aim, we design a multiple-output setting and compare the performance of three different ANN models. In order to evaluate the forecasting performance of the multivariate ANNs we also compare the forecasting accuracy of multiple-output predictions to those obtained country by country. To our knowledge, this is the first study to model tourism demand incorporating the common trends in international tourist arrivals form all visitor markets to a specific destination and to analyse whether this approach allows to improve the forecasting performance of ANN models.

The present study deals with tourist arrivals to Catalonia, which is a region of Spain. After France and the United States, Spain is the third most important destination of the world with almost 65 million tourist arrivals in 2014. Catalonia received 25% of all inbound tourist demand to Spain. Tourist spending in Catalonia grew by 14% in 2014. Barcelona is the capital of Catalonia, and the third most important destination in Europe in terms of tourist spending after London and Paris. It follows that tourism is one of the fastest growing industries in Catalonia, accounting for 12% of GDP and providing employment for 15% of the working population. These figures show the importance of accurate forecasts of tourism volume at the destination level for policy makers and professionals in the tourism industry. Capó, Riera, and Rosselló (2007) and Balaguer and Cantavella-Jordá (2002) have shown the important role of tourism in the Spanish long-run economic development.

The article proceeds as follows. The next section reviews the literature on tourism demand forecasting with AI-based techniques. Then we present the different NN architectures used in the analysis and describe the data. In the next section, results of the out-of-sample forecasting competition are discussed. Finally, the last section provides a summary, a discussion of the implications, and potential lines for future research.

2. *Tourism demand forecasting with AI-based techniques*

A growing body of literature has focused on tourism demand forecasting, but most research efforts apply conventional forecasting methods, either casual econometric models (Cortés-Jiménez & Blake, 2011; Page, Song, & Wu, 2012, Lin, Liu & Song, 2015), time series models (Chu, 2008, 2011; Assaf, Barros, & Gil-Alana, 2011; Gounopoulos, Petmezas, & Santamaria, 2012), or a combination of them (Shen, Li, & Song, 2008; Coshall & Charlesworth 2010). See Song, Dwyer, Li and Cao (2012) and Peng, Song, and Crouch (2014) for a thorough review of tourism economics research and tourism demand forecasting studies. Nevertheless, the need for more accurate forecasts has led to an increasing use of AI techniques, such as fuzzy time series models and support vector machines (SVMs), or a mix of them (Pai, Hung, & Lin 2014; Cang & Yu 2014), in order to obtain more refined predictions of tourist arrivals at the destination level.

Yu and Schwartz (2006) and Huarng, Moutinho and Yuo (2007) use fuzzy time series models in predicting annual U.S. tourist arrivals and monthly tourism demand in Taiwan respectively. Law, Goh and Pine (2008) apply a rough sets algorithm to forecast Japanese tourism demand for Hong Kong. The use of genetic algorithms for parameter selection has led to increased use of support vector machines (SVMs) (Pai & Hong, 2005) and their regression version (Chen & Wang, 2007; Chen, 2011; Hong, Dong, Chen, & Wei, 2011). In a recent meta-analysis of published tourism forecasting studies, Kim and Schwartz (2013) find that forecast accuracy is closely associated with data characteristics. The fact that ANNs are data-driven procedures that learn from past experience explain the growing interest in ANNs for tourism demand forecasting (Lin, Chen, & Lee, 2011; Teixeira & Fernandes, 2012; Claveria & Torra, 2014).

ANNs can be classified into two major types of architectures: feed-forward networks and recurrent networks. MLP networks are the most widely used feed-forward topology in tourism demand forecasting (Pattie & Snyder, 1996; Uysal & El Roubi, 1999; Law, 2000, 2001; Tsaur, Chiu, & Huang 2002; Zhang & Qi, 2005). A class of multi-layer feed-forward architecture with two layers of processing is the radial basis function (Broomhead & Lowe, 1988). RBF networks have the advantage of not suffering from local minima in the same way as MLP networks, which explains their increasing use in many fields. The first study to implement a RBF ANN for forecasting tourism demand is that of Kon and Turner (2005), who use a RBF network to forecast arrivals to Singapore. Cang (2014) generates predictions of UK inbound tourist arrivals and combines them in non-linear models. Çuhadar, Cogurcu, and Kukrer (2014) compare the forecasting performance of RBF and MLP NNs to predict cruise tourist demand at the destination level (Izmir, Turkey).

Recurrent networks are models with bidirectional data flow which allow for a temporal feedback from the outer layers to the lower layers. This feature is specially suitable for time series modelling. A special case of recurrent network is the Elman network (Elman, 1990). Whilst MLP networks are increasingly used with forecasting purposes, Elman neural networks have been scarcely used with forecasting purposes. The first study that uses Elman ANNs for tourism demand forecasting is that of Cho (2003), who applies the Elman architecture to predict the number of arrivals from different countries to Hong Kong.

Multivariate approaches to tourist demand forecasting are also few and have yielded mixed results. Athanasopoulos and Silva (2012) compare the forecasting accuracy of exponential smoothing methods in a multivariate setting against univariate alternatives. They use international tourist arrivals to Australia and New Zealand and find that multivariate models improve on forecast accuracy over the univariate alternatives. Contrary to what could be expected, du Preez and Witt (2003) find that multivariate time series models did not generate more accurate forecasts than univariate time series models.

With regard to studies on tourism in Spain at regional level, there have been several articles published in recent years (Aguiló & Rosselló, 2005; Roselló, Aguiló, & Riera, 2005; Garín-Muñoz & Montero-Marín, 2007; Bardolet & Sheldon, 2008; Santana-Jiménez & Hernández, 2011; Nawijn & Mitas, 2012; Andrades-Caldito, Sánchez-Rivero, & Pulido-Fernández, 2013; Cirer-Costa, 2014).

Concerning tourism demand forecasting, Palmer, Montaño, and Sesé (2006) design a MLP neural network to forecast tourism expenditure in the Balearic Islands. Medeiros, McAleer, Slottje, Ramos, and Rey-Maquieira. (2008) develop a NN-GARCH model to estimate demand for international tourism also in the Balearic Islands. Bermúdez, Corberán-Vallet, and Vercher (2009) calculate prediction intervals for hotel occupancy in three provinces in Spain by means of a multivariate exponential smoothing. Gil-Alana (2010) models international monthly arrivals in the Canary Islands using different time-series approaches to analyse the degree of persistence of the series. Claveria and Datzira (2010) use consumer expectations derived from tendency surveys to improve forecasts of tourism demand for Catalonia. Guizzardi and Stacchini (2015) also make use of business sentiment indicators form tendency surveys for real-time forecasting of hotel arrivals at a regional level, improving the forecasting accuracy of structural time series models.

3. Methodology

3.1. Neural Network Models

ANNs emulate the processing of human neurological system to identify related spatial and temporal patterns from historical data. ANNs learn from experience and are able to capture functional relationships among the data when the underlying process is unknown. The data generating process of tourist arrivals is too complex to be specified by a single linear algorithm, which explains the great interest that ANNs have aroused for tourism demand forecasting.

ANNs are composed of interconnected processing units called neurons and can also be classified into feed-forward networks and recurrent networks depending on the connecting patterns of the different layers of neurons. In feed-forward networks the information runs only in one direction, whilst in recurrent networks there are feedback connections from outer layers of neurons to lower layers of neurons. ANNs can also be classified according to their learning paradigm: supervised learning and non-supervised learning. MLP networks are supervised learning models, while RBF networks, combine both learning methods (hybrid learning). The MLP network is the most widely used feed-forward topology in tourism demand forecasting.

In this study we use three ANN models: MLP, RBF and Elman networks. Equations (1), (2) and (3) respectively describe the input/output relationship of the three architectures:

MLP

$$y_t = \beta_0 + \sum_{j=1}^{q} \beta_j g\left(\sum_{i=1}^{p} \varphi_{ij} x_{t-i} + \varphi_{0j} \right)$$

$$\left\{ x_{t-i} = \left(1, x_{t-1}, x_{t-2}, \cdots, x_{t-p}\right)', i = 1, \ldots, p \right\} \tag{1}$$

$$\left\{ \varphi_{ij}, i = 1, \ldots, p, j = 1, \cdots, q \right\}$$

$$\left\{ \beta_j, j = 1, \ldots, q \right\}$$

RBF

$$y_t = \beta_0 + \sum_{j=1}^{q} \beta_j g_j\left(x_{t-i}\right)$$

$$g_j\left(x_{t-i}\right) = \exp\left(- \frac{\sum_{j=1}^{p} \left(x_{t-i} - \mu_j\right)^2}{2\sigma_j^2} \right) \tag{2}$$

$$\left\{ x_{t-i} = \left(1, x_{t-1}, x_{t-2}, \ldots, x_{t-p}\right)', i = 1, \ldots, p \right\}$$

$$\left\{ \beta_j, j = 1, \ldots, q \right\}$$

Elman

$$
\begin{aligned}
&y_t = \beta_0 + \sum_{j=1}^{q} \beta_j z_{j,t} \\
&z_{j,t} = g\left(\sum_{i=1}^{p} \varphi_{ij} x_{t-i} + \varphi_{0j} + \delta_{ij} z_{j,t-1} \right) \\
&\left\{ x_{t-i} = \left(1, x_{t-1}, x_{t-2}, \cdots, x_{t-p}\right)', i = 1, \ldots, p \right\} \\
&\left\{ \varphi_{ij}, i = 1, \ldots, p, j = 1, \ldots, q \right\} \\
&\left\{ \beta_j, j = 1, \ldots, q \right\} \\
&\left\{ \delta_{ij}, i = 1, \ldots, p, j = 1, \ldots, q \right\}
\end{aligned}
\tag{3}
$$

Where y_t is the output vector of the MLP at time t; g is the nonlinear function of the neurons in the hidden layer; x_{t-i} is the input value at time $t-i$ where i stands for the number of lags that are used to introduce the context of the actual observation; q is the number of neurons in the hidden layer; φ_{ij} are the weights of neuron j connecting the input with the hidden layer; and β_j are the weights connecting the output of the neuron j at the hidden layer with the output neuron.

In the RBF specification g_j is the activation function, which usually has a Gaussian shape; μ_j is the centroid vector for neuron j; and the spread σ_j is a scalar that measures the width over the input space of the Gaussian function and it can be defined as the area of influence of neuron j in the space of the inputs. In the Elman network, $z_{j,t}$ is the output of the hidden layer neuron j at the moment t and δ_{ij} are the weights that correspond to the output layer and connect the activation at moment t. Further information about these three ANN architectures can be found in Bishop (1995) and Haykin (1999).

Once the topology of the neural network is decided, the parameters of the network are estimated by means of the Levenberg-Marquardt algorithm. Another aspect to be taken into account, is the fact that the training is done by iteratively estimating the value of the parameters by local improvements of the cost function. To avoid the possibility that the search for the optimum value of the parameters finishes in a local minimum, we have used a multi-starting technique that initializes the neural network several times for different initial random values and returns the best result.

In order to assure a correct performance of the RBF models, the number of centroids and the spread of each centroids have to be selected before the training phase. In this study the training was done by adding the centroids iteratively with the spread parameter fixed. Then a regularized linear regression was estimated to compute the connections between the hidden and the output layer. Finally, the performance of the network was computed on the validation data set. This process was repeated until the performance on the validation database ceased to decrease.

There are different strategies for estimating the parameters of the Elman neural network. In this study, the training of the network was done by back-propagation through time, which is a generalization of back-propagation for feed-forward networks. The parameters of the Elman neural network are estimated by minimizing an error cost function. In order to minimize total error, we use gradient descent. A potential problem with gradient descent for standard recurrent architectures is that error gradients vanish exponentially quickly with the size of the time lag. Therefore recurrent NN cannot be easily trained for large numbers of neuron units.

3.2. Data

Data on tourists arrivals (first destinations) are provided by the Institute of Tourism Studies (IET) and are available at the Statistical Institute of Catalonia (IDESCAT). Data include the monthly number of tourists arriving from each visitor market over the time period 2001:01 to 2012:07. Table 1 shows a descriptive analysis of the data. It can be seen that the first four visitor markets (France, the United Kingdom, Belgium and the Netherlands and Germany) account for more than half of the total number of tourist arrivals to Catalonia. Nevertheless, when comparing the growth rates (Fig. 1), Russia and the Scandinavian countries experienced the highest growth in tourist arrivals during this period. Russia is also the country that presents the highest relative dispersion and the highest levels of Skewness and Kurtosis.

We use the year-on-year rates of the seasonally adjusted series to eliminate both linear trends as well as seasonality. These series are obtained using a Census X12 filter. Given the common patterns displayed by most countries we test for multicointegration using Johansen's (1988, 1991) maximum eigenvalue test. The maximum eigenvalue test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r+1$ cointegrating vectors. In Table 2 we present the results of the unrestricted cointegration eigenvalue test. It can be seen that all different markets present correlated accelerations. The fact that the evolution of tourist arrivals is multicointegrated led us to use the correlations in the evolution of tourist arrivals between all different visitor markets.

Table 1. Descriptive analysis of tourist arrivals (levels)

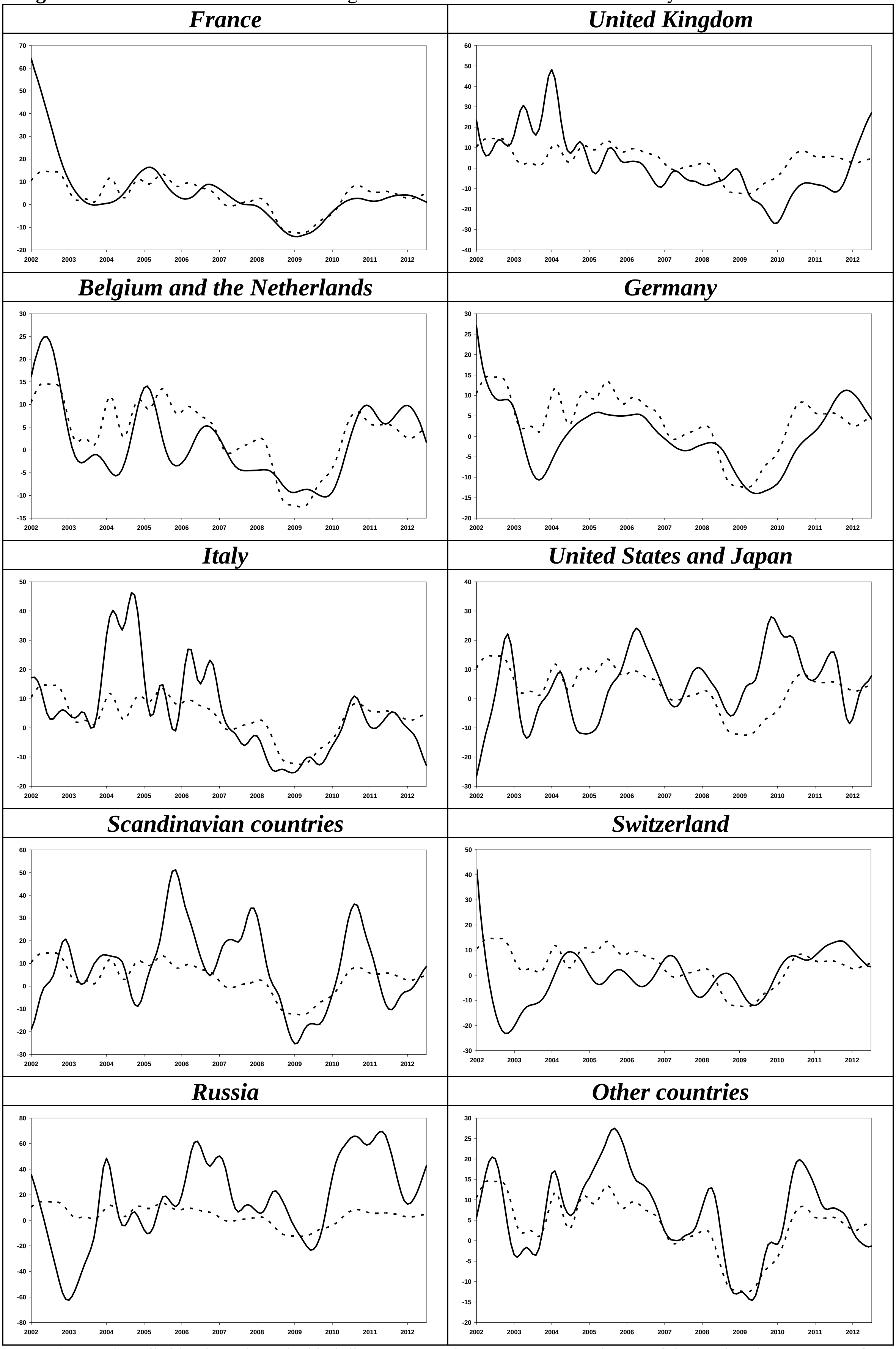
Country	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
France	59,886	869,535	300,137	161,364	1.22	4.35
United Kingdom	34,128	293,005	152,223	70,762	0.10	1.78
Belgium and NL	23,818	467,505	118,974	100,198	1.74	5.61
Germany	26,588	258,600	112,126	53,834	0.37	2.26
Italy	24,077	271,975	83,805	42,335	1.96	7.76
US and Japan	20,984	131,089	60,795	22,869	0.80	3.53
Scandinavian countries	7,439	99,879	38,155	19,790	0.74	3.27
Switzerland	8,867	98,924	28,120	14,173	1.42	6.83
Russia	1,687	162,505	23,486	27,998	2.38	9.64
Other countries	101,894	442,597	246,241	76,311	0.36	2.38
Total	360,281	2,302,855	1,164,061	496,152	0.55	2.45

Table 2. Cointegration test results. Unrestricted Cointegration Rank Test – Maximum eigenvalue

Hypothesized number of CE(s)	Type of test			
	Allow for linear deterministic trend in data			
	Intercept in CE		Intercept in CE	
	Test VAR		No trend in VAR	
	Maximum Eigenvalue	Critical value	Maximum Eigenvalue	Critical value
$H_0 : r = 0$ *	227.2916	64.50472	227.4935	68.81206
$H_0 : r \leq 1$ *	152.9724	58.43354	181.3408	62.75215
$H_0 : r \leq 2$ *	133.6029	52.36261	134.5977	56.70519
$H_0 : r \leq 3$ *	105.6646	46.23142	129.6588	50.59985
$H_0 : r \leq 4$ *	86.6518	40.07757	97.79509	44.4972
$H_0 : r \leq 5$ *	77.79057	33.87687	86.65054	38.33101
$H_0 : r \leq 6$ *	65.28306	27.58434	77.78193	32.11832
$H_0 : r \leq 7$ *	49.773	21.13162	64.52919	25.82321
$H_0 : r \leq 8$ *	36.80542	14.2646	49.7264	19.38704
$H_0 : r \leq 9$ *	10.98843	3.841466	35.64879	12.51798

1. Estimation period 2001:01-2012:07.
2. * Denotes rejection of the hypothesis at the 0.05 level **MacKinnon-Haug-Michelis (1999) p-values.

Figure 1. Growth rates of tourists coming to Catalonia: from each visitor country vs. total arrivals



1. Source: Compiled by the author. The black line represents the year-on-year growth rates of the trend-cycle component of tourist arrivals to Catalonia from each visitor country. The dotted line represents the year-on-year growth rates of the trend-cycle component of total inbound tourism demand to Catalonia.

4. *Empirical results*

In this section we design a multivariate multiple-output setting in which forecasts of tourist arrivals for all countries are obtained simultaneously, and we compare the results to those of a single-output approach, in which models are estimated country by country. To do so we carry out an out-of-sample forecasting competition between three different ANN models (MLP, RBF and Elman) using both a univariate (single-output) and a multivariate (multiple-output) architectures.

Following Bishop (1995) and Ripley (1996), we divided the collected data into three sets: training, validation and test sets. This division is done in order to assess the performance of the network on unseen data. Based on these considerations, the first sixty monthly observations (from January 2001 to January 2006) are selected as the initial training set, the next thirty-six (from January 2007 to January 2009) as the validation set and the last 20% as the test set.

To summarize the results of the out-of-sample competition and rank the methods according to their forecasting performance for different forecast horizons (1, 3 and 6 months) we compute the Mean Absolute Error (MAE) statistic for forecast accuracy. The results of our forecasting out-of-sample competition are shown in Table 3. We also apply the Diebold-Mariano test (Table 4) for significant differences between each two competing series (single vs. multiple-output) for each forecast horizons in order to assess the value of the different models and settings.

When comparing the forecasting performance of the different neural architectures, RBF networks show lower MAE values than MLP and Elman networks. An explanation for the better forecasting performance of RBF networks has to do with the fact that in this type of architecture, data are clustered. On the other extreme, Elman networks systematically obtain the highest MAE values. This result suggests that the feedback topology of the Elman network could not capture the specificities of the time series. The fact that the number of training periods had to be low in order to maintain the stability of the network suggests that the Elman architecture requires longer time series.

Table 3. MAE (2010:04-2012:02).

	Univariate ANN models			Multiple-output ANN models		
France	MLP	RBF	Elman	MLP	RBF	Elman
1 month	0.42	*0.38**	19.49	4.31	4.60	20.32
3 months	2.72	1.26	16.00	7.89	2.04	30.99
6 months	5.40	2.92	12.66	6.44	*1.48**	22.11
United Kingdom						
1 month	*2.77*	5.15	17.40	8.60	*4.58*	24.66
3 months	8.48	7.48	15.59	22.59	9.85	33.27
6 months	17.22	8.54	13.38	16.77	11.68	23.41
Belgium and the NL						
1 month	7.96	5.86	15.52	4.19	*3.89*	14.43
3 months	5.46	*3.29*	13.72	6.96	6.63	15.37
6 months	9.86	4.02	11.91	10.49	8.05	12.39
Germany						
1 month	7.95	7.48	15.03	*2.85*	4.77	10.43
3 months	5.07	4.12	16.96	5.34	5.81	13.82
6 months	5.68	*3.36*	9.25	7.71	6.41	11.34
Italy						
1 month	*1.45*	1.60	10.12	15.49	4.33	20.37
3 months	4.11	4.31	14.12	19.79	4.48	25.01
6 months	7.80	8.88	13.53	25.27	*3.96*	32.49
US and Japan						
1 month	5.12	*4.09*	12.94	8.45	*6.78*	17.50
3 months	8.28	7.62	20.39	14.02	10.00	19.29
6 months	10.01	9.78	13.79	15.90	10.06	19.40
Scandinavian countries						
1 month	4.10	*3.90*	18.84	16.36	*6.26*	26.34
3 months	9.85	8.99	16.70	26.95	14.15	30.29
6 months	13.38	12.75	23.33	30.20	14.42	34.02
Switzerland						
1 month	11.49	10.63	21.44	*5.38*	6.00	17.03
3 months	6.81	5.27	11.94	9.21	9.92	13.56
6 months	7.26	*5.05*	22.77	12.20	10.00	16.82
Russia						
1 month	29.74	*26.96*	34.59	23.39	*13.45*	41.46
3 months	34.47	29.33	32.57	39.12	35.81	48.67
6 months	35.39	33.68	49.63	50.01	43.01	60.74
Other countries						
1 month	2.64	*2.44*	11.11	9.73	*4.09*	13.51
3 months	5.88	4.59	13.24	14.40	4.98	17.93
6 months	8.02	6.92	12.03	17.27	5.90	18.35
Total						
1 month	*3.27*	3.41	15.64	6.64	*2.52*	8.25
3 months	5.98	3.75	13.37	10.49	2.53	11.07
6 months	14.72	3.45	10.88	8.68	2.67	9.78

1. *Italics:* best model for each country
2. * Best model

Table 4. Diebold-Mariano loss-differential test statistic for predictive accuracy

	MLP	RBF	Elman
	Single vs. Multiple-output	Single vs. Multiple-output	Single vs. Multiple-output
France			
1 month	*-6.58*	*-5.79*	-0.14
3 months	*-4.03*	*-2.95*	*-2.46*
6 months	-0.47	*2.82*	-1.87
United Kingdom			
1 month	*-5.45*	0.62	*-2.04*
3 months	*-2.99*	*-2.97*	*-2.16*
6 months	0.08	*-2.50*	*-3.08*
Belgium and the NL			
1 month	*2.41*	*2.12*	*2.12*
3 months	-0.86	*-2.92*	*-2.92*
6 months	-0.19	*-2.97*	*-2.97*
Germany			
1 month	*3.46*	*2.10*	1.64
3 months	-0.23	*-2.63*	0.73
6 months	-0.99	-1.71	-0.93
Italy			
1 month	*-5.03*	*-4.86*	*-2.50*
3 months	*-4.85*	-0.18	*-2.88*
6 months	*-3.96*	*2.56*	*-3.54*
US and Japan			
1 month	*-2.77*	-1.33	-1.71
3 months	-1.55	-0.93	0.36
6 months	*-2.88*	-0.13	-1.12
Scandinavian countries			
1 month	*-4.07*	-1.57	-1.28
3 months	*-2.35*	*-2.58*	*-4.27*
6 months	*-3.74*	-0.74	*-2.09*
Switzerland			
1 month	*4.06*	*3.52*	0.81
3 months	-1.27	*-3.02*	-0.29
6 months	-1.99	*-9.98*	1.53
Russia			
1 month	1.08	*3.13*	-0.91
3 months	-0.64	*-2.17*	-1.65
6 months	-1.59	*-2.31*	-1.04
Other countries			
1 month	*-3.81*	*-2.42*	-0.85
3 months	*-4.10*	-0.28	*-2.22*
6 months	*-3.86*	1.08	*-2.21*
Total			
1 month	*-3.84*	1.05	*4.38*
3 months	*-2.50*	1.42	0.88
6 months	1.46	0.95	0.67

1. Diebold-Mariano test statistic with NW estimator. Null hypothesis: the difference between the two competing series is non-significant. A negative sign of the statistic implies that the second model has bigger forecasting errors.
2. *Italics:* Significant at the 5% level (2.028 critical value).

When analyzing the differences between countries, the lowest MAE value is always obtained for France, while Russia displays the highest MAE values for all models. This result can be explained by the fact that France is the main visitor market, while Russian visitors only account for a small percentage of total arrivals and present high levels of dispersion. Countries can be grouped according to their forecasting performance as the horizon increases: while France, Germany and Switzerland show low MAE values for 6 months forecasts, forecasts for Scandinavian countries, Italy, UK, US and Japan worsen as the forecasting horizon increases. These clusters can be explained by the common patterns in the evolution of tourism demand for certain groups of countries. This result also highlights the importance of the origin-destination distance as an explanatory variable for the differences between groups of visitor markets.

When testing for significant differences between a multivariate and a univariate approach for each two competing series (Table 4), we find that the multivariate analysis does not outperform the single-output approach country by country. On the contrary, 83% of the cases in which there is a significant difference between single and multiple-output approaches (half of the 198 cases), the sign is negative, indicating that the multiple-output approach presents higher forecasting errors. Nevertheless for short horizons, we find that for Germany, Switzerland, Russia and Belgium and the Netherlands the multiple-output approach presents significantly better results. For total arrivals, MAE values are lower for RBF and Elman networks with the multivariate approach, but the differences are not statistically significant.

5. Summary and conclusions

The increasing importance of the tourism sector worldwide has led to a growing interest in new approaches to tourism demand forecasting. New methods provide more accurate estimations of anticipated tourist arrivals for effective policy planning. Artificial intelligence techniques such as Artificial Neural Networks have attracted increasing interest to refine the predictions of tourist arrivals at the destination level. From the wide array of neural network models, we have focused on three different architectures that represent three alternative ways of handling information: the multi-layer perceptron neural network, the radial basis function neural network and the Elman recursive neural network.

The main purpose of this study is to assess whether forecasts of tourism demand can be improved by incorporating the existing common trends in tourist arrivals form all visitor markets to a specific destination. Given that the evolution of tourist arrivals form origin countries to Catalonia presents a significant cross-correlation structure, we have test if a multivariate approach that takes into account the correlations in the evolution of tourist arrivals from different countries of origin has a significant effect on forecast accuracy.

When comparing the forecasting accuracy of univariate versus multivariate models country by country, we obtain better forecasting results with a univariate approach. Nevertheless, for total tourist arrivals we obtain lower forecasting errors with a multivariate approach. This result shows that a multiple-output setting proves useful to forecast the total inbound international demand to a destination when the evolution of tourist arrivals form all visitor markets share a common trend.

When comparing the forecasting accuracy of the different techniques, we find that radial basis function neural networks outperform multi-layer perceptron and Elman neural networks, being the Elman model the one showing the poorest forecasting performance. This result suggests that issues related with the divergence of the Elman neural network may arise when using dynamic networks with forecasting purposes. Recurrent neural networks are not easy to train for large numbers of input units and may present scaling issues. These results reveal the suitability of hybrid models such as radial basis functions for tourism demand forecasting.

This study contributes to the tourism forecasting literature and to the tourism industry by presenting a way of using the common trends in tourist arrivals from different visitor markets and assessing its performance. The proposed forecasting setting may prove useful for planning purposes, providing managers and practitioners with a new and practical forecasting approach. This research also highlights the suitability of applying radial basis function neural networks to improve forecasting accuracy. Nevertheless, the study is not without its limitations. First, a comparison between different tourist destinations would allow to analyze whether regional differences have a significant influence on forecasting accuracy. Another question to be considered in further research is whether the implementation of supervised learning models such as support vector regressions, or the combination of the forecasts of different topologies and different time aggregations, may improve the forecasting performance of practical neural network-based tourism demand forecasting.

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