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Forecasting tourism demand to Catalonia: Neural networks vs. time series models

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ABSTRACT

The increasing interest aroused by more advanced forecasting techniques, together with the requirement for more accurate forecasts of tourism demand at the destination level due to the constant growth of world tourism, has lead us to evaluate the forecasting performance of neural modelling relative to that of time series methods at a regional level. Seasonality and volatility are important features of tourism data, which makes it a particularly favourable context in which to compare the forecasting performance of linear models to that of nonlinear alternative approaches. Pre-processed official statistical data of overnight stays and tourist arrivals from all the different countries of origin to Catalonia from 2001 to 2009 is used in the study. When comparing the forecasting accuracy of the different techniques for different time horizons, autoregressive integrated moving average models outperform self-exciting threshold autoregressions and artificial neural network models, especially for shorter horizons. These results suggest that the there is a trade-off between the degree of pre-processing and the accuracy of the forecasts obtained with neural networks, which are more suitable in the presence of nonlinearity in the data. In spite of the significant differences between countries, which can be explained by different patterns of consumer behaviour, we also find that forecasts of tourist arrivals are more accurate than forecasts of overnight stays.

1. Introduction

Many stationary phenomena can be approximated by linear time series models. Nevertheless, it is generally believed that the nonlinear methods outperform the linear methods in modelling economic behaviour. Artificial intelligence techniques have become an essential tool for economic modelling and forecasting, as they are far better able to handle nonlinear behaviour. Neural networks have been applied in many areas, but only recently for tourism demand forecasting. Tourism data is characterised by strong seasonal patterns and volatility, thus the original series requires significant pre-processing in order to be used with forecasting purposes. While eliminating the existing outliers and adjusting the seasonal component of the series, this filtering process ends up conditioning the forecasting performance of the models. Therefore, tourism demand is a particularly interesting field in which to analyse the effects of data pre-pre-processing on forecast accuracy and to compare the forecasting performance of neural networks relative to that of time series models.

There has been a growing interest in tourism research over the past decades. Some of the reasons for this increase in the number of studies of tourism demand modelling and forecasting are: the constant growth of world tourism, the utilisation of more advanced forecasting techniques in tourism research and the requirement for more accurate forecasts of tourism demand at the destination level. The consolidation of tourism planning at a regional level in many countries, such as Spain (Ivars, 2004), is one of the main reasons behind the increasing demand for accurate forecasts of tourist arrivals in a specific region. Despite the consensus on the need to develop accurate forecasts, there are very few studies undertaken at a regional level due to the lack of statistical information. All this has led us to focus on forecasting inbound international tourism demand to Catalonia, which is one of the main tourist destinations in Europe (Gary and Cànoves, 2011).

Catalonia is one of the seventeen autonomous communities in Spain. Barcelona is its capital. Over 14 million foreign visitors come to Catalonia every year, leading to 111 million overnight stays. Tourism makes a major contribution to Catalonia's economic development: it accounts for 12% of GDP and provides employment for around 19% of the working population in the service sector. Therefore, accurate forecasts of tourism volume play a major role in tourism planning as they enable destinations to predict infrastructure development needs. The forecast of tourism volume in the form of arrivals is especially important because it is an indicator of future demand (Chu, 2009). Despite the fact that tourist arrivals are the most popular measure of tourism demand, some studies have used tourist expenditure in the destination (Li et al., 2006a), tourism revenues (Akal, 2004) or tourism employment

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(Witt et al., 2004). To our knowledge, there is only one previous study (Claveria and Datzira, 2010) that has used overnight stays as a proxy measure of tourism demand to compare the resulting forecasts to those of tourist arrivals.

According to Song and Li (2008), who reviewed the tourism literature on tourism demand modelling and forecasting, there is no one model that stands out in terms of forecasting accuracy. Following Coshall and Charlesworth (2010), studies of tourism demand forecasting can be subdivided into causal econometric models and non-causal time series models. On the one hand, the most commonly used casual econometric models found in the literature are: cointegration and error correction (ECM) models (Algieri, 2006; Dritsakis, 2004), time varying parameter (TVP) models (Song and Wong, 2003), structural equation (SEQ) models (Turner and Witt, 2001), vector autoregressive (VAR) models (Song and Witt, 2006) and linear almost ideal system (LAIDS) models (Han et al., 2006). These methods have also been combined (Li et al., 2006b).

On the other hand, the most widely used procedures in non-causal time series forecasting are the autoregressive integrated moving average (ARIMA) models (Goh and Law, 2002) and the exponential smoothing (ES) models (Cho, 2003). Less frequently applied are nonlinear methods such as self-exciting threshold autoregressions (SETAR) and Markov-switching regime models (Claveria and Datzira, 2010). Recently, artificial intelligence (AI) methods have also been implemented in tourism forecasting. The most commonly used AI methods are artificial neural network (ANN) models. ANN models have been applied in many fields, but only recently to tourism demand forecasting (Kon and Turner, 2005; Palmer et al., 2006).

This increasing interest in more advanced forecasting techniques together with the fact that tourism has become a leading global industry, contributing to a significant proportion of world production, trade, investments and employment, has lead us to evaluate the forecasting performance of artificial neural network models to that of the most widely used procedures on tourism demand modelling. We use different forecasting horizons and compare the forecasting performance of two different measures of tourism demand (tourist arrivals and overnight stays) for all the different countries of origin to Catalonia.

The main objective of the paper is to evaluate the forecasting performance of artificial neural networks relative to different time series models (ARIMA and SETAR models) at a regional level. We use official statistical data of inbound international tourism demand to Catalonia from 2001 to 2009. Then the root mean squared forecast error (RMSFE) is computed for different forecast horizons (1, 2, 3, 6 and 12 months) and the Diebold–Mariano loss-differential test for predictive accuracy is performed in order to compare the different methods for both tourist arrivals and overnight stays.

The structure of the paper is as follows. Section 2 briefly describes our methodological approach, including both time series models and artificial neural network models. The data set is described in Section 3. In Section 4 results of the forecasting competition are discussed. Last, conclusions are given in Section 5.

2. Methodology

2.1. Time series models

A time series model explains a variable with regard to its own past and a random disturbance term. Time series models have been widely used for tourism demand forecasting in the past four decades, with the dominance of the integrated moving-average (ARIMA) models proposed by Box and Jenkins (1970). In this work two different time series models are used to obtain forecasts for the quantitative variables expressed as year-on-year growth rates: autoregressive integrated moving average (ARIMA) models and self-exciting threshold autoregression (SETAR) models.

2.1.1. Autoregressive integrated moving average models (ARIMA)

The general expression of an ARIMA model is the following:

$$x_t^{\lambda} = \frac{\Theta_s(L^s)\theta(L)}{\Phi_s(L^s)\,\phi(L)\Delta_s^D\Delta^d}\varepsilon_t \tag{1}$$

where $\Theta_s(L^s) = (1 - \Theta_s L^s - \Theta_{2s}L^{2s} - \ldots - \Theta_{Qs}L^{Qs})$ is a seasonal moving average polynomial, $\Phi_s(L^s) = (1 - \Phi_s L^s - \Phi_{2s}L^{2s} - \ldots - \Phi_{Ps}L^{Ps})$ is a seasonal autoregressive polynomial, $\theta(L) = (1 - \theta_1 L^1 - \theta_2 L^2 - \ldots - \theta_q L^q)$ is a regular moving average polynomial, and $\varphi(L) = (1 - \varphi_1 L^1 - \varphi_2 L^2 - \ldots - \varphi_p L^p)$ is a regular autoregressive polynomial, λ is the value of the Box and Cox (1964) transformation, Δ_s^D is the seasonal difference operator, Δ^d is the regular difference operator, S is the periodicity of the considered time series, and ε_t is the innovation which is assumed to behave as a white noise. In order to use this kind of models with forecasting purposes we have designed an algorithm that identifies that best suited model, including the necessary number of differences D and d. To determine the number of lags that should be included in the model, we have selected the model with the lowest value of the Akaike Information Criteria (AIC) considering models with a minimum number of 1 lag up to a maximum of 12 (including all the intermediate lags).

2.1.2. Self-exciting threshold autoregression models (SETAR)

A self-excited threshold autoregressive model (SETAR) for the time series x_t can be summarised as follows:

$$B(L)\cdot x_t + u_t \text{ if } x_{t-k} \le x \tag{2}$$

$$\zeta(L)\cdot s_t + v_t \text{ if } x_{t-k} > x \tag{3}$$

where u_t and v_t are white noises, $B(L)$ and $\zeta(L)$ are autoregressive polynomials, the value k is known as delay and the value x is known as threshold. This two-regime self-exciting threshold autoregressive process is estimated for the CCI and a Monte Carlo procedure is used to generate multi-step forecasts. The selected values of the delay are those minimising the sum of squared errors among values between 1 and 12. The values of the threshold are given by the variation of the analysed variable.

2.2. Artificial neural network (ANN) models

In recent years the study of artificial neural network (ANN) models has aroused great interest, as they are universal function approximators capable of mapping any linear or non-linear function. Neural networks have been applied in many fields, but they are increasingly being used for prediction and classification, the areas where statistical methods have traditionally been used (Adya and Collopy, 1998; Estrella and Mishkin, 1998; Swanson and White, 1997). Only recently ANN models are being used for tourism demand forecasting (Cho, 2003; Kon and Turner, 2005; Law, 2000, 2001; Law and Au, 1999; Palmer et al., 2006; Tsaur et al., 2002).

ANN models have two learning methods: supervised and unsupervised. The neuronal network model most widely used in time series forecasting is the multi-layer perceptron (MLP) method. The MLP is a supervised neural network based on the original simple perceptron model, but with additional hidden layers of neurons between the input and output layers that increases the learning power of the MLP. The number of hidden neurons determines the MLP network's capacity to learn. Selecting the network which performs best with the least possible number of hidden neurons is most recommended.

Due to their flexibility, ANN models lack a systematic procedure for model building. Therefore, obtaining a reliable neural model involves selecting a large number of parameters experimentally through trial and error (Palmer et al., 2006). Kock and Teräsvirta (2011) and Zhang et al. (1998) review the main ANN modelling issues: the network