Chapter 7
Tourism Demand Forecasting Based on a Neuro–Fuzzy Model

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ABSTRACT
Tourism in Greece plays a major role in the country’s economy and an accurate forecasting model for tourism demand is a useful tool, which could affect decision making and planning for the future. This paper answers some questions such as: how did the forecasting techniques evolve over the years, how precise can they be, and in what way can they be used in assessing the demand for tourism? An Adaptive Neuro-Fuzzy Inference System (ANFIS) has been used in making the forecasts. The data used as input for the forecasting models relates to monthly time-series tourist arrivals by air, train, sea and road into Greece from January 1996 until September 2011. 80% of the data has been used to train the forecasting models and the rest to evaluate the models. The performance of the model is achieved by the calculation of some well known statistical errors. The accuracy of the ANFIS model is further compared with two conventional forecasting models: the autoregressive (AR) and autoregressive moving average (ARMA) time-series models. The results were satisfactory even if the collected data were not pleasing enough. The ANFIS performed further compared to the other time-series models. In conclusion, the accuracy of the ANFIS model forecast proved its great importance in tourism demand forecasting.

1. INTRODUCTION
When looking at the history of Greece, the growth rates were extremely high and exceeded the rest of Europe for the two decades after 1950. This boosted the country’s economy and the further development of tourism. For the years post-1980, Greece has attracted more than 15 million tourists each year and was ranked in 21st place for competitiveness in Europe by the World Economic

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Forum in 2011. Furthermore, in that year, travel and tourism contributed 16.5% to Greece’s GDP and 18.4% to employment.1

However, the perplexity that is inherent in tourism forecasting makes it hard to predict. Tourism is easily affected by internal and external conditions such as political, financial or environmental factors. Nevertheless, an accurate forecast of tourism demand can be beneficial to a country and tourism-related industries, which will benefit through building tourism infrastructures, in making fundamental strategic decisions or in taking precautionary measures for potential threats and opportunities.

Martin and Witt (1989) were some of the first groups of authors to study tourism demand forecasting. They used the ANOVA and Scheffé tests and produced more accurate forecasts by adapting simple forecasting methods than econometric forecasts. The use of Artificial Intelligence (AI) based techniques in tourism though, started around the mid-1990s and has become more popular over recent years. One of the oldest studies to apply AI was that of Pattie & Snyder (1996) who used a back-propagation neural network model to forecast tourism demand in US national park systems. Tsaur et al. (1997) used an Analytic Hierarchy Process method and a fuzzy Multiple Criteria Decision-Making method to conduct the evaluation of tourist risk. Law & Au (1999) presented a new approach that uses a supervised feed-forward neural network model to forecast Japanese tourist arrivals in Hong Kong, preferable to multiple regressions. A later study by Law (2000) demonstrated a back-propagation learning approach that can give more accurate results in a neural network’s forecast in relation to tourism demand for non-linearly separable dependent variables. Song et al. (2003) evaluated the forecasting accuracy of six alternative econometric models in the context of the demand for international tourism in Denmark. Pai & Hong (2005) presented an investigation of a support vector machine model with genetic algorithms (SVMGs) to accurately forecast arrivals in Barbados. Fernandon (2005) developed a comparison of a neuro-fuzzy model with other quantitative methods for tourism forecasting in Japan. Kon & Turner (2005) compared the forecasting accuracy of the basic structural method (BSM) and the neural network method to find the best structure for neural network models, using data for arrivals to Singapore.

Palmer et al. (2006) presented a study showing a step-by-step methodology to design a neural network for tourism time-series forecasting, corresponding to tourism expenditure in the Balearic Islands. A combination of techniques was used by Atsalakis (2005) and Atsalakis & Ucenic (2007) which was created from the Artificial Neural Networks (ANFIS) and from fuzzy logic to generate a neuro-fuzzy model in order to forecast the tourism demand for the following year in the island of Crete. A review of 121 studies on tourism demand modelling and forecasting published since 2000 was conducted by Song & Li (2008) to find out which forecasting technique outperforms the others. Chu (2009) applied three univariate ARMA-based models in tourism demand, as represented by the number of world-wide visitors to nine principal tourist destinations in the Asian-Pacific region, with the result that ARFIMA outperformed the rest. Hadavandi et al. (2011) developed a hybrid AI model which adopted ANFIS to deal with tourist arrival forecasting problems. Fernandes et al. (2011) presented a set of models for tourism destination competitiveness, using the Artificial Neural Networks methodology, focusing on the North and Centre Portuguese regions. Lin et al. (2011) tried to build the forecasting model of visitors to Taiwan using ARIMA, ANNs and (MARS) forecast models, with ARIMA producing the most accurate forecasting results. Hadavandi et al. (2011) presented a hybrid AI model to develop a Mamdani-type fuzzy rule-based system to forecast tourist arrivals with the aim of improving forecasting accuracy, using tourist arrivals to Taiwan data. One of the newest studies in tourism demand forecasting has been presented by