# FORECASTING TOURISM DEMAND USING ANFIS FOR ASSUARING SUCCESSFUL STRATEGIES IN THE VIEW OF SUSTAINABLE DEVELOPMENT IN THE TOURISM SECTOR

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*Abstract:* - The paper presents a new technique in the field of tourism modelling in order to forecast the tourism demand. Techniques from the Artificial Neural Networks and from fuzzy logic have been combined to generate a neuro-fuzzy model to forecast the tourism demand on next year in island of Crete. The tourist practitioners are very interesting in tourism forecasts in order to plan more effectively tourism strategies. To modeling the complexity and the uncertainty of tourism environment is important to apply fuzzy techniques. The input of the model is a time series of the previous annual overnight stays. Classical statistics measures are calculated in order to asses the model performance. Further the results are compared with an ARMA and an AR model. The results are very encouraged.

*Keywords*: ANFIS, forecasting, neural network, strategy, sustainable development, tourism

## 1 Introduction

The tourism industry has experienced a great explosion during latest years. To be competent in forecasting future trends as precisely as possible is imperative in the great effort to stay one step ahead of the competition. The correct prediction of tourism demand is very important for marketing managers, strategic planners in business, transportation planners and economic policy makers from the governments who must project demand for their products among tourists.

In the literature, there are provided different ranks of various forecasting techniques founded on their most suitable time horizon, implementation cost, complexity of the approach and forecasters' experience. There are numerous shortages in tourism demand modeling from the point of view of the way that methods are applied, as well as how are reported. The tourism demand forecasting has to be assessed not only in opposition with other methods, but also against the most common forecasting practice - "speculation".

The features that determine the choice of method include the intention, the time interval, the mandatory degree of correctness, the accessibility of information, the forecasting environment and the cost of prediction. Inexactnesses of prediction may result from diverse factors as:

- unsuitable model;
- inaccurate use of it;
- error calculation of relationships within the model;
- misplace of major variables;
- uses of inadequate data.

In the neoclassical notion of demand, it is considered as a price function but there are a lot of additional variables, or demand shifters which may influence the price. From the point of view of tourism, age, culture, taste, prior service experience, publicity, innovation, policies or new technology are among them. As a luxury good, the demand for tourism has propensity to be pretty elastic while the income elasticity of different tourism products can differ considerably. Several recreation goods may in reality demonstrate decreasing consumption with increasing income.

The evolution of the number of tourists from Greece, in the interval 1994-2003 is presented in the following figure.

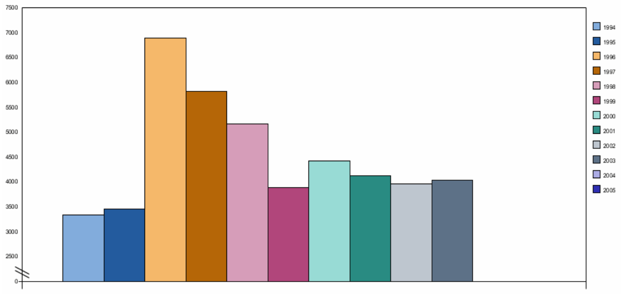


Figure 1: Number of tourists (1000) from Greece 1994-2003 (Source: Eurostat)

The number of hotels in 2005 was 9.036.000 in comparison with 8.342.000 in 2000, which provided an increase of 74.000 in the number of beds (682.000 in 2005 / 608.000 in 2000).

Among the Greek protected areas with destination for eco-tourism are listed 10 national parks, 2 water parks, 11 water biotypes with international importance, 7 controlled areas for hunting and 300 natural sites.

## 2 Using soft computing in time series forecasting

Soft computing is a new approach to design computationally intelligent systems. Complex real word problems require intelligent systems that combine knowledge and techniques from various fields. These systems have the ability to obtain human experience, to adapt themselves and to learn to perform effectively in changing environments. Also they have the ability to explain how they make decisions or take actions. Neuro-fuzzy systems belong to this category. They combine neural networks that recognize patterns and adapt themselves to cope with changing environment and fuzzy inference systems that incorporate human knowledge and perform inferencing and decision making [15].

Among the many areas that artificial neural networks have been applied is the area of time series forecasting, [35], [17], [13], [29], [30], [1]. Neural Networks have desirable properties as a time series forecasting tool, such as the ability to model arbitrary linear and nonlinear functions [18], [19], few a priori assumptions [12], and the ability to model nonlinearities. See Zhang et al. [35] for a good review of neural networks used for forecasting. Neural networks do not require the a priori determination of a functional model form. Neural networks have been theoretically shown to be universal approximators under certain conditions [17]. In traditional techniques, one would determine a functional form then estimate its parameters. In neural networks approach, both parameter estimation and the function approximation are done simultaneously.

Fuzzy sets were introduced by Zadeh [34], as a means of representing and manipulating data that is not precise, but rather fuzzy. It is specifically designed to mathematically represent uncertainty and vagueness and to provide formalized tools for dealing with the imprecision intrinsic to many problems. The human brain interprets imprecise and incomplete sensory information provided by perspective organs. Fuzzy set theory provides a systematic calculus to deal with such information linguistically, and it performs numerical computation by using linguistic labels stipulated by membership functions. Moreover, a selection of fuzzy if-then rules forms the key component of a fuzzy inference system that can effectively model human expertise in a specific application.

The fuzzy inference system has a structural knowledge representation in the form of fuzzy if-then rules. But it lacks adaptability to deal with changing external environments. Thus, neural network learning concepts are incorporated in fuzzy inference systems, resulting in neuro-fuzzy modeling. Neural network algorithms have been applied to improve the performance of a fuzzy system. Some researchers have applied neuro-fuzzy models to forecast time series data in various fields, [2], [3], [4], [5], [6], [7], [8], [9], [10], [31], [32], [33], [27], [16].

## 3 Related work in tourism forecasting

Tourism forecasters concentrate primarily on quantitative causal-relationship and time series methods. In this study is investigated how accurately the neuro-fuzzy models can simulate the relationships of tourism demand. The neural networks have been used by the researchers in hospitality and tourism include individual choice behaviour modelling [14], tourist behaviour forecasting [28], hotel room occupancy rate forecasting [20], tourism demand analysis for a single market [21], [22], [24], [25] and hotel spending by visitors [23]. Also Atsalakis [11] applied a neural network to forecast the tourism demand. In this paper is applied a neuro-fuzzy forecasting model that is called ANFIS (Adaptive Neuro-Fuzzy Inference System) that combines neural network and fuzzy logic techniques.

## 4 Model presentation

A neuro-fuzzy system is defined as a combination of neural networks and Fuzzy Inference System. Jang in 1993 introduced an Adaptive Neuro-Fuzzy Inference System (ANFIS) where the MFs parameters are fitted to a dataset through a hybrid-learning algorithm [15]. The basis of the ANFIS model is the theory of artificial neural networks (ANN).

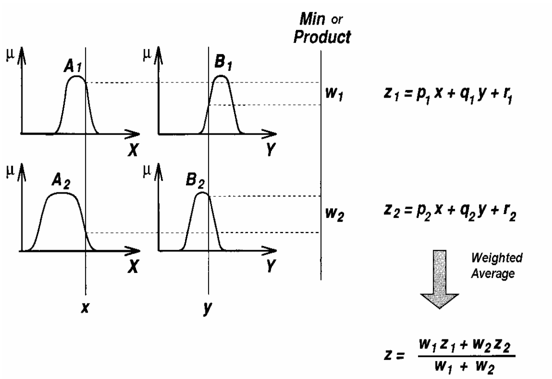
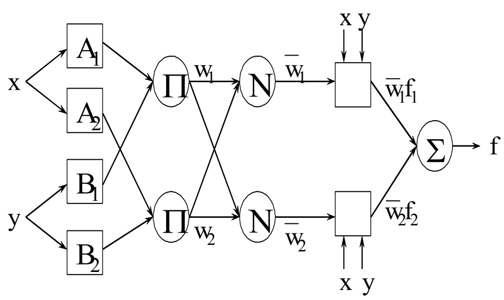



Figure 2: Fuzzy inference mechanism [15]

Figure 1 shows the fuzzy reasoning process. The example consists in a first order Sugeno type FIS, with two inputs variables (x and y), one output (z), and two if-and-then rules. Each input space has been characterized by two intuitively labeled gauss MFs, drawn separately for clarity and to give graphical representation of each rule.




**Layer 1 Layer 2 Layer 3 Layer 4**

**Layer 5**

Figure3: An illustration of reasoning mechanism of the ANFIS architecture [15]

Figure 3 presents the structure of the ANFIS if it is considered for simplicity as a fuzzy system with only two inputs and one output of first order Sugeno type. The output of each layer is the input of the next layer. The first layer is the input layer that is adaptive for the non-linear parameters and carries out the fuzzification of each numeric input variable and his output is the value of each membership function. The second layer that is non-adaptive makes T-norm operations of each combination of the defined fuzzy sets. His output is the firing strength value of each T-norm operation. The Layer 3 that is non-adaptive carries out the normalization of all firing strengths and his output is normalized firing strengths.

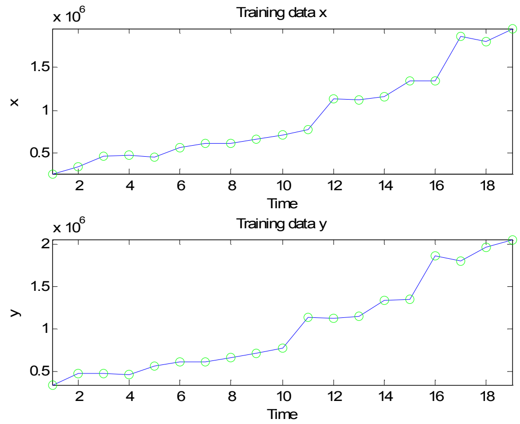



Figure 4: Training data

The Layer 4 that is adaptive for the linear parameters calculates the product of each normalized firing strength by each of the Sugeno first order crisp function value. The Layer 5 that is not adaptive makes the summation of all incoming signals (products) and gives as output the desired prediction.

The data concerns the number of annual overnight stays of tourists in Greece which are displayed as time series starting from 1975 until 1998. In this study, 19 annual observations are used. The sequence of input and output training data is displayed in Figure 3.

The trial and error method is applied in order to find out the best type and the number of the membership functions. Finally two gaussian membership functions are chose for the input of the follow formula.

$$gaussmf(x,c,\sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \quad (1)$$

The input of the model is a time series of previous values at time (t-1).

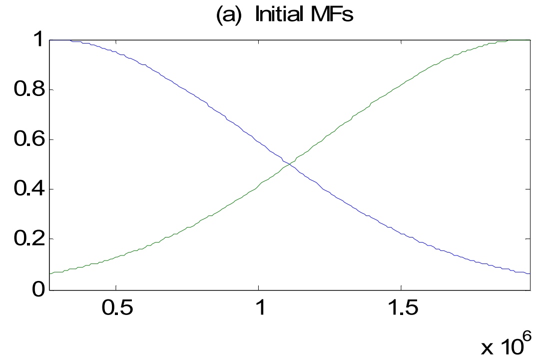



Figure 5: Initial membership functions

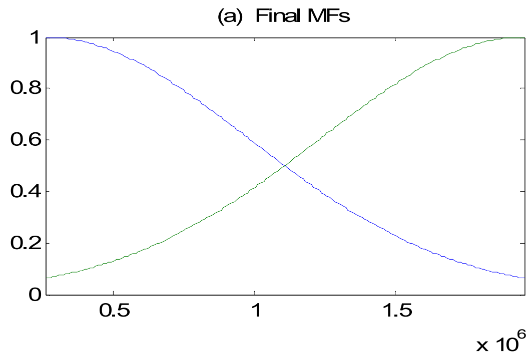



Figure 6: Final membership functions after training

The model uses the training data to adjust the parameters of the membership functions. Figures 5 and 6 present the form of the membership functions before the training and after the training.

Figure 7 shows the error and the step size during the training phase. The training stops in 300 epochs. The number of parameters is eight. Four of them are non linear and the other four are linear. The number of nodes is twelve.

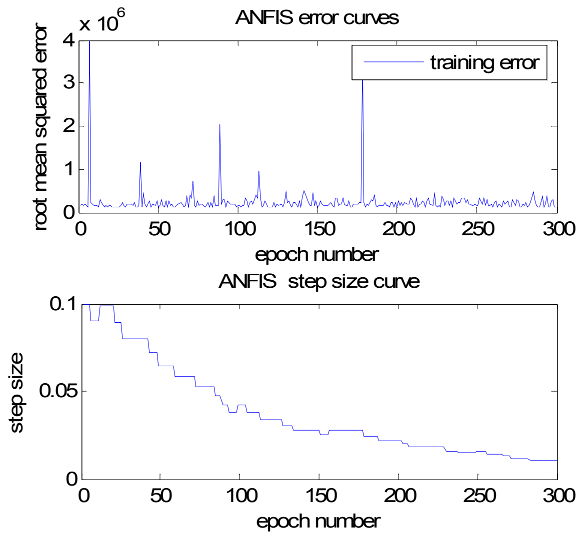



Figure 7: Error and step size during the training

The following two rules are created by the system:

**If** $x$ **is** small **then**

$$f_1 = p_1 \times x + r_1$$

**If** $x$ **is** big **then**

$$f_2 = p_2 \times x + r_2$$

Figure 8 presents a graphical representation of the decision mechanism after the training.

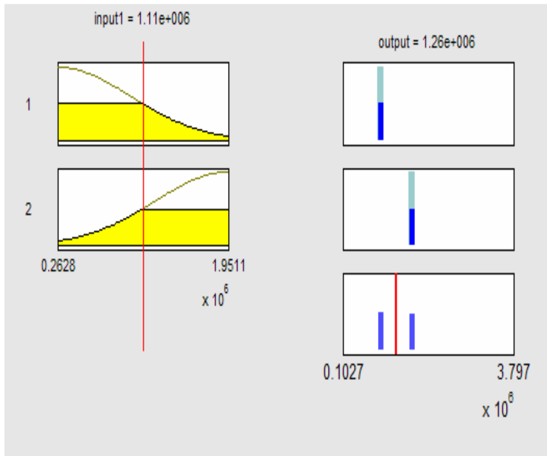



Figure 8: The inference mechanism

On the verification phase is compared the neural network output values with the actual values in order to be evaluated the one step-ahead prediction. As figure 9 illustrates the ANFIS output is very close to actual values and is overlaid by the actual value.

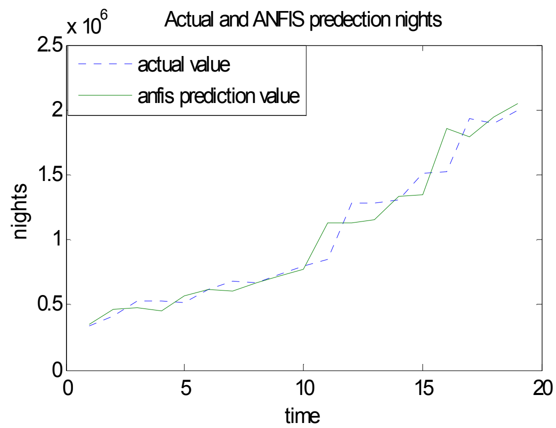



Figure 9: Actual and one-step ahead prediction

For further evaluation of the model the AR and ARMA model are calculated. To assessing the models some statistical error measures are estimated as is mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). These measures have been used by many researches for the model evaluation [26].

The ANFIS model achieves very good performance due to the small error in the four measures of errors as is presented in Table 1.

| Errors | ANFIS | AR | ARMA |
|---|---|---|---|
| MSE | **1.4256e+010** | 1.8693e+010 | 1.4991e+010 |
| RMSE | **1.1750e+005** | 1.3672e+005 | 1.2244e+005 |
| MAE | **7.1007e+004** | 9.0029e+004 | 7.5085e+004 |
| MAPE | **7.8825** | 9.1980 | 8.2964 |

Table 1: Forecasting results

## 5 Conclusion

The aim of this paper is to study the use of a neuro-fuzzy technique to predict the tourist demand one year ahead using time series data. The dynamics of tourism demand have been captured by the ANFIS network and the results are much promised. For further investigation the performance of the current model must be improved using scaling of the data and adding more lagged inputs to the model.

*References:*


[1] Adya, M. and Collopy, F. (1998), How effective are neural networks at forecasting and prediction? A review and evaluation, *Journal of Forecasting*, 17, pp.481-495.

[2] Atsalakis. G.. Exchange rate forecasting by Neuro-Fuzzy Techniques. *Journal of Financial Decision Making*. Vol. I (2). pp.15-26. (2006a).

[3] Atsalakis. G.. Forecasting Stock Market Trend using a Neuro-fuzzy controller. Technical University of Crete. Working paper. September. (2006b).

[4] Atsalakis. G.. Ucenic C.. Electric load forecasting by Neuro-fuzzy approach. WSEAS International Conference on Energy and Environmental Systems. Chalkida Evia. Greece. (2006c).

[5] Atsalakis. G.. Ucenic C.. Forecasting the Electricity Demand Using a Neuro-fuzzy Approach Versus Traditions Methods. *Journal of WSEAS Transactions on Business and Economics*. issue 1. vol. 3. pp. 9-17. (2006d).

[6] Atsalakis. G.. Ucenic C.. Forecasting the wind energy production using a Neuro-fuzzy model. *Journal of WSEAS Transactions on Environment and Development*. issue 6. vol. 2. pp. 823-829. (2006e).

[7] Atsalakis. G.. and C. Ucenic. Time Series Prediction of Water Consumption Using Neuro-fuzzy (ANFIS) Approach. *International Conference on Water Economics. Statistics and Finance.* Greece. (2005b).

[8] Atsalakis. G.. Ucenic C.. Plokamakis G.. Forecasting of Electricity Demand Using Neuro-fuzzy (ANFIS) Approach. International Conference on NHIBE. Corfu. Greece. (2005c).

[9] Atsalakis. G.. Ucenic C.. Forecasting the profit for the Greek food sector using a neuro-fuzzy approach. *International Conference on NHIBE. p.p.686-694.* Corfu. Greece (2005d).

[10] Atsalakis. G.. C. Ucenic. and Skiadas C.. Time series prediction of the Greek manufacturing index for the non-metallic minerals sector using a Neuro-fuzzy approach (ANFIS). *International Symposium on Applied Stochastic Models and Data Analysis. France. Brest.* (2005e).

[11] Atsalakis, G., Modeling Tourism Demand by Neural Networks Techniques. Management of Technological changes, *Proceeding of 4th International Conference on Management of Technological Changes, TUC, Chania, Greece*, (2005, a).

[12] Cheng, D. and Titterington, D. (1994), Neural Networks: A Review from a Statistical Perspective, *Statistical Science*, 47(2), pp. 2-54.

[13] Faraway, J. and Chatfield, C. (1998), Time series forecasting with neural networks: A comparative study using the airline data, *Applied Statistics*, 47(2), pp. 231-250.

[14] Jeng, J.M. and Fesenmaier, D.R. (1966), A neural network approach to discrete choice modelling, *Journal of Travel & Tourism Marketing*, 5(1/2), pp. 119-144.

[15] Jang JS., ANFIS: Adaptive –Network –based Fuzzy Inference System, *IEEE Trans systems, Man and Cybernetics*, vol. 23, (3), pp. 665-684, (1993).

[16] Jang, J-S.R., C-T.E. Sun and E. Mizutani, *Neuro-fuzzy and soft computing : a computational approach to learning and machine intelligence,* Prentice Hall, (1997).

[17] Hill, T., O' Connor, M. and Remus, W. (1996), Neural networks models for time series forecasts, *Management Science*, 42(7), pp. 1082-1092.

[18] Hornik, K. (1991), Approximation capabilities of multilayer feedforward networks, *Neural Networks*, 4, pp. 251-257.

[19] Hornik, K., Stinchcombe, M. and White, H. (1989), Multilayer feedforward networks are universal approximators, *Neural Networks*, 2, pp. 359-366.

[20] Law, R. (1998), Room occupancy rate

forecasting: A neural network approach, *International Journal of Contemporary Hospitality Management*, 10(6), pp. 234-239.

[21] Law, R. (2000a), Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting, *Tourism Management*, 21(3), pp. 331-3340.

[22]Law, R. (2001), The impact of the Asian Financial Crisis on Japanese demand for travel to Hong Kong: A study of various forecasting techniques, *Journal of Travel & Tourism Marketing*, 10(2/3), pp. 47-65.

[23] Law, R. (2000b), Demand for hotel spending by visitors to Hong Kong: A study of various forecasting techniques, *Journal of Hospitality & Leisure Marketing*, 6(4), pp. 17-29.

[24] Law, R. and Au, N. (1999), A neural network model to forecast Japanese demand for travel to Hong Kong, *Tourism Management*, 20(1), pp. 89-97.

[25] Law, R. and Pine, R. (2004), Tourism demand forecasting for the tourism industry: A neural network approach, *Neural Network in Business Forecasting*, Idea Group Inc (2004) pp. 121-141.

[26] Makridakis, S. and Hibon, M. (1979), Accuracy of forecasting: An empirical investigation, *Journal of the Royal Statistical Society*, A, 142, pp. 97-145.

[27] Nayak. P.C.. K.P. Sudheer. D.M. Rangan and K.S. Ramasastri. A neuro-fuzzy computing technique for modeling hydrological time series. *Journal of Hydrology.* 291. 52-66. (2004).

[28] Pattie, D.C. and Snyder, J.(1996), Using a neural network to forecast visitor behaviour, *Annals of Tourism Research*, 23(1), pp. 151-164.

[29] Tang, Z., de Almeida, C. and Fishwick, P. (1991), Time series forecasting using neural networks vs. Box-Jenkins methodology, *Simulation*, 575(5), pp. 303-310.

[30] Tang, Z. and Fishwick, P. (1993), Feedforward neural nets as models for time series forecasting, *ORSA Journal on Computing*, 5(4), pp. 374-385.

[31] Ucenic C.. and G. Atsalakis. Study the influences of the economic environment on the gross domestic product using a fuzzy model. *Management of Technological changes. Proceeding of 3rd International Conference on the Management of Technological Changes. TUC. Chania. Greece.* (2003).

[32] Ucenic C. and G. Atsalakis. Time series prediction of the Greek manufacturing index for the basic metals sector using a Neuro-fuzzy approach (ANFIS). *Management of Technological changes. Proceeding of 4th International Conference on the Management of Technological Changes. TUC. Chania. Greece*. (2005. a).

[33] Ucenic C. and G. Atsalakis. Forecasting the profit for the Greek non-metallic sector using a Neuro-fuzzy approach (ANFIS). *Management of Technological changes. Proceeding of 4th International Conference on the Management of Technological Changes. Technical University Crete. Chania. Greece*. (2005. b).

[34] Zadeh, L. A., Fuzzy sets*, Information and Control*, vol. 8, pp. 338-353, (1965).

[35] Zhang, G., Patuwo, B. and Hu, M.(1998), Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, 14, pp. 35-62.