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Employing a Time Series Forecasting Model for Tourism Demand Using ANFIS

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Abstract

Forecasting the future trends is of utmost importance for managers and decision makers in different sectors. Scholars thus have introduced various techniques to the service industry aiming at employing a prediction model with ultimate accuracy and high efficiency. The literature proves that adaptive neuro-fuzzy inference systems (ANFIS) are the most efficiency models. However, the literature lacks reports on how ANFIS parameters may affect the accuracy of the system. Employing tourist arrival records to Cyprus between 2015 and 2019, this study has developed an ANFIS system to evaluate the accuracy performance of different prediction models with varied number of inputs and number or type of membership functions. Results show that the forecasting accuracy of a model with four inputs and four membership functions when the type of membership functions is Gaussian is relatively better than other models. In other words, it can be concluded that the forecast model with four inputs and four Gaussian membership functions is ultimate with the most accurate prediction record with reference to MAE, RMSE, and MAPE. The results of this study may be significant for senior managers and decision-makers of the tourism industry.

Keywords: Decision making, Time series, Forecasting, Fuzzy rule-based system, ANFIS

1. Introduction

Having control and plan is indispensable in decision-making for managers in different industries, including tourism. The backbone of controlling and planning is forecasting future trends. Tourism, because of the multiple benefits and advantages it provides, is one of the crucial industries invested heavily. Meantime, it is one of the fastest-growing industries today, and it adds to a country's overall growth and development. The growth of tourism in a country leads to increasing its commercial activity, creates thousands of jobs, and contributes to the country's brand value, image, and identity.

Forecasting the future demand provides important data for managers while making their decisions. Nonetheless, accuracy in forecasting is essential in making efficacious decisions. When it comes to the tourism industry, forecasting the future, especially the future flow of tourists, is of utmost significance. However, due to the special characteristics of tourism and a large number of effective factors, forecasting the demand with little error is not an easy job.

To succeed in today's highly competitive market, the government, public and private sectors, as well as all responsible authorities, should work in harmony. Authorities in both government and private sectors measure the success rates of their plans by comparing the current year's performance to the previous year's records. Consequently, scholars have proposed different forecasting methodologies and techniques.

One of those methods, time series forecasting, is very popular among scholars. Time series forecasting is the process of using past data to forecast future values. To create a forecasting model based on the time series method, earlier observations are collected, analyzed, and processed to determine future trends. Using this method, several models have been introduced; however, the research findings recommended that a combination of different models rather than employing a single model may result in more accurate predictions.

Classical time series models have been applied in various types of applications; however, they have some drawbacks. They cannot capture the structure of non-linear relationships due to the assumptions based only on linear relationships among time-lagged variables [1]. They fail to predict the problems with linguistic values [2], [3] and fail to have high accuracy in complex problems. They require a large amount of data, and they are time-consuming [4].

Being proposed by Zadeh [5], the fuzzy logic has been applied and used in different complex systems successfully. When making decisions, fuzzy set theory plays an essential role in coping with uncertainty. As a result, fuzzy sets have attracted increasing interest and attention in modern information technology, decision making, production technique, data analysis, pattern recognition, and diagnostics [6]–[9].

Song and Chissom are the pioneers of defining fuzzy time series using fuzzy logic theory [10]. Fuzzy time series methods are used in different areas since they are applicable with ambiguous and non-complete data [11]. They are capable to tackle the uncertainty that is inherited in collecting data. Applying fuzzy logic can increase the accuracy of the model [12], and there is no need for any assumptions such as linearity and normality [13]. In addition, they do not require data from a large sample, or normal and stationary distribution during the data collection phase [14]. The key feature of fuzzy logic, however, is that there is no systematic procedure for designing a fuzzy controller. Therefore, many hybrid techniques have been proposed for forecasting [15]–[17].

Artificial neural networks (ANNs) are frequently used for prediction and have been considered as a potentially effective technique for modeling complicated nonlinear systems [18]. Modeling a system using ANNs is sample-based learning which should be trained using a trained data set. After completing the learning process then the proper ANN model is obtained. Some advantages of ANNs are mentioned as (a) working with incomplete and insufficient data (b) sample-based learning (c) realizing machine learning (putting machine learning into practice) (d) having capability in classification, association, and pattern recognition [19].

Neuro-fuzzy systems are fuzzy systems that use the theory of ANNs to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. They use the potential and advantages of both fuzzy logic and ANNs, by employing the ANNs' mathematical properties in tuning rule-based fuzzy systems. In the development of neuro-fuzzy systems, a specific approach is the adaptive neuro-fuzzy inference system (ANFIS).

ANFIS is a hybrid method, developed by Jang [20] which combines the ANNs adaptive capability and the fuzzy logic qualitative approach. It combines an optimized premise membership function with a consequent equation, using the Takagi–Sugeno rule format. To have input-output pairs with a high degree of accuracy, ANFIS combines the advantage of learning an ANN and making use of a set of fuzzy IF-THEN rules with appropriate membership functions. It has been employed successfully in modeling complex systems [21] and nonlinear functions [22].

The effect of temperature and air velocity on drying time was investigated by using ANFIS. The results show that ANFIS is one of the fastest methods with high accuracy. In the ANFIS structure, the number of inputs is considered as three and three Gaussian membership for each input [23].

To predict rainfall, ANFIS, as an artificial intelligence application, has been employed. Rainfall prediction based on ANFIS time series appears promising, according to analyses of six-year rainfall data on a monthly basis. In the ANFIS structure, the number of inputs is considered as three and the membership functions are Trapezoid and Bell-shaped [24].

To construct a successful fuzzy inference system to forecast a launching service in tourism, ANFIS is applied [25]. The ANFIS model has two inputs and five membership functions for each input. The type of selected membership function for this model is Gaussian.

The literature lacks reports on the effect of ANFIS parameters (number of inputs and number or type of membership functions) on the efficacy and accuracy of the employed model in forecasting the number of tourists arriving at a specific location. This paper thus aims to analyze the accuracy rate of ANFIS systems in forecasting the flow of tourists to Cyprus when the number of inputs and number or type of membership functions varies. To do so, the monthly records of tourist arrivals to the country between January 2015 and December 2019 have been used and analyzed.

2. Preliminaries

Time series. It is defined as:

$$X_t = G_q\left(X_{t-1}, X_{t-2}, \dots, X_{t-p}\right) \tag{1}$$

In Eqn. (1) G_q is any nonlinear function, the values of variable $X(t)$ in periods $t-1, t-2, \dots, t-p$ of time series are represented by $X_{t-1}, X_{t-2}, \dots, X_{t-p}$. A forecast value of the variable X for the period t is shown by *X(t)*. We need to find such a function *G(.)* and input number p to fulfill the condition.

$$\phi = \sum_{i=1}^{n} (X_i^p(t) - X_i^e(t))^2 \rightarrow min \tag{2}$$

Where $X_i^p(t)$ is a forecast value at a time t is based on the obtained model, and $X_i^e(t)$ is an experimental value of a variable [15].

Fuzzy time series. Let $U(t) \subset R^1$ be the universal set, where $R^1 \subset \mathbb{R}$, i.e., R^1 is a subset of real numbers, on $f_{k(t)}$ which is fuzzy set with $k = 1, 2, 3, \ldots$ and $t = \ldots, 0, 1, 2, \ldots$. The fuzzy time series on the set $U(t)$ is denoted by $F(t) = \{f_k(t)\}_{k \in I}$.

Fuzzy rule-based system. The expansion of the classical method of a rule-based system that is generally based on IF-THEN rules is a fuzzy rule-based system. The conditional statements have the form "IF C (condition) THEN R (restriction)" which is characterized by membership functions.

Takagi–Sugeno–Kang (TSK) type fuzzy rule-based system. The core of the TSK type fuzzy rule-based system is a set of IF-THEN rules that is shown by R_j with fuzzy implications and first-order functional consequence parts. A common rule R_j in the TSK type fuzzy rule-based system is defined as follows:

$$\begin{gathered}(R_j) : IF x_1 is A_{1j} \wedge x_2 is A_{2j} \wedge \cdots \wedge x_i is A_{ij} \\ \text{THEN } y_j = \alpha_{ij} x_i + \alpha_{(i-1)j} x_{i-1} + \cdots + \alpha_{1j} x_1 + \alpha_{0j} \qquad j = 1 \ldots, J.\end{gathered} \tag{3}$$

where a fuzzy subset that is subscribed by the input variable named x_i for the jth rule is represented by A_{ij}. A fuzzy conjunction operator and the number of fuzzy rules are shown by $\wedge$ and j, respectively. Each rule in Eqn. (3) is premised on $x^T = (x_1, x_2, \ldots, x_i)$ which is the input vector and maps the fuzzy sets in the input space $A_j \subset R_i$ to a y_j.

3. Adaptive Neuro-Fuzzy Inference System: Architecture and algorithm

An adaptive neuro-fuzzy inference system (ANFIS) is a neural network approach that is based on TSK type fuzzy rule-based system to find the solution for function approximation problems [20],[26]. ANFIS constructs a fuzzy inference system based on a given input-output where the parameters of membership function can be modified by applying the hybrid learning algorithm. The ANFIS forms the distribution of membership functions optimally by setting out the mapping relation between the input and output pairs. The strengths of both fuzzy logic and artificial neural networks are combined in ANFIS. It not only completes ANNs' computation power and the low-level learning with fuzzy systems it also brings the high-level IF-THEN rules to ANNs [27]. Such a system makes the ANFIS modeling more systematic which is also less reliant on the knowledge of experts. To construct an ANFIS, five layers are used where each layer is made up of several nodes. The nodes are described by the node function. The nodes in the previous layers provide the inputs for the current layers. To show the architecture of the ANFIS, a common fuzzy rule set with two fuzzy IF-THEN rules is considered. The IF-THEN rules are based on a first-order Sugeno model stated as follows:

$$(R_1): IF x \; is \; \tilde{A}_1 \wedge y \; is \tilde{B}_1 \; THEN \; f_1(x, y) = p_1 x + q_1 y + r_1$$
$$(R_2): IF x \; is \; \tilde{A}_2 \wedge y \; is \tilde{B}_2 \; THEN \; f_2(x, y) = p_2 x + q_2 y + r_2$$

where $\tilde{A}_i$ and $\tilde{B}_i$ $(i = 1,2)$ are the fuzzy sets for the inputs x and y of ANFIS, respectively. The output of the system is represented by $f_i(x, y)$ which is the first-order polynomial; p_i , q_i, and r_i are the parameters of $f_i(x, y)$ where $(i = 1,2)$. The architecture of typical ANFIS to implement the rules (R_1) and (R_2) has five layers including two different nodes such as adaptive nodes, shown by squares, and fixed nodes shown by circles as demonstrated in Figure 1. In the system, adaptive nodes represent the parameter sets that can be adjustable whereas fixed nodes show the parameter sets that are fixed.

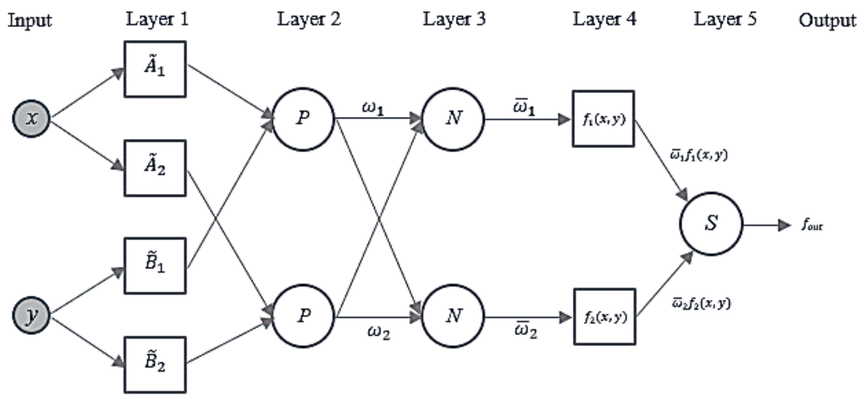

Figure 1. ANFIS architecture [20]

i. Layer 1: All nodes in the first layer of ANFIS are adaptive nodes. The outputs of this layer as shown by $O_{1,i}$ are the membership grades of the inputs, which are as follows:

$$O_{1,i} = \mu_{\tilde{A}_i}(x), \qquad i = 1,2 \tag{4}$$

$$O_{1,i} = \mu_{\tilde{B}_{i-2}}(y), \qquad i = 3,4 \tag{5}$$

where x and y are inputs, $\mu_{\tilde{A}_i}(x)$ and $\mu_{\tilde{B}_i}(y)$ are the membership functions of the fuzzy sets $\tilde{A}_i$ and $\tilde{B}_i$, respectively.

ii. Layer 2: All nodes in the second layer of ANFIS are fixed nodes. In Figure 1, they are marked with P to show the Product's operator. The outputs of this layer as shown by $O_{2,i}$ represent the firing strength of a rule which are as follows:

$$O_{2,i} = \omega_i = \mu_{\tilde{A}_i}(x)\mu_{\tilde{B}_i}(y), \qquad i = 1,2 \tag{6}$$

iii. Layer 3: All nodes in the third layer of ANFIS are also fixed nodes. In Figure 1, they are marked with N. The outputs $O_{3,i}$ are called normalized firing strength.

$$O_{3,i} = \overline{\omega}_i = \frac{\omega_i}{\sum_{i=1}^{2} \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1,2 \tag{7}$$

iv. Layer 4: All nodes in the fourth layer of ANFIS are adaptive nodes. The outputs of this layer as shown by $O_{4,i}$ are given by

$$O_{4,i} = \overline{\omega}_i f_i(x,y) = \overline{\omega}_i (p_i x + q_i y + r_i), \quad i = 1,2 \tag{8}$$

where p_i, q_i, and r_i are consequent parameters. The output is the multiplication of the normalized firing strength and a first-order polynomial as shown by $\overline{\omega}_i$ and $f_i(x,y)$, respectively.

v. Layer 5: The final layer has a single fixed node which is also called output node and is labeled with *S* in Figure 1. The output $O_{5,i}$ is computed as follows:

$$O_{5,i} = f_{out} = \sum_{i=1}^{2} \overline{\omega}_i f_i(x,y) = \frac{\sum_{i=1}^{2} \omega_i f_i(x,y)}{\sum_{i=1}^{2} \omega_i}, \quad i = 1,2 \tag{9}$$

The ANFIS is trained based on supervised learning. ANFIS has two adaptive layers in the first and fourth layers. The first layer has modifiable parameters which are related to the membership functions. In the fourth layer, it has modifiable parameters of the first-order polynomial. To make the output of the ANFIS matched with the training data, the learning algorithm of this architecture adjusts all the modifiable parameters. The learning procedure has two steps known as a hybrid learning algorithm. In step 1, the premise parameters are kept without any changes. Node outputs go forward till the fourth layer and the least square method identifies the consequent parameters. In step 2, the consequent parameters are kept without any changes. The error signals propagate (transmit) backward. To update the premise parameters, a gradient descent method is applied. The hybrid learning algorithm in more detail can be found in [20].

4. Methodology

Using the software Matlab, the computation of the data for the ANFIS was employed. The training algorithms of ANFIS, including the least-squares method and the gradient method, were set in Fuzzy Inference System Editor (FIS Editor) in Matlab software. This study includes the following stages:

1. In the first stage, data input stage, input sets, and corresponding outputs were formed by grouping the time series. Each input was made of a set with *n*-tuple with the form $(F_{i-1}, F_{i-2}, \dots, F_{i-n})$ and the output as F_i. The used structure was as follows:

$$f: (F_{i-1}, F_{i-2}, \dots, F_{i-n}) \rightarrow F_i \tag{10}$$

In the Eqn. (10), F_i represents the number of tourist arrivals in the *i*th month.

2. For each input, the number of membership functions and the type of membership functions had to be assigned. The Gaussian membership function (GMF) was used in this study due to its smoothness and concise notation.

$$Gaussian(u; c, \sigma) = \mu_{\tilde{A}(x)} = e^{\frac{-(c-x)^2}{2\sigma^2}} \tag{11}$$

where c is the center of the fuzzy set $\tilde{A}$ and σ is its width.
3. In the third stage, a fuzzy inference system was generated. To find the forecast value based on the given current inputs, Sugeno fuzzy inference system (also referred to as TSK type fuzzy rule-based system) was selected.
4. ANFIS training function in the Matlab fuzzy toolbox was employed for the training of the input data. This procedure has been performed automatically and as a result, an array of training errors was gained.
5. In the last stage, an ANFIS model with a forecasting function has been derived for output forecasting.

5. Numerical Example and Results

Cyprus, as a small country with limited industrial income but numerous natural and manmade attractions has paid significance to the advancement of its tourism industry against its rivals. This island with a population smaller than two million is one of the neighboring countries to the Mediterranean Sea favored by many regional and international tourists [28]. In addition, the geographical location of Cyprus at the gateway of three continents, Asia, Africa, and Europe, has given it a unique advantage. Considering all these, the country's government has employed policies aiming at boosting tourism resulting in economic recovery. The success of those policies is reflected in the tourism sector which is considered as one of the active sectors of the country.

This study aimed to develop an ANFIS to forecast the monthly number of tourist arrivals in Cyprus with high accuracy and low prediction error. The monthly number of tourist arrivals in Cyprus during 2015-2019 was employed as the data set. This data set has been collected and published by the Cyprus Ministry of Finance [29]. Figure 2 illustrates the monthly number of tourist arrivals in Cyprus from January 2015 to December 2019 and sketches based on the collected data.

For the first stage in section 4, a different number of inputs as x=2, x=3, and x=4 was selected. In the second stage in section 4, for each input different number of membership functions were applied as MFs=2, MFs=3, MFs=4, and MFs=5. There are various types of membership functions but the most commonly used ones are Gaussian, Bell-shaped, Triangular, and Trapezoidal membership functions. The Gaussian membership function was suggested in this study due to its smoothness and concise notation, furthermore, it uses only two parameters. Also, the Gaussian membership functions have the advantage of being smooth and nonzero at all points [30],[31]. After deciding about the number of inputs and membership functions for each input, ANFIS was applied to extract the TSK-type fuzzy rule-based system.

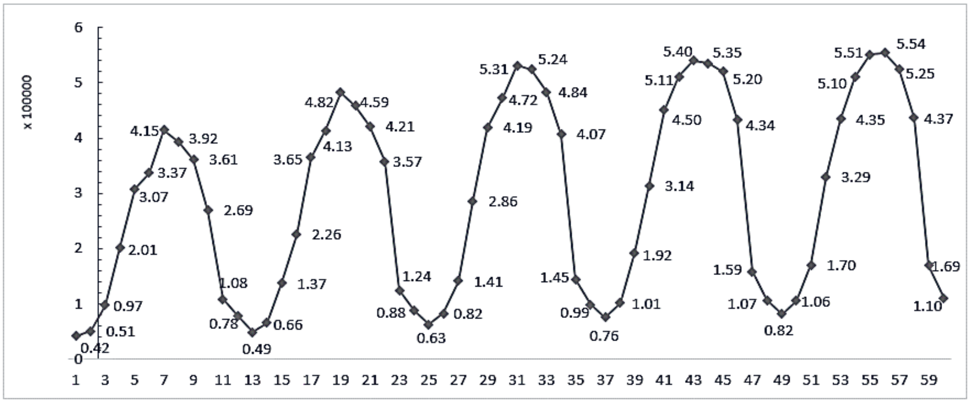

Figure 2. The monthly number of tourist arrivals in Cyprus from January 2015 to December 2019.

In Appendix A, Triangular, Trapezoidal, and Bell-shaped membership functions are defined and their effects on the accuracy of the models were tested. In developing a forecasting model, the selection of the number of inputs and the number of membership functions, and the type of membership functions for each input may affect the accuracy of the system significantly, which has been tested in this study.

By employing different number of inputs and membership functions, twelve models were designed and analyzed. The data set which includes the monthly number of tourist arrivals in Cyprus over 60 months was divided into the training data set (70%) and testing data set (30%) following other studies [32-34]. The training datasets were used to build the models, and the testing datasets were used to validate the models. The models were calibrated using the training data set by modifying the membership function parameters to better match the results. Testing data was used to check the accuracy of each model.

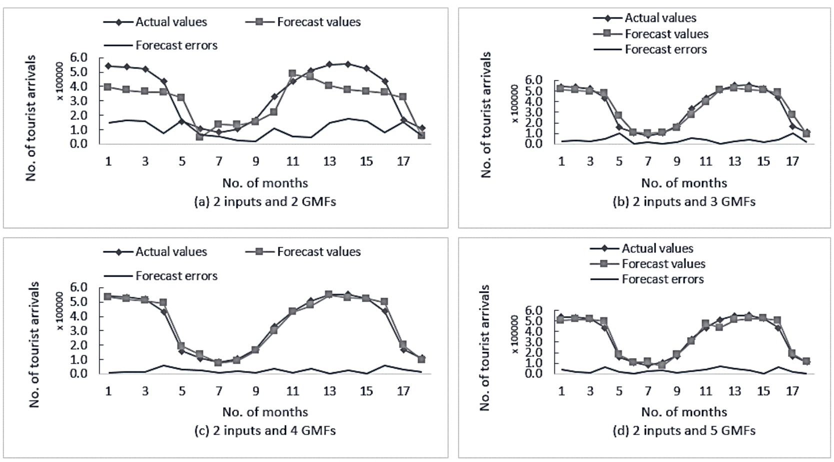

Figure 3. Forecasting results of ANFIS models using testing data with inputs x=2 and Gaussian membership functions $GMFs$=2, 3, 4, 5.

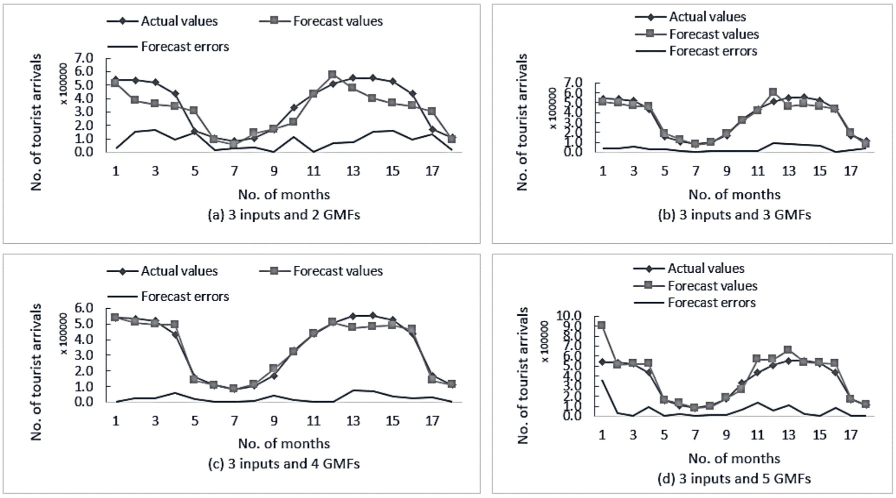

Figure 4. Forecasting results of ANFIS models using testing data with inputs x=3 and Gaussian membership functions *GMFs*=2, 3, 4, 5.

The efficiency and accuracy of each model were calculated based on three different common metrics for measuring the forecast accuracy. The performances of each model were tabulated and compared in Table 1, Table A1, Table A2, and Table A3.

Figure 3 illustrates the forecasting results of ANFIS models using testing data with inputs x=2 and Gaussian membership functions GMFs=2, 3, 4, 5.

Figure 4 illustrates the forecasting results of ANFIS models using testing data with inputs x=3 and Gaussian membership functions GMFs=2, 3, 4, 5.

Figure 5 illustrates the forecasting results of ANFIS models using testing data with inputs x=4 and Gaussian membership functions GMFs =2, 3, 4, 5.

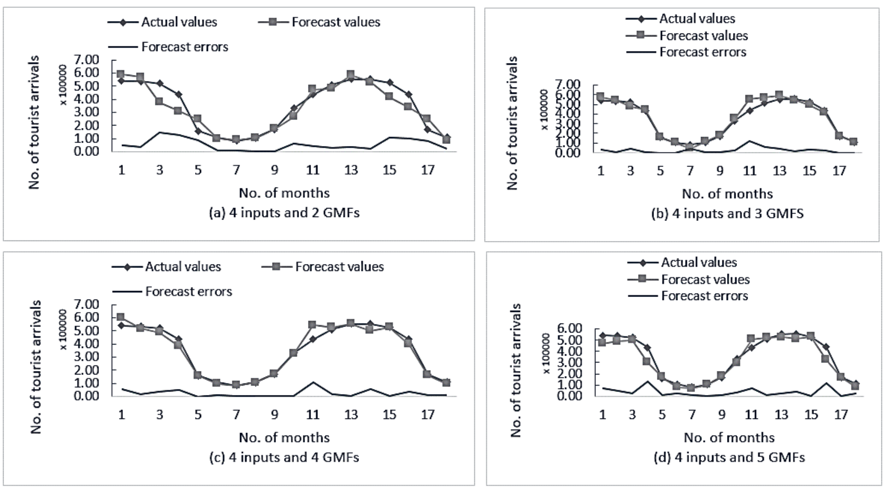

Figure 5. Forecasting results of ANFIS models using testing data with inputs x=4 and Gaussian membership functions *GMFs*=2, 3, 4, 5.

As shown in part (a) of Figures 3, 4, and 5, models with inputs x=2, x=3, and x=4 respectively, when the number of membership functions was *GMFs*=2, the models could not capture the trends of the data efficiently. Therefore, we could not have a desirable output with low forecasting errors and high accuracy.

However, as shown in Figure 4-(c) the model with x=3 and *GMFs*=4, and Figure 5-(c), the model with x=4 and *GMFs*=4 could capture the trends of the data efficiently. Thus selecting the number of membership functions *GMFs*=4 could reduce the forecasting error and increase the forecasting accuracy significantly. Gaussian membership function plot and homogeneous fuzzy partitions where *GMFs*=4 is illustrated in Figure 6.

As shown in Figures 3, 4, and 5 part (d) when *GMFs*=5 regardless of the number of inputs, the accuracy rate of the forecasting models dropped markedly.

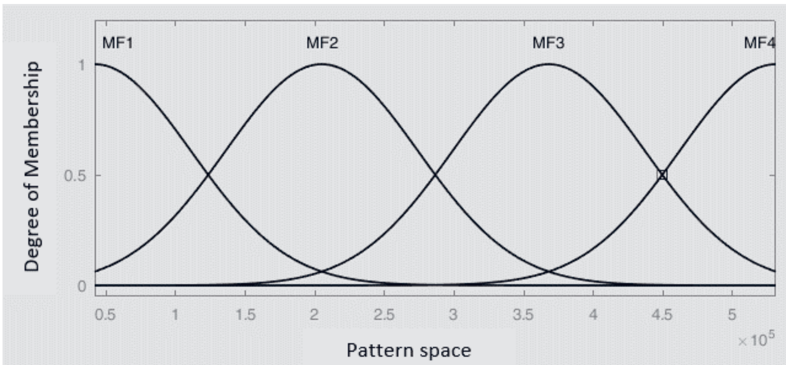

Figure 6. Gaussian membership function plot and homogeneous fuzzy partitions where MFs=4.

The tradeoffs between speed and accuracy, or good generalization and over-fitting, must be considered while determining the size of the membership function. It takes longer to train and generate predictions for a larger number of membership functions. In the ANFIS model with m number of inputs and n number of membership functions for each input, there are totally n^m rules produced. Therefore, the number of rules will increase exponentially by increasing the number of inputs and membership functions which decrease the time complexity of the model significantly.

The accuracy of each forecasting model was measured by applying the mean absolute error (MAE), the root mean square error (RMSE), and the mean absolute percentage error (MAPE). The lowest value of MAD, RMSE, and MAPE shows the desired system.

The formula of MAE is as follows:

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N} |Y_k^{p.} - Y_k^{e.}| \tag{12}$$

The formula of RMSE is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(Y_k^{p.} - Y_k^{e.})^2} \tag{13}$$

The formula of MAPE is as follows:

$$\mathrm{MAPE} = 100 \times \frac{1}{N}\sum_{k=1}^{N}\frac{|Y_k^{p.} - Y_k^{e.}|}{Y_k^{e.}} \tag{14}$$

where N is the number of data used in the testing data set, $Y_k^{p.}$ and $Y_k^{e.}$ represent the predicted and actual (experimental) values of the kth data, respectively.

Table 1 summarizes the parameters and comparison of forecasting models' accuracy in terms of MAE, RMSE, and MAPE(%) of testing data and the parameters of each model.

Programming Language					**MATLAB R2015**							
No. Inputs	2				3				4			
No. Gaussian MFs	2	3	4	5	2	3	4	5	2	3	4	5
ANFIS architecture	2-2	3-3	4-4	5-5	2-2-2	3-3-3	4-4-4	5-5-5	2-2-2-2	3-3-3-3	4-4-4-4	5-5-5-5
No. Rules	4	9	16	25	8	27	64	125	16	81	256	625
MAE	1.03E+05	5.37E+04	2.53E+04	2.89E+04	8.23E+04	3.47E+04	2.20E+04	3.73E+04	5.53E+04	2.43E+04	1.50E+04	3.57E+04
RMSE	1.16E+05	6.88E+04	3.66E+04	3.78E+04	1.01E+05	4.48E+04	3.42E+04	5.24E+04	9.06E+04	3.64E+04	2.78E+04	4.52E+04
MAPE (%)	37.09	14.29	9.18	10.12	27.81	11.26	7.31	13.05	17.03	8.06	**4.18**	11.45
Ranking	12	9	4	5	11	6	2	8	10	3	1	7

Table 1. Parameters and comparison of the forecasting models when MFs type is Gaussian

As it is evident in Table 1, the desired model is the one with 4 inputs (x=4) and 4 membership functions ($GMFs$=4) with the value of MAE equals to 1.50E+04, the value of RMSE equals to 2.78E+04, and the value of MAPE equals to 4.18%.

6. Conclusion

The development and examination of accurate forecasting methods are important topics of continuing interest and research. This study developed twelve adaptive neuro-fuzzy inference systems to reveal the effect of different parameters on the accuracy of the model. A comparative analysis of different models, x=2, 3, 4 and MFs=2, 3, 4, 5, shows that there is a significant positive correlation between the number of inputs, number of membership functions, and the type of membership functions on the forecasting accuracy rate of the models. When the number of inputs is x=2, x=3, or x=4 and the number of Gaussian membership functions is $GMFs$=2, the accuracy of the model is not reliable. However, the superiority of the model with x=4 and $GMFs$= 4 is evident in terms of the overall forecasting error with the lowest error of MAE=1.50E+04, RMSE=2.78E+04, and MAPE=4.18%. It needs to be highlighted that the results of this study show that when *GMFs*=5, the forecasting accuracy will be hindered. Therefore, it can be concluded that the model with 4 inputs *x*=4 and 4 Gaussian membership functions *GMFs*=4 offers a promising alternative for forecasting the number of tourist arrivals. Meantime, the results confirm the usefulness of ANFIS as a forecasting method for tourism demand. Therefore, ANFIS models seem to be applicable for the solution of real-world problems.

Appendix A.

Fuzzy triangular membership function: A triangular fuzzy number is defined by a triplet $\tilde{a} = (a, b, c)$. The membership function $\mu_{\tilde{a}}(x)$ of $\tilde{a}$ is given by

$$\mu_{\tilde{a}}(x; a, b, c) = \begin{cases} 0; & x \leq a \\ \dfrac{x-a}{b-a}; & a < x \leq b \\ \dfrac{c-x}{c-b}; & b < x < c \\ 0, & x \geq c \end{cases} \tag{A1}$$

Fuzzy trapezoidal membership function: A trapezoidal fuzzy number is defined by $\tilde{a} = (a, b, c, d)$. The membership function $\mu_{\tilde{a}}(x)$ of $\tilde{a}$ is given by

$$\mu_{\tilde{a}}(x; a, b, c, d) = \begin{cases} 0; & x \leq a \\ \dfrac{x-a}{b-a}; & a < x \leq b \\ 1; & b \leq x \leq c \\ \dfrac{d-x}{d-c}; & c < x < d \\ 0; & x \geq d \end{cases} \tag{A2}$$

Bell-shaped membership function: A bell-shaped membership function is given by the expression

$$\mu_{\tilde{a}}(x; a, b, c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \tag{A3}$$

where the parameter b is usually positive and defines the shape of the curve on either side of the central plateau, the parameter a shows the width of the curve and the parameter c shows the center of the curve.

Programming Language					MATLAB R2015							
No. Inputs	2				3				4			
No. Triangular MFs	2	3	4	5	2	3	4	5	2	3	4	5
ANFIS architecture	2-2	3-3	4-4	5-5	2-2-2	3-3-3	4-4-4	5-5-5	2-2-2-2	3-3-3-3	4-4-4-4	5-5-5-5
No. Rules	4	9	16	25	8	27	64	125	16	81	256	625
MAE	6.46E+04	3.51E+04	1.05E+05	4.82E+04	6.17E+04	3.66E+04	1.18E+05	4.14E+04	5.31E+04	3.08E+04	2.88E+04	4.96E+04
RMSE	8.46E+04	4.50E+04	2.53E+05	6.60E+04	7.89E+04	4.36E+04	2.45E+05	5.53E+04	6.83E+04	4.34E+04	3.32E+04	6.16E+04
MAPE (%)	30.28	14.49	83.00	22.39	24.20	14.99	82.36	15.96	23.67	13.91	**13.49**	20.47

Table A1. Parameters and comparison of the forecasting models when MFs type is Triangular

Programming Language					MATLAB R2015							
No. Inputs	2				3				4			
No. Trapezoidal MFs	2	3	4	5	2	3	4	5	2	3	4	5
ANFIS architecture	2-2	3-3	4-4	5-5	2-2-2	3-3-3	4-4-4	5-5-5	2-2-2-2	3-3-3-3	4-4-4-4	5-5-5-5
No. Rules	4	9	16	25	8	27	64	125	16	81	256	625
MAE	1.10E+05	6.38E+04	5.32E+04	5.04E+04	1.04E+05	5.14E+04	7.93E+04	5.61E+04	8.32E+04	5.47E+04	3.41E+04	7.24E+04
RMSE	1.32E+05	8.18E+04	8.66E+04	6.09E+04	1.23E+05	6.30E+04	1.13E+05	8.18E+04	1.28E+05	7.33E+04	4.08E+04	1.06E+05
MAPE (%)	45.64	26.59	20.97	15.64	40.24	20.65	27.20	22.37	30.91	21.62	**12.72**	22.66

Table A2. Parameters and comparison of the forecasting models when MFs type is Trapezoidal

Programming Language					MATLAB R2015							
No. Inputs	2				3				4			
No. Bell-shaped MFs	2	3	4	5	2	3	4	5	2	3	4	5
ANFIS architecture	2-2	3-3	4-4	5-5	2-2-2	3-3-3	4-4-4	5-5-5	2-2-2-2	3-3-3-3	4-4-4-4	5-5-5-5
No. Rules	4	9	16	25	8	27	64	125	16	81	256	625
MAE	9.05E+04	4.43E+04	2.92E+05	5.75E+04	7.93E+04	3.27E+05	5.77E+04	7.45E+04	5.10E+04	4.31E+04	3.90E+04	6.39E+04
RMSE	1.14E+05	6.05E+04	7.91E+05	7.36E+04	1.06E+05	6.85E+05	7.39E+04	9.56E+04	6.86E+04	6.23E+04	4.68E+04	8.13E+04
MAPE (%)	39.98	20.06	40.20	25.98	32.86	49.75	29.90	31.50	23.82	18.01	**12.26**	28.16

Table A3. Parameters and comparison of the forecasting models when MFs type is Bell-shaped

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