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A Comparison of the ANFIS Model with SARIMA for the Forecasting of Inbound Tourism Demand for Mauritius

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Abstract

Tourism planning is important while budgeting potential revenue and expenditure for the economy of a country, especially when large amount of funds are involved in the development of this sector. In this paper, we investigate the application of the adaptive network-based fuzzy inference system (ANFIS) model and the seasonal autoregressive integrated moving average (SARIMA) to predict monthly tourism demand from four continents to Mauritius and compare their performances. Based on the error measures, we find that ANFIS method gives better results than SARIMA method and it can be considered as the preferred tool for forecasting tourism demand for Mauritius.

Keywords: *Tourism demand, forecasting, ANFIS, SARIMA, modelling, fuzzy systems.*

**For correspondences and reprints*

1. INTRODUCTION

Mauritius is an island nation situated off the southeast coast of Africa in the southwest Indian Ocean, about 870 km east of Madagascar. It has a population of about 1.3 million with an annual growth of 0.5% and GDP per capita of 8654 USD. It has total area of 2040km2 and its capital is Port-Louis. Though Mauritius forms part of the African continent, the majority of its population is of Indian descent, the remaining population are of African descent while there are about 30000 Mauritians who are Chinese descent. In addition to the physical characteristics of the island in terms of sandy beaches and mild climate, the social harmony which emanates from the diversity and mixture of cultures from these different parts of the planet adds value to qualities of Mauritius. During the 70's, the main source of revenue for the Mauritian economy was from the agricultural sector. After forty years, Mauritius has now a diversified economy which is strongly driven by the services sector and secondly by the manufacturing sector. In fact, the tourism sector has now been established as a pillar industry for the Mauritian economy and actually the number of tourist arrivals per year exceeds the Mauritian population. Tourist arrivals from Europe have increased by 0.7% to account for 63.2% of total tourist arrivals. The main arrivals are from France which represents 31.3% of total tourist arrivals and 49.5% of the European market. Other tourist arrivals consisted of 24% from Africa, 9.4% from Asia while the remaining were from Oceania and America. While India and China form the major part of the Asian market, it is noted that there is an increase in arrivals from other markets such as Hong Kong (+42.9%), Malaysia (+38.3%), Singapore (+28.9%), United Arab Emirates (+8.9%) and Japan (+4.0%). The hotel room occupancy rate and the bed occupancy rate for all hotels in operation in 2011 were 65% .

The tourism industry is a sector that not only brings in foreign currency but also helps in other related sectors such as in job creation, air and sea transport, development in the island and small enterprises for handicraft. Therefore tourist forecasting is a crucial tool for a proper tourism management, especially when considering the impact of the financial crisis and the increase in airfare. Accurate forecasts of tourism demand are important for proper planning by different sectors of the tourism industry and one important factor is forecast accuracy since the tourism product is perishable (unused airplane seats, hotel rooms and hire car rentals cannot be stock-piled)(Hadavandi et al., 2011). Short term forecast help in many sectors such as scheduling, staffing and planning tour operator brochures. As mentioned by V. Cho (2003), the development of the tourism sector involves massive investments; forecasting is thus important when estimating the future demand market penetration. The tourism sector can flourish much better if one can analyse current and past tourist traffic and be able to predict the nature of changes in tourism demand.

In this paper, we investigate the application of two forecasting techniques, namely seasonal ARIMA (SARIMA) and Adaptive Network-Based Fuzzy Inference System (ANFIS) to predict the travel demand from four different continents. The SARIMA model has been widely used to forecast tourism arrival, whereas the ANFIS system has not been too popular. The novelty of this work is that no such forecasting methods have been done to the tourism sector in Mauritius. The findings can be useful to the government for long term planning. The remainder of this paper is organised as follows: section 2 gives a literature review of works done in this field; section 3 describes the SARIMA and the ANFIS models. In section 4 the methodology and the data collection is discussed followed by section 5 where the results are analysed. Finally the paper ends by some concluding remarks.

2. LITERATURE REVIEW

The important areas of tourism research which are tourism demand modelling and tourism forecasting have been an active topic of research throughout the world. Most of these studies deal with the applications of different techniques, both quantitative and qualitative, to model and forecast the demand for tourism in various destinations. Witt and Song (2000) and Li et al. (2005) have shown that the performance of the forecasting models varies according to the data frequencies used in the model estimation, the destination – origin country/region pairs under consideration and the length of the forecasting horizons concerned.

Early research works in the field of tourism forecasting were done by Archer (1987) and Morley (1991). In a recent work of Song and Li (2008), it was shown

that there is an average of 17 research publications of tourism demand modelling and forecasting studies which appear annually which accounts for a total publication of 119 papers for the period 2000-2006. The regions under consideration varied from various places over the world including the Indian Ocean particularly Seychelles islands, but Mauritius has not been a country of focus for this type of study. This has been the major motivation for the study in our paper.

Before the 1990s, regression analysis was used to predict tourist arrival but in the mid 1990s nonlinear models were applied and these were proved to be much more efficient than the traditional methods. These modern econometric techniques consists of Autoregressive Integrated Moving average (ARIMA), Autoregressive distributed Lag model, GARCH model (Lee et al., 2008), Error correction model, Vector Autoregressive Model (Wong et al., 2007), Artificial Neural networks (Palmer et al.; 2006) and Neuro-Fuzzy Logic Models (Wang et al., 2008). Dharmaratne (1995) applied the ARIMA model to forecast tourist arrivals in Barbados. Goh and Law (2002) concluded that the SARIMA model performed better than some other time-series models while Smeral and Wüger (2005) demonstrated the limitations of these linear models. An attempt to improve the univariate time series model the multivariate dimension approach was adopted. One application to tourism demand has been the Generalised Autoregressive Conditional Heteroskedastic (GARCH) model. Chan, Lim and McAleer (2005) applied three multivariate GARCH models in tourism demand.

Another type of the model that has been under study is the econometric model. The main advantage of these types of models lies in its ability to analyse the casual relationships between the tourism demand (dependent) variable and its influencing factors (explanatory variables). Econometric models consolidate existing empirical and theoretical knowledge of how economies function, provide a framework for a progressive research strategy, and help explain their own failures (Clements and Hendry, 1998). As far as tourism demand is concerned, econometric analysis has its empirical usefulness in interpreting the change of tourism demand from an economist's perspective, proving policy recommendations as well as evaluating the effectiveness of the existing policies.

Apart from the time series and econometric models, Artificial Intelligence techniques have also been a tool in this area of research. Heuristic methods such as genetic algorithms, fuzzy logic, artificial neural networks and support vector machine do not require any a-priori information about data such as distribution and probability as opposed to the linear statistical models. The flexibility of these models can be used to estimate the nonlinear relationship without the constraints of time series and econometric models. A comparison of exponential smoothing, univariate ARIMA and Elman's model of artificial neural networks was carried out by Cho (2003) and the analysis showed that ANN gave the best forecasted values. Wang (2004) compared used fuzzy time series with grey forecasting model GM(1,1) and Markov residual modified model for tourism forecasting but the use of ANFIS was first done by Chen et al. (2009). Their experiments showed that the ANFIS model performed better than the methods proposed by Wang (2004). However, no definitive criteria exist to determine which forecasting method outperforms for a particular data demand.

Some recent studies have also been carried by Çuhadar (2014) where the accuracy of a forecasting model was compared to that of the different exponential smoothing and Box-Jenkins models for the forecast of the monthly inbound tourism demand to Istanbul. Another work by Çuhadar et al. (2014) has showed that radial basis function neural network is more accurate than multi-layer perceptron and the generalised regression neural networks.

3. METHODOLOGY

In the field of statistics many linear and non-linear forecasting techniques exist and have many applications in various economic sectors. For the purpose of our study we have chosen a linear forecasting technique and a non-linear one. The main aim of this paper is to compare the seasonal ARIMA and ANFIS method on the Mauritian data. From literature review it can be noted that the ANFIS method has not been commonly used as a forecasting technique for tourism forecasting, hence our motivation to investigate this method on local data. In this section the theory of the two models are discussed.

3.1. Seasonal ARIMA

One of the models which are widely used in time series analysis is the ARIMA model. The latter is associated with three types of processes which are: auto-regression, differencing involved in the integration and moving averages. Each of these three processes respond to random disturbances in their own characteristics. The general linear equation governing ARIMA models is given as (Panktratz, 1983)

$$\phi_p(B)\phi_{sp}(B^L)\nabla^d\nabla_L^{sd}Z_t = \Theta_{sq}(B^L)\theta_q(B)\varepsilon_t$$

where Z_t is the stationary data point at time *t*; *B* the backshift operator, with $B(Z_t) = Z_{t-1}$; *L* is the seasonal periodicity; ε_t is the present disturbance at time *t*; $\phi_p(B)$ is $(1-\phi_1 B-\phi_2 B-\cdots-\phi_p B)$, non- seasonal operator; $\Phi_{sp}(B^L)$ is $(1-\phi_{1L}B^L-\phi_{2L}B^L-\cdots-\phi_{sp}B^L)$, seasonal operator; $\theta_q(B)$ is $(1-\theta_1 B-\theta_2 B-\ldots-\theta_p B)$,
non-seasonal operator; $\Theta_{sq}(B^L)$ is $(1-\Theta_{1L}B^L-\Theta_{2L}B^L-\cdots\Theta_{sqL}B^L)$, seasonal operator; ∇^d is $(1-B)^d$, non-seasonal differencing operator; and ∇_L^{sd} is $(1-B^L)^{sd}$, seasonal differencing operator. The parameters of the ARIMA $(p,d,q)(sp,sd,sq)_L$ model are defined as follows: *p* is the AR order which represents the number of parameters of ϕ, *d* the number of times the data series must be differenced to induce a stationary series Z, *q* the MA order which indicates the number of parameters of θ, *sp* is the seasonal AR order which indicates the number of parameters of Φ, and *sq* is the seasonal MA order which indicates the number of parameters of Θ, and *sd* is the number of times the data series needs to be seasonally differenced to induce a seasonally stationary series. The aim is to find the values of *p, d* and *q* needed in the general ARIMA model and to obtain estimates for the parameters. These

parameters are usually determined by inspecting the behaviour of auto-correlation function (ACF) and partial auto-correlation function (PACF) (Box et al., 1994). The ACF and PACF of a stationary series should show either a cut-off or rapidly dying pattern. In practice, the determination of *d* and *sd* requires guessing different combinations among the possible values until the desired patterns of ACF and PACF are achieved. But in our case the simulation was done using Matlab R2012 statistical toolbox where these steps are already inbuilt while the simulations are performed.

3.2 Adaptive Neuro-Fuzzy Inference Systems

ANFIS (Jang, 1993) is a hybrid fuzzy inference system implemented in a framework of adaptive network. It helps in finding a mapping relation between input and output data through hybrid learning to determine the optimal distribution of membership functions. In fact it constructs an input-output mapping based on both human knowledge and stipulated input-output data pairs. It has been widely used to model non linear functions, identify nonlinear components on-linely in a control system and predict a chaotic time series.

The inference system in ANFIS consists of five layers and each layer contains several nodes which are described by the node function. An adaptive network is a multilayer feedforward network in which a node function is applied on incoming signals and other related parameters by each node. The choice of the node function depends on the overall input-output function which the adaptive network is aiming at, and the formulas for the function depend from node to node. The nodes can be either illustrated by squares or circles. The square nodes denote the adaptive nodes which represent the parameter sets that can be updated according the given training data and a gradient based learning algorithm. The circle nodes denote the fixed nodes which represent the parameters that are fixed in the system. The output data from the nodes in the previous layers will be the input in the present layer.

Let us assume that the fuzzy inference system has two inputs *x* and *y* and one output *z*. Figure 1 illustrated the framework of ANFIS and the node functions in each layer are described as follows:

Layer1: Every node in this layer is an adaptive node with node function as

$$O_{1,i} = \mu_{A_i}(x), \text{ for } i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \text{ for } i=3,4$$

where *x* (or *y*) is the input of the node, A_i (orB_i) is the linguistic label, $\mu(x)$ (or $\mu(y)$) is the membership function, usually adopting bell shape with maximum and minimum equal to 1 and 0 respectively, as follows:

$$\mu(x) = \frac{1}{1+\left(\frac{x-c_i}{a_i}\right)^{2b_i}}$$

or

$$\mu(x) = \exp\left(-\left(\frac{x-c_i}{a_1}\right)^2\right)$$

where $\{a_i, b_i, c_i\}$is the parameter set. The bell shaped functions depend on the changes of the parameter and these are named premises parameters.

Layer 2: Every node in this layer is a circle node labelled Π which multiplies the incoming signals and sends the product out as illustrated,

$$O_{2,i} = \mu_{A_i}(x) \cdot \mu_{B_i}(y) = \omega_i, \text{ for } i = 1, 2.$$

The output node ω_i represents the firing strength of the rule.

Layer 3: Every node in this layer is a fixed node, marked by a circle and labelled *N*, with the node function to normalize the firing strength by calculating the ratio of the i^{th} node firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \frac{\omega_i}{\sum \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} = \varpi_i \text{, for } i = 1,2$$

Layer 4 Every square node *i* in this layer has a node function defined as

$$O_{4,i} = \varpi_i \cdot f_i \text{ for i =1,2}$$

where f_1 and f_2 are the fuzzy if-then rules as follows (Sugeno and Takagi, 1983):

Rule 1: if x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: if x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$

And where $\{p_i, q_i, r_i\}$ is the parameters set, referred to as the consequent parameters.

Layer 5 Every node in this layer, labelled as Σ is a circle node with node function that computes the overall output as the summation of all incoming signals, that is

$$O_5 = \sum \varpi_i \cdot f_i = z .$$

The construction of this inference system requires five layers where each layer contains the nodes described by the node function (Chen et al., 2010). Assuming that the training data set has *n* entries, we define the error as

$$E = \sum_{i=1}^{n} E_i = \sum_{i=1}^{n} (T_i - z_i)^2, \qquad (1)$$

where E_i is the error for each ith entry of the given training data set, T_i is the ith entry of the desired output and z_i is the ith entry of the ANFIS output.

From the design of ANFIS, if the parameters $\{a_i, b_i, c_i\}$ are fixed, the output z_i will be a linear combination of the consequent parameters $\{p_i, q_i, r_i\}$ as follows:

$$\begin{aligned} z &= \sum \varpi_i \cdot f_i = \varpi_1 f_1 + \varpi_2 f_2 \\ &= \varpi_1 (p_1 x + q_1 y + r_1) + \varpi_2 (p_2 x + q_2 y + r_2) \\ &= (\varpi_1 x) p_1 + (\varpi_1 y) q_1 + \varpi_1 r_1 + (\varpi_2 x) p_2 + (\varpi_2 y) q_2 + \varpi_2 r_2 \end{aligned}$$

The output vector *z* can also be expressed as

$$z = A\theta \tag{2}$$

where

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}, \ \theta = \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix}, \ A = \begin{bmatrix} \overline{\omega}_1 x_1 & \overline{\omega}_1 y_1 & \overline{\omega}_1 & \overline{\omega}_2 x_1 & \overline{\omega}_2 y_1 & \overline{\omega}_2 \\ \overline{\omega}_1 x_2 & \overline{\omega}_1 y_2 & \overline{\omega}_1 & \overline{\omega}_2 x_2 & \overline{\omega}_1 y_2 & \overline{\omega}_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \overline{\omega}_1 x_n & \overline{\omega}_1 y_n & \overline{\omega}_1 & \overline{\omega}_2 x_n & \overline{\omega}_2 y_n & \overline{\omega}_2 \end{bmatrix}$$

and θ is an unknown matrix whose elements come from the consequent parameters set.

The above description is equivalent to a type-3 fuzzy inference system. Figure 1 shows the type-1 ANFIS where the overall output is the weighted average of each rule's output induced jointly by the output membership function and the firing strength.

ANFIS consists of a hybrid learning algorithm which combines the gradient method with the least squares method to update the parameters in an adaptive network. The least square estimator is given by

$$\theta^* = (A^T A)^{-1} A^T z. \tag{3}$$

The epochs of this hybrid learning procedure are composed of the forward and backward pass. In the forward pass, the node output for each input vector is calculated until the matrices *A* and *z* given in (2) are obtained. Equation (3) is used to obtain the consequent parameters set and the error is calculated by using (1). In the backward pass, the error rate given by $\frac{\partial E_i}{\partial O}$ for each entry *i* of the training data set and for each output node *O*, is calculated. Defining α as a parameter of the premise parameters set, V as the set of nodes whose output depend on α, and $\tilde{O}$ as a node output which belongs to V, the overall error measure E with respect to α is given as

$$\frac{\partial E}{\partial \alpha} = \sum_{i=1}^{n} \frac{\partial E_i}{\partial \alpha} = \sum_{i=1}^{n} \sum_{\tilde{O} \in V} \frac{\partial E_i}{\partial \tilde{O}} \frac{\partial \tilde{O}}{\partial \alpha}.$$

The updated formula for the premise parameter α the gradient method is given by

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha}$$

in which η is a learning rate.

3.3 Data Collection

Tourist arrival data was obtained from the Ministry of Tourism and Leisure and these were categorised by different continents from the January 1983 to March 2011 as shown in Figure 1. The four continents namely, Europe, Asia, Africa and Oceania were considered for our simulations. Monthly data was considered for the simulations in the paper. It is to be noted that the number of tourist arrivals was affected by the financial crisis in the year 2009. Denoting the raw tourist arrival per month as RT_m, we define the arrival differences as $T_m = \log RT_{m+1} - \log RT_m$. The collected data was divided into two sets namely the training set and the testing set. The ratio of the training set to the testing set is 2:1. The same proportion set was applied to both methods so as a good comparison can be made. The MAPE, MAE and RMSE are the measures of accuracy that are used and they are defined as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{a_i}\right| \quad 100(\%), \text{where } e_i = a_i - f_i$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|a_i - f_i\right|$$

$$\text{and} \quad RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left|a_i - f_i\right|^2}{n}}. \tag{1}$$

4. RESULTS AND DISCUSSION

The simulations for both methods, ARIMA and the Adaptive Neuro-Fuzzy Inference Systems were done using Matlab R2012. The data set consisted of 338 months, the training set was considered for 200 months and the rest was left for the testing part. The time series plots of all data used in the study are shown in Figure 2. As mentioned earlier the best model for seasonal ARIMA is chosen by the toolbox itself model which gave the best results is ARIMA(0,1,1) with Model Seasonally Integrated with Seasonal MA(12). We have used a multiplicative seasonal ARIMA model with seasonal and non-seasonal integration, given by

model = arima('Constant',0,'D',1,'Seasonality',12, 'MALags',1,'SMALags',12).

The characteristics for the model in Matlab R2012 are then given as follows:

```
        ARIMA(0,1,1) Model Seasonally Integrated with Seasonal MA(12):
   ---------------------------------------------------------------
   Distribution: Name = 'Gaussian'
             P: 13
             D: 1
             Q: 13
        Constant: 0
              AR: {}
             SAR: {}
              MA: {NaN} at Lags [1]
             SMA: {NaN} at Lags [12]
     Seasonality: 12
        Variance: NaN
```

The ACF plots are presented for each data set before and after differencing in Figure 7. The Ljung-Box (Q*) statistics for checking ARIMA model for the four different data sets were computed and they were all equal to 1.

For the ANFIS method, we have used the MATLAB R2012 fuzzy inference toolbox for performing our simulations. Since our data set consist of tourists arrivals for 338 months, we first create mapping from N sample data points, sampled by a four dimensional vector of the form $[x(t\text{-}18)\ x(t-12)\ x(t-6)\ x(t)]$, to a predicted value $x(t+6)$. We have used the first 200 values of the data set for the ANFIS training while the remaining were used for validating the fuzzy model. The second step consists of creating a fuzzy inference system structure and initial parameters for the learning process. The initial membership functions for the European dataset are given in Figure 3 and were obtained by using the following command:

```
fismat = genfis1(trnData,2,'gbellmf','constant');
```

The generalized bell function was chosen as the initial membership function. In the third step, the training process of the toolbox is launched for training the input data. The command is given as follows:

```
[fismat1,error1,ss,fismat2,error2] = anfis(trnData,fismat,[3000 0 0.001 0.9 1.1],[],chkData);
```

Figure 4 shows the corresponding final membership functions for the Europe dataset after training. The final step consists of using ANFIS model with forecasting function to predict the tourist arrival for the remaining 128 months as given in Figure 5. This is done by executing the following command:

```
anfis_output = evalfis([trnData(:,1:4); chkData(:,1:4)],fismat2);
```

The parameters used for ANFIS are: 3000 training epochs, an initial step size of 0.001, a step decrease rate of 0.9 and a step increase rate of 1.1. The best model chosen by Matlab R2012 has 55 nodes, 16 linear parameters, 24 nonlinear parameters and 16 fuzzy rules for the four data sets. The error of the training set appeared to stabilise after about 361, 466, 1815 and 1486 training epochs for the Europe, Asia, Africa and Oceania dataset respectively.

From the testing set, the three measures mentioned in (1) are calculated for both methods and the results are given in Table 1. From the three measures of accuracy, it can be seen that ANFIS gives the smallest error term except for the case of Asia where MAPE is slightly larger as compared to the SARIMA. The result of ANFIS outperforms SARIMA in all the four series. The number of arrival of tourists in Mauritius is very dependent on the time period and on the type of climate. It is observed that when it is summer in the northern hemisphere there is a drop in the number of tourist arrivals to Mauritius. Furthermore this corresponds to the winter season in Mauritius and hence not many tourists are attracted to visit the island. Although seasonality exists in the data set, it can be said that ANFIS is a better method to predict the tourist arrivals in Mauritius. It captures the seasonality component and has been also able to cater for the drop in the number of tourist arrivals due to the financial crisis. We thus believe that this method will successfully predict sharp increase or decrease in case an unexpected event arises.

5. CONCLUSION

This paper investigates two forecasting methods on the Mauritian tourism arrival data from the four continents mainly Europe, Africa, Asia and Oceania. The highest number of tourist arrivals is from the European countries and seasonality is observed in the dataset. In all the four cases it can be seen that ANFIS is a better method to forecast the number of visitors coming to Mauritius. Such a study is an important economic factor for the island as tourism industry is one of the main industries that bring in foreign currency and development in the island. As a future work, a longer time series analysis taking into account weekly data could be considered in order to better capture the trend and seasonality. The number of passengers travelling in and out the island can also be studied using the same methods and this will help stakeholders of the tourism and aviation industries.

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