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# Combining Deep Neural Network and Fourier Series for Tourist Arrivals Forecasting

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**Abstract.** Accurate tourist arrivals forecasting is essential for governments and the private sector to formulate policies and allocate funds more effectively. In this paper, the modeling of tourist arrivals time series data was introduced in a hybrid modeling that combines the deep neural network (DNN) with the Fourier series method. The proposed model approach applies the DNN to get the forecasted value and then employs the Fourier series to fit the residual error produced by the DNN. To verify the accurate prediction of the proposed model, different single models such as ARIMA, ANN and DNN, and modified ARIMA and ANN models using Fourier series are investigated. Historical data on monthly tourist arrivals to Langkawi Island with high trend and strong seasonality is used to compare the efficiency of the proposed model. A series of studies demonstrates that the performance of the single model can be further improved by taking into account the residual modification by Fourier series. The result shows that the proposed model is capable of forecasting tourist arrival series with higher reliability than other models used.

## 1. Introduction

Tourism is a significant source of economic activity, foreign-exchange income and job creation. Accurate tourist arrivals forecasting plays a significant role in offering valuable information to tourism professionals and scientists to make decisions about operations such as allocating adequate operational funds, financial planning, investment and future hazards.

In the past, different statistical-based linear time series prediction methods were suggested in tourism forecasting, such as the Naïve [1-3], exponential smoothing [1-5], moving average (MA) [4-5] and the autoregressive integrated-moving average (ARIMA) [1-9]. Among the various statistical models, ARIMA model is widely used and attracting increasing attention. The ARIMA model's popularity is due to remarkable predictive precision and flexibility in depicting several distinct kinds of time series. However, ARIMA model is a linear model with a major limitation, so it is unsuitable to model real-world time series with high complexity and strong seasonality underlying its structure [10].

Over the past year, artificial intelligence (AI) models have been associated with soft computing techniques such as artificial neural networks (ANN) [1,3,5,6,8,11], support vector regression [1,12,13] and fuzzy time series theory [14] and have been found having increasing consideration in tourism demand forecasting. These AI-based models can explain non-linear data without a prior understanding of the interactions between input and output factors variables. ANN has drawn a good deal of attention from scientists and has shown powerful viability and ability to handle almost any type of non-linear data. However, choosing an optimal network structure (layers and nodes) and training algorithms



remain a challenging problem in ANN apps [15]. In addition to developing the ANN model, more parameters need to be designed and this can sometimes lead to over-fit and thus leads to unsatisfactory forecasting capability [16].

Recent advances in AI-based technique called deep neural network (DNN) techniques have been gaining special attention from the researchers. The DNN is the general form of an ANN with multiple non-linear hidden layers between the input layer and output layer. DNN can still handle complicated linear and non-linear time series and has been proven efficient for multiple apps such as natural language processing [17], image recognition [18], and forecasting problems [19-23]. Although DNN has accomplished excellent success in a diverse range of difficult applications, this technique has its disadvantage such as being very slow and much harder to train and it is usually difficult to adjust the complexity of the model with deep architecture [24].

However, despite several advantages of the ARIMA, ANN or DNN model, it might not be appropriate to use any single model alone to capture the time series with high complexity and seasonality. In order to make the single model of statistical models or AI models more effective, several prior researches have been suggested by combining different predictive models. The fundamental concept of the combined model is to solve the disadvantages of the single models and create a synergetic impact in the prediction. The combination of multiple models can be an efficient way to enhance the efficiency of these models in forecasting, and can decrease errors and enhance overall accuracy. There have been several studies showing that combination of forecasts has been a very efficient strategy in time series forecasting such as combination of the ARIMA and sine wave regression model [25], ARIMA and ANN [1,9,27], ARIMA and GARCH [27], SVR and ANN [2], ANN and Grey–Markov models [28], ARIMA and Fourier series [29-30], Grey model and Fourier series [31-34], ARIMA and deep learning model [19] and ANN and clustering [35].

Therefore, the main purpose of this study is to evaluate the combination of forecasting method based on the advantage of the DNN model and the Fourier series technique in order to build an efficacy model with the aim of enhancing predictive accuracy. The proposed model is a two-stage procedure: first, the DNN model is used to obtain the fitted value and then the Fourier series is used to modify the DNN model residual. The monthly tourist arrivals to Langkawi Island, Malaysia are chosen as a research study to verify the effectiveness of the proposed model.

## 2. Time Series Forecasting Models

This section provides an overview of some of the forecasting models including ARIMA, ANN, DNN and the proposed hybrid models.

### 2.1. The Autoregressive Integrated Moving Average Model

ARIMA model was one of the most popular models for the time series forecasting study [36]. The structures of the ARIMA models for the non-seasonal and seasonal compounds are referred to as ARIMA(p, d, q)(P, D, Q)s and can be written as

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D x_t = \theta_q(B)\Theta_Q(B^s)a_t \quad (1)$$

Here  $\phi_p(B)$  and  $\theta_q(B)$  are non-seasonal autoregression and moving average parameters of order p and q, respectively;  $\Phi_P(B^s)$  and  $\Theta_Q(B^s)$  are seasonal autoregression and moving average parameter of order P and Q, respectively; d number of regular differencing; D number of seasonal differencing and s length of season and  $a_t$  is white noise. The main task for modeling ARIMA model is to select an optimum order of d, D, p, q, P and Q. Reference [36] proposed a methodology to develop the ARIMA based on four-stage procedure: identification, estimation, diagnostic testing and forecasting.

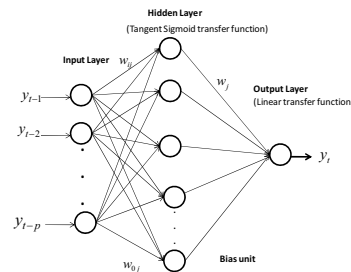
In this research, R software based on the Forecast package was used to model the ARIMA models [37]. The number of non-seasonal, d and seasonal differences, D, are determined using the Osborn-Chui-Smith-Birchhall test and seasonal unit root test [38]. Meanwhile, the order values of p, q, P and Q are determined using the Akaike Information Criterion (AIC). The ARIMA model with the smallest value of AIC is the best ARIMA model for modeling.

### 2.2. The Artificial Neural Networks Model

Artificial Neural Networks (ANN) are nonlinear forecasting models which are able to fit any nonlinear problems up to any desired degree of accuracy. The Multi-Layer Perception (MLP) of ANN with a single hidden layer is considered. Figure 1 shows the structure of ANN consisting of three layers: the input layer, the hidden single layer, and the output layer. The mathematical model of ANN can be written as:

$$y_t = g\left(w_0 + \sum_{j=1}^q w_j \cdot f\left(\sum_{i=1}^p w_{i,j} y_{t-i} + w_{0,j}\right)\right) \quad (2)$$

Here  $y_{t-1}, y_{t-2}, \dots, y_{t-p}$  are the input nodes,  $p$  is the number of nodes input,  $y_t$  is the output node,  $w_{i,j}$  the weight between input and hidden nodes and  $w_j$  is the bias at hidden nodes, the number of hidden nodes and  $f()$  and  $g()$  are the transfer functions from input layer to hidden layer and from hidden layer to output layer, respectively. In the present work, the common algorithm known as back-propagation algorithm with gradient descent and momentum terms was considered to train ANN.



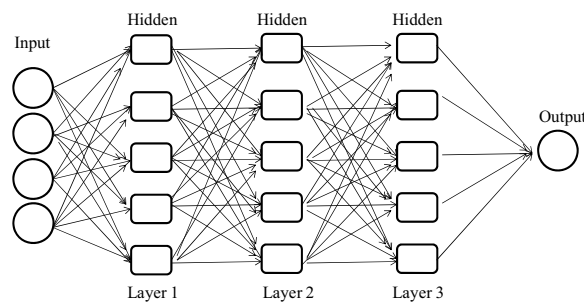
**Figure 1.** Three-layered feedforward ANN model.

### 2.3. The Deep Neural Network Method

Deep neural network (DNN) is an extension of ANN with more than one hidden layer as shown in Figure 2. The main problem for developing DNN is finding the number of hidden layers and the number of nodes for each layer. DNN employed in this study is composed by five layers: one input layer, three hidden layers and one output layer. The mathematical formulation of DNN model with 3 hidden layers can be written as the following equation.

$$y_t = \alpha_0 + \sum_{i=1}^s \alpha_i g\left(\sum_{j=1}^r \beta_{ij} \cdot f\left(\sum_{k=1}^q \gamma_{jk} h\left(\sum_{l=1}^p \theta_{kl} y_{t-l}\right)\right)\right) \quad (3)$$

where  $y_{t-1}, y_{t-2}, \dots, y_{t-p}$  are the input variables,  $p$  is the number of input variables,  $y_t$  is the output variable,  $\alpha_i, \beta_{ij}, \gamma_{jk}$  and  $\theta_{kl}$  are the weights, the number of variables in the first hidden layer, second hidden layer and third hidden layer are represented by  $q, r, s$  respectively, and  $g(), f()$  and  $h()$  are activation functions of the hidden layers. The feed-forward network using a back-propagation algorithm was used to train DNN and to find the optimum values of weights.



**Figure 2.** The DNN architecture.

#### 2.4. The Fourier Deep Neural Networks Model

Fourier series has been commonly used to modify the residuals of forecast models to enhance the precision of forecast models [31-34]. The procedure of constructing a modified forecasting model named Fourier Deep Neural Networks (FDNN) model is as follows:

- Step 1 - Fit a data,  $y_t$  using DNN model.  
 Step 2 - Find the forecast values of DNN,  $\hat{y}_t$  and generate the residual series  $e_t = \{e_1, e_2, \dots, e_n\}$  where  $e_t = y_t - \hat{y}_t$ .

- Step 3 - Fit a residual,  $e_t$  model using Fourier series as

$$e_t = \frac{a_0}{2} + \sum_{k=1}^M a_k \cos\left(\frac{2tk\pi}{n-1}\right) + b_k \sin\left(\frac{2tk\pi}{n-1}\right), \quad k = 2, 3, \dots, n \quad (4)$$

where  $M = (n-1)/2 - 1$  is integer number. The residual series can be written as  $e = SR$  where

$$S = (0.5 \quad P_1 \quad \dots \quad P_k \quad \dots \quad P_F), \quad R = [a_0, a_1, b_1, a_2, b_2, \dots, a_F, b_F]^T \quad (5)$$

$$S_k = \begin{pmatrix} \cos\left(\frac{2 \times 2\pi \times k}{n-1}\right) & \sin\left(\frac{2 \times 2\pi \times k}{n-1}\right) \\ \cos\left(\frac{3 \times 2\pi \times k}{n-1}\right) & \sin\left(\frac{3 \times 2\pi \times k}{n-1}\right) \\ \vdots & \vdots \\ \cos\left(\frac{n \times 2\pi \times k}{n-1}\right) & \sin\left(\frac{n \times 2\pi \times k}{n-1}\right) \end{pmatrix} \quad (6)$$

The parameters  $R$  are estimated using the ordinary least squares method (OLS)

$$\hat{R} = (S^T S)^{-1} S^T e^T \quad (7)$$

The residual modified by Fourier series can be found using the following equation:

$$\hat{e}_t = \frac{a_0}{2} + \sum_{k=1}^M a_k \cos\left(\frac{2tk\pi}{n-1}\right) + b_k \sin\left(\frac{2tk\pi}{n-1}\right), \quad k = 2, 3, \dots, n \quad (8)$$

- Step 4 - Finally, the forecast values of Fourier DNN (FDNN) model can be obtained by summing up the forecasts.

### 3. Examining the Performance

In order to check the performances of proposed model, two performance indices, i.e. mean absolute percentage error (MAPE) and root mean square error (RMSE) were utilized.

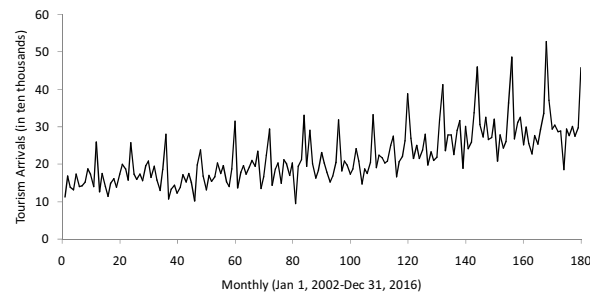
$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{x_i - \hat{x}_i}{x_i} \right| \quad \text{and} \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2} \quad (9)$$

where  $x_i$  is the actual value,  $\hat{x}_i$  is the forecasted value, and  $n$  is the total number of datasets. The model with the lowest MAPE and RMSE values is regarded as the best model for forecasting.

### 4. Data and Empirical Results

In this study, tourist arrivals to Langkawi Island in Malaysia that was obtained from the website of Langkawi Development Authority (LADA) Malaysia is considered for analysis. The simple data is monthly tourist arrivals to Langkawi Island from January 2002 to December 2016 (a total of 180 observations). The training data starting from January 2002 to December 2015, which contains 168 observations, and 12 months data from January 2016 to December 2016 are used to check their

forecasting capabilities. Figure 3 demonstrates the monthly tourist arrivals to Langkawi Island from January 2002 to December 2016. Figure 3 demonstrates that there is a trend, non-stationary and seasonal pattern in the curve of monthly tourist arrivals. In this research, three single models such as ARIMA, ANN, DNN and two combined models such as FARIMA and FANN were considered to assess the efficiency of the suggested model.



**Figure 3.** The monthly tourist arrivals to Langkawi Island in Malaysia from 2002 to 2016

#### 4.1. The model of ARIMA fits the data

The ARIMA model was simulated and optimized using the Forecast package in R provided by [37]. The Automatic-Arima in Forecast package was considered with the maximum order for  $p$  and  $q$  set to 5,  $d$ ,  $P$  and  $Q$  set to 2 and  $D$  set to 1 as default. The maximum likelihood estimate (MLE) has been used to estimate ARIMA models parameters and Ljung-Box test is needed to confirm that the chosen model is an adequate one for the series. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are used to determine the number of ordinary ( $d$ ) and seasonal ( $D$ ) differencing to make the series stationary, while the statistics AIC is used for selecting the values of  $p$ ,  $P$ ,  $q$  and  $Q$  for each ARIMA model.

Table 1 shows the comparison of AIC and p-value of Ljung-Box test for several selected ARIMA models based on Automatic-Arima in R software. The Ljung-Box test shows that the five selected models are adequate, and ARIMA(1,0,2)(0,1,1)<sub>12</sub> has the lowest values of AIC. The result shows that the ARIMA(1,0,2)(0,1,1)<sub>12</sub> found is the best model for modeling (i.e., it has the smallest AIC value). The model can be expressed as

$$(1-0.7771B)(1-B^{12})x_t = 941.745 + (1-0.810B + 0.287B^2)(1-0.330B^{12})a_t \quad (10)$$

**Table 1.** Recommended Comparison of AIC and P-value of the Ljung-Box Test for Chosen Candidate Models

No	ARIMA	AIC	p-value of Q(r) Test		
			Lag=12	Lag=24	Lag=36
1	(2,0,2)(0,1,1) <sub>12</sub>	3406.693	0.9771	0.9959	0.2189
2	(1,0,2)(0,1,1) <sub>12</sub>	3404.257	0.9972	0.9956	0.2259
3	(1,0,2)(0,1,2) <sub>12</sub>	3406.433	0.9972	0.9956	0.2263
4	(2,0,3)(0,1,1) <sub>12</sub>	3405.561	0.9999	0.9994	0.2811
5	(1,0,3)(0,1,1) <sub>12</sub>	3406.378	0.9969	0.9963	0.2071

#### 4.2. The Model of ANN Fits the Data

In this research, multi-layer perception (MLP) and back propagation algorithms were used to train the ANN model using library neuralnet in R software. At the first stage of constructing the ANN and DNN models, the dataset was scaled within the range of [0, 1]. Selecting the input variables is one of the most significant steps in creating a satisfying ANN model. Reference [39] discovered that the lagged variables in AR terms acquired from the ARIMA model are the most significant variables to be used as ANN model input variables. According to Table 2, the best ARIMA model is ARIMA (1,0,2)(0,1,1)<sub>12</sub> that can be written as

$$x_t = 941.745 + 0.771x_{t-1} + x_{t-12} - 0.771x_{t-13} - 0.095a_{t-14} + 0.267a_{t-13} - 0.330a_{t-12} + 0.287a_{t-2} - 0.81a_{t-1} + a_t \quad (11)$$

For the tourist arrivals data, the lagged variables from AR terms are selected as the input of ANN model and can be expressed as  $x_t = f(x_{t-1}, x_{t-12}, x_{t-13})$ . The activation logistic sigmoid function and linear function are used from input to hidden layer and from the hidden layer to output layer, respectively. For modeling ANN, there is no standard formula to determine the optimal number of hidden nodes (H). Table 2 shows recommended equations for finding the optimal number of hidden nodes in a hidden layer based on several researches.

**Table 2.** Recommended Equations to find the ideal number of hidden nodes

Equation	References
$H \leq 2I + 1$	[41]
$H = (I + O) / 2$	[42]
$H = \sqrt{I \times O}$	[43]
$H = 2I$	[44]

A trial-and-error method was used in this research to determine the optimum number of hidden nodes, beginning with one and then increasing it by 1 to  $2I + 1$ , where I is the number of input nodes and O is the output nodes. The best architecture of ANN for the dataset was identified by using MAE and RMSE during the training test. Table 3 gives the performance statistics on the training datasets for the ANN approach for different number of hidden nodes. As can be seen from Table 3, the best performing architectures for ANN used is a 3-6-1.

#### 4.3. The Model of DNN Fits the Data

We implement the DNN using Neuralnet package in R software. In this study, the lag variables form AR terms, which are lag 1, lag 12 and lag 13 (three input nodes) that were considered as the input nodes. The choice of the hidden nodes on each layer of the DNN was done by a trial and error process. Reference [40] suggested that each hidden layer's number of hidden nodes is 1 to 3 times that of input nodes. Therefore, in this research, we consider the combination of 3, 6 and 9 as the number of nodes for each hidden layer. The logistic sigmoid function was considered as the activation function from input to hidden layer and from hidden to another hidden layer, while linear function was used from hidden layer to output layer. The feed forward neural network architecture and a stochastic gradient descent considered via Resilient back propagation were used as training algorithm.

Table 3 gives the performance statistics on the training dataset for DNN for different number of hidden nodes. As can be seen from Table 3, the best architecture of DNN found consists of three input layers, three hidden layers with three nodes, six nodes and six nodes, respectively, and one output (3:3:6:6:1). Therefore, DNN's best architecture is chosen to be employed to forecast monthly tourist arrivals to Langkawi Island.

**Table 3.** The RMSE and MAE of ANN and DNN models in training period

Structure	ANN		Structure	DNN	
	RMSE	MAPE		RMSE	MAPE
3,1,1	51572.7	18.3	3,3,3,3,1	34202.6	13.068
3,2,1	35893.7	13.6	3,3,3,6,1	36897.3	13.494
3,3,1	35355.5	13.7	3,3,3,9,1	36175.3	13.511
3,4,1	34575.0	13.8	3,3,6,6,1	33200.5	12.861
3,5,1	35030.7	13.6	3,3,6,9,1	34144.3	13.054
3,6,1	32534.9	13.2	3,3,9,9,1	35693.3	13.347
3,7,1	34321.4	13.3	3,6,6,6,1	35397.4	13.476
			3,6,6,9,1	36357.6	13.8481
			3,6,9,9,1	36473.1	13.7965
			3,9,9,9,1	41682.1	15.7224

4.4. Comparison to Alternative Models

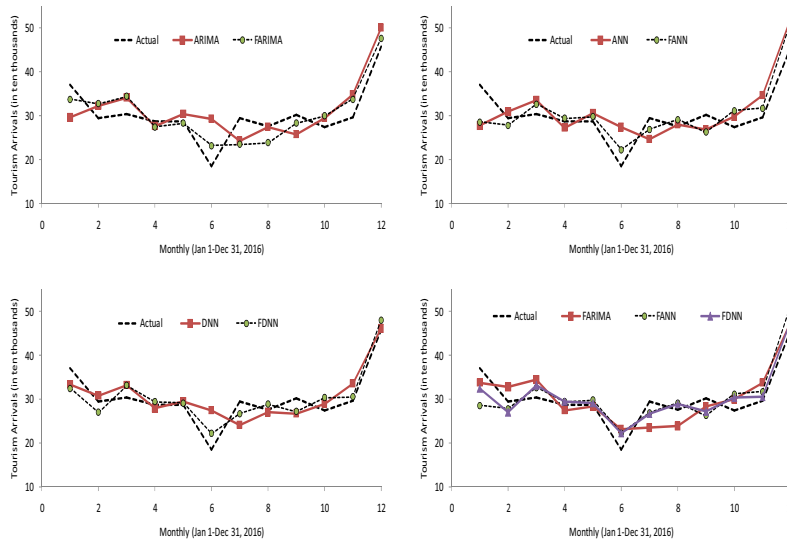
The residual series from the best models of ARIMA, ANN and DNN was then modified with Fourier series to become a new model called Fourier-ARIMA (FARIMA), Fourier-ANN (FANN) and Fourier-DNN (FDNN), respectively. The performance of the best ARIMA, ANN and DNN models, along with their Fourier series in terms of RMSE and MAPE is presented in Table 4. In Table 4, the RMSE of the ARIMA, ANN, DNN, FARIMA, FANN and FDNN models applied to the forecasting data are 49319.52, 48656.68, 45185.58, 34113.20, 37220.72 and 31247.26, respectively. The MAPE of the ARIMA, ANN, DNN, FARIMA, FANN and FDNN models are 14.64, 13.84, 12.15, 10.92, 10.05 and 8.65%, respectively.

According to the indices shown in Table 4, it is found that when the Fourier residual modification was used the degree of forecasting accuracy of the single ARIMA, ANN and DNN models has improved. The overall best testing phase performance was obtained by the FDNN model (RMSE = 31247.26 and MAPE = 8.65%). This reveals that FDNN model has obtained fewer errors than single ARIMA and ANN, and two combination models, FARIMA and FANN models. The FDNN model exhibits high forecasting ability in accordance to the RMSE and MAPE criteria. The findings above found that the FDNN model acquired the highest rank among all models considered in this research.

**Table 4.** Performance of The Forecasting Method for Monthly Tourist Arrivals Data

Model	RMSE	MAPE (%)
ARIMA	49319.52	14.64
ANN	48656.68	13.84
DNN	45185.58	12.15
FARIMA	34113.20	10.92
FANN	37220.72	10.05
FDNN	31247.26	8.65

The prediction results of ARIMA and FARIMA, ANN and FANN, DNN and FDNN, and FARIMA, FANN and FDNN techniques for monthly tourist arrivals to Langkawi Island are graphically displayed in Figure 4. It is noticed that by combining ARIMA, ANN and DNN model with their residuals modified using Fourier series, the forecasting accuracy can be improved (as shown in Figure 4). Figure 4 shows that the forecasts obtained from FDNN very closely fit to the actual data compared to the other two methods. The empirical results show that FDNN model can enhance the model forecasting precision effectively in forecasting of seasonal monthly tourist arrivals to Langkawi Island series.



**Figure 4.** Comparison of forecasted values with actual tourist arrivals



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