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Application of Artificial Neural Network in Forecasting Tourist Demand to Quang Binh, Vietnam

Van Hoa Le
School of Hospitality & Tourism – Hue University, Vietnam
levanhoa@hueuni.edu.vn

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Abstract

Accurate forecasting of tourist demand is crucial for guiding policies, planning, and developing strategies for a locality or country. There are various approaches to forecasting tourist demand, among which time series data-based forecasting attracts the most attention due to the unstructured nature of this type of data. Artificial neural network is evaluated as a particularly suitable forecasting method for unstructured data, although it is almost impossible to explain its internal processes. This paper uses an artificial neural network to forecast time series data on tourist demand to Quang Binh. Three network models, MLP (Multi-Layer Perceptron), RBF (Radial Basis Function), and ELN (Elman network), are evaluated. With the obtained simulation results, the RBF network provides the best forecasting performance, with the lowest MSE (Mean Squared Error), RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error), compared to the other two network types. This result further confirms that the feature of transforming non-linear space into linear space of the hidden layer has made RBF powerful for unstructured data.

I. INTRODUCTION

Recently, many localities and countries have realized that tourism is an important source of foreign exchange and creates many jobs for people. Tourism is one of the fastest-growing industries in the world. Tourism plays an important role for localities and countries and significantly contributes to growth. Promoting tourism projects often involves a significant investment, so to succeed, investors in this field need to be equipped with appropriate tools to analyze and interpret available data. Accurate forecasting of tourist demand is a prerequisite for the decision-making process in private and state tourism organizations.

Forecasting is the process of organizing past information about a phenomenon to predict what trends will occur in the future. In the tourism industry, demand forecasting is carried out based on historical data on tourism demand represented in time series. Tourism demand can be expressed in many different forms, such as the number of visitors, tourism expenditure/revenue, length of stay, number of nights at the accommodation, etc. [1]. Therefore, time series forecasting models attempt to determine this data's trend, slope, and cycle by performing measurements over consecutive time intervals. Unlike methods based on observing random samples, time series forecasting models rely on consecutive values representing consecutive measurements performed at evenly spaced time intervals (monthly, quarterly, or annually). When a sample needs to be established, time series models will generate predictions about future trends for the upcoming time series.

Artificial neural networks (ANN) have been instrumental for time series data forecasting for over two decades. One characteristic that makes ANN attractive is its ability to approximate complex non-linear functions into a linear one, under certain conditions. However, ANN's strength is also its challenge, as there is no one-size-fits-all approach for model building, relying mostly on experience for each specific problem. Constructing an efficient ANN often requires selecting various empirical parameters, such as the number of input units, hidden neurons, output neurons, learning rate, etc. This selection is highly dependent on the specific data and problem at hand.

In the past ten years, many studies have related to applying ANN models in predicting tourism demand based on time series data. Most of these studies examine specific data cases, such as predicting tourist demand in a locality [1]-[4] or in a country [5]-[10], predicting overnight demand at lodging facilities [7][11], and so on. There is no assertion about which ANN model is the best for all cases [15]; however, ANN is still a potential machine learning method and attracts much research attention. In this paper, we study the construction of a neural network model to predict tourism demand for Quang Binh's destination. Three ANN models, including Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), and Elman network (ELN), are constructed, modelled, and tested with data on tourist arrivals to Quang Binh from 01/2017 to 12/2019. The simulation results will indicate the forecasting effectiveness of the ANN models, and other potentials of ANN will be analyzed accordingly.

The main contributions of the paper include:

• Modeling the time series forecasting problem, including detailed data analysis and transformation in the data preprocessing stage.

• Building MLP, RBF, and ELN network models for forecasting purposes.

• Creating simulation scenarios with different input vectors tested, analyzing and investigating the number of hidden layer neurons. A suitable neural network model for unstructured time series data forecasting is identified from there.

The paper's next section includes the following topics: Section 2 provides a summary and evaluation of related studies, focusing on neural network models applied in tourism demand forecasting. Based on the analysis, Section 3 details the steps to build neural network models for tourism demand forecasting, including data analysis, normalization, and preparation for training, and constructing three models: MLP, RBF, and ELN for forecasting tourist demand to Quang Binh. Section 4 describes the analysis of the forecasting effectiveness. Finally, the conclusion is presented in Section 5.

II. RELATED WORKS

There have been many studies related to building models and applying ANN to forecast tourism demand. These proposed ANN models ranged from single neural network models such as MLP, RBF, ELN, etc., to more intricate combined models. The combined models may merge techniques such as genetic algorithms with neural networks to optimize the hidden neurons [12][13] or integrate Box-Jenkins with neural networks to calculate the weighted sum of forecast results [14]. In this paper, we focus solely on evaluating single ANN models, excluding hybrid or combined approaches. The objective is to evaluate these individual models' performance when applied to the specific task of forecasting tourism demand. The following is a summary of evaluations of ANN applications in forecasting tourism demand over the past 10 years.

In a study conducted by Fernandes et al. [2], the authors explored the application of the Multi-Layer Perceptron (MLP) neutral network to forecast tourist demand, specifically focusing on monthly overnight stays at hotels in the northern and central regions of Portugal. The experimental results showed that the ANN model had high forecasting accuracy. Therefore, the authors recommended that the ANN method should be used for non-linear time series data.

The study by Lin, Chen, and Lee [5] attempted to build a forecasting model for tourist arrivals in Taiwan using the ARIMA (autoregressive integrated moving average), ANN, and MARS (multivariate adaptive regression splines) methods. Upon evaluating the models using monthly data, they discovered that ARIMA outperformed both ANN and MARS. The superiority was evident across several metrics, including RMSE (root mean square error), MAD (mean absolute error), and MAPE (mean absolute per cent error), indicating ARIMA's potential as a potent tool for tourism forecasting.

In Teixeira and Fernandes' study [15], the feedforward neural network (FFNN), cascade forward neural network (CFNN), and recurrent neural network (RNN) were considered and compared. The inputs of the ANNs were the number of arrivals in the previous 12 months and two other inputs were the year and month of the year. They found that the three models yielded MAPEs in the range of 4% to 6%. Among these, the FFNN architecture stood out as the best performer, achieving the lowest error rate of 4.2% on both the validation and test datasets.

Claveria, Monte, and Torra [3] compared the effectiveness of three ANN architectures (MLP, RBF, and ELN) in predicting the number of tourists from multiple countries visiting Catalonia, Spain from 2001 to 2012. The results of the experiment showed that RBF and MLP performed better than the ELN network, with RBF having the best predictive ability. They also found that predictive accuracy improved with an increased number of input units, highlighting the value of increasing the size for long-term forecasting.

In [1], Cogurcu and Kukrer attempted to determine the best forecasting method by comparing MLP, RBF, and GRNN (generalized regression neural network) for predicting monthly sea tourism demand in Izmir, Turkey. Utilizing data on foreign and domestic sea tourists from January 2005 to December 2013, they found that RBF outperformed MLP and GRNN in terms of predictive accuracy.

Teixeira and Fernandes [4] conducted a study to investigate different MLP architectures with 4, 6, and 8 hidden nodes for predicting tourism demand in Cape Verde. With a continuous 12-month input and different architectures with different numbers of hidden nodes tested, the prediction performance was improved with an MRE value of 7.3% and a Pearson correlation coefficient of 0.92.

Melda Akın [6] examined three models, SARIMA (Seasonal ARIMA), SVR (Support Vector Regression), and MLP, and optimized their parameters for predicting international tourist demand in Turkey. Based on the experimental results, the author concluded the study by proposing a decision tree model as a framework for determining the appropriate forecasting model.

Constantino, Fernandes, and Teixeira [7] used an ANN model to model and forecast tourist demand in Mozambique from 1/2004 to 12/2013. The tourist demand in this study was the number of overnight stays at hotels from South Africa, the United States, Portugal, and the United Kingdom. The best model was found with a MAPE of 6.5% and a Pearson correlation coefficient of 0.696.

In the study by Cankurt and Subasi [8], MLR (Multi-layer Regression), MLP, and SVR were used to forecast tourist demand in Turkey. Unlike in [6], this study proposed an MLR model with data being the number of monthly tourists to Turkey from 1/1996 to 12/2013. The forecasting performance was compared based on RAE (relative absolute error) and RRSE (Root Relative Squared Error), and it showed that SVR had the best performance, with RAE = 12.34% and RRSE = 14.02%.

In [11], Panagopoulos and Nikas investigated and evaluated linear and non-linear forecasting models based on ANN for overnight tourism demand. To forecast effectively, MLP, SVR, and LR (Linear Regression) models were employed with two datasets of energy consumption and overnight hotel guests in the western region of Greece. The relative accuracy of MLP and SVR was compared with LR. The experiments showed that MLP and SVR yielded better forecasting results with smaller prediction errors than LR.

The purpose of Mavrommati and Karakitsiou [9] was to study the applicability and performance of ANN and SVM (Support Vector Machine) models in forecasting tourism demand for Greece from non-EU and Euro non-using EU countries. Time series data were collected from 1990 to 2015. The experimental results showed that the performance of these methods was not significantly different. No method is the best for all datasets.

Gregorić and Baldigara [10] designed an ANN to predict the number of German tourists visiting Croatia while considering the seasonal nature of the experimental data. The presence of seasonal factors that determine tourism demand is analyzed. The study is based on seasonal analysis and ANN is used to describe the behavior of German tourists to Croatia. Various ANN architectures are tested; the accuracy of the prediction and model performance is analyzed based on MAPE. The experimental results and analysis show that the achieved MAPE is 1.601%, indicating high accuracy of the model's predictions.

In summary, the studies aim to model the problem of forecasting tourism demand based on time series data and build various ANN models to test and evaluate their forecasting ability. No single ANN model is the best for all datasets. However, a significant proportion of studies suggest that MLP and RBF networks have a relatively high accuracy in forecasting compared to other models. Many studies focus on three types of networks, namely MLP, RBF, and ELN, to evaluate their forecasting effectiveness for tourist arrivals in different locations. Therefore, we continue to study the forecasting effectiveness of the three ANN models, MLP, RBF, and ELN, to forecast tourism demand in Quang Binh, Vietnam, in this paper.

III. MODELING NEURAL NETWORKS FOR TOURISM DEMAND FORECASTING

A. *The data on tourist demand*

The tourism demand data used in this study is the number of tourists to Quang Binh, Vietnam from January 2017 to December 2019, extracted from the information page of the Quang Binh Tourism Department [16]. Quang Binh, Vietnam is considered one of the new attractive destinations in Vietnam in recent years, which is why we are using data for this destination. Although tourism data for this destination has also been collected since 1998, the records prior to 2017 are largely on an annual basis, which is not suitable for monthly forecasting. Moreover, the influence of the Covid-19 pandemic has resulted in an unusual decline in the figures for 2020, 2021, and 2022, further limiting the number of tourists visiting Quang Binh from January 2017 to December 2019, with seasonal variations showing yearly cycles; this suggests that the input vector (number of time points) of the data samples should be 6 or 12-month time points.

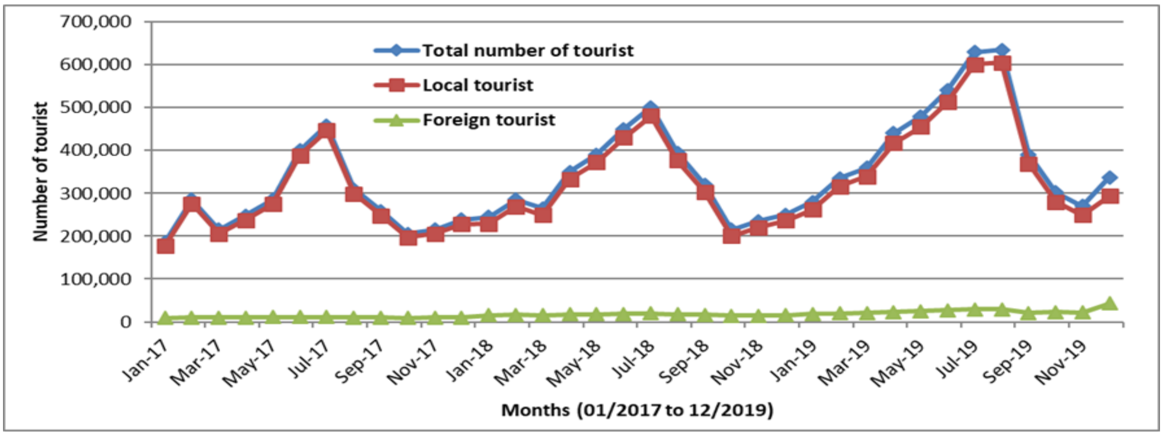


Figure 1. Distribution of tourist arrivals to Quang Binh from January 2017 to December 2019

In this paper, we use the dataset of the total number of visitors to Quang Binh and divide it into two parts: training data and testing data. As in most previous studies, the majority of the dataset (66.67%) is used for training, consisting of 24 samples corresponding to the number of visitors to Quang Binh from January 2017 to December 2018, which are used to train the network. The testing dataset (33.33%) is used to evaluate the accuracy of the network, consisting of 12 samples corresponding to the remaining 12 months (from January 2019 to December 2019).

B. *Normalization of data*

ANNs typically perform well with normalized data. Using raw data can slow down convergence during network training, so data needs to be normalized to improve accuracy, convergence speed, and network efficiency. Among the normalization methods, the scaling method is the most commonly used. The scaling method transforms the original data into a specific range, such as [-1, 1] or [0, 1]. In this paper, the original data is transformed into the range [0, 1] by Formula (1):

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

In which, x_i is the actual value, x_{min} is the minimum value, x_{max} is the maximum value in the dataset, and x'_i is the normalized value.

C. *Data Preparation for Training*

ANN is used to forecast future trends of a time series from the values of $x_{t-p+1}, x_{t-p+2}, \ldots, x_t$ up to the current time (time t). This means that the predicted value of x at time $t + d$ is calculated using Equation (2).

$$x_{t+d} = f(X_t) = f(x_{t-p+1}, x_{t-p+2}, \ldots, x_t) \tag{2}$$

In this equation, X_t is the vector of p delayed values of x from time t. Typically, d is set to 1, so the function f will predict the next value of x.

Next, different data matrices are created for training and testing based on the number of time steps (p) corresponding to the input units and the number of predictions (d) corresponding to the output neuron of the ANN. To illustrate the case of an ANN with 4 input units and 1 output neuron, Figure 2 shows the structure of the data matrix with p = 4 corresponding to time steps (months) and predicting the value at the next time step (d = 1).

Data samples	Input value				Output value
1	x_1	x_2	x_3	x_4	x_5
2	x_2	x_3	x_4	x_5	x_6
3	x_3	x_4	x_5	x_6	x_7
n	x_n	x_{n+1}	x_{n+2}	x_{n+3}	x_{n+4}

Figure 2. The data matrix structure corresponds to a neural network with 4 input units and 1 output unit.

D. Creating the training and testing dataset

In the ANN-based forecasting method, data is usually divided into two sets: training data and testing data. The training data set is used in the training phase, in which weights are adjusted based on the input values of the training data samples to minimize the error (difference) between the actual output and the target. The training process stops when the error is no longer significant or less than a given threshold. The testing data set is used to estimate the error of the generalization ability of the ANN.

There is no exact rule for the optimal size of these two data sets, although most agree that the training set should be larger than the test set. In this study, the data was divided as follows: the number of tourists from January 2017 to December 2018 was used as the training dataset (66.67%), and the number of tourists from January 2019 to December 2019 was used as the test dataset (33.33%).

E. Building a neural network for Forecasting

ANN is a distributed and parallel system, consisting of many simple processing units capable of computing functions, which in most cases are non-linear. Processing units are connected in different ways to create different ANN models [17]. ANN can learn through the application of a training method. Based on the learned results, ANN is capable of generalizing by proposing solutions for cases where there is no existing answer. In this paper, three ANN models are considered, including MLP, RBF, and ELN.

1) Multilayer perceptron (MLP)

The multilayer perceptron (MLP) consists of neurons arranged into multiple layers, where the signal from the input is passed through each layer of the network. As described in Figure 3(a), the MLP has 2 layers with one-way connections from the input layer to the hidden layer and from the hidden layer to the output layer; there are no connections between neurons in the same layer. The MLP is the most flexible architecture in terms of application and is used in many problems, such as pattern recognition, automatic control, time series data forecasting, optimization, and more.

The training process of MLP involves continuously adjusting the connection weights between neurons to find a weight set that can map desired events most accurately. The most common training method for MLP is gradient minimization using the backpropagation algorithm [17]. Specifically, the error signal of neuron j in iteration t is computed by Formula (3):

$$e_j(t) = d_j(t) - y_j(t) \tag{3}$$

In which, $e_j(t)$ is the error, $d_j(t)$ is the desired target, and $y_j(t)$ is the current output of the network.

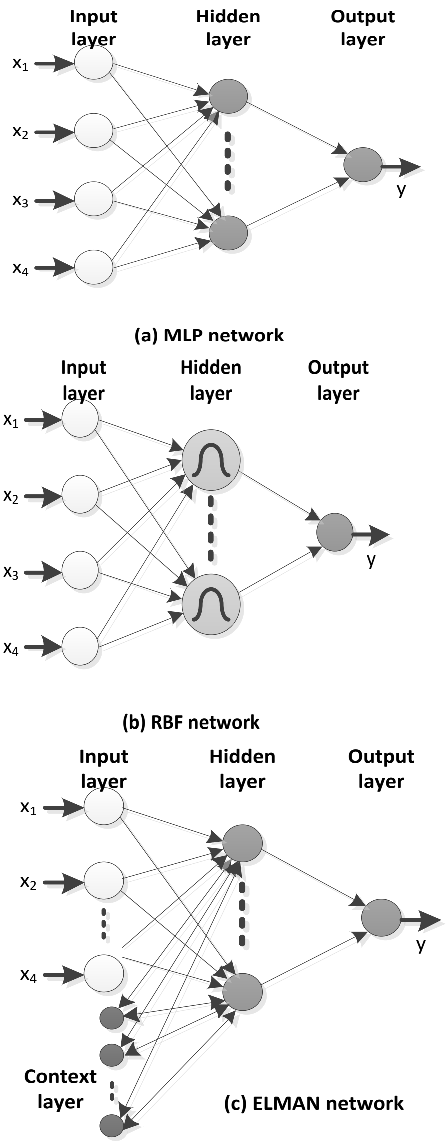


Figure 3. The architectures of MLP, RBF, and ELN networks.

Afterwards, the rule for updating the connection weights is given by Equation (4):

$$w_{ij}^m(t+1) = w_{ij}^m(t) - \eta \frac{\partial E(t)}{\partial w_{ij}^m(t)} \tag{4}$$

In which, $w_{ij}^m(t)$ is the weight of the connection to neuron j from input i of layer m at iteration t, η is the learning rate, and $\partial E(t)$ is the partial derivative of the error function $E(t)$.

The training algorithm consists of two stages. Initially, the input data is propagated through the network to obtain the current output $y_j(t)$. This value is then compared with the target value $d_j(t)$ to calculate the error $e_j(t)$. In the second step, the error is propagated back from the output layer to the input layer (backpropagation) to adjust the weights of the connections. In this way, all connection weights are adjusted according to the assumed error-correction rule, so that the network's output in the next iteration is closer to the target.

2) RBF network

Unlike MLP, the RBF network has only two layers: the hidden layer and the output layer. As described in Figure 3(b), the RBF network architecture is similar to a 2-layer MLP but differs in the function of the hidden layer neurons. Specifically, the activation function of the hidden neurons is based on the radial basis function (RBF) property [17], in which each hidden neuron determines the center of the input data similarly (distributed closely in the input space). One of the most commonly used activation functions for hidden neurons is the Gaussian function, such as Equation (5):

$$\varphi(x) = e^{\frac{(x-c)^2}{2\sigma^2}} \tag{5}$$

In which, x is the input sample value, c is the center of the Gaussian and σ^2 is its radius.

The training of RBFs is performed in two stages. Firstly, the weights of the hidden layer are computed by determining the centers based on the distribution of the input data. Data points that are "close" to each other are considered to belong to a cluster, and the center of that cluster is calculated using the Gaussian function as described in Equation (5). Subsequently, the weights of the output layer are adjusted through supervised training, similar to an MLP (Multilayer Perceptron) network [19].

3) ELN network

Elman Network (ELN) is a recursive architecture based on the MLP network proposed by J.L. Elman [18]. ELN network divides its layers into two parts: the first part consists of regular input units and the second part, called context units, includes the outputs of the hidden layer that are fed back as inputs (recursive), as shown in Figure 3(c). As context units of the ELN network are considered input units, they also have connection weights and can be adjusted by the backpropagation algorithm over time. In most implementations, the backpropagation version is sliced into time delays. The training process of the Elman network is similar to that of the MLP network, and weight adjustment will stop when the "weight variation" of the network becomes stable [17].

F. Evaluation Methods for forecasting results

There are many methods for evaluating the accuracy of forecasting models, among which the following four forecasting methods are commonly used:

Mean Squared Error (MSE): measures the average squared deviation of the forecasted values. MSE emphasizes that the sum of forecast errors is greatly affected by individual large errors but does not provide any insight into the direction of the overall error [19]. MSE is calculated using Equation (6).

$$MSE = \frac{1}{p}\sum_{t=1}^{p}\left(y_t - \hat{y}_t\right)^2 \tag{6}$$

Mean Absolute Error (MAE): measures the average absolute deviation of the forecasted values from the original values.

MAE shows the level of overall error that occurs due to forecasting but also does not provide any insight into the direction of errors [20]. The equation for this method is indicated in Equation (7).

$$MAE = \frac{1}{p}\sum_{t=1}^{p}\left|y_t - \hat{y}_t\right| \tag{7}$$

Mean Absolute Percentage Error (MAPE): this is not dependent on the measurement scale, making it a popular choice in forecasting problems, especially those based on ANN [21]. It is defined by Equation (8):

$$MAPE = \frac{1}{p}\sum_{t=1}^{p}\frac{\left|y_t - \hat{y}_t\right|}{\left|y_t\right|}\times 100 \tag{8}$$

Root Mean Square Error (RMSE): is defined as the standard deviation of the residuals between the predicted values and the actual values [21]. RMSE is simply the square root of MSE and is calculated using Equation (9).

$$RMSE = \sqrt{\frac{1}{p}\sum_{t=1}^{p}\left(y_t - \hat{y}_t\right)^2} \tag{9}$$

IV. SIMULATION AND RESULTS ANALYSIS

This paper used Matlab 2010b to simulate three models: MLP, RBF, and ELN, with data on the total monthly tourist arrivals to Quang Binh (from 1/2017 to 12/2019). This data was extracted from the information page of the Quang Binh Tourism Department [16]. The settings were performed on a PC with a configuration of 2.4 GHz Intel Core 2 CPU, and 4G RAM.

The convergence condition of the training process is based on the minimum value of MSE and the maximum number of iterations threshold. In these settings, the minimum MSE value and the maximum iteration threshold are set to 0.005 and 10,000, respectively. In fact, it is difficult to accurately set these thresholds and it is mostly based on experience, with many different trial runs to determine the most appropriate threshold value. We chose a relatively small MSE threshold to test the forecasting accuracy but also controlled the number of iterations as a stopping condition to prevent cases where the ANN cannot converge with the set MSE threshold. Furthermore, since the training data is relatively small in size and has been normalized to the range [0, 1], setting a small threshold value for MSE and the training iteration threshold as above is necessary.

There are two neural network architectures tested for each type of MLP, RBF, and ELN networks, including ANN (6:3:1) and ANN(12:6:1), meaning a structure with 6 (or 12) input units, 3 (or 6) hidden neurons, and 1 output neuron. Therefore, there are two different training and testing data matrices constructed, as shown in Figure 4. In practice, different network architectures can also be tested, but for tourism demand data, choosing 6 or 12 consecutive months as input values is appropriate because the seasonal nature of tourism demand always exists, although it is not clearly shown in the Quang Binh tourism data (Figure 1).

Data samples	Input value				Ouput value
1	x_1	x_2	--------	x_6	x_7
2	x_2	x_3	--------	x_7	x_8
3	x_3	x_4	--------	x_8	x_9
	------------------------				
n	x_n	x_{n+1}	--------	x_{n+6}	x_{n+7}

(a) ANN(6:3:1)

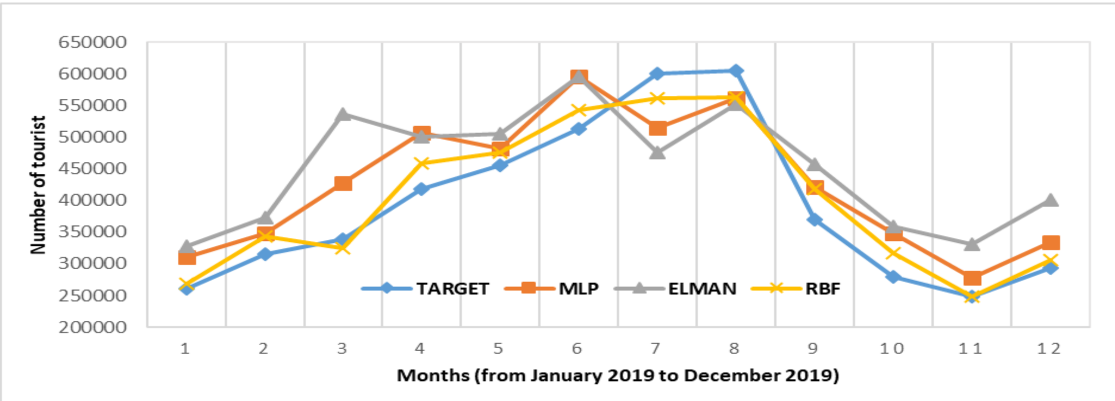
Data samples	Input value				Ouput value
1	x_1	x_2	--------	x_{12}	x_{13}
2	x_2	x_3	--------	x_{13}	x_{14}
3	x_3	x_4	--------	x_{14}	x_{15}
	------------------------				
n	x_n	x_{n+1}	--------	x_{n+11}	x_{n+12}

(b) ANN(12:6:1)

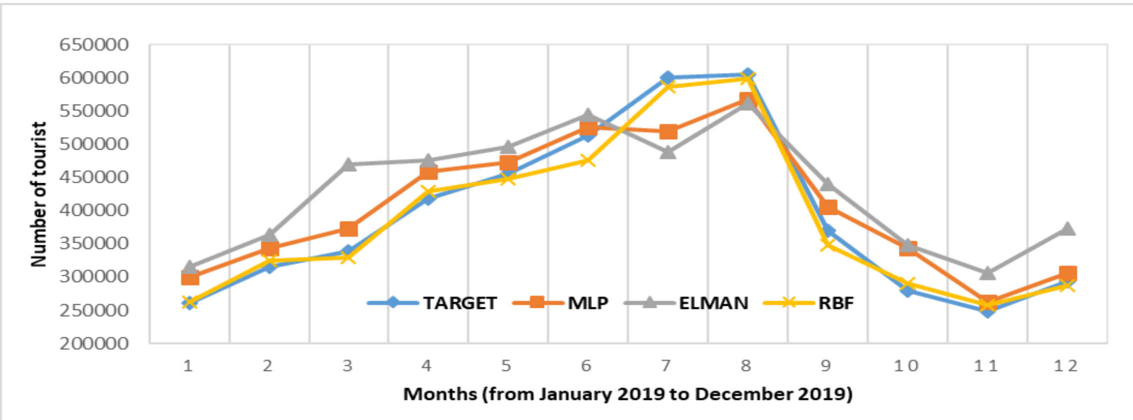
Figure 4. The data matrices for the ANN(6:3:1) and ANN(12:6:1)

The forecasting results of tourist arrivals for the test data of MLP, RBF, and ELN neural networks are shown in Figure 5(a) and Figure 5(b), respectively, corresponding to two different neural network architectures, ANN(6:3:1) and ANN(12:3:1). Clearly, the forecasting result of the RBF network is quite close to the actual tourist arrivals (target) for both ANN(6:3:1) and ANN(12:6:1) architectures, with the ANN(12:6:1) architecture providing the closest forecasting result to the actual values. When comparing based on MSE, RMSE, MAE, and MAPE values, the implementation results show that the RBF network achieved the lowest respective values, especially with the ANN(12:6:1) architecture, as shown in Table 1.

The forecasting results are consistent with previous studies [1][3] where the RBF network typically provides the most accurate predictions, especially for non-linear time series data. As analyzed in [19], the role of hidden neurons in the RBF network is to transform data from the original non-linear space to a linear space where data classification can be performed linearly. This is a very special feature of the RBF network that enables it to effectively solve non-linear problems such as time series data forecasting. For the ELN network, the poor prediction results indicate that the feedback connection structure of the Elman network cannot capture the specific characteristics of time series data.



(a) Compare the forecasting results of the months in 2019 using ANN (6:3:1)



(b) Compare the forecasting results of the months in 2019 using ANN (12:6:1)

Figure 1. The comparison of the prediction results of MLP, ELN, and RBF models with the target values in the two ANN architectures (6:3:1 and 12:6:1)

Table 1
Comparing the prediction errors of MLP, ELN, and RBF with the 2 neural network architectures ANN(6:3:1) and ANN(12:6:1)

	MLP		**ELN**		**RBF**	
	(6:3:1)	**(12:6:1)**	**(6:3:1)**	**(12:6:1)**	**(6:3:1)**	**(12:6:1)**
MSE	3.82E+09	1.59E+09	9.43E+09	4.65E+09	**9.44E+08**	**2.19E+08**
RMSE	60,793.39	39,911.82	92,028.58	68,220.12	**30,545.39**	**14,802.13**
MAE	54,079.96	33,573.43	80,207.27	59,672.59	**25,762.58**	**11,527.66**
MAPE	14.20	8.92	21.90	16.33	**6.33**	**2.89**

II. CONCLUSION

The paper successfully modelled and built a neural network to predict tourist demand in Quang Binh. With time series data collected over 36 months, data normalization and preparation were analyzed and described in detail. Three ANN models, namley MLP, ELN, and RBF were implemented and two ANN architectures of (6:3:1) and (12:6:1) were considered. The implementation and analysis results showed that the RBF network had the most accurate prediction capability, as evidenced by the lowest MSE, RMSE, MAE, and MAPE values. There have been many studies applying neural networks to forecast tourism demand, but each type of neural network performs best for specific datasets, and no neural network is the most effective in all cases. Although the data used in the paper is relatively small, the obtained MAPE value is quite low, below 10%, indicating the high accuracy of the neural networks in time series data forecasting.

REFERENCES

[1] M. Cuhadar, I. Cogurcu, and C. Kukrer, “Modelling and Forecasting Cruise Tourism Demand to Izmir by Different Artificial Neural Network Architectures,” International Journal of Business and Social Research, vol. 4, no. 3. pp. 12–28, 2014, doi: 10.18533/ijbsr.v4i3.431.

[2] P. O. Fernandes, J. P. Teixeira, J. M. Ferreira, and S. G. Azevedo, “Forecasting Tourism Demand with Artificial Neural Networks,” Tour. Manag. Stud., pp. 2009–2011, 2011.

[3] O. Claveria, E. Monte, and S. Torra, “Tourism Demand Forecasting with Different Neural Networks Models,” SSRN Electron. J., 2013, doi: 10.2139/ssrn.2507362.

[4] J. P. Teixeira and P. O. Fernandes, “Forecasting of a Non-Seasonal Tourism Time Series with ANN,” in International work-conference on Time Series – ETISE 2014, 2014, pp. 1–11.

[5] C. J. Lin, H. F. Chen, and T. S. Lee, “Forecasting Tourism Demand Using Time Series, Artificial Neural Networks and Multivariate Adaptive Regression Splines:Evidence from Taiwan,” Int. J. Bus. Adm., vol. 2, no. 2, 2011, doi: 10.5430/ijba.v2n2p14.

[6] M. Akin, “A novel approach to model selection in tourism demand modeling,” Tour. Manag., vol. 48, pp. 64–72, 2015, doi: 10.1016/j.tourman.2014.11.004.

[7] H. A. Constantino, P. O. Fernandes, and J. P. Teixeira, “Tourism demand modelling and forecasting with artificial neural network models: The Mozambique case study,” Tékhne, vol. 14, no. 2, pp. 113–124, 2016, doi: 10.1016/j.tekhne.2016.04.006.

[8] S. Cankurt and A. Subasi, “Tourism demand modelling and forecasting using data mining techniques in multivariate time series: a case study in Turkey,” Turkish J. Electr. Eng. Comput. Sci., vol. 24, pp. 3388–3404, 2016, doi: 10.3906/elk-1311-134.

[9] A. Mavrommati and A. Karakitsiou, “Machine learning methods in tourism demand forecasting: some evidence from Greece,” MIBES Trans., vol. 11, no. 1, pp. 92–105, 2018.

[10] M. Gregorić and T. Baldigara, “Artificial neural networks in modelling seasonal tourism demand - case study of Croatia,” Zb. Veleučilišta u Rijeci, vol. 8, no. 1, pp. 19–39, 2020, doi: 10.31784/zvr.8.1.2.

[11] A. Koutras, A. Panagopoulos, and I. A. Nikas, “Forecasting Tourism Demand Using Linear and Non-linear Prediction Models,” Acad. Tur. Innov. Journa, vol. 9, no. 1, pp. 85–98, 2016, [Online]. Available: http://academica.turistica.si/index.php/AT-TIJ/article/view/47.

[12] E. Noersasongko, F. T. Julfia, A. Syukur, , P., R. A. Pramunendar, and C. Supriyanto, “A Tourism Arrival Forecasting using Genetic Algorithm based Neural Network,” Indian J. Sci. Technol., vol. 9, no. 4, pp. 3–7, 2016, doi: 10.17485/ijst/2016/v9i4/78722.

[13] H.-C. Huang and C.- I Hou, “Tourism Demand Forecasting Model Using Neural Network,” Int. J. Comput. Sci. Inf. Technol., vol. 9, no. 2, pp. 19–29, 2017, doi: 10.5121/ijcsit.2017.9202.

[14] M. E. Nor, A. I. M. Nurul, and M. S. Rusiman, “A Hybrid Approach on Tourism Demand Forecasting,” J. Phys. Conf. Ser., vol. 995, no. 1, pp. 1–11, Apr. 2018, doi: 10.1088/1742-6596/995/1/012034.

[15] J. P. Teixeira and P. O. Fernandes, “Forecasting of a Non-Seasonal Tourism Time Series with ANN,” in 1st International Work-Conference on Time Series (ITISE), 2014, pp. 1–11.

[16] So Du Lich Quang Binh, Quang Binh Department of Tourism Electrical Information, https://sdl.quangbinh.gov.vn/ (accessed at 14:00 March 20, 2023).

[17] Shrestha and A. Mahmood, "Review of Deep Learning Algorithms and Architectures," in IEEE Access, vol. 7, pp. 53040-53065, 2019, doi: 10.1109/ACCESS.2019.2912200.

[18] Elman, J.L. Finding structure in time. Cogn. Sci. 1990, 14, 179–211.

[19] C. Hamzacebi, “Improving artificial neural networks’ performance in seasonal time series forecasting”, Information Sciences 178 (2008), pages: 4550-4559.

[20] R.K. Klimberg, G.P. Sillup, K.J. Boyle and V. Tavva, “Forecasting performance measures – what are their practical meaning?", Advances in Business and Management Forecasting, Vol. 7, 2010, Emerald Group Publishing Limited, Bingley, pp. 137-147.