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A new approach to modelling and forecasting monthly overnights in the Northern Region of Portugal

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Abstract

The need to analyze the main factors determining the evolution of demand within the tourism sector, which is the driving force of the whole tourism activity, and the importance that forecasting has in this domain, may be justified by the fact that the tourism sector plays a significant role in the economy of Portugal and its regions because of the large number of people employed directly and indirectly, and also because of its ability to bring in currency that reflects in different sector of economic activity.

Although tourism is less developed in the North of Portugal than in other regions of the country, it is essential to comprehend this phenomenon in order to empower local economic agents to carry out strategic measures to maximize profits from newly emerging situations.

The objective of the present research is to quantify national and international tourism flows by developing (mathematical) models and applying them to sensitivity studies in order to predict demand.

This work provides a deeper understanding of the tourism sector in Northern Portugal and contributes to already existing econometric studies by using the Artificial Neural Networks methodology.

This work's focus is on the treatment, analysis, and modelling of time series representing “Monthly Guest Nights in Hotels” in Northern Portugal recorded between January 1987 and December 2003. This was achieved through a study of the reference time series whose past values were known and whose objective was to obtain a model that better predicts the behaviour of the time series under study.

The model used 6 neurons in the hidden layer with the logistic activation function and was trained using the *Resilient Backpropagation* algorithm (a variation of backpropagation algorithm). Each time series forecast depended on 12 preceding values. The obtained model yielded acceptable goodness of fit and statistical properties and is therefore adequate for the modelling and prediction of the reference time series.

Keywords: Artificial Neural Networks, Training, Backpropagation and Forecasting.

1. INTRODUCTION

Several empirical studies in the tourism scientific area have been performed and published in the last decades. These studies agree in the consideration that the forecast process in the tourism sector must be done with particular care.

Nowadays, there is a great variety of models or methods for forecasting (from the most simple to the most complex ones) that have been developed for a variety of situations and present different characteristics and methodologies.

In this context, and related to tourism demand in Northern Portugal, a study has been carried out with the reference temporal sequence -"Monthly Guest Nights in Hotels"- using known previous values aiming to build a model that better fits the behaviour of the sequence. For this purpose the model used is supported in Artificial Neural Networks (ANN). The methodology of the ANN was inspired in the biologic theories of human brain function. The human brain is composed of several non-linear processors densely interconnected operating in parallel, these being the principal advantages compared with other forecast techniques.

This paper is organized in the following structure: first, there is an overview section that examines the theoretical foundation of neural networks. This section, in particular, analyzes the use of ANN models as a forecasting tool for business applications. Based on the theoretical analysis, a neural network is developed for forecasting tourism demand in Northern Portugal. Real data from official publications in Portugal is used for the neural network development. The model development process, the empirical and analysis results of forecasting are described in the next section. The quality of forecasting results is measured in mean absolute percentage error. Some concluding remarks are given in the final section.

2. Neural Network Models

The theory of neural network computation provides interesting techniques that mimic the human brain and nervous system. Neural networks are an information technology capable of representing knowledge based on massive parallel processing and pattern recognition based on past experience or examples. The pattern recognition ability of a neural network makes it a good alternative classification and forecasting tool in business applications (Thawornwong & Enke, 2004). In addition, a neural network is expected to be superior to traditional statistical methods in forecasting because a neural network is better able to recognize the high-level features, such as serial correlation, if any, of a training set. An additional advantage of applying a neural network to forecasting is that a neural network can capture the non-linearity of samples in the training set (Basheer & Hajmeer, 2000; Fernandes, 2005). Pattie and Snyder (1996) and Fernandes (2005), claimed that using a neural network to forecast non-linear tourist behaviour could achieve a lower mean absolute percentage error, lower cumulative relative absolute error, and lower root mean square error than Box-Jenkins models.

Artificial Neuronal Networks has been developed as generalizations of mathematical models of human cognition or neural biology, based on the assumptions (Rumelhard & McClelland, 1986a, 1986b) that:

a. Information processing occurs at several simple elements that are called neurons;

b. Signals are passed between neurons over connection links;

c. Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted;

d. Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal.

Through replicate learning process and associative memory, the ANN model can accurately classify information as pre-specified pattern. A typical ANN consists of a number of simple processing elements called neurons, nodes or units. Each neuron is connected to other neurons by means of directed communication links. Each connection has an associated weight. The weights are the parameters of the model being used by the net to solve a problem. ANNs are usually modelled into one input layer, one or several hidden layers, and one output layer (Tsaur *et al.*, 2002). Fig. 1 demonstrates a simplified neural network with three layers.

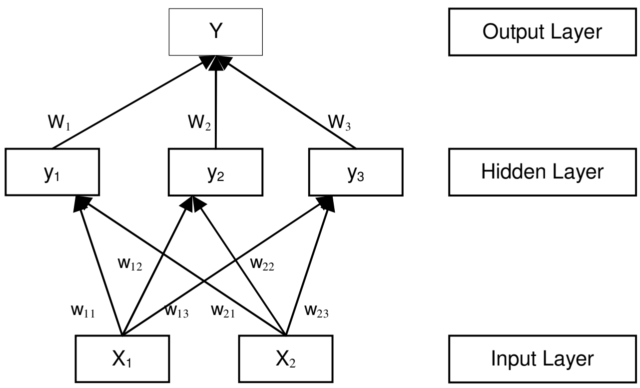

Fig. 1: A neural network model.

In Fig. 1, each node in the hidden layer computes $y_j (j=1,2,3)$ according to expression [1] (Haykin, 1999):

$$f_j = \sum_{i=1}^{2} x_i w_{ji} \qquad [1]$$

In addition, a *sigmoid function* (y_j) *,* in the following form, is used to transform the output that is limited into an acceptable range. The purpose of a *sigmoid function* is to prevent the output being too large, as the value of y_j (for j=1, 2, 3) must fall between 0 and 1:

$$y_j = \frac{1}{1+e^{-f_j}} \qquad [2]$$

Finally, Y in the node of the output layer in Fig. 1 is obtained by the following summation function:

$$Y = \sum_{j=1}^{3} y_j w_j \qquad [3]$$

Nodes in the input layer represent independent parameters of the system. The hidden layer is used to add an internal representation handling non-linear data. The output of the neural network is the solution for the problem. A feedforward neural network learns from a supervised training data to discover patterns connecting input and output variables. Feedforward recall is a one-directional information processing neural network in which the signal flows from the input units to the output units in a forward direction (Kuan & White, 1994; Nam & Schaefer, 1995; Yao *et al.*, 2000).

Backpropagation is the most popular neural network training algorithm that has been used to perform learning on feedforward neural networks. It is a method for assigning responsibility for mismatches to each of the processing units in the network, which is achieved by propagating the gradient of the activation function back through the network to each hidden layer, down to the first hidden layer. The weights are then modified so as to minimize the mean squared error between the network's prediction and the actual target (Thawornwong & Enke; 2004). The Backpropagation neural network consists of an input layer, an output layer and one or more intervening layers also referred to as hidden layers. The hidden layers can capture the nonlinear relationship between variables. Each layer consists of multiple neurons that are connected to neurons in adjacent layers. Since these networks contain many interacting nonlinear neurons in multiple layers, the networks can capture relatively complex phenomena (Hill, O'Connor & Remus, 1996; Chiang, Urban & Baldridge; 1996; Basheer & Hajmeer; 2000). Many variant were developed of Backpropagation training algorithm. In our case we adopted the *Resilient Backpropagation* [RP] (Reidmiller & Braun, 1993), because it can combine fast convergence, stability and generally good results.

Usually, the learning process involves the following stages (Zhang, 2003; Fernandes, 2005):

1. Assign random numbers to the weights;

2. For every element in the training set, calculate output using the summation functions embedded in the nodes;

3. Compare computed output with observed values;

4. Adjust the weights and repeat steps (2) and (3) if the result from step (3) isn't less than a threshold value; alternatively, this cycle can be stopped early by reaching a predefined number of iterations, or the performance in a validation set does not improve.

5. Repeat the above steps for other elements in the training set.

3. A neural network model for forecasting tourism demand in Northern Portugal

3.1 Methodology

For the selection of data we used the secondary source published in the Portuguese National Statistical Institute. Table A.1, in Appendix, containing relevant data for forecasting Monthly Guest Nights in Hotels in the North of Portugal recorded between January 1987 and December 2003. The Northern region of Portugal is delimited in Fig 2. During this study we call this time series Original Data (OD) (Fig. 3a). This time series suggests a power transformation, we take logarithms of the data to stabilize the seasonality and variance, and we have another time series - the Transformed Original Data (OD_Ln) (Fig. 3b).

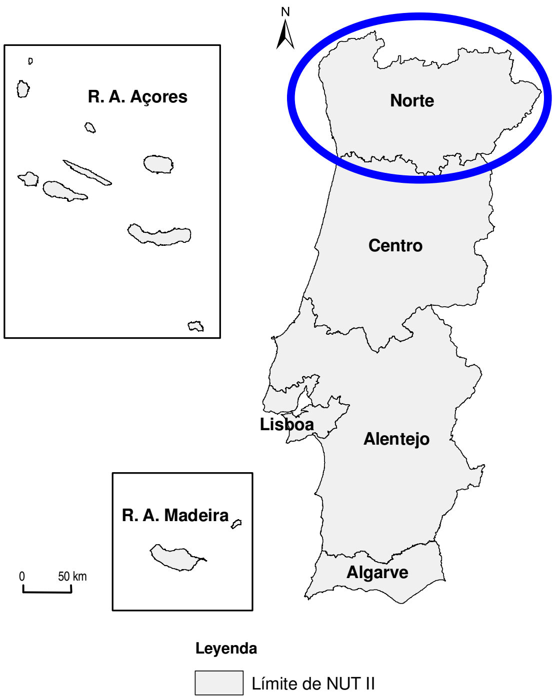

Fig. 2: Regions of Portugal.

Source: Fernandes (2005).

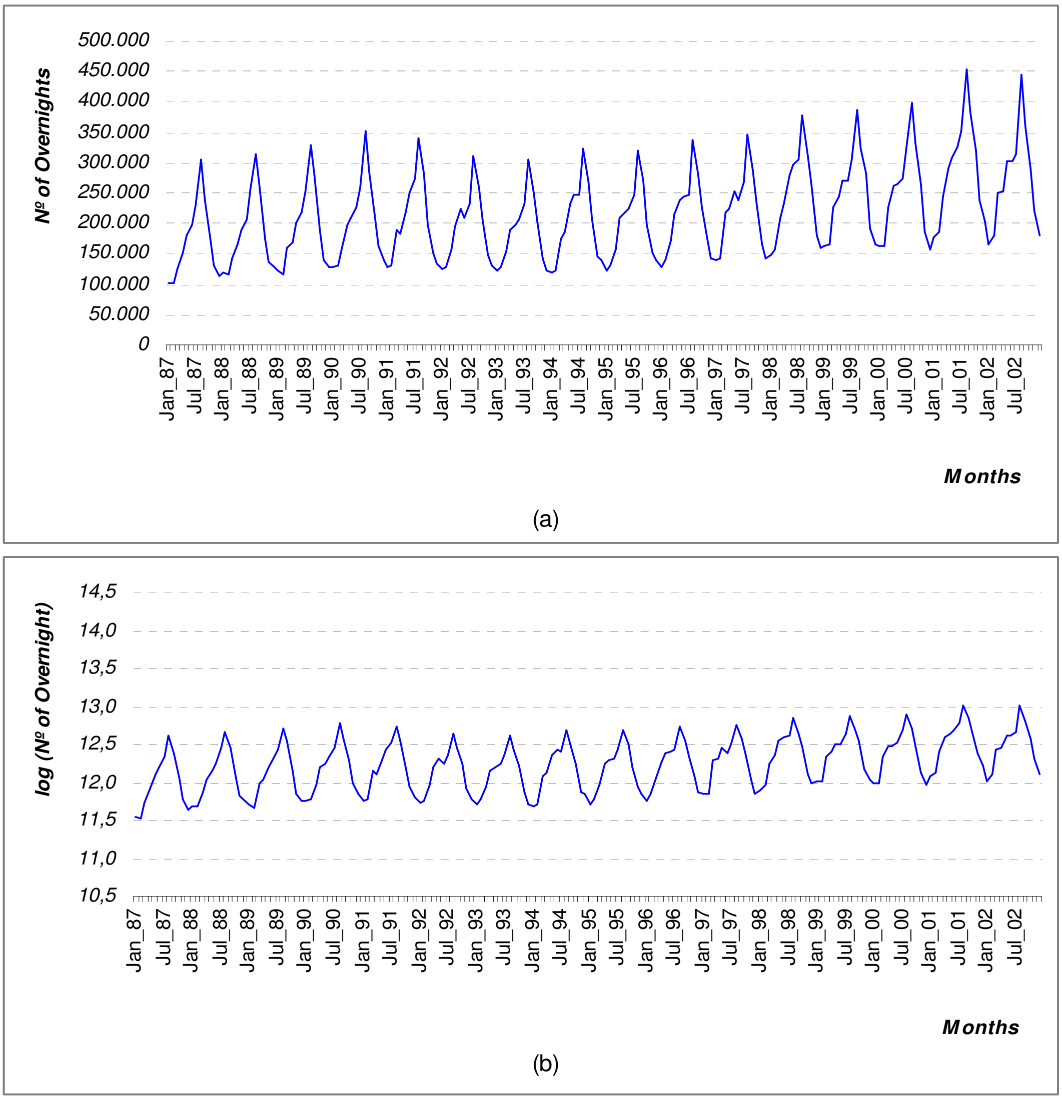

Fig. 3: Overnights in the North of Portugal from 1987:01 to 2002:12: (a) Original Data; (b) Natural Logarithms.

The ANN model used in this study is the standard three-layer feedforward network. Since the one-step-ahead forecasting is considered, only one output node is employed. The activation function for hidden nodes is the logistic function [*Logsig*]: $f(x)=\frac{1}{1+e^{(-x)}}$; and for the output node the identity function (pure linear function) [*Lin*]: $f(x)=x$. Bias terms are used in both hidden and output layer's nodes. The fast *Resilient* Backpropagation algorithm provide by the MATLAB neural network toolbox is employed in training process. The ANN is randomly initialised with weights and bias values. The selection of the architecture is supported in the author's work Fernandes (2005). For selecting the architecture several experiments with different architectures was carried out (train and test) and selected the better architectures according to the results in a validation set using hundreds of training session. The elected architecture consists of 12 input nodes in the entrance layer, 6 hidden nodes in the second layer and one node in the output layer - (1-12;6;1). The input of the model consists of the 12 previous numbers - corresponding to the last 12 months overnights. The output is the predicted overnights for the next month.

To make monthly predictions we have combined the following suppositions: consider as delayed inputs the most previous observations of the month we are predicting; due to the seasonal behaviour of the series we use a period of one year - twelve months.

In the training process of an ANN different end points are achieved, although with similar performance, for different initial values. Therefore, several training sessions for each identified situation have been performed with different initial weights. From this number of training sessions we retain the ANN (concerning its weights) that obtain better forecast results in each situation under the validation set. In this particular situation we performed 500 training sessions.

In order to compare the performance, the root mean squared error (RMSE[1]) between the observed and predicted values are used as the agreement index. The other agreement index used in this paper is the coefficient of correlation[2] between the observed and predicated values. We adopted the first index to select the best model/ANN.

Also in the training process, for each session we need to establish the number of iterations and the goal. In the present study we defined our goal as an error (RMSE between target and predicted values) of the order of $1x10^{-4}$. Anyhow, the training never stopped due to the achievement of this goal nor even by the predefined maximum number of iterations, but because of an early stop training condition.

The data set was divided in a sub-set for training, a sub-set for validation and a sub-set for test. The data set between January 1988 until December 2001 (in a total of 168 months) was used for training. It must be notice that the data between January and December 1987 was used as the input data for predicting January 1988 till December. The data between January and December 2002 was used for the validation set. This set is used for early stop training if the RMSE does not decrease in a number (5 in this case) of training iterations. This early stop training condition avoids the ANN to over fit the training data without improvements in a data not used in the training phase. Finally the data between January and December 2003 was used as data never seen in the training and selection process and used just to present the results of the model with never seen data.

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1 $RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - P_t)^2}{n}}$; *where A is the target value, P denotes the value of prediction and n the total number of observations.*

2 $r_{A,P} = \frac{\sum_{t=1}^{n}\left(A_t - \overline{A}\right)\left(P_t - \overline{P}\right)}{\sqrt{\sum_{t=1}^{n}\left(A_t - \overline{A}\right)^2\left(P_t - \overline{P}\right)^2}}$; *where A is the target value, P denotes the value of prediction and n the total number of observations.*

For an ANN model the prediction equation for computing a forecast of Y_t using selected past observations can be written as (Fernandes, 2005):

$$Y_t = b_{2,1} + \sum_{j=1}^{n} w_j f\left(\sum_{i=1}^{m} W_{ij} y_{t-i} + b_{1,j}\right) \quad [4]$$

where,

m, is the number of input nodes;

n, is the number of hidden nodes;

f, is a sigmoid transfer function such as the logistic;

$\{w_j, j = 0,1,\ldots,n\}$, is a vector of weights from the hidden to output nodes;

$\{W_{ij}, i = 0,1,\ldots,m; j = 1,2,\ldots,n\}$, are weights from the input to hidden nodes;

$b_{2,1}$ and $b_{1,j}$, are the bias associated with the nodes in output and hidden layers, respectively.

The equation shows a linear transfer function used in the output node.

In both models, for each time series, the resilient backpropagation algorithm was used for train the ANN. The sigmoid logistic activation function was used in the hidden layer nodes. The total number of parameter of the used ANN is 85. These alternatives are justified in Fernandes (2005) because of their improved results.

3.2. Empirical Analysis of the Results

In this section we will examine the results of each ANN under the test set. For this purpose we will compare the predicted data of each ANN with the target values for the year 2003 (the test set). We should emphasize that the target data is the original data of the time series and was never seen by the model in the training phase nor even in the selection process of the model. The selection process of the better ANN is governed by the minimum RMSE in the training set.

Table 1 presents for each ANN time series the performance measured by both the *r* (correlation coefficient) and the RMSE in the training set and test set.

Table 1: Results of ANNs models.

Type of Data	Performance Measured			
	Training set		Test set	
	r	***RMSE***	***r***	***RMSE***
OD	0.986	13.585	0.962	22.723
OD_Ln	0.989	12.268	0.983	18.969

Between both time series (original - OD, and transformed - OD_Ln) the transformed one is where the lower RMSE was achieved with correlation coefficient of 0.989 in the training set. We can never say that this is the better model, but comparing the results of the prediction between both implemented models and considering that these models resulted from a selection of several different architectures we can say that the final results are stable and has and interesting performance. Therefore, this model is selected based only in the training set.

We should look now at the performance in the test set. Regarding the performance in the test set presented in Table 1 the previous selected model (using OD_Ln) is confirmed now with lower RMSE and higher r. Both measures RMSE and r are better in the model using the transformed time series. Although the RMSE becomes deteriorated now, the correlation coefficient stills at a relatively high level.

The predicted values for the year of 2003 (data used as the test set) with both models and its APE and MAPE are presented in Table 2. APE is the absolute percentage error given by the expression [5]. MAPE is the Mean absolute percentage error given by the expression [6].

$$APE = \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100. \qquad [5]$$

$$MAPE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100. \qquad [6]$$

Table 2: Prediction of the forecasting ANN models, APE and MAPE in the period 01/2003 to 12/2003.

Months	Target Data	OD		OD_Ln	
		Values	**APE**	**Values**	**APE**
January	155.527	181.694	16.8%	181.216	16.5%
February	177.818	180.556	1.5%	181.937	2.3%
March	214.106	236.418	10.4%	227.828	6.4%
April	258.519	245.822	4.9%	268.781	4.0%
May	293.531	284.161	3.2%	295.410	0.6%
June	271.454	306.140	18.8%	304.296	12.1%
July	318.706	337.832	6.0%	329.653	3.4%
August	433.211	394.731	8.9%	411.745	5.0%
September	343.534	382.898	11.5%	374.685	9.1%
October	281.472	292.481	3.9%	304.717	8.3%
November	219.463	224.985	2.5%	230.618	5.1%
December	178.439	180.953	1.4%	185.487	3.9%
MAPE	***----***	***----***	***7.0%***	***----***	***6.4%***

Analysing the presented results in Table 2 we can observe that the prediction is better using the transformed time series than using the original time series. This result is concordant with the r and RMSE presented in Table 1.

According to the Criteria of MAPE for Model Evaluation in Lewis (1982), presented in Table 3, the predicted data with the selected model has an highly accurate forecast.

Table 3: Criteria of MAPE for Model Evaluation.

MAPE (%)	Assessment
<10	Highly Accurate Forecasting
10-20	Good Forecasting
20-50	Reasonable Forecasting
>50	Inaccurate Forecasting

Source: Lewis (1982).

Figure 4 displays the original and predicted time series for the 12 months of 2003 with both models. Both models follow the behaviour of the target data. Figure 5 displays the same data for the entire time series. As expected the predicted date fits better the target data in the training set than in the never previously seen test data. In Figure 5 we can observe an additional difficulty for the model imposed by the fact that years 2001 to 2003 have had and increasing number of overnights, and this increasing phenomena was present in the training set only in 2001. This phenomenon was due to the fact that the city of Guimarães and the Douro Region were considered World Cultural Heritage, and the city of Porto was the European Capital of Culture in 2001.

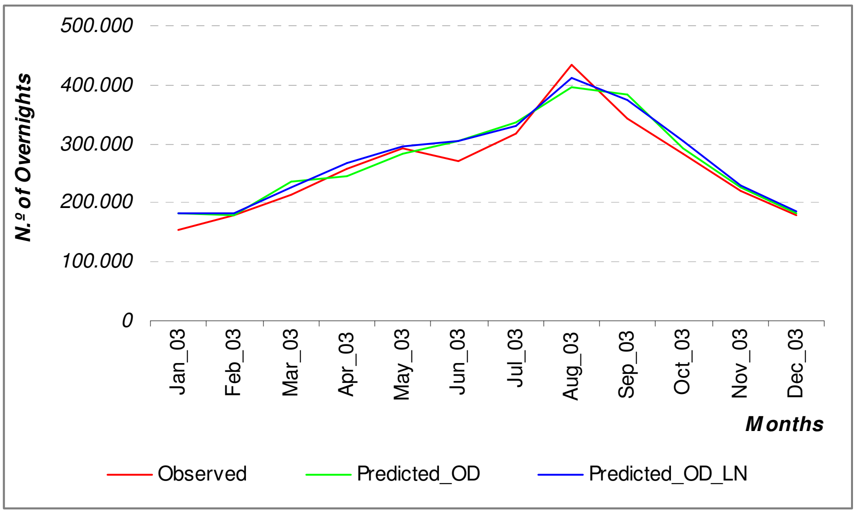

Fig. 4: Graphical presentation of overnights in the North of Portugal, from 01/2003 to 12/2003.

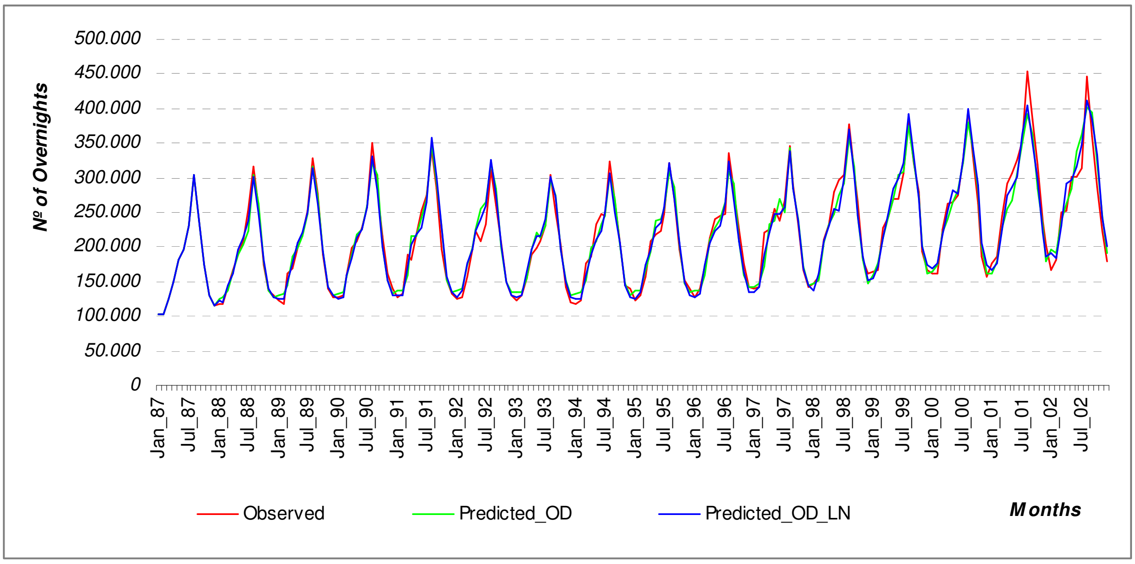

Fig. 5: Comparison between Original Data and Predicted Values, in the training data and validation data sets.

4. CONCLUSIONS

This paper describes the process of modelling tourism demand for the north of Portugal, using an artificial neural network model. Data used in the time series was obtained from official publications - Portuguese National Statistics Institute. The time series was considered in two different ways; one was the original data and another was the logarithmic transformed data. Both series were separate into a training data set to train the neural network, in a validation set, to stop the training process earlier and a test data set to examine the level of forecasting accuracy.

The model has 6 neurons in the hidden layer with the logistic activation function and was trained using the *Resilient Backpropagation* algorithm (a variation of backpropagation algorithm). The ANN model has the 12 preceding values as the input. The analysis of the output forecast data of the selected ANN model showed a relatively close result compared to the target data. In other words, the model produced, according to Lewis (1982) a highly accurate forecast. Therefore it can be considered adequate for the purpose of prediction in the reference time series.

The model applied to the logarithmic transformed data achieved better results evaluated by the RMSE, the correlation coefficient and MAPE.

Considering the results, the artificial neural network based models represent an effective alternative to classical models in tourism forecasting. This methodology becomes interesting to forecast because it allows the use of a non linear model for seasonal time series.

Finally, an accurate forecast from neural network models could certainly help economic agents of tourism activity and official policy makers improve their planning and decision making.

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Appendix A

Table A.1: Overnights in the North of Portugal from 01/1987 to 12/2003 Original Data.

Year / Month	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
January	102.447	118.011	122.217	126.671	126.826	124.194	121.469	118.606	122.480	126.910	140.430	148.218	163.696	162.389	176.690	165.653	155.527
February	102.123	117.547	116.837	129.802	131.653	127.474	129.284	122.988	130.393	139.403	141.183	157.415	165.988	162.637	186.586	181.005	177.818
March	125.401	142.687	160.658	158.701	188.999	157.536	154.734	175.261	156.645	172.393	219.465	209.929	228.149	226.010	245.261	249.214	214.106
April	150.042	167.118	169.326	197.757	182.290	196.087	189.142	185.525	209.263	213.973	224.382	232.767	242.744	262.865	291.395	253.274	258.519
May	180.430	189.823	199.158	207.876	219.187	223.918	198.402	232.075	218.666	239.142	253.833	280.326	269.854	264.497	306.743	302.028	293.531
June	197.113	207.729	218.595	227.159	251.295	207.907	207.216	248.237	222.720	245.264	238.334	296.612	270.126	273.881	325.568	301.465	271.454
July	229.293	254.523	252.634	257.633	273.927	231.801	231.453	246.274	247.589	248.398	266.993	303.866	306.031	324.962	351.955	314.560	318.706
August	304.847	315.113	329.014	351.500	341.490	312.026	304.576	322.366	320.750	336.086	345.672	377.645	385.868	397.405	452.581	444.991	433.211
September	238.542	258.287	278.074	284.867	283.378	259.023	249.583	266.094	269.433	280.769	288.409	309.700	321.248	331.155	383.793	361.181	343.534
October	173.503	174.359	189.664	216.286	197.241	205.400	202.792	206.256	196.466	225.734	232.052	263.522	280.597	263.217	319.417	287.383	281.472
November	130.187	137.933	138.683	162.062	152.554	149.289	141.976	144.803	152.340	175.438	166.835	180.796	193.062	186.445	238.925	221.910	219.463
December	114.229	128.774	127.730	139.683	132.802	130.963	120.748	139.706	140.643	143.163	141.349	161.273	166.990	157.210	202.351	179.766	178.439
Total	***2.048.157***	***2.211.904***	***2.302.590***	***2.459.997***	***2.481.642***	***2.325.618***	***2.251.375***	***2.408.191***	***2.387.388***	***2.546.673***	***2.658.937***	***2.922.069***	***2.994.353***	***3.012.673***	***3.481.265***	***3.262.430***	***3.145.780***

Table A.2: Experimental results of forecasting tourism demand in the north of Portugal in the period 01/1988 to 12/2002.

Year / Month	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
January	109.463	117.716	119.384	122.864	129.332	116.654	117.350	123.981	121.768	130.725	131.367	154.988	152.653	156.134	179.577
February	126.140	126.211	127.209	136.378	139.855	132.873	132.226	137.824	134.060	141.482	159.721	175.119	175.446	175.393	178.030
March	143.359	152.963	153.552	175.819	170.654	161.931	153.435	163.834	168.733	184.021	194.919	204.532	220.430	226.522	226.711
April	153.410	166.907	176.368	191.652	194.438	188.682	171.950	195.256	198.332	209.496	220.546	233.309	230.924	248.776	285.316
May	189.725	183.835	200.613	190.727	199.806	201.364	193.954	213.517	213.649	230.266	242.702	253.655	254.908	275.692	271.130
June	207.066	210.684	211.493	223.206	229.090	211.254	230.919	231.198	229.949	251.968	258.854	287.128	261.880	293.160	301.279
July	243.362	255.750	258.690	263.494	254.392	233.462	258.260	256.199	269.584	254.730	292.720	304.644	316.616	359.721	336.441
August	298.440	320.174	334.944	353.077	338.218	303.360	303.053	320.779	320.876	337.691	355.829	378.240	388.008	412.631	419.899
September	221.132	222.187	250.427	258.834	254.973	245.336	238.071	251.148	246.136	253.396	285.444	305.316	323.291	340.132	372.824
October	171.140	181.138	180.014	209.897	186.361	186.146	190.410	184.276	193.849	217.711	217.190	242.797	255.086	247.581	333.302
November	149.472	154.424	161.717	144.335	160.337	158.309	147.974	148.254	159.506	167.821	171.542	197.416	189.885	213.696	241.988
December	121.025	120.228	135.511	132.062	128.558	125.856	129.492	127.328	139.495	138.751	159.197	158.920	155.202	190.044	176.532
Total	2.133.734	2.212.217	2.309.922	2.402.345	2.386.014	2.265.227	2.267.094	2.353.594	2.395.937	2.518.058	2.690.031	2.896.064	2.924.329	3.139.482	3.323.029