FORECASTING EXPORT PRICE OF SABAH SAWN TIMBER USING NEURAL NETWORK

Noraini Abdullah
Department of Mathematics And Economics,
Faculty of Science & Natural Resources,
Universiti Malaysia Sabah,
88400 Kota Kinabalu, Sabah, Malaysia.
norainiabdullah.ums@gmail.com

Tiew Y. W.
Department of Mathematics And Economics,
Faculty of Science & Natural Resources,
Universiti Malaysia Sabah,
88400 Kota Kinabalu, Sabah, Malaysia.
jeniferywt@gmail.com

Tiffany Tiong W.T.
Department of Mathematics And Economics,
Faculty of Science & Natural Resources,
Universiti Malaysia Sabah,
88400 Kota Kinabalu, Sabah, Malaysia.
tiffany_thing91@msn.com

Rosmalina A.R.
Department of International Tropical Forestry,
Faculty of Science & Natural Resources,
Universiti Malaysia Sabah,
88400 Kota Kinabalu, Sabah, Malaysia.
rmalina@gmail.com

ABSTRACT

Sabah timber industry is facing a shortage of raw material due to to past over logging, and lack of sustainable forest management program. Hence, the implementation of Sustainable Forest Management (SFM) practices in line with the requirements of the Malaysia Criteria and Indicators for Forest Management Certification (MC&I), 2002 (Ministry of Plantation Industries and Commodities Malaysia, 2009). This critical situation has forced this industry to depend on alternative materials and other means for sustainability such as softwood and non-wood materials, especially when sawn timber is restricted (Borneo Post Online, 2012). Hence, this research introduces a mathematical approach for a more sustainable industry by modelling the export price of sawn timber using Artificial neural network (ANN). ANN is solved using the MATLAB version 7.11.0 R2010b Toolbox with one dependent (Export price) and two independent variables (Quantity and Unit value). Data on sawn timber export price of 228 observations were obtained from the Sabah Department of Statistics from 1991 to 2009. The best model in ANN is determined based on the eight selection criteria (8SC) with highest value of coefficient of determination (R^2) and the minimum values of the mean square error (MSE) and the norm of residuals. Finally, the mean average prediction error (MAPE) is used to check the validity of the best model. Results show that the best model using ANN is the fourth single layer with a fifth degree polynomial.

Key words: Artificial Neural Network (ANN), timber industry, export price, forecasting, modelling.

Introduction

The North Borneo British Company (NBBC) had been monopolizing the timber of Sabah since 1881 (Lee & Aleeya, 2005). The main locations of the timber industry were in Sandakan, Lahad Datu, and Tawau with direct labor taken from Indonesia and Philippines for logging. According to Pakhriazad & Mohd.Hasmadi (2010), Malaysia is a tropical country with a total land area of approximately 32.9 million hectares. For the case of Sabah, it has a total land-mass of 7.37 million hectares. In recent decades, forests have provided an important source of revenue for the state, contributing in excess of 50 percent of the total from the 1970s through to the early 1990s. In 2006, total forest revenue was RM505 million, contributing 22.3 percent of Sabah's total revenue, and generating about 47,200 jobs. In 2011, Malaysia exported wooden furniture valued at RM975,000 which had an increase of 148% from RM393,000.The main type of wooden furniture exported from Malaysia to other countries, for example Brazil, is furniture and its parts valued at RM538,000 in 2011.

According to Sabah Forestry Department (2013), round logs exported at a volume of 171,000.2743 m^3, RM 653.53 on average price of the round and RM 111,753,436.10 on the Free-On-Board (FOB) value in the year of 2012. The export of round logs had increased the national income of Malaysia which increased the economic growth of the country.According to Yap (2004), Malaysia is the second largest timber production exporter in the world and he believed that this timber production would increase rapidly again in Malaysia. For Sabah, timber production especially in plantation area is important for the revenue or income of the government, besides influencing Malaysia's economy. Sabah timber industry had started from many years ago, and is still important up to now due to several reasons. Consequently, a research on the sustainability of the timber industry would thus be crucial in determining the required strategies to elevate the production and price of sawn timber.

Zhang (2003) had stated that artificial neural network (ANN) is a very useful tool for time series modeling and forecasting because artificial neural network is a model that is able to approximate various nonlinearities in the data, while Pradhan & Kumar (2010) had stressed that ANN is an information process technique for modeling mathematical relationships between input variables and output variables. Hence, for a more sustainable timber industry, this paper intends to discuss the use of a mathematical modelling approach using multilayer feed-forward back-propagation ANN to forecast the export price of sawn timber in Sabah.This paper is thus organized into five sections. The introduction section discusss on the role of Sabah timber industry, its importance and motivational challenges in Malaysia. The next section discusses on the literature review related toartificial neural network in various fields and applications. Section three elaborates on the methodology used through out this research. The following section then presents on the results and discussions, followed by the conclusions and finally, the recommendations made on this research.

Literature Reviews

According to Hossein *et al.*(2011), there were three fundamentally different classes of neural network, namely, single-layer forward networks, multilayer feed-forward networks and recurrent networks. Recurrent neural network was basically a feed-forward neural network with a recurrent loop. It was contrary to the feed-forward network with the bi-directional data flow. The multilayer feed forward network made ANNs a powerful tool for modelling data sets.

Yaghouby *et al*.(2009) conducted a research on the classification of cardiac abnormalities using the Generalized Discriminant Analysis (GDA) feature reduction technique and the Multilayer Perceptron (MLP) neural network classifier. In their research, nine linear and nonlinear features were extracted from the HRV signals and then reduced to only three by GDA. After that, the MLP neural network was used to classify the HRV signals. Arrhythmia classification method was applied to input HRV signals, taken from the MIT-BIH databases. Four types of the most life threatening cardiac arrhythmias, such as left bundle branch block, fist degree heat block, Supraventricular tachyarrhythmia and ventricular trigeminy could be discriminated by MLP and reduced features with the accuracy of 100%.

Pradhan & Kumar (2010) used artificial neural network model to forecast the exchange rate in India. The data was taken from the year 1992 to 2009. These researchers conducted two types of data set(daily and monthly) for US dollar, British pound euro and the Japanese yen. The Root Mean Square (RMSE), Mean Absolute Error (MAE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) tests were used in this research in order to achieve accuracy forecasting measurements. The RMSE along with MAE and MAD were very low and varied from 0.02 to 0.40. The tests proved for the accurate prediction power for both daily data and monthly data. The linear unpredictability of exchange rate could be improved by using the neural network model. Therefore, researchers believed that ANN model could be a good tool to predict the exchange rate in India which was able to achieve the economic growth in that country.

In Kunwar & Ashutosh (2010) research, an artificial neural network technique was used for stock market forecasting. The data for the study comprised the daily stock returns form the 1 April 2005 to 30 March 2007 with a series of 500 observations. MAPE, MSE and RMSE were accessed for the forecasting purposes. The results showed that the neural network model, after trained with sufficient data, proper inputs and architecture, could predict the stock market prices perfectly. Therefore, neural networks could be used as a good alternative technique for forecasting the daily market prices.

Seyyed *et al.*(2013) conducted a research on using Artificial Neural Network in estimating participation in elections. In this research, ANN was used to anticipate the participation rate in the 11^{th} election of the Islamic Republic of Iran in Kohgiloye and Boyerahmad Provinces. The data included features and prospects of 100 qualified persons to attend in the election. Two layer-feed-forward networks with tan-sigmoid transmission functions were used in input and output layers. Ten neurons in hidden layers were also used in this research. ROC curve was used for the prediction of participation. The ROC curve made a conclusion that neural network showed good classification function. These researchers found out that the use of Artificial Neural Network (ANN) to anticipate participation results in election can provide 91% accuracy in the future election of Islamic Republic of Iran in the Kohgiloye and Boyerahmad Provinces.

Luis *et al.*(2009) had conducted a research on MOE prediction in Abies*pinsapo*Boiss. timber by using Artificial Neural Network (ANN). The modulus of elasticity of Abies*pinsapo*Buidd. timber through the parameters of density, width, thickness, moisture content,ultrasonic wave propagation velocity, and usual grading of the test pieces which were associated with MOE. The materials were collected in Sierra del Pinar de Grazalema, in the province of Cádiz, and Los Reales de Sierra Bermeja and Sierra de Ronda, in the province of Málaga. The trees were the natural forests of A.pinsapo in the Iberian Peninsular, and of adult specimens over 70 years old. The result showed that the feed-forward multilayer perceptron network that were used had achieved 75% success in the testing of unknown group.

Wang *et al.*(2012) had conducted a research on dynamic model prediction study of the forest disease, insect pest and rat based on BP neural network. In these studies, nearly ten years survey data of rodent pest were collected from the year 2000 to 2009 in order to meet the requirements of computer training and simulation. This research evaluated "n" neuron of the occurrence area on forest disease to make trials from the training and precision test of network. By taking the history data from 2005 to 2009 as sample data, prediction on pest and rat disease in 2010 can be done by using the BP neural network. These researchers predicted the occurrence areas and control areas of forest pest and rat disease in 2010-2014 and found out that the forest and rat disease showed a trend of decline. These researchers found that by using the BP neural network to stimulate and predict forest pest and rat disease, it would reduce errors between measured value and predicted value and thus had a higher reliability. Therefore, the BP neural network model was reliable in predicting the forest disease and insect and rat pests.

Dilip *et al.*(2011) conducted a research on neonatal disease diagnosis using artificial neural network. The technique involved training a Multi Layer Perceptron with a BP learning algorithm. The Backpropagation algorithm was used to test for the different categories of neonatal diseaseA comparative study by using different training algorithm of MLP, Quick Propagation, Conjugate Gradient Descent, showed the higher prediction accuracy. In this research, 94 patients who had symptoms of neonatal diseases had been collected. The multi layered feed-forward network architecture with 11 input nodes, 5 hidden nodes, and 13 output nodes had been used for the neural network architecture. The results of this study showed that 39.36% of the respondents had the symptoms of Septicemia, 17.02% had the symptoms of HIE III; and 9.57% of the patients had the symptoms of Metabolic Disorder-Hypocalcemia. This study exhibitedthe ANN based prediction of neonatal disease and improved the diagnosis accuracy of 75% with higher stability. Therefore, it can be concluded that neural network can perform better results compared to other techniques for the prediction tasks.

Mohsen & Zahram (2007) conducted a research of forecasting the weather temperature in neural network approach. In this study, weather temperature data for ten years from the year of 1996 to 2006 was trained and tested by the Multi Layer Perceptron (MLP). Hourly wind speed, dry and wet bulb temperature, relative humidity, pressure daily sunshine and radiation variables were taken as inputs for the ANN model. In order to improve the accuracy, the chosen data were split into four seasons namely spring, summer, fall, and winter where for each season one network was considered. In this study, the global test was divided into two selected groups. The training group, corresponding to 65% of the patterns while the test group, corresponding to 35% of the patterns. The forecasting reliability was evaluated by computing the Mean Absolute Error (MAE), which was a measure of error, between the exact and predicted values of the data conducted. The results showed that MLP network had the minimum forecasting error for each season and could be considered as a good method for temperature forecasting.

Many central banks had used forecasting models based on ANN methodology for predicting various macroeconomics indicators such as inflation, GDP Growth and so on. Adnan & Muhammad (2009) had carried out a research on forecasting the inflation in Pakistan by using the artificial neural network. The objective of this research is to forecast monthly inflation for Pakistan for FY08 using feed forward neural network model with 12 hidden layers on the basis monthly data of July 1993 to June 2007. ANN was trained using the Levenberg-Marquaedt algorithm which was the standard training algorithm. Forecasting efficiency was captured by minimizing the root mean square (RMSE). The result showed an upward continuous trend in inflation rate for FY08. Hence, ANN was found to be a good tool for inflation forecasting.

Neural networks are a good tool used to predict or forecast in many areas of civil engineering. Cachim (2011) conducted a research temperature prediction in timber under fire loading by using an artificial neural network. The temperature evolution within a timber member under fire loading was calculated using design methods of Eurocode 5 (EC5). The error occurred during the training and testing of the network was expressed as a root mean square error (RMSE) and as a mean absolute error (MAE). In this research, the data used in the multilayer feed forward neural network models were arranged in three input parameters such as the density of timber, the time of fore exposure and the distance from exposed side. The temperatures in timber were predicted by using these input parameter. RMSE of the network H2570 gave a value of 3.5 ºC and an R^2 equal to 0.9997.The training and testing results in the neural network model had shown that neural networks could accurately calculate the temperature in timber members subjected to fire. Therefore, ANNs were a powerful tool for solving complex civil engineering problems.

Methodology

In this study, all the data variables were obtained from the Department of Statistics Sabah and the Department of Statistic Malaysia's website. A total of 228 monthly data of sawn timber export price in Sabah from year 1991 until year 2009 would be used for data analysis, with 24 data sets reserved for forecasting. The data used for analysisusing artificial neural network (ANN), comprised of one dependent variable (Y) which was the export price of sawn timber (in RM'000),and two independent variables ($X_1$and X_2) which were quantity of sawn timber (in '000 M^3) and unit value (in RM/ M^3) respectively.

Neural Network (NN) Algorithm

Although in ANN there is no need to specify a particular model form in finding the optimal ANN model, but in this research, a basic model building of ANN model is developed in order for researchers to reach the goal of obtaining a best neural network forecasting model in a right approach and without missing any main steps for developing ANN models. In turn to build a best ANN forecasting model, there are five main steps that must be followed as shown in Figure 1. The neural network (NN) algorithm was applied using the following model-building procedures.Figure 1 showed the basic flowchart of the modelling approach using ANN model-building procedures. In contrast to Noraini *et al.*(2011) with the four phases of the model-building procedures in regression analysis, the ANN modelling procedures comprised of five steps, namely, data pre-processing, neural network creation, neural network training, best model, and error computation.

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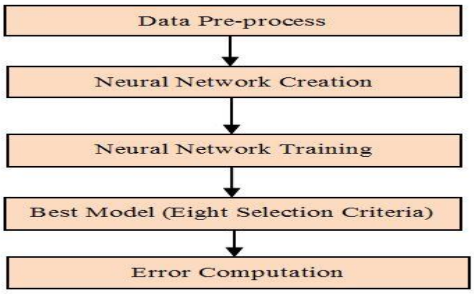
Figure 1. Basic Flow Chart of ANN Model-Building Procedures



1. **Data Pre-processing**: If the initial data is poor or insufficient, then it is not suitable to develop good models. Therefore, the initial data should be pre-processed before applying neural network algorithm (Li *et al.*, 2010). Data normalization is carried out in the pre-processing step toensure the suitability of data sets structures for analysis purposes (Maitha*et al.*, 2011), while Henzeh*et al.*(2008) stated that the estimation error and the computational time for training process and other risks can be reduced once the input normalized neural network had been done.
   with the formula in equation (1) where y is the output data, σ is the standard deviation and x is the input data.

$$y = \frac{x - mean}{\sigma} \quad \text{...(1)}$$

2. **Neural Network Creation**: The numbers of input layers, hidden layers and output layers have to be selected. In addition, the types of transfer function have to be selected in this step. According to Vahidinasab*et al.*(2008), the architecture of the network is important because a good prediction can be obtained if the transfer functions and input variables are selected appropriately.

3. **Neural Network Training**: During the training step, firstly, we have to determine the mean squared error (MSE) which represents the average squared error between the network's output and the target value. The maximum number of learning epochs has to be determined so that the training will stop no matter whether the MSE target has been achieved. Then, we can start to train the neural network. The training phase will stop once the MSE is achieved or the maximum number of learning epochs is reached.

4. **Best Model**: From the trained neural network, the best linear fit of the artificial neural network (ANN) model is obtained. The general equation for the best linear fit of the ANN model is as shown in equation (2).

$$A = mT + c \quad \text{... (2)}$$

   where A = actual value, m = gradient of the line, T = target value and c = constant for the equation. The m value and correlation constant, R is in the range from 0 to 1. When m value and R are closing to 1, this means that the c value is approaching 0. This indicates the precise response for the neural network. The best neural network model from multiple layers can then be obtained by using thecoeffiecient of determination (R^2), mean square error (MSE) and the norm of the standardized residuals, sum of square error (SSE) and the eight selection criteria (Ramanathan, 2002) given by Table 1 below.

Table 1. Eight Selection Criteria (8SC)

Criteria	Formula	Criteria	Formula
AIC (Akaike, 1974)	$\left(\frac{SSE}{n}\right)e^{\frac{2(k+1)}{n}}$	RICE (Rice, 1984)	$\left(\frac{SSE}{n}\right)\left(1-\frac{2(k+1)}{n}\right)^{-1}$
FPE (Akaike, 1970)	$\left(\frac{SSE}{n}\right)\frac{n+k+1}{n-(k+1)}$	SCHWARZ (Schwarz, 1978)	$\left(\frac{SSE}{n}\right)(n)^{\frac{k+1}{n}}$
GCV (Golub *et al.*, 1979)	$\left(\frac{SSE}{n}\right)\left(1-\frac{k+1}{n}\right)^{-2}$	SGMASQ (Ramanathan, 2002)	$\left(\frac{SSE}{n}\right)\left(1-\frac{k+1}{n}\right)^{-1}$
HQ (Hannan & Quinn, 1979)	$\left(\frac{SSE}{n}\right)(\ln n)^{\frac{2(k+1)}{n}}$	SHIBATA (Shibata, 1981)	$\left(\frac{SSE}{n}\right)\left(\frac{n+2(k+1)}{n}\right)$

5. **Error Computation**: Using mean squared error (MSE) and mean absolute percentage error (MAPE) to assess the prediction accuracy of the best model.

Multilayer Feed-Forward Back-Propagation Neural Network Model

In the feed-forward back-propagation neural network, there are many layers which include single layer and multiple layers. A single-layer network has one layer of connection weights, whereas a multilayer network is a net with one or more layers of nodes between the input units and the output units. Hence, in the multilayer network, it takes inputs from the previous layer and sends out to the next layer.

Figure 2. Feed-forward back-Propagation Neural Network

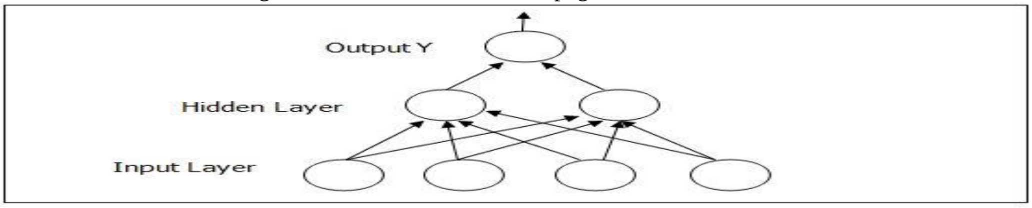


Figure 2 depicted a feed-forward back-propagation neural network. In this study, the tan-sigmoid transfer function will be chosen as the activation function given as in (3):

$$output = \frac{1}{1 + e^{-\,sum}} \quad \ldots\ldots (3)$$

The calculations to each layer of a three-layer in a one-middle-layer of ANN were as shown in Table 2 (Li, 1994):

Table 2. Matrix calculation of each layer in a one –middle-layer neural network

Input layer :With r nodes, each has no weight and no transfer function.

Input vector = X = Output vector =[$x_1\ x_2 \ldots x_n$]

Middle Layer: With q nodes, each has r weights and one transfer function :

$$\text{Weight Matrix} = \underline{W} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1q} \\ w_{21} & w_{22} & \cdots & w_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ w_{r1} & w_{r2} & \cdots & w_{r1} \end{bmatrix}$$

Transfer function = F = (f_1 , f_2 , …, f_q)

Output matrix = F[$\underline{XW}$] =[f_1 ($\sum_{i=1}^{r} x_i w_{i1}$), f_2 ($\sum_{i=1}^{r} x_i w_{i2}$), …, f_q ($\sum_{i=1}^{r} x_i w_{iq}$)

Output Layer: With p nodes, each has q weights and one transfer function

$$\text{Weight Matrix} = = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1p} \\ v_{21} & v_{22} & \cdots & v_{2p} \\ \vdots & \vdots & \ldots & \vdots \\ v_{q1} & v_{q2} & \cdots & v_{qp} \end{bmatrix}$$

Transfer function = T = (t_1 ,t_2 ,…,t_p)

Output vector =$\underline{Y}$=[$\hat{y}_1$,$\hat{y}_2$,…,$\hat{y}_p$] =T [F [$\underline{XW}$] $\underline{V}$] = [t_1 { $\sum_{j=1}^{q}$[f_j ($\sum_{i=1}^{r} x_i w_{ij}$) v_{j1}} ,

t_2 { $\sum_{j=1}^{q}$[f_j ($\sum_{i=1}^{r} x_i w_{ij}$) v_{j2}}, …, t_p{ $\sum_{j=1}^{q}$[f_j ($\sum_{i=1}^{r} x_i w_{ij}$) v_{jp}}

For the case of accuracy, the prediction of accuracy can be calculated using the coefficient of distribution (R^2) and the mean absolute percentage error (MAPE) as shown below in equations (4) and (5) respectively:

$$R^2 = 1 - [\ \textstyle\sum_{i=1}^{p} (\ t_i - o_i\ )^2 / \sum_{i=1}^{p} (\ t_i - \bar{t}\ )^2] \quad \ldots\ldots (4)$$

$$\text{MAPE} = \frac{1}{p}\sum_{i=1}^{p} |\ (\ t_I - o_i\ ) / t_i\ | \quad \ldots\ldots (5)$$

such that t_i is the exact values, o_i is the predicted values, p is the total number of the test data reserved for forecasting and $\bar{t}$ = average desired output. A lower mean absolute percentage error (MAPE) indicates a higher accuracy of the output.

Results And Discussions

The ANN modeling has *2n* layers where *n* is the single layer. For an example, if *n* is a single layer of three layers, then its double layer will be six layers. In this study, there were four single layers which included one layer, three layers, four layers and five layers, whilst the double layers were two layers, six layers, eight layers and ten layers. In the ANN analysis, there were 4 single layers and 4 double layers used to create the neural network, a total of 8 ANN models from single and double layers. The best layer would be chosen using step 4 of the ANN model-building procedures, and the best model can then be used for forecasting.Table 3 showed the outputs the single layers of 1, 3, 4 and 5 respectively. It can be seen that the single layer of four was the best with the highest value of R^2 and minimum values of MSE and SSE (highlighted in blue).

Table 3. Output for 1, 3, 4 and 5 Single Layers

No. of Layers	R^2	MSE	SSE	Best Linear Fit (*A*)
1	0.998560518	0.00107200	0.24120	-0.0098422*T* + 1.1622
3	0.998740397	0.00082813	0.18633	-0.0098987*T* + 1.1714
4	0.999480068	0.00010721	0.02412	-0.0098510*T* + 1.1640
5	0.995864285	0.00558020	1.25555	-0.0099218*T* + 1.1781

Table 4. Output for 2, 6, 8 and 10 of Double Layers

Number of Layers	R^2	MSE	SSE	Best Linear Fit (*A*)
2	0.99964003	0.00045698	0.1028205	-0.0098778*T* + 1.1668
6	0.99830072	0.00078636	0.1769310	-0.0098436*T* + 1.1607
8	0.99802098	0.00167610	0.3771225	-0.0098466*T* + 1.1614
10	0.99884034	0.00135840	0.3056400	-0.0097671*T* + 1.1515

Similarly, the outputs for the double layers of 2, 6, 8 and 10 were depicted in Table 4. The best model was chosen based on the highest R^2 value with the most minimum values of MSE and SSE. Comparing Tables 1 & 2, the double layer of 2 showed a better performance in the correlation coefficient of the highest R^2 value, but its MSE and SSE values were not the minimum. The best model which meet the highest R^2 in the range of 0.999 to 1, with the criteria of minimum residuals amongst all the layers was the single layer of four with the best linear fit equation of -0.0098510*T* + 1.1640 as shown in Table 5 below. Table 6 further showed that the best model selection based on the eight selection criteria (8SC). Table 6 had also reaffirmed the choice of the best model which was the single layer of layer 4 since it had all of the minimum values of the eight selection criteria (8SC) being met.

Table 5. Summary of The Best ANN Model

No. of Layers	R^2	MSE	SSE	Best Linear Fit (*A*)
4	0.999480068	0.00010721	0.02412	-0.0098510*T* + 1.1640

Table 6. Model Selection Criteria in Artificial Neural Network (ANN)

Layer	k	k+1	n	SSE	AIC	FPE	GVC	HQ	RICE	SCHWARZ	SGMASQ	SHIBATA
1	2	3	228	0.2412	1.09E-03	1.09E-03	1.09E-03	1.11E-03	1.09E-03	1.14E-03	1.07E-03	1.09E-03
3	2	3	228	0.1863	8.39E-04	8.39E-04	8.39E-04	8.54E-04	8.39E-04	8.78E-04	8.28E-04	8.39E-04
4	2	3	228	0.0241	1.09E-04	1.09E-04	1.09E-04	1.11E-04	1.09E-04	1.14E-04	1.07E-04	1.09E-04
5	2	3	228	1.2555	5.65E-03	5.65E-03	5.65E-03	5.76E-03	5.66E-03	5.91E-03	5.58E-03	5.65E-03
2	2	3	228	0.1028	4.63E-04	4.63E-04	4.63E-04	4.71E-04	4.63E-04	4.84E-04	4.57E-04	4.63E-04
6	2	3	228	0.1769	7.97E-04	7.97E-04	7.97E-04	8.11E-04	7.97E-04	8.33E-04	7.86E-04	7.96E-04
8	2	3	228	0.3771	1.70E-03	1.70E-03	1.70E-03	1.73E-03	1.70E-03	1.78E-03	1.68E-03	1.70E-03
10	2	3	228	0.3056	1.38E-03	1.38E-03	1.38E-03	1.40E-03	1.38E-03	1.44E-03	1.36E-03	1.38E-03
Minimum value=					**1.09E-04**	**1.09E-04**	**1.09E-04**	**1.11E-04**	**1.09E-04**	**1.14E-04**	**1.07E-04**	**1.09E-04**

Table 7. Standardized residuals of single and double layer for different equations

No. of Layers	Linear	Quadratic	Cubic	4th Degree Polynomial	5th Degree Polynomial	Minimum Value
1	11.524	10.6848	10.1086	8.4330	8.2921	**8.2921**
3	11.725	10.8867	10.3108	8.6391	8.4816	8.4816
4	11.616	10.7765	10.1998	8.5353	8.3858	8.3858

5	11.392	10.637	10.106	8.5545	8.3973	8.3973
2	11.625	10.7984	10.2218	8.5612	8.4071	8.4071
6	11.515	10.6962	10.1032	8.4539	8.3113	8.3113
8	11.628	10.8078	10.2532	8.6204	8.4800	8.4800
10	11.577	10.7459	10.1638	8.5063	8.3633	8.3633

Table 7 above showed the five different types of fitting equations used on the standardized residuals. The fitting equations included were linear, quadratic, cubic, 4th degree, and 5th degree polynomial equations. It could be clearly seen that the 5th degree polynomial equation had the most minimum value of the standardized residuals in all the number of layers. It could also be seen that the single layer of the 5th degree polynomial equation was the best fitting equation since it had the minimum value (0.82921) amongst all the single and double layers. The polynomial plots in Figure 3 (single layer) and Figure 5 (double layer) respectively further showed the distribution of the data points of the fitting equations, while Figure 4 and Figure 6 respectively showed the corresponding standardized of norm residuals of the 4th adegree and 5th degree polynomial equtions of the single and double layers.

Figure 3. Fitting Plot of Single Layer of 4th degree and 5th degree Polynomial Equations

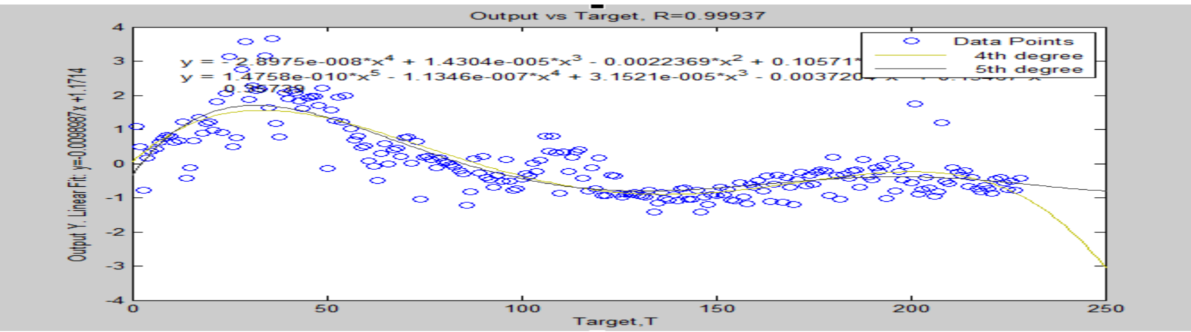


Figure 4. Standardized Residuals of Single Layer of 4th and 5th degree Polynomial Equations

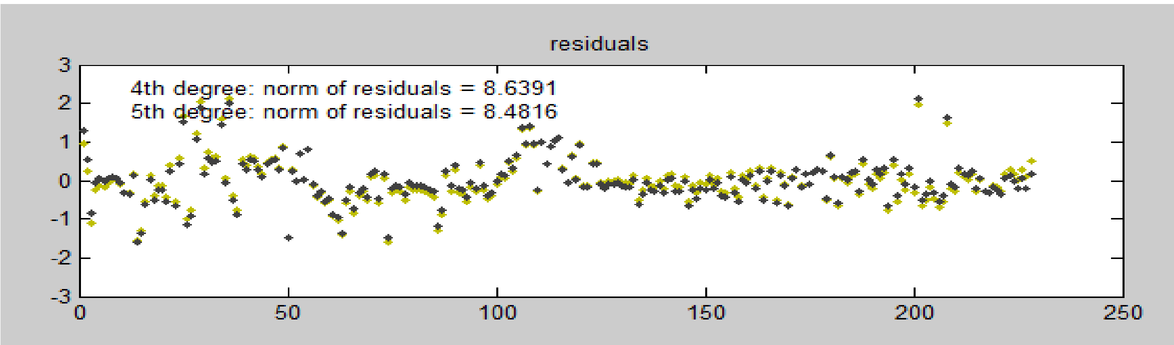


Figure 5. Fitting Plot of Double Layer of 4th degree and 5th degree Polynomial Equations

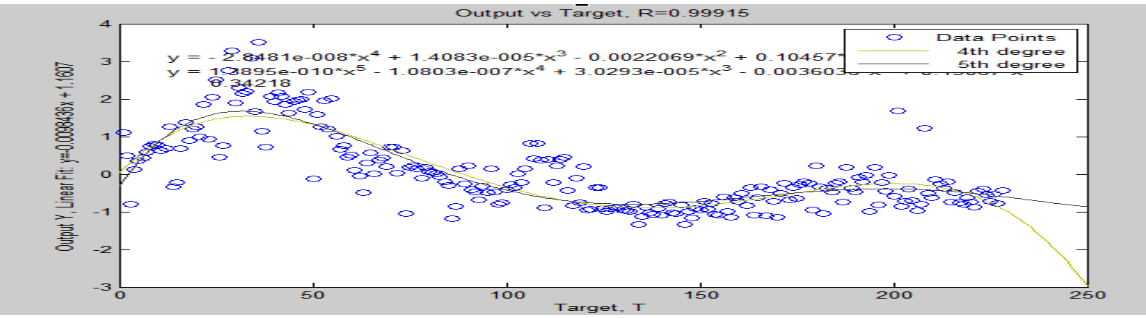
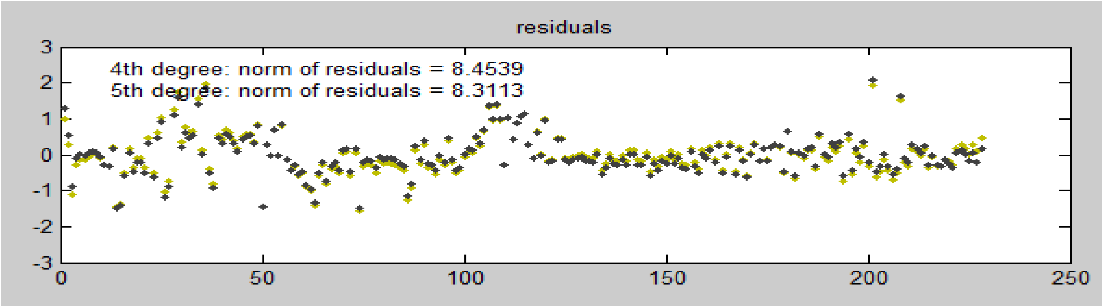


Figure 6. Standardized Residuals of Double layer of 4th and 5th degree Polynomial Equations



Efficiency of Neural Network Model

Based on the best model obtained from the neural network model (best linear fit, *A*), the efficiency of the model or the adjusted R^2 can be calculated by using the equation (6). The adjusted R^2 can be computed using the Microsoft Excel. Table 8 showed the efficiencies of the neural network models.

$$Adjusted\ R^2 = 1-(1-R^2)\left(\frac{n-1}{n-k-1}\right) \qquad (6)$$

Table 8. Efficiencies of the Neural Network Models

Number of Layers	R	R^2	Adjusted, R^2
1	0.99928	0.998560518	0.998547723
3	0.99937	0.998740397	0.998729200
4	0.99974	0.999480068	0.999475446
5	0.99793	0.995864285	0.995827523
2	0.99982	0.999640032	0.999636833
6	0.99915	0.998300723	0.998285618
8	0.99901	0.998020980	0.998003389
10	0.99942	0.998840336	0.998830028

Table 8 showed that the values of adjusted R^2 were smaller than the value of R^2. According to Newbold *et al.* (2007), the adjusted R^2 value was an appropriate indicator of variation values so as to compare the ANN models.The best linear fit equation as given by $A = mT + c$, and the adjusted R^2 value which was close to 1 indicated that it was the best fit model. Hence, it can be deduced the best model of single layer of four had 0.9995 of adjusted R^2 (up to four decimal places) showed a strong positive relationship between *T* with *A*. In conclusion, *T* which is 99.95% affects *A*, the export price of sawn timber.

Forecasting Using Best Neural Network

The estimated value of the best neural network model can be obtained from the MATLAB output of the best ANN model. There were 24 data sets being reserved forecasting. The difference of the export price of sawn timber, Y_t and the estimated value, $\hat{Y}_t$ can thus be determined by using the mean absolute percentage error (MAPE). The computation of MAPE can be calculated as follows:

$$MAPE = \frac{1}{24}\sum_{t=205}^{228}\frac{|Y_t-\hat{Y}_t|}{Y_t}\times 100\% = \frac{\left|\frac{-0.739603889 - (-0.721064228)}{-0.739603889}\right| + \cdots + \left|\frac{-0.413469094 - (-0.432466771)}{-0.413469094}\right|}{24}\times 100\%$$

$$=2.45919\%$$

The MAPE in this study was calculated as 2.45919%. According to Chang *et al.* (2007), if MAPE is less than 10%, then the model is an excellent model. Since the MAPE in this study is 2.45919% which is less than 10%, therefore it is an excellent model to be used for forecasting. In conclusion, the best neural network which is the single layer of four can be used to forecast the future export price of sawn timber for Sabah.

Discussions And Conclusions

In this study, it can be concluded that the eight selection criteria (8SC) can be used to choose the best artificial neural network (ANN) among the total eight models presented fron sinle and double layers. The results showed that the single layer of four is the best neural network because the most minimum values among the eight selection criteria had been met. In this study too, the coefficient of determination R^2, MSE and SSE of the best fitting equation acted as extra supporting evidences to prove that single layer of four was the best artificial neural network (ANN) model. The best ANN model had the value of adjusted R^2 which was 0.9995.

According to Zainodin and Khuneswari (2009), adjusted R^2 was useful to determine the fraction of variation of the dependent variable explained by the independent variables. Thus, the target value, T (the independent variables) were 99.95% affecting the actual value, A (dependent variable). This meant that the target value of best neural network model was highly correlated with the actual value compared. According to Beale *et al.* (2010), the error formed would be minimum if the MSE value was small. This indicated the precision of the neural network model since the single layer of four has the lowest MSE value. The single layer of four is the best neural network. The best linear fit (A) of the single layer of four is $-0.0098510T + 1.1640$. Based on the best linear fit equation, the gradient is -0.0098510 and the constant value is 1.1640.

Comparisons of the standardized residuals of five different types of fitting equations of single and double layers showed that the 5th degree polynomial equation was the minimum. Hence, the 5th degree polynomial equation was the best fitting equation for the standardized residuals. In the 5th degree polynomial, the single layer of one has the lowest in standardized residuals. Therefore, the best model which would be efficient in forecasting can be obtained through the single layer.

Although in ANN there is no need to specify a particular model form in finding optimal ANN model, but in this research, a model building of ANN model is developed in order for researchers to reach the goal of obtaining a best neural network forecasting model in a right approach and without missing any main steps for developing ANN models. In turn to build a best ANN forecasting model, there are few main steps that must be followed as shown in Figure 1. First of all the data had to be pre-processed, then followed by the neural network creation and neural network training, the best model selection using 8SC, and lastly would be the error computation for forecasting.

The MAPE of the best neural network model which is 2.45919% is an excellent forecasting model. On the other hand, comparing Table 3 and Table 4 respectively, the single layer of four had the lowest MSE value. This showed that it was a better layer in this study. However, according to Zou *et al.* (2007), the double layer is better than the single layer because the MSE values of the double layers are consistent whereas the single layers have huge changes in the MSE value. In this study, from Table 8, the R^2 value of the double layer is also consistent but for the single layer, there is a drastic drop of R^2 value from layer four to layer five. If taking the highest R^2 value minus the lowest R^2 value, the difference is very high. But for the double layer, the difference is very low. Hence, as an average, the double layer would show a better performance than the single layer in the long run, as indicated by Zou *et al.* (2007). Thus, neural network models can then said to be best suited for long term forecasting due to their high accuracy of performance.

Based on Table 8, the double layer two had the highest value in the adjusted R^2 which was 0.9996. This showed that the efficiency of this double layer two was 99.96%. Overall, the adjusted R^2 values for all the layerswere in between 0.998 to 1. Hence, it could be concluded that all the layers both single and double layers were good. However, from the eight selection criteria (8SC), the best neural network layer was seen to be single layer of four. The eight selection criteria were based on the sum of squared error (SSE) and the SSE of single layer of four was found to be the lowest. Anyway, by referring to the 8SC model selection in Table 6, the SSE value of single layer of five is the highest. This meant that the SSE value increased drastically from layer four to layer five. As for the double layer, the SSE value was consistent in the range 0.00046 to 0.0017. The 8SC model selection criteria showed that single layer of four was the best layer. This was contrary to Dawson *et al*. (2002) who had stated that the best neural network formed will usually be in the double layer because of its consistency.

In conclusion, the objective to build forecasting models for the sawn timber export price using artificial neural network (ANN) modelling techniques were achieved. The best neural network forecasting model was the single layer of four.The modeling procedures of ANN model had five main steps. By using the developed modeling procedures for ANN model, the best forecasting model can be obtained.The best neural network model in this study had R^2 value of 0.999480068. The MAPE of the best neural network was equal to 2.45919%. Hence, the results concluded that the best neural network was an excellent forecasting model with a high accuracy.

Recommendations

In this research, the multiple regression analysis method is applied in the artificial neural network by using MATLAB fitting tool. In future research, a dynamic time series method is recommended to forecast the time series data by using the MATLAB time series tool. In order to forecast the future export price of sawn timber in Sabah, the ARMA model and artificial neural network can be compared for future study. According to Koutroumanidis *et al.* (2009), an optimum prediction results can be obtained by using the ARIMA-ANN hybrid model. Koutroumanidis *et al.* (2009) also stated that by using the hybrid ARIMA-ANN model, decision makers are able to proceed with a more rational planning for the production. Hence, in order to obtain an optimum future export price or production of sawn timber, hybrid ARIMA-ANN model is recommended to be conducted in future research.

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