Electronic Journal of Applied Statistical Analysis
EJASA, Electron. J. App. Stat. Anal.
http://siba-ese.unisalento.it/index.php/ejasa/index
e-ISSN: 2070-5948
DOI: 10.1285/i20705948v7n2p180

Modeling the price trends of teak wood using statistical and artificial neural network techniques

By Sivaram M.

Published: 14 October 2014

Electronic Journal of Applied Statistical Analysis
Vol. 07, Issue 02, 2014, 180-198
DOI: 10.1285/i20705948v7n2p180

Modeling the price trends of teak wood using statistical and artificial neural network techniques

M. Sivaram*

Senior Scientist (Agricultural Statistics)
Southern Regional Station
National Dairy Research Institute
Adugodi, Bangalore - 560030
India.

Published: 14 October 2014

Modeling the trends and patterns in financial data is of great interest to the business community to support the decision-making process. In this study, the historical trends in the real prices of teak wood were described using spline models and the time periods for which the rate of change in real prices differed were identified. The possible reasons for this phenomenon such as impact of forest legislations and other factors have been explained. In forecasting teak wood prices, Artificial Neural Network (ANN) was compared with the traditional Auto Regressive Integrated Moving Average (ARIMA) model. The Mean Absolute Percentage Error (MAPE) was lesser in the case of ANN than the ARIMA model. Further, the turning points were more closely predicted by ANN. It appeared that forecast by ANN was heavily dependent on the previous value(s) immediate to the forecasting year. The study concluded that the next year price forecasts by univariate ARIMA and ANN models may be far from actual prices due to unanticipated factors.

keywords: Spline model, ARIMA, neural network, teak wood, forecasting, prices.

*Corresponding author: sivaram.kfri@gmail.com.

ISSN: 2070-5948
http://siba-ese.unisalento.it/index.php/ejasa/index

1 Introduction

The temporal variation in prices is usually influenced by some external factors. If the information on the influencing factors is not known, only the past values of the time series itself can be used to build a mathematical model for forecasting. In this context, one of the most popular forecasting models is autoregressive integrated moving average (ARIMA) model due to Box and Genkins (1994). These models, however, are linear and may fail to forecast the turning points because in many cases, the data may be highly non-linear. Recently, there have been applications of ANN to time series forecasting problems in variety of fields ranging from forecasting of rainfall to stock market prices (Guhathakurta, 2006; Lin et al., 1995; Rech, 2002). This is because ANN is free from assumptions including linearity and robust to missing observations.

Adya and Collopy (1998) examined the application of ANN to business forecasting and prediction. Of the 48 studies evaluated, 22 contributed to the knowledge regarding the applicability of ANN for prediction. Nineteen of these produced results that were favorable to ANN, three produced results that were not. Faraway and Chatfield (1998) found that the neural networks often gave poorer out-of-sample forecast for the airline data. In a forecasting exercise on 30 time series, ranging on several fields, from economy to ecology it was found that the linear models outperformed the ANN (Rech, 2002).

Stern (1996) found that the results of ANN were comparable to generalized additive model for certain time series data. Goh (1998) found that ANN outperformed the univariate Box-Jenkins' approach and the multiple log linear regression on quarterly data. In a comparison of ANN with Box-Jenkins and Holt-Winters exponential smoothing, Zhang (2001) using both 240 simulated linear series and three actual time series, concluded that ANN was able to outperform Box-Jenkins' autoregressive moving average model ARMA(p,q) in all but one of their cases. They found that simple ANN was often adequate in forecasting linear time series. Hwrang (2001) compared ANN with ARMA (p,q) structure on 320 generated time series. He concluded that ANN trained with a normal level of noise tend to perform better than ARMA (p,q) structures. Moshiri and Cameron (2000) found that ANN models were able to forecast as well as all the traditional econometric methods, and to outperform them in some cases. In a study of long term range monsoon rainfall prediction of 2005, the performance of ANN was far superior to the regression models (Guhathakurta, 2006).

Teak *(Tectona grandis)* is the premium wood, known internationally for its wood quality, appearance and durability. The studies analyzing the long term trends in timber prices are scanty (Krishnankutty, 2001a,b; Krishnankutty and Sivaram, 2003). The objectives of this study were i) to demonstrate the application of spline models to describe the historical price trends of teak wood in Kerala State, India. and ii) to compare the performance of ANN with ARIMA models for forecasting prices of teak wood.

2 Materials and methods

2.1 Dataset

In India, forests are managed by the respective State Forest Departments of the State Governments under the guidelines of the Government of India. The Kerala Forest Department is responsible for managing the forests in the State of Kerala. Timber felled from forest plantations by the Kerala Forest Department are deposited in Sales Depots and auctioned. The major species which is sold through Sales Depots is teak. The method of sale is both by tender and auction. The price data were collected from Sales Depots and compiled for the analysis. Teak wood is classified based on mid girth, length and quality. With respect to mid girth, there are 5 major girth classes viz., Export class (185 cm and above), Girth class I (150-184 cm), Girth class II (100-149 cm), Girth class III (75-99 cm) and Girth class IV (60-74 cm). Because girth classes II, III and IV represent around 85 percent of the teak sold in the market, the price data were analysed only for those classes. The weighted average prices per m^3 were worked out after duly accounting for the quantity of timber sold. The data relating to 1943-1994 is from Krishnankutty (Krishnankutty, 2001a,b) and data for 1994-98 is from Krishnankutty and Sivaram (2003). Data for the period 1998-2006 were collected and compiled during the study period. All the prices are expressed in Indian Rupees (Rs.) per m^3.

2.2 Real prices

The changes in current prices may be due to inflation (general price increase) in the economy of the country. Therefore, the average annual current prices were converted into average real prices by deflating of Wholesale Price Index (WPI) with the base year 1993-94. The formula used for deflating (Croxton et al., 1973) is

$$\text{Real price} = \frac{\text{Current Price}}{\text{Wholesale Price Index}}.$$

The WPI values for the period 1956- 2006 are available with different base years See Office of the Economic Adviser to the Government of India, Ministry of Commerce and Industry. http://eaindustry.nic.in.. The latest WPI series is available for the period 1993-2006 with the base year 1993-94. Therefore, the WPI values for the period 1956-1992 were recasted using the back shifting formula (Croxton et al., 1973) with the base year 1993-94.

$$\text{Recasted WPI of the year} = \frac{\text{Old WPI of the year}}{\text{WPI of new base year}} \times 100.$$

2.3 Spline model and its implementation

Spline model

Spline function offers a useful way to perform piecewise polynomial fitting when the rate of changes in prices behave differently in different parts of the range of the time period (Montgomery and Peck, 1982). Splines are piecewise polynomials of order k. The boundary points of each segment are referred to as break points or simply knots. Knots give the curve freedom to bend and more closely follow the data.

A spline with h knots, t_1¡ t_2¡ ···¡t_h, with continuous first *k-1* derivatives, can be written as

$$E(y) = \sum_{j=0}^{k} \beta_{0j} x^j + \sum_{i=1}^{h} \beta_i (x - t_i)_+^k$$

where $(x - t_i)_+ = \begin{cases} (x - t_i) & \text{if } x > t_i \\ 0 & \text{if } x \le t_i. \end{cases}$

This basic spline model can be easily modified to fit polynomials of different order in each segment, and to impose different continuity restrictions at the knots. If all $h + 1$ polynomial pieces are of order k, then spline model with no continuity restriction is

$$E(y) = \sum_{j=0}^{k} \beta_{0j} x^j + \sum_{i=1}^{h} \sum_{j=0}^{k} \beta_{ij} (x - t_i)_+^j$$

where$(x - t_i)_+^0 = \begin{cases} 1 & \text{if } x > t_i \\ 0 & \text{if } x \le t_i. \end{cases}$ Thus if the term $\beta_{ij}(x - t_i)_+^j$is in the model, this forces a discontinuity at t_i in the j^{th} derivative of $E(y)$. If this term is absent, the j^{th} derivative of $E(y)$ is continuous at t_i (Montgomery and Peck, 1982).

Implementation

The knots for the model were identified by visual examination of the price trends. Different spline models *viz.,* linear spline, linear spline with discontinuities at knots, quadratic spline, quadratic spline with discontinuities at knots on first and second derivatives and quadratic spline with discontinuities at knots were fitted. The least square method was used for estimating the parameters of the model. The PROC TRANSREG procedure in SAS was used to fit the models (SAS Institute, 2003). The best model was selected based on Root Mean Square Error *(RMSE),* Adjusted R^2, Akaike's Information Criterion *(AIC)* and Bayesian Information Criterion*(BIC)* (Hair et al., 2003). Since the interpretation of quadratic spline is more complicated, linear spline with discontinuities is used to find the rate of change of real prices of teak wood in different periods. Thus the rate of change of real prices of teak wood with respect to the year x for the period $x \le k_1, k_1 < x \le k_2$ and $x > k_2$ are β_{01}, $\beta_{01} + \beta_{11}$ and $\beta_{01} + \beta_{11} + \beta_{21}$ respectively.

2.4 ARIMA model and its implementation

ARIMA model

The application of the ARIMA methodology for the study of time series analysis is due to Box and Genkins (1994). ARIMA model is usually denoted as ARIMA*(p,d,q),* which can be expressed mathematically as

$$z_t = \phi_1 z_{t-1} + ... + \phi_p z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - .... - \theta_q a_{t-q}$$

where $z_t = \nabla^d y_t$

p = order of the autoregressive process in which the current value of the process is expressed as a finite, linear aggregate of previous values of the process and a shock a_t. Mathematically, an autoregressive model of order p can be represented as

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + a_t$$

where $\phi_1, \ldots, \phi_p$ are parameters. d = degree of differencing involved to make the data series that contains a trend (non-stationary) to stationary by taking successive differences of the data.

q = order of the moving average process in which the dependent variable y_t depends on the values of error term $(a_t, a_{t-1}, ..., a_{t-p})$ rather than variable itself. Mathematically, a moving average model of order q can be expressed as

$$y_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \theta_3 a_{t-3} .... - \theta_q a_{t-q}$$

where $\theta_1, \theta_2, \ldots, \theta_q$ are parameters, a_t is the error residual and $a_1, a_2, \ldots, a_{t-q}$ are previous values of error.

The parameters p, d and q can be estimated by maximum likelihood method (MLE).

Implementation

In order to find the suitable ARIMA model, first the sample autocorrelation of prices was examined for different girth classes. The estimated autocorrelation function did not die out rapidly suggesting that the underlying process should be treated as nonstationary. Therefore, the first differencing was done to remove the trend and make the time series stationary. The autocorrelation and partial autocorrelation were again worked out for the differenced series. The autocorrelations for the differenced data were found to fall within 2 times of standard error. This indicated that the autocorrelations were not statistically significant. Because the sample autocorrelation or partial autocorrelation function neither tailed off nor cut off, it appeared that the mixed model was required. Therefore, the values of p, d and q were varied and different combinations of ARIMA models examined. The best ARIMA model was arrived at based on the model selection criteria such as MAPE and AIC.

2.5 ANN and its implementation

ANN model

Haykin (1999) provides a comprehensive review of ANN. ANN is a powerful data modeling tool that is able to capture and represent complex input/output relationships whether it be linear or non-linear. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. ANN acquires knowledge through learning and knowledge is stored within inter-neuron connection strengths known as synaptic weights. The most common ANN model is the multilayer perceptron (MLP). This type of ANN is known as a supervised network because it requires a desired output in order to learn. In the MLP algorithm, the propagation of data through the network begins with an input pattern stimulus at the input layer. The data then flow through and are operated by the network until an output stimulus is yielded at the output layer (For example see Figure 1).

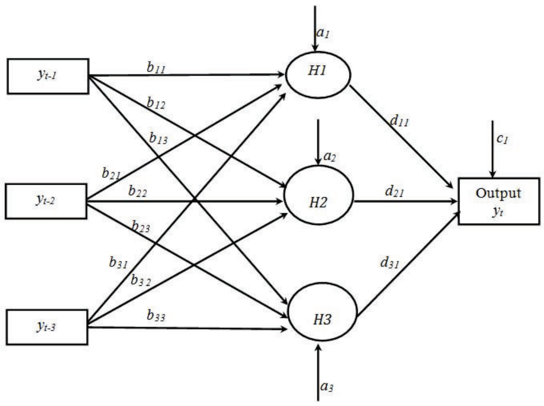


Figure 1: Diagrammatic representation of ANN $(i, j, k = 3)$ where i is the number of inputs, j number of neurons in the hidden layer and k lag period.

$H1$, $H2$ and $H3$ are hidden neurons in the hidden layer
b_{11} - weight connecting y_{t-1} and H1
b_{12} - weight connecting y_{t-1} and H2
b_{13} - weight connecting y_{t-1} and H3
b_{21} - weight connecting y_{t-2} and H1
b_{22} - weight connecting y_{t-2} and H2
b_{23} - weight connecting y_{t-2} and H3
b_{31} - weight connecting y_{t-2} and H1
b_{32} - weight connecting y_{t-3} and H1
b_{33} - weight connecting y_{t-3} and H1
d_{11} - weight connecting H1 and y_t
d_{21} - weight connecting H2 and y_t
d_{31} - weight connecting H3 and y_t
a_1 - bias of H1
a_2 - bias of H2
a_3 - bias of H3
c_1 - bias of y_t

Implementation

A variety of neural net architectures have been examined for addressing the problem of time series prediction. These architectures include: MLP, recurrent networks and radial basis functions (Kajitani et al., 2005). In this study, we applied MLP to solve the forecasting problem. We take a set of $m-1$ values $y_{t-1}, y_{t-2}, \ldots, y_{t-m+1}$ to be the input to a feed-forward network, and use the next value y_t as the target for the output of the network. By stepping along the time axis, we create a training data set consisting of many sets of inputs values with corresponding target values. Once the network has been trained, it can be presented with a set of observed values $y_{t-1}, y_{t-2}, \ldots, y_{t-m+1}$ and used to make prediction for y_t . This is called one step ahead prediction. If the prediction themselves are cycled around to the inputs of the network, then prediction can be made to further points y_{t+1} and so on. This is called multi-step ahead prediction.

In our study, the feed forward neural network architecture of the form ANN (i, j, k) is proposed. In this, i is the number of inputs, j is the number of neurons in the hidden layer and k is the lag period. A brief mathematical description of ANN (i, j, k) is given below.

The previous values $y_{t-1}, y_{t-2}, \ldots, y_{t-m+1}$ are the input features to forecast the target output y_t. When they are presented to the input nodes and output nodes respectively, the net output to the hidden nodes (g_j), $j = 1, 2, \ldots, n$ is calculated by

$$g_j = a_j + \sum_{i=1}^{k} b_{ij} y_{t-i}$$

where a_j is a bias (*i.e.* intercept) for the hidden layer, is the weight (*i.e.* coefficient) from the input (i^{th}) node to the hidden (j^{th}) node and n is the number of hidden neurons. Then an activation function is applied to , usually logistic function which introduces nonlinearity into the network to compute the output from the hidden nodes h_j as

$$h_j = f(g_j) = \frac{1}{1 + e^{-g_j}}$$

Next,h_j becomes the net input to the output nodes (q_t) which is calculated by

$$q_t = c_1 + \sum_{j=1}^{n} d_{j1} h_j$$

where c_1 is a bias (*i.e.* intercept) for the output layer, and d_{j1} is the weight from the hidden layer to the output layer. Again an activation function is applied to q_t to compute the predicted output p_t.

$$p_t = f(q_t) = \frac{1}{1 + e^{-q_t}}$$

Learning and training are fundamental to almost all ANN. Training is the procedure by which the network learns and learning is the end result of that procedure. Learning consists of making systematic changes to the synaptic weights to improve the performance of the network's response to acceptable levels. The aim of the training is to find a set of synaptic weights that will minimize the error. To accomplish the goal of optimizing the weights of g_j and q_t , the following objective function is to be minimized through some algorithm.

$$E = \frac{1}{2}\sum(y_t - p_t)^2$$

An error back-propagation algorithm is the commonly used one. However, among many of the optimization algorithms, the Levenberg-Marquardt (LM) algorithm is efficient and designed specially for minimizing sum-of squares error (Bishop, 1995).

The appropriate network was identified by varying the values of i, j and k on trial and error basis. However, the input values of these parameters were broadly based on autocorrelation co-efficient between successive year prices. The ANN was applied to raw prices, log transformed prices, prices after first order differencing and to prices obtained after linear detrending. However, only the log transformation improved the value of MAPE substantially. All the modeling exercises were performed using Enterprise miner module of SAS software (SAS Institute, 2003).

2.6 Performance evaluation of ARIMA and ANN models

Mean Absolute Percent Error ($MAPE$) was used to assess the performance of ARIMA against ANN.

$$MAPE = \frac{100}{n}\sum_{t+1}^{n} |\frac{y_t - \hat{y}_t}{y_t}|$$

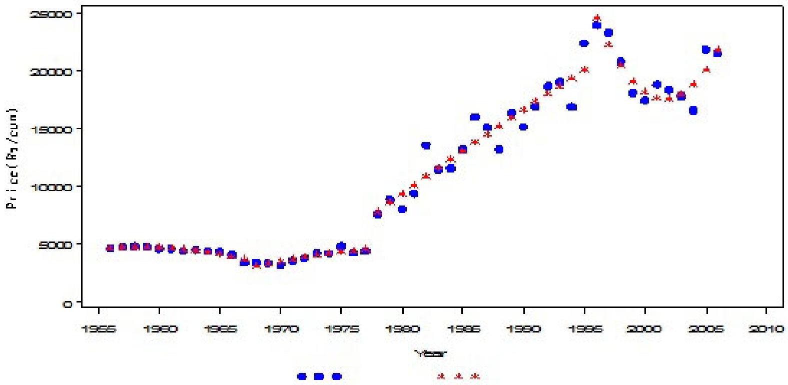
where n is the number of non-missing observations, y_t is the observed prices and $\hat{y}_t$ is the predicted prices. The performances of the models are usually evaluated by dividing the data set in to three subsets for the purpose of training (developing the model), which require about 75% of the total observations, testing and validation. In this study, the data was not sampled from the original data set for the purpose of testing due to limited number of observations. However, the models developed were validated for the next year forecast by comparing with the observed prices.

3 Results

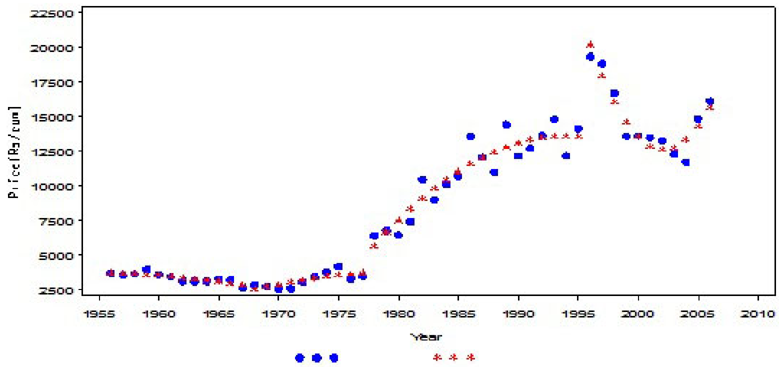
3.1 Trends in real prices of teak wood

The knots identified from the price trends for II and III are k_1=1967, k_2=1977 and k_3=1995. The knots for girth class IV are k_1=1977 and k_2=1998. Among the five different spline models fitted, linear spline with discontinuities at the two knots is the best model for girth class IV. The quadratic spline with discontinuities at the three knots is the best model for girth classes II and III. The functional form of the chosen spline models for describing the real prices of teak wood in different girth classes are given in Table 1. The observed and predicted real prices are presented in Figure 2. The rate of changes of real prices of teak worked out using linear spline model for different girth classes are given in Table 2.

a) Girth class II (Quadratic spline with discontinuity)



b) Girth class III (Quadratic spline with discontinuity)



c) Girth class IV (Linear spline with discontinuity)

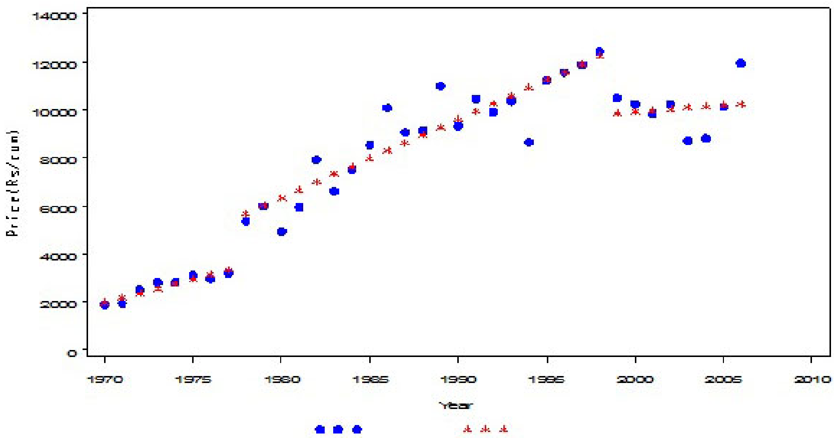


Figure 2: Predicted prices of teak wood using spline models for different girth classes a) Girth class II b) Girth class III c) Girth class IV

Table 1: The functional forms of the chosen spline models

Girth Class	Spline Model	Functional form
II	Linear spline with discontinuity	y =174115 - 86.51x - 915.09(x - 1967)$^0_+$ +2607.52(x -1977)$^0_+$ + 1333.84(x - 1995)$^0_+$ + 243.72(x -1967)$_+$ + 560.12(x -1977)$_+$ - 991.69(x -1995)$_+$
II	Quadratic spline with discontinuity	y = - 61025858 + 62315x-15.91x^2- 750.14(x - 1967)$^0_+$ +2494.33(x -1977)$^0_+$+ 7238.31(x - 1995)$^0_+$ +482.02(x -1967)$_+$+666.62(x -1977)$_+$- 3607.68(x -1995)$_+$+10.15(x -1967)$^2_+$+2.88(x - 1977)$^2_+$+224.95(x -1995)$^2_+$
III	Linear spline with discontinuity	y =162666 - 81.23x - 423.11(x - 1967)$^0_+$ +2785.35(x -1977)$^0_+$ + 2649.81(x - 1995)$^0_+$ + 210.28(x -1967)$_+$ + 338.08(x -1977)$_+$ - 921.53(x -1995)$_+$
III	Quadratic spline with discontinuity	y = - 18370964 + 18816x - 4.82x^2- 454.24(x - 1967)$^0_+$ +958.11(x -1977)$^0_+$+ 9245.90(x - 1995)$^0_+$ +322.98(x -1967)$_+$+954.66(x -1977)$_+$- 2832.74(x -1995)$_+$- 0.61(x -1967)$^2_+$-24.45(x - 1977)$^2_+$ +231.48(x -1995)$^2_+$
IV	Linear spline with discontinuity	y = - 378594+193.18x+2019.01(x -1977)$^0_+$ - 2428.85(x -1998)$^0_+$ +134.95(x -1977)$_+$ - 272.18(x -1998)$_+$

With regard to girth class II and III, there was a decline in real prices during 1956-1967, then an increasing trend from 1968 to 1995 and then a decreasing trend in real prices during 1996-2006. All these three classes showed a rapid increase in prices for the period 1977-1995 and the rate of change is ranged from Rs.467 to 717. The real prices of girth class IV also showed an increasing trend for the period 1970 to 2006 and the rate of increase ranged from Rs.56 in 1999-2006 to Rs.328 in 1977-1998.

3.2 ARIMA models

The best ARIMA models of the form ARIMA (p, d, q) based on fit statistics are ARIMA (1,2,2) for export glass and girth class III. ARIMA(1,2,1) for girth class I, girth class II and IV. It was also attempted to implement ARIMA models after log transformation. But such an attempt did not yield better results. The functional form of the chosen ARIMA models and values of the estimated parameters are shown in Table 3.

Table 2: Rate of change of real prices of teak wood in different girth classes

Girth Class	β_{01}	$\beta_{01}+\beta_{11}$	$\beta_{01}+\beta_{11}+\beta_{21}$	$\beta_{01}+\beta_{11}+\beta_{21}+\beta_{31}$
	$x \leq 1967$	$1967 < x \leq 1977$	$1977 < x \leq 1995$	$x > 1995$
II	-87	157	717	-274
III	-81	129	467	-454
IV	$x \leq 1977$	$1977 < x \leq 1998$	$x > 1998$	
	193	328	56	

Table 3: The functional form and co-efficient of the ARIMA models chosen for forecasting prices of teakwood of different girth classes

Girth Class	Spline Model	Functional form
II	Linear spline with discontinuity	$y=174115-86.51x-915.09(x-1967)^0_+ +2607.52(x-1977)^0_+ + 1333.84(x-1995)^0_+ + 243.72(x-1967)_+ + 560.12(x-1977)_+ - 991.69(x-1995)_+$
II	Quadratic spline with discontinuity	$y=-61025858+62315x-15.91x^2-750.14(x-1967)^0_+ +2494.33(x-1977)^0_+ + 7238.31(x-1995)^0_+ +482.02(x-1967)_+ +666.62(x-1977)_+ - 3607.68(x-1995)_+ +10.15(x-1967)^2_+ +2.88(x-1977)^2_+ +224.95(x-1995)^2_+$
III	Linear spline with discontinuity	$y=162666-81.23x-423.11(x-1967)^0_+ +2785.35(x-1977)^0_+ + 2649.81(x-1995)^0_+ + 210.28(x-1967)_+ + 338.08(x-1977)_+ - 921.53(x-1995)_+$
III	Quadratic spline with discontinuity	$y=-18370964+18816x-4.82x^2-454.24(x-1967)^0_+ +958.11(x-1977)^0_+ + 9245.90(x-1995)^0_+ +322.98(x-1967)_+ +954.66(x-1977)_+ - 2832.74(x-1995)_+ - 0.61(x-1967)^2_+ - 24.45(x-1977)^2_+ +231.48(x-1995)^2_+$
IV	Linear spline with discontinuity	$y=-378594+193.18x+2019.01(x-1977)^0_+ - 2428.85(x-1998)^0_+ +134.95(x-1977)_+ - 272.18(x-1998)_+$

3.3 ANN models

The best ANN models based on RMSE and MAPE is ANN (3,3,3) for all girth classes. The synaptic weights of these best models are presented in Table 4. However, with respect to girth class IV, ANN could not predict next year price sensibly. Therefore, ANN (2,2,2) was considered for forecasting next year price.

Table 4: The synaptic weights of the feed forward neural network models chosen for forecasting prices of teakwood of different girth classes

From	To	Notation	Synoptic weights		
			Girth Class II	Girth Class III	Girth Class IV
			ANN(333)	ANN(333)	ANN(222)
y_{t-1}	H1	b_{11}	-1.065	-0.937	6.397
y_{t-2}	H1	b_{21}	1.435	1.347	-4.709
y_{t-3}	H1	b_{31}	-2.441	-2.431	-
y_{t-1}	H2	b_{12}	4.279	-0.072	0.136
y_{t-2}	H2	b_{22}	-13.011	-64.62	0.397
y_{t-3}	H2	b_{32}	36.475	92.948	-
y_{t-1}	H3	b_{31}	-3.155	-2.678	-
y_{t-2}	H3	b_{32}	-4.038	-2.748	-
y_{t-3}	H3	b_{33}	0.005	1.643	-
Bias	H1	a_1	-0.852	-0.970	-0.078
Bias	H2	a_2	-41.104	-39.659	-0.465
Bias	H3	a_3	6.876	3.711	-
H1	Output	d_{21}	-4.655	-4.670	0.724
H2	Output	d_{21}	0.442	0.413	-15.882
H3	Output	d_{21}	-1.019	-1.445	-
Bias	Output	c_1	10.326	10.226	14.313

3.4 Comparison of ARIMA and ANN models

When the MAPE is compared among the chosen ARIMA and ANN models, ANN with the log transformed prices performed better than the ARIMA models for all the girth classes (Figure 3). The simulated prices using the best ARIMA and ANN models are depicted in Figure 4. The ANN's predictions were very closer to the observed prices than the predictions by ARIMA especially at the turning points of the trend. However, both ARIMA and ANN price forecast of teak wood for the year 2007 was validated with the observed prices. In all the three girth classes of teak wood, both the models failed miserably as the observed prices were very high especially in girth class II and girth class III (Table 5).

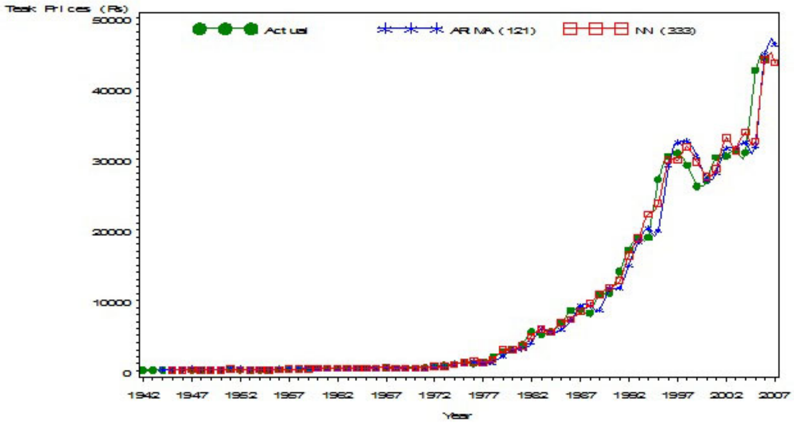
Figure 3: Comparison of performance of ARIMA and ANN models using MAPE

Table 5: Validation of Forecasted Teak wood prices using ARIMA and ANN model

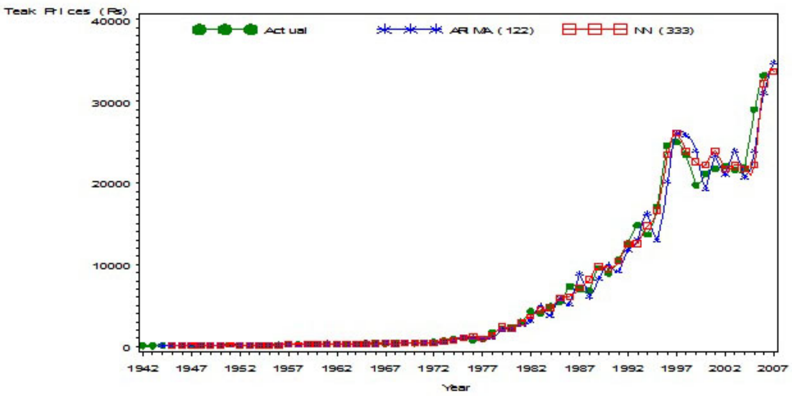
Girth Class	Observed Current Price (Rs/m^3) -2006	Observed Current Price (Rs/m^3) -2007	Forecasted Current Price (Rs/ m^3) -2007	
			ARIMA	ANN
Class II	44,295	68,645	46,231 (-32.7)*	43,651 (-36.4)
Class III	33,174	45,280	34,783 (-23.2)	33,618 (-25.8)
Class IV	24,638	29,201	25,949 (-11.1)	23,821 (-18.4)

*Percentage difference between observed and forecasted prices in 2007 is given in parenthesis.

4a) Prices of teak in Girth Class II



4b) Prices of teak in Girth Class III



4c) Prices of teak in Girth Class IV

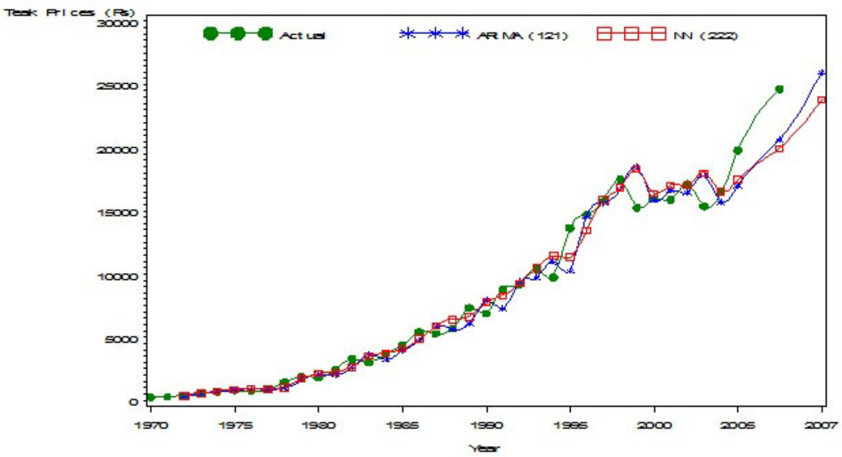


Figure 4: Forecasted prices of teakwood per m^3 using ARIMA and ANN models for different girth classes a) Girth Class II b) Girth Class III c) Girth Class IV

4 Discussion

Spline models were useful to describe the price trends and to the rate of change in prices in different time periods. Most of the teak wood produced and sold in a year was in girth class II and girth class III and generated most of the revenue from teak wood. The trends in these classes indicated the impact of government polices and acts. The National Forest Conservation Act, 1980 banned clear felling from natural forests and therefore the reduced supply during that period led to the price rise during the 1980's. The accelerated positive growth during the later part of 1980's and the first part of 1990's could be due to the Kerala Preservation of Trees Act, 1986 and the National Forest Policy, 1988 and stoppage of selection felling since 1987. The decline in real prices since the year 1995 could be due to globalization, increased wood import and availability of wood substitutes due to technology innovations. The increase in real prices of teak wood since 2005 could be due to significant decline in timber supply from forest plantations in Kerala coupled with timber demand from the unprecedented growth in real estate sector for house construction and furniture making. However, global wood market analyses indicate no long term real price increases for wood (Clark, 2001). The reasons suggested are i) sufficient supply from forests and forest plantations together with fibre resources (FAO, 1997, 1999) ii) global wood supply consumption has been matched by an outward shift in the wood supply schedule (Sedjo and Lyon, 1990) iii) wood saving technologies such as paper recycling and v) substituting sawn timber with more resource efficient wood based panel products and timber engineered products (Clark, 2001).

The studies conducted so far on comparing statistical and ANN models for forecasting problems have drawn mixed conclusions. In our study, ANN performed better than ARIMA. Especially the turning points were more closely predicted by ANN indicating that ANN captures the non-linear trend efficiently. The next year price forecasts of teak wood by univariate ARIMA and ANN models was very much on downside. The reason is that the supply to timber depots was much less in the year 2007 (Figure 5) and therefore the timber logs could fetch high prices in the timber auctions. Therefore, it is suggested that anticipated supply and other important factors should also be accounted while implementing ARIMA and ANN models.

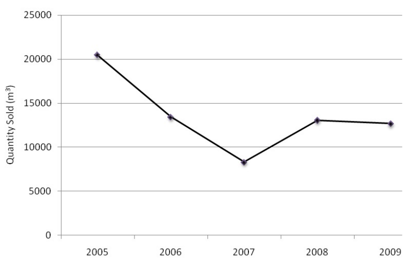


Figure 5: Quantity of round teak wood sold in selected Timber Depots of Kerala State during 2005-2009

Linear detrending is suggested as a preprocessing technique prior to modeling with ANN (Bishop, 1995). However, in this study, improved results could be obtained neither with linear detrending nor with first order differencing. The logarithmic transformation of price data dramatically improved the MAPE. Therefore, it is essential that the necessary transformation be made before applying ANN models. A simple ANN architecture with only one hidden layer was found to be sufficient. In building-up ANN for the time series data, one has to construct an input data with several lags. The way to select a number for the lag can be arbitrary, but a reasonable idea is to select a lag based on autocorrelations. When the number of input (previous observations) is equal to the lag period the prediction error was less. Similarly, when the number of input is equal to the number of hidden neurons the prediction error was less. By and large ANN with price values of previous 3 years as inputs and 3 neurons in the hidden layer was found better in predicting next year price except for girth class IV. It also appeared that forecast by ANN was heavily dependent on the previous value(s) immediate to the forecasting year.

The primary difference of ANN from most of the statistical techniques is the absence of any statistical inference tests and construction of confidence bounds for model weights of overall fit. While interpretations can be drawn on regression co-efficient as to know the extent and directionality of relationship between input and output variables, synaptic weight in ANN is not interpretable (Bishop, 1995). From a statistical perspective, ANN is a wide class of flexible modeling algorithm and robust to the problems such as non-gaussian distributions, non-linear relationships, outliers and noise presented in the data. However, our results and other studies show that ANN technology will not replace traditional quantitative techniques completely but it does offer an alternative to traditional quantitative techniques (Liu et al., 2002; Peng and Wen, 1999).

Aknowledgment

This work was supported by Plan Grant of Kerala Forest Research Institute (KFRI). We thank Dr.K.V.Sankaran, Director, KFRI for valuable guidance. We also thank Dr.K.Jayaraman, Programme Coordinator, Division of Forest Management Information and and Dr. P.Rugmini, Head of the Department of Forest Statistics for their useful suggestions. I thank Mrs.Rini George, KFRI for her kind help in preparing the manuscript in Latex.

References

Adya, M.S. and Collopy, F. (1998). How effective are neural networks at forecasting and prediction? A review and evaluation. *Journal of forecasting,* 17.

Bishop, C.M. (1995). *Neural Networks for Pattern Recognition.* Oxford University Press.

Box, G.E.P. and Genkins, G.M. (1994), *Time Series Analysis Forecasting and Control.* Pearson Education Inc.

Clark J. (2001). The global wood market, prices and plantation investment: an examination drawing on the Australian experience. *Environmental conservation 28,* 1.

FAO (1997), FAO *Provisional outlook for global forest products consumption, production, and trade to 2010,* Food and Agricultural organization of the United Nations, Rome, Italy. 391pp.

FAO (1999), *State of the World's Forests.* Food and Agricultural organization of the United Nations, Rome, Italy. 154pp.

Croxton, F.E., Cowden, D.J. and Klein, S. (1973), *Applied general statistics,* Prentice-Hall of India Private Limited.

Faraway, J and Chatfield, C. (1998). Time series forecasting with neural networks: a comparative study using airline data. *Appl.Statist,* 47.

Goh, B.H (1998). Forecasting residential construction demand in Singapore: a comparative study of the accuracy of time series, regression and artificial neural network techniques. *Engineering Construction & Architectural Management,* 5(3).

Guhathakurta, P. (2006). Long-range monsoon rainfall prediction of 2005 for the districts and sub-division Kerala with artificial neural network. *Current Science,* 90(6).

Hair, J.F., Anderson, R.E., Talham, R.L. and Black, W.C. (2003), *Multivariate data analysi,* Pearson Education Inc.

Haykin, S. (1999), *Neural Networks - A Comprehensive Foundation.* Pearson Education Inc.

Hwrang, H.B (2001). Insight into neural-network forecasting of time series corresponding to ARMA (p, q) structure. *Omega-International J. Management Science,* 29(3).

Kajitani, Y., Hipel K.W. and Mcleod A.I. (2005). Forecasting nonlinear time series with Feed-forward neural networks: A case study of Canadian Lynx data. *Journal of Forecasting.* 24.

Krishnankutty, C.N. (2001a). Teak price trends in Kerala State, India. *Indian Journal of Forestry.* 24(1).

Krishnankutty, C.N. (2001b). Forecasting of teak prices in Kerala State, India, using autoregressive integrated moving average models. *Indian Journal of Forestry.* 24(2).

Krishnankutty, C.N. and Sivaram, M (2003), Teak wood price projections for Kerala State, India up to 2020. In *International Conference on Quality Timber Products from Sustainable Forest management:2003, 2-5, December 2003, Kerala Forest Research Institute, Peechi.*

Lin, F, Yu, X.H, Gregor, S and Iron, R (1995). Time series forecasting with Neural Networks. *Complexity International* 2.

Liu, C., Zhang, L., Davis, C.J., Solomon, D.S., Brann, T.B and Caldwell, L.E. (2002). Comparison of neural networks and statistical methods in classification of ecological habitats using FIA data. *Forest Science.* 49(4).

Montgomery, C.C. and Peck, E.A. (1982). *Introduction to linear regression analysis.* John Wiley and Sons.

Moshiri, S and Cameron, N. (2000). Neural Network versus Econometric models in forecasting inflation. *Journal of forecasting,* 19.

Peng, C. and Wen, X. (1999). *Recent applications of artificial neural networks in forest resource management: An overview.* In: Environmental decision support systems and artificial intelligence. Ulises Corte and Miquel Sanchez-Marre, Cochairs (eds.). Pp. 15-22. Technical Report WS-99-07, AAAI Press, Menlo Park, CA, 1999.

Rech, G (2002), *Forecasting with neural network models.* SSE/EFI working paper series in Economics and Finance, Department of Economics Statistics, Stockholm school of Economics, Stockholm, Sweden.

SAS Institute Inc. (1999-2003). SAS Enterprise Miner Release 4.2. SAS Institute Inc., Cary, North Carolina. USA.

Sedjo, R.A. and Lyon, K.S. (1990), The long-term adequacy of world timber supply. Resources for the Future, Washington, D.C. USA.

Stern, H.S. (1996). Neural networks in applied statistics. *Technometrics.* 38.

Zhang, G.P (2001). An investigation of neural networks for linear time series forecasting. *Computers & Operational Research,* 28(12).