REVIEW OF SHORT-TERM DEMAND FORECASTING METHODS AND SELECTION OF THE APPROPRIATE MODEL FOR SOFTWOOD SAWMILLS IN TANZANIA

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ABSTRACT

This paper reviewed and tested forecasting methods for use-appropriateness in forecasting lumber demands in the sawmill industry in Tanzania. These methods included naïve or intuitive, simple moving average, weighted average, regression analysis, and exponentially weighted moving average (EWMA). The value of the mean absolute deviation (MAD) was used to test the models forecasting accuracy and the smaller the value of MAD the higher the forecasting accuracy. The best two methods were subjected to further analysis by forming a confidence interval for the difference emanating from the difference between MADs of the two methods. The naïve and EWMA were found to have the smallest MADs. The MADs produced by the two methods were 150.08 and 153.64 m^3 for naïve and EWMA methods, respectively. Although these errors were mathematically different, confidence interval [-52.21, 45.09] constructed for MADs' difference contained a zero indicating that the MADs difference was not significantly different from zero. Since the lumber demand behaviour in the country indicated presence of trend and seasonality, a phenomenon that cannot be accommodated by the naïve method and the fact that EWMA managed to capture such phenomenon and yet produced minimum error, it was recommended for use by sawmill managers in Tanzania.

Key words: Sawmill industry, demand forecasting, forecasting accuracy and lumber production.

INTRODUCTION

The lumber manufacturing sector like any other industrial sector in Tanzania has been experiencing times of changes both from within and outside the country. Trade liberalization and free market policies that were adopted by the government in the mid-eighties have led to loss of government-owned sawmills and the surfacing of more private-owned sawmills. Also, there is an influx of imported forest products into the local market from diverse origins, mainly from South Africa and countries of East Asia. All these changes culminate into new patterns of competition that require local existing enterprises to restructure their activities in order to stay in business. Demands for products vary from month to month. Conceivably, production rates must be scaled up or down to meet these demands. In such a situation sawmill managers must be smart in planning their operations. Critical ingredients to efficient planning of production are accurate demand forecasts (Fogarty *et al.* 1991). Forecasts can help managers by reducing some of the uncertainties, thereby enabling them to develop more meaningful plans than they might otherwise. Managers need forecasts so that they have enough lead time necessary to set up resources/production capacity to produce these variable monthly or quarterly demands. Making good estimates or decisions has a stake in whether to remain in business or disappear. For sawmill managers, short range forecasts are more important than medium or long range forecasts, since short range forecasts cater for day to day, weekly, monthly or quarterly production demands. Therefore, this study centred on short-range forecasts. A partial equilibrium model developed by Ngaga and Solberg (2001) was found to be not a good fit for the purpose as was developed for medium range forecasting. This study focused on softwood sawmill industry since as of now it forms the majority (about 80%) of sawmills in the country (MNRT 2005).

Organisations use three types of forecasting: economic, technological and demand forecasts (Heizer and Render 1993). This study was interested in the latter as it gives companies projections of demand which will drive company's production, capacity and scheduling systems. There are two general approaches for forecasting production demands, namely qualitative and quantitative (Slack, *et al.* 2007).

Qualitative approaches consist mainly of subjective inputs, which often defy precise numerical description. These approaches permit inclusion of sift information (human factors, personal opinions, intuitions, emotions, personal experiences, etc) in the forecasting process. Those factors are often omitted or downplayed when quantitative approaches are used because they are difficult or impossible to quantify.

Quantitative approaches consist mainly of analyzing objective or hard data. They usually avoid personal biases that sometimes contaminate qualitative methods (Stevenson 2005). Since this study used empirical data, quantitative techniques were considered more suitable for study.

According to Russel and Taylor III (2007) methods that fall under quantitative approaches include naive or intuitive, simple moving average, regression analysis, simple exponential smoothing and adjusted-exponentially weighted moving average forecasting methods.

When a naive or intuitive approach is used forecast for any period equals the demand in the most recent period. This method is quite simple and easy to use. However, regardless of its economic efficiency, the major objection to this method is its inability to provide accurate forecasts (Stevenson 2005).

A simple moving average approach uses several recent demand values to determine an average forecast value in any period. The advantage of such a method is that it is easy to compute and easy to understand. This approach works well in an environment where market demand is fairly steady (Heizer and Render 1993). However, a preliminary review of the behaviour of lumber demands for the period under review showed not only fluctuation in demand from year to year but also patterns of trend and seasonality i.e. gradual upward or downward movement of the data over time and a data pattern that repeats itself after a period, respectively. Therefore, the need for a steady demand contradicts with the actual situation in the country and thus disqualifies the usefulness of this approach.

A weighted average approach is similar to a moving average, except that it assigns more weight to the most recent values in a time series. The advantage of a weighted average over a simple moving average is that the weighted average is more reflective of the most recent occurrences. However, there is no set formula to determine the weights and therefore, weights are chosen somewhat arbitrarily. Choosing weights requires experience which, personnel in sawmills industry in Tanzania might be lacking.

The use of regression analysis is based on the development of an equation that takes-in several variables that are related to demand being predicted. Notwithstanding its power for producing accurate forecasts, it was considered cumbersome to most sawmill managers. For example, lumber demand is affected by several factors that may call for the use of multiple factors analysis. The majority of sawmill operators in the country have inadequate statistical skills to conjure and analyse multi-factor regressions, and therefore the technique was considered inappropriate.

A simple exponential smoothing approach is a forecasting method that is easy to use and effectively handled by computers (Heizer and Render 1993). Although it is a type of the moving average method, it involves very little record keeping of the past data. Each new forecast is based on the previous forecast plus a percentage of the difference between that forecast and the actual value of the series at that point (Fogarty *et al.* 1991). The method uses a smoothing constant, alpha (α), which damps the fluctuations of demands in the years used as inputs in the forecasts. Alpha has a value between 1 and 0 which can be changed to give more weight to recent data (when α is high) or more weight to past data (when α is low). This approach is considered more appropriate to the sawmill industry in Tanzania since in many applications (perhaps in most), the most recent occurrences are more indicative of the future than those in the more distant past. This being the case, the exponential smoothing approach, therefore could be the most logical and easiest method to use (Chase and Aquilano 1992). As it was pointed out earlier, that behaviour of lumber demand showed patterns of trend and seasonality, presence of such patterns dictates the need to have a forecasting model that takes in trend and seasonality factors in the forecast. As for any moving average technique, simple exponential smoothing fails to respond to trend and seasonality (Heizer and Render 1993). Therefore, there was need to adjust the simple exponential smoothing method so that demand, trend and seasonality were taken into consideration. Both trend and seasonality need to be smoothed as it is done to forecasts. To smoothen the trend, the equation for trend is smoothed using a constant beta (β); whereas seasonality is smoothed by a constant, gamma (γ) (Fogarty *et al.* 1991). The challenge in utilising this approach was to find the initial forecast, trend, seasonality and determination of α, β, and γ. A split sample model approach provided means to calculate them (Gaither and Frazier 2007).

Therefore, this study used a computerised adjusted-exponentially weighted moving average forecasting method to forecast lumber demand in the sawmill industry in Tanzania using a split sample model and compared forecasting errors with naive, simple moving average, regression analysis, simple exponential smoothing approaches.

METHODOLOGY

Determination of initial trend and seasonality lumber demand

Split sample model is a procedure which is used to determine initial trend and seasonality (Gaither and Frazier 2007) and was adopted in this study. In order to use this method, one needs data of at least five years. In this study, five-year data (2004-2008) was collected and used for determination of initial trend and seasonality (Table 1). Sample of the data from this data set was isolated and used to calculate trend and seasonal indices. Data for year 2008 was used for model validation and year 2006 was taken as a forecast initializing year. The determined trends and seasonal indices were accordingly smoothed and normalised and thereafter used in the adjusted EWMA for forecasting demand.

Table 1: Actual demand of lumber for the period of 2004-2008

	Demand, m^3				
Quarters	2004	2005	2006	2007	2008
1	306.6	489	559.7	494.4	833.9
2	387.8	312.5	417.5	623.4	893
3	645.3	595	522	593.2	986
4	422.4	576.3	463	458.7	913

Determination of initial demand trend and its adjustment in subsequent periods

Data for the first two years, i.e. 2004 and 2005 (Table 2) were used for estimating initial demand trend.

Table 2: Data for determination of initial trend

Quarter	2004	2005
1	306.6	489
2	387.8	312.5
3	645.3	595
4	422.4	576.3

The initial trend was estimated using the following expression (Gaither and Frazier 2007):

$$T_1 = \frac{Z_1 - Z_2}{m},$$ Equation 1

Where:

Z_1 is an average period-demand in the most recent year of the two years (i.e. 2005),

Z_2 is an average period-demand in the initial year of the two sub-series (i.e. 2004), and

m is the number of periods per year (in this study, data were collected quarterly, therefore, number of periods, m=4).

Trends in subsequent periods were adjusted based on the following expression as provided by Fogarty *et al.* (1991) and Gaither and Frazier (2007):

$$T_{t+1} = \beta(F_{t+1} - F_t) + (1-\beta)T_t$$ Equation 2

Where,

β = Trend smoothing constant

F_{t+1} = Forecast in the subsequent period

Ft = Forecast in the present period

Determination of initial seasonal demand indices and their adjustment in subsequent periods

The initial seasonal demand indices

Demands in the first two years i.e. 2004 and 2005 were used to determine the initial seasonal indices through a three-step approach:

Determination of average demand for the two year sub-series. This was done through summation of all demands in years 2004 and 2005 and then computation of the average (M) from the sum was done as shown in Table 3.

Table 3: Determination of initial seasonal indices

Quarter	2004	2005	M_i	S_i
1	306.6	489	M_1	M_1/M
2	387.8	312.5	M_2	M_2/M
3	645.3	595	M_3	M_3/M
4	422.4	576.3	M_4	M_4/M
Total	1762.1	1972.8		
	M=(1762.1+1972.8)/8=466.8625			

Determination of average demand(M_i) in the two years (2004 and 2005) for every quarter in the two years,

For example, for quarter one, from Table 3, M_1= (306.6 +489)/2= 397.5

Calculation of initial seasonal indices

S_i= (M_i/M), Equation 3

Where, S_i = Seasonal index in each quarter, for example in quarter four of 2005, the seasonal index will be S4= (422.4+576.2)/2÷ 466.8625= 1.069588687

Note that the sum of all seasonal indices must always be equal to four (the number of seasonal periods in a year) at this stage (Gaither and Frazier 2007).

Adjustment of demand-seasonal indices in subsequent periods

According to Gaither and Frazier (2007) the adjustment of demand seasonal indices is done annually at the end of fourth quarter. Whenever adjustment is required in a year, only the seasonal index of the fourth quarter in the previous year is adjusted and the adjusted index serves as an index of the fourth quarter in the subsequent year. Indices for the first, second and third quarters in the preceding year are maintained in the subsequent year. Therefore, to initiate forecasting, the fourth quarter seasonal index of 2005 served as seasonal index in the fourth quarter of 2006-the forecast initialising year. The indices for other quarters in 2006 i.e. one to three remained the same as those in 2005. Accordingly, seasonal index in the fourth quarter of 2007 was adjusted but index values for other quarters i.e. one, two and three were borrowed from 2006. The same sequence followed for forecasting 2008 demand.

The adjusted season indices for the fourth quarter in 2007 and the other subsequent years were determined using equation 4 (Fogarty *et al.* 1991):

$$S_{4+4} = \gamma(D_t / F_t) + (1-\gamma)S_t \qquad \text{Equation 4}$$

Where,

S_{4+4}- seasonal index for the 4th quarter of 2007

γ- Smoothing constant for seasonal indices

S_t - seasonal index for fourth quarter of the forecast initialising year, 2006

Dt, F_t – Demand and forecast level in the fourth quarter of the forecast initialising year, 2006, respectively.

Calculated example of seasonal indices for forecast initialising year is presented in Table 4

Table 4. Seasonal indices for forecast initialising year, 2006

Quarters (2006)	Seasonal Indices
q1/06	0.85207101
q2/06	0.75000669
q3/06	1.32833543
q4/06	1.06958687

Normalisation of seasonal indices for 2007 and 2008

Since only the fourth quarter seasonal index in 2007 was adjusted and other indices i.e. one to three quarters remained the same as in 2006, there was likelihood to contravene the *modus operandi*, i.e. that the sum of indices in a year should be equal to the number of seasonal periods in a year. And this likelihood proved true as indicated in Table 5. Therefore there was need to normalise them, i.e. to ensure that the sum of the indices was equal to the number of periods in a year.

Table 5. Seasonal index with adjusted fourth quarter in 2007

Quarter	Index
1	0.85207101
2	0.75000669
3	1.32833543
4	1.0676374 (adjusted)
Sum	3.99805053≠4.0

Normalization was done through multiplication of these indices by a normalization factor (NF) which was determined using the following expression (Russel and Taylor III 2007):

NF= $m/(m+S_{4+4}-S_4)$ Equation 5

where,

m- Number of quarters in a year, i.e. 4

S_{4+4} = the new calculated fourth quarter index for 2007

S_4 = the index in fourth quarter of 2006

Example of normalised indices is presented in Table 6.

Table 6: Normalisation of seasonal indices in the 2007

Quarter	Index	NF	Normalised index
1	0.85207101	1.0004876	0.8525
2	0.75000669		0.7504
3	1.32833543		1.329
4	1.0676374 (adjusted)		1.0682
Sum of indices	3.99805053		4

The normalised indices were used for prediction of lumber demand in subsequent year, i.e. 2007.

Determination of initial forecast level (or base) and subsequent adjustment

Initial trend and seasonal indices in the initialising year were determined using equations 1 and 3. The remaining challenge was to determine the initial demand level or base, i.e. demand without components of trend and seasonality for the forecast initialising year. For a particular period, Russel and Taylor III (2007) provide the following expression for forecast that has been adjusted for trend and seasonality:

$$AF_t = (F_t + T_t)S_t \qquad \text{Equation 6}$$

Where,

$AF_t =$ Adjusted forecast

$T_t =$ Trend

$S_t =$ Seasonal index

F_t = Base or level

In order to determine the initial demand level, it was first assumed that the adjusted forecast was equal to demand (D_t) in the first quarter of the initialising year (2006), i.e. 559.7 m^3 (Table 1). Therefore, adjusted forecast was equated to D_t (equation 7) and finally replaced by D_t (equation 8) in resolving for demand level.

$$AF_t = D_t = (F_t + T_t)S_t \qquad \text{Equation 7}$$

Since this demand was known, it was possible to determine the corresponding initial demand level by back-forecasting through re-organisation of equation 7. Therefore, demand initial level was calculated using equation 8.

$$F_t = \left(\frac{D_t}{S_t}\right) - T_t \qquad \text{Equation 8}$$

The found initial level was used to calculate adjusted forecasts in the subsequent periods using a three step-approach:

De-seasonalise (i.e. remove the effect of seasonality in actual demand) in the present period and calculate the new level for the next period using the following expressions as provided by Russel and Taylor III (2007):

$$F_{t+1} = \alpha(D_t / S_t) + (1-\alpha)(F_t + T_t) \qquad \text{Equation 9}$$

Determine the new trend for the next period:

$$T_{t+1} = \beta(F_{t+1} - F_t) + (1-\beta)T_t \qquad \text{Equation 10}$$

Adjust forecast with adjusted trend and seasonalise the trend-adjusted forecast using new seasonal index:

$$AF_{t+1} = (F_{t+1} + T_{t+1})S_{t+1} \qquad \text{Equation 11}$$

Where,

$F_{t+1} =$ Level in the subsequent period

$F_t =$ Level in the current period

$\alpha =$ Level smoothing constant

$\beta =$ Trend smoothing constant

$D_t =$ Demand in the current period

$S_t =$ Seasonal index in the current period

$T_t =$ Trend in the current period

$T_{t+1} =$ Trend in the subsequent period

2.3. Determination of smoothing constants

The EWMA process of forecasting model was mapped in MS Excel spreadsheet. The spreadsheet was used to iterative searching for best fitting smoothing constants to attain forecasts with minimum forecasting errors.

2.4 Forecasts from other forecasting methods:

Forecasts were determined using various expressions and function as detailed in the following sections.

2.4.1 Naïve method

Using this method, demand in the next period was assumed to be equal to demand in the most recent period

2.4.2 Simple moving average

Forecast was determined using the following expression

$$Moving\ average = \frac{\sum Demands\ in\ n\ periods}{n} \qquad \text{Equation 12}$$

2.4.3 Weighted moving average (WMA)

The following expression was used to determine the weighted moving average forecast:

$$WMA = \frac{\sum(Weight\ for\ period\ n)(Demand\ in\ period\ n)}{\sum Weights}$$ Equation 13

Simple regression analysis

A forecast worksheet function in MS Excel was utilised to calculate respective forecasts.

Comparison of errors among forecasting models

A more accurate forecasting model was considered to be the one with minimum forecasting error. Mean absolute deviation (MAD) was used as efficacy criterion as opposed to the more common MAPE (mean average percentage error). MAD error criterion was considered more appropriate for the sawmill industry than MAPE since the former has units and the latter is unit less. Since MAD has units, deviations of forecasts from the-would be actual demands could be off-set by keeping an inventory equivalent to the determined MAD. Demands for 2008 were used as a holdout sample (D_i) to test the validity of the models. MAD was calculated using the following expression:

$$MAD = \frac{\sum_{i=1}^{n} |D_i - AF_i|}{n}$$ Equation 14

MADs were computed for each forecasting model and compared.

The best two performers were subjected to further analysis by forming a confidence interval around the MAD difference between MADs of the two methods rather than a hypothesis test approach which ends only into a “reject” or “fail to reject” the hypotheses. This approach was considered more appropriate because the formed interval not only gives the same information as the hypothesis test, but also quantifies the difference in accuracy (Law and Kelton 2000). An issue of interest is whether the difference between the models was significant enough to affect any decision or conclusion derived from one of the forecasting models. Therefore a 95% paired-*t* confidence interval was constructed using equations 15, 16,17 and 81 as suggested by Law and Kelton (2000):

$$Z_j = X_{1j} - X_{2j}$$ Equation 15

where;

1, 2 = First and second best methods, respectively

X_{1j} = MAD of the best forecasting method

X_{2j} = MAD of the second best forecasting method

Z_j = the observed difference between the MAD values

$$\bar{Z}(n) = \frac{\sum_{j=1}^{n} Z_j}{n}$$ Equation 16

Where;

$\bar{Z}(n)$ = average MAD difference

$$\hat{V}ar[\bar{Z}(n)] = \frac{\sum_{j=1}^{n} [Z_j - \bar{Z}(n)]^2}{n(n-1)}$$ Equation 17

Where;

$\hat{V}ar[\bar{Z}(n)] =$ the variance of MADs differences

n – Number of periods per year (n=4)

The confidence interval was derived from expression (18).

$$\bar{Z}(n) \pm t_{(n-1),1-\alpha/2}\sqrt{\hat{V}ar[\bar{Z}n)]}$$ Equation 18

Results and Discussion

Pattern of lumber demands

The demand pattern (Figure 1) at a study mill indicated that there was an increasing trend in lumber demand within the period under review. Also, seasonality in demand was observed although it was not very clear. This demand behavior justified for a lumber demand predicting model that considers the influence of trend and seasonality factors.

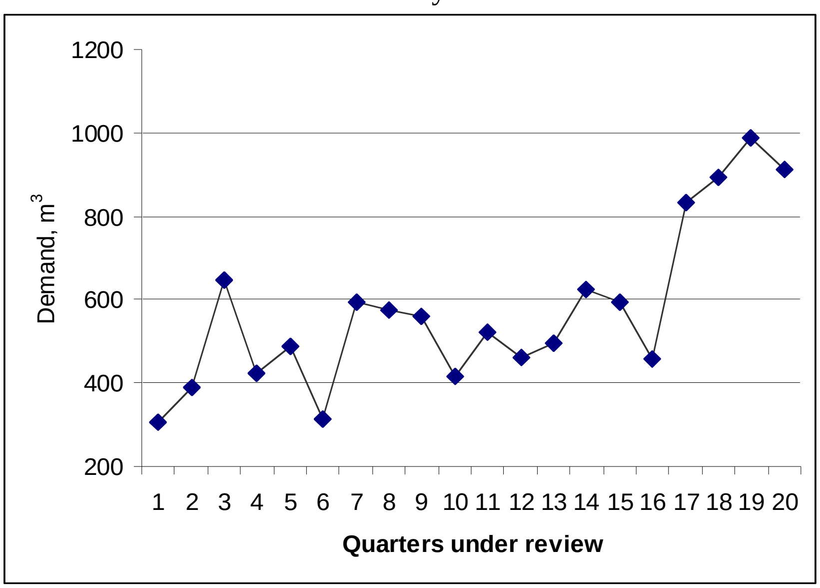

Figure 1: Pattern of lumber demands (2004-2008)

Smoothing Constants

A number of smoothing constants were iteratively used in the MS Excel spreadsheet in search for smoothing constants that produce minimum MAD. Best results were attained when values for α, β and γ were 0.001, 0.001 and 0.001 were used, respectively. Consequently, these values could be used for demand EWMA forecasts.

Comparison of EWMA with other reviewed forecasting techniques

Forecasting errors (MADs) determined from different forecasting methods are presented in Figure 2. The naïve method performed better than other methods because demand fluctuation in 2008 (a year of comparison) was minimal and thus as expected; the method ranked top of the list. However, Figure 1 shows that the behaviour of lumber demand in the country exhibit both trend and seasonality. Although the naïve method ranked high, it is an undependable model for capturing accurate forecasts in a turbulent lumber market like in Tanzania. Although EWMA ranked second, it was more reliable than the naïve method since it successfully (i.e. with minimum error) tracked demand, trend and seasonality behaviours. The MADs were 150.08 and 153.64 m^3 for naïve and EWMA methods, respectively. Although these errors were mathematically different, their differences were statistically insignificant since the confidence interval [- 52.21, 45.09] of MADs' difference contains a zero indicating that the difference was not significantly different from zero. This means that the sawmill operators could do away with the naive method and instead use EWMA which is equally accurate and in addition it is capable to map the actual demand behaviour.

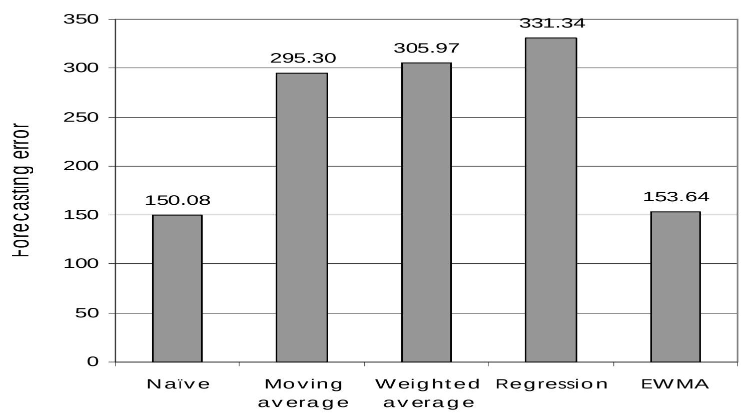

Figure 2: MADs for different forecasting methods

CONCLUSION

Based on the findings and the nature of lumber demand patterns in Tanzania, the Adjusted Exponentially Weighted Moving Average forecasting method was found to be suitable for use in the sawmill industry in Tanzania.

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