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*Research Article*

# A Study of Time Series Model for Predicting Jute Yarn Demand: Case Study

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In today's competitive environment, predicting sales for upcoming periods at right quantity is very crucial for ensuring product availability as well as improving customer satisfaction. This paper develops a model to identify the most appropriate method for prediction based on the least values of forecasting errors. Necessary sales data of jute yarn were collected from a jute product manufacturer industry in Bangladesh, namely, Akij Jute Mills, Akij Group Ltd., in Noapara, Jessore. Time series plot of demand data indicates that demand fluctuates over the period of time. In this paper, eight different forecasting techniques including simple moving average, single exponential smoothing, trend analysis, Winters method, and Holt's method were performed by statistical technique using Minitab 17 software. Performance of all methods was evaluated on the basis of forecasting accuracy and the analysis shows that Winters additive model gives the best performance in terms of lowest error determinants. This work can be a guide for Bangladeshi manufacturers as well as other researchers to identify the most suitable forecasting technique for their industry.

## 1. Introduction

To stay competitive in the global business environment, effective planning regarding scheduling, inventory, production, distribution, purchasing, and so on is very important as it is considered as the backbone of fruitful operations. Appropriate prediction of products plays a pivotal role in reducing unnecessary inventory and smoothing planning issues which result in increasing profit. Many organizations have failed due to the fault estimation. Prediction refers to the technique to probe the future event or occurrence. An event may be demand of a product, price of a commodity, unemployment rate, and so on. In modern business environment, satisfying customer's demand at right time at right quantity is the main driving force for generating profit. So, to ensure product availability with the lowest possible cost, prediction with as much accuracy as possible is very necessary. As prediction is an uncertain process, it is not so much easy task to predict consistently what will happen in future. Product diversification, short life cycle of product, rapid technological advances, and so on make prediction of product demand more difficult and too much challenging.

There are enormous research works in the arena of forecasting method selection with time series data. Time series data may be different types like electric power consumption, sales/demand of a product, price of commodities, and so on. Several authors have worked on time series analysis [1–3]. Cox Jr. and Loomis [4] conducted a 25-year survey on time series analysis and suggested some possible ways to improve the forecasting techniques. The sole purpose of their work was to observe the stimulus of text books on forecasting learning. Ryu and Sanchez [5] constructed a framework for the evaluation of the most appropriate forecasting method at an institutional food service dining facility. The authors applied different forecasting methods and calculated measures of forecasting accuracy using MAD, MSE, MAPE, MPE, RMSE, and Theil's $U$-statistic. The analysis showed multiple regression analysis as the most appropriate method among several alternatives.

Wallström and Segerstedt [6] applied Croston forecasting technique and single exponential smoothing approach to develop flexible and robust supply chain forecasting systems for slow moving or intermittent demand. The authors measured the apprehended performance of methods based on estimated forecasting errors. Sanwlani and Vijayalakshmi [7] conducted time series analysis for forecasting sales. Different statistical methods, namely, ARIMA, Holt, Winters, and exponential smoothing, were used and absolute percentage error (APE) was used for comparing the performance of different forecasting methods. Hossain and Abdulla [8] performed time series analysis on secondary data of yearly jute production in Bangladesh over the period of 1972 to 2013. The purpose of the work was to identify the Autoregressive Integrated Moving Average (ARIMA) model for forecasting the production of jute in Bangladesh. Davies et al. [9] measured the application of time series models including ARIMA and exponential smoothing for future requirements of volatile inventory. They also applied Monte Carlo simulation for forecasting and compared the output of simulation with time series forecasts. The contribution of the paper is to develop a framework that combines time series modeling and Monte Carlo simulation for forecasting. Miller et al. [10] did a comparison of different forecasting methods, namely, Naïve Approach, simple moving average, weighted moving average, exponential smoothing, and Linear Least Square Regression, for forecasting food production.

Matsumoto and Ikeda [11] examined the demand forecasting of an auto-part using time series analysis. The objective of the study was to examine the effectiveness of forecasting for remanufactured products by time series analysis. Li et al. [12] used vector forecasting model for fuzzy time series which were capable of dealing with ambiguity. The contribution of the work was to improve forecasting capability through the expansion of the vector forecasting model. Time series analysis is also used in tourism sector. Weatherford and Kimes [13] applied different forecasting methods on hotel revenue management and recommended that exponential smoothing, pickup, and moving average models were the most suitable for forecasting as well as revenue generation.

Different qualitative forecasting methods are used by managers to make forecast of product demand. Qualitative methods include past experience, best guess, or group discussion. To aid management in planning decisions, different quantitative techniques are available in the literature. The aim of this study is to develop a framework for identifying the most appropriate forecasting method for predicting jute yarn demand of a Bangladeshi jute yarn manufacturer. As no forecasting technique can provide accurate forecast, this paper can be a reliable guideline to reduce the deviation between actual and predicted values.

## 2. Methodology

The sole purpose of this study is to develop a framework that justifies the viability of different forecasting methods and select the best one with the least possible forecasting errors. Forecasting is a powerful tool to reduce the uncertainty in demand of product and help the manager to project demand for upcoming periods. In this study, several quantitative forecasting models like simple moving average method, single exponential method, double exponential method (Holt's), Winters method, decomposition method, and so on have been utilized. To identify the best one, three error determinants, namely, mean absolute deviation (MAD), Mean Absolute Percentage Error (MAPE), and mean square deviation (MSD), are calculated. All calculations are done by Minitab 17 package. The necessary data in this study was collected from Akij Jute Mills, Akij Group Ltd. in Noapara, Jessore, on weekly basis over four-year periods (1st week 2010 to 52th week 2013). To analyze data using statistical techniques, the historical demand data of jute yarn product was collected. The detailed descriptions of each method used in this study are illustrated in the following sections.

### 2.1. Forecasting Methods

*2.1.1. Simple Moving Average Method (SMA).* Simple moving average (SMA) or rolling average is the arithmetic mean of observations of the full data set and uses the arithmetic mean as the predictor of the future period. This method is used to smooth out short-term deviations of time series data and indicate long-term trends or cycles. The equation of SMA is as follows:

$$F_t = \mathrm{MA}_n = \frac{\sum_{i=1}^{n} D_i}{n}, \quad (1)$$

where $F_t$ is forecast for time period $t$, $D_i$ is demand in period $i$, and $n$ is number of periods in the moving average.

*2.1.2. Single Exponential Smoothing (SES) Method.* This sophisticated method is a kind of weighted averaging method which estimates the future value based on previous forecast plus a percentage of the forecasted error. It is easy to implement and compute as it does not need maintaining the history of previous input data. It fades uniformly the effect of unusual data. The equation of SES is as follows:

$$F_t = F_{t-1} + \alpha\left(F_{t-1} - A_{t-1}\right), \quad (2)$$

where $F_t$ is forecast for time period $t$, $F_{t-1}$ is forecast for the previous period, $A_{t-1}$ is actual demand for the previous period, and $\alpha$ is smoothing constant ($0 \leq \alpha \leq 1$).

*2.1.3. Double Exponential Smoothing (Holt's Method).* Double exponential smoothing or Holt's method by Holt (1957) is used to forecast data having linear trend. It is an extension of simple exponential smoothing. Holt's method smooths both trend and slope in the time series using two different smoothing constants (alpha for the level and gamma for the trend).

$$\begin{aligned} \text{Forecast equation } & y_{t+h} = l_t + hb_t, \\ \text{Level equation } & l_t = \alpha y_t + (1-\alpha)\left(l_{t-1} + b_{t-1}\right), \\ \text{Trend equation } & b_t = \gamma\left(l_t - l_{t-1}\right) + (1-\gamma)\, b_{t-1}, \end{aligned} \quad (3)$$

where $y_{t+h}$ is forecast for h periods into the future, $l_t$ is level estimate at time $t$, $b_t$ is trend (slope) estimate at time $t$, $h$ are periods to be forecast into future, $\alpha$ is smoothing constant for level $(0 \le \alpha \le 1)$, and $\gamma$ is smoothing constant for trend $(0 \le \gamma \le 1)$.

*2.1.4. Winters Method.* When both trend and seasonality are present in data set, this procedure can be used. It is used to smooth data employing a level component, a trend component, and a seasonal component at each period and provides short to medium range forecasting. There are two types of model: multiplicative and additive. Multiplicative model is used when the magnitude of the seasonal pattern varies with the size of the data. Additive model is just opposite to multiplicative model. The following equations are Winters method smoothing equations.

Smoothing equation for multiplicative model:

$$\text{Forecast equation } \acute{y}_t = \left(L_{t-1} + T_{t-1}\right) S_{t-p},$$
$$\text{Level equation } L_t = \alpha \left(\frac{y_t}{S_{t-p}}\right) + (1-\alpha)\left(L_{t-1} + T_{t-1}\right), \quad (4)$$
$$\text{Trend equation } T_t = \gamma\left(L_t - L_{t-1}\right) + (1-\gamma) T_{t-1},$$
$$\text{Seasonal equation } S_t = \delta\left(\frac{y_t}{L_t}\right) + (1-\delta) S_{t-p}.$$

Smoothing equation for additive model:

$$\text{Forecast equation } \acute{y}_t = L_{t-1} + T_{t-1} + S_{t-p},$$
$$\text{Level equation } L_t = \alpha\left(y_t - S_{t-p}\right) + (1-\alpha)\left(L_{t-1} + T_{t-1}\right), \quad (5)$$
$$\text{Trend equation } T_t = \gamma\left(L_t - L_{t-1}\right) + (1-\gamma) T_{t-1},$$
$$\text{Seasonal equation } S_t = \delta\left(y_t - L_t\right) + (1-\delta) S_{t-p},$$

where $\acute{y}_t$ is one-period ahead of forecast at time $t$, $L_t$ is level estimate at time $t$, $T_t$ is trend estimate at time $t$, $S_t$ is seasonal estimate at time $t$, $y_t$ is data value at time $t$, $p$ is seasonal period, $\alpha$ is smoothing constant for level $(0 \le \alpha \le 1)$, $\gamma$ is smoothing constant for trend $(0 \le \gamma \le 1)$, and $\delta$ is smoothing constant for seasonality $(0 \le \delta \le 1)$.

*2.1.5. Trend Analysis.* Trend analysis fits a general model to multiple time series data having trend pattern and provides idea to traders about what will happen in the future based on historical data. Trend can be linear, quadratic, or S-curve. A general linear type trend equation has the following form:

$$F_t = a + bt,$$
$$b = \frac{n\sum ty - \sum t \sum y}{n\sum t^2 - \left(\sum t\right)^2}, \quad (6)$$
$$a = \frac{\sum y - b\sum t}{n},$$

where $F_t$ is forecast for time period $t$, $t$ is specified number of time periods, $a$ is intercept of the trend line, $b$ is slope of the line, $n$ is number of periods, and $y$ is value of the time series.

*2.1.6. Decomposition.* Decomposition technique is used to separate the time series into linear trend and seasonal components, as well as error. Seasonal component can be additive or multiplicative with the trend. When seasonal component is present in time series, it is used to examine the nature of the component parts.

*2.2. Measures of Forecasting Accuracy.* Forecasting accuracy plays a vital role when deciding among several forecasting alternatives. Here, accuracy refers to forecasting error which is the deviation between the actual value and forecasted value of a given period. In this study, three forecasting error determinants are used: mean absolute deviation (MAD), the mean squared error (MSE), and the Mean Absolute Percentage Error (MAPE). MAD is the average absolute difference between actual value and value that was predicted for a given period, MSE is the average of squared errors, and MAPE is the average of absolute percent error. The formulas used to calculate above stated errors are

$$\text{MAD} = \frac{\sum\left|D_t - F_t\right|}{n},$$
$$\text{MSE} = \frac{\sum\left(D_t - F_t\right)^2}{n-1}, \quad (7)$$
$$\text{MAPE} = \frac{\sum\left|e_t / D_t\right|}{n} \times 100,$$

where $D_t$ is actual demand for time period $t$, $F_t$ is forecast demand for time period $t$, $n$ is specified number of time periods, and $D_t$ is forecast error $= (D_t - F_t)$.

## 3. Prototype Example and Result Analysis

The sole purpose of this study is to develop a framework for the future researchers as well as Bangladeshi manufacturers that can help to identify an appropriate forecasting method based on its error determinants. For real case demonstration, a practical case study on Akij Jute Mills, Akij Group Ltd. in Noapara, Jessore, was conducted. Eight forecasting methods are used and measures of forecasting accuracy, namely, mean absolute deviation (MAD), Mean Absolute Percentage Error (MAPE), and mean square deviation (MSD), are calculated using Minitab 17 package.

Figure 1 shows the time series plot of 208-week demand data of jute yarn from year 2010 to year 2013. It indicates that demand fluctuates over period to period. The trends of demand in 2010, 2011, and 2012 are quite the same with little fluctuations. Demand was steady until 4 weeks and then sharply increased at week 5. It continued as steady and then suddenly decreased at week 9. The trend of demand found in weeks 32–35 was highest for all four years and here the seasonality was found. Average demand has increased from year 2010 to year 2012. On the other hand, demand data

Table 1: Forecasting errors under SMA method.

| Length of average in weeks ($n$) | MAPE | MAD | MSD |
|---|---|---|---|
| 2MA | 8.3 | 70.5 | 19431.2 |
| 3MA | 10.8 | 91.4 | 24473.3 |
| 4MA | 13.2 | 112.1 | 29783.9 |
| 5MA | 14.1 | 121.9 | 32376.7 |
| 6MA | 14.7 | 127.5 | 33504.7 |
| 7MA | 15 | 131.1 | 33920.3 |
| 8MA | 15.1 | 133.2 | 33976.4 |
| 9MA | 15.3 | 135 | 33949.8 |
| 10MA | 15.1 | 134.7 | 33797.7 |
| 11MA | 15 | 133.5 | 33577.2 |
| 12MA | 14.7 | 131.4 | 33334.6 |
| 13MA | 14.4 | 129.6 | 33163.5 |
| 14MA | 14.2 | 128.9 | 33243.4 |
| 15MA | 14.3 | 129.8 | 33645.2 |

Table 2: Forecasting errors under SES method.

| Value of smoothing constant (alpha) | MAPE | MAD | MSD |
|---|---|---|---|
| 0.1 | 13.1 | 116.8 | 29939.5 |
| 0.2 | 12.6 | 109.1 | 26144.4 |
| 0.3 | 11.8 | 101.1 | 23576.3 |
| 0.4 | 10.8 | 92.2 | 21390.4 |
| 0.5 | 9.8 | 82.7 | 19528.3 |
| 0.6 | 8.7 | 73.6 | 18003.7 |
| 0.7 | 7.8 | 65.7 | 16822.2 |
| 0.8 | 7.1 | 59.1 | 15977.1 |
| 0.9 | 6.5 | 53.6 | 15457 |

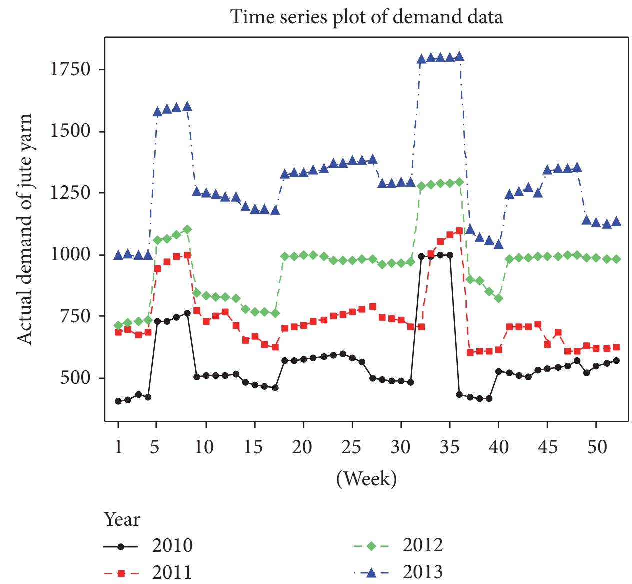


Figure 1: Time series plot of jute yarn demand.

Table 3: Forecasting errors under Holt's method.

| Smoothing constant alpha (Level) | Smoothing constant gamma (Trend) | MAPE | MAD | MSD |
|---|---|---|---|---|
| 0.1 | 0.1 | 15 | 128 | 32880.4 |
| 0.1 | 0.2 | 15.9 | 136.7 | 36354.1 |
| 0.1 | 0.3 | 18 | 152.1 | 42391.8 |
| 0.2 | 0.1 | 14.2 | 119.8 | 29969.1 |
| 0.2 | 0.2 | 16.3 | 135.5 | 34575.1 |
| 0.2 | 0.3 | 17.8 | 147 | 38415.1 |
| 0.3 | 0.1 | 13.2 | 110.6 | 27050.4 |
| 0.3 | 0.2 | 14.5 | 120.4 | 30592.1 |
| 0.3 | 0.3 | 15.1 | 125.9 | 33875.7 |

corresponding to year 2013 showed great change in demand at every week and these values were greater than the previous years. The lowest value of demand was above 1000 tons whereas it was the highest demand for year 2010. Table 1 depicts different forecasting errors for different forecasting periods under simple moving average method. In simple moving average method, fourteen trials are taken through putting different values of $n$. Fourteen sets of error determinants are measured and least values of MAD, MAPE, and MSE are obtained when value of forecasting period ($n$) is 15 weeks. The values of MAD, MAPE, and MSE for 15 weeks are varied between 70.5–135, 8.3–15.3, and 19431.2–33976.4, respectively. A graphical representation of actual demand versus forecasted demand for simple moving average method is portrayed in Figure 2. There are a sudden increase and sudden decrease in actual demand while forecasted demand fluctuates between the highest and lowest value of actual demand. The accuracy measures are 13.1, 117.4, and 26912.1 for MAPE, MAD, and MSD, respectively. On the other hand, to determine optimal smoothing constant ($\alpha$) in single exponential smoothing method, nine trials are made and least forecasting errors are obtained at higher value of smoothing constant. Different values of forecasting errors with varying smoothing constant are shown in Table 2. The values of MAPE, MAD, and MSE are varied between 6.5–13.1, 53.6–116.8, and 15457–29939.5, respectively. It is clear from Table 2 that the values of MAPE, MAD, and MSE decrease with increase of the value of smoothing constant. Figure 3 shows that the fluctuation of actual and forecasting demand is approximately same for single exponential smoothing method. It is found that the minimum errors occurred at optimum smoothing constant ($\alpha = 0.9$). In Holt's method, nine trials are performed with varying smoothing constants (both level and trend) from 0.1 to 0.3 which is shown in Table 3. Figure 4 shows the comparison of actual demand of jute yarn in ton with the forecasted demand in 2010–2013 using Holt's method at most suitable combination of smoothing constants. The lowest values of errors are achieved at $\alpha = 0.3$ and $\gamma = 0.1$.

From trend analysis on jute yarn demand data of 208 weeks, obtained trend equation is $Y_t = 425.1 + 4.47 * t$ which is shown in Figure 5. Figure 5 also shows the forecasting errors as well as forecasted values with respect to the actual demand. Besides these, two types of Winters model (multiplicative and additive model) are used to determine the errors. Total 27

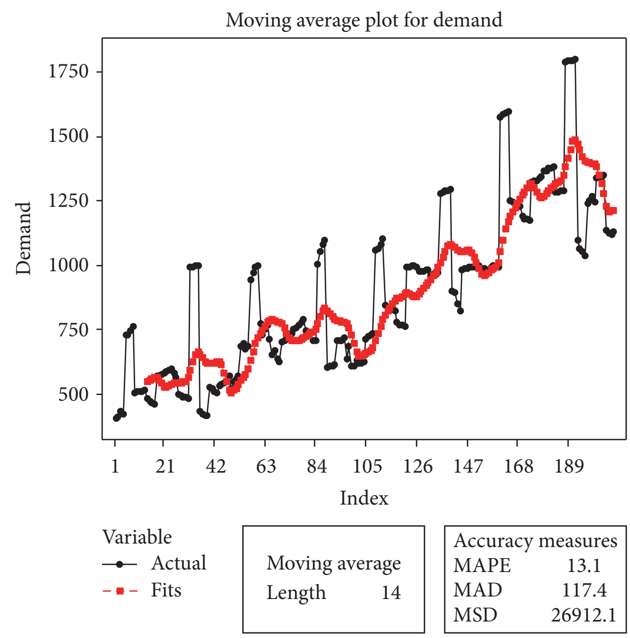


Figure 2: Comparison of actual sales with forecasted demand in SMA method.

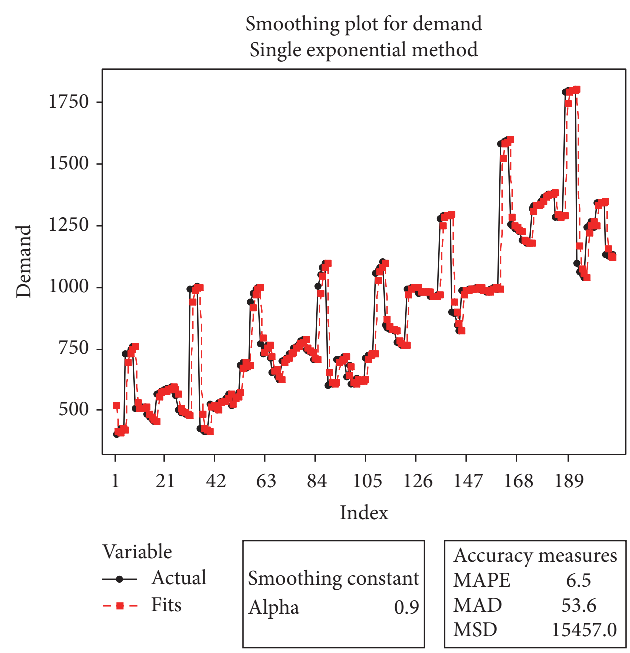


Figure 3: Comparison of actual sales with forecasted demand in SES method.

trials have been conducted by varying the values of three smoothing constants ($\alpha$, $\gamma$, and $\delta$) ranging from 0.1 to 0.3. For both cases, seasonal length is about 52 weeks. Twenty-seven sets of forecasting errors for 27 trials are obtained for multiplicative and additive Winters model and shown in Table 4. Optimum smoothing constants for additive and multiplicative models and corresponding MAD, MAPE, and MSE are given in Figures 6 and 7, respectively. The figures show that

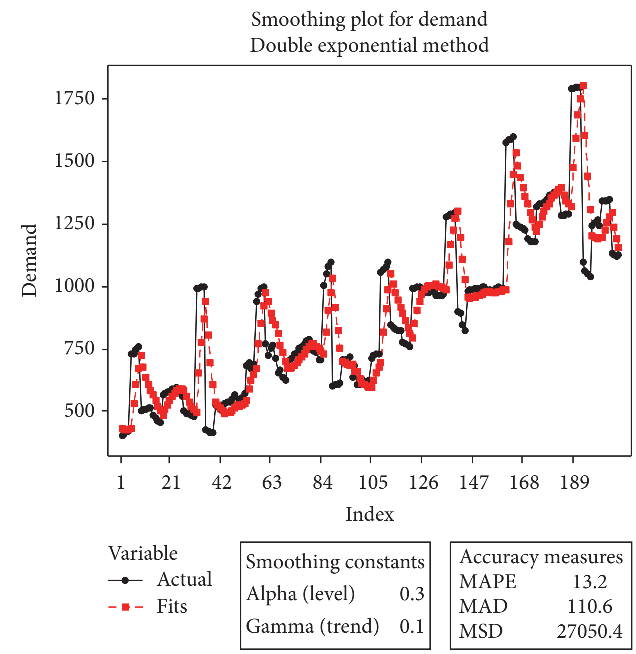


Figure 4: Comparison of actual sales with forecasted demand in Holt's method.

minimum errors are obtained for both models at $\alpha = 0.3$, $\gamma = 0.1$, and $\delta = 0.1$. But Winters additive model provides more satisfactory result than multiplicative model. Multiplicative and additive decomposition models considering both seasonal plus trend and only seasonal pattern are used to calculate measures of accuracy. Table 5 summarizes the results of both models and indicates that multiplicative decomposition model with trend and seasonal effect has minimum errors. Additive model having trend and seasonal effect also provides least error values.

Considering all the calculation and analysis, the entire output using eight different forecasting techniques is summarized in Table 6. Results show that differences are present among applied techniques. MAD values vary from 40.58 to 134.16; MAPE values of different forecasting methods vary from 5.06 to 15.39. The maximum value of MSD (33243.4) is found by moving average method while the lowest value (4705) is obtained by Winters additive method. Comparing the performance of anticipated methods, Winters additive model displays the minimum forecasting error values which indicates the greatest accuracy and implies the suitability of this method.

## 4. Conclusion

The main goal of this study is to determine the most appropriate forecasting technique for upcoming sale of jute yarn for jute products manufacturing industry in Bangladesh. The forecasting method will be selected on the basis of least forecasting errors, that is, minimum values of MAPE, MAD, and MSD. For this purpose, different time series analysis is performed on 208-week demand data using Minitab 17 package and measures of accuracy are calculated. Performance

Table 4: Forecasting errors under Winters method.

| Smoothing constant alpha (level) | Smoothing constant gamma (trend) | Smoothing constant delta (seasonal) | Winters additive model | | | Winters multiplicative model | | |
|---|---|---|---|---|---|---|---|---|
| | | | MAPE | MAD | MSD | MAPE | MAD | MSD |
| 0.1 | 0.1 | 0.1 | 6.08 | 48.51 | 5030.6 | 7.16 | 61.75 | 7560.57 |
| 0.1 | 0.1 | 0.2 | 6.21 | 49.99 | 5414.65 | 7.42 | 64.46 | 8376.62 |
| 0.1 | 0.1 | 0.3 | 6.36 | 51.73 | 5807.84 | 7.66 | 66.66 | 9235.14 |
| 0.1 | 0.2 | 0.1 | 6.21 | 49.55 | 5204.78 | 7.44 | 63.17 | 7537.56 |
| 0.1 | 0.2 | 0.2 | 6.38 | 51.38 | 5608.68 | 7.84 | 68.07 | 8643.47 |
| 0.1 | 0.2 | 0.3 | 6.57 | 53.43 | 6012.93 | 8.26 | 72.77 | 9873.75 |
| 0.1 | 0.3 | 0.1 | 6.48 | 51.77 | 5537.25 | 7.67 | 63.24 | 7413.21 |
| 0.1 | 0.3 | 0.2 | 6.61 | 53.44 | 5991.33 | 8.2 | 69.22 | 8616.98 |
| 0.1 | 0.3 | 0.3 | 6.79 | 55.46 | 6442.68 | 9 | 77.5 | 10167.7 |
| 0.2 | 0.1 | 0.1 | 5.35 | 43.04 | 4779.84 | 5.89 | 48.51 | 5563.59 |
| 0.2 | 0.1 | 0.2 | 5.45 | 44.28 | 5124.34 | 6.13 | 51.3 | 6212.32 |
| 0.2 | 0.1 | 0.3 | 5.56 | 45.63 | 5473.25 | 6.38 | 54.18 | 6908.63 |
| 0.2 | 0.2 | 0.1 | 5.59 | 45.14 | 5166.55 | 6.37 | 51.91 | 5863.92 |
| 0.2 | 0.2 | 0.2 | 5.68 | 46.48 | 5571.86 | 6.64 | 55.02 | 6609.84 |
| 0.2 | 0.2 | 0.3 | 5.83 | 48.21 | 5994.81 | 6.96 | 58.51 | 7481.55 |
| 0.2 | 0.3 | 0.1 | 5.93 | 48.24 | 5643.04 | 6.68 | 54.74 | 6380.57 |
| 0.2 | 0.3 | 0.2 | 6.07 | 50.14 | 6130.07 | 7.04 | 58.76 | 7246.09 |
| 0.2 | 0.3 | 0.3 | 6.28 | 52.5 | 6660.18 | 7.42 | 62.88 | 8305.83 |
| 0.3 | 0.1 | 0.1 | 5.06 | 40.58 | 4705.68 | 5.38 | 43.92 | 5089.33 |
| 0.3 | 0.1 | 0.2 | 5.11 | 41.38 | 5003.92 | 5.55 | 45.84 | 5624.94 |
| 0.3 | 0.1 | 0.3 | 5.19 | 42.43 | 5309.95 | 5.74 | 47.84 | 6204.97 |
| 0.3 | 0.2 | 0.1 | 5.39 | 43.47 | 5153.21 | 5.65 | 46.38 | 5550.05 |
| 0.3 | 0.2 | 0.2 | 5.47 | 44.51 | 5493.52 | 5.88 | 48.8 | 6141.81 |
| 0.3 | 0.2 | 0.3 | 5.56 | 45.74 | 5852.34 | 6.11 | 51.21 | 6803.38 |
| 0.3 | 0.3 | 0.1 | 5.7 | 46.13 | 5652.62 | 5.73 | 47.36 | 6066.61 |
| 0.3 | 0.3 | 0.2 | 5.78 | 47.21 | 6033.21 | 5.98 | 49.94 | 6723.87 |
| 0.3 | 0.3 | 0.3 | 5.89 | 48.56 | 6446.37 | 6.25 | 52.75 | 7472.54 |

Table 5: Summary of decomposition methods.

| Measure | Decomposition | | | |
|---|---|---|---|---|
| | Multiplicative | | Additive | |
| | Trend and seasonality | Only seasonality | Trend and seasonality | Only seasonal |
| MAPE | 8.35 | 31.8 | 8.16 | 31.8 |
| MAD | 67.66 | 252.6 | 65.93 | 252.4 |
| MSD | 7573.78 | 86107.7 | 7467.41 | 86446 |

Table 6: Summary of all forecasting methods and error calculations.

| Forecasting method | MAPE | MAD | MSD |
|---|---|---|---|
| Multiplicative decomposition model with trend and seasonality | 8.35 | 67.66 | 7573.78 |
| Additive decomposition model with trend and seasonality | 8.16 | 65.93 | 7467.41 |
| Moving average | 14.2 | 128.9 | 33243.4 |
| Single exponential smoothing | 6.5 | 53.6 | 15457 |
| Holt's method | 13.2 | 110.6 | 27050.4 |
| Trend analysis | 15.39 | 134.16 | 32031.66 |
| Winters multiplicative model | 5.38 | 43.92 | 5089.33 |
| Winters additive model | 5.06 | 40.58 | 4705.68 |

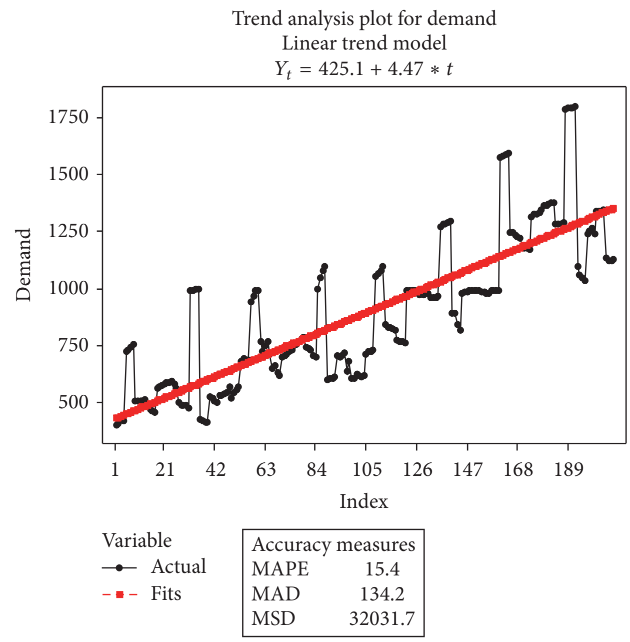


Figure 5: Linear trend line analysis of demand.

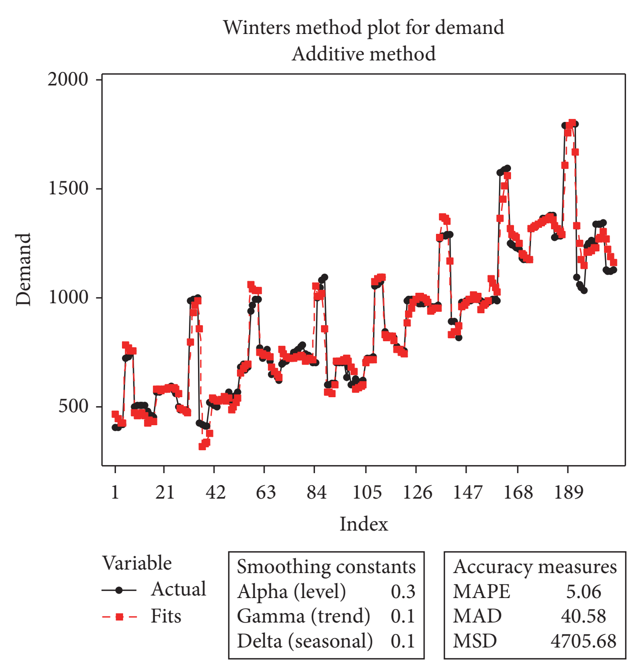


Figure 6: Comparison of actual sales with forecasted demand in Winters additive method.

of eight forecasting methods is evaluated and results show that the suitable method is Winters additive model to forecast their actual demand. This study can help the industry as well as others Bangladeshi manufacturers to reduce the deviation between actual and forecasted demand through the selection of the contingent forecasting method.

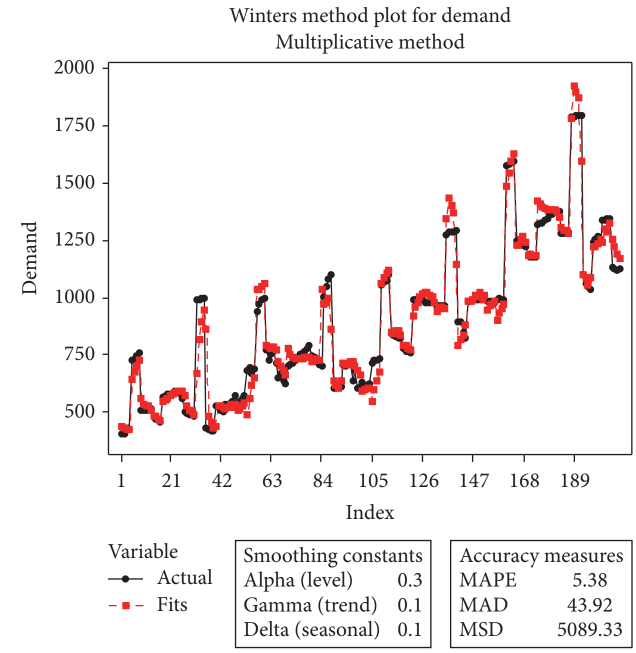


Figure 7: Comparison of actual sales with forecasted demand in Winters multiplicative method.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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