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FORECASTING OF BSE SENSEX USING SIMPLE EXPONENTIAL SMOOTHING (SES) METHOD

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ABSTRACT

Forecasting is the prediction of variable based on known past values of that variable or other related variables. The art of forecasting is learned by experience rather than by academic study. Forecasts must results in present action to improve future. In this study, we discussed about Simple Exponential Smoothing (SES) method. By using this method, we forecast the BSE SENSEX closing point value and then compare the method with the help of RMSE measure.

KEYWORDS: *Simple Exponential Smoothing (SES), Bombay Stock Exchange (BSE) and Root Mean Square Error (RMSE).*

INTRODUCTION

The current study is focused on financial variables and hence the data considered for empirical analysis is drawn from the financial organizations. The data for the study is collected from Bombay Stock Exchange (BSE) which is one of chief trading center where almost all Indian companies are listed out for trading. Even though, there are large number of financial indices are available in this domain, the planned variable considered for the analysis of the study is BSE SENSEX. SENSEX is the short form of sensitive index and it is one of primary indices of Bombay Stock Exchange. Based on SENSEX, several investors plan their financial investments. Some of the organizations look it as a standard index.

1.0 METHODOLOGY

1.1 EXPONENTIAL SMOOTHING FORECASTING MODELS

There are three types of exponential smoothing models. They are, simple exponential smoothing or first order exponential smoothing, second order exponential smoothing and higher-order exponential smoothing.

1.1.1 First Order Exponential Smoothing

The first and the simplest of all the smoothing methods is simple exponential smoothing. If we have data with no clear trend or seasonal pattern then we can use the simple exponential smoothing method. The graph in figure 1.1 is a better example of such Data.

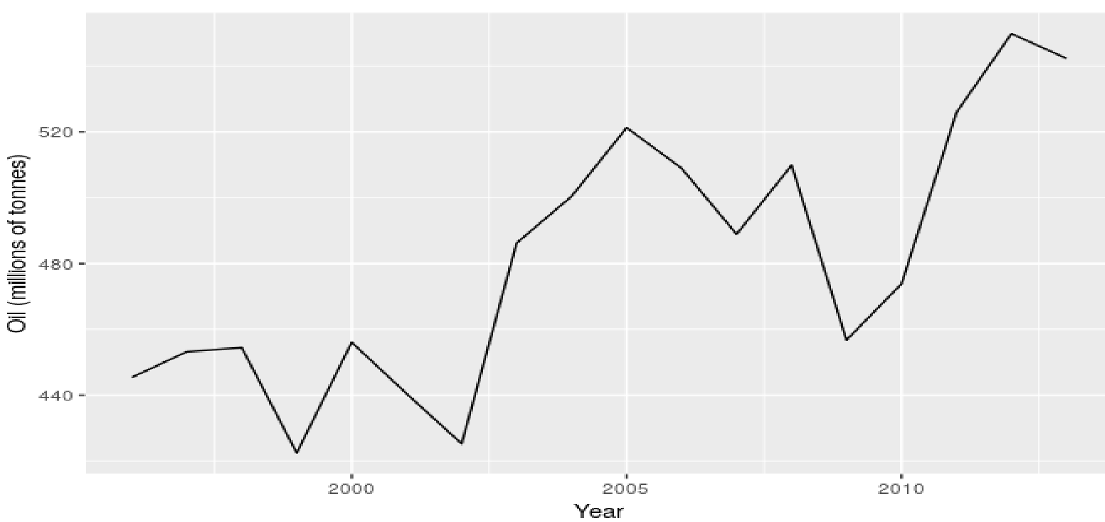

Figure 1.1: Time Series Plot for Simple Exponential Smoothing

The first order exponential smoothing extends this current approach by providing exponential to historical data points where weights decrease exponentially from the most recent data point to the oldest. The first order exponential smoothing can be defined as follows:

$$F_{t+1} = \propto x_t + \propto (1-\propto) x_{t-1} + \propto (1-\propto)^2 x_{t-2} + \cdots \qquad \ldots (1.1)$$

Here, α is the smoothing factor that lies in the interval [0, 1] and controls the rate at which weights decrease and x_t is the observed value at time t. In figure 1.2, smoothing process demonstrates the decay of weights with a different smoothing factor, α. Here, the higher value of α leads to a faster decay of weights; thus, historical data will have less impact on the forecasted value.

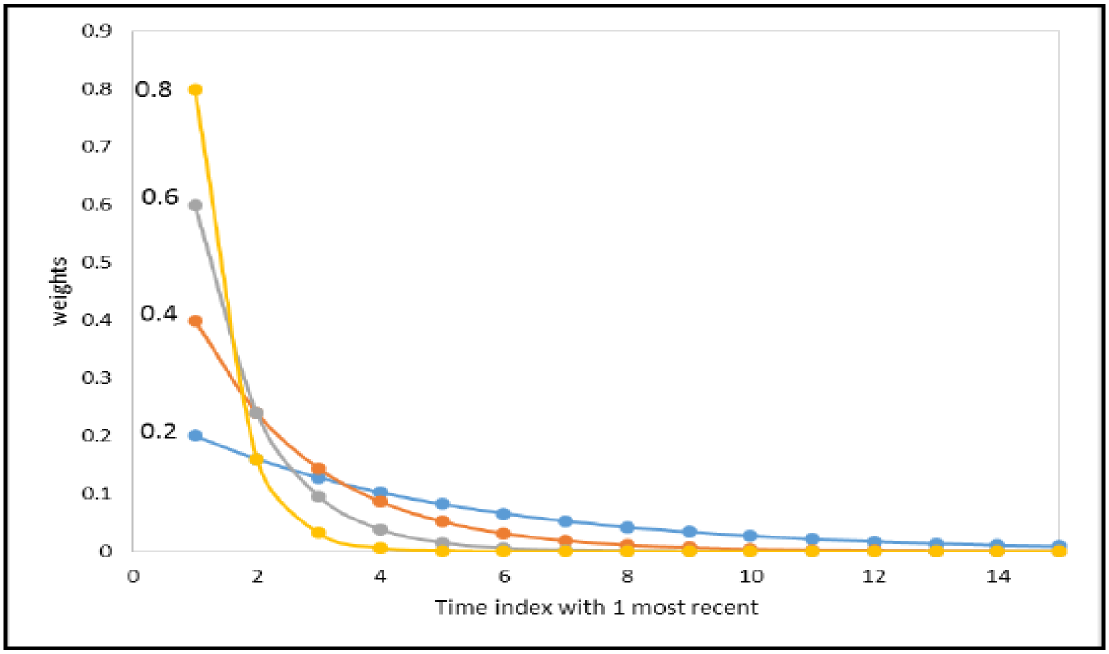

Figure 1.2: Smoothing Process with Different Smoothing Factors

1.1.2 Second Order Exponential Smoothing

If first order exponential smoothing does not perform well, then there is a trend in the time series data. The trend is commonly observed in many domains such as when marketing campaigns are run by e-commerce companies, the sales rise or any good annual performance by a company will have a bullish effect on its stock prices. The linear trend can occur due to relation between time and response, then,

$$x_t = \text{constant} + \omega_t + \varepsilon_t \qquad \ldots (1.2)$$

Here, ω is the coefficient that leads to trend. The second order exponential smoothing helps to capture the trend in time series data by including another term to the first order exponential smoothing as follows:

$$F_t = \propto x_t + (1 - \propto)(F_{t-1} + T_{t-1}) \qquad \ldots (1.3)$$

Here, T_t captures the trend component of the exponential smoothing and it can be represented as follows:

$$T_t = \beta(F_t - F_{t-1}) + (1 - \beta)T_{t-1} \qquad \ldots (1.4)$$

Also, α is the data smoothing factor and β is the trend smoothing factor with values that lies in the interval [0, 1]. The next stage forecast can be generated as follows:

$$F_{t+1} = F_t + T_t \qquad \ldots (1.5)$$

1.1.3 Higher Order Exponential Smoothing

The concept can be further extended to higher-order exponential smoothing with an n^th order polynomial model as

$$x_t = \alpha_0 + \alpha_1 t + \frac{\alpha_2}{2!} t^2 + \cdots + \frac{\alpha_n}{n!} t^n + \varepsilon_t \qquad \ldots(1.6)$$

Here, error $\varepsilon_t \sim N(0, \sigma^2)$ is normally distributed with mean 0 and variance σ^2. The exponential smoothers used for higher order are as follows:

$$\left.\begin{array}{l} F_t^{(1)} = kx_t^{(1)} + (1-k)x_{t-1}^{(1)}\alpha_1 t \\ F_t^{(2)} = kx_t^{(2)} + (1-k)x_{t-1}^{(2)}\alpha_1 t \\ \quad\vdots \qquad\quad \vdots \qquad\qquad \vdots \\ F_t^{(n)} = kx_t^{(n-1)} + (1-k)x_{t-1}^{(n)}\alpha_1 t \end{array}\right\} \qquad \ldots(1.7)$$

Now we will apply the exponential smoothing for the BSE data and forecast the BSE closing point value. The graph in figure 1.3 shows the movements of BSE closing points from January 2000 to February 2018.

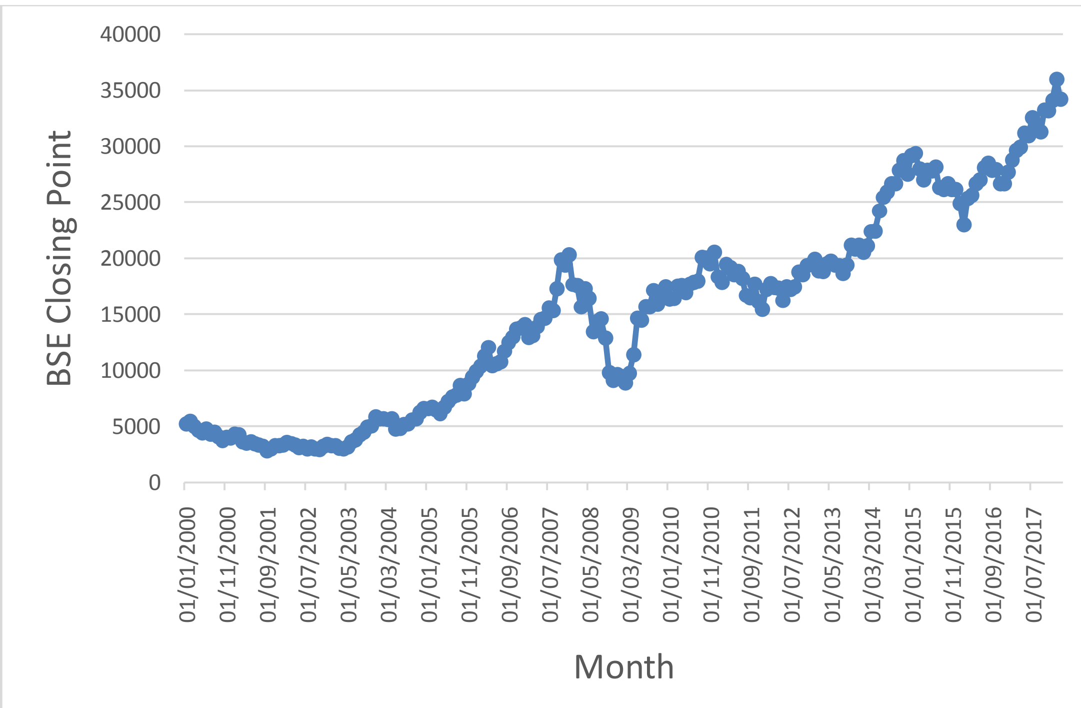

Figure 1.3: Time Series Plot for BSE Closing Points

To understand the movements of the BSE index, let us have a close look at the data by year. In figure 1.4, we have a Box-plot by year.

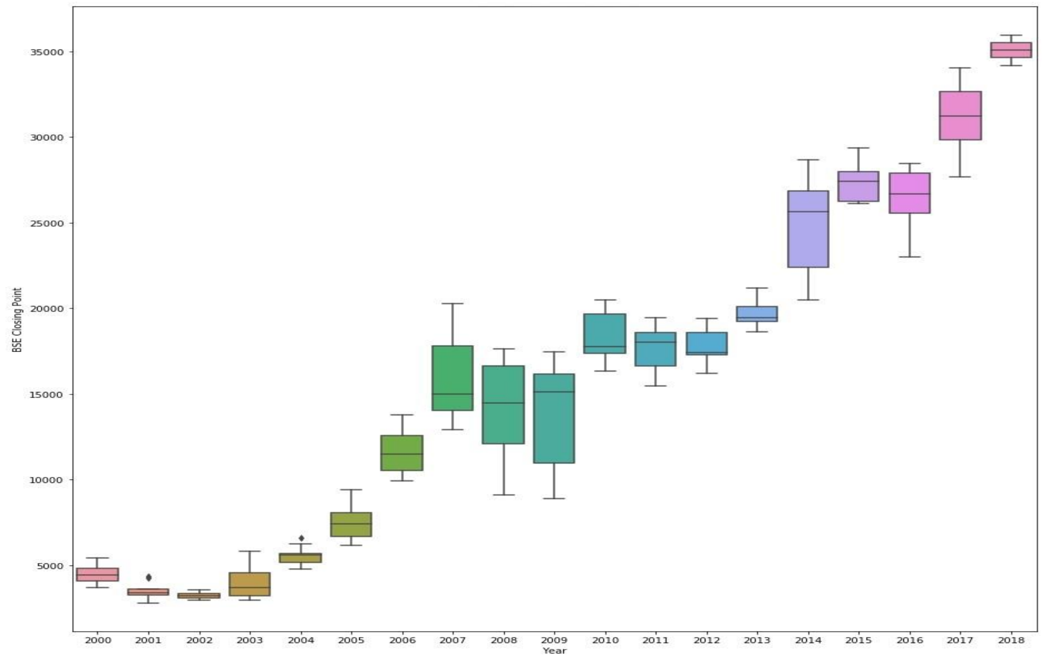

Figure 1.4: Box-Plot of Time Series for BSE Closing Points

From the above box-plot, we can observe that the BSE index has increased tremendously over the past 17 years from 5 thousand points to 35 points and there is high volatility in the years 2007, 2008 and 2009, which is caused by the global recession. From 2014, the Indian market got the momentum and ever since it has an increasing trend, the main reason may be the political conditions in India and global economic situations. Now let us see how exponential smoothing helps us in forecasting the BSE index.

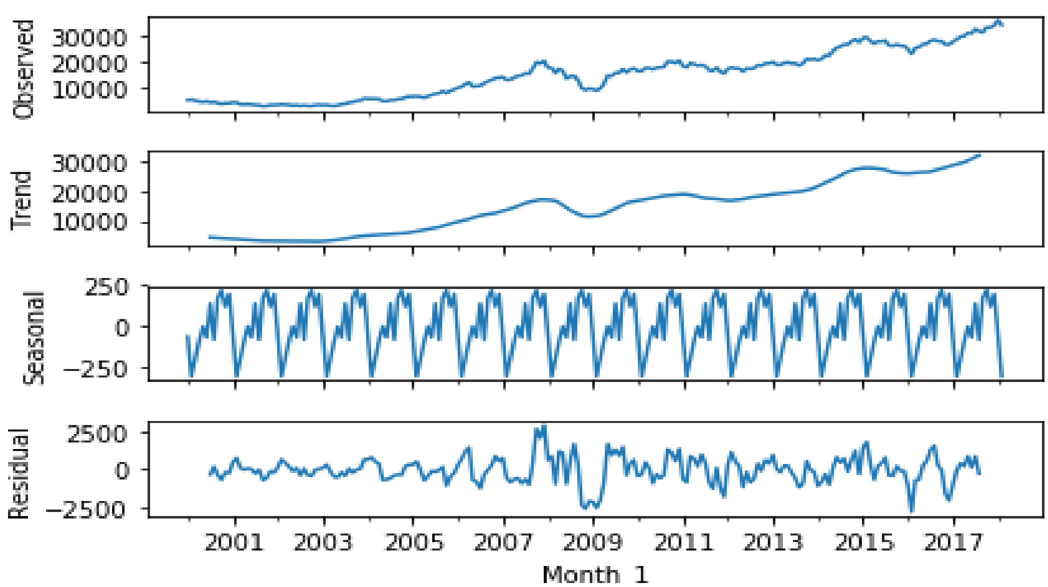

Figure 1.5: Time Series Decomposition Graph for Observed, Trend, Seasonal & Residual Values

In figure 1.5, from the above time series decompose graph, we can see that there is increasing trend in the BSE index data and it has high residuals around 2009 and 2015.

1.2 RESULTS AND DISCUSSION

Now we consider the method of fitting by simple exponential method to the BSE data and forecast the BSE closing point values. We know that the smoothing parameter α has a great impact on forecasting; so, the right α value is critical during forecasting. From the graphs in figures 1.6 to 1.8, we can see the actual values Vs the forecasting values at different α levels.

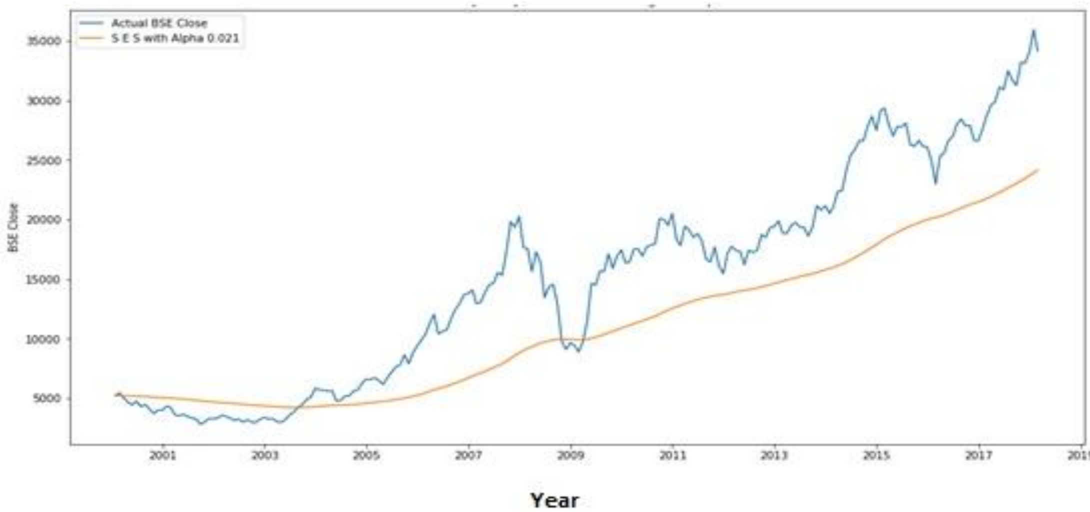

Figure 1.6: Actual Vs Forecasted Values by Simple Exponential Smoothing with α = 0.021

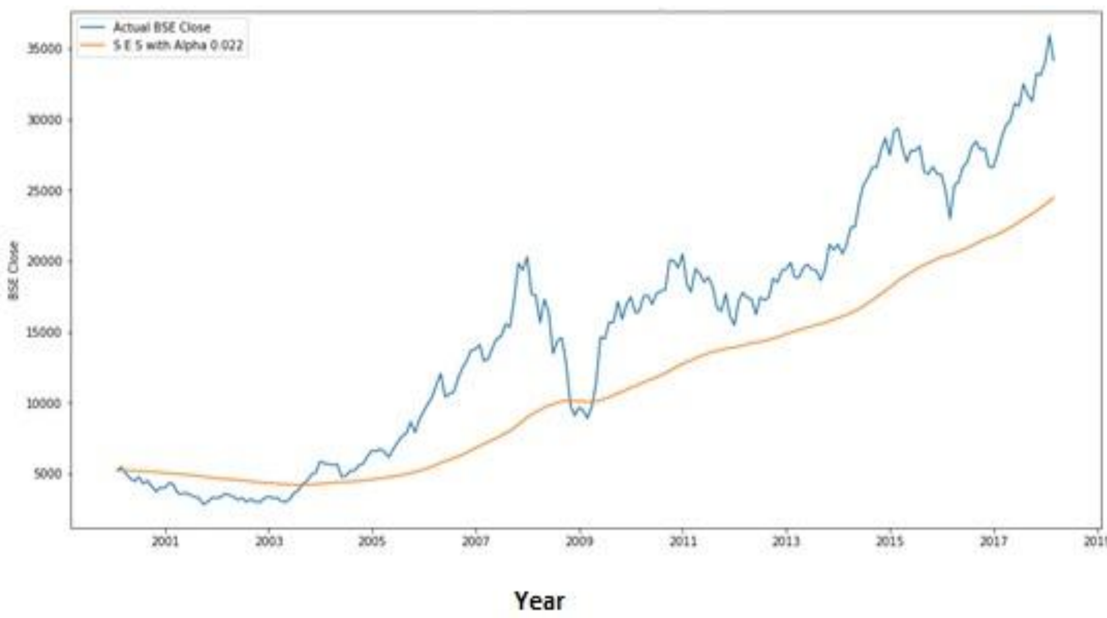

Figure 1.7: Actual Vs Forecasted Values by Simple Exponential Smoothing with α = 0.022

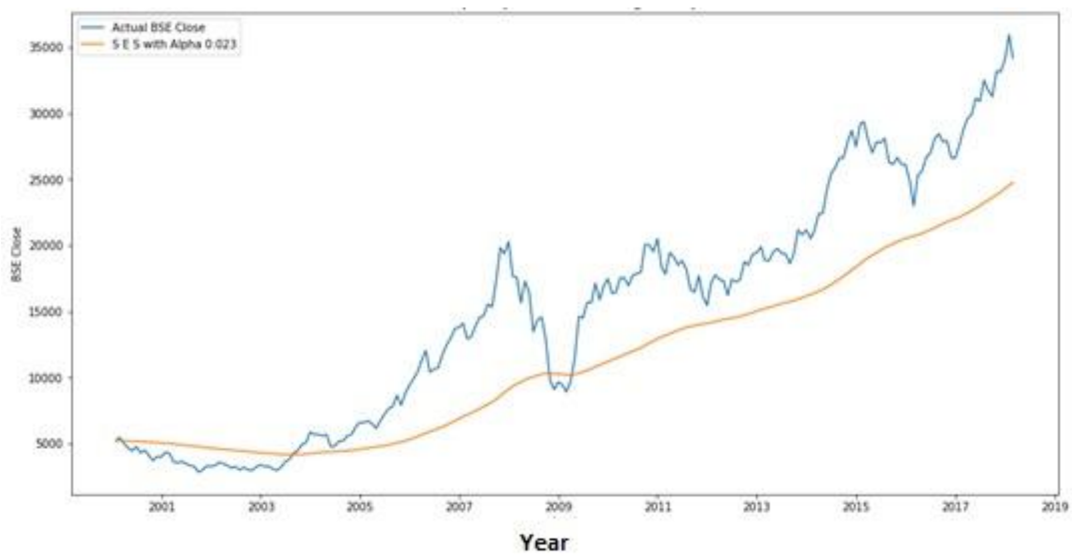

Figure 1.8: Actual Vs Forecasted Values by Simple Exponential Smoothing with α = 0.023

The graphs in figures 1.6 to 1.8 shows that the simple exponential smoothing with α equal to 0.023 has higher impact and also the forecasted values are close to the actual values. Since it is difficult to make a decision on the accuracy of values from the graph, we need to obtain accuracy measure like RMSE value which is given in table 1.1.

TABLE 1.1: RMSE VALUES FOR DIFFERENT A LEVELS

S E S Alpha Value	RMSE
0.021	5448.6706
0.022	5299.1995
0.023	5158.8394

The RMSE value at α = 0.023 is equal to 5158.8394 which is observed to be minimum compare to other RMSE values obtained from different values of α. Hence, the fitted equation under this method for BSE SENSEX Closing Point is given by

$$\mathrm{F}_{t+1} = 0.023 * X_t + (1 - 0.023) * F_{t-1} \qquad \text{…. (1.8)}$$

Here, F_{t+1} is the forecast for time period t +1

X_t is the actual value for time period t

F_{t-1} is the previous period forecast

In the figure 1.9, the fitted model is used to forecast the future values for all time periods of BSE SENSEX Closing Points.

Figure 1.9: Actual values Vs Forecasted Values of BSE SENSEX Closing points by using SES Method at α = 0.023

In figure 1.10, we have the actual values versus the forecasted values only for the forecasted period.

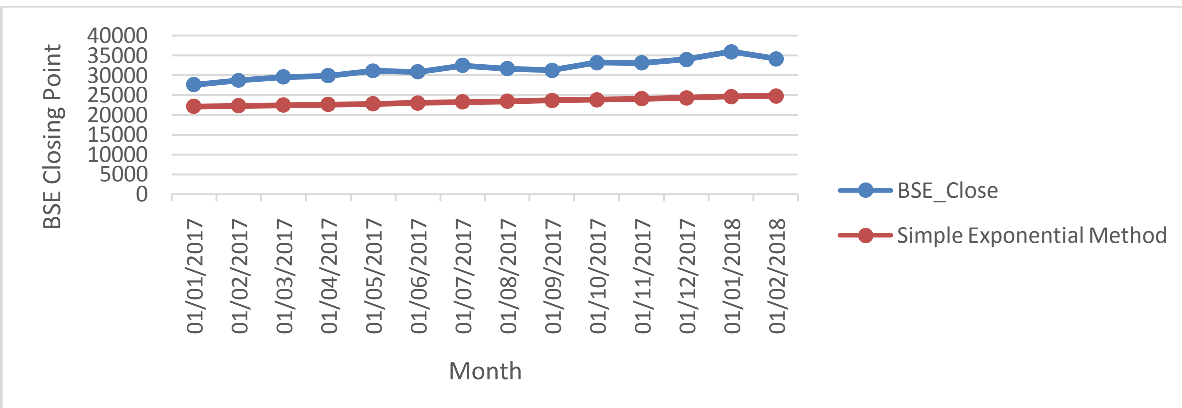

Figure 1.10: Actual values Vs Forecasted Values of BSE SENSEX Closing points by using Simple Exponential Smoothing Method only for Forecasted Period

Table 1.2 exhibits the Actual values and forecasted values that are obtained by using Simple Exponential Smoothing method. The RMSE value obtained by this method is 5158.8394

TABLE 1.2: ACTUAL AND FORECASTED VALUES OF BSE SENSEX CLOSING POINTS FOR THE FORECASTED PERIOD BY USING SES METHOD

	BSE Closing Index	
Month	**Observed values**	**Forecasted values**
01-01-2017	27655.96	22142.04581
01-02-2017	28743.32	22293.87511
01-03-2017	29620.5	22462.38749
01-04-2017	29918.4	22633.87577

01-05-2017	31145.8	22829.65003
01-06-2017	30921.61	23015.76511
01-07-2017	32514.94	23234.24613
01-08-2017	31730.49	23429.65974
01-09-2017	31283.72	23610.30313
01-10-2017	33213.13	23831.16815
01-11-2017	33149.35	24045.48633
01-12-2017	34056.83	24275.74723
01-01-2018	35965.02	24544.60051
01-02-2018	34184.04	24766.30762

1.3 CONCLUSION

In this Study, we discussed about the traditional time series forecasting method like Simple Exponential Smoothing (SES). We applied this method on the BSE SENSEX closing point value and forecasted the BSE closing point value for the period from January 2017 to February 2018. We used Root Mean Square Error (RMSE) measure to compare different values of α. The RMSE value at α = 0.023 is equal to 5158.8394 which is observed to be minimum compare to other RMSE values obtained from different values of α.

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