Comparative study of the Application of Seasonal ARIMA and Exponential Smoothing Methods in Nigerian Stock Exchange Market

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Abstract

This paper compared the performance of two forecasting models (Seasonal ARIMA and Exponential smoothing) in an attempt to identify the model that fits properly in forecasting Nigerian stock exchange market. A two-staged approach to forecasting was carried out using monthly data for the period of 1985 to 2013. The models were assessed in similarly structured setting at the beginning, and then best models identified at this level were compared in a differently structured setting. The results show that Seasonal ARIMA (4,1,3)(3,1,2)12 and Holt-Winters multiplicative smoothing method are effective in forecasting Nigerian stock exchange market in a similarly structured setting. Nonetheless, when the two models were compared under different structures, the performance of Holt-Winters multiplicative smoothing method outperformed that of Seasonal ARIMA (4,1,3)(3,1,2)12. This suggests that Holt-Winters multiplicative smoothing method with Alpha (0.01), Delta (0.11) and Gamma (0.11) is more effective in forecasting Nigerian stock exchange market in the short run and it can be used to aid planning processes in the stock exchange market. Likewise, the seasonality pattern that characterizes stock exchange highlights the need to promote more of stock exchange market so as to lessen the negative impacts associated with it. The two models can be adequately used to forecast stock exchange data as the results have shown their potentiality in that regard.

Keywords: Seasonal ARIMA, Exponential smoothing, Holt-winters, Forecasting model, stock Exchange

1.0 Introduction

The stock exchange sector is recognized as a growing exchange market which plays a significant role in trade, economic and social development. A large number of countries worldwide depend on this for their economic growth. Well-functioning stock exchange market enables economic growth and development by facilitating the mobilization of financial resources between business and institutions that needs capital to transform and grow..

Several studies have proposed that ARIMA and Exponential Smoothing methods are better Forecasting models and have been used by many researchers than either econometric or other time-series models. A study conducted by Kulendran and Wong (2005) suggests that ARIMA provides more accurate forecasts for a time series that has fewer seasonal variations, whereas SARIMA provides more accurate forecasts for a time series that has a strong seasonal variation. Also, from the ARIMA scheme's perception of forecasting the Nigerian stock market earnings, Ojo and Olatayo (2009) studied the estimation and performance of subset autoregressive integrated moving average (ARIMA) models. They estimated parameters for ARIMA and subset ARIMA processes using numerical iterative schemes shows the performance of the models and their residual variance were examined using AIC and BIC. The result of their study indicated that the SARIMA model outperformed the ARIMA model with smaller residual variance. On the other hand, Atis& Erer (2017) studied the NSE market returns series using monthly data of the All-Share-Index for the period January 1985 through December 2008. In his study, an ARIMA (1,1,1) model was selected as a tentative model for predicting index points and growth rates.

The results revealed that the global meltdown destroyed the correlation structure existing between the NSE All-Share-Index and its past values. Agwuegbo et al. (2010) also studied the daily returns process of the Nigerian Stock Market using Discrete Time Markov Chains and martingales. Their study provided evidence that the daily stock returns process follows a random walk, but that the stock market itself is not efficient even in weak form. Several other studies that have used ARIMA schemes for analysis and forecasting of stock market prices/or returns in Africa include Simons and Laryea (2004), Rahman and Hossain (2006), and Al-Shiab (2006) among others. These studies did not test whether or not the stock price/or returns processes are fractal in nature.

The other popular and widely used forecasting model in time series analysis is exponential smoothing. Ostertagova and Ostertag (2012) argue that exponential smoothing is characterized by simplicity, computational efficiency, ease of adjusting its responsiveness to changes in the process of forecasting, and it is reasonable accuracy. Ravinda (2013) in his study on Forecasting with Exponential Smoothing argues that when there is no trend in the data, simple exponential smoothing will yield a minimum error when α value is small, in the range 0.0 – 0.3. This is true to small series (n=12) as well as large (n=60) and when there is a linear trend in the data, the performance of double exponential smoothing depending on the initial estimates of the level and trend components is good. Dimitrov (2008) explains also the primacy of exponential smoothing in forecasting, as the name suggests the weights attached to past time periods in forming the forecast decline exponentially. That is, the weights decrease rapidly at first and then less and less and so as the time period becomes older. The weight attached to a particular value approaches, but never quite reaches zero. This method generates accurate forecasts for many time series variables, recognizing the decreasing impact of past time periods as they faded further into the past. There are several types of exponential smoothing models which can be applied in forecasting depending on the nature of data in consideration for instance single exponential smoothing smoothed data by computing exponentially weighted averages and provides short-term forecasts. Double exponential smoothing provides short-term forecasts as previous methods. This procedure can work well when a trend is present, but it can also serve as a general smoothing method. This method is found using two dynamic estimates, α and β (with values between 0 and 1). Whereas winter's Method smoothed data by Holt-Winters exponential smoothing and provides short to medium range forecasting. This can be used when both trend and seasonality are present, with these two components being either additive or multiplicative. Winters' Method calculates dynamic estimates for three components; level, trend and seasonal denoted by α, β and γ (with values between 0 and 1) (Holt, 1957). However, the literature shows that there is no single model that consistently outperforms other models in all situations; therefore, this paper attempts to compare the two approaches in order to arrive to the best method that can be used in forecasting Nigerian stock exchange market. Khan and Alghulaiakh (2020) expressed the potential of ARIMA model in stock forecasting so as to produce an accurate prediction on stocks data which will help investors in their investments decisions.

2.0 Statement of the Problem

Forecasting of stock exchange in the stock market is a noticeable subject for many years now. The current econometric models has been enhanced depending on uses (Zotteri.,et al.,2005). The efficient and robust models are Auto Regressive Integrated Moving Average (ARIMA) models, which are used to forecast the financial time series data for short term than the other techniques such as Artificial Neural Networks, etc., (Yung joo et al.,2007, Merh et al.,2010, Sterba, 2010). Many researchers worked in ARIMA forecasting models to predict the future stock exchange (Khasel et al., 2009, Lee, Ho, 2011 and Khashei et al. 2012).

Consequently, since many studies have suggested that ARIMA and Exponential Smoothing methods are better forecasting models than either econometric or other time-series models, this study therefore attempts to compare ARIMA model and exponential smoothing model to know which one is a better forecasting model for the stock exchange market

3.0 Research Questions

This paper is driven by three research questions as stated below:

i How ARIMA and exponential smoothing models enhance stock exchange forecasting?

ii Can each of the forecasting model contribute to the improvement of stock exchange forecasting?

iii What is the strength and role of the ARIMA and exponential smoothing in stock exchange market?

4.0 Data and Methodology

This paper uses monthly Nigerian stock exchange market data from January, 1985 to December, 2014. It uses two important methods of time series forecasting which are seasonal ARIMA and Exponential smoothing models.

4.1 Seasonal ARIMA

ARIMA models depend on a statistical modeling theory known as the Box–Jenkins methodology. This methodology is concerned with iteratively building a model that accurately represents the past and future patterns of a time series (Louvieris, 2002). The ARIMA modeling approach expresses the current time series value as a linear function of past time series values (AR) and current lagged values of a white noise process (MA). The ARIMA model, which can be fitted to seasonal time series (quarterly or monthly observations), consists of seasonal and non-seasonal parts; the seasonal part of the model has its own autoregressive and moving average parameters with orders P and Q while the non-seasonal part has orders p and q (Kulendran and Wong, 2005). The AR, MA, or ARMA models are often viewed as stationary processes, that is, their means and covariances are stationary with respect to time. Since we are using monthly data with seasonal pattern we use ARIMA (p, d, q), (P, D, Q)s.

Where

(p,d,q)= Non-seasonal part of the model, (P,D,Q)= Seasonal part of the model, (S)= Number of periods per session

$$(1-B^p)(1-B^s)Y_t f_p(B^p) = c + e_t q_{q(}B^q{}_{)+} Q_Q(B^Q) \qquad 1.0$$

Where

$(1-B^r)$ = The regular difference of order r, $(1-B^s)$ = the exchange data, $f_{b(B^p)}$ = the regular autoregressive terms, $F_{p(B^p)}$ = the seasonal autoregressive terms, C = Constant term, εt = the residuals (error term), $q_{q(B^q)}$ = the regular moving average terms and $Q_{Q(B^Q)}$ = The seasonal moving average terms.

Then, we create a catalog of autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to determine whether or not seasonal difference is needed. The graph of the sample of autocorrelation function (ACF) and partial autocorrelation function (PACF) are drawn. The ACF measures the amount of linear dependence between observations in a time series that are separated by a lag q. The PACF helps to determine how many autoregressive terms in p are necessary (Chang, 2012). The general features of theoretical ACFs and PACFs are shown in table 1

Table1: Features of ACF and PACF in seasonal ARIMA Model

Model	ACF	PACF
AR	Spikes decay towards zero	Spikes cutoff to zero
MA	Spikes cutoff to zero	Spikes decay to zero
ARMA	Spikes decay to zero	Spikes decay to zero

Source: Pankratz (1983)

Seasonal ARIMA model requires diagnostic checking (or model validation); before can be used for forecasting application. This is done by checking for normality of the residuals. The check of model adequacy is provided by the Ljung- Box Q statistic. The test statistic Q is given by

$$Q^1 = T(T+2)\sum_{k=1}^{p}\left(\frac{pk^2}{T-k}\right) \qquad 2.0$$

Where pk is the sample autocorrelation at lag k

4.2 Exponential Smoothing

While in seasonal ARIMA the past observations are weighted equally, on the other hand, exponential smoothing produces a smoothed time series. Exponential Smoothing assigns exponentially decreasing weights as the observation get older where as there are one or more smoothing parameters to be determined (or estimated) and these choices determine the weights assigned to the observations (Dimitrov, 2008). With regard to exponential smoothing, this paper uses two exponential smoothing techniques which are Holt-Winters additive and Holt-Winters multiplicative exponential smoothing to determine the appropriate forecasting model. Holt (1957 and winters (1960) extended Holt's method to capture seasonality. The holt-winters seasonal method comprises the forecast equation and three smoothing equations, one for the level, one for trend and the other for the seasonal component. There are two variations to this method that differ in the nature of the seasonal component. The additive method is preferred when the seasonal variations are roughly constant through the series while the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series. With additive method, the seasonal component is expressed in absolute terms in the scale of the of the observed series and in the level of equation, the series is seasonally adjusted by subtracting the seasonal component. With multiplicative method, the seasonal component will add up to approximately zero. The seasonal component is expressed in relative terms (percentage) and the series is seasonally adjusted by dividing through by the seasonal component. According to Hyndman and Athanasopoulos (2013), both multiplicative and additive models give the same point forecasts with varying prediction intervals. Here we report the most favorable results for ETS by evaluating between point forecasts and prediction intervals.

4.2.1 Holt-Winters Additive Method

The Holt-Winters methods include estimates of the seasonal factors for periods (denoted by S). The parameters p, states the number of seasonal periods in a year. For example, p = 12 would correspond to monthly seasonal adjustments and p = 4 would correspond to quarterly seasonal adjustments. In the additive version, the forecast for period t+n (n periods after the current period) is given by

$$E_t = \alpha\left(A_t - S_{t-p}\right) + (1-\alpha)\left(E_{t-1} + T_{t-1}\right) \qquad 3.0$$

$$T_t = \beta\left(E_t - E_{t-1}\right) + (1-\beta)T_{t-1} \qquad 4.0$$

$$S_t = \gamma\left(A_t - E_t\right) + (1-\gamma)S_{t-p} \qquad 5.0$$

$$F_{t+n} = E_t + nT_t + S_{t+n-p} \qquad 6.0$$

α and β smooth the base and the trend while the parameter $\gamma\left(0 < \gamma < 1\right)$ is used to smooth the trend.

4.2.2 Holt-Winters Multiplicative method

The multiplicative version of the Holt-Winters method uses seasonal factors as multipliers rather than additive constants. The forecast for period $t+n$ is given by

$$E_t = \alpha \frac{A_1}{S_{t-p}} + (1-\alpha)(E_{t-1} + T_{t-1}) \qquad 7.0$$

$$T_t = \beta(E_t - E_{t-1}) + (1-\beta)T_{t-1} \qquad 8.0$$

$$F_{t+n} = (E_t + nT_t) + S_{t+n-p} \qquad 9.0$$

4.2.3 Comparative Analysis between Seasonal ARIMA and Exponential Smoothing Models

When making comparison between Seasonal ARIMA and Exponential smoothing methods, forecasting was carried out for a period of 6 months. We use Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), the Bayesian Information Criterion (BIC), and Mean Absolute Deviation (MAE) to determine the most effective model in forecasting tourist arrivals. While MAPE is useful for purposes of reporting, it expresses accuracy as a percentage of the error, RMSE's value is minimized during the parameter estimation process, and it is the statistic that determines the width of the confidence interval for prediction. On the other hand, MAE gives the relative measure of error that is applicable to time series data, it expresses accuracy in the same unit as the data, which becomes easier to conceptualize the amount of error and BIC is preferred by statisticians because it has the feature that if there is a true underlying model, then with enough data BIC will select that model. We use the following measures of accuracy to identify the best model.

$$MAPE = \frac{100}{n} \sum \left| \frac{e_t}{A_t} \right| \qquad 10.0$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} e_t^{\,2}} \qquad 11.0$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |A_t - F_t| \qquad 12.0$$

$$BIC = -2\ln(L) + \ln(N)k \qquad 13.0$$

Where

e_t is the forecast error which is calculated by subtracting the forecast value from the actual value in the series. A_t and F_t represent actual and forecast values respectively. L is the value of the likelihood function evaluated at the parameter estimates while N and k denote the number of observations and the number of estimated parameters respectively. Minimum values of these accuracy measures provide the best results in the models.

5.0 Results and discussion of findings

Figure 1 below presents the time series plot of stock exchange from January, 1985 to December, 2013. According to Song and Li (2010), seasonality is a notable characteristic of a data request and cannot be ignored in the modeling process when monthly or quarterly data are used. In determining whether stock exchange data reveals some seasonality features or not, we use time series plot, descriptive statistics and seasonal factors to examine the pattern of data.

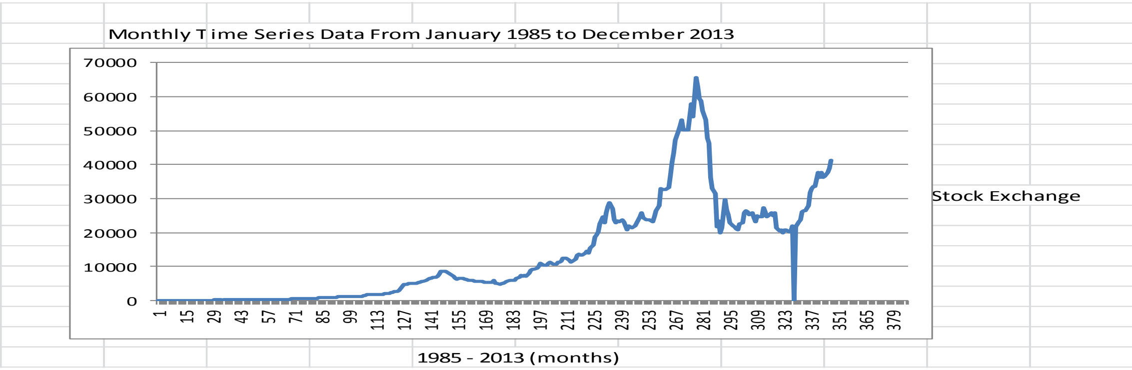

Figure1 showing the time series plot of the stock exchange data

5.1 ARIMA Models

The Box-Jenkins methodology was used in the choice of the appropriate Seasonal ARIMA model. The first stage of the Seasonal ARIMA model building is to identify whether the variable which is being forecasted is stationary in time series or not. By stationary we mean, the values of variables over time varies around a constant mean and variance. The time plot of the stock exchange data in figure1 above clearly shows that the data is not stationary. We then further, examine the Auto correlation Function (ACF) and Partial Autocorrelation Function (PACF).

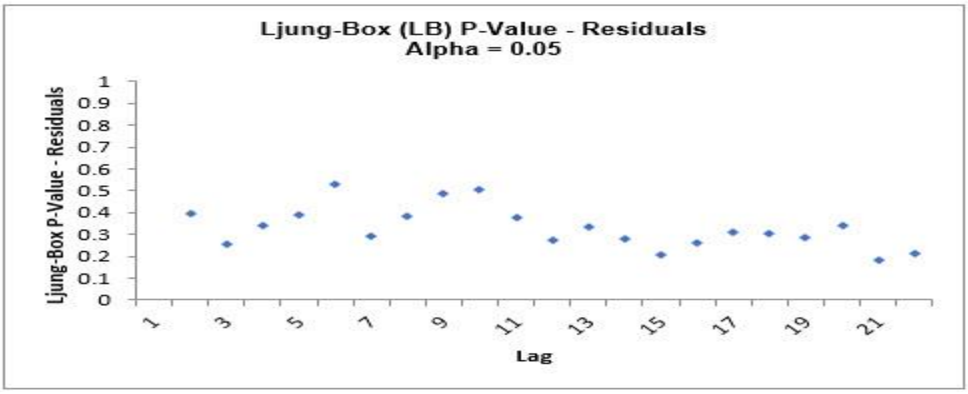

Figure2: Ljung-Box p-value

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) can provide valuable insights into the behaviour of time series data. They are frequently used to decide the number of Autoregressive (AR) and Moving Average (MA) lags for the ARIMA models. Also, they can help identify any seasonality within the data. Accurate application and interpretation are vital in extracting useful information from the ACF and PACF plots.

The ACF and PACF plots can be obtained from the original data, as well as from the residuals of a model. On the original data, these plots can aid in detecting any autoregressive or moving average terms that may be significant in the time series. When applied to the residuals, these plots can detect any remaining autocorrelation in the model. This also provides insight into whether additional AR or MA terms need to be included in the model. Similarly, they can detect any seasonal behaviour that must be accounted for in the model.

Plots for Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

ACF and PACF for Stock exchange

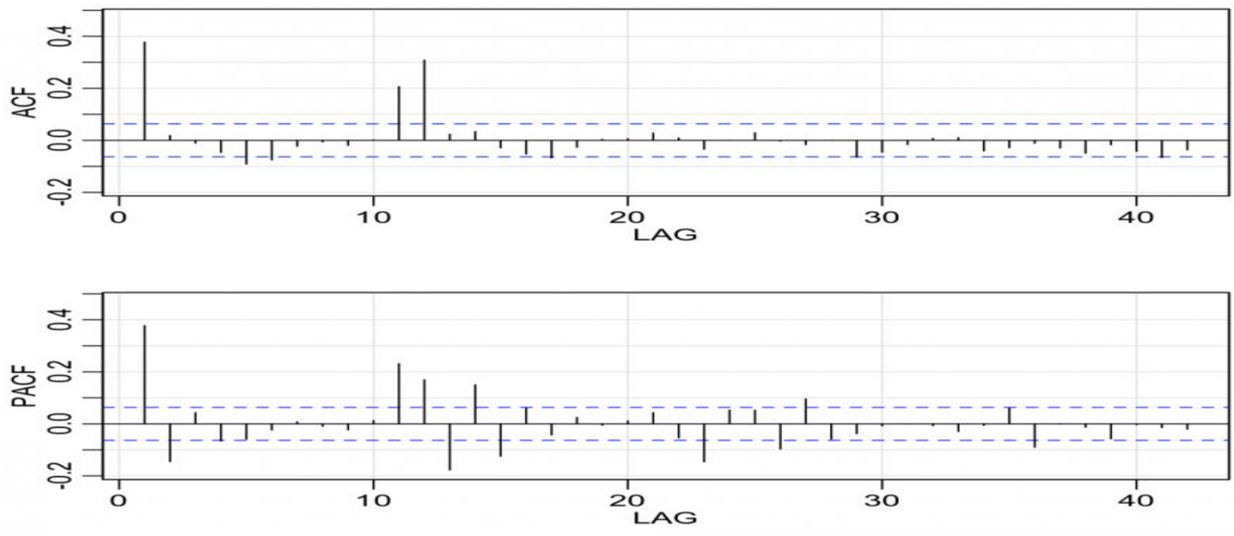

Figure3: ACF and PACF for the stock exchange data

The plots for ACF and PACF showed the presence of spikes outside the minor regions. ACF shows higher spikes at lag1, lag11 and lag 12 while PACF indicates spikes at lag1, lag11 and lag12. This suggests the seasonal structure of the data is non-stationary. Therefore, the differencing of the data was carried out in order to make the data stationary.

Table2: The Results of MAPE, RMSE, BIC and values of fitted Seasonal ARIMA

ARIMA Models	MAPE	RMSE	BIC	MAE
ARIMA (3,1,3) (3,1,4)	12.696	8541.112	17.814	6457.105
ARIMA (4,1,3) (3,1,2)	10.037	7138.342	17.017	5562.083
ARIMA (3,1,4) (4,1,2)	11.293	7555.440	17.729	5833.758
ARIMA (3,1,1) (3,1,5)	12.682	9545.769	17.850	6393.924
ARIMA (4,1,2) (4,1,4)	11.434	8738.117	17.748	6027.764
ARIMA (2,1,4) (2,1,4)	11.244	8426.463	17.519	5794.019
ARIMA (3,1,3) (2,1,1)	11.726	7347.621	17.587	5943.829
ARIMA (3,1,4) (2,1,4)	11.872	7415.091	17.553	6169.576
ARIMA (2,1,3) (2,1,2)	11.649	8339.253	17.592	6231.654

Table2 above shows the performance of Seasonal ARIMA, several seasonal models were identified. It was observed that out four measures of accuracy, the performance of ARIMA(4,1,3)(3,1,2)12 was comparatively better in three measures of accuracy which are MAPE (10.037), RMSE (7138.342) and MAE (5562.083) when compared with other ARIMA models.

The Ljung-Box (*Q*) statistics were computed for checking residuals in seasonal lags of 1, 11, and 12. The Ljung-Box *Q* statistics is a diagnostic measure of white noise for a time series, assessing whether there are patterns in a group of autocorrelations under the hypotheses with (kp-q-P-Q) degree of freedom (Çuhadar, 2014).

5.2 Exponential Smoothing Models

In examining exponential smoothing models we use the Sum of the Squared Error (SSE) and the Mean Squared Error (MSE). The minimum values of SSE and MSE are preferred. The parameters of Alpha (α), Gamma (β) and Delta (γ) which minimizes the values of SSE and MSE were identified through an iteration process.

Table3: Experimental Smoothing Parameters

Model	α (level)	β (Growth)	γ (Seasonal)	SSE	MSE
Holt-Winter's Multiplicative model	0.01	0.11	0.11	3.476E+09	3.218E+07
Holt-Winter's Additive model	0.10	0.12	0.11	3.537E+09	3.275E+07

Table3 above shows that Holt-Winter's Multiplicative exponential smoothing recorded relatively lower SSE and MSE values, this suggests that Holt-Winter's Multiplicative exponential smoothing is appropriate for forecasting stock exchange in similar structure model setting (exponential smoothing models). However, to identify the best model, the performance of Holt-Winter's Multiplicative was compared with that of ARIMA(4,1,3)(3,1,2)$_{12}$ using the results of MAPE, RMSE, BIC and MAE.

Table4: Comparative Analysis of Seasonal ARIMA (4,1,4)(3,1,4)12 and Holt-Winter's Multiplicative Exponential Smoothing

Model	MAPE	RMSE	BIC	MAE
Holt-Winter's Multiplicative model	8.0	3874.573	-50	4629.430
ARIMA(4,1,3) (3,1,2)	10.049	7149.542	17.807	5562.083

In comparative analysis between Seasonal ARIMA and exponential smoothing models, the results in table4 indicate that Holt-Winter's Multiplicative exponential smoothing model recorded relatively lower values in terms of MAPE (8.0), RMSE (3874.573), BIC(-50) and MAE (4629.43). This shows that Holt-Winter's Multiplicative has outperformed other Seasonal ARIMA models. Based on these results, we can conclude that Holt-Winter's Multiplicative model is the best model for forecasting tourist arrivals in the short run.

6.0 Discussion and Conclusion

The objective of this paper was to compare the appropriateness of two models in forecasting the stock exchange. In order to capture the seasonality pattern of the data, the performance of

Seasonal ARIMA, Holt-Winters Additive and Holt-Winters multiplicative exponential smoothing were examined. The findings show that Holt–Winters' multiplicative exponential smoothing model with alpha (0.01), Delta (0.11) and Gamma (0.11) is the more accurate model for forecasting stock exchange when a comparative analysis was carried out using measures of accuracy such as MAPE, RMSE, BIC and MAE. This finding suggests that the seasonal variations of the stock exchange data are changing in proportional to the level of the series. This result corroborates with the study of Nisantha and Lelwala who concluded that Holt–Winter's Exponential Smoothing model with multiplicative seasonality is more accurate. Similarly, studies of Lim and McAleer (2002) and Cho (2003) have confirmed the superiority of exponential smoothing methods in time series forecasting. However, Cuhadar (2014), reported that forecasts by the seasonal exponential smoothing models have provided quite good results among other applied models in forecasting different techniques involving exponential smoothing and univariate ARIMA

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