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APPLICATION OF AUTOREGRESSIVE INTEGRATED MOVING AVERAGE AND HOLT WINTERS METHODS FOR OPTIMUM SALES FORECASTING IN THE MANUFACTURING SECTOR

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Abstract: *This study investigated into the application of autoregressive integrated moving average (ARIMA) and Holt winters methods for optimum sales forecasting of Nestle Nigeria plc, Lagos Nigeria. The purpose of this study is to examine sales forecasting model using ARIMA and Holt Winters methods for short-term decision-making. The specific objectives are to: assess the future sales of Nestle Nigeria Plc. using ARIMA forecasting model, evaluate the future sales of Nestle Nigerian Plc. using Holt Winters forecasting model, examine the optimum forecasting model between ARIMA and Holt Winter for Nestle Nigeria Plc, determine the appropriate forecasting model for Nestle Nigeria Plc. short term forecasting. Secondary data were sourced from yearly sales revenue data of Nestle Nigeria Plc., from 1990 to 2017 and analysed with the aid of Minitab software. Holt winters multiplicative model MAPE, MAD and MSD were 2.3, 1.7 and 4.8 respectively, while ARIMA is 1.8, 1., and 5.4 respectively. The result shows that the appropriate model is ARIMA model for Nestle Nig. to predict short term forecasting since, it has the lower value of the performance metrics. The result also revealed that ARIMA method seem more effective and powerful going by the MAPE result. It was recommended that in advance of attempting simple method of prediction, it is helpful in trying more complex ones equally they have the capacity to make available additional and precise outcomes in certain conditions.*
Keywords*: Forecasting; ARIMA; MAPE; Holt Winter; Decision-Making; Performance metrics.*
JEL Classification*: C53, L25.*

1. Introduction

Forecasting plays a significant role in the effectiveness and performance of organisations and it is about predicting future. Forecasts are based on information of variables of interest. Makridakis *et al* (as cited in Omane-Adjepong, Oduro & Oduro, 2013) stated that the request for forecasting recently is growing, as managers plus executives of different business tries towards reducing over-dependency upon unplanned and instead focus extra on scientific in confronting the challenges. Suwanvijit, Lumley and Choonpradub, (2011) stated that projecting is around expecting the prospect by way of precisely as likely. Prediction is the beginning of planning. Reducing the risk in decision-making is the objectives of forecasting. Success depends largely on getting those forecasts rightly (Incesu, Asikgil & Tez, 2012). Sales forecast is an important element for many organizations, which lead to increase in organization efficiency, increase in revenue and average reduction in costs. Sales forecasting is highly complex because of inner and outside environmental influence. Though, dependable projecting of deals has the ability expand industry plan excellence (Yan & Tu, 2012). It is recognized that appropriate general technique of short-horizon projections of request is generalization of previous movement of transactions. Also, it is important to note that, while forecasting technique provides a prediction of the future, the forecast is only a tool to be used as part of decision-making process. Part of decision is the approval of forecast. That is, managers must decide whether to accept the forecast or devote more resources to obtaining a better forecast. Ultimately, the decision maker makes the decision, usually based on number of sources of information, both subjective and objective. Therefore, this study seeks to use two linear prototypes like ARIMA and HW prototypes to determine the best approach for short-term sales forecasting method in a manufacturing industry using Nestle Nigeria Plc. sales record.

2. Literature Review

Holt-Winters' Model

Holt-Winters model make use of weight to predict future values. According to Chatfield and Yar (as cited by Thoplan, 2014), the HW method is a widely applied predicting technique in TS analysis that considers any underlying trend and seasonal component irrespective of whether it is additive or multiplicative in nature. The HW forecasting procedure is a robust method which is relatively easy to apply. Generally, there are 2 forms of HW-SE technique, an additive or multiplicative process. The seasonal multiplicative HW is invalid where there empty or adverse values time series (Omane-Adjepong et al., 2013). According to Thoplan (2014), the multiplicative form of the HW predicting technique can be directly useful to a time series data outside all previous change. This kind of the HW technique is called non-linear as the idea prediction is a non-linear depending on the former remarks. Though, the additive version of the HW mode can likewise be useful in the hypothesis that the effects seasonality of time series is linear.

Additive Holt-Winters' Seasonal Model

The additive version of the HW forecasting procedure has been successful in some instances in forecasting competitions, Lawton (as cited by Thoplan 2014). The choice of the forecasting method to use depends on its simplicity, accuracy and stability on the time series, Umar (as cited by Thoplan 2014). The Holt-Winters additive way is labeled for the reason that seasonality is extra towards sequences movement that was characterized thru the totality of the degree in addition progress (Pereira et al., 2014). The formula is as shown in the following equations (Zheng & Kim, 2015). This additive periodic prototype at time n+1 was projected in winters as stated below:

$Z_{n+l} = T_{n+l} + S_{n+1} + I_{n+1}$.

Note that I_{n+1} is error term,

T_{n+l} is trend component and

S_{n+1} is seasonality component with the period of s.

If we assume linear trend of T_{n+l}, then

$T_{n+1} = \beta_{0,n} + \beta_{1,n}(n+1) = (\beta_{0,n} + \beta_{1,n}n) + \beta_{1,nl} = T_n + \beta_{1,n}l$ additive seasonality component of s as $S_i = S_{i+s} = S_{i+2s} = (i = 1,2,\ldots s)$ and $\sum_{i-0} S_i=0$. Then Z_{n+l} the forecasting value of future time on n is

$\hat{Z}_n(l) = \hat{T}_n + \hat{\beta}_{1,n} l + \hat{S}_{n+l-s}$, $l = 1, 2\ldots, s$,

$\hat{Z}_n(l) = \hat{T}_n + \hat{\beta}_{1,n} l + \hat{S}_{n+l-2s}$, $l = s + 1, s + 2\ldots,2s$,

$\hat{Z}_n(l) = \hat{T}_n + \hat{\beta}_{1,n} l + \hat{S}_{n+l-3s}$, $l = 2s + 1, 2s + 2, \ldots,3s$

Multiplicative Seasonal Model

The Holt-Winters multiplicative process is labelled for the reason that the seasonality is increased through the movement (Pereira et al., 2014). The formula is as shown in the following equations (Zheng & Kim, 2015).

$Z_{n+l} = T_{n+l} + S_{n+1} + I_{n+1}$

$= (T_n + \boldsymbol{\beta_{1,n} l})\, S_{n+l} + I_{n+l}$.

Where,

the notation for T_{n+l}, S_{n+l} and I_{n+l} are as above and multiplicative seasonal components s as $S_i = S_{i+s} = S_{i+2s} = \ldots$ $(i = 1, 2\ldots, s)$ and $\sum^{s}_{i=0} s_i = s$.

Then Z_{n+l} the forecasting value on n is

$\hat{Z}_n(l) = (\hat{T}_n + \hat{\boldsymbol{\beta}}_{\mathbf{1,n}}\boldsymbol{l}) + \hat{S}_{n+l-s}$, $l = 1, 2\ldots, s$,

$\hat{Z}_n(l) = (\hat{T}_n + \hat{\boldsymbol{\beta}}_{\mathbf{1,n}}\boldsymbol{l}) + \hat{S}_{n+l-2s}$, $l = s +1, s+2\ldots,2s$,

$\hat{}Z_n(l) = (\hat{}T_n + \hat{}\ \boldsymbol{\beta_{1,n}l}) + S\hat{}_{n+l-3s}$, $l = 2s+1, 2s+2\ldots,3s$,

ARIMA Model

The main principle ARIMA modeling method is based on the linearity postulation in the midst of variables. Though, the linearity assumption might not present in the numerous events of time series. In addition to non-seasonal prototype, the SARIMA prototype might be stated in a multiplicative manner such as ARIMA (*p*, *d*, *q*) (*P*, *D*, *Q*) s, where (*p*, *d*, *q*) signifies the non-seasonal portion of the prototype, (*P*, *D*, *Q*) s displays the seasonal element of prototype in addition *s* is number of periods per term. In the seasonal element, *P* signifies the Seasonal Autoregressive (SAR) period, *D* is the amount of seasonal variance(s) achieved also *Q* means the Seasonal Moving Average (SMA) period. The over-all notational usage of a fit beginning the Seasonal- ARIMA prototype may be written as;

$$(\mathbf{1}-\boldsymbol{\beta})^{d}(1-\boldsymbol{\beta})^{\boldsymbol{D}}\boldsymbol{Yt} = \mu + \frac{\Theta(\boldsymbol{\beta})\boldsymbol{\Theta}(\beta^2)}{\boldsymbol{\phi}(\boldsymbol{\beta})\Phi(\beta^2)}\varepsilon_t$$

Where, β is a backward shift operator and are the Seasonal Moving Average (SMA) and the Seasonal Autoregressive (SAR) polynomials of order *P* and *Q* respectively (Omane-Adjepong et al., 2013).

Model of regression is in this method:

$$Yt = bo + b1Yt - 1 + b2Yt - 2 + \cdots + bpYt - p + et \qquad (1)$$

Where

Y = projected factors,

X_1 - X_p = illustrative variables,

b_o - b_p = coefficients of linear regression and signifies the error.

If, though, these variables are well-defined as

$$X1 = Yt - 1, X2 = Yt - 2, X3 = Yt - 3, \ldots Xn = Yt - n + e$$

The above equation (1) become:

$$Yt = bo + b1Yt - 1 + b2Yt - 2 + \cdots + bpYt - p + et \qquad (2)$$

Equation 2 in ARIMA prototype for time series data signifies a regression equation, but then varies from Equation (1) as it has diverse descriptive factors which are preceding prices of judge variables Y_t, named AR. As it is likely towards regression historical worth's of a series over, present is the time series prototype which practices previous faults as descriptive factors:

$$\mathrm{Yt} = \mathrm{bo} + \mathrm{b1et} - 1 + \mathrm{b2et} - 2 + \cdots + \mathrm{bpet} - \mathrm{q} + \mathrm{et} \qquad (3)$$

Y_t is stable comparable of track if $w_t = \Delta^d Y_t$ is a stationary order. Bearing in mind that Δ means the variance:

$$\Delta \mathrm{Yt} = \mathrm{Yt} - \mathrm{Yt} - \mathrm{i}\ \mathrm{Yt} \qquad (4a)$$

$$\Delta 2\mathrm{Yt} - \Delta \mathrm{Yt} - \Delta \mathrm{Yt} - \mathrm{I} \qquad (4b)\ and\ so\ on$$

Likely to return to Y_t thru the total w_t in the whole of d periods. It can be written as $Y_t = \sum^d w_t$ where $\sum$ the summation operator:

$$\sum \mathrm{wt} = \sum \mathrm{t}\ \mathrm{i} = -\infty\ \mathrm{wi} \qquad (5a)$$

$$\sum 2\mathrm{wt} = \sum \mathrm{t}\ \mathrm{j} = -\infty \sum \mathrm{j}\ \mathrm{i} = -\infty\ \mathrm{wi} \qquad (5b)\ and\ so\ on$$

It is value noting that the sum operative $\sum$ is the reverse of the dissimilarity operator Δ. Since $\Delta Y_t = Yt - yt\text{-}1$, it can be written that $\Delta = 1\text{-}\beta$ and thus $\sum = \Delta^{-1} = (1\text{-}\ \beta)^{-1}$

While computing this summary for a dynamic series, generates the quantity one comment of the creative series without distinguishing (Y_0) then improves up succeeding prices of the series in variance.

Thus, if $w_t = \Delta Y_t$, Y_t can be calculated:

$$Y_t = \sum w_t = \sum^t{}_{i=-\infty} w_i = \sum^0{}_{i=-\infty} w_i + \sum^t{}_{i=1} w_i =$$
$$Y_0 + w_1 + w_2 + \ldots + w_t \qquad (6)$$

Number one phase is to know the level of similarity *d*, which is, the amount of period that the series is in desires to be distinguished to yield a fixed series. Then it inspects the association and incomplete auto-correlation task to regulate likely conditions of *p* and *q (*Pindyck & Rubinfeld, 2004 as cited in Pereira et al, 2014).

3. Evaluation Metrics

It was projected for the first time by Hyndman and Koehler (2006), such as scale-free error metric. It is a smaller amount of complex to outliers then have the ability towards comparing projecting procedures upon a series, at the same time projecting accurateness amid cycles. MASE is valid in addition does not give boundless or unclear standards in trend. MASE is suggested to be usual degree for assessment of projecting accurateness (Hyndman, 2006). MAPE is the complete mean error as proportion of demand. This process grants difficulties as soon as the series take prices of equivalent to nil.

The MAPE can be expressed as follows:

$$MAPE_n = \frac{\sum_{t=1}^{n}\left|\frac{E_t}{D_t}\right| 1000}{n}$$

Where:

$|E_t|$ Complete mistake worth in the period *t*;

$|D_t|$ Real demand in absolute worth in the time *t*;

n = total number of the times.

Hyndman and Koehler (2006) sated the methods are valuable while comparing diverse approaches of the same set of information, but then they strongly advised scholars in contradiction to use when relating through data sets that have diverse measures. MAPE is one of the fraction errors that have been steadily applied for associating prediction accurateness. In general, the smaller the value of the forecast accuracy measure, the better the forecast. However, there is no specific threshold for these measures. Instead, a smaller value produced by these accuracy statistics foretells the best forecasting methods among severally competing methods.

Moving Average

Gupta, and Starr (2014) specified that the moving average (MA) technique make available a forecast of future worth of goods based on current past history. MA is also called simple MA technique. The latest *n* consecutive values, which are observations of actual events such as daily, weekly, monthly, or yearly demand, are used in making a forecast. These data are recorded and must be updated to maintain the most recent *n* values. A decision must be made concerning how many data values should be included in the MA set (*n*). Moving average technique be an expected amount of current definite worth's, modernized as soon as innovative values develop and obtainable. A moving average forecast make use of figure of the furthermost fresh real facts ideals in producing a forecast (Williams, 2015). The MA technique is applied at the time that demand for a produce is objectively persistent over time and does not have a rapid growth rate or seasonal characteristics (Gupta & Starr, 2014). MA can be calculated using the subsequent equation:

$$ft = MA_n = \frac{\sum_{i=1}^{n} A_{t-i}}{n} - \frac{A_{t-n} \pm \cdots + A_{t-2} + A_{t-1}}{n}$$

Where:

Ft = Forecasting of period *t;*

MA *n* = MA period;

A_{t-I} = real worth in the period *t-I and*

n = MA No of periods

The method is mainly valuable in eliminating the fluctuations of random in the historical data. When the degree of the trend is great, and the pattern is very reliable, then the smaller amount of the number of periods (n) in the group the better it is. If the trend is slow (up or down), and if variations around the average are common, then having additional periods of time in the group is healthier than having excessively few. In choosing the worth of n, there are numerous contradictory special effects. The greater the worth of n, the bigger is the consequence of smoothing any random deviation.

Weighted Moving Average

A mode towards making predictions extra approachable to the best recent real events (demand) is to apply the WMA technique. Just like the MA technique, the most current n period is used in forecasting. On the other hand, for each period is assigned a weight between 0 and 1. The aggregate of entirely weights adds up to 1. The maximum bulk is allocated to the greatest fresh period and then the weights are allocated to the past periods in the downward direction of magnitude. The WMA technique permits the modern period to have the utmost influence, and later periods declining significance. Reminder that when all weights are equal ($1/n$), the WMA is the same as the MA (Gupta & Starr, 2014). The major weights are allocated to the freshest events as soon as there is an ongoing trend. In a rapidly fluctuating structure, wt may be much greater ($\gg$) than w_{t-1}. Williams (2015) enlightened the WA as it is related to a MA, excluding which is characteristically ascribes more weightiness to utmost current time series worth's.

$Ft = w_{t-n} (A_{t-n}) + ... + w_{t-2} (A_{t-2}) + w_{t-1}(A_{t-1}) + w_{t-1}(A_{t-1}) + ... + w_{t-n} (A_{t-n})$

Where:

w_{t-1} = Weight for period t -1, etc.;

A_{t-1} = Actual value for period t - 1, etc.

WMAs can track strong trends more accurately than UWMAs. An analysis of error with the use diverse values of *n in* addition different weights has to be done to find the best value of n and the corresponding weights.

Exponential Smoothing

The exponential smoothing (ES) method, like the WMA method, calculates an average demand (forecast). ES procedure remembers the last estimate of the average value of demand and combines it with the most recent observed, real value to form a fresh projected average. Demand for a particular time t is forecasted by ES by joining the forecasted past time ($t - 1$) with previous period ($t - 1$) real demand (actual demand for previous period is given a weight of 'α' and the forecast of the prior period is given a weight of ($1 - \alpha$)), where α is a smoothing constant whose value lies between 0 and 1 (Gupta & Starr, 2014). ES is a strong WA technique which is comparatively stress-free to apply and comprehend. Each new forecast is founded on the past forecast in addition to proportion of the variations among forecast and the actual value of the sequences at such point (Williams, 2015).

That is: Next forecast equal past forecast plus (actual - past forecast)

Where

(Actual - past forecast) signifies error in forecasting in addition is a proportion of the error. Additionally,

$F_t = Ft\text{-}1 + \alpha (At\text{-}1 – Ft\text{-}1)$

In a situation where

F_t = *projected period t*

F_{t-1} = projected for past period (i.e., period t-1)

α = Smoothing proportion

A_{t-1} = Actual demand or sales for the previous period

In a variety of situations ES has been found to be very effective. Because ES works better than the older methods of MAs and WMAs, many forecasting and control systems employ it. It has proved effective for various uses. Fighter aircraft make use of ES to target their guns at moving goals. In conclusion, they predict the position of enemy jets for the period of flying operations (Gupta & Starr, 2014). This use displays how fast the ES technique can track a steady, but dynamically fluctuating pattern. Industrialists make use ES to make forecast for demand levels, which the same experience kind of non-random but volatile changes from time to time. In such circumstances, the current past has the best facts about the near future. ES can hook these moves and make quick changes to inventory levels. Other manufacturers and organizations involve in service use it for the reason that it calls for less computational work and is readily understood.

Forecasting with a Seasonal Cycle

When seasonality is present, forecasting can be done by presumptuous that what occurred last year (or last month, etc.) will take place again. It is called the historic forecast technique. The form is expected to recurrence itself within the time period. This method works if a stable configuration (which is often seasonal) exists. Typically, the hotel and resort business is involved with historical forecasts, as the business in the area of agriculture. In each case, special situations can arise that lead to the desire to adjust the historic forecast.

Other Methods

Trend Analysis

Analysis of trend includes evolving an equation which will rightly define trend (presumptuous that trend is in the data). The trend elements might be linear, or not. An easy design of info regularly can make known the reality in addition environment of a movement. There are 2 vital systems which can be useful toward improving predictions as soon as movement is existing. One comprises the use of a trend; the rest is an addition of ES (Williams, 2015). If the period of time shows an increasing or decreasing trend, then the techniques discussed above (MA, WMA, and ES) may not be appropriate for making a forecast. The trend line equation is, $Y = a + bX$, where Y = sales forecast and X = period of time. X = autonomous factors and Y = dependent variable since the demand depends on the time period. As X increases Y increases in an increasing trend. Y will decrease as X increases in a decreasing trend (Gupta & Starr, 2014).

A linear trend equation has the form

$Ft = a + bt$

Where

Ft = period of forecasting t

a = worth of Ft a t = 0, which is the y intercept

b = Slope of the line

t = Identified no of periods starting from t = 0

Explanatory techniques

Though time series techniques depend on the historical opinions of information towards forecasting, illustrative techniques search for ways to build an equation that the variable to be forecast have an instructive association with one or more autonomous variables. That is, if we understand the values of the autonomous variables, we can originate the worth's of factors to be projected. The tenacity of the descriptive prototype is to derive the association among forecasted and autonomous factors and apply it to project future worth's of projected factors. Explanatory approaches depend on regression to discover these connections and make available forecasts Makridakis et al., 1998 (as cited by Niilo, 2013). The difficult for demand predicting is to look for a pointer that associates well with demand and happens before demand (Kerkkänen, 2010). So, the pointer desires towards observing steadfastly earlier than demand is encompassed in prototype. Even though such pointers are not unmanageable to locate, regression techniques are out of the range of this investigation for the reason that useful software boundaries in the part of experimental.

Qualitative methods

When sufficient objective data is not available, a number of qualitative techniques can be applied. The term judgmental forecasting is generally applied when describing forecasting with qualitative means (Kerkkänen, 2010). The definite techniques used in employing judgment range from informal (i.e. pure intuition) to structured methods, up to modeling methods that try to reproduce human decision making. Quantitative techniques such as time series and causal forecasts are based on historical data in its place of judgment. A time series forecast is an endogenous method that relies only on the historical data of the forecasting variable while causal models also use exogenous data from other causes (Decoster, 2012).

Judgmental Forecasting

This technique permits us to draw conclusions on present designs in addition associations into the prospect. Consequently, they convey the obvious hypothesis that designs would not adjust for the duration of the projection distance. Though, in actual domain unexpected in addition to dramatic variations will occur and when it happened, the conclusion is desirable to convey them into account in predicting (Makridakis et al., 1998). Judgmental methods are most valuable in forecasting situations where large changes are normal, since historical data is then not relevant due to the rapid changing circumstances. Qualitative forecasting is also preferable at the time where historic records on the variable of concern is not obtainable or too expensive to obtain, and when there is relevant knowledge of the item to forecast. Disadvantages of qualitative forecasts are the considerable amount of needed personnel time and the often biased and limited opinions (Decoster, 2012). Forecasting biases due to deliberately under or over-estimating the forecasts are common in organizations. In a survey of sales managers, Peterson (1990) showed this to be one of the major problems associated with judgmental forecasting. Cyert, March, and Starbuck, 1961 (as cited by Decoster, 2012) showed that the judgmental forecasting bias depends on the forecaster's role in the company. This is confirmed by a survey of sales forecasting practices by Sanders and Manrodt, 1994 (as cited by Decoster, 2012): most respondents preferred under forecasts (70,4%) while over forecasting was preferred by 14,6% and 9,8% said they had no preference (5% did not respond). Most respondents gave this as the main reason why they prefer an under forecast, the fact that there are far fewer management reviews when the forecast is surpassed.

Methods

To examine the evaluation amid HW and ARIMA prototypes, fundamentally the historic information was used from the sales record (secondary data) of Nestle Nigeria period from 1990 to 2017. This data was used to assess the future sales of Nestle Nigeria Plc. using ARIMA forecasting model and Holt Winters forecasting model, the optimum forecasting model between ARIMA and Holt Winter was examined and the appropriate forecasting model for Nestle Nigeria Plc. short term forecasting was selected.

Minitab Version 17 was being used for relevant inferential statistical analysis of the study whose targeted at liken the prototypes-ARIMA and HW to forecast the future for either acceptance or rejection at the end, these models was be used to answer the research questions, upon which conclusions and recommendations are based as final output of the study.

Holt-Winters prototype (HW) and ARIMA prototype was used in this study. The MAPE, MAD and MSD were used as a performance metrics. The two methods are based on the foundation of Box Jerkins procedure that give room to a stationary series in advance of model estimate.

ADF equation with no intercept and no trend: $\Delta Xt = \rho Xt{-}1 + \Sigma\ \delta i \Delta Xt{-}i + \epsilon t\ pi{=}1$ (1)

ADF equation with intercept: $\Delta Xt = \beta 0 + \rho Xt{-}1 + \Sigma\ \delta i \Delta Xt{-}i + \epsilon t\ pi{=}1$ (2)

ADF equation with intercept plus trend: $\Delta Xt = \beta 0 + \beta 1t + \rho Xt{-}1 + \Sigma\ \delta i \Delta Xt{-}i + \epsilon t\ pi{=}1$. (3)

Data Analysis and Discussion of Findings

Analysis of Data According to Objectives

Objectives 1: Assess the future sales of Nestle Nigeria Plc. using ARIMA forecasting model.

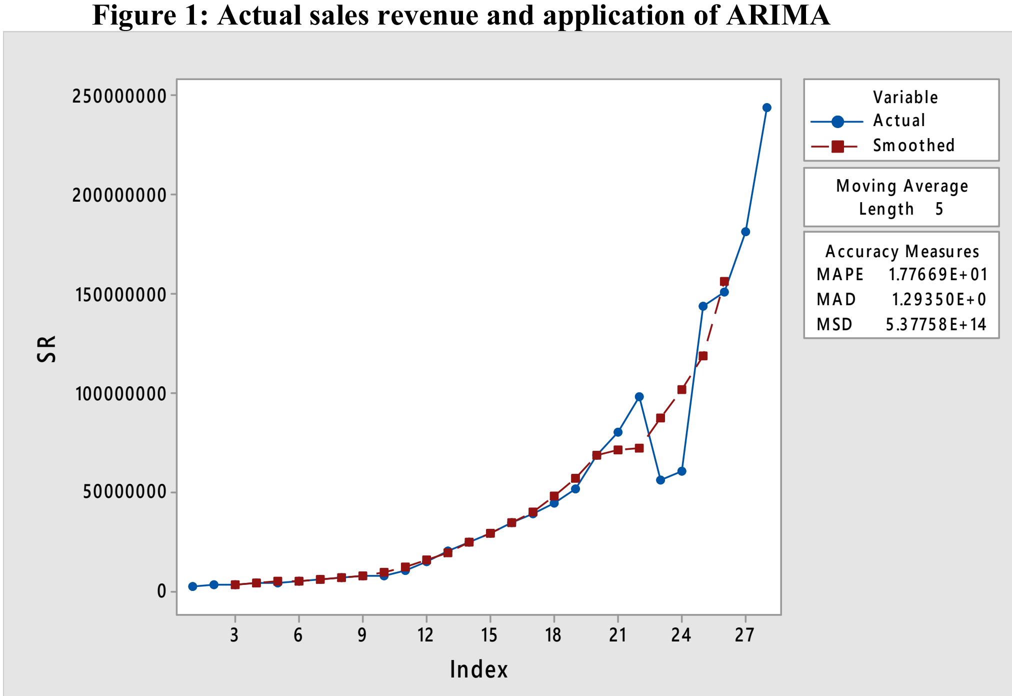
Table 1: ARIMA Model for Nestle Nigeria from 1990 to 2017

Accuracy Measures	ARIMA	
	Length 10	Length 5
MAPE	2.10619E+01	1.77669E+01
MAD	2.08660E+0	1.29350E+0
MSD	1.54006E+15	5.37758E+14

Source: Research Data, 2018

From the table 1, the ARIMA model using length 5 and 10 were generated to derive the best fitting model. MAPE, MAD, and MSD was 2.1, 2.0, and 1.5 respectively on the length 10, while it is 1.8, 1.3, and 5.4 respectively on length 5. The best of this model is the accuracy measure of the model at length 5.

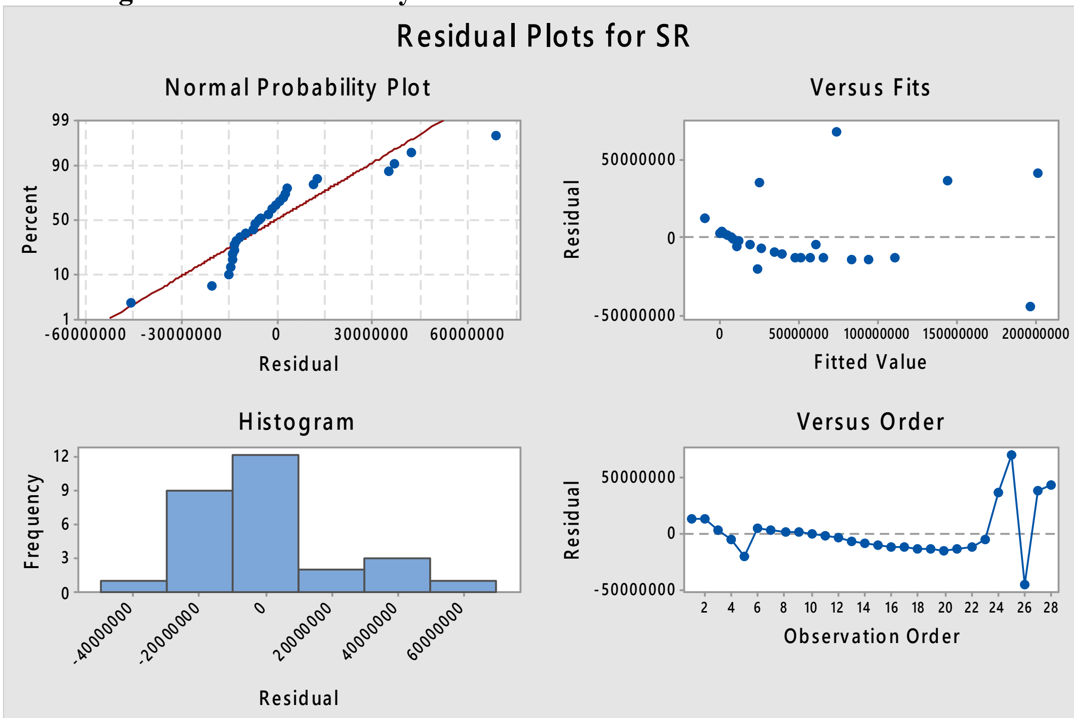
Figure 1: Actual sales revenue and application of ARIMA



Source: Research Data, 2018

The adjustment of prediction was made from 1990 to 2017 to foresee future forecast for year 2018, 2019 and above as we can see in figure 1 in graphical form. The result was obtained with the use of ARIMA model which shows an upward movement of actual demand of Nestle sales revenue.

Figure 2: Residual Analysis for ARIMA model



Source: Research Data, 2018

Centered on the residual analysis of ARIMA model, in figure 2 we observed that the model is within the required parameters established on time series.

Objectives 2: Evaluate the future sales of Nestle Nigerian Plc. using Holt Winters forecasting model.

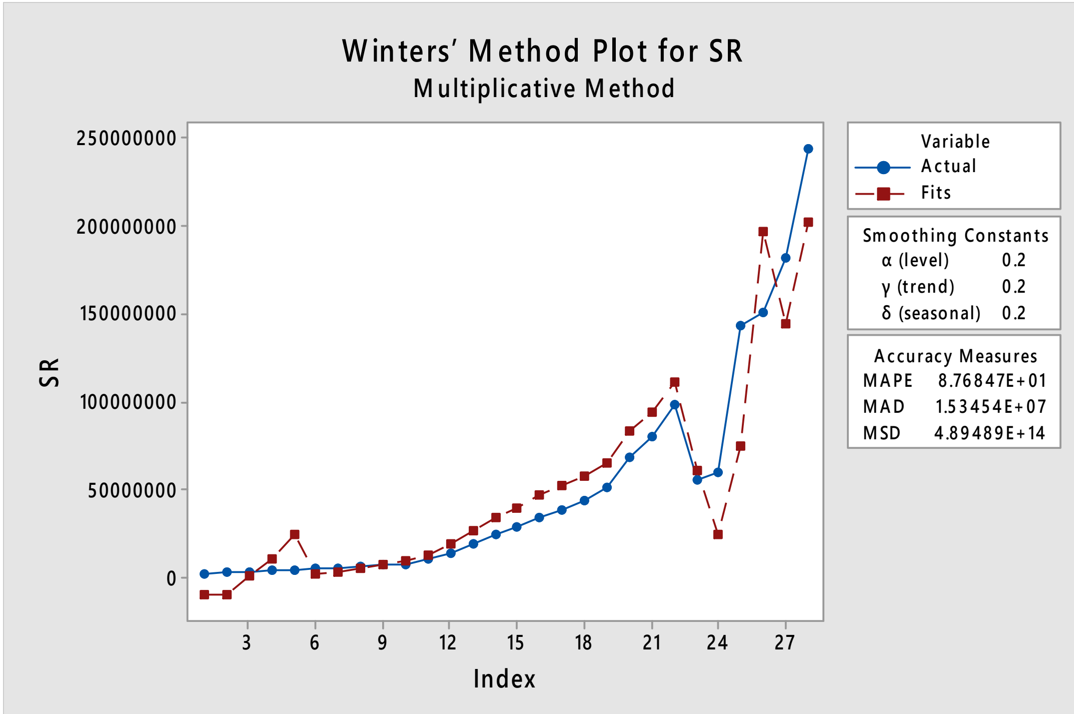
Table 2: Holt Winters model for Nestle Nigeria from 1990 to 2017

Accuracy Measures	**Winters'**	
	Additive	**Multiplicative**
MAPE	**8.76847E+01**	**2.31176E+02**
MAD	**1.53454E+07**	**1.70518E+07**
MSD	**4.89489E+14**	**4.84524E+14**

Source: Research Data, 2018

From the table 2 Holt Winters using additive and multiplicative model to derived best fitting model. Additive model shows that MAPE, MAD, and MSD were 8.8, 1.5, and 4.8 respectively, while it is 2.3, 1.7, and 4.8 respectively on multiplicative model. The best of this model based on accuracy measure of the model is the multiplicative model.

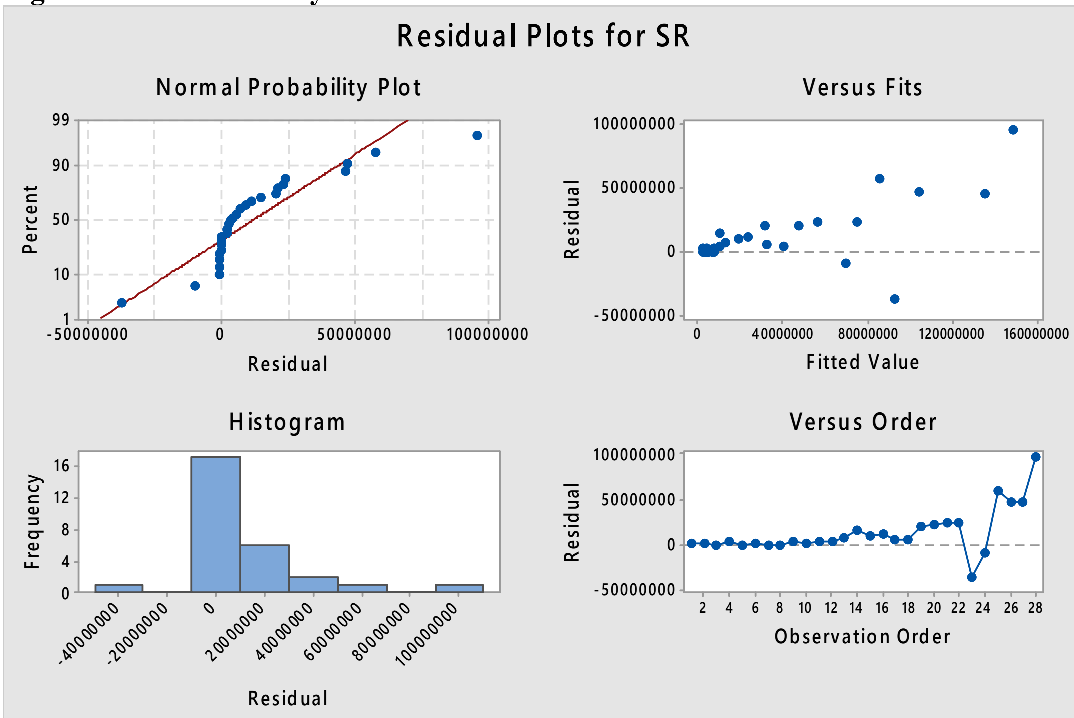
Figure 3: Actual sales revenue and application of Winters Multiplicative method



Source: Research Data, 2018

The adjustment of prediction was made from 1990 to 2017 to foresee future forecast for year 2018, 2019 and above as we can see in figure 1 in graphical form the result shows obtained with the use of ARIMA model shows an upward movement of actual demand of Nestle sales revenue.

Figure 4: Residual Analysis for Holt Winters model



Source: Research Data, 2018

Centered on the residual analysis of Holt Winters model, in figure 2 we observed that the model is within the required parameters established on time series.

Objectives 3: Examine the optimum forecasting model between ARIMA and Holt Winter for Nestle Nigeria Plc.

Table 3: ARIMA and Holt Winters model Accuracy for Nestle Nigeria from 1990 to 2017

Accuracy Measures	**ARIMA Length 5**	**Holt Winters' Multiplicative**
MAPE	**1.77669E+01**	**2.31176E+02**
MAD	**1.29350E+0**	**1.70518E+07**
MSD	**5.37758E+14**	**4.84524E+14**

Source: Research Data, 2018

From the table 3, we compare both ARIMA and Holt Winters model accuracy measure to derived best fitting model. From the Holt winters model MAPE, MAD, and MSD were 2.3, 1.7, and 4.8 respectively, while ARIMA is 1.8, 1.3, and 5.4 respectively. The best of this model is ARIMA model of length 5, since its accuracy measure is lower compared to the Holt winters multiplicative model.

Objectives 4: Determine the appropriate forecasting model for Nestle Nigeria Plc. short term forecasting.

From accuracy measures of both ARIMA and Holt Winters model in table 1 and table 2 Holt winters model MAPE, MAD and MSD were 2.3, 1.7, and 4.8 respectively, while ARIMA is 1.8, 1.3, and 5.4 respectively. The best of this appropriate model is ARIMA model for Nestle Nig., to predict short term forecasting.

4. Discussion of findings

This study applies autoregressive integrated moving average (ARIMA) and Holt-Winters methods for optimum sales forecasting of Nestle Nigeria Plc. The study assesses the future sales of Nestle Nigeria Plc. using both ARIMA and Holt-Winters forecasting methods. Several studies have attempted to use both methods to forecast sales revenue. For instance, Makatjane & Moroke (2016), did a comparative study of Holt-Winters exponential smoothing and Seasonal ARIMA to forecast car sales in South Africa. Shiva & Muniyappa (2014) compared ARIMA and Holt-Winter forecasting accuracy with respect to Indian motorcycle industry. On the research question one the study revealed that forecasted sales revenue of Nestle Nigeria Plc is increasing, going by ARIMA forecasting model and. On the research question two the study revealed that forecasted sales revenue of Nestle Nigeria Plc is increasing, going by HW forecasting model. This is in line with Omane-Adjepong, Oduro & Oduro (2013 on the study of determining the better approach to predicting in the short-term Ghana's inflation. SARIMA and HW approaches were used to attain short-horizon among the predicted sample. The precision of the sample estimate was measured via MAE, RMSE, MAPE and MASE.

For the research question three and four the result also revealed that ARIMA method seems more effective and powerful going by the MAPE and MAD results given above. This is in line with the study by Saayman and Saayman (2010) that revealed that SARIMA models bring maximum precise forecasts of arrivals for over the 3 times period. Moreover, our findings are not in agreement with the result of Makatjane & Moroke (2016) who revealed in their study that holt-Winter exponential smoothing forecasting is more effective and powerful in forecasting short-term seasonal car sales in South Africa.

5. Conclusions and Recommendations

Having studied and review related literature in the area of quantitative forecasting, the conclusion is that the Holt Winters' additive and multiplicative models are not the right option mainly due to the pattern of the data. In time series forecasting, selecting a particular method for the forecast of products cannot be a right decision. It is based on the behaviour of data on which the analysis should be made. The ARIMA model provided forecasts that were more accurate than those of the HW models. Because of this we are not just able to conclude that ARIMA model give the best and most accurate predictions but discuss the complexity in addition robustness of the contending models in food and beverages market. Therefore, we recommend that more complex methods of forecasting, rather than the simple methods as they do not reveal the full state of event in the organization. Furthermore, multi-approach system is recommended in making accurate sales and operational predictions for optimal firm performance.

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