Comparative Analysis and Short Term Sales Forecasting for an Ethiopian Shoe Manufacturing Company

** Tigist Wolde Gebre*
*** Rajwinder Singh*

Abstract

Forecasts are a basic input in the decision processes of operations management because they provide information on future demand and to increase revenue. The main purpose of this paper was to compare three different quantitative forecasting methods and develop a monthly short term sales forecasting model specifically on shoes of A-Shoe Company, Addis Ababa, Ethiopia. Twelve months (December 2013 - November 2014) sales data (of different types of pair of shoes) was collected from the company. From quantitative forecasting methods, a time-series model, that is, moving average, weighted moving average, and exponential smoothing were used to predict monthly sales forecast for the month of December 2014. Trend equation was formulated by using the least square regression method; analysis was done along with standard error of estimate. Prediction interval limits at 95% level of confidence were calculated. Exponential smoothing forecasting method (with alpha value 0.1) was found to be fit when comparing different mean absolute deviation *(MAD)*, mean squared error *(MSE)*, and mean absolute percent errors *(MAPE)*. The forecasted shoe sales value was found to be within the prediction interval limits. ANOVA results revealed that the calculated value of *F* (9.34) was less than the table value of *F* (10.04). Hence, the null hypothesis (*b* = 0) is accepted. The resulting forecasting method can be used to provide a framework to forecast sales, specifically for national and international products and can position an organization's manufacturing services by designing the manufacturing service.

Keywords: **sales forecasting, shoe demand marketing, quantitative forecasting methods, confidence level, ANOVA**

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Planning is an essential part of any business activity. However, business plans require objectives that are based on sales targets, which in turn require demand forecasts. Generally, companies focus on the forecasting of sales because they need to plan their expenses and still make a profit. Thus, forecasting is essential for planning. In addition, forecasts serve as input to many other business decisions. Obviously, these decisions can be only as good as the forecast results used to make them.

Sales forecasts are the foundation of planning. The forecasts enable an organization to have an optimum inventory level, to make appropriate purchasing decisions, and to maintain efficient daily operations. All these affect the profits of an organization. Therefore, forecasting is critical to profitability.

There are many techniques of forecasting, and they vary in complexity, ease of use, and the amount of data needed. Among the many forecasting techniques, many surveys (Sanders, 1997; Mahmoud, 1984) found the judgmental technique to be dominant. However, many studies (Armstrong, 1986; Bunn & Wright, 1991) found that the judgmental technique is less accurate, more biased, and more likely to lead to poor forecasts than other techniques.

* *First Year MBA,* School of Management Studies, Punjabi University, Patiala, Punjab.
E-mail : tigistwoldegebre4@gmail.com
** *Assistant Professor,* School of Management Studies, Punjabi University, Patiala, Punjab.
E-mail : rajwindergheer@gmail.com

Due to the use of improper forecasting techniques, most forecasts give inaccurate results. In addition to the use of inappropriate methods of forecasting, there are other reasons for forecasting errors (Shahabuddin , 2009):

- Many forecasts rely on historical data without understanding the underlying basis of the data. For example, an unexpected jump in sales becomes part of the historical data instead of being considered as an outlier that may not happen again.

- Forecasters tend to ignore likely changes that may influence the forecast, for example, increases in population, increases in competition, technological changes, and so forth. Any or all of these factors may affect the organization's sales and can easily be included.

- Using inappropriate computational methods for the data. Each type of data (e.g. time series, cross-sectional data) requires different forecasting techniques. Incorrect computational techniques cause errors in forecasts.

- Forecaster bias affects results and should be kept to a minimum. Individual biases as a result of personal optimism or pessimism have no place in forecasting. Bias increases the error in forecasts.

Forecasters can choose from a variety of forecasting techniques. However, each technique fits a limited set of situations, and thus, methods appropriate to different situations result in the highest accuracy. The accuracy of forecasts is further complicated when a forecaster uses available data that is not consistent and is statistically unsound. The use of regression to establish a relationship between the dependent variable and many independent variables is an appropriate method of forecasting. However, the selection of the independent variables is a critical first step to accurate forecasts.

Due to the abundance of the forecast methods (there are more than 200 methods mentioned in the economic literature), it is rather cumbersome to review all of them. Therefore, the analysis was carried out by classifying them into groups. Depending on the research area and research object, the most commonly used forecast method classification in the research literature is based on the following criteria (Bails & Peppers, 1993; Bolt, 1994; Peterson & Lewis, 1999):

- Type of information (quantitative and qualitative forecast methods),
- Forecast time span (short-term, mid-term, and long term forecast development methods),
- Forecast objects (micro and macro economic indicator forecast methods),
- Forecast goal (genetic and normative forecast methods).

The most popular, universal, and the most commonly applied in research papers is the classification based on quantitative and qualitative forecast methods because of its characteristic to involve the methods classified in other groups. The literature review discloses that qualitative or subjective methods are based on intuitive information (opinions, intentions, and feelings) which is received from various surveys (consumers, sales people, company personnel) by carrying out expert point of view analyses. Whereas, quantitative or objective methods analyze objective and reliable, most often, the past time data by making assumption that other values will not change, while current regularities will remain the same (Bolt, 1994). After the analysis of various research papers (Bails & Peppers, 1993; Bolt, 1994 ; Cox & Loomis, 2001; Kirsten, 2000), the assessment of positive and negative aspects of quantitative and qualitative forecast was performed and is depicted in the Table 1.

The analysis of the most significant forecast method criteria in the research literature discloses two-sided opinion: on the one hand, Bails and Peppers (1993) stated that the selection of the forecast method should be based upon the assessment of its accuracy; on the other hand, Waddell and Sohal (1994) and Clifton, Nguyen, Nutt, and

Table 1. Assessment of Quantitative and Qualitative Forecast

Positive Assessment	Negative Assessment
Quantitative Forecast:	
▪ Uncomplicated data accessibility;	▪ Unsuitable for new product demand forecast;
▪ Possibility to forecast business change points;	▪ High costs: often requires constant market analysis and regular compilation of data;
▪ Assessment of economic indicator interrelationship and fluctuation.	▪ Often complicates application and misinterprets results.
Qualitative Forecast:	
▪ The data of the previous periods is not necessary;	▪ Subjective experts' opinion;
▪ Suitable for demand forecast: (i) in new markets; (ii) in current markets through new sales people;	▪ Data sequence fluctuations (seasonal, cyclic, trend like, random) are not taken into consideration;
▪ Allows the development of opinion diversity;	▪ Economic data interrelationship is not assessed;
▪ Experts' anonymity increases forecast reliability.	▪ Not applicable

Source: Bails & Peppers, 1993; Bolt, 1994; Cox & Loomis, 2001; Kirsten, 2000

Clifton (1998) associated the forecast process with defined forecast objectives. However, the selection concept of the forecast method reflects only one criterion - either forecast accuracy or forecast objective.

The selection of the forecast method should be based at least on several criteria taking into account forecast method applicability and additional things proposed by researchers such as: forecast accuracy degree, time span, amount of necessary initial data, forecast costs, result implementation, and applicability level.

The priorities of forecast method application are determined according to the forecast time span which is traditionally divided into short- (1-3 months), mid- (3 months-2 years) and long- (more than two years). Simple quantitative forecast methods are applied for short- and mid- periods of time (simple moving average and exponential smoothing), while for the long- term, forecast regression and econometric models are applied.

Karjagi, Chakrabarty, and Mohite's (2010) study attempted to develop an econometric model for both long-term and short-term forecasting of wheat prices in India. The detailed methodology involved in developing the model and forecasting process can be understood in this paper. The short-term forecasting was studied by using a lagged response model ; whereas, the long-term forecasting was made with the help of a multivariate model.

Sharma and Borah (2011) attempted to examine some analytical perspective of 3G technology over 2G. The probable effects of 3G are forecasted both from customers' and companies' point of view, and a conceptual framework was developed relating 3G and its impact on various business verticals. The authors pointed out a few strategies for the companies, which can be beneficial for the firms to sustain in the competition.

Methodology

Three time series forecasting models were evaluated to fit the data for each subject, that is, simple moving average (SMA), weighted moving average (WMA), and simple exponential smoothing (SES) (Clifton et al.,1998) for sales projection.

(1) Simple Moving Average Model : The SMA method ignores the possible effects of seasonal, cyclical, or random fluctuations by taking the average of the last Δn historical data points. The SMA is calculated as per (1) :

$$F_t = \sum_{i=1}^{\Delta n} A_{t-i} \div \Delta n \qquad (1)$$

where, F_t = forecast value for the time period t (i.e. the average of the previous Δn observations), A_{t-i} = actual sales for period t-i, Δn = number of past time periods used in the averaging process.

(2) Weighted Moving Average Model : Experience shows us that a forecast sometimes can be improved when more recent data are of greater weight. The weighted moving average using Δn past time periods is given by (2):

$$F_t = \sum_{i=1}^{\Delta n} W_{t-i} A_{t-i} \qquad (2)$$

where, W_{t-i} = proportional weight assigned to time period $t - i$.

The WMA is an expedient forecasting method to use. It is a simple, quick, and an inexpensive method to employ when the behavior of the data is uncomplicated, the forecasting horizon is short, and the accuracy required is undemanding. However, the only way to determine the optimal forecast period and weighting scheme is to experiment. Unfortunately, the number of possible combinations of weighting schemes and forecast periods is huge-a serious drawback to using this technique. In addition, the number of historical data required for moving average-type forecasts is also large: Real-world applications employ at least 12 periods or more (Nahmias, 2005).

(3) Simple Exponential Smoothing Model : Another method that attempts to account for seasonal, cyclical, or random variations in chronological data is the family of exponential smoothing forecast models. The simplest algebraic form of this type of forecasting model, called simple exponential smoothing, is :

$$F_t = F_{t-1} + \alpha (A_{t-1} - F_{t-1}) \qquad (3)$$

where, F_{t-1} = forecast value of variable in period t-i, A_{t-1} = actual value of variable in period t-i, α = smoothing constant.

The value of the smoothing constant, α, selected is arbitrary but must range between 0 and 1. The trial-and-error process of selecting α will depend on how sensitive the model is to random fluctuations.

Any new forecast for period t, F_t, is simply the value of the earlier forecast period, F_{t-1}, plus some fraction of the earlier period forecast error, $\alpha (A_{t-1} - F_{t-1})$. The size of this correction fraction is determined by the value of α selected : The larger the α -values, the more rapid the adjustment. Times series with little random variation would be best modeled by using larger smoothing constants. However, when the fluctuation of the data is primarily random, the manager does not want the forecast to react too quickly, and thus to overreact ; smaller α -values would be more appropriate. Ultimately, the manager should be aware that if values of α larger than 0.5 are required to gain the level of predictive accuracy desired, it is possible that a better forecasting model exists (Levin, Rubin, & Stinson, 1986).

(4) Forecast Model Accuracy - Error Measurement : Ultimately, the manager will examine the fit of a number of forecast models on the particular time series in question. But which one should the manager select, and what guidelines should he/she use in selecting it? Picking the optimal forecast model will be greatly influenced by the accuracy that model provides. Although it is possible visually to examine a time series forecast graph or chart, a manager's perceptual assessment will rarely be viewed as concrete. Instead, visual impressions will be judged as subjective, highly suspect, and usually professionally unacceptable. It is ,therefore, essential to use a method that will provide a quantitative evaluation of the forecast accuracy.

Methods that evaluate model accuracy focus on some measure of the forecasting error or residuals associated with that model. The error or residual is simply the difference between the actual and forecast values for given values for a given time period. That is, (Baker & Kroop, 1998 ; Evans 2000) :

$$e_t = A_t - F_t \qquad (4)$$

where, e_t = forecast error during time period t, A_t =actual variable value during time period t, F_t = forecast variable value during time period t.

Forecast accuracy is a significant factor when deciding among forecasting alternatives. Accuracy is based on the historical error performance of a forecast. Among the most common error-measurement indices are: mean absolute deviation (MAD), the mean absolute percent error (MAPE), and the mean squared error (MSE). The MAD is the average of the absolute differences between the forecast and actual values (Baker & Kroop, 1998 ; Evans 2000) :

$$MAD = \sum_{i=1}^{n} |A_t - F_t| \div n \qquad (5)$$

where, n = number of time periods during which there is a comparison between actual data and a corresponding forecast value. MAD treats each error component, small or larger, equally - it does not address the magnitude of the data being assessed.

The MAPE is the average of the absolute percentage differences between the actual and forecast values, and is essentially identical to MAD except that it normalizes the magnitude of the measurements. The MAPE relationship is given by (Baker & Kroop, 1998 ; Evans 2000) :

$$MAPE = \sum_{i=1}^{n} \frac{|A_t - F_t|}{A_t} \div n \qquad (6)$$

Even though the MAD and MAPE assessment procedures provide the manager with useful information, both approaches treat error components equally, larger and small errors are weighted alike. The MSE method, unlike either MAD or MAPE, penalizes larger errors more severely.

The MSE is the average of the squared error. Many mangers prefer the MSE method to either the MAD or MAPE methods because, in fact, one large error may have a much greater influence on the vitality of a business than do numerous small errors. The MSE method is given by (Baker & Kroop, 1998 ; Evans 2000) :

$$MSE = \sum_{i=1}^{n} (A_t - F_t)^2 \div n \qquad (7)$$

It is important to know that it is not rare for these different error-measurement techniques to yield differing assessments of the accuracy between, say, two forecast methods. For example, it is quite possible that, in one setting, the MAD-MAPE family of assessment methods will give lower values than will the MSE method; in another instance, the reverse outcome may be true. So which of the various assessment methods is best when they yield conflicting findings? The manger must use his/her judgment after a thorough review of the various evaluative options.

Once a forecasting model has been selected and implemented, it is possible to monitor and evaluate the forecast errors by measuring (a) the bias, and (b) the tracking signal of the time series. These two measurements, although they have both focus on the accuracy of the forecast, are quite different. Bias indicates whether the forecast, taken as a whole, tends to be high or low, and by how much. It is, therefore, a summative measurement of the forecast accuracy.

Ideally, a good forecast model will have errors that tend to alternate high and low in approximately the same magnitude. Accordingly, over the entire forecast, these errors should come close to canceling out. It is essential for a manger to know whether the forecast predictions tend to be typically high or low. If a manger knew not only the amount of error in the forecast, but also whether the forecast was consistently under estimating or over estimating, he/she could build in correction factors as a hedge against the bias direction. The bias of a forecast is measured by (Baker & Kroop, 1998; Evans, 2000):

$$Bias = \sum_{n-1}^{n} (A_t - F_t) \div n \qquad (8)$$

If the selected forecast model is following the actual data in an unbiased manner, you should anticipate the numerator to be high and low nearly alternately. Also, displacement values should be approximately equal, so they should cancel out each other. This will result in a summed numerator value (and ratio value) of near zero. If the forecast is biased, however, it will tend to read either high or low more often.

(5) Linear Trend - Least Squares Regression : It is always valuable for a manager to understand the general, long term direction - or trend - of the time series. One of the techniques used to isolate this effect is called trend projection. Although there are several types of trend projection, this paper will only examine time series that have linear or near-linear performance. Trend projection borrows the least squares regression method from statistics for the purpose of attempting to fit a straight line to a set of time series data. The independent variable is time, and the dependent variable is the measure being forecast.

The simple regression equation for forecasting during any time period, *t*, is (Clifton et al., 1998):

$$Y = a + bx \qquad (9)$$

where, Y = forecast value of sales based upon a particular time period, X; a = the Y- axis intercept (when $X = 0$) ; b = the slope of the regression line, that is, the rate of change in sales per quarter, $\Delta Y \div \Delta X$.

The equations for solving these values are:

$$b = (\Sigma XY - n\overline{X}\,\overline{Y}) \div (\Sigma X^2 - n\overline{X}^2)$$
$$a = \overline{Y} - b\overline{X} \qquad (10)$$

The measure of variability about any point estimate (and the regression line) is called the standard error of the estimate, *Se*, and is given by:

$$Se = \sqrt{(\Sigma Y^2 - a\Sigma Y - b\Sigma XY) \div (n-2)} \qquad (11)$$

Prediction interval limits (PIL), about the regression line,

$$PIL = Y \pm t_e Se \qquad (12)$$

where, t_e = *t*-value associated with the standard error of the estimate, which is a function of the desired confidence level and sample size (degree of freedom) = $t_{(1-C1)\div 2,\ df = n-2}$; Se = standard error.

Data Collection and Analysis

A-Shoe Company's (Addis Ababa, Ethiopia) shoes sales data was collected (Table 2) for 12 months from December 2013 to November 2014 from sales managers of the company to forecast the shoe sales for December 2014. The data is expressed by a pair of shoes sold in that specific month. This data is the sum of all shoe models and types, whether shoes for men, women, and children. This forecast analysis ignores these specific criteria and assumes all as a single product. Therefore, considering this, different quantitative forecasting methods were applied to forecast the demand of December 2014 as follows :

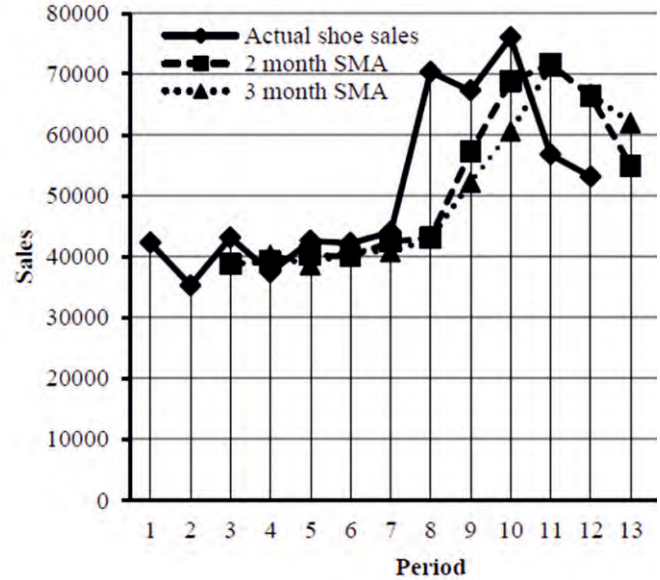
(1) Simple Moving Average Data Analysis : No tracking signal value is calculated for moving-average-type models. The tracking error value, which is accumulated over the duration of the forecast, could be biased toward longer periods and is, therefore, not used for moving-average models.

For the shoes data, the first SMA for a two-quarter time period interval ($\Delta n = 2$) is for the third period, as per (1):

Table 2. Sales Data Forecasting Using 2- and 3-Months Simple Moving Averages

Period	Months, Year	Actual shoe sales	Forecast sales	
			Two month	Three month
1	Dec. 2013	42278	-	-
2	Jan. 2014	35274	-	-
3	Feb. 2014	43130	38776	
4	March 2014	37439	39202	40227
5	April 2014	42600	40284.5	38614
6	May 2014	42215	40019.5	41056
7	June 2014	44062	42407.5	40751
8	July 2014	70353	43138.5	42959
9	Aug. 2014	67281	57207.5	52210
10	Sept. 2014	76012	68817	60565
11	Oct. 2014	56781	71646.5	71215
12	Nov. 2014	53151	66396.5	66691
13	Dec. 2014		54966	61981

Figure 1. Sales Data Forecasting using 2- and 3-Months Simple Moving Averages



$$F_3 = (42278 + 35274) \div 2 = 38776$$

As per (1), two- and three-quarter SMAs are summarized for the sales data in Table 2 and Figure 1, which shows greater variations. As per (5)-(8), two months : $MAD = 8487.6$, $MSE = 132528341.4$, $MAPE = 14.34$, $Bias = 2904.04$ and three months : $MAD = 10792.2$, $MSE = 1643819757.4$, $MAPE = 15.96$, $Bias = 2966.97$ are calculated.

(2) Weighted Moving Average Data Analysis : To calculate, say, company sales data, first determine the weighting profile for the two quarters. Let us assume that we arbitrarily select a weighting scheme of 0.75 and 0.25 (for two months), and 0.60, 0.30, and 0.10 (for three months) starting with the most recent through the two-removed quarter. The WMA for the third quarter, F_3, is then, 26455.5.

$$F_3 = (0.75)(35274) + (0.25)(42278) = 37025$$

As per (2), two- and three-quarter WMAs are summarized for the shoes sales data in Table 3 and in Figure 2, which shows greater variations. As per (5)-(8), two months : $MAD = 1454.275$, $MSE = 1222233375.44$, $MAPE = 13.86$, $Bias = 1791.90$ and three months : $MAD = 9053.93$, $MSE = 1286171508.26$, $MAPE = 13.66$, $Bias = 1833.1$ are calculated.

(3) Simple Exponential Smoothing Data Analysis : Using the sales data of Table 4, let us forecast sales for the period 2 by arbitrarily selecting an α -value of 0.1 and assuming that the first-period forecast value, F_1, is equal to the actual sales observed during that same time period, A_1. That is, $F_1 = A_1 = 42278$.

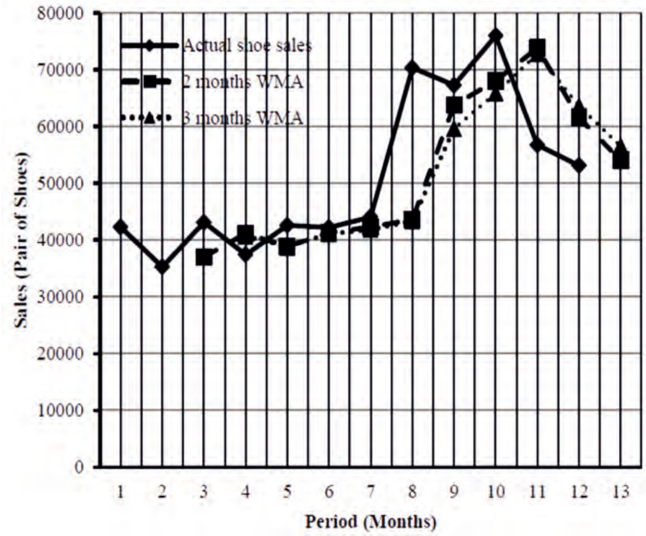
The forecast sale for period 2 is, then, as per (3) :

$$F_2 = 42278 + (0.1)(42278 - 42278) = 42278$$

Table 3. Sales Data Forecasting Using 2- and 3-Months Weighted Moving Averages

Period	Months, Year	Actual shoe sales	Forecast sales	
			Two month	Three month
1	Dec. 2013	42278	-	-
2	Jan. 2014	35274	-	-
3	Feb. 2014	43130	37025	-
4	March 2014	37439	41166	40688
5	April 2014	42600	38862	38930
6	May 2014	42215	41310	41105
7	June 2014	44062	42311	41853
8	July 2014	70353	43600	43362
9	Aug. 2014	67281	63780	59652
10	Sept. 2014	76012	68049	65881
11	Oct. 2014	56781	73829	72827
12	Nov. 2014	53151	61589	63600
13	Dec. 2014	-	54058	56526

Figure 2. Sales Data Forecasting using 2- and 3-Months Weighted Moving Averages



Let us proceed by forecasting of sales for period 3:

$$F_3 = 42278 + (0.1)(35274 - 42278) = 41577.6$$

The impact of α -values of 0.1 and 0.9 on the sales forecast for sales data assuming a first-period sales forecast of 42278 is presented in the Table 4 and Figure 3. The impact of α -values of 0.3, 0.5, and 0.7 on the sales forecast are calculated in same manner and only *MAD*, *MSE*, *MAPE*, *Bias* calculated values are shown in the Table 4.

As per (5)-(8),

When $\alpha = 0.1$: $MAD = 30962.71$, $MSE = 1134051689.53$, $MAPE = 61.84$, $Bias = 30962.71$;
When $\alpha = 0.3$: $MAD = 17210611.15$, $MSE = 427021033.4$, $MAPE = 35.98$, $Bias = 15771.21$;
When $\alpha = 0.5$: $MAD = 10316.61$, $MSE = 279897659$, $MAPE = 27.38$, $Bias = 15771.21$;
When $\alpha = 0.7$: $MAD = 10711.32$, $MSE = 230413898$, $MAPE = 22.07$, $Bias = 6570.77$;
When $\alpha = 0.9$: $MAD = 9727.43$, $MSE = 210647162$, $MAPE = 20.40$, $Bias = 4925.71$.

In order to appreciate the effect of the smoothing constant, we have graphed a particularly erratic series in Figure 3, along with resulting forecasts using values of $\alpha = 0.1, 0.3, 0.5, 0.5, 0.7$, and 0.9. Notice that for $\alpha = 0.1$, the predicted value of sales is in a relatively smooth pattern, whereas for other $\alpha = 0.3, 0.5, 0.5, 0.7$, and 0.9, the predicted values exhibit significantly greater variation.

Although smoothing with the larger value of α does a better job of tracking the series, the stability afforded by a smaller smoothing constant is very desirable for planning purposes.

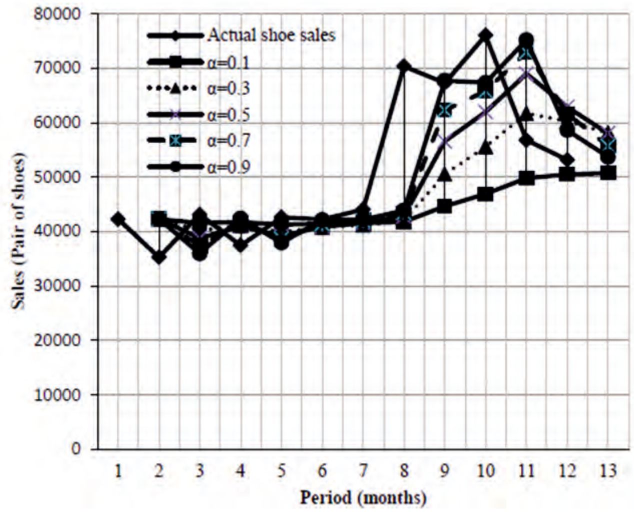
(i) Least Squares Regression Analysis : For the sales data, the dependent variable is the sales during each quarter. As per the Table 5, the regression equation can now be readily calculated as per (9) and (10).

$\overline{X} = 78 \div 12 = 6.50$; $\overline{Y} = 610576 \div 12 = 50881.33$

Table 4. Sales Data Forecasting Using Simple Exponential Smoothing

Period	Actual sales	α = 0.1	Error	α = 0.9	Error
1	42278	-	-	-	-
2	35274	42278.0	-7004.00	42278.00	-7004.00
3	43130	41577.6	1552.40	35974.40	7155.60
4	37439	41732.8	-4293.84	42414.44	-4975.44
5	42600	41303.4	1296.54	37936.54	4663.46
6	42215	41433.1	781.89	42133.65	81.35
7	44062	41511.3	2550.70	42206.87	1855.13
8	70353	41766.3	28586.6	43876.49	26476.51
9	67281	44625.0	22655.9	67705.35	-424.35
10	76012	46890.6	29121.3	67323.43	8688.57
11	56781	49802.7	6978.23	75143.14	-18362.14
12	53151	50500.5	2650.41	58617.21	-5466.21
13		50765.6		53697.62	

Figure 3. Sales Data Forecasting Using Simple Exponential Smoothing



First, calculate the slope, b :

$$b = \frac{4357572 - (12)(6.50)(50881.33)}{650 - (12)(6.5)^2} = 2719$$

Now, we find the Y- intercept, a :

$$a = 50881.33 - (2719)(6.5) = 33208$$

The single equation that best fits the sample data is, then as per (10), $Y = 2719\ (X) + 33208$ as is illustrated in Figure 4. Data may now use equation to estimate the most likely level of sales it will generate, Y, for a specific time period, X. For time period 13, the sales should be about 68555.

$$Y_{13} = 2719(13) + 33208 = 68555 \text{ pairs of shoes.}$$

The value of 2719 indicates that the sales increased at a rate of 2719 pair of shoes per month. The value 33208 is the estimated sales when $t = 0$. That is, the estimated sales amount for November 2013 (the base year) is 33208 pairs of shoes.

The company realizes that this value is, of course, just an estimate. The 12 quarters representing company database of sales are far from a perfect fit (Figure 4). Because of this, the company management wants to know by how much this specific point estimate, Y, might vary. As per (11),

$$Se = \sqrt{\frac{33534152704 - (33208)(610576) - (2719)(4357572)}{12 - 2}} = 11874$$

A the 95% level of confidence (CL= 0.95) and a sample size of 12 (representing the 12 time periods) gives $t_{(1-C1)\ \div\ 2,\quad df\ =\ n-2}$ = 2.228. The variability about Y is, then, as per (12), or, PIL = 68555 ± 2.228 (11874) or, $42100 \leq \text{PIL} \leq 95010$.

Table 5. Simple Regression of Period *(X)* and Sales *(Y)*

Period *(X)*	Sales *(Y)*	X^2	*X Y*	Y^2
1	42278	1	42278	1787429284
2	35274	4	70548	4977020304
3	43130	9	129390	16741772100
4	37439	16	149756	22426859536
5	42600	25	213000	45369000000
6	42215	36	253290	64155824100
7	44062	49	308434	95131532356
8	70353	64	562824	3.16771E+11
9	67281	81	605529	3.66665E+11
10	76012	100	760120	5.77782E+11
11	56781	121	624591	3.90114E+11
12	53151	144	637812	4.06804E+11
Sum=78	50881.33	650	4357572	2.30873E+12

Figure 4. Simple Regression Model of Periods *(X)* and Sales *(Y)*

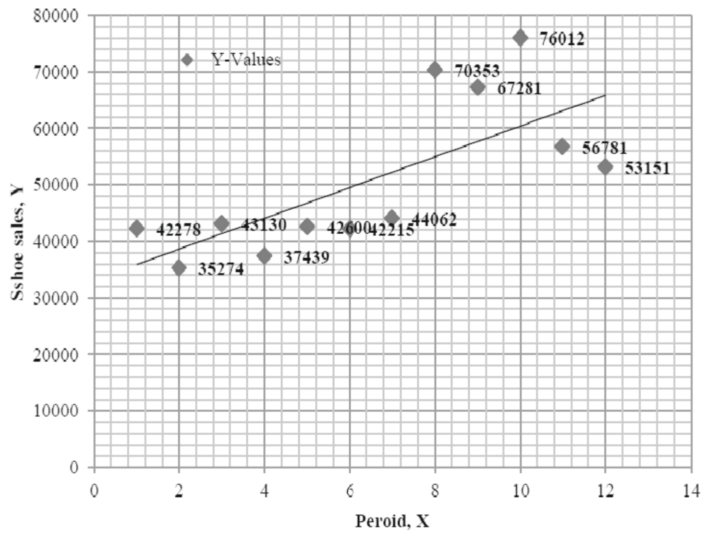


Table 6. ANOVA Table to Test the Significance of Regression

Source of variation	Sum of variation	DOF	MSS	*F* ratio
Due to regression	132529003600	1	132529003600	
Due to error	141923805900	10	14192380590	9.34
Total	33068983930	11		

DOF: Degrees of freedom, MSS: Mean sum of squares

The company can be 95% certain that a sale of a low 42100 pair of shoes and a high of 95010 pair of shoes will take place in the month of December 2014. After December 2014 is over, shoe sales data were again collected from the company, which was 65373 pairs of shoes. Therefore, December 2014 sales data fits within the PIL limits as calculated above.

(ii) Testing of Hypotheses on the Significance of Regression : After fitting a regression model for a real-world data, one should check whether the estimates from the regression model represent the real-world data. The related combinations of hypotheses are :

H0 : The slope, $b = 0$ (there is no linear relationship between Y and X as shown in the model, Table 5),

H1 : The slope, $b \neq 0$ (there is a linear relationship between Y and X, as shown in the model, Table 5).

By using the SPSS software (Version 20), the analysis of variance (ANOVA) result is shown in the Table 6. The Table 6 reveals that the calculated value of F is 9.34. The table value of F with (1, 10) degrees of freedom at a given significance level of 0.01 is 10.04. Since the calculated value of F (9.34) is less than the table value of F (10.04), we accept the null hypothesis (H0: b= 0) and reject the alternative hypothesis (H1: $b \neq 0$).

(iii) Forecasting Sale and Errors Comparison Results : The Table 7 shows the summarized forecasting results of three different models examined and comparison of errors. The Table 7 reveals that from all three forecasting

Table 7. Summarized Forecasting Models Sales and Error Results

Forecasting Models			
Simple moving average	**Weighted moving average**	**Simple exponential smoothing**	
Two months :	**Two months :**	α = 0.1:	α = 0.3:
Sale = 54966	Sale = 54058	Sale= 5076 5.63	Sale=58102.43
MAD= 8487.6	*MAD* = 7992.88	*MAD* = 8956	*MAD* = 8165.76
MSE = 132528341.4	*MSE* = 1222233375.44	*MSE* = 192747036.89	*MSE* = 138419399.8
MAPE = 14.34	*MAPE* = 13.86	*MAPE* = 14.63	*MAPE* = 13.87
Bias = 2904.04	*Bias* = 1791.9	*Bias* = 7073.03	*Bias* = 4395.68
Three months :	**Three months :**	α = 0.5:	α = 0.7:
Sale=61981	Sale=56526	Sale=55694.53	Sale=55694.53
MAD = 10792.2	*MAD* = 8 148.54	*MAD* = 7531.94	*MAD* = 7531.94
MSE = 1643819757.4	*MSE* = 1286171508.26	*MSE* = 108836870	*MSE* = 108836870
MAPE = 15.96	*MAPE* = 13.66	*MAPE* = 13.61	*MAPE* = 13.61
Bias = 2966.97	*Bias* = 1833.1	*Bias* = 1597.21	*Bias* = 1597.21
		α = 0.9: Sale=53697.62, *MAD* = 7096.06, *MSE* = 107827867, *MAPE* = 13.12, *Bias* = 1057.37	

Note: *MAD*: Mean absolute deviation, *MSE*: Mean squared error, *MAPE*: Mean absolute percent errors

methods examined, simple exponential smoothing forecast model (with alpha value 0.1) (Table 4) is found to be fit (forecast value 50765.63 pairs of shoe for December 2014) as compared to actual company sales value (65373 pairs of shoes for December 2014) for present case, which is almost near the actual value. As the error is less in SES model and graph (Figure 3), alpha = 0.1 is smooth as compared to rest of the other models.

Managerial Implications

This study shall help the managers and policymakers to forecast market, improve profits, and optimally utilize resources. The knowledge of multiple techniques shall help them to develop their own business model(s). However, in the study, we don't focus upon statistical validation of the results, but use the same for improving organizational performance. The main hurdle in this study is our failure to contact the top level officials, that is, CEO, President, and so forth of the company to obtain their opinions.

Conclusion

Even though there are numerous ways to categorize forecast models, the most common arrangement is to view them as either qualitative or quantitative. This paper was primarily interested in exploring the quantitative forecast models, that is, SMA, WMA, and SES.

The various smoothing methods, such as the moving-average and SES methods that have been examined can be useful in understanding the overall performance of business data only if there is no significant trend component present in the data. In addition, the SES methods are limited to short-term forecasting situations-one period into the future. If a manager wishes to extend his/her knowledge into the mid-range or long term forecasting, other more elaborate methods that can accommodate a trend will need to be employed.

There is no simple process for a manager to use in determining the forecast model that is most likely to be the best. However, the accuracy desired from the forecast-in combination with the limited resources available to conduct the forecast-will usually identify at least a few potential candidates. Once the models that are practical to consider for a particular application are tested, error-measurement methods can be used to find the one with the highest accuracy. In addition, it is important to determine whether the model has a bias (tracking error), and if it has an error, then it is important to make the necessary, on the-run accommodating adjustments, if possible. Finally, combining a number of different forecast models may provide the manager with more accurate results than will any individual model. This approach might be especially attractive if several methods have been tried, but have all provided unacceptable levels of forecast accuracy.

Limitations of the Study and Scope for Further Research

The following are the limitations of the study: The results are based on only 12 months data collected from the company. Only quantitative forecast models, that is, SMA, WMA, and SES are analyzed. The selected quantitative forecast models are applied only in one shoe manufacturing company.

The following points can be considered as scope for further research : Instead of monthly data, three or five years data can be collected and again, quantitative forecast models can be analyzed. Other quantitative forecast models can be analyzed in a similar manner. In addition, long-term forecasting can be made with the help of a multivariate model.

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