## Economic Development, Technological Change, and Growth

# Demand Forecasting and Measuring Forecast Accuracy in a Pharmacy

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**Abstract:** This study examines the application of structured forecasting methods to determine accurate demand forecasts using 12 monthly sales figures of a moderate busy pharmacy. The date were analysed using some forecasting techniques; Moving Average Method, Exponential Smoothing Method and Least Square Method. Also, the performances of the forecasting methods were evaluated using some accuracy measures such as Mean Absolute Deviation (MAD), Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) to. The findings reveal that exponential smoothing method which results to least forecast error is the best method. Hence, the pharmacy is advised to adopt this best forecasting method to determine its monthly demand forecasts. Pharmacy operators should maintain sound sales and inventory records; it is easier if the system can be computerized but it could be expensive to operate for small pharmacy outlet.

**Keywords*:*** Forecasting methods; pharmacy; performance; demand forecast and accuracy measures

**JEL Classification:** M11; M31

## Introduction

Forecasting has always been an attractive research area since it plays an important role in business planning process (Chao, Jamie & Jonathan, 2017). With rapid and often unpredictable changes in economic and market conditions, managers are making decisions without knowing what will exactly happen in future (Chan, 2000). To achieve competitive advantage in an environment subject to constant fluctuations, organizations have to make correct and timely decisions based on accurate information-forecast (Cassia, Claudimar & Liuz, 2010; Rakesh & Dalgobind, 2013). All decision making processes in the organization requires not just forecasts but accurate forecasts in order to select proper actions relevant for demand and sales planning, production planning, inventory control and so more. Demand planning is a fundamental business exercise that focuses on the forecasting of future actions

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which is a required for efficient supply chain operations and overall firm profitability (Yaro, Brent, Travis & Matthew, 2015) and retail pharmacy is not an exception.

Accurate forecast is a requirement for optimal inventory control and customer demand and reduction of operational costs (Olimpia, Nela & Camelia, 2016). Accurate forecasts help companies prepare for short and long term changes in market conditions and improve operating performance (Wacker & Lummus, 2002). Chihyun and Dae-Eun's (2016) study also confirmed that accurate demand forecasting is important for sustaining the profitability of the firm. This is because demand forecasts influence the firm in various ways, such as, in strategy-setting and developing production plans. Gupta, Maranas, McDonald and Doganis, (2000) asserted that exact sales forecasting is utilized for capturing the tradeoff between customer demand satisfaction and inventory costs. For this usefulness, especially in this recent rapid changing and less predictable business environmental variables, managers and academics have no choice but to devote more attention to how forecasting can be improved to increase demand forecast accuracy (Gilliland, 2011; Rakesh & Dalgobind 2013) In a retail pharmacy, successful sales forecasting systems can be very beneficial, due to the short expiring dates of many pharmaceutical products and the importance of the product quality which is closely related to the human health (Doganis, Alexandridis, Patrinos & Sarimveis, 2006 as cited by Neda, Mohammad & Hamid, 2014). As accurate demand forecasting is crucial to manufacturing companies and it must be taken more seriously in retail outlets such as supermarkets and retail pharmacy because of the high stock level, high customer needs and traffic they experience daily.

Generally, achieving forecasting accurate demand is difficult (Chihyun & Dae-Eun, 2016; Noorfa & Andrew, 2009) and the reasons for difficulty are due to several factors; (i) large variances between actual sales and demand, and (ii) no sales force forecast accountability (Xabier, 2017), (iii) product characteristics in terms of the product life cycle (PLC) (Chihyun & Dae-Eun, 2016), (iv) sources and information-gathering processes (e.g., what information should be collected, where and how it should be collected), (v) approaches to be adopted (e.g., who should be in charge of forecasting, and what roles should be designed), measurement of accuracy (e.g., using the proper metric and defining proper incentive mechanisms), (vi) and using of unstructured forecasting techniques (Kalchschmidt, 2010). In Pharmaceutical business especially retail pharmacy, forecasting the accurate demand for drug and medical supplies is a difficult task (Noorfa & Andrew, 2009) and one of the problems is the lack of a reliable inventory management system which should provide useful forecasting information (Ilma & Mursyid, 2013; Cadeaux & Dubelaar, 2012). Also, high demand volatility of numerous products faced by retail pharmacy (Papanagnou & Matthews-Amune, 2017) resulted to inaccurate demand forecasts. Betts (2014) opined that one major consequence of demand volatility is the increasing inaccuracy of forecasts which have resulted in excessive stocking leading to expiries and losses

especially when considering products with a predetermined shelf life. Considering, the high varieties of products and demand volatility pharmaceutical products, continuous evaluation of fluctuations of inventory is critical to accurate demand forecast, customer satisfaction and overall firm profitability.

Retail pharmacies are a popular choice in low-income countries like Nigeria, Ghana, Togo, etc., for individuals seeking healthcare for minor ailments as a result of the ease of access as compared to the bureaucratic processes, cost and time involved in hospital visitations. Also, in many smaller towns where hospitals are unavailable or reside in bigger cities, retail pharmacies are the first point of call for treatment and advice (Yadav, 2015). Retail pharmacy is confronted with several challenges, including high customer orders and traffic, high stock level, stiff competition, and tough government regulations and levies. It has to continually meet their customers' needs by stocking and delivering the right amount of products (medicines) at the right time.

In retail pharmacy, one of the major problems is the inability to predict the quantity of each drug and classes of drugs should be kept in the inventory (Neda, Mohammad, Sepehri & Hamid, 2014). Despite the high stock level of product varieties in retail pharmacy the forecasting for each drug or class of drugs (anti-malaria, analgesic, hypertensive, blood tonic, cough relief, injections, bone cares, ulcers multivitamins, etc.) are related. On this note, the study adopted top-down approach to forecast the aggregate products where percentages can be allocated to drugs or the individual class of drugs. Bottom-up is another approach where one could forecast for each part and then sum up the whole. The latter approach seems best when there is reasonably good information on sale records of each drug. Despite the fact that empirically, the bottom-up approach is more accurate (MacGregor, 2001), which implies that it can generate more precise demand forecasts but it was not considered in this study owing to inapplicability. Reasons been that, most Nigerian retail pharmacy stores are not automated in terms of inventory control and sales records, so they manually generate total daily or monthly sales figures for all products not each product (drug) sales figures. Thus, sale figures cannot be easily generated for individual products. It is pertinent to mention that the survey reveals that most if not all retail pharmacy stores in Sango-Ota, Ogun State unconsciously rely on qualitative and naïve forecasting methods which produce far less accurate demand forecasts. Considering these situations and the fact that the quality of demand forecasting, as indicated by its accuracy, required improvements as it did not meet expectations Therefore, this study examines how to increase the operational efficiency of the retail pharmacy by improving the accuracy of sales forecasts using a combination of quantitative forecasting techniques and forecast accuracy measures.

## Literature Review

### Forecasting Method

Forecasting is the art and science of predicting future events. It may involve taking historical data and projecting them into the future with some sort of mathematical model (Özlem, 2016). Adedayo, Ojo and Obamiro (2006) posited that forecasting involves the use of historical data, past experience, intuition, personal values and opinion to project future event. It is pertinent to mention that scientific forecasts are possible only when a historical data are available to project the future occurrence. Literature indicates that studies of structured forecasting techniques has been undertaken to improve on demand forecasts accuracy (Rakesh & Dalgobind, 2013; Chindia, Wainaina & Pokhariyal, 2014). Using Structured forecasting techniques refers to the use of quantitative (such as moving average, weighted moving exponential smoothing and regression) and/or qualitative approaches (such as the Delphi method, consumer representative method and panel of experts), rather than naïve methods, to elaborate sales forecasts. Quantitative techniques use specified and systematic procedures, whereas qualitative techniques involve aspects such as intuition, personal judgment, and experiences. Despite the plethora of studies on this issue, debate is still open on whether the adoption of structured forecasting techniques is always beneficial in improving forecast accuracy. In particular, during the last decade, several authors have challenged the assumption that: the greater the adoption of complex forecasting techniques – the better the forecast accuracy. For instance, many authors attempted to demonstrate that the efficacy of forecasting techniques in improving forecast accuracy depends on the fit between the type of technique adopted and the context (Makridakis et al., 1998; Sanders & Manrodt, 2003). Moreover, several researchers suggested that complex forecasting technique adoption is not enough to guarantee good forecast accuracy (Armstrong, 1987; Mentzer & Bienstock, 1998; Moon et al., 2003).

### Qualitative and Quantitative Forecasting Methods

According to Adedayo et al, (2006) and Cassia, et al, (2010), qualitative forecasting method which is subjective in nature involves the use of soft data like the decision maker's experiences, personal values, intuition, emotions and judgmental in reaching a forecast. Some of the common types of qualitative forecasting methods are; (1) Delphi Method, Sales Force Composite, (iii) Consumer Survey, (iv) Jury of Executive Opinions. Quantitative techniques use specified and systematic procedures in analyzing past or historical data by studying the pattern and projecting the pattern into the future using several methods to make a forecast. Generally, this method is assumed to be objectives because it's scientific in nature. Quantitative techniques fall into two categories; (i) trend projections using time series model and

(ii) casual method. Trend projection which is the focus of this study which is further divided into smoothing methods (moving average forecast and exponential smoothing) and time series decomposition. The commonly use quantitative forecasting techniques in the developing economy like Nigeria that has limited access to sophisticated quantitative forecasting methods and facilities are relatively simple methods. Some of the relatively simple forecasting methods include among others; naïve method, moving averages method, weighted moving average method, exponential smoothing method and regression analysis.

## Hybrid Forecasting Method

A third forecasting model is a hybrid of qualitative and quantitative methods of forecasting. This combination allows the use of hard data (historical data) and soft data (decision maker's intuition experiences, emotions, values and judgment) to predict more accurate forecasts. The combination process is dependent on the accuracy of performance forecasting a firm aims to achieve by either minimizing the Mean Square Error (MSE) of the resulting forecasts or combining forecasts to attain a simple average of the different forecasts used in the combination (Chidina et al, 2014). Combining forecasts therefore, tends to even-out uncertainties within the different forecasts used, but erratic changes in market rivalry could render this method less accurate. As useful as combining forecasting methods to generate more accurate forecasts is, it is pertinent to understand that application depends largely on the level of demand. In more demand volatile settings like Nigerian business environment where there is frequent changes of business indicators, combination of qualitative and quantitative methods of forecasting may not adequately predict future sales, so therefore, application of quantitative demand forecasting method(s) to determine future sales of retail pharmacy outlet is recommended. This decision is validity by (Cassia, Claudimar & Liuzs's, 2010) study.

A combination of simple structured forecasting methods such as simple moving average, exponential smoothing and least squared method were used to analyse past twelve (12) months sales data of a pharmacy in this study. Researches on time series forecasting argues that predictive performance increases through combined forecasting techniques (Kumar & Dalgobind, 2013; Armstrong, 2001). Bunn and Taylor (2001) got considerable improvements in accuracy when they combined judgmental forecasting method with a statistical method. Hibon and Evgeniou's (2005) study is of the opinion that selecting among combinations is less risky than selecting among individual forecasts. It was on these premises that a combination of simple quantitative forecasting methods was selected for this study. The performance of forecasting methods varies according to the accuracy measures being used **(**Makridakis & Hibon, 2000). Therefore, estimating the performance of forecasting

methods involves the application of some accuracy performance measures (Nijat, Davis, Peter & Peter, 2016).

**Forecasting Accuracy Measures**

In the past studies, various accuracy measures have been proposed, discussed and applied by many studies as evaluation criteria for forecasting methods (Nijat, Davis, Peter & Peter, 2016; Pradeep & Rajesh, 2014). Forecast accuracy measures provide necessary and decisive feedback to decision makers in order to use the better forecasting which associated with least forecast error. Due to large forecast errors which usually negatively affect companies' operational performance, forecast accuracy is often considered as a necessity (Danese & Kalchschmidt, 2011). Forecast accuracy in supply chain is typically measured using the Mean absolute deviation (MAD), Mean squared error (MSE) Adedayo, et al, 2006, Hyndman and Koehler, 2006) and mean absolute percentage error (MAPE) (Mathai, Amathai, Agarwal, Angampalli, Narayanan & Dhakshayami, 2016). The forecasting errors challenge the overall accuracy of the forecasting methods no matter how simple or sophisticated.

This study intends to evaluate the accuracy of the forecasting methods (i. moving averages method, ii. simple exponential smoothing method, iii. least square method) using mean forecast error (MFE), mean absolute deviation (MAD) and mean square error (MSE). This is in similar to the study conducted by Pradeep and Rajesh, (2014) except the addition of root Mean Square Error (RMSE) which is the squared root of MSE. Paul (2006) applied the forecast accuracy measures to evaluate naïve forecasting technique. Matsumoto and Ikeda (2015) adopted the forecast error measures in examination of demand forecasting by time series analysis for auto parts remanufacturing. Nijat, Davis, Peter and Peter, (2016) did a detailed description of accuracy measures and the performance of the prediction models are evaluated using a chosen dataset from the UCI Machine Learning Repository. Mathai, Amathai, Agarwal, Angampalli, Narayanan and Dhakshayami, (2016) instead used their newly developed accuracy forecast method; Symmetric mean average percentage error and other popular accuracy measures to measure the accuracy of forecast of the sales of the ten products various industries with products having intermittent demand. Rakesh Kumar and Dalgobind, (2013) evaluated the performance of forecasting methods using the accuracy of Mean Average Deviation (MAD), Mean Squared Error (MSE) but in different industry and location. The review of the above literature indicated that there are no best overall accuracy measures which can be used as a universally accepted single metric for evaluating and choosing the appropriate forecasting method

## Materials and Methods

This study adopted a survey and ex post facto descriptive designs which involved the conduct of pilot study, interview and the collection of secondary data of the sales record of the selected retail pharmacy outlet that sell both wholesale and retail products to customers. A combination of quantitative forecasting techniques of; (i) a moving average method; (ii) a simple exponential smoothing method and (iii) least square method were applied to generate demand forecasts for 12 months from January, 2018 to December, 2018 from Twelve (12) historical monthly sales figures from January, 2017 to December, 2017. The demand forecasts were subjected to accuracy test to identify errors made. The forecasting errors challenge the overall accuracy of the forecasting methods no matter how simple or sophisticated.

### Data Presentation

Twelve (12) historical monthly sales figures from January, 2017 to December, 2017 were collected from the sales records of the chosen retail Pharmacy as presented in table 1. The three forecasting methods (moving averages, smoothing constant and least cost method) were used to determine sales forecasts from January, 2018 to December, 2018. The performance of the forecasting methods was evaluated with forecast accuracy measures (MAD, MAPE and MSE).

**Table 1. 12 month's sales figures of Pharmacy**

| Month (x) | Jan | Feb | March | April | May | June | July | Aug | Sept | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Actual sales (y)(million) | 25 | 29 | 28 | 35 | 32 | 36 | 41 | 45 | 20 | 23 | 15 | |

*Source: Company's Sales Records*

## Results and Discussion

### Sales Forecast using 2-Month Moving Average Method

The study used 2-month moving average method to be able to even out the peak and valley in the sales figures for two months which tends to generate better forecast as indicated in table 2. Also, the accuracy of the forecasting method was evaluated as represented in table 2.

**Table 2. Actual and Forecasts using 2-Month Moving Average Method**

| **Month (x)** | **Actual sales (y) (million)** | Forecast | IEI | $IEI^2$ | E/Y x100 |
|---|---|---|---|---|---|
| 1 | 25 | - | - | - | |
| 2 | 29 | - | - | - | |
| 3 | 28 | 24.5 | 3.5 | 12.25 | 12.5 |
| 4 | 35 | 28.5 | 6.5 | 42.25 | 18.57 |
| 5 | 33 | 31.5 | 1.5 | 2.25 | 4.55 |

| | | | | | |
|---|---|---|---|---|---|
| 6 | 32 | 34 | 2 | 4 | 6.25 |
| 7 | 36 | 32.5 | 3.5 | 12.25 | 9.72 |
| 8 | 41 | 34 | 7 | 49 | 17.07 |
| 9 | 45 | 38,5 | 6.5 | 42.25 | 14.44 |
| 10 | 20 | 43 | 23 | 529 | 115 |
| 11 | 23 | 32.5 | 9.5 | 90.25 | 41.30 |
| 12 | 15 | 21.5 | 6.5 | 12.25 | 43.33 |

The forecast accuracy performance measures are;

MAD =Σ/E//T= 69.5/12 = 5.79, MSE =Σ/E/$^2$T = 795.75/12 = 66.31

MAPE = (Absolute error / Actual Observed Value) × 1 00 = 282.73/12= 23.56.

**Sales Forecast using Exponential Smoothing Method**

This is an advance method, weighted average method which overcomes the limitations of moving averages. In this study, α is assumed to 0.30 (30%). This implies that that 30% of the forecast will be affected by recent data while the while the older data will be affected by 70%. It is similar to the value of smoothing constant (α) applied in (Rakesh & Mahto's, 2013) study of evaluating the performance of forecasting methods to determine the level of accuracy.

**Table 3. Actual and Forecasts using Exponential Smoothing**

| | **Actual sales (y) (million)** | Forecast | IEI | IEI$^2$ | \|E\|/Y x100 |
|---|---|---|---|---|---|
| 1 | 25 | | | | |
| 2 | 29 | 25 | 4 | 16 | 13.79 |
| 3 | 28 | 25.9 | 2.1 | 4.41 | 7.5 |
| 4 | 35 | 28.56 | 6.44 | 41.47 | 18.4 |
| 5 | 33 | 29.89 | 3.11 | 9.67 | 9.42 |
| 6 | 32 | 30.52 | 1.48 | 2.19 | 4.63 |
| 7 | 36 | 32.17 | 3.83 | 14.67 | 10.64 |
| 8 | 41 | 34.82 | 6.18 | 38.19 | 15.07 |
| 9 | 45 | 37.87 | 7.13 | 50.84 | 15.84 |
| 10 | 20 | 36.26 | 16.26 | 264.39 | 81.3 |
| 11 | 23 | 24.14 | 1.14 | 1.30 | 5.65 |
| 12 | 15 | 21.40 | 6.4 | 40.96 | 42.67 |

The forecast accuracy performance measures are;

MAD =Σ/E//T= 58.07/12 = 4.84, MSE =Σ/E/$^2$T = 484.09/12 = 40.34

MAPE = (Absolute error / Actual Observed Value) × 1 00 = 224.91/12= 18.74

**Least Square Regression Model**

**Table 4. Actual and Forecasts using Least Squared Model**

| **Month (x)** | **Actual sales (y) (million)** | XY | $X^2$ | Forecast | IEI | IEI$^2$ | \|E\|/Y x100 |
|---|---|---|---|---|---|---|---|
| 1 | 25 | 25 | 1 | 32.92 | 7.92 | 62.73 | 31.68 |
| 2 | 29 | 58 | 4 | 32.42 | 3.42 | 11.70 | 11.79 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 3 | 28 | 84 | 9 | 31.92 | 3.92 | 15.37 | 14 |
| 4 | 35 | 140 | 16 | 31.42 | 3.58 | 12.82 | 10.23 |
| 5 | 33 | 165 | 25 | 30.92 | 2.18 | 4.75 | 6.61 |
| 6 | 32 | 192 | 36 | 30.42 | 1.58 | 2.50 | 4.94 |
| 7 | 36 | 252 | 49 | 29.92 | 6.08 | 36.97 | 16,89 |
| 8 | 41 | 328 | 64 | 29.42 | 11.58 | 134.10 | 28.24 |
| 9 | 45 | 405 | 81 | 28.92 | 16.08 | 258.57 | 35.73 |
| 10 | 20 | 200 | 100 | 28.42 | 18.42 | 339.30 | 92.1 |
| 11 | 23 | 253 | 121 | 27.92 | 4.92 | 24.21 | 21.39 |
| 12 | 15 | 180 | 144 | 27.42 | 12.42 | 154.25 | 82.8 |

**78 362 2282 650**

a= 33.42 b= -0.5

Therefore the regression line equation for forecast is F =

y = 33.42 + (-.5)X and (X=1=12) to generate the forecast for the 12 months.

The forecast accuracy performance measures are;

MAD =Σ/E//T= 92.1/12 = 7.675 = 7.68, MSE =Σ/E/$^{2/}$T = 1057.27/12 = 88.11

MAPE = (Absolute error / Actual Observed Value) × 1 00 = 356.4/12 = 29.7

**Table 5. Summary of the results of the Forecast Accuracy Measures**

| Measure of Accuracy | Moving Average Method | Exponential Smoothing Method | Least Cost Method |
|---|---|---|---|
| MAD | 5.79 | 4.84 | 7.68 |
| MSE | 66.31 | 40.34 | 88.11 |
| MAPE (%) | 23.56 | 18.74 | 29.7 |

Table 5 reveals that the values of MAD, MSE and MAPE under moving average method are 5.79, 66.31 and 23.56% respectively. For exponential smoothing method, the values of MAD, MSE and MAPE are 4.84, 40.34 and 18.74%, respectively. While the value of MAD is 7.68, MSE is 88.11 and MAPE is 29.7% under least cost method. In performance accuracy comparison, it was observed that exponential smoothing method is the best technique because it generates the optimal forecast accuracy. That is, exponential smoothing method having the least values of MAD (4,84), MSE (40.34) and 18.74 (%) indicates that it has least error and more accurate forecast than the other two methods. Therefore, the pharmacy is advised to consider the exponential smoothing method for accurate demand forecasting.

## Conclusion

Demand forecast of a retail pharmacy with high stock level and customer orders like most retail outlets such supermarkets and restaurant with comprehensive historical data can be determined using other statistical forecasting method(s) rather than relying on the use of naïve forecasting or qualitative forecasting methods owing to

lack of proper sales records and the understanding of the importance of scientific forecasting methods. It also evaluated the performance of the forecasting methods (moving average method, exponential smoothing and least square method) in terms of accuracy of sales forecasts using MAD, MSE and MAPE. The findings reveal that using Exponential Smoothing Method generates lowest forecast error, hence more accurate forecasts than other methods. However, the results may not necessarily be the same if a higher or lower smoothing constant (α) is assumed. Also, the usefulness of the statistical forecasting techniques depends on the availability and quality of the historical data which is a function of number and competency of workers, relevant equipment, inventory system (automated) and leadership commitment. It is pertinent to know that there is no method which could be considered as the best one among the others, although Exponential Smoothing Method is the best method that forecasts our data with the least error.

Although, this study is not without some limitations; first, the study used the most common forecasting methods ignoring the complex and sophistication methods. Second, the smoothing constant (α) of 30% (.30) may not be applicable in all retail pharmacy stores especially with different size or operate in another location. Different companies or industries may require another method(s) of forecasting. Also, data were obtained from pharmacy on the assumption that the sale figures were properly records. These limitations notwithstanding have no effect on the reliability and validity of the demand forecast and its accuracy. Therefore, it is recommended that retain pharmacy should maintain sound sales and inventory records; it becomes easier if the system can be computerized but it could be expensive to operate. Also, the operators should determine demand forecast by scientific (quantitative) forecasting techniques that use hard data instead of qualitative forecasting techniques that rely on soft information such as personal experience, intuition, values and opinions

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