LUKENYA UNIVERSITY

ISSN 2663-3183 MULTIDISCIPLINARY JOURNAL (LUMJ)

Vol 1, (1), p.109-115

Modelling a Forecasting Platform for Small and Medium Enterprises in Kenya

Mburu J. M

Kenya Methodist University

Corresponding author: mburujr@gmail.com

https://orcid.org/0000-0003-1874-7180

Article history
Received: June 2, 2020
Received in revised form: July 29, 2020
Accepted: September 19, 2020
Available online: https://research.lukenyauniversity.ac.ke/

ABSTRACT:

Small and medium enterprises' contribution to Kenya's GDP growth is vital. The use of technology to predict business operations and performance is the next frontier in ensuring business sustainability, job security and a generally good business environment. The study aimed at dealing with this information gap and equipping SME owners and managers with the right information to make informed decisions based on their data and experiences. Predicting business operations is a critical task for small and medium enterprises. With increased unpredictability in the business environment, small enterprises find themselves in the receiving end simply because they do not have the tools in decision making like their counterparts who have well established business decision-making tools. SMEs can now tap into the power of data to support decision-making. Data on sales and purchases collected by SMEs is readily available and SME owners can now benefit from the use of predictive analytics to forecast sales and purchases. The data allows SME owners to have added confidence in decision making to help propel their businesses to success.

Keywords: SMEs, Data-driven-decisions, Sales, Purchase, forecasting

1. INTRODUCTION

SMEs in developing economies experience unique sets of challenges towards attaining success (Juma & Han, 2018). In developing countries, SMEs are important pillars of the economy as they serve as a means for people's life sustenance and survival. By the fact that SMEs are owned or managed by single or few owners/managers, they bear a high cost in getting the relevant information as a base for rational decision-making. Therefore, possessing high level technology and financial literacy can greatly enhance the firm's decision-making process (Aremu & Adeyemi, 2013). The

Annual Report and Financial Statements 2017/2018 by the Central Bank of Kenya indicate that SMEs constitute 98 percent of all business in Kenya. Within the 4.7% increase in GDP, 3% was attributed to SMEs. However, according to the National Bureau of statistics micro, small, and medium establishment survey report of 2016, SMEs in Kenya contributed about 40% of Kenya's GDP as at 2008. Nevertheless, 62% of these SMEs close in less than 4 years. 2.2 million SMEs closed shop between 2011 and 2016 alone. These closures were attributed to the SMEs' lack of access to adequate market information, unlike the well-established businesses. This information gap leads to unpredictable market trends, which in turn hinders the SMEs' ability to plan their sales. (Bowen & Mureithi, 2009). In this light, SME owners and managers who are able to accurately forecast their products demand and supply are in a better position to grow their businesses.

1.1.FORECASTING METHODS

Predictive analytics is a broad term used to describe a variety of statistical and analytical techniques used to develop models that predict future events or behaviors (Nyce, 2007). There are two broad forecasting approaches: -

Qualitative method, in this type of forecasting approach where decisions are based on judgments, opinions, intuition, emotions, or personal experiences and are subjective in nature. They do not rely on any rigorous mathematical computations.

Quantitative Method, in this type of forecasting decisions are based on mathematical (quantitative) models, and are objective in nature. They rely heavily on mathematical computations. Quantitative methods are further categorized into associative methods and time series models which is the focus of this research. Figure 1 below summarizes the forecasting methods.

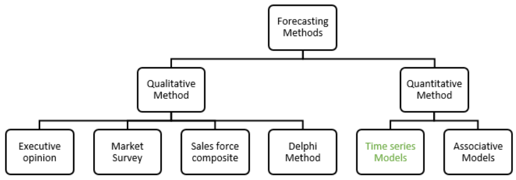

Fig 1. Forecasting Methods

1.1.1. SEASONAL NAÏVE FORECASTING

A forecast that is equal to the latest observation in a time series is known as a no change or "naïve 1" forecast. Because of its simplicity naïve forecasts is often used as a benchmark to determine if the costs and effort of applying methods that are more sophisticated are justified by their increased accuracy (McLaughlin, 1983).

A similar method is useful for highly seasonal data. In this case, we set each forecast to be equal to the last observed value from the same season of the year (e.g., the same month of the previous year). Formally, the forecast for time **T+hT+h** is denoted as follows: -

$$\gamma T + h|T = \gamma T + h - m(k+1)$$

Where ***m = the seasonal period***, and ***k is the integer part of (h−1)/***m. (i.e., the number of complete years in the forecast period prior to time **T+h).** This looks more complicated than it really is. For example, with monthly data, the forecast for all future February values is equal to the last observed February value. With quarterly data, the forecast of all future Q2 values is equal to the last observed Q2 value (where Q2 means the second quarter). Similar rules apply for other months and quarters, and for other seasonal periods.

Date (t)	Sales (A)	Forecast (F)
Month 1 D1	31	30
Month 1 D1	37	30
Month 2 D1	40	31
Month 2 D2		37

Table 1. Seasonal Naïve Example.

In R simple naïve is achieved by the following function on time series data.

snaive(y, h)

1.1.2. NAÏVE FORECASTING

I naive model, the forecast is equal to last observed value. Naïve forecasting is denoted by the formula: -

$$yT + h|T = yT$$

Date (t)	Sales (A)	Forecast (F)
1	31	30
2	37	30
3	40	37
4		40

Table 2. Naïve Example

In R, naive forecasting is achieved through the function

naïve (y, h)

1.1.3. SIMPLE EXPONENTIAL SMOOTHING FORECASTING

Exponential smoothing uses a weighted average procedure with weights declining exponentially as data age. The forecast for next period (period t) is calculated as follows:

$$\mathrm{Ft} = \mathrm{Ft}-1 + \alpha(\mathrm{At}-1 - \mathrm{Ft}-1)$$

Another way to calculate this is

$$\mathrm{Ft} = \alpha\mathrm{At}-1 + (1-\alpha)\mathrm{Ft}-1$$

Where α is is the smoothing coefficient whose value is between 0 and 1. A is the actual observation and F is the forecast value. A popular feature of exponential smoothing method is that forecasts made include a portion of every piece of historical demand. In addition, there are different weights placed on these historical demand values, with older data receiving lower weights.

Date (t)	Sales (A)	Forecast (F)
1	31	30
2	37	30.1
3	40	37.1
4		40.3

Table 3 Exponential Smoothing Calculation Example

The calculation for the forecast for day 2 is as follows 30+ 0.1(31-30) = 30.1

where $\alpha = 0.1$. Note that the Forecast for Day 1 is a guess because there is no historical data for the calculation. In R, exponential smoothing plot is achieved through the function

ses(y, h)

1.2.FORECASTING RESIDUALS

The residuals in a time series model are what is left over after fitting a model. For many (but not all) time series models, the residuals are equal to the difference between the observations and the corresponding fitted values. Residuals are useful in checking whether a model has adequately captured the information in the data. A good forecasting method will yield residuals with the following properties: -

The residuals are uncorrelated. If there are correlations between residuals, then there is information left in the residuals which should be used in computing forecasts (Cryer & Cha, 2005).

The residuals have zero mean. If the residuals have a mean other than zero, then the forecasts are biased (Cryer & Cha, 2005).

2. METHODOLOGY

For this research, a prototyping approach was used to assess the usefulness of a prediction model. Iteration was done based on the performance of the model. Prototyping in this research, is a software engineering 'process' (Floyd, 1984) that encourages the efficient development of applications by breaking complex problems down into several clear, smaller and simpler parts (Kaushaar & Shirland, 1985). A prototyping development approach helps in building, and subsequently refining, a product to meet end-user or market expectations. (Gomaa H., 1983)

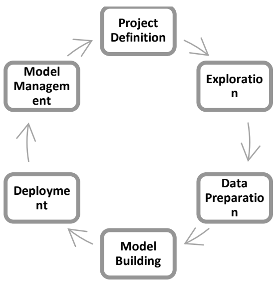

Figure 2 Predictive modeling

2.1. DATA

We solicited for one month sales orders and Purchase orders from Two SMEs in Kenya and used the data received to model a data acquisition tool that will be used in forecasting Demand and supply. The following data was identified as necessary for the forecasting of Supply and demand irrespective of the forecasting method in use.

Custom_Category – This can be a merchants' own categorization, or categorization of the business or products. Examples of possible values are [Product Names, Product Codes, Store Names, Sales person Names]. This option provides flexibility for classification

Date – This takes the format Day, Month, Year e.g (1, April 20). This records when the sales, refunds, purchases and purchase occurred.

Sales – Sales captures a complete sale order and does not take into account the products within the sales order. If users need to capture product-wise sales, then the sales here have to be in conjunction with having the product code or product description in the ***custom_category*** field

Sales_Refund – A sales return is an adjustment to sales that arises from actual return by a customer of merchandise he/she previously bought from the business.

Custom_Category	**Date**	**Sales**	**Sales_Refund**
Store A	01/04.2020	10	0
Store B	01/04.2020	5	3

Table 1. Example of Sales Grouped per Store

Custom_Category	**Date**	**Sales**	**Sales_Refund**
Product A	01/04.2020	7	2
Product B	01/04.2020	8	1

Table 4. Example of Sales Grouped per per Product

Sales and sales refunds represents demand forecasting from the perspective of the SME managers and owners. Ideally, a business will strive for high sales and low sales refunds.

Purchases **–** Purchases by the SME from its suppliers. The unit of measurement here is independent of the sale quantity

Purchase_Cancelation – Purchase-cancelation refers to when an SME returns purchased products back to its suppliers.

Custom_Category	**Date**	**Purchases**	**Purchase_Cancelation**
Store A	01/04.2020	10	0

Store B	01/04.2020	5	3

Table 5. Example of Sales Grouped per Store

Custom_Category	Date	Purchases	Purchase_Cancelation
Product A	01/04.2020	10	0
Product B	01/04.2020	5	3

Table 6. Example of Sales Grouped per Product

Supply- Ideally, a business will strive to have just enough quantities to fulfill its sales commitments. Having a high supply and low demand implies that a business has stock that it cannot sell, while having high sales and low supply means that a business cannot fulfil its customers demand. If the manufacturers supply goods at a rate equal to the consumer demand, the static classical theory would propose that the market is in equilibrium. However, what if there is a tremendous surplus in the store supply rooms? The manufacturers will lower the price and/or decrease production to return inventory to a desired level (Whelan & Kamil, 1996)

Location – The Location from which business operate can result in different behavior in terms of demand and supply, for this research this considered the following possibilities, Rural Area, Urban Area, and Both Rural and Urban Area.

Service – Service refers to the type of undertaking the SME carries out. The possible options here are; Merchandising, Service, Manufacturing and Hybrid Business,

Company_Size – Under the Micro and Small Enterprise Act of 2012, micro enterprises have a maximum annual turnover of KES 500,000 and employ less than 10 people. Small enterprises employ 10-49 people. Medium enterprises employ 50-99 employees (National Council for Law 2012)

Category – Categorization here refers to sectors in which an SME can belong to, according to the Global Industry Classification Standard, the possible values for this field are Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communications services and Utilities.

2.2. ARCHITECTURE

R shiny was used to implement the seasonal naïve forecasting model. Shiny is a reactive framework that allows building of interactive web apps straight from R.

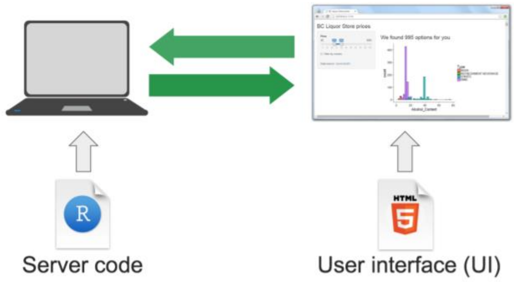

Fig 3 Reactive web framework

Data - The data folder holds the template .csv file that users and download and use it for prediction

Rsconnect - Holds a file in the Debian Control File (DCF) that contains the details about the application and the server hosting details

www- this directory is the directory expected by a Shiny application to locally store the elements that will be rendered in the web browser and are not the output of the scripts. This includes images, HTML, .js, .CSS Style sheets etc.

Server.R - The function helps **Shiny** build a distinct set of reactive objects for each user. As users interact with the widgets and change their values, **Shiny** will re-run the **R** expressions assigned to each reactive object that depend on a widget whose value was changed.

ui.R - Shiny uses the function *fluidPage* to create a display that automatically adjusts to the dimensions of the user's browser window. The user lays out the user interface of the app by placing elements in the *fluidPage* function.

3. FORECASTING ACCURACY

There are many possible ways to measure how well the forecasting models perform. The most general practice is to compare mean absolute error (MAE) or root mean square error (RMSE), which are scale-dependent measures [Gelažanskas & Gamage, 2015]

$$nMAE = \frac{mean(|et|)}{sd(yt)}$$

$$nRMSE = \frac{\sqrt{mean(e^2t)}}{sd(yt)}$$

4. IMPLEMENTATION & RESULTS

Based on the described architecture, the implemented model provides for users to be able to download the desired data format, fill it with their own data, upload the data through an interactive web page and forecast their sales, sales refund, purchases and purchase cancelations. Through the user interface, users are given an option to choose which forecasting model they are interested in. The application also provides for the ability of users to decide the number of days that they need to forecast.

```
RMSE     |         MAE
16.8357  |         9.271186
```

Fig Naïve Forecasting Accuracy

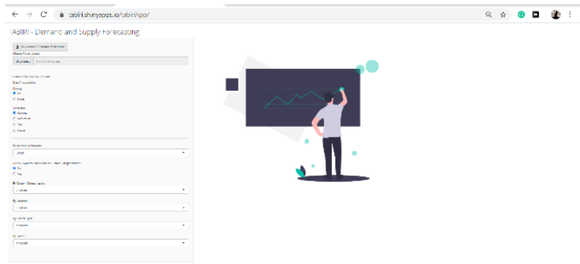

Fig 4 Forecasting Platform

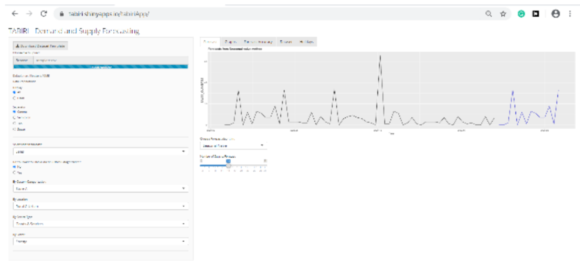

Fig 5 Seasonal Naïve Forecast

5. CONCLUSIONS & RECOMMENDATIONS

The main objective of this research was to research on the baseline forecasting models that can be used by SMEs in forecasting their daily sales, cancelled orders, purchases and canceled purchases. The baseline forecasting algorithms indicate that seasonal naïve forecasting is more accurate of the models explored. This Research forms the basis for further exploration of Seasonal Naïve Forecasting as a favorable forecasting model for Kenya's SMEs. The SME owners can take advantage of this predictive analytics to position their enterprises at an advantage and spur growth.

6. ACKNOWLEDGEMENT

I gratefully acknowledge the contributions of Mr. M Omwando & Dr. L. Muriira for

their great contribution towards this research.

REFERENCES

Kenya, C. B. (2018). *The Year of resilience - Annual report and financial statements 2017/2018.* Nairobi.

Christiane Floyd. (1984). *Systematic Look at Prototyping.*

RStudio. (2020). *Shiny RStudio Documentation.* https://shiny.rstudio.com/.

Global Industry Classification Standard . (2020). *Market cap Indexes.* Global Industry Classification Standard .

Hassan, G. (1983). *The impact of rapid prototyping on specifying user requirements.*

Cryer, D. J., & Cha, K.-S. (2005). *Time Series Analysis With Applications in R.*

Kamil , M., & Whelan, J. (1996). *Economic Supply & Demand .*

Juma, B. M., & Han, D. P. (2018). *Use of Technology and Financial Literacy on SMEs Practices and Performance in Developing Economies.*

Larry, S., & Kraushaar, J. M. (1985). *A Prototyping Method for Applications Development by End Users and Information Systems Specialists.*

Gelanzanskas, L., & Gemage, K. A. (2015). *Forecasting Hot Water Consumption in Dwellings Using Artificial Neural Networks.*

Aremu, M., & Adeyemi , S. (2013). *Small and medium scale enterprises as a survival strategy for employment generation in Nigeria. Journal of sustainable development.*

McLaughlin, R. (1983). *Forecasting models - sophisticated or naive. Journal of Forecasting.*

Bowen, M., Makarius, M., & Mureithi, S. (2009). *Management of Business Challenges Among Small and Micro Enterprises In Nairobi-Kenya.*

National Council for Law Reporting 2012. (2012). *Micro and Small Enterprises act no. 55 of 2012.* Kenya National Council for Law Reporting 2012.

Nyce, C. (2007). *Predictive Analytics.*