Demand Modelling of Alcoholic Beverages in Manicaland Province Using Time Series Analysis

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Abstract

The research explores time series models that can be adopted by Mutare Delta Beverages Centre to estimate volumes of lager beer cases required in its sub-depots. These models assist in regulating overstocking or under-stocking in sub-depots. Overstocking increases holding costs and transport costs through transfer of excess cases of lager beer from one sub-depot to the other. Under-stocking results in, loss of customer goodwill, insufficient preparation of spinning reserve, increase in commodity pricing and additional transport costs to retailers moving from one sub-depot to another in order to supplement lager beer stocks. Failure by the company to have a decision support tool to estimate the demand has resulted in overstocking and under-stocking in sub-depots. Statistical packages, MINITAB and R-15.2 were used for modelling. The Box-Jenkins methodologies which use integrated autoregressive and moving averages models were adopted for model development. A model for each sub-depot and the main depot supply capacity were developed and used for a six months forecasting period. The six months predicted weekly demand and supply of lager beer along with their 95% confidence intervals will assist Delta’s decision makers to establish strategies, priorities and ensure efficient distribution of the product and profit maximization in Manicaland.

Keywords: Time Series Analysis, Forecasting, Under-Stocking, Overstocking, Efficiency.

1. Introduction

Mutare Delta Beverages Centre delivers lager beer twice per week to each of the five sub-depots. The weekly quantities of lager beer demand in form of cases for each sub-depot from April 2010 to December 2012 were recorded by the researcher. The main depot has enough capacities of lager beer for its sub-depots but its greatest weakness was to determine optimum quantities of lager beer required at each sub-depot. Failure by the main depot to have a model that would help them to determine demand for the sub-depots gave rise to overstocking or under-stocking of the sub-depots. The increase in distribution costs was not a result of shortages in supply capacity but under-stocking or overstocking at the different sub-depots. Under-stocking resulted in, loss of customer goodwill, insufficient preparation of spinning reserve, increase in commodity pricing and also additional transport costs to retailers moving from one sub depot to another to get their correct quantities of lager beer. The key interviews carried out by the researcher have shown that the greatest cause for the overstocking or under-stocking is failure by the company to have a tool that can support their decisions in estimating the demands of the product at the sub depots. The researcher proposed to come up with a solution to the problem by developing some models that can be used to predict or estimate the demand of lager beer to sub-depots in cases. A case contains twenty-four units of lager beer.

1.1 An Overview of the Operations at Mutare Delta Beverages Centre

Manicaland has its main Delta depot in Mutare town. The main depot has three sub-depots in Mutare rural and two sub-depots in Mutare urban. Each depot has a sphere of influence to cover with the five lager brands. Villages take advantage of the sub-depot’s proximity but, if the brands are out of stock they can move to the next depot till they get their stock.

Depots used by Delta Beverages Centre-Mutare are Zuvarabuda, Mutyenyoka and Wengezi for Mutare rural district and Metro-Peech and Kap-Jeck for Mutare urban – Fig. 1. The communities serviced by these various sub-
depots include Penhalonga, Watsomba, Zimunya, Chimanimani North, Marange, Chikanga, Dangamvura, Sakubva and Mutare town.

Each sub-depot is serviced twice per week but some would fail to meet their customers’ demands, hence, they move around to get more stocks either from the main depot or from other sub-depots. The company does not have a formal instrument to use in estimating the quantities of brands needed at these sub-depots, hence some depots would complete the week with sufficient beer for their clients whilst other depots would run out of stock. It implies that the sub-depots are failing to forecast their lead demand inventory. However, if their demand was accurately predetermined, this problem would have been alleviated. The failure to have a proper tool for determining demand of the area can result in the increase of transportation costs, loss of customer goodwill, an effect on the production capacity and poor planning and scheduling of company’s activities, where distribution is one of the crucial activities.

![Fig. 1: Mutare Delta Centre’s Sphere of Influence](image)

Delta uses its own means of transport to deliver the brands to the various destinations straight from depots. However, some lager beer dealers sometimes offer their own transport services which would have an impact on the unit cost per brand to the final consumers and sometimes a lower selling price by the company to retailers. There are also cases where alcoholic brand dealers complain for not getting their deliveries in time which would force them to seek alternatives. Such operational problems are emanating from a weaker system of estimating the demand at sub-depots. Increased movements in search of or in delivering the beverages means more distribution costs. Planning and scheduling activities related to product distribution have been receiving growing attention for the past decade. Every company’s focal point should be on attending to all its client requirements at the lowest possible cost and without shortage. Every decision maker must deal with unforeseen events. He or she must plan for these events as well as responding to them.

Even though Delta is making profits from the brands business, it is facing a challenge in its product distribution. The method used by the company which depends on shortage reports from sub-depots to gauge and increase supply lacks a scientific approach in addressing such operational challenges. The danger that might arise is that the company might assume that as much as one produces more brands, increases the sphere of influence, see all vehicles moving, being able to pay wages to contractual plus permanent workers and make profit that is good enough of business. The researcher is of the opinion that one can be in the feasible range of making profit and do all what Delta is doing without optimally utilizing the available scarce resources. Delta’s demand and distribution challenges motivated the research to provide an alternative approach to the company’s operations.

A time series of data is a sequence of numerical observations naturally ordered in time (Wilson and Keating, 1990). When analyzing such data for forecasting purposes, two questions of paramount importance are that: Do the data exhibit a discernible pattern? Can this pattern be exploited to make meaningful forecast?

When choosing the most appropriate time series model, there are three basic types of black boxes to examine, although many variations can be deduced within each of the three types. The black boxes are: Moving Averages (MA) models, Autoregressive (AR) models and Autoregressive Integrated Moving Averages (ARIMA).

The ARIMA model is an important forecasting tool, and is the basis of many fundamental ideas in time series analysis. An autoregressive model of order $p$ is conventionally classified as AR $(p)$ and a moving average model with $q$ terms is known as MA $(q)$. A combined model that contains $p$ autoregressive terms and $q$ moving average terms is called ARIMA $(p, d, q)$ (Chatfield, 1996). If the data is differenced $d$ times to achieve stationarity, the model is classified as ARIMA $(p, d, q)$. 

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Collected data must be accommodated by at least one of the time series patterns after some tests, for example, using the Box-Jenkins’ approach, (Hyndman, 2008). If the series is not stationary, it will be necessary to modify the original series by transforming it into a stationary series. The main methods used in transforming non-stationary time series data are differencing and Box-Cox transformations.

As with most statistical models, model adequacy is performed by checking the residuals. The residuals should be normally distributed, independent of each other and have a constant mean and variance. The test for normality can be done in two ways, by plotting a histogram or dot plot of the residuals and construction of a normal probability curve. A normal probability plot will resemble a straight line otherwise the normality assumption is violated. In visualizing the straight line, more emphasis should be on the central values of the plot than on the extremes, (Montgomery, 1999). Two methods for testing for independence of residuals were implemented. The first method involved the plotting of residuals against the fitted values. Authors have argued that if the model is correct, the plot should be structure less, (Hicks and Turner, 1999). Another important tool is to plot the ACF of the residuals and this should not show any significant terms (though expect approximately 1/20 to be above $\pm \left(\frac{2}{\sqrt{n}}\right)$).

Data splitting method was used as a model validation tool. Data splitting is reasonably effective when the data set is large enough to split the data into two sets. The first set, called the “model building set” is used to develop the model. The second data set, called the validation or prediction set is used to evaluate the forecasting ability of the selected model. If the quality of the forecast is acceptable then, one can conclude that the model is right. Data splitting was adopted in this research.

The key factor in choosing a proper forecasting approach is the time horizon for the decision requiring forecasting. Forecasts can be made for various time frames: short term, medium term and long term, (Lawrence, 2012). In short term forecasting (1 day to 3 months), managers are interested in forecasts for disaggregated demand for a specific product. There is little time to react to errors made from demand forecasting hence, the forecasts need to be as accurate as possible. Time series is often used in the demand predictions. Medium term forecasting (3 months to two years) relates to aggregate planning (sales and operations planning). It is used to build up seasonal inventory. Long term forecast (exceeding two years) are used for process selection, capacity planning and location decisions. In the absence of historical data, managers use judgmental methods. This study is going to base on short term forecasting horizon.

Efficiency is about generating more or better output (volume or quality of service) from the available resources or achieving the same volume or quality of output with fewer resources, (Mapuwei et al., 2013). Efficiency in our scenario is all about matching the lager demands at the various sub-depots in the geographical area covered by Mutare Delta distribution centre.

2. Methodology

Key informant interviews were conducted with the Mutare Delta Beverages Centre distribution manager at their main offices and an interview guide was designed for the five sub-depots sales representatives. Observations was an additional way of coming up with the required information. The interviews’ main focus was to determine the weekly transportation systems of the company and also to establish the previous supply at every sub-depot and the demands at every community under investigation. Supplies to the main depot and the demands at every sub- depot were used in the formulation of the decision supporting tool to improve the distribution efficiency, minimize distribution costs and improve customer satisfaction in terms of service delivery. A case contains twenty-four units of lager beer.

Data used in the development of the models was presented and analyzed using Time Series analysis technique known as the Box-Jenkins Methodology. The secondary data for sub-depots lager beer demand was run on the MINITAB and R.15.2 statistical packages to give results of the time series models inform of graphs and tables with predicted values. The researcher gave quantitative and qualitative analysis and interpretations of the graphs and tables using the Box-Jenkins framework.

Data of lager beer demand for Zuvarabuda, Mutyenyoka, Wengezi, Metro-Peach and Kap-Jeck sub-depots including the main depot was collected on weekly basis from April 2010 to 31 December 2012. Data splitting method was adopted and weekly demands from April 2010 to March 2012 were used for the real model building whilst demands from April to December 2012 were used to validate the models from forecasts.

3. Discussion of Results

The main objective of the research was to develop a decision supporting tool that informs management of proper lager distribution methods to sub-depots. This will
Help improve on efficiency (reduce the occurrence of overstocking or understocking), increase profits, and increase customer satisfaction.

3.1 Analysis of Zuvarabuda Sub-depot Data

The main task in automatic ARIMA forecasting (Hyndman, 2008) is selecting an appropriate model order, (that is the values p, d and q). On the basis of the automatic ARIMA forecasting the selected model to represent Zuvarabuda’s data was ARIMA (1, 1, 2) + constant term - Table 1.

<table>
<thead>
<tr>
<th>Parameter type</th>
<th>AR 1</th>
<th>MA 1</th>
<th>MA 2</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>0.5010</td>
<td>1.1480</td>
<td>-0.1353</td>
<td>9.758</td>
</tr>
<tr>
<td>t-value</td>
<td>5.62</td>
<td>835.86</td>
<td>-3.11</td>
<td>4.29</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
</tr>
</tbody>
</table>

All parameters are significant in this model since all the p-values are below 0.05 as shown in Table 1. Diagnostic checks on the residuals and adequacy of the model was satisfied and a conclusion can be reached that lager beer demand at Zuvarabuda can be modeled by an Autoregressive Integrated Moving Average Model given by: ARIMA (1, 1, 2) + Constant term.

3.2 Analysis of Mutyenyoka Sub-depot Data

The ARIMA (1, 1, 1) (1, 1, 1)12 + Constant term model was selected as adequate to represent Mutyenyoka’s data and could be used to forecast the upcoming lager beer demand. Results are summarized in Table 2.

<table>
<thead>
<tr>
<th>Parameter type</th>
<th>AR 1</th>
<th>SAR 12</th>
<th>MA 1</th>
<th>SMA 12</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>0.61</td>
<td>-0.34</td>
<td>1.01</td>
<td>0.85</td>
<td>4.93</td>
</tr>
<tr>
<td>t-value</td>
<td>6.88</td>
<td>-2.80</td>
<td>1030.7</td>
<td>9.22</td>
<td>40.64</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

All parameters are significant as all the p-values are below 0.05 as shown in Table 2. Verifying the adequacy of the model, the Box- Pierce statistic was used where all the p-values were found to be greater than 0.05 confirming model adequacies. The diagnostic checks on the residuals for data independence were done and adequacy of the model was satisfied. All the forecasted values are within ninety-five percent (95%) confidence interval except one value on the first week of July and this validates that the model can adequately forecast the demand of lager beer cases needed at Mutyenyoka depot.

3.3 Analysis of Wengezi Sub-depot Data

An ARIMA model (1, 1, 2) + Constant term is adequate to represent Wengezi’s data and can be used to forecast the upcoming lager beer demand. Results are summarized in Table 3.

<table>
<thead>
<tr>
<th>Parameter type</th>
<th>AR 1</th>
<th>MA 1</th>
<th>MA 2</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>0.3567</td>
<td>1.1463</td>
<td>-0.1606</td>
<td>14.176</td>
</tr>
<tr>
<td>t-value</td>
<td>3.81</td>
<td>206.43</td>
<td>-4.03</td>
<td>3.78</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

All parameters are significant in this model since all the p-values are below 0.05 as shown in Table 3 and the t-values are supposed to be in the critical region ±1.96 as was found in the model. Several attempts were done to improve on the model but none of them could give a better model than the stated one. In order to verify the adequacy of the model, the Box- Pierce statistic was used where all the p-values were found to be greater than 0.05, which is the significance level and that confirmed model adequacy.

Diagnostic check of the residuals for independence was done and the model is found to be adequate. The researcher concluded that the demand for Wengezi lager beer can be modeled by an Autoregressive Integrated Moving Average Model given by: ARIMA (1, 1, 2) + Constant.

3.4 Analysis of Metro-Peech Sub-depot Data

An ARIMA model (1, 1, 1) + Constant term was selected and is adequate to represent Metro-Peech’s lager beer demand at the depot. Results are summarized in Table 4.

<table>
<thead>
<tr>
<th>Parameter type</th>
<th>AR 1</th>
<th>MA 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>0.5226</td>
<td>0.9872</td>
</tr>
<tr>
<td>t-value</td>
<td>5.92</td>
<td>66.48</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td>0.019</td>
</tr>
</tbody>
</table>

All parameters are significant in this model since all the p-values are below 0.05 as shown in Table 4. Diagnostic check of the residuals for independence was done and the model was found to be adequate. The demand for Metro-Peech lager beer can be modeled by an Autoregressive Integrated Moving Average Model given by: ARIMA (1, 1, 1) + Constant.

3.5 Analysis of Kap-Jeck Sub-depot Data
An ARIMA model (1, 1, 2) was selected and is adequate to represent Kap-Jeck data and could be used to forecast the upcoming lager beer data at the depot. Results are summarized in Table 5.

<table>
<thead>
<tr>
<th>Parameter type</th>
<th>AR 1</th>
<th>MA 1</th>
<th>MA 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>0.7475</td>
<td>1.4184</td>
<td>-0.4375</td>
</tr>
<tr>
<td>t-value</td>
<td>10.18</td>
<td>17509.74</td>
<td>-23.05</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

All parameters are significant in this model since all the p-values are below 0.05 as shown in Table 5 and the t-values are supposed to be in the critical region ±1.96 as was found in the model.

3.6 Analysis of Mutare Depot (Sub-depot) demand Data

The main depot’s major purpose is to supplement sub-depots demand deficits and also to provide service to those customers who want to deal directly with the main depot. Their sales are sometimes lower than the other sub-depots. An ARIMA model (0, 1, 1) (3, 1, 1)_{12} + constant was selected and is adequate to represent Main-Depot’s demand data. Results are summarized in Table 6.

<table>
<thead>
<tr>
<th>Parameter type</th>
<th>SAR 12</th>
<th>SAR 24</th>
<th>SAR 36</th>
<th>MA 1</th>
<th>SMA 12</th>
<th>Const</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>-0.37</td>
<td>-0.39</td>
<td>-0.53</td>
<td>0.86</td>
<td>0.73</td>
<td>-37.9</td>
</tr>
<tr>
<td>t-value</td>
<td>-2.45</td>
<td>-2.33</td>
<td>-3.37</td>
<td>14.64</td>
<td>4.03</td>
<td>-4.27</td>
</tr>
<tr>
<td>P-value</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

The data distribution shows a seasonal pattern that repeats itself after every twelve months. Seasonality of the demand is more pronounced at this sub-depot. This is anticipated at the main depot as demand is usually high during public holidays and festive seasons. Retailers prefer to order lager beer direct from the main depot as buffer stock anticipating high demand associated with such holidays and festive seasons.

3.7 Modelling the Lager Supply to Mutare Delta Centre

The sub-depots discussed previously get their supply of lager beer cases from Mutare Delta Beverages Centre (which is the main depot in Mutare). All the lager beer was supposed to have been sold from this Delta main depot. However, efforts to create a bigger market area and increase in customer service care have resulted in the establishment of these sub-depots. This implies that, the supply from the Beverages centre needs to be determined in order to address the research objective. The first step towards coming up with the weekly supplies needed by the company in Manicaland was to find the total weekly demands for all the sub-depots including its supply to local dealers who buy the product directly from the main depot. These totals became the data required to identify a suitable model for the weekly supplies by the company to the main depot. The small models at sub-depots will fit into the main model that will be developed here.

The R-15.2 statistical package use months instead of weeks in the model building and forecasts, and weeks are grouped into frequencies of fours per month. A dataset of 144 weeks would result in thirty-six months and thus, the data that was used to develop this fitted model. MINITAB is better in the model identification but R-15.2 package proved to the researcher to be finer in the prediction strength of the model.

The ACF and PACF of the original data in Fig. 2 and Fig. 3 shows that there were spikes outside the preferred zone, that is, ±1.92/√n (± 0.1706) where n =105 and the series is not stationary. In order to fit an ARIMA model, stationary data in both variance and mean are required.

The data distribution shows a seasonal pattern that repeats itself after every twelve months. Seasonality of the demand is more pronounced at this sub-depot. This is anticipated at the main depot as demand is usually high during public holidays and festive seasons. Retailers prefer to order lager beer direct from the main depot as buffer stock anticipating high demand associated with such holidays and festive seasons.
The ACF plot in Fig. 4, for the differenced lager beer supply data is stable which indicates that the series is now stationary in both the mean and variance after having first order non-seasonal difference. The ARIMA (1, 1, 2) + Constant model was adequate to represent the supply data and could be used to forecast the upcoming Mutare Delta Beverages Centre lager beer cases. From the ACF plot most of the sample autocorrelation coefficients of the residuals are within the limits ±1.96/√n i.e. ±0.1706 where n=105, then the residuals are white noise indicating that the model is a good fit.

Table 7 gives the maximum likelihood estimates and standard errors of the ARIMA (1, 1, 2) + constant model.

<table>
<thead>
<tr>
<th>Parameter Type</th>
<th>AR 1</th>
<th>MA 1</th>
<th>MA 2</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>0.3234</td>
<td>0.7242</td>
<td>0.2515</td>
<td>67.27</td>
</tr>
<tr>
<td>t-value</td>
<td>2.52</td>
<td>6.26</td>
<td>2.33</td>
<td>4.08</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.1284</td>
<td>0.1157</td>
<td>0.1080</td>
<td>16.49</td>
</tr>
<tr>
<td>P-value</td>
<td>0.013</td>
<td>0.000</td>
<td>0.022</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Inspection of the time plot of the standardized residuals had few outliers in the series. The ACF of the standardized residuals had no apparent departure from the model assumptions – Fig. 5, and the Q-statistic is never significant at the lags. The Ljung-Box test for this model gave a chi-squared value of 9.4 with 8 degrees of freedom at lag 12, leading to a p-value of 0.031, a further indication that the model has captured the dependence in the time series. The Q-Q plot of the residuals is not showing any significant divergence from normality – Fig. 6. The p-values for the Ljung-Box statistic are all greater than (>0.1), as tests for independence of residuals is the null hypothesis, we fail to reject $H_0$ and conclude that the model is correctly specified.
A comparison between the real values and the ones resulted from the developed ARIMA model for the period between April 2010 and December 2012 was performed. Using the model, the graphical plot for the actual peaks against the predicted peaks and from the visual inspection it is quite evident that the chosen model is good enough as the predicted series is very close to the observed series and this model could be used to forecast the supply capacity of Mutare Delta Beverages Centre – Fig. 7.

All the forecasted data values fall within the 95% confidence interval and this validates that the model can adequately forecast the supply capacity of Mutare Delta Depot. The forecasted demand plot is a true reflection of the actual demand trends as it predicts when to expect a peak demand and when it is likely to decline. A six months predicted weekly supply capacities will help decision makers to establish strategies, priorities and proper distribution of lager beer to the sub-depots.

4. Conclusion

It was established from the interviews made with Delta Mutare that it does not have any model(s) to use in predicting lager beer demand for its sub-depots, they base their demands on previous sales hence, over-stocking or under-stocking its sub-depots. The researcher was motivated to develop scientific models that can mitigate the problem.

An Autoregressive Integrated Moving Average (ARIMA) model \((1, 1, 2) + \text{Constant}\) can be used to predict the weekly lager beer demand at Zuvarabuda sub-depot, a Seasonal Autoregressive Integrated Moving Average (SARIMA) model \((1, 1, 1) (1, 1, 1)_1^{12} + \text{Constant}\) can be used to predict the weekly lager beer demand at Mutyenyoka sub-depot, an ARIMA model \((1, 1, 2) + \text{Constant}\) for Wengezi sub-depot, an ARIMA model \((1, 1, 1) + \text{Constant}\) for Metro-Pech sub-depot, an ARIMA model \((1, 1, 2) \text{ without constant}\) can be used to forecast demand at Kap-Jeck, a SARIMA \((0, 1, 1) (3, 1, 1)_1^{12} + \text{Constant}\) was found suitable for the main depot and a supply capacity model ARIMA \((1, 1, 2) + \text{Constant}\) can be used to forecast the weekly supply capacity of Mutare Delta Beverages Centre.

These models were arrived at after some diagnostic checks and model validation for adequacy. By comparing the fitted and actual values of lager beer cases using the determined models the forecasts are sufficiently accurate. The selected models gave a six months predicted weekly demand and supply of lager beer along with their 95% confidence intervals that can help decision makers to establish strategies, priorities and have efficient distribution of the product in Mutare.

The researchers hope that if the results of this study are implemented, distribution costs would be minimized giving rise to an improvement in profits. Simultaneously, delivery services of the product will improve and result in customer satisfaction by getting their orders at the right time and in required quantities. Cited consequences of under-stocking and over-stocking would be corrected whilst improving operational efficiencies. Regular and planned deliveries of lager beer to the sub-depots with limited or no unnecessary movements will be experienced. The two main parties who will benefit from the study is the company itself by
minimizing costs whilst improving revenue and the customers (retailers and general dealers) when their orders are met in time. The retailers’ profits are expected to improve as well. The general consumer of the product will eventually benefit if such scientific and informed decision making tools are adopted and implemented.

References


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