How Much Will They Buy?

Optimal Forecast Selection for Predicting a Bakery's Demand

Final Project Report

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BPJ 420 Project

at the

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Flow Chart on the Summary of the Project

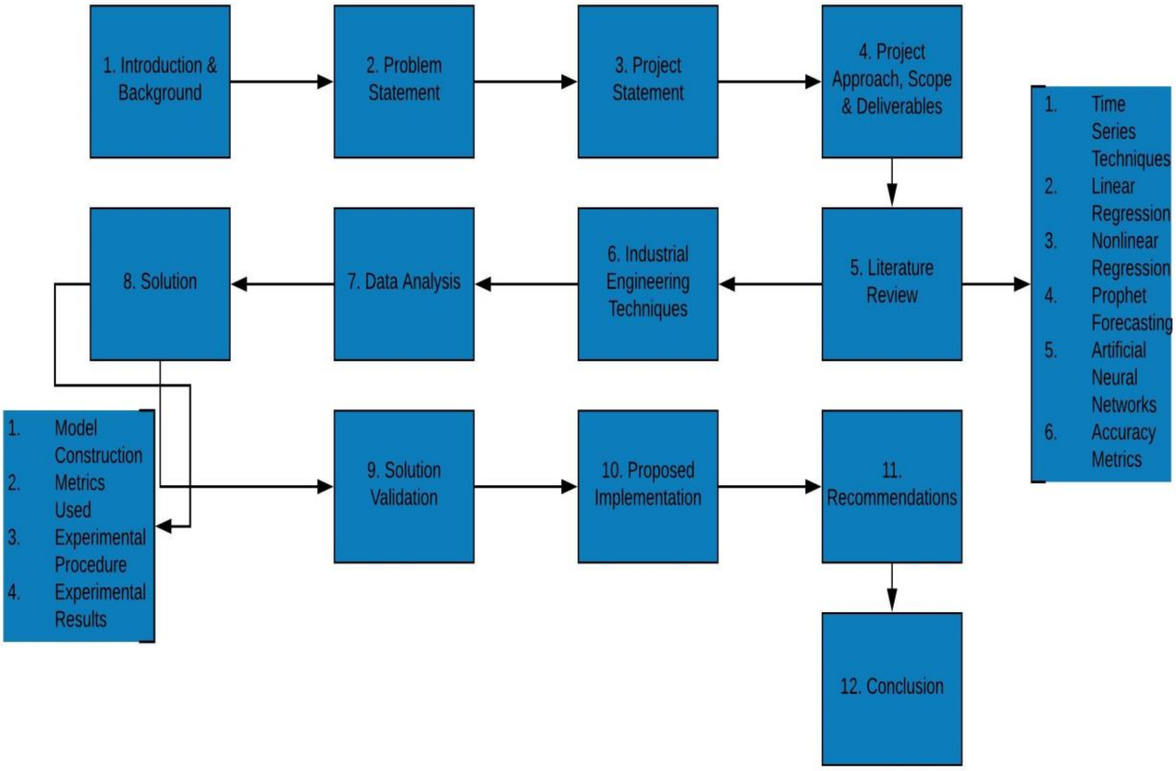

Figure 1 Flow chart on the summary of the project

The figure above (Figure 1) depicts the approach followed to successfully complete the project. Chapter 1 introduces the company and the problem at hand. In chapter 2, the problem is further investigated by performing an ABC analysis. Chapter 3 defines the project aim as well as the objectives. Chapter 4 expands on the project aim and objectives, and outlines the project approach followed, as well as the deliverables to be completed. Chapter 5 is based on in-depth research of different forecasting techniques. Demand forecasting is explained and five different techniques are investigated. Accuracy metrics are also investigated as this is necessary when comparing the different techniques. Chapter 6 explains the different industrial engineering techniques used and how they relate to the problem at hand. Chapter 7 focuses on the raw data received from the company and analyses this data which, in turn, serves as an indication of how to approach the solution. Chapter 8 focuses on the solution to the problem. The first section of chapter 8 explains how the different models are constructed. The different metrics used to measure accuracy are also discussed in chapter 8. The subsequent sections of the chapter are dedicated to outlining the experimental procedure followed as well as the experimental results. Chapter 9 focuses on validating the solution by ensuring the problem aim is reached. The overall accuracy of the four models is compared and discussed. Chapter 10 explains the proposed steps the company should take if they decide to implement the solution. Chapter 11 recommends further ideas that the company should take into consideration in order to get an even more accurate solution. Lastly, chapter 12 concludes the project report and explains why the recommended model was chosen.

Executive Summary

SPAR-Roodeplaat is part of an international group of independently owned and operated retailers who work together in partnership under the SPAR franchise brand. The store does not only offer a wide range of day-to-day grocery products, but they also have their own in-store bakery, deli and butchery. SPAR has been finding inventory management and planning of their ‘departments’ (bakery and deli) challenging as they do not have a set ordering system in place.

Products produced by the bakery and deli are perishable items as the freshness of these products decrease daily and therefore can only be sold to customers for a few days. Consequently, items not sold at the end of the day are considered as wastage and this leads to a loss. However, running out of stock also leads to a loss of revenue and will have an impact on customer satisfaction. An ABC analysis was conducted to investigate the problem and to determine the number of stock-outs occurring.

A literature review was conducted to obtain a better understanding of the problem and to get a general idea of how similar problems were solved. After reviewing the appropriate literature, the project goals have been determined. The project aim is to determine the most accurate and appropriate forecasting technique to be used for the bakery and deli departments. Numerous forecasting techniques were investigated but emphasis was placed on multiple linear regression, Prophet forecasting, autoregressive integrated moving average (ARIMA) and artificial neural networks (ANN) models.

The four models mentioned above were developed using ***R*** and were compared using four metrics to determine the most accurate model. Mean average percentage error (MAPE), mean average squared error (MASE), mean absolute difference (MDAE) and mean average error (MAE) were the four metrics used.

The overall accuracy, as per experimentation, and other practical reasons have concluded that Prophet forecasting is both the most practical and accurate of the four algorithms as defined by the methodology of this project. However, recommended improvements to be made include further optimisation of each model, the inclusion of promotional dates and better understanding of the each product unique time series. A proposed implementation plan has also been discussed.

The visual form of a Gantt chart was used as a guideline to complete the necessary activities within the given deadlines.

On completion of this project, it is apparent that an accurate forecasting model will make inventory planning easier within their bakery and deli departments. An accurate forecasting model will not only assist the retail store with production and inventory planning, but will also be useful when making important business decisions in areas of finance and marketing.

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1. Introduction and Background

1.1 Company Background

SPAR-Roodeplaat is part of an international group of independently owned and operated retailers who work together in partnership under the SPAR franchise brand. The store is based in Pretoria East on a plot that is also occupied by Tops at SPAR (liquor store) and Coop Trading, Angling and Hardware Store.

The location can be seen as a prime spot as it is situated along the route to the residential area. The store attracts a wide range of customers as there are multiple businesses close by, along with a few bed and breakfasts close to the SPAR. The store also has daily specials to further attract customers.

SPAR-Roodeplaat does not only offer a wide range of day-to-day grocery products, they also have their own in-store bakery, deli and butchery. Their goal is “to consistently meet the individual needs of every customer in a caring and homely environment” by continuously striving to achieve the highest standards of quality in all departments of their business.

1.2 Project Background

SPAR has been finding inventory management and planning of their ‘departments’ (bakery and deli) challenging. Raw materials are combined in different quantities to form final products, and these products also have variable demand which is not easily forecasted by the store manager.

Products produced by the bakery and deli are perishable items as the freshness of these products decrease daily and can therefore only be sold to customers for a few days. Consequently, items not sold at the end of the day are considered as wastage and are discarded, resulting in a loss. By the same token, however, running out of stock also leads to a loss of revenue and ultimately has an impact on customer satisfaction.

SPAR requires a solution for adequate stock ordering planning and therefore the project will focus on determining the most accurate forecasting technique for these departments. When this aim of determining the most accurate technique is achieved, the store will be able to plan more efficiently, ensuring that the right amount of stock is available at the right times and, in turn, leading to an increase in profits.

1.3 Process Overview

SPAR’s bakery and deli departments have no set ordering process in place for raw materials. The biggest issue with the current process is that production of items, as well as the reordering of raw materials, is based on assumptions and experience. This leads to either overproduction of items or stock-outs since the demand is not known.

It is vital that the demand for these items is known in order to develop an adequate stock ordering system. Once the demand is apparent, raw material usage can be optimized and a reordering policy may be developed. Therefore, in order to know the demand, an adequate demand forecasting system is required.

2. Problem Statement

The bakery department at SPAR-Roodeplaat consists of items produced in-house as well as items purchased from recognized brands such as Albany and Sasko. The store has no set ordering system or forecasting model in place for their bakery and deli departments. The store manager currently determines reorder points and reorder quantities based on the opinion of experience. This is a critical mistake which causes the store to suffer significant losses.

The store has identified white and brown bread as its most important items and therefore raw materials are prioritized for these items, causing other items to suffer stock-outs which leads to loss of revenue. However, although the store did not suffer a stock-out on white and brown bread over the past year, most days the store produced more items than needed, which leads to the bread being sold at a reduced price or treated as waste due to the nature of its limited shelf life which also leads to a loss.

The top 10 in-house items produced by the bakery were determined by conducting an ABC analysis (Appendix B: ABC Analysis) in terms of quantity and gross profit of products sold over the past year. It was also found that Albany white and brown bread are the most important items that the store purchases to sell in their bakery department. Table 1 below summarizes the number of days the following items have suffered a stock-out in the past year.

Table 1 Number of stock outs of top 12 products

Product	Number of Stock-outs
WHITE BREAD LOAF_-_35136	0
SPAR BROWN BREAD_-_65199	0
TRIFLE PUDDING_-_83825	84
PIE_-_65201	8
ROLLS HAMBURGERS 6'S_-_65447	110
VANILLA CAKE DESSERT TOPPING_-_72045	80
MASOKO BUNS_-_81047	58
CHOCOLATE CAKE DESSERT TOPPING_-_72046	75
MUFFINS_-_13056	67
MINI SCONES_-_65479	75
ALBANY SUPERIOR BROWN BREAD_-_88086	17
ALBANY SUP WHITE BRD SLICED_-_5502	15

2.1 Motivation

From Table 1, it is evident that the store requires a better ordering system in order to reduce the amount of stock-outs and to minimize over-production. It is imperative that the problem is addressed as the store is being affected financially and it further negatively influences customer satisfaction. In order to have better planning and control of raw materials, it is critical that the demand becomes known. Therefore, developing an accurate demand forecasting model is critical in solving the problem at hand.

3. Project Statement

The aim of this project is to investigate the different demand forecasting techniques and to ultimately determine which demand forecasting technique is the most accurate and most suited for the bakery and deli departments of SPAR.

3.1 Project Objectives

- Investigate which demand forecasting models may be used for these departments.
- Develop at least three different demand forecasting models.
- Compare the demand forecasting models in order to determine which model is the most accurate and most suited for these departments.
- Recommend the most accurate demand forecasting model to be used by these departments.

4. Project Approach, Scope & Deliverables

4.1 Project Approach and Scope

As mentioned above, the project will focus on the bakery and deli departments of the retail store. In order to develop an adequate forecasting model for these departments, the following approach will be adopted:

- In-depth research will be required, including the analysis of data ranging from previous years to current dates.
- A decision must then be made on which forecasting techniques are suitable and the actual forecasting models must be developed.
- The forecasting models must be compared in terms of accuracy and the most accurate model must be recommended.
- Developing and determining the most accurate forecasting model for these departments is the primary concern of this project and makes up most of the scope.

The following flow chart represented in Figure 2 gives an overall view of the project plan as it shows the specific process to be followed. This process is derived from the project approach and will be used to determine the deliverables of each stage of the project.

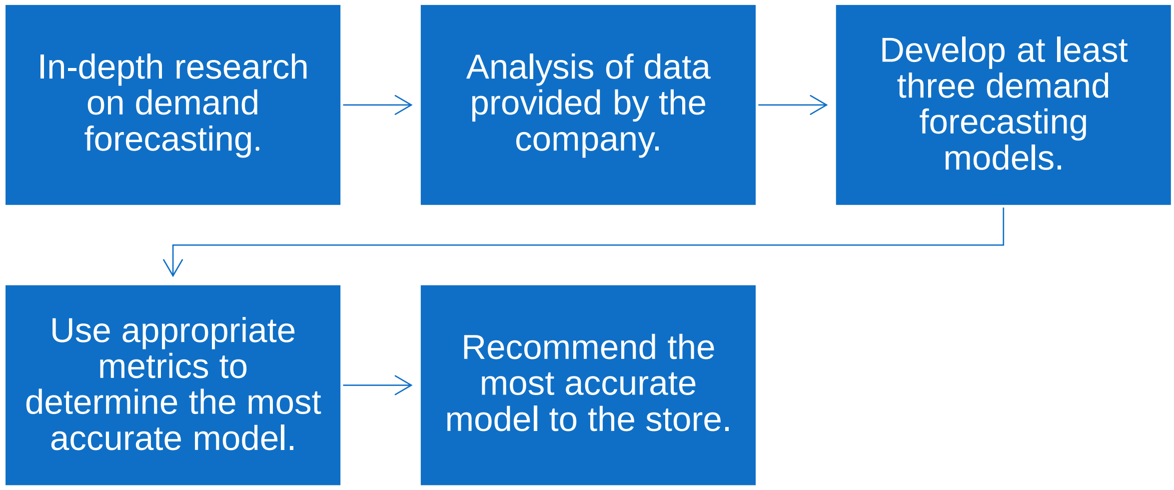

Figure 2 Process flow of project plan

4.2 Project Deliverables

At the conclusion of the project the following deliverables should be presented:

- The most suitable demand forecasting model for the bakery and deli departments.
- The predicted demand from the chosen model for the remaining months of the year.

5. Literature Review

Retail stores encounter a large degree of competition and small improvements may help the store to prosper. On average, a retail store’s margin is only about 1% of net sales (Ma and Fildes, 2017). Retailers offering perishable products with limited shelf life also face the challenge of providing the right quantity of products when needed. A retail store can increase revenue by ensuring the availability of products. However, the amount of wastage must be controlled and limited.

Excessive stock levels of baked items lead to a significant loss of revenue as these products are either thrown away or sold at a marked down price. Underestimating how much stock is needed also has a negative impact because it can result in the loss of potential sales as well as customers, who may decide to opt for a different retailer for future purchases. Baked items have a small profit margin and therefore it is necessary to limit all avoidable costs.

It is everyone’s wish to be able to predict the future, especially when it comes to making business decisions. In the perishable goods business where sales planning and demand planning are essential for the success of the business, application of large scale data analysis is a way to circumnavigate this challenge to a certain extent (Huber et al., 2017).To get accurate results, a huge amount of data has to be available that require data analysis skills such as pattern recognition, predictive modelling regression analysis and statistical analysis (Huber et al., 2017).

5.1 Demand Forecasting

The purpose of this chapter is to investigate some of the demand planning methods used by businesses to predict future demand for their product or service. Before investigating the different demand planning techniques, it is important to establish the difference between demand planning and demand management:
Stadtler and Kilger (2005) define demand planning as “the business process of deciding on the expected demand for a business’ products during a set period”. Whereas Coyle et al. (2003) define demand management as “the actions a business takes to satisfy actual demand and/or decrease demand to fall within the business’ supply capabilities during the planned period”.

Mentzer and Moon (2005) make the point that it is important to first determine the need for the sales forecast to be developed. Defining the need for the forecast helps to determine the time period (horizon) of the forecast as well as the interval to update the forecasts.

Table 2 summaries the different needs for forecasting as well as their horizon and interval as defined by Mentzer and Moon.

Table 2 Summary of forecasting requirements

Department	Needs	Horizon	Interval
Marketing	New and existing products or product changes, promotional effects and pricing	Annually	Monthly or quarterly
Sales	Setting goals for sales and used for motivating sales	1-2 years	Monthly or quarterly

	teams to exceed these goals.		
Finance/Accounting	Projecting cost and profit levels and capital needs	1-5 years	Monthly or quarterly
Production/Purchasing: Long Term	Planning the development of plant and equipment	1-3 years	Quarterly
Production/Purchasing: Short Term	Planning specific production runs	1-6 months	Daily, weekly, monthly
Logistics: Long Term	Planning the development of storage facilities and transportation equipment	Monthly to several years	Monthly
Logistics: Long Term	Specific decisions of what products to move to what locations and when	Daily, weekly, monthly	Daily, weekly, monthly

5.2 Demand Planning Techniques

There are numerous forecasting techniques available and applicable to demand planning. Forecasting techniques are characterised as either statistical analysis or subjective. Subjective and statistical analysis techniques can further be subdivided into three main categories: demand forecasting; namely time series (fixed model and open model techniques), regression (correlation) and judgemental. Nonlinear regression analysis may also be applicable. Judgemental forecasting is a subjective technique and relies on the opinions of experienced personnel; these methods will not be investigated further.

5.3 Time Series Techniques

Time series techniques are based on endogenous data (which only takes into consideration the history of sales) and can be subdivided into Fixed-Model Time Series (FMTS) and Open-Model Time Series (OMTS) (Mentzer and Moon, 2005). OMTS methods develop an appropriate forecasting equation based on data that has been evaluated and show patterns (level, trend, seasonality and noise) exist in the data, while FMTS methods use existing equations that assume one or more of these patterns exist in the historical data (Mentzer and Moon, 2005).

Examples of FMTS methods include:

- **Moving Average.**
  Moving average forecasting makes use of more recent data rather than all previous data. Making use of a smaller number of sales periods (e.g. N= 4 sales periods) ensures the forecast is actively alert to rapid changes in sales patterns. According to Chase et al. (1998), moving average forecasting methods are appropriate and commonly used for sales data that only show patterns of level and randomness.

  The equation for moving average forecasting is defined as follows (Mentzer and Moon, 2005) :

$$F_{t+1} = (A_t + A_{t-1} + A_{t-2} + \cdots + A_{t-N-1})/N \qquad (1)$$

Where: F_{t+1} = Forecast for period t + 1
A_t = Sales for period t
N = Number of periods in the Moving Average

- **Exponential Smoothing**

Inventory control models that consist of a large variety of items often make use of the exponential smoothing technique. It is also preferred when a small budget for forecasting is a priority (Mentzer and Moon, 2005).

The equation for exponential smoothing forecasting is defined as follows (Brown and Meyer, 1961):

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t \text{ , } 0 < \alpha < 1 \quad (2)$$

Where: α = Constant

- **Exponential Smoothing With Trend**

Exponential smoothing with trend is used when historical sales figures depict either a downward or upward trend (Mentzer and Moon, 2005).

The equations for exponential smoothing with trend forecasting is defined as follows (Mills et al., 1962):

$$L_t = \alpha A_t + (1-\alpha)\ (L_{t-1} + T_{t-1}),\ 0 < \alpha < 1 \quad (3)$$

$$T_t = \beta(L_t - L_{t\_1}) + (1-\beta)\ (T_{t\_1})\ ,\ 0 < \beta < 1 \quad (4)$$

$$F_{t+m} = L_t + (T_t \times m) \quad (5)$$

Where: L_t = Level in period t
T_t = Trend in period t
m = The period one is forecasting for

- **Exponential Smoothing With Trend and Seasonality**

Exponential smoothing with trend and seasonality is often preferred when sales data show trend and a periodic upward or downward characteristic (Mentzer and Moon, 2005).

The equations for exponential smoothing with trend and seasonality forecasting is defined as follows (Winters, 1960):

$$L_t = \alpha(S_t \div SA_{t\_c}) + (1-\alpha)\ (L_{t\_1} + T_{t\_1})\ ,\ 0 < \alpha < 1 \quad (6)$$

$$T_t = \beta(L_t - L_{t\_1}) + (1-\beta)\ (T_{t\_1})\ ,\ 0 < \beta < 1 \quad (7)$$

$$SA_t = \gamma(S_t \div L_t) + (1-\gamma)\ (SA_{t\_C})\ ,\ 0 < \gamma < 1 \quad (8)$$

$$F_{t+m} = \left(L_t + (T_t \times m)\right) \times SA_{t\_C+m} \quad (9)$$

Where: SA_t = Seasonal adjustment factor for period t
C = Cycle length of the seasonal pattern
S_t = Sales period for t

- **Adaptive Smoothing**
  Adaptive smoothing is used to determine the most suitable value for α using the following equations defined as (Trigg and Leach, 1967):

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t \quad (10)$$

$$\alpha_{t+2} = |(F_{t+1} - S_{t+1}) \div S_{t+1}| = |PE_{t+1}| \quad (11)$$

  The initial value of α can be set equal to 0.01 (Mentzer and Moon, 2005).

- **Adaptive Exponential Smoothing With Trend and Seasonality**
  Adaptive exponential smoothing with trend and seasonality is used to determine the most suitable values for α, β and ϒ Mentzer and Moon (2005) state that a great number of methods exist to identify these values. According to T. Mentzer (1988), the simplest technique to determine these values is called Adaptive Extended Exponential Smoothing (AEES).

FMTS forecasting methods are useful considering they only accommodate rapid changes in sales data, relatively small amounts of data are required (six months or less) and they are easy to understand and conduct. However, it is worth noting that if a forecasting method is unsuitably developed (e.g. moving average method developed when seasonality actually exists within the historical data) the FMTS forecast will be extremely inaccurate (Mentzer and Moon, 2005).

Examples of OMTS methods include:

- **Decomposition Analysis** (Shiskin, 1961)
  Through decomposition analysis, the four subcomponents of time series are broken down, analysed and combined to forecast. As previously mentioned, the four subcomponents include level, trend, seasonality and noise.

- **Spectral Analysis** (Nelson, 1973) **and Fourier Analysis** (Bloomfield, 2000)
  Spectral analysis and Fourier analysis both aim to decompose time series into a range of sine waves with different frequencies, phase angles and amplitudes (Mentzer and Moon, 2005) . Both methods have their own special features, however, both methods also strive to identify periodicity in a time series.

- **Box-Jenkins Methodology** (Box and Jenkins, 1970)
  Box-Jenkins methodology makes use of Auto-Regressive Integrated Moving Average (ARIMA) models. Mentzer and Moon explain in their book that ARIMA is a blanket term that describes a wide range of open-model time series forecasting models (2005).

  Makridakis et al. (1983) provide a more detailed explanation, elaborating on this statement:

  > Auto-regression aims to develop a function for a time series and then uses this function to generate forecasted values based on the previous values of the time series. Integration refers to the summation of the elements into which the time series has been broken up to form a forecast. Moving average refers to an error term that influences a forecast.

OMTS methods are known to be more accurate than FMTS methods when fewer forecasts need to be developed. However, bulky amounts of historical sales data is required (usually more than 48 months) and according to T. Mentzer and Kahn "OMTS methods are less accurate over long periods when compared to FMTS methods" (1995). The use of OMTS methods has been limited in industry because of the difficulties associated with OMTS techniques (Mentzer and Cox, 1984).

5.4 Regression Analysis (Linear Regression)

Regression (correlation) analysis is an application in the form of statistics (predictive modelling) forecasting which strives to develop a correlation between exogenous variables that affect sales. These exogenous variables, also known as predictors, explanatory variables and carriers, include numerous factors such as advertising, price, product quality, and economic activity (Mentzer and Moon, 2005) (Chatterjee and Hadi, 2012).

Previous data on these explanatory variables and sales data are analysed to determine their correlation. Variables that show a high correlation to demand can then be used to forecast future sales (Mentzer and Moon, 2005). This is accomplished by building a regression model in terms of a mathematical equation of the general form (Mentzer and Moon, 2005):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \epsilon \qquad (12)$$

Where: y = Dependent variable

x_i = Set of independent variables

ε = Error term

β_i = Regression parameters (unknown constants to be determined from the data)

According to Mentzer and Moon (2005), the most accurate forecasting available employs the use of regression analysis. However, a huge amount of data has to be analysed when performing regression analysis, where variables and regression line are identified. There are numerous regression analysis techniques available. According to Ray (2015), regression analysis techniques are characterised by three main traits. These characteristics (metrics) include: the number of predictors, the type of predictors and, lastly, the shape of the regression line. These different techniques of regression analysis relating to the problem at hand will be discussed in this section.

5.4.1 Multiple Regression

Multiple regression makes use of the general linear regression Equation 12 but has more than one input variable (predictor). Multiple regression requires the relationship between the dependent and independent variable to be linear. The line of best fit can be calculated using the Least Square Method (LSM). Use of LSM reduces the vertical deviations of data, where squaring of deviations reduces interference and ensures negative and positive values do not cancel each other out (Chatterjee and Hadi, 2012) (Ray, 2015).

The performance of the model can be evaluated using the Root Mean Squared Error (RMSE) (Ray, 2015):

$$RMSE = \sqrt{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2 / N} \qquad (13)$$

Where, N is the total number of observations. Forward selection, backward selection and step wise approach may be used in order to select the most significant predictors. Multiple regression is also known to suffer from multicollinearity (independent variables are strongly correlated) (Ray, 2015).

5.4.2 Ridge Regression

Ridge regression is frequently utilized when data undergoes hardship due to multicollinearity. Ridge regression minimizes the customary mistakes by attaching a degree of bias to the regression approximates. Ridge regression adds a penalty term that reduces over fitting and ensures that a solution may be found (Ray, 2015). This is represented by the objective function of ridge regression:

$$\mathrm{J}(\beta) = \underset{\beta \epsilon \mathbb{R}}{argmin} \, ||y - X\beta||_2^2 + \lambda ||\beta||_2^2 \tag{14}$$

The shrinkage parameter λ (lambda) in Equation 14 solves the multicollinearity issue. Equation 14 is comprised of two components where the first part is the least square term and the second part is the lambda summation (added to shrink the parameter to ensure a low variance) of beta-square. It is also important to take note that variables of ridge regression are matrices as the double absolute signs depicted in Equation 14 denote the norm of the matrix.

5.4.3 Least Absolute Shrinkage and Selection Operator (LASSO) Regression

LASSO regression is similar to ridge regression as it also penalizes the absolute size of the regression coefficients. LASSO regression strives to reduce variability and improves accuracy of regression models by making use of the following objective function (Ray, 2015):

$$\mathrm{J}(\beta) = \underset{\beta \epsilon \mathbb{R}}{argmin} \, ||y - X\beta||_2^2 + \lambda ||\beta||_1 \tag{15}$$

Equation 15 differs from Equation 14 in a way that LASSO regression makes use of the absolute values in the penalty function instead of squares (the variables are still in the form of matrices). This leads to a few of the parameter approximates to equal precisely zero. If a group of predictors that are highly correlated exist, LASSO regression solely chooses one of them and diminishes the rest to zero (Ray, 2015).

5.5 Nonlinear Regression

If a model does not follow the general form explained in Equation 12, it can be considered a nonlinear regression model. Linear regression is able to model curves but it is restricted in the shapes that it can fit. However, nonlinear regression has greater flexibility in the shapes of curves that it can fit (demonstrated in Figure 3, Figure 4 and Figure 5 below) (Frost, 2017).

Nonlinear regression equations do not only entail addition and multiplication. There are numerous nonlinear regression models available. Examples of nonlinear regression models (equations), as well as the shapes, include (Frost, 2017):

- **Power**

$$\theta_1 \times X^{\theta}2 \tag{16}$$

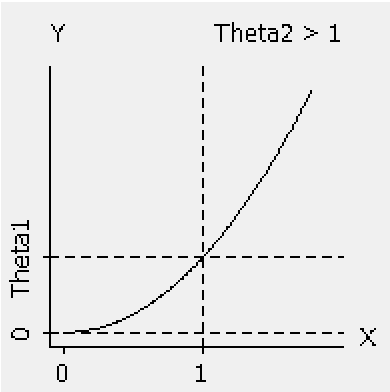

Figure 3 General form of a Power graph (Frost, 2017)

- **Weibull Growth**

$$\theta_1 + (\theta_2 - \theta_1) \times \exp(-\theta_3 \times X^{\theta}4) \tag{17}$$

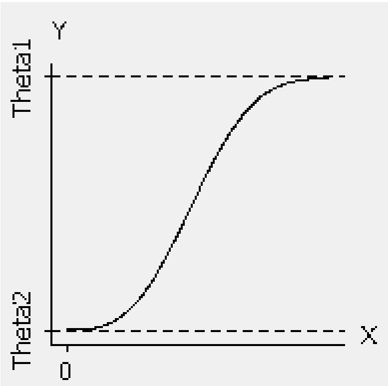

Figure 4 General form of a Weibull Growth graph (Frost, 2017)

- **Fourier**

$$\theta_1 \times \cos(X + \theta_4) + \theta_2 \times \cos(2 \times X + \theta_4) + \ \theta_3 \tag{18}$$

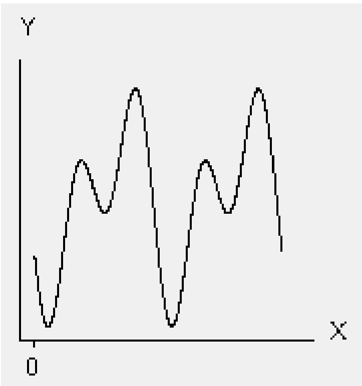

Figure 5 General form of a Fourier graph (Frost, 2017)

Where the θ's and X's illustrated above (Equations 16-18) represent parameters and independent variables respectively.

Frost (2017) states that linear regression is easier to use and interpret and also allows more statistics to assess the model. Nonlinear regression models are difficult to analyse as RMSE (Equation 13) statistic may not be used and it is impossible to calculate P-values for the predictor variables.

5.6 Prophet Forecasting

In February 2017, Facebook launched a forecasting tool named Prophet which is available in Python and ***R***. Prophet was developed with the intention of making it easier for experts and non-experts to develop high quality forecasts that are able to keep up with the demand.

Sean J. Taylor (2017) states that Prophet has been optimized for the business forecast encountered by Facebook and typically contains any one of the following characteristics:

- Observations, which are carried out either hourly, daily or weekly with a couple of months historical data required (ideally a year).
- Powerful multiple "human-scale" seasonality such as the period of the year and day of the week.
- Significant holidays which occur inconsistently and are acknowledged in advance.
- Acceptable amounts of missing observations or huge outliers.
- Historical trend changes, for example, due to product launches.
- Trends that are non-linear growth curves, where a natural limit is hit by a trend or saturates.

Prophet forecasting can be executed in numerous ways where use of smoothing parameters for trends and seasonality allows easy and timely adjustments to historical trends and cycles. In these models one can manually indicate growth curves with ability to specify irregular holidays such as Black Friday (Taylor, 2017).

Taylor further states that Prophet is able to develop accurate forecasts as its core procedure is an additive regression model with four main components:

- A piecewise linear or logistic growth curve trend. Prophet naturally identifies changes in trends by selecting change points from the data.
- A year-long seasonal component modelled using Fourier series.
- A week-long seasonal component making use of dummy variables.
- A user-provided listing of significant holidays.

5.7 Artificial Neural Networks

Artificial neural networks are forecasting methods that are based on simple mathematical models inspired by the functioning of biological neurons (Hill et al., 1996). Neural networks can be seen as an alternative to traditional time series forecasting methods as neural networks tolerate complex nonlinear relationships between the response variable and its predictors (Hill et al., 1996).

White states that "neural networks are capable in principle of providing good approximations just about anything one would like" (1990). Neural networks are known to be able to approximate ordinary least squares, nonlinear least squares regression, nonparametric regression and Fourier series analysis (Hill et al., 1996) (White, 1990). Neural networks are deemed superior compared to traditional forecasting methods as they are able to approximate whatever functional form best characterizes the time series.

Neural networks may seem difficult to compute as they are able to approximate different forms of time series, however, an R package "feed-forward neural networks with a single hidden layer and lagged inputs for forecasting univariate time series" is available which makes the development of a neural network model fairly simple (Hyndman, 2016).

5.8 Case Studies of Similar Problems

Demand forecasting models have been investigated and developed to solve issues similar to the problem at hand. Examples of these case studies include:

- Ma and Fildes (2017) developed a forecasting model to predict the demand of 500 products in a grocery store. Their research included the challenges of choosing appropriate predictor variables. A multistage LASSO regression model was chosen to solve this problem because of the high dimensionality of data.
- Liu et al. (2001) investigated the raw material usage of a restaurant. An automatic ARIMA model was chosen to solve this problem because there was a bulky number of extremely periodic data to analyse.

The approaches and techniques used to solve the above problems will be used as a guideline to solve the problem at hand.

5.9 Measuring Accuracy

Since there are so many demand forecasting techniques available, it is important to make use of different accuracy metrics to gauge the performance of a forecasting method. These metrics further help to determine which forecasting method delivers the best results (Mentzer and Moon, 2005):

- **The Forecasting Error *(E_t)*:**

$$E_t = F_t - A_t \tag{19}$$

Where: F_t = Forecast for period t
A_t = Actual Sales period for t

The smaller the value of E_t, the more accurate the forecasting method is.

- **The Percentage Error *(PE_t)*:**

$$PE_t = (E_t \div A_t) \times 100\% \tag{20}$$

The percentage error gives an indication of the relative size of the forecasting error.

- **The Mean Absolute Error *(MAE)*:**

$$MAE = \sum_{t}^{n} |E_t| \div n \tag{21}$$

Where: n = Total amount of periods that have been forecasted for

The absolute value of E_t is used to warrant that positive and negative forecasting errors do not cancel each other out. This ensures that the cumulative forecasting error is a true reflection.

- **The Mean Absolute Percentage Error *(MAPE)*:**

$$MAPE = \sum_{t}^{n} |PE_t| \div n \tag{22}$$

MAPE is an indication of the relative size of the mean percentage error.

- **The Year-to-Date Mean Absolute Percentage Error *(YTD MAPE)*:**

$$YTD\ MAPE = \sum_{t}^{t-11} |PE_t| \div 12 \tag{23}$$

YTD MAPE is useful if a large number of sales periods have already been forecasted as the true scale of new forecasting errors may be difficult to detect. *YTD MAPE* helps prevent the forecaster from overlooking large forecasting errors when forecasts have been developed for many time periods.

- **The Sales Forecasting Technique Accuracy Benchmark *(SFTAB)*:**

$$SFTAB = MAPE_c \div MAPE_n \tag{24}$$

Where: $MAPE_c$ = MAPE for forecasting method currently being evaluated
$MAPE_n$ = MAPE for a naïve forecast, whereas a naïve forecast expects that the sales for succeeding sales period to be alike the current period's sales.

SFTAB should serve as a warning to the forecaster when the current forecasting method is performing worse than a naïve forecast. Mentzer and Moon explain that if *SFTAB* ≥ 1, the forecaster "should use another forecasting method or develop naïve forecasts" (2005).

It is important to consider that these are not the only metrics available to test for accuracy. It is also suggested to make use of a control tool for forecasted results to detect if any non-random forecasting errors start to occur (Mentzer and Moon, 2005). Individual and moving range control charts may be used as they will act as a good indicator when common and special causes are responsible for forecasting errors.

5.10 Conclusion

There are numerous demand planning techniques available, each having unique qualities and advantages, as discussed above. In order to determine the most accurate demand forecasting model for the store, different models need to be developed and compared. Multiple linear regression techniques would be appropriate and should be considered as potential predictor variables may be incorporated in the model. If the model does not fit linear regression, then nonlinear regression techniques should be considered. A Prophet forecast could also prove to be accurate as it is a dynamic tool and incorporates time series and regression analysis characteristics. Since Prophet forecasting incorporates time series, it would not be necessary to develop a Fixed Model Time Series. Therefore, an ARIMA model will be considered instead.

Lastly, a neural network will also be considered as this model is known to tolerate complex nonlinear relationships between the response variable and its predictors. These four models mentioned above need to be developed and at least three accuracy metrics must be used to determine which model is the most accurate and appropriate for the store to use.

6. Industrial Engineering Techniques and Relevance to Project

An ABC analysis has already been conducted as it was used to investigate the problem in order to determine the number of stock-outs occurring. The ABC analysis will also be used as a guideline to indicate which products to utilize in the forecasting model.

The crux of the problem encountered by SPAR lies within inventory management. The most important industrial engineering technique required to solve this problem is demand forecasting. Determining the most accurate demand forecasting techniques for the store is the aim of this project. Therefore, multiple demand forecasting models need to be developed and compared in order to recommend the most accurate model to be used.

In order to make use of this inventory management technique, a great deal of data analysis will be required. Data analysis will be needed to develop the forecasting model. The use of a programming tool (***R***) will also be essential.

7. Data Analysis

The data points that are to be used in this project were collected from the company and included variables for each item within the bakery measuring units, stock-out quantity, gross profit and the date the unit(s) were sold. The data contained approximately 46 000 entries of 59 different products and were collected from 2015-11-01 to 2018-01-31. The data were reformatted in ***R*** whereby non-essential data and missing values were removed, and the remaining data were formatted correctly.

A preliminary exploratory analysis of the data was conducted and the following observations were made.

Figure 6 Graph indicating amount of units sold

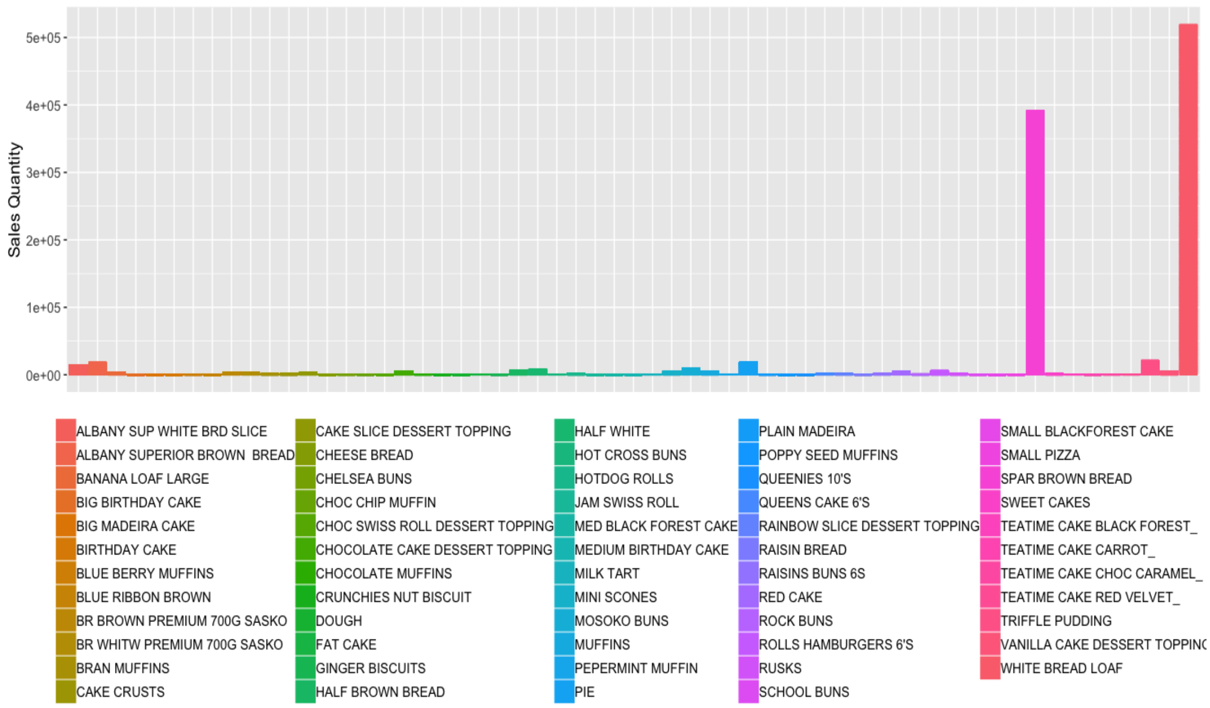

Figure 7 Graph indicating sales quantity of different products

Figure 6 and Figure 7 depict the total sales of all 59 products. The sales of “SPAR BROWN BREAD” and the “WHITE BREAD LOAF” outperform all of the other products stocked by SPAR’s bakery and deli. It should also be noted that there is a break in the data in early November of 2016. This can be seen in Figure 8. Several items were selected to visually inspect for any trends or seasonality (see Figure 9). There is a noticeable decline in sales of “SPAR BROWN BREAD” and “WHITE BREAD LOAF” from early 2017.

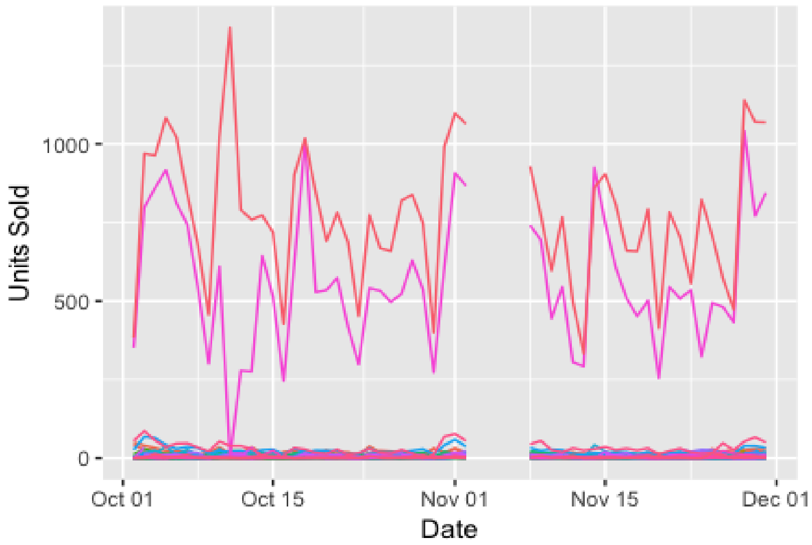

Figure 8 Graph indicating break in data

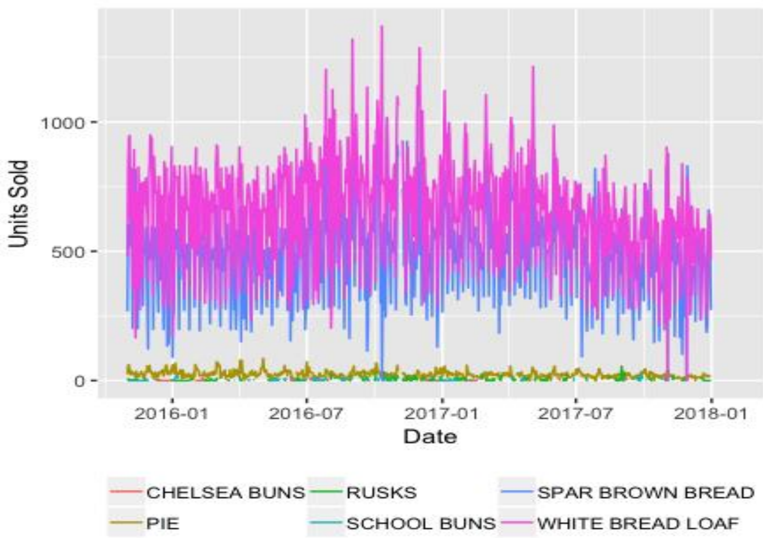

Figure 9 Graph used to inspect for trend and seasonality

From discussion with members from the company, it was noted that on certain days promotions are held, which leads to an increase in the number of items sold on a day. The numerous spikes in the data may be attributed to this and were not removed to smooth out the data

8. Solution

Forecasting is traditionally an inaccurate science as there are many confounding variables that a model may choose to omit or does not have the capability of interpreting. To determine the most applicable forecasting model for this particular dataset, the following experiment was conducted.

Four different models were selected to forecast over a period. Each model was constructed in ***R*** and a minimal amount of optimisation was used to improve the forecast accuracy – that is, four base models were created. The dataset was split into training and testing data. Each base model was constructed from the same training set and evaluated over the same testing set.

8.1 Model Construction

Each of the four models constructed had different requirements as to how the data was to be formatted in order for the forecast to be applied. The following section introduces each model and explains how they were constructed.

It should be noted that the dataset contained various items, as previously described. To manage this, all the sales data for each item was combined into a single data-frame. The new data-frame was then filtered by the specific item to create a permutation with a single item's information. Each model was built for a specific item.

8.1.1 Multiple Linear Regression (MLR) Model

The base ***R*** stats package contains a glm() function which is used to fit generalised linear models.

In order to predict future values, the multiple linear regression model requires a known relationship with one or more variables. The day of the week (DOW) and previous sales were chosen to predict a future sales value.

The day of the week was extracted from the timestamp attached. However, the period between current sales and previous sales was determined by the degree of autocorrelation. Below (Figure 10), the plot of the autocorrelation function (ACF) shows a high degree of autocorrelation around day 27 (other fast-moving items followed a similar pattern and exhibited high degrees of autocorrelation around days 20 to 35). This implies that today's sales correlate highest with sales that occurred 27 days ago.

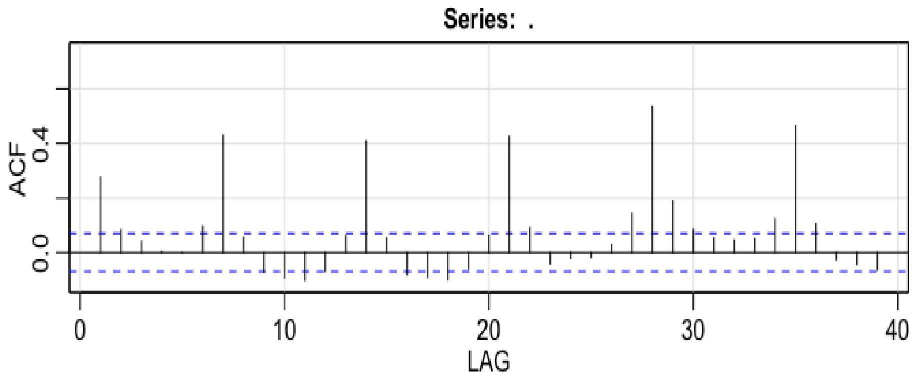

Figure 10 ACF of product demand for SPAR brown bread

The 27 day lag was applied to the entire dataset which removed the first 27 days' worth of data for all models. The model was then fit using the training data according to the following logic:

Future Sale = Sales 27 days ago + DOW

The model includes weekly effects as well as lagged sales effects. However, there was no data which could indicate when a promotion period occurs. The inclusion of a Boolean vector would allow the model to pre-empt unexpected hikes in sales demand, as discussed in the data analysis.

8.1.2 Prophet Forecasting Model

A large component behind the creation of Prophet was that it must be simple and intuitive to use. The prophet() function is available in the *prophet* package. The preprocessing requirements consisted of creating a data-frame of a date column labeled *ds* and a sales column labeled *y.* This data-frame is used to fit the Prophet model. An optional output of Prophet is created, breaking down the time series component.

Prophet is built to determine spikes in demand caused by a "special day". Such days include holidays or other days of the year where sales are inflated by an external force. However, a list of promotion days (days that affect sales quantity) can be parsed when fitting the Prophet model.

8.1.3 ARIMA and Neural Network (Nnetar) Models

ARIMA and Nnetar are both part of the *forecast* package and require very little preprocessing. A numeric vector containing sales quality is then parsed by the each model to fit the required model.

The sales quality was passed by the *auto.arima()* function to set the parameters for the ARIMA model, that is, to determine the ARIMA and lag components. The parameter *stepwise* in *auto,arima* was set to false. This increases the processing time of the *auto.arima()* function, but prevents the model from assuming certain parameters and ensures a better result.

The *nnetar()* function allows for an automatic Box-Cox transformation to be applied which was set to true to improve the performance slightly.

Both modifications were applied as they were recommended in the available documentation.

8.2 Metrics Used

Table 3 indicates which metrics were used to evaluate the models.

Table 3 Description of metrics used

Metric	Description
MAPE	Mean average percentage error
MASE	Mean average squared error
MDAE	Median absolute difference
MAE	Mean average error

8.3 Experimental Procedure

To evaluate the respective models, the following experiment was designed. As seen in Figure 11 below, the data are first processed into trading and testing data. All records before some date x are subset to the new training dataset and all records after some date x are subset to the new testing dataset. This simulates the real world where data only becomes available as time progresses. The chosen date (date x) was set to 2017/08/01.The models are fit using the training dataset (past values) and then a prediction is made over the same period that the testing dataset covers. The predicted values are evaluated against the actual sales values using the four metrics described earlier.

This procedure is run iterated times for each product. For each iteration, the forecast period is changed to:

1. A week (7 days)
2. A month (30 days)
3. A six month period (60 days)

This provides a metric with which to evaluate the effect of forecasting further into future, which inevitably has greater variation.

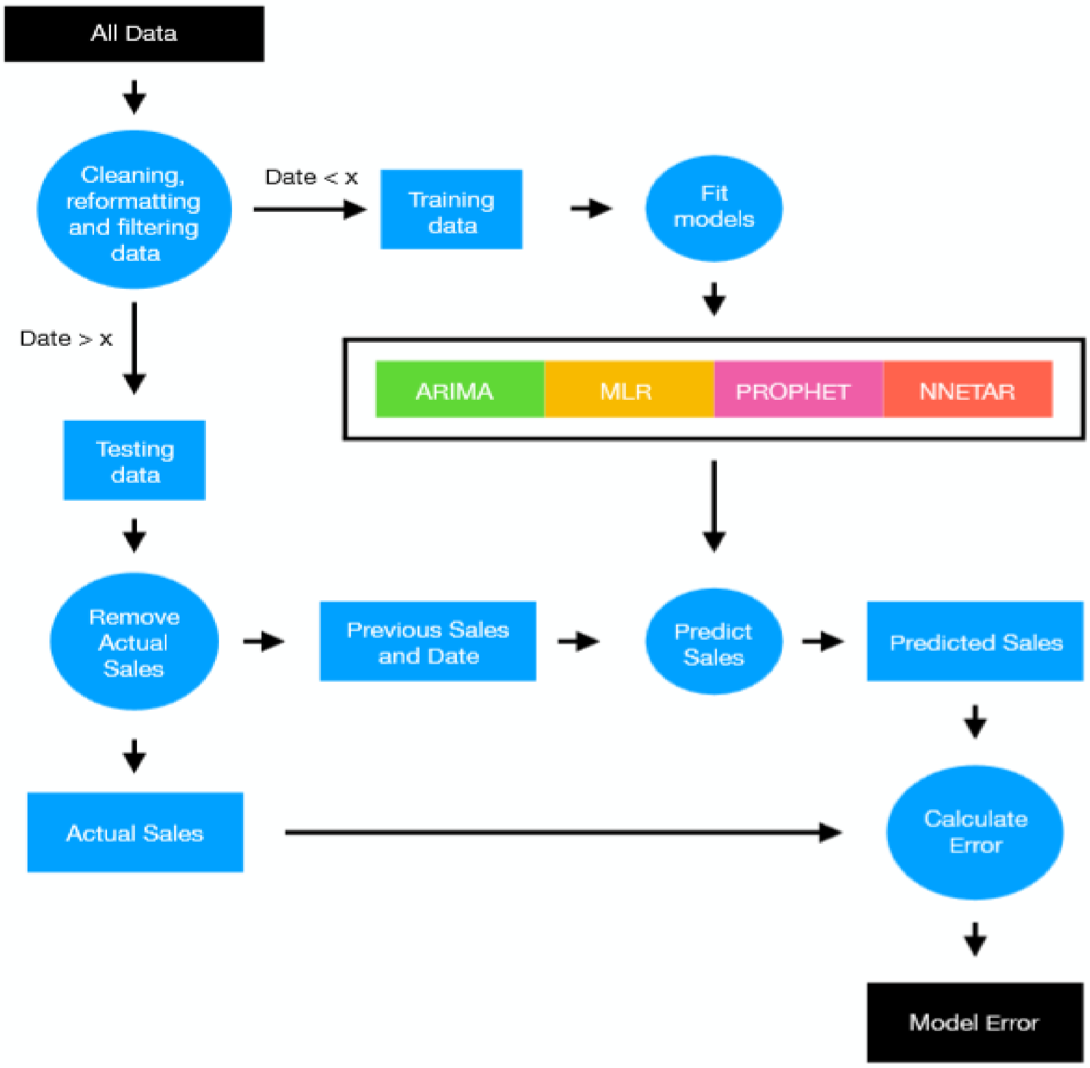

Figure 11 Experimental procedure design

8.4 Experimental Results

The results of the experiment were summarized as follows. The errors for each metric per product were grouped by model type and then an average, per model type, was calculated as seen in the Figure 12 below.

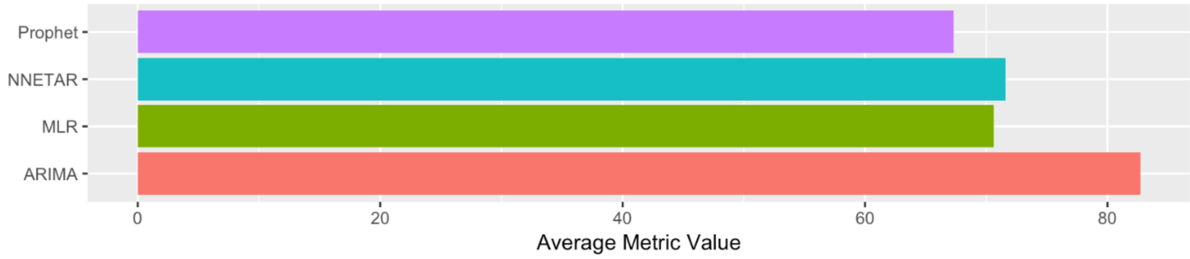

Figure 12 Experimental results

Out of the four models, the ARIMA model was the poorest performer by the greatest margin. Both the MLR and NNETAR offered similar levels of performance. According to the findings, the Prophet model was the best overall performer.

However, Figure 18 (see Appendix C: Results) shows the error of each model according to each metric for all products. In this instance, Prophet is not always the best performing model. Take the errors for SPAR BROWN BREAD and WHITE BREAD LOAF. Prophet is an acceptable "best choice" for the latter, but NNETAR is the preferred solution for the former. This may imply that the choice of forecasting model cannot be taken on best overall accuracy. Each model's outputs should be visually inspected to make an informed decision.

In Figure 19-Figure 22 (see Appendix C: Results), the ARIMA model tends to some historical mean. It was later found that after intensive tuning, the accuracy of an ARIMA model may be improved. Such tuning would involve estimating product-specific parameters within a second function called arima() from the same forecasts package. This level of parameter estimation requires a degree of knowledge that is beyond the scope of this project. In addition, multiple ARIMA models would need to be made – a model per product – as each parameter would need to be estimated individually. Thus, ARIMA models are not well-suited to forecast multiple items with minimal coding.

Figure 19 (see Appendix C: Results) of SPAR BROWN BREAD depicts the ability of the three remaining models to adjust and compensate for seasonality. The clear weekly cycle is well adjusted for by each model. However, Figure 22 (see Appendix C: Results) of SMALL BLACK FOREST CAKE has a low unit count and is sold sporadically. Each model assumes a cyclic trend, which may have only existed in the past. NNETAR (Neural Nets) estimates a 0 mean whilst Prophet and MLR (multiple linear regression) impose a cycle which does not exist. None of the models accurately suit the product as the demand is too chaotic to predict. Figure 24 (see Appendix C: Results) further elaborates on this statement, illustrating that the SMALL BLACK FOREST CAKE has one of the lowest standard deviations, which means low fluctuations can be expected with regards to this product.

In Figure 19 (see Appendix C: Results), between August 7 and August 14 there is a sharp drop in sales. Upon visual inspection, such a point seems uncharacteristically low, which implies that there is some underlying factor or confounding variable that is not captured in the data or by the model. Since four different models could not capture the behavior it may be concluded that the cause lies in the data. This is not to say that the data are of a poor standard, but rather that there are other influencing factors that have not been recorded. As stated in a previous chapter, the company allows for certain products to go on promotion. Such a promotion may increase the sales quantity of one item and reduce the quantity of another as the consumer substitutes one for the other. These events may hold the key to understanding such a deviation. Thus, a model with the ability to input multiple factors would be best suited.

The NNETAR model uses a univariate time series to estimate the future values. The model has the ability to be expanded to include multiple factors, but would require coding outside the scope of this project.

The last two models to consider, Prophet and MLR, are both well-suited to the problem at hand. They capture the seasonality, are less intensive to program and implement, and they may be scaled. However, Prophet remains the "best" proposed model for the following reasons:

A. Prophet recorded the lowest overall error.
B. Prophet is programmatically optimized for "plug and play" and can be quickly implemented.
C. Prophet has the ability to receive a vector that includes holidays and adjusts its forecast accordingly. The Prophet algorithm realizes that in the past there was a holiday, as specified by the user, which caused a positive increase in sales. The future prediction will include such an increase. This allows promotion days to be factored into the modelled behavior.
D. Prophet was designed to work at scale and to be simple to implement. The creators of Prophet, Facebook, designed the algorithm around a specified workflow to conduce to multiple product groups.

A large disadvantage of Prophet is that if the fluctuations in sales is caused by some other force, excluding promotional days, the error cannot be lowered and multiple linear regression would have to be implemented. Yet, such an implementation would require further exploratory analysis and shall be included in the recommendations, but has been omitted due to the scope of the project.

Prophet's overall accuracy, as proven per experimentation, as well as its practical components, make it the most suitable of the four algorithms to utilize in terms of the methodology of this project.

9. Solution Validation

This chapter serves to draw further comparisons between the different models in order to ensure that the most accurate and appropriate model is chosen for the store.

9.1 Overall Accuracy

Prophet may be the best model out of the four, but the overall accuracy must still be evaluated to determine suitability for use. The density plot and histogram below (Figure 13) describe the correlation between the actual sales value of an item and the forecasted value of an item. Using the correlation in this manner describes how well the model captured the variation of the population and, more specifically, how well the model was able to simulate the behaviour of the time series.

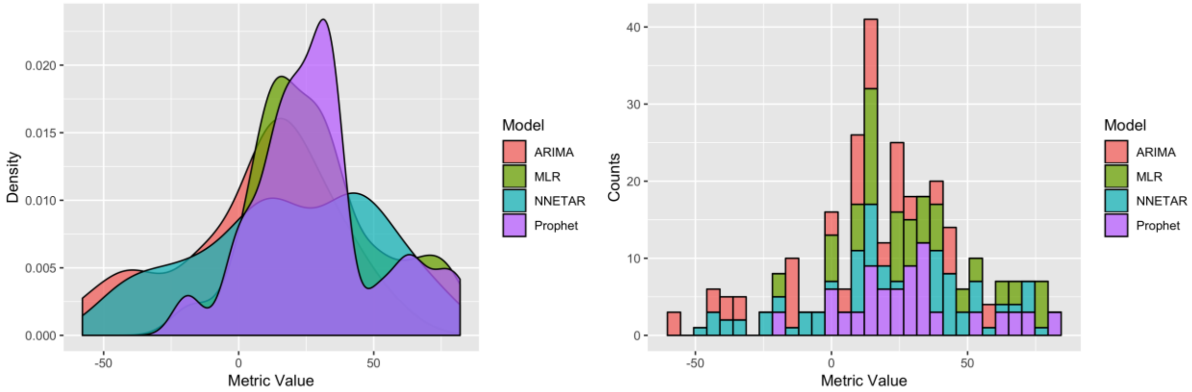

Figure 13 Density and histogram graphs of results

As discussed earlier, Prophet and MLR performed similarly. Table 4 below details the results. Although Prophet had an average of 29,086, from the above graphs it is apparent that there is a bimodal distribution. This implies that certain products were predicted at a much higher accuracy than others, which alludes to the potential in both Prophet and MLR as they are the only two models which exhibit this bimodal behaviour.

Table 4 Performance results of the different models

Model	Mean Correlation	Standard Deviation of Correlation
ARIMA	6,928	28,827
MLR	29,289	23,625
NNETAR	18,529	33,177
Prophet	29,086	23,498

9.2 Effects of Forecast Period

Figure 23 (see Appendix C: Results) shows the total error per product for each model. The right-hand side indicates the forecast period. When the three periods are compared, it becomes apparent that there is a moderate improvement when forecasting over 30 days, as opposed to 7 and 60 days respectively. However, the relative proportion of error within each product remains constant. Thus, it is recommended that forecasting is done over a 30 day period.

It takes about 20 minutes at most to run all of the algorithms (together) over the testing period specified, three times (as experimented with differing forecast horizons) and for all the products used. For a single product, over a single forecast horizon, it would be less than a minute. Therefore, the models will be practical to use in the real world.

9.3 Large Total Error for Two Big Movers

The total error of SPAR BROWN BREAD and WHITE BREAD LOAF are disproportionately larger than the other products. It was hypothesised that this error was due to the erratic behaviour of the time series (there were many unexplained spikes). Figure 24 (see Appendix C: Results) confirms that both products ranked disproportionately higher than the other products when comparing the standard deviation over all the available data. Aggregating the data may reduce the variability and thus the error. This will be elaborated upon in the proceeding sections.

10. Proposed Implementation

As all the models were coded in ***R***, they are open-source, requiring no licence fee. Thus, integrating the current systems in/on one site would be a worthwhile solution. The proposed implementation is as follows:

1) Create a standard exporting procedure. This entails standardising the format of the sales data and creating a reliable workflow. The data will then be sent to a specific local host (PC or server).
2) An R Shiny app will be developed. This app serves as a user interface for the ***R*** code and allows the user to select the products to forecast, input the desired forecast period and select the period that the model should forecast from (remove old data). Multiple models can be included.
3) The app will dynamically update the models and return a graph, as well as an option CSV designed according to a desired spec. Other outputs can be designed, but the app primarily serves as a dashboard for the ***R*** code, allowing any individual, irrespective of their knowledge of ***R***, to forecast.

11. Recommendations

The bimodal distribution amongst the correlation distributions implies that there is some unknown relationship between the model type and specific product time series. This relationship should be better understood so as to improve the forecast accuracy. By this, the products with the highest and lowest correlation values should be investigated to understand if or what the causal factor might be. If the factor can be manipulated, it should be used to improve the overall forecast capability.

Lastly, it is clear that certain products share a similar "time series" behaviour. Moving away from a generalised forecasting model used for all products, a class-specific model should be created in order to improve model accuracy. Such a classification should identify the "time series behaviour" of each product and then assign it to a class.

A large factor that reduced the overall accuracy of the models was the inconsistent spikes in data. The hypothesised relationship between promotion days and such spikes has already been put forward, however, a short-term solution would be to aggregate the time series into a week, creating a weekly moving average (see Figure 14 below). This will smooth out the spikes, but also reduces the precision of the model. Further investigation is required in order to determine the aggregation period.

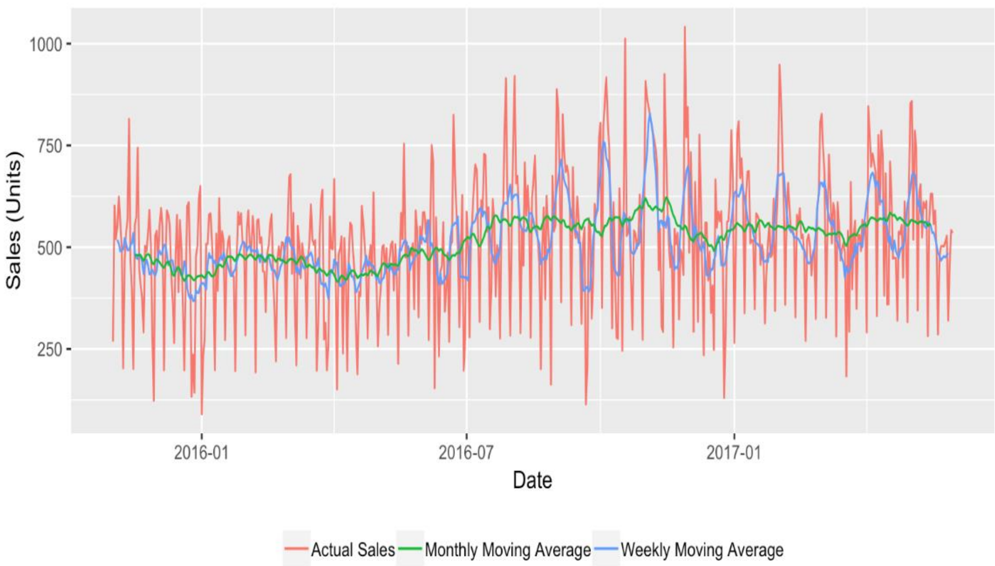

Figure 14 Weekly moving average graph

12. Conclusion

There was a definite need to improve the ordering system of the bakery and deli departments as the store is currently losing revenue through stock over- and underestimation. By implementing the forecasting model, there will be better inventory management within the bakery and deli departments. The manager will have better control and planning will be made easier.

From the results obtained by the project's methodology and through a review of the practical use of each method, it has been concluded that the Prophet forecasting model is the most applicable to forecast future sales. There are many potential improvements to be made, which include further optimisation of each model, the inclusion of promotional dates and an improved understanding of the each product's unique time series.

Despite these shortcomings, Prophet forecasting remains the most suitable technique to implement because it delivered the best results within the parameters of the study. Prophet is also advantageous because it is an existing open-source model, which means it is fairly simple to compute and understand, even for laypeople or those who do not have expert knowledge regarding forecasting techniques. In addition, Prophet forecasting is designed to handle large amounts of input data and comes with a seasonal component that could be used to improve the model further once promotional dates are investigated. The model also provides a user-listing of significant holidays that could also be used to improve the accuracy.

Going forward, once the forecasting model is implemented, the forecasting model's results can be used to optimize raw material usage with the aid of linear programming upon further investigation. An accurate forecasting model will not only assist the retail store with production and inventory planning, but will also assist when making important business decisions in areas of finance and marketing.

The Gantt chart (Appendix D: Gantt Chart) was used as a guideline to complete the project within the given timeframe.

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Appendix A: Reflection on Learning

Department of Industrial & Systems Engineering
University of Pretoria

Final Year Project Mentorship Form
2018

Introduction

An industry mentor is the key contact person within a company for a final year project student. The mentor should be the person that could provide the best guidance on the project to the student and is most likely to gain from the success of the project.

The project mentor has the following important responsibilities:

1. To select a suitable student/candidate to conduct the project.
2. To confirm his/her role as project mentor, duly authorised by the company by signing this **Project Mentor Form.** Multiple mentors can be appointed, but is not advised.
3. To ensure that the **Project Definition** adequately describes the project.
4. To review and approve the **Project Proposal**, ensuring that it clearly defines the problem to be investigated by the student and that the project aim, scope, deliverables and approach is acceptable.
5. To review and approve all subsequent project reports, particularly the **Final Project Report** at the end of the second semester, thereby ensuring that information is accurate and the solution addresses the problems and/or design requirements of the defined project.
6. Ensure that sensitive confidential information or intellectual property of the company is not disclosed in the document and/or that the necessary arrangements are made with the Department regarding the handling of the reports.

Project Mentor Details

Company:	INVOKE ANALYTICS
Project Description:	Develop a forecasting model for Spar Bakery and deli department to assist in developing an adequate stock ordering system.
Student Name:	Mohammed Alli Vally
Student number:	14035210
Student Signature:	[signature]
Mentor Name:	HERMAN CARSTENS
Designation:	CHIEF DATA SCIENTIST
E-mail:	herman@invokeanalytics.co.za
Tel No:	0836111279
Cell No:	
Fax No:	
Mentor Signature:	[signature]

Appendix B: ABC Analysis

	A	B	C	D	E
1	Product Description	Total sales	Accumulation	Accumulation %	% Cummulated
2	WHITE BREAD LOAF	62664	62664	45.97842835	45.97842835
3	SPAR BROWN BREAD	51207	113871	83.55051728	37.57208893
4	PIE	1927	115798	84.96441412	1.413896838
5	ALBANY SUPERIOR BROWN BREAD	1867	117665	86.33428718	1.369873065
6	TRIFFLE PUDDING	1775	119440	87.63665713	1.302369946
7	MOSOKO BUNS	1510	120950	88.74458874	1.107931616
8	ALBANY SUP WHITE BRD SLICED	1418	122368	89.78501724	1.040428498
9	B/REBBON PREMIER 1 BROWN SL	1252	123620	90.70364664	0.918629393
10	HALF WHITE	876	124496	91.34639372	0.642747083
11	HALF BROWN BREAD	732	125228	91.88348375	0.537090029
12	VANILLA CAKE DESSERT TOPPING	620	125848	92.33839607	0.454912319
13	MUFFINS	557	126405	92.74708343	0.408687358
14	CHOCOLATE CAKE DESSERT TOPPING	548	126953	93.14916722	0.402083792
15	ROLLS HAMBURGERS 6'S	543	127496	93.54758236	0.398415144
16	MINI SCONES	542	128038	93.94526378	0.397681415
17	SUNBAKE BREAD BROWN S/WICH SLI	503	128541	94.31432974	0.369065962
18	RAISINS BUNS 6S	487	129028	94.67165603	0.35732629
19	B/RIBBON PREMIER 1 WHITE BREAD	430	129458	94.98715973	0.315503705
20	BANANA LOAF LARGE	420	129878	95.29532614	0.30816641
21	RED CAKE	388	130266	95.58001321	0.284687064
22	FANTACY BOX BLACK FOREST	359	130625	95.84342211	0.263408907
23	BR WHITW PREMIUM 700G SASKO	322	130947	96.07968303	0.236260914
24	CAKE SLICE DESSERT TOPPING	316	131263	96.31154157	0.231858537
25	BR BROWN PREMIUM 700G SASKO	314	131577	96.54193264	0.230391078
26	BRAN MUFFINS	278	131855	96.74590946	0.203976814
27	SUNBAKE BREAD WHITE S/WIC	275	132130	96.94768508	0.201775626
28	HOTDOG ROLLS	211	132341	97.10250202	0.154816934

Figure 15 Snippet of ABC Analysis in terms of products sold

1	**Product Name**	**Sum of Gross.Profit**	Accumulation	% Accumulation	% Cummulated
2	WHITE BREAD LOAF_-_35136	740081.35	740081.35	41.55544111	41.55544111
3	SPAR BROWN BREAD_-_65199	624151.03	1364232.38	76.60141459	35.04597349
4	VANILLA CAKE DESSERT TOPPING_-_72045	54469.1	1418701.48	79.65984524	3.05843064
5	CHOCOLATE CAKE DESSERT TOPPING_-_72046	46492.96	1465194.44	82.27041698	2.610571745
6	PIE_-_65201	28748.6	1493943.04	83.88464595	1.614228969
7	TRIFFLE PUDDING_-_83825	23043.03	1516986.07	85.17850814	1.29386219
8	ROLLS HAMBURGERS 6'S_-_65447	19381.04	1536367.11	86.26675022	1.088242078
9	BIG BIRTHDAY CAKE_-_65460	16973.22	1553340.33	87.21979361	0.953043397
10	MEDIUM BIRTHDAY CAKE_-_65441	15940.38	1569280.71	88.11484322	0.895049608
11	MOSOKO BUNS_-_81047	15383.32	1584664.03	88.97861401	0.863770785
12	MUFFINS_-_13056	15029.52	1599693.55	89.82251898	0.843904975
13	VERY VERYBIG CAKE_-_65462	13937.99	1613631.54	90.60513473	0.782615752
14	MED BLACK FOREST CAKE_-_65475	9753.09	1623384.63	91.15276907	0.547634334
15	BIRTHDAY CAKE_-_65455	8651.82	1632036.45	91.63856728	0.485798212
16	FANTACY BOX BLACK FOREST_-_91572	8068.91	1640105.36	92.0916352	0.453067915
17	CAKE SLICE DESSERT TOPPING_-_72047	8024.24	1648129.6	92.5421949	0.450559702
18	MINI SCONES_-_65479	7564.14	1655693.74	92.96692006	0.424725166
19	RAINBOW SLICE DESSERT TOPPING_-_69563	7475.76	1663169.5	93.38668271	0.419762644
20	CAKE CRUSTS_-_69405	7043.04	1670212.54	93.7821482	0.39546549
21	SWEET CAKE_-_82547	6632.09	1676844.63	94.15453892	0.372390718
22	HALF WHITE_-_65200	6096.78	1682941.41	94.49687207	0.342333153
23	BANANA LOAF LARGE_-_65444	5568.1	1688509.51	94.80951993	0.312647862
24	RED CAKE_-_69554	4960.32	1693469.83	95.08804105	0.278521119
25	HOTDOG ROLLS_-_65448	4891.28	1698361.11	95.36268559	0.274644535
26	RAISINS BUNS 6S_-_65449	4762.83	1703123.94	95.63011767	0.267432089
27	SMALL CAKE ASSORTED DESERT TOPPING_-_88	4754.45	1707878.39	95.89707923	0.266961554
28	HALF BROWN BREAD_-_35138	4638.6	1712516.99	96.15753582	0.260456596

Figure 16 Snippet of ABC Analysis in terms of gross profit

	A	B	C	D	E	F
1	Product	Quantity F	Gross Prof	Total	Overall Ra	Stockouts
2	WHITE BREAD LOAF_-_35136	1	1	2	1	0
3	SPAR BROWN BREAD_-_65199	2	2	4	2	0
4	TRIFFLE PUDDING_-_83825	3	6	9	3	84
5	PIE_-_65201	4	5	9	3	8
6	ROLLS HAMBURGERS 6'S_-_65447	6	7	13	5	110
7	VANILLA CAKE DESSERT TOPPING_-_72045	11	3	14	6	80
8	MOSOKO BUNS_-_81047	5	10	15	7	58
9	CHOCOLATE CAKE DESSERT TOPPING_-_720	12	4	16	8	75
10	MUFFINS_-_13056	9	11	20	9	67
11	MINI SCONES_-_65479	10	17	27	10	75
12	ALBANY SUPERIOR BROWN BREAD_-_88086					17
13	ALBANY SUP WHITE BRD SLICED_-_5502					15
14						

Figure 17 Top 10 in-house products and top two purchased products in terms of quantity sold and gross profit

Appendix C: Results

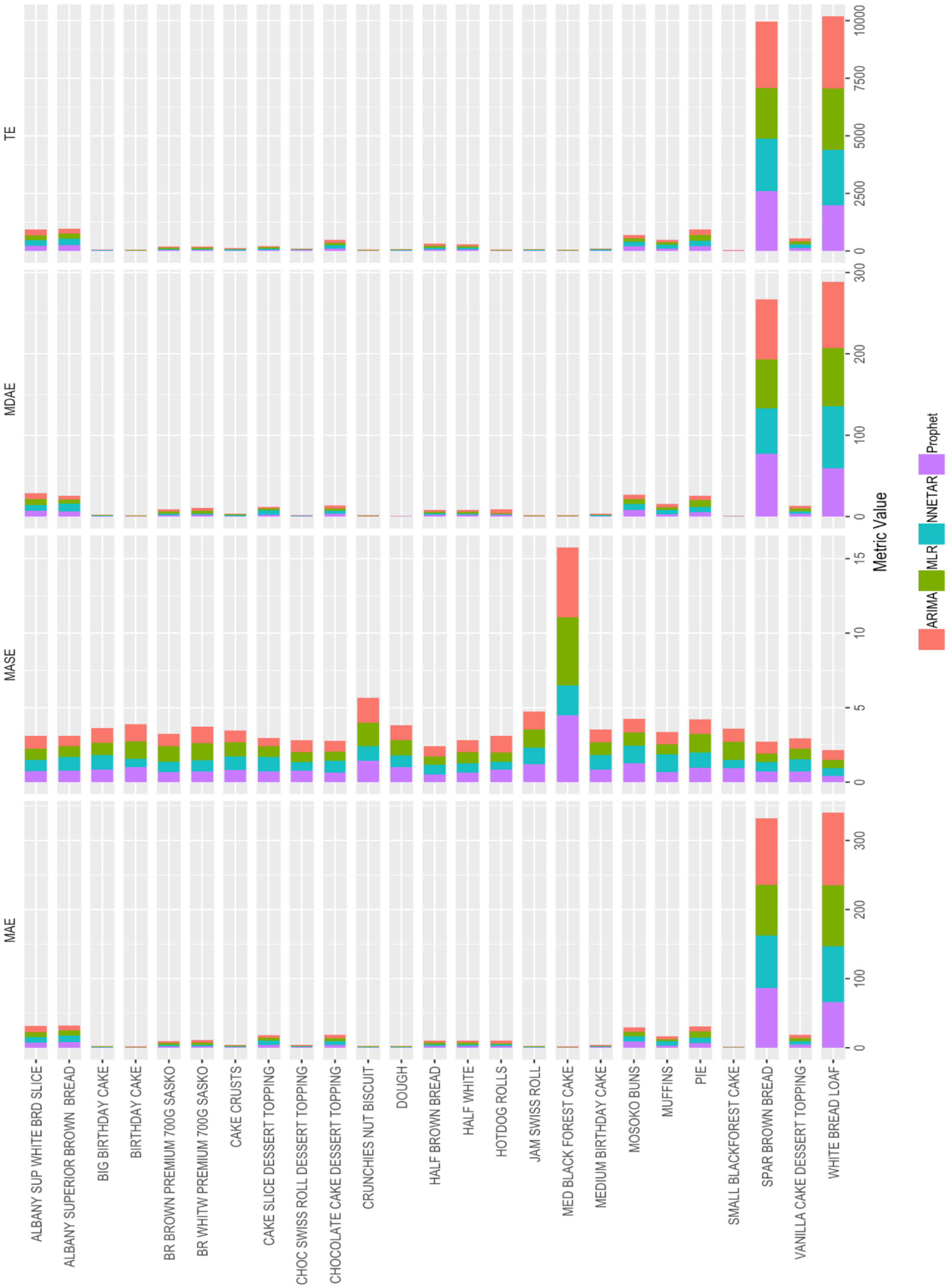

Figure 18 Error results of each model

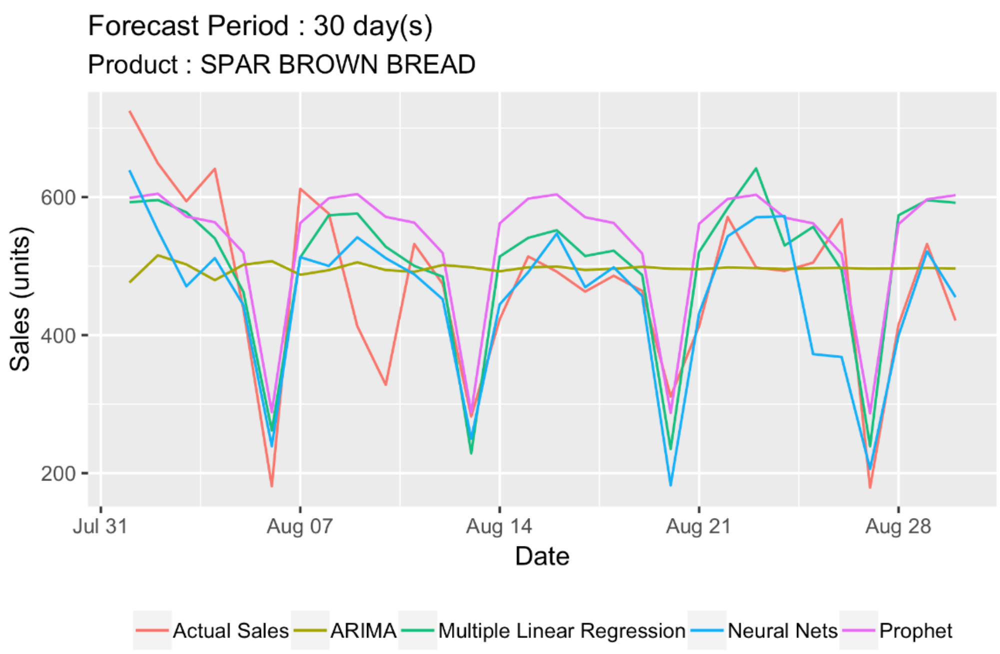

Figure 19 Forecast results of brown bread

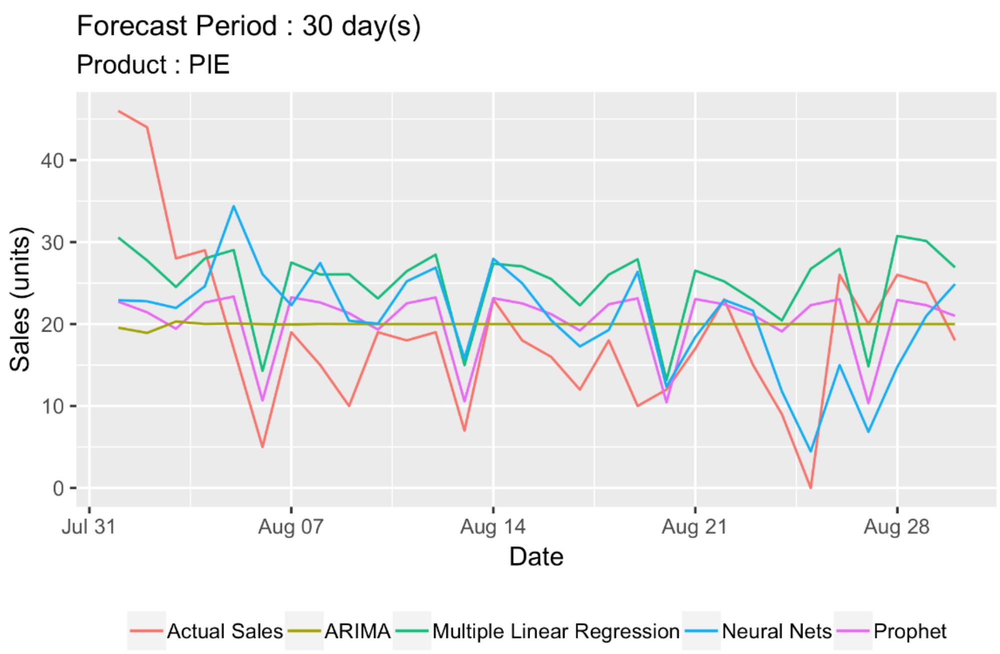

Figure 20 Forecast results of pie

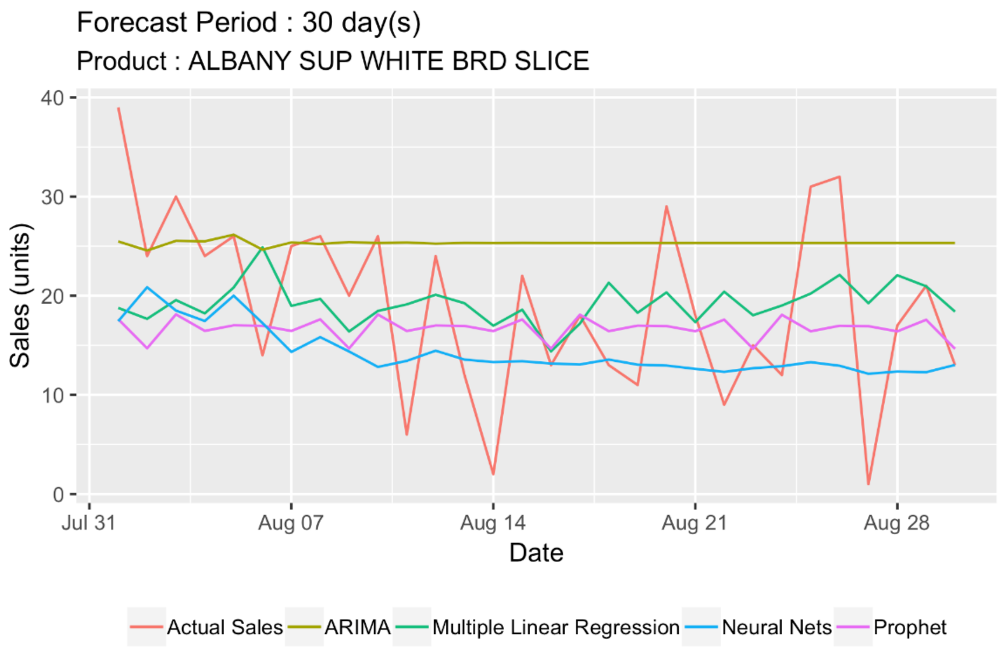

Figure 21 Forecast results of Albany white bread

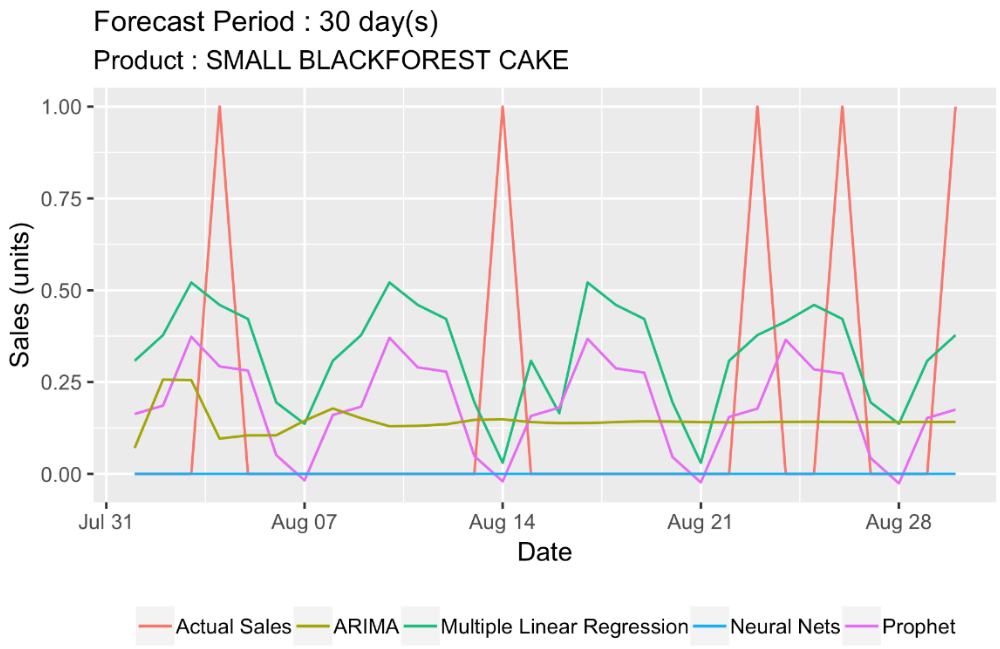

Figure 22 Forecast results of Black Forest cake

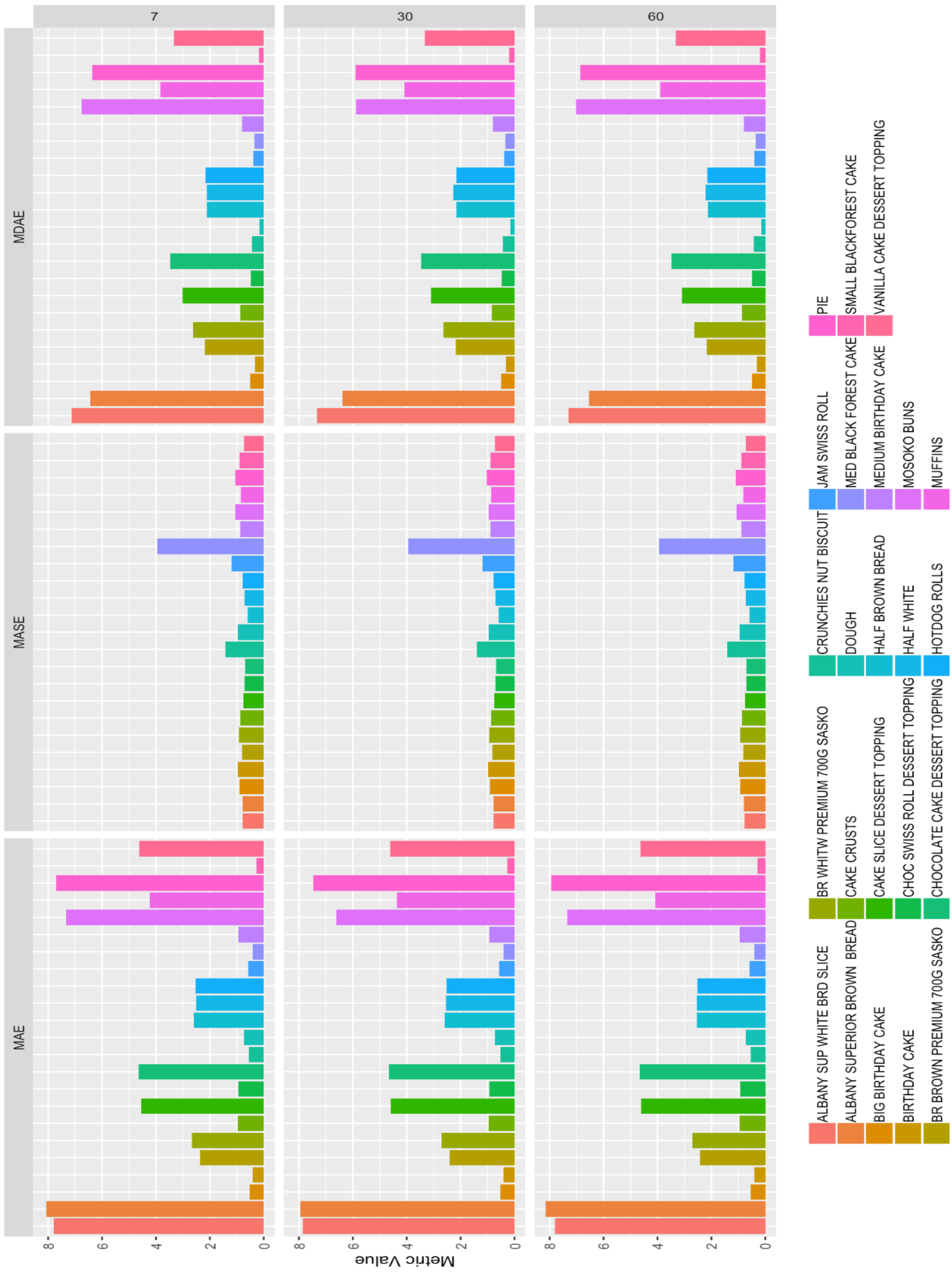

Figure 23 Total error per product

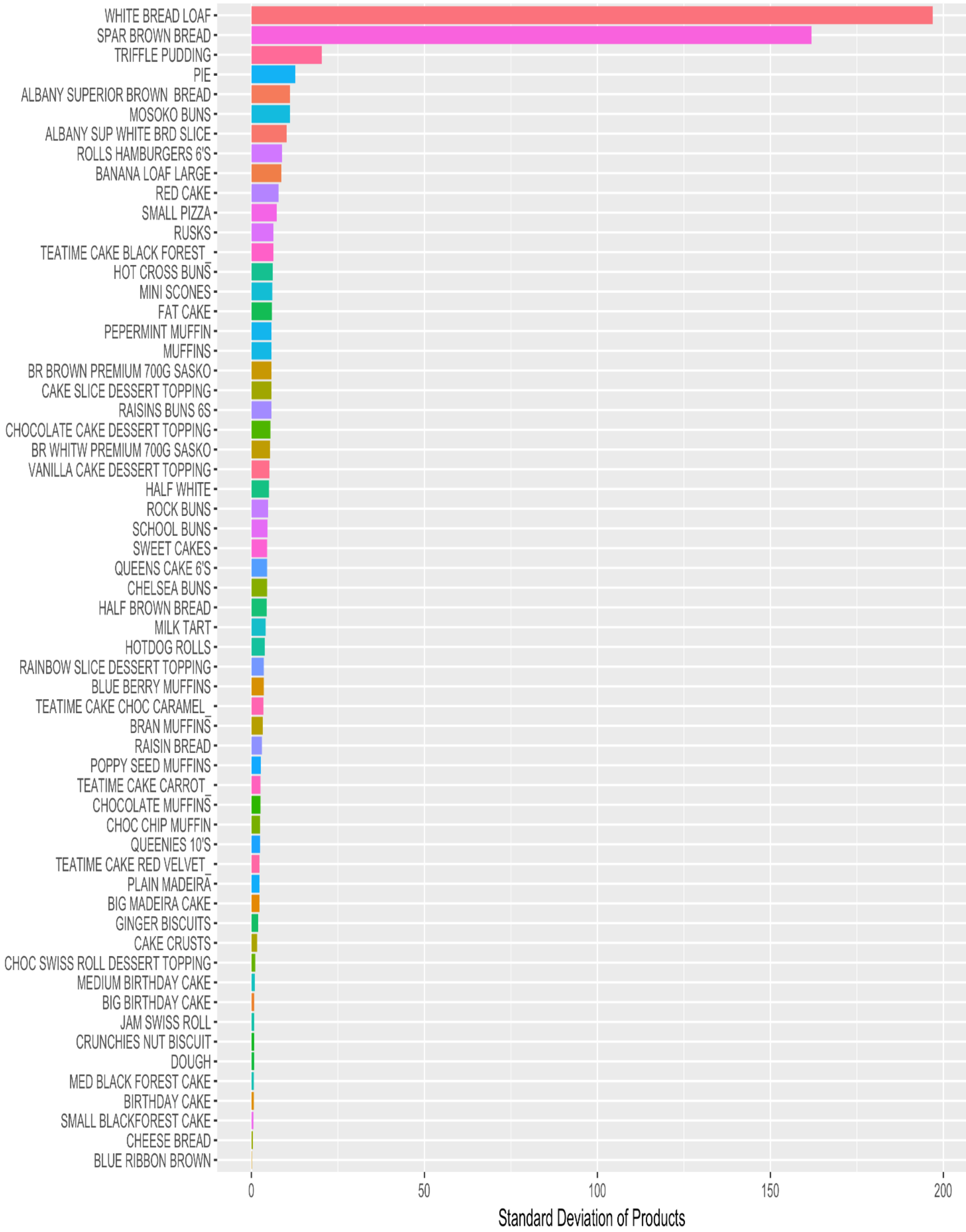

Figure 24 Standard deviation results of all products

Appendix D: Gantt Chart

Figure 25 Gantt chart