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DAIRY FORECASTING FOR CONVENIENCE STORES:

A CASE STUDY APPROACH

BY

SAMEER SARAN

A THESIS SUBMITTED IN FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

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IN

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MASTER OF SCIENCE IN SYSTEMS ENGINEERING
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2016

ABSTRACT

A large assortment of industrial engineering tools have been developed to help businesses and organizations in their continuous effort to improve. However, whether by design or by chance these tools are primarily targeted on helping larger scale businesses.

A majority of the businesses that currently operate in the United States are classified as small businesses. Many of these industrial engineering tools require a significant amount of resources or seem to only function in operations larger than those seen at a small business size.

The question of whether these tools seen in larger scale companies can be used on small business level operation is at the heart of this study.

This study analyzes dairy inventory at a local convenience store and looks at applying industrial engineering tools. Several tools are assessed but only a selected few forecasting methods are applied during the study. Whether or not large scale inventory forecasting methods still create value in small scale businesses is what is evaluated.

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LIST OF ABBREVIATIONS

TERM	DEFINITION
ERP	ENTERPRISE RESOURCE PLANNING
HTST	HIGH TEMPERATURE SHORT TIME
SCC	SOMATIC CELL COUNT
UHT	ULTRA HIGH TEMPERATURE
USDA	UNITED STATES DEPARTMENT OF AGRICULTURE
USDA ERS	UNITED STATES DEPARTMENT OF AGRICULTURE ECONOMIC RESEARCH DIVISION
POS	POINT OF SALE

CHAPTER 1: INTRODUCTION

This thesis is meant to discuss the application of industrial engineering tools such as inventory forecasting in a traditional small business space. Forecasting and other industrial tools such as agility or lean have been well documented and studied in large and medium scale businesses, but the growth and application of these tools in small business applications is less prevalent. From a traditional perspective, these tools have been designed primarily to cater to medium and large-scale businesses, and thus applying the same tools in a small business environment brings new challenges. How can six sigma or lean be applied or used when only one unit is produced? Can we incorporate lean or agility when every project changes the entire manufacturing line? Is it possible to gain value from inventory forecasts when a small store sells perishable items? This chapter will introduce the trend, which inspires the need to address questions like these, and later introduces a case study of a small company, who like other small businesses struggles to survive in a highly competitive market. The final section of this chapter discusses the product being focused on in this case study and the market in which this product operates.

1.1 BACKGROUND MOTIVATION AND RELATED PROBLEMS

Small businesses are much more vulnerable to failure, as they lack sizeable resource pools, which large and medium size businesses have at their disposal. This makes every action taken by a small business much more significant. However, the value of small business is large; “Looking back from the end of the 20th century, it

now seems clear that small business has been America's great economic strength all along." (Glover 2012). Small businesses are the foundation of all businesses large or small, and their value is continually understated. There is a point in all small businesses where the business will need to evolve and grow to stay relevant or become sedentary especially when there is a history of success. The placation caused by prior accolades and current prosperity turns into contentment which tends to be the point at which many small businesses cease to exist, and fail to take advantage of a critical growth opportunity. These opportunities may come in the form of acknowledging that the company's current cash cows are soon to become dinosaurs and that the company must pivot its attention and invest in potential rising stars; or it may be the fact that the company is a forerunner of an unrealized industry, and fails to see the potential or optimal timing for growth. After these sedentary companies realize the mistake they have made, they try to rectify the missed opportunity, by trying new strategies such as Lean, Six Sigma, Agility, or a hybrid model as a last ditch effort to save the company. Many of these strategies are meant for improvement for companies with a significant amount of resources and time. Large businesses fit into these models for the most part, because they tend to have a diversified portfolio of products and plenty of resources on hand to survive. In addition, these tools were designed and developed to help medium and large scale businesses survive and grow. In fact, many of today's tools are not well developed for the small-scale business level. "Less than one-quarter century ago, little or no attention was given to small business in the world of government statistics gathering or policymaking" (Glover 2012). Small businesses have not been focused on as a group, which is a failure on the part of the industry.

Larger firms tend to have the ability to track and analyze user needs and demands, and can potentially use that knowledge to influence future demand projections. In this way, they are able to control their environment to a degree. Due to these characteristics, large and medium size businesses can afford to execute large strategies or campaigns, such as lean or six sigma. Small businesses on the other hand, do not have the established resources to finance such campaigns. Their environment is influenced by the customer-defined needs, but forecasts and future strategy development can only be projected out to the next customer in many cases of small businesses.

The question of whether a large-scale strategy can be used in a small business space would be a significant stride in bridging the disparity in tools to meet the needs of small businesses that have made up a large percentage of the market. Forbes Magazine interviewed Neal Jensen, business consultant and founder of BBS consulting in Salt Lake City, about the challenges that businesses face. In his interview, Jensen notes, “navigating a business is extra tricky these days. The speed of economic and technological change means that the right path yesterday may not work today and could be a disaster by tomorrow. Solving these dynamic problems is what separates those who excel from the company who are closing the doors” (Conner 2013). Jensen’s insight into the challenges of businesses expresses the gap between customer demand and business capability. Small business has always been a major player in the economy as stated previously by Glover 2012. In fact, the value of small business can be seen by the fact that the United States government has a division dedicated to them. The Small Business Administration is a branch of the US

government, which monitors small business and its role in the US economy. Appendix 1 shows that that according to the U.S. census bureau as of 2008 there were a total of roughly 27 million businesses; of this, 21 million consist of only 1 employee and the remaining 6 million are broken down by percentage in Figure 1. Based on this data approximately 98% of the 6 million businesses employ 100 people or less (U.S. Census Bureau 2008). An article by the U.S. Small Business Administration states, “According to BLS and Census data, 98 percent of America’s manufacturing firms are small.” This article, written in 2012, is an acknowledgement that small business is dominating the landscape.

These facts show that support needs to be provided to grow these small business class enterprises, but the question remains as to how? Based on prior points made by 2008

CENSUS BUREAU BUSINESS EMPLOYMENT

FIGURE 1: 2008 CENSUS BUREAU BUSINESS EMPLOYMENT

Jensen it seems that small businesses either struggle or succeed based on the business strategy that they deploy. Many of these companies try to adopt complex strategies that do not seem to support the means or size of business. For some, the attempt to deploy Lean Manufacturing Principles is a “last ditch effort” to resurrect their already failing business, or is a proactive measure for problems arising within the production aspect of the business.

These large-scale tools help large companies manage waste and identify inefficiencies in their operation. The presence of waste and inefficiency within a small business can be fatal and carries a heavier weight for small businesses compared to large and mid-sized businesses. The resources for small businesses tend to be far scarcer which means the factor of safety is much lower than the other sizes. It would

be best for this research to focus on forecasting in small businesses, because if the company is better able to estimate demand it can eliminate many wastes and inefficiencies. The method of forecasting is still uncertain however, the ability to forecast will be a huge advance in a small firm's capability.

1.2 APPROACH

Large-scale business tools have not been fully evaluated in a small business environment. In addition, small businesses tend not to have the bandwidth to research or develop tools to improve the state of their operation. In addition, companies that may specialize in industrial and systems engineering tool applications most likely advertise and pivot their portfolio of tools to large and midsized companies because these classes of companies have the capability to pay a premium in acquiring new skillsets and have an easier market presence, which make them easy for these firms to target. Small firms tend not to have a large enough market presence, which is where the problem lies. The largest class of businesses by volume is small businesses but due to the multitude of unique characteristics and more modest revenue streams make them unattractive financial pursuits in the industrial and operation research fields. However, from a utilitarian approach, research in small business tools is an underserviced market and developing tools for this size of business will make large step in advancing the way business is conducted.

Prior to just applying these tools an understanding of the unique traits must be discovered. Understanding the realized and unrealized needs of small business must be identified. Unfortunately, many of the tools such as lean manufacturing and six sigma have become business buzzwords and many small businesses have attempted to

implement without understanding the tools they are trying to implement. Therefore, finding a business that has not attempted any of these tools would give large-scale tools the best chance of showing their capability to adapt.

1.3 DISCUSSION OF DAIRY INDUSTRY

The small business studied later on is a convenience store that is concerned with dairy industry forecasting. The store will be discussed in detail later on but the focus on dairy and customer demand is a key aspect of this research.

Milk consumption has gone down in recent years. Further research into this topic resulted in looking at data provided by the United States Department of Agriculture and Economic Research Service.

FIGURE 2: UNITED STATES DEPARTMENT OF AGRICULTURE ECONOMICS RESEARCH SERVICE DAIRY FLUID SALES

Figure 2 shows the general trend of milk products since 1975. Whole milk sales have been continuously declining and the sales of the three other types of milk, which are depicted in this graph, are showing an initial boost in sales between 1975 to around 1987. After this point, milk sales started to plateau. This trend could potentially show a substitution between higher fat milk products due to a larger awareness of the nutritional differences between whole milk and the light milks such as 2%, 1% or skim milk. Even if this is the case, figure 2 shows the fact that there has been a decline in milk sales since 1990 to the present.

1.4 SUMMATION OF RESEARCH GOALS

Large-scale businesses tools such as lean, six sigma, and forecasting have been a staple of business growth and prosperity. However, over time these tools have become stagnant and did not migrate with the patterns of modern businesses. A large majority of commerce is conducted by small or coined term “mom and pop” businesses.

By attempting to modify large-scale tools to be compatible to the needs of small-scale businesses, it may be possible to fill the void of small business tools needed to accommodate modern business needs.

The goal of this research is to identify whether large-scale business tools such as lean, six sigma, or inventory forecasting can be used directly in a small business environment. This is achieved by studying a small business and observing the current way that business is conducted and identifying issues that may be solved by large-

scale business tools. These selected tools will be tested in a case study format to determine if the tools can improve the business operations in an actual small-scale business.

CHAPTER 2: REVIEW OF LITERATURE

The following chapter is a compilation of literature reviewed to gain background knowledge needed for this research. A small business has been selected to help focus the research and will be discussed in more detail in later chapters. The business selected is a small local convenience store, which has recently experienced a significant amount of loss in the dairy segment of their business. The store owners are concerned about losses incurred due to excessive inventory that expires prior to sale. It is for this reason that the research will focus on inventory forecasting in an attempt to mitigate losses due to higher than needed inventory. The literature review reflects the focus on inventory forecasting and the dairy industry.

2.1 CURRENT TRENDS IN DAIRY INDUSTRY

The dairy industry as a whole struggles from a lack of forecasting and the ability to anticipate demand. Since the 1970's, dairy has seen a 36% decline in demand (Cardello 2013). Initially it appears that the industry perceived milk as an unrivaled product that all humans had a need for in daily life. It has become clear that milk producers were not listening to the signs which contra-indicated this belief, which was validated by the sales. Instead dairy producers focused on doubling milk production from cows while decreasing the milk producing cow population by 25% from 1970-2006 (Cardello 2013). When the milk industry acknowledged the problem

they launched advertising campaigns to change the public's perception, as well as re-designed the single serve packaging of dairy products, however these efforts were deployed far too late (Cardello 2013). In this same time frame, new milk substitutes were developed and produced as their own industry (Cardello 2013). The industry's inability to forecast is evident and clearly an issue that is seen in the larger market. Many of the milk producer's slow responses and attempts to change market perception show a lack of understanding on the part of the milk industry to identify root cause issues, which are affecting demand.

2.2 DAIRY INDUSTRY AND THE SHELF LIFE OF MILK

Understanding the limitations and the logic behind limited shelf life is vital to the dairy industry as a whole. There is a strong correlation between somatic cell count and the shelf life (Barbano et. al 2010). As the Somatic Cell Count (referred to as SCC) increases, the shelf life decreases. This correlation is due to the fact that Somatic cell count is a quantitative value that can provide a fairly linear relation of the total load of heat resistant enzymes in the milk (Barbano et. al 2010). These enzymes contribute to the bitter or rancid taste experienced by consumers that generally tends to be 2-2.5 weeks after the product reaches the store. A study by Barbano et al. (2010) suggests this shelf life to be approximately 17 days after production using the High Temperature Short Time (HSTS) pasteurization method. High Temperature Short Time is a common pasteurization method that heats milk above 161°F for a period of 15-17 seconds, to kill of bacteria and germs. Barbano et al. (2010)

FIGURE 3: BARBANO ET AL. 2010 SCC TO TASTE CORRELATION

Figure 3 shows the effect that a high SCC vs. Low SCC value has on the taste of the milk. According to (Barbano et al. 2010) an SCC level of <20,000 CFU/mL is classified as a low SCC value and will yield milk with much better shelf life. Much of the limitation behind having SCC values less than 20,000CFU/mL is caused by a variety of reasons such as milk handling, SCC growth from combining low and high SCC level milk within the production system, and even due to illness of milk producing cows. The ability to use filtration systems and other new technology will help in improving milk shelf life.

Another fact that may be looked at which may need to change is the method of pasteurization. In the United States, the general pasteurization method is HTST, and the general yield from this process is a product with an approximate 2-week shelf life. Organic milk in the United States tends to have shelf life of 30 days, which is due to

the UHT method. While this method provides great results, the ingrained sweet taste of milk produced using the UHT method is a less palatable milk compared to the current HTST processed milk. In either process, one fact is inevitable; that is that the milk will eventually expire, due to the fact that “30 to 40% of plasmin activity can remain (Alichanidis et al., 1986).” This enzyme is the largest contribution to the SCC value.

A study from the USDA indicates that dairy sales have declined for the overall consumption of milk, however within the dairy product industry there has been a pivot in consumption of certain types of milk. Low fat milks have replaced much of the demand that was once held by whole milk. However, low fat milks simply do not make up the margins at which whole milk was once sold.

Figure 1
Per capita, daily fluid milk consumption declining

Notes: *Whole* milk has a fat content of at least 3.25 percent. *Lower fat* milk includes products with less milk fat than whole like 2-percent, 1-percent, and skim milk.

Source: Loss-Adjusted Food Availability, USDA-ERS (2013a).

FIGURE 4: (STEWART ET AL. 2013) USDA GRAPH OF FLUID MILK CONSUMPTION

The findings from data collected by the USDA and the department of Economic Research Service (ERS) seen in figure 4, found through survey and other

economic data that the decline in dairy demand is due to a decreasing emphasis placed on the importance and frequency of milk consumption from one generation to the next.

Americans consume fluid milk less frequently per day

Notes: Notable changes from the older to the newer surveys include increases in the percentages of individuals reporting no fluid milk consumption, as well as decreases in the percentages who consumed fluid milk on three or more occasions. These changes are statistically significant at the 10-percent level.

Source: Calculated by the authors using the 1977-78 Nationwide Food Consumption Survey (NFCS), 1989-1991 Continuing Survey of Food Intakes by Individuals (CSFII), 1994-1996 CSFII, 2003-04 National Health and Nutrition Examination Survey (NHANES), and 2007-08 NHANES and accompanying sample weights.

FIGURE 5:(STEWART ET AL. 2013) USDA AND ERS SURVEY DATA ON MILK CONSUMPTION

Figure 5 comes from the paper published by the USDA and ERS and the data shows that there has been a significant drop in the consumption of three or more cups of milk per day as well as a drop in 1-2 cups drinking consumption for all ages. (Stewart et al. 2013) The contra-indicator being zero consumption of milk has gained the losses from the other categories. “ERS analysis of USDA food consumption surveys collected since the 1970s confirms that fluid milk intake has declined for preadolescent children (aged 2 to 12 years), as well as for Americans beyond childhood.” (Stewart et al. 2013) The decline described by Stewart et al. (2013) is graphically displayed in the Figure 6.

FIGURE 6: (STEWART ET AL. 2013) USDA FLUID MILK CONSUMPTION DATA

In Figure 6, over time not only is there a decline in the consumption by newer generations, but there is also a decline in prior generations as they transition into adulthood. This data supports the general market decline and provides indication that the store's micro economy may be a reflection of the larger dairy industry.

2.3 INVENTORY FORECASTING QUALITATIVE VS. QUANTITATIVE

The need for forecasting is best described by Scott Armstrong when he says, "Decision makers need forecasts only if there is uncertainty about the future." (Armstrong 2001) Uncertainty is a critical aspect in daily life; it is an even more critical aspect of business due to the cost, which is associated with decisions. A bad forecast can ruin a company and the impact will ripple through the individual company as well as the local and global economy. Whether it is by increasing the unemployment numbers in the local market or the loss of business felt by all the customers and vendors that work with that business globally, the impact echoes far past the front steps of the company. Therefore, a good forecast is imperative to the way the business develops its strategy.

Forecasting can be divided up into two groups; qualitative and quantitative (Anderson et. al. 2012). Some experts consider causal forecasting as a third group of forecasting.

Causal models are a very powerful tool. Chamber's et al. (1979) best describes causal models in this statement on the subject: causal models "uses highly refined and specific information about relationships between system elements, and is powerful enough to take special events formally into account. As with time series analysis and

projection techniques, the past is important to causal models.” Chamber’s et al. (1979) the methods are powerful, however causal models again require a significant knowledge base in their use, as well as require significant effort to develop in order to function properly.

Qualitative forecasting is based more around expertise and customer feedback (Anderson et. al. 2012). The data acquisition in qualitative forecasting tends to cost more compared to quantitative methods because it requires more work (GOR 2016).

Quantitative forecasts are developed through the application of mathematics - by combining data and applying it to an algorithm. The application of quantitative forecasting is ideal if any of these three primary preconditions exist:

- Easily available historical data
- Data that can be interpreted and evaluated in numerical terms
- Evidence to support that a past pattern existed and will continue to exist

(Anderson et al. 2012)

What is not obvious about qualitative and quantitative forecasts is that each group has its value and that can only be seen by their application.

Essentially quantitative forecasting is diametrically opposed to qualitative forecasting in that the subject being forecasted is well established or has a relatively stable cycle of demand rooted in the past and assumed to continue into the future.

(Anderson et al. 2012)

2.4 QUANTITATIVE METHOD

As previously stated, quantitative methods are comprised of several different types of forecast models which require data. The degree to which the data depicts a correlation between root stimuli that influences the data is a vital component in selection of this method. In many cases the correlation between the data and a specific stimulus tends to be weak, however the historical data clearly shows a pattern. The combination of weak correlations and historical data is known as the time series method. The objective of this sub group is to project a forecast of future events by applying forecast algorithms to data. Within the time series forecasting sub-group, several methods have been developed to solve the multitude of real life problems that can only be satisfied by this method. Among this group, three models stand out from the rest which are:

Time Series Plots

Weighted Average

Exponential Smoothing

Time series plots are a simple but useful means of initially identifying whether patterns exist with the data. A time series plot visually graphs data against some evenly spaced reference to time. The visual aspect of this method tends to quickly and easily portray any simple patterns in the historical data.

There are a multitude of patterns which may be easily recognizable in a time series plot. The first pattern is the horizontal pattern, which consists of relative

fluctuation of data points over time, which oscillates around a mean. In some cases, horizontal patterns can also identify whether data is dependent on time as a function of variation. Two conditions tend to indicate that the data is falling under a stationary time series. The first condition is when the mean value tends not to change over time, as well as a continuous and unvarying oscillation in the data over time.

If the data shifts gradually up or down when observed over a longer term horizon it is called a trend pattern. Unlike the trend pattern, a seasonal pattern is another pattern that is repetitive from one-time frame to the next; an example of this would be seeing that sales tend to be low through most of the year and climb to their peak during the Christmas shopping season every year. In this example, the time frame is one year in length and the comparison of multiple years shows that Christmas is the seasonal event which triggers the pattern.

2.5 WEIGHTED MOVING AVERAGE

Weighted moving average is a model that branches off from the forecast method moving average. Moving average stems from the basic mathematical concept of when provided with a series of data; there is a value that is the mean or average of the set of data. The mean value in mathematics is a great tool to find the middle ground of a set of numbers; however, it has its limitations. The mean value can be significantly distorted when the range between the largest number and the smallest number is immense. The definition of whether the range is large or small is dictated by the application and is not standard across data sets. In addition, data farther away from the present carries as much value as data that is recently collected. In many cases, this

old data may exaggerate what more recent data is indicating as a current pattern. Therefore, mean values tend to miss the current picture due to their inclusion and equal distribution of weight on each data point from the beginning of the data set to the most recent data.

The concept of moving average deviates from the mathematical concept of mean due to the fact that a simple mean looks at the whole data set whereas moving average is only concerned with the most recent subset of data that is still significant (Chiulli 1999). The definition of what is considered the most recent subset of data is defined by the forecaster. In addition, the advantage of removing historical data is that the average is dynamic due to the fact that it moves and responds on what data is closest to the point of the forecast which makes it much more capable of responding proactively to the present (Chiulli 1999). Another important point is that this method assumes that the variation in data shifts gradually. The nature of this model is to assume that historical data is considered no longer relevant to the forecast after a certain period of time. The moving average is a definite improvement over mean average; however, like mean averages it continues to weigh all data points with an equal value. A weighted moving average is true to its name in that it applies weight to data, meaning that data that is closer to the present can influence the forecast greater than older data that may have little correlation to the current forecast. This blending of weight and data elimination gives weight mean average a significant degree of accuracy (Chiulli 1999). The weighted method takes more work to use because of the fact that there is no finite way to apply weights. While the common practice is to assign the heaviest weight to the most recent data and the weight applied to

consecutive data sets decline, the amount of value applied is defined again by the forecaster (Chiulli 1999). Equation 1 shows the formulas used to obtain the weighted moving average.

<i>WEIGHTED MOVING AVERAGE FORECAST EQUATION</i>
$F_{t+1} = w_1 Y_t + w_2 Y_{t-1} \dots w_n F_{t-1}$
<p>Where</p> <p>F_{t+1} = <i>forecast of the time series for period $t + 1$</i></p> <p>Y_t</p> <p>= <i>actual value of the time series in period t closest to present</i></p> <p>Y_{t-1} = <i>actual value of the time series for periods after t</i></p> <p>w_n = <i>weight given to period t ($\sum w_n = 1$)</i></p>

EQUATION 1: WEIGHTED MOVING AVERAGE EQUATIONS AND VARIABLE DEFINITION

2.6 EXPONENTIAL SMOOTHING

Exponential smoothing takes on many of the characteristics of weighted average, and mean. In this approach, the attempt is to retain historical data and incorporate it into the forecast. However, unlike weighted average, exponential smoothing uses a constant value between 0 and 1 called the smoothing constant. The constant acts as a weight to increase the values of recent demand and reduce the contribution of older demand. The smoothing constant is assigned to all of the historical data sets included in the forecast and the value of the constant tends to go down as the data moves away from the present data (Hopp and Spearman 2011). Like

all forecast methods, exponential smoothing also must make some concessions in order to work and is not ideal for every scenario (Hopp and Spearman 2011).

The exponential smoothing constants, like that of the weight coefficient in weighted moving average, are assigned based on the expertise of the forecaster. The smoothing constant is simple in this sense as the constant can be tested easily to determine the best constant that works for the data set. The value of the constant is critical to proper use of this method; as the constant approaches 0, the more stable the model becomes. This also means that the model is not good at reacting to large change. In this model, experimenting with the constant is the time consuming portion of the forecast. (Hopp and Spearman 2011)

In general, the exponential smoothing model works best when applied in a stable data set. This means that the exponential smoothing model is not sensitive enough to detect trends within the data, hence the smoothing aspect of this model. (Hopp and Spearman 2011)

<i>EXPONENTIAL SMOOTHING FORECAST EQUATION</i>
$F_{t+1} = aY_t + (1 - a)F_t$
<p>Where</p> <p>F_{t+1} = <i>forecast of the time series for period $t + 1$</i></p> <p>Y_t = <i>actual value of the time series in period t</i></p> <p>F_t = <i>forecast of the time series for period t</i></p> <p>a = <i>smoothing constant</i> ($0 \leq a \leq 1$)</p>

EQUATION 2: EXPONENTIAL SMOOTHING EQUATION AND VARIABLE DEFINITION

Based on the model shown in equation 2 by Hopp and Spearman (2011), the forecast is represented by F_{t+1} , and the term Y_t is the most recent demand seen in that current period. The term F_t represents the forecasted or predicted demand for the period t. *The value of F_t* is developed based on the prior week's data. Alpha denoted by the symbol (α), is referred to as the smoothing constant, and is applied to the model. Alpha acts in duality to balance the model based on the forecaster or user's judgement. The duality of alpha can be seen in the weight given to alpha which ranges from 0 to 1. For example, if the current demand is a better representation of what forecasted future demand will look like. Then an alpha value of 1 would be applied so that the most recent periods demand - rather than the forecasted demand - will be used to predict the next periods forecast value. If the opposite were true, then an alpha of 0 would be chosen.

Forecast value is determined mainly by the forecast's accuracy. Hopp and Spearman (2011) state that there are three fundamental laws which are important to know prior to working with forecast models. These laws are:

- **First law of forecasting:** Forecasts are always wrong!
- **Second law of forecasting:** Detailed forecasts are worse than aggregate forecasts!
- **Third law of forecasting:** The further into the future, the less reliable the forecast will be! (Hopp and Spearman 2011)

2.7 FORECAST ERROR AND MODEL EVALUATION METHODS

While these rules may seem obvious the first law is the most pertinent to forecast value. In a realistic problem, the likeliness that demand or actual value matches the forecasted value is extremely rare, and this is the reason why forecasts are frequently wrong. Real world problems are complex and the goal of forecast models are to reduce these complications such that they can predict future values, however the sophisticated nature of these problems makes it impossible for a forecast model to exactly predict future demand (Wilson and Keating 1998). Therefore, measuring forecast error and adjustability of forecast model coefficients are designed into time series forecast models to improve accuracy (Hopp and Spearman2011).

MAD-mean absolute deviation

Mean Absolute Deviation is a significantly useful measure of error. Equation 3 shows the equation for MAD Hopp and Spearman (2011). Primarily this error method is useful for the fact that error is in the same units as the units that are used in the model. When comparing multiple forecast methods MAD allows the forecaster to see clearly which forecast method come closest to meet actual value.

MEAN ABSOLUTE DEVIATION
$MAD = \frac{\sum_{t=1}^n f(t) - A(t) }{n}$
<p>Where</p> <p>$f(t)$ = forecast of the time series for period t</p> <p>$A(t)$ = actual value of the time series in period t</p> <p>n = number of periods</p>

EQUATION 3: MEAN ABSOLUTE DEVIATION EQUATION AND VARIABLE DEFINITION

MSE-Mean Square Error

Mean square error differs from MAD due to the square of the error; in general, both MAD and MSE identify similar error traits. Even MAPE shows the error in the form of percentage, while there is little difference between these three methods the benefit is that all three are designed to compare multiple forecast models and compare their performance using the same reference (Anderson et al. 2012).

MEAN SQUARE ERROR
$MSE = \frac{\sum_{t=1}^n f(t) - A(t) ^2}{n - 1}$
<p>Where</p> <p>$f(t)$ = forecast of the time series for period t</p> <p>$A(t)$ = actual value of the time series in period t</p> <p>$n - 1$ = one less than the number of periods</p>

EQUATION 4: MEAN SQUARED ERROR EQUATION AND VARIABLE DEFINITION

Equation 4 provides the equation to MSE Hopp and Spearman (2011). This error analysis method would be ideal for this study because MSE is strong when multiple forecast models are applied to the same set of data Hyndman and Koehler (2006). The one major disadvantage to this method is the fact that this method is scale dependent Hyndman and Koehler (2006) therefore using MSE on different products which have none equivalent scales would not provide a robust analysis of error given these two conditions.

MAPE-mean absolute percentage error

MEAN ABSOLUTE PERCENTAGE ERROR
$MAPE = \frac{ A(t) - f(t) }{A(t)}$
<p>Where</p> <p>$f(t)$ = forecast of the time series for period t</p> <p>$A(t)$ = actual value of the time series in period t</p>

EQUATION 5: MEAN ABSOLUTE PERCENTAGE ERROR

Equation 5 shows the formula for mean absolute percentage error Hopp and Spearman (2011). The characterization of this error type was best described by McKenzie (2006) “This measure is intuitively appealing as it penalizes under- and over-prediction, relative to the actual outcome, in a symmetrical way. However, it is also well known that for a given prediction, actual outcomes above and below the prediction are treated asymmetrically” Unlike other error methods such as MSE, MAPE is not scale dependent which allows it to have the versatility to judge forecast accuracy across different data sets. Hyndman and Koehler (2006) However MAPE also comes with a set of flaws, when the actual value is equal to 0, the MAPE will output an error value of undefined or infinite. Hyndman and Koehler (2006) The issue with value of zero is

that while approaching zero, MAPE provides a very skewed value Hyndman and Koehler (2006). The most important issue to be cognizant of with MAPE value is best described by Davydenko and Fildes (2013); they stated “One well-known disadvantage of percentage errors is that when the actual value in the denominator is relatively small compared to the forecast error, the resulting percentage error becomes extremely large, which distorts the results of further analyses”.

Being aware of these flaws in forecast error analysis as well as their strengths are important to ensuring that models are accurately analyzed however, Davydenko and Fildes (2013) warning that many times this is not the case. “At the same time, the empirical evidence suggests that judgments under uncertainty are affected by various types of cognitive biases and are inherently non-optimal” Davydenko and Fildes (2013) Error analysis is a critical and vital aspect of Forecast models and must be looked at but objectively and in context. The subjective nature of the forecaster interpreting the data must be eliminated in order to ensure that the best forecasts are used and the voice of the data being analyzed comes through.

2.8 TRUE DEMAND VS. SALES DATA VS. ORDER DATA

The meaning of the data used and the data type are both critical aspects of its applications. Demand forecasting applies a combination of historical order data and sales data (Gilliland et al. 2015). Demand forecasting focuses on using unconstrained true demand, which is the demand of the customer. True demand disregards availability and the time needed to fulfill the order. Gilliland (2015) best states what true demand is when he says, “true demand is not directly measurable; it must be

forecast using an approximation constructed from the data” (Gilliland et al. 2015). True demand as stated by Gilliland is idealized because it assumes that the business can fulfill an unlimited demand at the time it is required by the customer. This assumption poses a significant issue for the business using forecasting because unconstrained true demand is not a level of demand the business can support. (Gilliland et al. 2015). Therefore, the forecaster will use or define a constrained demand to forecast what the business should order. As stated earlier many companies use a combination of order and sales data to estimate a constrained true demand. Order data looks at what is ordered to fulfill demand as indicated by the customer. This data shows what the business has done to meet the customer demand. Sales data shows what the customer actually bought. While both of these data sets seem to be similar to true demand, they are not. A few common scenarios show that there is a difference. For example, if a store runs out of product that the customer intended to purchase, the customer may substitute it with another product that is available, in order to meet the need. In another, case, awareness of a possible future change in the availability of a product will drive the customer to buy more or less than their true demand. (Gilliland et al. 2015). The last scenario looks at the possibility that the business is not reliable at keeping up with demand or getting the product in at the time the customer needs the product and this would reduce demand as well. (Gilliland et al. 2015).

2.9 CASH REGISTER VS. POS MACHINE

The cash register and the point of sale machine are both designed as devices which are meant to calculate sales and hold cash. While in many instances these two

devices may be misconstrued to be the same, they are in fact very different. The cash register is limited in its function. In general, the cash register has several key components that are seen on any cash register dating back to mechanical versions of this device (Khurana 2010). The a cash register will have a

- Number pad: to punch in pricing data
- LED- display:- to show that the customer the price charged and the description if the system is capable.
- Calculator Programming
- Limited memory to store sales transactions
- Printer
- Cash Drawer

An electronic point of sale (POS) machine is capable of performing these tasks as well back-office, ERP, and Inventory tracking (Khurana 2010). A POS machine is capable of all this because it has additional capability with the following features.

- Full Qwerty keyboard
- Larger touch screen display
- Larger storage: POS uses a hard
- Communications ports
- Connectivity: (such as LAN)
- Robust software

The communication port allows for a multitude of periphery to be attached to the POS. (Khurana 2010). The hard drive used for storage on and POS is the same as in a computer which allows it to record transactions and other data. Due to the

minimal storage requirements of sales and inventory data in comparison to the space available on a hard drive, the storage seems almost unlimited. (Khurana 2010). The connectivity capability of POS systems allows for remote servicing and the ability to link more than one POS together. This allows businesses the capability to expand with increases in sales volume. POS machine are needed. POS systems are also able to create and maintain data bases (Khurana 2010)

A normal POS system can cost \$1,500 dollars or more (Aldrich 2014). Cash register are far cheaper than POS systems however the limitation of the cash register warrants the lower price. A key difference between cash registers and POS systems is that the POS systems have real time data tracking and up-to-the-minute accurate assessment of inventory (Aldrich 2014).

2.10 COMPLEMENTARY PRODUCTS & LOSS LEADER

An important concept that relates to dairy products is the concept of complementary products and loss-leader. Complementary products are those which are sold in conjunction with another product (Kumar and Sharma 1998). In the case of a complementary products, if the change in the demand for one product affects the demand for another product then they are considered complementary (Kumar and Sharma 1998). An example of these type of products are milk and eggs, or milk and bread, however this relation tends to only be strong prior to inclement weather.

The term loss-leader refers to products which are sold below unit price. A loss-leader is used in multiple ways to stimulate sales. In some cases, a loss leader is used to boost sales of a primary product. Another application is to use a loss leader in order to retain customers (Kumar and Sharma 1998). There are several indicators, which

identify if a product is a loss leader. The first is the fact that the product has a profit at or near zero. The concept of loss leader may be applied to several products combined so that the group drives demand of another product (Hoang 2014). Some issues arise with this method. Reducing the price of the product creates a potential issue for the reputation of the product. (Hoang 2014). The term loss leader is a bit of a misnomer due to the fact that loss leader products tend to be very profitable. (Hoang 2014).

2.11 ABC INVENTORY CLASSIFICATION

ABC inventory analysis looks at classifying a portfolio of inventory products into three classes (Liu 2015). The product portfolio is broken down into product groups A, B, and C. This method sorts the inventory portfolio by value of annual usage from high to low. (Mercado 2008)

$$\text{Value of annual usage} = \text{Unit price} \times \text{Quantity of annual usage}$$

Equation 6: EQUATION FOR ABC ANALYSIS (MERCADO 2008)

The classification of ABC can vary, however in most cases the ABC product analysis with the Pareto 80/20 rule (Millstein et al. 2013)

Product Class	Annual Usage	Inventory Volume
	Value Percentage	Percentage
A	70-80%	5 %
B	15-20%	20 %
C	5-10%	75 %

Table 1: GENERAL ABC ANALYSIS GUIDELINES (MILLSTEIN ET AL. 2013)

The annual usage value percentage seen in table 1 is the predominant indicator which drives classification. However, the volume percentage is in many cases used in conjunction with the annual usage percentage.

2.12 HOTELLING'S T-SQUARED DISTRIBUTION AND CONTROL CHART

The T-Squared found in statistics is a univariate distribution which uses multivariate data to describe the Mahalanobis distance between two sample means (Weisstein 2002). The Mahalanobis distance multiplies the transpose matrix of the distances from the mean and multiplies it by the inverse covariance matrix, to find the relative distance between two means (Montgomery 2009).

This method is better known for its use as a control chart which can track the general vector of a process (Montgomery 2009). The control chart is similar to the Shewhart $\bar{x}$ -bar chart, in that it can detect shifts in the magnitude of the mean vector (Montgomery 2009). However, unlike the Shewhart $\bar{x}$ -bar chart the direction is not as discernable. The Hotelling T^2 control chart equation seen in equation 7, uses a two phase approach in order to function properly (Montgomery 2009). The first phase seen in equation 8, uses the chart to set the foundation for the control chart, by evaluating whether the process is currently in control (Montgomery 2009). If the system is not in control, Phase 1 continues to fine tune the process until the output data indicates the process is in control, at which point the control chart reverts over to phase 2 (Montgomery 2009). Once the control chart reach phase two the control chart goes into a monitoring phase using equation 9.

<i>HOTELLING T^2 CONTROL CHART EQUATION</i>
$T^2 = n(\bar{x} - \bar{\bar{x}})'S^{-1}(\bar{x} - \bar{\bar{x}})$
<p>Where</p> <p>$n = \text{sample size}$</p> <p>$(\bar{x} - \bar{\bar{x}})' = \text{transpose matrix of distances from the mean}$</p> <p>$(\bar{x} - \bar{\bar{x}}) = \text{matrix of distances from the mean}$</p> <p>$S^{-1} = \text{inverse covariance matrix}$</p>

EQUATION 7: HOTELLING T SQUARED CONTROL CHART EQUATION

<i>HOTELLING T^2 PHASE 1 CONTROL LIMIT</i>
$UCL = \frac{P(m-1)(n-1)}{mn - m - p + 1}$
$LCL = 0$
<p>Where</p> <p>$m = \text{preliminary subgroup}$</p> <p>$p = \text{related quality characteristic}$</p> <p>$n = \text{sample size}$</p>

EQUATION 8: HOTELLING T SQUARED PHASE 1 CONTROL LIMIT EQUATION

<i>HOTELLING T^2 PHASE 2 CONTROL LIMIT</i>
$UCL = \frac{P(m+1)(n-1)}{mn - m - p + 1}$
$LCL = 0$

Where

$m = \text{preliminary subgroup}$

$p = \text{related quality characteristic}$

$n = \text{sample size}$

EQUATION 9: HOTELLING T SQUARED PHASE 2 CONTROL LIMIT EQUATION

An emphasis must be put on how to apply multivariate methods such as the Hotelling T^2 control chart against data. In addition, selection of control limit is critical in order to apply this method correctly (Montgomery 2009). This method also requires a large sample group in phase 1 in order to ensure a quality result in phase 2 (Montgomery 2009).

2.13 KNAPSACK PROBLEM LINEAR PROGRAMMING APPROACH

Operations research is a field that has been around for many years; within the including the branch of linear programming which develops elegant means of solving problems (Winston 2003). Linear programming problems all start by looking at a decision and trying to find an optimal solution (Winston 2003). Most liner programs seek to either maximize or minimize an objective function which incorporates decision variables that depict all the consideration needed in order to make the decision (Winston 2003). Constraints are placed on decision variables to reflect real limitations in real life (Winston 2003)

The knapsack problem is a well-studied linear programming problem, which looks to maximize profits by selecting a subset of a group of products available, while staying within the constraints placed on the decisions variables (Kellerer 2013). There are several variations of this problem. The simplest version is commonly referred to as

the 0-1 knap-sack problem which looks at either incorporating or not incorporating a product. This method only allows for a single unit of the products selected to be incorporated into the final solution. A more robust model of the Knapsack problem is the bounded Knap sack problem seen in Equation 10

BOUNDED KNAPSACK PROBLEM EQUATION
$\begin{aligned} &\text{maximize } \sum_{j=1}^n P_j X_j \\ &\text{subject to } \sum_{j=1}^n w_j x_j \leq c, \\ &x_j \in \{0,1\}, \quad j = 1, \dots, n \end{aligned}$
<p>Where</p> <p>n = the set of products given</p> <p>j = each product</p> <p>p_j = integer profit related to each item j</p> <p>w_j = weight associated with item j</p> <p>x_j = Binary integer indicating whether item is included a part of solution set</p> <p>c = capacity constraint</p>

EQUATION 10: BOUNDED KNAPSACK PROBLEM EQUATION

The difference between the bounded and 0-1 knapsack models is that the bounded version allows for more than one unit of product to be included in the selected

subgroup. The knapsack serves a base platform on which many real world problems have been solved (Kellerer 2013).

2.14 SIX SIGMA PROGRAMMING APPROACH

Six sigma has become a corner stone of the process improvement industry. Six sigma uses different analysis tools which are meant to drive process improvement (Brewer et al. 2007).

There are several tools under the six sigma umbrella a common tool used is the DMAIC process (Brewer et al. 2007). DMAIC stands for Define, Measure, Analyze, Improve, and Control. Each letter represents a sequential step in the process. Each step and the general goals are listed in table 2 (Montgomery 2009).

STEP	GOALS
DEFINE	<ul style="list-style-type: none">• Identify and/or validate the Business improvement opportunity• Define critical customer requirements• Document (map) processes• Establish project charter, build team
MEASURE	<ul style="list-style-type: none">• Determine what to measure• Manage measurement data collection• Develop and validate measurement systems• Determine sigma performance level
ANALYZE	<ul style="list-style-type: none">• Analyze data to understand reasons for variation and identify potential root causes

	<ul style="list-style-type: none"> • Determine process capability, throughput, cycle time • Formulate, investigate, and verify root cause hypotheses.
IMPROVE	<ul style="list-style-type: none"> • Generate and Quantify potential solutions • Evaluate and select final solution • Verify and gain approval for final solution
CONTROL	<ul style="list-style-type: none"> • Develop ongoing process management plans • Mistake-proof process • Monitor and control critical process characteristics • Develop out of control action plans

TABLE 2:DMAIC STEPS & GOALS (MONTGOMERY 2009)

DMAIC is viewed as a means to improve operations through eliminating waste and cutting cost. As stated earlier, each step acts as a gateway, At the end of each step a review occurs which assesses whether the project is on track to meet its “value opportunity” (Montgomery 2009). The value opportunity is the target objective of applying the DMAIC process (Montgomery 2009). The end of step reviews are a critical aspect of ensuring that the process succeed in adding value. Attempting to quantify the financial value added from process improvement is difficult and does not have direct correlation to “bottom line” improvement. (Brewer 2007). Some books argue that the financial objective is critical and must be measurable as part improvement process (Montgomery 2009).

2.15 PERISHABLE INVENTORY CHARACTERISTICS

Broekmeulen and van Donselaar (2009) were inspired to write this article and conduct research due to a clear demand from several large European grocery chains that are looking for a way to incorporate perishability into inventory management. The key point of this research is to see if there is a means to accurately order perishable inventory, which can be incorporated into an order replenishment system already in use. This system has worked effectively on non-perishable inventory order replenishment, and having the capability to cover the entire portfolio of products with one method would be ideal.

Broekmeulen and Van Donselaar (2009) discuss many of the assumptions that they make in order to compare the replenishment methods being tested. One of the largest aspects being omitted from the data is the relationship between the times at which operations are conducted. Broekmeulen and van Donselaar (2009) clearly states that operations such as removing expired product from shelves and restocking shelves are conducted outside of normal business hours. However, these operations are accounted for at the beginning of the next business day.

Another point is that the experiment is being conducted at one location with only one product rather than with multiple products and multiple store locations. These simplifications create the assumption that all stores in this chain operate in exactly the same manner and have similar purchase and sales patterns. The second assumption that can be deduced is that by only sampling one good, all other perishable goods have a standard pattern, which they follow, and therefore any patterns derived from the models can be applied to any other perishable item indiscriminately.

Broekmeulen and van Donselaar (2009) also use a gamma distribution to model demand for each day.

In order for the EAW method to work, Broekmeulen and van Donselaar (2009) needed to assume that demand is unpredictable, and create a model to predict demand, which is then used as part of inventory replenishment.

The results that Broekmeulen and van Donselaar (2009) discuss in the model tend to express common weaknesses in forecasting. This states that the EAW model is weak in replenishing products with perishable shelf life limitations. In the case of a perishable good, shelf life ranges between 1-30 days. As the shelf life goes toward 30 days, the model pushes farther into the future to predict when inventory replenishment is needed. Therefore, if used on inventory with a long shelf life then the cost will increase because a larger volume of product will be classified as outdated and ready for removal prematurely. The point that was critical is the development of the inventory replenishment model, which would be tailored to the unique age parameters of perishable goods.

Broekmeulen and van Donselaar (2009) provide a means of replenishing perishable inventory automatically. The ability to do this accurately would be valuable in all applications of perishable goods whether it is done automatically or by hand. The ability to solve the dilemma of determining demand with minimal exposure to losses as it relates to expired inventory would be valuable. While this research was a good first step in attempting to resolve the inventory forecasting and ordering issue that businesses with perishable inventory experience, it did not yield a model that provided good enough results for forecasting need.

Duong et al. 2015 made a great point in their article when they said “even within a single echelon manager will have different metrics against which their work is judged. Therefore, setting up and implementing a performance metric is a challenging task that requires the partnership and collaboration.” (Duong 2015) This statement imbues the sense of hesitation that the owner of this convenience store and others in similar small businesses may have, which is that there is a fine line between useful and useless. The quote also indicates an advantage of small businesses, which is that the lack of layers of management allows for the testing and deployment of tools to be faster and possibly more effective.

2.16 SHIFT IN NUTRITIONAL GUIDELINES

Milk has been a building block of US dietary guidelines in the many iterations that have come since its founding. These guidelines are recommendations that the government developed to ensure healthy living for its citizens, and for the most part is a basis that people have followed. They have been around for over a hundred years. As stated earlier, these guidelines change and pivot their stance as science and technology develop new ways to fortify foods with more vitamins and minerals or learn of new benefits or demerits of recommended foods. The figure 7 shows a report put out by the USDA division of Economic Research, and the guidelines call out for dairy on a daily basis.

Table 1—Principal USDA Food Guides, 1916-92

(All food guide recommendations are for daily servings (svg), except where otherwise indicated.)

Food guide	Number of food groups	Protein-rich foods Milk/Meat	Breads
1916 Caroline Hunt buying guides	5	Meats/other protein-rich food 10% cal milk; 10% cal other <i>1 cup milk plus 2-3 svg other</i> (based on 3-oz. serving)	Cereals and other starchy foods 20% cal 9 svg (based on 1 oz. or 3/4 cup dry cereal svg)
1930's H.K. Stiebeling buying guide	12	Milk—2 cups Lean meat/poultry/fish—9-10/week Dry mature beans, peas, nuts—1/week Eggs—1	Flours, cereals— <i>As desired</i>
1940's Basic Seven foundation diet	7	Milk and milk products— 2 cups or more Meat, poultry, fish, eggs, dried beans, peas, nuts—1-2	Bread, flour, and cereals—Every day
1956-70's Basic Four foundation diet	4	Milk group—2 cups or more Meat group—2 or more (2-3 oz. svg)	Bread, cereal— 4 or more (1 oz. dry, 1 slice, 1/2-3/4 cup cooked)
1979 Hassle-Free foundation diet	5	Milk-cheese group—2 (1 cup, 1 1/2 oz. cheese) Meat, poultry, fish, and beans group—2 (2-3 oz. svg)	Bread-cereal group—4 (1 oz. dry, 1 slice, 1/2 to 3/4 cup cooked)
1984 Food Guide Pyramid total diet	6	Milk, yogurt, cheese—2-3 (1 cup, 1 1/2 oz. cheese) Meat, poultry, fish, eggs, dry beans, nuts—2-3 (5-7 oz. total/day)	Breads, cereals, rice, pasta— 6-11 svg • Whole grain • Enriched (1 slice, 1/2 cup cooked)

FIGURE 7: FROM USDA ERS-AMERICA'S EATING HABITS: CHANGES AND
CONSEQUENCES (FRAZÃO 2012)

It is clear that there is an emphasis put on the necessity of dairy in dietary guidelines given its appearance in the first guidelines in 1916, where the minimum requirement was 1 cup of milk and recommended to have 2-3 servings each day. In 1930, the minimum requirement was increased to 2 cups. The cup requirement stays relatively stable from 1930-1979, where cheese is combined with milk and added as an option for one of the 2 daily recommended servings of dairy. Then the requirements shift again in 1984 to include yogurt and the recommendation pivots to 2-3 servings. Milk is an interesting component of the dietary guidelines for the United States because it acts more like a foundation. It is the most consistent item included in the dietary guidelines over 68 years, as captured in this figure. It is important to see that the first shift up in the necessary daily requirement of milk occurs in the 1930's, which was during the Great Depression era of US history. "In the early 1930's, the economic constraints of the Depression influenced dietary guidance. In 1933, Hazel Stiebeling, a USDA food economist, developed food plans at four cost levels to help people shop for food (Frazão 2012). Even when the guidelines were attempting to pivot so that every American would be able, to afford a nutritious diet, milk played an increasing vital role in dietary needs. In the 2010, the dietary guideline stated this reason for milk's ever-important role in the US daily diet "Americans currently consume too much sodium and too many calories from solid fats, added sugars, and refined grains. These replace nutrient-dense foods and beverages and make it difficult for people to achieve recommended nutrient intake while controlling calorie and sodium intake. A healthy eating pattern limits intake of sodium, solid fats, added sugars, and refined

grains and emphasizes nutrient-dense foods and beverages—vegetables, fruits, whole grains, fat-free or low-fat milk and milk products, seafood, lean meats and poultry, eggs, beans and peas, and nuts and seeds.” (Dietary Guidelines 2010) Obesity in the population and the high consumption of fatty foods has caused the drive of milk’s value in the US Diet. The Figure 8 was developed for all ages and is based around the level of caloric intake.

Energy Level of Pattern ²	1000	1200	1400	1600	1800	2000	2200	2400	2600	2800	3000	3200
Fruits	1 c	1 c	1½ c	1½ c	1½ c	2 c	2 c	2 c	2 c	2½ c	2½ c	2½ c
Vegetables	1 c	1½ c	1½ c	2 c	2½ c	2½ c	3 c	3 c	3½ c	3½ c	4 c	4 c
Dark green vegetables	½ c/wk	1 c/wk	1 c/wk	1 ½ c/wk	1 ½ c/wk	1 ½ c/wk	2 c/wk	2 c/wk	2 ½ c/wk	2 ½ c/wk	2 ½ c/wk	2 ½ c/wk
Red/Orange vegetables	2½ c/wk	3 c/wk	3 c/wk	4 c/wk	5 ½ c/wk	5 ½ c/wk	6 c/wk	6 c/wk	7 c/wk	7 c/wk	7½ c/wk	7½ c/wk
Cooked dry beans and peas	½ c/wk	½ c/wk	½ c/wk	1 c/wk	1 ½ c/wk	1 ½ c/wk	2 c/wk	2 c/wk	2 ½ c/wk	2 ½ c/wk	3 c/wk	3 c/wk
Starchy vegetables	2 c/wk	3½ c/wk	3½ c/wk	4 c/wk	5 c/wk	5 c/wk	6 c/wk	6 c/wk	7 c/wk	7 c/wk	8 c/wk	8 c/wk
Other vegetables	1½ c/wk	2½ c/wk	2½ c/wk	3½ c/wk	4 c/wk	4 c/wk	5 c/wk	5 c/wk	5½ c/wk	5½ c/wk	7 c/wk	7 c/wk
Grains	3 oz eq	4 oz eq	5 oz eq	5 oz eq	6 oz eq	6 oz eq	7 oz eq	8 oz eq	9 oz eq	10 oz eq	10 oz eq	10 oz eq
Whole grains	1½ oz eq	2 oz eq	2½ oz eq	3 oz eq	3 oz eq	3 oz eq	3½ oz eq	4 oz eq	4½ oz eq	5 oz eq	5 oz eq	5 oz eq
Other grains	1½ oz eq	2 oz eq	2½ oz eq	2 oz eq	3 oz eq	3 oz eq	3½ oz eq	4 oz eq	4½ oz eq	5 oz eq	5 oz eq	5 oz eq
Meat and beans	2 oz eq	3 oz eq	4 oz eq	5 oz eq	5 oz eq	5½ oz eq	6 oz eq	6 ½ oz eq	6 ½ oz eq	7 oz eq	7 oz eq	7 oz eq
Milk	2 c	2 c	2 c	3 c	3 c	3 c	3 c	3 c	3 c	3 c	3 c	3 c
Oils	15 g	17 g	17 g	22 g	24 g	27 g	29 g	31 g	34 g	36 g	44 g	51 g
Maximum SoFAS ³ limit, 137	137	137	137			258			362			
calories (%total calories) (14%)	(14%)	(11%)	(10%)	121(8%)	161(9%)	(13%)	266 (12%)	330 (14%)	(14%)	395 (14%)	459 (15%)	596 (19%)

¹Food group amounts shown in cup (c) or ounce equivalents (oz eq). Oils are shown in grams (g). Quantity equivalents for each food group are:

- Grains, 1 ounce equivalent is: ½ cup cooked rice, pasta, or cooked cereal; 1 ounce dry pasta or rice; 1 slice bread; 1 small muffin (1 oz); 1 ounce ready-to-eat cereal.
- Fruits and vegetables, 1 cup equivalent is: 1 cup raw or cooked fruit or vegetable, 1 cup fruit or vegetable juice, 2 cups leafy salad greens.
- Meat and beans, 1 ounce equivalent is: 1 ounce lean meat, poultry, fish; 1 egg; ¼ cup cooked dry beans; 1 Tbsp peanut butter; ½ ounce nuts/ seeds.
- Milk, 1 cup equivalent is: 1 cup milk or yogurt, 1½ ounces natural cheese such as Cheddar cheese or 2 ounces of processed cheese.

²Food intake patterns at 1000, 1200, and 1400 calories meet the nutritional needs of children ages 2 to 8 years. Patterns from 1600 to 3200 calories meet the nutritional needs of children 9 years of age and older and adults. If a child ages 2 to 8 years needs more calories and, therefore, is following a pattern at 1600 calories or more, the recommended amount from the milk group should be 2 cups per day. Children ages 9 years and older and adults should not use the 1000, 1200, or 1400 calorie patterns.

³SoFAS are calories from solid fats and added sugars.

FIGURE 8: REPORT OF THE DIETARY GUIDELINES ADVISORY COMMITTEE ON THE
DIETARY GUIDELINES FOR AMERICANS 2010

It is important to note that as the caloric intake increases so does the level of the daily consumption of milk. The requirements posture has shifted within the guidelines where these guidelines are focused not on age or as an age-related broad spectrum requirement. This guideline takes the approach of including activity level and energy used. The figure still highlights some of the older methods of guideline application such as the last note which provides yogurt and cheese as substitutes for milk. It also

mentions that in general children between the ages of 2-8 years old should be eating between 1100-1400 calories, and that it is possible they may need more than this depending on their activity level.

Even though the government has invested heavily in dairy products from the dietary guidelines aspect, it is only just starting to learn whether most Americans can even digest dairy properly. A report out of the National Institute of Health said “The prevalence of lactose intolerance is difficult to discern because studies have varied in their interpretation of what constitutes this condition. To estimate accurately the prevalence of lactose intolerance, one first must define lactose intolerance to permit the identification of those individuals with the condition and the exclusion of those without the condition.” (Suchy et al. 2010). An article by USA Today argues that 60% of all adults are lactose intolerant (Weise 2009). Due to the fact that there have been no benchmarks created which define what is the standard for being intolerant is and what is defined as normal. The National Institute of Health has stated that it has only been looking into this phenomenon for 50 years whereas it has existed since the time of the Greeks. It is normal for adults to have some reduction in the ability to metabolize lactose as they age therefore adults in general adults should be somewhat lactose intolerant (Suchy et al. 2010).

There are many reasons for the reduction in the demand in the global market, whether it is due to the acknowledgement of lactose intolerance, the lack of generational transfer of the habit of drinking milk, or the introduction of milk substitutes, which provide a comparable nutritional profile with lower calorie content may stimulate the decline of fluid milk demand. Therefore, the lack of awareness of

the global market by the store is a failure of the store to be aware of how the product should be positioned.

CHAPTER 3: METHODOLOGY

3.1 RESEARCH CONCEPT

This research is looking at identifying tools that can be used in small businesses. Due to the fact that each large scale tool targets different aspects of large business a focus has been selected which is looking at forecasting demand. The ability to accurately forecast demand will provide small businesses with tools that mitigate waste and avoid exposure to overages and expiration of perishable goods.

The research project will start by developing a profile and identifying small businesses with the right characteristic to evaluate large scale tools in a case study format. Most likely, the company will have problems that have already been realized by those who work in the company. Once selected, understanding the company's needs and identifying how the company has arrived at this point with these issues will become prudent.

3.2 DESCRIPTION OF THE SAMPLE BUSINESS

The selection of the small company is a crucial aspect of the study. An ideal small business would be a “mom and pop” business in which owners who may not have a strong business background but are strong in the industry run the company. The owners have been in their industry and would not be defined as beginners in the industry. The owner would have their own non-conventional way of running their business. This ownership profile would be ideal because the owners are accustomed to how business is conducted and would be hesitant to change the way business is conducted. In addition, the lack of exposure to forecasting techniques and quantitative

business models makes this particular business owner ideal because they have no exposure to techniques that may be deployed to remedy the issues in the business. This type of owner would be the worst-case scenario and would be the best indicator of the tools' capability to function in uncompromising environments.

The industry is not as important; the company could be a store or it could be a small manufacturing facility; what matters more is the business complexity, such as the number of employees in a business unit and the number of business units within the company. A business unit is defined as the smallest group of personnel and assets which produce a profit center. Having the smallest unit possible would be best because as more resources and personnel are incorporated into the process the less effective the method deployment will be. The company should be in a fairly stable environment meaning that the company is not on the verge of bankruptcy, the business health is fairly stable however, improvements would be needed to increase prosperity of the business.

3.3 FORECASTING METHODS

While several methods were looked at in chapter 2, only a few will be selected for examinations. In order to better explain why many were eliminated, a recap on the problem and the store's condition need to be examined.

Initial discussion with the owners emphasized the lack of resources available at the store. Initial impressions of the store and store owners indicates that the all back office and ordering work is done without the use of a computer. The store currently has 3 employees and uses only one employee per shift at all times. The store's

financial resources are limited as well, therefore acquiring new equipment and personnel are not possible.

This reflection on the state of the store echoes the point of this research, which is that given the limited resources can industrial tools still function and provide some benefit to the small businesses that attempt to use it. In the case of the store, the goal will be to see if that some of the tools can reduce potential exposure to expired dairy product.

As previously stated, the store has a very limited number of employees, and during regular operations only one employee is working at a time. Therefore, the personnel needs to utilize the DMAIC process.

Due to the fact that the store is a standalone convenience store, the demand may be small, and the potential to meet the 20-50 preliminary sample size needed for the Hotelling control chart is likely to not be met by the store's inventory. In addition, employees at the store do not have the statistical knowledge or background to use these charts and the constant attention needed to shift between phase 1 and 2 of the control chart would require new personnel qualified to use the technique.

The store has a computer available but the computer is not equipped with data tracking software, needed to run linear programming models.

Inventory forecasting is a well-developed field. In general, there are three main branches of forecasting which are quantitative, qualitative, as well as causal models. The use of qualitative forecasting would work well because it is received from experts and end users. In addition, the data is collected in the form of surveys and testimonials

which easily lend themselves to be used in analysis. This method would be ideal because as mentioned in the literary review, qualitative forecasting methods work better in an environment of uncertainty which applies to this case because there is currently no existing data set.

The store's lack of resources and analytics rules the qualitative method out because the effort on the part of the store would be outside the store's capability. These facts make the qualitative method of forecasting impractical and unsustainable for the store. The return on investment into this strategy would take longer and be too expensive to be of value to the store.

Being able to use a causal method could potentially be successful, however given the diversity in customers and products being studied make it seem unlikely that there are a limited few parameters that drive demand. Chambers echoes the effort needed to support causal models: "Typically, a causal model is continually revised as more knowledge about the system becomes available." This means the store would need to be proactive in identifying the parameters which are driving demand. Causal methods would require that the store owners have a strong background in forecasting as well as a firm understanding of what drives dairy demand, in addition to a continuous effort to identify new driving parameters. The lack of alignment between causal models requirements and store capability make this group of forecast not feasible.

Deploying qualitative and causal forecasting methods would consume a significant amount of resources, which may not even be available to the store. The store is better off using quantitative methods discussed earlier such as weighted

moving average and exponential smoothing. These particular tools are oriented around time series forecasting which usually requires long period of data collection. However, this method has the best value with the least amount of impact on resources, and in addition the store would not have to strain resources to acquire data. The minimal change caused by this method of forecasting is best suited for the hesitant owners, and the alignment of this method with the current day-to-day activities have the best chance of incorporation into the current store model over the long term.

Forecasting Methods such as the Naïve Methods, Moving Average, Exponential Smoothing, and Trend Projections are all part of the time series analysis subset. While it is true that these methods are similar, the primary difference is the way in which data is applied. In the case of the store, the lack of existing demand data means that the store must be observed and data must be collected in order to test models such as exponential smoothing and weighted average. Some methods may be able to leverage other existing information such as trend projection. The methods below are best suited for short data collection and have the best chance of success because they do not require a long history of data collection:

Weighted Average

Exponential Smoothing

Trend Projections

In the case of all of these methods, data must be collected and value must be input. Initial setup of the experimentation to test these forecast methods will require the identification of dairy products to be observed. The ideal products will have no seasonality involved in their demand by customers or in their ordering scheme.

3.4 DATA COLLECTION

A survey will be conducted in order to establish a strong understanding of what drives the dairy segment of the convenience store decisions and what the limitations are in the environment.

Many experts note that there is a need for multiple forecasting means and they become necessary in order to best capture the needs of the target objective. Chambers et al. (1971) states that “Successful forecasting begins with a collaboration between the manager and the forecaster, in which they work out answers to the following questions.”

As part of determining whether a business is a viable candidate for study; the question from Chamber et al. 1 (1979) are listed below.

- Question 1: What is the purpose of the forecast—how is it to be used?
- Question 2: What are the dynamics and components of the system for which the forecast will be made?
- Question 3: How important is the past in estimating the future?

These questions are creating a “meeting of minds” between the forecaster and the owner; in addition, it helps mitigate inefficiency in the process if these questions are thoroughly answered (Chambers et al. 1971). These questions are used as an initial launch point to help in determining what forecast models will best suit the needs of the business.

The store participating in the study, currently retains two prior years of records for dairy orders. This data will be analyzed to see if any trends or patterns exist.

However, no data of customer demand is currently available which what is needed because demand is what drives sales and is need to apply exponential smoothing and weighted average.

The 2- year historical data received by the owners is different from the 6-week data collected. The 2- year data is only a reflection of order data which means that it does not reflect sales data as well as the losses of inventory which either did not sell or was damaged prior to sale. The lack of these key elements means the historical order data is susceptible to errors in forecasting which will increase the exposure to possible product that will expire prior to sale. The 6-week data will contain these important elements by recording incoming inventory, analyzing damaged and expired product and counting the remaining inventory on hand on a daily basis, which will provide the closest measure of true demand.

The convenience store does not have any means of collecting the data. Many businesses of this kind use POS machines, which track product sales in real time. In this case, these machines are a significant monetary investment for the store and therefore the data will be collected on a daily basis by hand. The period (t) used for the weighted average model and exponential smoothing is in units of weeks, because dairy orders occur on a weekly basis. As mentioned earlier, data will be collected daily and this is because there is potential in seasonality existing within the period. In order for this question to be evaluated, data must be collected on a daily basis. The argument could be made that the time of day in which the sale is made could add another level of seasonality, however the cost of collecting this level of data versus the value received does not seem to merit this level of more in depth data measurement.

Data will be collected for 6 weeks on a daily basis towards the afternoon; because the afternoon is assumed to have the least amount of sales given that most people are at work during the day. Capturing inventory during the afternoon will help in potentially identifying patterns dealing with sales on a given day. The 2-year order data is being used to identify any clear trends or pattern, and the demand data is applied to weighted average and exponential smoothing models. The study period of 6 weeks is chosen because the forecasting objective occurs within a week and the order data will provide an understanding if looking at data from a month or a year out will provide effect weekly dairy inventory forecasting.

The constraints required by the study, such as holding expired dairy for a longer period than normal operation and tagging inventory prior to sale, places significant stress on the store's routine operations. The storeowners agreed to guarantee a 6 week window in which to conduct study. In addition, the storeowners keep up to the prior six weeks of order data on hand which is used in the "gut instinct" method.

Research into dairy consumption discussed in chapter 2 shows a fairly inconsistent pattern of US dairy consumption. The variation suggests that there may not be a large benefit in looking at significantly long term data sets because the older data may not hold any influence on what is currently being seen in dairy demand. For the reasons previously stated, it seemed that any method applied should need to be able to forecast at a fast pace.

3.5 CURRENT INVENTORY AND SALES PROCESS

The owners of the convenience store are currently under the impression that the system of their “gut instinct method” is working well. This is due to the lack of data as well as a lack of knowledge of forecasting methods that could be used to analyze historical data. Their “gut instinct” ordering method is based on two critical components which influence the order. The first component is that the managing owner who runs the day to day operations observes the sales of milk during the week. This information is stored as a mental note. Daily observations entail noting significant levels of sale in a particular dairy product or the expiration of a large volume of units of a particular dairy product. Either of these scenarios generate an observation which the managing owner will keep and mentally note and hopefully will recall during the decision making process for the next weeks’ order. The second component is looking at the inventory shelves and stock shelves to find out how much inventory is on hand. From this information, the owner decides how much inventory to

order. Figure 9 shows the dairy inventory cycle from the stores perspective.

FIGURE 9: CURRENT BUSINESS INVENTORY AND SALES CYCLE

Figure 9 shows the three primary influences on the dairy cycle which are the vendor, store, and customer. The store is placed in the middle acting as the intermediary between the customer and the vendor. The weekly inventory and weekly inventory check show the data flow which all travels in the same direction back to the vendor. The boxes weekly delivery and below indicates feedback at the points in the cycle. While the owners have discussed a general idea of what they would like to achieve, it is far from a clear target objective needed to form the forecast.

The sales model seen in Figure 9 accurately depicts the current flow in the sales cycle for a majority of inventory. A group that is not accounted for in the model is damaged products which are ruined due to the products' container being compromised at any point prior to the sale. While damaged products are an important group to inventory, their unpredictable nature makes it necessary to omit them from

experimentation. The focus going forward will be on avoiding spoilage and other product losses, which have a predictable nature.

3.6 ANALYSIS OF LARGER DAIRY INDUSTRY

The United States Department of Agriculture (referred to as the USDA from this point forwards), distributed and analyzed surveys of the American population since the mid 70's. Below is a composite view of fluid milk sales starting in 1975 through 2013, The current trend shows a slow decline between 1975 to 1983, then a slight surge from 1984 to 1993, and then a decline from 1993 onward, representing a more exponential function. Due to the fact that the store does not keep any data going back more than 2 years, there is no way to verify that the store's market mimics the larger dairy market.

Since the store was purchased in 1998 by the current owners, the store should have experienced a significant decline in milk demand, since the time in which it was purchased aligns with the portion of the fluid sale graph matching closest to a negative exponential function. The statements by the store owners support the idea that the store's micro dairy economy is similar to the larger dairy economy, however the lack of data means there is no way to verify this correlation. Understanding the decline of fluid milk sales is critical. While there is no evidence to correlate the two markets, the verbal testimony from the store is in alignment with the graph.

FIGURE 10: COMPOSITE VIEW OF FLUID MILK SALES FROM THE USDA ERS

Sales since 2009 have shown a significant rate of decline in the total milk sold.

If the assumption is made that the store's demand trend aligns with the general trend seen in Figure 10, then it is reasonable to assume that the store should be reducing inventory to align with the demand as seen throughout the United States. The facts as they stand do not show the milk market as a growth or stable demand market.

However, the benefits of dairy sales to push sale of other products cannot be ignored and therefore the store must better align its dairy inventory to meet demand in order to continue benefitting from this product.

3.7 PROCEDURAL LAYOUT OF STUDY

Mentioned in chapter 2 is the fact that a small business has been selected which is why inventory forecasting was selected based on identifying the general

needs for the study and procedural outline of work to be conducted for this research that is tailored to the needs of the convenience store.

Preparation:

1. Identify small business which meets the profile laid out in section 3.2 and supports the general concept outlined in section 3.1. Both of these characteristics are met by the convenience store and point a and b listed below by the store
 - a. Business should be small, preferably run by owners with less than 10 employees
 - b. Business must have some kind of inventory
2. The business owner/owners will be interviewed along with initial observations of the business which allows for the development of a business profile.
3. The business profile, historical order and sales data will be analyzed to identify potential trends and pertinent data useful for forecasting.
4. As mentioned at the beginning of chapter 2, a convenience store has been selected as the small business to be evaluated. Weighted average and Exponential smoothing forecasting methods have been chosen to be applied because the store has easy access to historical data. The simplicity of these tools make it easy to train, implement, and comprehend, and therefore use of these tools have a better chance of success than more cumbersome and complex forecasting methods.
5. Due to the fact that the dairy segment of the store will be a key focus, dairy products will be selected which have continuous demand and will be tagged

using some kind of marking which will not harm the products appeal but still identify its inclusion in pre-existing inventory and not be considered a new unit of inventory that has not been accounted for.

6. The inventory will be counted initially on day one. The study will run for 6 weeks. Inventory must be checked daily in order to identify any seasonality within the period t , where t is one week in length. this will help identify patterns which can be used as weights for the weighted average model.
7. Exponential smoothing does not require a daily check of inventory because orders are placed on a weekly basis, therefore checking inventory on individual days is not critical. Given the fact that one period is a week, a weekly check would be sufficient however the data is the same for weighted average and exponential smooth therefore which needs daily inventory checks.
8. The value of alpha to be used in the exponential smoothing models will be tested at intervals between 0.1 through 0.9, which are equally spaced. Values of 0 and 1 are eliminated from the test because they eliminate either the theoretical forecast value or prior periods values
9. A solver linear optimization model will be used to verify the best exponential smoothing alpha value.
10. The weighted average model requires weights, which will be determined depending on the results of the survey, and historical data, which should help, identify key elements that influence demand.

CHAPTER 4: FINDINGS

4.1 BUSINESS PROFILE AND CASE STUDY SURVEY

This section includes a detailed profile of the business participating in the study as well as background into the issue at hand, whereby small businesses are an ideal environment for industrial tool development and design.

The business selected for the study is a local convenience store, located in the middle of a large residential area in Rhode Island. The store's inventory profile is a subsection of larger supermarket food products, over the counter medications, other houseware products, and more. As the name says, the store is designed for convenience when supermarkets tended to be located far from residential areas. Due to the remoteness of supermarkets, the ability to get a few items closer to home at a premium price had value. The business was sold to the current owners in 1998. At that time, the store was doing well; it had the support of the large residential area around it as well as a significant amount of foot traffic from the nearby businesses. The store is located between two major highways that also bring in a substantial amount of customers. Since then, the owners have seen a significant growth in competition. Large chain supermarkets such as Wal-Mart, Stop and Shop, as well as coffee shops and other stores all offering similar goods, have moved into the 5-mile radius. If this was not enough, the two major recessions as well as local government ordinances have wiped out many of the other local surrounding businesses and directly reduced the foot traffic for the business. Unprepared for all this, the business has not been able to adjust inventory properly to meet the current market conditions.

Many vendors offer a buyback of expired goods; however, this is not the case for all products. Dairy industry vendors' do not offer a buyback program. Dairy is a critical product sold by the store and accounts for a major portion of the current losses. Dairy products also increase the sales of conditional goods, meaning goods, which do not appeal or create a need for the customer without the purchase of another good. Some examples of conditional goods the store carries are cereal, baking mixes, and coffee, all of which usually necessitate a dairy purchase. This fact drives the importance of dairy products within the store. The store currently determines inventory forecasting and orders based on the storeowner's ability to recall sales during the week and counting the number of units on the shelf. These two pieces of information are what the storeowner bases judgement of the quantity needed for the next week. This "gut instinct method" for a long time seemed to have worked, however now seems to be proving less effective. Tools such as a Point of Sale machine (referred to as POS) which performs multiple functions such as being used as a cash register, also have the ability to act as an inventory tracking system. Based on the initial case, several questions arose which may increase the resolution of the inventory picture in the store at the time of an inventory order.

The storeowners have admitted that their biggest concern and goal is to reduce spoilage of dairy products due to the fact that product cannot be returned to vendors for credit on their next order. In light of this, the focus for the store must be on changing or improving the techniques that the store uses to predict the next weeks' dairy needs through inventory forecasting.

Defining this scope was done by asking about four key areas of dairy product demand in the convenience store environment:

- Dairy vendor and supply chain relationships
- Product nature
- Customer relationship and demands
- Existing product inventory forecasting methodology

Does the store get a discount for buying large volumes of milk?

No, the store does not buy a large enough volume to persuade dairy vendors to structure this type of contract.

Does the store have to meet a set of minimum criteria in order to make a dairy order/purchase?

The current dairy vendor requires that all orders made must be \$150.00 or above otherwise the company will not process the order.

What is the frequency of milk deliveries?

Currently the store has the option to order on Tuesday or Friday with the delivery 1 day later on Wednesday or Saturdays respectively. The owners have noticed that Saturday tends to have the highest dairy sales, which is why the order is typically placed on Friday. The Wednesday delivery was used as a safety net if Saturday looked to be selling quickly. The owners also discussed the fact that their current dairy vendor has just given notice that they will be cutting back on the delivery from twice a week to once a week. Once this change takes effect, a store in this type of contract will have to place orders on Thursday and will receive orders on Friday.

What is the shelf life of dairy products on the shelf?

The storeowners stated that they tend to have about 1.5 weeks to sell most milk products. The exceptions to this general rule are creamer and higher fat content milk products that have a shelf life closer to 1 month, and fat free and light cream, with a shelf life in the shorter range of 1 week or less. These shorter shelf life items tend to be purchased in significantly lower quantity primarily for the one or two customers who have requested it in the past. Furthermore, these products are ordered less because there is no indication of a significant demand beside the few special case regular customers. An article by Baumrucker (2008) supports the sell by time frame indicated by the store owners, “Retailers typically give pasteurized milk an expiration date of four to six days. Ahead of that, however, was up to six days of processing and shipping, so total shelf life after pasteurization is probably up to two weeks.” (Baumrucker 2008). Baumrucker also discusses Ultra High Temperature (UHT) processing, which is able to increase the shelf life past those of standard pasteurization methods used on milk in the United States. This would push the “sell-by” date out to a possible month from processing date and would allow for a longer shelf life. In addition, milk which goes through a UHT process does not require refrigeration. With all the benefits to UHT processed milk, the question arises as to why pasteurized milk is still a dominant dairy product in the United States. Baumrucker provides a possible answer to this question “One reason is that UHT-treated milk tastes different. UHT sweetens the flavor of milk by burning some of its sugars (caramelization). A lot of Americans find this offensive—just as they are leery of buying non-refrigerated milk. Europeans, however, don’t seem to mind.” (Baumrucker 2008).

Can product be sold past the sell by date?

Even though most dairy products last longer than their sell by date, stores cannot sell the product after that date if they are in compliance with state law. Sell by dates according to the USDA (United States Department of Agriculture) are not required by the Federal Government (FSIS 2015). However, the USDA does discuss the use of food dating and clearly defines the use of each type. In the case of this study, the focus is on sell by date which is the date by which the customer should purchase the milk. The owners of the store in this study explain that many of their customers perceive the sell by date as the last date of consumption rather than the last date of purchase.

How are expired product handled?

Expired product does not have a second market where the company can profit off of it, therefore owners will pour it down the sink. There is no salvage value when it comes to dairy products.

Does the store take back spoiled milk?

Technically the store will take back milk product if the customer complains that the product has gone bad. This has only happened a few times. The store would not usually take it back because of the fact that the store owner knows the product was sold before its sell by date and will still have some shelf life. The only reason the store may return the money is in order to retain its customer base.

What is the store's profit margin on the dairy products?

The store receives a profit of \$0.40 above unit resale price across all milk products. The owners have tried to increase the price however if the price goes too high the customer will no longer see the value and will go to a competitor instead. In this case,

everyone is aware that the store price is higher than most other stores in the area; however, the proximity to residential areas gives it an advantage and customers value the convenience more than the \$0.40 increase in purchase price. Other store owners in this region were questioned about the profit margins and stated that their markup is only \$0.10. One store owner stated that he also had 11 stores and therefore was able to negotiate a better price because of the volume of stores for which he purchases. In addition, this particular store owner discussed the fact that milk was not a large portion of his business' sales.

Has the store considered using another milk vendor?

The store has, in the past, used another vendor, however, customers complained that they had not heard of the brand and preferred the current vendor. This is besides the fact that the old vendor had a large fluctuation in price, which customers also complained about. In order to meet customer demands, the vendor was changed to the current vendor which customers show favor towards.

Based on the profile and questions answered by the business in this case, it is fair to assume that there is both room for growth and a need for tools which can improve the operational efficiency and stay within the constraints of the resources at the business's disposal. Further analysis of the inventory process must be detailed in order to understand how and what type of tools may prove valuable for this business. Once the process is analyzed, strategies will be recommended and tested to determine whether the business could benefit from these tools.

Dose the store have a Cash register or a POS system?

The store has used a cash register since before the recent owners purchased the store. Over the years the store has had to replace the cash register a few times. The owner pays \$300-\$500 for a new cash register.

Why did the cash register need to be replaced so many times?

The cash register in the store has been replaced twice because the computer which runs the cash drawer and tracks daily sales produces some kind of error in either calculating sales total correctly or losing a full days' worth of sale which then has to be tallied by reviewing the backup hard copy, built into the register. Reviewing the hard copy may take up to 1 hour to tally and then ensure that the drawer is balanced so the next cashier can use the register. This was a problem when it happened because the register went offline when there was a large amount of traffic in the store.

Has the Store considered buy a POS system instead of using a cash register?

The storeowners have thought about changing the cash register especially when they have had to replace the cash register. However, the last time they had looked at changing to a POS the cost to acquire this system was \$1,500-\$5,000. The owners believe that the cost of the unit is not justified by the added features and data received by the system. The owners understand that POS can provide accurate tracking of data but admit they would not use it and see this capability as a luxury rather than a necessity.

What does the store use any computer or analytics tools to do front or back office work?

The store has a computer that is currently only used for web browsing, Vendor catalogs, and websites. Currently, all book keeping and financial record keeping is

done by hand. Sales reports and sales transaction records are printed at the end of each business day and then tallied and checked by hand.

4.2 ANALYSIS OF INVENTORY PROCESS

The process was initiated by observations made by the owner throughout the week. Because of its size, the store can be run easily by one person, which in this case is the owner for a majority of the store's hours of operation. In the hours when the owner is not present, the store is run by an employee, which introduces the question of how the owner may account for periods in which he is not present to make observations. The owner remembers the general stock quantity of each milk product held in inventory prior to departing and identifies the shift in inventory positions once the owner resumes work at the store. The owner is typically not away from the store for more than 24 hours which is why he is able to maintain a running record of dairy inventory. The order for milk delivery is made by 11 am the day before the delivery date. The store owner counts the remaining inventory and then, based on his observations of what customers purchased throughout the week as well as the amount of each milk product received in the last shipment, the owner makes an educated guess as to what the demand will be for next week (also known as the period). The store does not track individual sales by product, and the only time that inventory is checked is when it is received and at the time in which a new order is made. This means that for the exception of checking expiration dates and re-stocking the shelves, milk is left unmonitored. This practice is fairly common based on discussion with other local store

owners. It is clear that no data is collected to help in the facilitation of order generation or to deduce the cost benefit of continuing to sell dairy products.

Based on the background and profile of the store and the needs and demands of the owner, there is a need for an upgrade on the current analog methods for inventory forecasting and inventory replenishment methods.

As part of determining whether the store was a viable candidate for study, the questions stated by Chamber et al. (1971) were used to determine whether proposed forecasting methods would make sense with the forecasting goals. The question from Chamber et al. listed in chapter 3 are restated and answered below.

1. What is the purpose of the forecast—how is it to be used?
2. What are the dynamics and components of the system for which the forecast will be made?
3. How important is the past in estimating the future?

These questions are reviewed to better narrow the focus of the forecasting. The first question was relatively simple for the owner.

Question 1

The purpose of this forecast is to eliminate or minimize loss due to expiration of the dairy products chosen by the owner. The profit on the dairy products at the store in this case study are approximately \$0.40 per unit sold based on the most expensive dairy product averaging at \$3.59 per unit and the lowest at \$1.89. Given these two values, the breakeven point is calculated based on the number of units that must be sold in order to recover the cost of a lost unit, as seen in equations 11 and 12.

$$\text{Break Even} = \frac{\text{Unit Cost } (\$3.59)}{\text{Markup } (0.40)} = 8.975 \text{ unit}$$

EQUATION 11: BREAKEVEN POINT HIGHEST COST OF GOOD PRODUCT

$$\text{Break Even} = \frac{\text{Unit Cost } (\$1.89)}{\text{Markup } (0.40)} = 4.725 \text{ unit}$$

EQUATION 12: BREAKEVEN POINT LOWEST COST OF GOOD PRODUCT

In order for the store to break even on a single spoiled dairy product, the store must sell 5-9 units. The profit margin calculated in equations 13 and 14 is the inverse of the breakeven point cost.

$$\text{profit margin} = \frac{\text{Markup } (0.40)}{\text{Unit Cost } (\$3.29)} \times 100\% = 11.14\%$$

EQUATION 13: PROFIT MARGIN ON HIGHEST COST DAIRY ITEM

$$\text{profit margin} = \frac{\text{Markup } (0.40)}{\text{Unit Cost } (\$1.89)} \times 100\% = 21.16\%$$

EQUATION 14: PROFIT MARGIN ON LOWEST COST DAIRY ITEM

The profit of 11.14%-21.16% is a low. If profit margin and breakeven are perceived as the upper and lower limit of buying a singular unit of inventory, then the risk of losing money far outweighs the profit of selling the unit. Therefore, it is important to mitigate the potential over buying of inventory, and it is for this reason that an inventory forecast is needed.

The store's current range illustrated by equations 11 through 14 provides a strong example of the reason that safety stock is an undesirable characteristic in an inventory system. The cost of retaining even one unit of safety stock far exceeds the profit margin on the unit. The store suffers from a lack of data which causes this decision to be difficult to define. However, a few facts are clear; currently the owners assume that the store is running fine because they have confidence in weekly observations to capture almost all of the information needed in deciding the volume of inventory for the next period. The managing owner who determines each inventory order based on his personal observations from the current week, and what they can recall from prior week's performance runs the store. This is the second piece of data that is used to get an understanding of what is selling and what is not selling. The store retains the purchase orders from the dairy vendor for up to 2 years. This 2-year data set is a vital resource which the owners do not use as part of their inventory decision making strategy, because even though the store does keep the sales data, the influence of the prior week's sales is the major contributing factor in each week's order. This is due to the gut instinct method the store currently has in place. The owners are hesitant in wanting to change the current method due to it being able to produce what appear to be fair results. In addition to that fact, new methods may cost more to operate in a business which is already lacking resources. These points all support the reason for needing a forecasting method. It also implies the driving parameters which are cost and resource usage. Forecasting which is limited or preferably causes no deviation to current operations would be tolerated. In addition to these preferred parameters, the severe penalty for spoilage as described by the break-even calculations show in

equations 13 and 14, and the lack of volume of units sold, the model should avoid spoilage at the sacrifice of potential profit gain.

Question 2

Chambers et al. (1979) narrows the focus of question two by providing examples. In essence, this question goes to the root purpose of the forecast and asks for what purpose is the forecast being developed. “The manager and forecaster must review a flow chart that shows the relative position of the different elements of distribution system, sales system, production system, production system, or whatever is being studied” (Chambers et al. 1979). In the case of the store, the system being studied is driven by the sales cycle. The fact that spoilage of product prior to sale occurs indicates that supply is more than capable to meet demand.

Based on the desire of the owner, it is clear that the driving parameter is having no product to spoil or become damaged before sale. This guiding parameter seems to be extremely idealized. A better measure would be to aim to have losses at a level less than the current state of losses and work to being near or at zero. In order to do so, the store must be able to better predict the dairy demand and meet that need exactly. The current method for order forecasting does not capture inventory change accurately or at a frequency fast enough to accurately define demand.

Question 3

This question seems to have the greatest impact on the case being studied. Chambers et al. (1979) made a point to explicitly describe how question three affects the selection of the forecasting method “Significant changes in the system—new products, new competitive strategies, and so forth—diminish the similarity of past and

future. Over the short term, recent changes are unlikely to cause overall patterns to alter, but over the long term, their effects are likely to increase. The executive and the forecaster must discuss these fully” (Chambers et al. 1979). Initially the owners did not see issues with dairy or any other products exactly as Chambers et al. (1979) states. Even when competition started to move into the area, the store did not see any of these problems, however over time these small changes turned into larger problems. Due to this, the store is operating as if these changes were not major impacts to customer demand, but unfortunately this is not the case. The decline in milk sales that the owners have noticed in recent years is also aligned with the trends seen in the dairy industry as a whole, discussed in section 1.3. This shows that the trends seen in the large dairy economy is reflected at the store level.

4.3 ORDER DATA ANALYSIS

The store retains 2 years of records on inventory purchased. Figures 11 through 23 show the data from the 2014-2016 years for the milk products.

GALLON WHOLE MILK

FIGURE 11: 2014 AND 2015 GALLON WHOLE MILK INVENTORY REORDER DATA

Figures 11 show that order data for gallon whole milk in 2014 and 2015 have several common order values excluding zero. In 2014, the common order sizes that are present are 12, 8, and 4 units. The store must order gallon dairy in minimum quantities of 4 units, which is what influences the order to be in multiple of 4 for gallon size milk only. It is possible to receive an order in the gallon size, which is not a multiple of 4, but this only occurs when the vendor is short on inventory. Along with the common data point seen in both years, the 2015 year also has several orders of 16 units, which occur toward the end of the year. A very interesting note about the data sets is the fact that at the beginning of 2014 the store's orders are either 8 or 12 unit orders for the first quarter and drops down to 4-8 units for the remainder of the year. At a certain point the order drops to zero or jumps to 12, however, these points appear to be more

like inventory volume corrections rather than a true reflection of current orders, because in most cases a zero order is followed by a 12-unit order. In 2015, the order range continues the trends seen at the end of 2014, as orders of 4 or 8 units are processed. This order continuance changes around the end of February 2015 when the order range increases to 12 units as a high and 4 units as a low. This trend changes at the beginning of October 2015. The range shifts up to 8 units as the low order and 16 as the high order value.

GALLON 2% MILK

FIGURE 12: 2014 AND 2015 GALLON 2% MILK INVENTORY REORDER DATA

The gallon 2% milk sales data in Figures 12 shows interesting data. The 2014 data shows that the milk order had a fairly consistent order pattern of approximately 4 units each period. There are several points at which there is no milk ordered, and another exception appears in one week where the order spikes to 8 units - however this

this deviation can most likely be justified. The first three months of data for the 2015 graph of gallon 2% milk shows a pattern consistent with the end of 2014 sales orders. From the middle of March 2015 to the middle of June 2015, the pattern shifts to a period where orders become sequential in which one week the order will spike high to 8 units and the next it will plummet to either 4 units or to zero units. From the end of June to to the end of the year the data shows a new pattern of stepwise increasing from 0 units and climbing over 3 weeks to 8 units with minor variations to this pattern.

GALLON 1% MILK

FIGURE 13: 2014 AND 2015 GALLON 2% MILK INVENTORY REORDER DATA

Similar to the sales data presented for the gallon whole milk product, Figure 13 for the 1% gallon milk shows some common order quantities which are prevalent in both 2014 and 2015. There is a more consistent appearance of a range of order quantities in 2014, where the majority of order lie between 4 and 16 units with a major

reoccurrence of the 8 or 12 unit order. Unlike other sales data for other products, the 1% gallon product tends to always have an order placed. The only exception to this would be 6/29/2014 and 6/25/2015 which are within 4 days of being a year apart and therefore show a pattern. In addition to the unique drop, both graphs have a v-shaped order pattern where the zero order date is the vertex point. This pattern is highlighted on the graph.

½ GALLON WHOLE MILK

FIGURE 14: 2014 AND 2015 1/2 GALLON WHOLE MILK INVENTORY REORDER DATA

Figure 14 represent the half gallon whole milk in 2014 and 2015 , and shows a steady pattern where several order values seem to consistently appear for the exception of a few weeks in which the order drops above or below this range. For the first 3 months of 2014 the store ordered significantly larger order quantities compared the rest of the

year. Halfway through March the orders drop to zero and slowly stabilized in the range of 4-7 units per order. By the end of June the range continues with 4-7 units ordered per period, however the trend line shows a drop in orders because there is an increase in the number of periods in which the store orders zero units. This product is a great example of how different product size influence the ordering scheme because this is a half gallon size product the owner is not required to buy a minimum of 4 units into make an order. The 2015 data seen in figure 14, shows a pattern similar to that of 2014, where there is an initial spike in inventory order quantity in the first 3 months and then the appearance of a range occurs at the end of March. The range continues toward the end of the year and in this case is remains around 4-7 units. The variation is a lot smaller in the sense that an order of 6 units is much more common than any other order quantity by a large margin. An interesting correlation between 2014 and 2015 order data, is the fact that the trend line declines in both years. In addition, the 2015 year saw the largest order of 9 units where 2014 on several occasions had orders of 9 units for each period, and in a few instances where more than 9 units were ordered; but figure 14 still shows a decline.

½ GALLON 2% MILK

FIGURE 15: 2014 AND 2015 1/2 GALLON 2% INVENTORY REORDER DATA

The half gallon 2% milk order in 2014 and 2015 shown in figure 15 has a increasing slope. Overall the milk order seems to be fairly consistent where orders tend to stay around 3-5 units. Towards the end of the year the range shifts toward 4-7 units, however orders of 3-5 units continue to be present in the end of the year. The 2015 data shown in figure 15 has a gradual decline in the order quantity, with the majority of the year staying in the 6-7 unit range with a few occasions where there are spikes up toward 9 units and sudden drops to zero. The 2014 data shows that order quantities tended to be much higher than demand based on the fact that frequency of zero unit ordered weeks occur at a greater frequency in 2014 than in 2015. However this does not indicate that 2015 is stable - there are more instances where the 2015 orders are of a higher order amount which may indicate a more frequent inventory level correction than seen in 2014.

½ GALLON 1% MILK

FIGURE 16: 2014 AND 2015 1/2 GALLON 1% INVENTORY REORDER DATA

The data seen in figure 16 for 2014 shows an overall trend of decline. The 2014 data for half gallon 1% is more sporadic; for the most part the weekly order fluctuates to hit every quantity between 0 and 6 units per order. A common pattern appears in the fact that the milk is ordered on a bi-weekly basis in which the subsequent week after a non zero order week is zero. The decline seen in the trend line of the 2014 data is reversed in the 2015 data seen in figure 16. In addition, the bi-weekly ordering becomes less frequent. The pattern only exists between the middle of July and the middle of October; after this point the pattern vanishes and shifts its range between 4-7 units per order and only spikes and drops once for the remainder of the year. From

the middle of October to the beginning of 2016, the order never comes close to dropping back down to zero.

½ GALLON FAT FREE MILK

FIGURE 17: 2014 AND 2015 ½ GALLON FAT FREE INVENTORY REORDER DATA

Figure 17 shows the 2014 and 2015 order data the fat free milk in the half gallon size. While it is possible for the store to order the fat free gallon size the store chooses not to because there is a lack of demand for the product at the larger size.. This data is very interesting in the fact that looking at both data sets, are almost mirror images. Both show a binary ordering frequency where the week with an order greater than zero is preceded and followed by an order of zero units. The 2015 graph shows only 3 large spikes which occur within the first 3 quarters of the years. The 2014 graph has a similar pattern but it is compressed into the last quarter of 2014. In both cases an

order for 2014 or 2015 will most likely be between the 0-4 units per order range per week.

QUART WHOLE MILK

FIGURE 18: 2014 AND 2015 QUART WHOLE MILK INVENTORY REORDER DATA

Whole milk in quart size shows a slight decline from the beginning to the end of 2014 as seen in figure 18. There is an increase in order quantity in 2015. In both 2014 and 2015 graphs of whole milk quart size there is a natural order value which is seen much more frequently than in any other number for the exception of 0. The store at times has placed larger orders however a comparison of 2014 and 2015 shows that these high orders occur on opposite ends of the year. For 2014, the high order period occurred between March until the end of April, and for 2015 the high order period occurred between July and the beginning of 2016. In both graphs the point either before or directly after a large order tends to have a significant drop in units. Orders

for whole milk quarts do not show any real seasonality which would explain the higher order volume. However it is important to note that there is a drop in inventory ordered prior to or after a period of large orders.

CHOCOLATE MILK

FIGURE 19: 2014 AND 2015 QUART CHOCOLATE MILK INVENTORY REORDER DATA

Figure 19 shows the order quantity for every purchase order made in 2014 for the chocolate milk product. The order quantity is in individual units and not in the minimum order size. A linear trend is applied to the data to indicate the change in volume ordered throughout the year. The data indicates that volume of low fat chocolate milk product ordered in 2014 decreased. Figure 19 suggests the inverse where there is an increase in order for 2015. However, 2015 saw a total purchase of 79 units, whereas in 2014 the store purchased 84 units. This is an overall decrease in purchase orders of 6% from year to year. The order volume is fairly binary where the

store will tend to order 2 units or 0 units in each order period that is seen in both 2014 and 2015 which may indicate the demand to be around 1 unit sold per week.

QUART HALF/HALF MILK

FIGURE 20: 2014 AND 2015 QUART HALF-AND-HALF CREAMER INVENTORY REORDER DATA

Half and Half quart size creamer demonstrated a decrease in 2014 and in the case of 2015 seen in figure 20 the data shows and increase in sales. In general sales in 2015 are consistent in the sense like other products discussed prior it has a biweekly ordering scheme where a week with an order greater than zero is followed by a week with zero units ordered. In 2014 a similar biweekly order pattern is seen however the period between the end of March to the end of August where there is a significant step down in the binary orders from 12 units per every 2 weeks down to 6 units every 2

weeks. The drop is significant and is the primary influence in the decreasing slope in 2014. The drop in inventory ordered seen in 2014 is not seen in 2015 for half and half, however the amount the frequency in which order are made is far less often in between the end of march and the beginning of october.

QUART 2% MILK

FIGURE 21: 2014 AND 2015 QUART 2% MILK INVENTORY REORDER DATA

The 2% quart size appears to have a relatively stable ordering pattern overall for 2014 and 2015 as seen in figure 21. There are two exceptions seen in 2014 and once except in 2015 where the order spikes much higher than the normal order. Typically the data indicates that orders stay between 0-3 units in 2014 and 2015. Of the milk products observed, the 2% milk has the most stable and consistent pattern. While the trendline in 2014 shows an extremely gradual increase and the slope of the trendline in 2015 shows an increase in inventory purchased in 2015, this may be

affected by the large volume orders at the beginning of 2016 which could bring the trend more in line with 2014's trend line.

PINT HALF/HALF MILK

FIGURE 22: 2014 AND 2015 PINT HALF-AND-HALF CREAMER INVENTORY REORDER DATA

The graph of half and half at the pint shown in figure 22 for 2014 and 2015 are more like one set of data rather than two independent years. The beginning of 2014 shows a relatively stable range of ordering, falling between 0-6 units. In January 2014 there is a consistent demand where the order is continually hitting 6 units. The pattern breaks at the beginning of February and then picks back up at a rate of 5 units per week until the end of March. Then the pattern shifts to a biweekly order after March where the normal order (when one occurs) is 6 units. At the beginning of September

the volume picks up to 12 units on a bi-weekly basis which is held consistently throughout 2015.

PINT LIGHT CREAM

FIGURE 23: 2014 AND 2015 PINT LIGHT CREAMER INVENTORY REORDER DATA

The store did not order any light cream in 2014, and in 2015, it ordered this product on only a few occasions as seen in figure 23. This is an example of the store purchasing a product as the result of a customer request even if it was not originally part of their normal product assortment. Due to it being a consistent product purchased in 2015, it seemed prudent to the store owners to incorporate this item into inventory forecasting. This is because while infrequently ordered, when it is part of an order it makes up a significant portion. As seen in the graph, the order for light cream in 2015 was either zero units or 12 units. Interestingly enough, in the instance of light cream, the store does not need to buy a full case at one time. However, the store chose to

purchase one case at a time because the owner is trying to evaluate customer interest in the product.

4.4 COMPOSITE SALES DATA YEAR TO YEAR ANALYSIS

The sales data from 2014 and 2015 that are refined further in Table 2 and Table 3, in order to see a composite view of all dairy products for the 2014 and 2015 years. While the data is the same as in the order graphs for each individual dairy product, the tables focus on the large macro picture for the dairy products in the store and the trends that might be seen for the dairy segment of the store.

<u>Product</u>	2014				
	Total Units Ordered	Trend	Most Common Order Size	AVG. ORD.	AVG. WK ORD.
Gallon Whole Milk	596	DEC.	8	6	11.5
Gallon 2% Milk	276	DEC.	4	3	5.3
Gallon 1% Milk	1016	DEC.	12	11	19.5
1/2 Gallon Whole Milk	504	DEC.	6	5	9.7
1/2 Gallon 2% Milk	321	INC	3	3	6.2
1/2 Gallon 1% Milk	240	DEC.	0	3	4.6
1/2 Gallon Fat Free Milk	173	INC.	0	2	3.3
Quart Whole Milk	195	DEC.	3	2	3.8
Quart Chocolate Low-fat Milk	84	DEC.	0	1	1.6
Quart Half/Half	429	DEC.	0	5	8.3
Quart 2% Milk	85	INC.	0	1	1.6
Pint Half/Half	293	INC.	0	3	5.6
Pint Light Cream	0	N/A	0	0	0

TABLE 3: GENERAL CHARACTERIZATION OF 2014 INVENTORY ORDER DATA

Overall 2014 showed a decline in the order volume for dairy products while some products showed an increase in order volume such as 2% and Fat Free milk in the Half gallon size. The data is viewed from 3 different perspectives in Table 2. The first looks at order opportunity which is given the fact that the store is placing an order with the dairy vendor, what is the most common order size that the store has placed for the specific product throughout the year. The second is the average order volume for each product type given the number of times the store places a milk order. The third and final perspective is the average weekly order size for 2014 if the order was to be laminar for the year.

<u>Product</u>	2015				
	Total Units Ordered	TREND	Most Common Order Size	AVG. ORD.	AVG. WK ORD.
Gallon Whole Milk	612	INC.	8	9	11.8
Gallon 2% Milk	304	INC.	4	5	5.8
Gallon 1% Milk	984	INC.	16	15	18.9
1/2 Gallon Whole Milk	373	DEC.	6	6	7.2
1/2 Gallon 2% Milk	306	DEC.	6	5	5.9
1/2 Gallon 1% Milk	269	DEC.	4	4	5.2
1/2 Gallon Fat Free Milk	139	DEC.	0	2	2.7
Quart Whole Milk	133	INC.	2	2	2.6
Quart Chocolate Low-fat Milk	79	INC.	2	1	1.5
Quart Half/Half	254	INC.	0	4	4.9
Quart 2% Milk	88	INC.	2	1	1.7
Pint Half/Half	252	INC.	0	4	4.8
Pint Light Cream	48	DEC.	0	1	0.92

TABLE 4: GENERAL CHARACTERIZATION OF 2015 INVENTORY ORDER DATA

Table 3 looks at the 2015 data. In many cases, the order quantities have varied a little from the 2014 table 2. A significant change is seen in the trend data from year to year. Many of the products as stated in the product graph section shows opposing trend line, meaning products that showed increases in order volume in 2014 were decreasing in 2015. However whole milk and 1% milk in the half gallon size, both had declining trends for both the 2014 and 2015 years. Two percent milk at the quart size and half-and-half at the pint showed a steady increase in 2014 and 2015. The most unique product is the light cream primarily because the product was not purchased in 2014 and started being tested in 2015 to see if this product was needed and purchased by customers. However, because of it not being purchased at all in 2014, the benchmarks used to measure change between 2014 and 2015 will not hold any value.

<u>Product</u>	TOTAL CHG. IN ORD. VOL.	CHG. IN Most COM. ORD.	CHG In AVG ORD.	CHG In AVG WK ORD.
Gallon Whole Milk	3%	0%	46%	3%
Gallon 2% Milk	10%	0%	56%	10%
Gallon 1% Milk	-3%	33%	37%	-3%
1/2 Gallon Whole Milk	-26%	0%	5%	-26%
1/2 Gallon 2% Milk	-5%	100%	35%	-5%
1/2 Gallon 1% Milk	12%	100%	59%	12%
1/2 Gallon Fat Free Milk	-20%	0%	14%	-20%
Quart Whole Milk	-32%	-33%	-3%	-32%
Quart Chocolate Low-fat Milk	-6%	100%	33%	-6%
Quart Half/Half	-41%	0%	-16%	-41%
Quart 2% Milk	4%	100%	47%	4%
Pint Half/Half	-14%	0%	22%	-14%

TABLE 5: VARIATION BETWEEN 2014 AND 2015 INVENTORY ORDERING

Table 4 shows the variation in ordering between years given the three perspectives looked at previously in tables 2 and 3. The sales data and the variation do a great job in showing whether there are hidden patterns in the orders that may not be seen without tracking the data. In addition, they provide a strong understanding of the supply and replenishment of inventory, however they lack the capability to prove that the demand is being met. This aspect of the store's operation can only be identified by tracking the store inventory on a daily basis, showing the influence of customer demand on inventory, which will be shown in section 4.5.

4.5 DEMAND DATA COLLECTION

Sales data was collected over a 6-week period, beginning in December 2015 and ending in January 2016. Figure 24 is the graph of milk demand as a whole for the store during this period. Figure 24 shows an interesting cycle where the wavelength is generally one half week meaning that there are two peaks or wave crests in sales within a forecast cycle. It is also important to note that the peaks seen in each week are never of the same amplitude; usually one peak tends to be 1 order of magnitude large than the other which occurs in the same week. Take for example in week 1, Friday saw sales of 24 units, while the Tuesday following that Friday saw sales of 14 units. Another point is that the larger of each peak occurs between Thursday-Friday with 50% of the weeks observed having their peak sales day on Sunday, and the other half being evenly distributed between Thursday-Saturday. Minor sales are occurring on Monday, Tuesday, Wednesday and Friday, with 50% of the minor peaks occurring on

a Tuesday, and the remaining weeks are distributed equally between Monday, Wednesday and Friday.

FIGURE 24: DAIRY SALES OBSERVATIONS

CHAPTER 5: ANALYSIS

Findings from Chapter 4 played a significant role in focusing analysis of data collected as well as influencing the selection of the forecasting method used in the convenience store.

Based on the business profile in Section 4.1, it is clear that there are significant limitations in this segment of the business. This means that making large changes to the business structure such as contracted vendors, trade agreements, and product selection (such as a change from HSTS to UHT milk) would generate their own issues and limitations, or maintain the current limitations being experienced. It is for this reason that operation changes, such as better forecasting and product handling are the best way to improve current losses on dairy.

Section 4.2 demonstrated that profit margin on dairy create low incentive for small stores to want to hold on to the dairy segment of their business. Other than the fact that dairy products increase the sales of other products within the store, dairy does not have much attraction to businesses. The cost of the products can be extremely harmful to the store's profit margin in cases where a unit of product expires or is damaged due to bad handling practices, and because dairy is perishable. Maintaining a low inventory and running the risk of a stock out is much more favorable than to lose a single unit of dairy. Historical data seen in Sections 4.3 and 4.4 does not show much seasonality or correlation of the orders from a "big picture" perspective. However, demand data in Section 4.5 showed some consistency on a smaller scale, which could

suggest that the scale of forecasts must be shrunk in order to see how the historical data has an influence on future demand and forecasting for future demand.

5.1 COMPARISON OF DEMAND CURRENT INVENTORY ORDERING METHODS

Table 5 shows the weekly demand of each dairy product at the store for the 6-week observation period from December 2015-January 2016.

PRODUCTS	1	2	3	4	5	6	Average Demand
GALLON WHOLE MILK	20.0	13.0	15.0	22.0	12.0	22.0	17.3
GALLON 2% MILK	3.0	6.0	8.0	9.0	12.0	14.0	8.7
GALLON 1% MILK	21.0	23.0	11.0	23.0	16.0	36.0	21.7
1/2 GALLON WHOLE MILK	8.0	6.0	4.0	7.0	7.0	10.0	7.0
1/2 GALLON 2% MILK	6.0	4.0	5.0	5.0	3.0	10.0	5.5
1/2 GALLON 1% MILK	5.0	4.0	4.0	1.0	4.0	6.0	4.0
1/2 GALLON FAT FREE MILK	1.0	4.0	3.0	4.0	2.0	4.0	3.0
QUART WHOLE MILK	3.0	3.0	4.0	3.0	3.0	5.0	3.5
QUART CHOCOLATE MILK	3.0	2.0	1.0	2.0	1.0	5.0	2.3
QUART HALF /HALF	5.0	4.0	11.0	9.0	7.0	11.0	7.8
QUART 2% MILK	2.0	2.0	2.0	2.0	1.0	3.0	2.0
PINT HALF/HALF	2.0	6.0	8.0	5.0	3.0	16.0	6.7
PINT LIGHT CREAM	2.0	0.0	2.0	0.0	2.0	0.0	1.0

TABLE 6: WEEKLY DEMAND BY PRODUCT

Table 6 shows the inventory ordered (which will be referred to as the supply), in which demand was monitored for all products. In essence, the table shows the order as a result of the current forecasting method used by the owners to meet what they expect to be the demand at the store. The data in weekly supply reflects the store order based on the managing owner's observations. The values for each week are a reflection of

the prior week's observations and the store owner's interpretation on how this value will correlate with next week's demand.

Weekly Supply							
Products	1	2	3	4	5	6	Average Supply
GALLON WHOLE MILK	12.0	12.0	16.0	16.0	16.0	16.0	14.7
GALLON 2% MILK	4.0	4.0	8.0	8.0	8.0	12.0	7.3
GALLON 1% MILK	12.0	12.0	16.0	20.0	24.0	20.0	17.3
1/2 GALLON WHOLE MILK	7.0	5.0	5.0	7.0	8.0	6.0	6.3
1/2 GALLON 2% MILK	6.0	5.0	6.0	0.0	7.0	3.0	4.5
1/2 GALLON 1% MILK	3.0	4.0	6.0	2.0	5.0	5.0	4.2
1/2 GALLON FAT FREE MILK	0.0	3.0	4.0	0.0	3.0	3.0	2.2
QUART WHOLE MILK	1.0	5.0	4.0	3.0	3.0	3.0	3.2
QUART CHOCOLATE MILK	2.0	3.0	2.0	0.0	1.0	2.0	1.7
QUART HALF /HALF	0.0	0.0	12.0	0.0	12.0	0.0	4.0
QUART 2% MILK	2.0	0.0	3.0	2.0	3.0	3.0	2.2
PINT HALF/HALF	0.0	12.0	0.0	0.0	12.0	0.0	4.0
PINT LIGHT CREAM	0.0	2.0	0.0	2.0	0.0	2.0	1.0

TABLE 7: WEEKLY SUPPLY BY PRODUCT

Based on the supply and demand from the observation weeks, the variation was determined. In an ideal case, the variation would be zero where all ordered goods are sold, but this is not pragmatic for the real world. Therefore, variation is expected and in some cases needed. An acceptable level of variation would be near or relatively close to 0%.

Due to short shelf life of dairy products, it would be in the best interest of the store to have an inventory system that mimics a pull system in manufacturing, where inventory is only ordered based on the demand; like the 0% variation discussed earlier, this is ideal but not feasible. However, the store could still apply some aspects of this

model and have a relatively minimal level of inventory of each product sufficient to meet anticipated demand. There would also be a small surplus each week, with the expectation that the remainder of the inventory would be purchased the week after. This way the store is not losing profit due to expired inventory. Table 7 reflects the performance of the store's current method against a pull like method, where demand is accommodated by supply with a small inventory buffer.

Variation Between Demand and Supply							
	Wk. 1	Wk. 2	Wk. 3	Wk. 4	Wk. 5	Wk. 6	Product Average
GALLON WHOLE MILK	-40%	-8%	7%	-27%	33%	-27%	-15%
GALLON 2% MILK	33%	-33%	0%	-11%	-33%	-14%	-15%
GALLON 1% MILK	-43%	-48%	45%	-13%	50%	-44%	-20%
1/2 GALLON WHOLE MILK	-13%	-17%	25%	0%	14%	-40%	-10%
1/2 GALLON 2% MILK	0%	25%	20%	-100%	133%	-70%	-18%
1/2 GALLON 1% MILK	-40%	0%	50%	100%	25%	-17%	4%
1/2 GALLON FAT FREE MILK	-100%	-25%	33%	-100%	50%	-25%	-28%
QUART WHOLE MILK	-67%	67%	0%	0%	0%	-40%	-10%
QUART CHOCOLATE MILK	-33%	50%	100%	-100%	0%	-60%	-29%
QUART HALF /HALF	-100%	-100%	9%	-100%	71%	-100%	-49%
QUART 2% MILK	0%	-100%	50%	0%	200%	0%	8%
PINT HALF/HALF	-100%	100%	-100%	-100%	300%	-100%	-40%
PINT LIGHT CREAM	0%	0%	0%	0%	0%	0%	0%
Average Dairy	-39%	-7%	18%	-35%	65%	-41%	-17%

TABLE 8: WEEKLY VARIATION BETWEEN SUPPLY AND DEMAND

The variation percentages listed in Table 7 are a reflection of the way the previous week's order is able to accommodate the current week's demand. For example, looking at week 1 for the gallon whole milk product there is a -40% variation. In tables 6 and 7, the demand was 20 units and the supply was listed as 12 units. The variation implies how the inventory replenishment order (see weekly supply) is able to meet or accommodate customer demand (see weekly demand), in this example, the margin indicated that the "gut instinct" forecast which the order is based on, failed to meet 40% of the total demand. This gap between demand and ordered inventory is filled by stocked inventory. The averages for each product across all the weeks of observation list in the far right column of table 6, the best variation being 0 % for light cream and the worst being the -49% for half and half quart size. The average for the week across all products is also taken. Based on a weekly basis, the store overall did the best job of meeting demand in week 2 with a variation of 7%. The average of the product average was also taken showing an overall average score of 17%, however this number is purely theoretical and is not a strong indicator of good forecasting and inventory management practices. This variation provides the best benchmark of improvement for the store.

	Spoiled Inventory						
	13-Dec	14-Dec	17-Dec	19-Dec	22-Dec	5-Jan	13-Jan
QUART CHOCOLATE MILK							1.0
QUART WHOLE MILK			1.0				
PINT LIGHT CREAM	8.0						
1/2 GALLON 2% MILK					1.0		

	Spoiled Inventory						
	13-Dec	14-Dec	17-Dec	19-Dec	22-Dec	5-Jan	13-Jan
1/2 GALLON 1% MILK				1.0		5.0	
GALLON 2% MILK		2.0			1.0		

TABLE 9: SPOILED INVENTORY RECORD

Table 8 shows the losses over the 6-week tracking periods. The losses expressed in this table are all due to the lack of sales on products prior to reaching the expiration date listed on the milk. During the period of observation, the store sold 542 products and lost 20, which is a total of 562 total units of dairy products that were held in inventory during this period. Therefore, the store lost approximately 3.55% of its total inventory to expired units. While this seems to be a relatively low margin, looking at it from the perspective of a breakeven point as to how many units would need to be sold in order to recover these losses puts the data in a different light.

	Spoiled Inventory			
	Lost Units	Cost Per Unit	Total Loss Per Product	Breakeven Point
1 QUART CHOCOLATE MILK	1.0 Unit	\$ 1.23	\$ 1.23	3.0 Units
1 QUART WHOLE MILK	1.0 Unit	\$ 1.07	\$ 1.07	3.0 Units
1 PINT LIGHT CREAM	8.0 Units	\$ 1.60	\$ 12.80	32.0 Units
1/2 GALLON 2% MILK	1.0 Unit	\$ 1.74	\$ 1.74	4.0 Units
1/2 GALLON 1% MILK	6.0 Units	\$ 1.63	\$ 9.80	25.0 Units
GALLON 2% MILK	3.0 Units	\$ 3.27	\$ 9.80	25.0 Units
Total	20.0 Units		\$ 36.45	92.0 Units

TABLE 10: SPOILED INVENTORY COST BREAKDOWN

Based on the \$0.40 profit margin per unit, the store would need to sell a minimum of 92 units in order to compensate for the losses, which means that 17% of the profit

from the 542 units sold during the 6 weeks went into recovering the cost of the 20 units that expired. Even though the loss of goods due to spoilage is low, its impact on profit is significant.

5.2 WEIGHTED AVERAGE MACRO MODEL

Figure 25 is a restatement of the demand data seen in Figure 24, the difference is the identification of peaks and breaks in data where a period ends or begins.

FIGURE 25: GRAPH OF TOTAL DAIRY SOLD

The modified graph shows the boundaries of the inventory ordering process as well as trends seen in each week. Given the way that the data is presented, it appears that there is a general pattern in which a majority of sales occur from Thursday through Sunday. In most cases Sunday is the day with the heaviest sales. A small percentage of sales occurs during the Monday-Wednesday part of the week, where

Tuesday is the day is the second heaviest sales day of the week. These patterns may allow for a weight average calculation to be evaluated by days within each period being one week. Two forecasts will be developed using the weight average approach in order to determine whether the day which dairy is sold or whether the product being sold can produce a better forecast method than the current gut instinct method being applied by the store owner.

The demand data seen in Figure 25 suggests that a period (a period is equal to 1 week) can be broken into 2 major sales cycles. The first cycle addressed is occurs between Thursday-Sunday, which according to the graphs tends to have higher sales, and the second cycle would be Monday-Wednesday group which tends to be the smaller and less profitable sales cycle. This approach looks at the week as having seasonality within the period, but uses the power of weighted average method to determine whether there is any forecast value in looking at the time at which dairy is sold on demand. Another potential way to use the day of a sale is to only apply the weights of the 2 highest sales day of the week and apply them as weight if a majority of the sales occur on these two days. Based on Figure 25, these days tend to be Sunday and Tuesday. Because half of the 6 week tracked period showed that there might be a pattern, it is reasonable to look and see if these two days are the predominant sales days in each week, and whether that is combined or independent.

	Week						Average
	1	2	3	4	5	6	
Thurs.-sun.	68%	62%	62%	73%	62%	42%	61%
Mon-wed	32%	38%	38%	27%	38%	58%	39%
Sunday	7%	12%	8%	45%	30%	15%	16%
Tuesday	17%	5%	18%	17%	11%	39%	16%

TABLE 11: CONTRIBUTION OF EACH DAYS SALES BY PATTERN AND WEEK

Table 10 quantifies the percentage of the total demand met by both day strategies. Based on table 10, the average total contribution of sales by Sunday and Tuesday is 32% which is less than half of the sales made, and therefore does not carry enough weight to be used in a model.

Breaking the week up into two cycles has not yet been disproven as lacking potential to be applied as a good weighted average model, and therefore will be tested in the model.

WEIGHTED AVERAGE FORECAST MODEL WEIGHT BY DAY

Equation 15 shows the formula used to test the weight and influence of the day of the week dairy is sold is a good forecast method. M_1^{n-1} represents the total sales from Thursday –Sunday of the prior week and M_2^{n-1} represents the total sales from Monday-Wednesday from the same week as M_1^{n-1} . This model is tested on each on each dairy product individually and then combine in the aggregate model.

$$\text{Macro weighted average model} = \sum (M_1^{n-1} * .61) + \sum (M_2^{n-1} * .39)$$

EQUATION 15: WEIGHTED AVERAGE FOR DAY FORECAST

The weights applied to these prior weeks data using the percentages found in table 10.

5.4 WEIGHTED AVERAGE FORECAST MODEL WEIGHT BY PRODUCT

PRODUCT PERCENTAGE CONTRIBUTION TO SALES

FIGURE 26: TOTAL PERCENTAGE CONTRIBUTION BY PRODUCT

Figure 26 shows the total average percentage contribution that each product contributes to sales over the 6 weeks observation period. This method highlights exactly how much of each product needs to be ordered on a weekly basis for each product.

Macro weighted average model

$$= \sum (M_1^{n-1} * .24) + \sum (M_1^{n-1} * .19) \dots + \sum (M_1^{n-1} * W_p)$$

EQUATION 16: FOR MACRO WEIGHTED AVERAGE BY PRODUCT

In this application of weighted average model M_1^{n-1} variable represents the total sales of the prior week and W_p represents the weight for each product by percentage identified in Figure 26.

The results of the Day and Product weighted average are compared in figures 27-40 below. The forecast starts on the second week of observations due to the fact that there was no data collected in the week prior to week 1 of the study, which is needed to develop a forecast.

FIGURE 27: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR GALLON WHOLE MILK

Figure 27 is a graph of the weighted average model forecasts tested on whole gallon milk product. The first model tested was the weighted average model using “the

by day” model seen in equation 15. In general, this model shows an inability to keep up with demand, except at one point where the demand plummets in week five and the model meets demand. However, the reason that the two align at that point is because the demand dropped significantly, which was coincidence, not a consistent pattern. The second model used is the “by product” weighted average model, and is better able to compensate and adjust to demand. The model cuts through the middle of the demand lines peaks and valleys. In some weeks, the forecast may suggest to order more than the next week’s demand. If followed, the store may be at risk of losing products to spoilage. However, over the study the model worked well.

FIGURE 28: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR GALLON 2% MILK

Figure 28 shows a relatively linearly increasing demand. If this is the nature seen in the weeks following the study time, using a simple algebraic expression in point slope form may be all that is needed to calculate the dairy forecast for Gallon 2% milk.

FIGURE 29: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR GALLON 1% MILK

The gallon 1% milk product seen in figure 29 is one of the higher sales volume dairy products. The demand for this product is large enough to accept weeks where the “by product “weighted average model forecasts a higher volume of product needed than the demand. However, the wholesale price on gallon 1% milk is on the higher side of the scale with a sales price of \$3.59 per unit. The breakeven point mentioned in equation 13-14 in chapter 3 shows that the cost of the loss of even one unit comes with the highest recuperation cost. This important fact still would make it difficult to see whether either model is best suited for forecasting. The errors on all of these models need to be quantified before make a final recommendation on what model works best.

FIGURE 30: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR 1/2 GALLON WHOLE MILK

Figure 30 shows similar results to other dairy products discussed earlier. One interesting characteristic is that in week 4 the weighted average “by product” meets demand. Even though the weighted average “by day” model is a much more desirable forecast, because it is much more cautious than the “by product” model which based on the break even cost discussed in chapter 3 and 4 is preferred. However it is possible that using this method would cause the loss of return customers because the store would definitely have stock outs using the “by day “ forecast model.

FIGURE 31: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR 1/2 GALLON 2% MILK

Figure 31 show the same results as figure 30 where the stronger forecast seems to be the “by product” forecast. The major issue with either forecast is that they lie above or below the demand line. The weighted average by product model tends to be much closer to the demand line, than the weighted average “by day” forecast model.

FIGURE 32: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR 1/2 GALLON 1% MILK

Figure 32's demand is much lower than the other half-gallon products seen in figure 30-31. The forecast for this product is still better suited using the “by product weighted average” rather than the “by day” forecast.

FIGURE 33: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR 1/2 GALLON FAT FREE MILK

Figure 33 shows that the demand for ½-gallon fat free milk product; is almost the same as the other products involved in the study. If this is the pattern throughout the rest of the year then the ½-gallon fat free product could be serviced by either forecast. However lighter or fat free dairy products tend to have a shorter shelf life therefore it would probably be better to use the “by day” forecast model because of its safety compared to the “by product” forecast. The loss of demand would only be a difference of 1-2 units whose profit is not high, and the risk of loss in 1-2 units is far worse than the potential gain.

FIGURE 34: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR QUART WHOLE MILK

Figure 34 shows the results for whole milk in quart size. Figure 34 shows the by product weighted average model to be more in step with the whole milk quart size. This model for this particular product fluctuates both above and below, however it is able to stay much more tightly wrapped around the demand. In the case of weighted

average "by day" never meets demand nor does it manage to stay close to the demand line, based solely on figure 34 data.

FIGURE 35: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR CHOCOLATE MILK

Figure 35 show the results of applying both the by day and by product weighted average models. Based on initial observations from figure 35 the weight average by day fluctuates both above and below and seems to be constantly shifting from surplus to shortage. The weighted average by product model estimates demand of chocolate milk to be much higher than actual demand for the entire observation period.

FIGURE 36: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR QUART HALF/HALF

Figure 36 shows a significant amount of fluctuation in demand for the quart Half and Half product. The Weighted Average “by day” model continues to under estimate demand and cannot manage the large variation seen in this product and other products with high volatility in demand. The “by product” weighted average model shows significant stability throughout the study. While the “by product” forecast model does not follow the peaks and valley of demand, it does provide a consistent forecast which cuts through the middle of the demand line.

FIGURE 37: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR QUART 2% MILK

Figure 37 follows suit like figure 28 and 30, meaning the trend of having the by product weighted average model predicting a large stock pile of inventory needed to meet the demand. However even though the demand is higher than the by day weighted average model; the by product weighted average model shows a higher capability of meeting demand in fact at 2 points between weeks 4-5 and 5-6 the demand and forecast converge at the same point. The by day weighted average model tends to underperform throughout the entire study aside from the exception at week 5 where demand plummets and the “by day” model stays consistent, making it able to meet demand. Due to the plummet in week 5 the Weighted Average forecast by day is underestimates the demand in week 6 by a large margin whereas by product model is much has a much shallower loss in this week despite having working of the same data set.

FIGURE 38: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR PINT HALF/HALF

In figure 38 the weighted average “by day” model is much closer to meeting demand however the pint half and half product has a much lower volume of sales over the study. In addition, demand from week to week varies by 2 units in week 6 order demand sky rockets however the demand in the rest of the study is very little.

FIGURE 39: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND FOR PINT LIGHT CREAM

Figure 39 provides proof the the weighted average “by day” struggles to respond to to large changes in demand. While it is expected that the response to change from one period will be seen in the forecast for the period. The bi-weekly ordering scheme for the pint light cream product demonstrates the slow response, because the weeks in which there is no demand an order is placed and nothing is ordered in weeks with demand for the product. This slow feedback is bad for this product, because as stated in chapter two milk can last for approximately 17 days and given that the product is order a week in advance of the demand, means that the customer may potentially percieve the product as being old and less desirable. Also the fact that the product is being ordered far in advance of demand, putting it at risk of expiring before it sells.

FIGURE 40: WEIGHTED AVERAGE FORECASTS V. ACTUAL DEMAND AGGREGATE DAIRY

Figure 40 is a composite model of all dairy products depicted in figure 28-39. The weighted average by day is a much more conservative model for the general group of dairy products observed in the 6-week study. The other model looked at is the weighted average by product model which forecasts at a level higher than where demand tends to lie which exposes the convenience store to a significant amount of loss.

5.3 EXPONENTIAL SMOOTHING MODEL

The exponential smoothing model seen in equation 2 uses an alpha value which when applied influences the model by selecting between the forecasting value and the prior periods actual demand. Due to the fact that the alpha value can range between 0 and 1 and the selection of this alpha value within this range is selected by the forecaster it would be difficult to make this selection initially, therefore a range of

alpha values were tested. Solver linear optimization model is used to confirm the best alpha value for each product in order to identify local and potentially and global alpha value.

The linear optimization model looks at the some of the deviations between demand and weighted average forecasting models and determines the lowest total losses to be expected from any value of alpha in the 0-1 range. This method expects product losses which is inherent within the data.

FIGURE 41: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR GALLON WHOLE MILK

Figure 41 shows alpha values range between .1 to .9 as part of the normal testing for the exponential smoothing model. The .9 and .5 model look more like they are following the demand a week behind and in quantities less than the amount seen in

demand lines. The pattern of these models definitely indicates the heavy influence of the prior periods demand and less influence of the forecast model. Throughout the study, the alpha values greater than .5 are unable to meet the demand at the correct time. The model does improve as the alpha value decreases from .5 to .1. The model for an alpha of 0.1 looks more like a line of best fit through the demand line. The solver found an alpha value of 0, which was less than the range tested. In this case, the alpha indicates that the forecast produces the smallest MAD error, which would be the most likely case to produce the lowest loss due to spoilage.

FIGURE 42: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR GALLON 2% MILK

Figure 42 compares the demand of 2% gallon of milk to the exponential smoothing forecasts of the different alpha values between .1-.9 as well as the solver

defined alpha value. As the alpha value goes from 1 toward 0 the model diverges from the demand and become extremely smooth. The Alpha value of .9 looks to be the closest to meeting the demand curve however the based on the solver an alpha value of 0 would provide the lowest MAD value during the study period. With an alpha value of .9 is the closest to actual demand for the exception of the solver which had an alpha value of 1

FIGURE 43: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR GALLON 1% MILK

Figure 43 is an interesting graph of the 1% gallon milk. The demand listed by actual value shows a large fluctuation in orders from one period to the next. In addition, demand overall curves up over the study. The alpha value from .9-.5 shows again that the forecast values are not as robust at meeting the future demand. The

forecast with an alpha value of .1 looks to be the best model because it is smoothest forecast given its appearance in figure 43. In addition, the forecasted values stay in between the peaks and valley for the demand line which appears to linearize the demand. However, the solver suggests that over the study life an alpha of 0 would provide the best results in mitigating MAD error. The gap between the demand line and the solver solution seems rather large as compared to other alpha values tested.

FIGURE 44: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR 1/2 GALLON WHOLE MILK

Figure 44 shows - like other products - that the prior period demands do not do as well as the forecasted values in accurately estimating future demand. This figure is interesting because the solver model is indicating that the prior period is also not strong enough to forecast future demand. However, a blend using alpha as .18 means a

blend of both, where most of the weight is placed on the forecast value and a small portion relies on prior periods demand. The values for the model with an alpha value of .1 in figure 44 are far too smooth and have a much wider gap between it and the demand line compared to the gap of the solver solution of alpha at .18.

FIGURE 45: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR 1/2 GALLON 2% MILK

The half-gallon 2% milk seen in figure 45 does not fluctuate much in comparison to other products like whole milk and 1% milk in the gallon size. No matter how small the fluctuation is the purely forecasted value are not very successful at forecasting demand. In this model a pure split between forecast and prior period demand which has an alpha value of 0.5 is the best model in which the total MAD

error value is at its lowest. The .5 alpha for most of the study is above the forecasted demand however, it follows demand, which the smallest overall gap.

FIGURE 46: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR 1/2 GALLON 1% MILK

Figure 46 shows the demand and exponential smoothing models for the half-gallon size version of 1% milk product. What is interesting about the data is the volume of sales being so much lower for 1% milk in the half gallon size than its larger version. The demand for this size also does not follow a similar pattern and may indicate that there may also be differences in the products besides the size. The data in this particular case shows a gradual decline in demand for the first 4 weeks of the study and a rebound in demand in the final 2 weeks of the study. In this, like in other

models, which used a .9 -.5 alpha values looked more like a phase shifts of demand, indicated that a models that are heavily dependent on prior demand tend to fail to accurately capture what factor influences future demand. The solver solution shows the best alpha value to be weight more on the forecast have an alpha value of .18 which leaves some room for the prior demand to influence the forecast. The forecasts model using an alpha of 0.1-0.5 tends to forecast demand to be higher than what it actually is in the period being forecasted. This appears to put the store at risk of losing inventory to spoilage even with is being the most optimal solution for the total MAD error value.

FIGURE 47: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR QUART WHOLE MILK

Figure 47 indicates that the demand stays rather consistent at an average of 3 units per week for the exception of week 3 and 6. In this case, the smoothed models would be best suited for forecasting demand. Due to the fact that in the weeks where demand deviates from 3 units increase only by 1-2 units which is a shift in demand of 33-66% more in demand the store would better off losing the \$.40-80 of profit in order to avoid losing a \$1-3 investment in inventory. This point is supported by the solver solution where the alpha value is at 0.0 and is a smoothed straight line at the 3-unit mark on the x scale.

FIGURE 48: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR CHOCOLATE MILK

Figure 48 shows like other products shows that the prior period's demand do not do as well as the forecasted values in accurately estimating future demand. The

Alpha value of 0.9-0.5 looks to be the closest to meeting the demand curve, at some point both 0.5 and 0.9 alpha value models forecast demand in opposite direction than that of demand in weeks 4-6 however the gap for these models appear to be smaller than the gap between the solver alpha value of 0.38. The solver solution is interesting because it looks to be a blend of the 0.1 and 0.5 alpha models. The solver solution initially forecasts a higher demand level than the actual demand and then around week 4 adjusts to meet demand. In the weeks 4-6 they remain stable whether demand increase or decreases, and therefore looks to miss out on a major portion of demand in week 6.

FIGURE 49: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR QUART HALF AND HALF

Figure 49 is interesting because the data both varies significantly in comparison to other products. This product also has a longer shelf life compared to other products which may not seem relevant except for the fact that because it lasts longer, it may discourage the customers from purchasing it as often as other dairy products. This looks to be the case given that figure 49 shows spikes in demand in weeks 3 and 6. The alpha for this particular product leans toward using the prior period demand and less on the forecast value given that the solver solution is a model with an alpha value of 0.7. Many of the prior products have solver solutions that depend on the forecast value rather than the prior period demand.

FIGURE 50: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR QUART 2% MILK

Figure 50 shows the exponential smoothing model for quart 2% milk product. Given the actual demand model there is a drop in demand in week 5 and a surge in demand in week 6 which both roughly average out to the 2 unit per week value seen in weeks prior to week 5. The solver solution is the only one which suggest this whereas the remaining model suggest this for all week except in week 6 where all other alpha value models decrease there forecast toward 1 unit in week 6.

FIGURE 51: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR PINT HALF AND HALF MILK

The Pint size half-and-half product shows a significant change in demand in the last week of the study in general the demand tends to fluctuate slightly as seen in figure 51. Again like many of the other products, the higher alpha values tend to phase shift and forecast much higher than normal demand and therefore expose the store to a

potentially large volume of spoilage in inventory. However, this product has a longer than normal shelf life compared to most products. If the 0.5-0.9 alpha value models are used, then there is a large drop in forecasted demand in week 6 which would allow for the excess inventory stock to sell off however because actual demand sky rockets to 16units the in the last week. This may be why the bi weekly orders are seen with high fat milk products such as creamers and half and half. In any case, the solver solution using an alpha of .35 looks to be ideal because even though it may miss some demand from week 6 overall it blends the prior period demand and forecast value to meet the maximum possible demand without increasing the total MAD error during the study window.

FIGURE 52: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR PINT LIGHT CREAM

The light cream product seen in figure 52 data is difficult to interpret. While the solver provides the best solution for the light cream product by setting alpha at 0, the store owner did not maintain consistent inventory for this product. The owner never bought more than 2 units of light cream, and given the “gut instinct” method the store owner did not observe whether or not the product was selling faster from week to week or whether the product was coming close to expiration prior to sale. After the significant loss of 8 units in the first week of observations seen in table 8 of section 4.5 the store owners limit the amount at 2 units, and does not accurately monitor the or study the sales for the light cream product.

FIGURE 53: EXPONENTIAL SMOOTHING FORECASTS V. ACTUAL DEMAND FOR TOTAL DAIRY PRODUCTS

Figure 53 is an aggregate look at the total dairy product demand and the exponential smoothing models it was tested against. Overall demand stays constant throughout the 6-week study for the exception of week 6 where all products showed a spike in demand. The forecasts using alpha values between 0.1-0.9 shows vary similar patterns where the model applies some part of prior demand and forecast value to estimate demand however, the best alpha value is 0 according to the solver solution. When looking at the data for all dairy products, this seems accurate because the solver values cut through the peaks and valleys seen in demand during the study. In addition, the solver solution maintains a more consistent reaction to shift in actual demand over the life of the study. Given the driving force is to limit exposure to product spoilage, the solver solution conservatively estimates demand at the cost of potential profits which not well incentivized for the store.

5.4 MAD AND MAPE ERROR ANALYSIS

The following section relates to error analysis methods proposed in section 3.6. The mean absolute deviation (also referred to as MAD) is determined for all exponential smoothing, weighted average, and “gut instinct” models evaluated in table 11. Along with the MAD error analysis, a Mean Absolute Percentage Error (also referred to as MAPE) was also mentioned in section 3.5 as a method used to look at the error as a percentage of whole demand, which is seen in table 12. The first column labeled gut shows how the current “gut instinct” model used by the store owner’s. The columns following show the MAD value for the forecast models tested. In both tables 11 and 12, the aggregate data for all dairy products under observation is also evaluated in addition to each product individually.

DAIRY PRODUCT	GUT	α 0.1	α 0.3	α 0.5	α 0.7	α 0.9	SOLVER	W.A. (BY DAY)	W.A. (BY PRODUCT)
QUART CHOCOLATE MILK	4	8	7	7	7	8	7	10	10
QUART WHOLE MILK	2	3	3	4	4	4	3	12	7
QUART 2% MILK	1	2	2	3	3	3	2	7	6
QUART HALF & HALF	23	17	14	13	13	15	13	28	20
PINT HALF & HALF	16	25	23	23	24	24	22	28	20
PINT LIGHT CREAM	0	6	6	7	8	9	6	10	7
1/2 GALLON WHOLE MILK	4	9	10	11	11	10	9	24	17
1/2 GALLON 2% MILK	6	11	10	10	11	12	10	20	17
1/2 GALLON 1% MILK	1	8	8	9	9	9	8	17	11
1/2 GALLON FAT FREE MILK	5	8	8	7	7	8	7	11	5
GALLON WHOLE MILK	16	25	27	28	30	34	24	61	45
GALLON 2% MILK	8	23	23	18	14	12	11	32	15
GALLON 1% MILK	26	38	38	41	45	50	26	84	59
TOTAL DAIRY PRODUCTS	108	91	91	94	98	103	87	329	198

TABLE 12: MEAN ABSOLUTE DEVIATION ANALYSIS OF ALL MODELS

In comparison to the “gut instinct” method currently deployed, the weighted average models tend to fail be more accurate than the “gut instinct” method in most cases. The exception is that the Half & Half product in the quart size is better forecasted by weighted average model.

The exponential smoothing models perform best on the Half& Half product in the quart size, just like the weighted average model, it too also fails to beat out the “gut instinct” method.

In the aggregate forecasting approach, the total dairy is better served using any of the exponential smoothing methods where the solver out performs the current method by 21 units. Table 8 in section 4.5 shows that during the 6-week period the

store recorded a loss of 20 units of dairy product that supports the notion that an aggregate exponential smoothing model would outperform the “gut instinct” method used currently.

DAIRY PRODUCT	GUT	α 0.1	α 0.3	α 0.5	α 0.7	α 0.9	SOLVER	W.A. (BY DAY)	W.A. (BY PRODUCT)
QUART CHOCOLATE MILK	15%	57%	50%	50%	50%	57%	50%	71%	71%
QUART WHOLE MILK	15%	14%	14%	19%	19%	19%	14%	57%	33%
QUART 2% MILK	20%	17%	17%	25%	17%	25%	17%	58%	50%
QUART HALF & HALF	10%	36%	30%	28%	28%	32%	28%	60%	43%
PINT HALF & HALF	18%	63%	58%	58%	60%	60%	55%	70%	50%
PINT LIGHT CREAM	4%	100%	100%	117%	133%	150%	100%	167%	117%
1/2 GALLON WHOLE MILK	28%	21%	24%	26%	26%	24%	21%	57%	40%
1/2 GALLON 2% MILK	10%	33%	31%	30%	33%	35%	30%	62%	51%
1/2 GALLON 1% MILK	29%	32%	34%	37%	38%	38%	33%	72%	46%
1/2 GALLON FAT FREE MILK	49%	45%	45%	41%	40%	46%	39%	59%	30%
GALLON WHOLE MILK	8%	24%	26%	27%	28%	32%	23%	58%	43%
GALLON 2% MILK	40%	44%	44%	34%	28%	23%	21%	61%	28%
GALLON 1% MILK	0%	29%	29%	32%	35%	38%	20%	64%	45%
TOTAL DAIRY PRODUCTS	20%	17%	17%	17%	18%	19%	16%	61%	36%

TABLE 13: MEAN ABSOLUTE PERCENTAGE ERROR ANALYSIS OF ALL MODELS

Table 12 shows the characteristics where the gut instinct method outperforms the forecast capability of exponential smoothing and weighted average when forecasting by individual product just like table 11. In addition to Half& Half product

in the quart size as well and the 2% milk in the quart size both show that the “gut instinct” forecast is weaker at predicting the forecast that the models tested. In addition, the aggregate forecasts also show the same traits as table 11 where the exponential smoothing model does a better job at forecasting dairy demand.

Based on the range of product costs listed in chapter 3, the exponential forecast model could save the store between \$27.09-\$81.69 on products at risk of expiring. When averaged, the \$27.09-81.69 is approximately 3-9% of the \$150-dollars minimum order value that the store must meet in order for the dairy vendor to process the stores dairy needs. The fact that the difference between the solver based exponential forecast and the gut instinct method used are within 1-unit difference provides a strong support to fact that forecasting models used in large scale business can retain value in smaller scale business.

In addition, it makes sense that the forecast operates better on the total dairy and not well on the products individually. This supports the second law of forecast stated by Hopp and Spearman (2011) which states that a detailed forecast is worse than the aggregate.

CHAPTER 6: CONCLUSION

6.1 RECOMMENDATIONS BASED ON STUDY

The store must look to limit its exposure to expiring product by applying forecast methods, which suit its needs. The exponential smoothing models tested would be a good candidate to be applied to the store's dairy product inventory. The reduction in potential expiring product exposure of 3-9 % per week.

	Week						Total
	1	2	3	4	5	6	
3% of Product "Gut instinct"	1.5	2.0	2.5	1.8	3.1	2.3	13.1
9% of Product "Gut instinct"	4.4	6.0	7.4	5.4	9.2	6.8	39.2
3% of Product by \$1.02 price	\$ 1.51	\$ 2.06	\$ 2.52	\$1.84	\$ 3.13	\$ 2.30	\$13.37
9% of Product by \$1.02 price	\$ 4.52	\$ 6.18	\$ 7.56	\$ 5.53	\$ 9.40	\$ 6.91	\$ 40.10
3% of Product by \$3.51 price	\$ 5.16	\$ 7.06	\$ 8.63	\$ 6.32	\$ 10.74	\$ 7.90	\$ 45.81
9% of Product by \$3.51 price	\$15.48	\$ 21.17	\$25.90	\$18.95	\$32.22	\$23.69	\$137.42

TABLE 14: PONTENTIAL LOSSES FROM USING "GUT INSTINCT" METHOD

The result proves that using forecast models given a short period of time would be better than the gut instinct model being used. Table 10 in section 5.1 showed that the store lost 20 units of dairy at a cost of \$36.45 during the 6-week study. Table 14 applies both the 3% and 9% risk exposure rate against the total weekly supply ordered (seen in table 7) using the "gut instinct method. Based on these values the storeowner exposed the store to losing between 13-40 units, considering on the cheapest and most expensive product by cost. The store could have potentially lost \$13.37-\$137.42 in capital over the six-week study because they used the "gut instinct" method instead of

using exponential smoothing methods that were applied in the study. At \$137.42 the store exposed itself to losing almost an entire week's order given that they must order \$150 minimum each week. The order data seen in section 4.3 shows little correlation or seasonality from month to month perspective, demand data seen in figure 30 and 31 show that on a weekly basis there may be the potential for seasonality. The store should use the forecast on a weekly basis to help in the process of placing dairy orders; the losses seen in table 10 over the 6 weeks of observations landed near the middle of the range seen in table 14.

The purchase of a POS system is strongly advised. It is true that at an initial cost of \$1500 for an POS versus the lower \$300-\$500 price on a cash register may seem appealing. The issues with inventory control, however suggest that A POS system would provide the detail the store would need to make better inventory decisions. Better data collection methods will allow the store to improve the pre-existing "gut instinct" method and apply the forecast methods tested in the study. During the study, data collection of demand data which entailed checking stock and accounting for expired product took 20-30 minutes each day, and on days where new inventory was received it took almost 1 hour. This means the store would have to commit between 2-4 hours to collecting dairy demand data on a weekly basis. In reality, the store should be tracking this number much more carefully. At a the minimum the store should check inventory at the beginning, middle, and end of every day to understand how dairy demand changes throughout the day. In addition, the storeowners would spend at minimum 1 hour to analyze data and produce a forecast and 10-15 minute to place orders

Activity	Cash Register	EPOS method
Collect Data	2-4 hrs.	0 hrs. Est.
Analyze	1 hrs.	.25-.5 hrs.
Place order	.25 hrs.	.25 hrs.
Total Labor commitment	3.25-5.25 hrs.	.5-.75 hrs.

TABLE 15: LABOR COMMITTED TO USING CASH REGISTER VS. POS

	Cash Register(Cost Per Week)	POS method (Cost Per Week)
Initial Cost	\$1.15-\$1.92 (Assuming \$600-1000 cost over 10 years)	\$2.88 (Assuming 1500 cost over 10 years)
Labor	\$32.5-\$52.5	\$5-\$7.5
Total Cost	\$33.65-54.42	7.88-10.38

TABLE 16: WEEKLY COST OF DAIRY FORECASTING USING CASH REGISTER VS. POS

Table 15 assumes that the store will maintain the same tracking as done during the study. In this case the store would consume almost 4-10 time the amount of labor.

Using an hourly labor rate of \$10/hr, the store would spend would spend approximately 4.2 times less per week if the store invested in a POS system.

A few assumptions were made in Table 15 and 16. The first is that the cash register cost is assumed to be double because of the fact that the store has replaced the cash register 2-3 times since they took ownership in 1998. Over an estimated life of 10 years for each unit the POS would cost less because as stated in the chapter 2 POS systems can usually be restored or repaired if an issue arises, which is not feasible with the cash register. In addition, the POS uses a scanner to ring in sales whereas the register requires manual input which increases risk exposure to human error. While this was not looked at, human error is far more likely than an error by a computer. The store also sells many other products, which also require inventory tracking and other data.

The products are not well incentivized. In order for the dairy product to sell the margins are held low. The product according to the store owners, dairy products are of value because they act as complementary product. Their low margins only provide value in the fact that they supposedly excite the sales of other grocery products. However, without a system like a POS which records and tracks sales and could provide what complementary products sell with milk, it is hard to tell whether this relation is true. The lack of knowing whether sales are excited by dairy reduces the incentive to position dairy within the store as a true loss leader.

6.2 LARGER DAIRY MARKETS AND ITS EFFECT

The store owners should look at data related to different business segments that the store operates. A look at dairy industry data, which is widely available on the USDA government website, would have shown the owners that the dairy market is not a growth market. This simple fact may have made the storeowners more conservative

in ordering dairy. If the storeowners analyzed the order data, alone they would have seen that whole and 1% milk products are the largest contributors to the dairy segment of the business. If that data was then compared to the USDA's data seen in figure 2 of section 1.3 or general industry data seen in figure 4 of section 2.2. The owners should have had a clear indication that when large changes to local environments such as new competition or declines in local economy occurs, dairy inventory must be monitored and analyzed to adjust inventory to meet new level of demand.

The reports by the US government on the change in dietary guidelines as well as society's general change in dairy drinking habits shows that milk is no longer a staple of the US diet. The rise in cases of lactose intolerance and the need to define what intolerance is poses other potential shifts in dairy's place on the food chain.

6.3 PRODUCT EVALUATION

Light cream is the product with the largest loss, based on information received from the business survey conducted, storeowners decided to evaluate light cream as a new product to be incorporated to the regular dairy order. The selection of the light cream was done based on the opinion and "gut instinct" method used by the owners which caused for a misinterpretation of trends in the store. The exponential forecast models and data used would have provided a strong argument the product and would have indicated no need to test the product.

The store must limit the variety of products ordered, based on the profit and breakeven point equation (13-14) the value of dairy is low. Based on the lower end of the break-even point analysis seen in equation 13 resulted in a minimum of 4 units of product needed to be sold in order to breakeven on a product with a unit cost of \$1.89.

the store should remove ½ gallon fat free milk, quart chocolate milk, quart 2% milk, and pint light cream products from the dairy product line, because at a minimum these products do not sell 4 units per a week as seen in table 5. The order data also supports this finding for 2014 and 2015 seen in tables 2 and 3 respectively.

6.4 FUTURE WORK

Future work maybe needed to extend the duration of the study. The six-week period did not provide enough time to produce a robust forecast. In order for the models to produce strong results the inventory ordering must be tested and determined whether order process is in control. If the forecast is applied over a longer period, each week will remove waste and eventually produce a stable model which the store owner will have to evaluate occasionally.

A factor that may need to be tracked is to look at general foot traffic coming into the store and what portion of this group commits to a purchase and in addition what products are being sold in each transaction. The study showed that there are days where there is a significant amount of sales. Current store setup does not allow us to analyze what portion of total sales dairy products occupy. This would provide a possibly better model given the limitation of resources such as labor and the lack of POS system made determining this information impossible.

In general, small business cannot ignore the larger markets they must adopt the adage “think globally act locally” the macro market would have provided indication to the store to be aware that demand has been on the decline, proper monitoring of the local environment and demand would help in these business decisions. The lack of

continuous improvement and awareness of change is what has led to this low performance in recent years for the store, which will need to be incorporated into store operations. The store must be proactive in changing with demand, meaning that even though there is a benefit to using exponential smoothing today it may not stay that way unless the store continues to test its capability.

These few changes to the operational approach of the company would accommodate the exponential forecasting need for dairy inventory without affecting resources. It is evident that large-scale forecasting methods have value in small-scale businesses and therefore need to be assessed and configured to meet the need of smaller scale businesses.

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