Right Sizing Safety Stock and Effectively Managing Inventory using Forecastability

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SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT

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ABSTRACT

In a commodity consumer product business, such as bottled water, the customer has the power. Therefore, the business incurs whatever cost necessary to meet demand. To reduce the cost of fulfilling demand and of stockout, businesses must thoughtfully set inventory safety stock levels to compensate for potential spikes in demand. The purpose of this capstone is to analyze the current inventory strategy and its effectiveness of the sponsor, a bottled water company. The team worked to explore the drivers of supply and demand variability to identify potential improvements in inventory management, which could reduce cost while maintaining service levels. The team analyzed the customer demand, production demand, strategic forecast, and inventory on hand for over 100 stock keeping units (SKUs) in a specific geographic region over the last three years. As a result of the analysis, the team proposes SKU segmentation by forecastability and appropriate safety stock calculation using the standard deviation of forecast errors. This method of calculating safety stock, as compared to the sponsor's current approach, reveals a clear opportunity to reduce the inventory by 28% for SKUs with predictable and positive demand. Another key finding is the opportunity to reduce the order quantities when the annual forecasted demand of a SKU is below an identified threshold. Lastly, the team recommends increasing the inventory level kept at supplier consignment to further minimize the risk of stockout at low cost due to consignment agreements. To further and continuously improve inventory position and service levels, the team recommends a quarterly strategic inventory review to adapt strategy as business needs and requirements shift.

Capstone Advisor: Tim Russell
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3 Introduction

The bottled water market has shown continuous strong demand growth year after year. Our sponsor Niagara Bottling LLC (Niagara), the largest bottled water manufacturer in the United States, has significantly grown its sales year over year for the past 5 years and foresees a similar growth rate continuing in the next few years. Niagara has grown its footprint in the United States and improved production efficiency through investment in automation technology. While Niagara is optimizing its production as much as possible, the availability of raw materials is crucial for the sponsor to operate in an environment where the customers' demand must always be met. For Niagara, raw materials are categorized as flexibles (labels and stretch film), corrugate, resin (used for plastic injection molding of bottles), and caps.

3.1 Problem Motivation

Niagara schedules its production with the assumption of 100% raw material availability, and it is experiencing challenges in ensuring raw material availability.

3.1.1 Demand Seasonality and Volatility

Niagara faces a seasonal distribution of demand for bottled water. Typically, sales double in the summer (Chua and Heyward, 2017), especially around the holidays, and dip significantly in the winter. Demand is also very volatile due to customer-driven promotions throughout the year. Niagara follows a traditional strategy to meet over-capacity peak demand, prebuilding inventory during the low season and storing finished goods in a third-party warehouse (3PL). In addition, Niagara is adding new production lines within existing plants to expand capacity and meet growing demand.

3.1.2 Short Customer Lead Times

Similar to most consumer-packaged goods (CPG) companies, Niagara is facing pressure from its customers to shorten its lead times. Niagara's typical customer lead time is 5-10 days; however, Niagara also accommodates customer orders with lead times as short as 24 hours. From conversations with the Niagara production planning team, the probability of production schedule changes 3 to 7 days out is as high as 40% (I. Liang, personal communication, Oct. 15, 2019). This variability imposes great challenges for Niagara to meet customer orders because of the large gap between raw material lead time (30 days) and potential customer lead time (24 hours).

3.1.3 One Rule-of-Thumb Inventory Ordering Strategy for all Stock Keeping Units (SKUs)

Niagara's strategic buying group relies on legacy day-on-hand (DOH) numbers to set its inventory target at their suppliers. Currently, a 90-DOH inventory target is applied to all stock keeping units (SKUs). When DOH for each SKU dips to 60 days, the buyer places an order for an additional 60 days of supply to bring DOH level back to 90 days, as illustrated in Figure *1*.

Figure 1: Standard Purchasing Guidelines (J. Valentin, personal communication, Oct.22, 2019)

This one-size-fits-all strategy for ordering raw materials is not optimal as each SKU has different demand volume and distribution. Optimizing inventory ordering policy after SKUs are classified and grouped has the potential to minimize inventory holding cost, reduce costs of expediting materials, and maintain high customer service levels.

3.1.4 Current Challenges

Niagara has vertically integrated its supply chain and manufactures its own plastic bottles. This allows Niagara to be more agile under volatile demand. However, our sponsor is continuously facing challenges in raw material availability specifically in one category: Flexibles. The Flexibles category consists of shrink film and labels, which are purchased under bill-and-hold arrangements with suppliers. Flexibles stay at a supplier consignment facility until Niagara releases the material to a plant.

The complexity of the Flexibles category is high and is driven by bottle/pack size, product type, marketing promotions, and traceability legal requirements in certain geographic areas. Moreover, the long lead time of these raw materials (30 days) creates challenges when not available at the supplier consignment facility. When Flexibles are not available at supplier consignment facility, the tactical material buying group at Niagara has to seek the following costly solutions:

- Finding Flexibles substitutions at plant
- Expedite Flexibles from suppliers
- Transshipment in network
- Dynamic sourcing (move production to another plant)

To buffer against demand volatility and shorter customer lead time, Niagara utilizes safety stock to cover demand uncertainty. Niagara holds safety stock in two physical forms: raw materials and finished goods. Safety stocks are held at multiple locations in the Niagara network. Finished good safety stocks are stored at Niagara plants and at third party warehouses (3PL). Raw material safety stocks are held at the raw material suppliers, as consignment inventory, and at Niagara plants as shown in Figure 2.

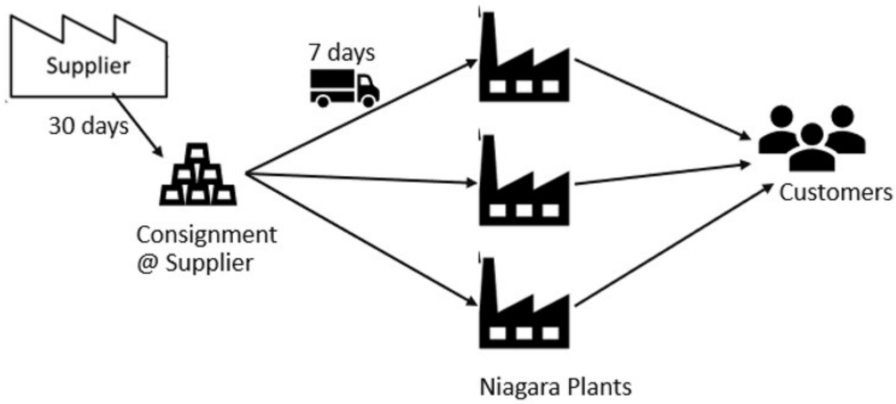

Figure 2: Inventory Network

Currently, Niagara determines safety stock levels with various measures. Customer demand variability is used in calculating required finished goods safety stock to be held at the plant, this approach is already deployed and used within Niagara network. However, raw material safety stock levels at plant and supplier consignment are driven by generic inventory DOH rules without clear SKU classifications. Niagara has been working on utilizing production plan variability to calculate required raw material safety stock needed at the plant, but this approach has not been fully validated and deployed.

3.2 Problem Statement

Niagara sees the need to improve its inventory positions to achieve lower cost without damaging customer service levels. Specifically, the team is interested in applying a data-driven approach to set safety stock inventory targets to optimize raw materials at supplier consignment locations and at Niagara plants.

The team believes the statistical approach of calculating inventory position by SKU classification could benefit Niagara's supply chain by eliminating additional effort spent on ensuring raw material availability. This approach will demonstrate the benefits of applying a data-driven approach to inventory decisions which could be leveraged across industries to companies facing similar inventory optimization problems.

4 Literature Review

Regardless of the product, market, or industry, supply chain costs often represent a significant portion of the price of a good or service. Businesses, therefore, dedicate significant time and energy to evaluating their own supply chains to become more efficient and ultimately improve profitability.

The fundamental question firms struggle to answer is how much and when to order raw materials in order to achieve the highest level of service at the lowest cost. The underlying drivers of inventory levels, demand, and supply variability, are common to all supply chains, making inventory optimization applicable to every industry (Willems, 2011).

The team reviewed information from two theses completed with Niagara: one is by V. Chandra and M. Tully (2016), which provides lead time and legacy inventory DOH targets that are still being used at Niagara today; the other is by I. Chua and T. Heyward (2017), which provides the economic production quantity (EPQ) model that is widely adopted at Niagara today. Both provided key insights to Niagara's past supply chain challenges and contributed to the potential approaches considered by the team along with the other high level concepts outlined within this Literature Review.

Topics on vendor consignment inventory, safety stock calculations, raw material ordering policies are explained and explored further in this section as applicable to the key research question of this capstone: how a consumer-packaged goods company, Niagara LLC, can optimize its inventory position to better buffer against demand volatility and shortened customer lead times, at low cost, without damaging customer service levels.

4.1 Vendor Consignment Inventory

Finding the correct inventory management policy to balance demanded high service level at low cost is often made easier with increased transparency and collaboration between supplier and buyer. Collaboration could range from straightforward information sharing, where a buyer will share the forecasted demand with supplier to inform the supplier's production planning, or a more formal commitment or partnership, where a supplier holds and manages inventories until the buyer withdraws them for use (Battini, 2010). This formal partnership is an example of a consignment inventory policy.

Consignment inventory can be implemented differently depending on the needs of the business. Recent literature explores minimizing the joint total expected cost (JTEC) also known as the total supply chain management cost, for both partners involved, supplier and buyer. Piplani and Viswanathan (2003) prove lower JTEC through a cycle time reduction when inventory is kept at the buyer's plant location which virtually eliminates procurement lead time.

Considerable work over the past decade has used mathematical models with inputs to account for factors such as demand variability, obsolescence cost, demand variation, and space limitations to quantify the optimal ordering policy for a buyer to order raw materials (Braglia and Zavanella, 2003; Valentini and Zavanella, 2003; Srinivas and Rao, 2004; Battini, Gunasekaran; Faccio, Persona and Sgarbossa, 2010). These models have demonstrated the applicability and attractiveness of consignment inventory policies in many different business environments and demand circumstances.

Niagara is not unique in struggling to balance competing priorities of high service levels and low total inventory cost. The consignment inventory policy agreements developed with raw materials suppliers allow Niagara more flexibility and absorbs demand fluctuation at lower overall cost due to a reducing in inventory holding costs. Due to Niagara's network for suppliers and plants, as well as space constraints at plant locations, all consignment inventory is kept at the supplier's location. While this shortens raw material lead time from lead time of producing and shipping the material (30 days) to lead time from supplier consignment warehouse to plant (seven days), the procurement lead time does not completely disappear as noted in many of the above studies. Moreover, while this strategic inventory approach has been proven effective, the effectiveness of consignment inventory is heavily impacted by variation in demand and ordering policies, both of which will be described below.

4.2 Safety Stock

4.2.1 Seasonal Demand

Safety stock is the level of extra stock maintained by a company to prevent stockouts. It is important to understand that the goal of having safety stock is to eliminate the majority of stockouts, not intended to remove all stockouts. Although this is not an exhaustive list of all possible drivers that can cause stockouts, typical influencing factors are customer demand variations, forecasting errors, and variability in lead times for raw material or manufacturing (King, 2011). Theoretical safety stock calculations can be in different forms, depending on which one of the following sources of variability is the primary concern: demand, lead time, or a combination of both, as illustrated in equation (1) - (4) (King, 2011). Equation (3) is used when both variability in demand and lead time are present, independent and normally distributed. Otherwise, equation (4) is used.

$$\mathrm{SS} = \mathrm{Z} \times (\sqrt{\mathrm{LT}} \times \sigma_D) \tag{1}$$

$$\mathrm{SS} = \mathrm{Z} \times (D_{AVG} \times \sigma_{LT}) \tag{2}$$

$$\mathrm{SS} = \mathrm{Z} \times \left(\sqrt{(\mathrm{LT} \times \sigma_D)^2 + (D_{AVG} \times \sigma_{LT})^2}\right) \tag{3}$$

$$SS = \mathrm{Z} \times \left(\sqrt{\mathrm{LT}} \times \sigma_D\right) + \mathrm{Z} \times (D_{AVG} \times \sigma_{LT}) \tag{4}$$

Demand fluctuation and seasonality is a common problem faced by many consumer goods companies. As most companies work diligently to improve their forecasting accuracy by using well-prepared data sources, they are often challenged to predict the impact of demand seasonality patterns on forecasts. The even more challenging task is how to strategically plan and place inventory physically in the supply chain to accommodate seasonal demand.

Neale, Willems, and Beyl (2012) explore a forward-coverage planning approach to safety stock policy. Common industry practice has been to set and adjust safety stock levels through analyzing at a targeted number of periods of future demand. However, the study identified that companies may experience “landslide effects” under seasonal demand, showing a significant drop in inventory and service levels as they transition out of peak seasons (Neale, Willems, and Beyl, 2012). Safety stock levels can drop prematurely prior to a low demand season, because low demand forecasts were used to set safety stock levels during high seasons under the forward-coverage planning approach.

To prevent this “landslide effect” and ensure correct timing used in inventory planning, Neale, Willems, and Beyl (2012) recommend a “backward-coverage” strategy when setting safety stock targets. Instead of using the forecasts in the future replenishment lead time periods, safety stock targets should be calculated using the preceding time periods (including the current period). Therefore, companies will not experience significant drops in inventory when transitioning from a high season to low season, avoiding increased stockouts and decreased customer service levels. This theory also applies when companies transition from a low season to high season. Although the effect is less damaging to costs, it can result in safety stock targets prematurely raising inventory levels while companies are still in the low demand season. As a result, companies would unnecessarily inflate inventory levels, thus increasing total inventory cost.

This study was of particular interest due to the extreme seasonality in Niagara's demand as their product demand doubles in the summer months. Moreover, current safety stock calculations at Niagara use forward-looking forecasts. If supported by internal data, this research could be directly applicable to Niagara's safety stock calculation and prevent additional costs associated with raw material shortages. It is important to recognize seasonality and trend in demand so that it can factor into inventory decisions and inform ordering policy.

4.2.2 Forecast Bias

Traditionally, as described above, the variability input to the safety stock equation is variation in historical demand, see Equations (1-4). This approach to calculating variability and, by extension, safety stock is effective for stationary demand and scenarios where past demand is a better predictor of future demand than the forecasted demand. However, to better capture deviation in demand caused by seasonality and life cycles, Manary and Willems (2008) propose calculating the variation using the difference between the forecasted demand and the real demand instead of variation in historical demand. Manary and Willems (2008) propose that characterization of demand is the most significant input to determine proper safety stock levels because the most appropriate safety stock equation can be identified only once the demand characterization is understood.

The variation between forecast and demand can be calculated using the Equation (5) to calculate the standard deviation of forecast errors (SDFE) for each SKU where F_i denotes the forecasted demand for period i, D_i denotes actual demand in period i and n is the number of period of data which are being analyzed (Manary and Willems, 2008).

$$\sigma_{SDFE} = \sqrt{\frac{\sum_{i=n}^{n}(F_i - D_i)^2}{n-1}} \tag{5}$$

Equation (6) is used to test for bias, that is to understand if there are any trends to historically over or under forecast a specific SKU. The ratio can be calculated for each period I to compute the relative forecast accuracy. A collection of θs across time centered around 0.5 for a specific SKU demonstrated unbiased forecasting (Manary and Willems, 2008).

$$\theta_i = \frac{F_i}{F_i + D_i} \tag{6}$$

Manary and Willems' (2008) method of approximating variation while accounting for deviation in demand due to seasonality was extremely valuable to this team due to the seasonal nature of Niagara's products. This model and these calculations were further explored to better identify the best policy for Niagara's specific demand pattern. Moreover, this research led the team to focus on first characterizing demand for Niagara's products.

4.3 Raw Material Ordering Policy

The fundamental purpose of an inventory replenishment system is to resolve the following three inquiries: i) when should an order be placed? ii) how large should the order be? iii) how often should the inventory status be reviewed? Inventory ordering policies work to minimize the total cost equation, the sum of purchasing, ordering, holding, and shortage costs. Inherent to every purchasing model is many assumptions, most significantly, assumptions on the form of demand for the good or service. Under the conditions of deterministic demand, the above three questions become straightforward and economic order quantity (EOQ) principles can easily be applied to determine optimal order size (Silver, Pyke, and Thomas, 2017).

Under probabilistic demand, answering the above three questions becomes much more complex. Silver, Pyke, and Thomas (2017) recommend managers ask themselves additional questions to best establish the appropriate inventory policy (Silver, Pyke, and Thomas, 2017). First, how important is the good or service? Second, does the inventory level of the product require constant attention, in other words, should it be continuously reviewed? Third, what form should the inventory policy take? Fourth, what are the specific cost and service goals set by the company?

The importance of the good or service can be determined by SKU segmentation or A, B, C classification. Niagara implements a volume-based segmentation policy currently on all raw materials and identifies A SKUs as those with highest volume consumption and therefore highest priority. Niagara currently employs a continuous review policy. At Niagara, buyers monitor inventory levels of all SKUs daily. A major advantage of continuous review ordering policy as compared to periodic review is that the same level of customer service can be achieved with less safety stock and, therefore, lower carrying costs (Silver, Pyke, and Thomas, 2017). However, continuous review policies are generally more expensive in terms of inventory reviewing costs and errors. Due to the volatility of demand and variation in forecast accuracy at Niagara, a continuous review policy is optimal to achieve the desired high service levels.

To answer the question: what form inventory policy is optimal for a given scenario, Table 1 summarizes the four most common ordering strategies as well as the best applications of each.

Table 1: Common Inventory Ordering Policies Summarized

Inventory Policy	Review Period	Description	Advantages	Disadvantages
Order-Point, Order Quantity **(s, Q)** system	Continuous	Fixed quantity Q ordered when inventory position drops to the reorder point, s, or below	Simple to understand; Errors unlikely to occur; Production requirements for supplier predictable	Ineffective for individual large transactions
Order-Point, Order-Up-to-Level **(s,S)** System	Continuous	When inventory levels reach the reorder point, s, an order must be placed to	Optimal (s,S) system has lower total relevant cost than the optimal (s,Q) system	Resources required to find optimal (s, S) pair;

		achieve the order-up-to inventory level, S		Variable order quantity cause more frequent errors
Periodic-Review, Order-Up-to-Level **(R,S)** System	Periodic	Every R units of time enough is ordered to raise inventory position to level S	Does not require sophisticated computer control; Coordination of orders can provide significant savings	Replenishment quantities vary; Carrying costs higher than continuous review systems
(R,s,S) System	Periodic	Every R units of time if inventory position is at or below re-order point, s, order enough to raise it to S	Optimal (R, s,S) system produces lower total relevant cost than any other system (under demand assumptions)	Requires significant resources to obtain best values of control parameters

Note. Data from Silver Pyke and Thomas (2017).

After review of various inventory ordering policies and best applications, the team believes the Order-Point, Order-Up-to-Level (s, S) System provides inherent advantages when applied to Niagara's dynamic operating environment. This ordering policy has been proven optimal for dynamic inventory models with fixed ordering costs and stochastic demand (Sethi and Cheng 1995). Moreover, raw material SKU segmentation can be utilized to help Niagara define re-order points and order-up-to levels appropriate to the specific SKUs to mitigate risk of stockout while minimizing cost.

4.4 Demand Classification

When determining safety stock, demand-side variation is one of the most influential parameters. To set safety stock targets and reorder points, it is important to understand not only the historical demand for products, but also the forecasted demand. However, widely accepted forecasting truisms are that the forecast is always wrong and improving it dramatically could be a daunting task. High forecast error can result in either excess inventory within the supply chain network or lost sales for businesses. Understanding the forecastability of products can provide companies ways to efficiently allocate efforts and manage inventory.

There are multiple ways for demand classifications to help one understand the forecastability of products. ABC classification is the most widely used SKU classification approach in businesses (Babai, Ladhari, and Lajili, 2015). Following the 80/20 Pareto principle, this classification method uses a single-criteria, normally revenue ('ABC'), price ('HIL') or demand volatility ('XYZ') (Gudehus, 2005). For ABC classification, SKUs with cumulative revenue reaching specified thresholds will be grouped into corresponding A, B and C categories.

K-means clustering is another technique that can be used for demand classifications. Different from traditional ABC classification by specifying exogenous thresholds, k-means clustering uses machine learning algorithms to group SKUs by minimizing the squared distance between the SKUs within a cluster and the cluster centers (Hastie, Tibshirani, and Friedman, 2009) to determine the best number of SKU clusters.

Instead of using a single-criteria, forecast-based classification uses two different dimensions, the probability of positive demand and the variation of the positive demand to distinguish four demand profiles: smooth, intermittent, erratic and lumpy (Boylan, Syntetos, and Karakostas, 2008). The two criteria for forecast-based classification is illustrated in equation (7) and (8) (Engelmeyer, 2016). Moreover, the relationship between the two equations and the four demand profiles is outlined in Figure 3.

$$\pi^+ = \frac{Number\ of\ time\ priods\ with\ D^+}{Number\ of\ total\ time\ priods} \tag{7}$$

$$CV^2 = (\frac{\sigma^+}{\mu^+})^2 \tag{8}$$

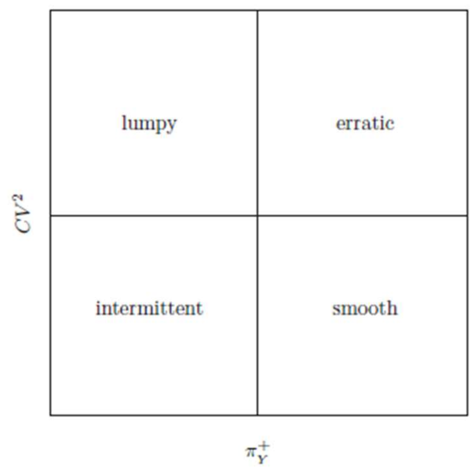

Figure 3: Forecast-based Classification Categories (Engelmeyer, 2016)

Similar to other businesses, Niagara struggles to produce accurate forecasts. The current generic forward-looking safety stock strategy, which is largely based on forecasted demand, may pose greater challenges for Niagara to ensure raw material availability when product forecastability is poor. In addition to traditional single-criteria SKU classification based on product demand, Niagara could benefit from classification techniques such as k-means clustering and forecast-based classifications to cluster SKUs with similar characteristics and manage SKUs based on their forecastability.

5 Data and Methodology

The team reviewed Niagara's legacy inventory targets and safety stock calculations to understand differences, sensitivities and drivers of safety stock inventory levels. Available data was analyzed to identify optimal strategies to reduce inventory levels and save cost while achieving target service levels.

5.1 Analysis Scope

Niagara manages inventory for five different types of raw materials: caps, labels, stretch film, corrugate and resin. For this safety stock analysis, the scope only includes labels. Niagara identified this material group as the most poorly managed with the most opportunity for improvement due to the volume of SKUs and custom nature of the material.

Moreover, the analysis focused specifically on production in a specific region of the United States. This specific region was chosen because there are additional regulatory requirements within the region that increase the SKU complexity. For example, regulations require any bottle that is shipping into a certain state to have a certification for that specific state listed on the label. Only a few Niagara plants in this region are cleared to produce bottles with these certifications. Therefore, Niagara must hold label SKUs for both state specific certified and non-state specific certified bottles in the region. These requirements limit Niagara's ability to shift raw material label resources among plants to support spikes in demand or production schedule changes. Due to the decreased flexibility in this region, it is even more critical for Niagara to properly manage inventory and set safety stock levels.

Throughout the project, the team dedicated a lot of time to cleaning and manipulating the data to identify the most meaningful and accurate way to aggregate the label SKUs. Many of Niagara's labels have multiple versions due to necessary and frequent artwork changes and updates. Additionally, two labels can be identical in every way except for the address listed as the production plant due to the regulatory requirements discussed above. The team decided it was important to aggregate labels that were interchangeable on the production floor, i.e. could be swapped out for each other during any given production run. However, care was taken to ensure the aggregated SKU groups were plant specific.

5.2 Current Raw Material Inventory Strategy

Niagara's current raw material inventory strategy can be broken into two policies: i) policy for inventory at the supplier and ii) policy for inventory at the plant. As mentioned in the Introduction (1.1.3), Niagara's current ordering and safety stock policy is a one size fits all approach meaning the same policy is applied to all SKUs. The raw material team responsible for inventory at the supplier works to ensure there is 75- 90 days of supply at the supplier site. When the inventory level of a particular SKU drops to 60 days of supply, the team places an order for an additional 60 days of supply to bring the inventory level back to 90 days. This stock sits at the supplier in consignment inventory until Niagara requests for it to be transferred to their plant locations. This ordering policy is driven by the three-week lead time for label production at the supplier.

Niagara's ordering policy for plant inventory is to ensure 14 days of forecasted production demand for each SKU on hand as safety stock. This safety stock is reserved to cover demand variation over the 1-week lead time from supplier to a specific plant location. In addition to this safety stock inventory, Niagara orders to the next 14 days of forecasted and firmed production demand to be held at the plant. Therefore, in total, Niagara aims to have 28 days of supply for each SKU at the plant. Again, the plant raw material ordering policy is a one size fits all approach applied to all SKUs.

Currently, Niagara struggles to collect the appropriate data to have an accurate and historical picture of its inventory position. While the company regularly reviews its inventory policies at a strategic level, Niagara does not archive its production schedule, which is constantly changing, to understand what may have driven buying behavior at a point in time. Instead, Niagara can only review and compare inventory buy decisions to the final executed production schedule. Additionally, to better understand inventory levels at supplier consignment, Niagara began collecting inventory on hand (IOH) data from suppliers via electronic data interchange (EDI) transfers in 2019.

Recently, Niagara recognized that the current raw material ordering policy and safety stock levels may not be optimal. The company dedicated resources to calculate a more optimal safety stock level for label SKUs at the plant. Instead of calculating safety stock as 14 days of future demand for any given SKU, Niagara has applied a more data driven approach to calculate safety stock as in equation (9), where Root Mean Squared Error (RMSE) can be defined as shown in equation (10):

$$\mathrm{SS} = \text{Service Level } \times \sqrt{\mathrm{LT}} \times RMSE \tag{9}$$

$$RMSE = \sqrt{\Sigma_{i=n}^{n} \frac{(P_i - Q_i)^2}{n}} \tag{10}$$

In equation (10), P_i is equivalent to Scheduled Production and Q_i is equivalent to Actual Production in that same period. This metric is meant to capture the accuracy of scheduled production. The accuracy is captured by comparing the scheduled production for a specific SKU 7 days prior to production to the actual production on that date. For example, today is March 1st and today P_i or scheduled production for SKU XYZ on March 8th is 1000 bottles. In a week, on March 8th, the actual production, or Q_i of SKU XYZ is 800 bottles. Therefore, the RMSE calculation for SKU XYZ on March 8th uses P=1000 and Q= 800 as inputs for comparison.

Niagara believes this RMSE approach is a more appropriate method of calculating safety stock using SKU specific data to set safety stock levels as compared to the previous Niagara method. The new safety stock values have not yet been implemented due to organizational challenges. For example, the RMSE method of calculating safety stock results in a higher total level of safety stock in pallets which would require additional space at the plants which cannot always be accommodated.

5.3 SKU Classification Using Customer Demand

Niagara currently segments SKUs based on sales volume. Category A SKUs cover 70% of the total volume. B and C categories cover the remaining 20% and 10% of total volume respectively. The team performed another SKU classification based on coefficient of variation and positive demand probability, as explained in literature review section, to segment SKUs into four sections that indicate forecastability level. An overview of the SKU distribution per segment with Niagara ABC and forecastability approach is shown in Figure 4. From ABC analysis, 14% of SKUs are category A, which covers 70% of the total sales volume. From forecastability analysis, 40% of SKUs are categorized as Smooth, which indicates high forecastability.

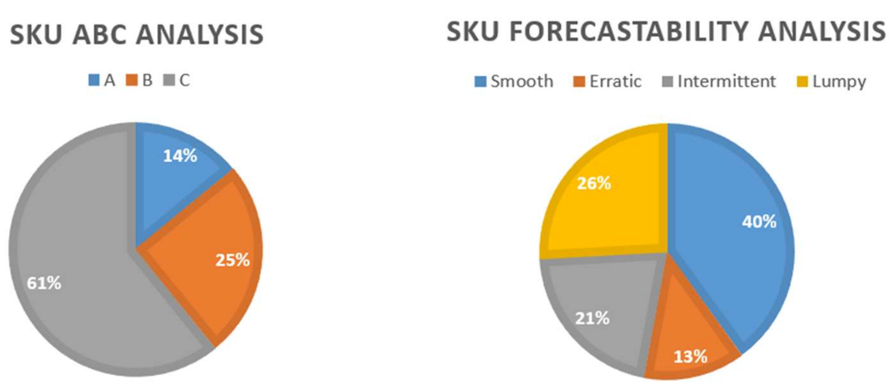

Figure 4: SKU Distribution per Classification Approach

Are SKUs that show high forecastability primarily in category A? A comparison of these two classification approaches was conducted, and the result is shown in Figure 5. Quite a few SKUs from category A show high volatility and low probability of weekly demand, indicating greater difficulty in forecasting these SKUs. Even though SKUs from category C have low sales volume, some of them have very low volatility and regular weekly demand, or Smooth behavior, indicating ease in forecasting.

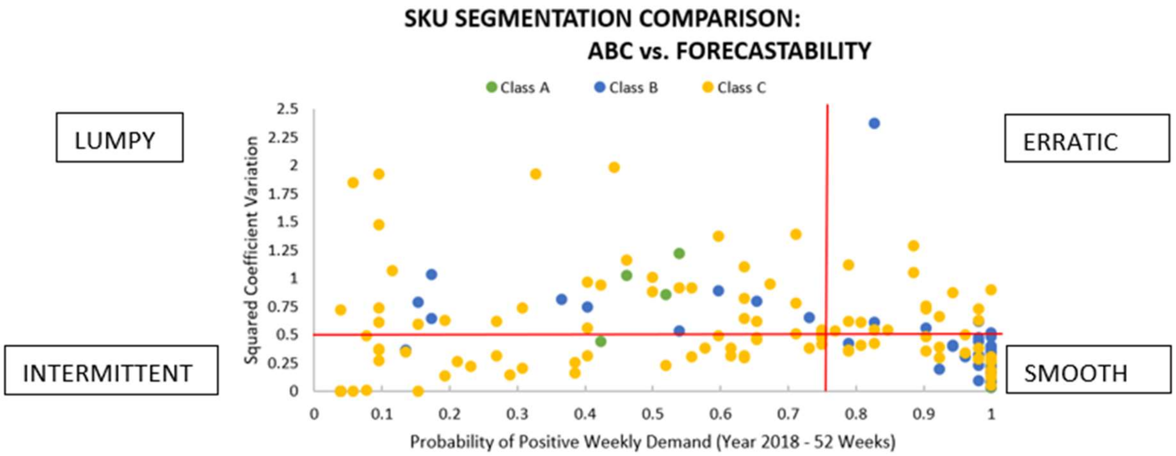

Figure 5: SKU Segmentation Comparison: ABC vs. Forecastability

As a common practice, a different customer service level (CSL) is assigned to different SKU segments. Category A SKUs usually required the highest CSL. Understanding SKU forecastability, in addition to the traditional ABC SKU classification, can be beneficial for supply planning process to properly set the SKU safety stock levels and meet the desired CSL without incurring unnecessary inventory cost.

This SKU classification approach is particularly valuable to Niagara because the current inventory holding target is largely derived from future demand forecast. Having a complete overview of SKU distribution based on forecastability, a supply planner can manage safety stock more proactively and efficiently. For example, for erratic SKUs a supply planner would expect more frequent sudden spikes in demand and therefore can alter inventory holding policy to ensure sufficient inventory is being held at the supplier.

5.4 SKU Forecast Bias

The team utilized the approach presented in section 4.2.2 (Forecast Bias) to evaluate the forecast bias for each raw material SKU with data from customer demand and strategic forecast of 2018. A SKU with a forecast bias at 0.5 is considered unbiased in forecasting due to forecasted demand the same as the actual demand. When forecast bias is below 0.5, a SKU is considered underforecasted, and it is considered overforecasted when the forecast bias is above 0.5. A forecast bias distribution for raw material SKUs in the identified region is shown in Figure 6.

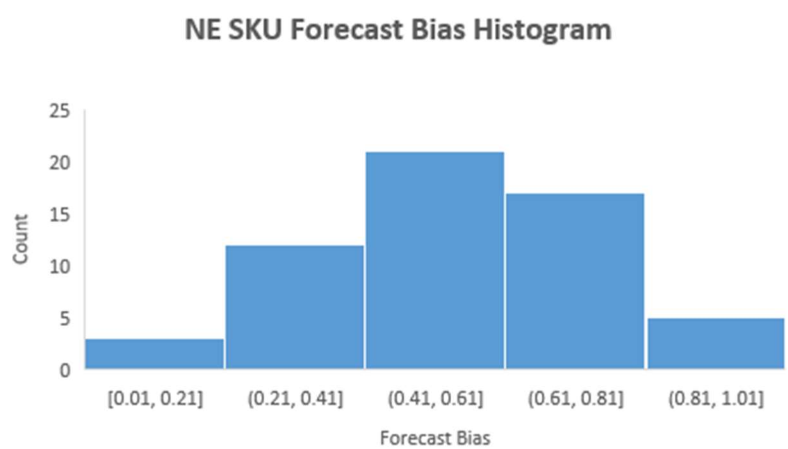

Figure 6: NE SKU Forecast Bias Histogram

The data shown in forecast bias histogram is left-skewed, which indicates more SKUs are overforecasted. If we drill down to see how SKUs behave on forecasting bias in each forecastability category, we found in intermittent and lumpy categories all the SKUs that we analyzed are overforecasted (larger than 0.5 forecasting bias). This data insight matches the current behavior of material buyer, who usually tends to stock up when SKUs demand are highly volatile or with high forecasting error.

It is not intuitively easy to interpret the forecast bias and see how it relates to forecast error. The relationship between these two is shown in Figure 7. Forecast bias changes faster when forecast error is below 0%, which means the SKU is underforecasted. Worst case for underforecasting would be there is actual demand but got forecasted as zero, which shows -100% in forecast error. When SKU gets overforecasted, forecasting bias increases a lot slower due to the larger sum of forecast and actual demand. Forecasting bias will be approximately 0.7 if the forecast is one times the actual demand, and around 0.75 if it is two times. The forecast bias will be one when actual demand is zero, but forecast is not.

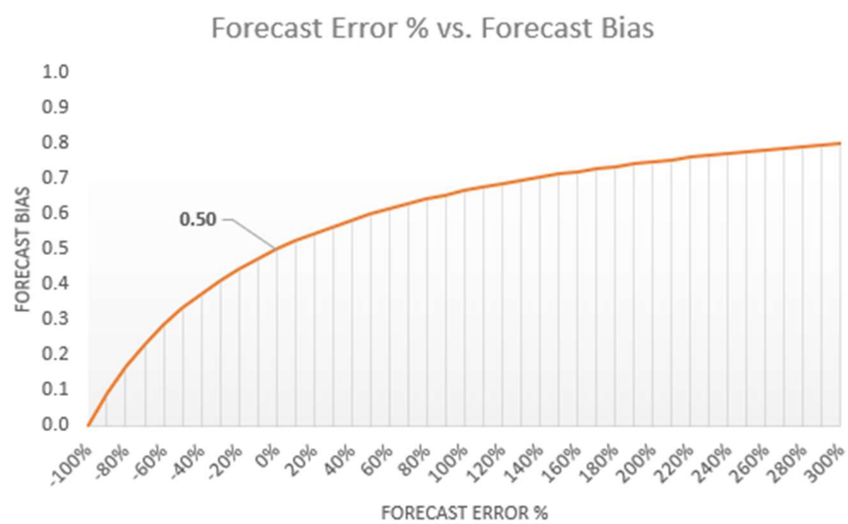

Figure 7: Forecast Error % vs. Forecast Bias

The benefit of understanding forecast bias and analyzing its distribution of SKUs can help the business focus on SKUs with high forecast bias due to their potential of high forecast error, and identify root causes per forecastability group to develop targeted action plans to improve forecasting accuracy.

5.5 Inventory on Hand Analysis

Using the same collected forecast and demand data for 2018 and 2019, the team worked to understand the actual production demand and customer demand for each SKU and compare this data to actual inventory on hand at each plant. Because the SKU groups were segmented per plant, this facilitated a comparison of forecasted demand, actual demand, and actual inventory held at that plant.

This was a good opportunity for the team to understand if Niagara's purchasing policy was actually being implemented at the plants and to identify current inventory levels at the plants.

For example, Figure 8 demonstrates the significant variance in actual inventory on hand (IOH) at the plant for a category A SKU.

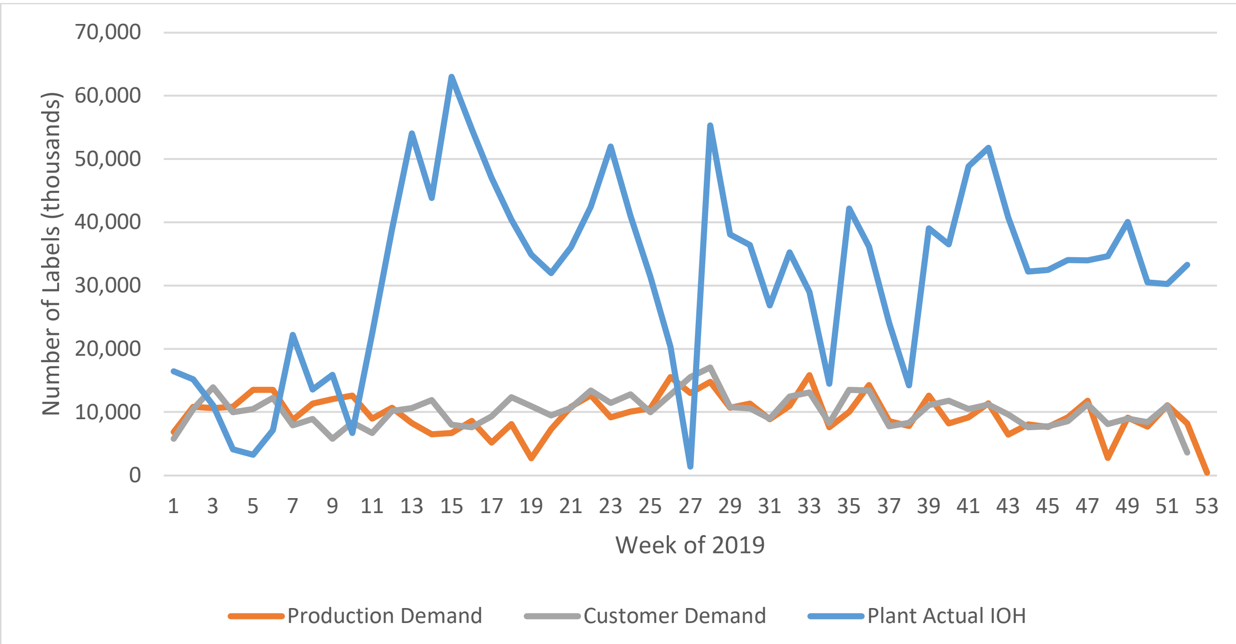

Figure 8: Segment A Smooth Forecastability SKU

The figure shows that the production demand and customer demand throughout 2019 are relatively similar and stable, with an average weekly demand of 10.2 million labels and a maximum weekly demand of 17.1 million labels. On the other hand, the actual IOH at the plant is extremely variable and erratic. According to Niagara purchasing policy, the plant should always have 14 days, or two weeks, of forecasted demand on hand at the plant as safety stock. Therefore, the inventory on hand should not dip below about 20 million labels. Nevertheless 13 weeks, or 25% of the year, the number of labels on hand at the plant is below the designated safety stock level. Moreover, based on the figure it seems as though the plant is holding much more inventory than needed during other weeks of the year.

The team aimed to further analyze what was causing these discrepancies and the best way to improve Niagara's inventory position.

5.6 Safety Stock Calculation

Two safety stock calculation approaches are explored and explained separately in this section. These two approaches differ on the standard deviation used in the safety stock equation: one is defined as the traditional strategy, using standard deviation of customer demand as explained under section 4.2.1. The other is defined as the forecast error strategy, using standard deviation of forecast error as explained under section 4.2.2. With the understanding of Niagara's pain points of demand volatility and struggles in forecasting accuracy, the team seeks to compare these two approaches and determine the most suitable one for Niagara business situation.

The common parameters used for these two safety stock approaches are cycle service level and lead time, as shown in Table 2 and Table 3. The calculation methods will be explained in detail under section 3.6.1 and 3.6.2.

Table 2: Cycle Service Level

Cycle Service Level

ABC Category	Cycle Service Level	Z-score
A	99.8%	2.88
B	99.0%	2.33
C	97.0%	1.88

Table 3: Lead Time

Lead Time

Replenishment Process	Net Replenishment Lead Time
Supplier consignment to plant	1 week
Supplier to supplier consignment	4 weeks

5.6.1 Standard Deviation Using Customer Demand for Traditional Strategy

Historical customer demand data from 2018 is used when calculating standard deviation. The customer demand is segmented into weekly buckets and a simple standard deviation formula in Excel is applied to calculate the customer demand standard deviation among one year of weekly demand data.

One raw material SKU from category A is used to illustrate the calculation results as shown in Table 4. Average demand, standard deviation of customer demand and safety stock are in Thousands of Labels. To convert the safety stock target into number of pallets, the team used: 3 million labels = 1 pallet. Number of pallets is rounded up as the final result.

Table 4: Example SKU Using Customer Demand

ABC Category	Forecastability	Avg. Demand	SD Customer Demand	Z-score	Lead Time	Safety Stock Target	Round up Pallets
A	Smooth	5136	1429	2.88	1 Week	4116	2

5.6.2 Standard Deviation Using Forecast Errors for Forecast Error Strategy

To calculate standard deviation using forecast error, both historical customer demand and strategic forecast data from 2018 are used. The customer demand and strategic forecast are segmented into weekly buckets. One raw material SKU from category A is used to illustrate the calculation result of forecast error for week 1 of 2018, as shown in Table 5. All data in Table 5 are shown in Thousands of Labels.

Table 5: Example SKU's Forecast Error

Week 1 Forecast Demand	Week 1 Customer Demand	Forecast Error
1747	2162	- 415

Weekly forecast error for each SKU is calculated, and then a simple standard deviation formula in Excel is applied to calculate the standard deviation of forecast errors among one year of weekly forecast error data.

One raw material SKU from category A is used to illustrate the calculation results as shown in Table 6. Average demand, standard deviation of forecast error and safety stock are in Thousands of Labels. To convert the safety stock target into number of pallets, the team used: 3 million labels = 1 pallet. Number of pallets is rounded up as the final result.

Table 6: Example SKU Using Forecast Error

ABC Category	Forecastability	Avg. Demand	SD Forecast Error	Z-score	Lead Time	Safety Stock Target	Round up Pallets
A	Smooth	5136	2457	2.88	1 Week	7070	3

5.6.3 Demand Simulation

The team used customer demand and strategic data from 2018 to calculate all relevant statistics and safety stock targets for each raw material SKU. A simulation was performed against 2019 actual customer demand and production demand data to determine the stockout probability for two safety stock approaches. The list of parameters used in the simulation are listed and explained in Table 7.

Table 7: Demand Simulation Parameters

Safety Stock Target	Traditional (Trad.) Strategy	Calculated safety stock as shown in 3.6.1
	Forecast Error (FE) Strategy	Calculated safety stock as shown in 3.6.2
Simulated Average Inventory on Hand	Cycle Stock	Two-week of average strategic forecast demand / 2
	IOH with Trad. Strategy	Safety Stock (Trad.) + Cycle Stock
	IOH with FE Strategy	Safety Stock (FE) + Cycle Stock

2019 Actual Demand	Customer Demand	Actual customer demand data in weekly buckets
	Production Demand	Actual production demand data in weekly buckets
End IOH for Traditional Strategy	Compare w/ Customer Demand	Simulated IOH (Trad.) – Customer Demand (2019)
	Compare w/ Production Demand	Simulated IOH (Trad.) – Production Demand (2019)
End IOH for FE Strategy	Compare w/ Customer Demand	Simulated IOH (FE) – Customer Demand (2019)
	Compare w/ Production Demand	Simulated IOH (FE) – Production Demand (2019)

For cycle stock, the team followed the current buying practice at Niagara, which uses two weeks of forecasted demand of a SKU. The weekly average demand from the 2019 strategic forecast was used in cycle stock calculation for the demand simulation. For calculating stockout probability, after comparing with either customer or production demand, a stockout event is occurred when the end IOH is less than 0. To help illustrate this demand simulation process, the calculation of one raw material SKU from category A is presented in Table 8.

Table 8: Demand Simulation Example

SKU A	**Safety Stock Target**		**Simulated Average IOH**			**2019 Actual Demand**		**End IOH for Trad. Strategy**		**End IOH for FE Strategy**	
Week	***Traditional Strategy***	***Forecast Error Strategy***	***Cycle Stock***	***IOH w/ Trad.***	***IOH w/ FE***	***Customer Demand***	***Production Demand***	***w/ Customer Demand***	***w/ Production Demand***	***w/ Customer Demand***	***w/ Production Demand***
1	7368	11292	8865	16233	20157	13401	9154	2832	7079	17325	11003
2	7368	11292	8865	16233	20157	11416	10073	4817	6160	15340	10084
3	7368	11292	8865	16233	20157	12797	10559	3436	5674	16721	9598
4	7368	11292	8865	16233	20157	9951	15516	6282	717	13875	4641
5	7368	11292	8865	16233	20157	12732	12997	3501	3236	16656	7160
6	7368	11292	8865	16233	20157	15523	14779	710	1454	19447	5378
7	7368	11292	8865	16233	20157	17056	10673	-823	5560	20980	9484
8	7368	11292	8865	16233	20157	10803	11359	5430	4874	14727	8798
9	7368	11292	8865	16233	20157	10561	8860	5672	7373	14485	11297
10	7368	11292	8865	16233	20157	8951	10993	7282	5240	12875	9164
11	7368	11292	8865	16233	20157	12438	15840	3795	393	16362	4317
12	7368	11292	8865	16233	20157	13118	7600	3115	8633	17042	12557

In the example shown in Table 8, the stockout probability for forecast error method while simulating against customer and production demand is 0%, since the end IOH are all above zero. The stockout probability for traditional safety stock strategy while simulating against production demand is

0%. However, while simulating against customer demand, the stockout probability is 8.3%. When stockout probability is 0%, the cycle service level is 100% since all demand is fulfilled within the replenishment cycle. Otherwise, the cycle service level would be the stockout probability subtracted from 100%. In this example, the cycle service level is 91.7% while using traditional safety stock strategy and simulating against customer demand.

5.7 Minimum Order Quantity (MOQ) vs. Full Pallet Analysis

Figure 8 in Section 5.5, which displays Niagara's current state inventory position for a category A SKU over 2019 illustrates erratic inventory holding quantities. One explanation for extreme spikes in inventory on hand at Niagara is the current policy to order only full pallets of labels. While not all label SKUs hold identical quantities on a pallet the difference is insignificant, so the team agreed on the generally true assumption that one pallet holds 3 million labels. The team expected this full pallet ordering behavior would have a clear negative impact on inventory holding for low volume SKUs with Smooth demand behavior. Therefore, the team decided to further explore the relevant costs to ordering, transporting, holding, and potentially scrapping raw material to understand if there was any justification for Niagara to order less than pallet quantities as detailed in Section 6.2.2.

6 Results and Analysis

Using the available 2018 data for customer demand, production demand and strategic forecast, the team calculated recommended safety stock levels using two different approaches as described in section 5.6 and compared to 2019 actual customer demand and production demand data. The simulation results revealed that the forecast error safety stock strategy resulted in fewer stockouts and higher cycle service levels as compared to the traditional safety stock strategy. Moreover, the analysis revealed that when compared with the actual IOH at Niagara plants, there is an opportunity for savings through lower safety stock inventory levels. While there are several limitations to our analysis, such as limited data, the team's findings suggest Niagara could significantly reduce inventory levels for SKUs in Smooth forecastability category while keeping the same high cycle service levels.

6.1 Safety Stock Simulation Results

6.1.1 Traditional vs. Forecast Error Safety Stock Strategy

After calculating the recommended safety stock level for each SKU with appropriate data available, 110 SKUs, using both approaches, the simulation was executed as described in section 5.6.3. Table 9 summarizes the cycle service level, or probability of fulfilling all demand during replenishment cycle, averaged across each week in 2019 per forecastability category. Each forecastability category consists of 5 representative SKUs chosen at random.

Table 9: Service Level Results from Simulation per Forecastability Category

SKU Forecastability Group	Traditional Strategy		Forecast Error Strategy	
	Production Demand	Customer Demand	Production Demand	Customer Demand
Erratic	91%	96%	96%	99%

Intermittent	79%	90%	83%	92%
Lumpy	90%	91%	94%	89%
Smooth	97%	99%	100%	100%
Total Average	**89%**	**94%**	**93%**	**95%**

As shown in the table, the forecast error strategy results in higher service levels, especially when the safety stock strategy is simulated against production demand. Moreover, the table demonstrates the very high service levels achieved within the Smooth forecastability SKU category. There were no stockouts during any of the 52 weeks in the simulation when safety stock levels were set using the forecast error approach. On the other hand, the table communicates the difficulty managing safety stock levels to accommodate the production demand for intermittent SKUs.

Using the same example SKU from Figure 8, the suggested safety stock for each approach was added to the graph to illustrate the differences between the forecast error strategy, the traditional strategy and Niagara's current safety stock approach in Figure 9. This raw material SKU is a high volume in the Smooth forecastability category.

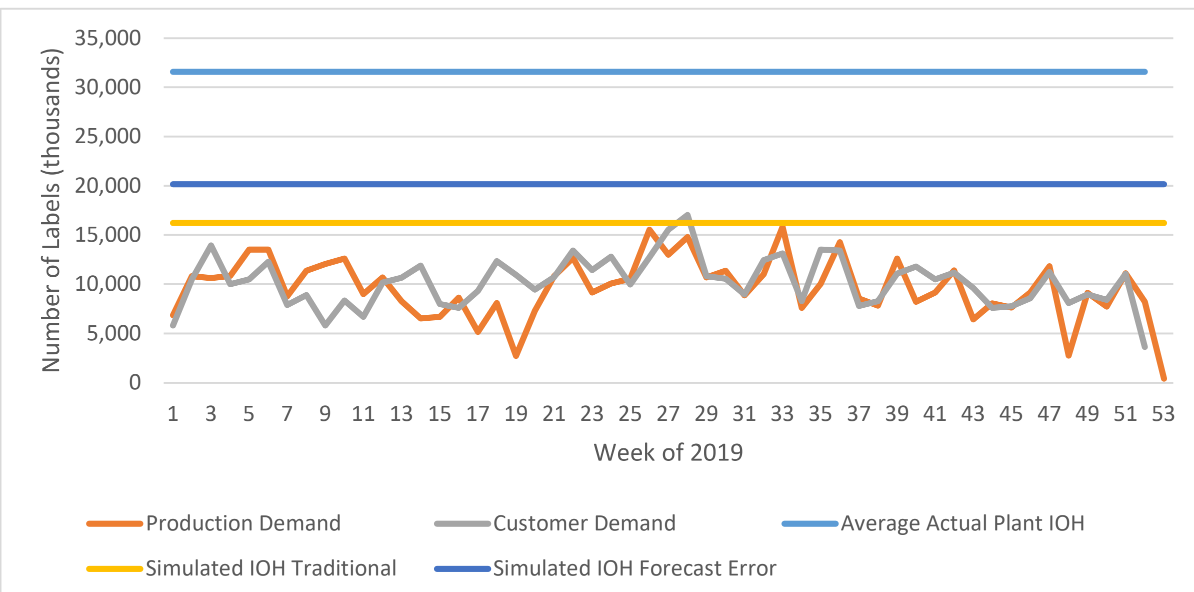

Figure 9: Safety Stock Approach for Segment A Smooth Forecastability SKU

The figure shows that the safety stock recommendation based on the forecast error approach results in a higher volume of raw material on hand at the plant as compared to the traditional safety stock approach. Moreover, because the customer or production demand is never higher than the 'Simulated IOH Forecast Error', it is clear the inventory policy developed using forecast error results in zero stockout. The same is not true for the inventory policy developed from the traditional safety stock formula or 'Simulation IOH Traditional' in Figure 9.

The team noticed the differences between traditional and forecast error inventory policies were generally attributable to the forecast bias as defined in Equation 6. When the forecast bias is close to 0.5, the forecast is not biased, and, therefore, the safety stock calculated using the two different methods will be very similar. On the other hand, when the bias is greater than 0.5 or less than 0.5 this suggests an overforecasting or underforecasting of demand. Therefore, the standard deviation of forecast errors will be greater, which will drive up the safety stock of these SKUs. Moreover, when a SKU is overforecasted, the inventory on hand will be greater not just due to higher standard deviation of forecast errors but also due to the higher than necessary cycle stock as cycle stock is based on the forecast for the next 14 days.

Lastly, the inventory position of the example SKU graphed in Figure 9 shows a clear disconnect between the suggested future inventory position and the current strategy. For the lower volume SKUs, this disconnect is driven by Niagara's minimum ordering policy of one full pallet or three million labels, however, for this high-volume SKU it suggests erratic ordering frequency and volume. This erratic ordering could be due to various factors such as infrequent review of inventory on hand, discrepancies between forecast and actual demand, or attempt to utilize the full capacity of trucks in transporting raw materials. Regardless, this erratic behavior represents an opportunity to smooth out raw material holding quantities to match demand trends and potentially save money depending on implications to transportation and ordering costs.

Ultimately, the team identified the forecast error safety stock method as the optimal strategy due to Niagara's seasonal demand, ability to continuously review inventory levels, the service levels generated from the simulation shown in Table 9. For the 110 SKUs analyzed, this approach resulted in a higher total number of pallets of safety stock at the plant when compared with the traditional safety stock approach, 143 pallets as compared with 118 pallets. However, when comparing total pallets of inventory on hand required at the plant for the 101 SKUs with available data, the number of pallets using the forecast error safety stock method, 165 pallets, was significantly less than the current state, 209 pallets. For all these calculations, labels were rounded up to order in full pallet as is Niagara's current practice. In the next section, the team will further explore trends in opportunities for reduced safety stock pallets at the plants using a forecast error approach to set safety stock levels.

6.2 Recommended Inventory Level Comparison

When further comparing the current state to suggested inventory levels by forecastability category, the team noticed that a majority of the inventory reduction opportunity was among SKUs within the Smooth forecastability category. Moreover, the team conducted an analysis to prove that depending on key assumptions regarding cost of obsolescence and cost to order, there are circumstances in which ordering less than a pallet is a more cost-effective inventory policy.

6.2.1 Opportunity in Inventory Level Reduction for Smooth SKUs

Figure 10 illustrates the potential change in pallets held at the plant when the forecast error approach of calculating safety stock is applied. In total, 47 pallets could be removed from the specific region network from the raw material inventory held for around 100 SKUs. As is obvious from Figure 10, a majority of the pallet reduction is from the SKUs within the Smooth forecastability category. It is important to note, that the 100% cycle service levels for the Forecast error approach and Smooth category SKUs shown in Table 9 were achieved in the simulation with this reduced number of SKUs. This demonstrates negligible impact on the customer and associated service levels, yet savings in inventory holding and additional space availability at the plants.

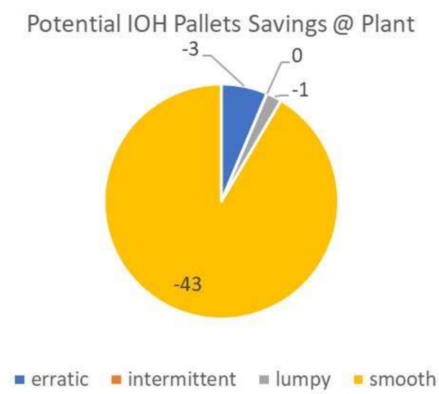

Figure 10: Potential IOH Pallet Savings

Figure 11 shows this change in pallets held at the plant per SKU. Again, it is clear the SKUs with the most obvious reduction in pallets all belong to the Smooth forecastability category, yet there are also some within this SKU segment that require additional pallets. A majority of the SKUs, over 60%, have no change in raw material holding volume using the new forecast error method of calculating safety stock and rounding all recommended volumes up to the next full pallet.

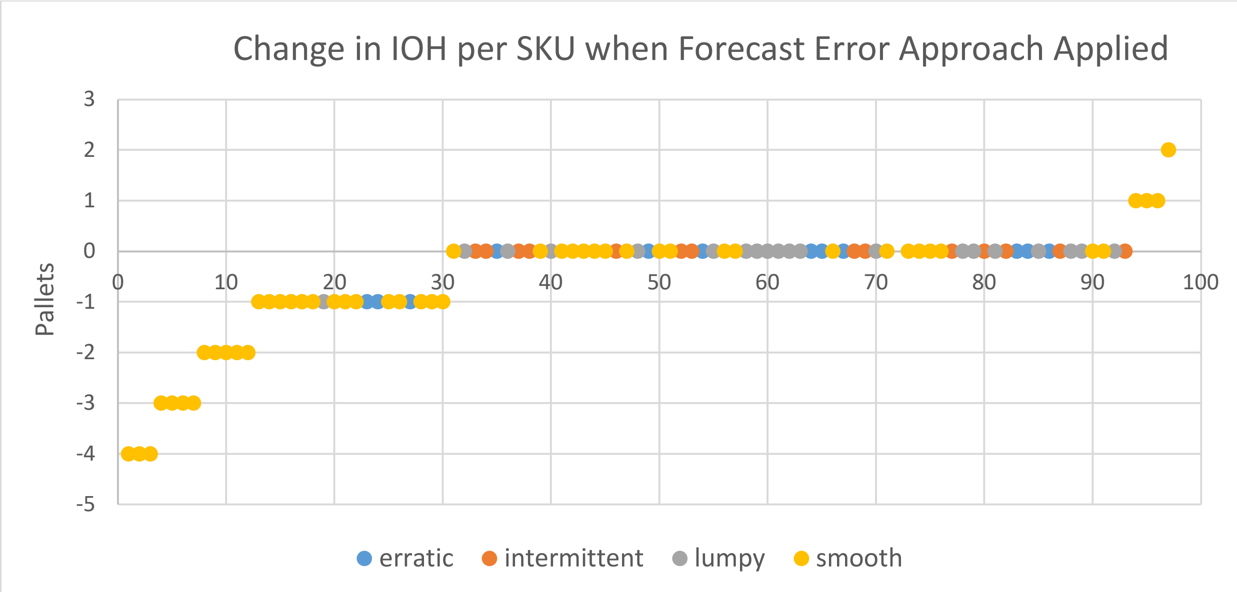

Figure 11: IOH Potential Pallet Savings per SKU

This reduction in pallets in the network results in potential cost savings for Niagara. Table 10 shows the difference in holding costs per pallet per plant as applied to the reduction in pallets due to the new forecast error approach of calculating safety stock. Using the assumptions listed, the total potential savings in the specific region's network is around $225,000. The team estimates if this policy is rolled across the entire Niagara network and all SKU groups, this has the potential to be increased to 10X this savings, or $2.25 million.

Table 10: Potential Cost Reduction using Forecast Error Safety Stock Approach

Cost Reduction						
Plant	**Annual Holding Cost/Pallet**	**Pallets Reduction**	**Number of Labels (Thou)**	**Raw Material Cost**	**Holding Cost**	**Total Savings**
P1	366	22	66000	99000	8051	107051
P2	33	5	15000	22500	163	22663
P3	313	1	3000	4500	313	4813
P4	410	13	39000	58500	5326	63826
P5	17	6	18000	27000	102	27102
Consignment	90					
					Total	**225456**

6.2.2 Opportunity in Ordering Minimum Order Quantity

The team identified an opportunity to order less than a pallet for low volume SKUs. For example, Figure 12 displays a SKU with intermittent and low customer and production demand throughout 2019. The actual IOH levels at the plant are high compared to demand due to the minimum ordering quantity of one pallet, or three million labels. While one pallet takes up the same amount of space at the plant, whether it is completely full or half full, the team wanted to better understand all associated costs to ensure this was the best ordering policy to balance all costs.

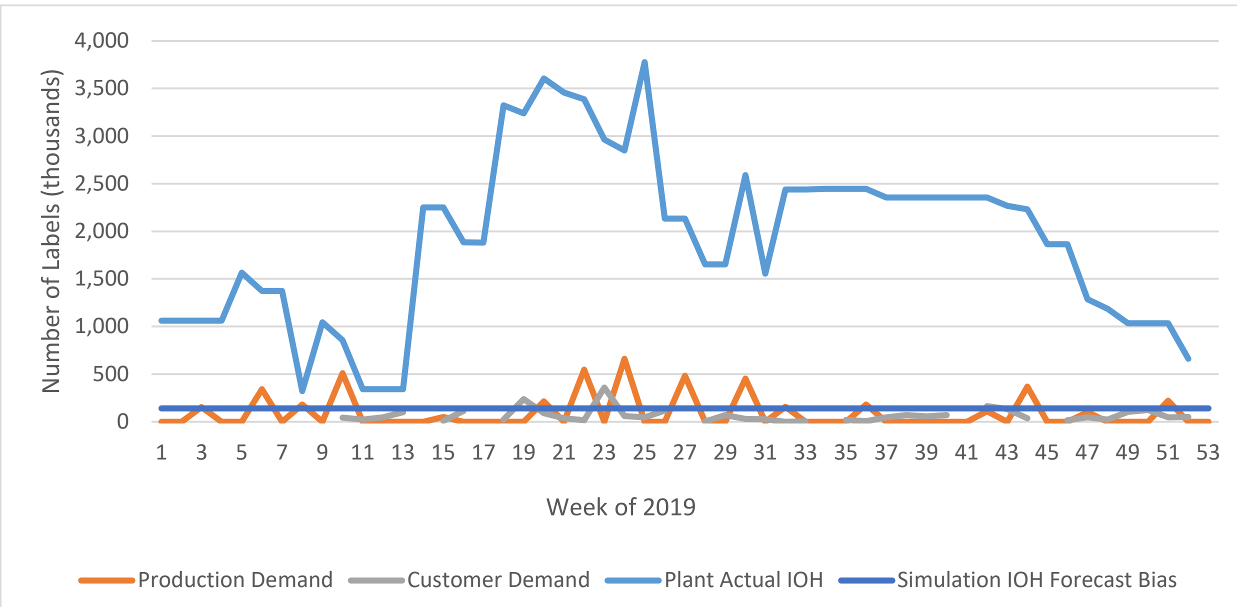

Figure 12: SKU with Low Demand Volume MOQ Example

A breakeven analysis was conducted to understand under what circumstances a lower ordering quantity would be cost effective. Relevant costs identified by the MIT and Niagara team included: ordering cost, transportation cost, inventory holding cost, obsolescence cost, and raw material costs. A majority of Niagara's raw material labels have significant cost savings per piece when ordered at higher quantities. Using assumptions agreed upon by the team on the above listed costs as well as operational assumptions such as a two-year label shelf life due to changing designs and regulations and an alternate

MOQ of 500,000 labels as inputs. The Figure 13 breakeven model was created based on forecasted annual demand of SKUs.

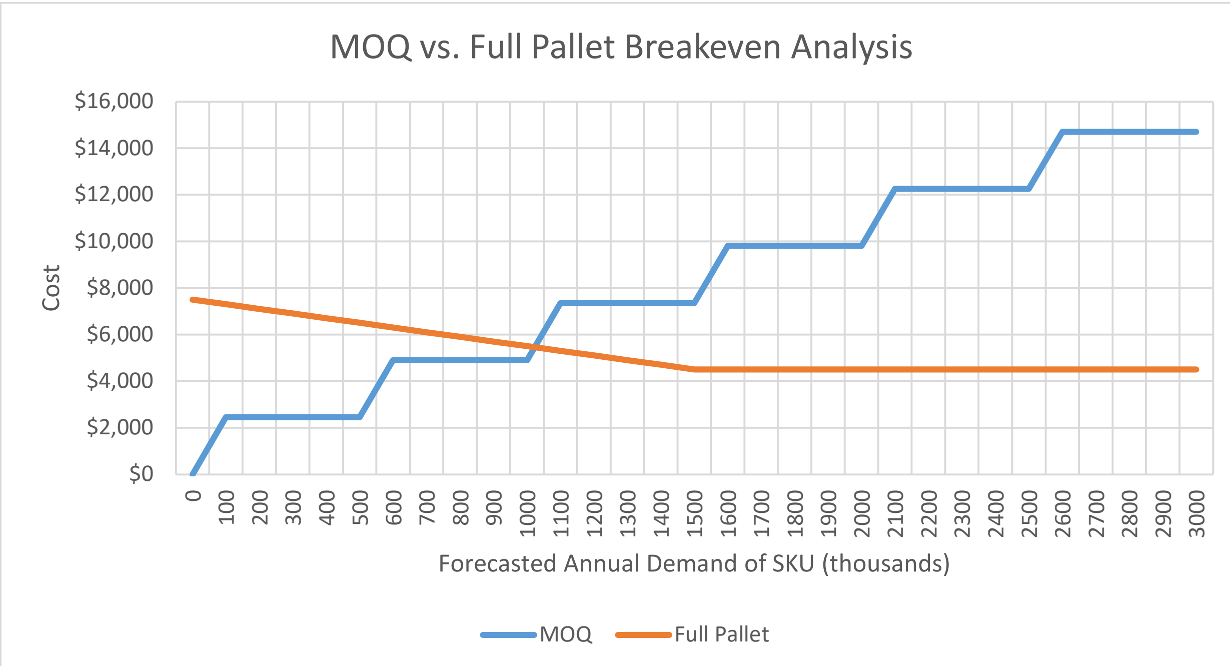

Figure 13: MOQ Breakeven Model

The MOQ breakeven excel model helped to illustrate to the team and the sponsor that in some circumstances, such as when the forecasted annual demand of a SKU is less than 1 million, it is more cost effective to order a MOQ of 500,000 labels. In operation, this only impacts around 13% of SKUs in the specific region. However, this was a learning to be passed on to buyers and potential cost savings, especially if rolled out across the entire Niagara network. The excel MOQ breakeven analysis tool is dynamic so that the sponsoring company can continue to change assumptions and costs to make effective and appropriate conclusions as needed in their changing business environment.

6.2.3 Summary

After a deep dive into the selected safety stock strategy, trends were revealed around the negative impact of Niagara's current inventory policy leading to excess inventory for SKUs with predictable and stable demand. The team identified the opportunity to apply the new safety stock approach and reduce pallets of these SKUs at the plant while keeping high service levels, 100%, as indicated through the simulation. The team also came to the conclusion that it is appropriate to have different ordering strategies for different SKU classification categories to capture the cost savings opportunities presented.

6.3 Limitations

Niagara is aware of the high volatility in its production demand, especially between day three and day seven during the seven-day firm production demand window. Both the team and Niagara are interested in learning how production demand variation, comparing planned production demand sent prior seven days with the actual production demand, would effect safety stock target and stockout probability. However, due to the difficulty of acquiring planned production data, the team was not able to conduct this analysis and analyze the results.

7 Conclusion

7.1 Recommended Safety Stock Strategy

Based on the analysis and results presented in the previous sections, the team recommends the forecast error approach as the optimal safety stock strategy for Niagara. During simulation against seasonal actual customer and production demand, this strategy demonstrates satisfactory cycle service levels on top of a reduction of current raw material inventory levels. Coupling with the recommended forecast error safety stock strategy, a new classification method to segment SKUs into different forecastability categories is also recommended to help Niagara target the right SKUs for the right corrective actions.

It is clear from our analysis that there should not be a one-size-fits-all safety stock strategy across all SKUs. Due to different demand characteristics and forecastability in SKUs, it is recommended to segment these SKUs into different forecastability categories that share similar demand patterns in order to efficiently review and drive inventory improvement. For Niagara, the biggest inventory reduction opportunity is in the Smooth forecastability category, which includes SKUs with lower demand volatility and better forecastability. Right sizing the inventory levels for these SKUs brings significant inventory reductions and cost savings.

For SKUs that are difficult to forecast and show high demand volatility, such as those in the intermittent and lump forecastability categories, the team recommends to right size the ordering quantity to improve inventory levels while maintaining the same or better cycle service levels. Niagara can choose to order in minimum order quantity when the annual forecasted demand of a SKU is under the threshold recommended from the analytical model.

Last but not least, ensuring the input data accuracy and integrity and establishing a periodic review practice are also the keys to a good safety stock strategy. Raw material SKU lists are dynamic due to new product introduction or obsolescence annually. Therefore, it is important to proactively manage these SKUs and preprocess the data before interpreting the results from the models.

7.2 Safety Stock Strategy Implementation

To help Niagara implement the forecast error safety stock strategy, the team decided to operationalize most of the analysis procedures. Excel was chosen as the tool for automation for several reasons. First, it is recognized as the most widely used tool at Niagara and employees have sufficient knowledge to quickly operate the models to see any immediate impact. Second, it provides enough flexibility for data input, parameter adjustments and data visualization for quick verification.

The team will provide Niagara a template of operationalized strategy in three main sections: SKU forecastability classification, SKU safety stock target calculation and the MOQ breakeven model. The required data input, parameter input and output for each template section are shown in Table 11.

Table 11: Operationalized Strategy Template

Template Section	Data Input	Parameter Input	Output
SKU Forecastability Classification	Historical customer demand (weekly) per SKU	Squared CoV, Probability of positive demand	Forecastability category assignment per SKU
SKU Safety Stock Target Calculation	Historical customer and forecast demand (weekly) per SKU, ABC category per SKU	Lead time, Cycle Service Level per ABC category	Safety stock target per SKU

MOQ Breakeven Model	Historical forecast demand annually per SKU	Raw material price (UOM), Ordering/holding/ obsolescence cost, time to obsolescence	List of SKUs that are recommended ordering in MOQ

7.3 Insights for General Management

One of the first opportunities identified by the team was to take advantage of supplier consignment inventory contracts. All label suppliers hold raw material inventory for 90 days free of charge. The more the team dug into the data, the more the team realized the extreme upside of these agreements, which essentially offer free inventory holding to buffer risk of potential spikes in demand with low downside due to low cost of obsolescence. Moreover, after the 90 days, suppliers charge a relatively small amount per pallet per month, less than the annual holding cost at three of the five plants in the specific region network. This early win has “already shifted our buying practices,” according to Niagara team members.

Additionally, the team identified an opportunity for better data collection and review to inform the inventory strategy and buying practices of Niagara. For example, as mentioned previously, the Niagara team uses planned production data as compared to actual production data to calculate the root mean square error as a potential alternative method to calculate safety stock. However, this planned production data is not archived. The only accessible historical data related to production data is the actual production data. This presents an opportunity for further data archiving to better understand the planned production, which is driving buying requirements and the inconsistencies as compared to what is executed on the production floor.

Additionally, while Niagara receives daily EDI transmissions from the supplier as of the past year to understand inventory position, there is an opportunity to more frequently aggregate and review this data on the strategic level. By collecting the data and filtering by plant, SKU classification, and supplier, this data can be compared to inventory on hand at the plant to identify trends and opportunities for potential inventory savings or service level improvements proactively. The team recommends a bi-annual or quarterly review of the inventory picture at both the supplier and the plant to ensure current inventory policies are being implemented and ensure the approach makes sense given the business environment.

When reviewing and evaluating inventory positions, the team recommends Niagara bucket inventory into safety stock and cycle stock and examine separately. Currently, all inventory is lumped together and not categorized or classified to clearly identify what volume is being held as safety stock and which is being ordered to future demand. By better categorizing the intent or purpose of the raw material inventory, it will be easier to make conclusions about whether adequate inventory levels are being held in each bucket and where adjustments might need to be made. This will allow Niagara to derive actionable items to address the real drivers of excess or shortages in inventory for the different inventory classes. Other potential classifications of inventory are pre-build stock and promotional stock. These classifications should be separated from actual demand so that the team has a better picture and understanding of the actual drivers and urgency of production demand. Furthermore, when reviewing inventory levels and stockouts from a strategic level, better conclusions can be drawn to address the root cause and continuously improve Niagara's inventory position and service levels.

As alluded to above, these bi-annual or quarterly inventory reviews should also include a review of specific high impact stockout events. By performing a detailed root cause analysis with the key stakeholders, the team can make valuable conclusions about what is working in the system and where additional opportunity for improvement is present. The SKU segmentation based on forecastability as recommended should also be reviewed to ensure SKUs are properly classified and to ensure newly added SKUs are appropriately added to the classification structure.

One final recommendation from the team is to ensure that actual customer demand is driving inventory levels as opposed to production demand. While it is true, production demand could be accounting for pre-stock buildup and other one-off events, the ultimate goal should be to order to customer demand and ensure customer demand is driving all associated production activities.

7.4 Future Research Recommendations

While the team's research focused specifically on raw material safety stock, future potential research could extend this analysis to create an optimization model for inventory levels within the plant between both the raw materials and the finished goods safety stock. Moreover, the team presented an alternate SKU classification method using the forecastability of the SKUs, but there is a further opportunity to segment SKUs based on profitability. This would allow Niagara to differentiate its service to ensure customers who provide the most profit receive the best service. It would also allow the sponsor company to identify customers with low profitability as potential clients to work to renegotiate prices and terms. Lastly, as the recommended safety stock strategy is based on forecastability, it is important to dedicate adequate resources to frequently review, revise, and update the forecast of finished goods and raw materials. While the forecast will always be wrong, when it's very wrong, it will have a significant impact on cycle service levels and raw material inventory across the network.

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