Supply Chain Simulation for Production Strategy Evaluation

By

RUI YIN TAN

and

CATHERINE OSWALD BALLALI

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Signature of Author: ____
Department of Supply Chain Management
May 14, 2021

Signature of Author: ____
Department of Supply Chain Management
May 14, 2021

Certified by: ____
Dr. Cansu Tayaksi
Postdoctoral Associate, Supply Chain Management Program
Capstone Advisor

Certified by: ____
Dr. Karla Gamez Perez
External Advisor

Accepted by: ____
Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

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RUI YIN TAN

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CATHERINE OSWALD BALLALI

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ABSTRACT

The Consumer Product Goods (CPG) industry such as the bottled water business is subject to bottlenecks, due in part to both product characteristics, stochastic nature of the demand of products, and customer lead time volatility. Nevertheless, CPG companies are expected to be able to serve customers that rely on their products, even as demand can be unpredictable and erratic. In CPG companies, where the multi-stock keeping units (SKUs) and multi-period nature of manufacturing systems are taking place, finding the right balance between Make-To-Order (MTO) and Make-To-Stock (MTS) production strategy proves difficult. To ensure customers' demand is fulfilled, this capstone analyzes the current production strategy of the capstone sponsor, a bottled water company, and incorporates the dynamic market demand and customer lead time volatility to determine the best production strategy that will be capable to meet 90% fulfilment rate In this capstone, we developed a System Dynamics (SD) and Discrete Event Simulation (DES) to understand the overall drivers of supply chain and production strategy that minimizes the total relevant costs (inventory holding and change over costs) whilst producing the highest fulfilment rate. We analyzed live orders, forecast orders, economic production quantity (EPQ), safety stock (SS) of 10 key SKUs and ABC SKU segmentation of 1300 SKUs for one production plant over the last year. Scenarios of demand, forecast and lead time uncertainty were simulated to provide insights into key drivers of the model behavior and guide insights into useful production policies. Our findings demonstrate that in manufacturing systems characterized by stochastic demand and volatile lead times, understanding SKU characteristics (EPQ, SS, and Inventory levels) is critical to meet market demand with the optimal cost more so than the order patterns.

Capstone Advisor: Dr. Cansu Tayaksi
Title: Postdoctoral Associate, Supply Chain Management Program

External Advisor: Dr. Karla Gamez Perez
Title: Logistics Transformation Manager, Sigma Alimentos

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1. INTRODUCTION

A fundamental problem faced by any manufacturing company is the trade-off between what to produce, how much to produce, and when to produce. Industry's best practices use fulfillment rate and operation cost as key performance indicators to balance production strategies and inventories. Leading manufacturing companies in the Consumer Packaging Goods (CPG) industry are changing their production strategies to be agile and robust while maintaining quality and quantity commitments to their customers. CPGs operate in great complexity, with moving parts that include vendors, distributors, third-party logistics, and consumers, to name a few. These components are often siloed, therefore, there is a need for a robust production strategy that captures end-to-end supply chain components.

In this capstone, we analyze the balance between Make-To-Order (MTO) and Make-To-Stock (MTS) production strategy given the multi-stock-keeping units (SKU) and multi-period nature of manufacturing systems to understand the overall drivers of supply chain and production strategy that minimizes the total relevant costs (inventory holding and change over costs) whilst producing the highest fulfillment rate.

1.1 Company Background

Niagara Bottling (will be mentioned as Niagara in the rest of the capstone), is the largest bottled water manufacturer in the US, supplying major retailers across the nation. In the US alone, it has a massive manufacturing footprint of 33+ plants and an annual logistical volume of over one million full truckloads. To meet the needs of seasonal inventory, build and operational inventory flows, Niagara also operates a network of 15+ offsite warehouses and contract manufacturers. Niagara also produces and delivers single-serve private label beverages for grocery, club, convenience, and wholesale customers.

Niagara as the leading company in the bottled water industry has its way of working to ensure they always meet customer demand on time. In this section, we will deep dive into the approaches used by Niagara on demand forecast, customer lead times, and their current production strategy to mitigate its challenges.

1.1.1 Demand Forecast - Seasonality and Volatility

Niagara faces a seasonal distribution of demand for bottled water. The demand usually peaks in the summer, from May to August, with the non-peak season running from September to April. Sales double in the summer (Chua and Heyward, 2017) especially around the July 4th holiday, and dip significantly during the winter months.

Given the seasonal demand distribution, Niagara's production strategy follows a hybrid model: make to stock (MTO), a production strategy used by a company to match anticipated demand during non-peak season and make to order (MTO), a production strategy that typically begins production process only when customers orders is received during peak season. Prebuilding of inventory during the low season ensures that production capacity is optimized. Prebuild inventory is then used to fulfill demand during peak season when production capacity is level. Prebuild inventory is usually stored in third-party warehouses (3PLs), which increases Niagara's inventory handling costs. Production at their 13 facilities is siloed, and Niagara is experiencing challenges ensuring that a harmonized production strategy is adopted across all its facilities.

1.1.2 Customer Lead Times

Niagara has vertically integrated its supply chain and manufactures its bottles and all packaging, including labels, and bottle caps. However, it still faces the challenge of fluctuating customer order patterns. Niagara's standard lead time is 3-7 days, but it has had to react to customer orders with less than 24 hours lead time (T.Zheng, personal communication, October 6, 2020). Without a robust production strategy, Niagara is unable to meet its customers' stochastic demand if there is no stocked inventory.

1.1.3 Current Production Strategy

Niagara's production strategy complexity is driven by inventory levels, shifting order demands, production capacity, order forecasts, and raw materials availability. Niagara's release production plan is based on a 21-day horizon. Their freeze daily production plan is 48 hours before an actual run. Economic Production Quantity (EPQ) is used in production planning to minimize the total production cost while maximizing output. However, due to volatility in demand and production line performance, the EPQ adherence rate is low, according to Niagara. In the event of an expedited request, such as requests caused by the demand surge during the pandemic, Niagara changes its production strategy from make-to-stock (MTS) to make-to-order (MTO) and just-in-time (JIT).

Niagara segments its SKU into 3 categories, A, B, and C. Segment A represents fast-moving items, which accounts for 85% of total SKUs. Niagara ensures that inventory for this segment is available for a minimum 1 to 3 days of supply. Segment B and C represents slow-moving items, which account for 15% and 5% of the total number of SKUs respectively. For these segments, the strategy adopted by Niagara is to review the demand every 3 to 4 weeks to ensure no shortage of supply.

1.2 Motivation

With the impact of the COVID-19 pandemic in 2020, CPG saw sales growth of 9.5% in the US over the past 10 months (Conway, 2020). The surge in demand significantly impacted the operations of most CPG companies. To maintain acceptable service levels of 90% during disruptions such as COVID-19 pandemic, CPG companies need to be agile in response to spikes and react quickly to fill customer orders. Companies that adapt quickly to market changes earn better market share. Therefore, forecasting the right inventory level can generate high profit and a dynamic production strategy adds value to supply planning.

To mitigate the risk posed by short customer lead times and demand volatility, Niagara uses finished goods (FGs) safety stock to cover the demand uncertainty. FGs are stored in Niagara's facilities and third-party warehouses. An increased level of safety stock has consequently increased inventory holding cost, causing a strain in Niagara's production cost. In the year 2020 alone, Niagara spent $1M in inventory holding cost, 14% of its operations cost.

Niagara aims to improve its production position to minimize the cost of inventory storage and the production strategy changeover cost associated with stochastic demand without compromising customer service levels. Therefore, we developed a robust system dynamics and discrete event simulation models to capture the optimal production strategy while considering driving factors such as customer order demands, inventory levels, transportation, capital equipment, and infrastructure. The simulation models we built aim to provide a production strategy that will reduce overall operating costs while keeping the customer service level within the company's targeted range of 90%.

The organization for the rest of this capstone is as follows: In chapter 2, we present the Literature Review to understand the production strategies and simulation models utilized in the industry and in literature that can be related to CPG companies like Niagara. In chapter 3, Data and Methodology, we analyzed the SKU data and segmentation, modeled various production strategies for SKUs, and studied their impact on the cost of the operations of the company by assessing change over costs and inventory holding cost. We also quantified the current inventory policy with recommended SKU segmentation and compared it to Niagara's SKU segmentation to understand the variance. The overal aim was to build a model that is flexible and robust enough to offer flexibility in its modifications. Finally, in chapter 5, the Result and Discussion section, we provide recommendations for the best production strategy for the Niagara team.

2. LITERATURE REVIEW

This literature review is organized as follows: the first section explores the Production Strategy literature, which covers three key methods: make to stock (MTS), make to order (MTO), and just in time (JIT). The second section explores simulation models that can be used to optimize production while achieving a high level of service at the lowest cost possible. The third section reviews the three capstones and theses by MIT Supply Chain Management students partnered with Niagara done by Sweeney and Pan (2020), which explored safety stocks and managing inventory using forecasted demand, Chandra and Tully (2016), and by Chua and Heyward (2017), which provided the EPQ model that is used in production planning at Niagara today. All three papers provided key insights into Niagara's past supply chain challenges and contributed to how we framed our approach to tackling the production strategy challenge currently faced by Niagara.

2.1 Production Strategies

Production strategies are distinguished based on how the strategy fulfills the demand of customers' orders. CPGs employ a production strategy that aims to reduce costs while also maintaining a high level of customer service. Inventory costs make up a large portion of total manufacturing costs in most production facilities. Therefore, efficiency is achieved when production and inventory systems are aligned. In a multi-product manufacturing facility like Niagara, the most important decision is when to produce and how much to produce. Production strategy policy answers these important decision points (Gunalay, 2010) .

Make-To-Order (MTO), also known as assemble-to-order, usually offers products that can be assembled rapidly in response to customers' orders. This strategy's complexities consider the outstanding orders and their delivery dates, inventory, and production status before fulfilling each order. Therefore, the decision of how much to produce in the MTO strategy can only be done after Inventory levels, Economic Production Quantity (EPQ) is determined (Donk, 2001).

As the manufacturing industry has seen an increase in operating costs, the implementation of lean manufacturing practices has increased in popularity. CPGs have gravitated towards running lean and efficient supply chain practices, such as maintaining minimal inventory, to curb the pressures of increasing inventory. Therefore, they rely on the MTO strategy to minimize costs and waste such as inventory holding costs (Donk, 2001).

On the other hand, for CPGs to maintain a competitive edge in the industry, a greater emphasis has been put on maintaining satisfactory customer service as a means of differentiating them from their competitors. Maintaining satisfactory customer service requires having inventory thresholds of Make-To-Stock (MTS) and prompt delivery of MTO products by their agreed-upon due dates (Kaminsky and Kaya, 2006).

Trying to minimize holding costs while at the same time ensuring reliable and short lead-time delivery for customers are conflicting objectives in supply chains that exhibit stochastic demand and processing times. Ideally, companies would like to initiate production at the time of customer order arrival to minimize inventory holding costs, however, this strategy usually leads to long lead times for customers' order delivery (Kaminsky and Kaya, 2006).

The tradeoff between MTS and MTO production strategy has pushed many companies to adopt a “hybrid” production strategy that combines both MTO and MTS at different stages of their supply chains and for different SKUs (Kaminsky and Kaya, 2006). For example, for Niagara, 92% of their SKU profile utilizes a hybrid production strategy throughout the year.

According to Hax and Candea (1984), the standard production planning strategy for multi-product and multi-period production like Niagara’s will need to consider the minimization of production costs such as variability change over costs, inventory, and shortage costs. MTS is a strategy usually utilized when demand experiences seasonality. Just-In-Time strategy is usually employed for products that have a very short lead time and/or high holding costs.

According to Schumer (1981), a strategy selection also depends on the tradeoff between holding inventory costs, uncertainty across customer demand patterns (quantity and lead time), and product type. He explained that companies with seasonal demand, such as Niagara, tend to adopt a make-to-stock policy because there is an economic justification for inventories having decreasing costs or increasing economies of scale (lowering the ordering and set up costs of production runs) in procurement and production. Schumer (1981) concluded that MTO policy also reduces the anticipated variability of raw materials and orders. Since Niagara’s demand is seasonal, their choice of employing MTS policy is justifiable.

2.2 Simulation Models

Simulation is a way to imitate the real-world operation to understand the trend and impact of the current design system over time. The simulation also refers to a broad collection of methods and applications to mimic the behavior of a real system usually on a computer with appropriate software (Smith, 2008). Simulations are usually built based on historical data to draw critical inferences from the real operations. It is a problem-solver methodology that allows the engineer to perform business analysis to understand the area of improvement and can also be used to pilot run new strategies. In Niagara's case, it is suitable to study the chronological order of production events and determine the best production strategy for the current operation. In this section, we focus to study on four different simulation approaches; system dynamics approach, linear programming mathematical modeling, discrete event simulation, and hybrid optimization and simulation approach.

2.2.1 System Dynamics Approach

System dynamics (SD) is robust a modeling method that can be used for discrete and continuous supply chains. It is composed of an integrated system of stock and flows where the state changes occur continuously over time according to Brailsford Hilton (2001). SD utilizes causal loop diagrams to map out the stock and flow diagram to confront any highly complex systems according to Sterman (2000). According to Tako and Robinson (2012), SD is primarily used to model supply chain problems at a strategic level more than operation and technical levels. SD is designed to look at the supply chain systems of a company over time and measure its performance under different conditions (Sweetser, 1999). Roman et al. (2014) argue that this mapping can help mitigate the bullwhip effect in production. It is useful in the CPG manufacturing process such as Niagara's because the model focuses primarily on issues at an aggregate level by looking at decisions in the form of patterns of behavior and system structures from all levels of management.

2.2.2 Linear Programming Mathematical Modeling

Another effective tool in modeling production is linear programming mathematical modeling. Nolan Sovereign (1972) studied the use of Mixed Integer Linear Programming (MILP) in optimizing production in car seat assembly. The purpose of their model was to find the optimal production rate of each subassembly product and for each period while minimizing material requirements planning needed. In doing so, they were able to highlight how applicable MILP was in optimization processes in manufacturing plants.

2.2.3 Discrete Event Simulation

A Discrete event simulation (DES) is a method of simulating the behavior of a process and allows experimentation with different parameters through multiple what-if scenarios without impacting the existing process The discrete event simulation model is an easier way to build up models for representing real-life circumstances to identify bottlenecks, to enhance system performance in terms of productivity, queues, resource utilization, cycle times, and lead time; one of the key controversial issues in any manufacturing systems bottlenecks. This is a computer simulation method to evaluate different manufacturing implementation scenarios to improve productivity and decrease bottlenecks.

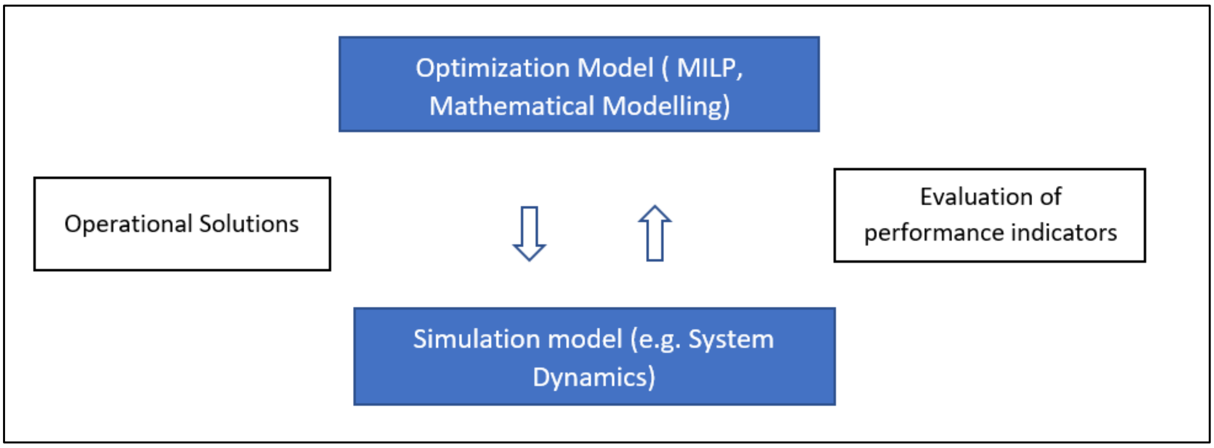
DES has been used in a wide range of applications. Most early applications involved analyses of systems with constrained resources, where the general aim was to improve the organization of delivered services. More recently, DES has increasingly been applied to evaluate specific technologies in the context of manufacturing and health technology assessment. DES was developed in the 1960s in industrial engineering and operations research to help analyze and improve industrial and business processes (Karnon et al., 2009). It has been applied in various business policy and strategy problems.

Computer simulation is useful in analyzing, designing, and scheduling the integrated manufacturing systems problems instead of using mathematical models. ARENA simulation software is generally used in industrial practice to simulate discrete events for production. In this capstone, we will use Arena software as a supplemental analysis tool for discrete event simulation of a production line, schedule, and strategy at Niagara.

2.2.4 Hybrid Optimization and Simulation Approach

A hybrid optimization and simulation model are usually employed to capture the benefits of a simulation on both the granular level (operational and technical) and master level (strategic). This approach has proven to be effective at minimizing production costs and optimizing utilization for the discrete and continuous production process (Belil et al., 2019). The authors proposed to use a hybrid approach which consists of a simulation model and Multi Integration Linear Programming (MILP) as shown in Figure 1, where simulation model used to evaluate the performance indicators and input into MILP to find out the optimum solution. The key to the case study they conducted was to identify the decision variables of simulation that resulted in an optimization solution and evaluate the solution produced.

Figure 1: Hybrid simulation approach



The design of a hybrid optimization and simulation approach heavily relies on the design and intersection of the two models and how data is exchanged between them.

Lee et al. (2020) also explored the advantages and disadvantages of linear programming and the System Dynamics model. They found that to optimize the overall production systems, the optimization approach using linear programming proves to be less effective as it does not do well in addressing the stochastic nature of production. Therefore, in the case of stochastic production, an SD simulation-based model is most appropriate in evaluating the performance of a production system.

2.3 Conclusion

Based on our literature review, we decided to build a hybrid model using System Dynamics to understand and evaluate the end-to-end supply chain process of Niagara's system and Discrete Event Simulation (DES) to create an optimized production strategy by determining the effect of production planning sequence and its impact on fulfillment rate and total relevant cost at Niagara’s production operation.

3. DATA AND METHODOLOGY

A simulation tool is required by Niagara to capture an optimized production strategy to observe the impact of the changes in production strategy over time. From our literature review, we determined that the best way to capture Niagara's production strategy on an aggregate and granular level was to create a hybrid simulation model that integrates a system dynamics model and discrete event simulation. The methodology used to deliver the hybrid simulation model followed these steps: i) Data gathering to understand the end-to-end processes of Niagara's supply chain; ii) Created a system dynamics model to studying the impact of production strategy change on the aggregate level of Niagara's supply chain; iii) Created a discrete event simulation model to deep dive into production scheduling and production execution processes to measure the total relevant cost and fulfillment rate; iv) created nine test scenarios with a combination of different test parameters—namely customer order quantity, inventory quantity, economic production quantity, and safety stock level—to simulate the hybrid model and find the optimized production strategy that provides the lowest total relevant cost and highest service level (see Figure 2).

Figure 2: Methodology

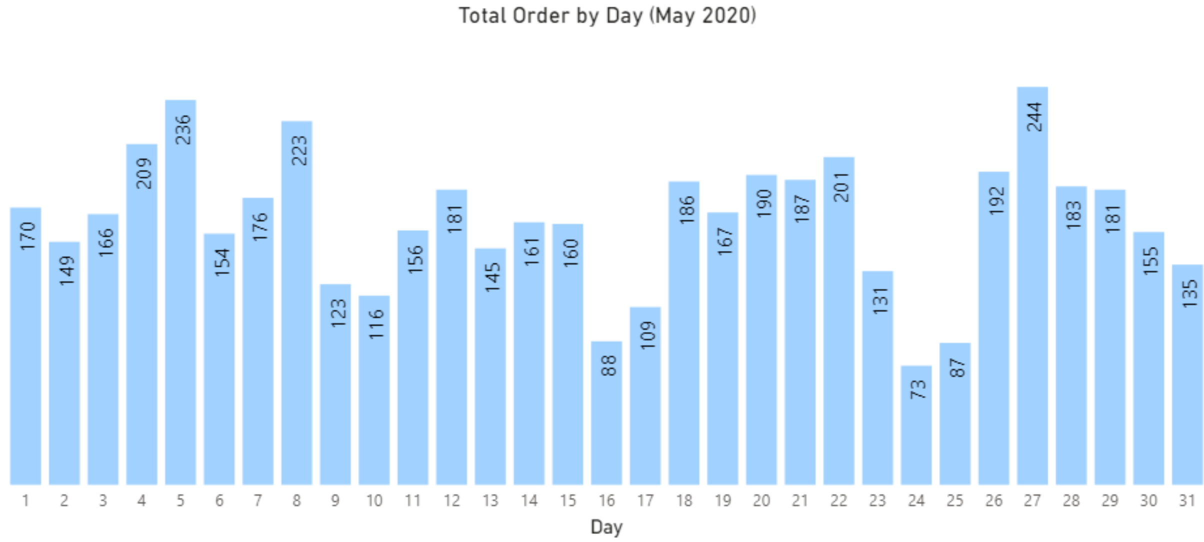
3.1 Data

Niagara is currently using a hybrid production strategy based on seasonality. The peak season runs from May to August. Forecast data is normally distributed. The forecast from September to April is based on historical data from the prior year. The scope of our analysis used one of Niagara's facilities' legacy data only – the Richmond plant. Niagara identified this plant as the only plant with a comprehensive supply chain architecture that is representative of the overall functions that are available in all its 33 plants.

To create a system dynamics model and discrete event simulation model, a series of datasets from the Richmond plant were obtained from Niagara's team. In this section, we discuss the data provided by Niagara. The files we received are Actual Orders, Forecast 2020, ABC categorization for MTO, production rate (BPM), and changeover data (RCH Cost Inputs). Based on the data collected, we analyzed the connection between data and mapped out the end-to-end supply chain processes within Niagara's operation.

Actual Orders is the dataset that contains production orders for the year 2020 with a combination of the order number, SKU item, pickup appointment date, customer, and total case per order. Figure 3 shown the demand pattern for May 2020 based on the actual production order.

Figure 3: Total Order by Day (May 2020)



Based on the Actual Orders file, there are a total of 49 SKUs available for May 2020. We start our analysis focusing on 10 SKUs (see Table 1) first and will continue for the rest of the SKUs once the baseline of the simulation model is completed. The number of observations was counted for each SKU and used to simulate the demand pattern in the simulation model.

Table 1: SKUs from Actual Order

ITEM	# Observation
SKU1	19
SKU2	61
SKU3	193
SKU4	728
SKU5	20
SKU6	487
SKU7	723
SKU8	15
SKU9	23
SKU10	2

Another data extracted from the Actual Orders file was the number of observations for bottle size (Table 2), water type (Table 3), pack size (Table 4), and label type (Table 5) produced in

May 2020. These observation data were used to determine the probability of characteristics assigned to each SKU during the simulation and treated as the unique identification of SKUs.

Table 2: Bottle Size from Actual Order

Bottle Size	# Observation
05L	4544
8OZ	425

Table 3: Water type from Actual Order

Water type	# Observation
DM	3406
DR	1622
SP	6

Table 4: Pack size from Actual Order

Pack Size	# Observation
15P	5
24P	1607
32P	711
35P	118
40P	1648
45P	487
6PK	60
70P	74
80P	324

Table 5: Label size from Actual Order

Label type	# Observation
SST	19
NDW	93
SLF	193
KRK	1088
MMK	522
GRV	1074
LDL	53

We used the same SKU list and extracted SKU item (Table 6), bottle size (Table 6), water type (Table 6), pack size (Table 7), and label type (Table 8) that used to simulate the forecast demand pattern and the possibility of SKU characteristic.

Table 6: SKU from Forecast 2020

ITEM	# Observation
SKU1	16
SKU2	406
SKU3	9
SKU4	177
SKU5	10
SKU6	175
SKU7	395
SKU8	87
SKU9	12
SKU10	47

Table 7: Bottle Size from Forecast 2020

Bottle Size	# Observation
05L	4660
8OZ	746

Table 8: Water type from Forecast 2020

Water type	# Observation
DM	1983
DR	2948
SP	445

Table 9: Pack size from Forecast 2020

Pack Size	# Observation
15P	20
24P	2233
32P	1039
35P	390
40P	979
45P	175
6PK	38
70P	244
80P	277

Table 10: Label size from Forecast 2020

Label type	# Observation
SST	16
NDW	963

SLF	14
KRK	512
MMK	277
GRV	789
LDL	54

ABC Categorization for MTO is the dataset that contains the summarized ABC segmentation of SKU. The SKU is segmented based on the daily average of the customer order size. We analyzed the data and the categorization of SKU segmentation is shown in Table 11. Order with SKU under category A is prioritized because they are fast-moving items with large demand that generate significant profit. Category B and category C follow in the priority list respectively.

Table 11: SKU Segmentation

Category	Average Customer Order Size	Strategy	Production Schedule
A	More than 1 truckload per day	MTS	Produce 7 days of customer demand + 3 days of forecast data
B	Between 2 to 7 truckloads per week	MTS	Produce 7 days of customer demand
C	Less than 2 truckloads per day	MTO/JIT	Product on target day of delivery

BPM is the dataset that contains filling line operation rate in bottle per minute and filling line operation efficiency in percentage as shown in Table 12. There is a total of three filling lines available at the Richmond plant. This data is used to restrict the capacity of filling lines using the efficiency in bottle per minute as an input parameter.

Table 12: BPM

Line	BPM	Efficiency
RCH-L1	1833	79%
RCH-L2	2333	75%
RCH-L3	2333	75%
RCH-L3	2333	65%

RCH Cost Inputs is the dataset that contains the setup cost and changeover cost of label change, water change, pack change, and bottle change. In any case when producing an SKU, if any of the current SKU's characteristics are different from previous SKU's characteristic that runs under the same filling line, changeover cost will incur based on Table 13.

Table 13: Setup Cost

Level1	Label Change	Water Change	Pack Change	Bottle Change
05L_24P	10.63	106.27	318.80	2,550.43
05L_32P	9.06	90.63	271.90	2,175.17
05L_35P	8.94	89.39	268.16	1,036.32
05L_40P	8.54	85.44	256.32	1,028.60
05L_45P	8.05	80.48	241.44	1,931.53
8OZ_24P	6.53	65.29	195.87	-
8OZ_32P	6.00	59.98	179.94	-
8OZ_70P	7.49	74.94	224.82	-
8OZ_80P	6.54	65.36	196.07	-

Storage, Handling, and Transfer Cost is the dataset that consists of the inventory holding cost, handling cost, and transfer cost. For the Richmond plant, only inventory holding cost is applicable to be used in the simulation model to determine the optimum inventory level with minimum inventory holding cost. For this simulation model, the ending inventory of the day will be charged $3.34 per pallet according to Niagara.

3.2 System Dynamics Model

After analyzing the data that was provided by Niagara, we drew the end-to-end supply chain using a system dynamics model to understand the overall picture and variable that weighted the model within the Niagara supply chain. We developed a causal loop diagram (CLD) to depute elements within Niagara's supply chain and their relationship to each other. The CLDs cover the end-to-end supply chain system at Niagara from customer order to product delivery.

CLDs are governed by reinforcing and balancing loops. Reinforcing loop is a feedback loop where the impact of a small increase in one variable, once traced along the whole loop, leads to further increase in the initial variable while balancing loop is a feedback loop leads to a further decrease in the initial variable under the similar conditions.

Below are the steps we used to build the CLDs:

i. Identifying the key variables (see Table 14) that impact the production and supply chain process.
ii. Establishing the links between related elements in the CLD of the Niagara Supply Chain.
iii. Indicating the direction (polarity) on each link.

iv. Identifying and labeling the reinforcing loop which is an action that produces the same action resulting in growth or decline, or balancing loop which is an action that produces the opposite action resulting in growth and decline. In the diagram of the supply chain system.

v. Identifying key leverage points in the production strategy and supply chain where interventions could be leveraged to increase competitive advantage for Niagara Bottling.

Table 14: Key Variables in our System Dynamics Model

#	Variables	Description
1	Adjustment for WIP	The adjustment to the production start rate from the adequacy of WIP inventory.
2	Change in Exp Orders	The demand forecast adjusts to the actual order rate over a period determined by the Time to Average Order Rate. The demand forecast is formed by first-order exponential smoothing, a widely used forecasting technique
3	Customer Demand	Actual Customer Demand from Niagara
4	Customer Order Rate	The customer order rate is exogenous. A variety of test inputs allow users to try different patterns, including a step, pulse, sine wave, and random noise.
5	Desired Inventory	The desired inventory level is sought by the plant. Experience suggests that to maintain customer service by providing full and reliable deliveries, the plant must maintain a certain coverage of throughput (demand), estimated by the demand forecast.
6	Desired Inventory Coverage	Desired inventory coverage is the number of weeks of the demand forecast the plant seeks to maintain in inventory. This inventory coverage is required to maintain delivery reliability by buffering the plant against unforeseen variations in demand or production. It consists of the normal order processing time plus an additional term representing the coverage desired to maintain safety stocks.

7	Desired Production	The desired Production is the demand forecast (Expected Order Rate) adjusted to bring the inventory position in line with the target inventory level.
8	Desired Production Start Rate	The desired rate of production starts, equal to the desired production rate adjusted by the adequacy of the WIP inventory.
9	Desired Shipment Rate	The desired shipment rate equals the customer order rate. In this model there is no backlog of unfilled orders: unfilled orders are lost as customers seek alternate sources of supply.
10	Desired WIP	The desired quantity of work in process inventory. Proportional to the manufacturing cycle time and the desired rate of production.
11	EPQ	Economic Production Quantity from Niagara to determine the inventory to produce
12	Expected Order Rate	The demand forecast is formed by adaptive expectations, using exponential smoothing, a common forecasting technique. The initial forecast is equal to the initial customer order rate.
13	Initial Customer Order Rate	Initial value of customer orders, set to 1000 pallets per week.
14	Input	Input is a dimensionless variable that provides a variety of test input patterns, including a step, pulse, sine wave, and random noise.
15	Inventory	The level of finished goods inventory in the plant. Increased by production and decreased by shipments. Initially set to the desired inventory level.
16	Inventory Adjustment Time	The inventory adjustment time is the time period over which the plant seeks to bring inventory in balance with the desired level. Initially set to 8 weeks.
17	Inventory Coverage	Inventory coverage is given by the ratio of inventory to shipments
18	Manufacturing Cycle Time	The average delay between the start and completion of production

19	Maximum Shipment Rate	The maximum rate of shipments the firm can achieve given their current inventory level and the minimum order processing time.
20	Minimum Order Processing Time	The minimum time required to process and ship an order.
21	MTS	Decision variable to enable Make-to-order or make-to-stock
22	Operation Target	The operation target us to measure the fulfillment rate of order
23	Order Fulfillment Ratio	The Fraction of customer orders filled is determined by the ratio of the normal shipment rate to the desired rate. The normal rate is the rate current inventory permits under normal circumstances. Low inventory availability reduces shipments below customer orders. Unfilled customer orders are lost.
24	Production Adjustment from Inventory	The desired production rate is adjusted above or below the forecast based on the inventory position of the plant. When desired inventory > inventory, desired production is increased (and vice-versa). Inventory gaps are corrected over the inv. adj. time.
25	Production Rate	Production is a third-order delay of the production start rate, with the delay time determined by the manufacturing cycle time.
26	Production Start Rate	The production start rate is the desired production start rate, constrained to be nonnegative.
27	Safety Stock	Safety stock from Niagara as input to determine the inventory to produce
28	Safety Stock Coverage	Safety stock coverage is the number of weeks of the expected order rate the firm would like to maintain in inventory over and above the normal order processing time. The safety stock provides a buffer against the possibility that unforeseen variations in demand will cause shipments to fall below orders.
29	Shipment Rate	The shipment rate is the desired shipment rate multiplied by the fraction of orders filled (the order fulfillment ratio. Shipments fall below desired shipments when the feasible shipment rate falls below the desired rate, indicating that some products are unavailable.

30	Table for Order Fulfillment	The ability to ship is constrained by inventory availability. As the inventory level drops, the fraction of customer orders that can be filled decreases. When inventory is zero, shipments cease. Unfilled customer orders are lost.
31	Time to Average Order Rate	The demand forecast adjusts to actual customer orders over this time period.
32	WIP Adjustment Time	The time required to adjust the WIP inventory to the desired level.
33	Work in Process Inventory	WIP inventory accumulates the difference between production starts and completions.

Defining the variables, we developed the SD model (see Figure 4). The main objective of this step is to create CLDs that can be used to form the basis of developing actions and implementing strategies that increase efficiency, service level while minimizing total relevant cost. 3 main balancing loops in our model is as below:

1) B1 Inventory Control

B1 balancing loop captures the inventory control flow of Niagara. When the demand for finished goods increases, the operation target increases. The increase of desired inventory triggers an increase in production adjustment from inventory and therefore increases the desired production.

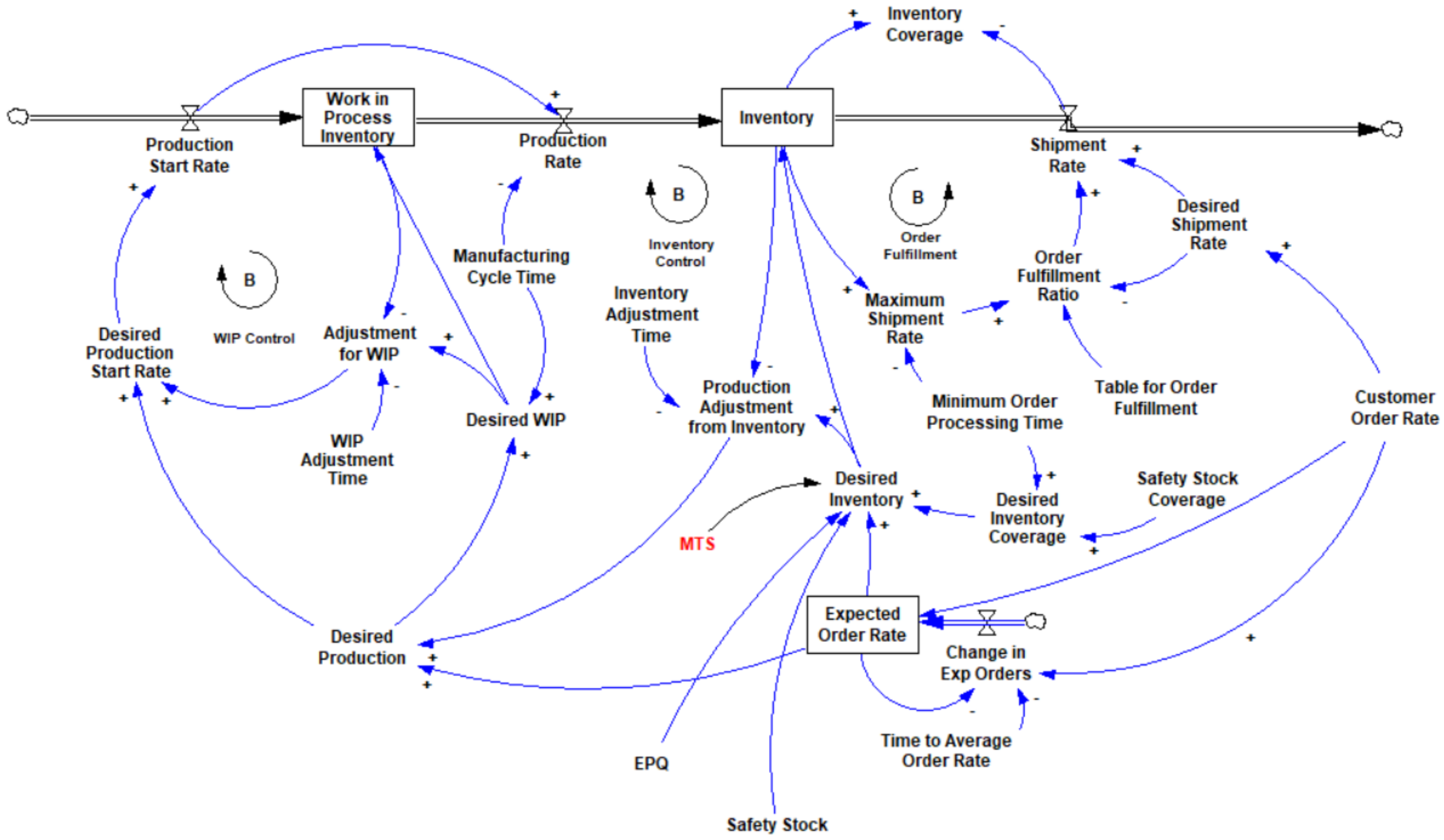
2) B2 WIP Control

B2 balancing loop captures the work in progress (WIP) control flow. When desired production increases, the desires WIP increases aiming to fulfill the production, therefore the adjustment for WIP increases, and desired production start rate increases. It triggers the production start rate to accelerate, resulting in work in process inventory increased, and finally increase the total inventory.

3) B3 Order Fulfillment

B3 balancing loop depicts the order fulfillment flow. The increase in inventory increase the maximum shipment rate, therefore increase the order fulfillment ratio, and the shipment rate increased. This leads to the decrease of total ending inventory because of inventory outflow hence the inventory coverage decrease.

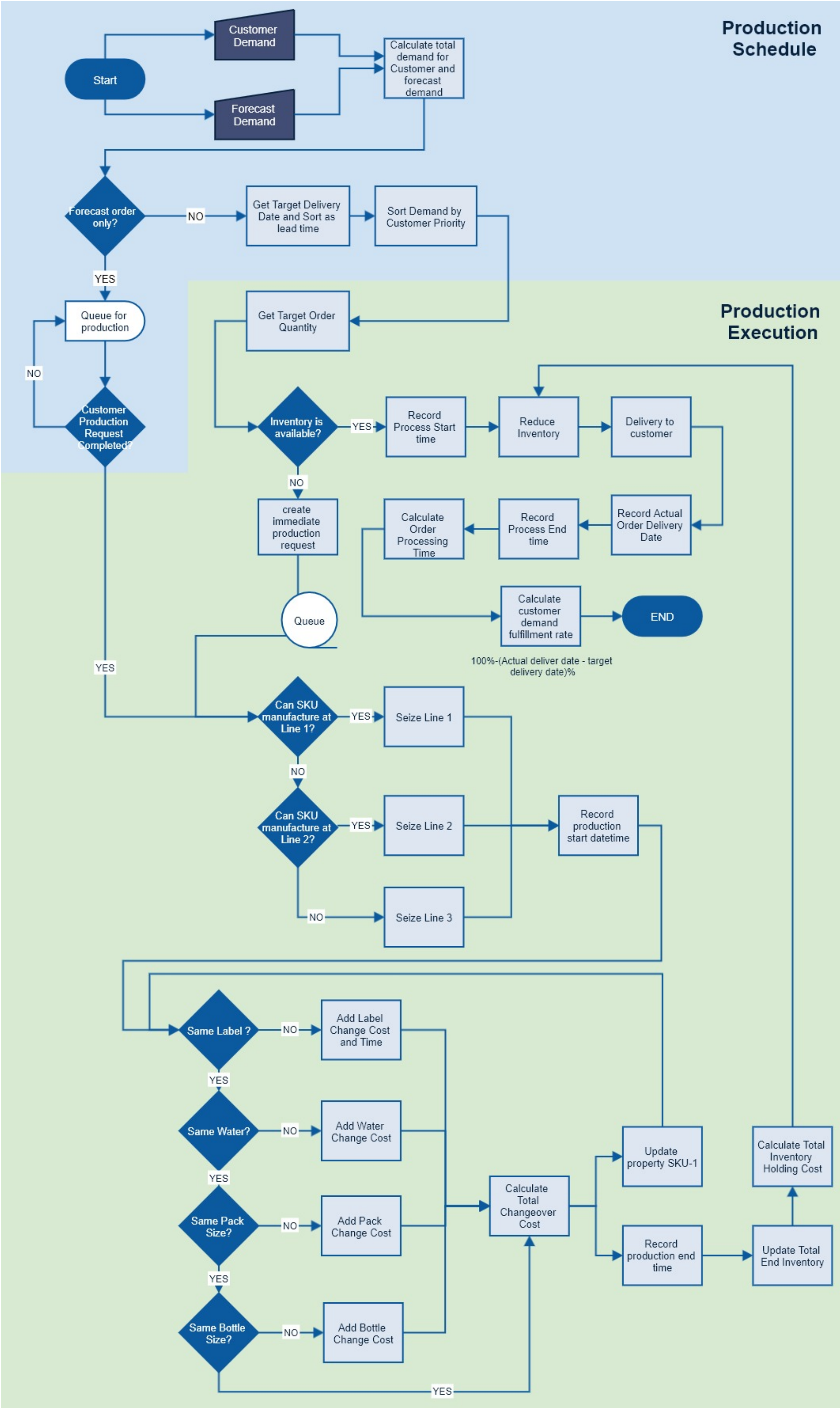
Figure 4:Casual loop diagram (CLD) of Niagara Bottling supply chain system



3.3 Discrete Event Simulation (DES) Models

The discrete simulation model is a way to build up models for representing real-life circumstances to identify bottlenecks, to enhance system performance in terms of productivity, resource utilization, cycle times, lead time, fulfillment rate, and total relevant cost. Following the System Dynamics modeling, we split the DES model into 2 sections: production schedule and production execution (Figure 5). We then built these sections using AnyLogic Software tool. After that, we tested the model using nine scenarios (see section 3.3.1) to evaluate and analyze the best production strategy that can be used by Niagara.

Figure 5: Production Schedule and Execution Flow



3.3.1 Production Schedule

Production scheduling is an essential part of modern manufacturing systems. It is a process of allocating resources to select a set of tasks that are carried out in each period (Ginting,2009). So, production scheduling is a form of ordering products or services, work well on multiple machines as well as the allocation of resources that support the production process to take place.

There are two types of demand input for production scheduling: customer order and forecast demand. Niagara always ensures production lines are operated 24 hours per day to produce sufficient inventory utilizing the customer demand and forecast demand. The production schedule triggers the production planner to plan production based on delivery lead time and customer prioritization.

The inventory volume is determined based on the condition below:

1) The make to stock (MTS) condition where customer order quantity is more than EPQ and inventory is more than safety stock; the total production order produces customer demand.
2) The MTS condition where customer order quantity is more than EPQ and inventory is less than safety stock; the total production order produces customer demand and safety stock.
3) The MTS condition where customer order quantity is less than EPQ and inventory is less than safety stock; the total production order produces EPQ and safety stock.

4) The MTS condition where customer order quantity is less than EPQ and inventory is more than safety stock; the total production order produces EPQ.
5) The MTS condition where there is no customer order quantity and inventory is less than safety stock; the total production order produces safety stock.
6) The MTO condition where production only needs to produce customer orders without considering inventory, EPQ, and safety stock.

3.3.2 Production Execution

Production execution starts after a production order has been confirmed. The production order contains the type of SKU and total demand to be produced. The simulation model uses this input data to determine which filling line is available to produce the order. Once the order can be produced at a filling line, the changeover cost is calculated based on the characteristic difference between the current SKU to be produced and the previous SKU produced at that filling line. If there are any differences in characteristics, changeover cost will incur for that characteristic. For example, if filling line 1 produces a 05L bottle now, but the same filling line was producing a 08 oz bottle previously, a changeover cost of $969.12 will incur. A similar concept is applied to the rest of the SKU characteristics. This changeover cost is part of operating expenses; therefore, it is a critical measurement to ensure production at Niagara is cost-effective.

Once inventory is produced, the amount of the inventory will add up into the ending inventory, and finally, the total holding cost will be calculated at the end of the day. Detailed logic is shown in Figure 5. All the cost calculations in this flowchart are the key measurements to determine the optimal production strategy at the end of our team's analysis.

3.3.3 Test Scenarios

We created 9 test scenarios to test the Discrete Event Simulation model build in Section 3.3.1 and Section 3.3.2. The scenarios mainly test nine different combinations of strategies that generate lower total change over cost and the highest fulfillment rate. The testing scenarios group into part 1 and part 2 refer to Table 15 and Table 16 respectively. For part 1, we tested using a different combination of Make-to-Order and Make-to-Stock ratios to analyze the total fulfillment rate and total relevant cost for 10 SKUs only. For part 2, we used different ratios of SKU segmentation to study its impact on fulfillment rate and total relevant cost for 1300 SKUs.

Table 15: Test Scenarios (Part 1)

Scenarios	MTO	MTS
	Actual Order	Forecast 2020
1	0%	100%
2	20%	80%
3	30%	70%
4	70%	30%
5	80%	20%
6	100%	0%
7	100%	100%

Scenario 1: This scenario tested to produce 100% volume from Forecast 2020 only to determine the fulfillment rate and total change over cost if to produce only based on forecasted demand for SKUs.

Scenario 2: Similar to scenario 6, we adjusted the percentage to produce 20% of the actual order and 80% of forecast order to understand the impact to fulfillment rate of the actual order and total change over the cost of the production line for 10 SKUs.

Scenario 3: This scenario tested to produce 30% of the actual order and 70% of forecast order to determine whether the fulfillment rate for actual order can be higher yet resulting in low change over cost for 10 SKUs.

Scenario 4: This scenario tested to produce 70% of Actual order and 30% of forecast order to determine whether 30% volume of forecast order can fulfill the demand with lower change over cost and higher fulfillment rate for 10 SKUs.

Scenario 5: Similar to scenario 4, this scenario we tweaked to test with 80% of the actual order and 20% of forecast order to determine whether 20% volume of forecast order can fulfill the demand with lower change over cost and higher fulfillment rate for 10 SKUs.

Scenario 6: This scenario tested to produce 100% based on actual order only without forecast order to determine the fulfillment rate and total change over cost to produce when demand is received for 10 SKUs.

Scenario 7: This scenario tested the combination condition of using 100% of volume from actual order and 100% volume from Forecast 2020, the simulation will evaluate the demand volume from both inputs and calculate the fulfillment rate and total change over cost to produce all demands for SKUs.

Niagara has more than 1300 SKUs. From scenarios 1 to 7, it was tested on 10 SKUs only. We decided to test the simulation model using 1300 SKUs data. Hence, we included another scenario to evaluate the production strategy using ABC segmentation that capable to group 1300 SKUs into 3 categories, A, B, and C by percentage.

Table 16: Test Scenarios (Part 2)

Scenarios	A	B	C	Remarks
8	84.7%	10.4%	4.9%	Niagara's segmentation
9	70.0%	20.0%	10.0%	Propose segmentation

Scenario 8: This scenario tested using ABC segmentation pre-defined by Niagara to generate the total fulfillment rate and total relevant cost for 1300 SKUs.

Scenario 9: This scenario tested using the best practice of ABC segmentation, which is grouping 70% of total volume to A segment, 20% of volume categorized under B segment, and 10% of volume under C segment for 1300 SKUs.

4. RESULTS AND DISCUSSION

The models detailed in the Methodology section allow decision-makers to evaluate production strategy options. The production strategy recommendation is tailored to a scenario the decision-makers choose on inputs. The models offer the flexibility to consider multiple SKUs and demand probability distributions or observations and can run infinite simulations. This section discusses the results obtained from the simulation models – Section 4.1's System Dynamics Model and Section 4.2's the Discrete Event Simulation Model.

4.1 System Dynamics Simulation Results

The System Dynamics Simulation shows that without sufficient inventory, the fulfillment rate suffers, and the customer service level is negatively impacted for a 90-week simulation period. Inventory reaches its lowest point around week 10 (Figure 6) when production begins to catch up with the new and higher demand. According to Figure 7, once inventory grows to meet the new demand, the customer service level recovers.

Figure 6: Inventory vs. Desired Inventory

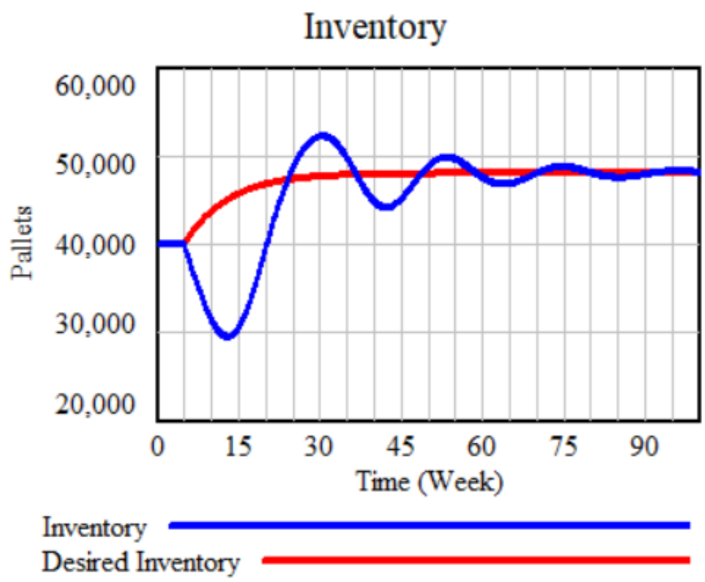
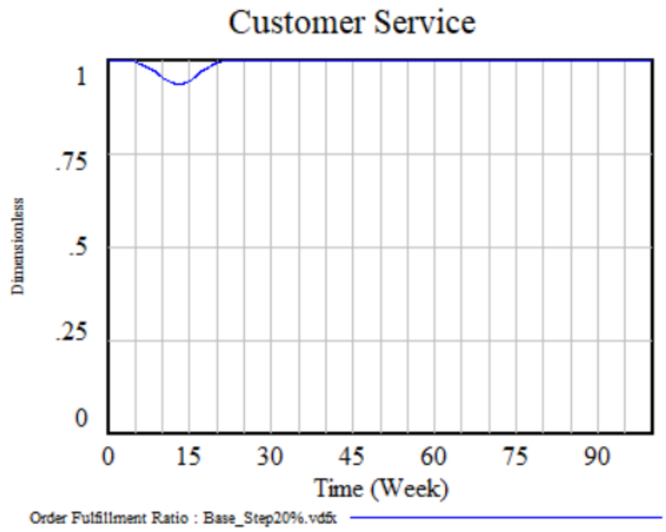
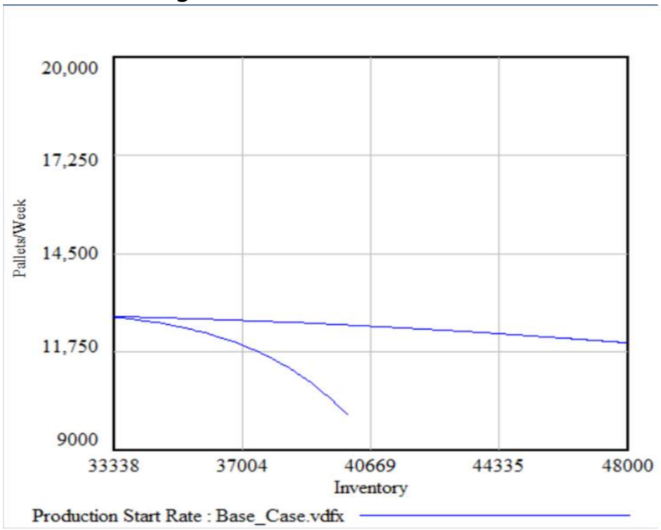


Figure 7: Customer Services Level



The impact of the inventory level on the production start rate can be seen in Figure 8. It shows that as the production start rate gradually increases, inventory increases. Though the production start rate is increasing, there is still an average manufacturing cycle time of four weeks, so inventory continues to decline during this period. Inventory starts to grow again after completed manufacturing cycle time and goods start to flow into inventory, at which point the production start rate begins to slow.

Figure 8: Production Start Rate



4.2 Discrete Event Simulation Results

Discrete Event Simulation outputs show the disaggregated costs associated with the 9 scenarios highlighted in the Methodology Section and Table 17. Figure 9 compares the cost metrics calculated using different production strategies. 100% policy means that the same production strategy is used for all SKUs. For hybrid policy, different percentage weights were used for MTS and MTO strategies. Figure 9 contains the cost breakdown of each scenario simulated by the model.

Table 17: List of Test Scenarios

No	Scenarios
1	0% MTO & 100% MTS
2	20% MTO & 80% MTS
3	30% MTO & 70% MTS
4	70% MTO & 30% MTS
5	80% MTO & 20% MTS
6	100% MTO & 0% MTS
7	100% MTO & 100% MTS
8	ABC (Niagara)
9	ABC (70-20-10)

Figure 9: Cost metrics of Scenarios

No	Scenarios	Total Relevant Cost	Total holding cost	Water_COC	Label_COC	Bottle_COC	Pack_COC
1	0% MTO & 100% MTS	3,011,940	310,807	173,422	29,228	1,568,000	939,636
2	20% MTO & 80% MTS	2,836,872	372,757	149,216	24,763	1,551,000	739,543
3	30% MTO & 70% MTS	1,947,778	268,431	100,931	16,751	1,049,000	512,378
4	70% MTO & 30% MTS	1,896,479	255,650	102,605	15,837	1,003,000	519,758
5	80% MTO & 20% MTS	1,977,356	271,162	106,701	16,712	1,047,000	535,375
6	100% MTO & 0% MTS	1,407,798	201,745	77,003	12,145	747,457	369,478
7	100% MTO & 100% MTS	3,854,874	525,172	202,980	33,848	2,039,000	1,054,000
8	ABC (Niagara)	968,604	37,931	60,436	9,775	556,462	304,000
9	ABC (70-20-10)	956,110	32,186	59,361	9,669	553,780	301,114

Figure 9 shows that ABC segmentation generated the lowest Total Relevant Cost followed by a 100% make-to-order scenario. To further analyze the total relevant cost, we included fulfillment rate into the same graph for comparison (see Figure 10).

Figure 10: Total Relevant Costs vs Fulfillment Rate

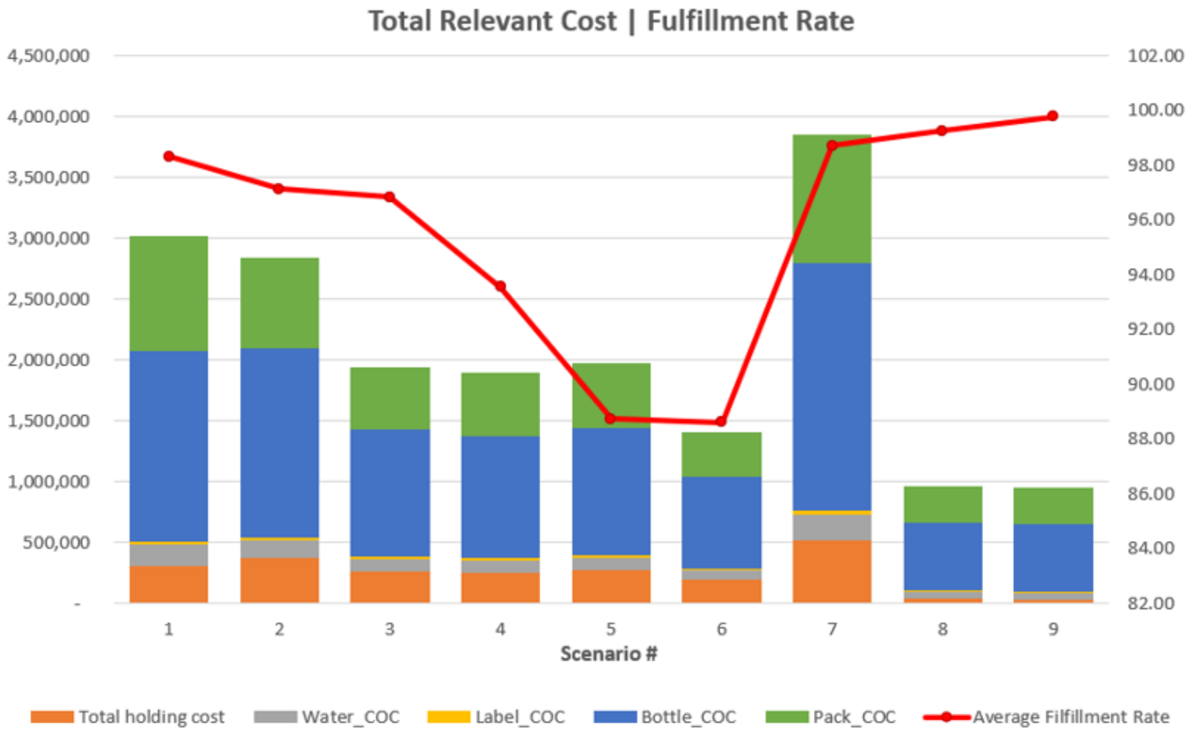


Figure 10 shows the relative merits of using a hybrid production strategy. As expected, the combined 100% MTS and 100% MTO policy resulted in the highest total relevant cost ($3.8M) and highest service level (98.72%) per week while 100% MTO provided the lowest total relevant cost ($1.4M) respectively.

Figure 11 and Figure 13 scenarios which were tested using ABC segmentation, have the lowest total relevant cost yet with a high fulfillment rate compared to scenarios run for individual SKUs in Figure 10. We compared the Niagara segmentation method (Figure 11) and industry best practices ratio; 70% for segment A, 20% for segment B, and 10% for segment C (Figure 12), the results show no significant difference between the total relevant cost, a 3% difference, but the average fulfillment rate is higher for Figure 12 which adopted the industry best practices.

This means some of the SKUs under Niagara's segment A or B or C are under forecasted, hence the fulfillment rate is lower. On the other hand, the SKUs segmented based on 70-20-10 allocation have generated a higher fulfillment rate, which means the inventory hold is sufficient to supply the demand. Normally ABC segmentation is used as an actionable measurement to reduce total relevant costs and drive profit at the tactical or strategic level. This methodology can be used as the first level of analysis prior to conducting analysis on an operational level.

Figure 11: Total Relevant Costs vs Fulfillment Rate for Niagara's ABC segmentation

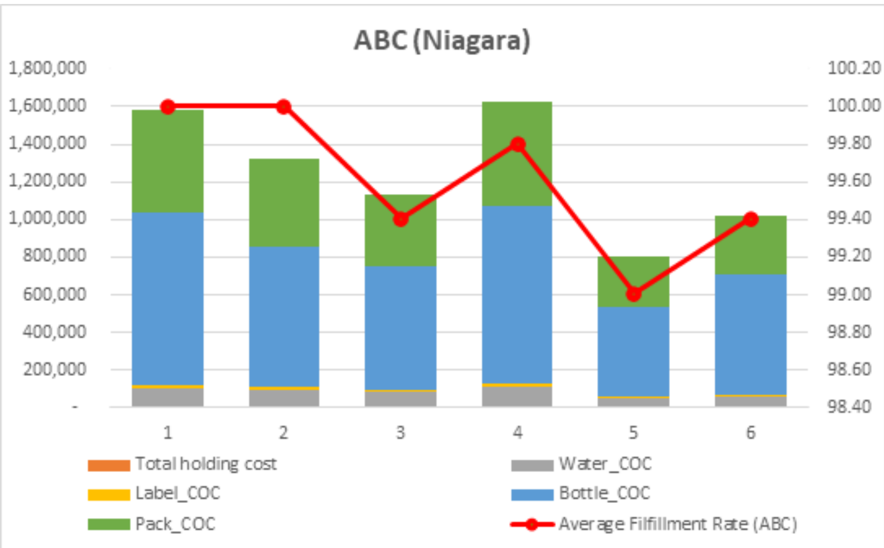


Figure 12: Cost metrics of Scenarios for Niagara's ABC Segmentation

No	Scenarios	Total Cost	Total holding cost	Water_COC	Label_COC	Bottle_COC	Pack_COC	Seg A	Seg B	Seg C	Average Filfillment Rate (ABC)
1	ABC-0% MTO & 100% MTS	1,580,049	10,088	93,961	17,038	912,275	546,687	100.0	100.0	100.0	100.00
2	ABC-20% MTO & 80% MTS	1,322,908	11,117	87,201	15,833	737,542	471,216	100.0	100.0	100.0	100.00
3	ABC-30% MTO & 70% MTS	1,128,641	2,908	79,968	11,748	654,968	379,059	100.0	100.0	98.2	99.40
4	ABC-70% MTO & 30% MTS	1,623,583	5,907	104,143	17,729	947,309	548,495	100.0	100.0	99.4	99.80
5	ABC-80% MTO & 20% MTS	802,937	1,063	51,973	8,747	477,543	263,611	100.0	98.2	98.8	99.01
6	ABC-100% MTO & 0% MTS	1,022,807	1,025	60,938	10,322	633,866	316,656	99.4	99.4	99.4	99.41

Figure 13: Total Relevant Costs vs Fulfillment Rate for Niagara's ABC (70%-20%-10%) segmentation

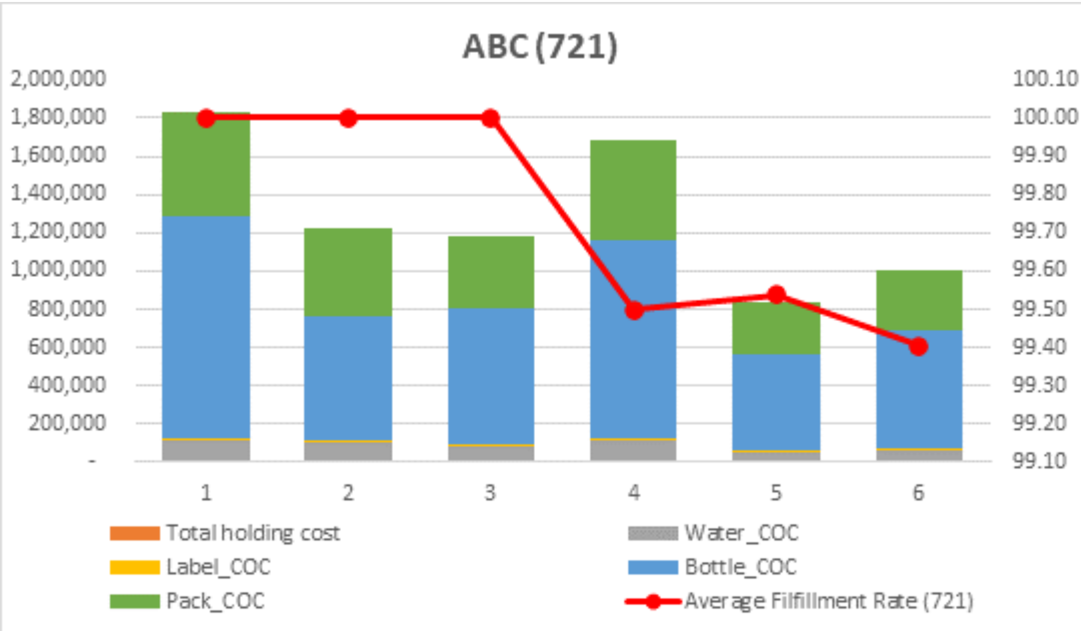


Figure 14: Cost metrics of Scenarios for 70-20-10% ABC Segmentation

No	Scenarios	Total Cost	Total holding cost	Water_COC	Label_COC	Bottle_COC	Pack_COC	Seg A	Seg B	Seg C	Average Filfillment Rate (721)
1	721-0% MTO & 100% MTS	1,829,160	12,920	99,678	16,809	1,153,000	546,882	100.0	100.0	100.0	100.00
2	721-20% MTO & 80% MTS	1,226,443	14,032	87,796	15,736	641,196	467,683	100.0	100.0	100.0	100.00
3	721-30% MTO & 70% MTS	1,178,196	5,419	80,185	12,028	704,561	376,003	100.0	100.0	100.0	100.00
4	721-70% MTO & 30% MTS	1,687,532	8,697	103,525	18,107	1,026,000	531,691	100.0	100.0	98.5	99.50
5	721-80% MTO & 20% MTS	836,911	2,529	53,921	8,867	504,266	267,328	100.0	100.0	98.6	99.54
6	721-100% MTO & 0% MTS	1,003,357	2,490	60,795	10,345	616,170	313,557	99.4	99.4	99.4	99.41

For both segmentation methods (Niagara's and Industry's best practice) showed that Scenario 5 (80% MTO and 20% MTS) provided the lowest total relevant cost (~$800K) while maintaining a fulfillment rate of above 99% (Figure 12 and 14). The reason can be the fact that at 20% MTS, the inventory holding cost is significantly reduced and consequently the total relevant cost reduces.

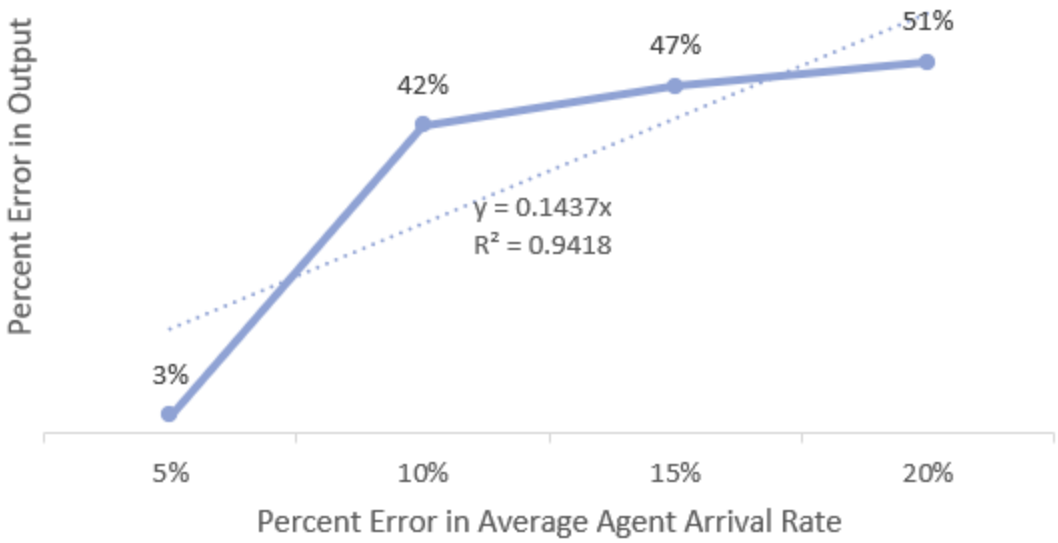
Overall, the qualitative results obtained have been on par with our intuition and theoretical understand of production strategies.

4.3 Sensitivity Analysis

We used sensitivity analysis to measure how errors in input variables affected the output in the simulation model because it important that the output of a discrete event simulation model is not too sensitive to errors in the input. In addition, when certain inputs are highly sensitive to errors, then it is best to know them before the model is used.

The sensitivity of the total relevant cost to production strategy was studied by introducing errors to the agent arrival rate. We chose this input to analyze the sensitivity of the model because it accounts for a significant amount of the operations task load. We introduced the errors by shifting the average value of the observation of the average agent arrival rate by 5% 10%, 15%, and 20%. The output errors were estimated by comparing the total relevant costs from the original output to the total relevant costs after introducing the error to the inputs.

Figure 16: Sensitivity of Agent Arrival Rate



As the percentage of the average agent arrival rate for forecast and live order increases, the percentage error in the output (total relevant cost) increases as well (Figure 12). As the graph shows, the total relevant cost is highly sensitive to the number of orders received and produced. As the percent error in the average agent arrival rate increase from 5% to 10%, the percent error in output increases by 39%. However, beyond 10% percent error in average agent arrival rate, the percent error in output plateaus showing that the model becomes less sensitive to inputs beyond a certain threshold.

4.4 Model verification and validation

We verified out simulation model using a visual test by keeping track of generated entities and how the model corresponded to different entities. Following the verification. we validated the model using the same production policy used in Niagara's production facilities.

5. Conclusion

The purpose of this capstone is to develop a roadmap to help Niagara identify the best production strategy for their bottled water product that offers the optimal total relevant costs and fulfillment rate. To achieve this aim, we modeled Niagara's supply chain process using a System Dynamics (SD) model and simulated the demand (live orders and forecast orders) and production line by using a Discrete Event Simulation model (DES). The results of our models offer Niagara the ability to gain insight into their current production process and to understand the common causes of total relevant cost and fulfillment rate variability of different SKUs and SKU segmentations. The models we created can be used to simulate different scenarios such as understanding if increasing the production capacity or lines can influence its total relevant costs and overall fulfillment rate.

5.1 Managerial Insights

Driving cost savings is critical for companies especially those in the CPG industry. Our study shows that employing a mixed hybrid production strategy using the traditional SKU segmentation while considering customer prioritization and lead time can have significant cost savings in the long term. It is however critical for Niagara to study the type and nature of individual SKUs to understand the forecastability accuracy and demand distribution patterns before determining a production strategy.

In addition, decisions between production and inventory trade-offs are made at the strategic level. The results of our simulation model shows that the understanding of individual SKU type and characteristics (demand, forecast, EPQ, SS, and MOQ) is more beneficial than a forecast and demand order patterns. Understanding the aspects that are of importance in battling demand fluctuations and uncertainties will allow decision-makers at Niagara to allocate their time and resources in SKUs that ensure the highest profit margin, lower relevant cost, and have high fulfillment rates because these are the ones that have the highest impact in the operations costs and profitability of the company.

5.2 Limitations and Recommended Future Research:

The main objective of this capstone is to provide insights into the best production strategy that can be employed by Niagara Bottling Company. While we were able to achieve this and provide recommendations to Niagara, there were several limitations to our models.

Our models and analysis allow decision-makers to quickly tradeoff between how much stock to hold in inventory and how much to produce on-demand based on customer orders to cover demand uncertainties and lead time volatility. The DES model is, however, limited in scope to only assess 10 SKUs produced at one plant at a time. Scaling the model to 1300 SKUs and expanding it to 33 plants will provide a more holistic production strategy to be implemented by the Niagara team. In addition, production cycle time (timestamps) was not included in the model. The addition of production cycle time will allow Niagara to manipulate the order sequence and determine individual production line performance.

In addition, our analysis for DES was conducted using May 2020 data only. Therefore, the COVID-19 disruption was factored into the demand. As mentioned earlier in this study, COVID-19 pandemic caused the CPG sales growth of 9.5% in the US alone in 2020. Therefore, by using the May 2020 data in our analysis, we were only able to offer insights of an outlier year. In the future, Niagara needs to use data from non-pandemic years to draw insights to what production strategy is suitable for years without disruptions e.g. the 2020 pandemic.

Also, to ensure its long-term usability, we recommend Niagara to regularly update the model to incorporate new production processes, new SKUs or demand volume in order to provide the model with real-time data to simulate. This will enable Niagara to always obtain insights concurrently.

In today's turbulent competitive environment, Niagara more than ever needs a production strategy that will offer it a competitive advantage in the market. As COVID-19 pandemic has revealed to us, only companies who were able to be lean, agile to respond to customer demand spikes in 2020 were able to weather the pandemic's disruptions. Ensuring a constant study of its supply chain, SKUs, demand, and forecast patterns will help Niagara determine and adopt the best production strategy as it grows and expands its market share.

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7. APPENDIX

Table 18: System Dynamics Formula

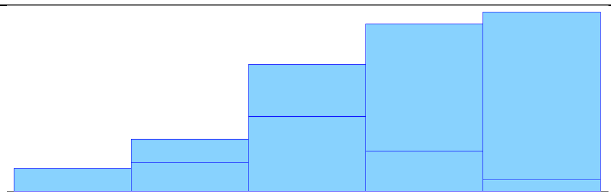
#	Variables	Formula	Units
1	Adjustment for WIP[SKU]	(Desired WIP[SKU] - Work in Process Inventory[SKU])/WIP Adjustment Time[SKU]	Pallets/ Week
2	Change in Exp Orders[SKU]	(Customer Order Rate[SKU]-Expected Order Rate[SKU])/Time to Average Order Rate[SKU]	(Pallets/ Week)/ Week
3	Customer Demand[SKU]	GET XLS DATA('Niagara Data.xlsx', 'SKU List', '1', 'E2')	Pallets
4	Customer Order Rate[SKU]	Initial Customer Order Rate*Input	Pallets/ Week
5	Desired Inventory[SKU]	(EPQ[SKU]+Safety Stock[SKU]*MTS[SKU])+(Desired Inventory Coverage[SKU]*Expected Order Rate [SKU])	Pallets
6	Desired Inventory Coverage[SKU]	Minimum Order Processing Time[SKU] + Safety Stock Coverage[SKU]	Week
7	Desired Production[SKU]	MAX(0,Expected Order Rate[SKU]+Production Adjustment from Inventory [SKU])	Pallets/ Week
8	Desired Production Start Rate[SKU]	Desired Production[SKU] + Adjustment for WIP [SKU]	Pallets/ Week
9	Desired Shipment Rate[SKU]	Customer Order Rate[SKU]	Pallets/ Week
10	Desired WIP[SKU]	Manufacturing Cycle Time[SKU]*Desired Production[SKU]	Pallets

11	EPQ[SKU]	10.9956,10.9956,1,1,39.4842,15.9936,1,95.9616,83.4666,1,1,1,27.489,27.489,43.9824,1,40.9836,16.4934,394.342,164.434,142.943,1,1,161.206,1,54.4782,1,1,1,55.9776,41.0525,229.908,1,1,403.129,1,1,30.4878,1,1,1,1,1,1,10.9956,28.4886,1,1,120.952,1,36.4854,162.435,1,1,1,11.0141,1,11.0088,671.215,11.0035,1,37,118.538,1,49.98,38.9844,49.4802,10.9956,38.9844,1,11.9952,11.0035,1,420.332,1,197.563,47.9808,169.932,10.9956,10.9956,13.9944,58.9764,11.0035,29.5094,1,1,1,1,1,1,1,13.0166,1,1,1,11.0035,1,1,1,1,1,48.9804,1,1,353.858,30.9876,14.994,13.4946,24.99,66.4734,88.4646,19.0243,81.4674,98.4606,27.9888,10.9956,1,1,1,11.0141,11.0141,36.9852,1,205.066,1,1,1	Pallets
12	Expected Order Rate[SKU]	INTEG (Change in Exp Orders[SKU], Customer Order Rate[SKU])	Pallets/ Week
13	Initial Customer Order Rate	10000	Pallets/ Week
14	Input	1+STEP(Step Height,Step Time)+(Pulse Quantity/TIME STEP)*PULSE(Pulse Time,TIME STEP)+RAMP(Ramp Slope,Ramp Start Time,Ramp End Time)+Sine Amplitude*SIN(2*3.14159*Time/Sine Period)+STEP(1,Noise Start Time)*Pink Noise	Dimensionless
15	Inventory[SKU]	INTEG(Production Rate[SKU]-Shipment Rate[SKU],Desired Inventory [SKU])	Pallets
16	Inventory Adjustment Time[SKU]	1	Week
17	Inventory Coverage[SKU]	Inventory[SKU]/Shipment Rate[SKU]	Week
18	Manufacturing Cycle Time[SKU]	1	Week
19	Maximum Shipment Rate[SKU]	Inventory[SKU]/Minimum Order Processing Time[SKU]	Pallets/ Week
20	Minimum Order Processing Time[SKU]	2	Week
21	MTS[SKU]	0	Dimensionless [0,1,1]

22	Operation Target[SKU]	10.9956,12.495,1,2.00128,53.9784,20.9916,1,134.446,125.95,1,1,1,35.9856,37.485,88.4646,1,58.9764,21.9912,653.738,164.434,235.906,1,1,215.275,7.4974,65.9736,4.4986,1,1,89.964,52.5672,289.384,1,1,727.233,1,1,37.485,1,1,32.4874,1,1,3.00256,11.9952,30.9876,1,1,168.932,1,80.9676,177.929,1,1,1,19.525,1,14.0112,1046.33,11.0035,1,37,202.565,1,79.968,58.4766,68.9724,10.9956,83.4666,1,14.4942,49.5158,1,666.733,1,211.068,70.4718,209.416,13.4946,12.495,16.9932,73.9704,12.0038,50.5162,1,1,1,1,1,1,16.0205,1,1,1,11.0035,1,1,1,1,36.9856,10.4962,48.9804,42.9832,1,470.312,44.982,16.9932,15.9936,30.9876,86.9652,134.446,24.0307,106.457 ,138.944,33.4866,10.9956,1,1,1,11.5147,11.0141,61.4754,1,311.1,1,1,1	Pallets
23	Order Fulfillment Ratio[SKU]	Table for Order Fulfillment[SKU](Maximum Shipment Rate[SKU]/Desired Shipment Rate[SKU])	Dimensionless
24	Production Adjustment from Inventory[SKU]	(Desired Inventory[SKU] - Inventory[SKU])/ Inventory Adjustment Time[SKU]	Pallets/ Week
25	Production Rate[SKU]	DELAY3(Production Start Rate[SKU],Manufacturing Cycle Time[SKU])	Pallets/ Week
26	Production Start Rate[SKU]	MAX(0,Desired Production Start Rate[SKU])	Pallets/ Week
27	Safety Stock[SKU]	0,1.4994,0,1.00128,14.4942,4.998,0,38.4846,42.483,0,0,0,8.4966,9.996,44.4822,0,17.9928,5.4978,259.396,0,92.9628,0,0,54.0691,6.4974,11.4954,3.4986,0,0,33.9864,11.5147,59.4762,0,0,324.104,0,0,6.9972,0,0,31.4874,0,0,2.00256,0.9996,2.499,0,0,47.9808,0,44.4822,15.4938,0,0,0,8.51088,0,3.0024,375.12,0,0,0,84.0269,0,29.988,19.4922,19.4922,0,44.4822,0,2.499,38.5123,0,246.401,0,13.5043,22.491,39.4842,2.499,1.4994,2.9988,14.994,1.00032,21.0067,0,0,0,0,0,0,0,3.00384,0,0,0,0,0,0,0,0,35.9856,9.4962,0,41.9832,0,116.453,13.9944,1.9992,2.499,5.9976,20.4918,45.9816,5.0064,24.99,40.4838,5.4978,0,0,0,0,0.50064,0,24.4902,0,106.034,0,0,0	Pallets

28	Safety Stock Coverage[SKU]	2	Week
29	Shipment Rate[SKU]	Desired Shipment Rate[SKU]*Order Fulfillment Ratio[SKU]	Pallets/ Week
30	Table for Order Fulfillment[SKU]	([(0,0)-(2,1)],(0,0),(0.2,0.2),(0.4,0.4),(0.6,0.58),(0.8,0.73),(1,0.85),(1.2 ,0.93),(1.4,0.97),(1.6,0.99),(1.8,1),(2,1),(2,1))	Dimensionless
31	Time to Average Order Rate[SKU]	8	Week
32	WIP Adjustment Time[SKU]	2	Week
33	Work in Process Inventory[SKU]	INTEG(Production Start Rate[SKU] - Production Rate[SKU],Desired WIP[SKU])	Pallets

Table 19: Actual Order Distribution

Distribution	Formula	Square Error	Plot
Empirical	DISC (0.000, 3.000, 0.129, 4.576, 0.290, 6.152, 0.710, 7.728,	N/A	

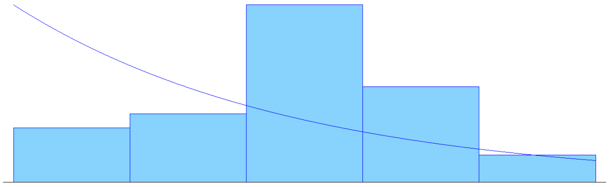
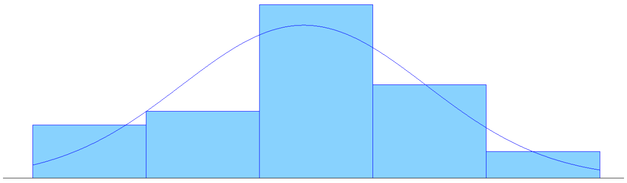
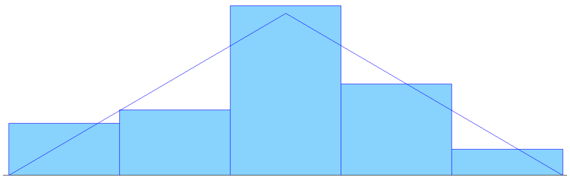
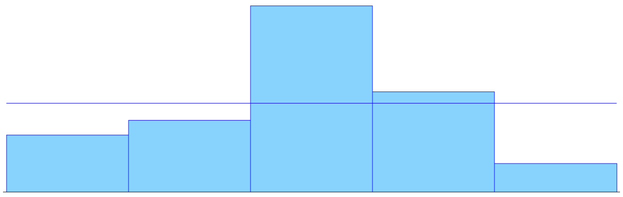
	0.935, 9.304, 0.935, 10.880)		
Exponential	3 + EXPO(3.77)	0.139464	
Normal	NORM(6.77, 1.7)	0.015873	
Triangular	TRIA(3, 6.94, 10.9)	0.012564	
Uniform	UNIF(3, 10.9)	0.073673	

Table 20: SKU Characteristic Distribution

Bottle Size	Probability	Cumulative
8OZ	0.1811	0.1811
05L	0.8189	1.0000
Water Type	**Probability**	**Cumulative**
DM	0.1770	0.1770
DR	0.6132	0.7901
SP	0.2099	1.0000
Pack Size	**Probability**	**Cumulative**
24P	0.7119	0.7119
32P	0.0988	0.8107

35P	0.0658	0.8765
40P	0.0658	0.9424
45P	0.0082	0.9506
70P	0.0082	0.9588
80P	0.0412	1.0000

Table 21: Fulfillment rate for Scenarios (Part 1)

No	Scenarios	SKU 1	SKU 2	SKU 3	SKU 4	SKU 5	SKU 6	SKU 7	SKU 8	SKU 9	SKU 10	Average Filfillment Rate
1	0% MTO & 100% MTS	98.1	99.5	100.0	100.0	98.7	100.0	100.0	98.3	98.6	90.0	98.32
2	20% MTO & 80% MTS	100.0	100.0	100.0	100.0	98.3	100.0	100.0	100.0	98.1	75.0	97.15
3	30% MTO & 70% MTS	100.0	99.2	99.7	99.9	100.0	100.0	100.0	96.3	98.4	75.0	96.85
4	70% MTO & 30% MTS	96.8	100.0	99.8	100.0	97.8	100.0	100.0	93.8	97.4	50.0	93.55
5	80% MTO & 20% MTS	97.3	98.4	100.0	100.0	97.7	100.0	100.0	96.0	98.0	-	88.74
6	100% MTO & 0% MTS	96.3	100.0	99.6	100.0	96.4	100.0	100.0	96.3	97.5	-	88.61
7	100% MTO & 100% MTS	100.0	99.6	99.9	100.0	100.0	100.0	100.0	100.0	98.9	88.9	98.72