Inventory Optimization and Simulation Analysis for Supply Chain Disruption Events

By

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Abstract

Increasing volatility in the global supply chain following the Covid-19 pandemic has led to a challenge in reliably managing inventory, especially for high-complexity medical devices. An optimization and simulation-based inventory management model was developed to augment the decision making of supply planners in these networks. The model supports supply planners in safety stock allocation decisions by quantifying inventory cost and stockout probability risk for products with multi-stage, converging supply networks. Components of the model include iterative multi-echelon inventory optimization, monte carlo simulation of a custom base-stock inventory model and cycle service level modelling. An application of the model is explored in a case study of the J&J Ethicon surgical stapler supply chain. In addition, operational considerations for implementing inventory models are discussed, including data architecture, standardization, and centralization for complex supply chains.

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1 Introduction

1.1 Project Motivation

One of the critical functions of any supply chain is the ability to provide accurate forecasts and production plans to meet customer demand. Supply planners face many challenges in developing these plans, including data visibility issues, right sizing inventory, and the lasting impacts of the supply and demand shocks caused by the Covid-19 pandemic. These combined challenges have caused record backorder issues in recent years, impacting the lives of patients as well as the financial stability of manufacturers.

At Johnson and Johnson (J&J) Ethicon, one product family that has suffered from backorder issues are Surgical Staplers, critical medical devices used in endoscopic surgeries. The Ethicon Endo division which produces surgical stapler devices has invested in digital technologies as part of a greater J&J digital transformation effort to address gaps in the supply chain management process. Building on these digital efforts, there is an opportunity to develop predictive models to better predict and prevent supply chain disruptions before they occur.

1.2 Project Goals

One of the key questions facing planners is how to set safety stock for a product at each stage in the supply and distribution network. Historically, planners have employed Multi Echelon Inventory Optimization (MEIO) models to optimize the safety stock at each distribution node of the supply chain. These models use demand and lead time variability to inform the minimum safety stock that can be held at a given node to still hit overall service level targets. However, currently these models rely on static assumptions of the supply chain structure and inventory management policies. Simulation provides the opportunity to refine optimization methods to better customize the model for the specifics of the supply chain. Optimization models are purely analytical and often standardized across the entire organization and therefore are not always accurate at a local level. The refinement of optimization models by simulation can improve accuracy and create more predictive models based on the unique supply chain variables of a given product.

This project aims to address some of the opportunities for predictive modeling in the surgical stapler supply network including:

1) Create a representative model of the surgical stapler supply network.
2) Develop a predictive model to inform the safety stock targets for surgical staplers to balance both the backorder probability and inventory holding costs.
3) Analyze the real-world operational considerations for implementation of a predictive safety stock model.

1.3 Scope

This project focuses on developing a model for optimizing the safety stock in the supply network of surgical staplers at J&J. The model is generalized in parts and can be a framework for other use cases, but the model formulation and assumptions are targeted within this context. Historical supply and demand data were used as available to inform the model, but not all data sources were available within the time frame of the project. Specific data challenges include access to supplier data, which was often not forthcoming due to competition and contracting reasons. In addition, some data and inputs were modified to protect confidentiality and generalize the model.

The project consisted of a discovery, development and validation phases. Discovery involved literature review and background analysis as well as data collection and process mapping. The supply chain was mapped and modeled, and key stakeholders were identified. The development phase first involved descriptive statistics of supply and demand metrics followed by proof-of-concept optimization and simulation models. These models were iteratively improved through validation with key stakeholders and review with advisors.

1.4 Thesis Organization

The thesis is organized as follows:

Chapter 2 provides background on J&J, surgical staplers and the Ethicon supply chain.

Chapter 3 contains a literature review of inventory management models, multi echelon inventory optimization and simulation methods.

Chapter 4 describes the optimization and simulation inventory model,

Chapter 5 explores a case study application of the inventory model and comparison to current practice.

Chapter 6 discusses the operational considerations of implementing a new inventory model.

Chapter 7 summarizes the project, conclusions and next steps.

2 Background

2.1 Johnson & Johnson

Johnson and Johnson is one of the world's largest and most admired pharmaceutical and medical device companies.(1) The company was founded in 1886 with just 14 employees and today has over 150,000 employees and greater than $17 billion in profit.(1) The scale and scope of J&J makes it one of the most valuable and important medical technology companies in the world.

At the heart of J&J is "Our Credo", a guiding document first drafted in 1943 by co-founder of J&J, Robert Wood Johnson.(2) The Credo has stayed largely the same, with minor edits, for the past 80 years and details the company's mission and responsibility to employees, patients, communities, and stockholders. The Credo is a revered document within J&J and serves to guide the principles and actions of employees for the betterment of all stakeholders.

J&J has historically had three business sectors (Pharmaceutical, Medical Device and Consumer Health), however in 2023 the company completed the divestiture of the Consumer Health division which is now a publicly traded company named Kenvue.(1) This strategy refocuses the J&J business around the more specialized and more profitable businesses in Pharmaceuticals and Medical Devices.

2.1.1 Ethicon

The Medical Device division is now known as J&J MedTech and consists of multiple franchises that specialize in different products or care areas. The Ethicon franchise is a wholly owned subsidiary of J&J that develops medical products for general and advanced surgery as well as sutures and other wound closure devices. Ethicon had $8.3 billion in sales in 2017, making it the global market leader by sales in all but one division.(3)

Each franchise of J&J operates as a company within the J&J brand and therefore has its own administrative, corporate, operations and R&D functions which are largely independent of similar functions in other franchises. This structure allows each franchise to operate semi-autonomously within the greater J&J organization and lead initiatives within the smaller structure to address their needs.

Within Ethicon, there are three divisions: Wound Closure, Bio Surgery, and Endo Surgery. Ethicon Endo Surgery, known as Ethicon Endo, specializes in the development of medical devices for endoscopic surgery. These devices include trocars, surgical staplers, dissection tools, and energy sealing tools among others.(4)

2.2 Endoscopic Surgery

Endoscopic surgery is a method of minimally invasive surgery characterized by the use of small incisions and insertion of specialized surgical devices such that a surgery may be performed largely within the patient's body, and not requiring major open surgery. The major benefits of endoscopic surgery are minimized bone, muscle and tissue damage, more rapid recovery, lower risk of infection, and reduced pain.(5)

These benefits have been realized by over a century of dedicated invention by physicians and engineers. In the 1960s and 1970s endoscopic surgery became more widely accepted as a surgical practice with the development led by gynecologists and later gastroenterologists.(5) By the 1990s, endoscopic surgery was recognized as the preferred surgical method for many surgeries including cholecystectomy for gall bladder removal, and transforaminal endoscopic spine surgery for herniated disc removal.(6) This uptake of new and transformational surgical methods demonstrates the broad clinical applications of endoscopic surgery and the significant benefits over traditional open surgery.

2.2.1 Surgical Staplers

Surgical staplers are now considered commonplace and indispensable tools for the temporary or permanent joining of tissue during surgery, however the first device designed specifically for surgical stapling wasn't developed until 1908 by the Hungarian surgeon Hümer Hültl, and engineer Victor Fischer.(7) The first applications of the device were used for gastric surgeries and this remained the primary use for the devices for the first few decades of the 20th century until the Soviets pioneered the first vascular surgical stapler device following WWII.(7)

The basic design of the first surgical stapler device has changed little to the present day with two lines of staples actuated simultaneously to clamp and hold tissue. However, several key innovations have expanded the usability and effectiveness of the device over the years. Notably, German Surgeon H. Friedrich pioneered the concept of removable staple cartridges with a reusable actuation device in the 1930's.(7) Additional innovations driven by competition and expanded applications have led to specialized surgical staplers with circular staple areas, cutters integrated into the staple mechanism, battery operated actuation mechanisms for improved repeatability, and improved staple designs to ensure reliable closure without restricting blood supply to healing tissue.(7)

2.2.2 J&J Surgical Stapler Products

In 1977 Ethicon entered the surgical stapler market and by 2017 the Ethicon Endocutter division was the market leader in surgical staplers by sales.(3) The Endocutter portfolio of surgical staplers today includes linear and circular staplers, powered and unpowered actuators, a range of disposable staple cartridges, as well as a number of devices for specialized gastrointestinal, thoracic, pediatric, gynecological, vascular and anastomotic surgeries among others.

A selection of Endocutter products can be found in Figure 1.(4)

Figure 1. Ethicon Endocutter Family

2.3 Ethicon Supply Chain

The Supply Chain organization within Ethicon works across all divisions to ensure reliable supply of products to customers. This is a highly cross functional group which must integrate closely with the R&D, Manufacturing, Sales and other groups internally and externally to Ethicon. This integration challenge is only enhanced by the global operations of Ethicon, the critical nature of the products, and regulatory compliance for medical devices.

In recent years, the Ethicon supply chain has also been impacted by the effects of the Covid-19 pandemic on global supply chains. Covid-19 caused massive disruptions to both the demand and supply of goods globally. Sharp changes in demand patterns caused by the illness in conjunction with stay-at-home orders were compounded by supply shocks caused by disruptions in global shipping, production stoppages, and production shifts to meet changing demand.(8) These varied disruptions have led to greater demand unpredictability and supply shortages for many products.

2.3.1 Supply Chain Digital Transformation

One approach to better manage supply chains and minimize supply chain disruptions is through greater adoption of digital supply chain management systems. This digital transformation has been accelerated by Covid-19 and has led to significant investment by J&J in a slate of digital technologies to support manufacturing and supply chain management.(9)

These technologies include digitized manufacturing facilities to better monitor production efficiencies and quality, as well as more highly integrated supply chain control towers, analytical tools and data management infrastructure. The eventual goal of these technologies is to move from descriptive to predictive and eventually prescriptive data analytics. This allows the organization to proactively and automatically set targets in the supply chain that will reduce overall costs, as well as predict and prevent disruption events.

2.3.2 Surgical Stapler Supply Chain Network

The surgical stapler supply chain is divided between the supply and distribution network which together make up the entire end to end supply chain. The supply chain originates with Suppliers who may provide raw materials or subassemblies to a central Assembly stage. After Assembly, devices are Packaged and sent for Sterilization before being shipped to a central Global Distribution Center. Once devices are checked into the Global Distribution Center they exit the supply network and enter the distribution network which is made up of multiple Regional Distribution Centers which in turn send devices to local customers. Some stages of the supply network are J&J owned and operated, whereas others are contracted to 3rd party suppliers or contract manufacturers depending on the complexity, criticality and cost of the component or assembly.

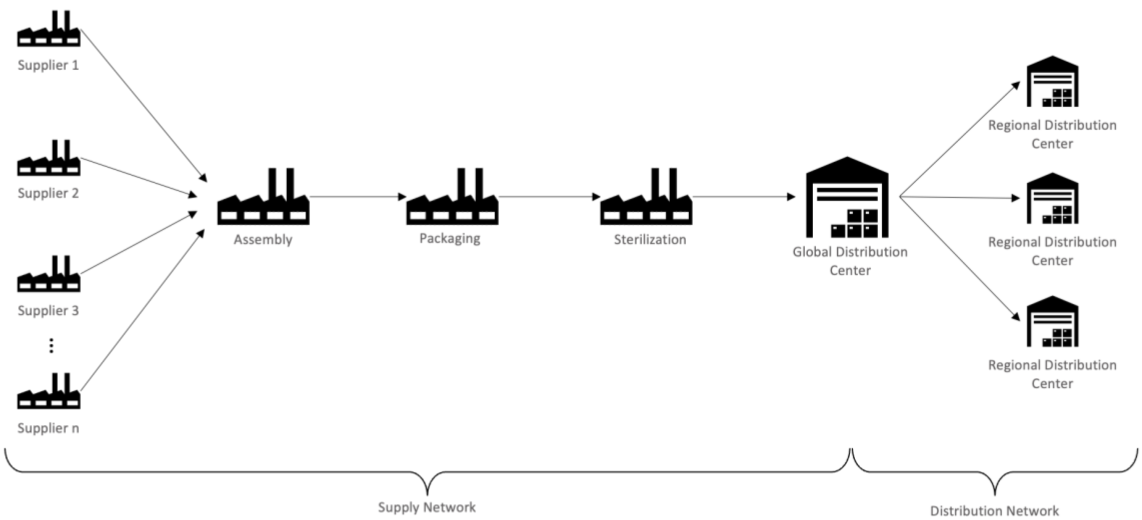

Figure 2. J&J Surgical Stapler Supply Chain Including Supply and Distribution Networks

3 Literature Review

3.1 Inventory Management Models

Supply chains can be very complex, but standard models have been developed over the last century to represent inventory dynamics under different assumptions. These models help to quantify and standardize practices to optimize the inventory availability in different circumstances. As Ziukhov notes, nearly all inventory management decisions can be summarized as:

> "1. How large should an inventory replenishment order be?
>
> 2. When should an inventory replenishment order be placed?"(10)

A model can help represent the logic to answer these questions for a given supply chain, with the eventual goal of setting inventory levels such that the right amount of stock is produced at the right time to hit the service level and cost targets of an organization.

Two important considerations in model selection are the number of stages in the network, and the sources of uncertainty.

3.1.1 Single Stage Inventory Models

A single stage model represents some process under the assumption that there are one or more upstream suppliers and a single downstream product with some demand.(11) Additional complexity can be added to represent capacity constraints, queueing, and on-hand inventory. A single stage model may represent a process in single or multiple periods.

One of the first single stage models is the Economic Order Quantity (EOQ) model developed by Ford Whitman Harris in 1913.(12) The EOQ model is a simplified model in that it assumes deterministic demand over time and no stockouts, but it provides a powerful analytical approach to balancing the cost of re-ordering inventory versus holding inventory.

The Newsvendor model is another classic single stage model used to maximize expected profit of a single order given a probabilistic demand profile of a perishable good. The optimization function of a Newsvendor model minimizes the cost of excess inventory in the case of overproduction and the cost of lost sales in the case of underproduction to find the optimal production quantity.(10) This model still holds high applicability today for fashion and high-tech goods with short product life cycles and long purchase periods.(13)

Building on the Newsvendor model, the Base Stock model is a commonly utilized model to represent multi-period, recurring purchases but unlike the Newsvendor model, goods are assumed to be durable over time so on hand inventory or stockouts carry on to the next period.(14)

There are two basic variations on the Base Stock model, fixed-order quantity and fixed-period, also known as periodic review.(14) A fixed-order quantity is similar to an EOQ model in that a fixed quantity of goods is ordered, typically when an event such as an on-hand inventory limit is hit. A fixed-order quantity model usually assumes continuous review, therefore the on hand inventory can be lower than a periodic review model because safety stock only needs to cover the lead time of the item, not the additional review period.(14) However, continuous review can be a greater administrative burden and not optimal for all circumstances.

In a periodic review model, orders are placed at a given interval using the order-up-to method of placing a variable order quantity depending on the difference between on hand and target inventory at the time of review.(15) This model is commonly used in part because periodic review is easier to manage than continuous review. An example of a periodic review base stock policy with stochastic demand can be found in Figure 3 where the lead time is less than the review period so there are no overlapping orders.

The base stock is the order up to quantity and orders are placed at the end of regular review periods, with the orders being fulfilled after some lead time. Some models additionally account for stochastic lead times which can greatly increase the safety stock requirements to cover the distribution of lead times from an upstream supplier.(16)

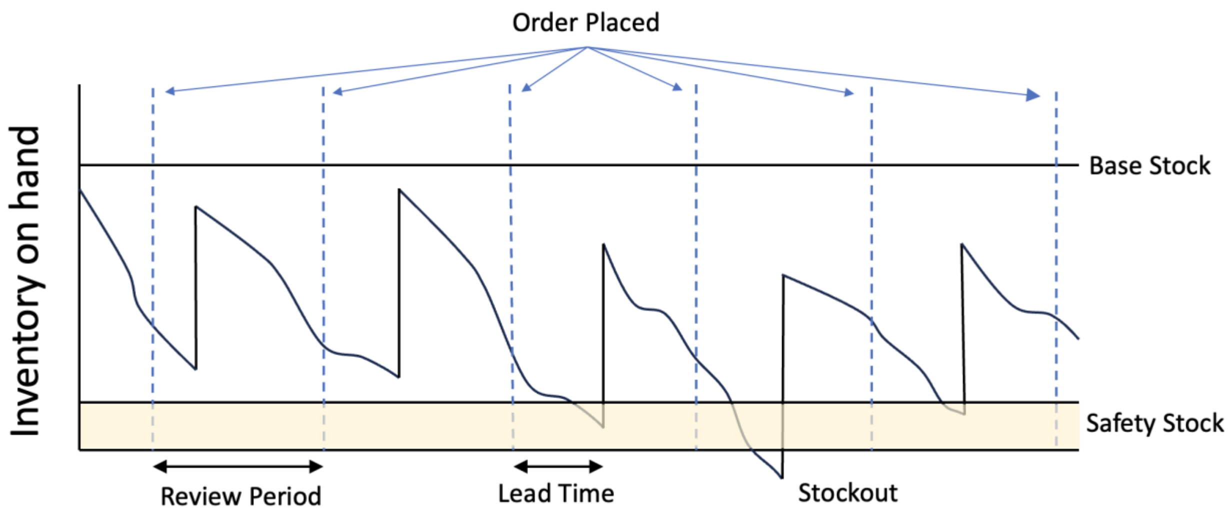

Figure 3. Base Stock Inventory Policy Example

3.1.2 Multi Echelon Inventory Optimization

Multi Echelon Inventory Optimization (MEIO) is a method of optimizing inventory across multiple stages or echelons to achieve the total lowest inventory cost at a target service level across the entire network. A multi-stage model increases model complexity due to the interactions between stages as inventory moves through a network, and MEIO is one technique to manage the lead times and inventory across all stages.

The goal of MEIO is to minimize the total cost of safety stock across a network.(17) Safety stock is inventory held at strategic locations in a supply chain to buffer the effect of stochastic demand or supply. Unlike cycle stock and pipeline stock which are set by the order quantity over a certain period, safety stock is an additional fixed inventory target that is set at the discretion of a planner to meet service level requirements.(18) The balance of setting safety stock targets is setting a high enough service level target to prevent most stockouts, while trying to keep total inventory low to reduce costs.

There are two methods of MEIO, guaranteed service models and stochastic service models.(17) A stochastic service model assumes variable service levels from supply stages, so customer orders cannot always be filled from stock and lead times may vary within the network as delays are incurred.(17) Comprehensive surveys of stochastic service models have been performed by de Kok et al and Simchi-Levi and Zhao.(19,20)

In the guaranteed service model, each supply stage provides guaranteed service at some quoted level to its downstream stage.(17) In this model each supply stage must hold enough inventory to guarantee service. This makes planning more predictable because the replenishment times are fixed. The first generalized guaranteed service model was described by Graves and Willems in 2000 and later expanded to describe supply chains with nonstationary demand among other contributions.(21,22) Humair et al. described a guaranteed service model with non-stationary lead times and Eruguz has further expanded the guaranteed service model for optimization of reorder intervals and order up to quantities.(16,23)

3.1.3 Service Level

An important component of MEIO and characterization of safety stock is the service level selection. Chopra and Meindl refer to service level as a product availability metric given the service being provided in an inventory model is on-hand inventory availability.(24) They go on to discuss the three most common types of service level: product fill rate, order fill rate, and cycle service level.(24)

Product and order fill rate relate to the percentage of total product or total orders, respectively, that are filled from on hand inventory over a given quantity of product or orders.(24) Product fill rate is the most common service level metric in industry because it relates directly to customer service level, as opposed to an internal organizational metric.(25)

Cycle service level is the proportion of replenishment cycles within a given time period that do not have a stockout within that period, which is also the same as the probability of not having a stockout in a given replenishment period.(24) Although less intuitive than fill rate, cycle service level still remains the basis of many safety stock calculations including the those used in the guaranteed service model by Graves and Willems.(18,21)

3.2 Simulation Methods for Supply Chain

Whereas optimization is an analytical approach to inventory management, simulation is a computational approach which utilizes the power of numerical methods to approximate the solution to a complex problem. Simulation has become more common and more powerful in recent years with increased processing capabilities of modern computers. One benefit to simulation models is the ability to represent supply chain complexity that otherwise can't be represented by optimization methods.(26)

Multi echelon inventory management policies were first described by Clark and Scarf in 1960 and simulation has been utilized for multi echelon inventory management since at least 1982.(27,28) Continued research by Chan and Chan used simulation to evaluate multiple different inventory models.(29) Today, simulation is commonly utilized in inventory management software to aid planners in setting safety stock and reorder targets.(26)

Common simulation methods include Discrete Event Simulation, Monte Carlo Simulation, System Dynamics and Agent-Based Simulation.(26) Discrete Event Simulation, System Dynamics and Agent-Based Simulation are powerful techniques for simulating the relationship between multiple stages of a supply chain or flow of material through a stage. Monte Carlo simulation introduces random sampling, allowing it to effectively simulate uncertainty in various conditions.(26)

3.2.1 Monte Carlo Simulation

There are many forms of Monte Carlo simulation but generally these simulations model a variable with some probability density function, sample from this distribution and compute summary statistics from a series of iterations.(30) This technique makes use of the Law of Large Numbers, which states that the average of a large number of independent and identical random sample will converge to the true result.(31)

Jung et al. utilize Monte Carlo simulation as a method of testing customer satisfying level to refine safety stock in coordination with an optimization model.(32) This method effectively uses Monte Carlo simulation to represent the complexity of the real-world supply chain and iteratively evaluate and improve the estimate of safety stock for a given customer satisfaction level. Others including Chu et al. have used a combination of methods including optimization, Agent Based Simulation and Monte Carlo simulation in the same model to find optimal solutions under real world constraints.(33) Similarly to Jung, Chu uses Monte Carlo simulation to test and refine the outcomes of other models. This reinforcement learning approach is further explored by Perez et al. who find that reinforcement learning approaches using simulation provide inventory solutions that may be more robust to disruption compared to purely analytical models.(34)

4 Inventory Model Process

4.1 Model Development Methodology

Optimization and simulation models were developed which operate in an iterative process to determine the optimal safety stock and resulting holding cost for a given product and service level target. The process draws on the complementary strengths of each model to refine the solution space as the process progresses.

The purpose of the optimization model is to establish the Net Replenishment Lead Time (NRLT) for the final stage of a supply network (assumed to be a distribution center) based on the optimized distribution of safety stock in the network. The distribution center (DC) is the lynchpin in the supply network because it serves as the linkage between the supply and distribution network and is the supplier to the downstream distribution network. A planner in the supply chain organization is most concerned with the level of inventory at the distribution center as this determines the strategy for inventory deployment and market entry.

The simulation model evaluates the stockout risk and cost of inventory at the distribution center given real-world scenario planning. This serves to inform a planner of the tradeoffs in inventory planning and best modify safety stock targets to hit performance and cost targets.

As shown in Figure 4, the model takes input on the supply chain of a product, and through successive processing, outputs the optimized NRLT and safety stock allocation as well as the final holding cost and service level at the DC. In total, these outputs provide actionable data for a planner to manage product inventory. The successive nature of the models also provides an opportunity for a planner to validate the assumptions in the model and outputs as it progresses.

The technical development for this project was completed in a Jupyter Notebook using Python 3.11.

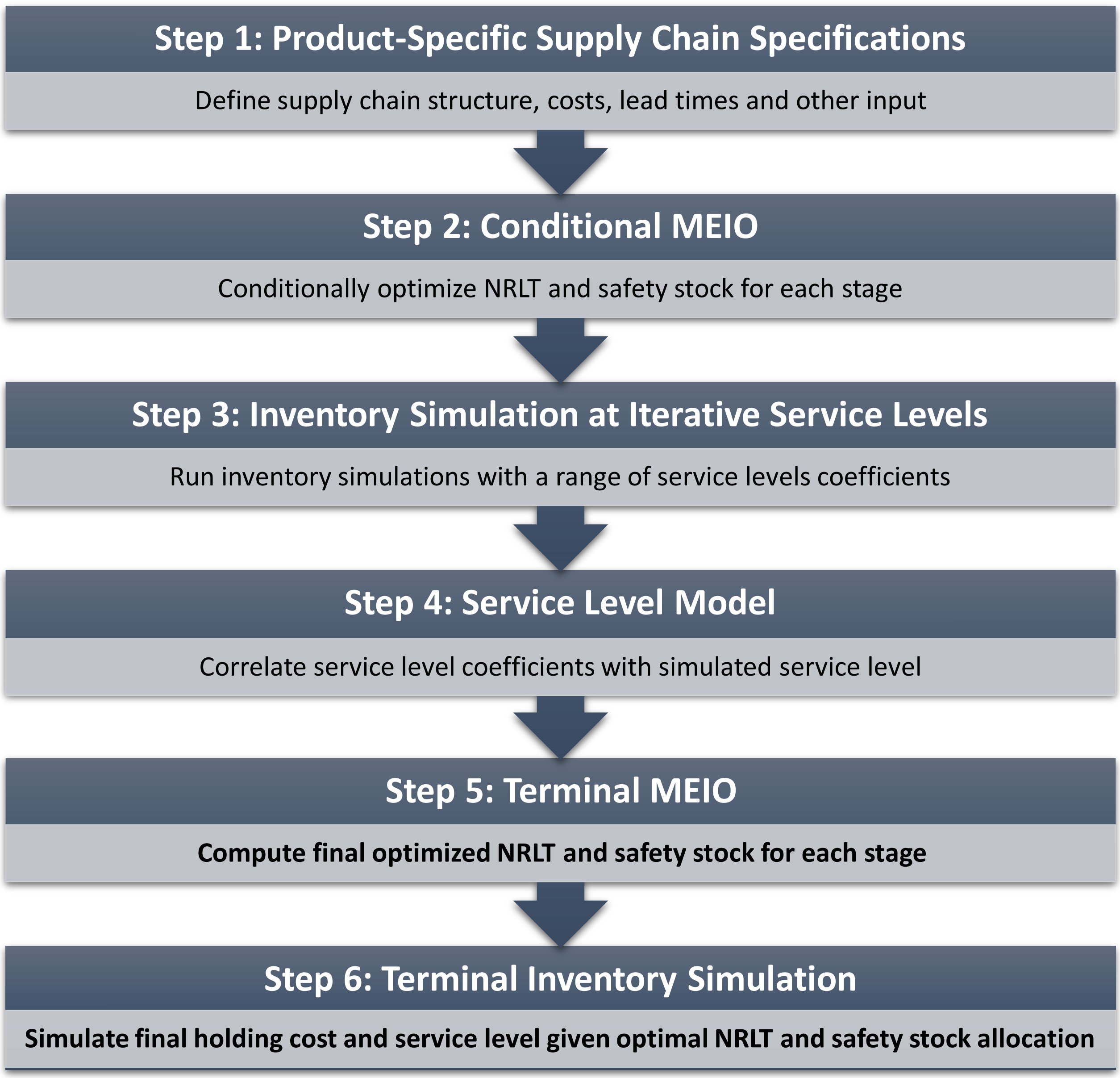

Figure 4. Inventory Optimization and Simulation Model Process Flow (recorded outputs in bold)

4.2 Product Specific Supply Chain Specifications

The start of the process is to define inputs to the MEIO model that represent the structure of a product's supply chain, as well as relevant information on costs and lead times of each stage in the supply chain. In addition, product-specific inputs are needed for the simulation to properly simulate different supply and demand scenarios. These inputs are discussed in more detail in the respective MEIO and simulation sections.

4.3 Multi Echelon Inventory Optimization

A guaranteed service model approach is used for the MEIO model to ensure predictable service times. This is valuable from a planning perspective and serves to simplify the simulation model as all supply lead times are assumed to be deterministic. In addition, cycle service level is used as a service level metric because it better represents the reporting practices at J&J. The number of cycles is assumed to be large, covering planning for a year.

An MEIO model comprises an objective function, and constraints on the function. An optimizer is used to algorithmically determine the optimal solution to the optimization function across the entire network.

4.3.1 MEIO In the Inventory Modeling Process

MEIO models are run twice during the complete inventory modeling process; first a Conditional MEIO model is run to set a baseline, and finally a Terminal MEIO is run to generate reported outputs once the service level factor has been established for a product.

The purpose of the Conditional MEIO model is to find the optimal NRLT and safety stock across the supply network, specifically at the distribution center stage, conditional on an unknown service level factor. The conditional MEIO model follows the MEIO logic discussed in this section, however, the service level factor (k) is set equal to 1. This serves to represent that the service level factor is unknown, as it will be determined in successive simulation modeling and analysis. The output of the Conditional MEIO model is not a reported value and is only used to inform the inputs to the Inventory Simulation at Iterative Service Levels.

The Terminal MEIO model is the penultimate step in the modeling process and serves to generate the optimal NRLT and safety stock across the supply network based on a derived service level factor. The Terminal MEIO model inputs the service level factor from the Service Level Model and the output of the Terminal MEIO model informs the input to the Terminal Inventory Simulation. The output is also a reported value to the planner, independent of the successive simulation step.

4.3.2 Model Formulation

The objective of the MEIO model is to minimize the total inventory holding cost across all stages by optimizing the NRLT of each stage in the system. This model accounts for variability in demand but not supply due to lack of supply data at the time of the project.

The model is adapted from the guaranteed service model developed by Graves and Willems.(17)

<u>Objective function:</u>

$$min \sum_{i \in N} \alpha C_i k \sigma \sqrt{\tau_i}$$

<u>Where:</u>

α = holding cost ratio

C_i = cumulative cost at stage *i*

k = service level factor

σ = standard deviation of demand at stage *i*

τ_i = net replenishment lead time at stage *i*

<u>Subject to the following constraints:</u>

Set the incoming service times to the raw material stages as 0 to confine the input to the system.

$$SI_0 = 0$$

Set the outgoing service time from the DC stage to 0 to confine the output to the system.

$$S_{DC} = 0, \qquad where\ DC = final\ stage\ at\ DC$$

Constrain the incoming service time to a stage to be equal to the max of the outgoing service times to that stage. *A* is the set of all arcs in the system.

$$SI_i - S_k \geq 0, \qquad \forall (k, i) \in A$$

Constrain the Assembly and Packaging stage (AP) to have a NRLT of 0 to reflect that this stage does not hold any SS.

$$\tau_{AP} = 0, \qquad where\ AP = Assembly\ and\ Packaging$$

Constrain the relationship of service times at a given stage in relation to NRLT. *N* is the set of all stages in the system.

$$\tau_i = SI_i + r_i + T_i - S_i, \qquad \forall i \in N$$

SI_i = incoming service time at stage *i*

S_i = outgoing service time at stage *i*

r_i = review period at stage *i*

T_i = process time (lead time) at stage *i*

Constrain the NRLT to be non-negative.

$$S_i - SI_i \leq r_i + T_i, \qquad \forall i \in N$$

Constrain the maximum outgoing service time from each stage to ensure each stage quotes a service time within reasonable constraints. E is the maximum outgoing service time value.

$$S_i \leq E, \qquad \forall i \in N$$

Set the minimum incoming and outgoing service time to 0 to ensure all values are non-negative.

$$SI_i \geq 0, \qquad \forall i \in N$$

$$S_i \geq 0, \qquad \forall i \in N$$

4.3.3 Linearization

The objective function is a nonlinear program and must be linearized in order to utilize the standard Gurobi solver. This is achieved by using a linear dummy variable in the objective function in place of the root function and additionally adding a constraint to define the decision variable as a square of the dummy variable.

4.4 Inventory Model Simulation and Evaluation

4.4.1 Simulation Methodology

The purpose of an inventory simulation is to probabilistically predict inventory metrics into the future. For this simulation, a 1-year time period is considered as is standard for forecasting at J&J.

The simulation model employs a Monte Carlo simulation of inventory for a product over the course of a year. The model simulates the realistic variability in a product's supply chain by running 1000 simulations factoring in both stochastic demand and supply scenarios. In addition, the model factors in the inventory management policies such as order quantities, lead times, and re-order levels that govern how products are ordered and when they are delivered over the course of each simulation. The outputs of the model are summary statistics for key metrics including average holding cost and service level over all simulation iterations.

An example of the simulation process shows how for each iteration (1-year simulation), a demand scenario is probabilistically selected and for each week in the simulation a supply event probabilistically occurs or not. The inventory management process governs the inventory level over the course of the simulation period. A stockout is flagged when the demand exceeds available inventory for any week. We assume that all iterations start with inventory at the safety stock level.

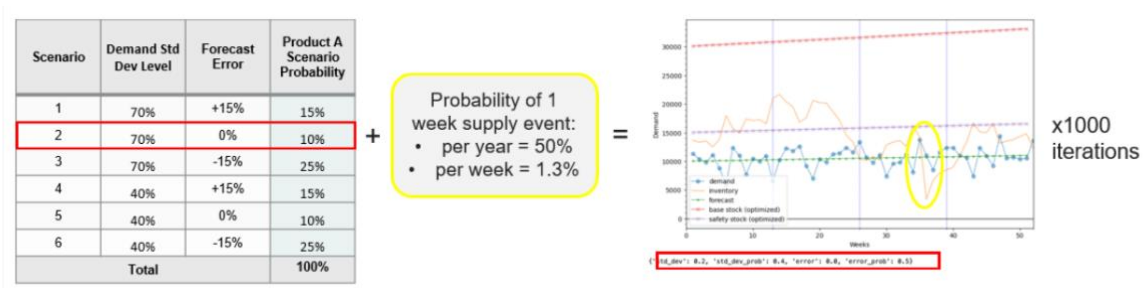

Figure 5. Simulation Process Including Demand Scenario Selection, Weekly Supply Event Probability, and Resulting Inventory Level Graph Over Time for a Single Iteration

4.4.2 Simulation in the Inventory Modeling Process

In the inventory modeling process, simulation is utilized twice. First, simulations are run with a range of service level factors to develop the data to analyze correlation between service level factor and cycle service level at the DC, which is an output of the simulation. Secondly, a Terminal Inventory Simulation is run to generate the reported service level and inventory holding cost outputs.

The cycle service level is an output of the simulation and is calculated as the percentage of cycles without a stockout out of all the cycles in the simulation. Assuming a weekly cadence of ordering and receipt of product, the cycle number is equal to the number of weeks in the year-long simulation. Given that the simulation factors in real-life variability that is not easily analytically modeled, the simulation model is a better predictor of service level than assuming a specific service distribution.

The first set of simulations in the inventory model process assumes that the correlation between service level factor (k) and actual cycle service level is unknown. Simulations are run at a range of service level factors from 0 to 6 at intervals of 0.1. The service level factor is effectively a multiplier on the safety stock determined by the conditional MEIO and a greater service level factor correlates with a higher service level and higher holding cost. The output of the inventory simulation with iterative service level is the input service level factor and the corresponding simulated service level across a broad range of values. This data is used in the service level model to find the service level factor at a given service level target. We assume that a single service level factor is used for all stages.

The terminal simulation is run after the terminal MEIO has determined the final allocation of safety stock and NRLT. This final simulation serves to validate the previous model and generate the final reported holding cost and service level outputs. Although service level is determined earlier in the inventory model process, the reported value may change slightly in the final simulation based on small probabilistic differences in the simulation.

4.4.3 Inventory Ordering Model

A supply planner is responsible for placing orders with suppliers and manufacturers based on forecasted demand signals. To help standardize the inventory ordering process and to ensure inventory targets are met, an inventory management policy dictates the cadence and quantity for all orders. This policy may vary between products and planners however a model policy can represent the most common inventory practice.

For this model we assume that a one-year production forecast has been developed based on an initial demand forecast. Modifications to the production schedule are made on a monthly basis. These modifications are capacity constrained, and we assume that production cannot increase or decrease by more than 25% of the initial forecast for that month. This creates an interesting case where the actual review period is monthly, but orders are planned on a weekly cadence so the simulated review period is weekly. This model reflects actual planning strategies and is not modified to optimize performance by minimizing the actual and simulated review periods. The simulation accounts for varying week length for each month.

The lag time in the system is the time between when an order is placed and that order is fulfilled at the DC. The lag time is equal to the sum of the lead time and review periods between the DC and the most recent upstream safety stock holding location given a safety stock holding location will decouple upstream and downstream supply. The lag time can be calculated as the NRLT for the DC when employing an MEIO model for inventory allocation in the supply network.

The current inventory on hand is calculated as the sum of the previous weeks inventory and the received production order, less the demand for that week.

$$Inventory_k = Inventory_{k-1} + \ Order_{k-x} - Demand_k$$

Where

$$k = current\ week$$

$$x = lag\ time\ (wks)$$

$$Order_k = Base\ Stock_k - Inventory_k - \sum_{k-1}^{k-x} Order_k$$

The lag between a production order and realizing the inventory creates inherent instability in the system because corrections to the demand can build up over the course of the lag period and create an inventory bullwhip. To dampen the bullwhip, we assume that any order takes into account the total orders over the course of the preceding lag period as well the quantity needed for that week which is the difference between the Base Stock level (order-up-to quantity) and inventory on have for the week.

For example, if there is a difference in 100 units between the inventory target and the inventory on hand but there is already a sum of 100 units already ordered, then no production order is needed for that week. However, if 100 units is needed and only 50 additional units are already on order, then the production order would be 50 units for that week.

If the production order exceeds the surge capacity constraint in a given month then it is capped at the capacity constraint. It is also important to note that at the start of each month, the required production order is distributed over the weeks of the following month and no additional orders are counted for that month. In other words, the ordering process is only run once a month, not weekly. This can impact the rate at which the system can react to supply disruption or major demand disruption beyond the inherent lag time.

4.4.4 Base Stock Model

The system operates as a modified base stock model with the inventory target as the base stock for each week. The base stock is calculated as the sum of the pipeline stock, cycle stock and safety stock.

$$\text{Pipeline stock} = Forecast_i * NRLT_{DC}, \quad \forall i \in A$$

$$\text{Cycle stock} = (Forecast_i * r_{DC})/2, \qquad \forall i \in A$$

$$\text{Safety stock} = SS_{DC} * Demand\ Standard\ Deviation$$

$$\text{Base stock} = \text{pipeline stock} + \text{cycle stock} + \text{safety stock}$$

Where A is the set of all weeks (i) in a given simulation period.

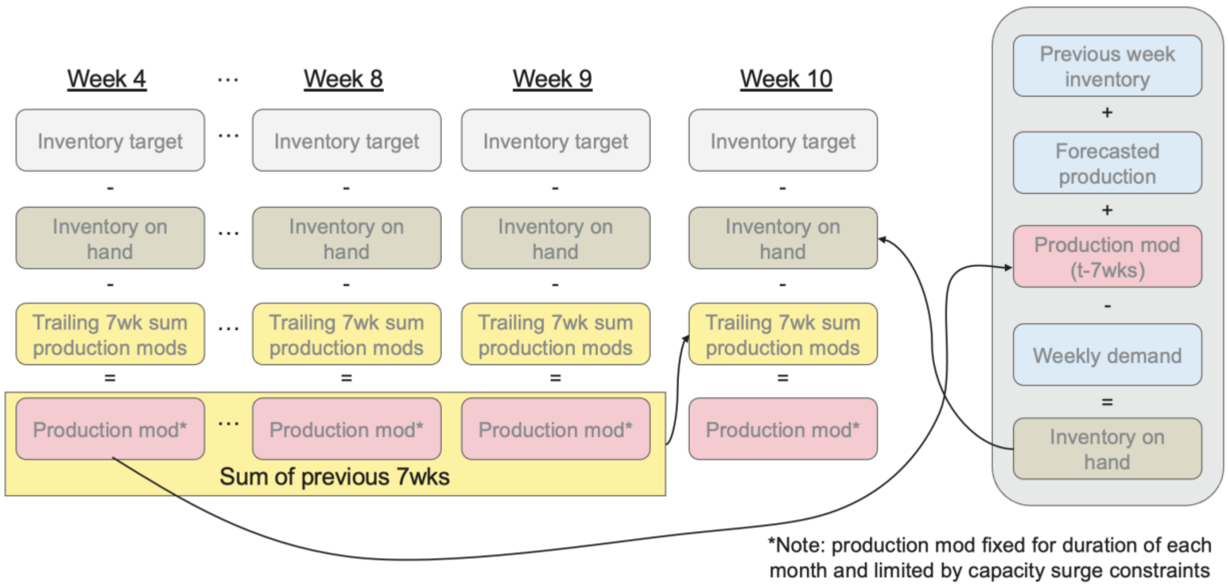

Figure 6. Inventory Management Process Model with an Example 7wk Lag Time

4.4.5 Demand Scenarios

Demand is modeled as a normally distributed random variable generated weekly. Note that the week was chosen as the base unit of time measurement as this was the minimum granularity of data available for lead times. This variable is dependent on three inputs (forecast average, forecast error and standard deviation) which are in turn probabilistically determined from a range of user generated scenarios.

Demand scenarios are a series of weighted scenarios combining forecast error and standard deviation of demand that are unique to a given product and represent expected possible scenarios for demand variability and forecast unpredictability over the following year. These scenarios are selected based on their probability for Monte Carlo simulation.

4.4.6 Forecast Baseline

The forecast average is dependent on an initial forecast at the beginning of the period and a fixed linear growth rate. This value can be calculated from forecast data by fitting a linear trendline to the data. The y intercept and slope can be extracted to determine the approximate initial forecast and growth rate and converted to weekly values.

4.4.7 Forecast Error

The forecast error and standard deviation of demand are user input with scenario probabilities. To determine the historical forecast error for each product the percent forecast error can be calculated for each month of data and averaged. This gives the Mean Percent Error (MPE) for the forecast.

4.4.8 Demand Variability

To determine the standard deviation of demand, the root mean square error (RMSE) can be calculated based on the error between actual and linear fit demand data. This is necessary because the demand is increasing over time and the trend must be considered in the variance.

4.4.9 Total Demand Scenarios

The complete list of demand scenarios for each product is every combination of standard deviation and forecast error for that product The individual probabilities of occurrence for the standard deviation value and forecast error value can be multiplied to determine the probability of overall occurrence for a given demand scenarios.

For any given iteration of the simulation, a demand scenario is selected based on the probability of occurrence. This demand scenario informs the stochastic demand profile of that iteration.

Additionally, the weighted average standard deviation across all scenarios for each product can be calculated. This value is used as a modifier to calculate the safety stock target for each product. The weighted average standard deviation is used for this purpose because we assume that a planner knows the probabilities of standard deviation and forecast scenarios but is not aware of which scenario type is occurring over a given period.

4.4.10 Supply Scenarios

In addition to the demand scenarios, a supply disruption event may be randomly generated for each week in an iteration based on the probability of occurrence. We assume that the supply disruption event stops all production at the point of Assembly for 1 week. This assumption simplifies a number of different possible real-world supply events including raw material shortages, quality holds, and work stoppages into a single supply event. Based on information from supply planners, a 1wk supply shut down is a major event and occurs with low probability in the normal course of business.

4.5 Service Level Model

The output of the simulation at iterative service levels in the inventory model process is data correlating service level factor and cycle service level. The purpose of the service level model is to curve fit this data and find the service level factor associated with a user-input target service level.

The cycle service level to service level factor curve shows the cumulative distribution function for the cycle service level which can be represented as a logistic function. This function will approximate a normal distribution given the demand is assumed to be normally distributed, however it is modified by the other variability in the simulation. The full cumulative probability function is not represented as the minimum service level factor calculated is 0 which represents no safety stock.

The scipy.optimize.curve_fit library are used to curve fit a logistic function.

$$Logistic\ Function = \frac{a}{1 + e^{-c(x-d)}} + b$$

Where *a, b, c,* and *d* are parameters defining the shape of the curve and x is the independent variable, in this case the service level factor. Once the curve fit model has been established and validated, the service level factor corresponding to a user input target cycle service level can be output. Typical cycle service levels targets are 80-99.9% and vary depending on the criticality and cost tradeoff for a product.

5 Case Study

For the purposes of this project, two J&J surgical stapler products were selected for modeling and analysis. These products were selected as representative of different variations of the supply chain and will be referred to as Product A and Product B.

Product A is representative of a new product introduction and shows strong growth over a short period, but still has low sales compared to legacy products in the space. Given that it is a new product, there is high uncertainty in the demand profile and greater variability in supply as manufacturing is scaled up.

Product B is representative of a legacy product with a strong sales history but little growth, as the market position is stable over time. The demand for Product B is well characterized and forecasting is more accurate than with a new product. In addition, the supply network is robust and supply disruptions are minimal.

Using the actual supply chain of each of these products, a model supply chain was developed to represent the key components and variables. This serves to limit the scope of the model to capture the most impactful variables while eliminating unnecessary complexity and preserving confidentiality. It also serves to abstract the model to be more broadly applicable across multiple products and supply chains, instead of limited to a single use case.

The optimized supply network for Product A and B can be compared to standard practice to determine the tradeoffs between using an optimization and simulation based model and using heuristics for managing safety stock in a supply network.

5.1 Supply Chain Network

The model supply chain consists of five primary stages: 1) Suppliers, 2) Assembly, 3) Packaging, 4) Sterilization, and 5) Distribution Center (DC). Each of these stages has many subassembly, shipping, waiting and other minor handling steps. However, for the purposes of modeling the supply chain these secondary steps can be rolled into the primary stage.

5.1.1 Suppliers

There can be more than 80 Suppliers for any given product, each with varying lead times, costs, shipping requirements, and supply reliability. To buffer this variability, different suppliers hold different safety stock levels for each component they supply. This creates a very complex supplier network, which can be simplified by bucketing different suppliers by lead time, as Graves and Willems do in their case study of a notebook computer.(35) The size of these buckets was approximated based on the lead times of suppliers and cost of goods for products within that time range. Each bucket is abstracted to represent the Raw Materials contained in that bucket.

5.1.2 Assembly and Packaging

The Assembly and Packaging stages occur sequentially at separate facilities. Assembly consists of assembling all raw material components into a single finished good device. These devices are then shipped to a Packaging facility where they are boxed in the appropriate quantity for the product and additional information such as the Instructions for Use are added to the package. Multiple automated and manual quality checks occur throughout the Assembly and Packaging and any reject components or devices are scrapped. For the purposes of the supply chain model, we assume that the yield is 100% at all stages.

Assembly and Packaging are performed in facilities with single piece flow following lean manufacturing practices which means that no excess inventory is held at these stages. Given that these are pass-through stages, Assembly and Packaging can be modeled as a single process incorporating the total time and cost of both stages with no inventory holding.

5.1.3 Sterilization

Sterilization is performed at multiple different sites depending on the products, but costs and lead times are similar across sites so they can be modeled as a single stage type. Sterilization is performed in a specific batch size depending on the validation procedures for a given product. Depending on the production volumes and shipping schedule, the Sterilization site may hold inventory for different periods of time before reaching the target batch size to perform a sterilization run. This leads to the Sterilization site holding some inventory at any given time and the ability to hold safety stock as needed. The amortized Sterilization cost across all products is assumed to be negligible.

5.1.4 Distribution Center

Following Sterilization, all products are processed at a Distribution Center. The central DC is the final stage in the supply network and the first stage in the distribution network. The distribution network is out of scope of this model.

The supply network model assumes a 1wk lead time for handling of products at the DC largely due to intake and processing time. It is also assumed that the DC holds safety stock for all downstream distribution and customer demand.

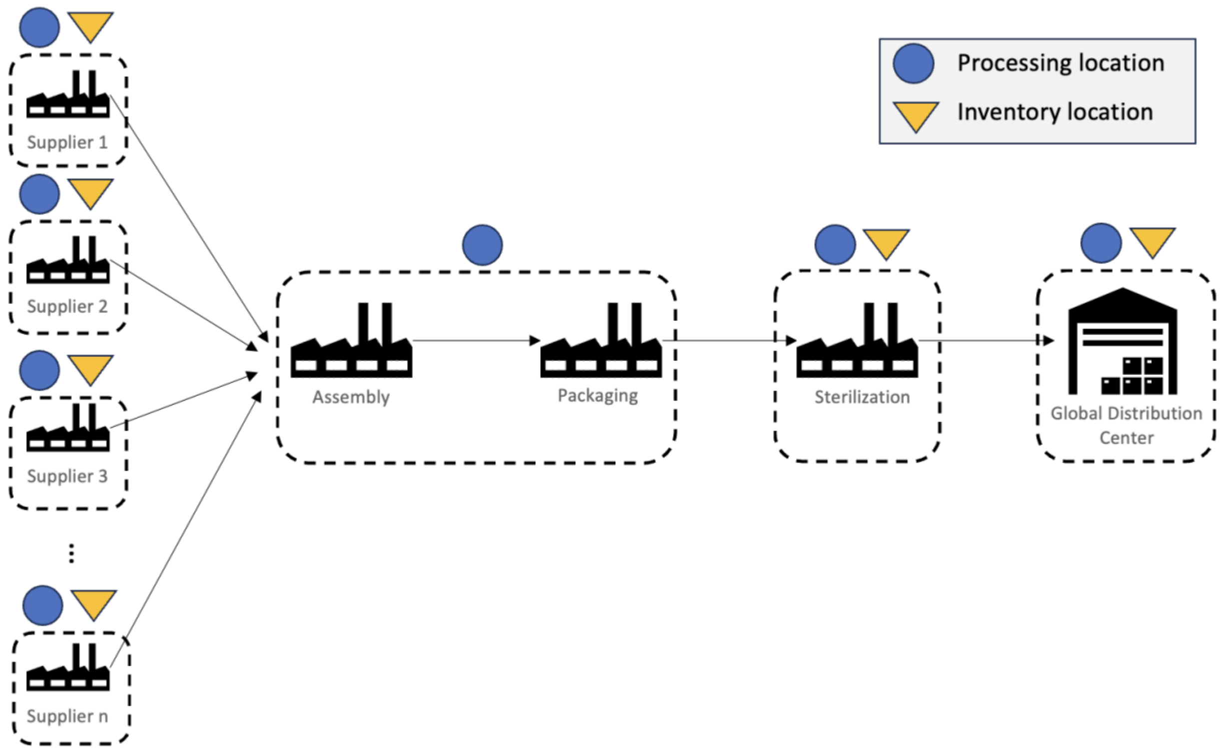

Figure 7. Model Supply Chain with Each Bucketed Stage Highlighted

5.2 Data Sources

Key data sources for modeling, analyzing and developing predictive models include Bill of Materials, cost data, lead times, and demand data. In cases where data were not available for a given product, interviews were conducted with supply and demand planners to approximate the necessary values.

5.2.1 Bill of Materials

The Bill of Materials (BOM) lists the name and quantity of the parts and subassemblies in a device, allowing for all components to be traced through the system. The BOM also allows for a single source of truth on a released part or assembly revision. This information was received in Microsoft Excel files for Product A and were extrapolated for Product B.

5.2.2 Cost Data

Cost data comprises the cost of all raw material components well as the added cost at each stage of the supply chain. This information is used in an MEIO to inform the model on costs in the system. All costs were normalized to $100 per device to generalize the model and protect confidential information.

Product A is a new device with relatively higher assembly and packaging costs than Product B, due to smaller lot sizes and higher start-up costs. In turn, product A has lower raw material costs relative to the total device cost. Both products have greater costs from suppliers that have short lead times because a greater proportion of the total raw materials is delivered within 2-4wks. There is a long tail of raw materials with lead times exceeding 1 year in some cases, however these materials account for a very small proportion of the total cost of goods.

5.2.3 Lead Time Data

Lead time for any stage is defined as the total processing time for that stage including shipping to the stage and any work done to the item at that stage. We assume that this is running lead time, where the system is in an active state and does not require excessive start up time at the beginning of an order. This is an important assumption for raw materials which may have a much longer lead time if starting a line cold rather than in an active cadence. Furthermore, it’s assumed that lead times include all delays in the ordering and processing of an item. Again, this is an important assumption for raw materials which may have a long queue of parts in front of them causing delays in the lead time of that part.

Detailed lead time data for all products was not available, however general lead times for each stage were provided by supply planners. All lead times are considered deterministic in the model.

5.2.4 Demand Data

Demand data comprises 1) the forecast for each product by month, and 2) the actual demand for each product by month. Forecasted and actual demand data were received in Microsoft Excel format for all products. These data were used to develop the demand scenarios for each product.

5.3 Inventory Model Process

The inventory model process is run independently for each product. In this section, the assumption and results for each product are discussed. Additional model inputs and results can be found in Appendix 8.1.

5.3.1 Conditional MEIO

The assumptions for standard deviation of demand and service level are discussed in 4.3. The holding rate, (α) is 0.25, based on standard practice in literature. Lastly, the maximum outgoing service time (E) is set to 1000. A test of different values for E within the range of 100 to 5000 showed no difference in output indicating this is an acceptable value that is not influencing the model outputs.

The key outputs of the conditional MEIO are the NRLT at the DC for each product and the safety stock at the DC for each product given a service level factor of 1. These values serve as baseline factors for the Inventory Simulation at Iterative Service levels. For Product A the NRLT at the DC is 7wks, and safety stock is 1707ea. For Product B the NRLT at the DC is 9wks and the safety stock is 9498ea.

Gurobi optimizer version 11.0.0 in Python (gurobi.py) was used for this model.

5.3.2 Inventory Simulation at Iterative Service Levels

A series of simulations was run at a range of service level factors from 0-6, resulting in a range of cycle service levels of 0.590 to 0.991 for Product A and 0.497 to 0.998 for Product B.

5.3.3 Service Level Model

The service levels were fit to a logistic curve for each product with a resulting R^2 fit of 0.996 and 0.997 for Product A and Product B respectively. Using the curve fit, and a user defined target cycle service level of 0.95, the service level factor for each product was calculated to be 3.37 for Product A and 3.21 for Product B.

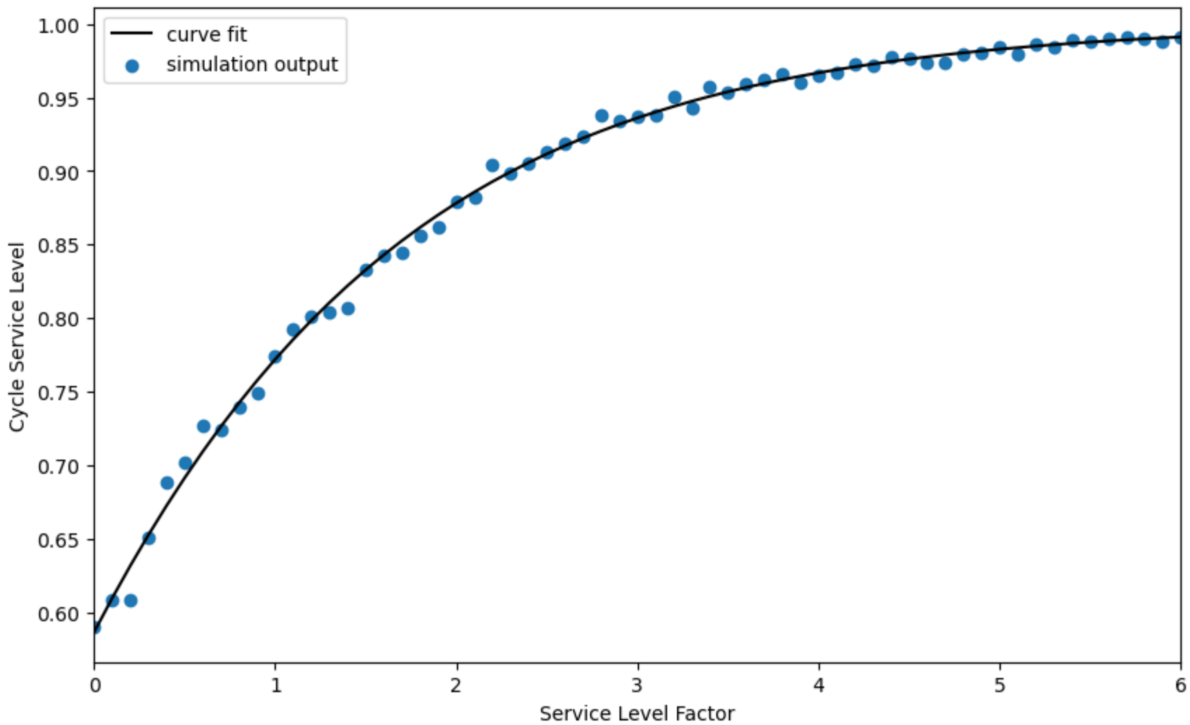

Figure 8. Service level curve for Product A

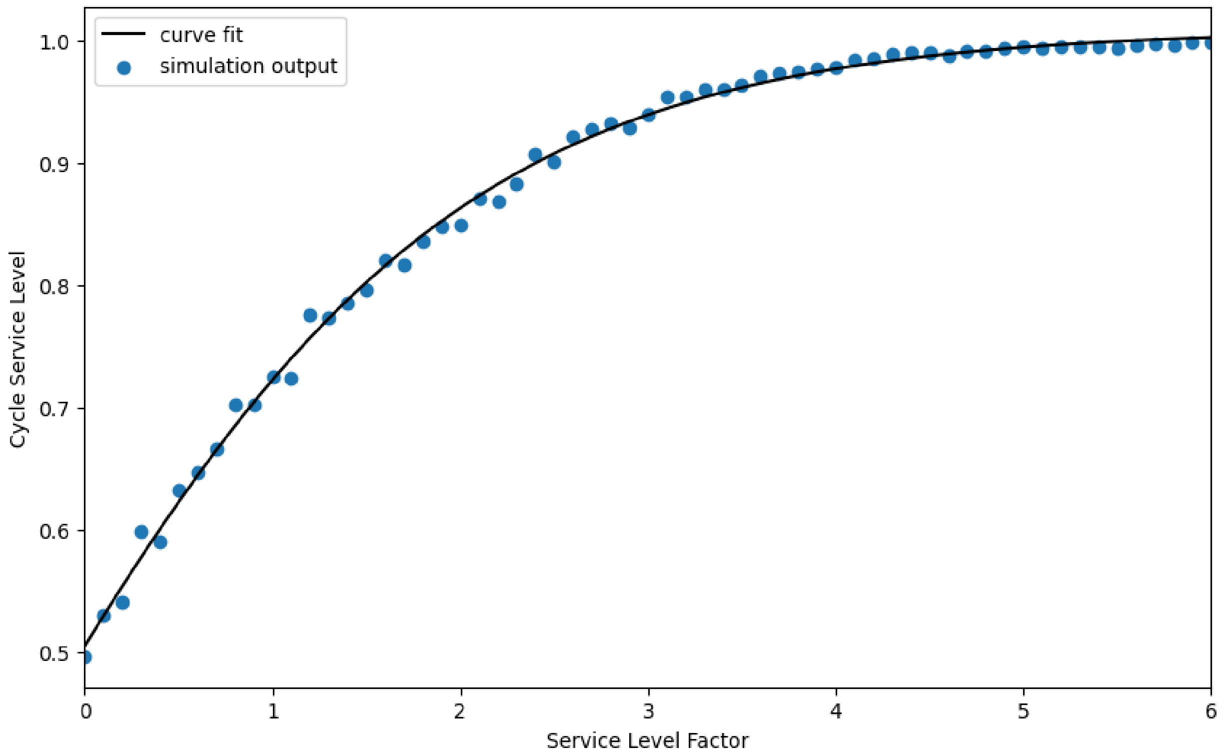

Figure 9. Service level curve for Product B

5.3.4 Terminal MEIO

An optimal solution to the supply network MEIO was achieved using the service level factors found in the Service Level Model for each product. For both products, the optimal allocation of safety stock is at the raw material and DC level, with no safety stock at the assembly and packaging or sterilization stages. However, the optimal safety stock for Product A at the Raw Material level effectively decouples all suppliers from assembly and packaging by recommending holding enough safety stock to cover the entire NRLT for that Raw Material. For Product B, the optimal solution based on minimizing cost is for Raw Material suppliers to hold safety stock for greater than 2wks which pushes the NRLT for 2 weeks of inventory supply up to the DC level. Thus, the NRLT for Product A is 7wks, and for Product B is 9wks. This difference in NRLT and therefore safety stock levels can be fully accounted for based on the relative cost differences in each supply network as the input lead times and review periods are the same across products.

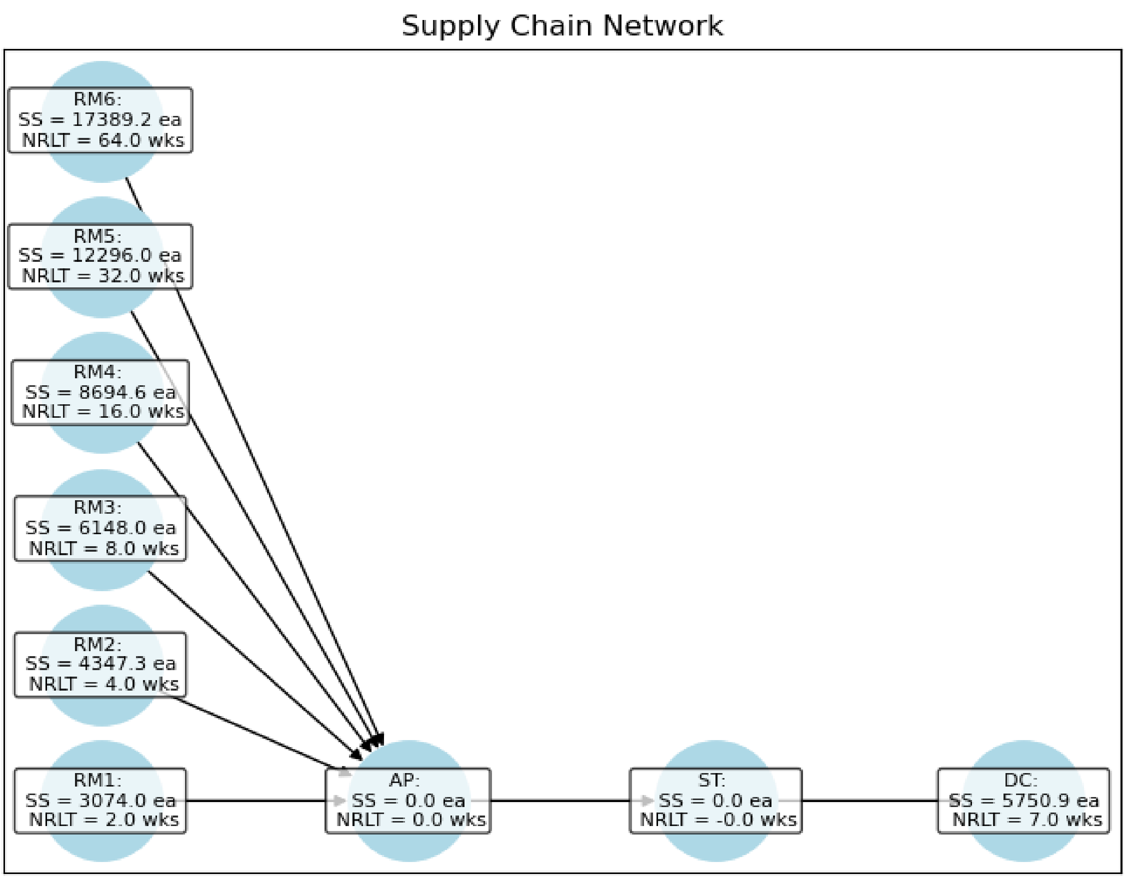

Figure 10. Product A Terminal MEIO Network

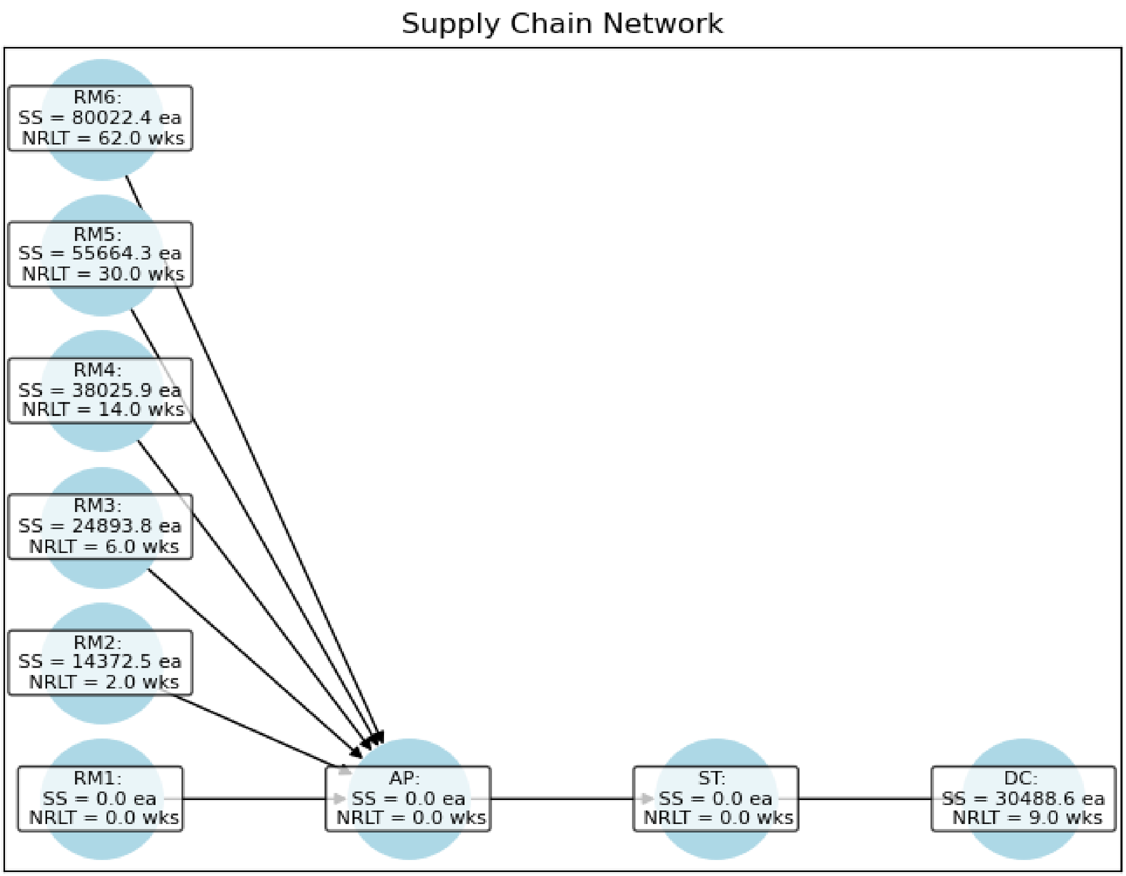

Figure 11. Product B Terminal MEIO Network

5.3.5 Terminal Inventory Simulation

The Terminal Inventory Simulation was performed using the NRLT and safety stock inputs from the Terminal MEIO. The cycle service level was 0.948 and 0.953 for Product A and B respectively, confirming the selection of the service level factor correctly targeted 0.95 cycle service level with expected minor variation due to the variability in the simulation.

It was found that the average annual holding cost for Product A at the DC was $115,061, and for Product B was $411,870 across all simulations. These values were in line with expectations from J&J (when properly scaled to actual product costs) although a detailed holding cost analysis had not been previously performed.

5.4 Heuristic Safety Stock Simulation

Although new supply models are in development for managing inventory, it is still standard practice within Ethicon to use heuristic targets for safety stock. Typically, these heuristics are a set number of weeks of supply (WOS) to hold for safety stock at the DC level based on the maturity of a product and other factors determined by the supply planner.

For the purposes of comparison, we will assume a safety stock target of 8 WOS for Product A and 3 WOS for Product B. Using the NRLT determined in the Terminal MEIO, the Terminal Simulation can be run with the WOS targets for each product in lieu of the calculated safety stock based on service level. This provides a comparison of the model-based approach and the heuristic-based approach under the same simulation conditions. The results of the simulation are shown in Table 1.

5.5 Use Case Results

The comparison of safety stock allocation methods shows that the Optimization and Simulation based model allows for more targeted inventory levels based on customer needs. The Optimization and Simulation model with optimized service level factor results in a cycle service level that hits the cycle service level target of 0.95. However, using a heuristic approach, the cycle service level is high for Product A and low for Product B. This disparity is difficult for a planner to quantify without simulation capabilities but shows that although heuristics can be close to the right service level targets set by the organization, it’s difficult to hit them exactly. In the case of Product A, this results in higher average holding cost as more safety stock is kept on hand, and for Product B the average holding cost is lower, but the resulting cycle service level is significantly lower than needed. The cycle service level is a customer satisfaction metric and therefore the cost of low cycle service level can be lost customers, missed demand and potentially harmful impacts to patients who can receive devices in time.

		Optimization and Simulation Model	Heuristic Approach
Product A	Cycle Service Level	0.948	0.980
	Average Holding Cost	$ 115,061.00	$ 150,181.00
Product B	Cycle Service Level	0.954	0.882
	Average Holding Cost	$ 411,870.00	$ 273,387.00

Table 1. Comparison of Safety Stock Methods

5.6 Discussion of Inventory Optimization and Simulation Model

MEIO is a valuable tool, but it's difficult to capture the full dynamics of a complex supply chain with different inventory policies in a single model. Simulation can help augment the optimization model by challenging and validating the behavior of the optimization model. Simulation can also help provide quantitative probabilities and visualizations of the supply chain to better communicate the tradeoffs in safety stock and inventory management methods.

This use case represents the value and risk of using MEIO. The benefit of MEIO is clear in that costs can be minimized across the supply network and allocation can be analytically determined, removing a manual process from planner's workload. However, inter-connections of a supply network and simplification of supply planning are not considered in the model. For example, if Product A and Product B share raw materials, it may be best to have a single safety stock allocation policy because it reduces total orders and saves on shipping costs from a supplier. It may also be simpler for a single supply planner to manage a single safety stock allocation policy for each supplier, rather than by product. These tradeoffs are worth evaluating across a broad range of products to understand total optimized costs, not just optimized costs by product.

In addition, optimization methods can be complex and opaque once implemented in a standardized tool. This can lead to a loss of transparency for supply planners, compared to heuristic methods. The operational value of concise and clear rules for managing a supply chain may outweigh the efficiency gained from an optimization and simulation based modelling technique in some instances.

The results of the model highlight the tradeoffs in safety stock allocation as well as the opportunities and limitations of inventory modeling. The inherent tradeoff of greater safety stock leading to higher cost and lower stockout probability, is observed in the results. The magnitude of this tradeoff is hard to predict, but the model results help to quantify this tradeoff.

6 Operational Application of Inventory Planning Models

The use and impact of inventory planning models has been demonstrated, however the more general applicability and operational challenges of implementing inventory planning models is worth discussion. The optimization and simulation model described in this work is a powerful tool, however it may not be the right model for all inventory planning situations and planners should be mindful of the specifics of their supply chain before attempting to implement any model.

Some of the key challenges for organizations that are looking to implement inventory planning models are digitalization and data, process standardization, planning centralization, and the role of supply planners. J&J faces each of these changes in managing their supply chain and are implementing many new methods in their digital transformation effort.

6.1 Data Practices

Data accessibility and data validation are critical to implementing robust, accurate inventory planning models. The need for easily accessible, regularly updated, accurate data on a supply chain is more and more critical as the complexity and scale of a supply chain increases. For simple supply chains with a small number of stages and products, it may be possible to effectively implement an inventory planning model while still relying on manual data collection and input methods. However, this process becomes infeasible for many modern supply chains that have many stages, global networks, and interconnected product components.

Digitalization is a critical first step for any organization with complex supply chain challenges. This includes digital data collection from both internal and external sources including suppliers, contract manufacturers and customers. Next, an organization must develop a robust strategy for data management including the data architecture, data access hierarchy, validation tools, and automated collection tools that allow for a flexible, secure and accurate single source of truth for all data. The balance of security, reliability and ease of use is non-trivial and requires significant enduring investment by an organization.

One pitfall that J&J is working to address is encouraging uptake of new digital infrastructure and technologies that many employees may not be comfortable adapting. J&J has invested in new data architecture across the organization, including in the surgical stapler group, however many planners still use manual methods of data collection and analysis. This includes locally owned spreadsheets with custom inventory calculations, and emailed data sources. This creates a challenge to the organization as it tries to scale and implement new data-based practices. However, planners are faced with many fast-paced decisions that determine inventory availability and old, reliable methods may be preferred over new, unfamiliar methods.

One way that J&J is addressing this challenge is by creating local digital champions who work with individuals and teams to understand their issues. Digital champions are broadly dispersed, empowered to implement solutions, and given institutional backing, creating an environment of low-level enthusiasm and voice to digital transformation priorities. These champions also create a network to share best practices, new technologies and help addressing technical challenges. This is just one tool among others that helps to scale digital practices.

6.2 Standardization and Centralization

In large organization, especially organizations that have semi-independent operating companies and new acquisition such as J&J, there can be many different inventory management practices across the organization. These differences may include varying definitions of common terms, metrics, reporting periods, and inventory policies. The goal of process standardization is to create similar practices across similar product types for easy implementation of optimal processes in different parts of the organization.

It is important to note that standardization across all products, even products that share a product family may not always be the most optimal approach. For example, if the same product is sold in different geographies with significantly different regulations, or distribution logistics then those products may be better managed to locally optimal inventory practices rather than standardized across all geographies. However, in many cases the operating ecosystem is similar across many products and markets, in which case standardization of practices provides an operational advantage to organizations that can scale optimal practices.

Due to the size, complexity and structure of J&J, there are many different digital tools and data points that are used locally in the organization, but with little system-wide standardization. This means that individual data or metric owners typically control access or know the details of different data reporting. This also extends beyond the raw data to the digital tools (control towers, dashboards, databases) that are used by different people in different groups. This creates a challenge to information sharing, data access and the pace of innovation, because the limiting factor is often identifying individual owners and building relationships to understand their data uses.

Additionally, there are some strategic processes that are managed by central supply chain planners, however largely the tactical decision making is owned by local or product specific planners. The benefit of this structure is that individual planners have autonomy and intimate knowledge of their supply chain to locally optimize their inventory. However, the downside is that the local optimum may not be the best global optimum when there are shared resources between planners. In addition, a planner can be siloed with limited data and information sharing and therefore limited in their ability to work to best practices or with the best information available.

The push and pull of standardization and centralization over dispersed ownership is an ongoing balance that all organizations face. The key for decision makers is not determining whether one extreme is better than the other but to understand to the connections and relations of individuals and products to map the dependencies in decision making. This is an additional opportunity for digital tools to provide more detailed, automated maps of supply chains than an individual can manage. The better that an organization understands the actual processes and dependencies in their network, the better they can standardize and centralize practices at the right level of granularity.

7 Conclusion

7.1 Summary

This thesis discusses the development of an Optimization and Simulation based inventory management model to serve as a tool for supply planners to set safety stock more quantifiably in their supply networks to hit cost and customer service targets. The model consists of a Conditional MEIO to set baseline supply chain parameters, followed by an Iterative Simulation and Service Level model to establish the correlation between service level and service level factor for a given product. Finally, a Terminal MEIO and Terminal Simulation provide outputs for the allocation of safety stock in the supply network, and the cycle service level and average annual holding cost.

A use case exploring the supply network of surgical staplers at J&J demonstrates how the model can be applied in practice for a medical device. The model in the use case is compared to current heuristic approaches to safety stock management and demonstrates that a model-based approach can better optimize for a cycle service level target and quantify the holding costs. For Product A it was shown that a model-based approach can help reduce holding costs by approximately 23% while hitting service level targets. For Product B the model helps show that cycle service level is 7% lower than the target value when using heuristics, hurting customer satisfaction for the product.

Lastly, the operational considerations for implementing inventory models were explored. It is key for organizations with complex supply chains to digitize their supply and demand data in a robust, and secure manner with consideration for a data architecture that allows for flexible digital tools to be integrated and accessed widely across the organization. It is a challenge to train employees on these new tools and encourage uptake, but creating local digital leaders in different teams can help. Another challenge is standardizing practices and centralizing decision making at the scope and granularity that is appropriate to keep a supply chain effective and flexible to local impacts.

7.2 Future Work

Moving forward, there is both technical and operational work that can help move J&J and others toward achieving a more robust and optimized supply network. From a technical perspective, it would be valuable to collect and analyze lead time variability data and integrate this variability into the MEIO. Additionally, the supply and distribution network MEIO models can be integrated to create an end-to-end optimized supply chain model. The Simulation in the current model is a good generalization of inventory management practices, however the simulation can be modified to better fit specific use cases by changing the order timing in the model.

There are many operational changes that can be studied including different training methods, levels of standardization and centralization and the impact on supplier when safety stock is managed optimally downstream. One prerequisite to any of this work is establishing a highly robust and flexible data architecture with full real-time data accessibility across the supply and distribution network

Lastly, the impact of this model on supply planners and how planners adapt to more digitally managed supply chains is worth investigating.

8 Appendix

8.1 Case Study Inputs and Process Outputs

8.1.1 Supply Chain Inputs

Stage Name	Code	Lead Time (wks)	Review Period (wks)	Stage Cost ($/ea)
Raw Material 1	RM1	2	0	$12.00
Raw Material 2	RM2	4	0	$10.00
Raw Material 3	RM3	8	0	$7.00
Raw Material 4	RM4	16	0	$7.00
Raw Material 5	RM5	32	0	$5.00
Raw Material 6	RM6	64	0	$5.00
Assembly and Packaging	AP	3	0	$50.00
Sterilization	ST	2	0	$2.00
Distribution Center	DC	1	1	$2.00

Table 2. Product A Model Supply Chain Stage Data

Stage Name	Abbreviation	Lead Time (wks)	Review Period (wks)	Stage Cost ($/ea)
Raw Material 1	RM1	2	0	$15.00
Raw Material 2	RM2	4	0	$15.00
Raw Material 3	RM3	8	0	$10.00
Raw Material 4	RM4	16	0	$5.00
Raw Material 5	RM5	32	0	$5.00
Raw Material 6	RM6	64	0	$5.00
Assembly and Packaging	AP	3	0	$42.00
Sterilization	ST	2	0	$2.00
Distribution Center	DC	1	1	$1.00

Table 3. Product B Model Supply Chain Data

8.1.2 Forecast Data

	Initial Forecast for Simulation (ea)	Weekly Forecast Growth Rate for Simulation
Product A	1,000	2.5%
Product B	10,000	0.1%

Table 4. Baseline Forecast Inputs

8.1.3 Forecast Error

The forecast error for Product A is approximated to be -25% and Product B to be -5%. Historical analysis and discussions with supply planners informed the user-selected forecast error ranges for each product as well as the probability of that forecast error occurring. For Product B, a positive or negative error is equally likely because it's a legacy product and any error is unpredictable form historical trends. However, Product A is more likely to have negative forecast error and that error can be more extreme. This is because planners have significant leeway to control the supply and demand profile of a new product and err on the side of excess inventory. Planners may choose to have a slower launch or delay launch in new markets than to stockout early with new customers.

Product A		Product B	
Forecast Error Scenarios	**Scenario Probability**	**Forecast Error Scenarios**	**Scenario Probability**
+15%	30%	+15%	25%
0%	20%	0%	50%
-25%	50%	-15%	25%

Table 5. Forecast Error Inputs

8.1.4 Standard Deviation of Demand

The normalized standard deviation of demand is approximately 90% of the weekly forecast for Product A. This value is very high on paper, but is smoothed in practice because the timing of new market launches or holds can be planned in advance and therefore factored into the forecast. Given that the demand planners perform some modification of the forecast and inventory plan separately from these data sources it was assumed that Product A can have up to 70% normalized standard deviation and a minimum of 40%.

The normalized standard deviation of demand for Product B is approximately 30% of the weekly forecast. It was assumed that this is typical performance and therefore the max normalized standard deviation scenario is 40% with a minimum of 20%. Given the maturity and predictability of this product, it is slightly more likely to have the minimum standard deviation scenario than the maximum (60% v. 40% probability) respectively.

Product A		Product B	
Demand Std Dev Scenarios	**Scenario Probability**	**Demand Std Dev Scenarios**	**Scenario Probability**
70%	50%	40%	40%
40%	50%	20%	60%

Table 6. Standard Deviation Inputs

Demand Scenarios

The normalized weighted average standard deviation is 31.6% and 65.4% of the weekly forecast for Product A and B respectively.

Product A Demand Scenarios			
Scenario	**Demand Std Dev Level**	**Forecast Error Level**	**Overall Scenario Probability of Occurence**
1	70%	+15%	15%
2	70%	0%	10%
3	70%	-25%	25%
4	40%	+15%	15%
5	40%	0%	10%
6	40%	-25%	25%

Table 7. Product A Demand Scenarios

Product B Demand Scenarios			
	Demand Std Dev Level	**Forecast Error Level**	**Overall Scenario Probability of Occurence**
1	40%	+15%	10%
2	40%	0%	20%
3	40%	-15%	10%
4	20%	+15%	15%
5	20%	0%	30%
6	20%	-15%	15%

Table 8. Product B Demand Scenarios

8.1.5 Supply Scenarios

We assume that there is a 50% probability of a supply disruption event in a year for Product A and a 10% chance for Product B. These probabilities are converted to weekly probabilities by taking the difference of the probability of the event not occurring for 1 year (52 weeks).

$$p = 1-(1-P)^{(1/n)}$$

Where:

p = *weekly probability*

P = *annual probability*

n = *number of weeks in a year*

8.1.6 Conditional MEIO Outputs

Product A MEIO Results, Std Dev = 645 ea/wk, a = 0.25							
Stage	**Abbreviation**	**Stage Lead Time (wks)**	**Stage Review Time (wks)**	**Stage Cost ($/ea)**	**NRLT (wks)**	**SS (ea)**	**Holding Cost ($)**
Raw Material 1	RM1	2	0	$ 12.00	2	912	$ 2,736.60
Raw Material 2	RM2	4	0	$ 10.00	4	1290	$ 3,225.00
Raw Material 3	RM3	8	0	$ 7.00	8	1824	$ 3,192.53
Raw Material 4	RM4	16	0	$ 7.00	16	2580	$ 4,515.00
Raw Material 5	RM5	32	0	$ 5.00	32	3649	$ 4,560.88
Raw Material 6	RM6	64	0	$ 5.00	64	5160	$ 6,450.00
Assembly and Packaging	AP	3	0	$ 50.00	0	0	$ -
Sterilization	ST	2	0	$ 2.00	0	0	$ -
Distribution Center	DC	1	1	$ 2.00	7	1707	$ 42,662.50
Total							$ 67,342.51

Table 9. Product A Conditional MEIO Results

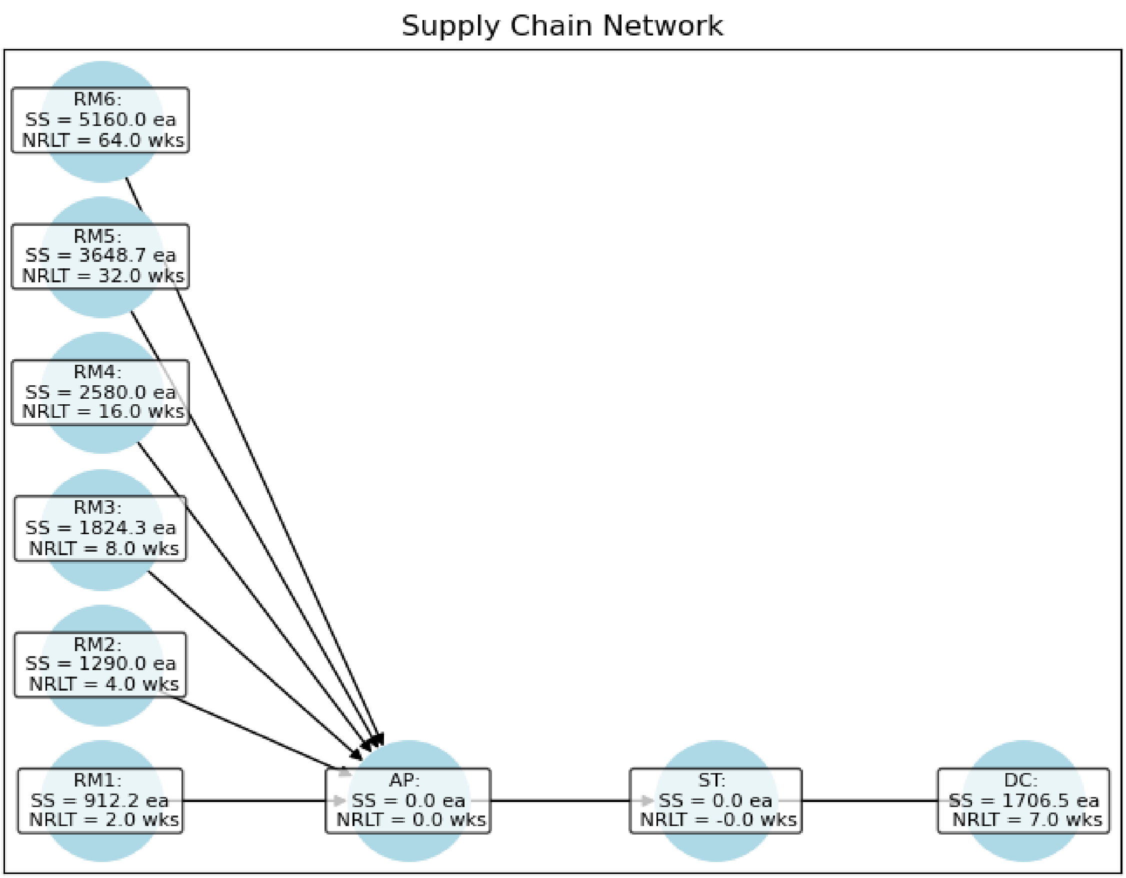

Figure 12. Product A Conditional MEIO Supply Network

Product B MEIO Results, Std Dev = 3166 ea/wk, a = 0.25							
Stage	**Abbreviation**	**Stage Lead Time (wks)**	**Stage Review Time (wks)**	**Stage Cost ($/ea)**	**NRLT (wks)**	**SS (ea)**	**Holding Cost ($)**
Raw Material 1	RM1	2	0	$ 15.00	0	0	$ -
Raw Material 2	RM2	4	0	$ 15.00	2	4477	$ 16,790.25
Raw Material 3	RM3	8	0	$ 10.00	6	7755	$ 19,387.75
Raw Material 4	RM4	16	0	$ 5.00	14	11846	$ 14,807.62
Raw Material 5	RM5	32	0	$ 5.00	30	17341	$ 21,676.12
Raw Material 6	RM6	64	0	$ 5.00	62	24929	$ 31,161.38
Assembly and Packaging	AP	3	0	$ 42.00	0	0	$ -
Sterilization	ST	2	0	$ 2.00	0	0	$ -
Distribution Center	DC	1	1	$ 1.00	9	9498	$ 237,450.00
Total							$ 341,273.12

Table 10. Product B Conditional MEIO Results

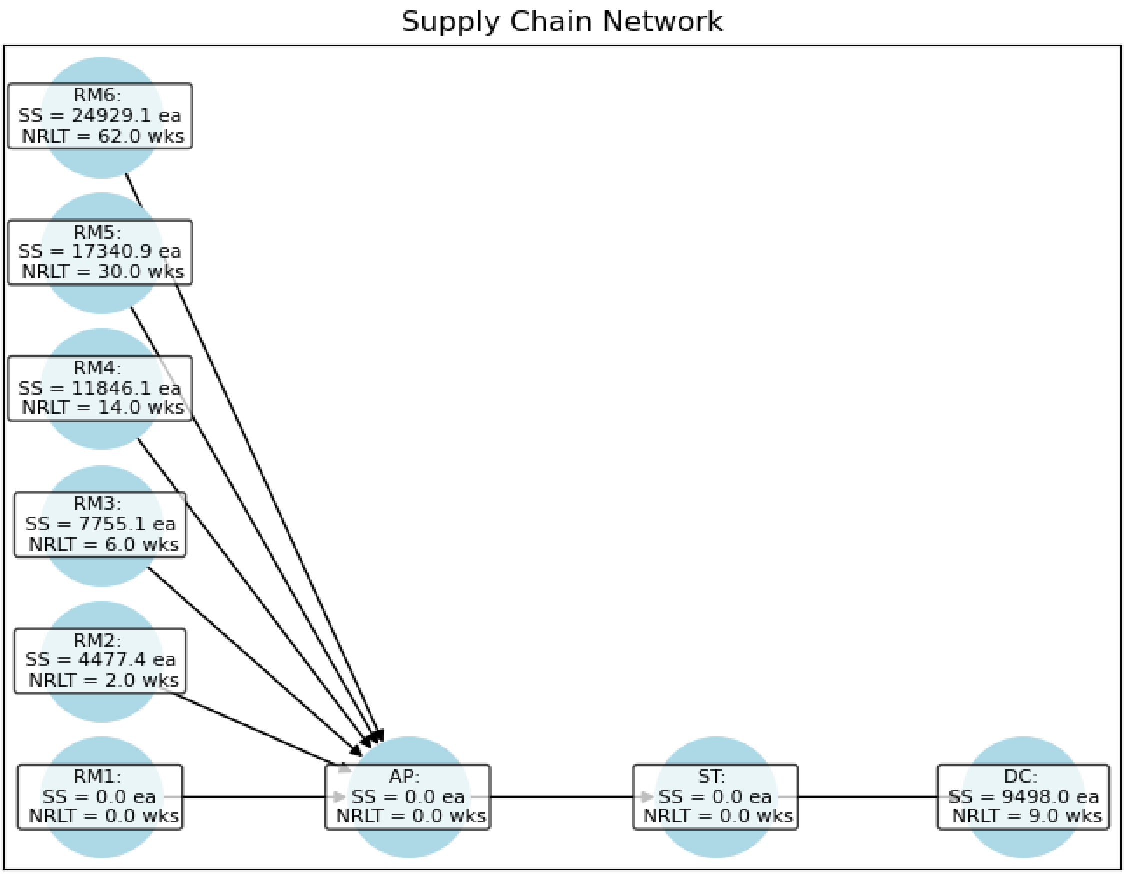

Figure 13. Product B Conditional MEIO Supply Network

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