DDMRP Feasibility Assessment in the Pharmaceutical Industry

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ABSTRACT

DDMRP, a supply chain methodology introduced in 2011, aligns planning activities around incoming demand signals without the use of forecasts to predict future demand. The Demand Driven Institute (DDI) claims that DDMRP can reduce median inventory levels by 31%, improve median service levels by 13%, and reduce the order lead time. This capstone explores the DDMRP framework to assess the feasibility and the potential value-added of adopting this methodology in an established supply chain. A simulation model was built to test DDMRP in a multi-echelon environment and quantify the impact of altering planning parameters. This simulation model was then extended to match the specifications of one of the partner company's supply chains to compare the relevant metrics to their existing key performance indicators. The research identified several difficulties experienced when DDMRP is adopted in this simulated complex and highly constrained supply chain. These issues must be taken into consideration before full-scale implementation.

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1 Introduction

The partner company of this capstone is a global developer and manufacturer of pharmaceuticals, vaccines, and consumer healthcare products. The company would like to streamline its demand forecasting process for vaccines and pharmaceuticals, which for certain product categories is labor-intensive.

The pharmaceutical supply chain starts with the procurement of raw materials from chemical suppliers. These materials are converted into active pharmaceutical ingredients (API), a pure, raw form of the drug. The API is then transformed into drug products with the proper dosage and form suitable for human administration. These products, which must be stored at prescribed temperatures and humidity levels for specified time periods, are packaged and labeled in accordance with strict regulatory requirements imposed by governments in the target markets. The finished products are then distributed through networks of logistics service providers to end-users such as retail pharmacies and healthcare institutions, or through direct contracts established with governments or aid organizations.

Pharmaceutical production is costly. The required testing for product purity and the procedures for validating equipment between process runs result in high fixed costs. These dynamics encourage large, infrequent manufacturing campaigns to optimize production efficiency. This strategy drives the organization to hold large amounts of inventory to ensure it can meet customer demand, which raises costs.

These and other supply chain challenges drive the long-term forecast horizons that are typical in the pharmaceutical industry. Extended lead times are common at each step of the manufacturing process, for example, it can take over a year from work order to the production of an API, the first stage in the manufacturing process (Bazerghi, 2015). The partner company's lead times vary across their portfolio of APIs from several weeks to eight months.

1.1 Partner Company Demand Planning Processes

The partner company's demand planning group is responsible for generating demand forecasts that will be shared with the organization to build production schedules, capacity plans, and product stocking plans. The group employs a Material Requirements Planning (MRP) system, which utilizes forecasting models to plan inventory targets to meet predicted customer demand. Forecasts are performed along multiple time horizons, up to 36 months. The long horizon forecasts, predicting demand up to three years in the future, are used by the supply planning group to structure future production-asset allocations, and to assess long-term capacity availability. The shorter horizon forecasts, looking several months in the future, are used to fine-tune the planned production volume to match anticipated demand. Short Term forecast accuracy, while considered acceptable, generally hovers around 80% (Partner company, personal communication)

1.2 DDMRP Overview

A push system initiates batch productions at the raw materials stage of the supply chain based on forecasts of future customer demand (Orlicky, 1974). To deliver the proper inventory of finished goods, as indicated by the demand forecast, planning must consider the lead time and variability at each step of the production process.

In contrast, pull-driven materials planning systems respond to actual customer demand and pull materials at various stages of work in progress (WIP) to deliver finished goods. These design methodologies, push and pull, are not mutually exclusive; over time, academics and operations professionals have improved the individual methodologies and designed hybrid approaches that attempt to combine the strengths of each system.

DDMRP is one such hybrid methodology. For the partner company, implementing DDMRP could reduce the reliance on forecasting, reduce waste within the system, and allow the company to strategically store work in progress inventories to alleviate bottlenecks that could slow response to demand.

Traditional segmentation strategy separates products based on high value or highly variable stock keeping units (Miclo, 2019). In the partner company's case, its ABC segmentation divides drug products into high-priority products requiring more attention and lower-priority items that require less attention.

DDMRP will instead divide segmentation into two categories along each step of the supply chain: buffered and non-buffered. *Non-buffered* items are non-strategic parts that generally do not have extended lead times, are in ample supply, and do not cause bottlenecks. With non-buffered parts, a traditional MRP system can be used to push demand through the system. *Buffered* items are those that have uncertainty in lead times, high variability, is at a bottleneck position in the supply chain, or due to their nature in the market require a higher level of attention (Ptak and Smith, 2016). For buffered segments in a pull-driven DDMRP system, the planners determine the number of strategic stocks of WIP material to hold at each step of the production process to rapidly respond to demand fluctuations. The decision-making thus transitions from forecast generation to strategically maintaining decoupled buffer stocks at key points throughout the supply chain.

1.3 Motivation

For the partner company, demand forecasting is a labor-intensive process involving the combined efforts of internal demand forecasting groups around the world. The internal groups are supplemented with extensive external support from outsourced demand planning partners.

As the number of markets the company serves has expanded and the number of product offerings has increased, the number of stock keeping units (SKUs) has grown. The demand planning group recognized the need to sustainably meet growing business requirements without continually expanding the department's headcount. Accordingly, they have begun to explore methods for streamlining the demand planning process to reduce their reliance on human labor.

As part of that initiative, in 2020 the demand planning group began segmenting SKUs based on demand variability and contribution to company profit. Prior to 2020, all SKUs received the same amount of attention from the demand planners, regardless of sales volume or profitability. The segmentation is performed in two primary steps: conducting an ABC classification based on contribution to net sales, and then splitting each segment into XYZ categories based on demand variability. This approach allowed the group to define demand planning strategies based on the characteristics of a particular SKU segment.

One strategy the group has been testing is the automation of forecasting using statistical models and machine learning algorithms. On a large scale, across the asset portfolio, automation capabilities are not mature enough to take on the complexity, extended lead times, variability, and quality requirements to reduce reliance on human-generated forecasts. However, automation has proved beneficial for some lower-value products with stable demand, often providing better accuracy than human-generated forecasts. These initial results allowed the demand planning function to free up resources to focus attention on higher-priority products. The demand planning group is now interested in automating the forecasting function for lower-value products that exhibit high levels of demand variability. These products, however, are considered "not forecastable" with traditional, statistics-based models such as time series analysis or predictive machine learning algorithms.

Instead, the partner company has proposed using Demand Driven Material Requirements Planning (DDMRP), a multi-echelon planning and execution methodology, to eliminate its reliance on forecasts for low-volume, highly variable SKUs. DDMRP is designed to synchronize supply and demand by providing visibility across the supply chain without the use of predictive forecasts. This pull system drives production planning based on the actual demand signal coming from the customer.

1.4 Research Objective

The goal of this research study is to gain a deeper understanding of the mechanics of a DDMRP system and assess the feasibility and potential value added by adopting this methodology in an established supply chain. The partner company's supply chains are characterized by many dependent production stages, long lead times, and infrequent production cycles. DDMRP in complex environments is not well studied in academic literature. There have not been many studies outlining how DDMRP performs in a multi-echelon supply chain environment like that of the pharmaceutical industry.

The primary objective of this study, therefore, is to employ a simulation model to test how DDMRP performs within the processes and constraints of the pharmaceutical supply chain. Proponents of DDMRP claim that the system reduces inventories and decreases lead times while improving service levels. Will DDMRP provide the value advertised while also meeting the high service levels demanded by the pharmaceutical industry?

The second objective is to adapt the model to simulate one of the partner company's existing supply chain networks under DDMRP principles. The results from the simulation model provide a framework for discussions with stakeholders throughout the partner's supply chain. Transitioning to DDMRP requires changes to supply chain processes, these conversations outlined the feasibility of implementing the required process changes within the partner's existing capabilities.

The lessons learned from simulating the material flows in a complex, multi-echelon supply chain, and necessary process changes necessary for implementation, will provide a valuable perspective not only to the partner company but also to others that are considering the potential value added by DDMRP planning.

2 Literature Review

Supply chain management is an evolving field. There has been a progression of new inventory management methodologies each designed to eliminate a limitation posed by the existing management system. Some of these proposed systems have been minor changes while others represent major shifts in organizational thinking and ways of managing the supply chain. A major shift can be seen in the transition from Pull to Push driven inventory management systems. DDMRP has many proposed benefits over a traditional MRP system, although the pharmaceutical industry has complex supply chains with many tightly constrained and interconnected production stages that may challenge the feasibility of DDMRP implementation.

This literature review will provide a background on the existing prevalent supply chain management methodology, Materials Requirements Planning (MRP). Next, an overview of the components of the DDMRP framework is presented to provide context to the relevant features. These DDMRP features will provide the underlying structure and operation of the simulation model as described in the methodology, Section 4. As this section will comprise just an overview of the relevant DDMRP features, further reading into the relevant texts is recommended to gain a complete view of DDMRP (Ptak and Smith, 2019; Ling, Ptak, and Smith, 2022; Ptak and Smith, 2018; Ptak and Smith, 2017; Smith and Smith, 2014; Eagle, 2017). Then the relevant context of the pharmaceutical industry will be outlined to orient the reader to the relevant features of the industry which will be incorporated into the feasibility assessment. This literature review will conclude by presenting the existing academic research on DDMRP to frame the current understanding of system design and performance.

2.1 MRP (Material Requirements Planning)

According to the APICS dictionary, MRP is defined as "a set of techniques that uses bill of material data, inventory data, and the master production schedule to calculate requirements for materials" (APICS, 2015). First conceived in the late 1950s, as the earliest computer-based inventory management system, MRP is a push-based system that relies on forecasts to make planning decisions.

MRP intends to make every link between production and demand integrated and dependent on one another. Minor changes in the supply chain downstream often cause a significant impact on the upstream level, which is known as the bullwhip effect, or, as Smith describes, nervousness in the system (D. Smith & Smith, 2014). Forecasts are never able to perfectly anticipate future demand. MRP plans around this signal with the knowledge that the demand signal will change. This uncertainty triggers nervousness by introducing constantly changing material target levels which distort the planning and production process to compensate for the nervousness (Ptak and Smith, 2016). While variability at a single level may be manageable, the compounding effect at a system level can result in uncontrollable turbulences.

The circumstances, including characteristics of low complexity, low variability, and high customer tolerance, under which the MRP was first designed are no longer suitable to depict the current business conditions. Within the past 30 years, the industries have gone through dramatic change, as summarized in Table 1. These changes should be reflected in the inventory management system (D. Smith & Smith, 2014). With little modification to MRP management systems since its founding days, skepticism is raised as to whether MRP still is the optimal choice of inventory control for today.

Table 1:

Relative changes in supply chain management since the inception of MRP in 1965

Supply chain Characteristics	1965	Today
Supply chain Complexity	Low	High
Product Life Cycles	Low	High
Customer Tolerance Times	Long	Short
Product Complexity	Low	High
Product Customization	Low	High
Product Variety	Low	High
Long Lead Time Parts	Few	Many
Forecast Accuracy	High	Low
Pressure for leaner Inventories	Low	High
Transactional Friction	High	Low

Source: (Ducrot and Ahmed, 2019)

2.2 DDMRP (Demand Driven Material Requirements Planning)

In response to the challenges MRP faces, Carol Ptak and Chad Smith developed a pull-based system, DDMRP. This methodology was originally introduced in Orlicky's Material Requirements Planning – Third Edition, an edition updated by DDMRP founders Carol Ptak and Chad Smith (Ptak and Smith, 2011). The pair founded the Demand Driven Institute (DDI) to promote DDMRP education and business adoption. To support supply chain leaders' understanding of the DDMRP framework and potential value addition, Carol Ptak and Chad Smith wrote the book: *Demand Driven Material Requirements Planning (DDMRP),* currently in the third revision (Ptak and Smith, 2019).

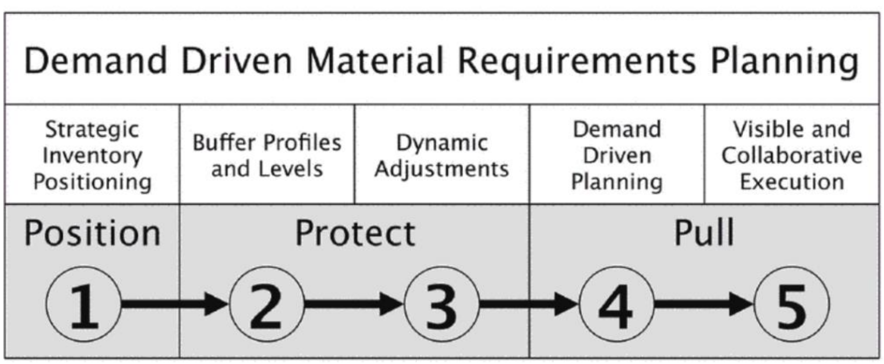
DDMRP is a "formal multi-echelon planning and execution method to protect and promote the flow of relevant information and materials" by placing strategic buffer stocks within the supply chain network. The buffer stock creates independence between supply chain stages by acting as a shock absorber, dampening variability from the demand and supplier sides (Ptak and

Smith, 2016). Decoupling can result in a shift of the critical path to a shorter one, thus compressing the system lead time. However, the individual process lead times remain unchanged. Compressed lead times allow inventory to respond directly to changes in demand and reduce unnecessary inventory waste while protecting from demand fluctuations.

DDMRP will instead build a resilient and dynamic system that is able to rapidly adjust to the demand signal coming in from the customer, without relying on forecasts. The DDMRP design can be broken down into three primary functions: position, protect, and pull. These functions are then broken down into five steps, shown in Figure 1, explained in detail below: 1) examine the network and identify key decoupling points, 2) position and properly size buffers stocks, 3) dynamically adjust the buffer size to incoming demand 4) protect the buffer stocks by coordinating production around the replenishment signal, 5) give the buffer stocks control to pull production from upstream processes by aligning planning processes around the DDMRP principles (Ptak and Smith, 2016).

Figure 1:

DDMRP Core Foundations



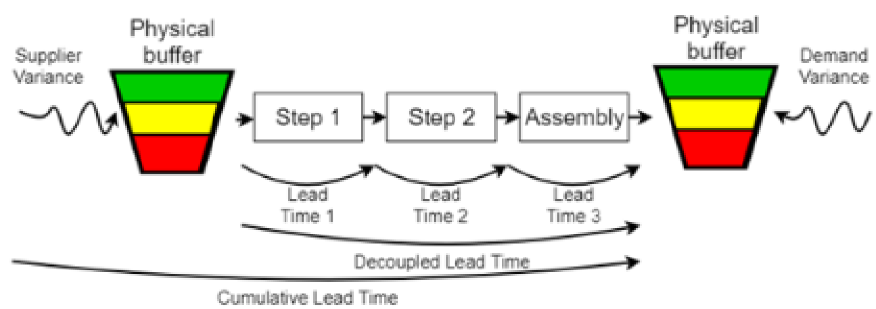
Source (Ptak and Smith, 2016)

2.2.1 Position

The focus of decoupling a supply chain is to identify areas where there are bottlenecks in the system that constrain material flow. These are traditionally stages where there is an aggregation of dependent steps leading to a single stage. By establishing a buffer inventory at the strategic point, the proceeding processes will be effectively decoupled from the rest of the production network. This decoupling point creates a new parameter, the decoupled lead time (DLT) which is measured between adjoined buffers within the DDMRP system. Ptak and Smith (2019) describe the DLT as the "qualified cumulative lead time defined as the longest unprotected or unbuffered sequence in a bill of materials." The impact of decoupled buffer points on the lead time within the supply chain network is shown in Figure 2.

Figure 2:

Visualization of the benefits of decoupling on absorbing variability and decoupling lead times



Source: (Ptak and Smith, 2019)

2.2.2 Protect

When the strategic decoupling points have been identified, buffer stocks are established at these key locations. The buffer zones accomplish three strategic functions within the supply chain. The first is to absorb shocks by dampening the variability in supply and demand which traditionally leads to system nervousness and bullwhip. The second is to compress the system lead time by having strategic work-in-progress materials to supply downstream processes, shorting the aggregate lead time. The last function is to control the supply order generation signal. The buffers take in the relevant demand, on-hand supply, and on-order stock to determine the reorder point to protect the buffer stock (Ptak and Smith, 2019). The core calculations of the

DDMRP framework establish the buffer zone into three distinct zones, the red zone, the yellow zone, and the green zone (Ptak and Smith, 2019).

To accomplish the described functions, the buffer zone must be established to provide 5 key benefits to the system. The buffer must decouple the supply lead time by providing a clear break in lead time dependency of the end-to-end supply chain. The stock of buffer material must be available for all dependent production stages: shared inventory is not dedicated directly to a specific product. Buffers must provide a benefit to the upstream and downstream sides. The supply side gets an aggregated order that corresponds to actual demand and consumption, and the consuming side gains higher product availability and a compressed lead time. All replenishment signals upstream must be made through the buffer calculations including when and how much to order. Lastly, to respond to incoming demand, the buffer must dynamically readjust its profile levels based on the past demand signal over a user set time horizon (Ptak and Smith, 2019).

2.2.2.1 Green Zone

The green zone represents the order up to the point which defines the order size and the average frequency that the buffer position requests a replenishment. The green zone allows the planner to incorporate relevant ordering constraints such that the zone is either calculated by the demand over the lead time, the Minimum Order Quantity (MOQ), or the imposed order cycle in the case of constrained capacity (Equation 1). The Average Daily Usage (ADU), Equation 2, provides the demand signal which is fed into each supply chain buffer zone to adjust target inventory levels.

Equation 1:

$$Top\ of\ Green\ Zone\ (TOG) = TOY + Max(Parameter\ 1, Parameter\ 2, Parameter\ 3):$$

$$Parameter\ 1: DLT * ADU * Lead\ Time\ Factor\ (0 - 1)$$

$$Parameter\ 2: Minimum\ Order\ Quantity$$

$$Parameter\ 3: Imposed\ Order\ Cycle\ *\ Lead\ Time$$

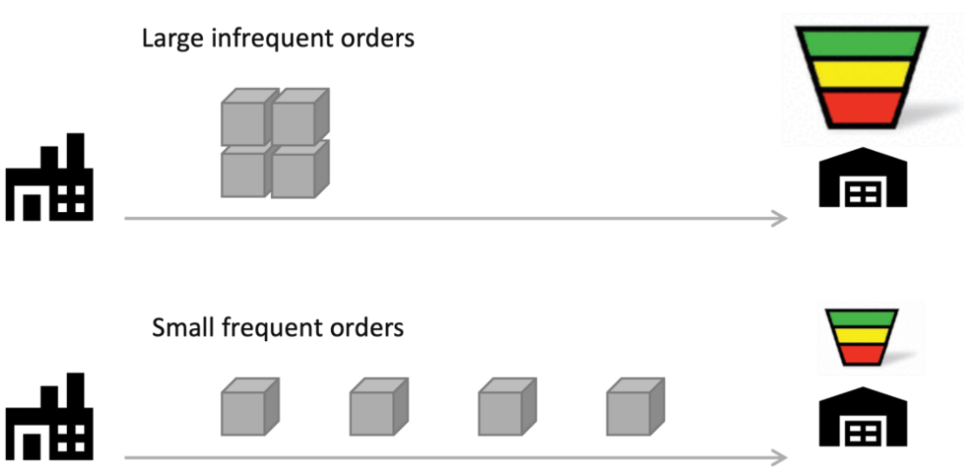
Equation 2:

$$Average\ Daily\ Usage\ (ADU)\ =\ Planned\ Adjustment\ Factor\ (PAF)\ *\ 1/n\ *\ \sum_{t=0}^{n} Demand_t$$

Within the green zone calculation, there is the "lead time factor" which is a scalar adjuster between 0.0-1.0. With a long lead time part, within reason, it is best to choose a lower factor. This will force the production stage, here forth named node, to hold smaller buffer zone levels, increasing the frequency of production orders to the upstream node. This effectively creates a "flow" of smaller orders coming into the node with the benefit of a lower inventory holding and a stronger ability to react to trends in demand. Figure 3 shows the impacts of the lead time adjust factor on production frequency and batch size. The bottom scenario shows the impact of choosing a small lead time factor which breaks a single order into 4 smaller orders.

Figure 3:

Altering the lead time adjust factor influences buffer inventory size and order frequency.



Source: (Ptak and Smith, 2019)

Ptak and Smith (2019) do not provide a mathematical framework for determining the lead time factor, but rather they present a qualitative framework for classifying buffered components into profiles based on lead time category, as seen in Table 2. This parameter represents a strategic decision for management to consider as it will impact the balance between the cost of production cadence and the cost of holding inventory within the supply chain network (Ptak and Smith, 2019).

Table 2:

Recommended lead time categories and associated lead time factor

Lead Time Category	Lead Time Factor Range
Long Lead Time	0.20 - 0.40
Medium Lead Time	0.41 - 0.60
Short Lead Time	0.61 - 1.00

2.2.2.2 Yellow Zone

The yellow zone provides inventory coverage to meet the anticipated demand over the replenishment lead time. This buffer component is calculated, as shown in Equation 3, by multiplying the decoupled lead time (DLT) by the average daily usage (ADU). The level for the top of the yellow (TOY) is simply the top of red (TOR), introduced below, plus the yellow zone. Dividing the yellow zone by the green zone will indicate the average number of pipeline orders (Ptak and Smith, 2019).

Equation 3:

$$\text{Top of } Yellow\ Zone\ (TOY) = TOR + Decoupled\ Lead\ Time * ADU$$

2.2.2.3 Red Zone

The red zone acts as a safety inventory within the buffer. It is comprised of two components: the Red Base, and the Red Safety. Together these make up the Top of Red (TOR). The Red Base is calculated by applying the same lead time factor as used in the green zone calculation and multiplying this by the expected demand over the lead time. This will set the red base level to provide inventory coverage over the anticipated buffer replenishment lead time. The recommended red zone buffer size denoted as Top of Red (TOR) is then considered the sum of the Red Base and Red Safety. Equation 4 outlines the red zone calculations.

Equation 4:

$$Red\ Base\ =\ Lead\ Time\ *\ ADU\ *\ Lead\ Time\ Factor$$

$$Red\ Safety = RedBase * Variability\ \text{Adjust Factor}\ (0.0 - 1.0)$$

$$Top\ of\ Red\ (TOR)\ =\ Red\ Base\ +\ Red\ Safety$$

Within the calculation for the Red Safety is the “variability factor” which is a scalar adjustment factor from 0.0-1.0. This provides a lever for planners to size the safety zone based on the anticipated level of variability in the incoming demand. Like the lead time factor, the core calculations within DDMRP do not provide a mathematical calculation for determining the value for this scalar factor, but rather provide a classification scheme and corresponding recommended values, Table 3. This is a departure from traditional safety stock calculations which are sized to a targeted service level by meeting a statistical range of demand variability (Silver et al., 2017).

Table 3:

Recommended demand variability categories and associated variability factor

Variability Category	Variability Factor Range
High Variability	0.61 – 1.0
Medium Variability	0.41 – 0.60
Low Variability	0.0 – 0.40

2.2.2.4 Dynamic Adjustments: Average Daily Usage (ADU) and Net Flow Equation

The average daily usage (ADU) sets the horizon of past demand that the DDMRP inventory position incorporates in calculating the buffer zone levels. This parameter is a moving average of the demand over the management set time horizon, see Equation 5. A short time horizon may make the overall network more reactive to changes in demand, with buffer stocks recalculating to adapt to short period demand spikes. If the time horizon is too short, however, the nervousness will drive the bullwhip effect as the buffer levels will rapidly jump between extremes in the demand signal.

Another possible downside is that a buffer size will recalculate based on short-term increases in demand. The target buffer size will normalize afterward, but the built-up inventory level will remain until it is consumed. The opposite impact may also be observed, temporary periods of low demand will drive buffer calculations low, leaving the buffer at a higher risk of stockout when demand suddenly increases. Defining the time frame for calculating the average past demand for the ADU is an important managerial decision that will be assessed in the methodology, Section 4.

Equation 5:

Average Daily Usage (ADU) Formula

$$ADU = 1/n * \sum_{t=0}^{n} \text{Customer Demand}_t$$

$$n = ADU\ backtrack, days$$

The Net Flow Position (NFP) represents the current stock positioning of the buffer. This is used to identify the timing and quantity of replenishment orders. The components of the NFP are shown in Equation 6. The NFP and ADU should be recalculated as often as possible, daily is preferable (Ptak and Smith, 2019). With frequent updates to these parameters based on the latest demand signal, the buffer zones will dynamically adjust to the right size to efficiently cover demand. The NFP is examined by planners and compared to the current buffer position to determine the level of replenishment priority.

Equation 6:

$$Net\ Flow\ Position = On\ Hand + On\ Order - Qualified\ Demand + \text{Current Period Demand}$$

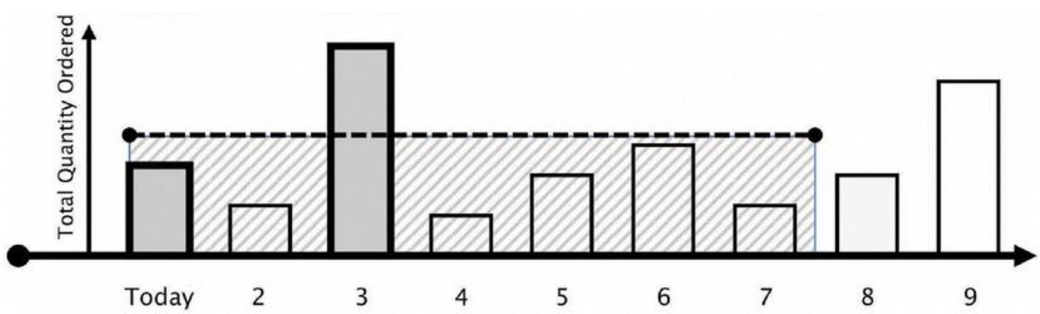
2.2.2.5 Planned Adjustment Factor, and Order Spike Threshold and Horizon

Buffer zones are designed to be robust in their ability to absorb variability in the absence of forecasts, but they can be jeopardized by large changes in the demand pattern. The Planned Adjustment Factor (PAF) provides planners a means to incorporate insights into future demand trends such as promotions, seasonality, or product phase in or phase out. DDMRP does not require forecasts to run, but the PAF provides a means to improve forward-looking planning by adjusting to known factors (Ptak and Smith, 2019).

In addition to the PAF, which is used to plan for changes in future demand patterns, the demand spike threshold is used to adjust buffer sizes for known qualified demand. Qualified demand is considered a sales order or other agreement with a customer to fulfill demand on an agreed-upon future date (Ptak and Smith, 2019). Managements sets an order spike threshold and an order spike horizon, as seen in Figure 4. Qualified order spikes are then incorporated into the net flow position, Equation 6, to make the appropriate adjustments to adapt the buffer profile in anticipation of the future qualified demand. The order spike horizon is recommended to be at a minimum the decoupled lead time so that production can be initiated in time to provide material for the order spike (Ptak and Smith, 2019).

Figure 4:

Order Spike Threshold and Horizon. Image source (Ptak and Smith, 2019)



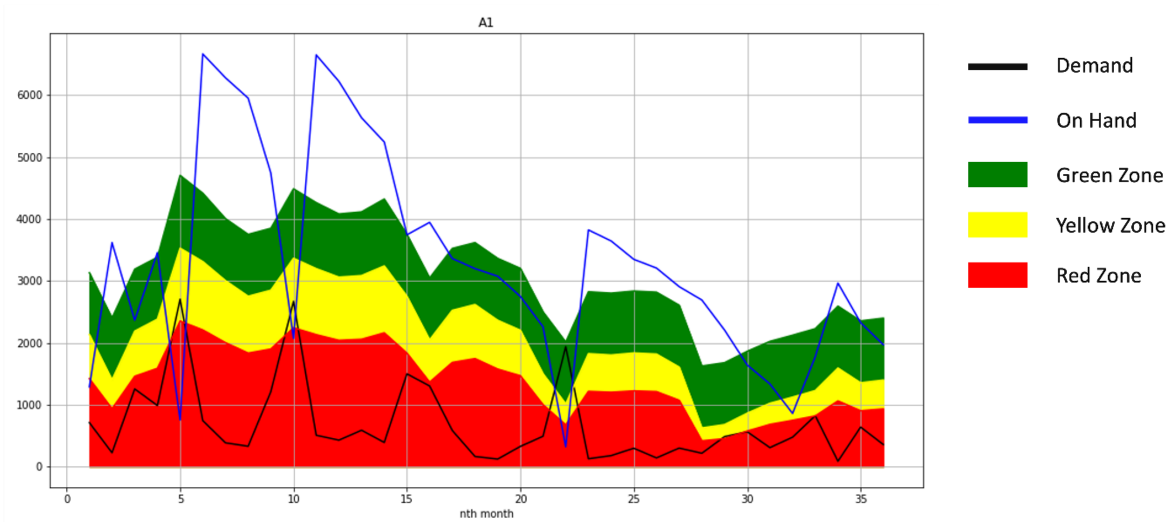
2.2.3 Pull

In DDMRP, flow is the focus: maintaining this flow means protecting the key buffer stocks throughout the system. Planning shifts from long-horizon production planning based on forecasts to a reactive system that pulls inventory to protect the buffer zone. When the NFP is in the green zone of the buffer, no attention from planners is necessary, when the level falls into the yellow zone, this is a sign to planners to initiate a replenishment order to protect the buffer level. For buffers requesting replenishment from a shared asset, prioritization is given to the buffer at a higher risk of stockout. A key consideration with DDMRP planning is that the smooth functioning of the network depends on buffer replenishment within the expected lead time. If the positioning falls into the red zone, this is an urgent message to planners to expedite replenishment as the buffer is at elevated risk of stocking out (Ptak and Smith, 2019).

The buffer calculations will adjust continually based on incoming demand signals: in periods of high demand, the order up to and reorder points will increase. Figure 5 shows an example of a buffer stock adjustment over time, with the incoming demand shown in black, the net flow position shown in blue, and the buffer profile levels based on DDMRP calculations shown in their respective buffer zone colors.

Figure 5:

Dynamic adjustment of buffer inventory in response to demand



2.3 Industry Context

DDMRP represents a departure from the traditional planning processes in place at many organizations. A complete assessment of feasibility must consider relevant metrics and system constraints to determine if DDMRP holds strategic value to replace existing planning systems in the pharmaceutical supply chain.

A Pharmaceutical company must ensure the continual availability of products to customers throughout the markets in which it operates. Drugs must be available to patients suffering from sickness and disease when and where they are needed. Pharmaceutical companies target high service levels as large financial penalties are imposed by customers if demand is not fulfilled, missing sales of high margin products has serious implications for company profitability, and failing to deliver lifesaving medications will harm the company's reputation and ability to maintain long term customer contracts. The goal is to design a supply chain to achieve service levels as close to 100% as possible (Uthayakumar and Priyan, 2013).

To achieve a near-perfect service level, large amounts of inventory must be held in preparation for infrequent demand spikes. Improving service level by increasing inventory provides diminishing returns: covering low probability high demand scenarios requires significant investment (Silver et al., 2017). Due to the importance of meeting customer demand, cost optimization is generally a low priority in pharmaceutical supply chain design (Schaber et al., 2011). In this industry, it is normal for companies to hold up to 24 weeks of finished goods inventories, and up to 90% of annual demand as work-in-progress inventory, resulting in 1 to 8 inventory turns per year (Shah, 2004).

The manufacture of early-stage pharmaceutical materials, the Active Pharmaceutical Ingredients (API), is normally planned on a campaign basis. Regulatory oversight imposed by the Food and Drugs Administration (FDA) in the US and federal agencies in the target market mandate high standards of quality and uniformity between batches (Schaber et al., 2011). Stringent analytical testing for purity must be conducted at each stage of production. At the completion of a campaign, process equipment and the facility must be thoroughly cleaned and validated to ensure there is no cross-contamination between batches.

These setup, testing, validation, and change-over processes add considerable fixed costs to a campaign. The cost drivers of production are primarily from fixed costs, and uniformity benefits infrequent large campaigns. It is not uncommon in the industry to produce all APIs to meet the annual forecasted demand during a single campaign (Shah, 2004). The head of an API manufacturing site at the partner company has indicated that the balance point for operational efficiency is 3-4 campaigns per year (Partner company, personal communication).

The lead times for API manufacturing can extend to a year from initiating the production order (Bazerghi, 2015). In a DDMRP system, this lead time would be overcome by placing frequent smaller orders to replenish strategic buffer stocks (Ptak and Smith, 2016). The challenge for pharmaceutical companies will be to commit to a system that allows the accrual of high fixed production costs to drive up the per-volume price of APIs in this sub-economic order quantity (Silver et al., 2017). Shah argues that the supply chain for pharmaceuticals already resembles a hybrid push and pull approach. The stockpiling of API as work in progress inventory is driven by a long-term forecasting push methodology, but this strategic stock is pulled through value-added steps as needed to meet customer demand (Shah, 2004).

Batch size in the pharmaceutical industry is set by the registered production process as approved by the relevant regulatory agency. Altering a batch size requires revalidation and filing with regulatory agencies, so this parameter is considered fixed. The flexibility in manufacturing volumes to meet anticipated demand is achieved by defining the number of batches to produce during an established campaign. Any production campaign then must produce material in increments of the batch size (Partner company, personal communication).

To fully assess the cost of holding inventory, management must set an inventory holding rate based on the operating expense incurred during storage and the cost of tying up cash in inventory. Both metrics are difficult for an organization to accurately assess. Often the cost of holding inventory is highly undervalued (Timme, 2003). The production costs may be higher by switching to a DDMRP system. However, with accurate cost accounting, the extra investment may be offset by tying up less cash in inventory holding and losing less material to expiration.

2.4 Existing Literature Assessing DDMRP

DDMRP is a relatively new supply chain methodology that has not been fully evaluated in academic literature. The primary sources of information are books authored by DDMRP proponents, case studies and testimonials from practitioners on the Demand Driven Institute's website, and articles in trade journals. There is limited exposure to academic research in the form of published papers and academic thesis. This section review will examine the relevant academic literature in the following categories: comparison of DDMRP to other supply chain methodologies, recommendations for improvements to the DDMRP framework, and simulation models analyzing and quantifying the performance of DDMRP.

The primary comparison seen in the literature examined the differences between DDMRP and MRP (Miclo et al., 2016; Shofa & Widyarto, 2017). Other researchers took this comparison further by examining other relevant methods such as the theory of constraints, lean, and just in time (Dessevre et al., 2020; Favaretto & Marin, 2018; Ihme & Stratton, n.d.; Kortabarria et al., 2018; Miclo et al., 2019).

Several studies have identified limitations and proposed improvements to supplement the traditional DDMRP framework. Dessevre et al. (2019), challenged the assumption that the DLT for a node is a static parameter and proposed instead to consider the variability of the DLT as part of the buffer stock dynamic adjustment process. This study found that the DLT parameter has a major impact on the DDMRP performance and adjustments to the DLT cause associated impacts on other parts which are produced on a shared production asset.

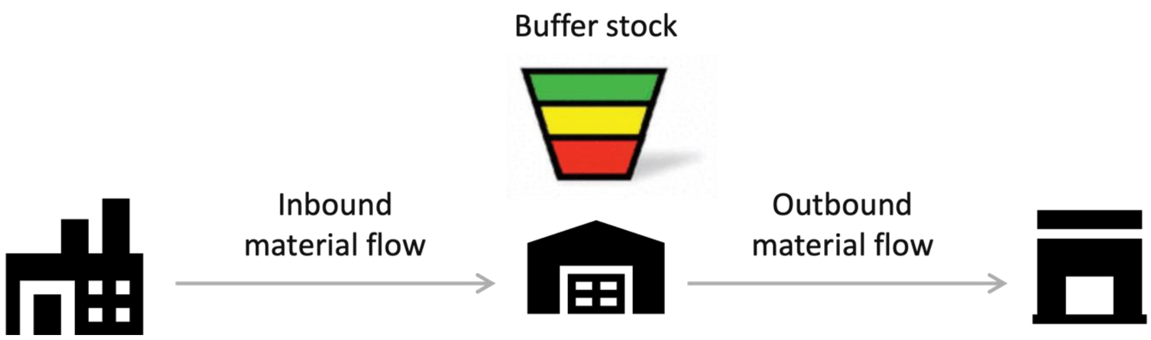
Another study challenged the method for calculating the red zone of the inventory buffer profile as it is not based on a mathematical calculation, but rather on users subjectively selecting values from a suggested range (Lee & Rim, 2019). The DDMRP framework provides guidance on which locations through a product's bill of materials to place buffer stocks. One study provided a method to mathematically optimize the decoupling buffer zone positioning points (Jiang & Rim, 2016). There is a lack of standardized processes for assessing and implementing DDMRP. For the methodology to progress further research is needed to build a standard process for implementing this method (Orue et al., 2020; Velasco Acosta et al., 2020).

Many of the existing studies incorporating simulation modeling of DDMRP performance have focused on a single or two-node system (Ducrot & Ahmed, 2019; Ihme & Stratton, n.d.; Kortabarria et al., 2018; Shofa et al., 2018; Shofa & Widyarto, 2017; C. Smith, 2013). A visualization of this simulation scope can be seen in Figure 6.

Other models have examined the impact of utilizing DDMRP with multiple products produced on the same manufacturing asset to quantify the impact of capacity constraints (Miclo et al., 2015). Shofa and Widyarto modeled a three-part supply chain system with DDMRP and compared it to a forecast driven MRP simulation. This study noted that while demand fulfillment performance increased with DDMRP, inventory levels within the system increased substantially (Shofa & Widyarto, 2017). Only one study was found that assessed the performance of DDMRP in a multi-echelon system. The production stages on a manufacturing line were used to evaluate the impact of deciding where to place decoupling buffer stocks (Velasco Acosta et al., 2020).

Figure 6:

DDMRP implementation with a single node buffer location



There are also no published results that incorporate the relevant constraints of the pharmaceutical industry in the DDMRP model. The long lead times and infrequent production runs provide considerable challenges for building a supply chain that aligns with the principles of DDMRP.

3 Methodology Context

The project evolved in scope as the researcher's and the sponsor company's knowledge of DDMRP matured. It is relevant here to outline the project maturity process to give the reader the perspective on the path taken to define the boundaries of this study. The following sections provide context into the decision-making process for assessment and insight into the level of complexity involved in observing the performance of an end-to-end supply chain network.

3.1 Initial Scope

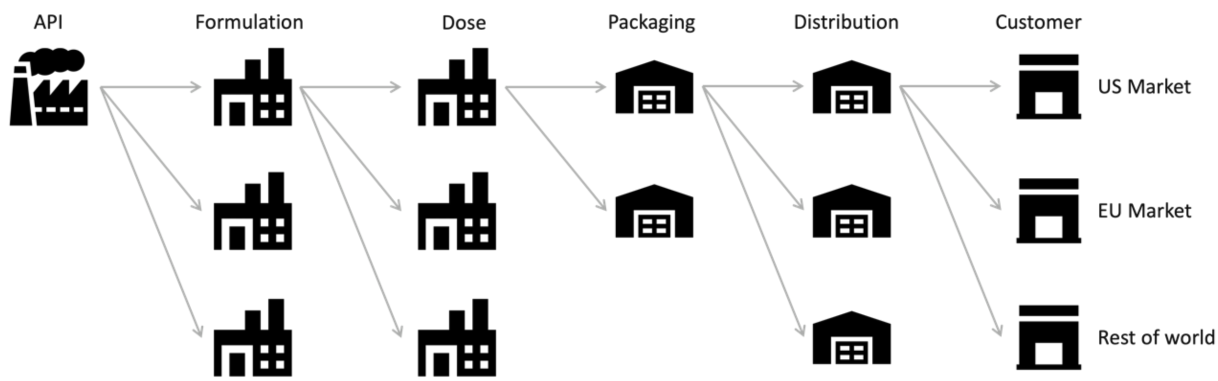
This study began with assessing DDMRP as a demand planning solution to be implemented in the place of forecasting on an individual SKU basis. The assumption initially was that upstream production stages were dedicated to the production of the SKU. Through interviews with members of the supply and demand planning groups, we learned that the SKUs of interest make up a small portion of the overall production of many products under the same drug class. As presented in the literature review, DDMRP is an overall multi-echelon production system that synchronizes across demand and supply planning. The following explains the difficulty in applying DDMRP at the SKU level.

An SKU in this context is defined as a packaged product intended for a target market. Forecasts are performed on the SKU level to predict the demand in that market which are then aggregated for each upstream production stage to define the expected demand that the facility must prepare for. The production of these materials is shared across the drug substance supply chain, production runs supply material to meet the need of many dependent SKUs. As manufacturing is shared, and these SKUs make up a very small percent of the global production: there is little leverage to transition an individual SKU to a reactive production philosophy following a DDMRP methodology within the confines of the broader production system.

A hypothetical example of the end-to-end production process for a class of drugs is shown in Figure 7, to provide context on the scale of SKUs that are manufactured in shared production runs. This figure outlines the low leverage position of the target SKU for controlling the upstream production process.

Figure 7:

A simplified view of the pharmaceutical supply chain outlining the shared production of products under a drug class.



(Icon Source: Flaticon.com)

In this example, we have one API which is transformed into multiple different drug formulations which represent the physical form of the drug and the delivery method. This single API is formulated into a pill, an inhaler, a drinkable liquid, or an injectable form. We will assume that each formulation makes up 1/4 of the allocation of that API. Within each of the formulations, there will be a variety of dosage strengths of the active ingredient offered. We will assume 5 dosages each making up 1/5 of the total demand of the formulation. The delineated drug forms are then packaged into their retail form of different units of sale, each representing 1/3 of the dosage.

The largest customers for our partner company are the United States, the European Union, Japan, and the rest of Asia. These customers will make up about 95% of the total demand for the packaged goods. The last step is when the product is dedicated to the target market, with the proper labeling to comply with local regulations. For the SKU of interest, we are looking at low volume markets which exhibit difficulty to predict demand, which is the feature of products introduced to new markets with little historic demand data. This individual SKU will then make up <0.5% of the total demand for the packaged good.

Then for this hypothetical example, the SKU we are investigating makes up 0.00165% of the parent API, 0.0066% of the formulation, 0.033% of the dosage, and 0.16% of the packaged goods. In this case, as parent production stages are shared along with a wide portfolio of products, it was not feasible to leverage DDMRP flow-based production methodologies at the SKU level.

3.2 Updated Project Scope

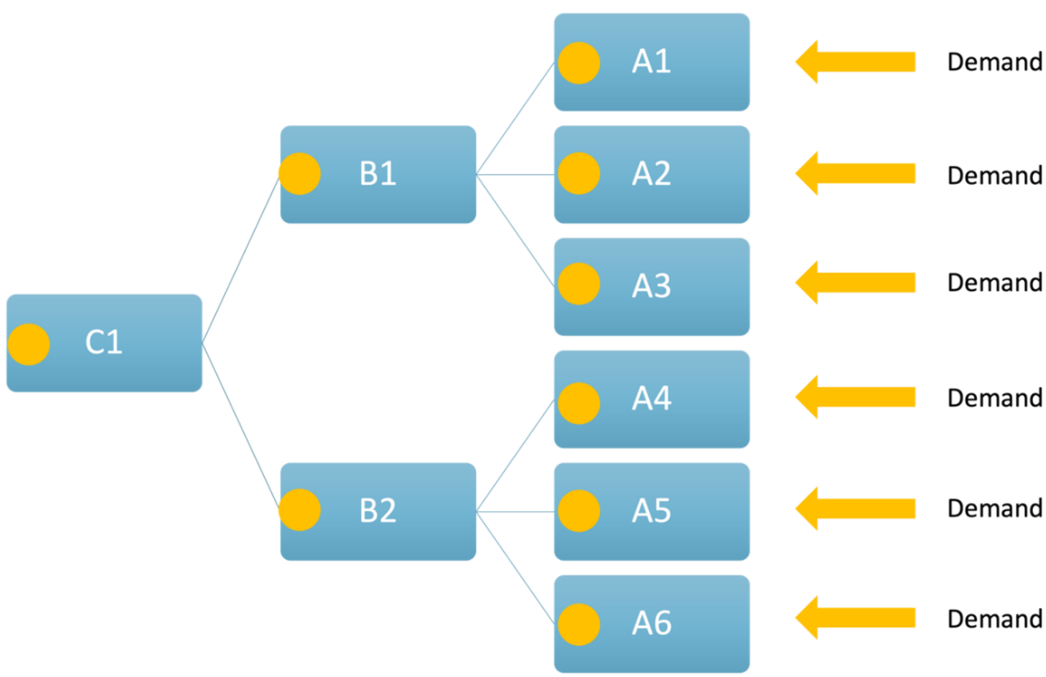
Through interviews with members of the partner company, it became apparent that DDMRP was not a methodology to meet the immediate needs of demand planning, but it could provide strategic value to the overall supply chain group. We returned to the original goal of our research, to understand if DDMRP is feasible given the constraints of the pharmaceutical industry. The primary concern of our partner company was that the long lead times at the API stage and infrequent production campaigns would drive a DDMRP system to hold excessive inventory in the absence of forecasting future demand.

We determined that a full pharmaceutical supply chain would need to be assessed from the API stage through the stages of production to meet the demand of the end markets. After presenting these initial findings we provided preliminary results of a DDMRP simulation model using a fictitious multi-echelon production network fed with actual demand data for a product class. The initial simulation results also served as a communication tool to initiate conversations with relevant stakeholders in the production network. These results outlined the information required for further modeling and sharing our goals with new project collaborators.

This initial test network was defined as shown in Figure 8. This network consisted of three stages in total, starting at the parent stage of API manufacture (Node C1), through two types of formulations (Node B1-B2), serving the demand of 12 separate customer locations (Node A1-A6). Constraints at each stage including production lead times and desired order frequency were estimated based on the typical parameters as learned through conversations with planners of the respective production processes. Monthly demand data over the past three years for 6 SKUs was provided by the demand planning group. The model incorporated the DDMRP features as outlined in the literature review. This represented a simplified version of the simulation model which was customized to the partner's parameters as presented in Section 4.

Figure 8:

Production network for the early-stage testing of the DDMRP simulation model



3.2.1 Strategic Integration

We had planned an initial option for assessing a hybrid DDMRP approach which would be integrated into a forecast-driven supply chain at a strategic decoupling point. All processes upstream from the decoupling point would be planned using forecasts. The demand signal would then be used to plan downstream stages from the differentiation point, the push/pull boundary, with DDMRP planning principles.

Several limitations moved us past this approach. The first is that the partner company utilizes third-party logistics and warehousing providers for downstream processes so there is little control over transitioning these stages to the new methodology. The second limitation is that the goal of this project was to assess if DDMRP can be implemented when considering the long lead time and limited production of the upstream manufacturing process, with the API stage providing a particular challenge. If this study analyzes the system in absence of the upstream stages, it does not integrate the complexity of the pharmaceutical industry production process. The third challenge was that a hybrid approach could not be assessed without modeling the relevant MRP portion using the partner's planning parameters, this was beyond the scope of assessment for this study. Lastly, a major interest in adopting DDMRP was to move away from forecasting. For a hybrid push/pull model to work, upstream push stages need to be planned using forecasts, so this hybrid approach did not align with the project goals.

3.2.2 Realistic End to End Supply Chain Modeling

The next scope involved modeling the company's full end-to-end production network to outline how a full drug class would be managed under DDMRP. This provides a high level of realism, with the ability to compare to the metrics of their existing system. Modeling this full system was deemed infeasible through conversations with our partners. The hypothetical network shown in Figure 7 can be referenced to understand the rapidly expanding scope of this model. The complexity of the network model quickly grows when looking downstream from the API stage. One parent API, four unique drug formulations, five dose strengths per formulation, three types of retail packaging, and 30 market-specific labeling for each. This overall network encompasses 1,800 SKUs and the full network of upstream value-added steps to model. This level of complexity was beyond what was required to assess the research goal: to determine how a multi-echelon production network would operate using DDMRP principles and the relevant constraints of the pharmaceutical industry.

3.2.3 Simplified Full End to End Supply Chain Modeling

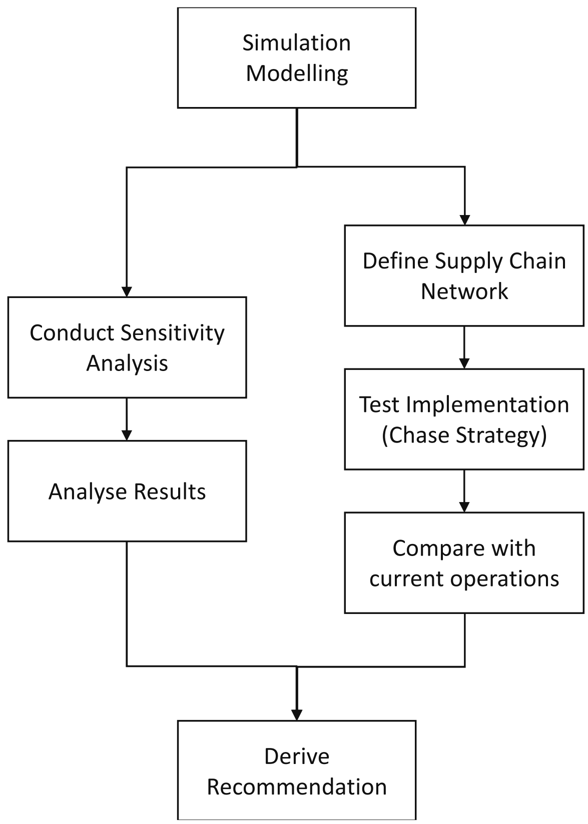
The final simulation, as described in Section 4, was built using a representative model of the partner's supply chain. The relevant steps were modeled to follow the path of an individual product through the production stages from API to dedication to an end customer. This scope provided the proper granularity of detail to test the functionality of DDMRP and assess how it handles the constraints of the pharmaceutical industry. Relevant data is difficult to pull out of the company's Enterprise Resource Planning (ERP) system. This narrow scope gave a manageable volume of information to process without the partner dedicating too many resources to data gathering. The methodology section goes into much greater detail on the design of the simulation model, the network map, relevant data parameters for analysis, and the modeling outputs.

4 Methodology

Figure 9 outlines the process flow for the project. Each stage is described in detail in the following sections.

Figure 9:

Process flow diagram for DDMRP simulation



4.1 The Simulation Model

A simulation model was created to observe the flow of materials in a multi-echelon system including realistic constraints to match the partner's production environment. The primary goal for the model was to determine if the calculations and the foundations of DDMRP can be extended from single node simulations to multi-node systems without cascading effects of stockouts at production stages throttling production. The outputs of the model provide an understanding of how this system performs based on the key performance indicators as identified in Section 4.4.

The simulation model was built using the python programming language, utilizing an object-oriented programming (OOP) approach. OOP is a modular programming scaffold that is easily scalable to allow for easy customization and experimentation. As the research scope matured, this afforded the ability to quickly adapt to a new production network. The simulation environment was built based on the principles of the DDMRP methodology as outlined in the literature review section. Data sources, assumptions, and limitations of the research model are outlined in the subsequent sections of the methodology section. The source code for the simulation model can be found at the following link: https://github.com/sahararunner/DDMRP-Simulationhttps://github.com/sahararunner/DDMRP-Simulation

The mechanics of this model flow in the following stages stepping through time daily. First, take in demand from the customer nodes. Then assign the aggregated demand to the relevant upstream nodes in the system and adjust the buffer stocks with this demand signal. Next, compare the on-hand inventory levels to the net flow equation and determine if ordering is needed. Initiate an order if the buffer dictates, adjust the upstream inventory on hand level, and assess the node's inventory position and initiate an order there if needed. Material is received by the node for the transportation lead time if the upstream node has adequate material on hand. If the upstream does not have material available, this is recorded as a stockout, and the downstream node must wait until the full production and transportation lead time to replenish its inventory. The model will continue to move along on a daily time step in this way over the length of the simulation time at which point the relevant metrics can be assessed.

4.2 Defining the Production Network

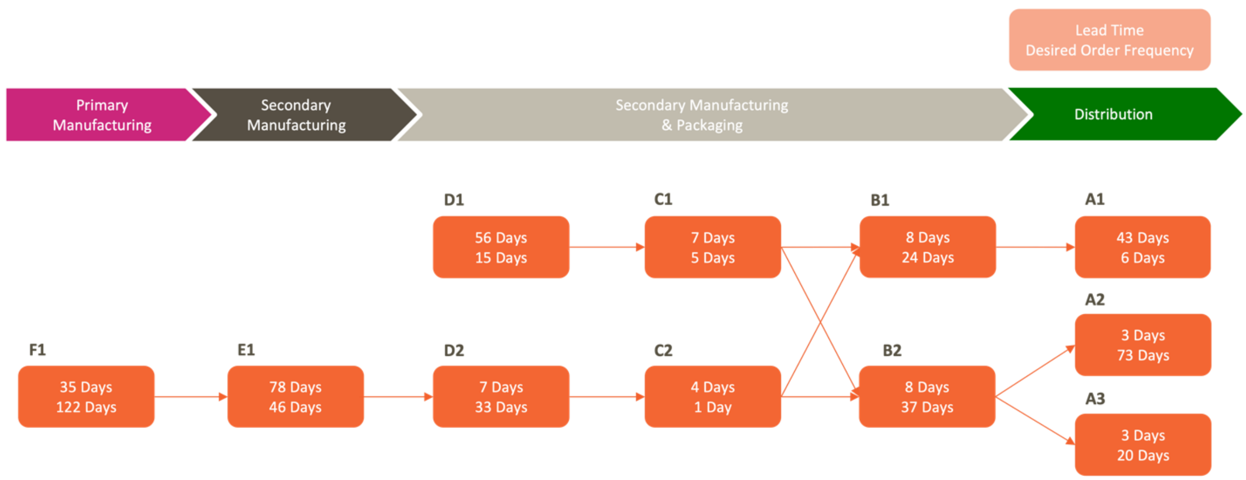
The results of the initial model, which was presented in Section 3, provided a tool to guide the discussion with stakeholders to define a network map of the relevant production stages. The focus was to build a production environment that incorporates features representative of the partner company's supply chain without adding the full complexity of their network. This network produces a portfolio of products representative of demand planning segments.

4.2.1 Production Network

The network model follows parallel production paths: API production through the value-added steps and the carrier device which is combined in later stages for the finished drug product. These parallel paths show how separate upstream processes interact and combine under DDMRP planning to meet customer demand. Figure 10 shows a graphical representation of the production model.

Figure 10:

Final supply chain map to match partner company parameters



Each stage represents a major processing function in the network, from primary manufacturing, secondary manufacturing, packaging, labeling, and distribution. Arcs denote the linkage between a stage, with the arc being the parent process, and the arrow leading to the downstream dependent child process. Each location that requires multiple inputs, in our case B1 and B2, is denoted with the relevant linkage arcs. Customer stages, where demand is fulfilled, are locations with no arcs emanating downstream. The initial stages do not have any incoming arcs, the stage time is dependent on the procurement and transportation of raw materials, and the processing time to transform those raw materials for preparing for the next stage.

These stages were chosen as key locations for buffer stock to decouple steps in the production process. With the buffer stock in place, the overall complexity of the supply chain is reduced, and the actions at each stage are isolated from the other stages between buffer locations. For this network, there are multiple stages contained between each node in our, but from a modeling perspective, these steps are aggregated into one stage.

4.2.2 Customer Nodes

The demand planning group choose to focus on three SKUs that are produced by this network to understand how DDMRP will perform with different types of demand signals. The first demand profile, customer node A1, serves a large market that experiences high variability of demand and higher overall demand compared to the other customers. This customer node is also complicated with an extended lead time and 43 days of ocean transport from the point of differentiation due to the geographic location of the market. The second customer node, A2, represents a well-established market with comparatively stable demand and a short lead time for the transit of three days. The last customer node A3 is an established market with relatively predictable demand, but due to the market size, the demand is low relative to the other customers. This lead time is also short at three days.

4.3 Data Requirements for Modeling

The relevant data inputs for the simulation model proved difficult to pull out of the company's ERP. Translating the existing network to the simulated network proved challenging. Filling in the missing parameters required conversations with multiple stakeholders within the supply chain group to define proxies within their data to drive the parameter when information was not accessible. The following sections describe the process for determining the inputs used in the simulation model.

4.3.1 Demand Signal

The demand signal used for the three customer nodes represents monthly customer demand over the past three years. The simulation model parameters measure lead time in days and time steps within the model occur daily. Daily demand was generated assuming a normal distribution of demand using the normal random number generator in python's NumPy library. When disaggregating demand to a shorter time period, the standard deviation does not change in a linear manner, but rather to the square root of the number of time periods (Silver et al., 2017). The formula for converting from monthly standard deviation and monthly demand is shown in Equation 8.

Equation 7

$$\sigma_{daily} = \frac{\sigma_{monthly}}{\sqrt{30}}$$

$$\mu_{daily} = \frac{\mu_{daily}}{30}$$

For modeling, this historic demand is fed into the DDMRP calculations one day at a time. Future demand periods are held hidden from the system, and not incorporated into the model until the simulation reaches that time. Past demand is used to simulate how the DDMRP system would react in real-time as the model steps along each day of the study time frame.

4.3.2 Desired Production Frequency

The cadence of production at each stage is defined by the individual plant managers, there is not an overall target set by upper management. This decision is based on achieving their target performance metrics: reducing the costs of production, maintaining level production schedules for smooth plant operations, and meeting service level requirements of the downstream stage. For the simulation model, it is important to capture the constraints of the pharmaceutical industry, as defined by our partner company, regarding production cadence. This is a key constraint for determining the feasibility and functionality of DDMRP in this study.

In the absence of a targeted number of production runs, production batch records over the course of the previous calendar year were examined. The records include the volume and date of each batch leaving the production line, with a campaign encompassing multiple batches over the course of several days to a month. The batch dates were then examined to determine where there were natural breaks between a campaign for the product type, as indicated by company stakeholders. The number of campaigns in the given year was used to serve as a realistic production frequency for input into the model.

4.3.3 Lead Time

The lead times between each stage encompass the relevant time required to pass material from the upstream buffered stage, through the value-added steps, to provide material to the next buffered stage. The transportation lead time is the total time to pass a completed material from the parent to the child stage if the material is available in the buffered inventory. Both lead times are used within the simulation model. If an upstream node has sufficient inventory to cover the demand the downstream node is replenished following the transportation lead time. If the upstream node stocks out, it passes along its remaining inventory and the downstream node is replenished with the backordered amount after the production lead time plus the transportation lead time.

The DDMRP model only considered the buffered production steps to be relevant in the simulation analysis. The unbuffered stages then are aggregated together to determine the lead time between buffered stages, as the relevant path becomes the total lead time from the upstream parent through the processes to the next buffer zone. The parameters for the lead time within the company's ERP system were aggregated to define the DLT between each buffered node.

4.3.4 Planned Adjustment Factor

The planned adjustment factor (PAF) is the primary mechanism within the DDMRP framework for accounting for product seasonality or other exogenous factors which can predict future demand. The demand planning group indicated that the demand used for the simulation model is not impacted by known exogenous factors or seasonality. This assessment is testing the feasibility of the overall DDMRP framework, so it was important to incorporate relevant planning parameters which can impact model performance.

To test if the seasonal correlation was present in the demand data, an Autocorrelation Function (ACF) was performed using the ACF function in python's Statsmodels library. ACF is a commonly used methodology for analyzing time series data to assess seasonality trends. The results of the ACF analysis, Appendix 1, did not indicate a compelling trend in seasonality for the demand data on a 95% confidence interval. The PAF was not used in the DDMRP simulation as there were no forward-looking planning features to incorporate into the demand signal.

4.3.5 Order Spike Threshold and Order Spike Horizon

This study used the demand signal for the product in the target market, as used by the demand planning group for forecast generation. The demand does not include what is known as tenders, which represent obligations to fulfill demand in the future if a contract is awarded. Tenders frequently represent 6 months of the total stock allocated to the target market. Contract terms often require fulfillment within a 4-month time frame. The planning around tenders represents a high level of uncertainty, given that production must be initiated before winning the contract due to the long lead time within the partner's supply chain. Failing to fulfill the contract carries heavy penalties in the form of fines, alternatively reallocating existing inventory puts the rest of the supply chain at high risk of stocking out. As the tenders carry uncertainty, planning is handled separately by the partner company. The tenders are held separately from the market demand signal used by demand planning for time series analysis, otherwise, forecasts would incorporate large spikes of nonexistent demand in future time periods.

As tenders are planned separately, this was considered outside of the scope of the assessment. Without tenders, the DDMRP model did not have qualified demand to incorporate into the net flow equation of the simulation model. The model as run does not incorporate the order spike threshold or order spike horizon as described in the DDMRP literature.

4.3.6 Minimum Order Quantity and Batch Size

Minimum order quantity (MOQ) and batch sizes in the existing production network proved problematic to extrapolate to the simulated environment. The order size must be a multiple of the batch size for the given process. The MOQ is then a target number of batches that make financial sense to initiate a production campaign. Due to high fixed costs at many production stages, this MOQ can be quite large to maintain profitability.

The production for certain nodes within the supply chain is shared with the global production of all products that use the shared material. This simulation model drew the network boundary on the production steps required to produce our three target SKUs, ignoring the real network steps that were not relevant to our environment. The API for example is produced for over 1000 SKUs within the real network, so the minimum order quantity and required batch sizes, would not be able to be met by the demand placed from our three SKUs. The percentage of the total demand from those three SKUs could be estimated from overall demand data, but this would be a data-intensive process.

The MOQ and batch size were omitted from this analysis due to the challenges of translating the system constraints to the simulated network. The desired frequency of production at each stage would then be the primary binding factor to limit the number of production runs to be relevant to the partner's supply chain. The simulation model will assume that there are no binding requirements in this regard, minimum order size and batch size will be set to 0. This omission is a recognized limitation of this study, and an area for future consideration as our partner company matures along its DDMRP feasibility assessment process.

4.3.7 Unit Conversions Between Stages

For each stage in the production process, the bill of materials (BOM) outlines the required inputs in the form of raw or work-in-progress materials to produce the planned outputs. This "recipe" outlines the required material inputs and defines how they are combined and outputted into the units of production of materials leaving the stage. For example, 10 kilograms of API is taken into the formulation stage and mixed with inactive ingredients, known as excipients, to produce the 100 kilograms of formulated product.

The use of buffer stocks allows the model to decouple stages in the supply chain network such that the relevant parameters are the aggregate of the processes between stages. With the aggregation of stages between each of the decoupled buffer locations, defining the full conversion of materials for each of the combined stages is challenging.

Instead of focusing on tracking actual volumes of material at each stage, days of inventory provide a unitless measurement that outlines the number of days of demand coverage the stage holds. As this is the key metric to compare to the existing supply chain system, the conversion of units between stages can be omitted. For this reason, flows of inventory were measured in days of inventory, rather than converting the BOM between stages.

4.4 Model Outputs and Relevant Metrics

When assessing a new methodology, it is important to identify the key performance metrics to judge merits and limitations. The metrics are outlined in Table 4 and described in detail in the following sections.

Table 4:

Key Performance Metrics

Metric	Relevance	Comparable to Reality
Order or Production Frequency	Proxy for production costs in the simulated environment and manufacturing capacity requirements.	Yes, existing production runs are known at stages in the supply chain. It can be used to estimate "desired" runs.
Days of Inventory	Proxy for identifying the amount of inventory buffer profiles held within the DDMRP network. Costs associated with inventory include capital costs and operational costs.	Days of inventory provide an idea of the holding requirements, but it is not indicative of real system performance. It can be compared with limitations.
Stockout Events	Frequency for a customer node missing a sale due to lack of inventory.	Yes, existing stockout events are known within company metrics.
Item Fill Rate	Metric for determining the performance of the DDMRP system in meeting customer demand.	Yes, existing fill rates at customer-facing nodes are known, and model performance can directly compare to real fill rate metrics.

4.4.1 Order or Production Frequency

The constraint on the frequency of initiating orders in the pharmaceutical industry is an important factor to determine if DDMRP processes are feasible. Within the chosen network, upstream assets and production lines are generally multipurpose facilities and not dedicated to an individual product type. Planning must balance the needs of a portfolio of products on these shared assets. This feasibility study will consider adopting DDMRP within the sponsor's current production environment, so it is important to keep the network producing at a cadence that is feasible given the current constraints.

Planners within the pharmaceutical industry must balance the cadence of production or orders to meet demand without driving excessive costs of production in the system. The calculation of relevant costs is outside of the scope of this research assessment, this study will not attempt to optimize overall supply chain network costs. The metric tracking the desired order frequency will provide insight into the overall operational efficiency and scheduling feasibility.

4.4.2 Days of Inventory

Inventory represents a cost to the system in the form of tying up capital and the associated physical storage costs. This simulation model will calculate the inventory not based on cost, but rather on the days of demand that the inventory at a given stage covers. This is shown in Equation 10 below. The existing supply chain metrics do not hold inventory for each SKU, but rather track the aggregate inventory stored at the stage. This is then used in performance metrics to determine how many days of demand coverage are held at each location. With this metric, our simulated days of inventory can be compared to the existing days of inventory held.

Equation 8

$$Days\ of\ inventory\ = \sum_{t=0}^{365} \frac{(Inventory\ on\ hand_t + Inventory\ on\ order_t)}{Demand_t}$$

The model will only produce inventory to cover the demand nodes included in the simulation, in this case, three customer locations. The actual production environment will pool the demand signal from many downstream customer demand signals. The level of variability denoted as the standard deviation, does not increase linearly but rather the square root of the summed variance as shown in Equation 11. This metric then will provide an insight into the operation of DDMRP and the impact of inventory holding levels in our simulated environment, but not a perfect comparison to the partner's existing metrics.

Equation 9

$$\sigma_{aggregate}\ = \sqrt{\sigma_i^2\ + \sigma_{i+1}^2 \ldots \sigma_{i+n}^2}$$

$$i = customer$$

$$\sigma\ =\ standard\ deviation$$

4.4.3 Stockout Events

Extremely high on time in full (OTIF) metrics are required of planners in the pharmaceutical industry as described in the literature review. The simulation model defines the penalty for this parameter based on the number of time periods when the stock on hand was able to meet the incoming demand. If the inventory is not available when requested, then the model will consider the day a stockout event and place the demand on back order to be fulfilled when the material is available.

4.4.4 Item Fill Rate

The item fill rate (IFR) was used as a second metric to represent the model's performance based on the level of service provided to customers. Instead of imposing a penalty for not fully fulfilling the customer demand for a day, the IFR will quantify the percentage of total customer demand that the model fulfilled. This will give an impression of the ability of DDMRP to perform in meeting total customer demand, with the weight of the penalty based on the number of units short on a given day. Equation 12 shows the IFR formula.

Equation 10

$$IFR = \frac{1}{n} * \sum_{t=0}^{n} Demand\ fulfilled / total\ demand$$

n = *number of time periods in assessment*

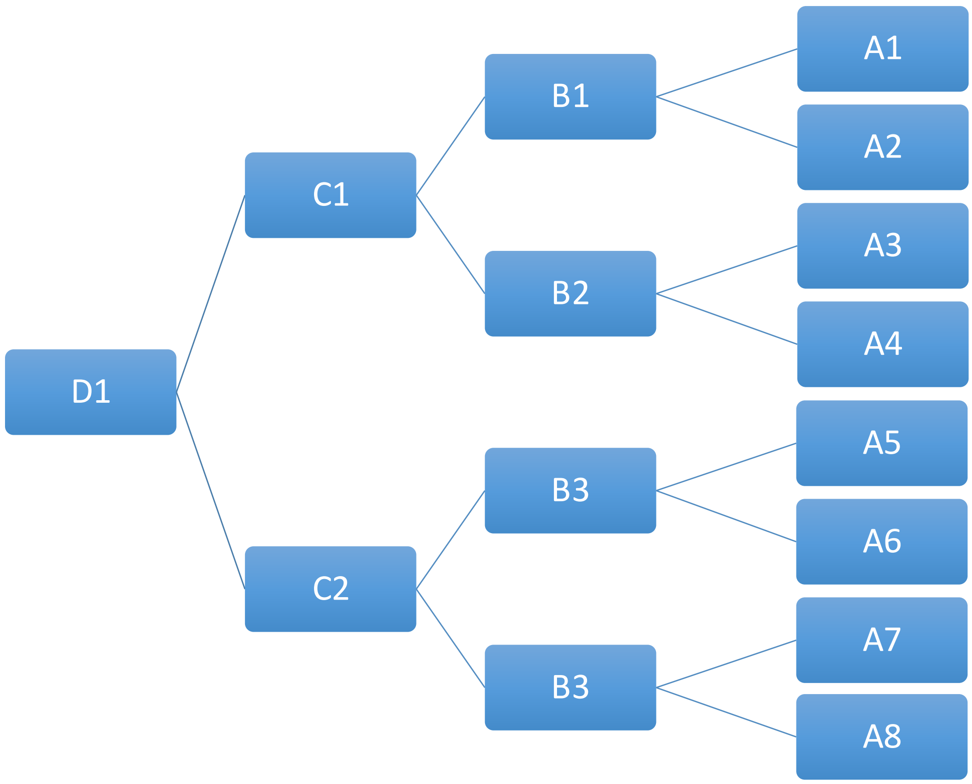
4.5 Sensitivity Analysis

Experimenting in a simulated model provided an environment to determine the impact of altering strategic parameters and deep dive into the system-level constraints of the DDMRP methodology. The lead time factor and variability factor values were suggested based on a categorical classification scheme. To set the baseline of the analysis, lead time, and variability of the nodes are each categorized into three classes.

To provide a framework for the partner company to set these parameters, a key research question for the study is to demonstrate the system's impact on tuning the values. The simulation modeling environment of the sensitivity analysis incorporates similar constraints to the pharmaceutical industry in the form of a balanced tree-like supply chain as indicated in Figure 11. The purpose of stress testing the parameters in a general treemap, instead of any specific product is to assist identification of system-wide dynamics. These findings can be applied to our customized simulation model.

Figure 11:

Supply chain network map for sensitivity testing



It is important to understand the overall system impacts of altering the current way of supply chain planning and execution. By altering parameters such as the desired order frequency and the location of buffer stocks, the impact of strategic system design decisions can be observed and quantified. This assessment will quantify the system changes based on altering the parameters summarized in Table 5.

Table 5:

Description of the DDMRP input parameters

Parameter	Parameter Flexibility*	Purpose	Type
ADU Time Frame	Managerial lever	Adjust the time frame of the demand signal.	Time Horizon (Days)
Lead Time Factor	Managerial lever	Adjust buffer zones based on lead time.	Scalar Factor (0-1)
Variability Adjustment Factor	Managerial lever	Define red safety size based on demand variability.	Scalar Factor (0-1)
Planned Adjustment Factor	Managerial lever	Account for seasonality or other known factors impacting demand (not covered in our study).	Scalar Factor (multiplicative)
Order Spike Threshold	Managerial lever	Reduce the impact on buffer sizing for non-sustained demand spikes (not covered in our study).	The threshold for including a future demand as qualified demand. Set as a demand threshold
Desired Order Frequency	System constraint	Constrain the frequency of production runs or orders at each stage.	Sets buffer sizes to meet demand over the desired time horizon between productions or orders
Location of Buffer Stocks	Managerial lever	Determine the network map. Buffers decouple stages within the supply chain, fewer buffers aggregate more processes into a single stage.	Managerial Decision
Lead Time	System constraint	Determine the impact of long lead time at a node in the supply chain.	Days of lead time
Demand Variability	System constraint	Test model with demand scenarios.	Demand Profile adjustment

* Managerial lever parameters can be adjusted without further verification of practicality. System constraint parameters are inherent constraints that existed in specific products.

4.6 Chase Strategy

The learning from the sensitivity analysis built a foundation to test the implementation of DDMRP on existing portfolios within the partner company. The product network experimented with is shown in Figure 10 from Section 4.2.1.

A chase strategy was implemented to determine the optimal range for each of the parameters in the context of our simulated supply chain. First, the fixed system constraints were set based on information gathered from the partner company. The categories considered managerial levers represented factors that could be adjusted without altering the supply chain system. These included lead time adjust factor, ADU horizon, and variability adjust factor. The relevant DDMRP features are outlined in Table 5. Then, according to insights gained while tuning parameters in the sensitivity analysis, the simulation system was set to target a service level of zero stockouts at the customer-facing nodes. One parameter was altered at a time in incremental steps to determine the optimal setting. When the parameter no longer improved the metrics, this value was set, and the next parameter was tuned.

5 Results

5.1 Output From Sensitivity Analysis

The results from the initial sensitivity analysis provide insight into the mechanics of a complex multi-echelon DDMRP network. The primary benefit of performing this analysis is to understand the impact of altering the managerial lever parameters to tune the model performance. The following sections will outline the impact of each parameter on the metrics of days of inventory and service level.

Table 6:

Sensitivity analysis Result

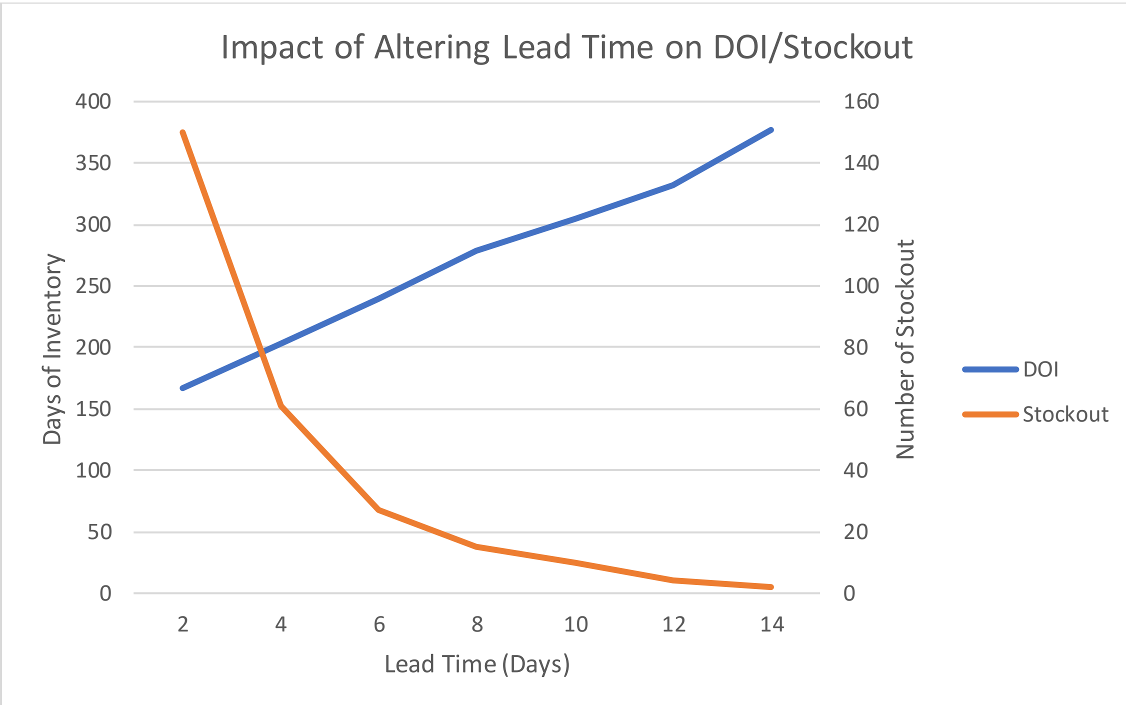
Lead Time	2	4	6	8 (Baseline)	10	12	14
DOI	167	202	239	278	304	333	377
Stockout	150	61	27	15	10	4	2
DOI Diff/Stockout Diff from Baseline	0.82	1.65	3.25	-	5.18	4.94	7.59
Desired Order Frequency	2	4	6	8 (Baseline)	10	12	14
DOI	225	225	239	278	301	329	355
Stockout	8	8	6	15	13	18	9
DOI Diff/Stockout Diff from Baseline	-7.54	-7.54	-4.36	-	11.49	-16.86	12.81
LT Adj Factor		0.2	0.4	0.6 (Baseline)	0.8	1.0	
DOI		195	258	278	313	353	
Stockout		125	23	15	4	2	
DOI Diff/Stockout Diff from Baseline		0.76	2.56	-	3.19	5.78	
Var Adj Factor		0.2	0.4	0.6 (Baseline)	0.8	1.0	
DOI		243	258	278	291	306	
Stockout		34	23	15	9	7	
DOI Diff/Stockout Diff from Baseline		1.86	2.56	-	2.09	3.43	
ADU Back Track	15	30	45	60 (Baseline)	75	90	105
DOI	290	269	271	278	271	272	278
Stockout	49	28	13	15	11	7	12
DOI Diff/Stockout Diff from Baseline	-0.35	0.74	-3.52	-	-1.72	-0.81	-0.09
Demand Coefficient of Variation	0.6	0.8	1.0	1.2 (Baseline)	1.4	1.6	1.8
DOI	265	264	266	278	274	276	273
Stockout	5	10	13	15	19	29	29
DOI Diff/Stockout Diff from Baseline	-1.32	-2.87	-6.15	-	1.10	0.15	0.38

5.1.1 Lead Time

Reducing the lead time reduces the days of inventory held within the supply chain network, with the result of increasing the number of stockout events observed. Conversely, increasing the lead time between each network node increased the inventory holding, and reduced the number of stockouts at the nodes. Table 6 outlines the performance metrics with varying lead time, and Figure 12 shows the resulting impact on stockouts and inventory levels.

Figure 12:

Impact of adjusting replenishment lead time

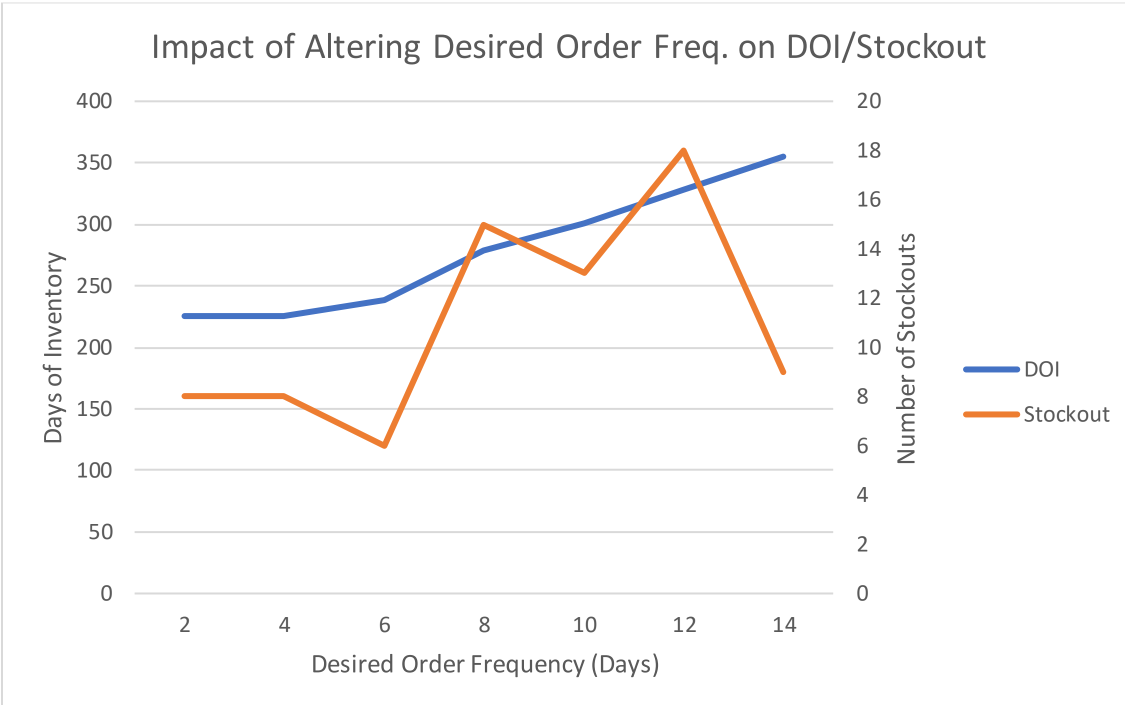


5.1.2 Desired Order Frequency

The model had a better performance of inventory and service level metrics with lower desired order frequency. This allowed nodes in the supply chain to replenish more frequently and adjust to changes in demand. The lower inventory level was held due to the shorter period of demand coverage the buffer needed to plan for. Table 6 outlines the performance metrics with varying the desired order frequency, and Figure 13 shows the resulting impact on stockouts and inventory level.

Figure 13:

Impact of altering desired order frequency on days of inventory and stockout metrics

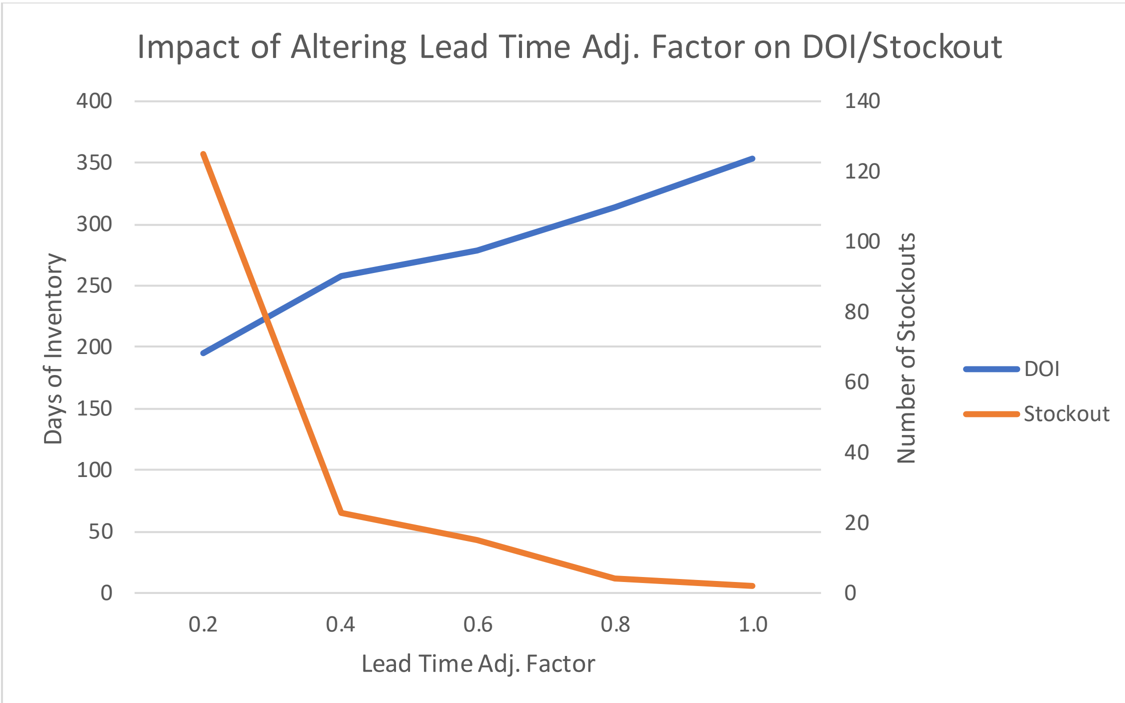


5.1.3 Lead Time Adjustment Factor

As the lead time adjust factor was increased, the days of inventory in the system increased and the number of stockouts decreased. The most pronounced impact on system performance was observed between a lead time adjust factor of 0.2 to 0.4 on both the inventory holding and the stockout metrics. As the lead time adjust factor was increased, the inventory in the system continued to increase but resulted in an impact on the stockout performance. Table 6 outlines the performance metrics with varying lead time adjust factors, and Figure 14 shows the resulting impact on stockouts and inventory levels.

Figure 14:

Impact of altering lead time adjust factor on days of inventory and stockout metrics

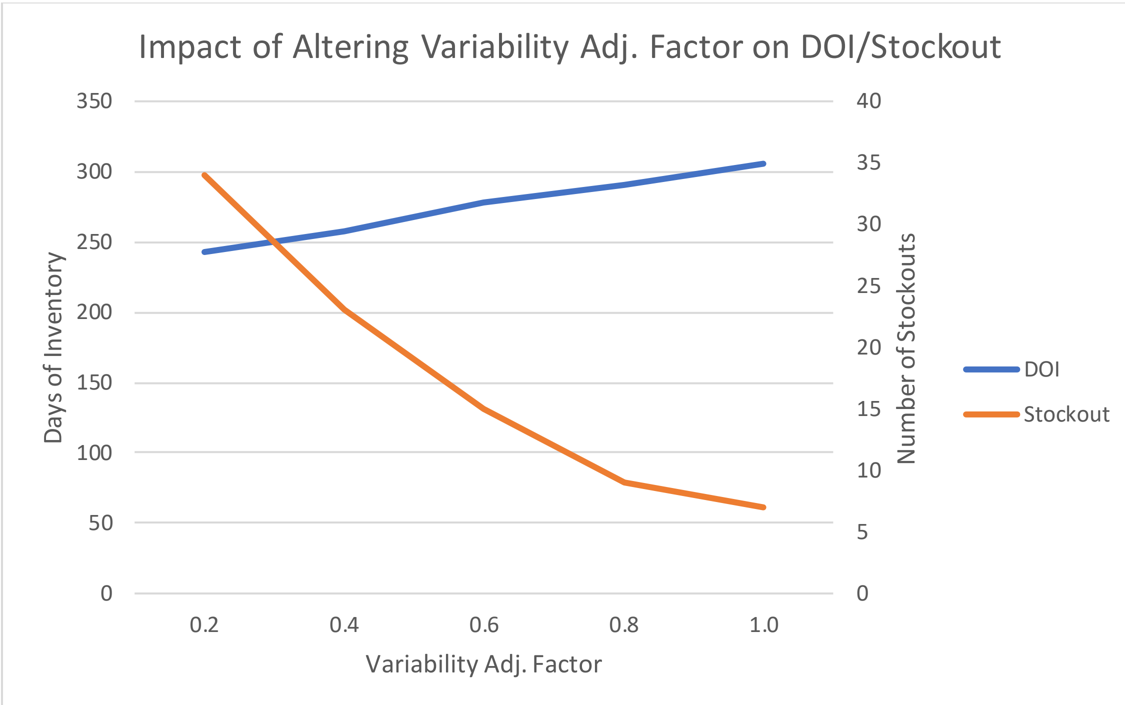


5.1.4 Variability Adjustment Factor

Increasing the variability adjustment factor increases the days of inventory, leading to a lower number of stockouts. Reducing the variability adjustment factor decreases the days of inventory, leading to a higher number of stockouts. Table 6 outlines the performance metrics with changing the variability adjust factor, and Figure 15 shows the resulting impact on stockouts and inventory level.

Figure 15:

Impact of altering variability adjust factor on days of inventory and stockout metrics

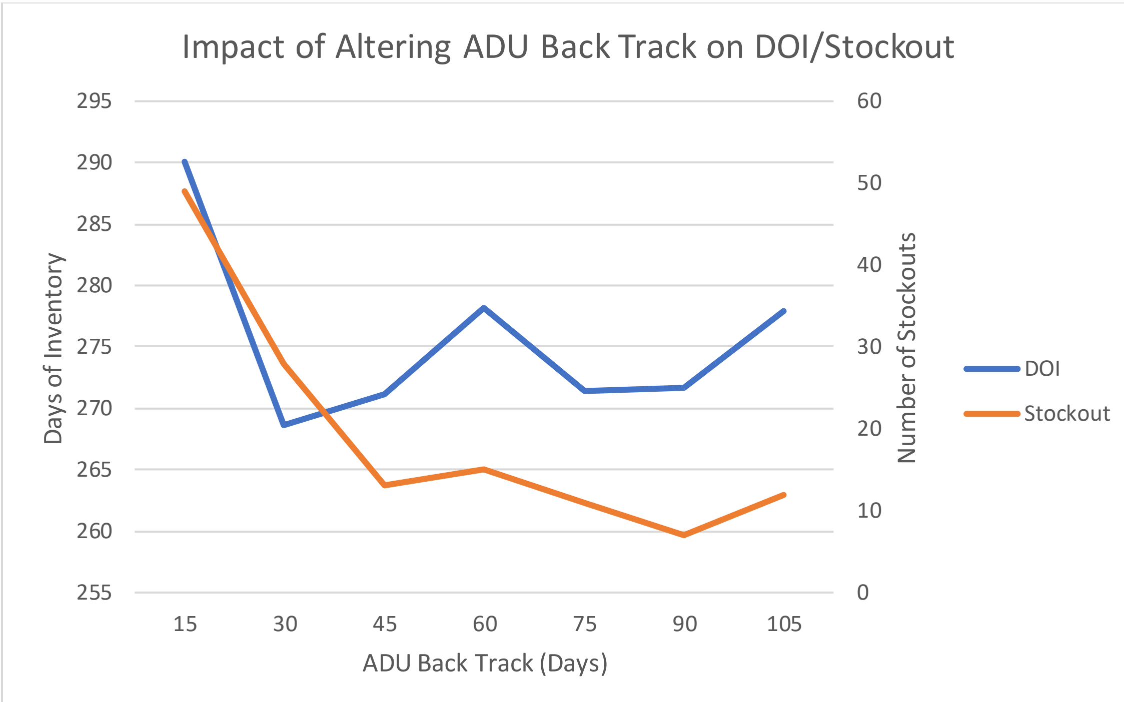


5.1.5 ADU Back Track

Increasing the number of days of demand incorporated into the ADU signal reduced the number of stockouts, between 15 and 45 days. Further increases did not have a predictable impact on the number of stockouts. The best performance on the stockout metric was seen at 90 days of demand signal, although it is not clear if the same optimal value will translate to other demand profiles. According to the graph, the days of inventory and stockout metrics run parallel. Table 6 outlines the performance metrics with changing the amount of historic demand to include in the ADU calculation, and Figure 16 shows the resulting impact on stockouts and inventory level.

Figure 16:

Impact of altering ADU time horizon on days of inventory and stockout metrics

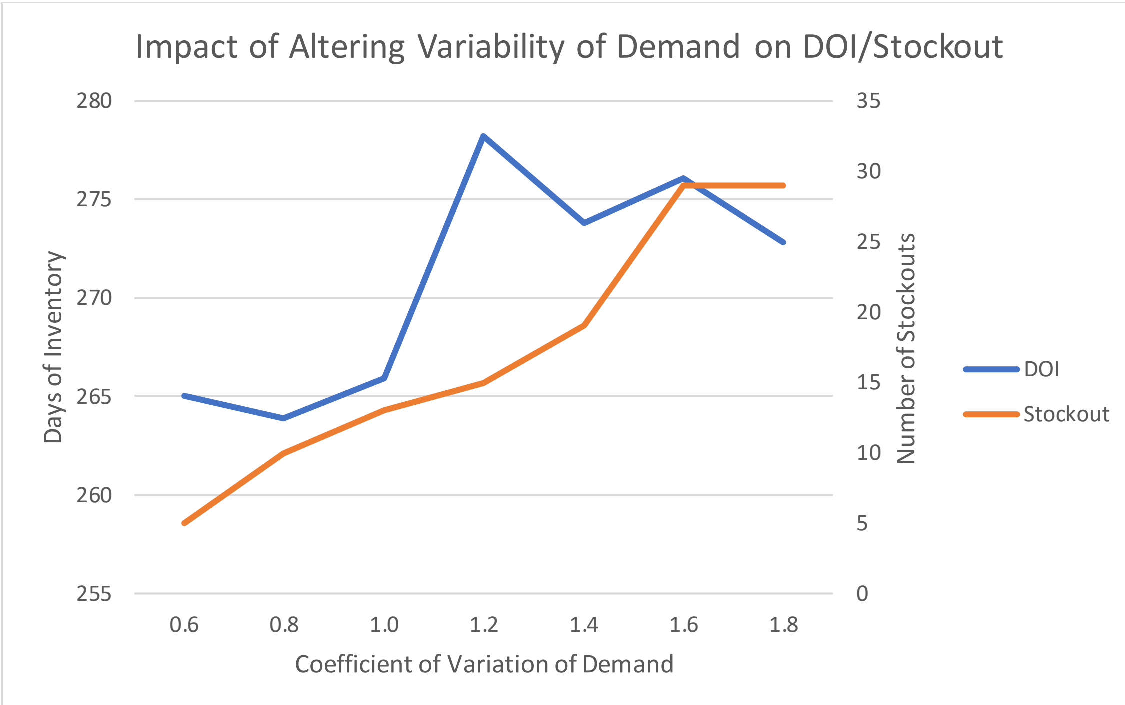


5.1.6 Variability of Demand

Smaller demand variability in this model resulted in better performance in both inventory level and service level. Reducing the variability had the strongest impact on performance in this experimental simulation. Table 6 outlines the performance metrics with changing the standard deviation of demand, and Figure 17 shows the resulting impact on stockouts and inventory levels.

Figure 17:

Impact of altering variability of demand on days of inventory and stockout metrics



5.2 Output From Applying Chase Strategy on Actual Product

Chase strategy was applied to tune the DDMRP model for an actual product in the partner company's portfolio. The results of the experimental steps can be found in Appendix 2. Managerial levers were tuned one at a time with the service level and inventory level results shown in Figures 18 and 19.

The experiment ended when all A nodes have zero stockouts or when the results cannot further improve purely by adjusting the managerial levers. The first three scenarios, 001-003, focused on tuning the variability and lead time adjustment factors. The total number of stockouts in all the A-level nodes decreased when the adjustment factors were increased. Scenario 004-005 focused on adjusting the ADU back track days to align with each SKU's demand portfolio, which the impact is shown in Section 5.1.5. When A1 and A2 nodes reached the desired service level, A3 remained with one stockout even after maximizing the adjustment factors and fine-tuning the ADU back track days.

Figure 18:

Stockout performance for chase strategy scenarios for A level nodes

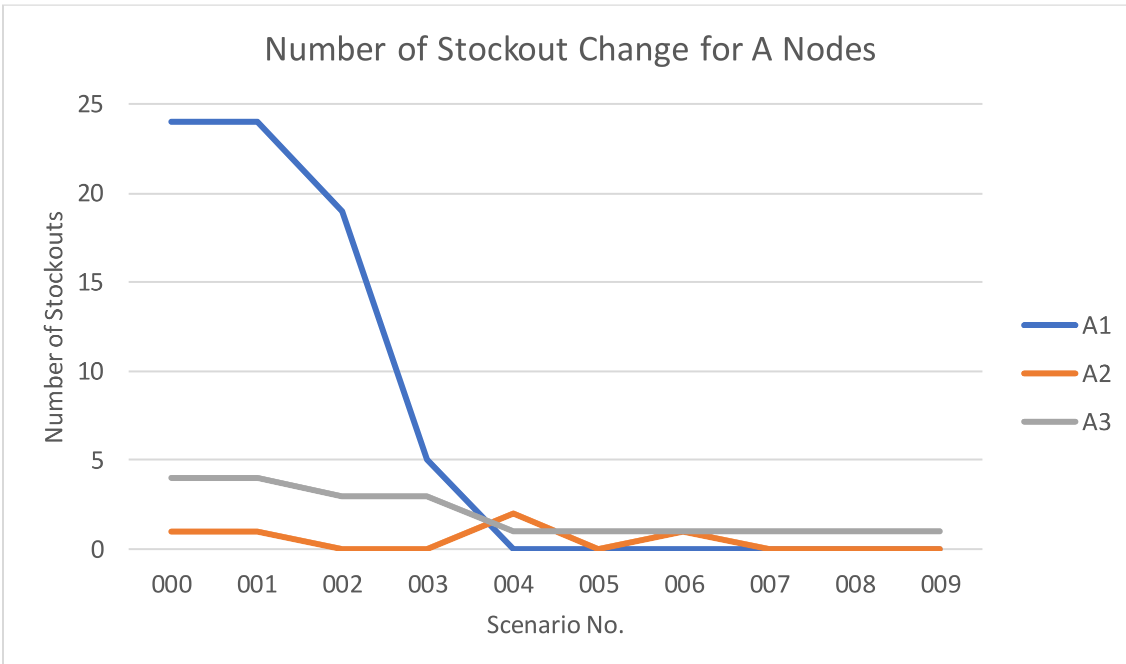
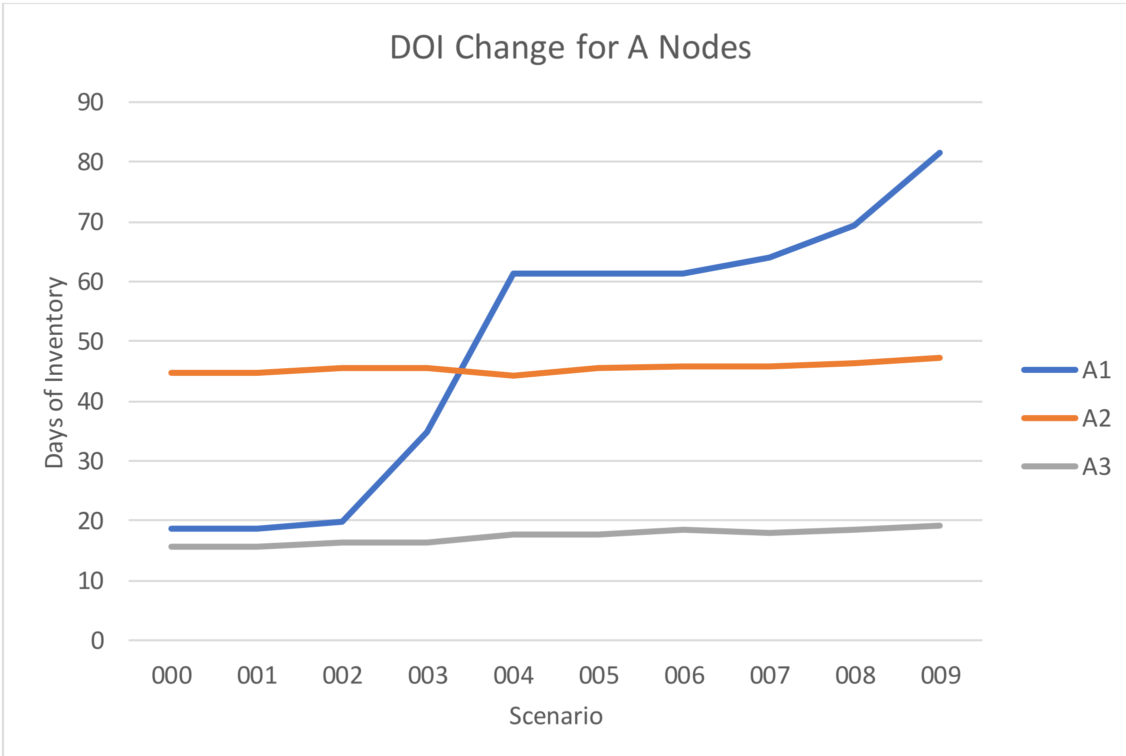


Figure 19:

Days of inventory performance for chase strategy scenarios for A level nodes



On other nodes, an inconsistent stockout pattern was observed, while days of inventory remain relatively constant except for node F1, as shown in Figures 20 and 21. A negative impact on downstream service level is observed with the improvement in service level in all A level nodes, showing that the layers in the system are not independent but their performance was interrelated.

Figure 20:

Stockout performance for chase strategy scenarios for B/C/D/E/F level nodes

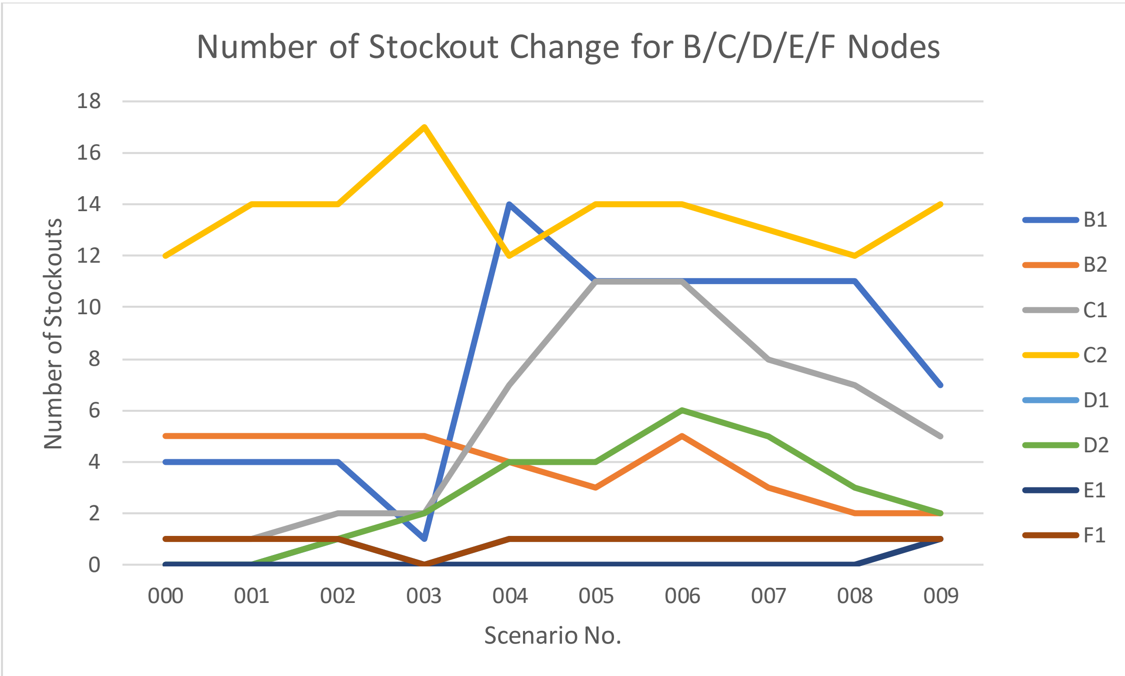
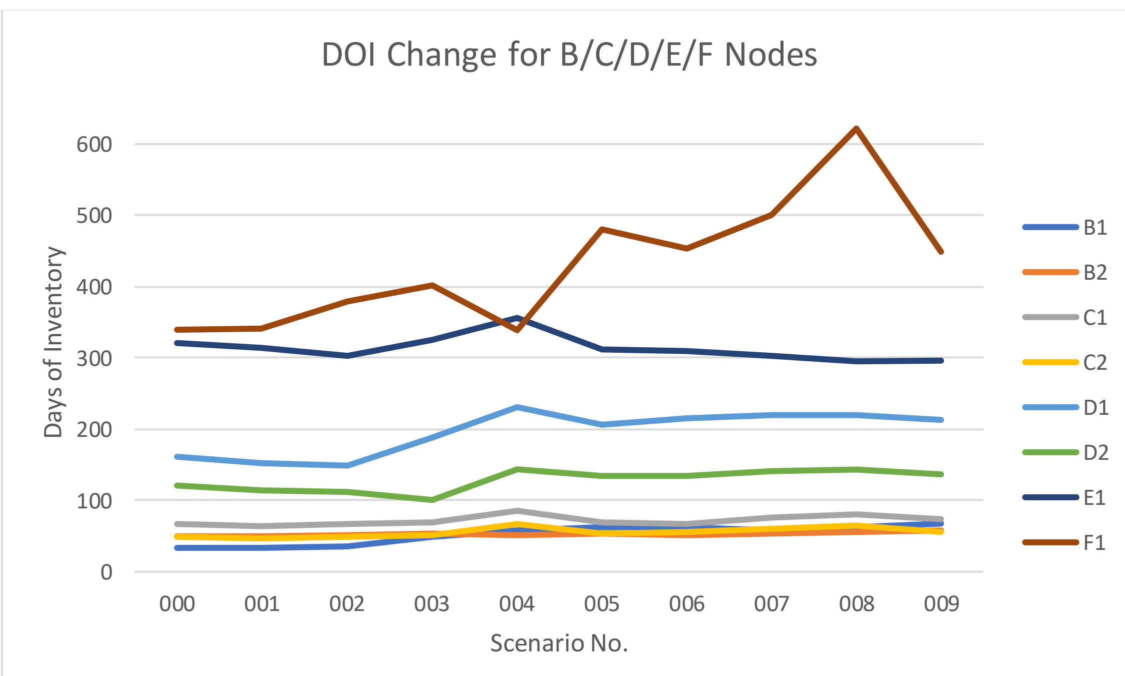


Figure 21:

Days of inventory performance for chase strategy scenarios for B/C/D/E/F level nodes



6 Discussion

6.1 Insights from Sensitivity Analysis

The sensitivity analysis allowed us to observe the fundamental functionality of the DDMRP system. This provided insights that can be observed across industries. These insights are presented and discussed in the sections below.

6.1.1 Parameter Tuning Suggestions

We categorized the inventory level-service level relationship of the parameters tested into three groups: opposite tradeoff, extreme value, and correlated. These categories provide guidance on the expected outcome of altering strategic parameters.

The “opposite tradeoff” category includes lead time, lead time adjustment factor, and variability adjustment factor. In this category, the total number of stockouts decreases as the days of inventory increase, and vice versa. Except for lead time which cannot be easily adjusted due to inherent system constraints, the other two parameters can serve as a managerial lever to fine tune the multi-echelon DDMRP system to achieve strategic service or operational objectives.

The “extreme value” category includes the desired order frequency and demand coefficient of variation. Both parameters point to better performance on inventory and service levels at one extreme end. While both are considered system constraints and cannot be adjusted freely, they provide an entry point for the partner company to examine whether there are product segments within their current SKU portfolio that are suitable for DDMRP introduction.

The “correlated” category consists of parameter ADU back track days. Days of inventory move in a similar pattern to the total number of stockouts. This hints that the best ADU back track days are highly dependent on the system and that there is no single definite good value for all cases. ADU back track days should be set appropriately by studying the demand profile for all nodes to maximize DDMRP performance.

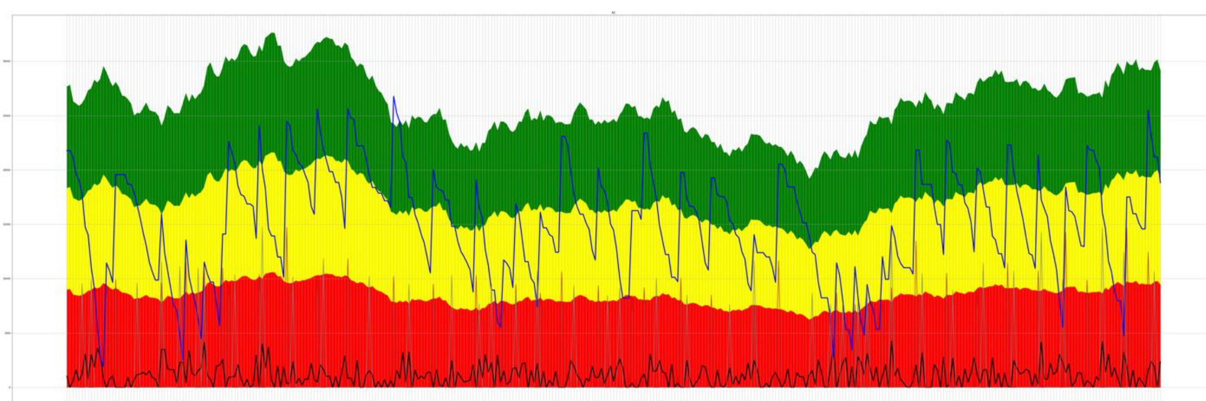
6.1.2 Buffer Zone Designed for Stable Demand

A DDMRP system, as shown in Table 6, performs better when facing relatively stable demand. The results of tuning the demand coefficient of variation are shown in Figure 22. The number of stockouts decreased significantly by cutting the demand coefficient of variation from 1.2 to 0.6.

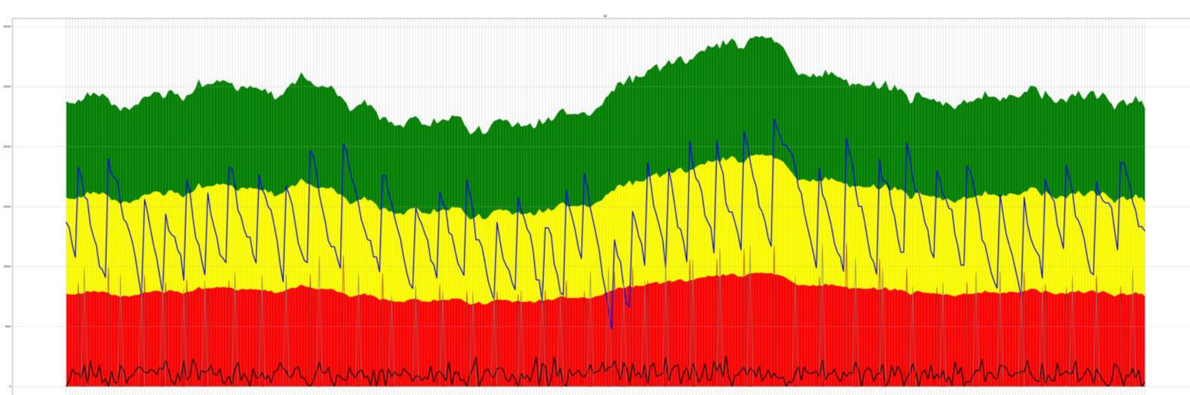
Figure 22:

Inventory position of node A2 under different demand variability scenarios

A2 output from baseline case; Demand coefficient of variation = 1.2



A2 output from sensitivity analysis scenario 29; Demand coefficient of variation = 0.6



Without forecasting to predict upcoming demand, a DDMRP system will have difficulty reacting to uncertainty while providing a high service level. Hedging against uncertainty can be achieved by holding more inventory or holding excess capacity to enable rapidly pulling materials through the value-added stages of manufacturing. Both options represent costs to an organization.

Demand variability has a major impact on the service level performance of a DDMRP supply chain. This is an important factor to consider when implementing DDMRP. The pharmaceutical industry strives for near-perfect service levels, so there is likely to be a narrow portfolio of stable demand SKUs which would be amenable to DDMRP methodology. For products that are deemed too variable, future research can assess if forecast predictions can be incorporated through the PAF to improve the performance. Is the DDMRP SKU portfolio's total contribution to the company's value proposition adequate to justify the investment in training, technology, and organizational change management.

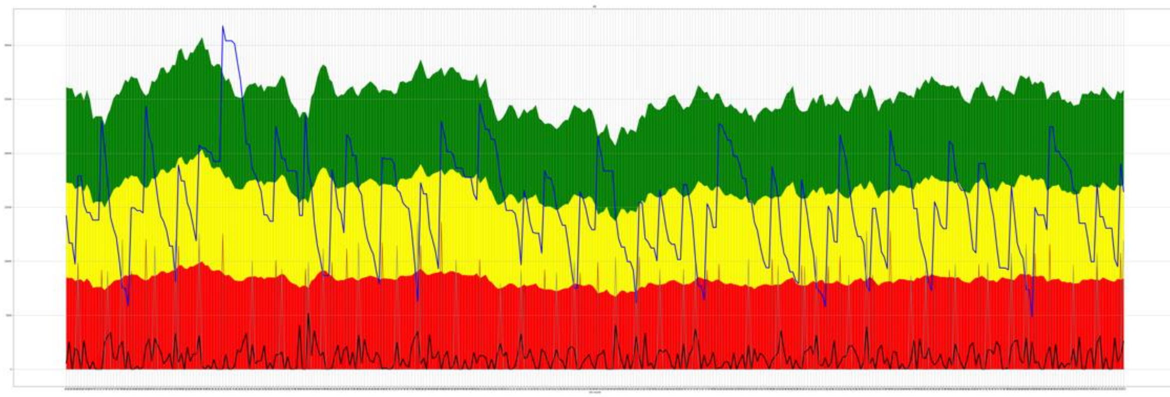
6.1.3 Demand Clustering

From the simulation model, we observed that the buffer stock profiles have the effect of storing the demand signal and releasing the clustered demand to the upstream node. This leads to each stage clustering an increasing amount of the demand signal as we move up the supply chain. The design of the network map for the sensitivity test is presented again in Figure 11 to orient the reader during the following section.

The result of a simulation for customer-facing node A1 over a period of 24 months is shown in Figure 23. Here, it is observed that the demand is flowing in continually on a daily basis with a coefficient of variation of 0.95, Table 6, and the inventory on hand is being consumed daily as well until it requires reorder and is replenished by the upstream node.

Figure 23:

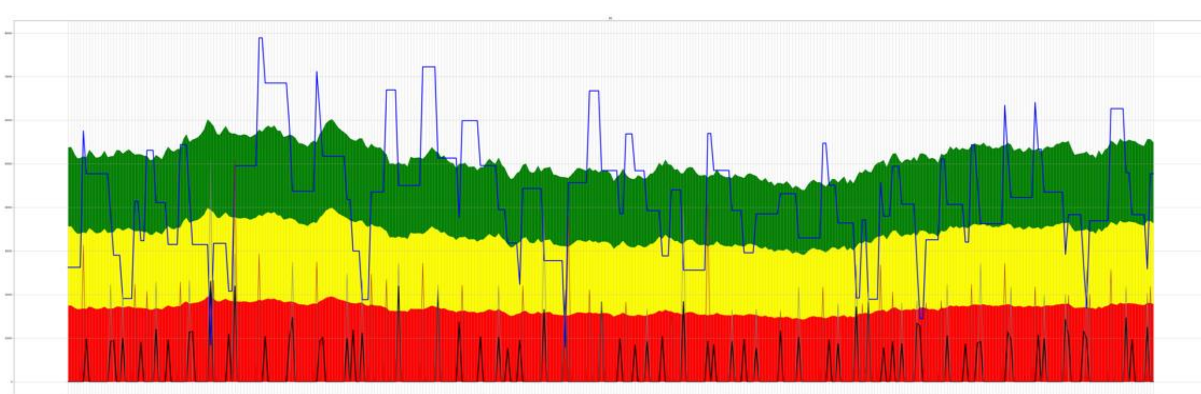
Buffer profile level for node A1 in the sensitivity analysis



The upstream node, B1, is planning the buffer levels based on the sum of the raw demand coming in at the customer-facing nodes incorporating the sum of A1 and A2 into its ADU calculation. However, this node only receives a demand signal when either of its downstream nodes requires replenishment. With node B1, shown in Figure 24, as is observed with the black line denoting demand, the actual demand on the node becomes infrequent. This is due to the downstream nodes holding a buffer inventory which will be depleted and replenished on average based on the number of days of inventory coverage in the green zone of A level's buffer stock. This in effect aggregates the demand signal and pushes a larger more infrequent replenishment request to the upstream node, the coefficient of variation at this node becomes 2.21, Table 6.

Figure 24:

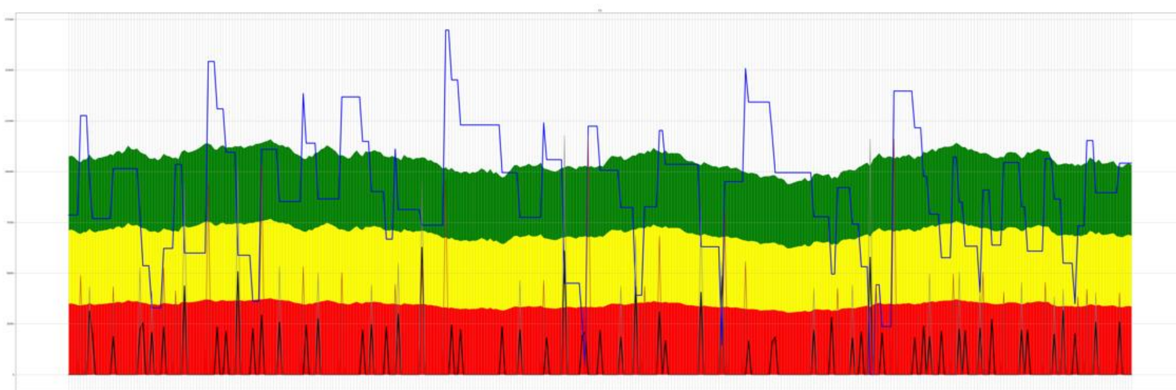
Buffer profile level for node B1 in the sensitivity analysis



This observed clustering of the actual demand signal becomes more pronounced as we move through the upstream echelons of the supply chain environment. Level C1, shown in Figure 25 is still planned based on the demand from its dependent customer-facing nodes, the ADU calculation is based on the sum of A1 through A4. This node is observed to have large infrequent spikes in demand from the downstream stages. The coefficient of variation of demand is now about 2.43, Table 6. Individual spikes that exceed the safety buffer level and enter the yellow zone are now being ordered on this node. This leaves the node at high risk for stocking out, as the inventory level will routinely fall into the yellow zone while the buffer is awaiting replenishment over the lead time.

Figure 25:

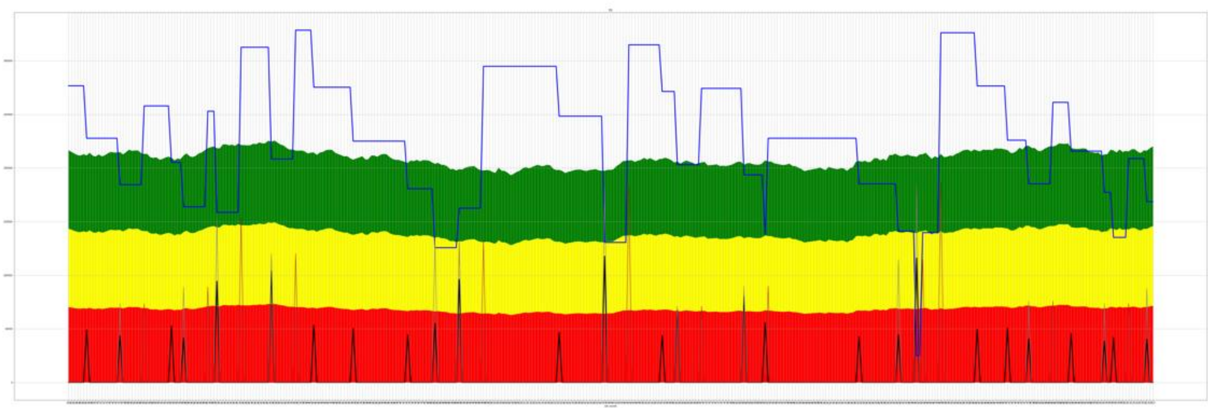
Buffer profile level for node C1 in the sensitivity analysis



Lastly, as the downstream nodes have been accumulating demand signals in their buffer stock and making requests upstream increasingly less frequently and in a larger magnitude, we observe interesting characteristics in the furthest upstream node D1, Figure 26. The coefficient of variation of demand reaches 3.86, Table 6. As with the other nodes, this location plans its inventory buffer levels on the incoming demand at the dependent customer-facing nodes, in this case, it plans for the sum of demand at nodes A1 through A8. The demand signal here comes so infrequently and in such a large volume that the buffer zone is consumed by the early demand signal. The calculations for orders up to quantity incorporate the buffer recommended order quantity plus the amount of the last demand so this node will produce and hold a large amount of inventory, much larger than the buffer zone is calculated to require. This inventory is then slowly used by following infrequent demand signals, but the buffer no longer will replenish on the desired order frequency.

Figure 26:

Buffer profile level for node D1 in the sensitivity analysis



Traditional supply chain systems will plan each node in the system based on their immediate downstream requirements. This leads to the variability incoming from the customer amplifying as the message progresses up the supply chain due to the lack of visibility between nodes. This amplification of variability is known as the bullwhip effect. DDMRP removes this bullwhip effect by aligning the planning of each node in the supply chain to the signal of the actual demand coming from the downstream customers.

The side effect of this however is that each node will not plan for its requirements from the downstream stage, but rather around its own replenishment to match the customer demand. This issue is further explored in Section 6.2.3. This leads to inventory levels that are not aligned to the anticipated size of the direct downstream order due to the clustering of accumulated demand. DDMRP has provided a means to reduce the bullwhip effect, but in the process, a new phenomenon is introduced which is not addressed in the current framework.

The clustering effect of orders is not a phenomenon distinctive to DDMRP, but across many other inventory planning methodologies. Different methodologies encompass different remedies for the problem, such as relying on the forecast to estimate demand and plan operations according to smoothed out demand, and planning inventory targets to meet the anticipated downstream partners' ordering pattern. Complete automation with little to no intervention, which speaks to the partner company's goal of reducing planning labor, will not overcome the progressive increase in demand variability.

6.2 Insights from Test Implementation: Chase Strategy

The chase strategy was performed to test the DDMRP framework in a realistic environment that is relevant directly to our partner company. With the interactive tuning of the managerial levers, we were not able to achieve a perfect service level as one market still exhibited a stockout over the simulated two-year time horizon. This is an indication that DDMRP may not be suitable for this product in this simulated environment.

6.2.1 High Inventory at Upstream Stages

The results of the optimal DDMRP simulation, after tuning, were presented to the partner company's planning and manufacturing functions. The primary concerns addressed by the stakeholders are that the system still exhibited stockouts, and upstream stages were holding excessive amounts of inventory. As presented in Table 7 of the results, an average of more than 340 days of inventory were held at the farthest upstream stage, the API. This compares with an average of three months of cycle stock, representing the infrequent production campaign scheduling, and an average of three months of safety stock for a total of about 180 days of inventory held at the API stage (Partner company, personal communication).

This problem is likely related to the clustering of demand introduced in Section 4.1.3. This is supported by the large amounts of inventory held at the API stage, indicating that DDMRP may not be able to handle the complexity of this many buffered stages in this setting.

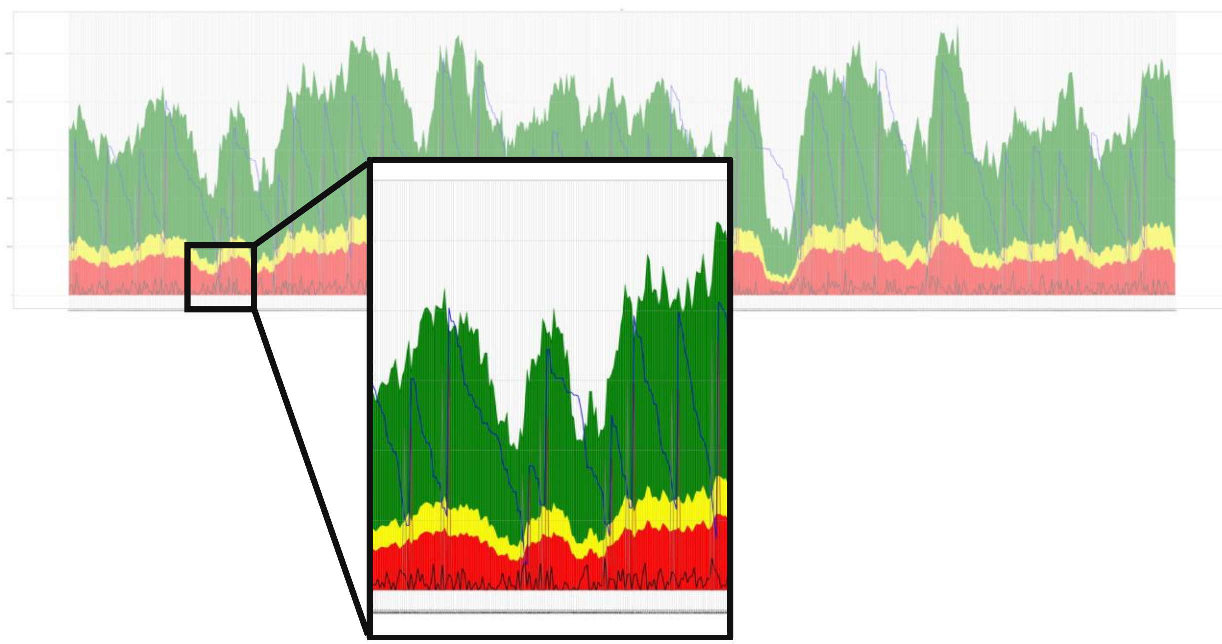
6.2.2 Demand Tolerance Over the Replenishment Lead Time

We reached the limit of the tuning of the managerial levers and still had one stockout as shown in Figure 27. The customer node experienced a high level of demand during the period after it called for replenishment. This is the time when the node is at its lowest inventory level, therefore the highest risk for stockout. At this time the node is protected by inventory coverage of only the yellow zone, representing the demand over the replenishment lead time, and the red zone.

The calculation for the red safety zone as stated in Equation 4 in Section 2.2.2.3, is not based on a target service level. At a maximum, this safety zone calculation will call for an additional two times the expected demand over the replenishment lead time, see Equation 4. This will lead to a maximum of three times the expected demand over the lead time, to cover any incoming demand during the replenishment period. Therefore, if the demand over that lead time increases to an average of three times the ADU factor, this node will stock out.

Figure 27:

The stockout incident can be seen during the period after the node has placed an order. High demand occurred over the lead time producing a stockout.



6.2.3 Relationship Between Node Inventory Calculations

We observed that, across multiple scenarios, C1 has an average of 67 days of inventory on hand, but C2 had significantly fewer average days of inventory at 48 days and experienced significantly more stockouts, Table 7. These nodes take in the exact same demand signal, both having the same amount and frequency of order from the downstream B1 and B2 nodes.

Table 7:

Output metrics of DDMRP simulation on partner company's supply chain

Node	Demand Avg	Lead Time	Actual Order Frequency	Desired Order Frequency	LT Adj Factor	Var Adj Factor	ADU Back Track	DOI	Avg Demand	Order Freq	Num of Stockout	Fill Rate
A1	21,253	43	66	6	0.2	0.2	60	19	22,605	70	24	97.5%
A2	842	3	5	73	1.0	0.2	60	45	886	10	1	100.0%
A3	2,531	3	18	20	1.0	0.2	60	16	2,550	34	4	99.8%
B1	21,253	8	15	24	0.8	0.4	60	34	22,201	24	4	99.7%
B2	3,373	8	10	37	0.8	0.4	60	50	3,466	16	5	99.5%
C1	24,626	7	77	5	1.0	0.6	60	67	13,092	22	1	100.0%
C2	24,626	4	327	1	1.0	0.6	60	48	13,092	23	12	99.5%
D1	24,626	56	24	15	0.2	1.0	60	162	13,030	12	0	100.0%
D2	24,626	7	11	33	1.0	1.0	60	121	12,970	9	0	100.0%
E1	24,626	78	8	46	0.2	1.0	60	320	13,183	6	0	100.0%
F1	24,626	35	3	122	0.2	1.0	60	340	12,881	2	1	100.0%

This observed performance discrepancy may be due to the inventory buffers only considering the incoming customer demand at the end stage, but they do not plan to the immediate downstream node's requirements. In the case of the C-level nodes, the downstream node has a considerably longer lead time and a less frequent desired order frequency. The green zone, reorder point, then is much larger than what is being planned at the upstream stage. The downstream node is designed to order from C2 in an amount greater than the total inventory on hand at that buffer location leading to a stockout. C1 holds a larger inventory buffer due to a slightly longer lead time, so this node performs better than C2. This will be exacerbated as the demand increases, the ADU signal increases and is multiplied by a larger lead time in the downstream node but is increased by a smaller amount at the upstream. Then as demand increases, the gap between the downstream and the inventory on hand to fulfill that demand gets wider. This situation is displayed in Figure 28.

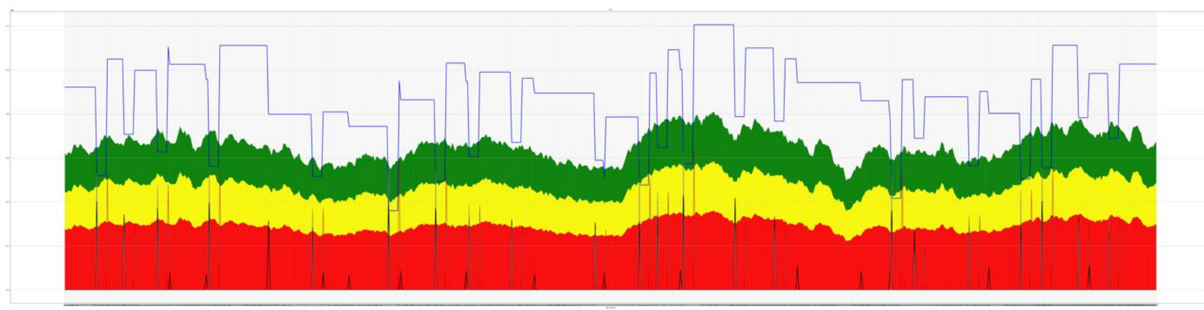
In this figure we also observe the system trying to correct for the large demand spike by ordering the spike plus its normal order amount. This leads to a buffer zone that no longer holds inventory as directed by the DDMRP calculations, but rather a high level to cover over the last demand spike. If the next incoming demand is lower than the previous, the buffer will be safe. But the next spike, if it is larger, will cause a stockout.

The lack of communication between nodes within the DDMRP framework point to the importance of examining the supply chain before implementation. At times, if the nodes are not aligned in lead time, supply chain restructuring may need to be done prior to implementing DDMRP.

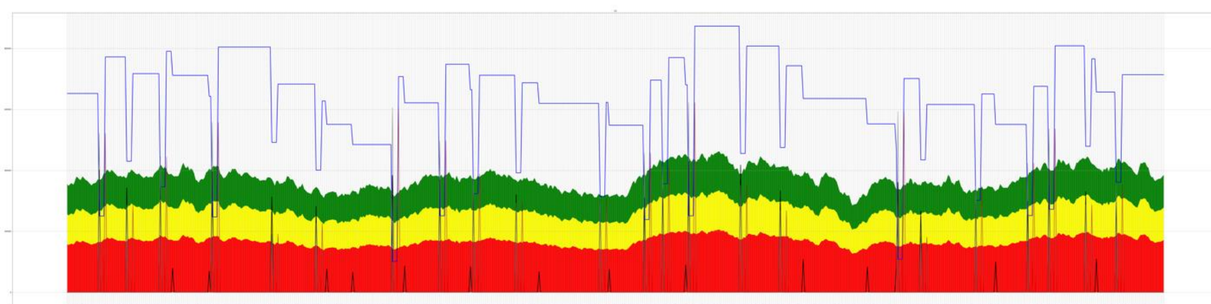
Figure 28:

The inconsistent response to the same incoming demand for nodes C1 and C2

C1



C2

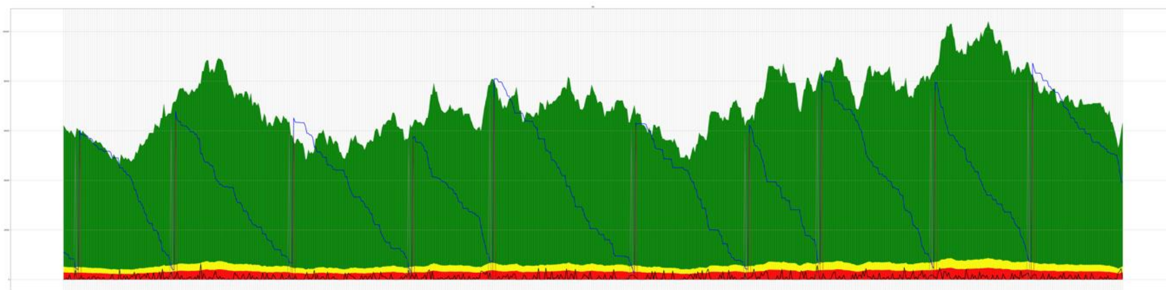


6.2.4 Lead Time Adjust

The simulation model uncovered an important consideration involving the lead time adjust factor. Refer to Equation 1. If Parameter 1 in this equation is not the maximum value, the lead time adjust will have no impact on the green zone. However, in Equation 4, the red zone will always scale down in size based on the lead time factor. If the part has an MOQ or a desired order frequency that is binding on the reorder point, this will no longer provide a pipeline of orders coming into the system. The safety zone will reduce in size expecting more frequent replenishment, but the benefit that allows for this reduction will not be present. This was the case in 6 out of the 11 nodes for this supply chain network. This impact can be seen by the small red zone safety coverage in Figure 29.

Figure 29:

Outcome of node A2 (desired order frequency: 73 days; lead time: 3 days)



Practitioners must be careful when implementing DDMRP to provide a provision that the lead time adjust is not binding on the safety stock if it is not used in the green zone calculation.

6.2.5 Buffer Zones are Not Sized for Target Service Level

When running simulations, and iteratively tuning the parameters, we realized that there is no clear path to target a customer service level within the DDMRP framework. In traditional inventory calculations as described by Silver et al. (2017), the service level can be used to calculate a safety value for the inventory, denoted as "k" in Figure 30. Providing coverage over an assumed underlying probability distribution of demand is not perfect, but these calculations provide a clear path for planners to translate a service level into an inventory target.

Figure 30:

Service level-based inventory calculation

$$\boldsymbol{Inventory = Mean_{LT+R} + Forecast\ Error * K}$$

Cycle stock: Expected Usage over Replenishment + Lead Time

Safety Stock: Expected Variability * Target Service Safety Factor

In DDMRP, the green zone represents the inventory coverage over the review period, and the yellow zone represents the inventory coverage over the lead time after that order is placed. Together the green and yellow represent the same "cycle stock" portion of the traditional inventory calculation, Figure 30. DDMRP differs from the traditional inventory formula in the safety portion calculation, as there is no clear mechanism for setting the safety stock to a management-directed service level. The safety portion is not set based on a mathematical characterization of the underlying demand pattern or the error in forecasting accuracy.

The safety zone instead is sized to provide additional coverage of the buffer over the replenishment lead time. The categorization scheme helps to provide guidance on how to size the safety zone, but it is not clear how well a system will perform in the initial phases of transitioning to DDMRP. This is likely to present a trial-and-error tuning of the safety level parameters until the system performs to the expectation of management. During this tuning period, the company may need to invest capital in building excessive inventory, or it may be caught with insufficient amounts and harm its customer service metrics. In the current state of DDMRP development, our partner company may see risk in this service level targeting approach. Further development of the DDMRP framework could provide better control in targeting a service level.

6.2.6 Implementation Difficulty

Test implementation of DDMRP relied on tuning the parameters on an incremental basis to achieve optimal outcomes. However, in actual implementation, the managerial levers and the positioning of the buffer stocks need to be determined at a strategic level for each individual node. For implementing any other inventory planning methodologies, high performance in the system is usually achieved through an iterative learning process across different functions. This is supported by a large amount of data collecting and analyzing system performance over time. The same is with implementing DDMRP, many parameters need to be set, standardized, and improved through a long-term iterative learning process. The set-up work may require significant investment and is to be considered by the partner company, and an understanding that a long-term organizational learning process will need to be undertaken to achieve performance goals.

7 Conclusion

The foundation of the predominant supply chain methodology in use today, Material Requirements Planning (MRP), was introduced by Joseph Orlicky in 1975 (Orlicky, 1975). Since this time, MRP has been the subject of extensive assessment and refinement by academic researchers and industry practitioners. DDMRP introduces several key features to address the shortcomings of MRP planning systems. First aligning the end-to-end supply chain around the incoming customer demand signal with the assumption that forecasts always contain errors. In MRP, this forecast error is propagated and amplified down the length of the supply chain creating what is known as the bullwhip effect. Second, placing buffer stocks in key decoupling points effectively reduces the lead time between dependent stages of a supply chain network and dampens supply and demand variability. The buffer stocks also provide planners with visibility across the supply chain to facilitate demand-driven planning and execution. Third, the system is built with the principles of flow. Products are pulled through the supply chain to rapidly react to changes in demand, achieving high customer service levels.

This capstone has provided insight into the interaction between strategic buffer stocks within a DDMRP system in a complex multi-echelon supply chain environment. A simulation model was created to serve as a tool to examine network behavior. This tool allowed for experimentation by altering the planning levers within the DDMRP framework. The model was then expanded to create an environment that incorporates the constraints of the pharmaceutical industry's supply chain. This includes a long chain of dependent processes, long lead time between stages, and infrequent production runs driven by high fixed manufacturing costs. This research has identified several difficulties experienced when DDMRP is adopted in a complex multi-echelon supply chain with a focus on the pharmaceutical industry.

Without forecasting future demand, a DDMRP supply chain must absorb variability to maintain high service levels. Thus, it performs best with relatively stable demand, stockouts increase as demand becomes more variable. Without a forecast, there is no quantifiable forecast error for planners to use to size their safety stock inventory. For this reason, there is no clear path to building the supply chain to achieve a target customer service level. The buffer safety zone is not planned based on a level of variability in demand, but rather to provide extra coverage over the replenishment lead time. This will guarantee a stockout event if the demand over the replenishment lead time increases to three times or more of the ADU. The lead time adjust factor also can lead to incorrectly decreasing the size of the safety zone, in a system that has target reorder points or large minimum order quantities.

Aligning the full supply chain around the incoming demand signal along with placing buffer stocks in key locations is a strong step towards eliminating the bullwhip effect. The DDMRP methodology however does not incorporate a key part of the MRP framework, where inventory levels are planned to meet the requirements of the downstream partners' ordering pattern. For example, if a downstream node produces infrequently, it is likely to hold a large inventory. This node will then place large, infrequent orders which can cause stockout events at the upstream node. The DDMRP planning framework provides visibility across the supply chain, but this information is not used to synchronize direct partners in the network. Future research may build upon these findings to form a stronger link between partners in complex multi-echelon supply chains, taking advantage of the benefits provided by visibility. DDMRP has promised to provide strategic benefits to organizations, but we believe organizational learning, as well as further framework development, is required to reap the benefits.

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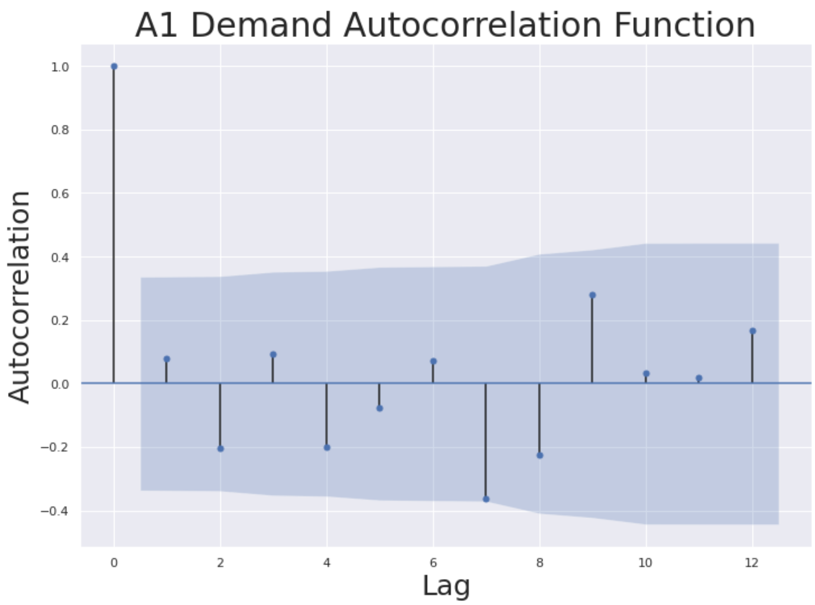
Appendix 1:

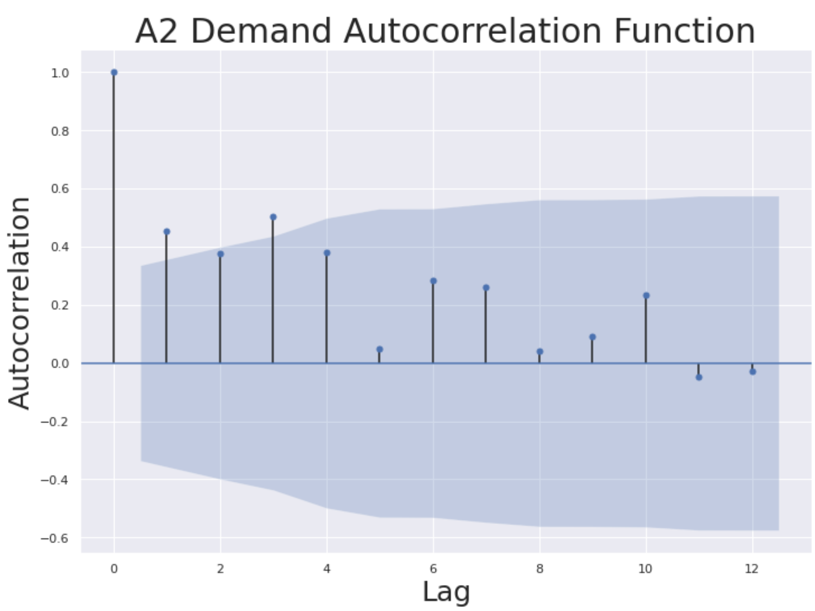
Results from Autocorrelation Function (ACF) Function

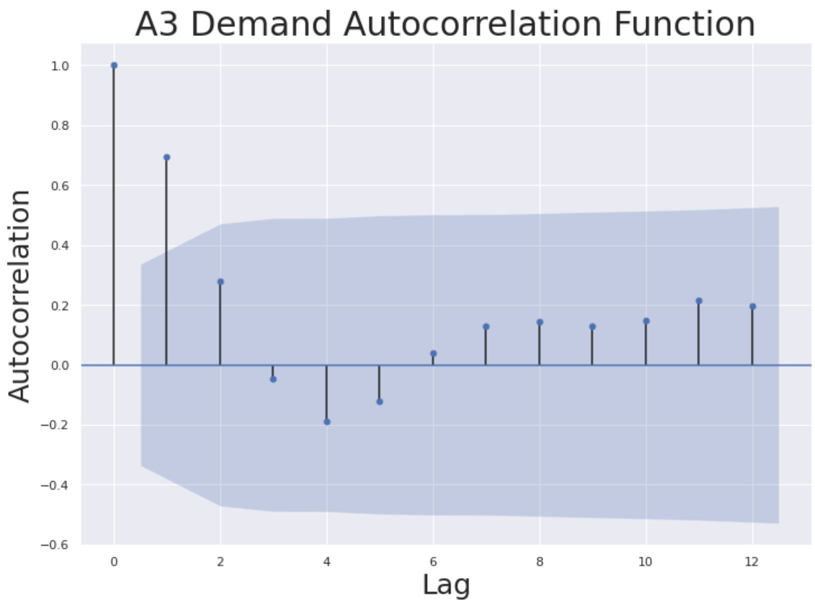
Autocorrelation analysis estimates the influence of other time periods on a given time period based on a user-set number of time lags. The demand data provided by the partner company was monthly demand, so the number of lags was set to 12, representing the 12 months of a year. The ACF plots for the three demand profiles are shown in Appendix XXX. This plot shows the level of correlations between a data point and the relevant data points at each lag step, 1 month apart. The correlation at the 0 point is equal 1, signifying a perfect correlation, to be expected as this indicates the data point is perfectly correlated with itself. The relevant parameters are for each time frame going outwards at 1 for the next month, 6 is half a year away, and 12 represents the correlation between data points and the same month in the other years of the data set. This graph includes the blue shaded section which represents the 95% confidence interval, correlations falling inside of this zone are not considered correlated with a 95% confidence.

A statistically significant correlation was found in the A2 and A3 data profiles at 1 time lag which indicates that the observed demand in the current period is a good predictor of the demand in the next period. This is an indication of a trend of demand, where the strongest correlation is the next closet time period. A2 also had a moderate correlation at 3-time lags, indicating some level of correlation on a quarterly basis. None of the demand profiles showed a strong correlation at the point of 12-time lags, which the researchers would expect to observe for annual seasonality. For example, the value in January does not provide a strong predictor of the value for other time periods in January.

The PAF is also considered a mechanism for adding known features into the forward-looking aspect of the demand signal, such as product ramp up or ramp down. The SKUs the researchers investigated are well-established products in their respective markets. The partner company did not believe these products were near the beginning (ramp-up) or end (ramp down) of their product cycle. The PAF then was not used to model known seasonality or forward-facing demand trends for the simulation model.






A3 Demand Autocorrelation Function
Autocorrelation
Lag
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
0
2
4
6
8
10
12

Appendix 2

Result for Applying Chase Strategy on Actual Product

Scenario No.	Parameter Adjusted	Node	Demand Avg	Lead Time	Order On Hand	Actual Order Frequency	Desired Order Frequency	LT Adj Factor	Var Adj Factor	ADU Back Track	DOI	Avg Demand	Cov Demand	Avg Onhand	Order Freq	Num of Stockout	Fill Rate
000	Start	A1	21,253	43	1,133,194	66	6	0.2	0.2	60	19	22,605	1.0	421,857	70	24	97.5%
000	Start	A2	842	3	5,557	5	73	1.0	0.2	60	45	886	1.3	39,745	10	1	100.0%
000	Start	A3	2,531	3	16,705	18	20	1.0	0.2	60	16	2,550	0.9	39,896	34	4	99.8%
000	Start	B1	21,253	8	360,446	15	24	0.8	0.4	60	34	22,201	3.1	743,912	24	4	99.7%
000	Start	B2	3,373	8	57,206	10	37	0.8	0.4	60	50	3,466	4.1	172,508	16	5	99.5%
000	Start	C1	24,626	7	448,188	77	5	1.0	0.6	60	67	13,092	4.8	874,269	22	1	100.0%
000	Start	C2	24,626	4	256,107	327	1	1.0	0.6	60	48	13,092	4.8	633,786	23	12	99.5%
000	Start	D1	24,626	56	1,930,655	24	15	0.2	1.0	60	162	13,030	5.8	2,111,966	12	0	100.0%
000	Start	D2	24,626	7	517,140	11	33	1.0	1.0	60	121	12,970	5.7	1,564,550	9	0	100.0%
000	Start	E1	24,626	78	2,689,127	8	46	0.2	1.0	60	320	13,183	9.0	4,219,816	6	0	100.0%
000	Start	F1	24,626	35	1,206,659	3	122	0.2	1.0	60	340	12,881	11.2	4,373,895	2	1	100.0%
											278					51	
001	Var Adj Factor	A1	21,253	43	1,133,194	66	6	0.2	0.2	60	19	22,605	1.0	421,857	70	24	97.5%
001	Var Adj Factor	A2	842	3	5,557	5	73	1.0	0.2	60	45	886	1.3	39,745	10	1	100.0%
001	Var Adj Factor	A3	2,531	3	16,705	18	20	1.0	0.2	60	16	2,550	0.9	39,896	34	4	99.8%
001	Var Adj Factor	B1	21,253	8	360,446	15	24	0.8	0.4	60	34	22,201	3.1	743,912	24	4	99.7%
001	Var Adj Factor	B2	3,373	8	57,206	10	37	0.8	0.4	60	50	3,466	4.1	172,508	16	5	99.5%
001	Var Adj Factor	C1	24,626	7	413,712	77	5	1.0	0.4	60	64	13,092	4.8	837,140	22	1	100.0%
001	Var Adj Factor	C2	24,626	4	236,407	327	1	1.0	0.4	60	47	13,092	4.8	612,643	23	14	99.4%
001	Var Adj Factor	D1	27,157	56	2,007,423	24	15	0.2	0.6	60	152	13,022	5.8	1,978,500	11	0	100.0%
001	Var Adj Factor	D2	49,251	7	896,376	11	33	1.0	0.6	60	115	12,966	5.7	1,488,954	9	0	100.0%
001	Var Adj Factor	E1	52,624	78	5,582,397	8	46	0.2	0.8	60	313	13,168	9.0	4,125,843	6	0	100.0%
001	Var Adj Factor	F1	76,408	35	3,743,997	3	122	0.2	1.0	60	341	12,809	11.2	4,362,160	2	1	100.0%
											273					53	2.23
002	Var Adj Factor	A1	21,253	43	1,169,749	66	6	0.2	0.4	60	20	22,605	1.0	449,158	69	19	97.9%
002	Var Adj Factor	A2	842	3	6,062	5	73	1.0	0.4	60	45	886	1.3	40,276	10	0	100.0%
002	Var Adj Factor	A3	2,531	3	18,223	18	20	1.0	0.4	60	16	2,550	0.9	41,421	34	3	99.9%
002	Var Adj Factor	B1	21,253	8	387,649	15	24	0.8	0.6	60	36	22,322	3.1	805,333	23	4	99.9%
002	Var Adj Factor	B2	3,373	8	61,524	10	37	0.8	0.6	60	51	3,466	4.1	175,394	16	5	99.5%
002	Var Adj Factor	C1	24,626	7	448,188	77	5	1.0	0.6	60	68	12,964	4.9	883,380	22	2	100.0%
002	Var Adj Factor	C2	24,626	4	256,107	327	1	1.0	0.6	60	50	12,964	4.9	645,171	23	14	99.4%
002	Var Adj Factor	D1	27,157	56	2,068,254	24	15	0.2	0.8	60	149	13,700	5.8	2,040,368	13	1	100.0%
002	Var Adj Factor	D2	49,251	7	965,328	11	33	1.0	0.8	60	111	13,635	5.7	1,513,138	9	1	100.0%
002	Var Adj Factor	E1	52,624	78	5,746,585	8	46	0.2	1.0	60	303	14,156	9.1	4,294,487	5	0	100.0%
002	Var Adj Factor	F1	76,408	35	3,743,997	3	122	0.2	1.0	60	380	11,375	12.3	4,326,698	2	1	99.9%
											286					47	2.13
003	LT Adj Factor	A1	21,253	43	1,425,631	66	6	0.4	0.4	60	35	22,605	1.0	789,801	38	5	99.4%
003	LT Adj Factor	A2	842	3	6,062	5	73	1.0	0.4	60	45	886	1.3	40,276	10	0	100.0%
003	LT Adj Factor	A3	2,531	3	18,223	18	20	1.0	0.4	60	16	2,550	0.9	41,421	34	3	99.9%
003	LT Adj Factor	B1	21,253	8	442,056	15	24	1.0	0.6	60	49	22,473	4.3	1,096,597	21	1	100.0%
003	LT Adj Factor	B2	3,373	8	70,158	10	37	1.0	0.6	60	54	3,466	4.1	185,979	16	5	99.7%
003	LT Adj Factor	C1	24,626	7	448,188	77	5	1.0	0.6	60	70	13,783	5.3	965,432	20	2	100.0%
003	LT Adj Factor	C2	24,626	4	256,107	327	1	1.0	0.6	60	52	13,783	5.3	718,684	21	17	99.2%
003	LT Adj Factor	D1	27,157	56	2,615,734	24	15	0.4	0.8	60	189	13,955	6.3	2,636,218	11	0	100.0%
003	LT Adj Factor	D2	49,251	7	965,328	11	33	1.0	0.8	60	101	14,093	6.2	1,419,537	7	2	99.9%
003	LT Adj Factor	E1	52,624	78	7,388,467	8	46	0.4	1.0	60	325	14,340	9.7	4,665,624	4	0	100.0%
003	LT Adj Factor	F1	76,408	35	4,813,711	3	122	0.4	1.0	60	402	16,092	13.9	6,465,907	3	0	100.0%
											321					33	2.42
004	ADU Back Track	A1	21,253	43	1,425,631	66	6	0.4	0.4	10	61	22,605	1.0	1,388,062	26	0	100.0%
004	ADU Back Track	A2	842	3	6,062	5	73	1.0	0.4	70	44	886	1.3	39,222	10	2	99.9%
004	ADU Back Track	A3	2,531	3	18,223	18	20	1.0	0.4	20	18	2,550	0.9	44,745	35	1	99.9%
004	ADU Back Track	B1	21,253	8	442,056	15	24	1.0	0.6	30	58	24,225	5.4	1,411,876	15	14	98.9%
004	ADU Back Track	B2	3,373	8	70,158	10	37	1.0	0.6	50	52	3,501	4.0	182,892	15	4	99.7%
004	ADU Back Track	C1	24,626	7	448,188	77	5	1.0	0.6	30	86	13,531	6.3	1,157,767	13	7	99.6%
004	ADU Back Track	C2	24,626	4	256,107	327	1	1.0	0.6	30	67	13,531	6.3	905,658	15	12	98.9%
004	ADU Back Track	D1	27,157	56	2,615,734	24	15	0.4	0.8	60	231	13,841	8.1	3,196,625	8	1	100.0%
004	ADU Back Track	D2	49,251	7	965,328	11	33	1.0	0.8	80	144	13,640	7.8	1,960,269	6	4	99.7%
004	ADU Back Track	E1	52,624	78	7,388,467	8	46	0.4	1.0	120	356	14,630	10.8	5,209,744	4	0	100.0%
004	ADU Back Track	F1	76,408	35	4,813,711	3	122	0.4	1.0	360	340	14,549	14.7	4,945,531	1	1	99.9%
											386					40	9.87
005	ADU Back Track	A1	21,253	43	1,425,631	66	6	0.4	0.4	10	61	22,605	1.0	1,388,062	26	0	100.0%
005	ADU Back Track	A2	842	3	6,062	5	73	1.0	0.4	60	45	886	1.3	40,276	10	0	100.0%
005	ADU Back Track	A3	2,531	3	18,223	18	20	1.0	0.4	20	18	2,550	0.9	44,745	35	1	99.9%
005	ADU Back Track	B1	21,253	8	442,056	15	24	1.0	0.6	60	62	24,225	5.4	1,509,461	19	11	99.1%
005	ADU Back Track	B2	3,373	8	70,158	10	37	1.0	0.6	50	53	3,514	4.0	187,475	16	3	99.9%
005	ADU Back Track	C1	24,626	7	448,188	77	5	1.0	0.6	60	68	14,188	5.6	968,366	16	11	99.2%
005	ADU Back Track	C2	24,626	4	256,107	327	1	1.0	0.6	30	53	14,188	5.6	749,865	17	14	98.8%
005	ADU Back Track	D1	27,157	56	2,615,734	24	15	0.4	0.8	60	207	14,225	7.2	2,944,103	9	1	100.0%
005	ADU Back Track	D2	49,251	7	965,328	11	33	1.0	0.8	60	134	14,363	7.2	1,923,214	8	4	99.9%
005	ADU Back Track	E1	52,624	78	7,388,467	8	46	0.4	1.0	60	311	16,605	9.3	5,166,041	4	0	100.0%
005	ADU Back Track	F1	76,408	35	4,813,711	3	122	0.4	1.0	60	480	15,214	14.4	7,302,652	2	1	99.9%
											361					40	7.59

Scenario No.	Parameter Adjusted	Node	Demand Avg	Lead Time	Order On Hand	Actual Order Frequency	Desired Order Frequency	LT Adj Factor	Var Adj Factor	ADU Back Track	DOI	Avg Demand	Cov Demand	Avg Onhand	Order Freq	Num of Stockout	Fill Rate
000	Start	A1	21,253	43	1,133,194	66	6	0.2	0.2	60	19	22,605	1.0	421,857	70	24	97.5%
000	Start	A2	842	3	5,557	5	73	1.0	0.2	60	45	886	1.3	39,745	10	1	100.0%
000	Start	A3	2,531	3	16,705	18	20	1.0	0.2	60	16	2,550	0.9	39,896	34	4	99.8%
000	Start	B1	21,253	8	360,446	15	24	0.8	0.4	60	34	22,201	3.1	743,912	24	4	99.7%
000	Start	B2	3,373	8	57,206	10	37	0.8	0.4	60	50	3,466	4.1	172,508	16	5	99.5%
000	Start	C1	24,626	7	448,188	77	5	1.0	0.6	60	67	13,092	4.8	874,269	22	1	100.0%
000	Start	C2	24,626	4	256,107	327	1	1.0	0.6	60	48	13,092	4.8	633,786	23	12	99.5%
000	Start	D1	24,626	56	1,930,655	24	15	0.2	1.0	60	162	13,030	5.8	2,111,966	12	0	100.0%
000	Start	D2	24,626	7	517,140	11	33	1.0	1.0	60	121	12,970	5.7	1,564,550	9	0	100.0%
000	Start	E1	24,626	78	2,689,127	8	46	0.2	1.0	60	320	13,183	9.0	4,219,816	6	0	100.0%
000	Start	F1	24,626	35	1,206,659	3	122	0.2	1.0	60	340	12,881	11.2	4,373,895	2	1	100.0%
											278					51	
001	Var Adj Factor	A1	21,253	43	1,133,194	66	6	0.2	0.2	60	19	22,605	1.0	421,857	70	24	97.5%
001	Var Adj Factor	A2	842	3	5,557	5	73	1.0	0.2	60	45	886	1.3	39,745	10	1	100.0%
001	Var Adj Factor	A3	2,531	3	16,705	18	20	1.0	0.2	60	16	2,550	0.9	39,896	34	4	99.8%
001	Var Adj Factor	B1	21,253	8	360,446	15	24	0.8	0.4	60	34	22,201	3.1	743,912	24	4	99.7%
001	Var Adj Factor	B2	3,373	8	57,206	10	37	0.8	0.4	60	50	3,466	4.1	172,508	16	5	99.5%
001	Var Adj Factor	C1	24,626	7	413,712	77	5	1.0	0.4	60	64	13,092	4.8	837,140	22	1	100.0%
001	Var Adj Factor	C2	24,626	4	236,407	327	1	1.0	0.4	60	47	13,092	4.8	612,643	23	14	99.4%
001	Var Adj Factor	D1	27,157	56	2,007,423	24	15	0.2	0.6	60	152	13,022	5.8	1,978,500	11	0	100.0%
001	Var Adj Factor	D2	49,251	7	896,376	11	33	1.0	0.6	60	115	12,966	5.7	1,488,954	9	0	100.0%
001	Var Adj Factor	E1	52,624	78	5,582,397	8	46	0.2	0.8	60	313	13,168	9.0	4,125,843	6	0	100.0%
001	Var Adj Factor	F1	76,408	35	3,743,997	3	122	0.2	1.0	60	341	12,809	11.2	4,362,160	2	1	100.0%
											273					53	2.23
002	Var Adj Factor	A1	21,253	43	1,169,749	66	6	0.2	0.4	60	20	22,605	1.0	449,158	69	19	97.9%
002	Var Adj Factor	A2	842	3	6,062	5	73	1.0	0.4	60	45	886	1.3	40,276	10	0	100.0%
002	Var Adj Factor	A3	2,531	3	18,223	18	20	1.0	0.4	60	16	2,550	0.9	41,421	34	3	99.9%
002	Var Adj Factor	B1	21,253	8	387,649	15	24	0.8	0.6	60	36	22,322	3.1	805,333	23	4	99.9%
002	Var Adj Factor	B2	3,373	8	61,524	10	37	0.8	0.6	60	51	3,466	4.1	175,394	16	5	99.5%
002	Var Adj Factor	C1	24,626	7	448,188	77	5	1.0	0.6	60	68	12,964	4.9	883,380	22	2	100.0%
002	Var Adj Factor	C2	24,626	4	256,107	327	1	1.0	0.6	60	50	12,964	4.9	645,171	23	14	99.4%
002	Var Adj Factor	D1	27,157	56	2,068,254	24	15	0.2	0.8	60	149	13,700	5.8	2,040,368	13	1	100.0%
002	Var Adj Factor	D2	49,251	7	965,328	11	33	1.0	0.8	60	111	13,635	5.7	1,513,138	9	1	100.0%
002	Var Adj Factor	E1	52,624	78	5,746,585	8	46	0.2	1.0	60	303	14,156	9.1	4,294,487	5	0	100.0%
002	Var Adj Factor	F1	76,408	35	3,743,997	3	122	0.2	1.0	60	380	11,375	12.3	4,326,698	2	1	99.9%
											286					47	2.13
003	LT Adj Factor	A1	21,253	43	1,425,631	66	6	0.4	0.4	60	35	22,605	1.0	789,801	38	5	99.4%
003	LT Adj Factor	A2	842	3	6,062	5	73	1.0	0.4	60	45	886	1.3	40,276	10	0	100.0%
003	LT Adj Factor	A3	2,531	3	18,223	18	20	1.0	0.4	60	16	2,550	0.9	41,421	34	3	99.9%
003	LT Adj Factor	B1	21,253	8	442,056	15	24	1.0	0.6	60	49	22,473	4.3	1,096,597	21	1	100.0%
003	LT Adj Factor	B2	3,373	8	70,158	10	37	1.0	0.6	60	54	3,466	4.1	185,979	16	5	99.7%
003	LT Adj Factor	C1	24,626	7	448,188	77	5	1.0	0.6	60	70	13,783	5.3	965,432	20	2	100.0%
003	LT Adj Factor	C2	24,626	4	256,107	327	1	1.0	0.6	60	52	13,783	5.3	718,684	21	17	99.2%
003	LT Adj Factor	D1	27,157	56	2,615,734	24	15	0.4	0.8	60	189	13,955	6.3	2,636,218	11	0	100.0%
003	LT Adj Factor	D2	49,251	7	965,328	11	33	1.0	0.8	60	101	14,093	6.2	1,419,537	7	2	99.9%
003	LT Adj Factor	E1	52,624	78	7,388,467	8	46	0.4	1.0	60	325	14,340	9.7	4,665,624	4	0	100.0%
003	LT Adj Factor	F1	76,408	35	4,813,711	3	122	0.4	1.0	60	402	16,092	13.9	6,465,907	3	0	100.0%
											321					33	2.42
004	ADU Back Track	A1	21,253	43	1,425,631	66	6	0.4	0.4	10	61	22,605	1.0	1,388,062	26	0	100.0%
004	ADU Back Track	A2	842	3	6,062	5	73	1.0	0.4	70	44	886	1.3	39,222	10	2	99.9%
004	ADU Back Track	A3	2,531	3	18,223	18	20	1.0	0.4	20	18	2,550	0.9	44,745	35	1	99.9%
004	ADU Back Track	B1	21,253	8	442,056	15	24	1.0	0.6	30	58	24,225	5.4	1,411,876	15	14	98.9%
004	ADU Back Track	B2	3,373	8	70,158	10	37	1.0	0.6	50	52	3,501	4.0	182,892	15	4	99.7%
004	ADU Back Track	C1	24,626	7	448,188	77	5	1.0	0.6	30	86	13,531	6.3	1,157,767	13	7	99.6%
004	ADU Back Track	C2	24,626	4	256,107	327	1	1.0	0.6	30	67	13,531	6.3	905,658	15	12	98.9%
004	ADU Back Track	D1	27,157	56	2,615,734	24	15	0.4	0.8	60	231	13,841	8.1	3,196,625	8	1	100.0%
004	ADU Back Track	D2	49,251	7	965,328	11	33	1.0	0.8	80	144	13,640	7.8	1,960,269	6	4	99.7%
004	ADU Back Track	E1	52,624	78	7,388,467	8	46	0.4	1.0	120	356	14,630	10.8	5,209,744	4	0	100.0%
004	ADU Back Track	F1	76,408	35	4,813,711	3	122	0.4	1.0	360	340	14,549	14.7	4,945,531	1	1	99.9%
											386					40	9.87
005	ADU Back Track	A1	21,253	43	1,425,631	66	6	0.4	0.4	10	61	22,605	1.0	1,388,062	26	0	100.0%
005	ADU Back Track	A2	842	3	6,062	5	73	1.0	0.4	60	45	886	1.3	40,276	10	0	100.0%
005	ADU Back Track	A3	2,531	3	18,223	18	20	1.0	0.4	20	18	2,550	0.9	44,745	35	1	99.9%
005	ADU Back Track	B1	21,253	8	442,056	15	24	1.0	0.6	60	62	24,225	5.4	1,509,461	19	11	99.1%
005	ADU Back Track	B2	3,373	8	70,158	10	37	1.0	0.6	50	53	3,514	4.0	187,475	16	3	99.9%
005	ADU Back Track	C1	24,626	7	448,188	77	5	1.0	0.6	60	68	14,188	5.6	968,366	16	11	99.2%
005	ADU Back Track	C2	24,626	4	256,107	327	1	1.0	0.6	30	53	14,188	5.6	749,865	17	14	98.8%
005	ADU Back Track	D1	27,157	56	2,615,734	24	15	0.4	0.8	60	207	14,225	7.2	2,944,103	9	1	100.0%
005	ADU Back Track	D2	49,251	7	965,328	11	33	1.0	0.8	60	134	14,363	7.2	1,923,214	8	4	99.9%
005	ADU Back Track	E1	52,624	78	7,388,467	8	46	0.4	1.0	60	311	16,605	9.3	5,166,041	4	0	100.0%
005	ADU Back Track	F1	76,408	35	4,813,711	3	122	0.4	1.0	60	480	15,214	14.4	7,302,652	2	1	99.9%
											361					40	7.59