Doctor of Business Administration

Document 5

Comparing inventory policies for replenishment planning: A simulation study

by

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A thesis submitted in partial fulfilment of the
requirements of Nottingham Trent University
for the degree of Doctor of Business Administration

Jan 2025

Abstract

Problem Statement: In the dynamic context of supply chain replenishment, selecting an effective inventory policy is critical for better performance. However, a lack of comprehensive comparative analysis of the legacy and emerging approaches leaves a gap in this research paper, necessitating further research to guide policy selection.

Purpose: This research aims to compare the supply chain performance under various inventory policies and identify influential factors for their selection. It explores the mechanisms of these policies under multiple parameters, including re-order level, quantity, buffer size, lead times, safety stock, lead time factor, and variability.

Design/methodology/approach: This research uses a comparative simulation study design in the AnyLogistix (ALX) dynamic simulator, to provide risk-free experiments before implementation, for three inventory policies. The simulation analysis uses demand data collected over prolonged demand periods from three variable industry cases for comparison without human intervention. The simulator applies the statistical variation of lead time/demand with comparison experiments for supply chain performance evaluation.

Findings: The simulation results show that the Re-order Point (ROP) inventory policy is more effective than both Make-to-Availability (MTA) Dynamic Buffer Management (DBM) and Demand-Driven Material Requirements Planning (DDMRP), during prolonged demand intervals. Furthermore, DDMRP outshines MTA DBM when there is an anticipated spike in demand. Regarding adjusting buffer parameters, MTA DBM proves easier to handle than DDMRP. Another key observation is evidence of a reduction in Service Level by Revenue (SL) with an increase in Supply Variation (SV) for Transportation Lead Time (TLT).

Originality/value: This work grants a richer understanding of inventory policy selection, especially in rapidly changing business environments. Furthermore, these data-driven insights offer guidelines for choosing inventory policies in various contexts, which are presented in the form of an innovative policy selection decision table. While practitioners will find the table a valuable and pragmatic tool for decision-making, its design and foundation also pave the way for further research.

Limitation: While simulation can project performance outcomes based on quantitative causality and statistical impact, it may not replicate the dynamic nature of human decision-making in real business contexts. There is a need for further research to combine qualitative case studies with quantitative simulation to broaden this analysis.

Keywords: Supply Chain Replenishment, Inventory Policy, AnyLogistix (ALX) Dynamic Simulator, Re-order Point (ROP), Make-to-Availability (MTA) Dynamic Buffer Management (DBM), Demand-Driven Material Requirements Planning (DDMRP), Simulation Study, Data-Driven Insights, Policy Selection Decision Table, Service Level (SL), Supply Variation (SV), Transportation Lead Time (TLT)

Paper type: A simulation study

Acknowledgements

I express my deepest gratitude to my supervisors, Dr. Roy Stratton, Dr Ehsan Sabet and Dr. Ramez Kian, for their unwavering support, insights, and guidance throughout this research journey.

I am profoundly grateful to my mentor and role model, Dr. Joseph Yau and Dr. Edith Mok, for their unwavering support, invaluable guidance, and inspiring dedication throughout my doctoral studies

To Dr. Justin Kwan of HKU SPACE, whose profound insights and meticulous approach to research methods illuminated my thesis journey and instilled in me a deep appreciation for the intricacies of academic exploration. Your teachings were pivotal, and I remain ever grateful.

My heartfelt thanks go to my family for their endless love and encouragement during the challenging times of this research. My friends, especially Mr. Alex Kwong, Ms. Beatrice Kwong, Mr. Brad Mitchler, Ms. Caroline Pierrou, Mr. Erik Bush, Ms. Joyce Lam, Mr. K. L. Lee, Mr. Ken Kwong, Mr. Leo Zhuang, Ms. Lydia So, Mr. Raymond Leung, Mr. Robert Bolton, Mr. Roman Jirka and Mr. Ray Cooke, have been a great source of strength and companionship.

I sincerely thank the software subcontractor's CEO - Dr. Hassan, for supporting and believing in the project. Their guidance and commitment were instrumental in ensuring the successful completion of my research. I would also like to express my gratitude to Mr. Seyed, whose expertise and dedication significantly contributed to developing and implementing the software solution used in this study. Furthermore, I thank Mr. Ben Ong, a dear friend, for his invaluable assistance in resolving outstanding bugs in the partially completed software development. His willingness to lend his expertise at a crucial juncture was invaluable and showcased the strength of true friendship and collaboration.

I would also like to acknowledge the contributions of GS1 Hong Kong, especially for Ms.

Anna Lin, Ms. Heidi Ho and all managers in my Case Study interview process for providing the necessary resources and facilities.

I would like to sincerely thank Ms. Kerryn for her invaluable coaching and meticulous proofreading, which greatly contributed to the clarity and quality of this thesis. Her guidance and support have been instrumental in this achievement.

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List of Acronyms

Acronym	Full Form	Description
ADU	Average Daily Usage	A metric in DDMRP to calculate buffer levels based on average daily demand.
ALX	AnyLogistix	Simulation software used for supply chain modelling and optimization.
BM	Buffer Management	A process for managing and adjusting inventory buffers dynamically.
BOM	Bill of Materials	A comprehensive list of raw materials, components, and assemblies required for production.
BP	Best Practice	Established methods and procedures widely recognized as the most effective.
BS	Buffer Size	The amount of stock maintained to absorb variations in demand or supply.
BSF	Base Safety Factor	A parameter defining the minimum safety stock level to ensure service continuity.
B2B	Business-to-Business	Transactions conducted directly between businesses.
B2C	Business-to-Consumer	Transactions conducted directly between businesses and individual consumers.
CCR	Capacity-Constrained Resource	A resource in a system that limits throughput, requiring careful management.
CoV	Coefficient of Variation	A statistical measure representing demand variability relative to the mean.
CODP	Customer Order Decoupling Point	The point in the supply chain where customer orders trigger specific operations.
COGS	Cost of Goods Sold	The direct costs attributable to the production of goods sold by a company.
CRP	Capacity Requirement Planning	A process for determining production capacity needed to meet demand.

DA	Demand Absorption	A parameter reflecting the ability to smooth demand variations across the supply chain.
DBM	Dynamic Buffer Management	A method for actively adjusting inventory buffers based on real-time data.
DBR	Drum-Buffer-Rope	A scheduling and workflow method in TOC focusing on constraints management.
DDAM	Demand-Driven Adaptive Model	A model integrating adaptive mechanisms to respond effectively to dynamic supply chain demands.
DDIBP	Demand-Driven Intelligent Business Planning	A planning framework leveraging AI and real-time data for advanced decision-making.
DDMRP	Demand-Driven Material Requirements Planning	A dynamic inventory management system utilizing buffer zones for flexibility.
DDOM	Demand-Driven Operating Model	A framework for managing supply chains by aligning operations with real-time demand.
DDS&OP	Demand-Driven Sales and Operations Planning	An advanced version of S&OP, aligning operations with real-time demand.
DES	Discrete-Event Simulation	A simulation method used to model the operation of systems as a sequence of discrete events.
DLT	Decoupled Lead Time	The time buffer within a DDMRP system separating supply lead time from demand.
DTA	Distribute-to-Availability	A TOC strategy where production and inventory are synchronized with distribution demand.
DV	Demand Variation	The variability in customer demand, often measured using CoV.
EBQ	Economic Batch Quantity	The optimal batch size to minimize costs associated with production and setup.
EOQ	Economic Order Quantity	The optimal order quantity that minimizes total inventory costs.
ERP	Enterprise Resource Planning	Integrated management of core business processes, often in real-time.

ESG	Environmental, Social, and Governance	A framework for evaluating the sustainability and ethical impact of a business.
IBS	Initial Buffer Size	The predetermined stock level for maintaining buffer capacity in inventory.
IL	Inventory Level	The stock quantity held at a specific time within the supply chain.
JIT	Just-in-Time	An inventory strategy minimizing waste by receiving goods only as needed.
KPI	Key Performance Indicator	A measurable value demonstrating the effectiveness of a process or policy.
LT	Lead Time	The time required to procure or produce an item in the supply chain.
LTA	Lead Time Absorption	A parameter measuring the system's ability to absorb variability in lead times.
LTF	Lead Time Factor	A parameter in DDMRP used to calculate buffer levels based on lead times.
MI	Multiple Imputation	A statistical technique for handling missing data by creating multiple datasets.
ML	Maximum Likelihood	A statistical method for estimating parameters that maximize the likelihood of observed data.
MOQ	Minimum Order Quantity	The smallest amount of stock that can be ordered at one time.
MPC	Manufacturing Planning and Control	A system for managing production and materials planning processes.
MPS	Master Production Schedule	A plan for individual commodities to be produced in each time period.
MRP	Material Requirements Planning	A system for calculating materials and components needed to manufacture a product.
MRP II	Manufacturing Resource Planning	An extension of MRP that includes additional data like labor and machine capacity.
MTA	Make-to-Availability	A strategy focusing on maintaining availability of products to meet demand.

MTA DBM	Make-to-Availability Dynamic Buffer Management	A consumption-based inventory policy that adapts to demand variations.
NFP	Net Flow Position	A key calculation in DDMRP determining net stock flow based on supply and demand.
OE	Operating Expense	The ongoing cost of running a process or business, used in TOC analysis.
OEM	Original Equipment Manufacturer	A company that produces components or products used in another company's end product.
OOF	Overdue Order Frequency	A measure of how often customer orders are delayed beyond their due date.
OOS	Out-of-Stock	A situation where inventory is insufficient to meet customer demand.
OPP	Order Penetration Point	The point in the supply chain where a customer order is accepted and processed.
OSH	Order Spike Horizon	A parameter in MTA DBM for managing sudden demand surges over a defined period.
OST	Order Spike Threshold	A parameter in MTA DBM defining the threshold for demand spikes triggering action.
PAB	Projected Available Balance	A measure of stock available after planned future consumption.
POQ	Periodic Order Quantities	A lot-sizing technique based on fixed periods for order intervals.
PPB	Part Period Balancing	A lot-sizing method aiming to balance order cost with carrying cost over time.
Q	Order up-to Maximum Level	The maximum stock level at which replenishment orders are triggered.
R	Reorder Point	The inventory level that triggers replenishment orders.
RL	Revenue Level	A measure of total revenue derived from inventory and supply chain management.

ROI	Return on Inventory	A measure of inventory performance focusing on profitability.
S&OP	Sales and Operations Planning	A process that aligns production and demand, integrating sales and operations.
S-DBR	Simplified Drum-Buffer-Rope	A simplified version of DBR, focused on managing production constraints.
SA	Stock Availability	The measure of stock sufficiency to meet customer demand.
SCM	Supply Chain Management	The management of the flow of goods and services.
SCOR	Supply Chain Operations Reference	A model for supply chain performance and process improvement.
SE	Simulation Experiment	Used in simulation studies to test inventory policies under various conditions.
SKU	Stock Keeping Unit	A unique identifier for each distinct product available for sale.
SL	Service Level	A key performance indicator reflecting the ability to meet customer demands.
SS	Safety Stock	Additional stock maintained to account for uncertainties in demand or supply.
STP	Spike Threshold Percentage	A parameter in DDMRP for identifying sudden demand surges.
SV	Supply Variation	Variability in supply conditions, such as lead time or availability.
TLT	Transportation Lead Time	The time required to transport goods from one location to another.
TOC	Theory of Constraints	A management approach focusing on identifying and addressing system bottlenecks.
TOC-SCRS	Theory of Constraints Supply Chain Replenishment System	A TOC methodology focusing on supply chain replenishment practices.
TMG	Too Many Green	A term in MTA DBM referring to excessive

		inventory in the green zone, indicating potential overstock.
TMR	Too Many Red	A term in MTA DBM referring to excessive inventory in the red zone, indicating potential understock or risk of stockouts.
TOG	Top of Green	The maximum inventory level within the green zone in DDMRP buffers.
TOY	Top of Yellow	The maximum inventory level within the yellow zone in DDMRP buffers.
TOR	Top of Red	The maximum inventory level within the red zone in DDMRP buffers.
VF	Variability Factor	A measure of demand or supply variability impacting supply chain performance.
VMI	Vendor-Managed Inventory	An inventory management strategy where the supplier manages stock levels for the customer.

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1. Introduction

General Introduction

Supply chains' inherent dynamics and unpredictability are amplified by increasing variation and uncertainty in supply and demand, with inventory performance becoming a critical aspect of supply chain management. Disruptive events, such as the recent global pandemic, have complicated supply chain management further, resulting insignificant impacts like factory shutdowns and suspended transportation networks. These have led to delivery lead time delays and temporary capacity constraints. Supply chain stakeholders should adapt their inventory planning policies to these volatile environments.

Various inventory planning systems, including the Reorder Point (ROP), Material Requirements Planning (MRP), Make-To-Availability (MTA) Dynamic Buffer Management (DBM), and Demand-Driven Material Requirements Planning (DDMRP), have been developed and evolved over time. However, drawing from the author's consultancy experience since 1997, three common challenges have consistently emerged in most of the supply chain projects he has worked on. Firstly, it is crucial to determine the appropriate stock levels to struggle between stock surplus and stock shortage. At the same time, the promised service level is a critical business requirement. Secondly, identifying the optimal timing for inventory replenishment remains a complex task. Lastly, the choice of inventory policies must align with expected outcomes in terms of service level and return on stock investment. The characteristics for three cases detailed in **Table 1** influence the parameters of inventory replenishment policies, which are critical in addressing this challenge in distribution-side supply chains.

While there is extensive literature on ROP and MRP, few studies have thoroughly investigated the planning systems of MTA DBM and DDMRP. A significant gap exists in understanding how these policies interact with performance metrics within distribution-side scenarios, particularly under varying demand levels and supply lead time stability. This thesis seeks to address this gap by exploring the complexities of inventory policy selection through supply chain simulation analysis and quantitative analysis based on the actual case demand data.

The selection of case data for this research draws extensively from the author’s professional experience in supply chain management across various industries, which are facing the challenges from the unpredictable demand forecast and unreliable supply lead time. With direct involvement in implementing ROP, MTA DBM and DDMRP policies, the author brings a nuanced understanding of the practical challenges and opportunities associated with these approaches.

As mentioned previously, **Table 1** provides an overview of the core elements of supply chain dynamics and critical variables influencing inventory performance. These factors are directly encountered in the author’s professional practice and set the stage for understanding the intricate relationships explored in this study.

This research, Document 5, uses the dynamic simulator software "AnyLogistix (ALX)" to apply variable characteristics across a set of experiments designed to evaluate the inventory policies, that will then be compared to each other and across each of the three case studies. By generating and comparing performance outcomes under different inventory policies with variable parameters, ALX facilitates the robust exploration of these policies. The research draws upon the three cases as sources of actual demand data, thereby enhancing the reliability and generalisability of the study.

Table 1 - Different cases' supply chain characteristics (Data Collected: 2021 – 2022)

Characteristics	Case 1	Case 2	Case 3
Product Nature	Finished goods for healthcare sensor devices	Raw materials yarn for garment factory	Electronic components for an automotive assembly line
Stock locations	Distribution centres in USA B2C and Europe B2B	Central automated warehouse in Bangladesh	Main warehouse in China
Frequency of demand	Low	Medium	High
Supply lead time	180-365 days	65-90 days	60-150 days
Supply variability	High	Low	Low
Demand variability	Low	Medium	High
New product introduction impact	Low	Medium	High
Product Items in simulation	LITE, NODE, WB	20D, 30NE1, 40NE1	2816, 3542, 9396
Period in simulation	2021.1.1 - 2021.12.31	2020.1.1 - 2021.9.30	2021.9.15 - 2022.7.22
MOQ requirement	No MOQ in the simulation	No MOQ in the simulation In real Case, 20D: 7000 kg 30NE1 / 40NE1: 21000-22000 kg	No MOQ in the simulation In real Case, 10K
Simulated days	365	639	311

Research Questions

This research seeks to address the following questions using quantitative analysis and simulation studies based on the actual demand data drawn from the above three cases:

RQ1 - How do inventory policies, particularly forecast-based and consumption-based methods, interact with performance metrics in distribution-side supply chain scenarios?

RQ2 - How do the performance outcomes of inventory policies (ROP, MTA DBM, DDMRP) vary across different demand levels and supply lead time stability in the distribution-side supply chain?

RQ3 - What are the key influential factors and assumptions that underpin the selection and effectiveness of various inventory policies?

Motivation for Research

A primary motivation behind this research is to identify key decision-making factors that will guide the selection of inventory policies to achieve optimal inventory performance. The research aims to provide supply chain practitioners with a general framework for making informed, context-specific decisions in an increasingly complex and dynamic supply chain environment. More personally, outcomes from this research will help me and my customers in our decision-making in the early stage of the design of supply chain planning and execution.

This document has been structured into five additional main chapters:

1. **Literature Review (Chapter 2):** This chapter reviews the relevant literature on inventory policies and simulation studies.
2. **Research methodology (Chapter 3):** This chapter explains the justification for using a simulation study design and details the methodological approach.
3. **Simulation analysis (Chapter 4):** This chapter presents and analyses the insights derived from the simulation results.
4. **Discussion (Chapter 5):** This chapter discusses how the simulation analysis addresses the research questions and compares findings with existing literature.
5. **Conclusion and further research (Chapter 6):** The final chapter summarises the critical findings and suggests areas for further research.

2. Literature review

2.1 Introduction

This chapter provides a comprehensive review of the theoretical foundations and practical applications underpinning the inventory management strategies and policies examined in this study. The chapter begins by exploring the core concepts of inventory management, including its fundamental principles, performance metrics, and decision-making frameworks. Subsequently, the focus shifts to three key inventory policies—Reorder Point (ROP), Make-to-Availability Dynamic Buffer Management (MTA DBM), and Demand-Driven Material Requirements Planning (DDMRP)—highlighting their theoretical underpinnings, practical applications, and associated challenges. A synthesis of relevant literature follows, critically examining how these policies interact with key performance indicators, such as Return on Inventory (ROI) and Service Level (SL). Finally, the chapter outlines the research gaps and contextualizes this study within the broader academic discourse, providing a clear justification for the chosen methodologies and KPIs. Together, these sections establish the conceptual framework that guides the subsequent analysis in this thesis.

Figure 1 highlights the initial conceptual model and how it is designed to help answer this study's research questions. It is the foundation and cross-reference of the literature review.

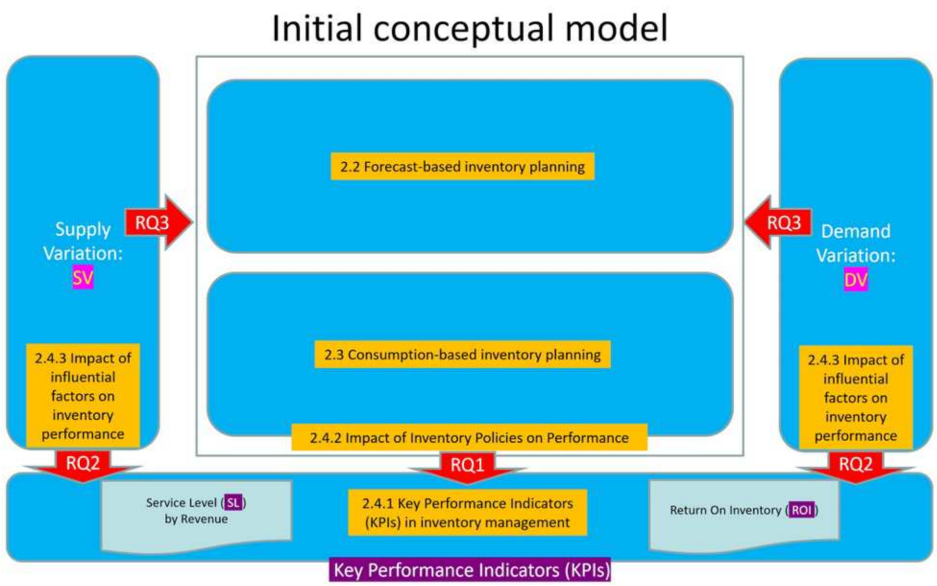

Figure 1 – Initial conceptual model

ROP inventory planning models lean on demand forecast accuracy. They use this accuracy to set when to replenish and determine how much to order economically. In contrast, DDMRP focuses on actual consumption. They keep a buffer stock at specific points in the supply chain. The goal of this chapter is to dig into their roots, pinpoint their fundamental differences, and see how this leads to the research questions of this study.

Other concepts are also core to understanding ROP and DDMRP. The Toyota Production System (TPS) and the Theory of Constraints (TOC) form the bedrock of these buffering techniques such as time buffer, stock buffer and capacity buffer, which will be discussed within this chapter.

To comprehend the interrelationship of various policies' strengths and limitations, the development of stock planning models must be elucidated. The development of Material Requirements Planning (MRP) served as a precursor to more advanced production planning techniques. While the TOC and its derivative, Optimised Production Technology (OPT), have since significantly influenced the evolution of replenishment planning systems, MRP laid the foundation for these later advancements. Furthermore, a synthesis of TOC, MRP, and TPS principles resulted in the development of DDMRP. DDMRP enhances MRP by applying dynamic buffer sizing methodologies, alerts for sudden demand surges, and predetermined minimum order quantities. The Demand-Driven Adaptive Model (DDAM) utilises DDMRP logic as a two-way communication hub: Demand-Driven Sales and Operations Planning (S&OP) and Adaptive S&OP.

This review, therefore, also examines the factors influencing how these inventory policies and performance are related. However, despite theoretical and technical advancements, inventory planning has its challenges. Bullwhip and ripple effects can cause disruptive events and affect forecast accuracy. They induce adjustments to lead times, ordering quantities, and the frequency of replenishment, which increases supply and demand volatility. Stakeholders frequently keep safety stock at key locations, termed decoupling points, to reduce this fluctuation. Additionally, they set up exchanges of information across the supply chain.

A comprehensive conceptual framework outlining the parameters of various inventory policies closes the chapter. This model provides the framework for defining dependent and independent variables and their relationships.

2.2 Forecast-based inventory planning

Forecasting is the process of predicting future outcomes based on historical data and trends. It serves as a powerful tool in model creation because it enables informed decision-making, allowing businesses to anticipate demand, manage resources efficiently, and align strategies with projected market conditions (Blackburn et al., 2014). In inventory planning, forecasting bridges the gap between independent demand-driven by external customer requirements-and dependent demand derived from higher-level products using Bill of Materials (BOM) and production schedules (Olhager, 2003). This transition from managing independent to dependent demand further reinforces the importance of accurate forecasting as a foundational mechanism for synchronising procurement production, and distribution activities, ensuring supply chain resilience and operational agility (Jacobs et al., 2011).

The study of inventory planning and forecasting research is over fifty years old, with the development of system dynamics, control theory and statistical forecasting methods (Syntetos, Boylan and Disney, 2009). Despite those forecasting methods, empty shelves in shops, the result of out-of-stock situations, still occur (Aastrup & Kotzab,2010), as do over-stock situations in the market.

> The world is sitting on roughly $8 trillion worth of goods held for sale, and nearly $2 trillion in the U.S. alone, according to a report by Council of Supply Chain Management Professionals. (Winston, 2011)

This section investigates the development of different forecast-based inventory planning systems in society's attempts to cope with the above out-of-stock and over-stock situations at the lowest estimated cost.

2.2.1 Reorder Point (ROP) with Economic Order Quantity (EOQ)

When inventory management relies on forecasting annual demand to plan the optimal economic lot size for the lowest total cost, inventory planners and purchasers will reduce the unit cost by maximising the batch lot size. Harris (1913) addressed this issue with Economic Batch Quantity (EBQ) and EOQ formulas, as shown in **Figure 2**, where manufacturing quantities curves are drawn to identify the intercept point of carrying cost and order cost as lowest total cost as economic lot size.

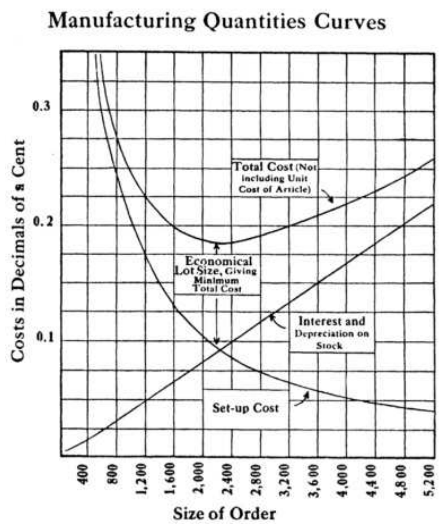

Figure 2 - EBQ/EOQ (Harris, 1913)

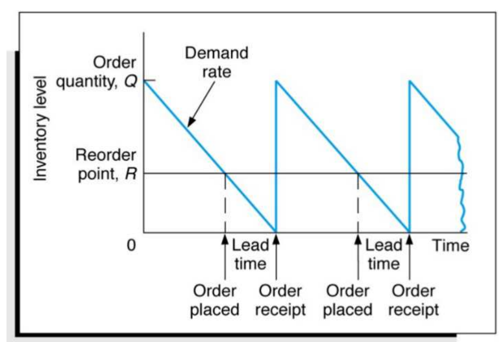

Figure 3 - Concept from ROP (Wilson, 1934)

Permission to reproduce this figure has been granted by Harvard Business Publishing for the use of an exhibit from Wilson, R.H. (1934). "A Scientific Routine for Stock Control," Harvard Business Review, *13, 116-128.*

With a predictable demand rate by forecasting and stable lead time, Harris (1913) suggested an equation that optimises the batch size to balance the trade-offs between setup cost, interest and depreciation on stock costs. Wilson (1934) further established the reorder point (R) to help stock control clerks determine the reorder quantity (Q), as illustrated in **Figure 3,** EBQ/EOQ and ROP models aim to minimise the total inventory cost. The higher reorder point (R) will induce more inventory with less chance of stock-out, and the replenishment quantity (Q) will influence the cycle stock. The reorder point (R) is calculated as the average daily demand time and average lead time (Hopp and Spearman, 1996). However, the high demand variation causes a cost penalty using EOQ as (Q) (Vasconcelos and Marquest, 2000). Moreover, both models relied on reliability of demand forecasting.

When planning more items and ordering independently with the ROP method, the probability of simultaneously getting all stock in full-kit is much lower than the probability for individual items (Orlicky, 1975). For example, if there is only one component item in the Bill of Materials (BOM) with a 90% probability of getting it on time, it is a 90% service level. Two-component items' stock availability in the BOM will be 0.9 times 0.9, producing an 81% service level. If there are five component items, it is 0.9 x 0.9 x 0.9 x 0.9 x 0.9 to become 59% service level only.

Manufacturers will assemble parts into a final complex product structure, and they require dependent demand in the Bill of Materials (BOM). Developers created the Material Requirements Planning (MRP) software with the rise of computing technology. Furthermore, MRP systems are essential for inventory management and production planning in manufacturing environments. Although MRP systems provide vital information to multiple departments inside an organisation, they frequently face criticism for their inflexibility and inability to adjust to changing external factors (Sapry et al., 2018). The integration of MRP with advanced technologies and methodologies, like stochastic inventory control and fuzzy logic, has been suggested to mitigate these limitations, facilitating improved management of uncertainty in manufacturing environments (Khayyam & Herrou, 2018).

2.2.2 Material Requirements Planning (MRP)

Orlicky (1975) developed the material requirements planning (MRP) logic to calculate materials and capacity plans. Sales and Operation Planning (S&OP) confirms the monthly production plan aggregated in Master Production Scheduling (MPS) as the critical input to MRP (Jacobs et al., 2011). The master production scheduling process breaks down the monthly volume into the item's level with the due date of planned purchase orders or production orders. This MPS confirms the planned orders that then become scheduled receipts. Using computational speed to cascade calculations rapidly and repeatedly while still embracing cost-based local optimisation enhances the efficiency and precision of MRP. This enables dynamic adjustments to material and capacity plans in response to changing demand and supply conditions.

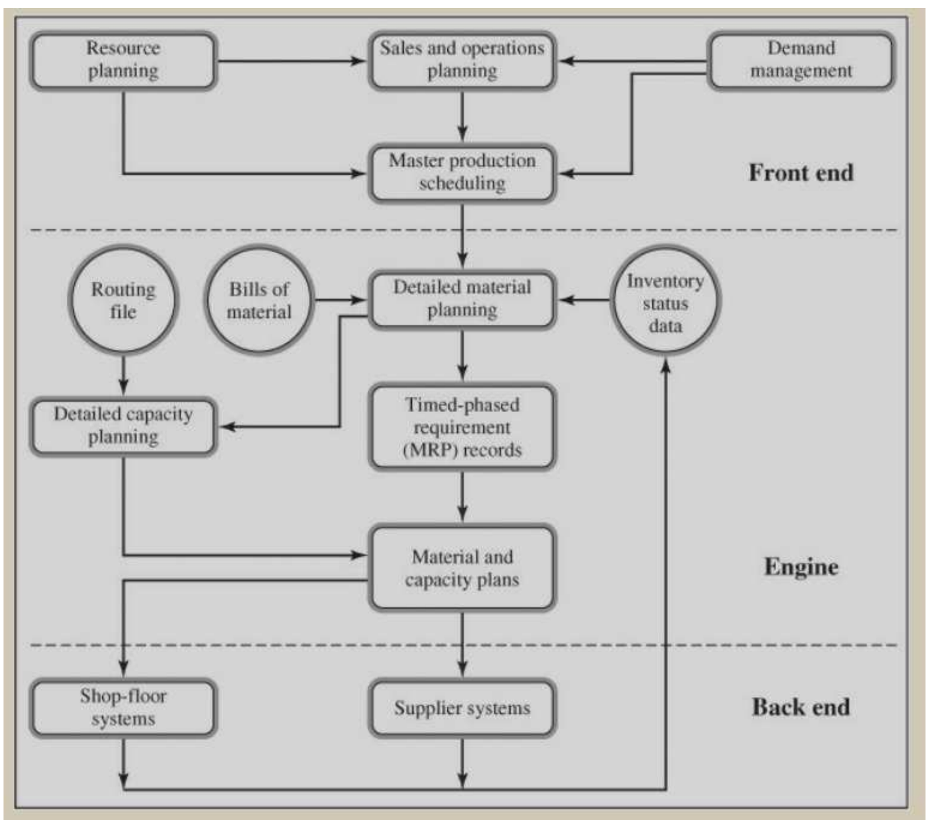

Figure 4 - Manufacturing Planning and Control System (Jacobs et al., 2011)

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Figure 4 shows that the MRP is part of the Manufacturing Planning and Control System. MRP only calculates the dependent-demand quantities within multi-levels of the product structure defined in the Bill of Material (BOM). MRP logic calculates all scheduled release dates according to the upper level of demand due date as time-phased inventory management. MRP also evaluates the current stock level and the net requirement for suggesting replenishment supply quantity. This foundational logic cascades into broader planning processes, including capacity requirement planning (CRP), master production scheduling (MPS), and the resource-driven focus of Manufacturing Resources Planning (MRP II), illustrating the progressive emergence of interconnected planning components with the MPC system. MRP is based on the lot size policies such as EOQ, Periodic Order Quantities (POQ), Part Period Balancing (PPB) to generate manufacturing order quantities (Jacobs et al., 2011, p. 440-443).

		Period				
	On hand	1	2	3	4	5
Forecast		5	5	8	10	15
Projected available balance	20	15	10	32	22	7
Master production schedule				30		
Lot size = 30 Safety stock = 5 units						

Figure 5 - Lot sizing in the MPS (Jacobs et al., 2011)

Figure 5 demonstrates the forecast demand for future periods in a MPS with lot size and safety stock policy. This commonly increased the artificial batch size to maximise the utilisation of resources. The MPS is the primary input to MRP, combining firm and forecasted independent demand orders (Plossl, 1994). The BOM and Inventory status calculate the shop floor production order and purchase order release schedules by due-date offset logic.

One of the key strengths of MRP is the optimisation of inventory levels and balance of production schedules, particularly by minimising excess inventory and reducing carry costs.

This method is especially compatible with just-in-time (JIT) methods, allowing manufacturers to become more responsive to market demands (Rossi et al., 2016). MRP's integration with Enterprise Resource Planning (ERP) further enhances its value by improving overall operational efficiency (Er et al., 2018). Recent developments, such as using digital twins, have additionally improved MRP's accuracy in production planning by providing real-time data for better decision-making (Luo et al., 2021).

However, MRP also has notable limitations. One significant weakness is its dependency on accurate demand forecasting, which lacks the capacity to effectively address demand uncertainty. Additionally, MRP focuses primarily on locally optimising intermediate stocks rather than viewing and streaming the entire flow across the system, which limits its ability to compress lead times and adapt dynamically to variability in supply chain conditions. Inaccurate forecasts can cause stockouts or overproduction, which will cause inefficiencies and higher costs (Rossi et al., 2016). Traditional MRP systems also need to account for production capacity constraints, potentially resulting in infeasible schedules and fluctuating workloads, which can hinder responsiveness to changes in demand (Rossi et al., 2016; Er et al., 2018). The complexity of MRP systems adds to this challenge, increasing the cognitive load on users and possibly affecting decision-making efficiency (Björnfot et al., 2018).

MRP systems are also sensitive to dynamic changes in lead times and supplier reliability, which is a significant drawback. Fixed lead times, commonly assumed in MRP, can be problematic in dynamic environments where frequent delays make it difficult for manufacturers to adjust to supply chain disruptions or shift customer demands (Rossi et al., 2016; Er et al., 2018). Er et al. (2018) suggest additional studies to assess the feasibility of utilising frozen periods and periodical re-planning in the case company, which evaluates its impact on service level and the cost of flexibility to improve adaptability.

In summary, while MRP excels at optimising inventory and production processes, its dependence on accurate forecasting, lack of consideration for capacity constraints, and rigidity in handling lead time fluctuations present notable challenges. To fully leverage its potential in today's complex manufacturing environments. These challenges induce the need for a more structured method of managing production plans in the medium to more extended time horizon. Master Production Scheduling (MPS) becomes critical, providing a higher-level framework to align demand forecasts, production capacity, and inventory planning. All of those issues will be explored in the next section.

2.2.3 Master Production Scheduling (MPS)

Frequent changes in the forecast prompt businesses that re-plan the MPS, causes instability to the cascade through the ordering systems. Fluctuations in the supply of materials, unreliable sales forecasts, and variations in lot sizing often drive this instability. Blackburn, Kropp & Millen (1985) highlighted how this instability affects priorities across multiple Bill of Materials (BOM) layers. Moreover, Jacobs, Berry & Whybark (2011, Chapter 7) found that a stable MPS leads to consistent dependent demands at the materials level, improving production plant efficiency. To counter this volatility in the MPS, businesses commonly employ time fences, ensuring schedules remain unaffected by further changes. While this approach addresses the need to distinguish between planning and execution. It often lacks sufficient capacity focus, requiring most resources to operate with buffer capacity. This limitation underscores the need then for greater integration of capacity considerations to effectively mitigate the impact of MPS instability (Hopp and Spearman, 1996).

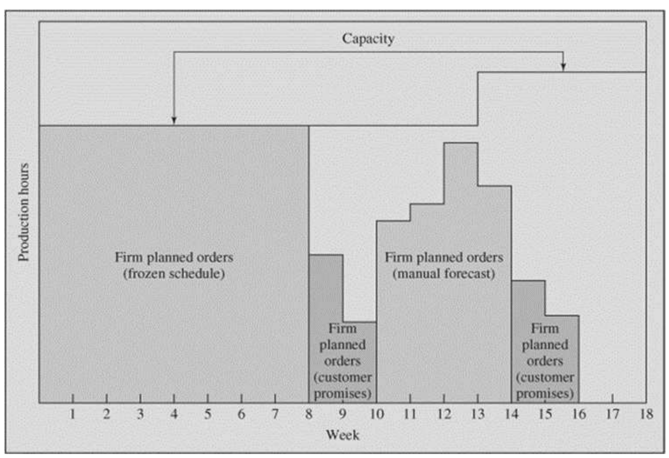

Figure 6 - Freezing and Time Fencing (Jacobs et al., 2011, p. 203)

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Figure 6 demonstrates frozen schedule to stabilize the capacity load in the MPS as a frozen zone, protected by the demand time fence. The projected available balance inside the demand time fence includes the forecast quantity and confirmed order quantity. In this instance, this demand time fencing policy will not change the MPS dynamically. After the frozen zone, a planning time fence occurs, which requires management attention to make trade-off decisions if there are any changes in MPS (Jacobs et al., 2011).

It therefore became clear that using computers to crunch numbers without considering the broader variability issues mechanistically was naive. Through Sales and Operations Planning (S&OP), Master Production Scheduling (MPS) has led to a more effective interface between MRP and consensus production volumes (Ivert el al., 2015). The literature consistently supports the assertion that relying solely on computational methods in Sales and Operations Planning (S&OP) without considering broader variability factors, including demand fluctuations and production constraints, may be insufficient for effective decision-making (Fitzgerald & Howcroft, 1998; Voss et al., 2002). A flexible and comprehensive approach to planning is essential as supply chains become more complicated (Dubois, 2018). This emphasises the importance of including flexibility in the S&OP process to improve decision-making skills; this will be discussed in more detail in the following section.

2.2.4 Sales and Operations Planning (S&OP)

Ling (1988) introduced Sales and Operation Planning (S&OP), a systematic communication process that balances customer demand and supply capacity. This structured process enables different divisions of manufacturing organisations to align their sales and operations by agreeing on strategies such as Chase, Level, or Hybrid capacity planning (a blend of Chase and Level). Here, S&OP serves as a platform for fine-tuning production strategy priorities. Moreover, separating planning from execution enhances the role of S&OP by practically linking sales and operations. This connection enables organizations to better manage uncertainty by implementing strategic buffers to handle variability. This includes implementing strategic buffers to manage variability. However, traditional S&OP frameworks often lack the dynamic tools and focus required to adjust these buffers in real time, limiting their responsiveness to fluctuating market conditions.

Participants in the S&OP process update the latest supply and demand forecasts, which helps balance resource utilisation and adapt to unpredictable market demand over more extended planning horizons. Participants share their perspectives and assumptions about changes in sales markets and resource supplies. They present different scenarios for executive decision-making, evaluate resource levels using Rough Cut Capacity Planning (RCCP), and adjust forecasted customer demand patterns to agree on a MPS. S&OP links a business plan with corporate strategies and the execution of sales and operations.

(Wang et al., 2012) highlight that S&OP is progressively acknowledged for its function in delivering a systematic methodology for production planning, encompassing careful evaluation of production capacities and cost structures. The dynamic nature of consumer demand requires a flexible reaction mechanism inside the S&OP framework to accommodate unforeseen changes. (Grimson & Pyke, 2007) assert that S&OP seeks to establish a consensus-driven operating model while serving as a real-time mechanism to adapt to market variances. This paradox underscores the difficulty of achieving a compromise between systematic planning and the necessity for adaptability in response to variations in demand.

The increasing complexity of an organisation increases the need for sold planning procedures like S&OP. According to Seeling et al. (2019), the implementation of S&OP methods has a positive correlation with performance, especially in complex manufacturing environments. This suggests that S&OP is most beneficial in these kinds of settings. Even though the structured approach of S&OP provides certain benefits, it does not eliminate these challenges. Instead, this complexity can also lead to difficulties in accurately forecasting demand and aligning production capabilities; Thomé et al. (2014) found that process complexity can moderate the effectiveness of S&OP on operational performance dimensions such as quality and delivery. This indicates that while S&OP can enhance performance, the inherent unpredictability of demand and the need for flexible resource allocation complicate its implementation.

Customer demand volatility and uncertainty increase difficulties in maintaining the balance between supply and demand. Goh and Eldridge (2019) emphasise that external integration with customers and suppliers can enhance the effectiveness of S&OP. This also suggests further study of the complexities inherent in these relationships. The study underscores the importance of establishing adaptive strategies that respond to demand fluctuations and effectively manage internal resources to sustain operational alignment. This highlights a crucial point: successful S&OP requires dynamic integration beyond basic alignment and actively responding to market shifts and supply chain constraints. Moreover, Goh and Eldridge (2019) point out that a rigid, formalized approach to S&OP may limit its potential benefits, suggesting that flexibility in governance and coordination could lead to better outcomes.

Mokadem and Khalaf (2023), who argue that supply chain strategies must be dependent upon the unique needs and risks of each environment, further reinforce this viewpoint. In their study of 112 Egyptian manufacturing firms, they found that responsiveness and agility are essential to mitigate variations and uncertainties in customer demand and that a lack of flexibility in supply chain activities could result in inefficiencies. Thus, improving supply chain performance requires keeping a balance between adaptability and a structured S&OP approach, where demand volatility and complexity are common.

Manufacturing Resources Planning (MRP II) emerged to address those challenges as an enhanced version, which integrates capacity planning, resource allocation, and other key manufacturing processes into a more comprehensive framework. It enlarges the scope of traditional S&OP, allowing businesses to better synchronise internal production capabilities with external fluctuating demand.

2.2.5 Manufacturing Resources Planning (MRP II)

MRPII improves upon MRP logic to address capacity issues. However, it still operates assuming that capacity will always be available to meet demand within the established lead time, which can lead to significant challenges in production scheduling. The introduction of rough-cut capacity planning (RCCP) allows for adjustment of the order release schedule to balance resource loading (Plossl, 1994). However, while RCCP improves the comprehensive system plan. It lacks a clear connection to execution, especially in the dynamic management of capacity and inventory buffer. This separation highlights the necessity for more cohesive strategies that combine aggregate capacity planning with execution mechanisms, ensuring that capacity and inventory buffers can adequately adjust to real-time changes (Hopp and Spearman, 1996; Jonsson & Mattsson, 2013).

RCCP plays a crucial role in Manufacturing Requirements Planning (MRP II) systems by providing a more accurate assessment of capacity needs, thereby addressing some of the limitations inherent in traditional MRP systems (Rossi et al., 2016; Sun et al., 2012). Traditional MRP often assumes infinite capacity, leading to unrealistic production schedules that can cause inefficiencies and bottlenecks. RCCP facilitates a more realistic approach to capacity management by evaluating whether sufficient resources are available to meet production demands before finalizing the schedule. However, it also introduces complexities, as adjustments are required to align production with available capacity, which can lead to longer lead times (Koh et al., 2002; Poláček & Žákovská, 2018). By incorporating RCCP, MRP systems can better balance production efficiency with resource constraints, resulting in improved overall supply chain performance.

The above system's attempt to balance variable capacity and demand can result in longer lead times and higher inventory levels due to the cyclical nature of the adjustment process. According to Rossi et al. (2016) and Koh et al. (2002), this circumstance is made worse by the inherent variability and uncertainty in manufacturing processes and consumer demand. It is challenging to make accurate lead time estimations and manage effective capacity utilisation in this situation. Studies show that these uncertainties are a common problem. For example, aerospace, electronics, medical device, and automotive manufacturing enterprises face similar circumstances. Demand in these sectors is often highly variable and involves intricate, multi-tiered supply systems. Because typical ERP frameworks lack finite capacity planning, they frequently run into unrealistic production schedules and unexpected lead times. (Koh et al., 2002; Sun et al., 2012). Consequently, the reliance on fixed lead times can result in significant operational inefficiencies, as companies may find themselves overcommitted or underutilised in their resource allocation (Rossi et al., 2016; Poláček & Žákovská, 2018).

These challenges prompted the transition from forecast-based inventory planning, that focused on minimising cost and meeting predicted demand, to consumption-based approaches that emphasised improving the flow of supply chain. This shift is critical in environments where variability and uncertainty dominate, as it helps mitigate the limitations of forecast-based planning models.

2.3 Consumption-based inventory planning

High demand variability and uncertainty can make sales forecasting less reliable. This relationship aligns with the law of variability, which states that variability slows the flow velocity of production system performance (Hopp & Spearman, 1996, p. 295). This law is consistent with Little's Law:

$$\boldsymbol{WIP = TH \times CT}$$

At every WIP level, WIP is equal to the product of throughput and cycle time.
(Hopp & Spearman, 1996, p. 223).

Variability in production processes coupled with supply and demand uncertainty increases cycle time and WIP, extending the production lead time. As a solution, the buffering law and the law of variability buffering recommend using a mix of inventory, capacity, and time buffers to reduce WIP, late orders, under-utilised capacity, lost throughput, and lead time (Hopp & Spearman, 1996). Methods such as Reorder Point (ROP) with Economic Order Quantity (EOQ), Materials Requirements Planning (MRP), Master Production Schedule (MPS), and Manufacturing Resource Planning II (MRPII) all heavily rely on the accuracy of forecasting.

The upcoming sections will discuss how a similar buffer management (BM) signalling system actively manages market or internal capacity constraints, effectively reducing variability and boosting flow velocity. Toyota closely links to this development, though it originated from the work of Ford (1926) and Goldratt (1987).

2.3.1 Toyota Production System (TPS) with Kanban

To mitigate the effects of unreliable demand forecasting and supply variability, managing flow by strategically placing the stock buffer becomes essential. Building on the idea of Ford (1926) to cut non-value-added waste, Ohno updated these principles, with a radical focus on flow rather than local cost-based optimisation, as mentioned in the publisher’s foreword in Ohno (1988). This implicitly acknowledges the role of capacity buffering and avoids MRP’s tendency to embrace intermediate buffers.

Sugimirori (1977) defines just-in-time (JIT) production as a method that involves producing only the necessary products at the necessary time, minimising stock on hand, and eliminating waste by assuming that anything beyond the minimum essential for production raises costs. This has been updated. Monden (1993) provided an updated perspective on the first edition of "Toyota Production System (TPS)" originally published in 1983, incorporating new insights and advancements that reflected the evolving understanding of TPS principles and practices. To simplify understanding of the system, Spear & Bowen (1999) have further identified four unwritten rules integral to TPS's success. One such rule targets the improvement of product and service flow. The subsequent section will elaborate on how Kanban can enhance flow through TPS pull planning and control methods.

Sugimori (1977), Ohno (1988) and Monden (1993) presented "Kanban" as a simple system, embodying the “Just-in-Time (JIT)” concept. Ohno deployed the inventory buffering method as a "pull" signalling tool. Monden provides a method to calculate the correct number of Kanban card for reducing stock and enhancing performance. This method mimics the replenishment process shown in a supermarket rack. The "pull" production system calls for supply from the preceding operation, guided by the logic of Kanban.

> Kanban is a way to achieve just-in-time; its purpose is just-in-time. Based on this, production workers start work by themselves and make their own decisions concerning overtime. The Kanban system also makes clear what must be done by managers and supervisors. This unquestionably promotes improvement in both work and equipment. (Ohno, 1988, p.29)

> In reality practicing these rules [the six rules of Kanban] means nothing less than adopting the Toyota Production System as the management system of the whole company. (Ohno, 1988, p.41)

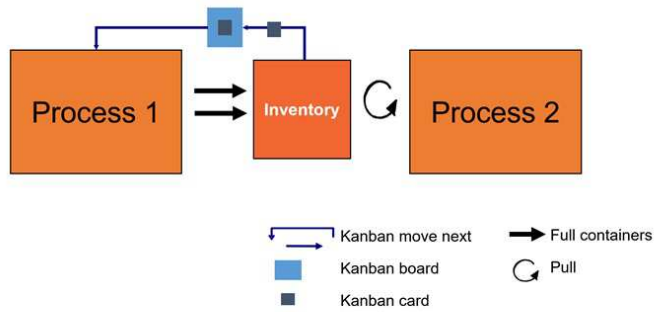

Figure 7 - Kanban system

As illustrated in **Figure 7**, Kanban serves as a card that signals the preceding station to initiate production. When the work-in-process inventory reaches a pre-set level, it triggers a Kanban signal sent to the previous station via a card on a Kanban board. This signal allows the last station to manufacture the required quantity for the next production step. The pre-set limit in the Kanban system keeps a check on the work-in-process inventory level. Kanban guarantees a smooth production flow, preventing material shortages from the preceding location and avoiding the overproduction that can lead to high work-in-process stock. The production line produces materials only when the next station requires them, thereby minimising the inventory buffer and limiting resource loading.

The Kanban system aligns the production pace with customer demand for a similar product family, ensuring continuous demand in high volume. Kanban provides a mechanism to systematically reduce inventory buffering and focus efforts on minimising the sources of variability and uncertainty that drive it. Kanban, as a pull-based control system, is designed to manage production by signalling when to produce or move materials, thereby minimising excess inventory and aligning production with actual demand (Thun et al., 2010). Yet, the implementation of Kanban systems in production environments is significantly influenced by variability and uncertainty in product mix, which can disrupt the production flow. The inherent variability in product demand can lead to challenges in maintaining a smooth production flow. For instance, traditional Kanban systems often struggle with load balancing, which can exacerbate issues related to variability and uncertainty in production environments (Thürer et al., 2015).

The upcoming section will delve deeper into the Theory of Constraints (TOC) buffering mechanism and how to manage variability. It emphasises identifying and addressing bottlenecks within the process, which can be particularly effective in environments characterized by uncertainty (Yang, 2000).

2.3.2 Theory of Constraint (TOC) with OPT, DBR and S-DBR

Whereas Kanban addressed the more stable demand environment, there was still a need to discuss consumption-based planning, emphasising actual consumption rather than forecasting in planning and execution. To manage this MTO environment where MRP II had become the mainstay, Eliyahu M. Goldratt, a prominent figure in management science, developed the Optimised Production Technology (OPT) scheduling software through his company, Creative Output, Inc., which was established in 1979. (Verma, 1997). The OPT software embraced a flow-based rather than a cost-based way of thinking, reflected in the ten rules of OPT (Fox, 1982; Jacobs, 1983) featured in **Table 2**, below. Goldratt explicitly acknowledged the importance of flow as a proxy for improved productivity, as evident in his early works (Goldratt and Cox, 1984; Goldratt and Fox, 1986), where he outlined the means of applying flow thinking to more complex MTO environments. In this way, OPT integrated with MRP to handle finite scheduling, allowing organisations to optimise production by focusing on throughput while minimising unnecessary costs and delays.

Table 2 - The Ten Commandments of OPT (Gelders & Van Wassenhove, 1985)

THE 10 COMMANDMENTS FOR CORRECT SCHEDULING	THE OPT SYSTEM
1. The utilisation of a non-bottleneck resource is not determined by its own capacity, but by some other constraints in the system.	Schedules all non-bottleneck resources based on the constraints in the system. Brain of OPT feeds Serve.
2. Activating a resource is not synonymous with utilising a resource.	Generates schedules to maximise throughput, minimise inventory and protect schedule from disruption - not to activate resources.
3. An hour lost at a bottleneck is an hour lost of the total system.	Saves setups at bottleneck operations to maximise throughput.
4. An hour saved at a non-bottleneck is a mirage.	Schedules additional setups at non-bottlenecks when there is sufficient idle time in order to minimise inventory.
5. The transfer batch may not and many times should not be equal to the process batch.	Uses both transfer and process batches.
6. The process batch should be variable and not fixed.	Utilises variable process batches.
7. Capacity and priority need to be considered simultaneously and not sequentially.	Mathematical algorithms simultaneously consider capacity and priority.
8. Murphy is not an unknown and his damage can be isolated and minimized.	Uses both safety capacity and safety stock strategically to immunize the schedule.
9. Plant capacity should not be balanced.	Balances flow not capacity.
10. The sum of the local optimums is not equal to the global optimum.	Optimises throughput while minimizing inventory and operating expense.

The evolution from OPT to Drum-Buffer-Rope (DBR) and Simplified Drum-Buffer-Rope (S-DBR) represents a significant advancement in production management methodologies rooted in the TOC. Initially, OPT was developed as a scheduling software aimed at optimising production schedules by focusing on the constraints within a manufacturing system (Watson et al., 2006). This approach laid the groundwork for TOC, which emphasises the identification and management of constraints to enhance overall system performance (Wojakowski, 2016).

As TOC evolved, Goldratt introduced the DBR method, which further refined the scheduling process by integrating the concepts of buffers and synchronization of material flow. DBR operates on the principle that the "drum" (the constraint) sets the pace for production, while "buffers" protect the system from variability, ensuring that the constraint is always fed with work (Telles et al., 2022; Atwater & Chakravorty, 2002). This method not only improves production flow but also enhances responsiveness to market demands by aligning production schedules with customer requirements (Wang et al., 2009).

S-DBR emerged as a simplified version of DBR, designed to streamline the scheduling process further. In S-DBR, the drum is adjusted to reflect market demand more directly, allowing for a more agile response to changes in customer orders (Telles et al., 2022; Filho, 2023). The simplification of the DBR system helps organizations manage their resources more effectively by reducing complexity while maintaining the essential principles of buffer management and constraint protection (Wojakowski, 2016).

Buffer management in both DBR and S-DBR is crucial for maintaining production flow, especially for environments and organisations characterised by high levels of uncertainty and variation. Buffers serve as protective measures against variability in production processes, ensuring that constraints are not starved of work (Souza et al., 2013). Effective buffer management involves careful consideration of stock levels, time, and capacity, allowing organizations to optimise throughput while minimizing lead times (Souza et al., 2013). In practice, this means that organizations must continuously monitor and adjust their buffer sizes based on real-time production data to respond to fluctuations in demand and operational performance (Wang et al., 2009).

In summary, the transition from OPT to DBR and S-DBR reflects a comprehensive evolution in production management that emphasises the importance of constraints, buffer management, and responsiveness to market demands. This progression illustrates how TOC principles can be effectively applied to enhance production efficiency and overall organizational throughput (T) performance. To maximise the throughput (T) and mitigate the disruption, TOC advocates using the buffer for protection mechanism as stated in the following 2nd edition of the TOCICO dictionary:

> Buffer - Protection against uncertainty. The protection is aggregated and may take the form of time, stock (inventory), capacity, space or money. Buffers are strategically located to protect the system from disruption.
>
> (TOCICO, 2012)

TOC classifies buffers into three types: time buffer, stock, and capacity buffer, discussed in the following sections.

2.3.3 Make-To-Availability (MTA) and Distribute-To-Availability (DTA) with Dynamic Buffer Management (DBM)

The concepts of Make-to-Availability, Distribute-to-Availability (DTA), and Dynamic Buffer Management (DBM) are inter-related in supply chain management, particularly as they relate to the Theory of Constraints (TOC) and its associated methodologies, including OPT, DBR and S-DBR. Those frameworks emphasise the importance of managing constraints and optimising flow within the supply chain to enhance overall performance and responsiveness to customer demand. Goldratt extended his flow theory to provide practical means of applying it to distribution, focusing on stock buffers. This approach actively manages these buffers by dynamically monitoring buffer consumption using a variant of his buffer management flow signalling mechanism originating in DBR (Goldratt, 1984; Goldratt, 1990). By leveraging these dynamic adjustments, TOC-based methodologies ensure supply chains remain agile, responsive, and efficient (Cox & Schleier, 2010). This approach prioritises flow over local optimisations, balancing capacity, inventory, and lead times (Hopp & Spearman, 1996).

MTA, defined as "a combination of a marketing message of commitment to the availability of particular items at a particular location with the required production policies for achieving it" (TOCICO, 2012), is a strategy that focuses on producing goods based on a calculated buffer size, which is dynamically adjusted by Dynamic Buffer Management (DBM) according to the actual demand consumption pattern. This strategy is consistent with the principles of supply chain management (SCM), which prioritises effective coordination among supply chain partners to fulfil client demands (Xu & Beamon, 2006). The MTA model is effective when demand is stable and foreseeable, enabling organisations to maintain inventory levels that quickly fulfil client orders (Nel & Badenhorst-Weiss, 2011). A grocery store sustains optimal inventory levels of essential commodities like bread and milk using MTA. This method improves customer satisfaction and promotes supply chain performance by decreasing lead times and reducing stockouts (Lei et al., 2017).

DTA is a distribution strategy that emphasises the role of a central warehouse in managing inventory flows efficiently (TOCICO, 2012). In this approach, manufacturers or suppliers ship products to the central warehouse based on consumption data gathered from both the central and regional warehouses. Subsequently, distributors and retailers pull inventory from the central warehouse to fulfil demand based on their consumption levels. This system provides a consolidated control over inventory, allowing for efficient replenishment and reducing the risk of stockouts across different distribution points. The centralization inherent in DTA offers greater visibility and coordination throughout the supply chain, facilitating better decision-making and ensuring that inventory is available at all levels to meet customer needs.

Dynamic Buffer Management (DBM) is another critical concept in inventory control, specifically within a make-to-availability system (TOCICO, 2012). DBM refers to the procedure of adjusting target inventory levels dynamically based on the observed behaviour of finished goods inventory. It aims to ensure that inventory levels are appropriate for current market conditions by responding to fluctuations in demand and supply. By adjusting buffer sizes according to actual consumption patterns, DBM enables organizations to minimize excess inventory while maintaining a high service level, thereby reducing overall costs and improving responsiveness to changes in demand. This adaptive approach is particularly valuable in managing uncertainty and aligning inventory levels more closely with actual customer needs.

In many ways, this approach has similarities to Vendor-Managed Inventory (VMI). However, while VMI focuses on inventory replenishment based on predefined agreements between suppliers and retailers, it often lacks execution management (Waller et al., 2001). Goldratt's DBM builds on this concept by introducing an active execution component, enabling real-time buffer adjustments and enhancing the system's ability to respond dynamically to market fluctuations. This combination of dynamic adaptation and execution focus makes DBM a more robust solution for aligning inventory with actual customer demand (Schragenheim, 2009).

Conversely, DTA emphasises the distribution of products based on availability rather than production schedules. This approach enhances organizational flexibility in responding to customer preferences and market conditions (Fisher, 1997). This adaptability is crucial for improving service levels while simultaneously reducing excess inventory, as discussed by

Mentzer et al. (2001), who highlighted the importance of responsive inventory strategies in mitigating supply chain inefficiencies. The DTA approach stresses aligning inventory levels with actual market demand, which helps to minimize the risks associated with overstocking and stockouts (Christopher & Towill, 2000).

Research indicates that implementing TOC DBM principles, particularly in distribution-side supply chain management, significantly reduces inventory levels and enhances responsiveness to market fluctuations. For instance, studies have demonstrated that organizations employing TOC-Supply Chain Replenishment Systems (TOC-SCRS) experience decreased stockout rates and improved customer satisfaction due to their ability to adjust inventory levels based on real-time demand signals (Jiang & Wu, 2013; Jiang et al., 2013). This adaptability is vital in today's fast-paced market environment, where customer preferences can shift rapidly.

Moreover, the relationship between inventory management and lead time is critical in understanding how TOC can improve service levels. According to Little's Law, there is a direct relationship between work-in-progress (WIP) inventory and lead time; thus, reducing inventory not only shortens lead times but also enhances product quality and overall service performance (Gupta & Boyd, 2011). This reduction in lead time allows organisations to respond more swiftly to changes in customer demand, thereby improving service levels. Additionally, TOC's focus on eliminating bottlenecks and optimising resource utilization further contributes to enhanced flexibility.

By systematically addressing constraints within the supply chain, organizations can streamline operations, reduce operational costs, and improve throughput (Souza & Pires, 2010). This operational efficiency is essential for maintaining competitive advantage in dynamic markets. The empirical evidence supporting these claims is robust. Companies that have adopted TOC methodologies report significant improvements in inventory turnover rates and service levels, as well as reductions in operational costs associated with excess inventory (Gupta & Boyd, 2008; Wu & Tsai, 2008). For example, a study on the application of TOC in the manufacturing sector demonstrated that organizations could achieve better alignment between supply and demand, leading to increased forecast accuracy and customer service levels (Wu et al., 2011). One of the critical success factors in MTA and DTA implementation is therefore consumption-driven pull planning policy integrated with DBM.

Dynamic Buffer Management (DBM), as derived from TOC principles, involves the strategic placement and adjustment of inventory buffers throughout the supply chain to mitigate risks and uncertainties. This approach is essential for managing variability in demand and supply, allowing organisations to maintain a balance between responsiveness and efficiency (Olena et al., 2019). To optimise inventory levels, companies should dynamically adjust buffer sizes by leveraging real-time data and forecasts, which helps to effectively reduce carrying costs and improve service levels (Fri et al., 2019; Narita et al., 2021). The dynamic buffer management (DBM) method allows companies to maintain appropriate inventory levels while achieving high service rates even in the presence of demand variability. The integration of dynamic buffer management into the supply chain also supports continuous improvement initiatives, as organizations can analyse performance metrics and adjust their strategies accordingly (Croxton et al., 2001).

The Theory of Constraints (TOC) and its application in dynamic buffer management (DBM) within warehouse settings are critical for optimising inventory levels and production order priorities. In a make-to-availability (MTA) environment, central or factory warehouses maintain stock buffers of finished goods to consolidate orders from downstream connections. This approach allows for a more responsive production system, where the status of these buffers directly influences production order priorities, ensuring that manufacturing aligns with actual demand rather than forecasts alone (Reyes et al., 2015). Dynamic Buffer Management is particularly advantageous in managing raw material supplies. By employing DBM, organizations can maintain target inventory levels rather than striving for complete elimination of stock, which is often impractical in fluctuating market conditions (Reyes et al., 2015). This method allows for careful observation and adjustment of inventory buffers, thereby enhancing a company's competitive position by mitigating the effects of supply chain variability (Reyes et al., 2015). Furthermore, storing raw materials at the factory reduces supplier lead times, facilitating regular replenishment and ensuring that production can proceed without delays (Reyes et al., 2015). In contrast, Material Requirements Planning (MRP) systems are designed to manage inventory and production scheduling based on the Bill of Materials (BOM) and lead-time considerations. However, MRP operates under certain assumptions that can lead to inefficiencies, particularly in environments characterized by demand variability. One of the primary assumptions of MRP is the presumption of a stable balance between supply and demand. This assumption often neglects the importance of buffers, which can mitigate the effects of variability in demand and supply (Louly et al., 2008; Bagherpour et al., 2012; Relich et al., 2014).

This section shows how MTA operates as a consumption-driven pull planning system with integrated buffer management. Reacting swiftly and dependably to the consumption patterns of downstream components, the upstream supply chain supplies the necessary materials or finished goods.

Under the TOC environment, we could use a time, stock and capacity buffer to protect against variability and uncertainty.

Time buffer

The 2nd edition of the TOCICO Dictionary defined a time buffer in the following statement:

> Protection against uncertainty that takes the form of time. The Constraint, assembly and shipping buffers used in drum-buffer-rope scheduling and the production buffer used in simplified drum-buffer-rope are examples of time buffers.
>
> (TOCICO, 2012)

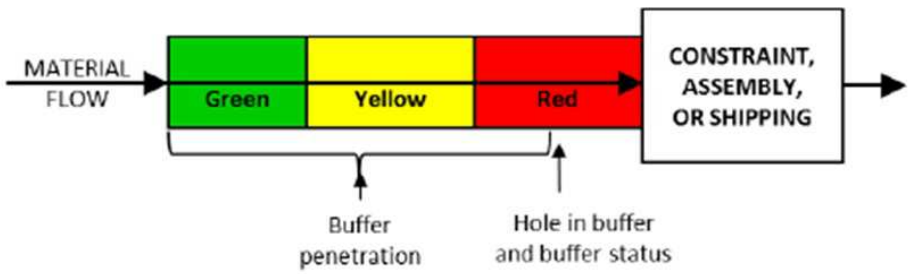

Figure 8 - A time buffer for a work order (TOCICO, 2012)

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In Figure 8, the time buffer for a work order shows the priority on the shop floor and uses the following formula to determine the stock status by percentage:

Buffer status (%) = (*available time*) / (*standard production lead time*) x 100%

(TOCICO, 2012)

Time buffer management is a scheduling method to set the pace of production flow or the gate of releasing a work order. The time buffer in TOC provides protection time in critical areas, and the rope is a mechanism to keep all elements working at the same rate (Ronen & Starr, 1990). On the other hand, S-DBR focuses on market constraints, sets the protection time and monitors the buffer status for priority based on the due date (Schragenheim, 2000).

Stock buffer

MTA applies stock buffer management to ensure stock availability. According to the 2nd edition of the TOCICO Dictionary, a stock buffer is defined as the following statement:

> Stock buffer - A quantity of material held at a point in the supply chain to decouple demand from supply stock buffers can be held at the raw material stage, at intermediate production stages (as work-in-process inventory) or at the finished gate. Stock buffers reduce the lead time to market (quoted lead time) and protect the system's throughput and due date performance.
>
> (TOCICO, 2012)

When the production as the internal supply chain extends to the external supply chain, the integration of internal and external supply chains through Make-to-Availability (MTA) and buffer management (BM) is a strategic approach that enhances operational efficiency and market responsiveness. MTA focuses on maintaining sufficient inventory levels to meet anticipated demand, aligning closely with buffer management techniques that help manage uncertainties in supply chain operations. This integration is particularly crucial in environments where market dynamics are volatile, necessitating a robust framework for managing both internal resources and external supply chain relationships.

A well-coordinated supply chain can benefit marketing strategy by ensuring the availability of products when needed, improving customer satisfaction and competitive advantage. Sutia (2022) emphasises that attaining these objectives necessitates combining supply chain management with marketing strategies since it enables companies to respond to customer demands and market trends more quickly. This analysis demonstrates how a well-coordinated supply chain boosts marketing efforts, resulting in better customer service, differentiation in the market, and a solid commitment to sustainability through a multinational retail chain case study. Jüttner et al. (2010), through an analysis of three supply chains, spanned the volume-variety continuum, from high volume low variety (FMCG) through medium volume and variety (automotive) to low volume, high variety (electronics), it also supports the synergistic effects of coordinating supply chain and marketing initiatives, implying that this integration can increase customer value and enhance organisational performance. This alignment is particularly relevant in the context of MTA, where the focus is on ensuring product availability through effective inventory management.

Capacity buffer

In an MTA environment, the extra capacity buffer of the Capacity-Constrained-Resource (CCR) or other heavily loaded resources is available quickly and at a reasonable cost (possibly through subcontracting) to react to sudden increases in total demand (TOCICO, 2012).

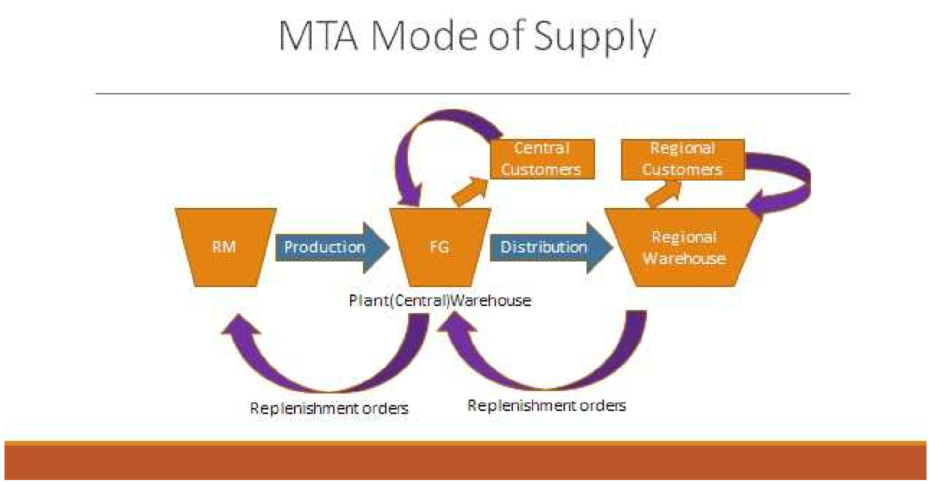

Figure 9 - MTA Mode of Supply (Cohen, 2010, p.395)

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To mitigate the variability and uncertainty across dispersed global supply chain links, Cohen (2010) and Schragenheim & Dettmer (2009) extended Goldratt's theory of constraint (TOC) buffering mechanism in distribution and supply chain networks as shown in **Figure 9**. The solution is a pull-based method as a system approach by TOC way. However, MTA focuses on the finished stock buffer in central and distribution warehouses across a supply chain. The production orders are scheduled to meet the buffer stock level in the main warehouse. The priority setting in MTA is based on stock availability instead of a time buffer according to the due date. The subsequent downstream links from the central warehouse to the point of sales follow the same replenishment method. Replenishment operation is similar to Kanban in between different production processes. Still, MTA dynamically adjusts the buffer stock size, also called inventory target, according to the consumption rate from downstream locations. **Figure 10** illustrates the buffer stock level as divided into three colour zones: the red zone at the bottom, the yellow zone in the middle and the green zone at the top. Keeping the current inventory buffer size without changes is safe if the on-hand stock level falls into the yellow zone. If the buffer stock level falls into the red zone over one replenishment cycle time as "Too Many Red" (**TMR**), the buffer size will be increased by one-third of the buffer level to catch up with the increasing consumption rate. If the buffer stock level is maintained in the green zone over one replenishment time as "Too Many Green" (**TMG**), the buffer size will be reduced to one-third of the level to chase the decreasing consumption rate. This buffer adjustment mechanism is termed "Dynamic Buffer Management (DBM)" (Schragenheim & Dettmer, 2009, p. 157-8).

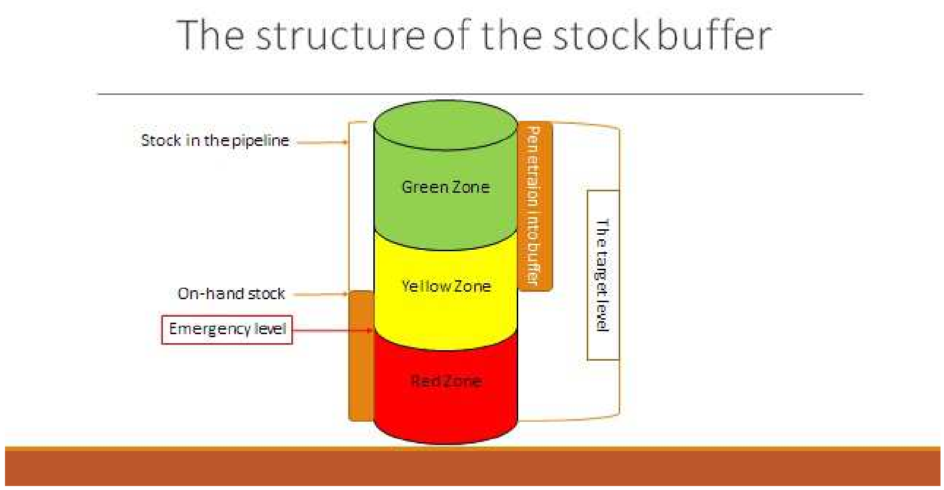

Figure 10 - Defining Buffer Status (Cox & Schleier, 2010, p. 247)

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So, the re-ordering batch size by each replenishment cycle fills the gap between the on-hand stock level and the target buffer level on the top of the green zone. Replenishment cycle time and transfer batch size are minimal (Cox & Schleier, 2010). The MTA approach reduces the supply chain's overall inventory level and costs due to reduced variability by smaller batch sizing and a higher replenishment frequency. The aggregated demands minimise the fluctuations from different consumption points in the central warehouse and production schedule. The dynamically adjusted stock buffers in different decoupling positions reduce the main warehouse's bullwhip effects (Lee, 1997). Schragenheim & Dettmer (2009) also propose monitoring capacity in a mixed mode of the MTO and MTA environments with the S-DBR method with shared production resources.

DBM mainly focuses on the execution side of supply chain management. This contrasts with MRP, which is fundamentally oriented towards planning, calculating the necessary materials and scheduling based on anticipated demand and lead times. MRP's methodology involves determining planned releases based on due dates within a specified planning horizon, rather than on immediate shop floor execution (Jodlbauer & Reitner, 2012; Rossi et al., 2016).

The operational framework of DBM includes key planning factors such as monitoring and adjusting buffer stock levels, which are essential for maintaining optimal inventory levels and ensuring that production can meet demand without excessive delays. In contrast, the Simplified Drum-Buffer-Rope (S-DBR) methodology modifies promised due dates based on short-term load monitoring, allowing for more agile responses to fluctuations in production capacity and demand (Benavides & Landeghem, 2015; Filho, 2023). This adaptability is crucial in environments where demand can vary significantly, necessitating a more dynamic approach to scheduling and resource allocation.

One of the primary strengths of TOC's MTA strategy is its focus on customer demand satisfaction through the strategic placement of inventory buffers, which ensures product availability (Marco, 2016). This pull-based approach effectively reduces lead times and enhances customer satisfaction by maintaining a ready supply of products without the complexity of intricate dependencies, thus improving operational efficiency.

Moreover, the Make-To-Availability (MTA) strategy diverges from traditional MRP logic by decoupling dependent demands. It has emerged from production planning systems such as S-DBR. This decoupling provides greater flexibility in inventory management by eliminating the complex dependencies that MRP establishes between components and finished goods. However, MTA does not consider the logical sequence of dependent setups during scheduling, which also causes the same difficulties in the S-DBR (Castro et al., 2022). For instance, in the textile dyeing industry, the colour shade in the production scheduling sequence may conflict with MTA's buffer priority system and the need to accommodate such dependencies effectively.

While MRP provides visibility into requirements, especially for items with long lead times, MTA focuses on ensuring that products are available when needed, regardless of the traditional MRP underlying capacity requirement and risk-based scheduling methods (Sadeghi & Golbaghi, 2016; Sun et al., 2012).

The following section will explore another way of the buffer priority system in planning and execution.

2.3.4 Demand-Driven MRP (DDMRP) to Demand-Driven Adaptive Model (DDAM)

The key features of MTA provide a clear priority in the production schedule and stock replenishment in a distribution network through the logic of DBM. The upstream suppliers and downstream customers within the supply chain network could monitor the buffer signal of each item to schedule the priority in different stock locations (Dalal, 2015). While a relatively recent development, DDMRP has been widely accepted and adopted and, not surprisingly, builds on prior methodologies, such as MRP, TOC, and Lean principles (Ptak & Smith, 2011). A key evolution of DDMRP lies in its dynamic buffer management, enabling real-time adjustments to stock levels in response to demand signals, which enhances agility and responsiveness in managing supply chain variability (Krishnan, 2024). Compared to MTA DBM, DDMRP introduces a more robust mechanism for safeguarding critical items and optimising material flow, yet it inherits complexities associated with its implementation and the need for comprehensive data analytics to ensure efficiency. As such, this chapter critically examines DDMRP's features and their implications for supply chain performance, especially in relation to MTA and its evolution from earlier methodologies.

As mentioned in the previous section, MTA and Distribute-To-Availability (DTA) ignore the MRP logic with the decoupling of dependent demands. The critical difference between MRP and DDMRP is the replenishment signal according to daily sales consumption instead of potential forecast orders (Pekarcíková et al., 2019). At the same time, MRP provides clear visibility of the total requirements, especially on long lead time items (Ptak & Smith, 2011).

DDMRP as adaptive supply chain environment: DDMRP is a pull-based system in an end-to-end supply chain for a longer planning horizon and adaptive execution of the supply chain. DDMRP is a multi-level planning and execution system. DDMRP strategically positions the decoupling point stock buffers, protects the flow and pulls to ensure relevant information and materials flow.

There are three phases in DDMRP implementation – Position, Protect and Pull (Ptak and Smith, 2016). In phase one, "position", DDMRP selects the strategic positions for buffering as decoupling points to minimise the manufacturing lead time according to BOM's structure and reduce the purchasing and distribution lead time according to the design of the distribution network.

In phase two, "protect", buffer profiles and levels are a calculation of protection levels grouped into a defined template by similar item type, lead time and variability as parameters profiles mentioned in the book (Ptak and Smith, 2026). The buffer sizing of traditional methods focuses on demand variability and uncertainty of replenishment lead time. DDMRP is based on buffer profiles' parameters to determine the level of protection at those decoupling points. The initial inventory target for a buffer size of DBM is based on the maximum forecasted consumption within a reliable replenishment lead time (Cohen, 2010, p. 431).

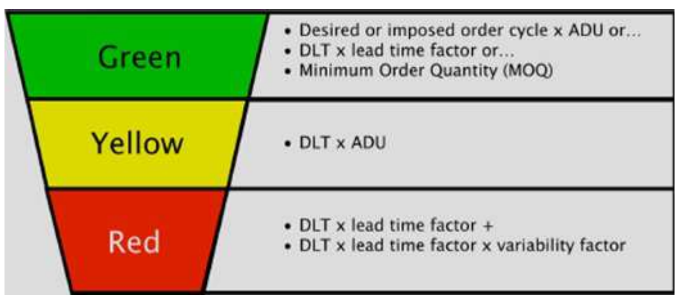

Figure 11 - The buffer equation summary: (Ptak & Smith, 2016, p. 115)

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Figure 11 illustrates that the calculation of buffer size in DDMRP is divided into three zones, but it is not equally allocated as MTA DBM (see **Figure 10)**. In DDMRP, the green zone is determined by three key factors: the Average Daily Usage (ADU) over the defined minimum order cycle, the Lead Time Factor (LTF), and the Minimum Order Quantity (MOQ). The green zone is set based on the highest value among these three factors. The yellow zone in DDMRP is based on average daily usage (ADU) multiplied by Decoupled Lead Time (DLT). The red zone in DDMRP is the sum of the red base (DLT x lead time factor) and red safety (DLT x lead time factor x variability factor). The lead time factor is categorised into high, medium and low variability factors. The more extended lead time item will use a lower factor value to trigger smaller, more frequent replenishment signals. The red safety base is calculated by multiplying the lead-time factor by the ADU by the lead time. The variability factor values are based on the percentage of safety base (Ptak & Smith, 2016).

A buffer's position in DDMRP strategically focuses on reducing the longest cumulative coupled lead time path in a manufactured item's product structure. It is similar to the (Ptak & Smith, 2016). Compared with Kanban and Order Penetration Point (OPP)/CODP, the buffer locations depend on the design of sequential production flow and customer tolerance time in expected manufacturing environments, respectively (Olhager, 2003). On the other hand, the DBR/S-DBR buffer location is constraint focused. The DBR/S-DBR buffers position is placed before capacity-constrained resources to reduce the production lead time. Kanban buffers are set up between all production workstations to ensure production flow. DDMRP strategically aims to compress the overall manufacturing and distribution lead time. MTA and DTA focus on the central warehouse to build common stock buffer, ensure stock availability and reduce order lead time.

MRP and Distribution Requirement Planning (DRP) provide the necessary linkage of dependent demand, enabling a holistic view of the entire flow system (Jacobs et al., 2011). Strategic positioning merged with MPS and S&OP acknowledging the need for strategic immediate buffers to compress lead time (Lapide, 2004). TOC provides the concept of dynamically managing these buffers through the different forms of buffer management (Goldratt, 1990). Lean and TOC stress the importance of lead time and flow in controlling the release of work into system as pull mechanism (Hopp, 2008) as opposed to the local optimisation commonly associated with earlier push-based approaches. This embraces TOC-based MTA DBM and visual signalling mechanisms from lean principles.

In summary, all buffering methods are standard tactics in the compression of lead time to reduce variability and uncertainty across the end-to-end supply chain network.

When the minimum order quantity is relatively significant, as required in specific industries, DDMRP will effectively regulate the buffer size. In conventional Dynamic Buffer Management (DBM), overseeing substantial Minimum Order Quantities (MOQs) becomes notably difficult when the MOQ surpasses one-third of the buffer size, often resulting in overstock (Cox & Schleier, 2010; Schragenheim & Dettmer, 2009). DDMRP resolves this issue by considering the MOQ directly when calculating the logic of the green zone. When the MOQ exceeds other factors for calculated size, the green zone is adjusted according to the MOQ to ensure proper inventory management (Ptak & Smith, 2016).

The dynamic nature of demand patterns and long lead times will benefit from dynamic buffer adjustments. DDMRP adjusts buffer levels dynamically using various parameters, such as Average Daily Usage (ADU), Lead Time Factor (LTF), and Variability Factor (VF) (Ptak & Smith, 2016). This method optimises replenishment decisions in real time, ensuring that buffers are appropriately sized to satisfy MOQ requirements without excessive inventory inflation (Azzamouri et al., 2021). DDMRP successfully sustains balanced stock levels and mitigates excess inventory by addressing both present consumption rates and historical variability, especially in the presence of substantial MOQs (Ptak & Smith, 2016; Velasco et al., 2020).

Contrastingly, DBM used in S-DBR/DBR/MTA/DTA methods only instigate buffer size modifications under specific circumstances. For instance, a change might be initiated when stock levels swell into the green zone extensively, termed as "Too Much Green" (TMG), or when the red zone is prevalent for an extended period, termed "Too Much Red" (TMR). However, despite their operational differences, all these buffering strategies converge on a singular objective: ensuring the consistent availability of products to meet customer demand.

DDMRP provides the alignment mechanism by a planned adjustment factor (PAF), demand adjustment factor (DAF), and zone adjustment factor for planned and known events such as seasonality, promotion, and product life cycle. Those factors adjust the buffer size to adapt to the anticipated changes in future demand. It is similar to the consensus plan in S&OP monthly communication on MPS changes. DAF and PAF are human adjustments through internal communications.

In phase three, as "pull", demand-driven planning handles the anticipated changes in the longer planning horizon, providing visible and collaborative execution. It defines the fundamental operational aspects of a DDMRP system: planning and execution. The traditional buffering methods focus on performance in the short term, and implementing all buffering strategies is similar to recovering the consumed buffer penetration as soon as possible. The key differences are the batch size and frequency of replenishment in generating the supply replenishment orders.

The process of generating supply replenishment orders (such as purchase orders, manufacture orders, and stock transfer orders) in DDMRP is based on demand-driven planning. DDMRP provided the "available stock position" referred to in DDMRP literature before 2016. In the latest definition, it is named - "Net Flow Equation":

On-hand + On-order - Qualified sales order demand = Net Flow Position
(Ptak & Smith, 2016, p. 150)

The On-hand Inventory refers to the physical count of the items currently available in the Stock. Incoming Stock is the total of items scheduled to be added to the inventory through purchase orders, manufacturing orders, and transfer orders. Qualified Sales Order Demand refers to confirmed customer orders that are yet to be fulfilled.

The Net Flow Position (NFP) is similar to the Project Available Balance (PAB) in MRP with a different formula:

Projected Available Balance (*PAB*) = previous *PAB* or on-hand + Master Production Schedule (*MPS*) - The customer order or forecast, whichever is higher
(Jacob, 2011, p. 185)

DDMRP introduces the concept of qualified sales order demand, which includes the past due sales orders, sales order due today, and qualified order spikes. These spikes occur when the total daily demand exceeds a certain threshold within a specific time frame. This time frame is called the “Order Spike Horizon” (OSH), and the threshold is referred to as the “Order Spike Threshold (OST) The qualified order spike is the total accumulative daily demand within a qualifying time window over the OST within OSH that significantly impacts the buffer protection (Ptak & Smith, 2016).

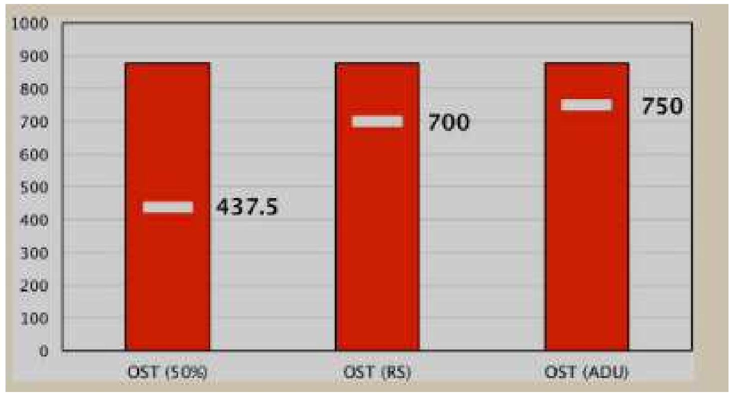

Figure 12 - different ways to set the order spike threshold (Ptak & Smith, 2016)

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In **Figure 12** shows the order spike threshold can be set to three options: the border of the red base (OST-RS) and red safety portion of the buffer for the finished item, the red safety portion of the red zone related to the variability of the part position (OST-50%) or an intuitive estimation based on the ADU of a specific part (OST-ADU). In the early DDMRP implementation, it was 50 per cent of the red zone. The primary purpose of qualified sales order demand is the protection of a significant surge in the long-range accumulative daily demand within OSH. DDMRP includes the qualified sales order demand in calculating the Net Flow Position to ensure sufficient buffer protection. On the other hand, the PAB heavily relies on the accuracy of the forecast. In MRP, PAB can also project the future stock balance, provided that the forecast is accurate. The net flow position is also unreliable if the qualified sales order demand is too uncertain or dynamically changing in the OSH planning horizon.

DDMRP planning monitors the net flow position for supply order creation. If the on-hand stock position is below the *Top Of Yellow* (TOY), supply orders will be recommended to recover the gap between the *Top Of Green* (TOG) and the current net flow position. For MRP, the open planned order triggers the suggested supply orders according to a net requirement of dependent demand within the BOM according to the due date. The Kanban system triggers the supply orders upon reaching the pre-defined levels by the demand for downstream processes. For DBM, suggested supply orders are based on the total consumption before the next replenishment cycle. S-DBR/DBR/MTA/DTA provide only the current buffer status for short-term planning. Those replenishment methods are inherent in the reorder point (ROP) concept with different formulas for calculating the inventory buffer level. While DBM triggers the replenishment orders according to accumulated consumption before the next replenishment cycle, DDMRP generates replenishment orders upon NFP reaching the TOY level.

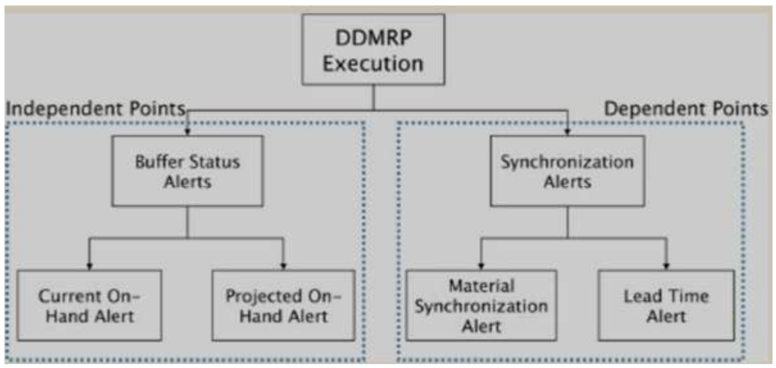

Figure 13 - DDMRP basic execution alerts (Ptak & Smith, 2016)

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In **Figure 13**, DDMRP execution alerts refer to the process after supply order generation in planning. The fundamental difference between planning and execution in DDMRP is the two priority systems of buffer status. The priority planning process uses the net flow equation for buffer status. The execution process focuses on the current and project on-hand balance to evaluate the buffer status. There are two major types of alerts in DDMRP execution: Buffer status alerts and Synchronisation Alerts. Buffer status alerts included current on-hand alerts and projected on-hand alerts for independent points. The current on-hand alert shows which parts may need to be immediately expedited from the on-hand perspective. The projected on-hand alert provides the projected on-hand status with the risk of stock-out for the coming day based on ADU and some known demand, whichever is higher. The synchronisation alerts include material synchronisation alerts and lead time alerts for dependent points. Material synchronisation alerts display supply shortages against known demand allocations when the projected on-hand alert on child parts potentially affects the reconciliation of parent parts. The lead time alert warns the non-buffered items at dependent points when the expected item is not delivered after two-thirds of the promised lead time has passed. The last one-third of lead time is termed "Lead time alert horizon". This alert system is similar to the DBR/S-DBR time buffer to provide warning signals. In OPP/CODP and DTA/MTA methods, there are no early warning signals in a longer planning horizon as buffer status alerts and synchronisation alerts in DDMRP.

According to the DDMRP policy, planners need to make decisions for many parameters, such as the strategic positioning of buffers, the percentages of lead time and variability factors in buffer profiles and the review interval for the buffer re-adjustment (Velasco et al., 2020). Azzamouri et al. (2021) pointed out the reliability and creditability issues in DTL, LTF, VF and ADU and recommended further research to analyse the DDMRP and performance to cope with the variability of demand and capacity. Ling et al., (2022) repackaged the above DDMRP logic as a demand-driven operating model (DDOM) and embraced it into a demand-driven adaptive model (DDAM):

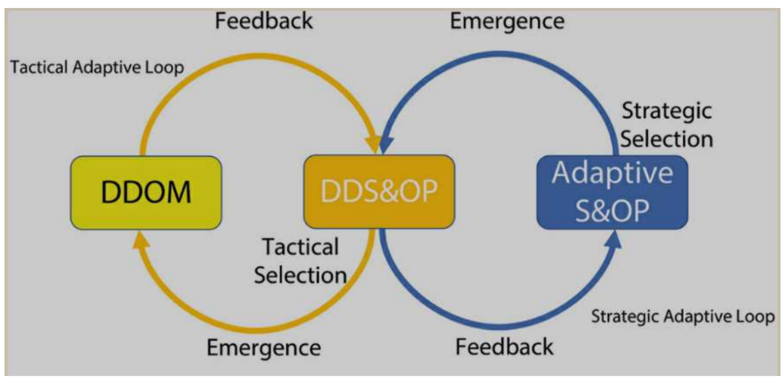

Figure 14 - The adaptive loops of the DDAM model (Ling et al., 2022)

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Figure 14 illustrates that DDAM applied the adaptive method according to the *Complex Adaptive Systems* (Smith & Smith, 2013), which aligned with strategic fitness between sub-systems and overall system objectives to promote and protect the flow for return on investment (ROI). It also matched the *first law of manufacturing* – "All benefits will be directly related to the speed of flow of information and materials" (Plossl, 1994). The key objective of DDAM is to create the visibility of relevant information in the operational, tactical and strategic relevant range.

Demand-Driven Sales and Operations Planning (DDS&OP) created the bidirectional reconciliation between DDOM and Adaptive S&OP with feedback and tactical selection information (Ling et al., 2022). This communication protocol bridged strategic direction and operational capability. On the other hand, Adaptive S&OP is the platform for the cross-functional team to provide tactical inputs (demand, budgetary range, capability definition and performance targets) for DDOM configuration. DDS&OP also provided strategic recommendations, tactical model projects, and tactical exploration opportunities for Adaptive S&OP to adjust the business planning information to the DDS&OP team.

Demand-Driven Sales and Operations Planning (DDS&OP) created a reciprocal reconciliation between DDOM and Adaptive S&OP by including feedback loops and tactical decision information, so effectively connecting strategic objectives with operational capacities (Ling et al., 2022). Empirical research demonstrates the superiority of DDS&OP compared to standard S&OP in dynamic circumstances. Bozutti & Espôsto (2019) illustrated how DDS&OP enhances responsiveness and agility in volatile manufacturing sectors by deliberately decoupling inventory and utilising real-time feedback, a characteristic absent in conventional S&OP, which adheres to a more inflexible top-down structure. Furthermore, Kim and Shin (2024) focus on the adaptability of DDS&OP within the manufacturing and retail companies in South Korea, as it enabled superior alignment between strategic leadership and operational requirements, in contrast to conventional approaches that frequently struggle to adjust quickly to changing market demands. Vidal et al. (2018) demonstrate that DDS&OP's ongoing feedback facilitates accelerated tactical decision-making, hence reducing response times to demand variations, which is essential in dynamic manufacturing operations. These studies demonstrate that DDS&OP not only improves the communication between strategy and operations but also surpasses traditional S&OP by facilitating more agile adaptations to market fluctuations.

The evolution of traditional S&OP to DDS&OP illustrates the shift towards more dynamic and integrative planning processes, aligning strategic objectives with real-time operational capabilities. This progression reflects broader trends in inventory management, where different paradigms – forecast-based model emphasising cost efficiency and consumption-driven models prioritising flow and responsiveness – are increasingly intertwined. To understand how these varying approaches complement one another and address the complexities of model supply chains, it is essential to compare the core differences between the primary inventory policies discussed throughout this review.

Table 3 – Summary of key differences between reviewed inventory polices

Inventory Policy	Focus	Key Strengths	Key Weaknesses	Planning Approach	Buffering Approach
Reorder Point (ROP) with EOQ	Forecast-based, economic order quantity	Minimizes total inventory cost, stable demand	Dependent on accurate forecasts, fails under high variability	Forecast-driven, independent demand	No buffer except safety stock (SS) at reorder point (R), reorder quantity (Q)
Material Requirements Planning (MRP)	Forecast-based, time-phased inventory management	Optimises inventory levels, integrated with ERP	Inaccurate demand forecasts lead to inefficiencies, doesn't account for capacity constraints	Forecast-driven, dependent demand	Uses safety stock at various BOM levels
Master Production Scheduling (MPS)	Forecast-based production volume management	Provides aggregate production plan, aligns with S&OP	Prone to instability due to forecast changes	Forecast-driven, adjusts production plans	Time fences and frozen schedules to manage instability
Sales & Operations Planning (S&OP)	Balances demand and supply, cross-functional	Enhances communication and resource alignment	Complex and prone to issues with forecasting accuracy	Aggregate planning, aligns cross-functional teams	No specific buffering method, focuses on coordination
Manufacturing Resource Planning II (MRPII)	Capacity-based, extension of MRP	Considers capacity constraints, balances resource loading	Complex to implement, assumes capacity availability	Capacity-driven, integrates RCCP	Uses time buffers and capacity buffers
Toyota Production System (TPS) with Kanban	Flow-based, pull production system	Minimizes waste, enhances flow and efficiency	Struggles with variability and load balancing in complex environments	Pull-based, actual consumption	Uses Kanban cards for controlling WIP and replenishment
Theory of Constraints (TOC) with DBR/S-DBR	Bottleneck-based, throughput optimisation	Focuses on constraints, maximizes system throughput	Complex to implement, dependent on constraint identification	Pull-based, focuses on constraints	Uses time, stock, and capacity buffers
Make-to-Availability (MTA) and Distribute-to-Availability (DTA)	Availability-based, buffer-driven	Improves responsiveness, reduces stockouts	Less effective in environments with high variability	Pull-based, consumption-driven	Dynamic Buffer Management (DBM) starts from initial buffer size (IBS) adjusts buffer sizes according to Too-Many-Green (TMG) and Too-Many-Red (TMR)
Demand-Driven MRP (DDMRP)	Consumption-based, demand-driven	Adapts to real-time demand, reduces lead times	Relatively new, requires significant data and system integration	Pull-based, real-time demand	Uses dynamic buffers adjusted based on Average Daily Usage (ADU), Decoupled Lead Time (DLT), Lead Time Factor (LTF) and Variability Factor (VF)

The above **Table 3** provides a comparison for clearer understanding of the unique contributions and limitations of each inventory planning model, setting the foundation for further exploration into their application in different simulation contexts stated in **Figure 15**, presented later in the chapter.

Distinct inventory management paradigms have taken shape over time. ROP, MRP, MPS and S&OP focus on forecasting methodologies emphasising cost reductions, while DBR, S-DBR, DTA and DDMRP, rooted in consumption-based planning, values a smooth flow velocity. Although these methods might appear divergent, they merge under the expansive umbrella of inventory management. The bidirectional reconciliation exemplified by DDS&OP attests to this harmonious blend, effectively combining strategic vision with tactical execution. The emergence of the Adaptive S&OP paradigm marks a significant evolution, promoting greater collaboration by inviting cross-functional teams to share their expert perspectives, distinguishing it from the conventional S&OP approach. This adaptive and integrative trend sets the stage for delving deeper into the influential factors affecting performance within these paradigms.

2.4 Performance and Influential Factors

Having underscored the interplay and alignment between forecast-driven and consumption-based inventory planning, it becomes imperative to understand the specific elements that steer performance within these frameworks. Simulation models rise to prominence in this context, offering stakeholders a lens to envision performance paths under different policy applications, serving as a blueprint for tangible implementation. This discourse will methodically assess the impact of policies like ROP, MTA DBM, and DDMRP on performance. In addition, a keen examination of the key performance metrics such as Return on Inventory (ROI) and Service Level by Revenue (SL) vital for simulation studies will unfold, illuminating the factors that considerably influence inventory policies’ performance outcomes.

2.4.1 Key Performance Indicators (KPIs) in inventory management

This section defines the key performance indicators (KPIs) used to evaluate inventory policies in the simulation analysis discussed in Chapter 4. The indicators comprise Revenue Level (RL), Inventory Level (IL), Service Level by Revenue (SL), Out-of-Stock (OOS), Overdue Order Frequency (OOF), and Return on Inventory (ROI) based on Cost of Goods Sold (COGS).

The above KPIs can be used to evaluate the supply performance between different policies and in the broader literature and are relevant for this research. Revenue Level (RL) quantifies the income produced by a business through product sales to customers, while Inventory Level (IL) indicates the number of product units in stock. Service Level by Revenue (SL) indicates an organization's ability to satisfy customer demand, determined by the revenue lost from unfulfilled orders (AnyLogistix, n.d.).

Out-of-Stock (OOS) indicates situations in which the inventory of a particular product has been exhausted, limiting the prompt satisfaction of customer demands. Overdue Order Frequency (OOF) quantifies the frequency with which an order misses its scheduled delivery date, indicating difficulties in adhering to delivery schedules. Return on Inventory (ROI), defined as the ratio of revenue to inventory levels or Cost of Goods Sold (COGS), is an essential metric for assessing the effectiveness of an organisation in utilising its inventory to produce profits (TOCICO, 2012).

Another important indicator is Inventory Turns, which indicates the velocity at which inventory moves the supply chain with minimum stock waste. The calculation of Inventory Turns is based on the ratio of annual COGS to average inventory, reflecting the performance of inventory strategies (Hopp & Spearman, 1996; Koumanakos, 2008; Blackstone, 2010; Martin, 2010). The average inventory level strongly impacts ROI and inventory turnover, but service level, assessed by OOS, is crucial for maintaining customer satisfaction (Mekel et al., 2014).

Effective inventory management, including the elimination of non-value-added activities and unnecessary inventories, immediately improves performance indicators such as inventory turnover and return on investment (Rao & Rao, 2009). Furthermore, the proficient management of KPIs, including Service Level by Revenue (SL) and ROI, is necessary for assessing the effectiveness of inventory strategies (Ogbo & Ukpere, 2014; Eroglu & Hofer, 2011; Gołaś, 2020). A study on the 7up Bottling Company in Enugu, Nigeria, evaluated the impact of flexible inventory practices on organizational performance (Ogbo & Ukpere, 2014). These practices included flexibility in inventory service, supply chain management, and inventory management, which contributed to minimizing stock holding costs, reducing waste, and enhancing inventory utilization.

Return on Inventory (ROI) is crucial for evaluating the effectiveness of inventory in generating profits. Effective inventory management reduces holding costs and optimises stock, hence increasing profitability and enabling businesses to respond swiftly to market demands (Ogbo & Ukpere, 2014; Eroglu & Hofer, 2011; Gołaś, 2020; Galankashi & Rafiei, 2021).

Service Level by Revenue (SL) similarly assesses the ability of an organization to satisfy client orders, directly impacting customer satisfaction and loyalty. Liang and Atkins emphasise the role of Service Level Agreements (SLAs) in inventory management, which are designed to ensure that service levels are met consistently, thus aligning operational performance with customer expectations (Liang & Atkins, 2013). Research has repeatedly demonstrated a strong association between effective inventory management and improved financial performance, rendering SL and ROI critical for assessing inventory management strategies (Cranimar & John, 2021; Manikas, 2017; Ngugi, 2019). For instance, a study examining private hospitals in Western Uganda found that robust inventory management systems significantly predicted financial performance (Ngugi, 2019). The study, which employed a positivist approach and a cross-sectional research design across 32 hospitals, recommended adopting effective inventory management to optimise stock levels and minimize costs for substantial financial improvement (Cranimar & John, 2021). However, the authors acknowledged that their positivist approach may have introduced method bias, potentially affecting the validity of their findings. Similarly, research conducted on manufacturing companies in Eldoret Town, Kenya, including firms like Rift Valley Bottlers and Rai Plywoods (K) Ltd, found that inventory holding costs were influenced by long-run price increases (Ngugi, 2019). The study recommended the implementation of Material

Requirement Planning (MRP) systems to reduce holding costs of finished goods, using both quantitative and qualitative analyses, including descriptive and inferential statistics, to derive its conclusions.

In conclusion, ROI and SL are essential measures for evaluating the performance of inventory policies. They offer insights into financial performance and indicate operational effectiveness in fulfilling client expectations. Literature regularly indicates that good inventory management methods improve profitability and service levels, making these KPIs important when assessing inventory management systems in distribution-side supply chains.

2.4.2 Impact of Inventory Policies on Performance

Inventory management has continually evolved, echoing the shifting market dynamics. The traditional Reorder Point (ROP) method, established over the years, is a consistent mechanism to stabilize inventory amidst unpredictable demand, a viewpoint further endorsed by Silver et al. (1998). Scholars, including Zipkin (2004), have underscored the indispensability of steadfast systems like ROP, particularly in navigating the turbulent waters of volatile demand. The complexity of inventory systems, the interplay between management and engineering perspectives, and the role of centralized and decentralized control are crucial for effective inventory management, emphasising an engineering approach to problem-solving and careful analysis in decision-making. Furthermore, advancements in information technologies and the historical evolution of inventory research highlight the continuous efforts to optimise inventory control, incorporating approaches like just-in-time and incentive-based theories.

Waters (2003) provides an in-depth analysis of inventory management methodologies, particularly emphasising the crucial role of the ROP. According to Waters, the ROP acts as a buffer against unexpected demand fluctuations and ensures supply chain continuity. Axsäter (2006) reinforces this perspective, suggesting that by defining a specific threshold for reordering, the ROP manages to keep stock levels optimal, thereby averting potential operational disruptions. These revelations align with the beliefs of Mattsson (2010) and Tersine (1994), who argue that the fusion of traditional ROP with advanced ERP platforms can effectively cater to the complex patterns of shifting demand.

Nevertheless, Mattsson (2010) highlights the limitations of the conventional Reorder Point (ROP) model, particularly concerning seasonal demand variations. He proposes an extended ROP model, suitable for ERP systems, that accounts for these seasonal variations, offering potential performance improvements through simulation and providing heuristic guidelines for practitioners. This model aims to address the challenges of systematic medium-term demand fluctuations, such as seasonal variations, which traditional ROP systems struggle to manage effectively.

Tersine (1994) reflects this pursuit of refinement, advocating a proactive strategy that synchronises inventory management with volatile markets. His focus on adaptive inventory management is theoretically substantiated; nonetheless, Tersine reinforces his claims through case studies (i.e. solid wood furniture, builder and contractor) and industrial examples (i.e. job shops and voltage circuit breakers manufacturer) instead of novel empirical research. These examples demonstrate that linking inventory policies with overall supply chain objectives can enhance responsiveness to fluctuating demand situations, supporting Mattsson's argument for an improved ROP model. Tersine’s work lacks direct empirical research and provides a theoretical framework and real-world applications that yield practical insights into mitigating risks and enhancing supply chain performance in unanticipated circumstances through adaptive approaches.

In a contemporary context, Pathom (2023) highlights the potential benefits of combining time-tested inventory models with sophisticated technological solutions. The resultant synergy offers more profound insights, manifested in reduced daily inventory levels. The study employing discrete-event simulation also supports this view, as it determined the optimal reorder point for a retail store based on an acceptable service level under uncertainties like demand, lead time, and product damage. This simulation-based approach effectively optimised inventory policies, impacting total daily inventory, profitability, and product damage, thereby demonstrating the practical benefits of advanced modelling.

Miclo (2018) further expounds on the revolutionary shift brought about by DDMRP, placing demand at its core. Miclo's research underscores DDMRP's prowess in resolving predicaments intrinsic to older methodologies. The performance gap between DDMRP and its predecessors, as Miclo suggests, is only sometimes significant, but DDMRP's flexibility and dynamic buffer management prove beneficial for various settings. Similarly, the use of Discrete-Event Simulation (DES) allows for predictive analysis and dynamic modelling of constraints, demonstrating the utility of advanced simulation tools in assessing inventory policy modifications under varied scenarios, supporting DDMRP’s adaptability.

The study by De Pacheco et al. (2015) examines the dynamic behaviours of a two-level supply chain under stochastic demand, using discrete event simulation to model information and material flows. It proposes Lead Time Absorption (LTA) and Demand

Absorption (DA) metrics to evaluate supply chain performance in terms of lead time and inventory levels, emphasising the importance of variable reorder points to minimize disruptions in meeting demand. De Pacheco et al. (2015) and Nahmias (2009) further illuminate the intricate relationship between supply chain structures and the significance of accurate demand forecasts. Nahmias's simulation-based approach in their research explores the effectiveness of dynamic versus static reorder point policies by simulating inventory systems under uncertain lead times and varying demand patterns. The simulation demonstrates that dynamic policies can maintain service levels while significantly reducing inventory costs, thereby enhancing supply chain efficiency. De Pacheco et al.'s work builds on these insights by demonstrating how adapting variable reorder points can effectively reduce inventory disruptions and ensure responsiveness to market uncertainties, further validating the value of flexibility in inventory management.

Industry-specific practices, as explored by Reyes et al. (2015) within the footwear sector, exemplify the unique challenges faced by various sectors. The footwear industry faces intense competition due to globalization, especially from mass production in Asian countries, leading to a need for improved inventory management. Their findings advocate for adopting Dynamic Buffer Management (DBM), primarily due to cost-saving benefits and better inventory control. The footwear sector also struggles with balancing inventory levels to avoid both shortages and overstock, which can lead to substantial financial losses. By implementing DBM, the study reports an 18.7% reduction in annual inventory costs, showcasing how this approach can enhance competitiveness and responsiveness in a challenging market environment.

Emerging inventory management paradigms like DBM and DDMRP garner significant attention in contemporary research. Marco (2015) argued that DBM parameters are relatively stable and proved that the performance of DBM is better than ROP under high demand variability. While DBM's adaptability, promises a bright future (Ikeziri et al., 2023), it is not without its challenges (Narita et al. 2021). As DDMRP garners more traction, supported by scholars like Hung et al. (2004) and McCullen & Eagle (2015), precision and attention to detail are paramount in realising the full potential of these methodologies.

To holistically grasp the effectiveness of these varied inventory management strategies, there is an undeniable need for precise metrics that meticulously quantify their impact on business outcomes.

2.4.3 Impact of influential factors on inventory performance

Several influential factors affect inventory performance in the supply chain. This section explains the rationale for focusing on inventory management and reviews the literature about the bullwhip effect, ripple effect, forecast accuracy, lead times, replenishment review timing, lot size and disruptive events for the variability of demand or supply. On the other hand, safety stock, strategic decoupling of stock locations and information sharing mitigate those negative impacts.

The focus on inventory performance in supply chain management is critical due to its significant impact on overall supply chain performance and financial outcomes. Effective inventory management directly influences essential business objectives, including cost efficiency, customer satisfaction, and operational responsiveness. In dynamic and uncertain supply chain environments, where demand patterns and supply lead times fluctuate, adaptive and efficient inventory policies are necessary to balance supply and demand effectively.

Cost efficiency is a primary reason for emphasising inventory performance. Improved inventory management strategies can lead to reduced operational costs, as they minimize excess stock and associated holding costs. For instance, Crowe et al. (2010) highlight that without efficient supply chain and inventory management strategies, achieving competitive advantage becomes increasingly difficult, emphasising that improved inventory management contributes to lower costs and increased revenue. Furthermore, Almajali et al. (2016) assert that effective electronic supply chain management enhances inventory control, leading to significant cost reductions and improved customer service. This relationship underscores the importance of inventory performance in achieving financial efficiency.

Customer satisfaction is another critical aspect influenced by inventory performance. Effective inventory management ensures that products are available when customers need them, thereby enhancing their overall experience. Tarurhor and Osazevbaru (2021) demonstrate that inventory management directly correlates with customer satisfaction in the public health sector, indicating that timely availability of products is crucial for meeting customer expectations (Tarurhor & Osazevbaru, 2021). Additionally, Muhammad emphasises that customer satisfaction directly influences client loyalty, which is essential for long-term success (Muhammad, 2023). This connection between inventory performance and customer satisfaction highlights the necessity of maintaining optimal inventory levels to meet consumer demand promptly.

Adaptability to variability in supply and demand is essential in today's fast-paced market. The ability to adjust inventory policies in response to changing conditions is vital for maintaining service levels and minimizing stockouts. Xu and Cao (2019) discuss the importance of optimal inventory policies for omnichannel retailers, which must adapt to varying customer demands across multiple sales channels. Similarly, the concept of leagility, which combines lean and agile supply chain principles, allows firms to respond quickly to market changes while maintaining cost efficiency (Vinodh & Aravindraj, 2013). This adaptability is crucial for sustaining competitive advantage in fluctuating market environments.

Eventually, supply chain agility is widely acknowledged as a critical indicator of success in inventory management. Daryanto and Krämer (2016) claim that agility in logistics and supply chain management is essential for quickly and effectively addressing market demands. This agility is enabled by effective inventory management procedures that permit rapid modifications in stock levels and replenishment tactics. The incorporation of sophisticated technologies, including electronic inventory control systems, significantly improves agility by delivering real-time data and insights for enhanced decision-making (Mondo et al., 2022).

However, despite the latest technologies, challenges such as the bullwhip effect still pose significant risks to inventory performance. Lee et al. (1997) argued that the bullwhip effect exaggerated orders across the supply chain to degrade the inventory performance. Kaipia et al. (2006) reported that the variation in planning accuracy caused the planning nervousness to amplify the impact, which increased the ratio of the maximum order changes between supply chain nodes. Paik (2003) identified this ratio as a demand amplification factor, which reflected the rate of order fluctuations (Paik & Bagchi, 2007). This amplification of order variability formed the bullwhip effect (Erraoui et al., 2019), which measured the bullwhip ratio between input and output flows (Chen et al., 2000).

The forecast inaccuracy, lead times, seasonality and desired service level will affect the bullwhip effect, directly relating to the total inventory cost and fill rate performance. Bayraktar et al. (2019) emphasised that forecast inaccuracy is the most critical factor in mitigating the bullwhip effect. Chen et al. (2000) further substantiates this by highlighting how variable lead time can magnify the bullwhip effect, underscoring companies' need to optimise and streamline their lead time processes. The Ripple effect is also the driver for bullwhip impact from the other direction of ordering oscillations (Dolgui et al., 2020).

The procurement and sales order lead time might increase cycle and safety stock (Yang & Geunes, 2007). The shorter suppliers' replenishment lead time reduced the impact of bullwhip and improved the recovery speed (Chang & Lin, 2019). The lead time is a strategic factor for the financial performance in return on investment (ROI) (Tidemann et al., 2020).

Chen et al. (2000) further touch upon the intricacies of replenishment policies and how they, when not optimised, can inadvertently intensify the bullwhip effect. The replenishment review interval determined the lead time and created a batching bullwhip effect with a different depletion rate of inventory (Boute et al., 2007; Waller et al., 2008). When the batching lot size by EOQ induces the effects of lost sales without backorder, the inventory order policy should be adaptive to reduce the backlogging cost (Sharma & Sadiwala, 1997). The upstream supplier imposed MOQ for large lot size to justify their production cost (Chow, 1999). Therefore, an efficient inventory policy should consider the current inventory level demand forecast with MOQ requirements to reduce the total cost (Park, Kim & Shin, 2018). On the other hand, Brandenburg et al. (2014) suggested broadening the decision criteria for supply chain performance improvement from cost efficiency to value creation. However, external disruptive events may challenge the ability to maintain the expected performance.

> Disruptions are random events that cause a supplier or other element of the supply chain to stop functioning, either completely or partially, for a (typically random) amount of time.

(Snyder et al., 2016)

The disruptive events created uncertainty in yield, capacity, lead time and input cost for variable pricing, which increased the stochastic variability in supplier lead time and order quantity. Chen et al. (2000) emphasises the need to account for these disruptions, as they can introduce variances, particularly in lead time, exacerbating the bullwhip effect.

According to the above influential factors, the supply chain organisation faces the challenges of variability from supply and demand. Neale & Willems (2009) presented a model to handle stochastic and nonstationary demand by determining the inventory locations and safety stock levels. The model showed a case with high demand uncertainty measured by the Coefficient of Variation (**CoV**), how to reduce lead time by 30 per cent and total inventory by almost 50 per cent. The standard deviation (**SD**) divided by the mean calculates the **CoV** (Hopp & Spearman, 1996). George et al. (2019) reviewed 54 articles to identify the factors affecting supply chain performance, including supply chain structure, inventory control policy, information sharing, customer demand, forecasting method, lead times, and review period length.

Due to the dynamic of the above internal and external factors, several articles studied safety stock, strategic decoupling of stock locations, and information sharing across the supply chain to mitigate those negative impacts. However, Cannon (2008) argued that the inventory performance improvements could not link with overall company performance.

The management of safety stocks remains a paramount consideration in inventory control and optimisation. Nahmias (2009) elucidates the intricacies of the safety stock formula, noting its derivation by multiplying the safety factor by the expected service level and the standard deviation of demand during the lead time. This concept traces its origins to the works of Silver et al. (1998). While the bullwhip effect, a manifestation of increased demand variability in supply chains, has garnered attention in scholarly circles, Fransoo & Wouters (2000) unearthed several overlooked challenges concerning its practical measurement. Specifically, the duo highlighted issues stemming from data aggregation, the incompleteness of data, and the isolation of demand data for distinct supply chains within a more extensive supply web. Drawing from hands-on experiences in an industrial setting, they dissected these conceptual measurement predicaments and shared empirical insights from two supply chains.

A deep dive into this area by Waller et al. (2008) underscores incorporating these safety stock calculations within the period review inventory model. Their approach targets the bullwhip effect, seeking to alleviate its impact, primarily from the variability of both the review interval and lead time, all in a bid to counteract potential stockout risks.

Transitioning to the realm of DDMRP, Lee & Rim (2019) shed light on a pivotal limitation within the DDMRP replenishment model. This inherent flaw pertains to selecting safety and variability factors within prescribed bounds. Their solution, a meticulously crafted mathematical safety stock model, offers a more objective lens to discern safety factors for DDMRP parameters. Compared to the traditional DDMRP guidelines, their model's efficacy is evident; it engenders significantly reduced excess inventory while nearly nullifying inventory shortages.

Further embedding the importance of strategic stock placement, Miclo et al. (2019) vouch for the demand-driven approach. This methodology anchors buffer stock at strategic decoupling junctures, wielding dual benefits: a conspicuous reduction in lead time and a palpable absorption of variability, both acting to mitigate the bullwhip effect. Building on this narrative, Tiedemann (2020) holistically explores demand-driven supply chain strategies, encapsulating segmentation, agility, customisation, transparency, and postponement. Their findings accentuate the intricate dance between decoupling points and lead time, emphasising how these elements shape ROI, particularly when determining the oscillations and length of lead time.

The influence of information sharing between entities, the standard deviation of lead time, the mean of lead time, and cooperation among involved parties on the bullwhip effect in the supply chain is substantiated by various studies. Li (2010) underscored these aspects as pivotal in understanding the bullwhip effect. This perspective aligns with subsequent simulation studies conducted by Hall & Saygin (2012), Jonsson & Mattsson (2013), and Dev et al. (2013). These combined insights set the stage for a deeper exploration and synthesis of the existing literature's findings.

In conclusion, focusing on inventory performance is essential for achieving cost efficiency, enhancing customer satisfaction, adapting to variability, and fostering supply chain agility. These factors collectively contribute to improved overall supply chain performance and better financial outcomes for organizations.

2.5 Conclusion

By the above literature review, we can establish an initial understanding regarding research question (**RQ1**), which is also the foundation for **RQ2** and **RQ3**:

> **RQ1.** How do inventory policies, particularly forecast-based and consumption-based methods, interact with performance metrics in distribution-side supply chain scenarios?

It is important to make it clear that the selection of three inventory policies – ROP, MTA DBM, and DDMRP – is a deliberate attempt to justify why they have been chosen for review in this research. Each of these policies represents a distinct approach to managing inventory and responds to different challenges in supply chain environments of selected cases listed in **Table 1**, making them relevant for comparative analysis.

ROP is a traditional, forecast-based method that is widely used but struggles with variability. MTA DBM focuses on dynamic buffer management, aligning inventory availability with real-time consumption to ensure product availability. DDMRP, on the other hand, combines elements of both approaches, using adaptive buffer sizing and real-time demand signals to optimise inventory flow and responsiveness. By comparing these three methods, the research seeks to understand their effectiveness under different conditions and explore how each policy impacts key performance indicators such as service levels (SL) and return on inventory (ROI). This comparative review forms the foundation for addressing RQ1 and examining how these inventory methods interact with performance metrics in distribution-side supply chains.

Chapter 2.4 explicitly emphasises how those inventory policies are linked to key performance outcomes, particularly SL and ROI. The interplay between these performance metrics and the inventory policies forms the foundation of the analysis, offering insights into their operational effectiveness and ability to meet performance objectives under varying supply chain conditions.

From the literature reviewed, it is anticipated that ROP will excel in ensuring higher ROI during stable demand conditions due to its reliance on fixed safety stock and reorder points, which minimise holding costs. However, this approach may underperform in terms of SL when faced with significant demand variability or unpredictable lead times, as its static parameters lack adaptability (Wilson, 1934; Mattsson, 2010).

Conversely, DDMRP is expected to outperform in achieving high SL under volatile demand conditions due to its dynamic buffer adjustments and responsiveness to real-time demand signals (Ptak & Smith, 2016). However, this flexibility often comes at the cost of a reduced ROI, driven by higher inventory levels and the resource-intensive nature of its implementation (Miclo, 2018; Lee & Rim, 2019).

MTA DBM, positioned between these two approaches, is anticipated to deliver a balance by maintaining consistent SL in moderate variability scenarios through its straightforward buffer size adjustments (Ikeziri et al., 2023). While it may lack the advanced adaptability of DDMRP in high-demand volatility, its simplicity ensures more efficient ROI compared to DDMRP, particularly in environments with stable or predictable demand patterns.

In addressing RQ1, the research explores how and why these planning and control approaches have developed to influence distribution systems. These performance metrics drive the evolution of these methods, ensuring that inventory policies align with the dynamic needs of modern supply chains. This foundation is crucial for subsequent research questions (RQ2 and RQ3), which delve deeper into the comparative performance and influential factors underpinning policy choices.

As a summary of the journey from MRP to MTA DBM, it starts with simple inventory management for a single item by EBQ/EOQ and ROP. EBQ/EOQ and ROP optimise the cost performance by calculating the economic lot size (Q) and reordering point (R) time. When the product gets multiple levels of components in the structure, it contains the dependent demands instead of single-item inventory planning. Then, BOM calculates the net requirement by MRP logic according to the dependent demand from parent items in BOM. It is assumed to generate time-phased production and purchase orders, offsetting lead time. To utilise resources efficiently, MRP is based on the MPS to schedule planned items in batches to reduce the unit cost of production according to the sales forecast in

MPS. Because different factors dynamically influence the variable demand from sales forecast and uncertain supply from suppliers, S&OP is deployed to build up the communication protocol to bridge the sales and operation to balance external demand and internal resources. To balance the demand and resources, S&OP tries to make a consensus about the supply of the available resources and sales plan in the medium to long term before converting the monthly production plan into MPS. Then, the master scheduling process adjusts MPS according to RCCP, which enhances MRP's logic as MRP II. Under an MRP system, MPS scheduling is a critical mechanism for planning and control according to push-based forecasts.

On the other hand, the MTA DBM planning, and control system focuses on the flow velocity of the production system. Starting from the origin of TPS, it schedules the production according to the actual demand rate. It places the Kanban between different workstations to maintain the production flow with a limited WIP level according to actual downstream consumption as a JIT operation. TPS with Kanban can effectively support the continuous sales demand and constant consumption. When production is based on the MTO environment, TOC for MTO applies the OPT method. OPT schedules the production according to the internal constraint resources for balancing the flow instead of resources. When customers do not tolerate order lead time by MTO, the MTS environment can meet the customer's lead-time expectation. MTA planning and control system uses dynamic buffer management to manage the inventory level according to the actual consumption from the internal and external downstream supply chain. According to pull-based consumption, dynamic buffer management in MTA is crucial for planning and control.

DDMRP inherits from TOC’s Dynamic Buffer Management (DBM) with modified buffer sizing logic to apply ADU for daily dynamic buffer size. DDMRP applies for the standard inventory position minus qualified spike order quantity to form the Net Flow Position (NFP) as dynamic ROP for replenishment. The reorder quantity DDMRP generates is similar to the MTA DBM buffer's top of the green.

MRP relies on reliable forecasts and static safety stock to optimise cost-efficiency with infinite resources. However, MTA DBM and DDMRP are assumed to be based on the actual consumption and DBM to increase the flow velocity holistically. Most DDMRP literature compared the performance with the MRP model, but few comparisons study exists with ROP and MTA DBM. The bullwhip and ripple effect influences forecast accuracy, replenishment review timing, lead time, and lot size. In addition to external disruptive events, the variability of demand or supply is amplified to affect inventory performance. ROP uses safety stock to absorb the variability. MTA DBM and DDMRP strategically place the decoupling stock buffer to replenish by sharing demand signal information from the downstream supply chain.

In conclusion, the evolution from MRP to MTA DBM and DDMRP signifies the adaptation of inventory policies over time. While MRP relies on reliable forecasts, MTA DBM and DDMRP pivot towards real-time consumption and dynamic buffer management, emphasising flow velocity. This evolution indicates a pressing need to understand which policies are more effective in today's volatile supply chain environment, thus underscoring the importance of our research.

After reviewing the above literature shows two conflicting directions of inventory planning: forecast-based and consumption-based. ROP, MTA DBM and DDMRP share a similar mechanism in their use of buffer management to ensure product availability and manage inventory levels. All three methods rely on predefined thresholds to trigger replenishment orders, ensuring that stock is available when needed.

- ROP triggers orders based on a set reorder point calculated from forecasted demand and lead time.
- MTA uses dynamic buffer adjustments based on real-time consumption to maintain availability at key points in the supply chain.
- DDMRP similarly manages stock through buffer zones, dynamically adjusting replenishment based on actual demand signals rather than forecasts.

It explores the two research gaps. Firstly, most of the literature for performance comparison is on MRP and DDMRP. Further research should help supply chain practitioners identify which policies perform better under the same supply chain network and demand as fair judgement. Secondly, inventory policies require subjective decisions for initial parameters and various adjustment factors for lead time, demand variability of promotional events, seasonal fluctuation and promotional events and minimum order quantity (MOQ). Another research question should study the decision-making insight according to the influential factors and parameters for improving performance.

To enhance clarity, the conceptual framework (**Figure 15**) aims to pinpoint and examine the key constructs used in simulation analysis, including three inventory policies (ROP, MTA, DDMRP), supply variation from transportation lead time and demand variation based on three real-world cases. Additionally, it incorporates key performance indicators (KPIs) on ROI and SL.

Each element in framework serves different purpose, defined as follows:

1. Supply Variation (SV) refers to the fluctuations and uncertainties within the supply chain, particularly with regard to transportation lead times, material availability, and consistency in deliveries. In this simulation context, supply variation will be impacted by transportation delays, which are factored into the model to reflect read-world disruptions.

2. Demand Variation (DV) refers to the unpredictability and changes in customer demand patterns, which can arise due to factors such as seasonal trends, market shifts or consumer behaviour from the three cases' characteristics (see Table 1). DV influences inventory levels, order fulfilment, and production or replenishment strategies, often creating challenges in maintaining desired service levels and optimising supply chain performance.

3. Inventory Policy Parameters (highlighted in **YELLOW**) affect inventory buffer sizing. These polices – Reorder Point (ROP), Make-to-Availability (MTA) with Dynamic Buffer Management (DBM), and Demand-Driven MRP (DDMRP) – each utilise distinct parameters that influence Service Level by Revenue (SL) and Return on Inventory (ROI), either positively or negatively.

The conceptual framework also highlights the relationship between independent variables (supply and demand variations) and dependent variables (Key Performance Indicators). It serves as a guide to compare how different inventory policies – ROP, MTA with DBM, and DDMRP – performance in terms of service levels and return on inventory under varying supply and demand conditions

The next chapter elaborates on the research methods, addressing the following research questions (RQs) and filling the research gaps identified:

RQ1. How do inventory policies, particularly forecast-based and consumption-based methods, interact with performance metrics in distribution-side supply chain scenarios?

RQ2 – How do the performance outcomes of inventory policies (ROP, MTA DBM, DDMRP) vary across different demand levels and supply lead time stability in the distribution-side supply chain?

RQ3 - What are the key influential factors and assumptions that underpin the selection and effectiveness of various inventory policies?

Figure 15 shows the conceptual framework, illustrating the interconnectedness of these variables and their impact on the simulation outcomes.

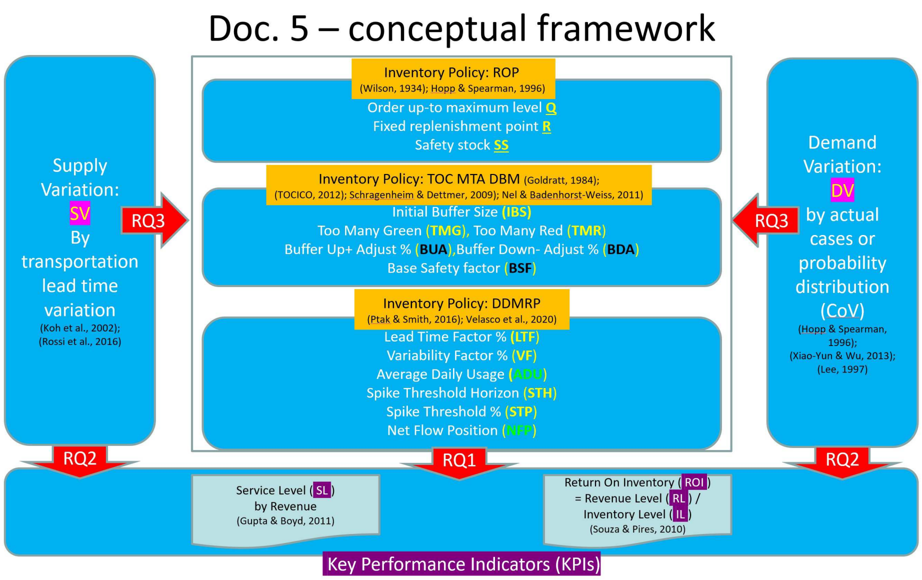


Figure 15 - Conceptual framework in Document 5

The literature reviewed that related to **RQ1** offers a comprehensive analysis of how forecast-based and consumption-based inventory policies interact with performance metrics in supply chain scenarios. However, empirical assessments of these policies across different demand levels and supply conditions remain underexplored, leading to **RQ2**, which investigates the performance variations of ROP, MTA DBM and DDMRP under several different conditions, using case studies to guide the parameters of these conditions.

In addressing these research questions, the selection of Return on Inventory (ROI) and Service Level by Revenue (SL) as key performance indicators (KPIs) is critical. ROI measures the profitability and efficiency of inventory management, aligning with the Throughput (T) and Inventory (I) components of the Theory of Constraints (TOC). It reflects the financial outcomes relative to inventory levels, highlighting the balance between maintaining sufficient stock and avoiding excessive holding costs. Similarly, SL captures the system's ability to meet customer demand while contributing to revenue, tying it to the Throughput (T) component.

Chapter 3 (specifically in Section 3.4.4: A Note on the Main KPIs) will further highlight the relevance of these specific KPIs based on theoretical insights and practical considerations form the literature review, connecting those measures to supply chain performance metrics within the distribution-side supply chain context.

Both KPIs implicitly assume fixed Operating Expenses (OE), consistent with TOC principles, which focus on maximising throughput while minimising inventory and maintaining OE. This unified view gives strong basis for comparing how well ROP, MTA DBM, and DDMRP work in different demand and supply situations. It also lays the groundwork for RQ2 and places this study in a bigger theoretical and practical context.

Moreover, the literature reveals various assumptions and influential factors related to the selection and effectiveness of inventory policies, but a deeper understanding, and detailed comparison, is needed. This gap leads to **RQ3**, which aims to uncover the key factors driving the effectiveness of these inventory policies.

The following chapter outlines the research methodology that will be used to explore these questions in detail, providing a robust framework for empirical assessment.

3. Research methodology

3.1 Introduction

This chapter comprehensively reviews the research methodologies leading to the research design. It begins by addressing the ontological, epistemological, and methodological levels, offering insights into why the simulation study was chosen as the primary research method. The discussion then shifts to explaining how the selected research design maintains rigour and relevance, the key to ensuring that the findings are credible and applicable to real-world industry scenarios.

This chapter describes and justifies of simulation to look at how well three important inventory policies—reorder point (ROP), make-to-availability with dynamic buffer management (MTA DBM), and demand-driven material requirements planning (DDMRP)—work in the three different supply chain settings based on existing case studies. The simulation method was chosen because it can simulate the dynamics of a real-world supply chain in a controlled environment. This lets variables like supply variation (SV) and demand variation (DV) be tested in a planned way. Key performance indicators (KPIs) like Return on Inventory (ROI) and Service Level by Revenue (SL) are central to evaluating the effectiveness of these policies under varying conditions.

The **Table 1** in previous chapter has stated that the simulation will use collected data from actual industry scenarios in three different sectors, namely healthcare devices, garment factories, and automotive assembly. These cases provide different contexts suitable for testing the selected inventory policies under varying characteristics in demand frequency, supply lead times, and market volatility. The software tool AnyLogistix (ALX) is also introduced, with an explanation of experimental scenarios and how to use data analysis and visualisation for reporting.

The simulation research processes section outlines the phases of best practices used to design and execute the simulations, from defining objectives and setting optimised baseline parameters based on real-world case data to running the simulation experiments and analysing the outcomes.

Moreover, research processes will be discussed, including how to align with best practices to handle practical challenges. By adhering to established best practices, the research ensures that the findings are robust and trustworthy and can provide actionable insights into the selection of inventory policies.

Finally, reflecting on the obstacles during the simulation study induces mitigation strategies for the research and provides opportunities for continuous improvement of limitations.

3.2 Different Paradigms in Research Methodologies

Morgan and Smircich (1980) argue that the difference between quantitative and qualitative methods is too simple. They say that subjectivists and objectivists are based on connected core beliefs, such as ontological, human nature, epistemological, metaphors, and research methods. They propose that researchers look from an external perspective and within the subject of study.

Fitzgerald and Howcroft (1998) classified research methods into hard and soft categories. This classification spans the ontological, epistemological, methodological, and axiological levels. These levels deal with various aspects of research: reality and its existence, the relationship between the inquirer and known reality, procedures and steps to acquire knowledge, and the evaluation of what is valued.

Table 4 - Summary of hard and soft research methods (Fitzgerald & Howcroft,1998)

Soft	**Hard**
Ontological level (metaphysics)	
Relativist	Realist
Epistemological level	
Interpretivist/phenomenological Subjectivist	Positivist Objectivist
Methodological level	
Qualitative Exploratory Induction Field	Quantitative Confirmatory Deduction Laboratory
Axiological level	
Relevance	Rigour

The research methods classified into hard and soft by Fitzgerald & Howcroft (1998) summarised are presented in the above **Table 4**:

Ontological assumptions ask questions about the nature of reality and its existence in two extreme positions between realism and relativism. Philips (1987, p. 205) defined *philosophic realism* as "the view that entities exist independently of being perceived, or independently of our theories about them." On the other hand, relativism believes that knowledge is a social reality, so it is value-laden in representing multiple realities through individual interpretation. The ontological position of the researcher will influence the direction of the epistemological paradigm.

Epistemological assumptions ask questions about the relationship between the inquirer and the known reality and knowledge of the world. It studies the nature and character of knowing how humans learn, acquire and confirm it. Collier (1994) advocated critical realism with three levels of context experience, events and mechanisms to study the known reality and knowledge of the world at an epistemological level. Positivists advocated working with observable social reality and emphasised structured methodologies produced by physical and natural scientists. Interpretivists focused on understanding the difference between humans in the role of the social actor instead of objects such as machines and vehicles. Conflict and tension exist between the positivist and interpretivist paradigms (Bryman, 2015). The epistemological position will influence the direction of the methodological paradigm.

Methodological assumptions refer to the procedures and steps for learning and acquiring knowledge of the world and phenomena of nature. The methodological position will affect the decisions regarding data collection methods that are aligned with a predetermined methodology (Lincoln & Guba, 1994, p. 108).

Table 5: Matching resource purpose with methodology (Source: Voss et al., 2002)

Purpose	Research question	Research structure
Exploration Uncover areas for research and theory development	Is there something interesting enough to justify research?	In-depth case studies, Unfocused longitudinal field study
Theory Building Identify/describe key variables, Identify linkage between variables, Identify 'why' these relationships exist	What are the key variables? What are the patterns or linkages between variables? Why should these relationships exist?	Few focused case studies In-depth field studies Multi-site case studies Best-in-class case studies
Theory Testing Test the theories developed in the previous stages Predict future outcomes	Are the theories we have generated able to survive the test of empirical data? Did we get the behaviour predicted by the theory, or did we observe another unexpected behaviour?	Experiment Quasi-experiment Multiple case studies Large-scale sample of population
Theory extension/ refinement To better structure the theories in light of the observed results	How generalisable is the theory? Where does the theory apply?	Experiment Quasi-experiment Case studies Large-scale sample of the population

For matching resource's purpose with methodology, Voss et al. (2002) discussed the relationship between research purpose, questions and structure in the above **Table 5**:

The choice of a simulation study as the primary research methodology in this research can be justified in terms of Voss et al. (2002) framework, as presented in **Table 5**. This research aligns with the purpose of theory testing, where it tests previously developed inventory policy theories and predicts future outcomes. A simulation study serves as a potent tool to answer the research questions.

Bertrand & Fransoo (2002, p. 242) distinguish between quantitative models and other types of research in operations management with the following definition:

> Quantitative models are based on a set of variables that vary over a specific domain, while quantitative and causal relationships have been defined between these variables.

A simulation study shares structural similarities with experiments and quasi-experiments, facilitating the controlled manipulation of the variables to investigate their impact on outcomes. This approach enables the generation of large-scale data through numerous iterations, thereby enhancing the generalisability of the findings.

For theory testing, experiments and quasi-experiments with a large-scale population sample dominated the research structure as quantitative methods (Voss et al., 2002).

3.3 Justification of Choice of Paradigm

The former sections discussed the different research methodologies associated with primary research questions. This section discusses why simulation modelling is appropriate for answering these research questions. Firstly, the nature of this study should be reviewed before examining the specific data and using actual cases to set the modelling criteria.

Computer simulation is a favourable tool for businesses with performance issues; it provides automated experiments under different sets of parameters to minimise operating costs (Adegoke et al., 2012). This analytical situation fits the nature of quantitative research methods discussed by Buglear (2005, Chapter 12), Copper & Schindler (2014), and Dubios (2018). Copper and Schindler (2014) have also pointed out that simulation can replicate the business context under various situations with a represented mathematical model. Because this research environment requires simulated variation, simulation fits this study's purpose. Experimental simulations can establish cause-and-effect relationships under a researcher's control to become good problem-solving and decision-making tools (Sekaran & Bougie, 2016, p. 184). Dubois (2018) explained why simulation helps show unbiased or controlled analysis for rational decision-making processes. Buglear (2005, Chapter 12) suggests employing probability distributions to depict random processes, aiming to simulate the repercussions of variations. This approach aligns with the criteria of **RQ2** and **RQ3**, which delve into the outcomes generated by diverse models under fluctuating supply and demand levels.

Simulations for this research are tested using the data from three cases, chosen because they have different types of supply chains, and their characteristics match the research questions that look into what happens when supply and demand conditions change and how inventory policies (ROP, MTA DBM, and DDMRP) affect those changes. Each case represents different industry sectors—healthcare sensor devices, garments, and automotive components—allowing for a comprehensive analysis across diverse product types and operational environments. The variation in demand frequency, supply lead times, and the impact of new product introductions provide an ideal basis for examining how these inventory policies perform in stable and volatile market conditions. The study therefore uses real-life data from different industries to examine how inventory strategies change when demand and supply change. This approach directly answers RQ2 about performance outcomes and RQ3 about the factors that affect how well these policies work. These cases, with their contrasting supply chain dynamics, offer a robust and broad framework to respond to the research questions.

As a result of the above discussion, this research project is a comparative study of an operational nature. It aligns with realism at the ontological level, objectivism at the epistemological level, and quantitative at the methodological level. Quantitative modelling is also the basis of initial research for operations (Bertrand & Fransoo, 2002). Simulation is a predictive tool to forecast the system's behaviour, and there are two intrinsic benefits, as listed:

Intrinsic benefit 1: testing cheaper with more possibilities.
Intrinsic benefit 2: accumulate and improve knowledge.

(Dubios, 2018)

Based on the above-stated benefits, the simulation study provides several benefits:

1. Cheaper testing costs in different models without deploying the changes in the planning system.
2. Ability to test variable performance measurements among other models.
3. Attempt the variation without taking real risks.
4. Ability to perform multiple tests to give participants a deeper understanding of the system.
5. The simulation results could be accumulated and share knowledge effectively.

In summary, “the model is the crystallisation of the know-how of a team” (Manuel Tancrez, as cited in Dubios, 2018). Modelling with a simulation method is very effective in testing the performance outcomes between ROP, MTA DBM and DDMRP and therefore answering the research questions.

While the simulation method aligns well with our research questions, providing the required framework for comparative analysis, it is imperative to adhere to best practices for simulation to ensure the validity and reliability of the results. Therefore, the ensuing section will comprehensively explore various best-practice tactics for simulation research processes.

3.4 Simulation research processes with best practice

As mentioned above, this simulation study used actual Case data with different supply chain characteristics (**Table 1**) and simulated ROP, MTA DBM and DDMRP performance outcomes. The scope is that only materials and finished parts in the distribution-side supply chain are evaluated. Defining the objective function that comprehensively encapsulates our research ambitions' pivotal tenets in our exploration of supply chain simulations is imperative. Predominantly, our analytical focus hinges on two quintessential key performance indicators (KPIs): Return on Inventory (ROI) and Service Level by Revenue (SL). This section will describe the case study data used to model and test the simulations, followed by details about the simulated experimental scenarios simulated and the software used in this research.

It is worth noting that Law (2015) and Dubios (2018) provide insightful recommendations for enhancing the verification and validity of a research design, which proved valuable for the current simulation study.

3.4.1 Case Study Data

In this study, we simulated different supply chain scenarios using data derived from three distinct case studies. These cases, though anonymised for confidentiality, represent various industries with diverse supply chain complexities. Each case has unique demand patterns, supply lead times, and operational characteristics, making them suitable for testing and comparing different inventory policies: Reorder Point (ROP), Make-To-Availability with Dynamic Buffer Management (MTA DBM), and Demand-Driven Material Requirements Planning (DDMRP).

Case Selection and Data Sources

The data for these case studies is drawn from proprietary company datasets, which are agreed and provided by the case companies' top management. The data covers different periods and sectors, and each case reflects the operational realities of companies dealing with significant supply chain challenges. These cases have been selected due to their diversity in operational environments and ability to highlight the variability needed to examine the performance of the different inventory policies.

- **Case 1**: This case focuses on a company that manufactures healthcare sensor devices, distributing to both B2C and B2B networks in the USA and Europe. The data spans 2021 to 2023 and includes detailed information on sales orders, supply lead times, and stock movement. The company operates in an environment with low demand frequency and long, variable lead times (180 to 365 days). This case was chosen because its high supply variability offers a challenging scenario to test the resilience of inventory policies in managing long and unpredictable supply chains.

- **Case 2**: The second case comes from a garment factory that sources raw materials, specifically yarn, and operates a central automated warehouse in Bangladesh. The data covers operations from 2020 to 2022 and captures medium demand frequency with relatively stable supply lead times ranging from 65 to 90 days. The case was selected due to its moderate demand and low supply variability, allowing us to evaluate how inventory policies respond to fluctuating yet moderately predictable demand.

- **Case 3**: This involves an automotive assembly line that handles electronic components. The data spans from 2019 to 2022 and focuses on operations from a main warehouse in China. This case deals with high-frequency demand and lead times ranging from 60 to 150 days, coupled with both high demand and supply variability. This fast-paced environment presents an ideal setting to test how inventory policies can balance service levels with inventory costs when variability is at its peak.

The selection of these cases ensures that the study covers a broad spectrum of supply chain challenges. They provide variability across key dimensions such as:

- **Demand Patterns**: Low, medium, and high demand frequencies allow us to test how different policies perform regarding responsiveness and stock availability.
- **Supply Lead Time Stability**: With cases experiencing both stable and highly variable supply lead times, we can examine how inventory policies adjust to disruptions and supply chain uncertainties.
- **Industry Sectors**: The diversity in sectors—healthcare devices, garment manufacturing, and automotive electronics—enables us to generalize the findings to a broader range of industries.

These cases offer a rich dataset, allowing robust testing of the three inventory policies. Each case presents unique challenges that are relevant to our research questions:

- **RQ2**: The cases provide scenarios with varying demand levels and supply lead time stability, allowing us to assess how the performance outcomes of different inventory policies (ROP, MTA DBM, and DDMRP) compare in distribution-side supply chains.
- **RQ3**: The diverse nature of these cases also helps us identify the key influential factors and assumptions that underpin the selection and effectiveness of the inventory policies, such as demand predictability, supply variability, and operational constraints.

Data Collection for Simulation

The data used for this study was collected through historical inventory records and inventory management logs kept in one standardized data collection template from each case company. Researcher worked with those case companies directly in their supply chain projects to get the approval from their top management for using the data with signed agreement. For upcoming Simulation Experiments (SE) discussed in the next section, SE1 and SE2, actual company data—spanning demand patterns, order cycles, lead times, and inventory movement—was used to build the foundational simulation models. The data was extracted from case companies' systems and validated by cross-referencing with operational reports by case companies' management to ensure accuracy and relevance to the study's objectives.

For two of the simulations (SE3 and SE4), which will be further described in the section below), synthetic data sets were created to simulate more extreme variations in demand and supply scenarios. These data sets were generated based on ALX's built-in random generator parameters for demand variation with specific probability distribution and supply variation in transportation lead time. For example, SE3 represents an increased demand variation in different normal distributions to stress-test the policies. SE4, on the other hand, models scenarios with increased supply disruptions, mimicking potential challenges like transportation delays. This setup allows for the evaluation of how inventory policies adapt to more volatile and less predictable conditions.

By using real-life case data in two of the simulations (SE1 and SE2) and combining it with synthetic data in SE3 and SE4, this study provides a complete framework for checking the stability of various inventory policies in a wide range of supply chain scenarios. These data sets offer a nuanced approach to understanding how ROI and Service Level by Revenue (SL) vary depending on supply and demand conditions, ensuring that the research findings are generalisable and applicable to various industry contexts.

In conclusion, combining these cases enables a comprehensive analysis of how inventory policies operate under different real-world scenarios, ensuring the results are applicable to a wide range of industries and supply chain variables for simulation.

3.4.2 Simulation Software and Case Variables

This research project used a simulation tool called AnyLogistix (ALX) to generate simulated outcomes with different demand data sets for comparative study. ALX is a dynamic simulation tool that provides "what-if" scenarios, such as disruptive events in the supply chain, that can be modelled into the simulation. It also provides additional experimentation by applying planned steps to various parameters in simulation with comparison experiments. ALX offers end-to-end supply chain visualization to observe performance outcomes, validate models, and verify assumptions. In analytical optimisation, ALX does better than Excel-based simulation because it uses formula-based programming logic and flexibility with dynamic, non-linear equations (AnyLogistix, n.d.).

However, the predefined models in ALX do not include specific inventory policies like Make-To-Availability with Dynamic Buffer Management (MTA DBM) and Demand-Driven Material Requirements Planning (DDMRP). To integrate these inventory policies into the simulation, the author leveraged the **AnyLogistix Java Extension**, which allows custom models to be developed using Java code. By creating new MTA DBM and DDMRP models using Java Extension, the simulation tool was changed to work with these more advanced inventory strategies. This flexibility ensured they could be adequately tested in the simulation study. This capability allowed for greater flexibility and precision in analysing the supply chain performance under varying conditions, as predefined models alone would not have been sufficient for this research (AnyLogistix, n.d.).

In ALX with the Java Extension, the logical rules of Reorder Point (ROP), MTA DBM, and DDMRP are based on the conceptual framework presented in the previous chapter (Figure 15) and the independent variables listed as simulation parameters in **Table 6**.

Table 6 – Logical rules and examples of ROP, MTA DBM and DDMRP

Inventory Policy	Logical Rules/ Variables	Description	Example
Reorder Point (ROP)	1. Reorder Point (R) 2. Economic Order Quantity (EOQ) 3. Lead Time (LT) 4. Demand Forecast (D)	ROP triggers a replenishment order when inventory drops to a predetermined level (R). EOQ calculates optimal order quantity, and demand forecast determines replenishment frequency.	If the reorder point is set at 200 units, and the demand forecast is for 50 units per day with a lead time of 5 days, a new order is placed when inventory falls to 200 units.
Make-To-Availability (MTA DBM)	1. Buffer Size (BS) 2. Dynamic Buffer Adjustment (TMR and TMG) 3. Stock Availability (SA) 4. Order Spike Horizon (OSH) 5. Order Spike Threshold (OST)	MTA DBM relies on dynamically adjusted buffers based on consumption patterns. Buffer size is regularly updated based on Too Many Red (TMR) or Too Many Green (TMG) logic. When stock levels fall into the red zone (TMR), the buffer is increased. When stock levels remain in the green zone (TMG), the buffer is reduced.	If the stock falls into the red zone for an entire replenishment cycle, the buffer is increased by one-third to respond to the higher consumption rate. Conversely, if the stock remains in the green zone for too long (TMG), the buffer is reduced by one-third to avoid overstocking.
Demand-Driven MRP (DDMRP)	1. Net Flow Position (NFP) 2. Decoupling Points 3. Average Daily Usage (ADU) 4. Decoupled	DDMRP calculates replenishment orders based on actual consumption using the net flow equation. Decoupling points and buffer zones (red, yellow, green) are	If the net flow position (on-hand + on-order – qualified demand) drops below the top of the yellow zone, the system triggers replenishment to bring the buffer level back to the top

	Lead Time (DLT) 5. Buffer Zones (Red, Yellow, Green)	established to protect inventory from variability in lead times and demand.	of the green zone, ensuring optimal stock availability.

This computer simulation eliminates human intervention and adheres strictly to standard inventory policies' replenishment logic, ensuring consistency and reliability in different experiential scenarios for analysis.

3.4.3 Experimental Scenarios

Five experimental scenarios are compared within this research using the simulation software ALX. Each scenario (SE0-SE4), presented in the following **Table 7** represents a distinct simulation experiment designed to test different supply and demand variability combinations, along with inventory policies such as ROP, MTA with DBM, and DDMRP. These simulations aim to assess the performance of each policy under varied conditions, focusing on the key performance indicators (KPIs) like Return on Inventory (ROI) and Service Level (SL).

The development of the simulation scenarios SE0 to SE4 is based on insights from the literature review in Chapter 2, which discusses inventory policies and their influence on supply chain performance. Each scenario is designed to test specific aspects of inventory policies. This section provides a clear explanation and justification for each scenario, informed by relevant theoretical findings.

Scenario SE0 focuses on optimising the planning parameters for each inventory policy using the variation experiments in AnyLogistix (ALX) simulation tool. By varying parameters such as buffer sizes, replenishment quantities and safety stock levels, the goal is to identify the planning parameters that maximise Service Level by Revenue (SL) and Return on Inventory (ROI). According to Law (2015) and Dubois (2018), parameter optimisation is critical in balancing cost efficiency and service quality. This scenario aligns with the best practices outlined by Voss et al. (2002), who suggest that simulation is an effective tool for identifying optimal inventory settings. SE0 provides a baseline for evaluating the performance of ROP, MTA DBM, and DDMRP by ensuring that variation experiments test each policy to select optimised parameters before comparison experiments in SE1 to SE4.

Scenario SE1 compares the performance of ROP, MTA DBM, and DDMRP using identical demand data in each case. The purpose is to determine which policy performs best under the same demand patterns, particularly regarding SL and ROI. Findings from Fitzgerald and Howcroft (1998) emphasise the importance of comparative analysis in understanding the trade-offs inherent in different inventory policies. This scenario reflects the literature's argument that each policy has unique strengths, with ROP offering stability in predictable environments and DDMRP excelling in more dynamic conditions. SE1 seeks to empirically validate these theoretical positions by examining how each policy maintains performance under the same demand patterns.

Scenario SE2 evaluates the same inventory policies across different case industries and supply chain environments to assess their performance outcomes. As discussed in Chapter 2.4, Influential Factors with Performance, industry-specific factors, such as demand patterns and supply lead times, play a significant role in determining the success of an inventory policy (Buglear, 2005). Including cases from healthcare devices, garments, and automotive components in SE2 allows one to explore how each policy performs in diverse operational contexts. Philips (1987) notes that generalisability across industries is essential for assessing an inventory policy's broader applicability, and SE2 directly addresses this by testing the policies in varying supply chain conditions.

Scenario SE3 explores the effect of demand variation (DV) on the performance of ROP, MTA DBM, and DDMRP. Dubois (2028) identifies demand variability as a critical challenge for inventory management, with policies like DDMRP being designed to handle high levels of demand fluctuation. In contrast, ROP may be less effective in managing unpredictable demand, as it relies heavily on stable conditions (Fitzgerald & Howcroft, 1998). SE3 simulates different levels of demand variation to test these theoretical expectations, providing insight into how resilient each policy is when demand becomes erratic.

Scenario SE4 tests how each inventory policy handles supply variation (SV), particularly with transportation lead time changes as supply disruptions. Supply chain resilience is crucial in maintaining service levels during periods of uncertainty (Adegoke et al.,2012), Sekaran and Bougie, 2016). Due to their dynamic buffer management mechanisms, MTA DBM and DDMRP are expected to perform strongly under these conditions. This scenario examines how these policies can maintain optimal inventory levels when faced with supply chain disruptions. SE4, therefore, addresses a critical aspect of supply chain management —adaptability to supply variability—and provides empirical evidence to support or challenge the theoretical claims regarding each policy's robustness.

In summary, the development of SE0 through SE4 is informed by critical findings from the literature on inventory management, particularly concerning how different policies perform under varying demand and supply conditions. Each scenario tests specific aspects of ROP, MTA DBM, and DDMRP, ensuring a comprehensive analysis of their performance across different supply chain environments. These scenarios serve as a foundation for answering the research questions by providing a structured approach to evaluating each policy's effectiveness.

The following outlines how the specific objectives of each simulation experiment group (SE0 to SE4) align with the simulation scenarios and their performance results, ensuring consistency in addressing the research questions. Using the selected parameters and key performance indicators (ROI and SL) is integral to achieving these objectives.

The primary objective of SE0 is to establish a foundational understanding of how different planning parameters impact the performance of the three inventory policies. This scenario involves varying key parameters such as buffer sizes, reorder points, and lead times using multivariate analysis to identify the combinations that maximise ROI and SL. The goal is to optimise the planning parameters for each policy, creating a baseline from which all subsequent simulations will derive.

The objective function designed specifically for the **SE0** scenario in our simulation experiment is:

Objective:
Maximise *F(x)*
Where *F(x)* = {*f1*(x), *f2*(x)}

Subject to:

Let x ∈ X: X belongs to the feasible set X

- *f1*(x) = Return on Inventory (ROI)
- *f2*(x) = Service Level by Revenue (SL)

The ***f1*** represents the ROI, denoted as the revenue ratio to the ending inventory balance, and ***f2*** symbolises the Service Level by Revenue. Seamlessly deploying this consistent and robust function across the various scenarios for **SE0** will ensure that our investigation remains inherently focused on evaluating these paramount KPIs, irrespective of the distinctive characteristics of each scenario, for fair comparison in **SE1** to **SE4**. By systematically testing different configurations, SE0 ensures that future comparisons across cases and policies will be based on each inventory model's most effective parameter settings. This initial experiment is critical for providing the groundwork for further exploration in SE1 to SE4.

By conducting multivariate analysis to be discussed in next Chapter, SE0 aims to establish a **baseline** that defines the best-performing parameters across various simulations, ensuring that future experiments (SE1 to SE4) have a consistent basis for comparison.

SE1 uses the same demand patterns and supply data to evaluate each inventory policy's performance under the same case scenario. The primary goal is to compare the simulated performance of ROP, MTA DBM, and DDMRP within a single operational environment. This approach allows direct comparisons of the policies' effectiveness in achieving high ROI and SL under identical conditions. The objective is to determine which policy provides the most efficient and responsive solution for managing the supply chain, helping to address RQ2 by highlighting how different policies impact performance within a specific case. This experiment establishes a clear understanding of the strengths and weaknesses of each policy in a controlled, real-world context.

In SE2, the focus shifts to testing the performance of a single inventory policy across multiple case studies. The objective is to assess how consistently ROP, MTA DBM, or DDMRP performs across different operational environments, each with unique supply chain characteristics. By using the same policy across various cases, SE2 provides insights into the generalisability and adaptability of the policy to diverse conditions, such as different industries, demand profiles, and lead times. This experiment is crucial for addressing RQ2 by exploring whether the policy's effectiveness varies depending on the context or whether it maintains consistent performance across different scenarios.

SE3 introduces demand variability into the simulation to evaluate how demand fluctuations impact each inventory policy's performance. The objective is to determine how resilient ROP, MTA DBM, and DDMRP are to changes in demand levels and how these changes influence ROI and SL. By simulating different degrees of demand variation, SE3 explores each policy's ability to maintain optimal performance under dynamic and unpredictable market conditions. This experiment contributes to answering RQ3, which focuses on understanding the external factors—such as demand variation—that influence the effectiveness of inventory management strategies.

The objective of SE4 is to examine how variations in supply lead times, specifically in transportation, affect the performance of the inventory policies. Supply-side variability can significantly impact inventory management, and SE4 seeks to evaluate how well ROP, MTA DBM, and DDMRP handle such uncertainties. The simulation tests how each policy adapts to unpredictable lead times and supply disruptions, assessing their ability to mitigate risks while maintaining high ROI and SL. This scenario is critical for addressing RQ3, as it highlights how supply variation influences the robustness of inventory strategies in real-world supply chains.

Table 7 below illustrates the five simulation experiment scenario groups and their respective performance result sets for comparison and analysis.

Table 7 - Simulation experiments scenarios vs. performance result set for **RQ2**

Simulation Experiment Groups (SE)	Scenarios	Performance Result Sets
SE0	Varied planning parameters in ALX to identify maximum service level by revenue and return on inventory ending balance ratio	Case1.ROP.VarExp, Case1.MTA.VarExp, Case1.DDMRP.VarExp, Case2.ROP.VarExp, Case2.MTA.VarExp, Case2.DDMRP.VarExp, Case3.ROP.VarExp, Case3.MTA.VarExp, Case3.DDMRP.VarExp
SE1	Compared performance outcomes of different inventory policies with each cases' demands	Case1.actual, Case1.ROP.Best, Case1.MTA.Best, Case1.DDMRP.Best, Case2.actual, Case2.ROP.Best, Case2.MTA.Best, Case2.DDMRP.Best, Case3.actual, Case3.ROP.Best, Case3.MTA.Best, Case3.DDMRP.Best
SE2	Compared performance outcomes of the same policy across different cases' demands	Case1.actual, Case1.ROP.Best, Case1.MTA.Best, Case1.DDMRP.Best, Case2.actual,

		Case2.ROP.Best, Case2.MTA.Best, Case2.DDMRP.Best, Case3.actual, Case3.ROP.Best, Case3.MTA.Best, Case3.DDMRP.Best
SE3	Compared inventory policies with different demand variation levels	Case1.ROP.DV, Case1.MTA.DV, Case1.DDMRP.DV, Case2.ROP.DV, Case2.MTA.DV, Case2.DDMRP.DV Case3.ROP.DV, Case3.MTA.DV, Case3.DDMRP.DV
SE4	Compared inventory policies with different supply variation levels	Case1.ROP.SV, Case1.MTA.SV, Case1.DDMRP.SV, Case2.ROP.SV, Case2.MTA.SV, Case2.DDMRP.SV, Case3.ROP.SV, Case3.MTA.SV, Case3.DDMRP.SV

Summary of Objectives:

- **SE0**: Identifies optimal planning parameters through variation experiments by ALX, presented in scatter plot by Zoho Analytics and generated in multivariate analysis by JMP, setting the baseline for comparison in future scenarios.

- **SE1**: Compares the performance of different inventory policies within the same case, evaluating how each policy manages supply chain replenishment under demand patterns.

- **SE2**: This test, which assesses the performance of a single inventory policy in different supply chain environments, tests its consistency across multiple cases.

- **SE3**: This section focuses on the impact of demand variation on policy performance, examining how each policy responds to fluctuating demand conditions.

- **SE4**: Evaluate how supply variation, particularly in transportation lead times, affects the effectiveness of each inventory policy.

This analysis utilises a systematic methodology that integrates cross-case and within-case evaluations to examine the effects of various inventory practices across simulated scenarios. By executing within-case analysis in SE1 and SE2, we may assess the effectiveness of each inventory policy in different circumstances and scenarios, enabling us to examine policy performance under specific demand and supply conditions. The cross-case analysis in SE3 and SE4 facilitates the comparison of results across many situations to identify how policies adjust to fluctuating factors, such as changes in demand and supply. This dual method thoroughly comprehends each inventory policy's advantages, drawbacks, and flexibility in dynamic supply chain contexts.

3.4.4 A note on the main KPIs

The justification for selecting **Return on Inventory (ROI)** and **Service Level by Revenue (SL)** as the key performance indicators (KPIs) for this simulation study is drawn directly from the theoretical insights and practical considerations highlighted in the literature review, particularly within the scope of inventory management and supply chain performance metrics.

Return on Inventory (ROI) is a fundamental financial metric widely used in supply chain management to evaluate the efficiency and profitability of inventory investments. As the literature references (Dubois, 2018; Buglear, 2005), **ROI is crucial for businesses aiming to optimise their inventory levels** while maintaining operational efficiency. The literature underscores the importance of inventory management strategies that can maximise inventory profitability without overstocking or understocking, negatively impacting ROI.

ROI reflects the balance between inventory holding costs and revenue generation, making it a vital metric in assessing the effectiveness of different inventory policies. **The selection of ROI aligns with the broader literature that emphasises cost-efficiency and profitability in supply chain management.** The study is based on ROI to capture the financial implications of each inventory policy (ROP, MTA DBM, DDMRP) and their capacity to balance inventory levels and profitability, which is central to the research objective.

Service Level by Revenue (SL) measures a supply chain's ability to meet customer demand without stockouts, which is directly tied to customer satisfaction and revenue generation. The literature, particularly studies like those of Voss et al. (2002) and Bertrand & Fransoo (2002), highlights **the growing importance of service levels as a non-financial KPI that directly affects supply chain competitiveness.**

SL reflects how well inventory policies can respond to fluctuations in demand, ensuring that products are available when customers need them. In the context of this study, where demand and supply variation are critical factors (as outlined in the literature review, sections 2.2 and 2.3), SL clearly measures how resilient and responsive the different policies are to changes in supply chain conditions. **SL complements ROI by focusing on the operational effectiveness of inventory strategies**, ensuring that financial gains do not come at the expense of service quality.

The literature review discusses **forecast-based inventory planning** (section 2.2) and **consumption-based inventory planning** (section 2.3) as two approaches that aim to balance cost-efficiency with customer satisfaction. ROI and SL are the natural extensions of these approaches. **ROI measures financial efficiency,** while **SL measures operational effectiveness and customer responsiveness**—both central themes in inventory management theory.

Furthermore, the dynamics between inventory policies and performance measurement (section 2.4) emphasise assessing financial and non-financial KPIs to gain a holistic view of supply chain performance. As per the relevant literature, ROI and SL provide this dual perspective, ensuring the study captures both profitability and customer service.

Thus, the selection of ROI and SL as the primary KPIs is strongly justified based on their alignment with established research in supply chain management and their ability to address both the financial and operational aspects of the research questions (RQ2 and RQ3).

By systematically structuring these simulation experiments, the research ensures that the key performance indicators (ROI and SL) are consistently evaluated across a range of conditions. This allows for a comprehensive analysis of the inventory policies' strengths and weaknesses by the following software tools.

3.4.5 Data Analysis, Visualisation, and Reporting Tools

This research employs JMP statistical software and Zoho Analytics for comprehensive data analysis, visualisation, and reporting. These tools are utilised to investigate how supply variation (SV), demand variation (DV), and inventory policies such as ROP, MTA DBM, and DDMRP impact key performance indicators (KPIs) such as Return on Inventory (ROI) and Service Level by Revenue (SL).

JMP Statistical Software

JMP statistical software effectively conducts multivariate analyses, making it particularly appropriate for this study. Multivariate analysis facilitates the examination of correlations among several independent factors (e.g., reorder level (Q), replenishment amount (R), and other buffer parameters) and their combined effect on dependent variables such as ROI and SL. This study utilises multivariate analysis to analyse the inter-relationship between independent variables and dependent variables related to the performance outcomes (JMP Help, n.d.).

The assessed multivariate model's independent variables encompass supply and demand fluctuations (SV and DV), policy-specific characteristics like reorder points, buffer sizes, lead time factors, and variability factors such as market conditions or transportation delays. The dependent variables are the performance metrics: ROI, which assesses financial efficiency, and SL, which gauges customer service levels concerning inventory availability. These models vary by scenario based on the inventory policy under examination (ROP, MTA DBM, or DDMRP) and the specific data pertinent to each case.

The purpose of using JMP in this study is to evaluate the statistical significance of each independent variable. The analysis will help us identify the factors that have the most significant impact on supply chain performance under different combinations of independent variables and various planning policies.

Furthermore, the prediction profiler function of JMP is essential for enhancing the research findings for further research. By modifying crucial parameters in the prediction models, the analysis can ascertain how minor alterations in independent factors influence overall performance, thereby comprehensively comparing dependent variables among many scenarios. JMP's extensive reporting capabilities, including full regression models, correlation matrices, and interactive visualisations, guarantee that the results are statistically validated and prepared for thorough academic and practical examination. The output generated by JMP, encompassing specific regression and correlation data, is shown in Appendix C.

Zoho Analytics

Zoho Analytics enhances JMP by offering sophisticated visualisation and business-centric reporting capabilities crucial for presenting intricate statistics more understandably and engagingly. JMP specialises in statistical analysis and model-fitting, whereas Zoho Analytics provides dynamic charting outputs that enable a more precise comparison of performance measures across various scenarios and policies. The document primarily imports ALX's experimental variation data for scatter plots to identify optimum planning factors that yield the maximum ROI and SL, as detailed in Appendix B.

This study utilises Zoho Analytics to combine extensive datasets produced by the simulations and visually contrast the outcomes. JMP specialises in clarifying complex statistical outcomes, including regression coefficients and correlations. Conversely, Zoho Analytics provides interactive dashboards that facilitate tracking performance across several variables and cases throughout the period. For instance, Zoho's real-time charting capabilities may clearly illustrate the fluctuations in ROI and SL across various inventory policies (ROP, MTA DBM, DDMRP) with differing demand and supply variability levels.

The key benefit of Zoho Analytics is providing online collaborative data analysis. This functionality facilitates online sharing of dashboards and visual reports to stakeholders. This function is beneficial in an academic context to allow multiple participants for sharing information and validating outcomes. Zoho's role in the analysis is to condense complex data into visual summaries, enhancing the presentation of results in this study. Therefore, the case companies' stakeholders can easily review and validate the simulated performance outcomes in online dashboard.

JMP is strong in the development and validation of regression models, while Zoho Analytics enables the lucid and persuasive display of data, rendering the study's conclusions comprehensible to both academic and business audiences. By applying both software tools, it provides a robust foundation for accurately communicating the results of the simulation results, ensuring that the insights generated are both rigorous and practical.

The research method employs a cross-case analysis of data from three actual businesses to comprehensively evaluate different inventory techniques across different case contexts. To generate relevant, robust, and valuable data, it is essential to align the utilisation of contemporary analytical tools like JMP and Zoho Analytics with recognised best practices in simulation research. The following section will look at the critical elements of reliability, validity, and reproducibility that are needed for a high-quality simulation study. By adhering to established standards and methodologies, the research guarantees that the simulation models provide accurate results and endure thorough scrutiny, thereby validating the findings' trustworthiness and importance in both scholarly and practical contexts.

3.5 Best practice for a simulation study

To evaluate the quality of social research, Bryman (2015) identified three critical criteria: reliability, validity, and replication. Reliability requires a consistent measure of the conceptual model (CM) with stability, internal reliability, and inter-observer consistency. Validity refers to using the correct measurement for the conceptual model, established through face, concurrent, predictive, construct, and convergent validity. Lastly, replication ensures the reliability of research to achieve the quality of quantitative analysis (Bryman, 2015, chapter 7).

In the realm of simulation modelling, robustness and credibility remain paramount. Pace (2004) identified seven pivotal challenges related to verification and validation, emphasising the need to establish modelling and simulation as trustworthy designs.

Verification is a tool to confirm that the simulation model meets the research's design and implementation parameters. Supplementing this perspective, Law (2015) offered four essential techniques for model verification from a software engineering standpoint:

1. Develop Incrementally: Begin with basic structures and progressively advance to more complex configurations.
2. Invite Multiple Reviews: Multiple experts should scrutinise the model to ensure comprehensive evaluation and reduce biases.
3. Test Broadly: Subject the model to diverse input parameters, assessing the output's reliability across different conditions.
4. Trace Actively: Model developers must interactively monitor the system, immediately detecting inconsistencies or issues.

On the other hand, validation assesses if the simulation model fulfils the anticipated conceptual and result-based requirements. **Table 8** provides a summary of the verification and validation challenges highlighted by Pace (2004).

Table 8 - Seven challenges reviewed by Pace (2004)

No.	Challenges
1	Qualitative Assessment
2	Use of Formal Assessment Processes
3	Modelling and Simulation/Verification &Validation Costs/Resources (Accounting, Estimation, Benefit)
4	Inference
5	Coping with Adaptation
6	Aggregation
7	Human Involvement/Representation

In addition to the above seven challenges, Osborne (2008) suggested best practices for handling data cleaning of outliers and missing data. There are different data errors: outliers from humans, misreported sampling, standardisation failure, faulty distributional, and legitimate cases sampled from the correct population. Osborne argued that removing outliers enhanced the accuracy of estimates and reduced the inference, as stated in the above challenges 4. On the other hand, Osborne proposed Maximum Likelihood (ML) and Multiple Imputation (MI) methods with sensitivity analyses to handle missing data (Osborne, 2008, Chapter 15). With a quality level of standardisation, simulation should begin with clearly written participant objectives before the experiment (Lioce, Reed, Lemon et al., 2013). Dubois (2018, Chapter 4.3) extended the standard with eight technical best practices in connection with the simulation steps in the following **Table 9**, that is presented and expanded upon in the following section.

The following section explains how the simulation study research procedures followed different ways of verification and validation for improving research reliability according to those best practices.

3.5.1 Ensuring reliability and validity in the simulation study

The following section delves into the meticulous steps involved in ensuring the research credibility of the simulation study, focusing on reliability and various aspects of validity, such as the face, predictive, and structural validity.

Reliability speaks to the consistency and reproducibility of the simulation results. Using the ALX simulator's variation analysis with a replication option, the simulator can generate the results by several runs with different parameters for comparative analysis, which affirms the reliability of our model. Moreover, this replication technique in the independent runs (Law, 2015) enhanced the stability of our model's outcomes across different experiments.

Validity refers to how well the simulation model represents the real-world situation. The simulation study deployed several measures for this purpose. Firstly, the simulation data providers from the three companies (refer to **Table 1**) reviewed our model to examine the reasonable and accurate representation of their existing stock replenishment context according to the supply chain network diagram (refer to **Figures 19, 20 and 21** in Section 4.4.3). Secondly, the simulation experiments compared companies' stock performance in the same simulation period to assess how well our model predicted real-world outcomes. Lastly, the intensive testing plan with debugging logs (refer to **Appendix D**) shows our model's cross-checked logical, mathematical, and causal relationship under our inventory policies in the simulation study. This exercise validated our model's structure and mirrored real-world dynamics but did not reflect subjective human intervention.

In summary, ensuring the reliability and validity of the simulation study requires meticulous adherence to best practices, as Law (2015) and Dubois (2018) proposed. These rigorous steps, encompassing aspects of verification and validity, lay the groundwork for a robust research design. With the foundation of reliability and validity established, the following section (3.5) will expand on the simulation research processes themselves, delving into the specific tactics and best practices that further support the credibility and integrity of the study.

Table 9 - Connection between the phases of simulation, the technical best practices (Dubios, 2018) and related data interactions

Simulation phases	Technical best practices	Data Interactions
A/ Defining the aim of the simulation study	BP1. Defining the objective	Revising the RQs to ensure they align with research objectives
B/ Building the mathematical/ physical problem	BP2. Including sufficient and necessary physical phenomena BP3. Converting into equation	Building the conceptual model to define simulation data structure and relationships for validation (**Figure 15**)
C/ Converting the model into a numerical model	BP4. Picking the software BP5. Managing the numerical and IT issues	Exporting AnyLogistix (ALX) simulated data into JMP and Zoho Analytics for further analysis
D/ Producing and delivering results	BP6. Managing the validity level of the results BP7. Producing useful results	Running the ALX simulation with Java extension, debugging the code, and generating the expected output
E/ Storing the model and its results	BP8. Maintaining and storing the models	Generating scatter plots, charts in Zoho Analytics and conducting multivariate analysis in JMP using ALX simulated data output

The alignment between the simulation phases and the best practices proposed by Dubois (2018) is illustrated in the above table, which demonstrates the connection between each phase of the simulation and the corresponding best practice that was implemented to enhance robustness and validity.

3.5.2 Design Flow and Research Phases

The following **Figure 16** shows a logical sequence of overall simulation research processes with feedback validation and verification to respond to the research questions according to the five phases and eight best practices:

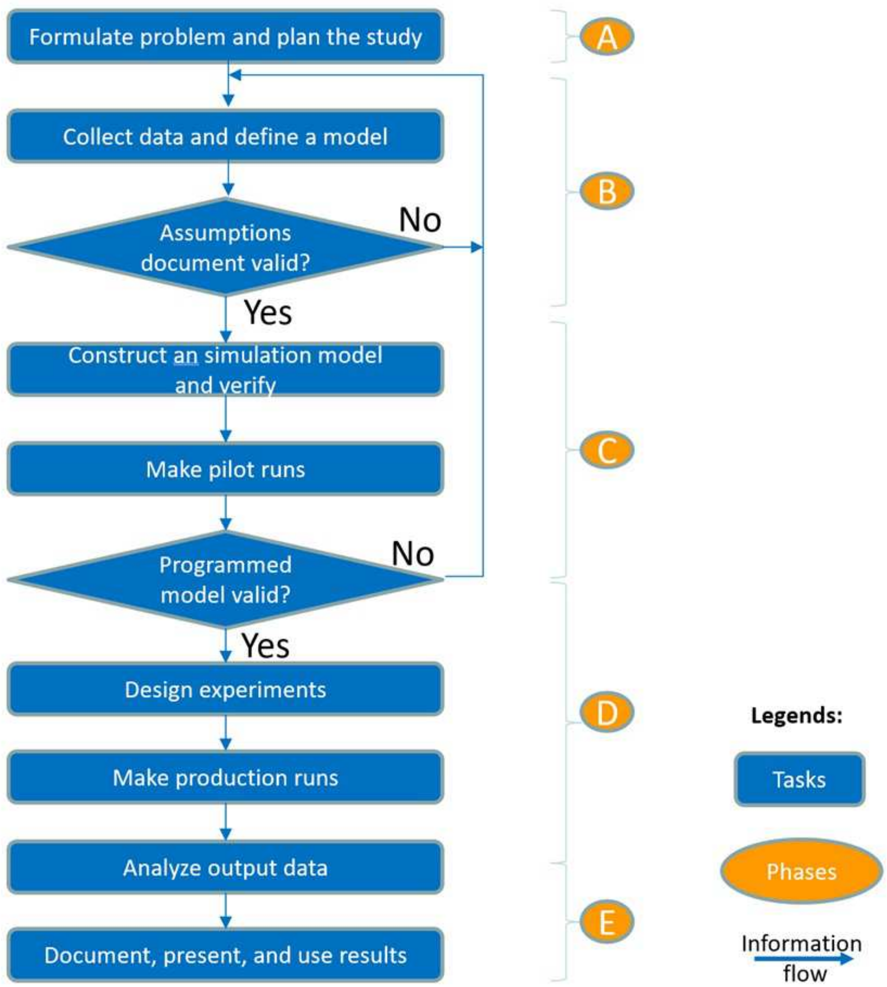


Figure 16 - Logical sequence with tasks and phases for simulation study (Law, 2015, page 67)

The research design consists of five phases. Phase (A) clearly defined the simulation objectives in RQs. Phase (B) built the conceptual model. Phase (C) translated the conceptual model into a numerical one-Phase (D) generated and delivered the results. Phase (E) stored the model for comparison in subsequent analysis and discussion under chapters 4 and 5.

Adopting the eight best practices proposed by Dubois (2018) enhanced the simulation study's robustness and validity. Each BP was aligned with a specific phase.

Phase A involved defining the aim of the simulation study. This phase focused on formulating the problem and planning the study by clearly articulating the research questions (RQs) and objectives. In alignment with BP1 (Defining the Objective), the goals of investigating inventory policies—Reorder Point (ROP), Make-To-Availability with Dynamic Buffer Management (MTA DBM), and Demand-Driven Material Requirements Planning (DDMRP)—and their impact on supply chain performance were established. This phase also gathered a comprehensive understanding of the actual cases' supply chain scenarios and the key variables, including supply variation (SV) and demand variation (DV), to ensure that the study objectives were well-suited to real-world challenges. This approach directly addressed Challenge 1 (Qualitative Assessment), as Pace (2004) identified, ensuring that the study's goals were clearly defined, and that subsequent model development and experimentation efforts were well-guided.

Phase B focused on building the conceptual model, which was underpinned by the data collected and the critical assumptions associated with the supply chain dynamics. This phase adhered to BP2 (Including Sufficient and Necessary Physical Phenomena), ensuring that the model incorporated all relevant components, such as Order level (Q), Fixed replenishment point (R), Safety Stock (SS), Initial Buffer Size (IBS), Too Many Green (TMG), Too Many Red (TMR), Lead Time Factor (LTF), Variability Factor (VF), Spike Threshold Horizon (STH) and Spike Threshold % (STP), while avoiding unnecessary complexity. Following this, BP3 (Converting into Equations) was applied to translate the conceptual framework (Figure 15) into relationships and data flow diagrams in Figure 17, providing a solid foundation for comparative simulation study. This phase was instrumental in addressing Challenge 5 (Coping with Adaptation) by iteratively validating the model's assumptions. This process ensured that the numerical model could adapt effectively to various supply chain scenarios while accurately representing the intended reality.

Phase C involved converting the conceptual model into a numerical model, which was facilitated using AnyLogistix (ALX) simulation software. By BP4 (Picking the Software), ALX was selected for its capacity to simulate complex inventory dynamics and to meet the study's requirements for comparative analysis of inventory policies. Subsequently, BP5 (Managing the Numerical and IT Issues) was employed to configure the model accurately, involving the development of a customised Java extension for ALX to implement advanced inventory policies, specifically MTA DBM and DDMRP, which were not natively supported by the software. This phase effectively addressed Challenge 3 (Modelling and Simulation Costs/Resources) by ensuring that available resources were optimally managed and that the selected software and custom extensions were used effectively to handle model complexities, ultimately enabling successful implementation.

Phase D concentrated on producing and delivering the results of the simulation. In this phase, BP6 (Managing the Validity Level of the Results) was crucial in verifying the model's validity. This method involved conducting pilot simulations, debugging the model, and ensuring that it accurately adhered to the defined inventory policies' logic. The iterative process continued until all outcomes were validated, demonstrating adherence to best practices. Additionally, BP7 (Producing Useful Results) guided the subsequent process of designing production runs and analysing the output data, ensuring that the results generated were meaningful and directly aligned with the research objectives. This phase addressed Challenge 4 (Inference) and Challenge 7 (Human Involvement / Representation) by ensuring that the simulation outcomes represented actual decision-making processes in inventory management, enhancing the quality and reliability of the inferences drawn.

Phase E focused on storing the model and its results, ensuring the documentation and presentation of findings for further analysis and discussion in subsequent chapters. This phase adhered to BP8 (Maintaining and Storing the Models) by systematically storing all simulated results within JMP and Zoho Analytics, which allowed for comprehensive data visualisation and analysis. The models' documentation and outputs provided a robust repository for subsequent comparative analysis across different scenarios, thereby addressing Challenge 6 (Aggregation) by ensuring that results were systematically archived for future reference and synthesis.

The connection between the simulation workflow and best practice is therefore ensured. For instance, BP1 defined the RQs as study objectives for simulation, while BP2 validated assumptions and confirmed the conceptual model in **Figure 15**. BP3 converted the conceptual model into equations, formulae, or data flow interrelationships. BP4 selected the AnyLogistix (ALX) as a simulation tool. BP5 configured the model correctly by developing a customised Java extension for ALX's MTA DBM and DDMRP inventory policies.

This process used different input parameters to verify the models for various experiments. It was an iterative process to debug the Java programming with the ALX extension module until all formula logic was validated. The BP6 managed to ensure the validity level of the results in the following simulation structural context diagram in **Figure 17**:

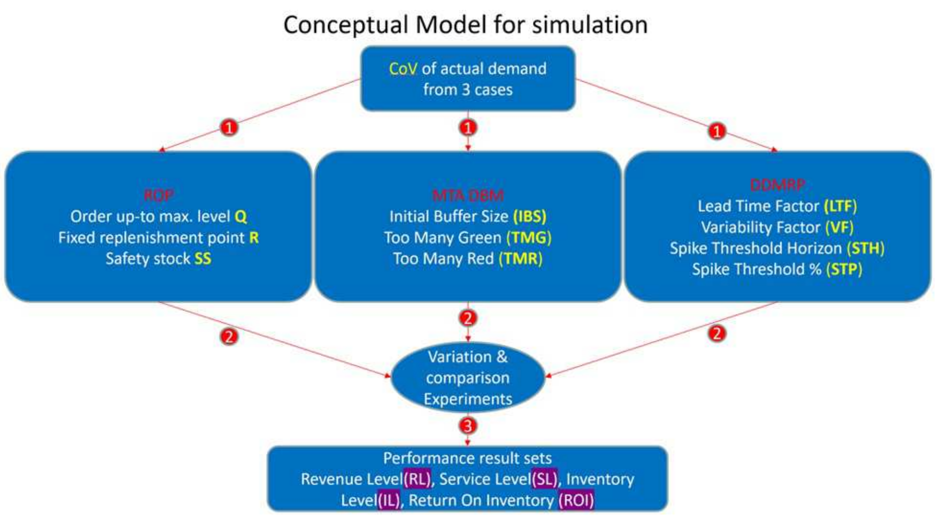


Figure 17 – Conceptual Model for simulation data structure and relationship for validation

Key participants, including the case data providers and the researcher, reviewed all logic in the data structure and simulated results according to the red connections numbered in **Figure 17**. This review involved the following validation steps:

1. Verifying the Coefficient of Variation (CoV) from the three actual cases' demand data.
2. Confirming the accurate output of the ROP, MTA DBM, and DDMRP model by the policy parameters with simulated performance results.
3. Checking the various performance results set with different variations of policy parameters for comparison.

The **BP7** organized the numerical results systemically presented by the statistical tools JMP and Zoho Analytics with insightful analysis. The independent variables (**yellow**) are stated in **Figure 17** to show their relationship and impact on the performance result sets. The Chapter 4 simulation analysis will focus on the actual and simulated key performance measures stated in **Table 10** in each of the experiments - **SE1, SE2, SE3**, and **SE4**.

Table 10 - Performance result sets for comparison under different experiments

Figures cross-reference in Appendix A	**Key Performance Index Short codes**	**Performance measures in charts**
A1	RL	Revenue Level
A2	IL	Inventory Level
A3	SL	Services Level by Revenue
A4	ROI	Return On Stock Balance or Cost of Goods Sold (COGS)

Building on performance outcomes from the real-life cases listed in section 3.4.1 with the ALX simulator, the subsequent chapters provide a thorough analysis and discussion of these findings. A fundamental underlying assumption in this study is the complete delivery of any back-ordered items. The results are systematically arranged, setting the stage for a detailed examination in Chapters 4 and 5. However, first, addressing a crucial caveat becomes necessary. Modifying the ALX simulator to align with specific policies, particularly MTA DBM and DDMRP, presented challenges. These challenges will be detailed in the following sections.

3.6 Obstacles and Limitations of a simulation study

3.6.1 Introduction to the obstacles and limitations

Before utilising the simulator ALX to generate the expected outcomes, it required enhancement to incorporate the logic of the MTA DBM and DDMRP policies, which are vital to exploring and comparing more updated policies. However, the standard ALX package only supports the traditional ROP policy. Subcontracting a programmer to develop the Java programming logic in ALX additionally introduces several challenges. During this software development process, for instance, technical limitations emerged, leading to data-related obstacles and methodological challenges that have significant implications for the reliability and validity of the simulation study. These challenges are explored in detail in the following sections in connection with the specific research context

3.6.2 Specific Obstacles in the Study

In developing new plug-in policy components for ALX, specific obstacles emerged that challenged the study's execution. The first obstacle was the complexity of understanding and implementing the buffer management logic of MTA DBM and DDMRP. This understanding was crucial for the subcontracted programmer, and achieving it took lengthy iterative processes in BP1 to BP5 (refer to Figure 16), fraught with miscommunication and bugs.

A sudden personnel change further complicated matters. The original programmer caught Covid-19 and left the software company, leaving behind partially completed Java source code. This incomplete coding posed significant challenges in completing the project.

In addition to these issues, the internal ALX database structure had to be adjusted to produce the expected analytical outputs. Customised logic was developed to make reporting data in an external database, introducing inconsistency between the ALX and external databases. Synchronising data across both databases proved difficult.

These specific obstacles had potential implications for the validity and reliability of the simulation study, as they introduced uncertainties in the data integrity and software implementation. Strategies for overcoming these challenges are discussed in subsequent sections.

3.6.3 Mitigation Strategies

Implementing focused mitigation strategies was necessary to address the challenges in developing the ALX extension. A pressing concern emerged from a subcontracted programmer's unexpected departure, leaving the software development incomplete and Java coding abandoned. Consequently, the researcher assumed responsibility for all programming tasks. Despite being unfamiliar with Java, the researcher dedicated five months to learning the language and correcting the existing code. Remarkably, this strategy yielded significant benefits, not only completing the required coding but also eliminating potential miscommunication and notably reducing debugging cycle time. However, this approach necessitated an extension of the research project's timeline.

Another considerable challenge was synchronising the ALX database with an external one. The researcher implemented corrective measures to modify the anticipated outcomes to align with ALX's outputs, negating the need for an external database. Maintaining the external database was essential for supplying secondary data for cross-verification and specific reporting requirements.

These mitigation strategies were pivotal in safeguarding the validity and reliability of the simulation study and underscored the importance of adaptability and problem-solving throughout the research process.

3.6.4 Limitations of a simulation study

Dubois (2018) identified two prominent limitations to simulation that must be acknowledged in the context of this research. The first limitation pertains to the preciseness of simulations. Simulations can only represent a partial reality, often necessitating simplification. This inherent constraint means that simulations may only partially capture the complexity and nuances of real-world phenomena. Aware of this limitation, this study compared three actual case data in parallel with simulated results, as Law (2015) has recommended enhancing the trust level for comparison.

The second limitation is concerned with the technical workability of simulations. Various constraints may arise, such as limitations in storage size and the speed of calculation, depending on the computer's capabilities. Moreover, the effectiveness of the simulation is inherently tied to the model designer's technical knowledge and ability to construct an appropriate simulation context. This study utilised the simulation tool "AnyLogistix", following pre-defined programming logic based on known factors and parameters. It is important to note that this simulation study did not account for unexpected events, such as a pandemic disruption, but it is possible for future research.

The highlighted limitations reveal the inherent challenges and restrictions when solely on simulations. This underlines the importance of meticulous design, validation, and analysis of simulation outcomes. Adopting an action research method to authenticate the simulated findings within a real-world project experiment helped counteract these limitations in future studies. By juxtaposing simulated results with actual data and evaluating human interactions across various policies, the study bolstered the credibility of its conclusions, even in light of the noted constraints.

3.7 Conclusion

As detailed in this chapter, this research used ALX software to conduct five simulation experiments. These experiments include the data from three case studies, with relevant parameters adjusted to explore the performance outcomes of different policies. The simulation study design process followed the best practices to overcome different challenges, organised into five logical phases. With the specific obstacles, or limitations experienced during the simulation processes, mitigation strategies were discussed, which are vital to ensuring the quality and reliability of the simulation research.

These findings show the opportunities and difficulties of simulation studies while highlighting their rewarding and complicated context. The previous section lays the groundwork for the next chapter, which will examine the performance outcomes from the simulation study and provide the foundation for analysis discussion with forthcoming findings.

4. Simulation analysis

4.1 Introduction

This chapter analyses performance outcomes from various simulation scenarios, emphasising selected parameters from SE0 within the ROP, MTA DBM, and DDMRP supply chain replenishment models. It starts with a simulation overview, which sets the foundation for subsequent discussions. It outlines the different process groups and explains the methods of processing source data.

Following the overview of simulation preparation, setup and supply chain network, software and tools deployed during simulation are introduced. A list of charts provides the representation of performance outcomes, such as for ROI and SL. These graphical representations pave the path for an in-depth exploration of experimental outcomes SE1 and SE2 in Group B, anchoring them to the second research question.

Another process of group C focuses on the performance outcomes generated in SE3 and SE4, highlighting their implications in the context of the third research question. By comparative analysis, it pinpoints trends, subtle differences, and distinctive strengths within the results.

Consequently, twelve preliminary findings will logically culminate in four key findings presented in this chapter. This method guarantees the flow of information, aligning with the primary research objective. The chapter aims to clarify the simulation processes for highlighting the aspects that have significantly influenced the performance outcomes.

4.2 Simulation Overview

This chapter bases its simulation on actual demand data from three unique business natures within the distribution-side supply chain. The three cases cover different types of industries and geographical areas in the supply chain distribution-side network:

Case 1: This focuses on the distribution of finished healthcare sensor devices. Specifically, it operates B2C in the USA and B2B in Europe.
Case 2: This is a garment manufacturing unit in Bangladesh.
Case 3: This spotlights an automotive assembly facility in China.

The companies representing the above cases provided the required data exported from their computer systems and saved in standardised Excel files. The collected data are from the years 2021-2022 (see **Table 1**) and includes stock master data and actual demand from the stock movement such as quantities of stock received and issued, together with purchase orders as supply. These were converted into AnyLogistix (ALX) readable Excel file format for import as summarised below in **Table 11**.

Table 11 – Data Summary of data collection

Data Category	Specific Input Variables	Description
Stock Master Data	ID, Scenario Name, Timestamp, Period Name, Date, Location Name, Policy Type	Static details defining the inventory framework, including policy type and location.
Actual Demand Data	Product, Stock In, Stock Out, Daily Stock On-Hand, Actual Demand	Dynamic data tracking stock movements and demand, essential for real-time analysis.
Purchase Order Data	Overdue Backorder History, Generated Supply Order	Data on order fulfilment and replenishment activities, highlighting system responsiveness.

Table 11 lists the structured dataset, which integrates static policy data with dynamic inventory transactions, forming a comprehensive foundation for evaluating inventory performance through simulation.

For a deeper dive into the nature of these businesses, **Table 1** in chapter 1 details each case's intricate supply chain characteristics.

To understand the orchestration of these simulations from **SE0** to **SE4**, refer to **Figure 18** below:

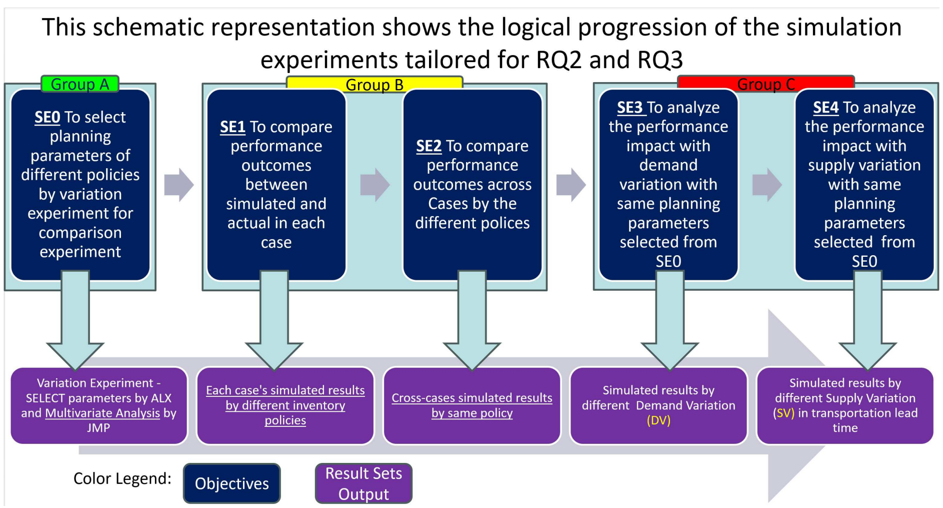


Figure 18 - Logical flow of the simulation experiments for RQ2 and RQ3

To clarify the logical flow of the simulation experiments for RQ2 and RQ3, three groups of simulation experiments are classified to highlight the corresponding objectives and their inter-relationships between groups of experiment processes. Each group produces planned result sets output as stated in last chapter – **Table 7**.

Group A aims to identify planning parameters with optimised performance as a baseline for comparison to be used in Group B and Group C. Group A includes only SE0, and the data simulated by ALX is exported and then imported into JMP for regression and multivariate analyses.

Group B focuses on the comparison of performance outcomes generated by ALX software under the same demand pattern of each case for each of the inventory policies. SE1 and SE2 generates the clear comparison of performance outcomes in each case and across different policies.

Group C uses ALX simulated variation in demand and variation in supply transportation lead time under the same planning parameters used in Group B. SE3 and SE4 explore the impact of performance outcomes under the impact of those simulated variations.

By comparing and analysing the output from all groups, the generated reports and charts by JMP and ALX provide the results necessary to answer the RQ2 and RQ3.

The performance outcomes provide insightful information to address RQ2 and RQ3 for comparative analysis. According to the above foundation, section 4.3 examines the details of data preparation, explaining the rigorous processes utilised to guarantee the validity and robustness of the simulation study.

4.3 Data Preparation

In **Phase (B)** of the research method chapter, data collection is critical in a simulation study. To address this significance, a standard data template was created. This design ensures that data complies with ALX requirements and remains consistent, echoing the data structure of the conceptual framework presented in **Figure 15**.

Within **SE0**, the study conducted a sensitivity analysis. By adjusting different inventory planning parameters, the simulator identified optimal configurations. This detailed exercise yielded a multivariate analysis in **Appendix C**, generated by SAS JMP statistical software.

SE1 and **SE2** are then based on the simulated results by different inventory policies in the same case and cross-cases simulated results by the same policy, as summarised in **Table 7**.

As mentioned above, data providers from three case companies participated in this study, with rigorous review sessions, where each dataset underwent close examination. The stakeholders of those data providers reviewed our provided summary of demand patterns in average, total of stock in and out quantities and opening and closing balances. This process underwent 2-4 rounds for each of the cases, with validation meetings during the data cleansing process. These reviews had a clear goal: to identify discrepancies or gaps within the data and then correct them, ensuring the data's reliability.

Having established the foundation of data preparation, the following section delves into how the simulation study used these datasets and assumptions in specific simulation configurations.

4.4 Simulation Setup

4.4.1 Introduction

After finalising the data preparation, the research transitions into importing this data into the ALX simulation platform. The study then initiates risk-averse experiments, simulating real-world situations drawn from genuine case data. This section delves into the intricacies of the simulation configuration, spanning from incorporating unique supply chain networks to examining variables like transportation lead time and demand fluctuations. The primary objective is to furnish a comprehensive comparison of diverse inventory policies in action. Subsequent sections shed light on the details of this simulation framework.

4.4.2 Data Sources and Cases in the simulation study

The strength of the simulation study largely hinges on integrating real-world data. To ensure the applicability of the findings, demand data was sourced from three distinct supply chain contexts.

Case 1: Distribution of Finished Goods for Healthcare Sensor Devices

Originating from production units in the China Original Equipment Manufacturer (OEM) factory (see yellow icon), the first case shows the distribution network from China to the USA for B2C business and from China to Europe for B2B business with three unique items and two distribution centres (see red icon) for healthcare sensor devices. The case 1 supply chain network manages the movement of these devices to two distribution centres in the USA and Europe destinations. **Figure 19** offers a visual presentation of the supply chain network.

Case 2: Procurement of Raw Materials for a Garment Factory

Sourcing raw materials for three primary yarns for the garment factory in Bangladesh, the second case utilises dual sources of supply from India (see blue icons) and Vietnam (see yellow icons). **Figure 20** provides a detailed layout of the distribution network.

Case 3: Distribution of Electronic Components for Automotive Assembly

The third case maps the distribution of electronic components essential for an automotive assembly line in China. The procurement of those components focuses on local China and Singapore (see yellow icons). Efficient movement of these components is crucial to maintain the assembly line's momentum. The distribution network is detailed in **Figure 21**.

Having dissected the data sources and the specific cases that form the backbone of the simulation study, a deeper dive into the granular details of each supply chain network becomes essential. These descriptions will offer insights into the operational intricacies, logistical challenges, and unique nuances of each supply chain – pivotal factors when analysing and comparing the performance of various inventory policies.

4.4.3 Supply Chain Network Descriptions

The simulation integrates demand data from three authentic cases, each presenting a unique supply chain network, as illustrated in **Figures 19, 20, and 21**. Each case consists of three distinctive product items characterised by varied demand patterns, operating within a single supply chain level but with multiple distribution points. Cumulatively, the simulation covers 36 stocking points for the product items. **Table 11** compiles the specific demand traits for these product items across the cases.

Case 1 - Distribution of Finished Goods for Healthcare Sensor Devices in both the USA and Europe:

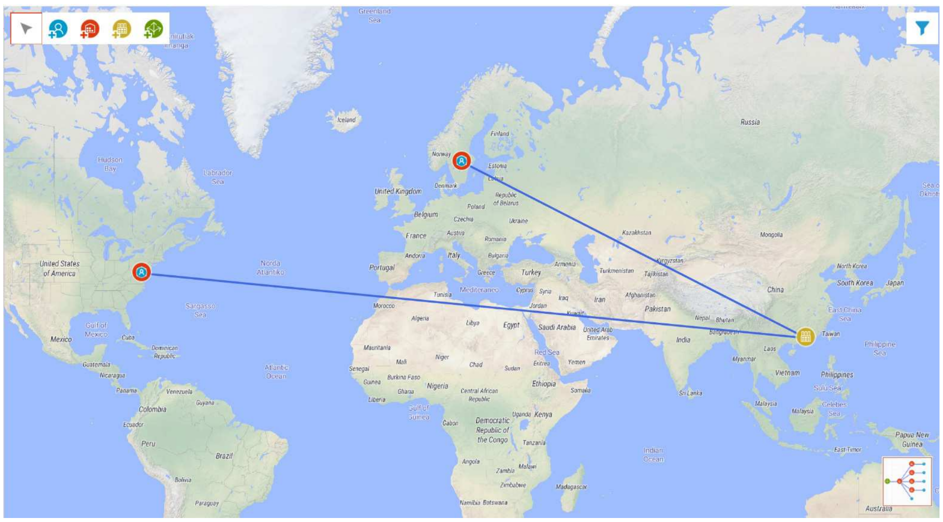


Figure 19 - Supply Chain Network Diagram for Case 1

Case 2 - Procurement of Raw Materials, specifically Yarn, for a Garment Factory in Bangladesh:

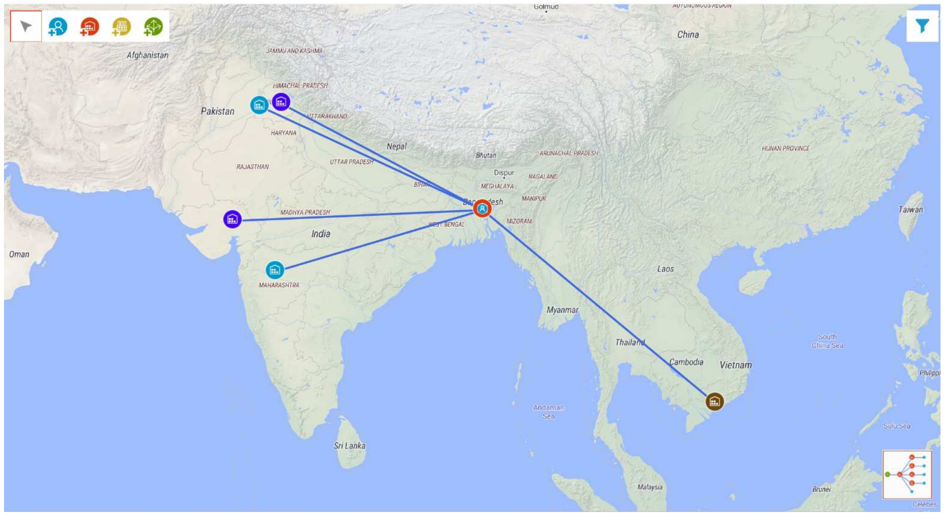


Figure 20 - Supply Chain Network Diagram for Case 2

Case 3 - Distribution of Electronic Components for an Automotive Assembly Line in China:

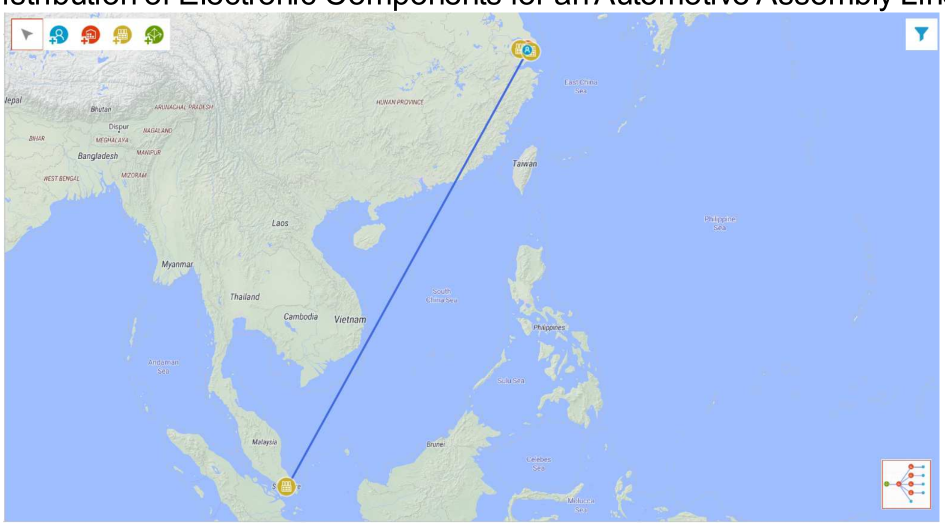


Figure 21 - Supply Chain Network Diagram for Case 3

While the supply chain network diagrams offer a bird's-eye view of the distribution network, the individual products and their demand patterns play a crucial role in the dynamics of supply chain operations. Delving deeper into product specifics provides a clearer understanding of nature in different supply chain cases.

4.4.4 Product Details and Demand Patterns

To understand the cases better, it is essential to consider the demand patterns associated with the products in these supply chains. Each product exhibits unique demand characteristics, whether in terms of lead time, daily usage, or variability. **Table 12** showcases a comprehensive breakdown of these demand patterns across all products for each case.

Table 12 - Product items demand characteristics

Case.Policy.Item stocking points	Lead Time (LT)	Total Demand	Average Daily Usage (ADU)	Coefficient of Variation (CoV)
Case1.ROP.Lite US B2C	180	652	1.786	8.01
Case1.ROP.Node US B2C	180	273	0.747	8.27
Case1.ROP.WB US B2C	180	434	1.189	7.95
Case1.ROP.Lite EU B2B	180	1074	2.942	13.55
Case1.ROP.Node EU B2B	180	1471	4.03	7.37
Case1.ROP.WB EU B2B	180	778	2.131	7.36
Case1.MTA.Lite US B2C	180	652	1.786	8.01
Case1.MTA.Node US B2C	180	273	0.747	8.27
Case1.MTA.WB US B2C	180	434	1.189	7.95
Case1.MTA.Lite EU B2B	180	1074	2.942	13.55
Case1.MTA.Node EU B2B	180	1471	4.03	7.37
Case1.MTA.WB EU B2B	180	778	2.131	7.36
Case1.DDMRP.Lite US B2C	180	652	1.786	8.01
Case1.DDMRP. Node US B2C	180	273	0.747	8.27
Case1.DDMRP.WB US B2C	180	434	1.189	7.95
Case1.DDMRP.Lite EU B2B	180	1074	2.942	13.55
Case1.DDMRP.Node EU B2B	180	1471	4.03	7.37
Case1.DDMRP.WB EU B2B	180	778	2.131	7.36
Case2.ROP.20D	65	2169345.51	3394.9	1.45
Case2.ROP.30NE1	65	3281775.38	5135.79	1.56
Case2.ROP.40NE1	65	3016409.55	4720.51	1.90
Case2.MTA.20D	65	2169345.51	3394.9	1.45
Case2.MTA.30NE1	65	3281775.38	5135.79	1.56

Case2.MTA.40NE1	65	3016409.55	4720.51	1.90
Case2.DDMRP.20D	65	2169345.51	3394.9	1.45
Case2.DDMRP.30NE1	65	3281775.38	5135.79	1.56
Case2.DDMRP.40NE1	65	3016409.55	4720.51	1.90
Case3.ROP.3542	133	2437120	7836.39	1.22
Case3.ROP.2816	144	1141566	3670.63	6.17
Case3.ROP.9396	46	2577849	8288.9	7.17
Case3.MTA.3542	133	2437120	7836.39	1.22
Case3.MTA.2816	144	1141566	3670.63	6.17
Case3.MTA.9396	46	2577849	8288.9	7.17
Case3.DDMRP.3542	133	2437120	7836.39	1.22
Case3.DDMRP.2816	144	1141566	3670.63	6.17
Case3.DDMRP.9396	46	2577849	8288.9	7.17

Upon analysing the specifics from **Table 12**, we derive the following insights:

Case 1: The Healthcare Sensor Devices distributed in the USA and Europe manifest a notably elongated sourcing lead time, extending up to 180 days. Coupled with a low Average Daily Usage (ADU) between 0.747 to 4.03, this indicates a protracted demand interval, emphasising potential storage and inventory planning challenges. The unpredictable demand for these devices becomes evident with a Coefficient of Variation (CoV) oscillating between 7.36 and 13.55. Within this case, three stock-keeping units (SKU) items form distribution across two key locations: the US, catering predominantly to B2C, and the EU, catering to B2B. This distribution results in two unique stock locations designated for replenishment across hubs, all sourced from the OEM factory in China.

Case 2: Situated in Bangladesh, the Garment Factory, which primarily sources yarn as its raw material, presents a more moderate procurement lead time of 65 days. A remarkable aspect of this case is the demand stability, with a CoV consistently remaining below 2. This stability suggests a somewhat predictable demand pattern, albeit presenting its distinct planning challenges. Structurally akin to Case 1, this case encompasses three SKU items, forming six stocking locations across the network.

Case 3: The Automotive Assembly Line in China showcases a spectrum of lead time, ranging from a relatively short 46 days to a more extended duration of 144 days. Such variations indicate the inherent complexities associated with synchronising supply chain processes. Furthermore, a CoV that spans from 1.22 to a more challenging 7.17 accentuates the dynamic demand nature in this scenario. This setup more closely mirrors that of **Case 2**, with three SKU items distributed across supply chain, cumulatively resulting in four stocking locations.

Drawing from the insights acquired from **Table 12**, the subsequent sections intend to explore the strategies and methodologies utilised to discern the inherent nature of each supply chain. However, before embarking on this comparative analysis, it is paramount to delineate this study's foundational assumptions and guiding simplifications. This ensures that the findings remain anchored in practical contexts and preserve their real-world applicability.

4.4.5 Assumptions and Simplifications

In rigorous analytical investigations, especially within supply chain simulations, foundational principles such as assumptions and simplifications often become paramount. Such principles not only guide the research to ensure manageability and focus but also prevent the introduction of undue complexities. Moreover, they provide a transparent lens to view and comprehend the results.

For instance, the present simulation assumes that the lead time required for replenishing purchase orders demonstrates high reliability, indicating a near-perfect consistency rate. Such reliability features prominently in SE0, SE1, and SE2—conversely, SE3 and SE4 present variable scenarios, introducing unpredictable variations in transportation lead time. The simulation follows a stringent protocol in emerging back-order situations: completing any outstanding order before initiating its dispatch. Adhering to this approach aligns with current industry norms and favours complete order dispatches over partial ones for practical and economic reasons. Actual demand data, reflecting the operational dynamics collected from Case companies, underpins the study and receives confirmation from the data custodians.

Besides these assumptions, specific simplifications have been incorporated to sharpen the analytical focus. One notable simplification pertains to streamlining the objective function in SE0. Focusing on ROI and Service Level by Revenue helps to analyse and compare outcomes effectively while temporarily disregarding low-impact variables. For another simplification in the SE0, variation experiments use the default planning parameters within ALX, ranging from theoretical baselines of parameters to a 50% increase.

In conclusion, the outlined assumptions and simplifications play a dual role: directing the research towards insightful findings and demarcating the boundaries of the investigation. Thus, readers should acquaint themselves with these foundational premises for a contextually anchored and informed engagement with the results.

4.4.6 Simulation Software and Tools

In the academic literature regarding supply chain simulation, selecting suitable software and analytical tools is paramount, enabling accurate modelling, analysis, and presentation of data. The tools utilised should reflect the current state of technological advancement and cater to the specific nuances of the research in question. In the context of this investigation, an ensemble of specialised tools was judiciously chosen, reflecting their pertinence to the study's objectives and methodological framework. These were mentioned in the previous chapter and are expanded upon here.

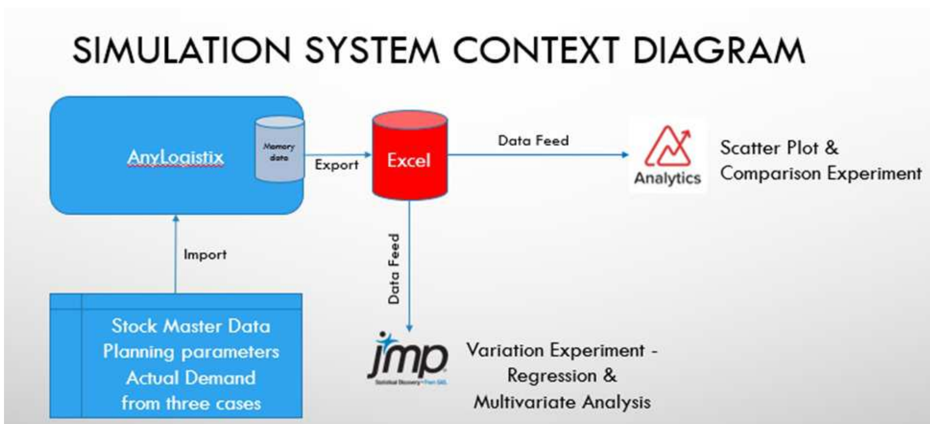


Figure 22 – Simulation system context diagram

The above simulation system context diagram (**Figure 22)** shows the data flow and setup between different software tools. Firstly, the stock master data - item code, description, opening balance, and planning parameters - standard lead time and actual demand history are imported into AnyLogistix. After running the various simulation experiments, the result sets of performance outcomes are exported into Excel. Finally, the result sets of different performance are fed into JMP for the multivariate analysis and Zoho Analytics for scatter plot generation and the comparison experiment. Highlighted below are the primary software and tools employed, coupled with a brief exposition of their attributes and contributions to the research:

ALX Software: Recognised for its prowess in dynamic supply chain design and analysis, ALX presents a multidimensional simulation approach encompassing discrete event, agent-based, and system dynamics modalities. Given the study's need to delineate complex supply chain structures across varied scenarios, this software's scalability and flexibility were deemed indispensable. **Figure 23** shows an example of an ALX simulation screenshot, including the supply chain network and performance dashboard that will be used to provide the information necessary comparison and analysis.

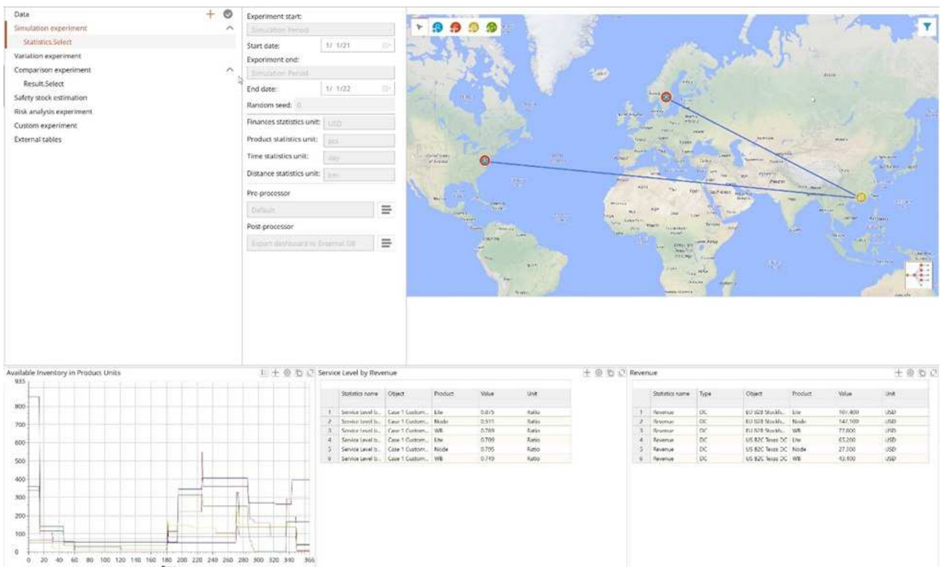


Figure 23 – ALX simulation and dashboard screenshot (AnyLogistix Features, n.d.)

In **Figure 23**, there are three reports generated by ALX during the simulation process. First one in the left shows the available inventory balance on a daily basis, generated in SE0 for Case1 by ROP policy. The middle table lists out the service level by revenue (SL). The right table states the total revenues accumulated by the end of simulation period. Then, these performance outcomes are exported and imported into JMP and Zoho Analytics for further analyses.

JMP Statistical Software: Originating from the SAS Institute, JMP is renowned for its dynamic data visualisation and exploratory data analysis capabilities. Within this research, its suite of statistical tools facilitated rigorous hypothesis testing, data mining, and predictive modelling, thereby cementing the empirical validity of the findings. **Figure 22** illustrates the JMP statistical software with visual, power and interactive interface to accelerate the identification of insight information.

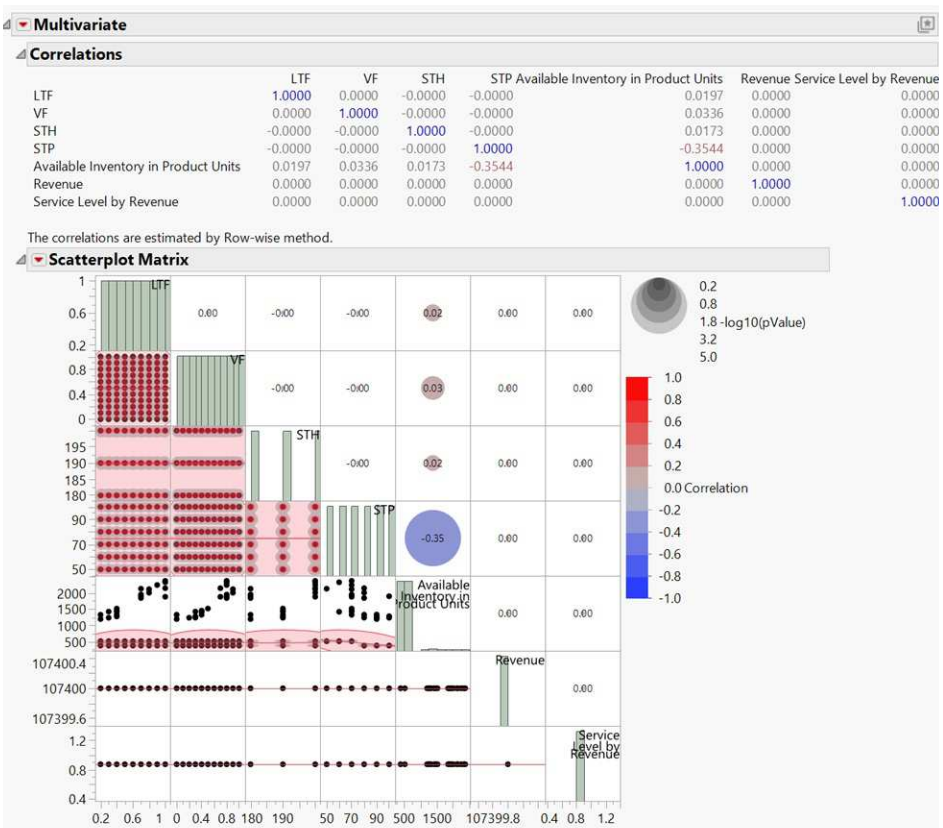


Figure 24 – JMP statistical software screenshot example

Figure 24 illustrates a snapshot from JMP statistical software, demonstrating its features for data analysis and visualisation. The interface presents multiple components, such as a correlation matrix and scatterplots, which illustrate the relationships among variables. The correlation matrix visually represents the strength and direction of correlations, whereas scatterplots allow for a thorough examination of the interactions among individual data points across variables. This flexible option allows users to examine trends, rendering it highly effective for statistical analysis and research findings.

Zoho Analytics: It is a leading self-service BI and data analytics software that transforms raw data into clear, interactive dashboards. This tool was chosen for its ability to create visual narratives and provide real-time insights, aligning with the study's focus on data transparency and accessibility.

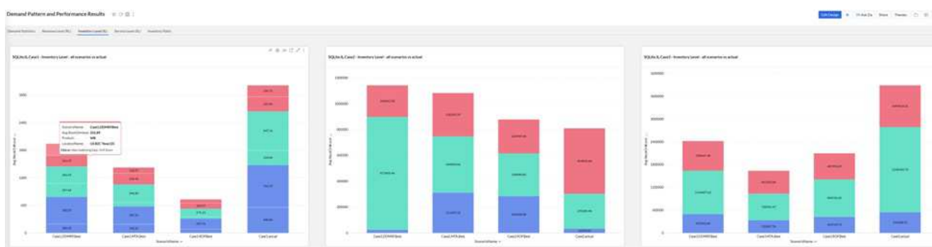


Figure 25 – Zoho Analytics collaborative dashboard (Zoho Analytics Features)

Figure 25 provides a comparative view of inventory levels across multiple scenarios. It highlights the average stock-on-hand level between actual and simulated outcomes of different inventory policies (ROP, MTA DBM, DDMRP). Each bar represents a specific case with a breakdown of stock levels, enabling a clear comparison between actual and simulated results.

The imperative to adopt these distinct tools stems from their confluence of capabilities tailored to address the multifaceted requirements of the research. ALX, with its specialised focus on supply chain intricacies, laid the foundational groundwork for simulating diverse supply chain frameworks. However, as mentioned in the previous chapter, ALX only provides the standard polices in simulation such as Reorder Point, Min-Max and MRP. For MTA DBM and DDMRP, therefore, ALX Java extension for customised Java coding (see **Appendix F** for sample Java source code) is required according to the logic presented in the previous section 3.4.2. **Table 6**. JMP Statistical Software buttressed the analytical rigour in parallel, ensuring data integrity and robustness. With its visualisations, Zoho Analytics enhanced the interpretative dimension of the study.

The curated ensemble of software and tools was more than merely a matter of convenience. Instead, their integration was meticulously orchestrated to bolster the study's comprehensiveness and precision, facilitating an exploration that resonates with academic rigour and relevance.

4.4.7 Conclusion for Data Sources, Product Details and Simulation

The section has illuminated the critical data sources, product details, and simulation tools that underpin the research. A diverse range of real-world supply chain contexts enriches the depth of the simulation study. Including case studies from healthcare sensor devices, garment factories, and automotive assembly lines provides various B2B and B2C scenarios, each showcasing distinct challenges and dynamics.

Table 12 offers valuable insights into the subtleties of demand patterns across these supply chains. It highlights the intricacies linked with extended lead time observed in the healthcare sensor devices distribution network and its unpredictable demand. By contrast, Bangladesh's garment factory operates within a predictable framework despite its significant demand. The automotive assembly line in China introduces layers of complexity, presenting a range of challenges from fluctuating lead time to assorted demand attributes.

The outlined assumptions and simplifications hold significant importance. They guide the simulation study towards its objectives while ensuring readers are anchored in the correct context. Readers must consider these principles when interpreting results, ensuring conclusions align with real-world applications.

The choice of simulation tools and software – AnyLogistix, JMP Statistical Software, and Zoho Analytics – underscores the research's commitment to accuracy, adaptability, and empirical thoroughness. With its unique capability, each software supports the research's goals, ensuring a comprehensive and cutting-edge approach to data modelling, analysis, and presentation.

In conclusion, this section serves as the cornerstone for forthcoming analyses. Detailing data sources, explaining the variations in demand across supply chains, and spotlighting robust simulation tools set the stage for a thorough analysis and interpretation of findings. Insights await that promise to enhance supply chain dynamics across various real-world settings.

4.5 Results Presentation

4.5.1 Introduction to Results and Key Performance Indicators (KPIs)

The forthcoming sections will present the findings from our simulation study. We primarily compare inventory policies in various industries, such as healthcare devices, garment factories, and automotive assembly lines. As described previously, we have organised the results into three distinct scenario groups: **Group A** represents **SE0**, **Group B** includes **SE1** and **SE2**, and **Group C** covers **SE3** and **SE4,** as shown in **Figure 18**. The three groups each have different objectives, and the logical flow for comparison from real cases with simulated variations in supply and demand is used to address RQ2 and RQ3.

This structure improves the clarity of our discussions and provides a clear framework to explore the key performance indicators (KPIs). It highlights the findings relevant to each specific supply chain simulation scenario.

Key Performance Indicators (KPIs) Used in Experimental Comparisons

A series of KPIs emerge from the experiments, instrumental for comprehensive comparative analysis. Below, **Table 13** outlines each KPI, encapsulating its definition and formulaic rationale.

Table 13 - Key Performance Indicators Utilised in Experiments

Short-code	**Key Performance Indicators**	**Definition and Formula Logic Explanation**
RL	Revenue Level	Defined as the product of the number of items in all shipped orders and the item price.
IL	Inventory Level	Represents the daily average volume of stocked items, either by quantity or cost of goods sold (COGS).
SL	Services Level by Revenue	Calculated based on the revenue lost from unfulfilled orders. SL = 1 - (items in unfulfilled orders x item price) / (total items in all orders for the facility x item price)
ROI	Return On Inventory by Stock Balance Or Cost of Goods Sold (COGS)	ROI = RL / IL (end-of-period stock balance) OR ROI = RL / (IL x unit cost)

These KPIs serve as foundational metrics, facilitating an understanding of the intricate supply chain dynamics and providing a yardstick for evaluation. As the exploration advances to the next section, a detailed breakdown of each simulation experiment group will interpret the findings through these KPI lenses.

4.5.2 Preliminary Findings by Simulation Experiment Group

The stratification of simulation experiments into three distinct cohorts - **Group A (SE0)**, **Group B (SE1 and SE2)**, and **Group C (SE3 and SE4)** - unearths pivotal insights into supply chain dynamics, as delineated in section 4.2 - **Figure 18**. Such results provide an intellectual bridge to the overarching research questions, fortifying the academic exploration.

The results from Groups A, B and C provide critical insights into the performance of forecast-based and consumption-based inventory policies in distribution-side supply chains. These findings will be demonstrated in the subsequent sections.

Group A (SE0) provides three clear insights. Safety Stock (SS) significantly affects the Available Inventory in Product Units (IL). Its strong influence on the Services Level by Revenue (SL), particularly within the Reorder Point (ROP) policy, stands out **(Finding-1)**. The close relationship between the Initial Buffer Size (IBS) and the Available Inventory (IL) is also evident within the MTA DBM policy **(Finding-2)**. Furthermore, the comparison between the mostly negative relationship of the Spike Threshold Percentage (STP) and the positive one of the Lead Time Factor (LTF) regarding Available Inventory Level (IL) highlights the complexity of supply chain dynamics within the DDMRP policy **(Finding-3)**.

For the second research question exploring how inventory policies perform under varying demand and lead time, **Group B (SE1 and SE2)** provides essential details. In specific situations for Case 1 within SE1, the ROP policy has a clear advantage regarding Return on Inventory (ROI) **(Finding-4)**. ROP also achieved higher ROI than MTA DBM and DDMRP in Case 2 **(Finding-5)**. However, the MTA DBM policy also shows strength, reaching the highest ROI in SE1's Case 3 **(Finding-6)**. At the same time, DDMRP achieves a 100% Service Level by Revenue (SL) in Case 3 with the lowest ROI within SE1 **(Finding-7)**. ROP and MTA DBM could achieve 100% Service Level by Revenue (SL) in Case 3 for product items with Demand Variation (DV), where CoV is below seven **(Finding-8)**. In Case 3, DDMRP secured the highest Service Level (SL), while ROP demonstrated superior Return on Inventory (ROI) performance in Cases 1 and 2 (**Finding-9**).

Finally, considering the third research question, which focuses on factors influencing the choice and effectiveness of inventory policies, **Group C (SE3 and SE4)** gives valuable information. The MTA DBM policy effectively handles changing demands without harming the Service Level by Revenue (SL) in Case 3 **(Finding-10)**. Meanwhile, when looking at the Coefficient of Variation (CoV) by Demand Variation (DV), the ROP policy often outperforms MTA DBM and DDMRP regarding ROI in Case 1 and Case 3. **(Finding-11)**. The Supply Variation (SV) of Transportation Lead Time (TLT) is also crucial, as it can decrease Service Level by Revenue (SL) **(Finding-12)**.

After reviewing the preliminary findings, multiple aspects appear to influence the performance of inventory policies and supply chain processes. While the conclusions written help explain things, graphs can offer a clearer view. The following section, **4.5.3 Graphical Representations**, presents these findings visually. This section uses Graphs to make it easier to see patterns and understand the results from the simulation experiments.

4.5.3 Graphical Representations and Correlations

After elucidating the principal findings from the simulation groups, the research now focuses on the study's visual facets. Incorporating graphical illustrations stems from their innate ability to bolster and complement textual revelations. Such representations afford a more precise grasp of the intricate dynamics between diverse elements and the resulting implications.

Parameters setting for variation experiments in SE0

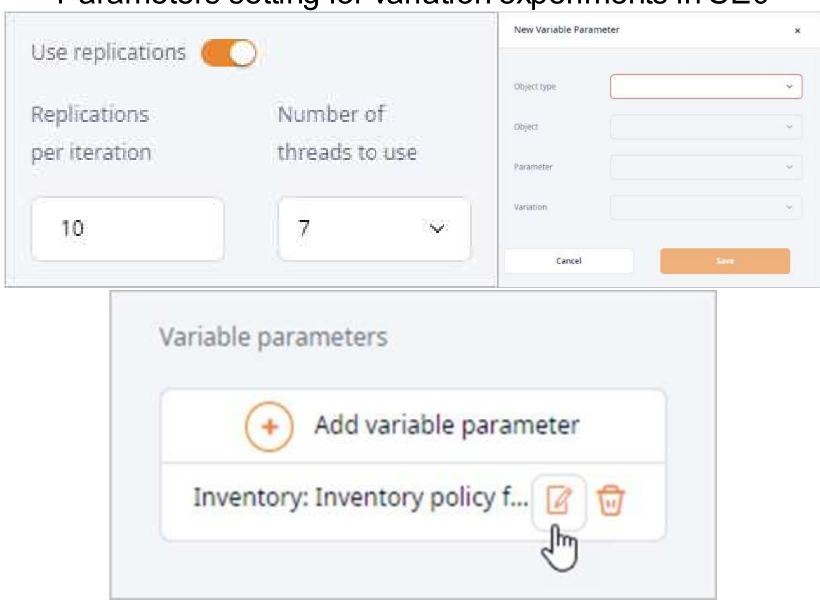


Figure 26 – ALX variation experiment parameters (AnyLogistix variation experiment, n.d.)

The above **Figure 26** illustrates the different options of running variation experiments. During the simulation process for **Group A (SE0)**, ALX variation experiment provides selectable variables parameters to identify the optimised performance of each policy. We can then test different parameters of various policies to obtain the optimised performance outcomes before **Group B (SE1, SE2)** and **Group C (SE3, SE4)**. The performance outcomes of each case generated by variation experiments are imported into ALX for the generation of a scatter plot and JMP for regression with multivariate analysis.

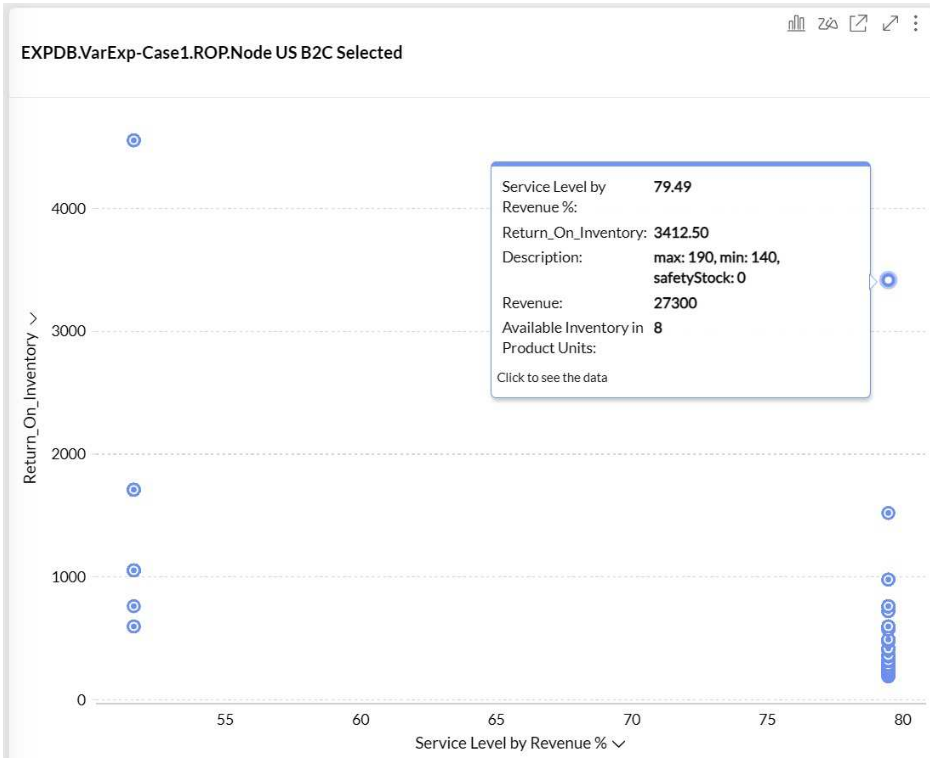


Figure 27 – Zoho Analytics used for scatter plot analysis

The above **Figure 27** provides the scatter plot for selecting the planning parameters with highest ROI and highest SL, which will be used in Group B and C simulation experiments as baseline.

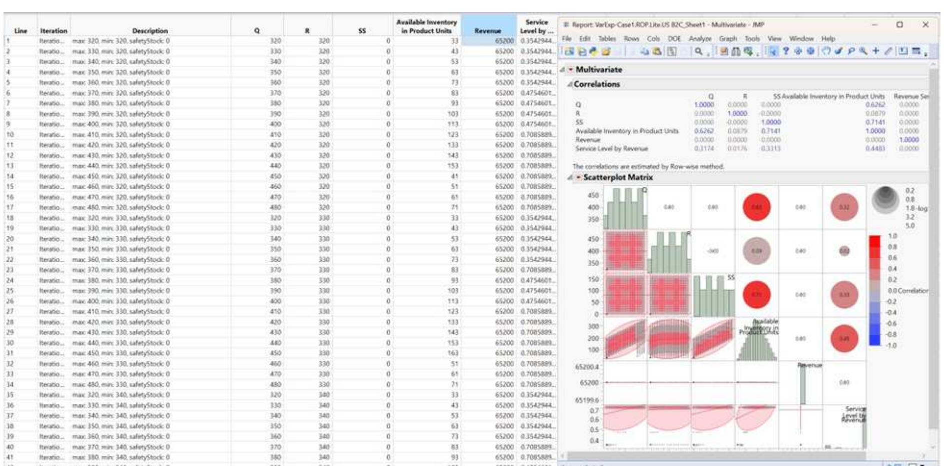


Figure 28 – JMP – regression analysis with multivariate analysis

Figure 28 illustrates a multivariate analysis of the data exported from ALX to JMP. On the left, the imported data encompasses several inventory scenarios' outcomes, while on the top-right, the table illustrates the correlation matrix between key planning factors and performance outcomes, providing insights about the strength of correlations among variables (i.e. Q, R, SS, IL and SL). Scatter plots below the matrix demonstrate the manifestation of those connections, facilitating as in-depth additional visual analysis of how specific policy factor such as Safety Stock (SS) influences major KPIs, thereby generating essential insights for addressing RQ2 and RQ3.

This section presents an array of Graphs and visual aids delineating the outcomes of the simulation experiments. These graphical representations offer a more concrete grasp of the data, spotlighting patterns, trajectories, and irregularities potentially elusive in purely textual descriptions. For each finding in the previous section:

Correlation related to Finding-1 from SE0: Correlation analyses demonstrate the statistically significant relationship between Safety Stock (SS) and both Available Inventory in Product Units (IL) and Service Level by Revenue (SL) under the ROP policy. The data demonstrates a strong positive association between SS and IL, with correlation values exceeding 0.6, indicating that changes in SS are strongly associated with variations in IL levels. The link between IL and SL is considerable ($p < 0.05$), underscoring the essential significance of inventory availability in achieving optimal service performance, which in turn improves revenue outcomes.

Table 14 – Correlation Matrices for SE0 (**14-A to 14-F**)

Table 14-A

Correlation Matrix for Case1.ROP.Lite.US B2C in SE0

Variable	1	2	3	4	5	6
1. Q	—					
2. R	0	—				
3. SS (Safety Stock)	0	0	—			
4. Available Inventory in Product	.63**	0.09	.71**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	.32*	0.02	.33*	.45**	0	—

Note. **p < .01, *p < .05.

Table 14-B

Correlation Matrix for Case1.ROP.Node.US B2C in SE0

Variable	1	2	3	4	5	6
1. Q	—					
2. R	0	—				
3. SS (Safety Stock)	0	0	—			
4. Available Inventory in Product	.55**	0.18	.73**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	.38*	0.07	.44**	.55**	0	—

Note. **p < .01, *p < .05.

Table 14-C

Correlation Matrix for Case1.ROP.Node.US B2C in SE0

Variable	1	2	3	4	5	6
1. Q	—					
2. R	0	—				
3. SS (Safety Stock)	0	0	—			
4. Available Inventory in Product	.55**	0.18	.73**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	.38*	0.07	.44**	.55**	0	—

Note. **p < .01, *p < .05.

Table 14-D

Correlation Matrix for Case3.ROP.9396 in SE0

Variable	1	2	3	4	5	6
1. Q	—					
2. R	0	—				
3. SS (Safety Stock)	0	0	—			
4. Available Inventory in Product	.71**	0	.71**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	.49**	0.05	.39*	.62**	0	—

Note. **p < .01, *p < .05.

Table 14-E

Correlation Matrix for Case3.ROP.2816 in SE0

Variable	1	2	3	4	5	6
1. Q	—					
2. R	0	—				
3. SS (Safety Stock)	0	0	—			
4. Available Inventory in Product	-0.11	0.31	.70**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0.25	0	0.25	0.09	0	—

Note. **p < .01, *p < .05.

Table 14-F

Correlation Matrix for Case3.ROP.3542 in SE0

Variable	1	2	3	4	5	6
1. Q	—					
2. R	0	—				
3. SS (Safety Stock)	0	0	—			
4. Available Inventory in Product	0.08	0.26	.71**	—		
5. Revenue	0.13	0.12	0.14	0.21	—	
6. Service Level by Revenue	0.16	0.13	0.17	0.2	.89**	—

Note. **p < .01, *p < .05.

A series of correlation matrices illustrate how Safety Stock (SS) impacts Available Inventory (IL) and Service Level by Revenue (SL) within the ROP policy across diverse scenarios. The correlation matrices in **Table 14** show these strong correlations, highlighting on relationships with a correlation value of 0.7 or higher. Upon further scrutiny of these matrices, one observation emerges: the correlation coefficient often surpasses 0.7. This robust correlation signifies a strong and impactful relationship between the variables under scrutiny.

In Case 1 (refer to **Table 14-A**), the matrix correlation reveals several strong positive associations: the correlation coefficient between Safety Stock (SS) and Available Inventory (IL) is roughly 0.71, indicating a strong association between a boost in safety stock and a rise in available inventory. Furthermore, a strong positive relationship exists between Order Quantity (Q) and Available Inventory (IL) (0.63), signifying that increased order quantities result in increased inventory levels. The previously mentioned correlation matrices provide a quantitative illustration of these relationships, illustrating how variations in SS and Q result in IL. Case 1 demonstrates that effective management of Safety Stock and Order Quantities is critical for maintaining optimal inventory levels, affecting customer service levels.

In Case 2 (refer to **Table 14-E**), the correlation analysis indicates a strong correlation of 0.70 ($p < 0.01$) between safety stock (SS) and inventory levels (IL), demonstrating a strong positive relationship between the management of safety stock and available inventory levels. This conclusion underscores the significance of Safety Stock as a vital factor in maintaining inventory levels. However, results show a lack of statistically significant connections between IL and SL indicating that additional factors may affect service levels in Case 2. The findings suggest that although Safety Stock is essential for inventory management, its direct influence on Service Level by Revenue may be affected by other variables or operational processes in this specific instance.

In Case 3 (refer to **Tables 14-D and 14-F**), the correlation analyses indicate many strong connections. **Table 14-D** reveals a strong correlation of 0.71 ($p < 0.01$) between SS and IL, signifying a substantial positive association, as in Cases 1 and 2. Increases in safety stock (SS) are generally correlated with increases in available inventory levels (IL). The association between IL and SL is 0.62 ($p < 0.01$), indicating that sufficient inventory levels are essential for attaining improved service levels. **Table 14-F** demonstrates a strong correlation of 0.71 ($p < 0.01$) between SS and IL. In contrast, an extremely high correlation of 0.89 ($p < 0.01$) is noted between Service Level by Revenue and Revenue, suggesting that enhancements in service levels are intricately linked to revenue growth. These results highlight the pivotal function of Safety Stock in sustaining inventory levels and the subsequent impact of inventory availability on service performance and financial success.

The findings from several scenarios (refer to **Table 14**) highlight the statistically significant effect of Safety Stock on Available Inventory and its significant impact on Service Level by Revenue. The significant correlation values in the matrices suggest that effectively managing key inventory characteristics, including safety stock and order quantities, is vital for reaching adequate inventory levels, improving service performance, and encouraging revenue growth. This study underscores the significance of strategic inventory management strategies in enhancing operational performance.

Correlation related to Finding-2 from SE0: The strong correlation between Initial Buffer Size (IBS) and Available Inventory (IL) within the MTA DBM policy.

Table 15 – Correlation Matrices for SE0 (**15-A to 15-K**)

Table 15-A

Correlation Matrix for Case1.MTA.Lite.US B2C in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 15-B

Correlation Matrix for Case1.MTA.Node.EU B2B in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 15-C

Correlation Matrix for Case1.MTA.Node.US B2C in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	.58**	.57**	0	—

Note. **p < .01, *p < .05.

Table 15-D

Correlation Matrix for Case1.MTA.WB.EU B2B in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 15-E

Correlation Matrix for Case1.MTA.WB.US B2C in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	.61**	.61**	0	—

Note. **p < .01, *p < .05.

Table 15-F

Correlation Matrix for Case2.MTA.20D in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 15-G

Correlation Matrix for Case2.MTA.30NE1 in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	.87**	.87**	0	—

Note. **p < .01, *p < .05.

Table 15-H

Correlation Matrix for Case2.MTA.40NE1 in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	.87**	.87**	0	—

Note. **p < .01, *p < .05.

Table 15-I

Correlation Matrix for Case3.MTA.2816 in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	.98**	—		
5. Revenue	0	0	.68**	.53**	—	
6. Service Level by Revenue	0	0	.72**	.59**	.97**	—

Note. **p < .01, *p < .05.

Table 15-J

Correlation Matrix for Case3.MTA.3542 in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	.85**	—		
5. Revenue	0	0	.94**	.62**	—	
6. Service Level by Revenue	0	0	.94**	.63**	.99**	—

Note. **p < .01, *p < .05.

Table 15-K

Correlation Matrix for Case3.MTA.9396 in SE0

Variable	1	2	3	4	5	6
1. TMG	—					
2. TMR	0	—				
3. IBS	0	0	—			
4. Available Inventory in Product Units	0	0	1.00**	—		
5. Revenue	0	0	0	0	—	
6. Service Level by Revenue	0	0	.43*	.43*	0	—

Note. **p < .01, *p < .05.

In the correlation matrices presented in Table 15, a significant finding is the strong correlation between Initial Buffer Size (IBS) and Available Inventory (IL) within the MTA DBM policy. Each scatterplot matrix reveals the relationships between different operational variables, with a particular focus on how the initial buffer impacts available inventory levels.

For Case 1, as shown in Tables 15-A to 15-E, there is a consistently strong positive relationship between IBS and IL across various regions and contexts, including US B2C, EU B2B, and WB. Specifically, the correlation coefficients between IBS and IL are all equal to 1 or very close to 1, indicating a near-perfect correlation (refer to Tables 15-A to 15-E). This suggests that under the MTA DBM policy, increasing the initial buffer size directly results in an increase in available inventory, thereby reflecting an efficient alignment between inventory planning and availability requirements. The consistency of this relationship across the different cases and regions highlights the robustness of the policy in ensuring adequate inventory levels.

For Case 2, Tables 15-E to 15-G shows different scenarios, yet a similar pattern emerges. In Table 15-F, the correlation between IBS and IL is again equal to 1, indicating a perfect relationship. In Tables 15-G to 15-H, the correlations are slightly lower but remain very high, at 0.872 and 0.838, respectively. These figures demonstrate that even under varied operational settings, the MTA DBM policy maintains a strong and positive correlation between IBS and IL. The slight decrease in correlation in these figures may suggest minor external factors affecting inventory levels, but the relationship remains fundamentally strong.

In Case 3 (refer to Tables 15-I to 15-K), a perfect correlation ($R = 1.00$, $p < 0.01$) is noted between Initial Buffer Size (IBS) and Available Inventory in Product Units (IL) in Table 15-K for product stocking location Case3.MTA.9396. The exact relationship indicates that variations in buffer size immediately led to corresponding variations in available inventory, indicating that effective management of IBS is critical for properly regulating inventory levels in this scenario.

Besides a perfect relationship in Table 15-K, Tables 15-I and 15-J show strong correlations nearing 1 in Table 15-I for product stocking location Case3.MTA.2816, the correlation between IBS and IL is 0.98 ($p < 0.01$), indicating a strong relationship. Increases in buffer size are directly correlated with increases in inventory levels, highlighting the crucial function of IBS to ensure stock availability.

Table 15-J for product stocking location Case3.MTA.3542 illustrates a strong and significant correlation between IBS and IL, shown by a coefficient of 0.85 ($p < 0.01$). Despite being slightly smaller than observed in other scenarios, this still demonstrates a strong correlation, indicating that variations in IBS significantly influence inventory levels. Table 15-J shows a significant correlation between revenue and Service Level by Revenue (SL), indicated by a coefficient of 0.99 ($p < 0.01$), indicating that improvements in service levels are largely related to higher revenue.

The correlation matrices in **Tables 15-A to 15-K** illustrate a consistent and strong correlation between Initial Buffer Size and Available Inventory under the MTA DBM policy. This finding points out the necessity of determining an optimal initial buffer to ensure inventory availability, which is vital to keeping adequate service levels and avoiding stockouts. The variations in correlations among different cases indicate specific operational variations; however, the overall pattern highlights the effectiveness of the MTA DBM policy in synchronising inventory planning with demand.

Correlation related to Finding-3 from SE0: There are contrasting behaviours when it comes to Spike Threshold Percentage (STP) and Lead Time Factor (LTF) vis-à-vis Available Inventory Level (IL) within the DDMRP policy.

Table 16 – Correlation Matrices for SE0 (**16-A to 16-I**)

Table 16-A

Correlation Matrix for Case1.DDMRP.Lite.US B2C in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	0	0	0	-.90**	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	0	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 16-B

Correlation Matrix for Case1.DDMRP.WB.EU B2B in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	0.03	0.02	0	-.80**	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	0	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 16-C

Correlation Matrix for Case1.DDMRP.WB.US B2C in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	0.01	-0.01	0.01	-.86**	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	0	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 16-D

Correlation Matrix for Case2.DDMRP.20D in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	.91**	0.14	-0.01	0.01	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	0.06	0.02	0.1	-0.24	0.05	0	—

Note. **p < .01, *p < .05.

Table 16-E

Correlation Matrix for Case2.DDMRP.30NE1 in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	.93**	0.16	0.01	-0.02	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	.54**	0.13	0.15	-0.21	.53**	0	—

Note. **p < .01, *p < .05.

Table 16-F

Correlation Matrix for Case2.DDMRP.40NE1 in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	.89**	0.27	0	0	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	-.55**	-0.21	0.19	-0.32	-.51*	0	—

Note. **p < .01, *p < .05.

Table 16-G

Correlation Matrix for Case3.DDMRP.2816 in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	.85**	0.29	0	0.02	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	0	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 16-H

Correlation Matrix for Case3.DDMRP.3542 in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	.95**	0.28	0	0	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	0	0	0	0	0	0	—

Note. **p < .01, *p < .05.

Table 16-I

Correlation Matrix by for Case3.DDMRP.9396 in SE0

Variable	1	2	3	4	5	6	7
1. LTF	—						
2. VF	0	—					
3. STH	0	0	—				
4. STP	0	0	0	—			
5. Available Inventory in Product Units	.90**	0.27	-0.03	0.18	—		
6. Revenue	0	0	0	0	0	—	
7. Service Level by Revenue	.44*	0.06	-0.02	.72**	.59**	0	—

Note. **p < .01, *p < .05.

The data in **Table 16** show the different behaviours of the Lead Time Factor (LTF) and Spike Threshold Percentage (STP) for Available Inventory Levels (IL) under the Demand-Driven Material Requirements Planning (DDMRP) policy. Each table presents an analysis of the correlation matrices for different cases, highlighting the interactions of these variables under various situations.

Tables 16-A to **16-I**, related to Case 1, show a consistent pattern within the DDMRP policy across various scenarios. As illustrated in Table **16-A**, there is a strong negative correlation between STP and IL ($R = -0.90$, $p < 0.01$). This signifies that an increase in the DDMRP parameter on STP corresponds with a reduction in IL, indicating that proper setting of the STP leads to more effective inventory control. In contrast, the relationship between LTF and IL in Case 1 is almost insignificant ($R = 0$, $R = 0.03$, $R = 0.01$) for the three different scenarios, as highlighted by the green colour in **Tables 16-A**, **16-B**, and **16-C,** and those correlations lack statistical significance ($p > 0.05$). This indicates that STP variations affect inventory levels whereas LTF does not.

Tables 16-D to **16-I**, related to Cases 2 and 3, provide a pattern of strong positive correlations between LTF and IL, with R values between 0.85 (see Table **16-G**) and 0.95 (see **Table 16-H**) ($p < 0.01$). These results indicate that LTF strongly correlates with increased IL, suggesting a strategy of holding higher inventory levels to mitigate problems associated with long lead times. In Case 2 (refer to **Tables 16-D** to **16-F**), the correlations between LTF and IL are 0.91 (see **Table 16-D**), 0.93 (see **Table 16-E**), and 0.89 (see **Table 16-F**) ($p < 0.01$), underscoring the significance of LTF as a critical factor of inventory levels. This indicates that organisations should prioritise maintaining increased inventory levels whilst lead times are extended to provide supply chain resilience. **Table 16-H** for Case 3 similarly exhibits a strong positive correlation between LTF and IL ($R = 0.95$, $p < 0.01$), emphasising the importance of lead time management in keeping acceptable inventory levels.

The findings indicate that while both LTF and STP influence inventory levels, their impacts differ significantly. The strong positive correlations between LTF and IL, indicated by $R = 0.91$, $p < 0.01$ in Table 9-D, and $R = 0.85$ ($p < 0.01$) in **Table 16-G**, indicate that prolonged lead times lead to increased inventory levels as a protection against disruptions. The negative correlation between STP and IL is, $R = -0.90$ ($p < 0.01$) in **Table 16-A**, shows the importance of adjusting spike thresholds to manage inventory levels. This data highlights the distinctive characteristics of LTF and STP within the DDMRP framework, further confirmed by the consistent patterns in **Tables 16-D** to **16-I**.

After the identification of findings from SE0 by JMP multivariate correlations, the following section turns to the key findings of Group B simulation experiments (SE1 and SE2) using ALX to compare performance outcomes in each case.

Graphs related to Finding-4 from SE1: ROP shows superior performance in terms of ROI in specific contexts for Case 1 within SE1

Figure 29-A depicts the simulated ROI results for Case 1. There is a striking differentiation among inventory policies. The ROP strategy stands out, boasting an ROI of **76.69**. The ROP is notably higher than MTA DBM, which has an ROI of **39.19** and greatly surpasses DDMRP at **28.86**. This variance underscores ROP's superior efficiency in balancing revenue generation against inventory costs in this simulation.

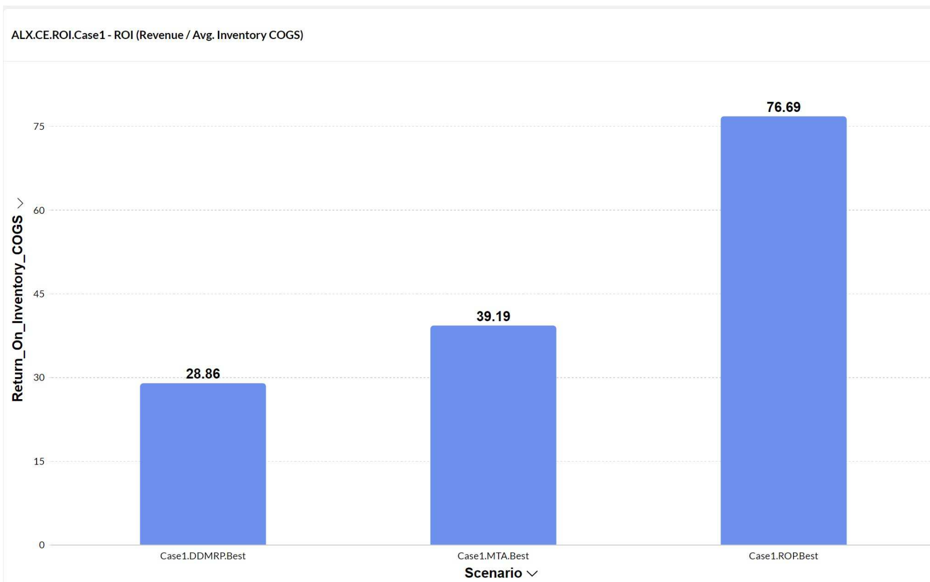


Figure 29-A - Case 1 ROI (Revenue / Average Inventory COGS)

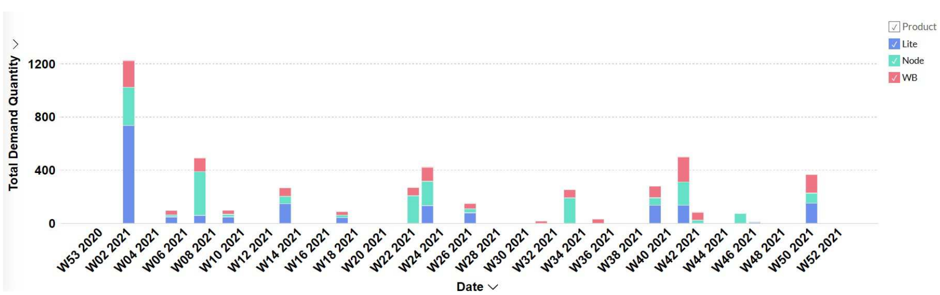


Figure 29-B - Case1.Demand.Distribution

Case 1 company is a Series B startup with erratic sales demand pattern, marked by extended order intervals. This distinctive demand pattern, with its low monthly orders and lengthy gaps between three product items (Lite in blue, Node in green and WB and red), is graphically represented in **Figure 29-B**.

One significant observation emerges from the data presented in **Figure 29-B**. ROP's unwavering initial buffer size (IBS) provides it a distinct advantage in these scenarios. Throughout the simulation, the consistency of ROP ensures a foundational inventory level for this policy. Nevertheless, this approach assumes that annual demand is predictable, resonating with the accurate setup of the IBS for Reorder Quantity (Q) and Reorder Point (R). Consequently, ROP outperforms both MTA DBM and DDMRP in terms of ROI.

Graphs related to Finding-5 from SE1: ROP shows dominance over MTA DBM and DDMRP in ROI for Case 2 within SE1

Figure 30 showcases the simulated ROI outcomes for Case 2, illustrating a compelling performance hierarchy among the inventory strategies. ROP takes the lead with an ROI of **44.38**, markedly ahead of both MTA DBM, which registers at **35.92**, and DDMRP, trailing slightly behind at **34.08**. This pattern emphasises ROP's effectiveness in maximising revenue against inventory costs, outpacing its counterparts in the Case 2 scenario.

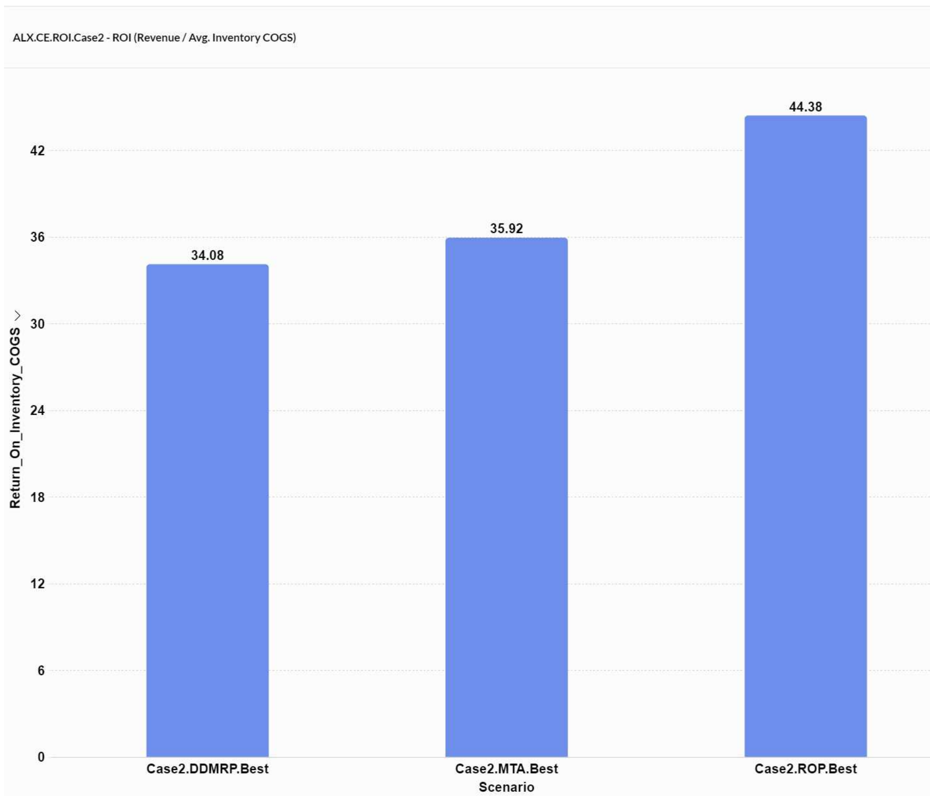


Figure 30- Case 2 ROI (Revenue / Average Inventory COGS)

Table 17 - Case2.Demand.CoV.Product

Product	Standard Deviation of Demand Quantity	Average Demand Quantity	Case 2- CoV of Demand
20D	491.91	338.96	1.45
30NE1	8019.79	5127.77	1.56
40NE1	8951.63	4713.14	1.9

When observing Case 2, we find a stable demand variation with a CoV of less than 2. The specifics for this variation are tabulated in above **Table 17**.

As evident in Case 2, a lower demand variation underscores the advantages of employing ROP with a consistent initial buffer size. If the demand over a year remains predictable and stable, using ROP as the primary inventory policy appears validated. ROP achieves a higher ROI than MTA DBM and DDMRP in Case 2, as shown in **Figure 30**.

Graphs related to Finding-6 from SE1: MTA DBM's produces the highest ROI in SE1's Case 3

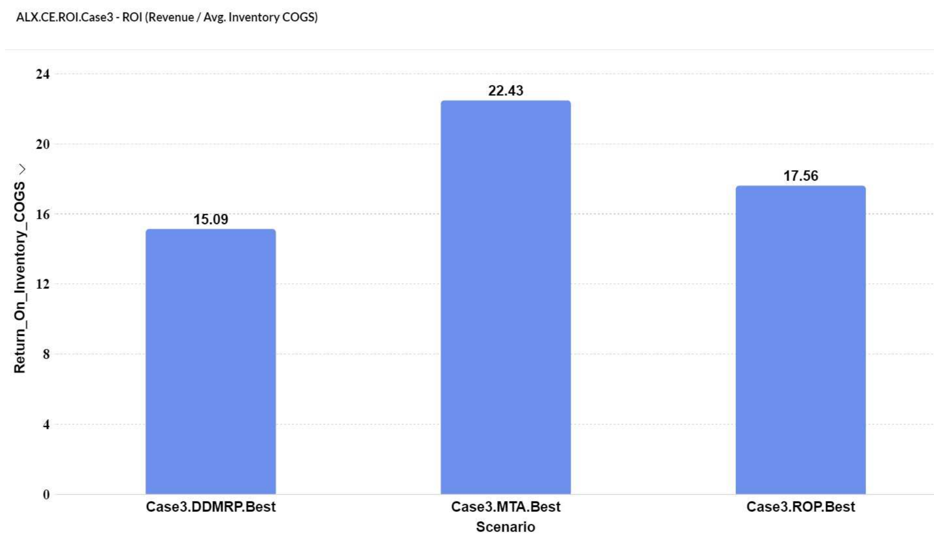


Figure 31 - Case3.ROI (Revenue / Average Inventory COGS)

Table 18 - Case3.Demand.CoV.Product

Product	Standard Deviation of Demand Quantity	Average Demand Quantity	Case3 - CoV of Demand
2816	22582.2	3658.87	6.17
3542	9549.64	7811.28	1.22
9396	59265.72	8262.34	7.17

In **Figure 31**, which visualises the simulated ROI results for Case 3, MTA DBM emerges as the most efficient inventory strategy, boasting an ROI COGS of **22.43**. This outperformance is set against ROP and DDMRP, which secure ROI COGS figures of **17.56** and **15.09**, respectively. It is worth noting that the distinctiveness of this case is underscored by the considerably high demand variation for two products, as they exceed a coefficient of variation (CoV) of **6**, as shown in **Table 18**.

MTA DBM policy will adjust the buffer size according to the penetration percentage of Too-Many-Green (TMG) and Too-Many-Red (TMR) as Dynamic Buffer Management (DBM) logic. Therefore, it is automatically adjusted according to the actual consumption rate of demand and adapts to the changes of dynamic demand variation.

Graphs related to Finding-7 from SE1: DDMRP 100% Service Level by Revenue (SL) in Case 3 despite having the lowest ROI within SE1

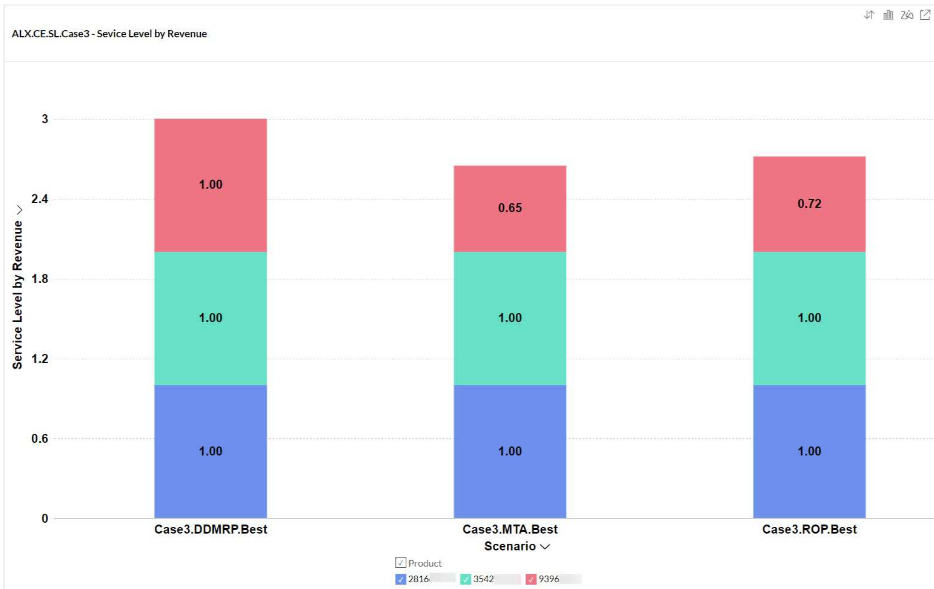


Figure 32 - Case3.Service Level by Revenue

Figure 32 presents a nuanced view of inventory strategies in Case 3. While DDMRP reaches the zenith with a 100% Service Level by Revenue, this success only translates proportionally to financial efficiency. Specifically, DDMRP registers the lowest ROI of **15.09 (see Figure 31)**, shedding light on the trade-offs businesses might face between service levels and return on investment.

Based on **Figure 32**, DDMRP achieved a 100% "Service Level by Revenue" for all three product items in Case 3. In comparison, MTA DBM and ROP accomplished the "Service Level by Revenue" of 65% and 72% on product item 9396 (red segment of the stacked bar graph), with the highest CoV of demand of 7.17. According to the **Table 18**, the 3rd product item (9396) is getting a CoV higher than 7. In this scenario, the ROP and MTA DBM could not achieve a 100% service level as DDMRP. However, DDMRP can adjust the buffer size according to the moving Average Daily Usage (ADU). At the same time, it will also trigger one indirect MTO order by net flow equation to cover the spiking demand within the Order Spike Horizon (OSH) if the Spike is qualified with the demand over "Order Spike Threshold (OST)". However, to keep the highest service level in Case 3 within SE1, the DDMRP maintained the highest buffer stock. It is a trade-off decision between inventory level and service level.

Graphs related to Finding-8 from SE1: Both ROP and MTA DBM consistently attain 100% Service Level by Revenue (SL) for items with Demand Variation (DV), where CoV is below seven.

In Case 3, as illustrated by above **Figure 32**, both ROP and MTA DBM demonstrated remarkable efficiency, achieving a 100% Service Level by Revenue for product items with a CoV under **7**, signifying lower demand variation. This data is additionally shown in section 4.6.3 - **Table 22 for Finding-8**. However, DDMRP's approach was more conservative, opting for a larger stock buffer to ensure the same 100% service level (SL). This decision potentially incurs higher opportunity costs, highlighting the balance between inventory levels and service reliability.

On the other hand, ROP and MTA DBM could also achieve a 100% Service Level by Revenue for the lower CoV of demand between 1.22 and 6.17. There is no order spike management in ROP and MTA DBM. Without getting very large demand spikes, ROP safety stock and MTA dynamic buffer management could effectively handle the range of CoV below 6.17 in Case 3 within SE1.

Graphs related to Finding-9 from SE2: DDMRP attained peak Service Level (SL) performance during Case 3. In contrast, ROP consistently secured the highest Return on Inventory (ROI) in Case 1 and 2 across varied scenarios.

Figures 33 compare ROI and Service Level by Revenue (SL) across the three cases, revealing distinct policy effectiveness. DDMRP emerges as having the highest value in Service Level (100%) achievement during Case 3 (see **Figure 33-A**). On the other hand, ROP has the largest ROI (76.96 and 44.38), topping the charts (see **Figure 33-B**) in both Case 1 and 2. These variations underscore the inherent trade-offs and unique advantages of each policy.

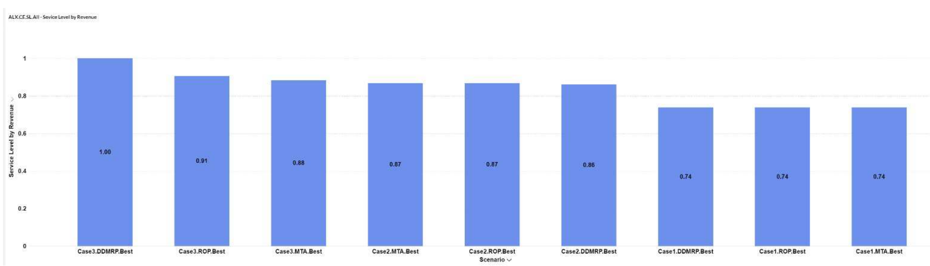


Figure 33-A - Service Level by Revenue (SL) ranking

Figure 33-A shows the descending ranking of SL across three cases with different policies.

Return on Inventory (ROI) ranking

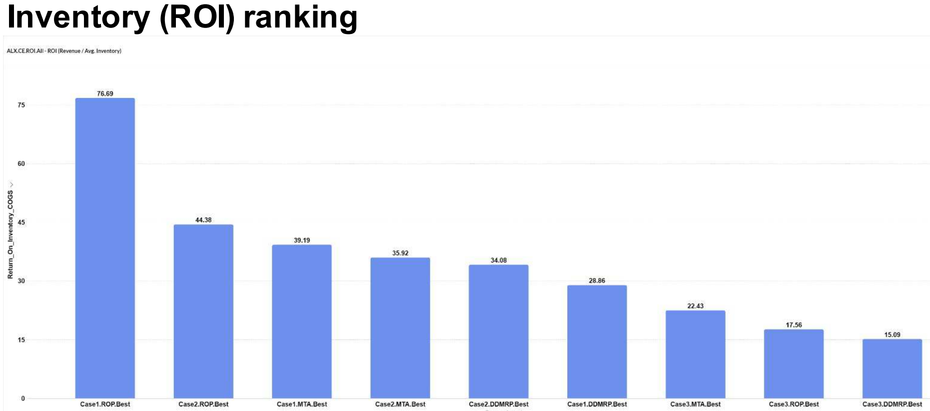


Figure 33-B shows the descending ranking of ROI across three cases with different policies.

Figures 33 illustrate the varied ROI and Service Level by Revenue rankings across the cases and policies. Within identical demand profiles and contexts, DDMRP excels in service level but maintains the most extensive inventory buffer, resulting in the lowest ROI. In contrast, ROP boasts the highest ROI, closely followed by MTA DBM.

Graphs related to Finding-10 from SE3: MTA DBM's resilience in accommodating fluctuating demands without big impacting the Service Level by Revenue (SL) in Case 3

The **SE3** and **SE4** simulation studies under experiment **Group C** aim to assess the comparative analysis performance of ROP, MTA DBM and DDMRP inventory policies using different Demand Variation (DV) and Supply Variation (SV) ranges in the same case context. Before analysing the detailed outcomes, **Table 19** lists the Coefficient of Variation (CoV) and Transportation Lead Time (TLT) per product item across three cases before simulated variation experiments.

Table 19 - Demand CoV vs Transportation Lead Time (TLT) across 3 Cases

Product Items	Actual Demand CoV	Transportation Lead Time (TLT) in days
Case1.Lite.EU B2B	**13.55**	180
Case1.Lite.US B2C	8.01	180
Case1.Node.EU B2B	7.37	180
Case1.Node US B2C	8.27	180
Case1.WB EU B2B	7.36	180
Case1.WB US B2C	7.95	180
Case2.20D	1.45	65
Case2.30NE1	1.56	65
Case2.40NE1	**1.9**	65
Case3.2816	6.17	144
Case3.3542	1.22	133
Case3.9396	**7.17**	46

Table 19 indicates that there is one exceptionally high CoV in each Case highlighted in red colour.

Figures 34-A to 34-C illustrate the resilience of MTA DBM against escalating Demand Variation in CoV during the simulation experiment SE3. While the Service Level by Revenue (SL) for ROP and DDMRP exhibited a downward trend (1.0 to 0.94 for ROP and 1.0 to 0.8-0.95 for DDMRP) in response to increased demand fluctuations, MTA DBM's SL remained relatively steady (1.0) without decline (see Figure 34-C). This behaviour is particularly pronounced in Case 3, emphasising the unique stability of MTA DBM compared to the other policies. In essence, ROP and DDMRP present a clear inverse relationship between Demand Variation in CoV and SL, a characteristic not shared by MTA DBM.

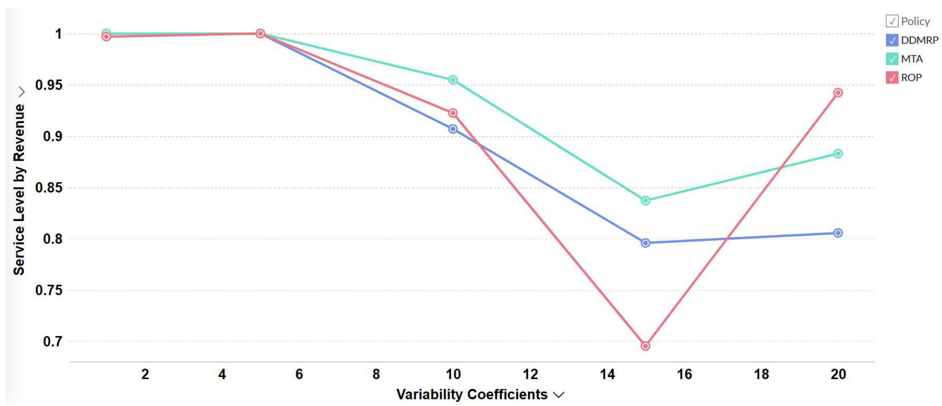


Figure 34-A - DV Impact on Service Level by Revenue in Case1

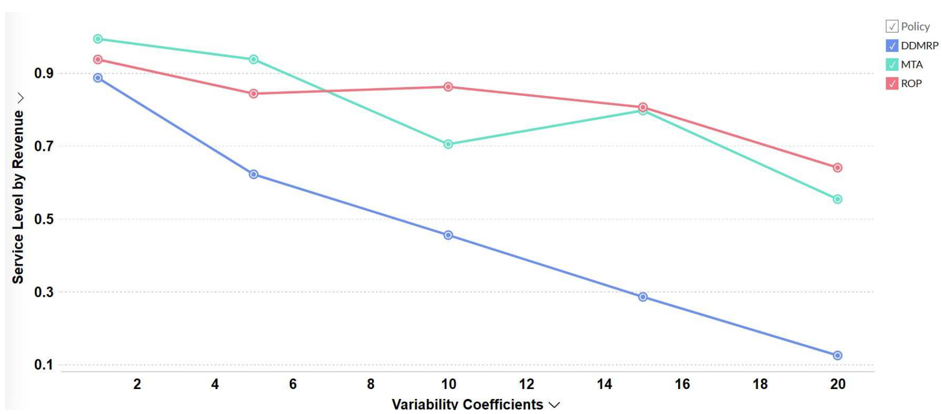


Figure 34-B - DV Impact on Service Level by Revenue in Case2

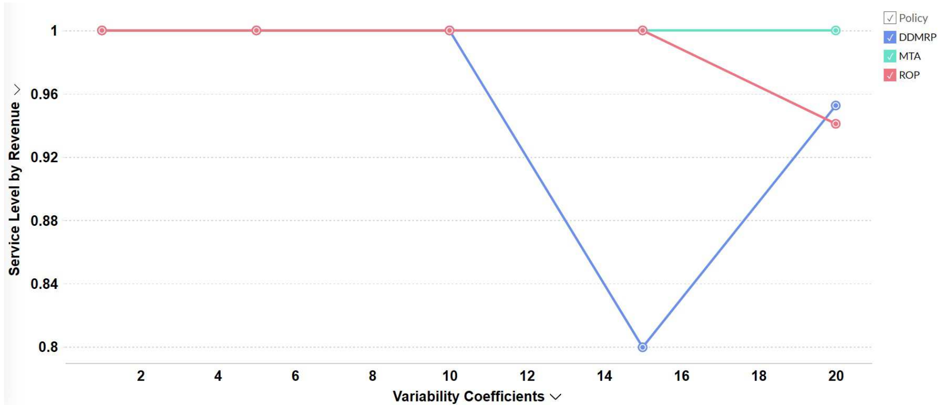


Figure 34-C - DV Impact on Service Level by Revenue in Case3

The inverse relationship between the Demand Variation in Coefficient of Variation (CoV) and “Service Level by Revenue” is found in ROP and DDMRP, except for MTA DBM in Case 3 (see **Figure 34-C**).

Graphs related to Finding-11 from SE3: ROP consistently outperforms MTA DBM and DDMRP in terms of ROI, significantly when increasing the CoV by Demand Variation (DV) in Case 1 and 3

Figures 35-A to C underscore the resilience of ROP in terms of Return On Inventory (ROI) in response to rising CoV due to Demand Variation (DV) in simulation experiment SE3. As the CoV increases, the ROI by Stock Balance for ROP showcases a consistent and linear ascent, particularly in Case 1 (ROI from 44 to 160.37) and 3 (ROI from 32.98 to 182.28). While increased DV amplifies the demand variability coefficients (1, 5, 10, 15, 20) during the simulation, ROP stands distinct, maintaining its initial buffer size at an appropriate level, unlike the adaptive measures of MTA DBM and DDMRP.

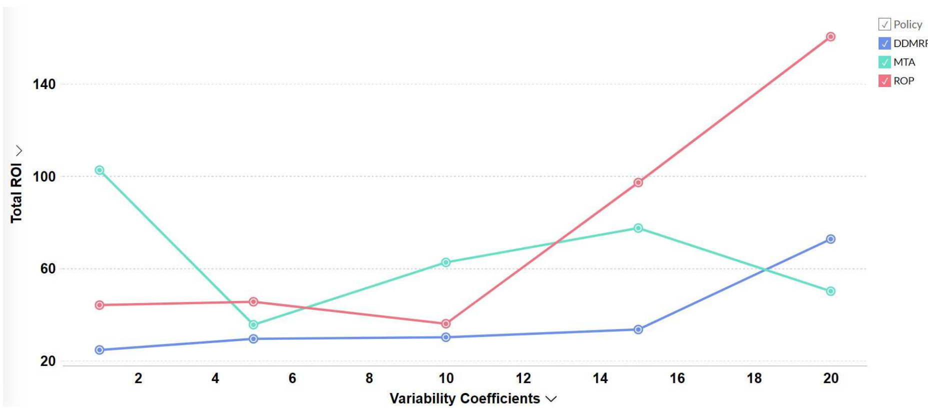


Figure 35-A - DV impact on ROI by Stock Balance in Case1

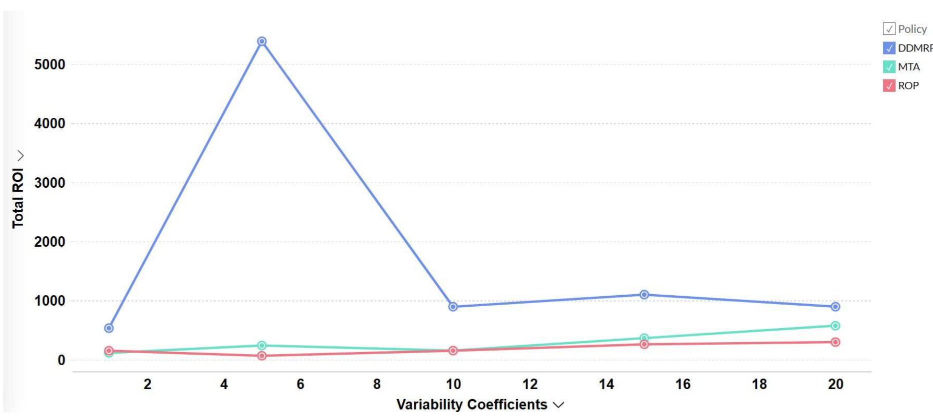


Figure 35-B - DV impact on ROI by Stock Balance in Case2

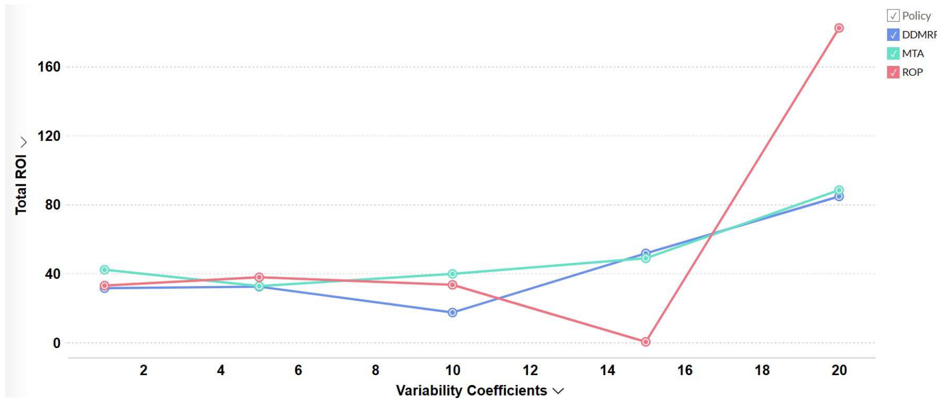


Figure 35-C - DV impact on ROI by Stock Balance in Case3

The increased Demand Variation by the variation coefficients in CoV will accelerate the demand variation in the simulation period., but ROP will not adjust the initial buffer size as MTA DBM and DDMRP. Based on **Figures 35-A to 35-C**, the static reorder point in ROP policy keeps a minimum safety stock level and will not over-react the demand variation by increasing buffer size as MTA DBM and DDMRP. In return, it could make a higher ROI.

Graphs related to Finding-12 from SE4: The impact of Supply Variation (SV) of Transportation Lead Time (TLT) and its role in diminishing Service Level by Revenue (SL).

Figure 36 illustrates the impact of increasing Supply Variation in Transportation Lead Time (SV.TLT) across three cases. As this variation grows, there is a discernible decline in the Service Level by Revenue (SL), albeit at differing rates for each Case. This situation underscores a consistent inverse relationship between SV.TLT and SL.

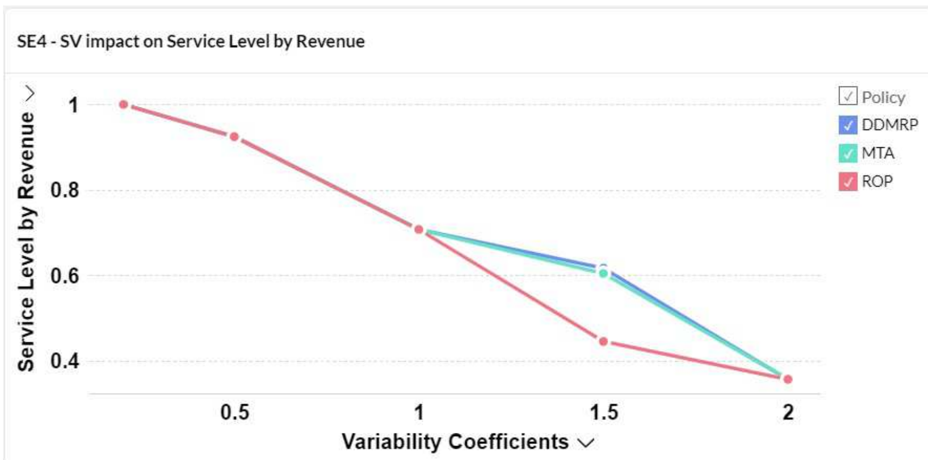


Figure 36-A - SV.TLT Impact on Service Level by Revenue in Case1

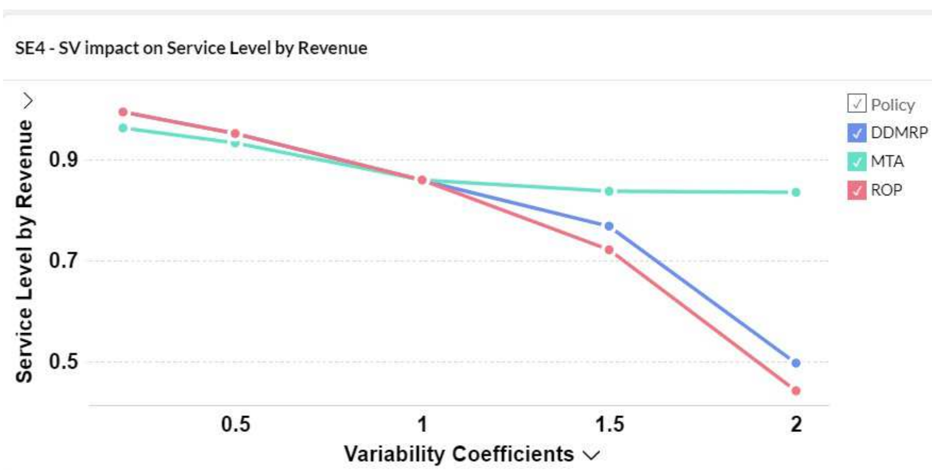


Figure 36-B - SV.TLT Impact on Service Level by Revenue in Case2

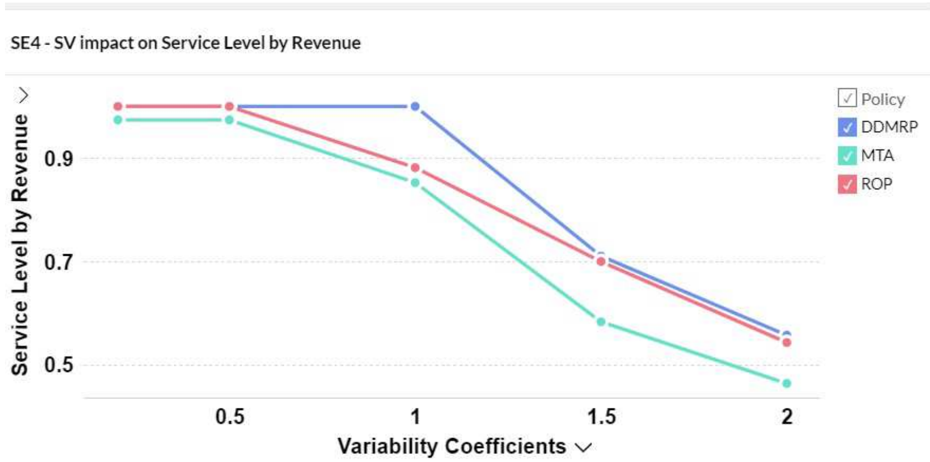


Figure 36-C - SV.TLT Impact on Service Level by Revenue in Case3

As depicted in **Figures 36-A to 36-C,** there is a pronounced influence of Transportation Lead Time (TLT) on the Service Level by Revenue (SL). Delays in delivering replenished items due to simulated variations in TLT compromise supply reliability. Such disruptions prevent timely buffer stock recovery, rendering the system ill-equipped to cope with fluctuations in demand.

Summary

While the Graphs offer crucial snapshots of the overarching scenario, one must recognise them as a visual gateway to delve deeper into the intricate dynamics of inventory policies and their varied performances. By aligning these graphical illustrations with the in-depth statistical findings, the intention is to provide a holistic exploration of the research questions. This ensures that the insights are both profound and easily graspable. The forthcoming other results will further examination of the outcomes.

4.5.4 Other Results broken down by Experiment Group

This section offers a breakdown of other results generated through these experiments, and categorised by each simulation experiment group (i.e., A, B, and C) as illustrated in section 4.2 - **Figure 18**. By delving into the specifics of each group's outcomes, the analysis strives to elucidate the nuances of inventory policy performance, facilitating a thorough examination of the posed research questions.

Group A: Simulation Experiment SE0 - Planning Parameter Variation Experiments in ALX and Multivariate Analysis in JMP

There are two analytical steps related to SE0 in Group A. First, ALX imported stock master data, planning parameters and actual demand from three cases to generate simulated performance outcomes, which were imported into Zoho Analytics shown in Appendix B through various scatter plots. Then, the selected parameters are listed in Appendix E – a summary of parameters after the simulation experiments (SE0). Second, JMP imported the simulated outcomes of those cases for multivariate analysis to generate those scatterplot matrices in Appendix C.

The objective of the **SE0** simulation experiment endeavours to establish scenarios, each highlighting unique performance outcomes for selecting the optimised planning parameters. The principle guiding this selection is firmly rooted in the maximisation of the objective function defined as:

Maximise $F(x) = \{f1(x), f2(x)\}$
Subject to: $x \in X$

Here, *f1* signifies Return on Inventory (ROI), and *f2 represent*s Service Level by Revenue (SL). The variable X and the functions *f1* and *f2* exhibit different representations based on the policy type being evaluated, as delineated below:

1. **ROP Policy**: $F_{\_rop}(Q, R, SS) = \{f1_{\_rop}(Q, R, SS), f2_{\_rop}(Q, R, SS)\}$
2. **MTA DBM Policy**: $F_{\_mta}(IBS, TMG, TMR) = \{f1_{\_mta}(IBS, TMG, TMR), f2_{\_mta}(IBS, TMG, TMR)\}$
3. **DDMRP Policy**: $F_{\_ddmrp}(LTF, VF, STH, STP) = \{f1_{\_ddmrp}(LTF, VF, STH, STP), f2_{\_ddmrp}(LTF, VF, STH, STP)\}$

Table 20 - Summary of planning parameters selected in the simulation experiment (SE0)

Case.Policy.Item Demand Points	Policy Parameters	Variables	Theoretical Default	Upper Range +50%	Selected Parameters	Ending Available Inventory	Service Level by Revenue	Revenue	ROI by Stock Balance
Case1.ROP.Lite US B2C	Order up to max. level	Q	320	480	**450**	41	70.86%	65200	1590.24
	Fixed replenishment point	R	320	480	**320**				
	Safety stock	SS	0	160	**0**				
Case1.ROP.Node US B2C	Order up-to max. level	Q	140	210	**190**	8	79.49%	27300	3412.50
	Fixed replenishment point	R	140	210	**140**				
	Safety stock	SS	0	70	**0**				
Case1.ROP.WB US B2C	Order up-to max. level	Q	220	330	**280**	2	74.88%	43400	21700.00
	Fixed replenishment point	R	220	330	**220**				
	Safety stock	SS	0	110	**40**				
Case1.ROP.Lite EU B2B	Order up to max. level	Q	540	810	**540**	396	87.52%	107400	271.21
	Fixed replenishment point	R	540	810	**540**				
	Safety stock	SS	0	270	**0**				
Case1.ROP.Node EU B2B	Order up-to max. level	Q	740	1110	**940**	292	51.12%	147100	503.77
	Fixed replenishment point	R	740	1110	**740**				
	Safety stock	SS	0	370	**0**				
Case1.ROP.WB EU B2B	Order up-to max. level	Q	400	600	**540**	166	78.92%	77800	468.67
	Fixed replenishment point	R	400	600	**400**				
	Safety stock	SS	0	200	**40**				
Case1.MTA.Lite.US B2C	Initial Buffer Size	IBS	320	480	**320**	337	70.86%	65200	193.47
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.MTA.Node.US B2C	Initial Buffer Size	IBS	130	210	**130**	119.5	79.49%	27300	228.45
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				

	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	**1**	1.5	**1.5**				
Case1.MTA.WB.US B2C	Initial Buffer Size	IBS	210	330	**210**	150.5	74.88%	43400	288.37
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	**1**	1.5	**1.5**				
Case1.MTA.Lite.EU B2B	Initial Buffer Size	IBS	520	800	**600**	734.5	87.52%	107400	146.22
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.MTA.Node.EU B2B	Initial Buffer Size	IBS	720	1080	**720**	939	51.12%	147100	156.66
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.MTA.WB.EU B2B	Initial Buffer Size	IBS	380	580	**380**	431	78.92%	77800	180.51
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.DDMRP.Lite US B2C	Lead Time Factor	LTF	0.2	1	**0.2**	681	70.86%	65200	95.74
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike	STP	50	100	**100**				

	Threshold %								
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP. Node US B2C	Lead Time Factor	LTF	0.2	1	**0.3**	743.88	79.49%	27300	36.70
	Variability Factor	VF	0	1	**0.9**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**190**				
	Spike Threshold %	STP	50	100	**80**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP.WB US B2C	Lead Time Factor	LTF	0.2	1	**0.5**	670.8	74.88%	43400	64.70
	Variability Factor	VF	0	1	**0.9**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP.Lite EU B2B	Lead Time Factor	LTF	0.2	1	**0.5**	382	87.52%	107400	281.15
	Variability Factor	VF	0	1	**0.9**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP.Node EU B2B	Lead Time Factor	LTF	0.2	1	**0.2**	809	51.12%	147100	181.83
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP.WB EU B2B	Lead Time Factor	LTF	0.2	1	**0.2**	523	78.92%	77800	148.76

	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case2.ROP.20D	Order up to max. level	Q	441337	660000	**441337**	224402	88.98%	21693451	96.67
	Fixed replenishment point	R	220669	330000	**220669**				
	Safety stock	SS	0	220000	**0**				
Case2.ROP.30NE1	Order up to max. level	Q	667653	990000	**667653**	328928	88.27%	32817753 8	997.72
	Fixed replenishment point	R	333826	480000	**333826**				
	Safety stock	SS	0	330000	**200000**				
Case2.ROP.40NE1	Order up to max. level	Q	613666	900000	**713666**	231130	83.02%	30164095 5	1305.07
	Fixed replenishment point	R	306833	450000	**406833**				
	Safety stock	SS	0	300000	**0**				
Case2.MTA.20D	Initial Buffer Size	IBS	220000	340000	**220000**	416849	88.98%	21693451	52.04
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Dow n- Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case2.MTA.30NE1	Initial Buffer Size	IBS	330000	510000	**410000**	317150	88.27%	32817753 8	1034.77
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Dow n- Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case2.MTA.40NE1	Initial Buffer Size	IBS	300000	460000	**360000**	353406	83.02%	30164095 5	853.53
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					

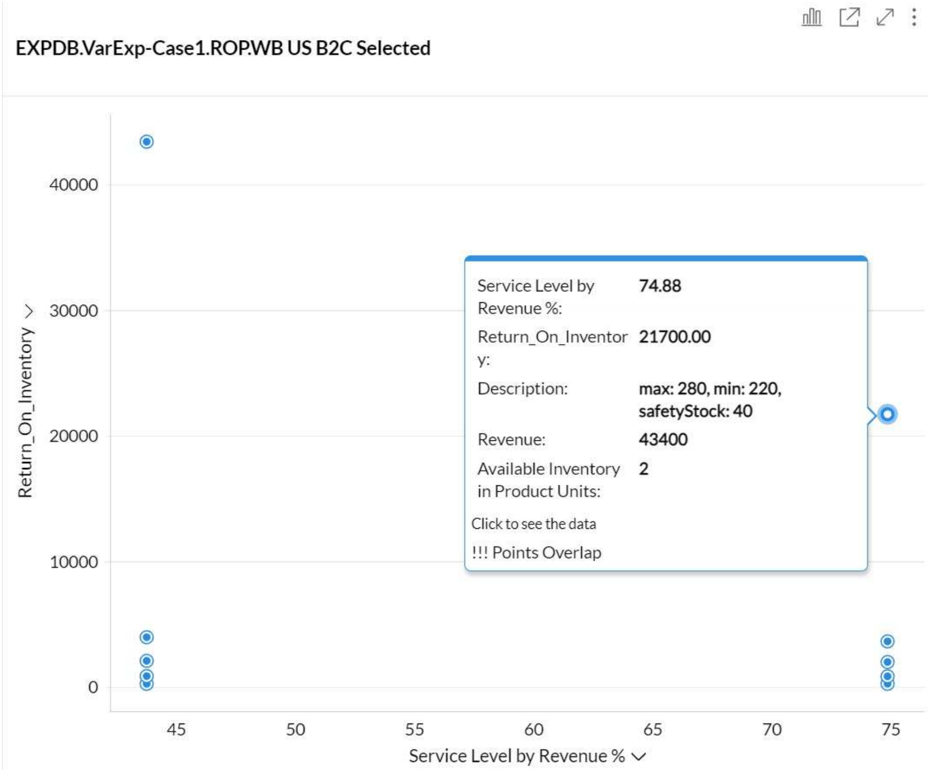
	Buffer Dow n-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case2.DDMRP.20D	Lead Time Factor	LTF	0.2	1	**0.2**	14751	88.98%	21693451	1470.64
	Variability Factor	VF	0	1	**1**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	65	75	**75**				
	Spike Threshold %	STP	50	100	**50**				
	Net Flow Position	NFP	N/A	N/A					
Case2.DDMRP.30NE1	Lead Time Factor	LTF	0.2	1	**1**	1259602	88.27%	32817753 8	260.54
	Variability Factor	VF	0	1	**0.1**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	65	75	**75**				
	Spike Threshold %	STP	50	100	**50**				
	Net Flow Position	NFP	N/A	N/A					
Case2.DDMRP.40NE1	Lead Time Factor	LTF	0.2	1	**0.2**	345245	83.02%	30164095 5	873.70
	Variability Factor	VF	0	1	**0.1**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	65	75	**65**				
	Spike Threshold %	STP	50	100	**60**				
	Net Flow Position	NFP	N/A	N/A					
Case3.ROP.3542	Order up-to max. level	Q	2084479	3150000	**2184479**	47359	100.%	24371200 0	5146.05
	Fixed replenishment point	R	1042239	1560000	**1042239**				
	Safety stock	SS	0	1050000	**300000**				
Case3.ROP.2816	Order up-to max. level	Q	1057141	1560000	**1157141**	15575	100.%	114156600	7329.48
	Fixed replenishment point	R	528570	780000	**528570**				
	Safety stock	SS	0	520000	**0**				
Case3.ROP.9396	Order up-to max. level	Q	762578	1140000	**862578**	975562	71.67%	25778490 0	264.24
	Fixed	R	381289	570000	**481289**				

	replenishment point								
	Safety stock	SS	0	380000	**300000**				
Case3.MTA.3542	Initial Buffer Size	IBS	1040000	1560000	**1040000**	214797	100.%	24371200 0	1134.62
	Too Many Green	TMG	50	100	**90**				
	Too Many Red	TMR	50	100	**90**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Dow n-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case3.MTA.2816	Initial Buffer Size	IBS	520000	780000	**580000**	291846	100.%	114156600	391.15
	Too Many Green	TMG	50	100	**90**				
	Too Many Red	TMR	50	100	**90**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Dow n-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case3.MTA.9396	Initial Buffer Size	IBS	380000	580000	**580000**	732984	64.79%	25778490 0	351.69
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Dow n-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case3.DDMRP.3542	Lead Time Factor	LTF	0.2	1	**0.2**	465718	100.%	24371200 0	523.30
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	133	143	**133**				
	Spike Threshold %	STP	50	100	**90**				
	Net Flow Position	NFP	N/A	N/A					
Case3.DDMRP.2816	Lead Time Factor	LTF	0.2	1	**0.2**	719431	100.%	114156600	158.68
	Variability Factor	VF	0	1	**0.1**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	144	154	**144**				
	Spike	STP	50	100	**100**				

	Threshold %								
	Net Flow Position	NFP	N/A	N/A					
Case3.DDMRP.9396	Lead Time Factor	LTF	0.2	1	**0.2**	3205565	100.%	257784900	80.42
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	46	56	**56**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					

As listed in above **Table 20**, these scenarios are derived from variation experiments for the planning parameters within the ALX, ranging from theoretical baselines to a 50% increase. Following data aggregation, the focus is on identifying the selected planning parameters for a fair comparison in SE1 to SE4, as indicated in the "Selected Parameters" column of **Table 20**. These parameters are chosen due to their efficacy in attaining an optimal Return on Inventory (**ROI**) as f1 and the peak Service Level by Revenue (**SL**) as f2. For a detailed depiction of the selection method, refer to **Figure 37**, which presents one of thirty-six scatter plots extracted from Appendix B and parameters selected from Appendix E illustrating the outcomes from the ALX simulator for selecting parameters.

The selected points in the following Scatter plot matched with the above **Table 20** – ”Selected Parameters” column:



Case.Policy.Item Demand Points	Policy Parameters	Variables	Theoretical Default	Upper Range +50%	Selected Parameters	Ending Available Inventory	Service Level by Revenue	Revenue	ROI by RL/Stock Balance
Case1.ROP.WB US B2C	Order up to max. level	Q	220	330	**280**	2	74.88%	43400	21700
	Fixed replenishment point	R	220	330	**220**				
	Safety stock	SS	0	110	**40**				

Figure 37 - **SE0** variation experiments planning parameters selection example

Figure 37 in **Appendix B** presents an illustrative example (i.e. Case1.ROP.WB US B2C) of planning parameter selected (i.e. Q=280, R=220 and SS=40) from SE0 variation experiments, demonstrating the utilisation of objective functions for optimising the "Selected Parameters". ALX based on the actual demand data from Case1 by ROP policy for item WB at stock point US B2C for simulation. The simulated outcomes were generated according to the policy parameters ranging from the theoretical default to 50% increase in ALX variation experiments. Then, the highest value of SL (i.e. 74.88%) and the ROI (i.e. 21700) were spotted in the scatter plot in the top right-hand corner as well as in the other scatter plots shown in **Appendix B**.

Appendix B includes diverse scatter plots representing the "Selected Parameters". These plots visually represent the interrelation and trade-offs between Return on Inventory (ROI) and Service Level by Revenue (SL) under varying policies and parameter settings. A thorough analysis of these plots yields valuable insights into the influence of parameter variations on the objectives *f1* and *f2*, thereby aiding in identifying optimal settings for different inventory management policies. In summary, **Appendix E** shows thirty-six sets of the "Selected Parameters" in the table.

Appendix C shows the correlational aspects of the study, the results of the multivariate analysis of the **SE0** variation experiment variables. This analysis ascertains the absence of overlapping among independent variables and highlights dependent variables, which maintain a regression association with other determinants.

Group B: Simulation Study SE1 - Analysing Identical Demand Profiles across Different Inventory Policies

Table 21 - Contextual variables for simulation experiments

Inventory policies	**Independent variables (planning parameters)**	**Dependent variables (see Appendix A - KPIs)**
ROP	Order up=to maximum level (**Q**) Fixed replenishment point (**R**) Safety Stock (**SS**)	A1. Revenue Level (**RL**) A2. Inventory Level (**IL**) A3. Service Level (**SL**) by Revenue A4. Return On Inventory (**ROI**)
MTA DBM	Initial Buffer Size (**IBS**) Too Many Green (**TMG**) Too Many Red (**TMR**)	
DDMRP	Lead Time Factor (**LTF**) Variability Factor (**VF**) Spike Threshold Horizon (**STH**) Spike Threshold % (**STP**)	

As highlighted in the "Simulation Overview" section 4.2 and depicted in **Figure 18**, the anticipated outcomes are the simulated performance metrics across various inventory policies, all subjected to the same case's demand pattern.

Group B: Simulation Study SE2 - Comparative Simulated Outcomes Across Cases for Various Policies

SE2's primary objective is to juxtapose the performance of ROP, MTA DBM, and DDMRP replenishment strategies across various case scenarios. Preliminary to this comparison, **Figures 38-A to C** depicts the demand patterns for the three cases.

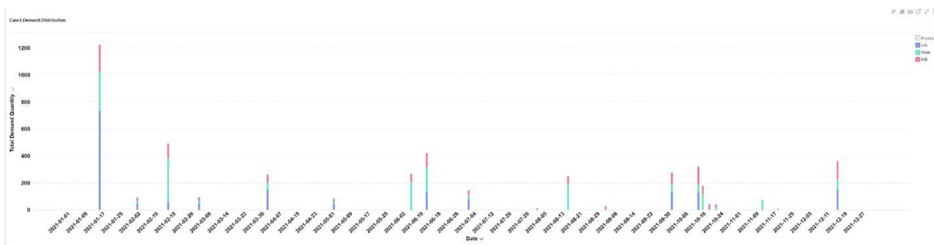


Figure 38-A Demand.Distribution pattern on Case1

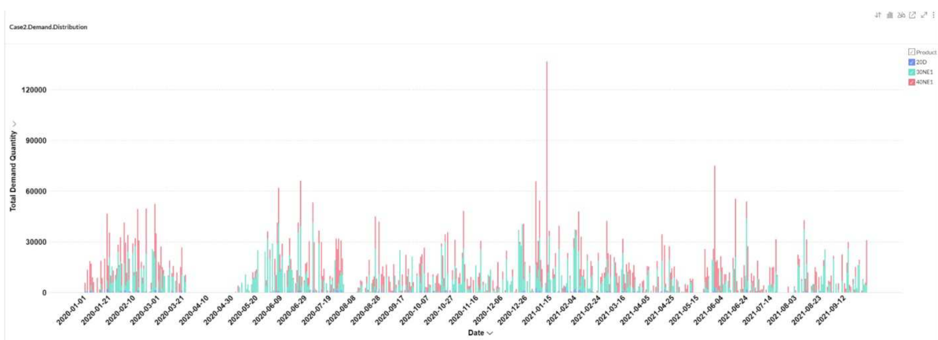


Figure 38-B Demand.Distribution pattern on Case2

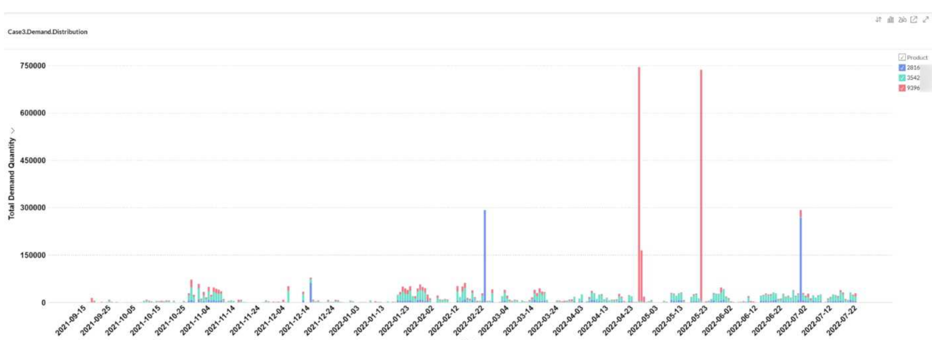


Figure 38-C Demand.Distribution pattern on Case3

Figures 38-A to C reveals that Case 1 encounters infrequent, irregular demand, whereas Cases 2 and 3 experience more frequent spikes in order demands.

Group C: Simulation Experiment SE3 - Simulated results by different Demand Variation (DV) in the same case

The main objective of SE3 is to evaluate the performance impact under multiple steps of variation coefficients in the demand variation in CoV. The CoV ranges from 1.22 to 13.55 for the actual demand, as stated in **Table 12**. For SE3, we will deploy the five steps of random demand as variation coefficients in CoV as 1, 5, 10, 15 and 20. Also, we will keep all demand intervals as five days across all policies and items. All other parameters and key performance indexes (KPIs) are kept unchanged and inherited from SE1 and SE2. So we could see the impact and the performance trends.

Group C: Simulation Experiment SE4 - Simulated results by different Supply Variation (SV) in the same case

The key objective of **SE4** is to evaluate the performance impact under multiple steps of variation coefficients in the supply variation in transportation lead time (TLT). The experiment applied the variation coefficients - 0.2, 0.5, 1, 1.5 and 2 for the existing transportation lead time to simulate the impact of supply variation in transportation lead time (TLT). So, we can compare the same performance measures with those supply variation (SV) transportation lead time impacts.

Group C's results reveal the importance of inventory policy selection as more than just an operational choice; it significantly impacts business outcomes. With ever-changing demand and supply dynamics, the right inventory policies become essential. Group C demonstrates the need to strategically deploy different policies depending on specific Demand and Supply Variation scenarios.

With these insights in mind, the study delves deeper into further observations across all simulation experiments.

4.5.5 Additional Observations Across Simulation Experiments

This section dives deeper, extending beyond the preliminary observations of Groups A, B, and C. It captures overarching patterns that surfaced during the simulation experiments, providing a richer, more comprehensive understanding of inventory policy dynamics in varying situations.

Zero Out-Of-Stock for all cases by different policies

One standout observation is evident from **Figure 39** in **SE2**: all inventory policies maintained a zero Out-Of-Stock (OOS) status across the three Case simulation studies.

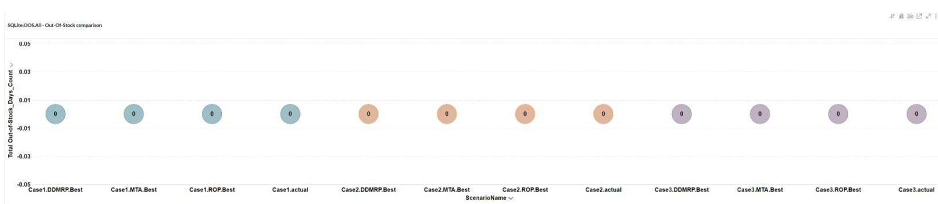


Figure 39 - Out-of-stock comparison across 3 Cases

Interpreting **Figure 39**, a Zero Stock-Out denotes a consistent positive stock balance throughout. A critical contributor to this result is the full backorder policy in ALX, which prevents partial deliveries for backorders. Instead, it ensures that all outstanding backorders receive complete deliveries once stock becomes available during the simulation. However, this absence of Out-Of-Stock (OOS) does not necessarily translate to a lack of Overdue Order Frequency (OOF), as explored further below.

Overdue Order Frequency (OOF) is similar except DDMRP as Zero OOF in Case 3

DDMRP stood out in Case 3 by registering zero Overdue Order Frequency (OOF) across all product items. This remarkable achievement is visualised in **Figure 40**. ROP and MTA DBM policies recorded varying OOF levels, primarily influenced by their Service Level on Revenue (SL).

DDMRP's unique capability to integrate spike management into its inventory policies becomes instrumental here. Such a mechanism equips DDMRP to effectively manage abrupt and significant demand variations, significantly when the CoV exceeds 7.

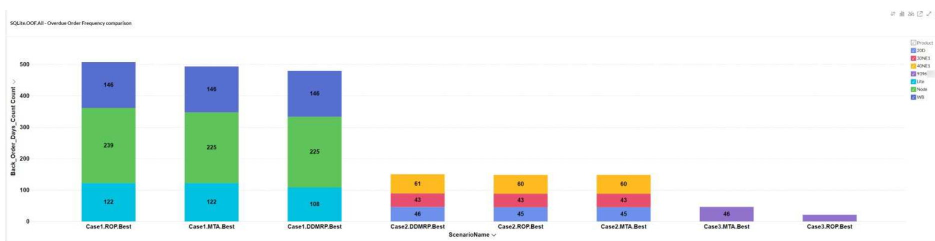


Figure 40 - Overdue Order Frequency (OOF) comparison across 3 cases

In sum, when pieced together, these additional observations broaden the spectrum of understanding concerning inventory policy performances. They highlight the intricate nuances that can significantly impact outcomes and provide direction for future strategies in inventory management.

4.5.6 Summary of Results broken down by Experiment Group and Overall

In synthesising the research outcomes, this section combines the exhaustive examinations of Groups A, B, and C, illuminating the salient patterns derived from the simulation experiments.

Group A: Impact of Inventory policies' Parameters on performance

There is one situation stemming from **Group A**, which focuses on the impact of inventory policy parameters on performance. Safety Stock (**SS**), an important part of the ROP policy, maintains significant influence over inventory levels, hence maintaining stable service levels. Extending the analysis, parameters inside the MTA DBM and DDMRP policies surface act as strong factors. The MTA DBM policy primarily relies on the Initial Buffer Size (**IBS**). Conversely, the DDMRP policy is dynamically derived from the Spike Threshold Percentage (**STP**) and the Lead Time Factor (**LTF**). These characteristics jointly support the keeping of optimal inventory levels. **Tables 14 to 16** in section 4.5.3 should be referenced to provide a more concrete understanding of these interactions. These graphics convert the theoretical foundations of **Finding-1**, **Finding-2**, and **Finding-3** into graphical illustrations.

Group B: Performance comparison by different policies in the same case and cross-cases

Venturing into **Group B**, the focal point shifts to a comparative lens, evaluating the performance benchmarks of varying inventory policies. A juxtaposition of ROI results reveals that ROP and MTA DBM policies carve out a niche, displaying pronounced ROI strengths. Conversely, DDMRP performs the best in terms of service levels, particularly when confronted with high spike demand patterns. This juxtaposition finds further reinforcement in **Figures 29 to 33** from section 4.5.3, visually mapping the landscapes of **Finding-4 to Finding-9**.

Group C: Performance comparison by different policies under demand variation and supply variation

Pivoting to **Group C**, the analysis probes the nuances of policy performance under the dual umbrellas of demand and supply variations. Here, the MTA DBM policy stands out, countering the variability, and is distinctly evident in Case 3. In stark contrast, the ROP policy produces the excellent ROI figures, especially pronounced in the environs of Cases 1 and 3. However, the narrative could be more straightforward; supply variations pose challenges, casting a shadow on service levels, with transportation lead time emerging as a particularly sensitive touchpoint. **Figures 34-36** within section 4.5.3 clarifies these dynamics, framing the intricate dances of **Finding-10, Finding-11, and Finding-12**.

In culmination, this section serves as an analytical tapestry, weaving together multifaceted insights from the triad of groups, crafting a harmonised and enriched narrative. As we pivot from these detailed findings, Section 4.6 - Comparative Analysis promises a more holistic examination of the results in juxtaposition. This strategic progression positions us to delve deeper into the nuances of inventory policy dynamics.

4.6 Comparative Analysis

4.6.1 Introduction

The Comparative Analysis aims to synthesise insights derived from our simulation experiments, ensuring a holistic understanding of inventory policies' impact on distribution-side supply chain performance metrics. Within this scope, we will juxtapose findings from Groups A, B, and C, highlighting the intrinsic roles of parameters like Safety Stock (SS), Initial Buffer Size (IBS), and more. This section will also provide a consolidated view of the effectiveness of ROP, MTA DBM, and DDMRP policies under varying demand and lead-time conditions and the underlying factors influencing these results. In our pursuit of a comprehensive analysis, we have delineated several criteria pivotal to evaluating the inventory policies in question.

First and foremost, we emphasise the importance of **Performance Consistency**. **Evaluating** each policy's ability to yield desired outcomes across various scenarios is paramount. For this, we refer to the key performance indicators outlined in Chapter 4.5, Results Presentation, explicitly highlighting the insights from Table 10.

Secondly, the **Trade-off between ROI and SL** emerges as a crucial criterion. It is essential to balance two primary objectives: the economic benefits of Return On Inventory (ROI) and the efficiency of meeting demand, reflected by the Service Level by Revenue (SL). These dual objectives, encapsulating the essence of inventory decision-making, offer a clear lens through which we can assess the relative strengths of the policies at hand.

Lastly, the **Adaptability to Demand and Supply Variations** criterion holds significant weight. Here, we gauge the resilience and adaptability of each inventory policy amidst fluctuating market conditions. The variation experiments, marked by their diverse stages and coefficient factors, serve as our foundational criteria for this evaluation, effectively simulating real-world market dynamics.

Collectively, these criteria anchor our analysis in the core tenets of inventory management and provide a systematic approach to unravel the intricacies of the ROP, MTA DBM, and DDMRP policies.

4.6.2 Comparative Overview by Group and Policy

To fathom the depths of each inventory policy, distilling them through a group-wise lens is pivotal. As presented here, such an approach permits an explicit understanding of each policy's operational nuances across diverse scenarios. **Table 22**, featured below, shows a clear snapshot of crucial parameters extracted from the simulation experiments. These will play a pivotal role in ensuing discussions.

Table 22 - Comparative Overview by Group and Policy with all critical parameters

Findings No.	Groups	Simulation Experiments	Policy and Influencing Factors	Inventory Level (IL) Impact	Service Level (SL) Impact	Return On Inventory (ROI) Impact
1	A	SE0	ROP – SS	Positive (SS increases as IL increases)	Positive (IL increases as SS increases)	
2	A	SE0	MTA - IBS	Positive (IBS increases as IL increases)		
3	A	SE0	DDMRP – STP	Negative (IL decreases as STP increases)		
3	A	SE0	DDMRP – LTF	Positive (LTF increases as IL increases)		
4	B	SE1	ROP Policy			Highest ROI in Case 1
5	B	SE1	ROP Policy			Highest ROI in Case 2
6	B	SE1	MTA Policy			Highest ROI in Case 3
7	B	SE1	DDMRP Policy		100% SL in Case 3	Lowest ROI across 3 cases
8	B	SE1	ROP and MTA Policy		100% SL in Case 3 (CoV < 7)	
9	B	SE2	DDMRP Policy		Highest SL in Case 3	
9	B	SE2	ROP Policy			Highest ROI in Case 1 and 2
10	C	SE3	MTA Policy		Steady SL in Case 3	
11	C	SE3	ROP Policy			Higher ROI in Case 1 and 3
12	C	SE4	DDMRP – SV in TLT		Negative (SV of TLT increases as SL decreases)	

This tabular overview will serve as a compass, guiding us through the maze of findings and insights as we dissect each policy's merits and limitations.

Group A: Interaction of Inventory Policies with Performance Metrics

Within Group A, the Reorder Point (ROP) policy with Safety Stock (SS) forms the influencing factor in Inventory Level (IL)-the Graphs for **Finding-1** Scatterplot Matrix. The MTA DBM and DDMRP policies have similar relationships in that the Initial Buffer Size (IBS) and Lead Time Factor (LTF) significantly affect the Inventory Level (IL), as shown in Graphs for **Finding-2** and **Finding-3**. On the other hand, the Spike Threshold Percentage (STP) in DDMRP policy shows the opposite pattern: when STP goes up, IL goes down.

Group B: Performance Across Different Demand Patterns in three cases

Group B examines how policies perform under different demand patterns. The ROP policy does particularly well regarding Return On Investment (ROI) in Case 1, better than MTA DBM and DDMRP, as seen in Graphs for **Finding-4** and **Finding-5**. For MTA DBM, it achieved the highest ROI in Case 3, as shown in Graphs for **Finding-6**. When the demand variation is lower, with CoV below 7, ROP and MTA DBM Policies could achieve 100% Service Level (SL) in Case 3, as shown in Graphs for **Finding-8**. However, DDMRP is good at keeping a steady service level, even when surged demand is high in Case 3, as seen in Graphs for **Finding-9**.

Group C: Influential Factors and Assumptions under simulated Demand Variation (DV) and simulated Supply Variation (SV) in Transportation Lead Time (TLT)

This Group helps us understand what influences our choice of inventory policies. MTA DBM is vital; even when demand variation increases, it keeps a steady Service Level by Revenue (SL) in Case 3, as shown in Graphs for **Finding-10**. ROP shows highest ROI, especially in Cases 1 and 3, as stated in Graphs for Finding-11. Nevertheless, there is a challenge with increasing Supply Variation (SV) in transportation lead time. The Service Level by Revenue (SL) tends to drop, showing that our performance of policies will decrease due to factors in supply chain supply variation, as shown in Graphs for **Finding-12**.

To sum up, each Group gives us a clear picture of how inventory policies work. As we move forward, we will dive deeper to understand these findings and see how they fit in today's supply chain world.

4.6.3 Key Observations and Patterns

Delving into our group-wise examination, several patterns and insights emerge. It is unmistakably evident from the Group A study that the Safety Stock (SS), under the Reorder Point (ROP) policy, significantly influences inventory levels. This observation is imperative for businesses as it underscores the essence of judiciously adjusting their safety stocks. By doing so, they could effectively balance the juxtaposition of inventory holding costs against the desired service level.

Moreover, Group B's findings shed light on the ability of the ROP policy in attaining a superior Return On Investment (ROI), particularly amidst fluctuating demand patterns. This emphasises the economic leverage this policy could proffer under specific circumstances. Simultaneously, DDMRP’s capability in maintaining service levels, even amidst heightened demand oscillations, must be noted. This trait indicates the policy's suitability for business environments characterised by volatile demand.

Shifting our gaze to Group C, it becomes abundantly clear that the MTA DBM policy offers stability amidst escalating demand variations. Its consistent performance, even when confronted with tumultuous demand changes, positions it as an indispensable tool for situations ridden with demand unpredictability.

However, universal challenge, cutting across all policies, was their vulnerability to supply variations, especially regarding transportation lead times. This observation spotlights a pivotal area for further exploration and potential improvement.

4.6.4 Implications of Comparative Findings

The insights from this comparison have profound implications for supply chain management. Notably, there is an inextricable linkage between the efficacy of an inventory policy and its contextual business landscape. For instance, the resilience of DDMRP in ensuring consistent service levels makes it an attractive proposition for businesses grappling with unpredictable demand surges.

Nevertheless, while the ROP policy's prowess in specific ROI scenarios is commendable, it becomes incumbent upon businesses to embrace a more holistic perspective. They must weigh the tangible economic benefits against pitfalls like stockouts or excessive inventory.

A pressing concern that emerges from our findings is the urgent need to fortify supply chains for the future. Given the challenges unearthed in the face of supply variations, it becomes paramount for businesses to mull over strategies that transcend inventory policies. Diversifying supplier bases or making strategic forays into predictive analytics might be worth considering.

4.6.5 Summary

Our detailed comparison showed how different inventory methods work in various situations. Simply put, there is no one-size-fits-all answer. Companies should consider many things when picking an inventory method, like changing demand and their broader financial aims. As supply chains keep changing, businesses should regularly check their approach and make necessary changes.

4.7 Summary of Key Findings

Upon doing an in-depth examination of the many aspects of our analysis, it becomes evident that the dynamics of inventory management are complex and have multiple dimensions. Selecting an acceptable inventory strategy is not solely a theoretical exercise but a process that strongly relies on practical, real-world events and the unique intricacies of each corporate environment.

Further expanding on these findings, the comparative results from our simulation present vital insights. The Re-order Point (ROP) inventory policy is the most effective in ROI, particularly in contexts with extended demand intervals. However, when a known surge in demand is on the horizon, Demand-Driven Material Requirements Planning (DDMRP) assumes prominence, outclassing both ROP and Make-to-Availability (MTA) Dynamic Buffer Management (DBM). It is also imperative to consider the practicality of these policies: the MTA DBM policy allows for more straightforward adjustments in buffer parameters compared to the nuanced calibrations required in DDMRP. Additionally, a pivotal observation from the study was the discernible decline in Service Level by Revenue (SL), as there was an uptick in Supply Variation (SV) in Transportation Lead Time (TLT). These discernments deepen our comprehension and may provide invaluable guidance for enterprises seeking to refine their inventory approaches in varied scenarios.

4.8 Conclusion

Chapter 4 shows the outcomes of the simulation with respect to the three case studies and in light of differing inventory dynamics, yielding valuable insights.

The foundational structures are presented in sections 4.1 to 4.4.7, and the simulation results are then described in 4.5, and undergo a comparative analyses in 4.6. Section 4.7 provides the '**Summary of Key Findings**' to present discernible patterns.

While inventory management's foundations are rooted in well-established theories, these theories are stress-tested against unpredictable and diverse real-world scenarios. The findings emphasise the situational supremacy of inventory policies:

A. **Re-order Point (ROP) Efficiency:** The ROP inventory policy delivers the highest ROI in scenarios with longer demand intervals (**Finding-11**).

B. **DDMRP's Edge During Demand Surges:** When faced with a foreseeable increase in demand, DDMRP demonstrates superior performance, outshining both ROP and MTA DBM policies (**Finding-7** and **Finding-9**).

C. **The practicality of MTA DBM:** MTA DBM provides a simple and user-friendly method for automatic buffer level adjustments compared to the meticulous tuning demanded by DDMRP. (**Finding-2**) For turning parameters of MTA DBM, only IBS is influencing factor for the performance outcomes. The single factor streamlines decision-making and reduces complexity. On the other hand, DDMRP requires multiple parameters (LTF and STP), which can induce the conflicting decisions between the trade-off of IL (**Finding-3**).

D. **Service Level Variation:** A marked reduction in Service Level by Revenue (SL) was observed, corresponding to increased Supply Variation (SV) in Transportation Lead Time (TLT) (**Finding-12**).

These findings illuminate the strengths and limitations of each inventory policy and highlight their contextual implications. While ROP is more conventional and uncomplicated, DDMRP possesses much potential, and MTA DBM seems more adaptable. Inventory management involves selecting an appropriate policy according to a certain scenario rather than merely selecting a superior policy in isolation.

In conclusion, these findings underscore the criticality of adaptability and contextual decision-making in inventory management. Beyond their empirical richness, it serves as a reminder that supply chain practitioners should adapt to select and change inventory policies according to the variability of demand and supply in the constantly evolving world of supply chains.

5. Discussion

5.1 Recap of Research Questions

This chapter explores the findings from the simulation analysis, compares them with related literature, and explains how the conclusions were derived through the supporting evidence in previous chapters. The structure of this chapter encompasses a recap of research questions along with the conceptual framework, an interpretation of critical findings, a comparison with prior studies, theoretical and practical implications, and a reflection of the limitations of this research.

Research Questions:

RQ1 - How do inventory policies, particularly forecast-based and consumption-based methods, interact with performance metrics in distribution-side supply chain scenarios?

RQ2 - How do the performance outcomes of inventory policies (ROP, MTA DBM, DDMRP) vary across different demand levels and supply lead time stability in the distribution-side supply chain?

RQ3 - What are the key influential factors and assumptions that underpin the selection and effectiveness of various inventory policies?

This study employs a simulation-based approach to evaluate the performance of inventory policies according to the research questions. It employs AnyLogistix (ALX) to model inventory policy scenarios under variable demand patterns and supply lead times. Simulation methods focus on three major inventory policies–Reorder Point (ROP), Make-to-Availability Dynamic Buffer Management (MTA DBM), and Demand-Driven Material Requirements Planning (DDMRP)–for comparative analysis across various experimental groups.

Conceptual framework

Figure 41 shows the comprehensive inter-relationship between simulated performance results as dependent variables and planning parameters as dependent variables in simulation experiments. The sources of variation in demand are generated by probability distribution in the variation coefficient ratio in CoV as 1, 5, 10, 15 and 20. The sources of supply variation are generated by multiplying Transportation Lead Time (TLT) with the variation coefficients ratio as 0.2, 0.5, 1, 1.5 and 2.

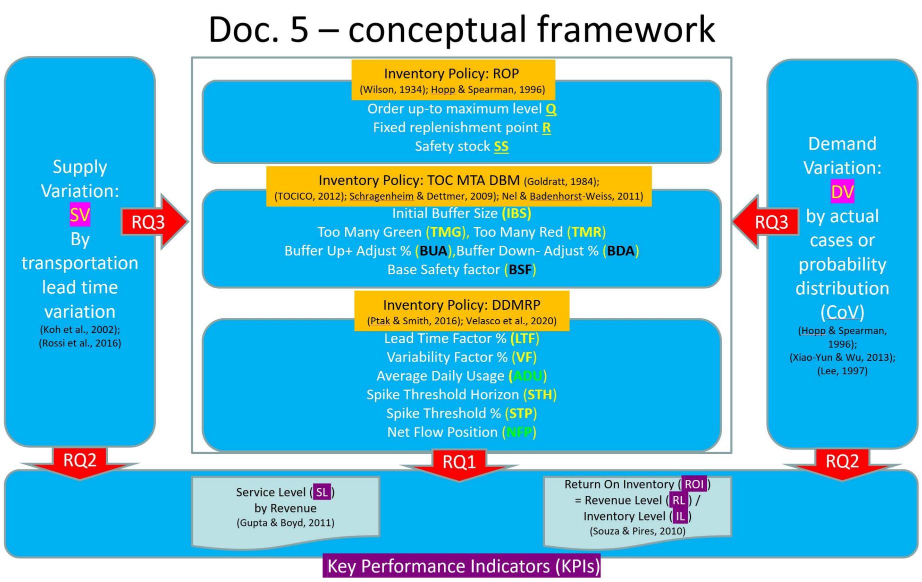


Figure 41 - Conceptual framework in Document 5

Buffer Up+ Adjust % (BUA), Buffer Down- Adjust % (BDA), and Base Safety Factor (BSF) are static factors within the simulation context. Conversely, Average Daily Usage (ADU) and Net Flow Position (NFP) are calculated dynamically. When considering Order up-to maximum level (Q), Fixed replenishment point (R), and Safety Stock (SS) within ROP, Service Level by Revenue (SL), Revenue Level (RL), and Inventory Level (IL) are dependent variables. For MTA DBM, they are determined by Initial Buffer Size (IBS), Too Many Green (TMG), and Too Many Red (TMR). Meanwhile, Lead Time Factor (LTF), Variability Factor (VF), Spike Threshold Horizon (STH), and Spike Threshold Percentage (STP) are independent variables in DDMRP. Lastly, Supply Variation (SV) and Demand Variation (DV) serve as modifiers, specifically adjusting the transportation lead time and demand distribution. The above conceptual framework sets the foundation for the simulation context in Chapter 4, which adequately answers RQ1, RQ2 and RQ3.

5.2 Interpretation of Key Findings and Literature Comparison

5.2.1 Introduction

In this section, we delve into the results of our simulation experiments, highlighting the complex interplay between different inventory policies and their effects on supply chain performance metrics. Drawing upon past research provides context and depth to our current findings. This section will compare our simulation results with those from earlier literature reviewed in Chapter 2. We aim to spotlight both similarities and differences. This comparison helps root our research in the broader narrative of supply chain planning and execution.

The supply chain planning and execution environment is ever evolving, demanding the alignment of current findings with historical research. This section commences with our key findings from the literature review, utilising the key factors in section 2.4 to present a structure and context. These factors – forecast accuracy, lead time variability, buffer management, demand variability, the bullwhip effect, safety stock, service level (SL), lead time (LT), replenishment review timing and information sharing are central to understanding the performance of different inventory policies in supply chain management. Through this comparison, we strive to root our research within the broader supply chain management context.

5.2.2 Interaction of Inventory Policies with Performance Metrics (Addressing RQ1)

In addressing **RQ1**, our findings revealed that given the fundamental mechanism of the Reorder Point (**ROP**) inventory policy, Safety Stock (**SS**) exhibits a strong correlation with both Service Level by Revenue (**SL**) and Return on Inventory (**ROI**) (**Finding-1** from SE0). As the Safety Stock (SS) parameter increases, SL invariably amplifies, while there is a potential decline in **ROI**. This interrelationship highlights the classic trade-off often seen in inventory management. For Simulation Experiment **SE0**, we employed the ALX simulator to use the variation experiments, aiming to select the parameters boasting the highest **SL** and maximum **ROI** for subsequent simulation experiments (SE1-SE4). Essentially, **ROP**'s performance hinges on the forecast demand accuracy to set the order up to the top level (**Q)** and the fixed replenishment point (**R**). When forecasting errors occur, the Safety Stock (**SS**) is a buffer, absorbing demand and supply variations. Hence, forecasting accuracy is the critical factor influencing the initial parameter setting for **ROP** performance.

In contrast, **MTA DBM** employs the Initial Buffer Size (**IBS**) as its primary parameter. An enlarged **IBS** boosts the system's Service Level (**SL**), though it may come at the expense of **ROI**. This observation reinforces the notion that buffer sizes are crucial in determining the agility and responsiveness of **MTA DBM** policies. In **MTA DBM**, **IBS** remains the solitary critical planning parameter, overshadowing adjustments like **TMG** and **TMR**, which do not yield significant performance outcomes. Therefore, the accurate estimation of the initial **IBS** setting is paramount for optimal **MTA DBM** performance (**Finding-2** from SE0).

Similarly, **DDMRP** consistently achieves stellar service levels, primarily due to its capability to manage confirmed demand spikes within the Spike Threshold Horizon (**STH**). This performance is further influenced by the Spike Threshold Percentage (**STP**), which has an inverse relationship with Inventory Level (**IL**). Concurrently, the Lead Time Factor (**LTF**) positively correlates with **IL**. The underlying implication is that a heightened service level invariably leads to a bolstered **IL**, which often diminishes **ROI** (**Finding-3** from SE0).

Key Finding A relevant to RQ1: Based on the three actual cases' demand profiles and scenarios, the simulation results suggest that the ROP method provides superior ROI performance, particularly during prolonged demand intervals.

Historically, the Reorder Point (ROP) has been fundamental to inventory management systems (Wilson, 1934; Tersine 1994). Earlier research highlighted ROP's effectiveness in managing inventory holding costs while minimising stockouts, an essential assumption in modern supply chain management.

Silver et al. (1998) broadened this viewpoint, highlighting ROP's ability to regulate inventory levels in response to unforeseen market variations. Our results match these essential viewpoints of ROP's effectiveness in inventory management. ROP consistently yielded a high return on investment in the simulated experiments for Finding-4, Finding-5, and Finding-9, while demand remained somewhat stable. The stability arises from the requirement of the ROP method for accurate forecasts of demand and safety stock to reduce unpredictability, as Nahmias (2009) highlighted in his evaluation of safety stock as a vital buffer against unpredictable demand within the replenishment cycle.

A vital factor of ROP's performance is the accuracy of demand forecasts. Bayraktar et al. (2019) indicated that forecast inaccuracy is a primary factor contributing to inventory management challenges, such as the bullwhip effect, resulting in increased inventory holding costs and deteriorated service levels. Our findings indicate that the static characteristics of ROP's planning parameters assume the accuracy of anticipated demand, facilitating appropriate reorder point setup and inventory level management. Nonetheless, when demand substantially differs from forecasts, the system's adaptability declines, exposing the limitations of static safety stock levels. Mattsson (2010) proposed the agile ROP framework that it is necessary to build adaptive tactics to respond to variable market situations. This corresponds with the challenge identified in our study, where the static safety stock model intermittently struggled to manage unpredictable demand fluctuations.

A significant factor affecting ROP's performance is the variability in lead time. Chen et al. (2000) recognised lead time variability as a substantial factor in increasing inventory costs and the degradation of service levels, especially when coupled with demand shifts. In our study, the ROP approach demonstrated a stable ROI with consistent supply lead times, as the fixed safety stock levels effectively accommodated minor fluctuations in demand. When there is significant variability in Transportation Lead Time (TLT), as seen by Yang & Geunes (2007), the ROP method's need for static reorder positions makes it more susceptible to stockouts and delayed replenishment.

To address these challenges, De Pacheco et al. (2015) introduced a dynamic reorder point system that adapts according to lead time and demand fluctuations. This method provides adaptability by using adjustable ordering thresholds and performance indicators such as Lead Time Absorption (LTA) and Demand Absorption (DA). Our study concentrated on a conventional ROP model; however, the findings from De Pacheco et al. indicate that integrating variable lead time and demand parameters into the ROP framework may improve its adaptability, especially under fluctuating market situations.

Buffer inventory, or safety stock, is essential for maintaining a high return on investment in ROP systems, especially when demand patterns fluctuate. Miclo et al. (2019) highlighted the significance of strategic decoupling points and safety stock to mitigate variability and reduce the bullwhip impact. Our simulation experiments similarly revealed that the effectiveness of ROP with prolonged demand patterns in reducing stockouts and maintaining ROI was closely related to safety stock levels, which served as a buffer against supply and demand variations. The alignment with Nahmias (2009) is evident, as the safety stock in our ROP simulations was computed to ensure service levels were achieved despite unpredictable demand fluctuations.

The bullwhip effect is another factor influencing ROP performance. Lee et al. (1997) describe that the bullwhip effect occurs when minor fluctuations in demand at the consumer level are amplified upstream in the supply chain. It will induce poor stock performance with overstock and out-of-stock situations regularly. Our simulations revealed that ROP’s static parameters made it vulnerable to the bullwhip effect in scenarios where demand variability was high. This is particularly relevant in cases where demand amplification occurs, as Paik & Bagchi (2007) additionally identified, which can cause substantial deviations in order quantities and lead to overstocking or stockouts. The findings suggest that ROP is suitable for stable demand patterns. However, it is vulnerable to the bullwhip effect that induces the need for adaptive mechanisms, such as those proposed by De Pacheco et al. (2015), designed for variable reorder points and dynamic adjustments to safety stock levels.

Our study reinforces the traditional view of ROP as an exceptionally efficient inventory management method, particularly in contexts characterised by extended, stable demand intervals; nevertheless, new research promotes more dynamic methodologies. Pathom (2023) emphasised the application of discrete-event simulation to enhance ROP parameters and reduce product damage, a technique that facilitates real-time adjustments in response to changing demand and supply dynamics. This contemporary methodology for ROP, which relies significantly on sophisticated simulation approaches, corresponds with our findings, especially in instances when static ROP methods could gain from enhanced flexibility in parameter adjustment. Mattsson (2010) argued that the static characteristics found in traditional ROP models may be inadequate for contemporary dynamic market conditions, characterised by frequent demand and supply variations.

In conclusion, our simulation findings demonstrate that ROP provides enhanced ROI performance with extended demand patterns, as its built safety stock and reorder points effectively regulate inventory under predictable situations. Nevertheless, as forecast errors, lead time variability, and the bullwhip effect increase, the weaknesses of static ROP systems become noticeable. Integrating more dynamic elements, such as variable reorder points and adaptive buffer inventory, as suggested by De Pacheco et al. (2015) and Mattsson (2010), may further enhance ROP's performance in fluctuating markets. While ROP remains a valuable tool in inventory management, evolving market conditions necessitate adopting more agile strategies to maintain high service levels and ROI.

5.2.3 Variations in Inventory Policy Performance (Addressing RQ2)

In addressing **RQ2**, interactions between demand levels, lead times stability, and the resultant performance trajectories of distinct inventory policies highlight some depth and nuance.

Our investigative lens focused on the performance dynamics of inventory policies - ROP, MTA DBM, and DDMRP - against the backdrop of diverse demand settings and the stability of lead times in the supply chain's distribution segment. The simulated experiments from SE1 and SE2 illuminated these aspects.

ROP emerged as a stalwart performer in SE1's Case 1, showcasing the best ROI performance (**Finding-4** from SE1). The unique demand pattern in Case 1, captured in **Figure 29-B**, highlights the sporadic nature of monthly demands and elongated order intervals, accentuating ROP's adeptness in such scenarios. Moreover, ROP's superiority was further underscored in Case 2, consistently outpacing MTA DBM and DDMRP regarding ROI (**Finding-5** from SE1). It's pertinent to note that for Case 2, as deduced from section 4.5.3 **Table 17**, the Coefficient of Variation (**CoV)** of Demand Variation **DV** remained steadfastly below **2**, marking it as stable.

While overshadowed by ROP in Cases 1 and 2, MTA DBM outperformed the other inventory policies SE1's Case 3. Here, it overshadowed its peers to command the highest ROI (**Finding-6** from SE1), a testament to MTA DBM's adaptability and context-driven efficiency.

On the other hand, DDMRP, despite its comparatively subdued ROI, also showed some potential. In SE1's Case 3, its commitment to ensuring service levels was evident as it achieved a 100% Service Level by Revenue (**SL**) despite sever challenges in high demand variability (**Finding-7** from SE1). Intriguingly, ROP and MTA DBM matched this **SL** performance in Case 3 for products whose **DV** of **CoV** remained under **7** (**Finding-8** from SE1). However, the highest level of DDMRP's SL in Case 3 presented a contrast to ROP's consistent ROI superior performance in Cases 1 and 2 (**Finding-9** from SE2).

Key Finding B relevant to RQ2 and RQ3*:* DDMRP becomes more relevant during anticipated demand surges, outperforming ROP and Make-to-Availability (MTA) Dynamic Buffer Management (DBM).

The Demand-Driven Material Requirements Planning (DDMRP) approach is more effective in handling expected demand surges, outperforming the Reorder Point (ROP) method and Make-to-Availability (MTA) Dynamic Buffer Management (DBM) in simulated experiments. DDMRP indicated greater flexibility and adaptability, making it more suitable for handling demand surges, a conclusion that supports the findings of Miclo (2018). Historically, DDMRP has been characterised as an agile and flexible approach, capable of real-time responsiveness, in contrast to the conventional but less dynamic ROP. This fundamental distinction highlights the increasing significance of DDMRP in contexts marked by sharp demand variations.

DDMRP's flexibility in addressing demand variability was highlighted by McCullen and Eagle (2015), who compared DDMRP with conventional planning methods. Their research emphasized DDMRP’s ability to reduce lead times and improve order fulfilment rates, which explains its superior performance during demand surges. In this research, namely **Finding-7** in SE1 and **Finding-9** in SE2, this flexibility was particularly obvious when DDMRP maintained a 100% Service Level by Revenue (SL) even during periods of highly volatile demand. This further corroborates Narita et al. (2021), who argued that DDMRP's structure allows for a proactive response to market fluctuations, a feature critical in handling demand surges.

The main factors influencing the previously mentioned flexibility are Spike Threshold Horizon (STH) and Spike Threshold Percentage (STP), which are significant DDMRP parameters for managing projected demand surges. These properties enable DDMRP to dynamically modify buffer sizes and initiate advanced make-to-order (MTO) placements in response to demand surges, as described by Ptak and Smith (2016). The ability to react immediately by generating additional buffer stock to cope with demand spikes makes DDMRP a more agile system than ROP and MTA DBM.

DDMRP's ability to handle demand variability is a crucial differentiator from traditional inventory strategies like ROP and MTA DBM. According to the simulation experiment (SE1) in **Finding-7** and **Finding-9** with Case 3, DDMRP achieved a 100% service level for items with a Coefficient of Variation (CoV) over **7**. On the other hand, MTA DBM did not perform better in terms of service level than DDMRP in this, scenario (SE1). DDMRP effectively manages increased demand fluctuation through its DDMRP Buffer Management logic, which continuously adapts to real-time demand signals. This supports Ikeziri et al. (2023), who showed that DDMRP is better suited to handling extreme demand variability compared to traditional methods like ROP and MTA DBM. Although DBM is helpful under specific circumstances, it is insufficient to address extreme demand surges, for which DDMRP is more suitable.

Lee et al. (1997) and Paik & Bagchi (2007) highlight that the bullwhip and ripple effects are crucial in addressing demand variability. In the context of elevated order fluctuation, DDMRP's adaptive buffer adjustment mitigates the negative impacts of the bullwhip effect, a phenomenon that frequently affects less flexible systems such as ROP. By employing a more adaptable buffer sizing strategy, DDMRP reduces unnecessary order fluctuations upstream in the supply chain, facilitating a more consistent flow of goods despite increased demand volatility.

Despite its benefits, DDMRP presents challenges, especially regarding resource intensity and implementation difficulty. Hung et al. (2004) emphasised that although DDMRP delivers enhanced service levels during demand spikes, its deployment requires more resources than traditional systems. This underscores the trade-off between service level (SL) and Return on Inventory (ROI), especially when resources are constrained. Our **Finding-7** in SE1 supports this view, indicating that while DDMRP attained a 100% service level, its total return on inventory was worse than that of MTA DBM, mainly due to the extra buffer stock required to accommodate demand fluctuations. This supports Lee & Rim's (2019) claim that the complex nature of DDMRP necessitates a comprehensive system for ongoing monitoring and prompt parameter adjustments.

The trade-off between service level and inventory investment is a central theme in evaluating DDMRP's performance. Pathom's (2023) research on discrete-event simulation for DDMRP also revealed that while DDMRP can minimize product shortage and enhance profitability, its overall efficiency is contingent upon the quality of execution. In the simulation study, DDMRP's advanced replenishment model, driven by factors like Lead Time Factor (LTF) and Variability Factor (VF), allowed it to outperform traditional methods in Service Level (SL), but this came at the cost of increased inventory levels. The challenge here, as noted by Azzamouri et al. (2021), lies in the reliability and interrelated nature of these planning parameters, making DDMRP more complex to implement than simpler systems like MTA DBM or ROP.

DDMRP's handling of anticipated demand surges through its Order Spike Horizon (OSH) and Order Spike Threshold (OST), as detailed by Ptak and Smith (2016), allowed it to maintain high service levels by pre-emptively adding buffer stock during periods of anticipated demand. This flexibility in buffer management is a distinct advantage over ROP, which relies on static reorder points that may not adequately account for sudden demand spikes. Similarly, MTA DBM, though more adaptive than ROP, struggled with maintaining high service levels for products with higher demand variability (**CoV > 7**), indicated in **Finding-8** SE1, while DDMRP could easily manage these fluctuations. This shows that DDMRP's advanced buffer management logic is indispensable in scenarios with higher demand variability.

In conclusion, DDMRP is an agile and adaptable inventory policy that is exceptionally proficient in managing projected demand spikes. Although conventional systems such as ROP and MTA DBM retain their importance in stable settings, DDMRP's adaptability, immediate reactivity, and advanced buffer management make it the preferred approach in volatile markets characterised by significant demand variability. Nonetheless, the complexity and inventory resources demanded indicate that it may only sometimes be the most appropriate choice for all businesses. The **Key Finding B** indicates that MTA DBM provides a more straightforward, less inventory-demanding approach capable of maintaining high service levels under specific conditions. At the same time, it lacks the flexibility of DDMRP. The choice between these inventory policies should ultimately be guided by the organisation's specific demand patterns, resources, and strategic objectives.

To synthesise, the complex interplay between demand fluctuations and lead time consistencies differs for to each inventory policy. Every policy showcases strengths and vulnerabilities for different cases and experimental conditions. Consequently, supply chain architects must exercise discernment in adopting and operationalising these policies, calibrated to the fluidity of supply chain dynamics.

5.2.4 Influential Factors and Assumptions Underpinning Policy Choice (Addressing RQ3)

In response to **RQ3**, many influential factors and assumptions affect the policy selection for different scenarios. The choice of an inventory policy is seldom arbitrary; it is rooted in many intrinsic and extrinsic factors. While the inherent mechanics of each policy play a role, external factors such as demand predictability, lead times stability, and even broader market dynamics can heavily influence policy selection.

MTA DBM's tenacity emerged in Case 3, adeptly navigating the stormy seas of fluctuating demands without compromising the Service Level by Revenue (**SL**) (**Finding-10** from SE3). This resilience underscored the strength of its foundational mechanisms, emphasising the role of estimation in the Initial Buffer Size (**IBS**). Then, the MTA DBM policy will use the **TMG** and Too Many Red (**TMR)** as autopilot to adjust the buffer size for adapting the variation in Demand Variation (**DV)** and Supply Variation (**SV)**.

ROP's consistent outperforming of MTA DBM and DDMRP in ROI**,** especially evident when amplifying the Coefficient of Variation (**CoV**) by Demand Variation (**DV**) in Cases 1 and 3, attested to its robust design and adaptability (**Finding-11** from SE3).

After including the impact of **DV** and **SV** into the simulation experiments, all planning parameters were kept unchanged according to selected parameters used in SE0 variation experiments to ensure a stable and fair comparison. Therefore, the experiments did not adjust the parameters in DDMRP, such as Lead Time Factor (**LTF)**, Variability Factor (**VF)**, Spike Threshold Horizon (**STH)** and Spike Threshold Percentage (**STP)**. The dynamic adjustment on all parameters of **DDMRP** is a critical success factor in handling different supply chain scenarios.

Moreover, a pivotal revelation stemmed from evaluating **SV** with respect to Transportation Lead Time (**TLT**). Results suggest that **SV** plays a decisive role in dwindling the Service Level by Revenue (**SL**) in all three cases in SE4 (**Finding-12** from SE4).

Key Finding C relevant to RQ3: The MTA DBM policy, in practice, allows for easier adjustments to buffer parameters, contrasting with the intricate adjustments essential for DDMRP.

This observation has practical implications, especially for businesses striving for agility without taxing their operational processes with undue complexity.

Buffer management, as detailed in section 2.3, plays a central role in determining the performance outcomes of inventory policies. The literature emphasises the requirement to adjust buffer sizes to address variations in demand and supply (Ikeziri et al., 2023; Marco, 2015). Our Key Finding C indicates that in the scenario of MTA DBM, the Initial Buffer Size (IBS) is the main factor affecting inventory levels (IL). MTA DBM employs IBS as its primary buffer parameter, in contrast with DDMRP, which depends on various interrelated parameters. This simplification corresponds with the Theory of Constraints (TOC) paradigm stated by Ikeziri et al. (2023), whereby Dynamic Buffer Management (DBM) systems are recognised for their simple methodology in inventory management that simplifies operational operations.

In contrast, DDMRP relies on more complex variables such as the Lead Time Factor (LTF) and Spike Threshold Horizon (STH), which require constant monitoring and fine-tuning. Research by Narita et al. (2021) emphasizes that DDMRP’s complexity, though effective in highly dynamic environments, poses challenges in environments with moderate variability, where simpler systems like MTA DBM can perform equally well with less effort. The Graphs for Finding-8 show that ROP and MTA DBM could achieve 100% SL when the demand variation (CoV) is lower than 7 with less noise by surge demand.

Demand variability and the bullwhip effect are critical factors affecting inventory performance, as discussed by Lee et al. (1997) and Dolgui et al. (2020). The bullwhip effect refers to the amplification of demand fluctuations propagating through the supply chain. In environments with low to moderate demand variability, as seen in our study (with a Coefficient of Variation (CoV) below 7), MTA DBM was able to achieve 100% Service Level (SL) without requiring intricate adjustments. This confirms the insights from Narita et al. (2021), which highlighted DBM's ability to maintain stability in less volatile conditions.

Conversely, DDMRP effectively reduces the bullwhip impact during significant demand spikes but with increased complexity in regulating many parameters. Miclo (2018) notes that although DDMRP is very adaptive, its dependence on parameters such as Average Daily Usage (ADU) and Spike Threshold Percentage (STP) renders it more resource intensive. Consequently, although DDMRP is efficient in contexts with significant volatility, MTA DBM's ability to manage moderate demand changes with little adjustments provides a practical benefit in more stable markets.

Safety stock management is another influential factor in inventory performance, particularly in mitigating demand uncertainties (Nahmias, 2009; Waller et al., 2008). Our finding C shows that MTA DBM adjusts safety stock levels primarily through IBS, simplifying stock management compared to DDMRP's use of multiple buffer zones. This simplicity enables MTA DBM to maintain high service levels without requiring complex parameter adjustments, as demonstrated in the simulation experiment SE1 in Finding-8.

The literature consistently highlights that maintaining optimal safety stock levels is crucial for avoiding stockouts while minimizing excess inventory (Nahmias, 2009). In this regard, MTA DBM's straightforward approach to buffer sizing is well-suited for businesses that need to balance inventory levels with minimal operational disruption. In contrast, DDMRP's more intricate safety stock mechanisms, which involve continuous adjustment of buffer zones based on real-time demand signals, offer greater flexibility but require more robust systems for monitoring and adjustment (Lee & Rim, 2019).

Lead time variability (LT) and replenishment review timing are critical in determining inventory performance, as discussed in Chen et al. (2000) and Yang & Geunes (2007). The ability of an inventory policy to respond to changes in lead time and replenish stock efficiently determines its overall effectiveness in maintaining service levels. MTA DBM, with its more straightforward buffer management system, maintained high service levels even when Transportation Lead Time (TLT) variability increased. This aligns with Chang & Lin (2019), who noted that reduced complexity in lead time management can improve inventory recovery times without burdening the system with unnecessary adjustments.

DDMRP, on the other hand, requires more sophisticated lead time management involving adjusting parameters like LTF and STH. As Azzamouri et al. (2021) noted, unpredictable supply chain disruptions can challenge the reliability and accuracy of DDMRP's lead time management, necessitating constant parameter adjustment. For businesses operating in environments with moderate lead time variability, MTA DBM's more straightforward approach to managing lead times through basic buffer adjustments is a clear advantage, offering efficiency without extensive operational oversight.

In conclusion, MTA DBM's simplicity in adjusting buffer parameters, particularly the Initial Buffer Size (IBS), provides businesses with an effective and flexible solution for managing inventory in moderately variable environments. The factors of buffer management, demand variability, bullwhip effect mitigation, safety stock, and lead time management, which were anticipated from the literature, all support the finding that MTA DBM offers a streamlined, less resource-intensive alternative to the more complex DDMRP.

Key Finding D relevant to RQ3: A noticeable trend was the decline in SL as Supply Variation (SV) in Transportation Lead Time (TLT) increased.

This finding is crucial for global supply chains or industries with volatile and unpredictable transportation logistics to trigger demand and supply variability by the following influential factors:

The bullwhip effect is a well-documented phenomenon in supply chain management that exacerbates supply chain disturbances by amplifying order variability across multiple stages (Lee et al., 1997). Our findings align with this understanding, showing that as supply variation increases—specifically through extended or unpredictable transportation lead times—this amplified demand distortion leads to stock shortages and delayed replenishment, causing a decline in service levels. Dolgui et al. (2020) introduced the ripple effect concept, which can arise from disruptions at different supply chain nodes. Our study supports this, as the ripple effect amplifies the negative consequences of supply variability on service levels, mainly when transportation delays propagate throughout the network.

The bullwhip and ripple effects highlight how small lead time or demand fluctuations can snowball, significantly affecting service levels. Our findings show that the ROP policy, which relies heavily on forecast accuracy and fixed reorder points, becomes vulnerable when lead times fluctuate unpredictably. As supply variation grows, the reliance on a fixed safety stock becomes insufficient to absorb the variability, leading to more frequent stockouts and lower service levels.

Demand forecasting inaccuracy and lead time variability are interrelated issues that reduce service levels. Bayraktar et al. (2019) emphasised the need for precise forecasting in mitigating the bullwhip effect. In instances when forecasting accuracy is compromised, as evidenced by our simulations, minor variations in transportation lead times can markedly reduce service levels. Moreover, Chen et al. (2000) demonstrated that variable lead times could exacerbate the bullwhip effect, impacting inventory costs and fill rates.

Our research validates these results, particularly when MTA DBM and DDMRP attempt to cope with demand surges and transportation variations. DDMRP, with its adaptive buffer sizing, can more effectively control demand surges. However, under significant lead time volatility, this policy still faces challenges sustaining constant service levels. The replenishment system's failure to quickly adjust to fluctuating lead times highlights the necessity for more dynamic, real-time adjustments.

Lead time variability is critical to service levels and overall supply chain performance. Yang & Geunes (2007) pointed out that procurement and order lead times significantly affect the cycle stock and safety stock levels, directly influencing service performance. As our results indicate, as TLT variability increases, safety stock becomes inadequate to buffer against uncertainties, leading to missed orders and declining service levels.

Shorter lead times can mitigate the bullwhip effect, as suggested by Chang & Lin (2019), but when lead times are unpredictable or extend beyond their expected range, inventory policies like ROP and MTA DBM suffer performance declines. Tidemann et al. (2020) further emphasized the importance of lead time management in improving financial performance metrics such as ROI. In Finding-12, the SE2 observed that longer or more variable transportation lead times led to service level drops and negatively impacted Return on Inventory (ROI), as stockouts increased while excess inventory was kept elsewhere in the supply chain.

Replenishment plans are crucial for reacting to supply chain disruptions and maintaining constant service levels. Snyder et al. (2016) emphasised that disruptive events, such as transportation delays, create volatility in lead time, yield, and input prices, hence increasing stochastic variability in order amounts and further reducing service levels. Chen et al. (2000) highlighted that suboptimal replenishment policies enhance the bullwhip effect, resulting in inadequate inventory performance. Our simulations indicate that increased variability in transportation lead time hampers programs such as ROP, which rely on established reorder points and safety stock that are inadequate for managing unpredictable supply disruptions.

MTA DBM and DDMRP, utilising dynamic buffer management systems, exhibited superior performance under variable lead time scenarios. Nonetheless, even DDMRP, despite its more adaptive replenishment mechanism, encountered difficulties during transit disruptions. This conclusion indicates that although DDMRP is more adaptable than ROP, it still necessitates enhancements in handling significant fluctuations in transportation lead times.

Safety stock is crucial for mitigating variations in demand and supply. Nahmias (2009) claims that safety stock is affected by expected service levels and the standard variance of demand during the lead time. Our research revealed that ROP strategies maintaining fixed safety stock levels saw increased stockouts as supply variability increased. The fluctuation in Transportation Lead Time (TLT) caused the safety stock in ROP systems to be inadequately flexible, resulting in a significant decrease in service levels.

Conversely, DDMRP improved its effectiveness in regulating variation through decoupling points and dynamic buffer adjustments. Miclo et al. (2019) and Waller et al. (2008) underscored the purposeful positioning of buffer stock at critical decoupling points to reduce variability, a concept corroborated by our findings. Nonetheless, despite these tactics, the increasing variability of TLT increased pressure on the system, resulting in periodic service level shortcomings, especially during demand surges and transportation delays.

The importance of information exchange in mitigating the bullwhip effect is fundamental. Li (2010), alongside research by Hall & Saygin (2012) and Jonsson & Mattsson (2013), highlighted the importance of timely and accurate data communication in mitigating supply chain variability. Our literature review demonstrates that inadequate information sharing causes the negative consequences of supply volatility on service levels. In global supply chains, where transportation lead times are frequently unreliable, enhanced information exchange among supply chain nodes can substantially reduce service level drops by facilitating quicker response times and enhancing demand forecasting accuracy.

The decline in service levels observed in our simulations, particularly as Supply Variation (SV) in Transportation Lead Time (TLT) increased, is a multifaceted problem linked to several key factors identified in the literature. Forecast inaccuracy, bullwhip and ripple effects, variable lead times, safety stock management, and information sharing all interact to affect inventory performance.

ROP policies faced challenges in managing increasing volatility because of their static safety stock levels, whereas MTA DBM and DDMRP demonstrated superior resilience through their adaptive buffer management systems. Nevertheless, even these more dynamic rules necessitate additional optimisation to manage extreme supply fluctuations proficiently, such as those caused by worldwide transportation disturbances. Cannon (2008) observed that deliberate decisions concerning safety supplies, decoupling points, and information exchange can alleviate these impacts. Their direct association with overall performance enhancements can occasionally be complex.

Our findings highlight the necessity for cohesive solutions that integrate ROP, DBM, and DDMRP components to respond to the increasingly volatile patterns within the supply chain. These techniques must include adaptable safety stock management, instantaneous information exchange, and refined replenishment policies to sustain improved service levels despite huge supply fluctuations.

While each inventory policy has unique strengths, its effectiveness invariably is impacted by intrinsic policy mechanisms and external demand-supply dynamics. The choice of an inventory policy thus hinges on a comprehensive understanding of these determinants, guiding supply chain stakeholders towards informed and strategic decisions.

5.3 Contributions

Within the dynamic field of supply chain management, it is very uncommon for previous research and approaches, regardless of their innovative nature, to require a certain period to develop so they can effectively tackle current difficulties. The rapidly changing global market, shaped by technological advancements, unpredictable demand and supply fluctuations, and various external socio-economic factors, underscores the critical need to identify gaps in established practices and foster innovations. This section outlines the key contributions that may be interpreted from this research, and how it has addressed these gaps, improving our knowledge of supply chain planning and execution approaches and their practicality. By filling in these gaps, our research offers insightful analysis and creative solutions that contribute to existing knowledge and offer practical enhancements for industry processes.

One crucial gap is in addressing supply chain practitioners' challenges in selecting and adjusting policies effectively in dynamic environments. Supply chain practitioners struggle to choose between different policies, yet it is not always clear as to how they can make intelligent choices. Furthermore, after deploying established policies, there was a need to understand how to adjust the planning parameters to appropriately adapt to the changing environments impacted by demand and supply variation. In this way, this research identified two crucial gaps, and the key contributions stemming from these are as follows:

Contribution 1 - Selection of Policies:

Delving into the intricacies of supply chain management reveals the monumental challenge practitioners face when confronted with many policies. Even after implementing these conventional policies, a pressing question emerges: How can one aptly fine-tune planning parameters in volatile demand and supply dynamics? At the core of this difficulty is the critical task of policy selection. While seminal research has traversed the vast landscapes of inventory policies, the journey to uncover the quintessential policy, fine-tuned to situations, remains ongoing. With its unique merits and drawbacks, every policy becomes even more intricate when juxtaposed with unpredictable external changes. For instance, the indispensability of static ROP policies is evident, yet they frequently underscore the need for more adaptive inventory strategies considering seasonality (Mattson, 2010).

In contrast, DBM's steadfastness against the onslaught of DDMRP during sudden demand surges does not negate its inherent limitations (Ikeziri et al., 2004). Echoing this sentiment, Hung et al. (2004) advocate for inventory strategies that align seamlessly with projected customer service standards and the resources at one's disposal. Complicating this scenario further is the unpredictable element of "system noise," as Narita et al. (2021) detailed, which can have profound implications in specific instances.

Innovation 1 - Hybrid Deployment of Policies:

A rigorous analysis of various inventory policies, set against the backdrop of their performance indicators and foundational premises, heralds the dawn of an innovative approach. This approach champions the synthesis of disparate policies, culminating in the creation a hybrid model. By seamlessly merging DDMRP's spike order management with MTA DBM and integrating MOQ requirements within the DBM's green zone as a core component of DDMRP, a more cohesive and productive DDMRP is developed. Notably, integrating the straightforward DBM method allows for the simultaneous utilisation of the benefits associated with DDMRP logic.

By forging this streamlined DDMRP iteration or a hybrid model that marries MTA with DDMRP, the principal benefit reaped is the marriage of DBM's operational simplicity with DDMRP's adeptness in managing known spike orders. Furthermore, it offers a significant solution to align the DBM green zone when the adjusted buffer level surpasses the top of green due to a substantial minimum order quantity (MOQ)

Contribution 2 - Dynamic adjustment of planning policies or parameters for desired performance with trade-off decisions

Even if the correctly selected policy can maintain the expected performance initially, how can one ensure that the planning policies or parameters sustain the performance according to the changing supply chain environments?

In our key findings, the identified factors could provide some signals for triggering the adjustment. However, there needs to be a systematic way to sense and respond to those factors in one centralised dashboard according to the supply chain context. De Pacheco et al. (2015) and Lee & Rim (2019) mention that the research suggests a need for adaptable planning parameters in response to changing market demands. Fransoo & Wouters (2000) discuss the similar problems associated with data aggregation, highlighting the importance of having a sophisticated system to handle those issues effectively. The complexity of interrelationships between DDMRP parameters increases the difficulty of parameter adjustments (Azzamouri et al., 2021). The overall adjustment goal is mainly a trade-off between service and inventory levels (Ptak & Smith, 2016).

Innovation 2 - Data-Driven Intelligent Business Planning (DDIBP) dashboard with alerts and signals for modelling prediction profiler

A database engine should capture and store the data for exceptional events or demand patterns in a dashboard for balanced trade-off decisions, which refer to the influential factors and assumptions for data modelling. The ALX will use those real-time data feeds for simulation and then interface them into SAS JMP for prediction profiler. Then, the dashboard can monitor buffer adjustments in real-time with alert signals for necessary adjustments based on demand patterns or other factors such as “system noise” (Narita et al., 2021), bullwhip effects and ripple effects in supply chains (Lee et al., 1997 & Doulgui et al., 2020) and external disruptions (Snyder et al., 2016 & Chen et al., 2000).

The beauty of using a dashboard with a prediction profiler is keeping transparent information for an effective decision-making process on policies or parameter adjustments. Any stakeholders could make the judgement and discussion before making any changes and might leverage the ALX simulator to generate the projected results according to the proposed changes. Moreover, according to the latest SCOR Digital Standard model, the dashboard could include any sustainability indexes to enhance disclosures in environmental, social and governance (ESG) measurement (Peter, 2007; SCOR Digital Standard, 2022).

Moreover, the author enhanced the ALX by developing customised Java code (Appendix

F) that allows for the evaluation of new emerging inventory policies (MTA DBM and DDMRP), which were not available in standard ALX. This provides more policy options for practitioner wishing to design or simulate analyses in future research.

With these innovations in place, we pave the way for an enhanced and transparent decision-making process in supply chain management.

5.4 Theoretical and Practical Implications

Having delineated the critical gaps and our innovative approaches, we now turn to the broader repercussions these insights hold for both academic discourse and real-world applications in supply chain management.

The primary outcomes highlight the importance of choosing policies based on specific assumptions and indicate that a blended approach using various models is the most effective, as no one-size-fits-all solution exists. A combined approach using both MTA DBM and DDMRP could offer advantages, allowing for a flexible strategy in supply chain planning and execution. Rather than determining which model is superior, this study suggests that policy choices should be adaptable, varying with trends and events. This perspective paves the way for more in-depth research in the future.

Understanding the impacts of different planning parameters on the expected performance of various scenarios for organisational management led to better planning decision-making. The proposed gaps and innovations indicate that the dashboard and prediction profiler provide different projected performance outcomes by adjusting various planning parameters. Supply chain practitioners could benefit from the proposed innovations to identify the way of selection and adjustment rather than a trial-and-error approach. Recognising the strengths and weaknesses of different policies can maximise the expected performance.

However, integrated with simulation, the suggested Data-Driven Intelligent Business Planning (DDIBP) dashboard could not capture all events and signals from all angles. It could only be based on available data according to identified factors and assumptions. The latest artificial intelligence (AI) technology could enhance the relevant data model with Big Data analytics and suggested actions in the dashboard.

While our findings offer valuable insights into supply chain management, it is crucial to recognise the context in which this research was conducted. Various challenges, both anticipated and unforeseen, shaped the methods and results of our study.

5.5 Limitations and Constraints of this Research

Amid the backdrop of a global pandemic and the intricate intricacies of supply chain simulations, our investigation encountered specific obstacles. These challenges, which inherently affected our research's scope and depth, are detailed in this section.

Time and People Constraints during the Pandemic Period

The pandemic-imposed time restrictions, hindering access to crucial stakeholders. This situation limited our data breadth, compelling us to focus primarily on quantitative data for comparisons and bypass in-person interviews for qualitative data.

Sampling Constraints: Pre-set Demand Data:

Our dataset was rooted in pre-determined demand data from three real cases, restricting flexibility in sample selection. The collected data led us to select only three product items per case, most of which shared different demand patterns. Consequently, there is a possibility of average-out effects skewing the underlying distribution.

Experimental Parameters' Limited Range:

Time pressures meant that our demand and supply variation experiments in transportation lead time were constrained to a five-step range. Because the complete factorial experiments in the simulator will take a very long computing time, a more extensive parameter scope might have given richer insights, especially in gauging performance impacts across broader demand and supply variations.

Technical Hurdles: Custom Java Development for MTA DBM and DDMRP in ALX:

Since MTA DBM and DDMRP were not part of the standard ALX software, we took on the challenge of adding custom Java coding to include these policies. This allowed us to compare them with the default ROP policy supported by ALX. The original ALX software and the custom coding were used, as explained earlier in Section 3.6. Though initially backed by a subcontracted Java programmer, his untimely exit added a five-month debugging stint to our schedule after an extra modification fee. A wide range of workarounds were developed to tackle technical problems. For instance, alternative ROI formulas (by inventory balance or COGS) are unavoidable because multiple data sources exist. Particularly, synchronization problems with ALX's internal database forced us to abandon the external database for reporting in favour of a post-processing method using ALX export data.

Acknowledging these limitations improves our comprehension of the parameters of our investigation and analysis of the outcomes. These revelations guarantee that our conclusions stay rooted in the difficulties encountered.

5.6 Summary of discussion

Building on the preceding discussions, **Tables 23, 24, 25 and 26** provide a structured summary addressing **Key Findings A to D** for **RQ1**, **RQ2**, and **RQ3**, respectively.

Table 23 - Discussion summary related to **Key Finding A for RQ1**:

Aspects	Interaction between KPIs and Related Policies	Related Literature
ROI (Emphasis on optimal inventory levels and profitability)	Superior performance of the ROP method during prolonged demand intervals, ensuring optimal inventory levels and improved ROI.	Wilson (1934), Tersine (1994)
Adaptive Inventory Strategies (Addressing uncertainties in demand)	The Agile ROP framework's introduction emphasises the possible inconsistencies in the traditional ROP approach and the need for more adaptive inventory strategies.	Mattsson (2010)
Use of Simulation in ROP (Enhancing the ROP method)	Emphasis on the transformative role of discrete-event simulation in refining the ROP policies, especially regarding profitability and minimising product damages.	Pathom (2023)
Absorption Inventory	Strategic increase in	De Pacheco et al. (2015)

(Strategic response to market demand variations)	absorption inventory (similar to safety stock in ROP) in response to more considerable demand variations and reduced lead time, helping to counteract potential disruptions.	

Table 24 - Discussion summary related to **Key Finding B for RQ2 and RQ3**:

Aspects	Interaction between KPIs and Related Policies	Related Literature
DDMRP's Historical Context	DDMRP exhibits flexibility, adaptability, and real-time responsiveness, making it adept at handling demand peaks.	Miclo (2018)
Comparison between Planning Methods	DDMRP reduces lead time and boosts order fulfilment rates, outperforming dynamic demand contexts.	McCullen and Eagle (2015)
DBM vs. DDMRP	DBM has benefits, but when faced with significant demand shifts, DDMRP appears more responsive and proactive.	Ikeziri et al. (2023), Narita et al. (2021)
Implementation of DDMRP	DDMRP excels in service levels during demand surges, but its efficiency depends on resources and implementation quality.	Hung et al. (2004)
Service Level Performance	In specific cases, DDMRP achieves 100% service level by revenue due to its "Order Spike Horizon (OSH)" and "Order Spike Threshold (OST)" features, ensuring it doesn't deplete its standard stock buffer	Ptak and Smith (2016)

	rapidly.	
Trade-offs in DDMRP	While DDMRP excels in service levels, ROI COGS might be affected due to additional buffer stock for managing order spikes.	Ptak & Smith (2016), Lee & Rim (2019)
Complexity in DDMRP	Implementing DDMRP can be intricate, requiring a robust system to monitor demand signals and timely parameter adjustments.	Lee & Rim (2019)

Table 25 - Discussion summary related to **Key Finding C for RQ3**:

Aspects	**Impact on Selection and Effectiveness of Policies**	**Related Literature**
Ease of Management	MTA DBM provides a straightforward approach to buffer management with its simplicity in adjusting Initial Buffer Size (IBS). Such simplicity allows a more agile response to changing business conditions without undue complexities.	Ikeziri et al. (2023), Marco (2015)
Contrasts with DDMRP	ROP and MTA DBM, which can effectively handle low-demand variation scenarios with higher service levels. In contrast, DDMRP requires intricate adjustments in several parameters, making it more complex to set up and manage. Despite its strengths, DBM has vulnerabilities like susceptibility to system noise.	Narita et al. (2021), Azzamouri et al. (2021)
Operational Implications	MTA DBM is ideal for businesses seeking agility without the complexities of intricate systems. It suits organisations with limited	Narita et al. (2021)

	resources. Conversely, well-resourced companies can harness the potential of DDMRP, especially in fluctuating demand situations.	
Relative Dominance of MTA DBM	The agility and ease of use of the MTA DBM policy potentially make it more suitable in specific industry contexts over DDMRP, especially when simplicity and adaptability are of prime concern.	Narita et al. (2021)

Table 26 - Discussion summary related to **Key Finding D for RQ3**:

Aspects	**Impact on Selection and Effectiveness of Policies**	**Related Literature**
Bullwhip and Ripple Effects	The bullwhip effect results in amplified order oscillations across the supply chain, which might require changes in inventory policies to mitigate. The ripple effect further complicates supply chain disruptions, emphasising the need for policies that address both phenomena.	Lee et al. (1997), Dolgui et al. (2020)
Forecast Inaccuracy and Variable Lead Time	Poor forecasting and unpredictable lead time can result in policy misalignment. Correct policy selection becomes essential to combat these issues and maintain service levels.	Bayraktar et al. (2019), Chen et al. (2000)
Strategic Role of Lead Time	Varying lead time can lead to inflated stock levels. Policy adaptation that emphasises shorter replenishment cycles might be essential to lessen the impact of the bullwhip effect.	Yang & Geunes (2007), Chang & Lin (2019), Tidemann et al. (2020)

Replenishment Policies and Disruptions	Disruptions introduce uncertainties, stressing the need for resilient replenishment policies. Non-optimized policies can further exacerbate the bullwhip effect.	Snyder et al. (2016), Chen et al. (2000)
Safety Stock, Strategic Decoupling, and DDMRP Relevance	Positive correlation between Safety Stock with Inventory Level and Revenue Level implies a need for policies strategically placing buffer stock. The DDMRP replenishment model offers a potential solution.	Nahmias (2009), Miclo et al. (2019), Waller et al. (2008), Lee & Rim (2019)
Information Sharing's Role	Effective policies should promote and facilitate information sharing and cooperation to manage and reduce the bullwhip effect.	Li (2010), Hall & Saygin (2012), Jonsson & Mattsson (2013), Dev et al. (2013)
Conclusion	A Decline in service levels with increasing supply variation requires multifaceted solutions. Policy adjustments focusing on safety stocks, decoupling points, and enhanced information sharing can be potential remedies.	Cannon (2008)

Drawing upon the summarised discussions from **Tables 23** to **26**, a few paramount observations emerge. The ROP method's longstanding efficacy with predictable demand, especially in extended demand intervals, the adaptive prowess of DDMRP, and MTA DBM's streamlined approach spotlight the diversity and evolution of inventory policies. Concurrently, the complexities of the supply chain, marked by phenomena like the bullwhip effect and demand fluctuations, underline the urgency for innovative, resilient, and adaptable strategies. With these critical takeaways, and before we delve into comprehensive conclusions and charting paths for future research, it is imperative to briefly reflect upon the foundational aims and objectives that catalysed this research journey.

6. Conclusion and Further Research

6.1 Reflection on Research Aims and Objectives

This research compares the supply chain replenishment planning inventory policies by simulation study. At the inception of this research, three research questions were postulated: (**RQ1**) How do inventory policies, particularly forecast-based and consumption-based methods, interact with performance metrics in distribution-side supply chain scenarios? (**RQ2**) How do the performance outcomes of inventory policies (ROP, MTA DBM, DDMRP) vary across different demand levels and supply lead time stability in the distribution-side supply chain? (**RQ3**) What are the key influential factors and assumptions that underpin the selection and effectiveness of various inventory policies?

These inquiries were rooted in the observed conflicts between forecast-based and consumption-based planning paradigms, where recent technological advancements and unpredictable pandemic period market dynamics necessitated a deeper exploration of adaptive inventory strategies. The imperative to answer these inquiries was of utmost importance for ensuring scholarly integrity and for supply chain practitioners seeking to enhance the performance of supply chain planning systems within a swiftly evolving supply chain environment. The research methodology utilised in this study involved a simulation approach, including a quantitative examination of data collected from three actual cases. This research sought a comprehensive view of comparing inventory policies and their performance outcomes under the same demand patterns. It also simulated disruptions in demand patterns and transportation lead times in supply through the variation and comparison experiments in AnyLogistix (ALX) simulations.

After detailing the research aims and methods, the next step in this chapter is to synthesise the main findings and their impact on supply chain performance.

6.2 Synthesis of Key Insights

The total effectiveness of the supply chain is contingent on comprehensive collaboration and coordination across the whole supply chain network. The dependability of forecasting plays a vital part in planning forecast-based reorder point (ROP) stock policies, mainly when dealing with high-demand predictability (Wilson, 1934).

Alternatively, MTA DBM and DDMRP replenishment for consumption-based planning, the size of the initial buffer, the planning factors and the strategic location of the buffer stock are vital in determining how to cope with various sources of variation and uncertainty in a supply chain network. MTA DBM and DDMRP rely on different influential factors to adjust the buffer sizing parameters according to the uncertainty in external situations, such as promotional effects, seasonal trends, and internal constraints, such as holiday periods and resource contention. These policies, replete with the influences presented in emerging literature like Mattsson's, are sculpted to adjust to both external and internal fluctuations, ranging from marketing-driven variabilities like promotional tempests to internal scheduling disruptions such as festive hiatuses and resource gridlocks (Mattsson, 2010).

The alignment of both forecast-based and consumption-based planning methods with their respective influential factors underscores the difficulties of managing variability of supply chain contexts. To better understand how these strategic elements interact with real-world scenarios, **Table 27** outlines the relationship between the theoretical concepts and practical outcomes to elucidate the interactions of those strategic aspects with real-world scenarios.

Table 27 – Alignment of Preliminary Findings with Key Findings

Finding Number from SE	Preliminary Findings	Aligned Key Finding
Finding-1 from SE0	Correlation analysis demonstrates the statistically significant impact of SS on IL and its significant effect on SL under the ROP policy.	A. Based on the three actual cases' demand profiles and scenarios, the simulation results suggest that the ROP method provides superior ROI performance, during prolonged demand intervals.
Finding-4 from SE1	ROP shows superior performance in terms of ROI in specific contexts for Case 1 within SE1.	
Finding-5 from SE1	ROP shows dominance over MTA DBM and DDMRP in ROI for Case 2 within SE1.	
Finding-11 from SE3	ROP consistently outperforms MTA DBM and DDMRP in terms of ROI, significantly when increasing CoV by DV in Case 1 and 3.	
Finding-7 from SE1	DDMRP achieves 100% SL in Case 3 despite lower ROI.	B. DDMRP becomes more relevant during anticipated demand surges, outperforming ROP and Make-to-Availability (MTA) Dynamic Buffer Management (DBM).
Finding-9 from SE2	DDMRP attained peak SL performance during Case 3, while ROP consistently secured the highest ROI in Cases 1 and 2 across varied scenarios.	
Finding-2 from SE0	The strong correlation between IBS and IL within the MTA DBM policy.	C. The MTA DBM policy, in practice, allows for easier adjustments to buffer parameters, contrasting with the intricate adjustments essential
Finding-3 from SE0	Contrasting behaviours of STP and LTF vis-à-vis IL within the DDMRP policy.	

Finding-6 from SE1	MTA DBM produces the highest ROI in SE1's Case 3.	for DDMRP
Finding-10 from SE3	MTA DBM's resilience in accommodating fluctuating demands without significantly impacting SL in Case 3.	
Finding-12 from SE4	The impact of Supply Variation (SV) of TLT and its role in diminishing SL.	D. A noticeable trend was the decline in SL as Supply Variation (SV) in Transportation Lead Time (TLT) increased.

While **Table 27** provides a comprehensive alignment between most preliminary findings and key insights, it does not explicitly include **Findings 6, 8 and 10**. These findings did not directly align with the broader trends discussed in the key findings, but will be briefly discussed in the next section.

Gleaning insights from synthesising twelve preliminary and four key findings across the actual case demand profiles, as shown in **Table 19**, the strategic finesse of ROP emerges most potently in environments punctuated by extended demand intervals. Simultaneously, MTA DBM emerges as the adaptive buffering strategy for low-demand variability scenarios but seeks a superior ROI. In contrast, the dynamism and adaptability of DDMRP, as corroborated by recent scholastic contributions, shine in the management of pronounced order fluctuations and environments characterised by high demand variability yet necessitating stellar service levels (Ptak & Smith, 2016; Lee & Rim, 2019).

Table 28 - Generalisation for stock policies selection decision table

	Demand Variation - Low	Demand Variation - High	
Demand Interval - Long	ROP *(A)	ROP *(8)	**Demand Forecast Accuracy - High**
Demand Interval - Short	MTA DBM *(6,10)	DDMRP *(B)	**Demand Forecast Accuracy - Low**
	ROI - High	**Service Level - High**	

* Preliminary and Key findings cross-reference inside the parentheses ().

Table 28 serves as a strategic decision-making mechanism to select inventory strategies based on critical factors: demand variability (low versus high), demand interval (short versus long), and demand forecasting accuracy (high versus low). It also emphasises the expected outcomes of Return on Inventory (ROI) and Service Level (SL). The table consolidates insights from the twelve preliminary findings and four key findings, referenced in brackets to ensure that the recommendations are generalised with evidence.

Top-Left Quadrant: Low Demand Variation, Long Demand Interval, High Demand Forecast Accuracy, High ROI

In this scenario, ROP is the ideal policy, and is particularly effective when demand is stable over long intervals and the forecast accuracy is high. The twelve preliminary findings such as **Findings 4** and **5** show that ROP maximizes ROI by keeping inventory costs low while efficiently meeting demand. **Finding 11** emphasizes that the longer demand interval allows for stable inventory replenishment, reducing the need for frequent adjustments.

Together, **Key Finding A** supports ROP's suitability for environments with high demand forecast accuracy, where predictable demand and longer intervals provide the necessary stability for ROP to maintain effective stock levels. However, Service Level (SL) is high, focusing on cost efficiency rather than maximizing service.

Top-Right Quadrant: High Demand Variation, Long Demand Interval, Low Demand Forecast Accuracy, High SL

Although there are significant demand fluctuations and low forecasting accuracy, ROP can still operate well by integrating safety stock. **Finding 8** emphasises that ROP can mitigate high variability (CoV < 7) through increased inventory, resulting in moderate ROI as holding costs build. The long demand interval allows ROP to respond and restock, while demand volatility escalates overall costs and diminishes performance.

The Service Level (SL) remains moderate in this quadrant, as ROP's primary strength lies in managing costs over extended cycles rather than responding rapidly to variability in shorter time frames. However, its ability to handle stock fluctuations helps prevent stockouts despite unpredictable demand.

Bottom-Left Quadrant: Low Demand Variation, Short Demand Interval, High Demand Forecast Accuracy, High ROI

In this scenario, where demand variation is low and demand intervals are short, MTA DBM shines. **Finding 6** shows that MTA DBM delivers a high Service Level (SL) by dynamically adjusting buffers, ensuring customer demand is consistently met. With short demand intervals, MTA DBM can respond quickly, reducing the risk of stockouts while maintaining an optimal inventory level.

Finding 10 further emphasizes that MTA DBM also provides a high ROI in predictable environments. The policy allows companies to maintain efficient stock levels with minimal intervention, optimizing both service and costs. The focus on Initial Buffer Size (IBS) as the key influencing factor simplifies the management of buffer sizes with minor impacts by TMR and TMG parameters, making it an efficient policy choice when demand is frequent but predictable.

Bottom-Right Quadrant: High Demand Variation, Short Demand Interval, Low Demand Forecast Accuracy, High SL

In volatile environments with high demand variation, short intervals, and low forecast accuracy, DDMRP offers the most responsive solution. **Finding 7** highlights that DDMRP's dynamic buffer adjustments ensure high SL, even in highly fluctuating demand environments. The policy's ability to handle spikes in demand and short-term variability makes it under these conditions as the best choice for maintaining customer satisfaction.

However, **Finding 9** indicates that while SL remain high, ROI may be high due to the higher costs associated with maintaining buffer stock and adapting to frequent demand changes. DDMRP's complexity, involving multiple parameters such as the Lead Time Factor (LTF) and Spike Threshold Percentage (STP), requires significant resources to manage effectively but ensures that service levels are maintained in unpredictable markets.

Together, **Key Finding B** supports that DDMRP becomes more relevant during anticipated demand surges, outperforming ROP and Make-to-Availability (MTA) Dynamic Buffer Management (DBM).

Considering the limitations and constraints highlighted in **Section 5.5**, the generalised decision table for stock policy selection requires further scrutiny. This is primarily due to the Group C simulation experiments (SE3 and SE4), where the relevant step in the variation experiments only encompassed a partial scale range. Subsequent research should consider a complete factorial analysis of supply and demand variation coupled with stochastic demand experiments. This approach will yield wider generalised results, offering refined insights to build the broader applications' decision table.

In synthesising these findings, it becomes evident that the intricacies of inventory policies are not merely mathematical constructs but pivotal tools in navigating the multifaceted landscapes of modern supply chains. The choices between forecast-based and consumption-based planning, between ROP, MTA DBM and DDMRP, represent more than mere strategic decisions; they reflect an evolving understanding of supply chain dynamics in the face of rapid technological and market shifts. As the discussion transitions into recommendations, it is crucial to recognise that these insights are not just observations but the foundation upon which actionable steps for the future can be built.

6.3 Recommendations

Based on the in-depth analysis of inventory policies, several clear action points have emerged for supply chain experts. Using the insights from earlier sections, the subsequent recommendations offer practical steps towards a more resilient supply chain future.

With the increasing unpredictability of market dynamics, especially post-pandemic, relying solely on traditional forecasting methods can expose businesses to significant risk. On the other hand, consumption-based methods, while adaptive, may sometimes lead to overstocking or missed opportunities in specific scenarios.

Companies should initiate simulation projects according to the proposed hybrid inventory policies in Section 5.3 Contributions. The simulation compares policies' different scenarios and planning parameters with performance outcomes. Based on the expected performance, management can identify which methods to deploy for the target customer segment and align the supply chain strategy. It will reduce the implementation risk with proof of concept provided by the simulation process. However, the next challenge is adjusting the parameters after actual deployment.

To address this companies should build a dashboard using their analytical findings concerning about influential factors and assumptions. Dashboard applying the latest artificial intelligence (AI) technology can provide additional benefits, such as through alerts or signals as a decision-support system to improve all planning parameters.

In summary, today's supply chains need flexible strategies. Merging old and new inventory methods and using advanced technology like AI is essential for a robust supply chain. The advice comes from real-world data and offers practical steps for supply chain experts. These strategies also present new opportunities for research, which we will explore next.

6.4 Opportunities for Further Research

In the constantly changing world of supply chain management, each solution presents opportunities for further investigation. The recommendations provided herein give a roadmap and highlight untapped areas in inventory management, inviting deeper exploration.

This research was confined to simulations based on the demand data from three cases. This limited the ability of this research to comprehensively explore various demand patterns, thus restricting a complete factorial performance analysis. Further research should consider exploring additional or varied cases to enable a more extensive examination of demand variations and enhance the robustness of the findings.

With the prediction profiler feature of JMP shown in **Figure 42**, there is potential to probe varied demand data patterns in Demand Variation (DV) and Supply Variation (SV). Such an approach would address and transcend the historical case demand profile limitations. Additionally, predicting profiles could facilitate comparisons across diverse planning parameters, considering objectives like inventory returns, service levels, and expected desirability. Such tools would empower supply chain decisions, offering more nuanced trade-offs between anticipated results and policy choices.

Therefore, a pertinent research question for future explorations could be:

How are the selected planning parameters of the inventory policies projecting the desirability of performance?

This question could broaden our understanding of supply chain networks and their planning systems. For robust findings, it is imperative to devise methods that objectively set parameters for anticipated performance results, factoring in variations within a multi-echelon supply chain framework. The intricate balance between different performance desirability, including aspects like buffer sizing, can be visualised in **Figure 42**, showcasing the prediction profile model.

Collaborating with experts across varied domains might yield more influential, diversified insights. Further, keeping abreast with recent advancements in supply chain methodologies would be beneficial, ensuring the research remains at the forefront of the discipline.

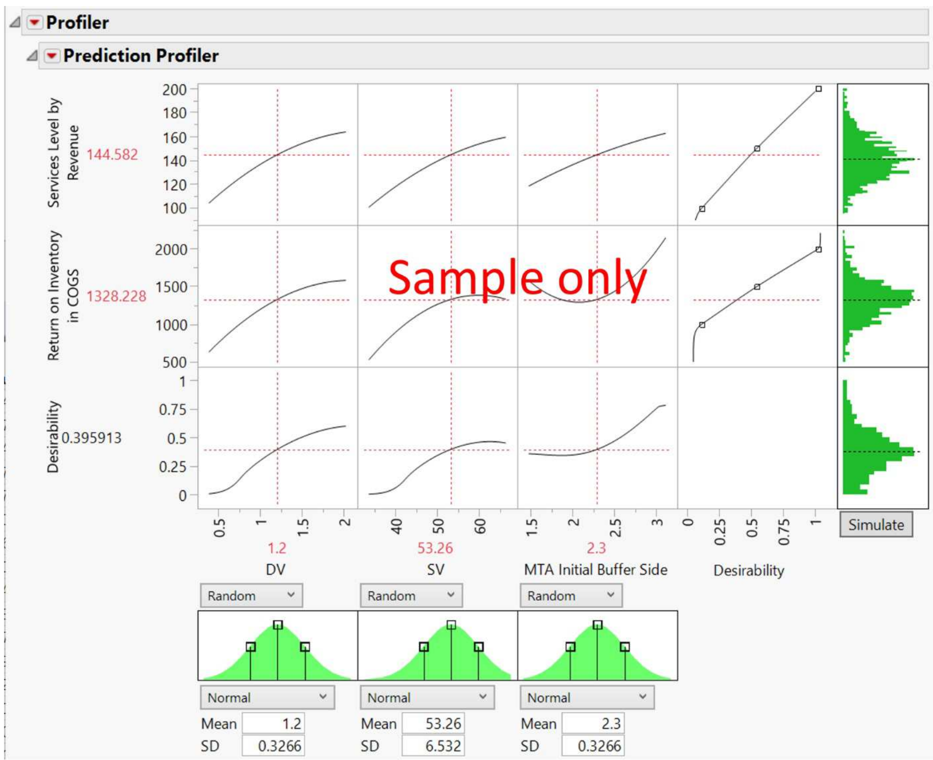


Figure 42 - Prediction Profile for the Desirability of Performance Outcomes

With these new paths for research laid out, the focus shifts to this study's contributed value and a summary of the final insights.

6.5 Concluding Remarks

In the intricate realm of supply chain management, envision a meticulously constructed tapestry—each decision, methodology, and insight interwoven to represent organisational prosperity. This research decoded the intricate layers of inventory policies and their interrelationships. Furthermore, it crafted a compelling narrative that underscores the paramount adaptability amidst the volatile currents of the contemporary market.

These findings, upon deeper introspection, do not merely exist in isolation. Collectively, they shed light on a broader schema with profound implications for the academic and industrial sectors.

Key insights drawn from this study for supply chain practitioners include:

Universality and Inventory Policies: No single policy fits every scenario. Optimal performance arises from a harmonious integration of diverse models tailored to specific situations.

Dynamics of Policy Adaptation: A rigid adherence to static policies risks redundancy. Continuous policy updates are paramount and aligned with evolving internal and external factors. In this context, data-driven dashboards emerge as indispensable, guiding enlightened business decisions.

The Role of Simulation and Analytics: These tools are essential for achieving supply chain excellence. Their integration forms the bedrock of strategic supply chain planning.

Visionary Flexibility in Management: Moving from a narrow, cost-centric viewpoint to a broader, holistic perspective is crucial. The flexible mindset entails a shift from departmental silos to an all-encompassing view of the supply chain, underscored by real-time analyses and adaptable strategies. While this research has only used three cases to demonstrate these insights, further research can more fully explore these using additional cases and deeper interrogation of the planning parameters.

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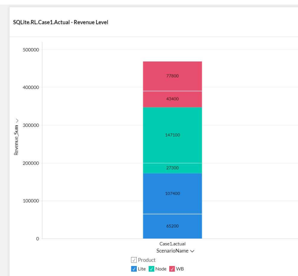
Appendix

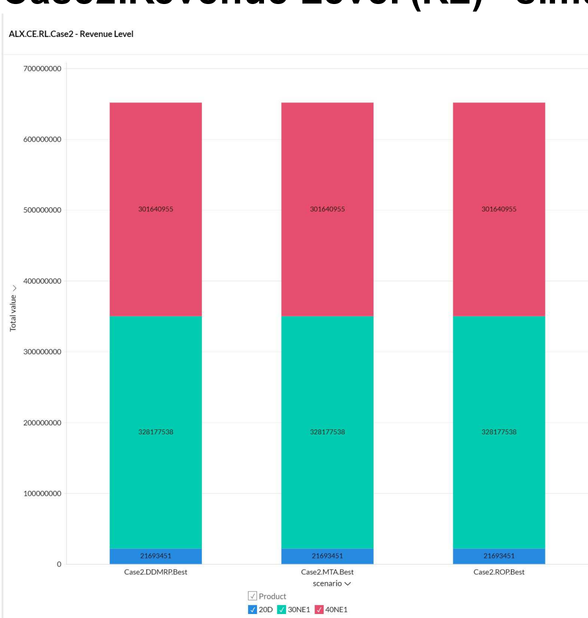
Appendix A - KPIs performance charts

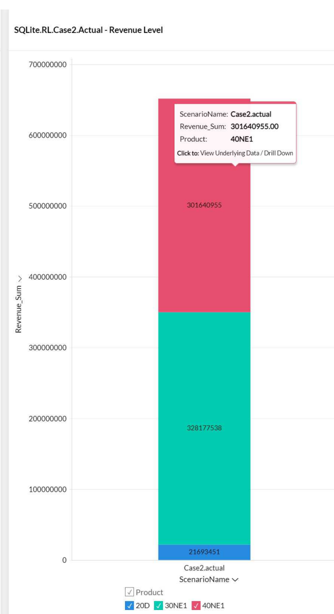
A1 - Revenue Level (RL)

Case1.Revenue Level (RL) - simulated vs actual case

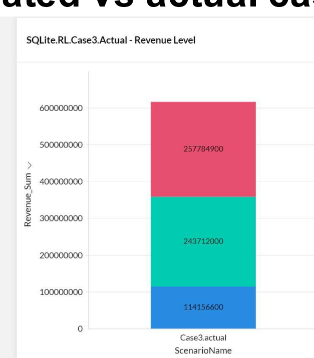


Case2.Revenue Level (RL) - simulated vs actual case



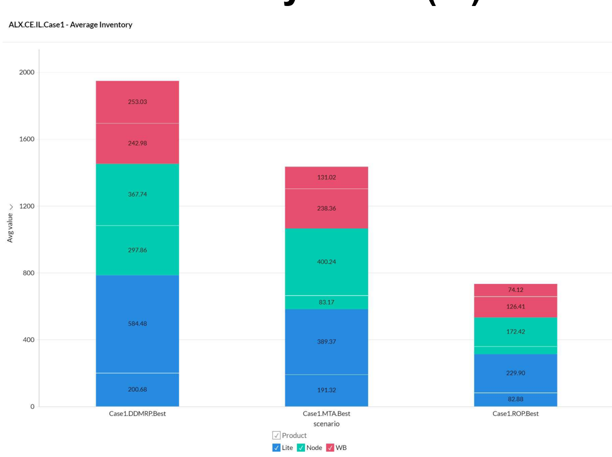


Case3.Revenue Level (RL) - simulated vs actual case

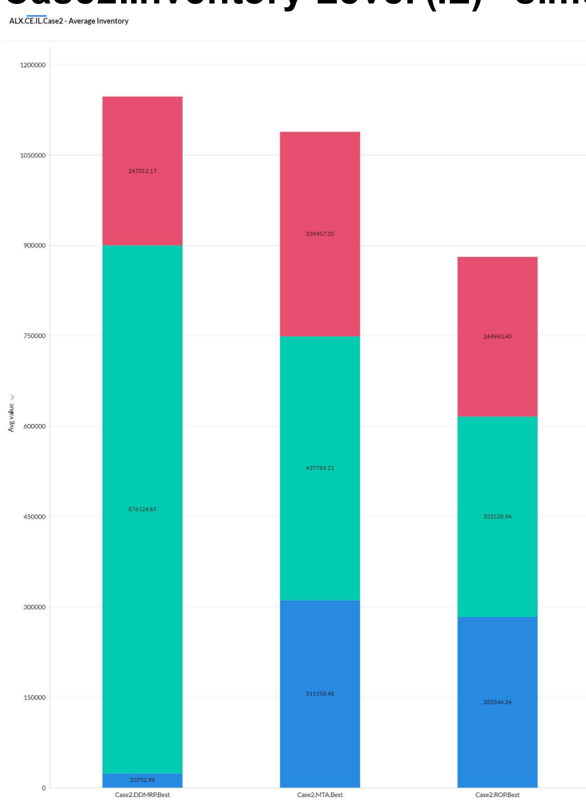


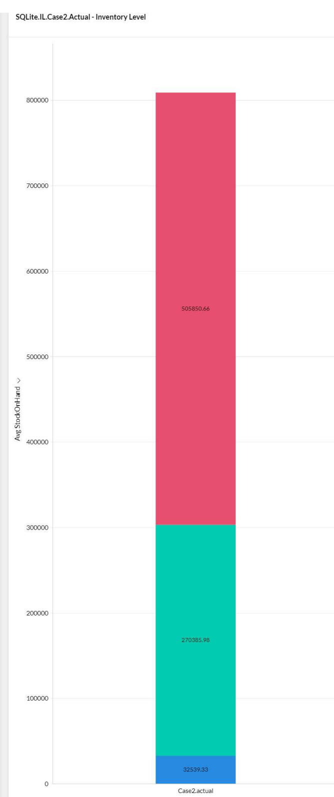
A2 - Inventory Level (IL)

Case1.Inventory Level (IL) - simulated vs actual case

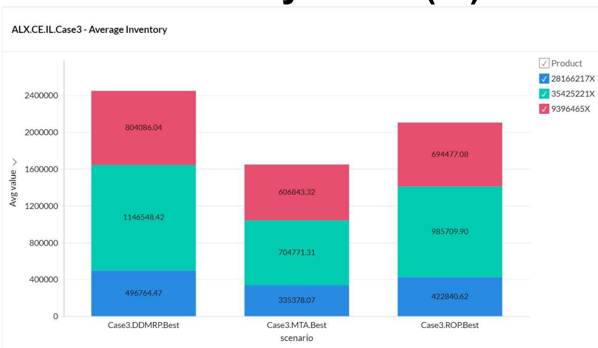


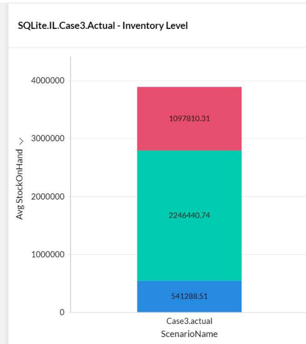
Case2.Inventory Level (IL) - simulated vs actual case





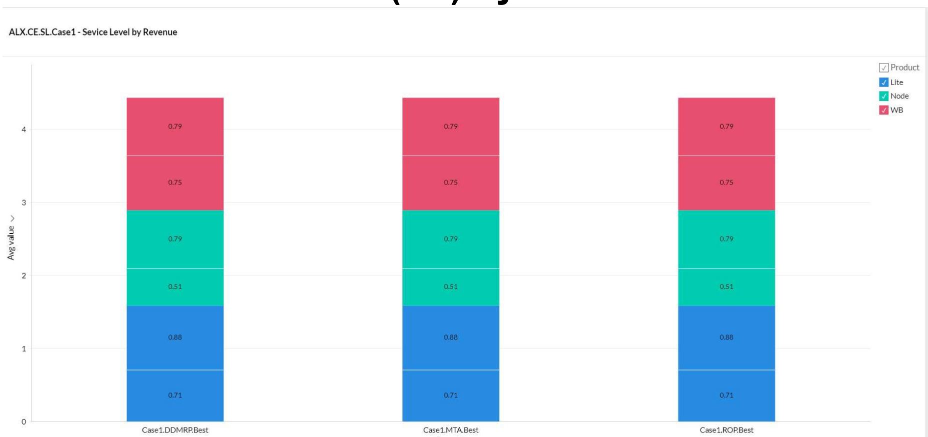
Case3.Inventory Level (IL) - simulated vs actual case



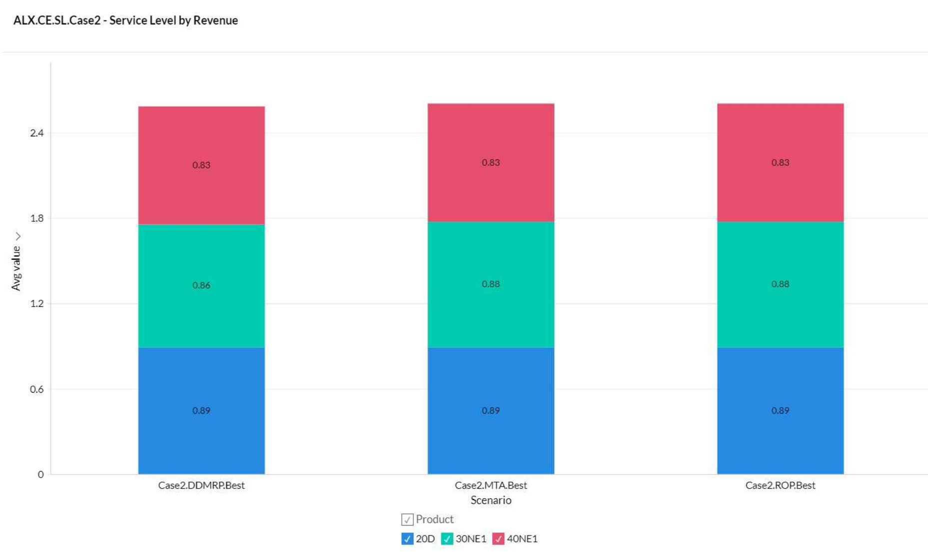


A3 - Service Level (SL)

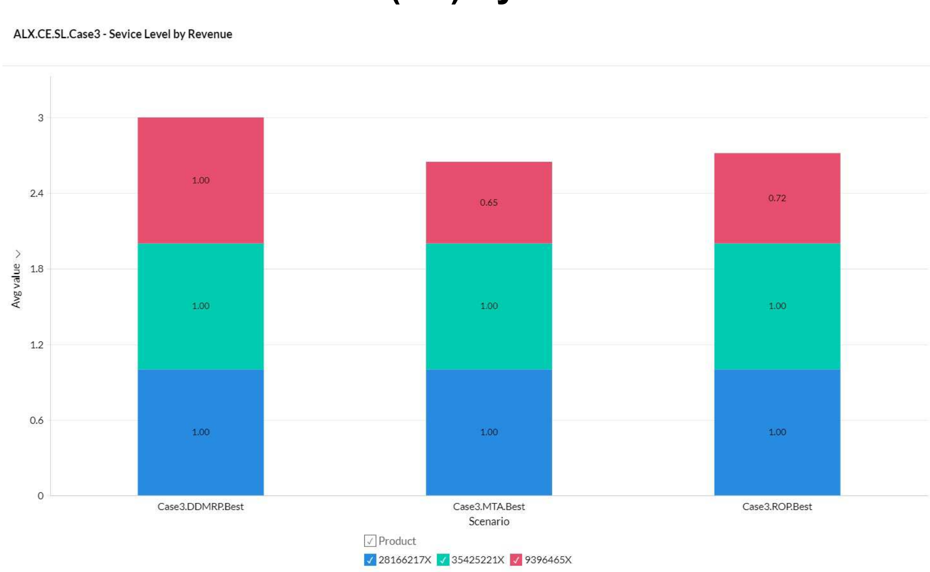
Case1.Service Level (SL) by Revenue - simulated



Case2.Service Level (SL) by Revenue - simulated

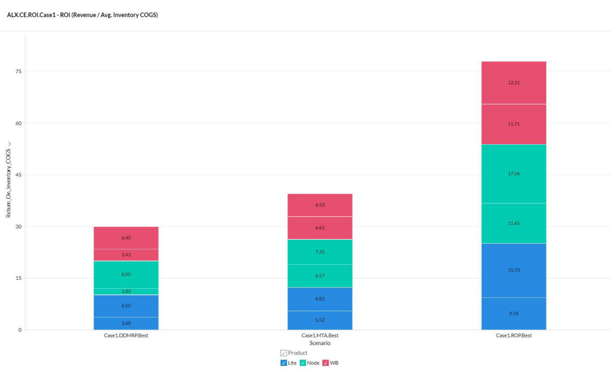


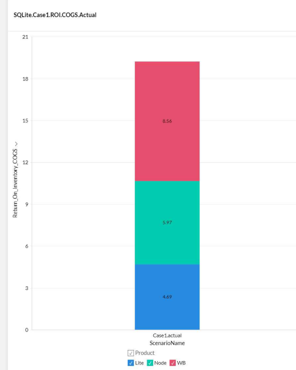
Case3.Service Level (SL) by Revenue - simulated



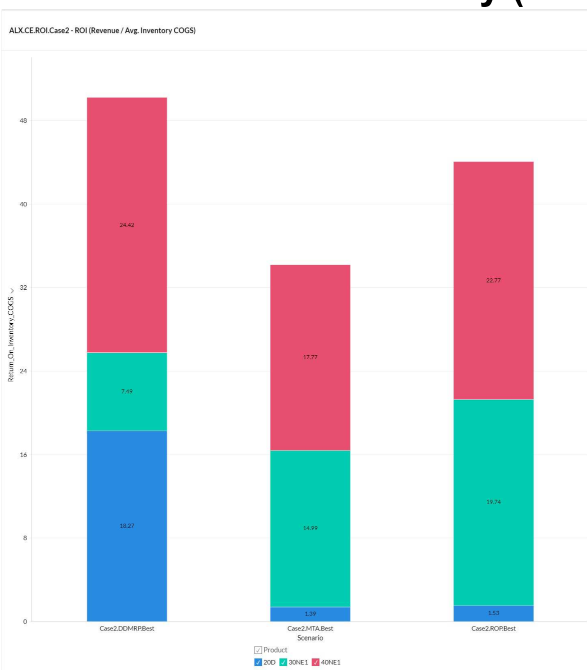
A4 - Return On Inventory (ROI)

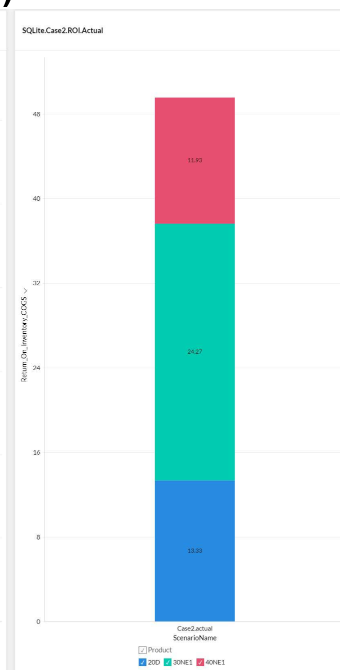
Case1.Return On Inventory (ROI) COGS - simulated vs actual case



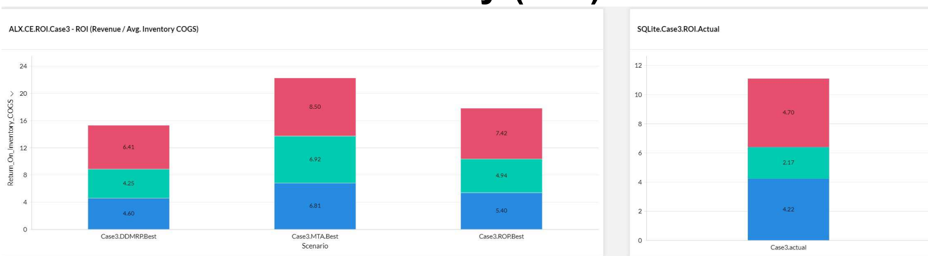


Case2.Return On Inventory (ROI) COGS - simulated vs actual case



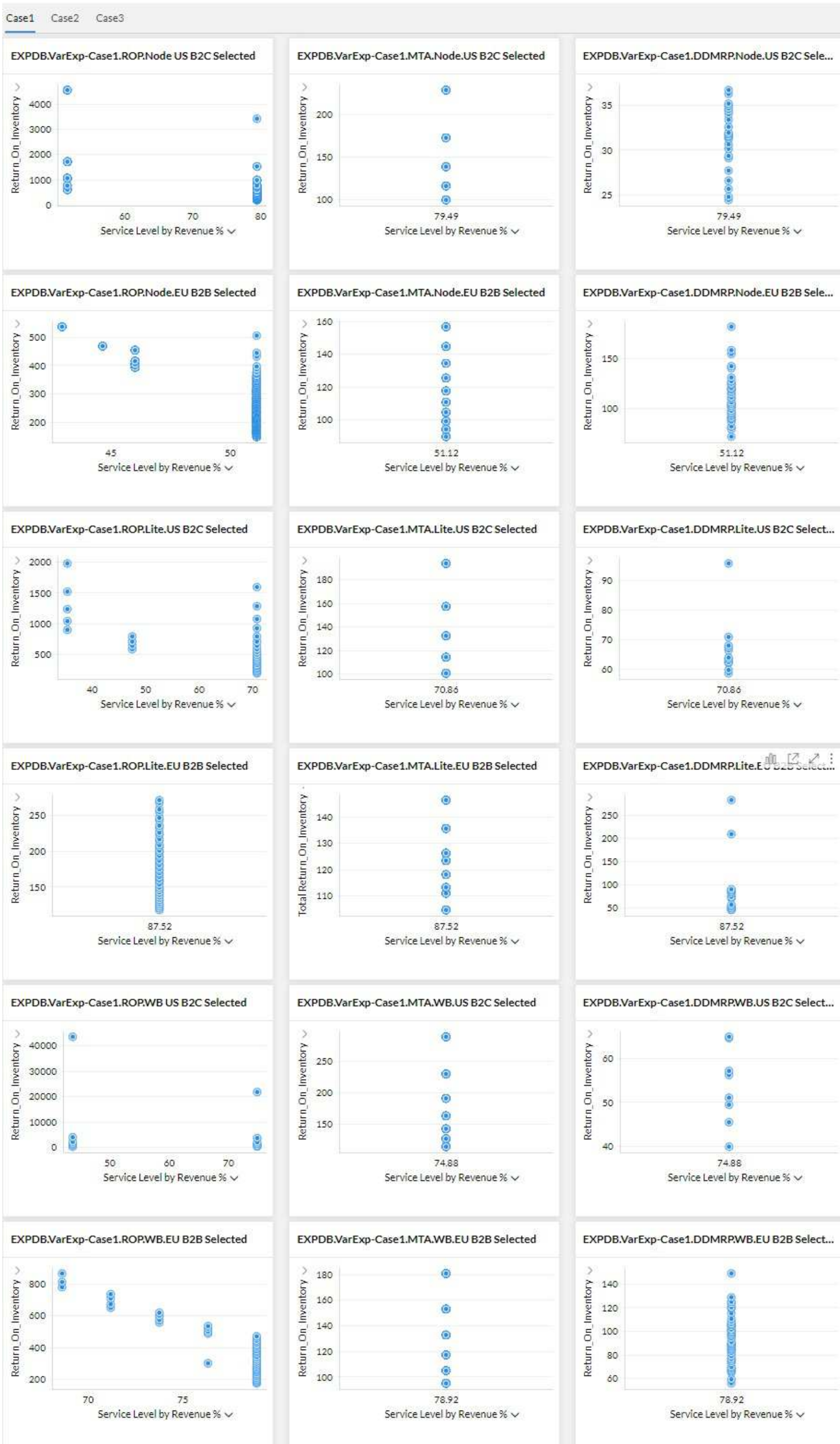


Case3.Return On Inventory (ROI) COGS - simulated vs actual case

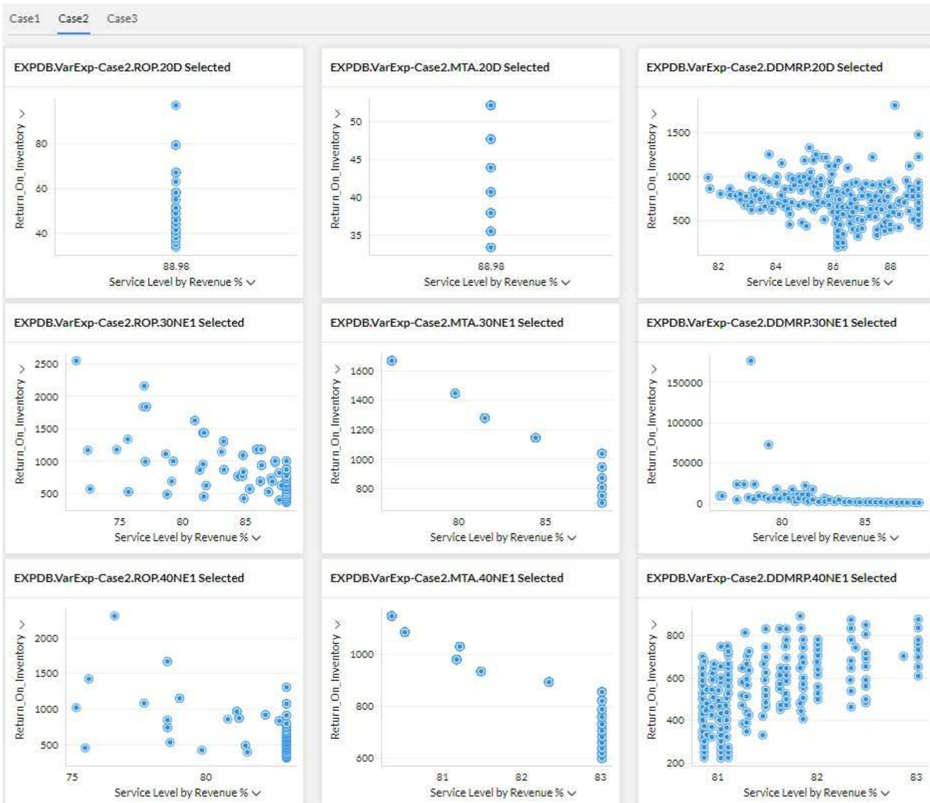


Appendix B - Scatter plot in SE0

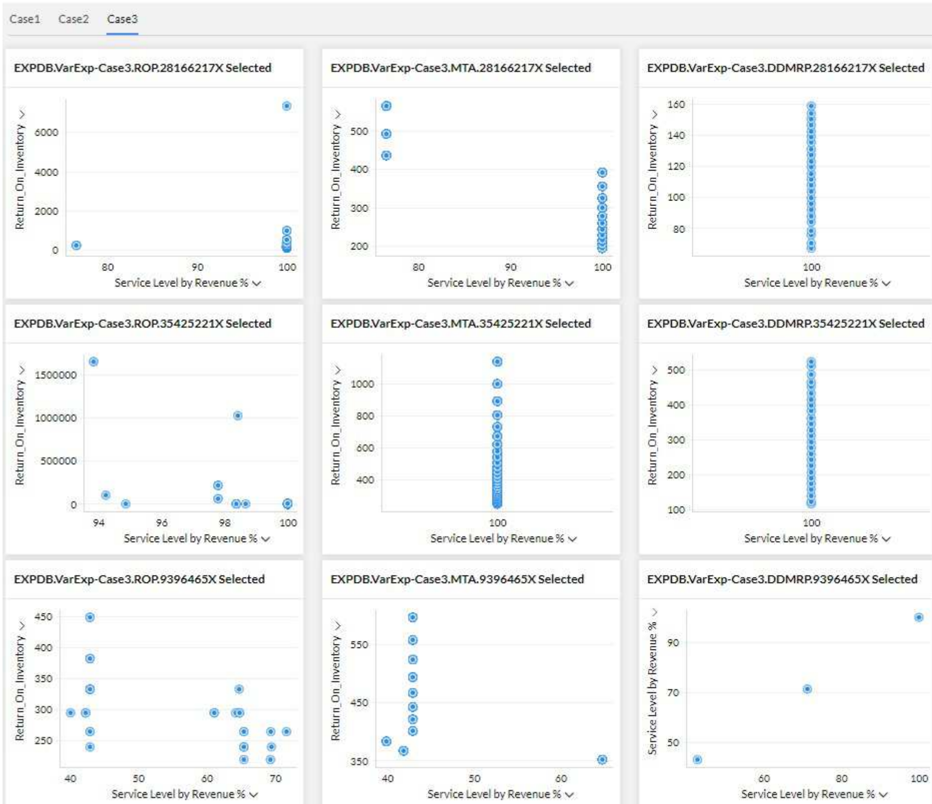
Case 1 Variation Experiment Scatter plot output for ROI and SL



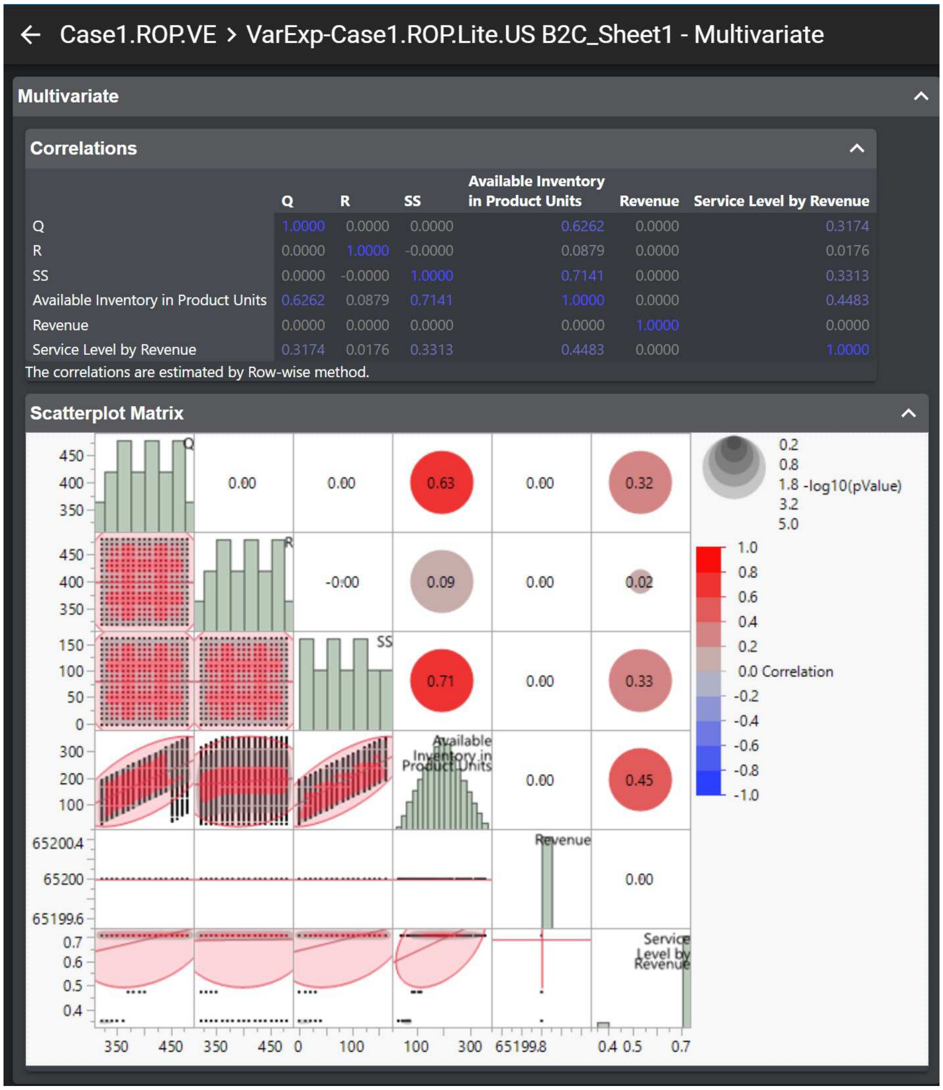
Case 2 Variation Experiment Scatter plot output for ROI and SL



Case 3 Variation Experiment Scatter plot output for ROI and SL



Appendix C - Multivariate analysis in simulation experiment (SE0)



Case1.ROP.VE > VarExp-Case1.ROP.Lite.US B2C_Sheet1 - Multivariate

Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	0.0000	0.0000	0.6262	0.0000	0.3174
R	0.0000	1.0000	-0.0000	0.0879	0.0000	0.0176
SS	0.0000	-0.0000	1.0000	0.7141	0.0000	0.3313
Available Inventory in Product Units	0.6262	0.0879	0.7141	1.0000	0.0000	0.4483
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.3174	0.0176	0.3313	0.4483	0.0000	1.0000

The correlations are estimated by Row-wise method.

← Case1.ROP.VE > VarExp-Case1.ROP.Lite.EU B2B_Sheet1 - Multivariate

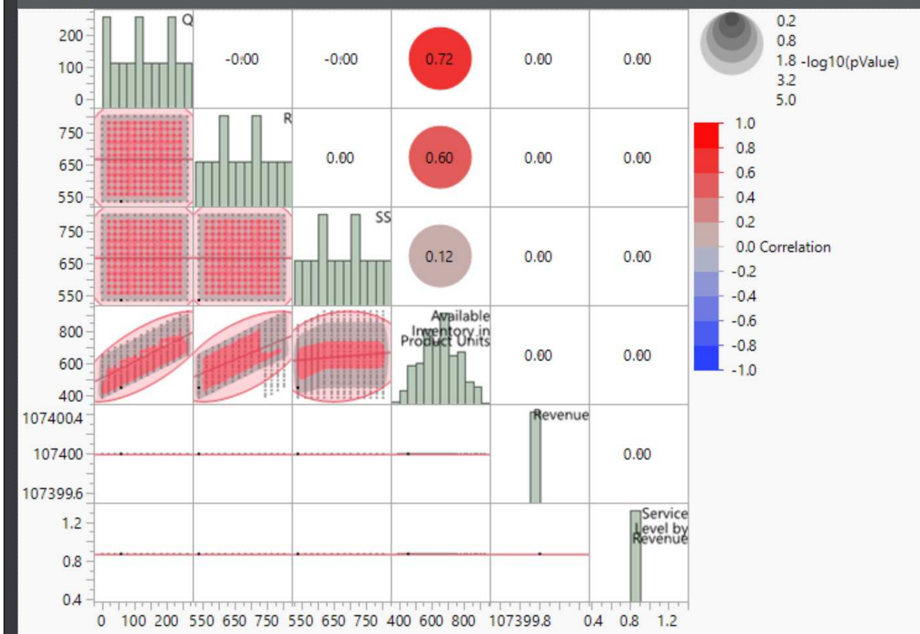
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	-0.0000	-0.0000	0.7170	0.0000	0.0000
R	-0.0000	1.0000	0.0000	0.5969	0.0000	0.0000
SS	-0.0000	0.0000	1.0000	0.1201	0.0000	0.0000
Available Inventory in Product Units	0.7170	0.5969	0.1201	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case1.ROP.VE > VarExp-Case1.ROP.Node.US B2C_Sheet1 - Multivariate

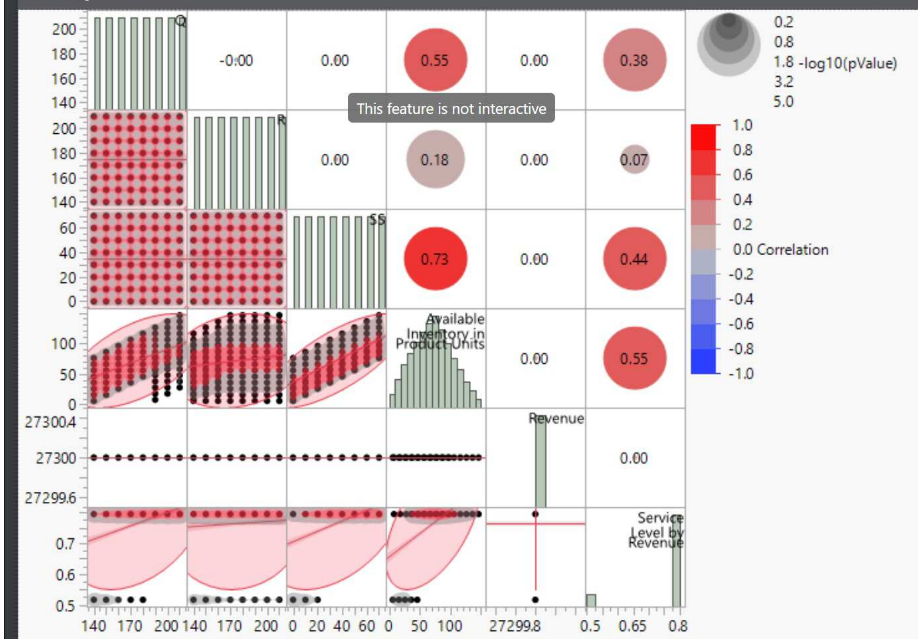
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	-0.0000	0.0000	0.5512	0.0000	0.3781
R	-0.0000	1.0000	0.0000	0.1768	0.0000	0.0718
SS	0.0000	0.0000	1.0000	0.7279	0.0000	0.4404
Available Inventory in Product Units	0.5512	0.1768	0.7279	1.0000	0.0000	0.5452
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.3781	0.0718	0.4404	0.5452	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.ROP.VE > VarExp-Case1.ROP.Node.EU B2B_Sheet1 - Multivariate

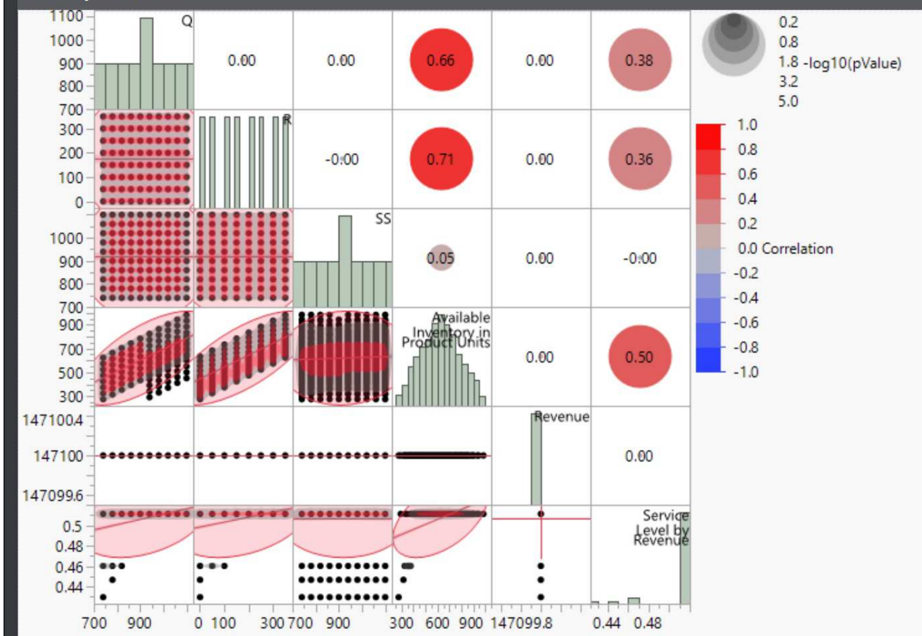
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	0.0000	0.0000	0.6620	0.0000	0.3767
R	0.0000	1.0000	-0.0000	0.7093	0.0000	0.3552
SS	0.0000	-0.0000	1.0000	0.0493	0.0000	-0.0000
Available Inventory in Product Units	0.6620	0.7093	0.0493	1.0000	0.0000	0.5041
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.3767	0.3552	-0.0000	0.5041	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.ROP.VE > VarExp-Case1.ROP.WB.US B2C_Sheet1 - Multivariate

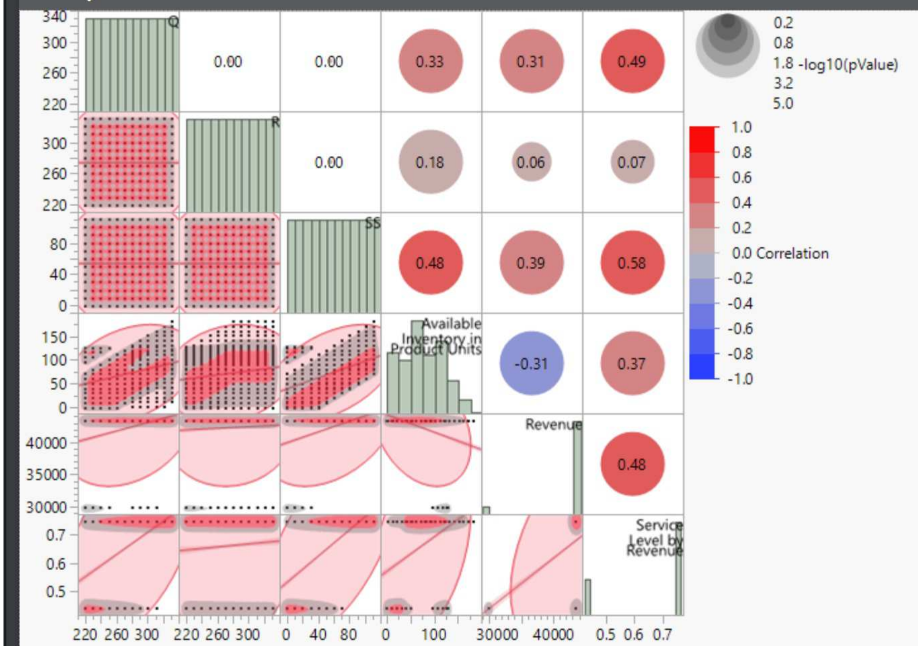
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	0.0000	0.0000	0.3268	0.3072	0.4894
R	0.0000	1.0000	0.0000	0.1773	0.0584	0.0668
SS	0.0000	0.0000	1.0000	0.4824	0.3901	0.5785
Available Inventory in Product Units	0.3268	0.1773	0.4824	1.0000	-0.3069	0.3695
Revenue	0.3072	0.0584	0.3901	-0.3069	1.0000	0.4781
Service Level by Revenue	0.4894	0.0668	0.5785	0.3695	0.4781	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.ROP.VE > VarExp-Case1.ROP.WB.EU B2B_Sheet1 - Multivariate

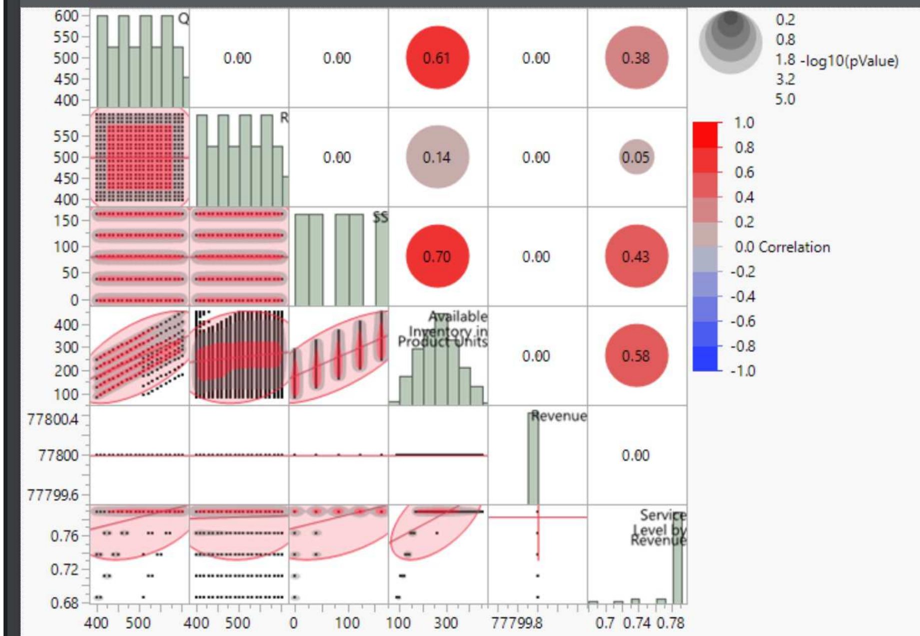
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	0.0000	0.0000	0.6101	0.0000	0.3763
R	0.0000	1.0000	0.0000	0.1429	0.0000	0.0453
SS	0.0000	0.0000	1.0000	0.7035	0.0000	0.4282
Available Inventory in Product Units	0.6101	0.1429	0.7035	1.0000	0.0000	0.5805
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.3763	0.0453	0.4282	0.5805	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case1.MTA.VE > VarExp-Case1.MTA.Lite.US B2C_Sheet1 - Multivariate

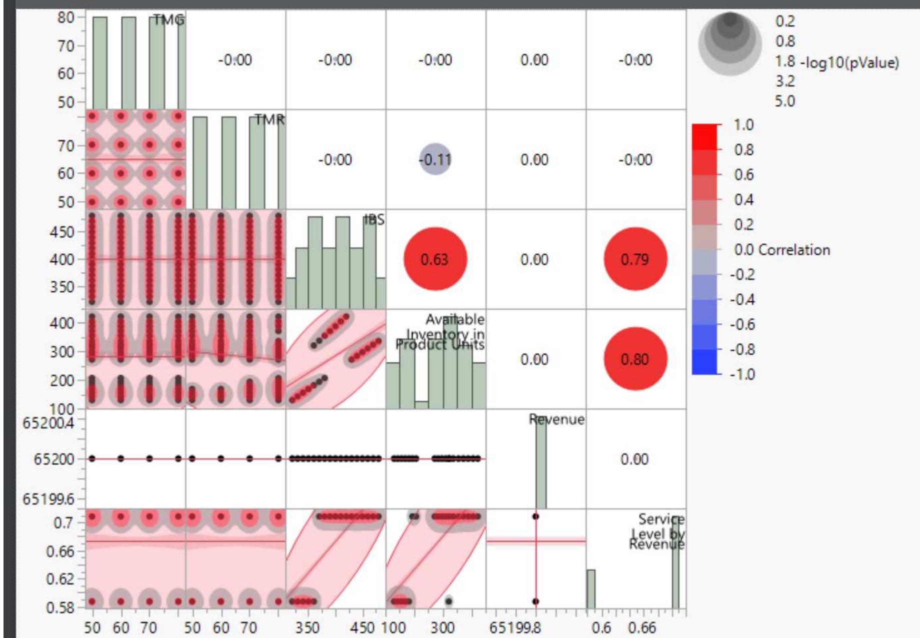
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
TMR	-0.0000	1.0000	-0.0000	-0.1112	0.0000	-0.0000
IBS	-0.0000	-0.0000	1.0000	0.6289	0.0000	0.7906
Available Inventory in Product Units	-0.0000	-0.1112	0.6289	1.0000	0.0000	0.7976
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.0000	-0.0000	0.7906	0.7976	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.MTA.VE > VarExp-Case1.MTA.Lite.EU B2B_Sheet1 - Multivariate

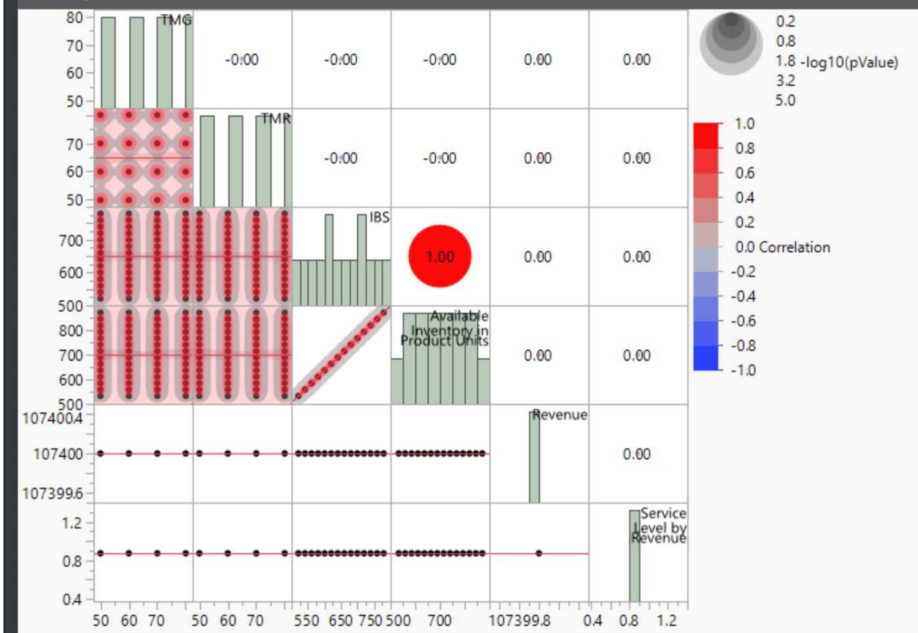
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
TMR	-0.0000	1.0000	-0.0000	-0.0000	0.0000	0.0000
IBS	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.0000
Available Inventory in Product Units	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.MTA.VE > VarExp-Case1.MTA.Node.US B2C_Sheet1 - Multivariate

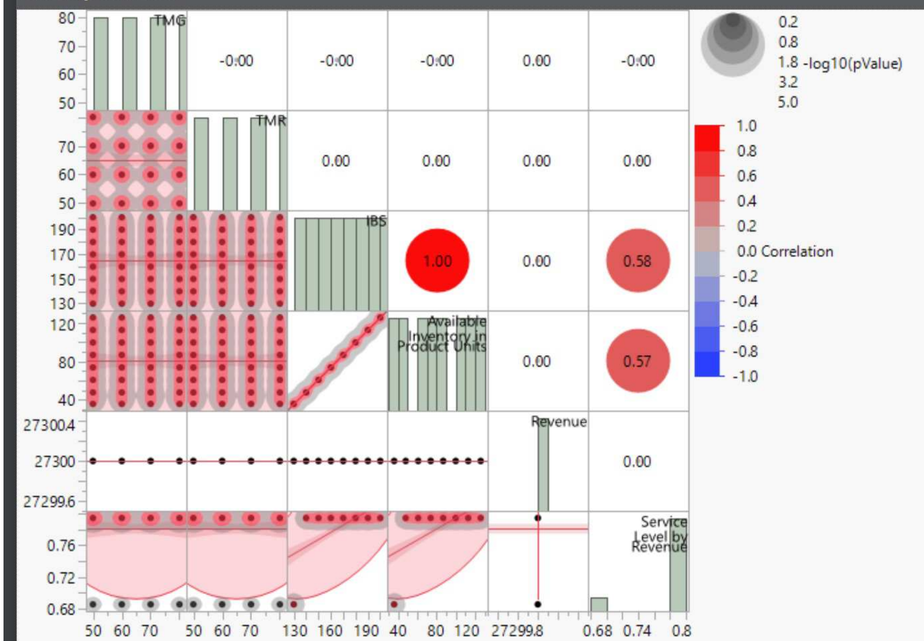
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
TMR	-0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
IBS	-0.0000	0.0000	1.0000	1.0000	0.0000	0.5774
Available Inventory in Product Units	-0.0000	0.0000	1.0000	1.0000	0.0000	0.5699
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.0000	0.0000	0.5774	0.5699	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.MTA.VE > VarExp-Case1.MTA.Node.EU B2B_Sheet1 - Multivariate

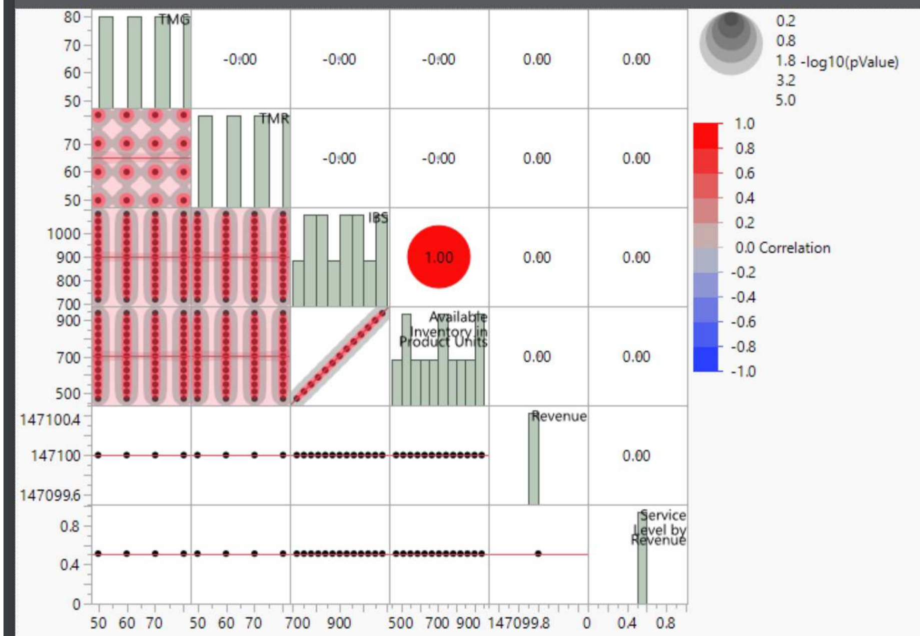
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
TMR	-0.0000	1.0000	-0.0000	-0.0000	0.0000	0.0000
IBS	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.0000
Available Inventory in Product Units	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case1.MTA.VE > VarExp-Case1.MTA.WB.US B2C_Sheet1 - Multivariate

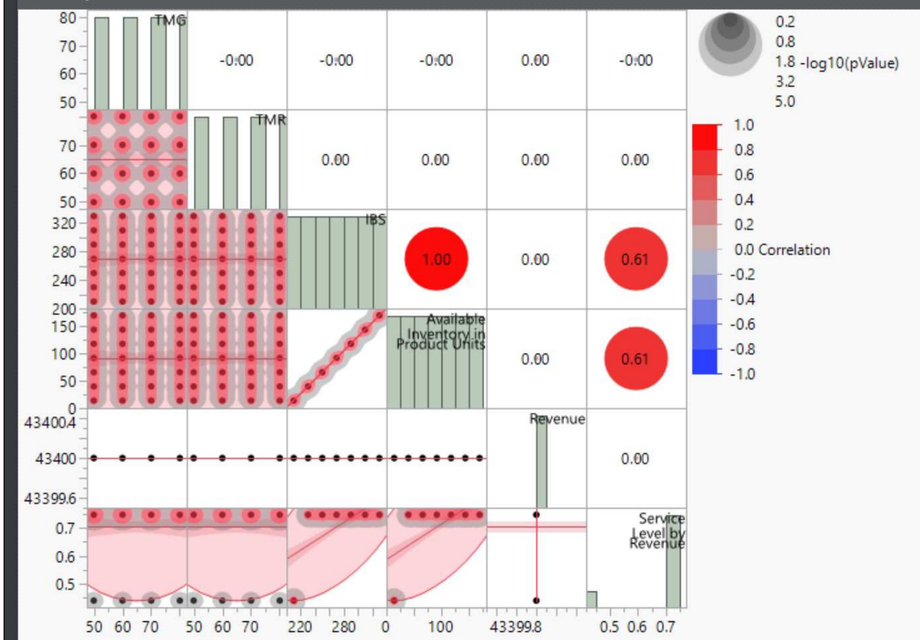
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
TMR	-0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
IBS	-0.0000	0.0000	1.0000	1.0000	0.0000	0.6124
Available Inventory in Product Units	-0.0000	0.0000	1.0000	1.0000	0.0000	0.6124
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.0000	0.0000	0.6124	0.6124	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case1.MTA.VE > VarExp-Case1.MTA.WB.EU B2B_Sheet1 - Multivariate

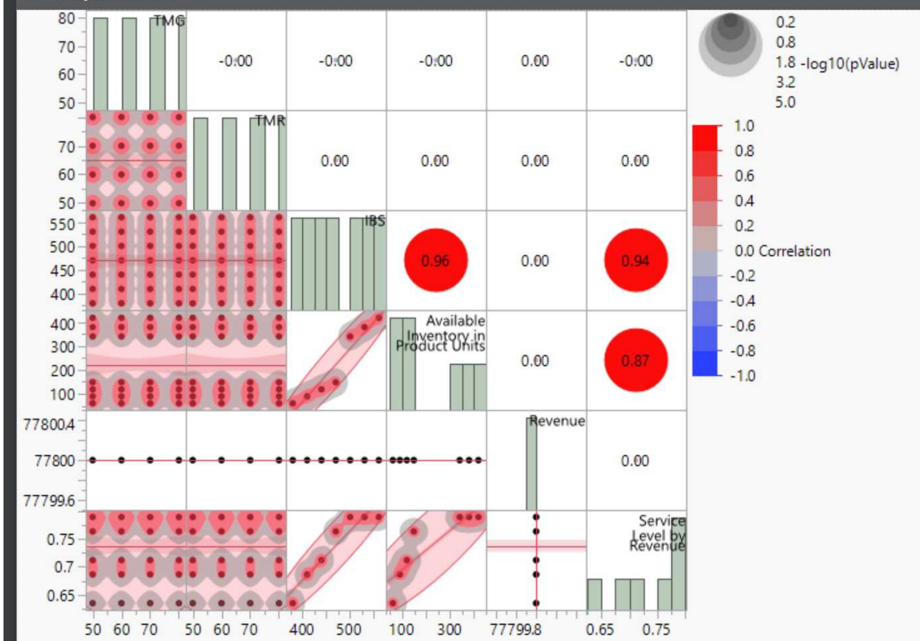
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
TMR	-0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
IBS	-0.0000	0.0000	1.0000	0.9572	0.0000	0.9399
Available Inventory in Product Units	-0.0000	0.0000	0.9572	1.0000	0.0000	0.8731
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.0000	0.0000	0.9399	0.8731	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.DDMRP.VE > VarExp-Case1.DDMRP.Lite.US B2C_Sheet1 - Multivariate

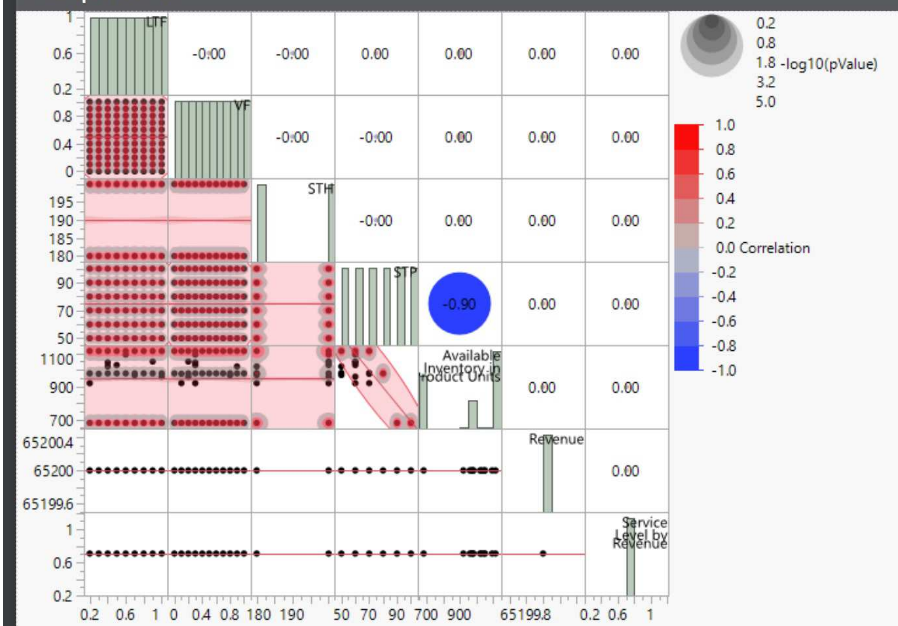
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	-0.0000	-0.0000	0.0000	0.0022	0.0000	0.0000
VF	-0.0000	1.0000	-0.0000	-0.0000	0.0030	0.0000	0.0000
STH	-0.0000	-0.0000	1.0000	-0.0000	0.0011	0.0000	0.0000
STP	0.0000	-0.0000	-0.0000	1.0000	-0.9020	0.0000	0.0000
Available Inventory in Product Units	0.0022	0.0030	0.0011	-0.9020	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.DDMRP.VE > VarExp-Case1.DDMRP.Lite.EU B2B_Sheet1 - Multivariate

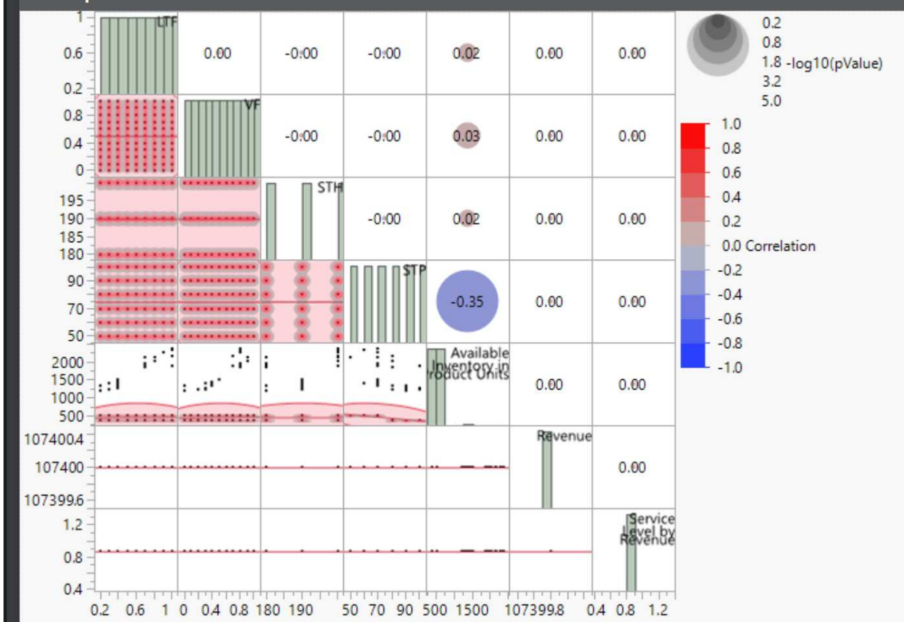
Multivariate

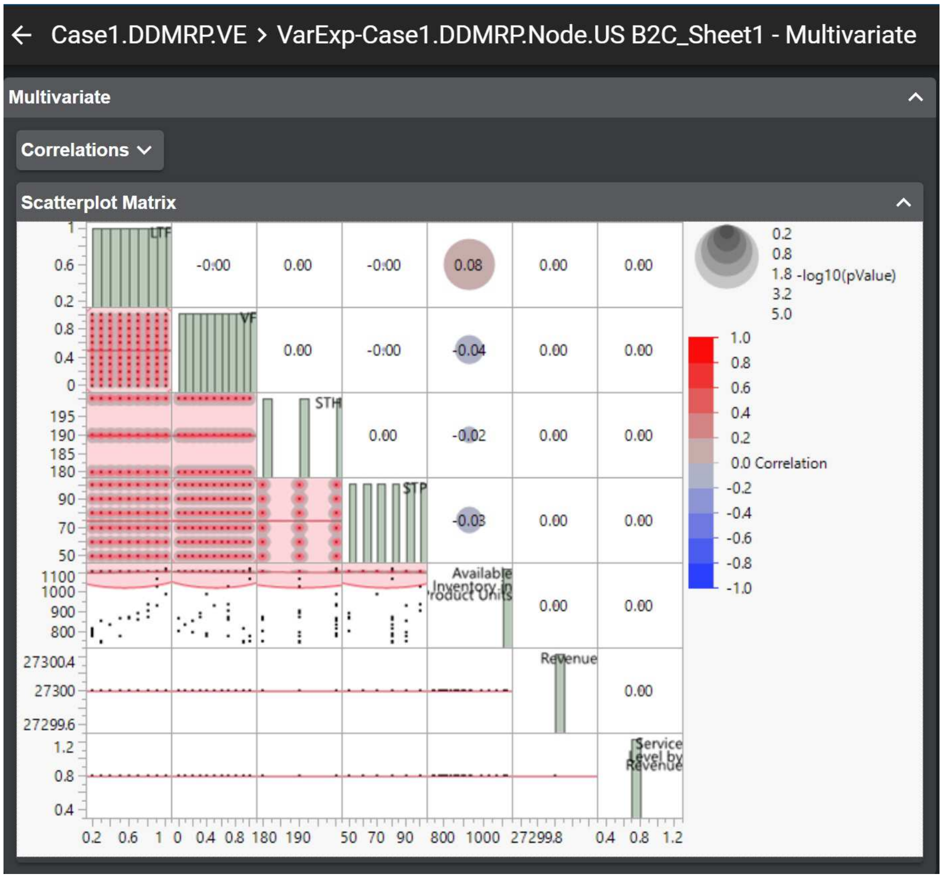
Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	0.0000	-0.0000	-0.0000	0.0197	0.0000	0.0000
VF	0.0000	1.0000	-0.0000	-0.0000	0.0336	0.0000	0.0000
STH	-0.0000	-0.0000	1.0000	-0.0000	0.0173	0.0000	0.0000
STP	-0.0000	-0.0000	-0.0000	1.0000	-0.3544	0.0000	0.0000
Available Inventory in Product Units	0.0197	0.0336	0.0173	-0.3544	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix





Case1.DDMRP.VE > VarExp-Case1.DDMRP.Node.US B2C_Sheet1 - Multivariate
Multivariate
Correlations
Scatterplot Matrix
LTF
VF
STH
STP
Available Inventory in Product Units
Revenue
Service Level by Revenue
-log10(pValue)
Correlation

← Case1.DDMRP.VE > VarExp-Case1.DDMRP.Node.EU B2B_Sheet1 - Multivariate

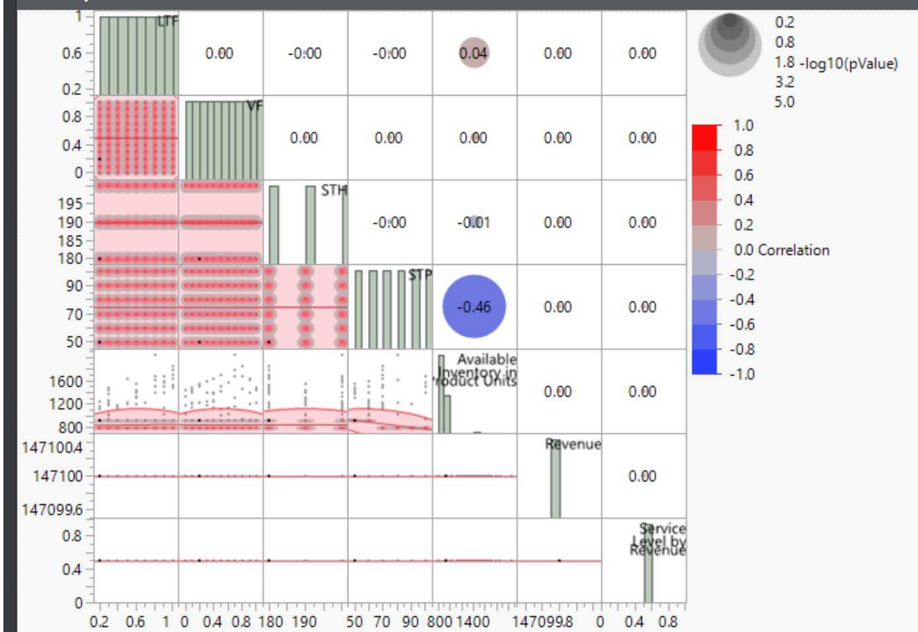
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	0.0000	-0.0000	-0.0000	0.0415	0.0000	0.0000
VF	0.0000	1.0000	0.0000	0.0000	0.0027	0.0000	0.0000
STH	-0.0000	0.0000	1.0000	-0.0000	-0.0092	0.0000	0.0000
STP	-0.0000	0.0000	-0.0000	1.0000	-0.4608	0.0000	0.0000
Available Inventory in Product Units	0.0415	0.0027	-0.0092	-0.4608	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case1.DDMRP.VE > VarExp-Case1.DDMRP.WB.US B2C_Sheet1 - Multivariate

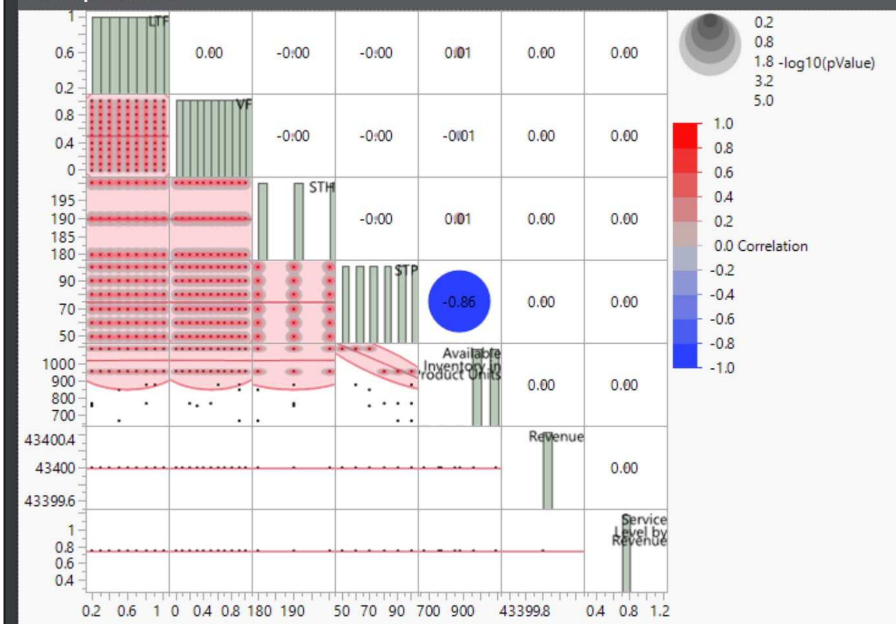
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	0.0000	-0.0000	-0.0000	0.0081	0.0000	0.0000
VF	0.0000	1.0000	-0.0000	-0.0000	-0.0051	0.0000	0.0000
STH	-0.0000	-0.0000	1.0000	-0.0000	0.0080	0.0000	0.0000
STP	-0.0000	-0.0000	-0.0000	1.0000	-0.8579	0.0000	0.0000
Available Inventory in Product Units	0.0081	-0.0051	0.0080	-0.8579	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case1.DDMRP.VE > VarExp-Case1.DDMRP.WB.EU B2B_Sheet1 - Multivariate

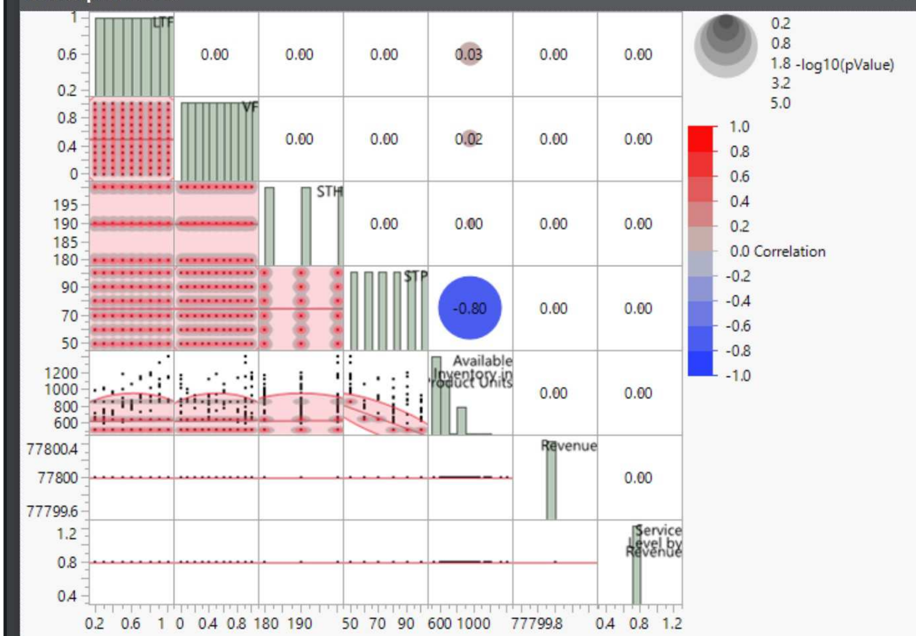
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	0.0000	0.0000	0.0000	0.0279	0.0000	0.0000
VF	0.0000	1.0000	0.0000	0.0000	0.0170	0.0000	0.0000
STH	0.0000	0.0000	1.0000	0.0000	0.0036	0.0000	0.0000
STP	0.0000	0.0000	0.0000	1.0000	-0.7967	0.0000	0.0000
Available Inventory in Product Units	0.0279	0.0170	0.0036	-0.7967	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case2.ROP.VE > VarExp-Case2.ROP.20D_Sheet1 - Multivariate

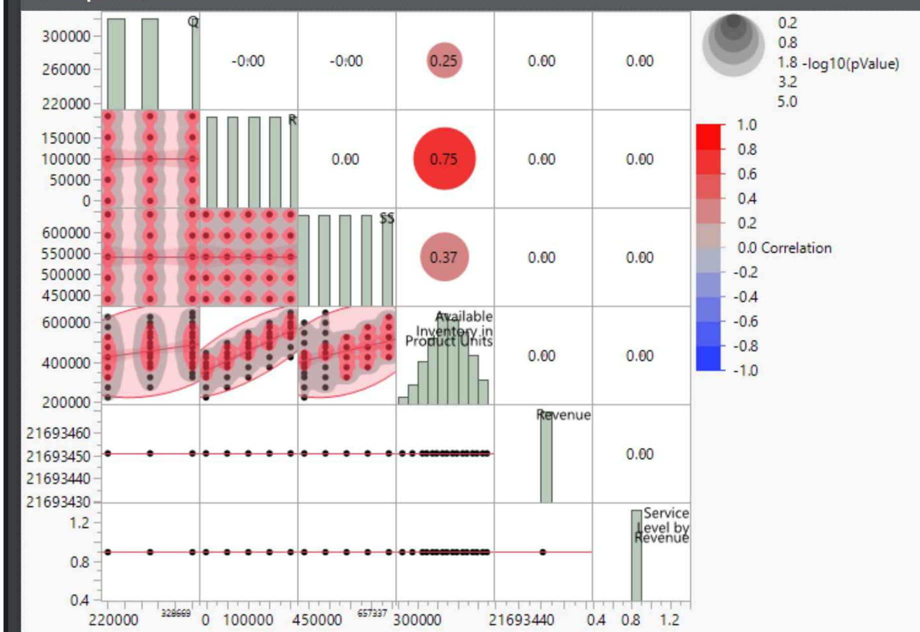
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	-0.0000	-0.0000	0.2532	0.0000	0.0000
R	-0.0000	1.0000	0.0000	0.7500	0.0000	0.0000
SS	-0.0000	0.0000	1.0000	0.3722	0.0000	0.0000
Available Inventory in Product Units	0.2532	0.7500	0.3722	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	Service Level by Revenue
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case2.ROP.VE > VarExp-Case2.ROP.30NE1_Sheet1 - Multivariate

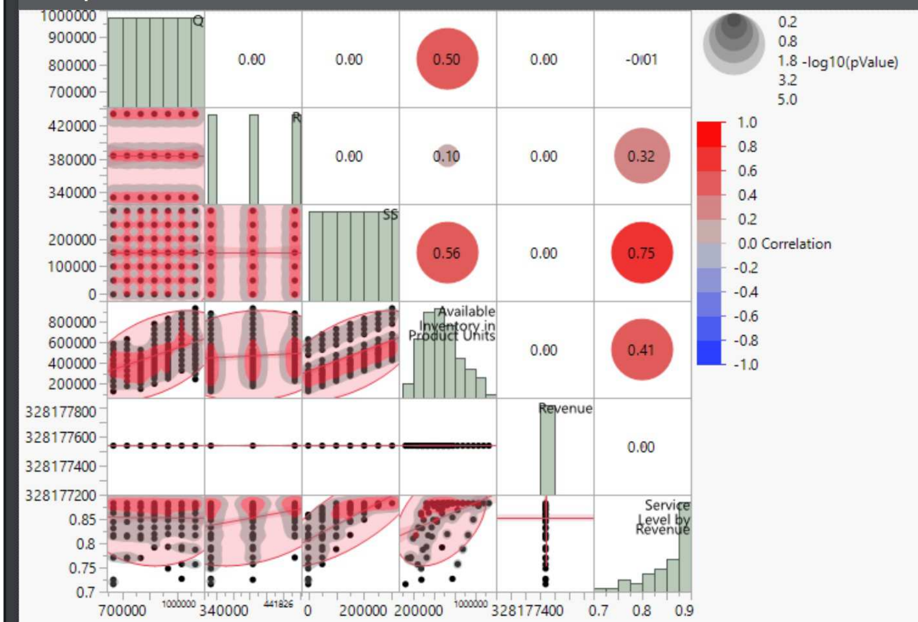
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	0.0000	0.0000	0.4980	0.0000	-0.0091
R	0.0000	1.0000	0.0000	0.0963	0.0000	0.3178
SS	0.0000	0.0000	1.0000	0.5620	0.0000	0.7504
Available Inventory in Product Units	0.4980	0.0963	0.5620	1.0000	0.0000	0.4086
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.0091	0.3178	0.7504	0.4086	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case2.ROP.VE > VarExp-Case2.ROP.40NE1_Sheet1 - Multivariate

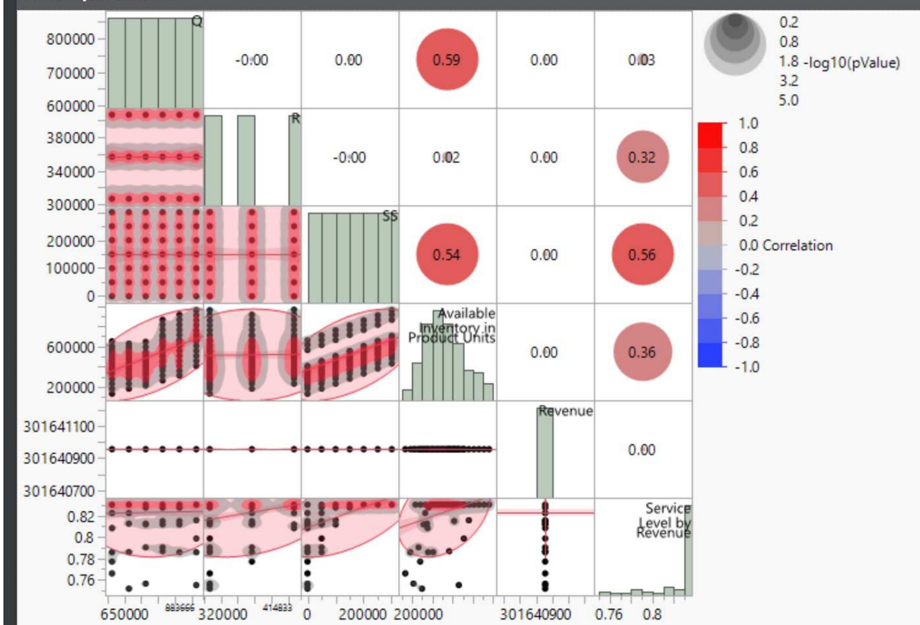
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	-0.0000	0.0000	0.5895	0.0000	0.0315
R	-0.0000	1.0000	-0.0000	0.0228	0.0000	0.3180
SS	0.0000	-0.0000	1.0000	0.5382	0.0000	0.5607
Available Inventory in Product Units	0.5895	0.0228	0.5382	1.0000	0.0000	0.3598
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0315	0.3180	0.5607	0.3598	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case2.MTA.VE > VarExp-Case2.MTA.20D_Sheet1 - Multivariate

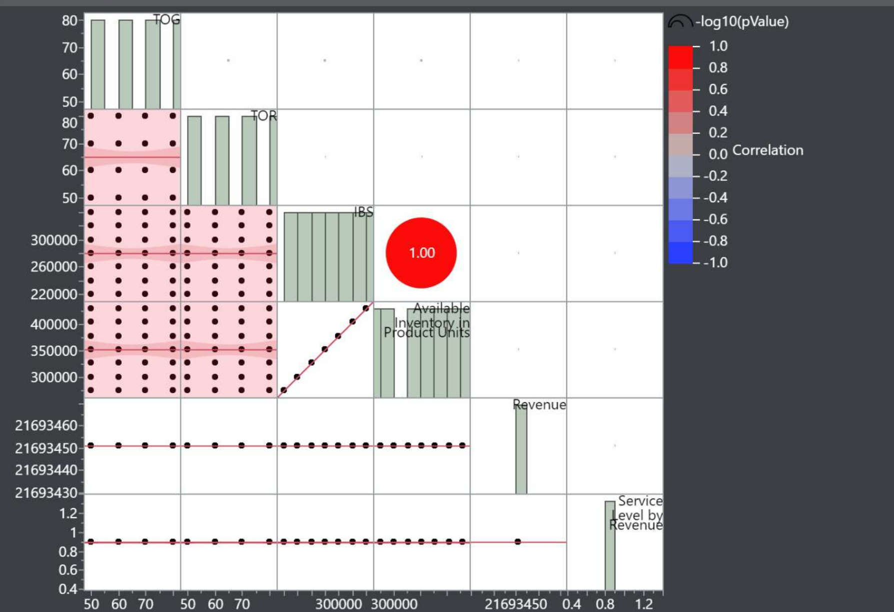
Multivariate

Correlations

	TOG	TOR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TOG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
TOR	-0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
IBS	-0.0000	0.0000	1.0000	1.0000	0.0000	0.0000
Available Inventory in Product Units	-0.0000	0.0000	1.0000	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case2.MTA.VE > VarExp-Case2.MTA.30NE1_Sheet1 - Multivariate

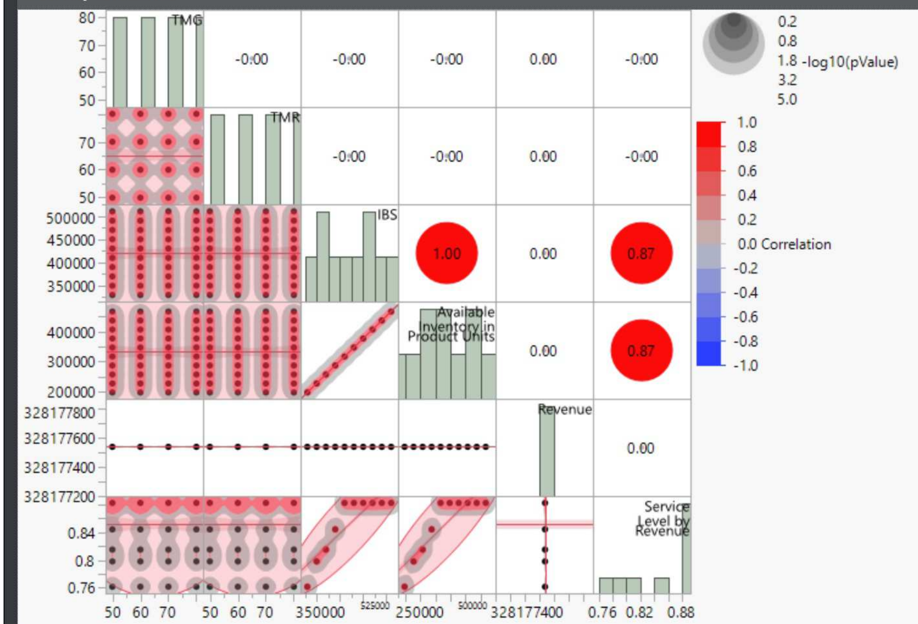
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
TMR	-0.0000	1.0000	-0.0000	-0.0000	0.0000	-0.0000
IBS	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.8723
Available Inventory in Product Units	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.8723
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.0000	-0.0000	0.8723	0.8723	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



<- Case2.MTA.VE > VarExp-Case2.MTA.40NE1_Sheet1 - Multivariate

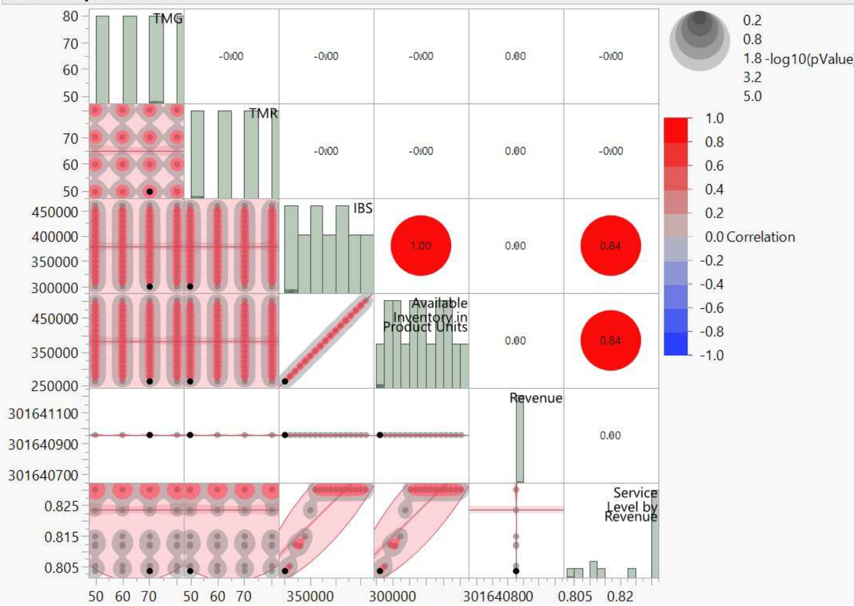
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000
TMR	-0.0000	1.0000	-0.0000	-0.0000	0.0000	-0.0000
IBS	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.8381
Available Inventory in Product Units	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.8381
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.0000	-0.0000	0.8381	0.8381	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case2.DDMRP.VE > VarExp-Case2.DDMRP.20D_Sheet1 - Multivariate

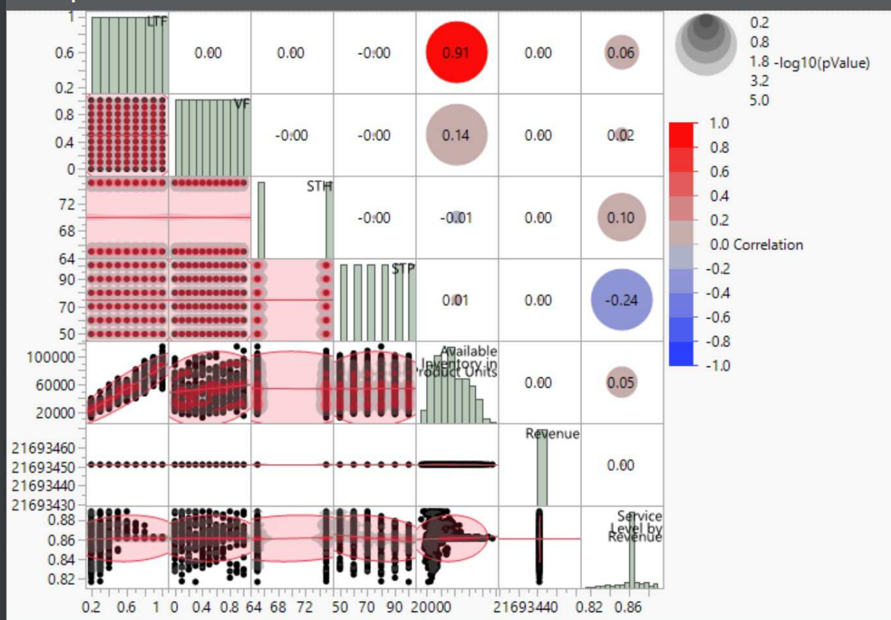
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	0.0000	0.0000	-0.0000	0.9073	0.0000	0.0626
VF	0.0000	1.0000	-0.0000	-0.0000	0.1364	0.0000	0.0159
STH	0.0000	-0.0000	1.0000	-0.0000	-0.0125	0.0000	0.0960
STP	-0.0000	-0.0000	-0.0000	1.0000	0.0091	0.0000	-0.2421
Available Inventory in Product Units	0.9073	0.1364	-0.0125	0.0091	1.0000	0.0000	0.0544
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0626	0.0159	0.0960	-0.2421	0.0544	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case2.DDMRP.VE > VarExp-Case2.DDMRP.30NE1_Sheet1 - Multivariate

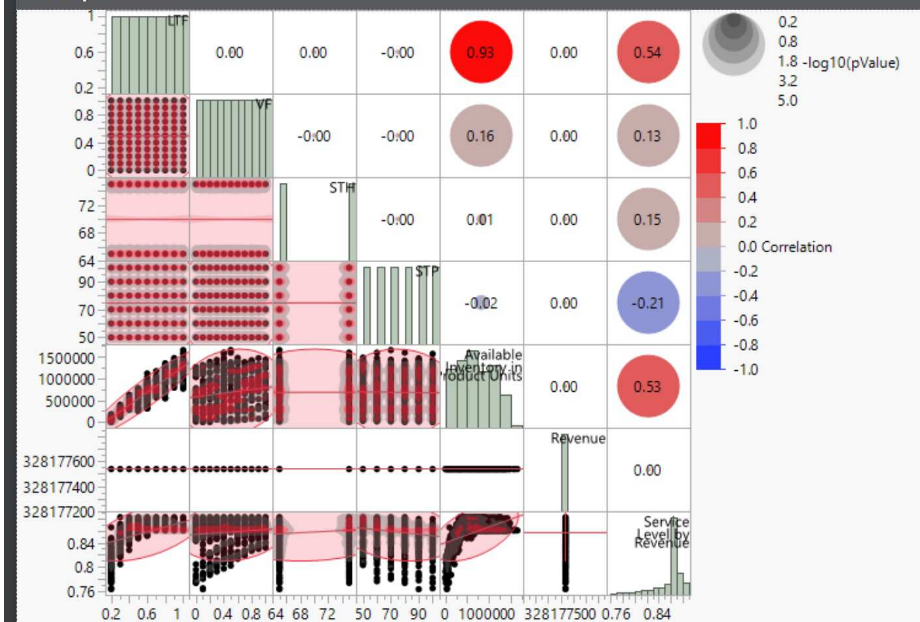
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	0.0000	0.0000	-0.0000	0.9330	0.0000	0.5361
VF	0.0000	1.0000	-0.0000	-0.0000	0.1629	0.0000	0.1289
STH	0.0000	-0.0000	1.0000	-0.0000	0.0064	0.0000	0.1507
STP	-0.0000	-0.0000	-0.0000	1.0000	-0.0158	0.0000	-0.2138
Available Inventory in Product Units	0.9330	0.1629	0.0064	-0.0158	1.0000	0.0000	0.5339
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.5361	0.1289	0.1507	-0.2138	0.5339	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case2.DDMRP.VE > VarExp-Case2.DDMRP.40NE1_Sheet1 - Multivariate

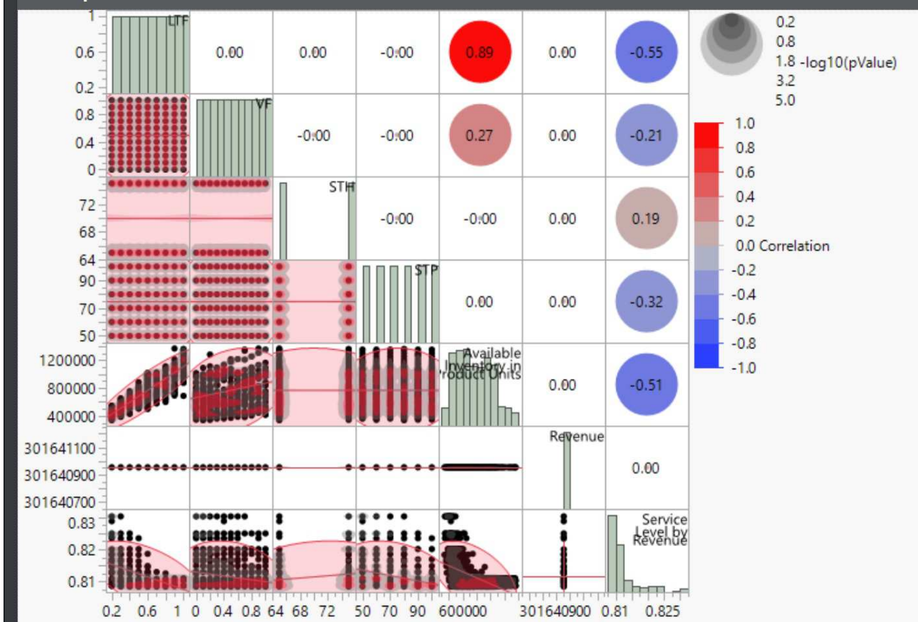
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	0.0000	0.0000	-0.0000	0.8895	0.0000	-0.5478
VF	0.0000	1.0000	-0.0000	-0.0000	0.2659	0.0000	-0.2052
STH	0.0000	-0.0000	1.0000	-0.0000	-0.0008	0.0000	0.1919
STP	-0.0000	-0.0000	-0.0000	1.0000	0.0008	0.0000	-0.3161
Available Inventory in Product Units	0.8895	0.2659	-0.0008	0.0008	1.0000	0.0000	-0.5113
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	-0.5478	-0.2052	0.1919	-0.3161	-0.5113	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case3.ROP.VE > VarExp-Case3.ROP.28166217X_Sheet1 - Multivariate

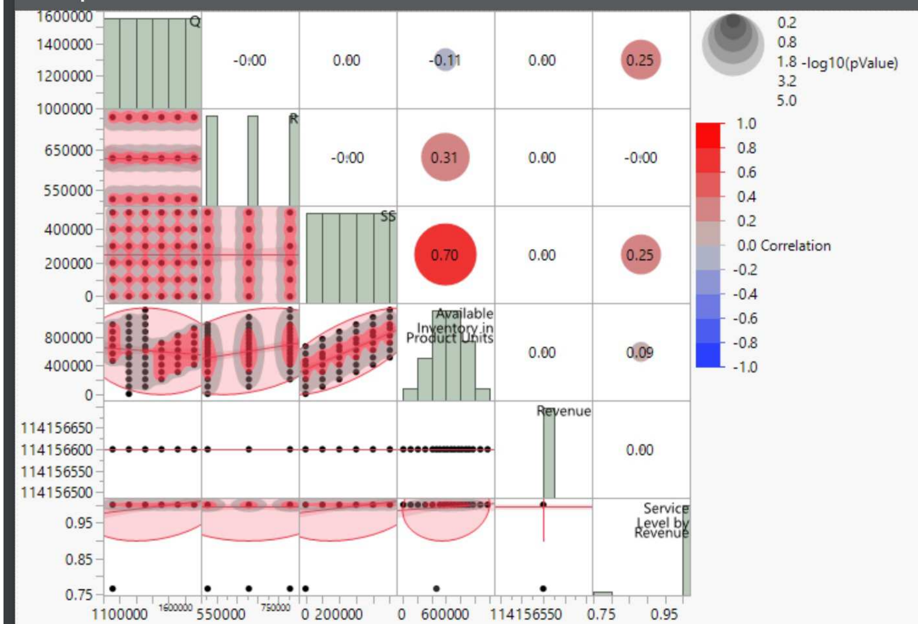
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	-0.0000	0.0000	-0.1124	0.0000	0.2474
R	-0.0000	1.0000	-0.0000	0.3107	0.0000	-0.0000
SS	0.0000	-0.0000	1.0000	0.7046	0.0000	0.2474
Available Inventory in Product Units	-0.1124	0.3107	0.7046	1.0000	0.0000	0.0914
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.2474	-0.0000	0.2474	0.0914	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case3.ROP.VE > VarExp-Case3.ROP.35425221X_Sheet1 - Multivariate

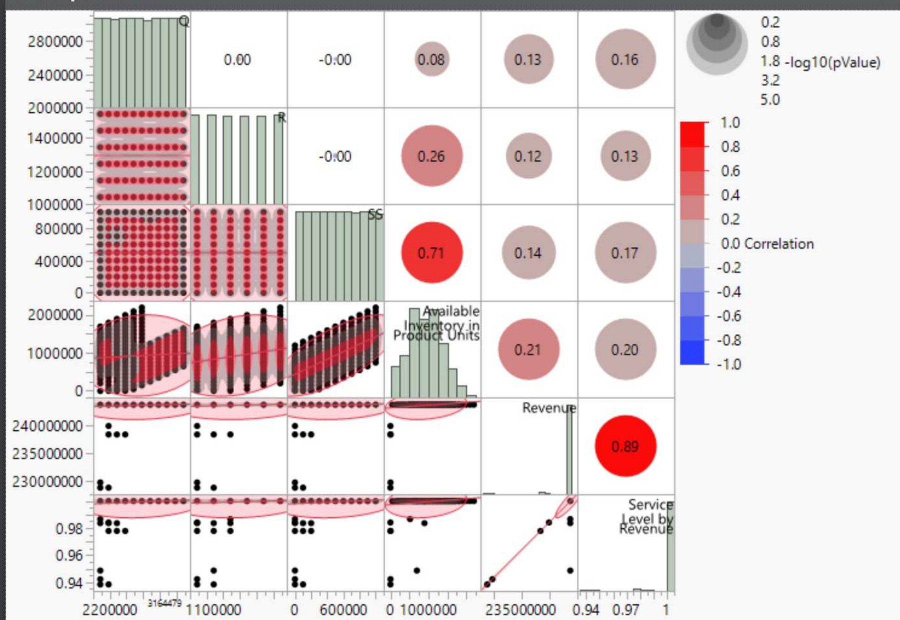
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	0.0001	-0.0006	0.0806	0.1275	0.1604
R	0.0001	1.0000	-0.0015	0.2577	0.1156	0.1292
SS	-0.0006	-0.0015	1.0000	0.7106	0.1401	0.1716
Available Inventory in Product Units	0.0806	0.2577	0.7106	1.0000	0.2087	0.1985
Revenue	0.1275	0.1156	0.1401	0.2087	1.0000	0.8878
Service Level by Revenue	0.1604	0.1292	0.1716	0.1985	0.8878	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case3.ROP.VE > VarExp-Case3.ROP.9396465X_Sheet1 - Multivariate

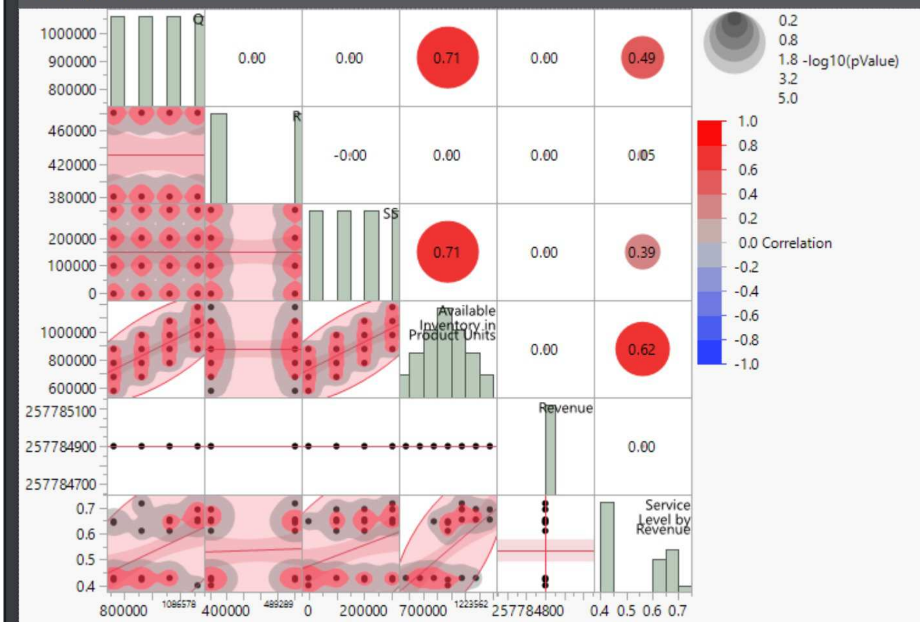
Multivariate

Correlations

	Q	R	SS	Available Inventory in Product Units	Revenue	Service Level by Revenue
Q	1.0000	0.0000	0.0000	0.7071	0.0000	0.4871
R	0.0000	1.0000	-0.0000	0.0000	0.0000	0.0475
SS	0.0000	-0.0000	1.0000	0.7071	0.0000	0.3897
Available Inventory in Product Units	0.7071	0.0000	0.7071	1.0000	0.0000	0.6200
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.4871	0.0475	0.3897	0.6200	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



<- Case3.MTA.VE > VarExp-Case3.MTA.2816 - Multivariate

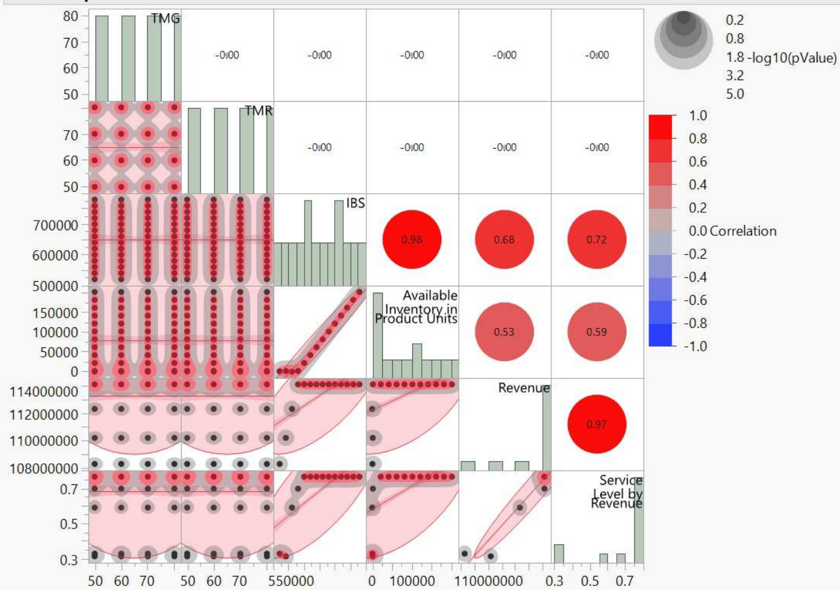
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
TMR	-0.0000	1.0000	-0.0000	-0.0000	-0.0000	-0.0000
IBS	-0.0000	-0.0000	1.0000	0.9826	0.6825	0.7234
Available Inventory in Product Units	-0.0000	-0.0000	0.9826	1.0000	0.5348	0.5901
Revenue	-0.0000	-0.0000	0.6825	0.5348	1.0000	0.9686
Service Level by Revenue	-0.0000	-0.0000	0.7234	0.5901	0.9686	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



<- Case3.MTA.VE > VarExp-Case3.MTA.3542_Sheet1 - Multivariate

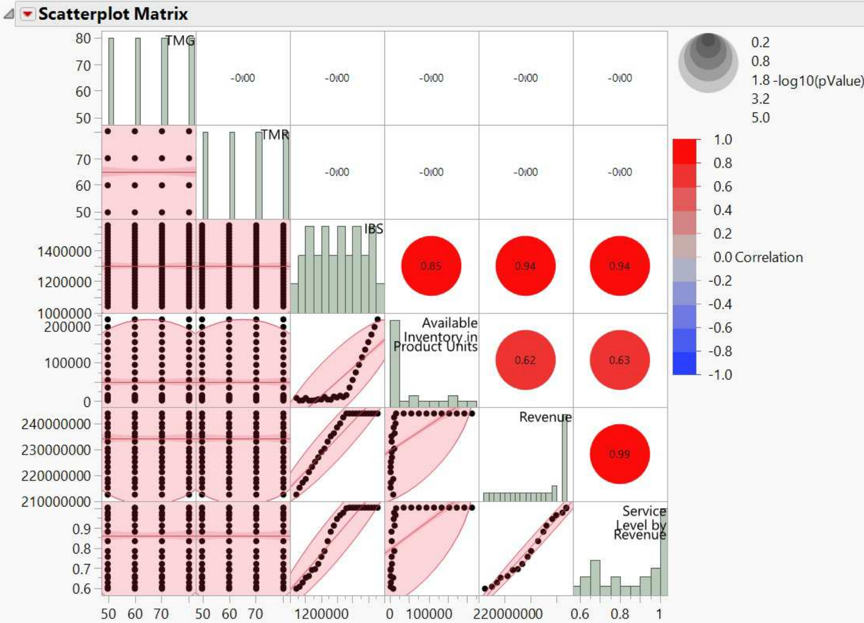
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
TMR	-0.0000	1.0000	-0.0000	-0.0000	-0.0000	-0.0000
IBS	-0.0000	-0.0000	1.0000	0.8491	0.9406	0.9385
Available Inventory in Product Units	-0.0000	-0.0000	0.8491	1.0000	0.6192	0.6255
Revenue	-0.0000	-0.0000	0.9406	0.6192	1.0000	0.9929
Service Level by Revenue	-0.0000	-0.0000	0.9385	0.6255	0.9929	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



<- Case3.MTA.VE > VarExp-Case3.MTA.9396_Sheet1 - Multivariate

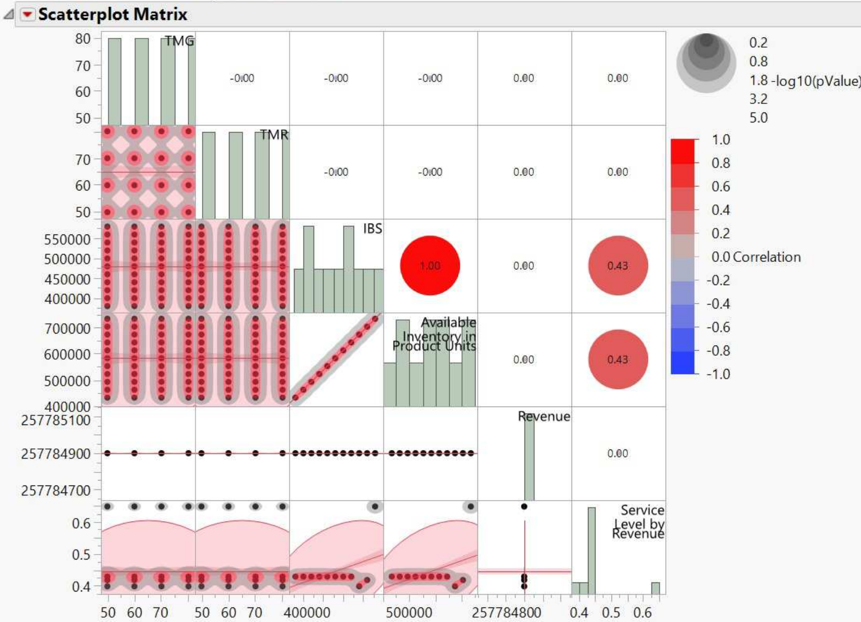
Multivariate

Correlations

	TMG	TMR	IBS	Available Inventory in Product Units	Revenue	Service Level by Revenue
TMG	1.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
TMR	-0.0000	1.0000	-0.0000	-0.0000	0.0000	0.0000
IBS	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.4264
Available Inventory in Product Units	-0.0000	-0.0000	1.0000	1.0000	0.0000	0.4264
Revenue	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.4264	0.4264	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



← Case3.DDMRP.VE > VarExp-Case3.DDMRP.28166217X_Sheet1 - Multivariate

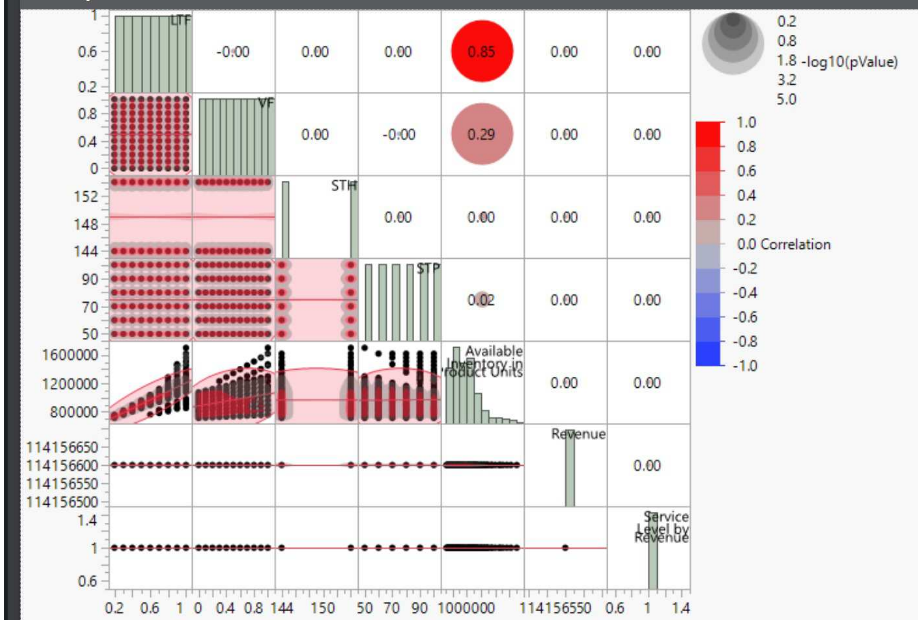
Multivariate

Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	-0.0000	0.0000	0.0000	0.8540	0.0000	0.0000
VF	-0.0000	1.0000	0.0000	-0.0000	0.2858	0.0000	0.0000
STH	0.0000	0.0000	1.0000	0.0000	0.0039	0.0000	0.0000
STP	0.0000	-0.0000	0.0000	1.0000	0.0192	0.0000	0.0000
Available Inventory in Product Units	0.8540	0.2858	0.0039	0.0192	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix



Case3.DDMRP.VE > VarExp-Case3.DDMRP.35425221X_Sheet1 - Multivariate

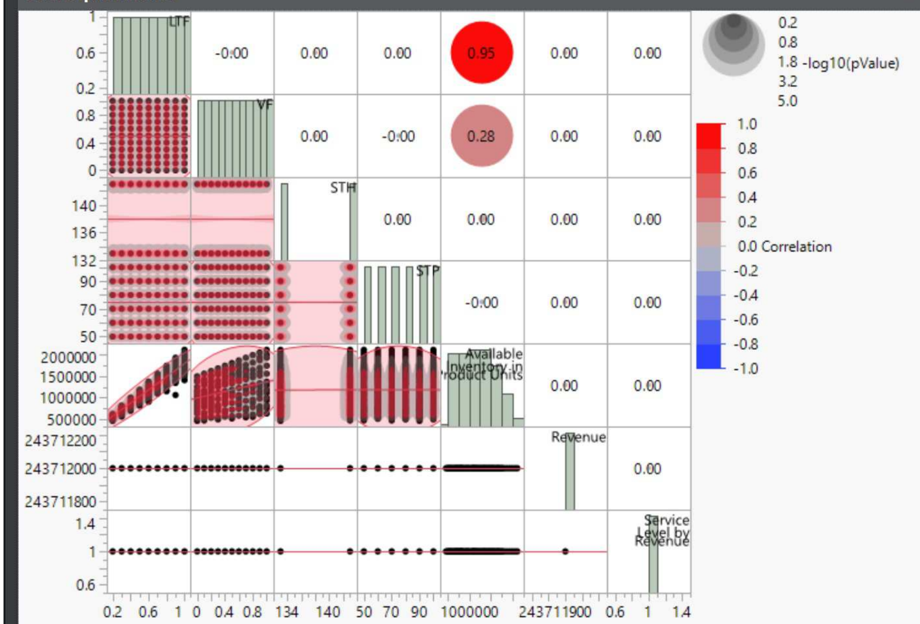
Multivariate

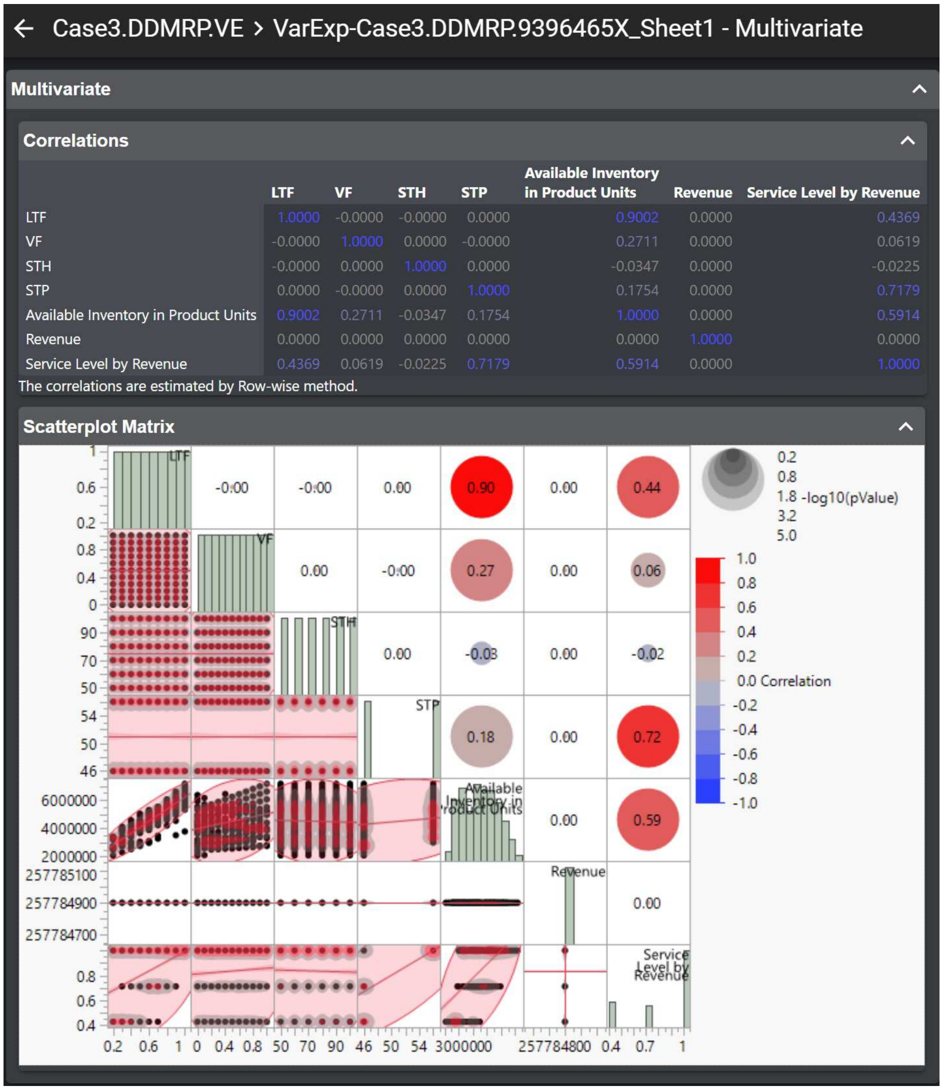
Correlations

	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	-0.0000	0.0000	0.0000	0.9491	0.0000	0.0000
VF	-0.0000	1.0000	0.0000	-0.0000	0.2826	0.0000	0.0000
STH	0.0000	0.0000	1.0000	0.0000	0.0028	0.0000	0.0000
STP	0.0000	-0.0000	0.0000	1.0000	-0.0011	0.0000	0.0000
Available Inventory in Product Units	0.9491	0.2826	0.0028	-0.0011	1.0000	0.0000	0.0000
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

The correlations are estimated by Row-wise method.

Scatterplot Matrix





Case3.DDMRP.VE > VarExp-Case3.DDMRP.9396465X_Sheet1 - Multivariate

Multivariate

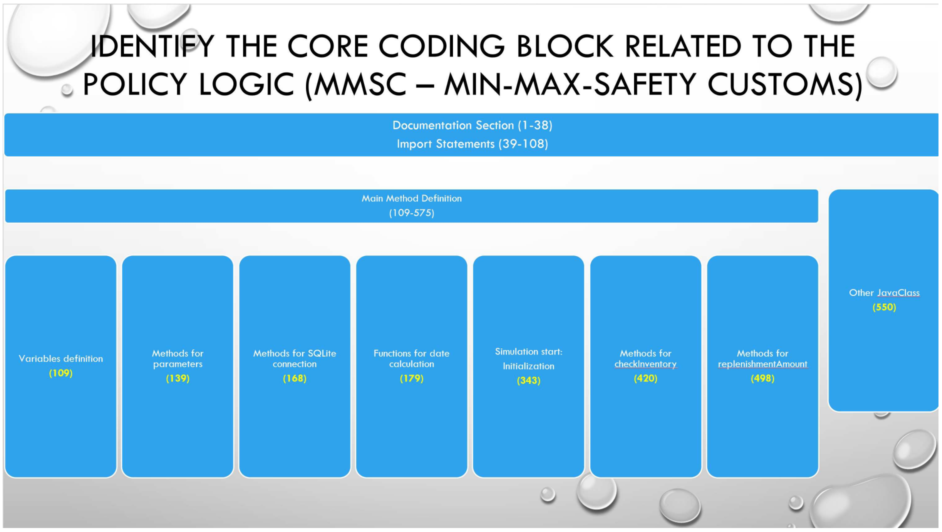
Correlations

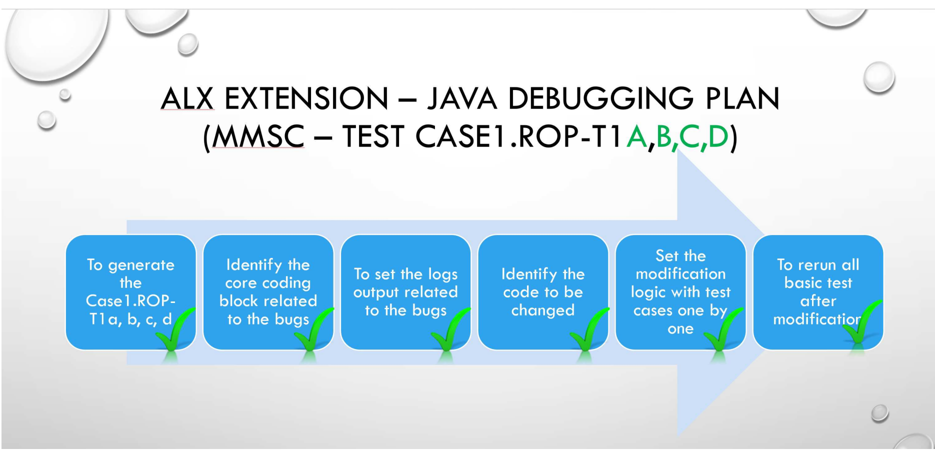
	LTF	VF	STH	STP	Available Inventory in Product Units	Revenue	Service Level by Revenue
LTF	1.0000	-0.0000	-0.0000	0.0000	0.9002	0.0000	0.4369
VF	-0.0000	1.0000	0.0000	-0.0000	0.2711	0.0000	0.0619
STH	-0.0000	0.0000	1.0000	0.0000	-0.0347	0.0000	-0.0225
STP	0.0000	-0.0000	0.0000	1.0000	0.1754	0.0000	0.7179
Available Inventory in Product Units	0.9002	0.2711	-0.0347	0.1754	1.0000	0.0000	0.5914
Revenue	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
Service Level by Revenue	0.4369	0.0619	-0.0225	0.7179	0.5914	0.0000	1.0000

The correlations are estimated by Row-wise method.

The End of Appendix C

Appendix D - Testing and Debugging Logs

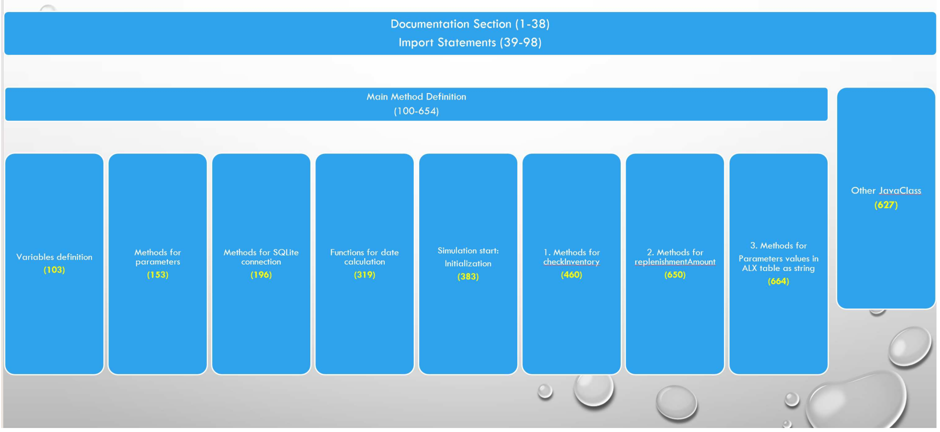




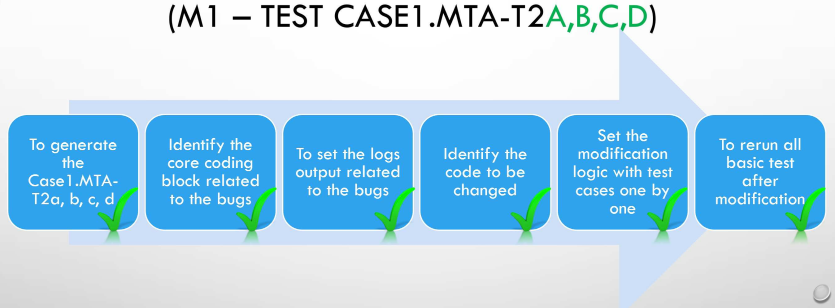
MMSC(ROP) POLICY DEBUG LOG

Debug#	Summary of problems and solutions	Status
1	generatedSupplyChain: reset 0 and formula	Done
2	ActualDemand: error in getDemandByDate: To replace `getDemandByDate` by calculated `ActualDemand = stockOut or lastOverDueBackOrder`, add round(waitingAmount) Note: The unfulfilled OBO cannot be included in Actual Demand when EOD=Y: • Debug2: To skip the firstDay actualDemand • Debug2A: To set the actual demand as last OBO or stockOut, add round(waitingAmount) • Debug2B: To add condition (OBO=0) for avoiding the getDemandByDate with OBO • Debug2B: To set the actual demand from getDemandByDate(date) when the stock-out is zero • Debug2C: To add condition (stockOut=0) for actualDemand with OBO on the same day • Debug2D: To set actcualDemand = lastOBO when stockIn > 0 and lastOBO > 0	Done
3	Set the correct readLastRecordDate in SQL: `UPDATE Statistics SET EOD = 'YES' where ROWID in (select rowid from Statistics WHERE LocationName = '" + this.facilityName + "' AND Product = '" + this.productName + "' ORDER BY rowid DESC LIMIT 1`	Done
4	To show both EOD Yes/No in report for stock-in and stock-out	Done
5	To rest EOD = NO	Done
6	getDemandByDate is mixed up with other product(s) in the same location. to add Product in filter : && dd.getProduct() == getProduct()	Done

IDENTIFY THE CORE CODING BLOCK RELATED TO THE POLICY LOGIC (M1 – MTA)



ALX EXTENSION – JAVA DEBUGGING PLAN (M1 – TEST CASE1.MTA-T2A,B,C,D)

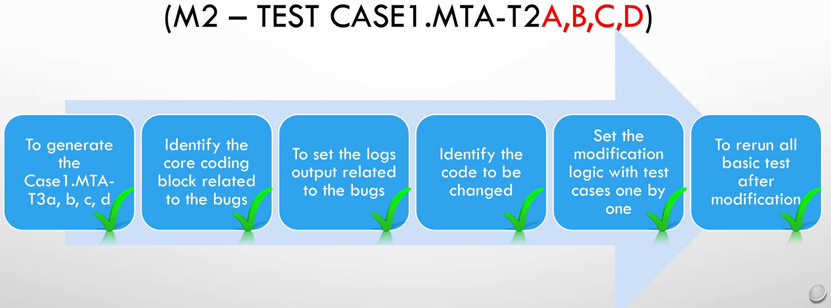


M1(MTA) POLICY DEBUG LOG

Debug#	Summary of problems	Status
1	Buffer adjustment error: continuous Buffer-up staring from 2 July 2021 (without waiting for one lead time cycle), add PenetrationResetPeriod(PRP) in setup parameter	Done
2	ActualDemand: error in getDemandByDate: `lastOverDueBackOrder only if EOD = YES or stockout,` add round(waitingAmount) Note: The unfulfilled OBO cannot be included in Actual Demand when EOD=Y: • Debug2: To skip the firstDay actualDemand • Debug2A: To set the actual demand as last OBO or stockOut, add round(waitingAmount) • Debug2B: To add condition (OBO=0) for avoiding the getDemandByDate with OBO • Debug2B: To set the actual demand from getDemandByDate(date) when the stock-out is zero • Debug2C: To add condition (stockOut=0) for actualDemand with OBO on the same day • Debug2D: To set actcualDemand = lastOBO when stockIn > 0 and lastOBO > 0	Done
3	Set the correct readLastRecordDate in SQL: `UPDATE Statistics SET EOD = 'YES' where ROWID in (select rowid from Statistics WHERE LocationName = '" + this.facilityName + "' AND Product = '" + this.productName + "' ORDER BY rowid DESC LIMIT 1`	Done
4	`To update the ActualDemand=stockout, reset EOD=NO after UPDATE and EOD=YES in UPDATE SQL`	Done
5	getDemandByDate is mixed up with other product(s) in the same location. to add Product in filter : && dd.getProduct() == getProduct()	Done

IDENTIFY THE CORE CODING BLOCK RELATED TO THE POLICY LOGIC (M2 – DDMRP)

ALX EXTENSION – JAVA DEBUGGING PLAN (M2 – TEST CASE1.MTA-T2A,B,C,D)



M2(DDMRP) POLICY DEBUG LOG

Debug#	Summary of problems	Status
A	Forecasts->InitialADU, variabilityFactor, netAvailableBalance	Done
B	Forecasts->InitialADU, InitialADU = IYS / LT or ATH	Done
1	Check the Adjusting TOG,TOY and TOR block moving into EOD block?	Done
2	ActualDemand: error in getDemandByDate: To replace getDemandByDate by calculated ActualDemand = stockOut or lastOverDueBackOrder : • Debug2: To skip the firstDay actualDemand • Debug2A: To set the actual demand as last OBO or stockOut, add round(waitingAmount) • Debug2B: To add condition (OBO=0) for avoiding the getDemandByDate with OBO • Debug2B: To set the actual demand from getDemandByDate(date) when the stock-out is zero • Debug2C: To add condition (stockOut=0) for actualDemand with OBO on the same day • Debug2D: To set actcualDemand = lastOBO when stockIn > 0 and lastOBO > 0	Done
3	Set the correct readLastRecordDate in SQL: UPDATE Statistics SET EOD = 'YES' where ROWID in (select rowid from Statistics WHERE LocationName = "' + this.facilityName + "' AND Product = "' + this.productName + "' ORDER BY rowid DESC LIMIT 1	Done
4	To add one more day for skipping the current day's demand for spikeDemand and /100 for correct spikeThresholdPercentage	Done
5	To assign stockOnHand to next day's openingStockOnHand (note: To set Backorder Policy = Allowed Total	Done
6	waitingAmount = overdueBackOrder, expectedInventory = openSupplyOrder	Done
7	netAvailableBalance overstated QSD error, because it is mixed up with other product(s) in the same location. to add Product in filter : && dd.getProduct() == getProduct()	Done
8	To fix the TOG, TOY, TOR aligned with DGZ, DYZ, DRZ – round up problems – adjust buffer to form ADU as round()	Done
9	Green Zone Option 130 : this.dynamicGreenZone = this.orderDayInterval * this.effectiveDailyUsage;	Done

ROP Test Plan and error log

Alpha test	Test case	Parameters
MMSC-Simple SIM-t1	Using Simple SIM as testing	
MMSC-aTest1	No buffer adjustment	Stable demand
MMSC-aTest2	Buffer up adjustment	Surge demand without MOQ
MMSC-aTest3	Buffer down adjustment	Low demand without MOQ

M1 - MTA Test Plan and error log

Alpha test	Test case	Parameters
M1-aTest1	No buffer adjustment	Stable demand
M1-aTest2	Buffer up adjustment	Surge demand without MOQ
M1-aTest3	Buffer down adjustment	Low demand without MOQ
M1-aTest4	Buffer down adjustment	Low demand with MOQ
M1-aTest5	High Demand with MOQ	High Demand with MOQ
M1-aTest6	Buffer up adjustment with backorders (no partial order delivery)	High demand without MOQ
M1-aTest7	Buffer up adjustment with backorders and MOQ (no partial order delivery)	High demand with MOQ

M2 - DDMRP Test Plan and error log

Alpha test	Test case	Parameters
M2-Test1	Replenishment according to NAB (MOQ=1)	Stable demand without MOQ
M2-Test2	Replenishment according to NAB (MOQ=1)	Surge demand without MOQ
M2-Test3	Replenishment according to NAB (MOQ=1)	Low demand without MOQ
M2-Test4	Replenishment according to NAB (MOQ=300)	Low demand with MOQ Green Zone Option: **110 used**
M2-Test5	Replenishment according to NAB(MOQ=350 w/o QSD)	High Demand with MOQ Green Zone Option: **110 used**
M2-Test6	Replenishment according to NAB (MOQ=1 with QSD)	High demand without MOQ Green Zone Option: **100 used**
M2-Test7	Replenishment according to NAB (MOQ=500 with QSD)	High demand with MOQ Green Zone Option: **110 used**
M2-Test8	Replenishment according to NAB (MOQ=500 with ODO)	High demand with MOQ, ODO Green Zone Option: **110 used**

Appendix E - Parameters selected in SE0

Summary of Parameters Chosen for Inventory Policies in the Simulation Experiment (SE0)

The following table consolidates the planning parameters drawn from the **SE0** simulation experiments. Notably, the **SE0** Variation Experiment designated these parameters as independent variables in the comparative studies of **SE1** and **SE2**.

Summary of planning parameters selected in the simulation experiment (SE0)

Case.Policy.Item Demand Points	Policy Parameters	Variables	Theoretical Default	Upper Range +50%	Selected Parameters	Ending Available Inventory	Service Level by Revenue	Revenue	ROI by Stock Balance
Case1.ROP.Lite US B2C	Order up to max. level	Q	320	480	**450**	41	70.86%	65200	1590.24
	Fixed replenishment point	R	320	480	**320**				
	Safety stock	SS	0	160	**0**				
Case1.ROP.Node US B2C	Order up-to max. level	Q	140	210	**190**	8	79.49%	27300	3412.50
	Fixed replenishment point	R	140	210	**140**				
	Safety stock	SS	0	70	**0**				
Case1.ROP.WB US B2C	Order up-to max. level	Q	220	330	**280**	2	74.88%	43400	21700.00
	Fixed replenishment point	R	220	330	**220**				
	Safety stock	SS	0	110	**40**				
Case1.ROP.Lite EU B2B	Order up to max. level	Q	540	810	**540**	396	87.52%	107400	271.21
	Fixed replenishment point	R	540	810	**540**				
	Safety	SS	0	270	**0**				

	stock								
Case1.ROP.Node EU B2B	Order up-to max. level	Q	740	1110	**940**	292	51.12%	147100	503.77
	Fixed replenishment point	R	740	1110	**740**				
	Safety stock	SS	0	370	**0**				
Case1.ROP.WB EU B2B	Order up-to max. level	Q	400	600	**540**	166	78.92%	77800	468.67
	Fixed replenishment point	R	400	600	**400**				
	Safety stock	SS	0	200	**40**				
Case1.MTA.Lite.US B2C	Initial Buffer Size	IBS	320	480	**320**	337	70.86%	65200	193.47
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.MTA.Node.US B2C	Initial Buffer Size	IBS	130	210	**130**	119.5	79.49%	27300	228.45
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	**1**	1.5	**1.5**				
Case1.MTA.WB.US B2C	Initial Buffer Size	IBS	210	330	**210**	150.5	74.88%	43400	288.37
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+	BUA	30	N/A					

	Adjust %								
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	**1**	1.5	**1.5**				
Case1.MTA.Lite.EU B2B	Initial Buffer Size	IBS	520	800	**600**	734.5	87.52%	107400	146.22
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.MTA.Node.EU B2B	Initial Buffer Size	IBS	720	1080	**720**	939	51.12%	147100	156.66
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.MTA.WB.EU B2B	Initial Buffer Size	IBS	380	580	**380**	431	78.92%	77800	180.51
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case1.DDMRP.Lite US B2C	Lead Time Factor	LTF	0.2	1	**0.2**	681	70.86%	65200	95.74
	Variability	VF	0	1	**0**				

	Factor								
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP . Node US B2C	Lead Time Factor	LTF	0.2	1	**0.3**	743.88	79.49%	27300	36.70
	Variability Factor	VF	0	1	**0.9**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**190**				
	Spike Threshold %	STP	50	100	**80**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP .WB US B2C	Lead Time Factor	LTF	0.2	1	**0.5**	670.8	74.88%	43400	64.70
	Variability Factor	VF	0	1	**0.9**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP .Lite EU B2B	Lead Time Factor	LTF	0.2	1	**0.5**	382	87.52%	107400	281.15
	Variability Factor	VF	0	1	**0.9**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				

	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP .Node EU B2B	Lead Time Factor	LTF	0.2	1	**0.2**	809	51.12%	147100	181.83
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case1.DDMRP .WB EU B2B	Lead Time Factor	LTF	0.2	1	**0.2**	523	78.92%	77800	148.76
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	180	200	**180**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case2.ROP. 20D	Order up to max. level	Q	441337	660000	**441337**	224402	88.98%	21693451	96.67
	Fixed replenishment point	R	220669	330000	**220669**				
	Safety stock	SS	0	220000	**0**				
Case2.ROP. 30NE1	Order up to max. level	Q	667653	990000	**667653**	328928	88.27%	328177538	997.72
	Fixed replenishment point	R	333826	480000	**333826**				
	Safety stock	SS	0	330000	**200000**				
Case2.ROP. 40NE1	Order up to max. level	Q	613666	900000	**713666**	231130	83.02%	301640955	1305.07

	Fixed replenishment point	R	306833	450000	**406833**				
	Safety stock	SS	0	300000	**0**				
Case2.MTA.20D	Initial Buffer Size	IBS	220000	340000	**220000**	416849	88.98%	21693451	52.04
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case2.MTA.30NE1	Initial Buffer Size	IBS	330000	510000	**410000**	317150	88.27%	328177538	1034.77
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case2.MTA.40NE1	Initial Buffer Size	IBS	300000	460000	**360000**	353406	83.02%	301640955	853.53
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case2.DDMRP.20D	Lead Time Factor	LTF	0.2	1	**0.2**	14751	88.98%	21693451	1470.64
	Variability Factor	VF	0	1	**1**				

	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	65	75	**75**				
	Spike Threshold %	STP	50	100	**50**				
	Net Flow Position	NFP	N/A	N/A					
Case2.DDMRP.30NE1	Lead Time Factor	LTF	0.2	1	**1**	1259602	88.27%	328177538	260.54
	Variability Factor	VF	0	1	**0.1**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	65	75	**75**				
	Spike Threshold %	STP	50	100	**50**				
	Net Flow Position	NFP	N/A	N/A					
Case2.DDMRP.40NE1	Lead Time Factor	LTF	0.2	1	**0.2**	345245	83.02%	301640955	873.70
	Variability Factor	VF	0	1	**0.1**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	65	75	**65**				
	Spike Threshold %	STP	50	100	**60**				
	Net Flow Position	NFP	N/A	N/A					
Case3.ROP.3542	Order up-to max. level	Q	2084479	3150000	**2184479**	47359	100.%	243712000	5146.05
	Fixed replenishment point	R	1042239	1560000	**1042239**				
	Safety stock	SS	0	1050000	**300000**				
Case3.ROP.2816	Order up-to max. level	Q	1057141	1560000	**1157141**	15575	100.%	114156600	7329.48
	Fixed replenishme	R	528570	780000	**528570**				

	nt point								
	Safety stock	SS	0	520000	**0**				
Case3.ROP. 9396	Order up-to max. level	Q	762578	1140000	**862578**	975562	71.67%	257784900	264.24
	Fixed replenishment point	R	381289	570000	**481289**				
	Safety stock	SS	0	380000	**300000**				
Case3.MTA. 3542	Initial Buffer Size	IBS	1040000	1560000	**1040000**	214797	100.%	243712000	1134.62
	Too Many Green	TMG	50	100	**90**				
	Too Many Red	TMR	50	100	**90**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case3.MTA. 2816	Initial Buffer Size	IBS	520000	780000	**580000**	291846	100.%	114156600	391.15
	Too Many Green	TMG	50	100	**90**				
	Too Many Red	TMR	50	100	**90**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety factor	BSF	1	1.5	**1.5**				
Case3.MTA. 9396	Initial Buffer Size	IBS	380000	580000	**580000**	732984	64.79%	257784900	351.69
	Too Many Green	TMG	50	80	**80**				
	Too Many Red	TMR	50	80	**80**				
	Buffer Up+ Adjust %	BUA	30	N/A					
	Buffer Down-Adjust %	BDA	25	N/A					
	Safety	BSF	1	1.5	**1.5**				

	factor								
Case3.DDMRP .3542	Lead Time Factor	LTF	0.2	1	**0.2**	465718	100.%	243712000	523.30
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	133	143	**133**				
	Spike Threshold %	STP	50	100	**90**				
	Net Flow Position	NFP	N/A	N/A					
Case3.DDMRP .2816	Lead Time Factor	LTF	0.2	1	**0.2**	719431	100.%	114156600	158.68
	Variability Factor	VF	0	1	**0.1**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	144	154	**144**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					
Case3.DDMRP .9396	Lead Time Factor	LTF	0.2	1	**0.2**	3205565	100.%	257784900	80.42
	Variability Factor	VF	0	1	**0**				
	Average Daily Usage	ADU	N/A	N/A					
	Spike Threshold Horizon	STH	46	56	**56**				
	Spike Threshold %	STP	50	100	**100**				
	Net Flow Position	NFP	N/A	N/A					

Appendix F - Code in ALX Java extension

ROP policy source code in ALX Java Extension

The following source code has been reproduced with permission from AnyLogic North America, LLC. The original implementation was developed by AnyLogic and is used here with authorization.

```
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************************************************
         AnyLogic Project File
************************************************

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    <ImportSettings>
    </ImportSettings>
    <ExportSettings>
      <ExportExcelFilePath><![CDATA[]]></ExportExcelFilePath>
    </ExportSettings>
  </Database>
  <JavaClasses>
    <!--   =========   Java Class   ========  -->
    <JavaClass>
      <Id>1652858358219</Id>
      <Name><![CDATA[InventoryPolicyMinMaxSafetyStockCustom]]></
Name>
      <Text><![CDATA[import
com.alx.data.custom_type.CustomTypeClass;
import com.alx.data.custom_type.EditorType;
import com.alx.data.custom_type.Parameter;
import com.alx.data.simulation.inventory.AbstractInventoryType;
import com.alx.data.simulation.inventory.InventoryPolicyWithSafetyStock;
import com.alx.data.util.DataModelUtils;
import com.alx.data.util.Formatters;
import com.alx.data.validation.ValidationField;
import com.alx.data.validation.ValidationFieldRuleEnum;


import com.alx.data.basic.demand.DemandData;
import com.alx.data.basic.facility.*;
import com.alx.data.basic.product.*;
import com.alx.data.basic.demand.DemandForecast;
import com.alx.data.basic.demand.DemandData;
import com.alx.data.basic.demand.IDemandType;
import com.alx.data.basic.facility.CustomerData;
import com.alx.data.basic.facility.AFacilityData;
import com.alx.data.basic.facility.FacilityGroup;
import com.alx.data.basic.facility.FacilityData;
import com.alx.data.basic.facility.IDestinationData;
import com.alx.data.basic.facility.IFacilityData;
import com.alx.data.basic.product.Product;
import com.alx.data.scenario.*;
import com.alx.data.simulation.inventory.AbstractInventoryType;
```

```
import com.alx.data.simulation.model.*;
import com.alx.data.simulation.sourcing.SourcingData;
import com.alx.data.DateUtils;
import com.alx.data.no.period.TimePeriod;
import com.alx.data.PersistableUtilities;
import com.alx.data.custom_type.CustomTypeClass;
import com.alx.data.custom_type.EditorType;
import com.alx.data.custom_type.Parameter;
import com.alx.data.experiment.simulation.ALX;
import com.alx.data.external_table.ExternalTableData;
import com.alx.data.resource.Messages;
import com.alx.data.simulation.model.IFacility;
import com.alx.data.simulation.sourcing.SourcingData;
import com.alx.data.validation.ValidationField;
import com.alx.data.validation.ValidationFieldRuleEnum;
import com.alx.data.DateUtils;
import com.alx.data.custom_type.*;
import com.alx.data.validation.ValidationField;
import com.alx.data.validation.ValidationFieldRuleEnum;


import java.util.stream.*;
import java.lang.Math.*;
import java.time.LocalDate;
import java.time.LocalDateTime;
import java.util.TimeZone;
import java.time.format.DateTimeFormatter;
import java.util.ArrayList;
import java.util.Calendar;
import java.util.Date;
import java.util.HashMap;
import java.util.HashSet;
import java.util.LinkedList;
import java.util.List;
import java.util.Map;
import java.util.Set;
import java.text.DateFormat;
import java.text.SimpleDateFormat;
import java.sql.Connection;
```

```
import java.sql.DriverManager;
import java.sql.PreparedStatement;
import java.sql.SQLException;
import java.io.*;
import java.util.Calendar;
import java.math.BigDecimal;
import java.math.RoundingMode;


@CustomTypeClass(name = "Min-max policy with safety stock CUSTOM")
//
@ValidationClass(rule=ValidationClassRuleEnum.INVENTORY_POLICY_
MIN_MAX_SS_BOUNDS_ERROR)
public class InventoryPolicyMinMaxSafetyStockCustom extends
AbstractInventoryType implements InventoryPolicyWithSafetyStock {


    public static final String TYPE_VALUE = "MinMax"; //$NON-NLS-1$

    private Map<Date, String> timePeriodByDate = new HashMap<>();

    // List of customers sourcing their demand from this facility
    private List<IDestinationData> customerCollection = new ArrayList<>();

    // Hashmap returning the demand by date
    private Map<Date, Double> demandByDate = new HashMap<>();

    private String productName;

    private String facilityName;

    private String scenarioName;

    private double stockIn;

    private double stockOut;

    private double stockOnHand;
```

```
   private double generatedSupplyOrder = 0;


   private double lastOverdueBackOrder = 0;                    // Debug2: To
keep the last overdueBackOrder before receipt


   private double actualDemand = 0;                             // Debug2: To add
actualDemand variable for calculation

   private boolean firstDay = true;                             // Debug1: To use
firstDay boolean for skipping the first actual demand

   @Parameter(name = "SQLite File", type = EditorType.StringEditor)
   public String sqliteFileName;


   @Parameter(name = "Min", type = EditorType.DoubleEditor)
   private double min;


   @Parameter(name = "Max", type = EditorType.DoubleEditor)
   @ValidationField(rule =
ValidationFieldRuleEnum.INVENTORY_POLICY_MIN_MAX_SS_BOUND
S_ERROR)
   private double max;


   @Parameter(name = "Safety stock", type = EditorType.DoubleEditor)
   private double safetyStock;


   public InventoryPolicyMinMaxSafetyStockCustom() {
      min = 0;
      max = 0;
      safetyStock = 0;
   }
```

```
   public InventoryPolicyMinMaxSafetyStockCustom(double min, double
max, double safetyStock) {
       this.min = min;
       this.max = max;
       this.safetyStock = safetyStock;
   }


   public
InventoryPolicyMinMaxSafetyStockCustom(InventoryPolicyMinMaxSafetyS
tockCustom inventoryPolicy) {
       this(inventoryPolicy.getMin(), inventoryPolicy.getMax(),
inventoryPolicy.getSafetyStock());
   }
```

******** Partially listed ********

Due to copyright restrictions by the original software developer, reader wishing to access the full source code utilized in this thesis are encouraged to contact the author directly. Please include a detailed request specifying the purpose and intended use of the code. The author can be reached via the contact information provided on the title page of this document or through the institution's official communication channels.

The End.