



Demand variability in engineer-to-order supply chains: insights from a DDMRP case study

Oskari Huttunen & Petri Helo

To cite this article: Oskari Huttunen & Petri Helo (10 Feb 2026): Demand variability in engineer-to-order supply chains: insights from a DDMRP case study, International Journal of Production Research, DOI: [10.1080/00207543.2026.2625958](https://doi.org/10.1080/00207543.2026.2625958)

To link to this article: <https://doi.org/10.1080/00207543.2026.2625958>



© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 10 Feb 2026.



Submit your article to this journal [↗](#)



Article views: 457



View related articles [↗](#)



View Crossmark data [↗](#)

Demand variability in engineer-to-order supply chains: insights from a DDMRP case study

Oskari Huttunen  and Petri Helo 

School of Technology and Innovations, Industrial Management, University of Vaasa, Vaasa, Finland

ABSTRACT

Engineer-to-Order (ETO) supply chains with modular T-plant structures face critical inventory challenges: shared components must buffer against demand variability across multiple product variants, while planners struggle to balance responsiveness and cost efficiency under stochastic demand. Demand-Driven Material Requirements Planning (DDMRP) has been proposed to enhance resilience and inventory efficiency, yet its effectiveness in such contexts remains underexplored. This study simulates a two-echelon industrial piping chain, where shared components are managed as Make-to-Stock and final assemblies as ETO. Using real purchase order data, DDMRP is compared with the current push-based method at the supplier level, tracking inventory levels, fill rates, and order counts. Results show that DDMRP reduced weighted average on-hand inventory by 21.4%, improved fill rates by 7.5 percentage points, and cut backorders by 76%, while increasing order frequency by 1.5%. Sensitivity analysis highlights the Average Daily Usage (ADU) window as the primary lever for balancing service and inventory. The study demonstrates that resilience can be achieved through adaptive response rather than static redundancy alone, identifies signal averaging horizon as a key parameter affecting the balance between responsiveness and efficiency, and supports selective use of DDMRP, suggesting particular effectiveness under high uncertainty in demand timing, or both timing and quantity.

ARTICLE HISTORY

Received 19 June 2025
Accepted 26 January 2026

KEYWORDS

Demand variability; resilience; inventory management; engineer-to-order; demand driven material requirements planning

1. Introduction

The ability to respond efficiently to variable customer demand while maintaining cost-effective operations is a defining challenge in Supply Chain Management. Inventory management is central in this balance (Boylan and Syntetos 2010; Zhao and Simchi-Levi 2006; Zinn 1990), especially in multi-echelon supply chains (MESCs) where inventories span several interconnected stages (Sbai and Berrado 2018; Schmitt et al. 2017; Wang 2011) and replenishment coordination is critical to minimise stock-outs and excess inventory (Dessevre et al. 2023; Vicente, Relvas, and Póvoa 2020; Zinn 1990). These challenges intensify in environments with high product complexity and customisation, characterised by demand lumpiness and low forecasting accuracy (Boylan and Syntetos 2010).

A relevant example is the ETO environment, where customer orders penetrate design and trigger production (Gosling and Naim 2009; Olhager 2010). In parallel, modular architectures such as the T-plant structure play a critical role in managing complexity. A T-plant refers to a configuration where numerous end products share common components (Umble 1992). While

ETO defines the fulfilment strategy, T-plant describes the structural design that supports postponement: delaying final product differentiation until customer demand is known (Aviv and Federgruen 2001; Bagchi and Gaur 2018; Zinn 1990). When these two concepts intersect, managing upstream inventories of shared components becomes strategically important, as their usage reflects correlated and dependent demand patterns (Aviv and Federgruen 2001; Casado et al. 2020; Dessevre et al. 2023; Thürer, Fernandes, and Stevenson 2022; Zinn 1990). Effective coordination at this level can reduce safety stock requirements, improve fill rates, and increase resilience to market variability (Aviv and Federgruen 2001; Dessevre et al. 2023; García-Dastugue and Lambert 2007; Graman 2010; Ptak and Smith 2011; Saghiri and Barnes 2016; Zinn 1990).

While many competent Production Planning and Control (PPC) systems exist, managing inventories in MESCs remains challenging, especially in ETO environments, where fluctuating demand patterns introduce uncertainty. Traditional push and pull methods often struggle to absorb the risks associated with high demand

CONTACT Oskari Huttunen  oskari.huttunen@uwasa.fi  School of Technology and Innovations, Industrial Management, University of Vaasa, Vaasa, Finland

variability and customisation (Miclo et al. 2019; Ptak and Smith 2011). Customer-specific requirements for finished products impose demand irregularities, stemming from variability in both order frequency and order size, to upstream echelons for shared components, making forecasting difficult and responsiveness essential. As Boylan and Syntetos (2010) note in the context of spare parts, demand lumpiness makes forecasting difficult. This observation aligns with the challenges found in managing upstream component inventories for shared components, where demand emerges irregularly on Stock Keeping Unit (SKU) level and in varying volumes depending on customer-specific requirements. To address these challenges, demand-driven systems offer an alternative by dynamically adjusting buffer levels based on historical or near-future demand signals, enabling more flexible inventory positioning and replenishment strategies aligned with actual consumption (Ptak and Smith 2011). This study investigates how such demand-driven logic can be applied within an ETO system and a two-echelon inventory structure to improve responsiveness and resilience under demand uncertainty.

Recently, DDMRP has emerged as an innovative approach to materials management, integrating elements from Material Requirements Planning (MRP), Distribution Requirements Planning (DRP), Lean Manufacturing, and the Theory of Constraints (TOC) into a dynamic hybrid push-pull system (Ptak and Smith 2011). Unlike traditional MRP, which relies heavily on forecasts, DDMRP focuses on actual demand signals to drive replenishment decisions, aligning more closely with Just-in-Time (JIT) and Kanban principles (Ptak and Smith 2011). This responsiveness makes DDMRP particularly promising for improving inventory efficiency and resilience in environments characterised by variability and customisation, by helping ensure that the right SKUs are in the right quantities at the right time.

While reviews (Azzamouri et al. 2021; Butturi et al. 2021), case studies (Kortabarria et al. 2018), parameterizations (Damand, Lahrichi, and Barth 2023), and success stories of DDMRP implementations (Butturi et al. 2021; Miclo et al. 2019) can be found, there are areas worthy of more exploration. Comparative studies in complex manufacturing environments remain limited. Additionally, little attention has been paid to demand categorisation and supplier-level implementations, despite the fact that upstream inventory decisions directly influence system-wide responsiveness, cost efficiency, and fill rates (Dessevre et al. 2023; Li et al. 2025; Ohta, Ikeno, and Rahim 2009; Rota, Thierry, and Bel 2002). To address this gap, this study investigates the impact of implementing DDMRP at the supplier level within a two-echelon, ETO supply chain using categorised demand profiles.

The research question is: *How does integrating DDMRP at supplier level impact the efficiency and resilience of inventory management in ETO supply chains?*

The study conducts a simulation using real world data from manufacturing case company to evaluate inventory performance in a two-echelon supply chain. The suppliers sub-component (SC) inventory acts as a strategic inventory position, and it is simulated with two management methods for a comparative analysis: (1) DDMRP and (2) a static push-based method combining Safety Stock (SS), Reorder Point (ROP), and Economic Order Quantity (EOQ), which reflects the current state of operations. Although this baseline may not represent state-of-the-art inventory management practices available today, it reflects the current approach used by the case company and remains common in industry due to its simplicity and familiarity, making it a relevant benchmark for assessing the potential benefits of adopting DDMRP in similar contexts. The simulation uses real purchase order (PO) data to derive demand distributions and lead times for all SKUs, and inventories are simulated daily over an 18-month period. Efficiency and is assessed by comparing total on-hand inventory levels and total number of orders, metrics that reflect inventory holding costs and ordering costs (Azzamouri et al. 2021; Butturi et al. 2021; Miclo et al. 2019; Ptak and Smith 2011; Thüerer, Fernandes, and Stevenson 2022). Additionally, resilience is treated as a performance dimension reflected through fill rate, which translates to service reliability and the ability to absorb demand variability (Lücker, Timonina-Farkas, and Seifert 2025). Furthermore, results are analysed in relation to distinct demand categories identified from the sample data (Syntetos, Boylan, and Croston 2005), providing insights into whether supplier level integration of DDMRP can improve inventory management efficiency and resilience in modular ETO supply chains under varying demand conditions.

DDMRP is studied in an ETO setting operating within a modular T-plant structure. In this context, customer orders influence design and finalise product definition, while the T-plant architecture enables postponement by consolidating shared components upstream (Olhager 2010). This yields order – specific or configured Bills of Materials (BOM), embeds engineering lead time within cumulative lead time, and orients execution around project specific kits and due-date reliability rather than single-SKU service (Gosling and Naim 2009; Olhager 2010). These contingencies differ from Assemble-to-Order or Make-to-Stock contexts where product structure is fixed and forecastability is typically higher. In the setting of this study, the system can be described as impure ETO (Gosling and Naim 2009; Ptak and Smith 2016), since shared components are managed as MTS

across variants creating aggregated demands. The shared components therefore present distinct pull patterns (Syntetos, Boylan, and Croston 2005) at upstream nodes, shaping DDMRP's strategic decoupling, ADU windows, and buffer parameters. While postponement ideology and decoupling are used as general mechanisms to mitigate effective variability (Bagchi and Gaur 2018; Saghiri and Barnes 2016; Zinn 1990), they are not claimed as ETO – exclusive. Rather, it is argued that ETO's design – penetrating orders and project specific execution make buffer placement and sizing particularly consequential. This ETO orientation aligns with established literature on ETO supply chains and Customer Order Decoupling Point (CODP) theory (Gosling and Naim 2009; Olhager 2010), and it connects to the broader Demand – Driven/TOC heritage that applies buffer management not only to materials (DDMRP) but also to projects (Critical Chain) (Goldratt 1997; Smith 1999).

The remainder of this paper is organised as follows: Section 2 reviews the theoretical background and relevant literature. Section 3 describes the research design and simulation methodology. Section 4 presents the results and sensitivity analysis. Section 5 discusses key findings, theoretical contribution, and managerial implications, and Section 6 concludes with limitations directions for future research.

2. Literature review

A literature review was conducted to explore inventory management in ETO supply chains, with a focus on modular T-plant structures and multi-echelon systems where product variety and demand variability complicate planning. It examines how decoupling and component-level strategies improve responsiveness. The review also evaluates DDMRP's principles and potential advantages over traditional PPC methods, while highlighting key gaps, particularly in empirical validation, supplier-level implementation, parameterisation, and integration with other methods.

2.1. Demand variability in modular ETO supply chains

Modular ETO supply chains face a dual challenge: managing volatile demand and coordinating shared components across product variants. These conditions make inventory management fundamentally different from more standardised environments. Firms often keep minimal to no finished goods inventory and instead rely on flexible production triggered by confirmed customer orders (van Jaarsveld and Scheller-Wolf 2015; Zhao and Simchi-Levi 2006). In modular context, sub-components

are procured in advance while final differentiation is postponed, creating T-plant-like structures where many customised products stem from a limited set of shared components (Umble 1992). Demand for these components is both dependent and correlated across BOM levels, since the same components are required for multiple product variants, the configuration of one product may influence which other products are selected (and thus which components are required), and certain components are only compatible with specific others (Aviv and Federgruen 2001; Casado et al. 2020; Thüerer, Fernandes, and Stevenson 2022). Forecasting dependent demand particularly difficult when customer demand for end products is volatile, creating irregular patterns that are hard to capture with traditional forecasting-based policies (Boylan and Syntetos 2010; Syntetos, Boylan, and Croston 2005). From a resilience perspective, demand variability represents a recurrent risk that inventory systems must absorb without creating excessive cost or service failures (Lücker, Timonina-Farkas, and Seifert 2025). Fill rate therefore serves as a key indicator of resilience, reflecting the system's ability to satisfy demand on time despite uncertainty.

To quantify such uncertainty, measures such as the Coefficient of Variation (CV) are widely used, as they normalise fluctuations relative to average demand and enable comparison across products (Jalilibal et al. 2021). Building on this, Syntetos, Boylan, and Croston (2005) proposed a demand categorisation framework that classifies items as smooth, intermittent, erratic, or lumpy based on inter-demand intervals and $CV \geq 2$, providing a structured basis for differentiated control policies. While demand classification has been widely studied for forecasting and stock control, its adaptation as a lens for differentiated control policies remains underexplored.

Postponement and upstream decoupling have been widely emphasised as strategies to mitigate variability amplification by buffering common components and delaying final differentiation (Saghiri and Barnes 2016; Van Hoek 2001; Zinn 1990). Postponement aligns production more closely with actual orders by delaying product differentiation until customer demand is known, reducing the mismatch between predicted and realised demand (Aviv and Federgruen 2001; García-Dastugue and Lambert 2007; Graman 2010). A central mechanism for achieving this is modularisation, which allows firms to pool demand at the component level and lower the need for large buffers (Bagchi and Gaur 2018; Yang and Burns 2003; Zinn 1990). The choice of the point of differentiation is critical for balancing cost and risk (Vanteddu and Chinnam 2014). Importantly, collaborative implementation across the supply chain can amplify these benefits, whereas isolated adoption may shift costs

upstream or downstream (García-Dastugue and Lambert 2007).

Postponement and customer order decoupling are not specific to ETO, but they cut across manufacturing and fulfilment strategy typologies. However, postponement in partial ETO (via modular shared components and late differentiation) reflects a general variability – mitigation mechanism that our case exploits. In such settings, postponement stabilises upstream operations by enabling common components to be stocked and later configured into end-products (Aviv and Federgruen 2001; Zinn 1990). Dynamic buffer-based methods such as DDMRP extend this principle by continuously adjusting component buffers in response to realised demand, combining the long-recognised advantages of postponement with adaptive, data-driven control (Ptak and Smith 2016). Still, there is limited empirical validation of DDMRP in ETO or T-plant settings, and little is known about how it interacts with postponement to manage shared components under volatile demand.

Together, strategies such as modularisation, postponement, and dynamic buffering can address the dual challenges of variability and complexity by consolidating demand for shared components and aligning inventories more closely with actual requirements (Bagchi and Gaur 2018; Ptak and Smith 2016; Thürer, Fernandes, and Stevenson 2022; Yang and Burns 2003). When integrated with demand categorisation frameworks (Syntetos, Boylan, and Croston 2005), these approaches can be tailored to SKU-specific profiles, enabling selective adoption of buffer policies that reflect both the structural features of modular supply chains and the variability patterns of individual items.

2.2. Managing variability with DDMRP

Demand Driven MRP (DDMRP), introduced in the third edition of *Orlicky's Material Requirements Planning* (Ptak and Smith 2011), is a methodology designed to maintain material flow by using buffer status to trigger replenishment orders. The Demand Driven Institute's programmes frame DDMRP within an enterprise model that includes operations and project components (DDI 2025). DDMRP is part of a broader Demand – Driven/TOC lineage that also addresses project environments through buffer management, which protects schedules using project and feeding buffers and manages execution by buffer consumption (Goldratt 1997; Ptak and Smith 2011; Smith 1999).

Unlike traditional push or pull systems, DDMRP emphasises responsiveness to actual demand, aiming to mitigate stockouts and excess inventory (Azzamouri et al. 2023; Kortabarria et al. 2018; Miclo et al. 2019). This

capability is particularly relevant in environments with high product customisation and volatile demand, where conventional planning methods struggle to absorb variability (Miclo et al. 2019). DDMRP implementation follows a structured process comprising five core steps: strategic inventory positioning, buffer profiling and sizing, dynamic adjustments, demand-driven planning, and visible execution (Damand, Lahrichi, and Barth 2023; Kortabarria et al. 2018; Ptak and Smith 2011), with a sixth step of continuous adaptation recently recognised by the Demand Driven Institute (DDI 2025). As such, DDMRP has built-in variability control mechanisms through three interrelated principles. These mechanisms aim to stabilise material flow by absorbing fluctuations in demand and lead time, reducing nervousness, and mitigating stockouts or excess inventory.

First, strategic decoupling and selective buffering relocate inventory to nodes that absorb the greatest variability impact, thereby decoupling upstream supply from downstream volatility. This supports upstream decoupling and selective buffering in multi-product systems where common parts face asynchronous usage (Dessevre et al. 2023; Miclo et al. 2019). In postponement contexts, decoupled buffers at common components stabilise upstream flows while allowing late configuration downstream (Bagchi and Gaur 2018; Van Hoek 2001; Zinn 1990).

Second, temporal demand signal smoothing via the ADU window filters short-term noise. Theoretically, shorter windows increase responsiveness, whereas longer windows emphasise stability. Evidence from prior studies suggests that continuous buffer adjustment improves responsiveness when orders are infrequent, whereas periodic adjustments suit high-frequency replenishment (Azzamouri et al. 2023). This positions ADU as a primary service-inventory trade-off lever, aligning DDMRP parameterisation with control-theoretic notions of signal filtering and feedback (Thürer, Fernandes, and Stevenson 2022).

Third, adaptive buffer sizing scales to lead times and variability through Lead time Factor (LTF) and Variability Factor (VF). Parameterisation remains a decisive factor in how effectively DDMRP manages variability. However, these parameters are often set subjectively (Butturi et al. 2021; Damand, Lahrichi, and Barth 2023; Miclo et al. 2019; Uzun Araz et al. 2024). While flexibility supports adaptation, it also raises concerns about reliability and transparency. Algorithmic approaches to tuning these parameters have been proposed (Damand, Lahrichi, and Barth 2023; Uzun Araz et al. 2024), but empirical validation is limited. This underscores the need for further exploration of data-driven methods that link buffer sizing to observed variability and lead time exposure.

DDMRP's potential relevance is clear in multi-product systems and modular architectures with complex BOMs, where shared components amplify variability across product variants (Azzamouri et al. 2021; Dessevre et al. 2023). In such contexts, selective buffering at upstream nodes can decouple variability, while ADU-based signal smoothing prevents overreaction to short-term spikes. Comparative analyses between DDMRP and other planning methods show that simulation-based studies often report favourable results for DDMRP (Miclo et al. 2019). While empirical studies remain limited (Butturi et al. 2021), the consistent pattern suggests that DDMRP's core mechanisms offer advantages in environments characterised by variability and uncertainty. These dynamics position DDMRP as a planning logic that has potential in managing demand variability, yet there are some areas warranting further exploration.

2.3. Research gaps and positioning

Despite increasing interest in DDMRP, the literature remains in a formative stage, particularly in terms of empirical validation and theoretical consolidation (Azzamouri et al. 2021). Case studies such as Kortabarria et al. (2018) acknowledge the potential benefits of DDMRP on supply chain performance in uncertain conditions, but also highlight the lack of consistent, context-specific validation.

This study highlights four gaps that persist in the DDMRP literature. First, evidence on multi-stage systems performance remains scarce, as most studies focus on the focal firm, leaving upstream applications largely unexplored. Yet, supplier-level buffering directly influences system-wide responsiveness and cost efficiency (Dessevre et al. 2023; Li et al. 2025; Ohta, Ikeno, and Rahim 2009; Rota, Thierry, and Bel 2002). Second, contextual evidence is lacking (Azzamouri et al. 2023), and modular configurations such as T-plants with shared components and high interdependencies are underrepresented, despite their relevance as production strategies (Aviv and Federgruen 2001; Umble 1992). Third, parameterisation lacks standardisation: while the original method and subsequent studies propose sizing logics for factors such as ADU window, LTF, and VF, these approaches often rely on managerial judgment and heuristic ranges rather than fully algorithmic or data-driven tuning, limiting reproducibility and theoretical consolidation (Butturi et al. 2021; Damand, Lahrichi, and Barth 2023; Miclo et al. 2019; Ptak and Smith 2016). Fourth, claims about resilience benefits and hybrid integration with other PPC systems remain largely conceptual, with little empirical validation

(Lücker, Timonina-Farkas, and Seifert 2025; Thüerer, Fernandes, and Stevenson 2022).

This study addresses these gaps by simulating DDMRP at the supplier level in a modular ETO system, applying a transparent parameterisation method, conducting sensitivity analysis to identify key levers, and benchmarking against EOQ/ROP/SS. Evidence on DDMRP's performance is still dominated by simulations and limited empirical studies, reinforcing the value of examining it under ETO – style variability and T-plant structures (Butturi et al. 2021; Miclo et al. 2019).

3. Materials and methods

This study adopts a simulation approach using real purchase order data from an industrial piping supply chain. Simulation is particularly well-suited for complex, stochastic environments such as ETO modular supply chains, where interdependencies between components and fluctuating demand complicate the use of purely analytical models (Calleja et al. 2018). The case supply chain is modelled as a two-echelon system, comprising a supplier-managed sub-component inventory and the manufacturer's demand for finished items. Specifically, this study focuses on the supply chain of industrial piping, which exemplifies a T-plant environment (Umble 1992), where many end items are built from a limited set of common components. In this context, customised pipes are sourced from a specialist supplier and used as components in the manufacturer's modular assembly system. While all pipes initially undergo an ETO design process to fit project-specific requirements, their degree of standardisation varies: some items are semi-standard with limited revisions, whereas others are subject to frequent design changes or are entirely new.

Initially, essential data, including BOMs and historical PO records, were collected and organised. The dataset comprised 1 561 unique SKUs, 3 439 orders, and 21 395 ordered units over a span of 524 days. The procedure involved following steps: data collection, data cleaning, product grouping, demand categorisation, inventory modelling, simulation, and result analysis. Data analysis and modelling were performed using MATLAB. All data used in this study were anonymized to protect the confidentiality of the participating companies.

The study relies on historical demand data within a limited time frame, which may not fully capture all nuances. However, the data enables the analysis of a real environment, creating a foundation to study broader challenges in similar supply chains. To realistically capture demand uncertainty, the study applies a non-parametric bootstrapping method to reconstruct empirical demand distributions directly from historical data

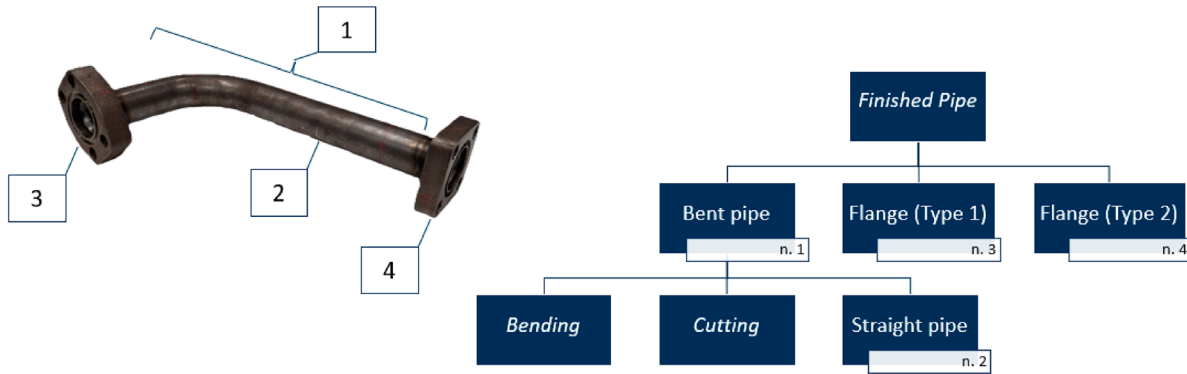


Figure 1. Example pipe BOM.

(Boylan and Syntetos 2010). This approach accommodates the irregular nature of real-world demand without relying on potentially incorrect assumptions. Although historical inventory data was unavailable for direct comparison, the model uses actual demand data. The created model has been validated for logical behaviour under both zero demand and extreme spikes. Flow conservation was verified through daily results, supporting the internal consistency of the simulation.

The CODP acts as a strategic buffer between forecast-driven upstream operations and demand-driven downstream execution, enabling standardised SCs (e.g. straight pipes, flanges, and valves (Figure 1)) to be scheduled efficiently while absorbing variability from uncertain customer orders (Gosling and Naim 2009). These SCs exhibit relatively low form variability and shelf value, making them cost-effective to hold in inventory. Additionally, their long replenishment lead times increase the risk of backlogs in case of stockouts. These attributes align with the critical inventory positioning factors identified by Ptak and Smith (2011), suggesting that SC inventory is a strategic decoupling point and buffer position. Among these SCs, straight piping is particularly influential in determining the specifications of the parent product. It varies across multiple dimensions: material, diameter, wall thickness, length, surface treatment. It requires 3D bending and the addition of e.g. flanges or grooves. Due to its central role in final configuration, straight piping was selected as the representative item for modelling the supplier's inventory, serving as a proxy for SC flow.

Furthermore, SCs were categorised by demand characteristics to enhance the analysis of DDMRP effectiveness. Demand categorisation was based on the work of Syntetos, Boylan, and Croston (2005), utilising CV^2 of demand sizes and the Average Demand Interval (ADI) to differentiate between demand variability in quantity and timing, respectively. These metrics help distinguish between smooth, intermittent, erratic, and

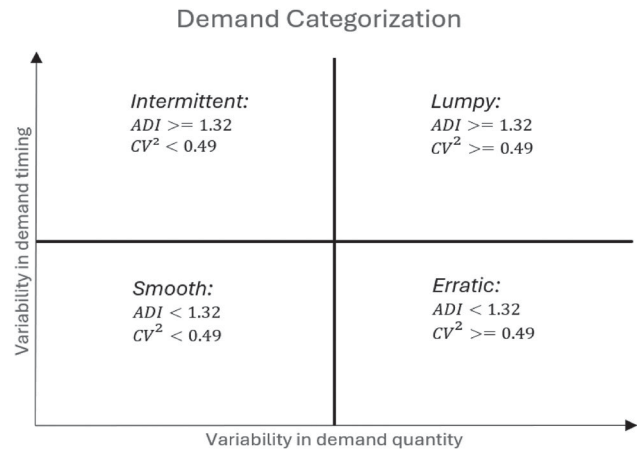


Figure 2. Demand categorisation, adapted from Syntetos, Boylan, and Croston (2005).

lumpy demand, providing insights into variability in both demand timing and quantity (Figure 2).

A comparison between the current state (Figure 3) and the proposed demand-driven approach was made by modelling and simulating inventory flow using collected data. The model includes the supplier's (Stage 1) and the manufacturer's (Stage 2) inventories. The manufacturer assembles final products using the customised pipes sourced from the supplier, who stores standardised SCs until customisation and assembly according to manufacturer's specification.

For both scenarios, customer demand is represented by three sequential order signals, where n is a given day in simulation: (1) manufacturer's POs to supplier with demand $D_{POm}(n)$, (2) supplier's Assembly Orders (AO) with demand $D_{AOs}(n)$ initiated after a delay of Decoupled Lead Time for Stage 1 (DLT1) + 1 from the manufacturer's PO, and (3) manufacturer's AOs for final assembly with demand $D_{AOm}(n)$, which are initiated after cumulative Lead Time (LT) + 1 following the supplier's AO. This means today's arriving replenishment orders are

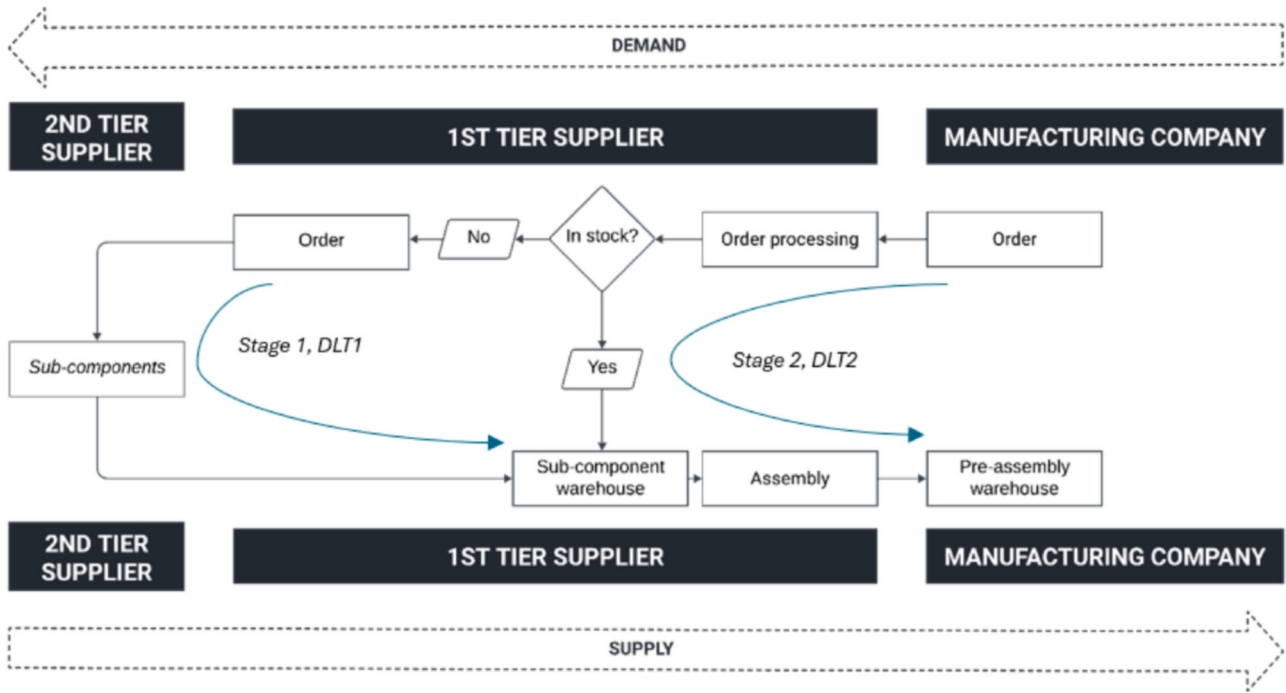


Figure 3. Flow chart of current state supply chain.

usable the next day. A stockout can occur if replenishment orders cannot sustain inventory, and a stockout in Stage 1 leads to an incomplete order in Stage 2. If no stockouts occur, finished pipes arrive at the manufacturer's pre-assembly warehouse by JIT principle after $DLT1 + DLT2 = LT$, specifically the day before they are needed in production. The model operates on a daily level, including maximum one demand and one replenishment order signal each day. Finally, inventory levels, fill rates, and order numbers are calculated each day for both Stages during examination period (524 days) and averaged or summed at the end for results.

Each SKU in both stages has a constant, non-zero replenishment lead time based on data averages. The model assumes guaranteed arrival times. This approach isolates the effect of inventory control logic by removing variability in supply reliability. Additionally, no capacity constraints were modelled at either stage of the supply chain. Both supplier and manufacturer were assumed to have unlimited production and transportation capacity, ensuring that replenishment decisions were not influenced by resource limitations. These simplifications allowed for controlled evaluation of DDMRP parameterisation and demand-driven buffering under consistent conditions, while acknowledging that real-world systems may experience lead time variability and capacity restrictions.

The current state (Control scenario) is modelled as follows: For each SKU, Stage 1 starts on day 1 with an initial on-hand-inventory $I_{OH1}(1) = ROP + 1$, and

Stage 2 starts at $I_{OH2}(1) = 0$. Manufacturer's POs arrive at the supplier, triggering a demand signal $D_{POm}(n)$ for pipes, and the required parts through BOM. After $DLT1 + 1$, supplier's AO requires the SCs from $I_{OH1}(n)$ by $D_{AOs}(n)$, and that demand is satisfied if $I_{OH1}(n) \geq D_{AOs}(n)$. Otherwise, orders are backlogged. No backlog or stockout cost was defined in this study, as those are case specific and provide little generalisable results. The Stage 1 inventory is replenished using net flow principle (Equation 1) with predefined SS (Equation 2), ROP (Equation 3), and EOQ (Equation 4) for each SC. The replenishment rules are calculated from PO data. SS in particular can be calculated in various ways, and a method for normally distributed demand with uncertainty was selected for this study (Thieuleux 2025). A 99% fill rate was pursued, affecting the SS through the Z-score, as seen in Equation (6). The Z-score (approximately 2.33) corresponds to the 99th percentile of the standard normal distribution.

$$I_{NF1}(n) = I_{OH1}(n) + I_{CO1}(n) - D_{AOs}(n) \quad (1)$$

where I_{NF1} is Net Flow Inventory at Stage 1, I_{OH1} is On-hand Inventory at Stage 1, I_{CO1} is Cumulative On-order Inventory at Stage 1, and D_{AOs} is Demand from Supplier's Assembly Order

$$SS = Z * StDev(ADU) * \sqrt{LT(S1)} \quad (2)$$

where SS is Safety Stock, Z is Z-score, ADU is Average Daily Usage, LT(S1) is Lead Time for Stage 1

$$ROP = ADU * LT(S1) + SS \quad (3)$$

where ROP is Reorder Point, ADU is Average Daily Usage, LT(S1) is Lead Time for Stage 1, and SS is Safety stock

$$EOQ = \sqrt{\frac{2 * AAD * C_o}{C_h}} \quad (4)$$

where EOQ is Economic Order Quantity, AAD is Average Annual Demand, C_o is Ordering Cost (per order), and C_h is Holding Cost (annual)

When $I_{NF1}(n) \leq ROP$, a replenishment order $O_R = EOQ$ is sent to a second-tier supplier, and items are added to replenished inventory $I_{R1}(n)$ after DLT1. Items added to $I_{R1}(n)$ are usable the day after, meaning $I_{OH1}(n) = I_{R1}(n - 1)$. If $I_{NF1}(n) \leq SS$, then $O_R = \text{MAX}(EOQ; ROP - I_{NF1}(n))$ is placed instead.

In the DDMRP scenario (Figure 4), the Stage 1 inventory is managed with DDMRP buffer zones: Red (Equation 5), Yellow (Equation 6), and Green (Equation 7), allowing buffers to be maintained dynamically for common components. Stage 2 is managed with JIT principle, like the Control scenario. As with the Control scenario, the replenishment was executed using inventory net flow principle (Miclo et al. 2019). Stage 1 inventory buffers are adjusted daily based on a 30-day moving average for ADU calculated from arriving manufacturer POs (Equation 8). Demand spikes are included in buffer calculations, meaning they are not considered separately. Suppliers AO is delayed by DLT1 + 1 from manufacturer's PO, giving the ADU calculation a forecast horizon equal to DLT1 for Stage 1 replenishment, which reflects DDMRP's short-horizon forecasting ability. Each SKU starts at the same $I_{OH1}(1)$ as in the Control scenario. A replenishment order $O_R = (TOG(n) - I_{NF1}(n))$ is placed when $I_{NF1}(n) \leq TOY(n)$. SKU lead times remain the same for both scenarios.

$$\begin{aligned} \text{Redzone} &= \text{TOR} = \text{Redbase} + \text{Redsafety} \\ &= \text{ADU} * \text{DLT} * \text{LTF} \\ &\quad + \text{ADU} * \text{DLT} * \text{LTF} * \text{VF} \end{aligned} \quad (5)$$

when TOR is Top of Red zone, which is the sum of red base and red safety. ADU is Average Daily Usage, DLT is Decoupled Lead Time, LTF is Lead Time Factor, and VF is Variability Factor.

$$\text{Yellow zone} = \text{TOY} - \text{TOR} = \text{ADU} * \text{DLT} \quad (6)$$

where TOY is Top of Yellow zone, ADU is Average Daily Usage, and DLT is Decoupled Lead Time.

$$\begin{aligned} \text{Green zone} \\ &= \text{TOG} - \text{TOY} \\ &= \text{Max}\{\text{MOQ}, \text{ADU} * \text{DLT} * \text{LTF}, \text{ADU} * \text{OC}\} \end{aligned} \quad (7)$$

where TOG is Top of Green zone, TOY is Top of Yellow zone, MOQ is Minimum Order Quantity, ADU is Average Daily Usage, DLT is Decoupled Lead Time, LTF is Lead Time Factor, and OC is Order Cycle.

$$\begin{aligned} \text{ADU}(n) &= \frac{1}{30} (D_{POm}(n - 29) + D_{POm}(n - 28) + \dots \\ &\quad + D_{POm}(n)) \end{aligned} \quad (8)$$

where ADU is Average Daily Usage, D_{POm} is Demand from manufacturer's purchase order, and n is a given day.

The last step involves a detailed analysis of the results, focusing on average on-hand inventory levels, fill rates, and number of orders. To analyse the average on-hand inventory levels, the mean of on-hand beginning of day inventories was calculated (Equation 9). This helps in understanding the inventory holding costs. Fill rates were measured to determine the ability of the supply chain to meet variable customer demand without incomplete orders or stockouts. Total fill rates were computed as demand-weighted averages rather than simple daily averages, ensuring that high-demand periods exert appropriate influence on the metric (Equation 10). Only days with actual demand were included in these calculations to avoid distortion from zero-demand days. Inventory levels were constrained to remain non-negative throughout the simulation. Instead, stockouts were captured through backorder calculations, allowing measurement of both the frequency and depth of unmet demand. The number of orders was tracked to evaluate the frequency of replenishment orders (Equation 11), providing insights into ordering costs. This approach aimed for a comprehensive evaluation of the research question by providing numeric insights.

$$\overline{I_{OH}} = 1 - \frac{\sum_{n=1}^N I_{OH}(n)}{N} \quad (9)$$

where I_{OH} is On-Hand Inventory, n is a given day, and N is total number of days.

$$\overline{\text{Fill rate}} = 1 - \frac{\sum_n \text{backorders}(n)}{\sum_n D_{AOs}(n)}, \text{ if } D_{AOs}(n) > 0 \quad (10)$$

where n is a given day, and D_{AOs} is Demand from Supplier's Assembly Order.

$$N_{orders} = \sum_{n=1}^N O(n) \quad (11)$$

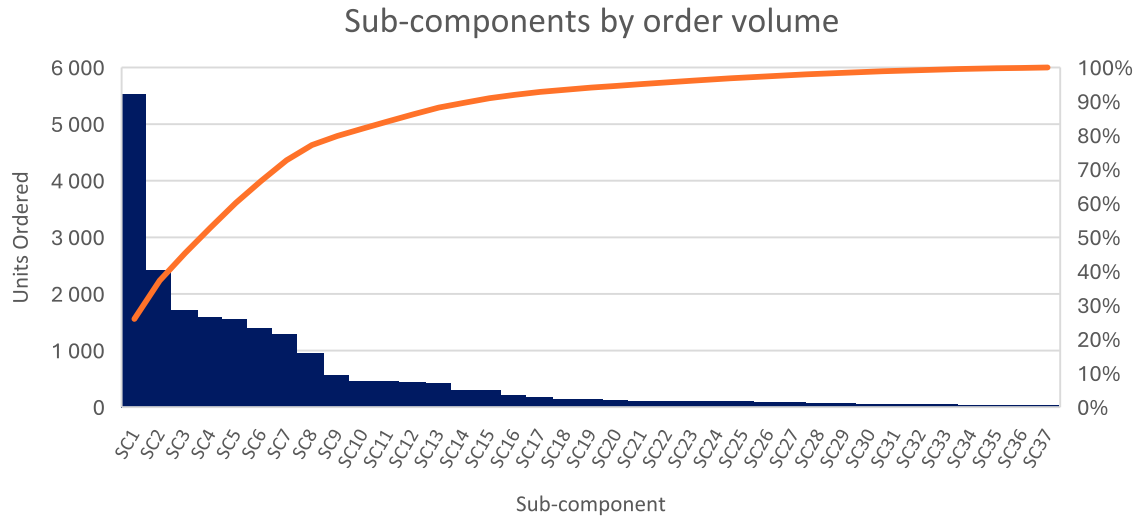


Figure 5. Distribution of sub-components by volume (units ordered).

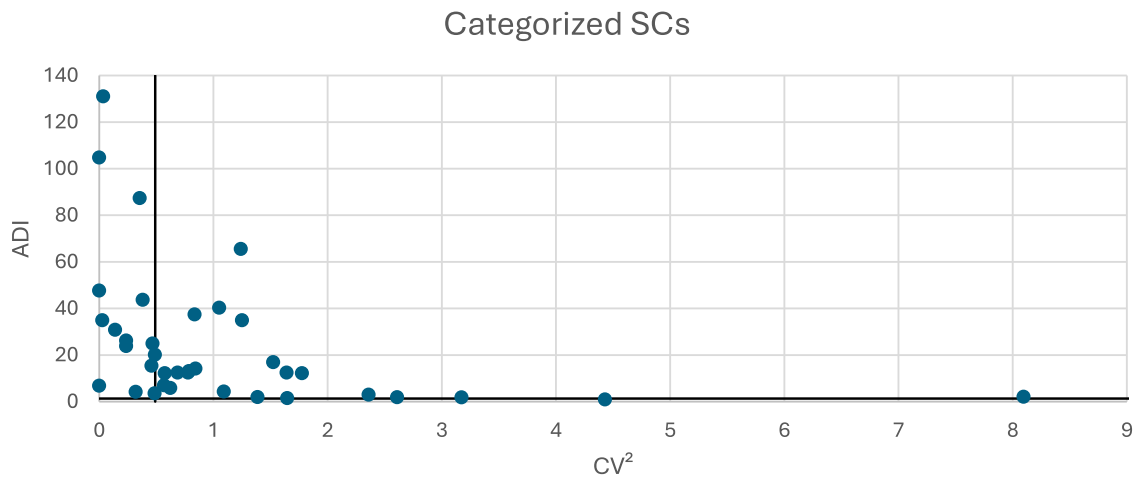


Figure 6. Categorisation of sub-components by demand variability, thresholds adapted from Syntetos, Boylan, and Croston (2005).

Table 1. Demand categorisation.

	Short LT	Moderate LT	Long LT
Smooth	0	0	0
Intermittent	12	2	1
Erratic	1	0	0
Lumpy	20	1	0

Table 2. Used LTFs and VFs.

Lead time	DLT1 (d)	LTF	Variability	CV	VF
Long	53.27	0.20	Low	0.00	0.00
	41.60	0.40		1.14	0.40
Moderate	41.01	0.41	Moderate	1.17	0.41
	29.92	0.60		1.71	0.60
Short	29.33	0.61	High	1.74	0.61
	6.56	1.00		2.85	1.00

data by identifying the minimum and maximum values observed across all SKUs. These boundary values were then mapped to the recommended lower and upper bounds for LTFs and VFs as proposed by Ptak and Smith (2016). For SKUs falling between these extremes, corresponding factor values were interpolated using a linear function (Equation 9). This approach enabled a consistent assignment of buffer factors across the SKU portfolio, ensuring that items with greater demand variability or longer replenishment times received proportionally higher buffer protection, in alignment with DDMRP

principles.

$$DLT \text{ or } CV = (\text{Factor} - b)/a \tag{12}$$

where DLT is Decoupled Lead Time, CV is Coefficient of Variation, b is intercept (1.1124 for DLT; 0 for CV), and a is gradient (−0.0171 for DLT; 0.3514 for CV).

The comparison was made between two scenarios: one where the supplier’s SC inventory is managed with a combination of EOQ, SS, and ROP, and another where the inventory is managed using DDMRP (example result

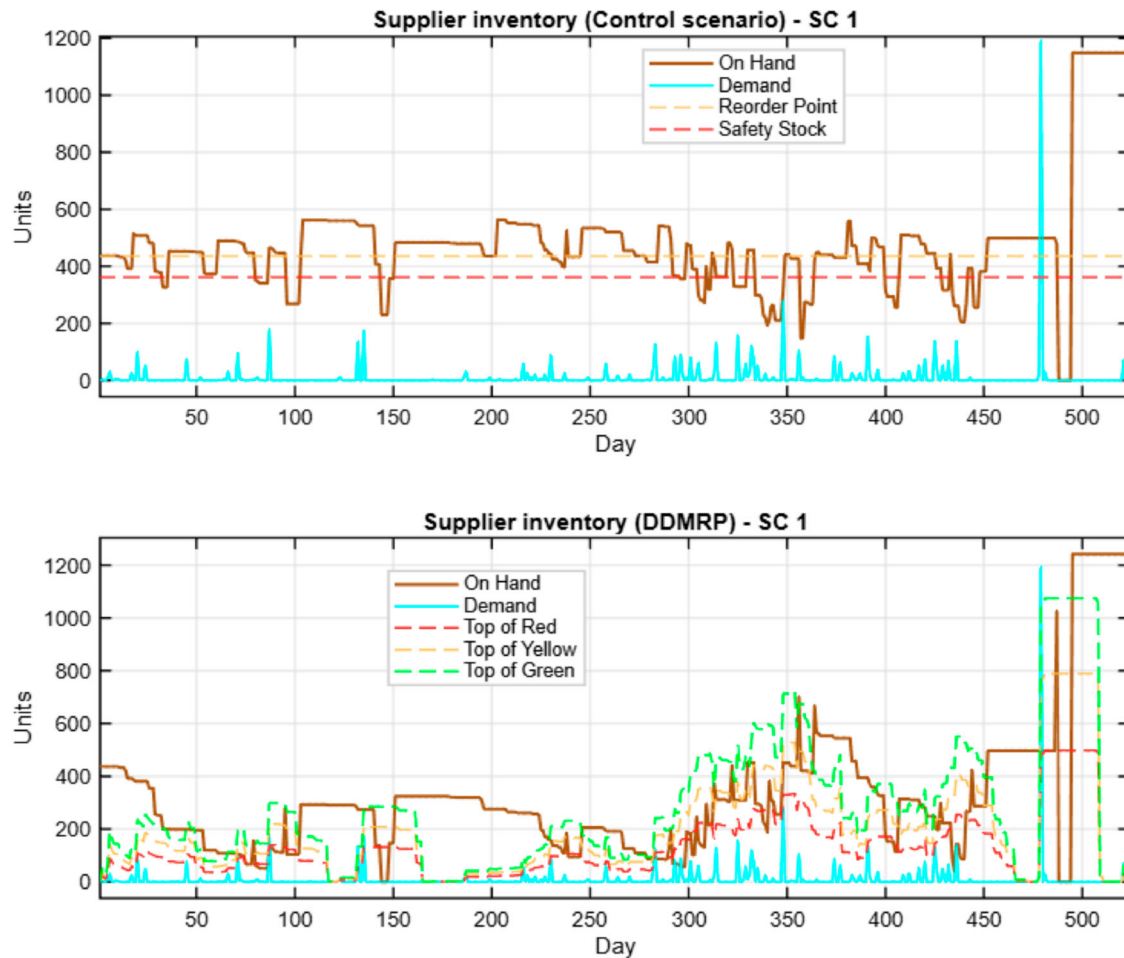


Figure 7. Example simulation results for sub-component 1.

SC1 in Figure 7). In both scenarios, the manufacturers inventory is managed using JIT principle.

The overall results are presented below in Table 3. The findings suggest that integrating DDMRP at supplier level can positively impact inventory management efficiency and resilience in a two-echelon modular ETO supply chain. The simulation analysis with this sample shows a 16.7% average and a 21.4% volume-weighted average reduction in on-hand inventory levels across two inventory stages. This marks a notable reduction in excess inventory and can directly lower inventory holding costs. Additionally, an average of 8.1% and a weighted average of 7.5% increase in total fill rates were achieved, indicating DDMRP's ability to absorb demand variability. The target fill rate for Stage 1 inventory in the control scenario was set at 99% through safety stock calculation, yet the simulation resulted in 91.3% fill rate, while 98.12% was achieved with DDMRP. Furthermore, average stockout depth decreased by 81%, and total number of backorders was reduced by 76%, meaning that most previously occurred stockouts were avoided. Lastly, the overall results indicate an average of 4.6% and a weighted

average of 1.5% increase in the number of orders. In this case, a 1.5% increase in total number of orders translates to c. 25 more orders across the portfolio. However, as with the other result, the outcome is highly dependent on the specific SKU.

The study also examined the effectiveness of DDMRP in the context of categorised demand environments. While the results in this case suggest an overall improvement in performance when using DDMRP, its effectiveness was found to vary depending on component-specific demand characteristics (Table 4). The analysis suggests improvement in all three metrics only for erratic short lead time items, of which there was only one item in the sample. Most samples exhibited intermittent or lumpy demand with short lead time. For those items, DDMRP achieved moderate to significant reductions in on-hand inventory levels, significant improvement in fill rates, while number of required orders rose on average. On-hand inventory levels were improved for all other categories identified in the analysis, except for intermittent items with moderate and long lead times. The number of orders decreased for intermittent moderate lead time and

Table 3. Overall results compared to control scenario.

ID	Relative volume	Category	DLT1	CV	Average on-hand	Average fill rate	Number of orders
SC1	25.97%	Erratic	Short	High	-30.4%	10.6%	-3.8%
SC2	11.32%	Lumpy	Short	Moderate	-16.6%	4.8%	-1.8%
SC3	8.07%	Lumpy	Short	High	-43.2%	19.5%	2.2%
SC4	7.47%	Lumpy	Short	Moderate	-33.6%	12.5%	0.9%
SC5	7.30%	Lumpy	Short	High	28.1%	7.7%	-10.3%
SC6	6.49%	Lumpy	Short	Moderate	-24.8%	6.1%	9.1%
SC7	6.07%	Lumpy	Short	Moderate	-25.0%	6.8%	-10.8%
SC8	4.49%	Lumpy	Short	Moderate	-2.8%	4.0%	-6.2%
SC9	2.66%	Lumpy	Short	Low	-40.1%	5.3%	9.1%
SC10	2.16%	Intermittent	Short	Low	0.6%	10.3%	-10.9%
SC11	2.13%	Lumpy	Short	Low	-29.3%	13.4%	0.0%
SC12	2.10%	Lumpy	Short	Low	-21.6%	25.5%	0.0%
SC13	1.99%	Lumpy	Short	Low	-40.4%	7.2%	11.1%
SC14	1.38%	Lumpy	Short	Low	-43.4%	8.1%	21.1%
SC15	1.37%	Intermittent	Short	Low	6.0%	3.9%	1.5%
SC16	0.99%	Lumpy	Short	Low	-8.6%	7.6%	0.0%
SC17	0.84%	Lumpy	Short	Low	-27.1%	4.0%	5.3%
SC18	0.65%	Lumpy	Short	Moderate	-51.1%	0.0%	17.2%
SC19	0.63%	Lumpy	Short	Low	-51.4%	8.9%	21.4%
SC20	0.53%	Lumpy	Moderate	Low	-23.2%	2.8%	3.1%
SC21	0.52%	Lumpy	Short	Low	13.8%	11.0%	-15.4%
SC22	0.51%	Lumpy	Short	Moderate	-36.9%	3.2%	9.5%
SC23	0.48%	Intermittent	Short	Low	-29.1%	12.0%	13.8%
SC24	0.47%	Lumpy	Short	Low	-29.7%	2.0%	0.0%
SC25	0.47%	Intermittent	Short	Low	-24.8%	0.0%	-6.3%
SC26	0.39%	Intermittent	Short	Low	-23.7%	1.2%	0.0%
SC27	0.36%	Intermittent	Long	Low	2.7%	2.7%	3.6%
SC28	0.35%	Lumpy	Short	Low	-35.8%	0.0%	29.4%
SC29	0.31%	Intermittent	Moderate	Low	-2.2%	0.0%	-5.6%
SC30	0.27%	Intermittent	Short	Low	-1.7%	0.0%	0.0%
SC31	0.26%	Intermittent	Short	Low	18.3%	31.0%	0.0%
SC32	0.24%	Intermittent	Short	Low	-18.7%	0.0%	9.5%
SC33	0.23%	Intermittent	Short	Low	-43.1%	0.0%	26.7%
SC34	0.16%	Intermittent	Short	Low	33.5%	17.2%	0.0%
SC35	0.13%	Intermittent	Short	Low	2.9%	0.0%	28.6%
SC36	0.12%	Intermittent	Short	Low	6.5%	18.2%	20.0%
SC37	0.12%	Intermittent	Moderate	Low	26.9%	31.6%	0.0%
Average					-16.7%	8.1%	4.6%
Weighted Average					-21.4%	7.5%	1.5%

Table 4. Results based on categorised demand.

Sub-component category	Number of samples in data	Average on-hand	Average fill rate	Number of orders
Intermittent, Short LT	12	-6.11%	7.81%	6.91%
Intermittent, Moderate LT	2	12.35%	15.79%	-2.78%
Intermittent, Long LT	1	2.71%	2.67%	3.57%
Erratic, Short LT	1	-30.39%	10.63%	-3.85%
Lumpy, Short LT	20	-25.98%	7.88%	4.59%
Lumpy, Moderate LT	1	-23.17%	2.75%	3.13%

erratic short lead time. Finally, the average fill rate in the two-echelon system was improved in every category with DDMRP.

The results align with previous studies in terms of potentially significant reductions in on-hand inventory levels as well as maintaining if not improving already high fill rates (Butturi et al. 2021; Kortabarria et al. 2018; Miclo et al. 2019). However, the number of orders slightly increased on average, while SKU-specific results varied, highlighting the need for more detailed examination. Furthermore, even though the number of orders is directly linked to ordering costs, which can be a significant cost in some cases, the use of this metric is rarely mentioned in previous studies, promoting further

research on that front. Overall, these findings underscore the potential importance of demand categorisation when selecting appropriate inventory management methods.

4.1. Sensitivity analysis

A one-factor-at-a-time sensitivity analysis over the observed demand horizon (days 1–524) was conducted for the DDMRP configuration in Stage 1. Four factors were varied with designated high and low values, aiming for realistic changes: (1) the ADU window, (2) the upstream decoupled lead time DLT1, (3) VF, and (4) LTF, while holding other parameters at their baseline values.

Table 5. Results of the sensitivity analysis.

Variable	Level	Fill rate	Δ Fill rate	Avg on-hand	Δ Avg on-hand	Orders	Δ Orders
Baseline	–	98.12%	–	50.3	–	405	–
ADUWindow	Low (15d)	100.00%	1.88%	76.7	26.4	292	–113
	High (60d)	89.97%	–8.15%	41.8	–8.5	460	55
DLT1	Low (–2d)	94.22%	–3.90%	44.9	–5.4	451	46
	High (+2d)	99.86%	1.74%	57.2	6.9	372	–33
VF	Low (0.75x)	97.89%	–0.23%	48.7	–1.6	403	–2
	High (1.25x)	98.30%	0.18%	51.6	1.3	405	0
LTF	Low (0.75x)	95.51%	–2.61%	44.4	–5.9	462	57
	High (1.25x)	98.17%	0.05%	52.9	2.6	389	–16

For VF and LTF, the values were capped at the suggested range of factors (Table 2). The same three KPIs used in other results are reported for Stage 1 DDMRP scenario and compared to the control scenario. The baseline performance for DDMRP scenario was an average of 50 on-hand inventory and 98.1% fill rate across portfolio, with 405 total upstream replenishment orders. For control scenario, the Stage 1 KPIs were 64, 91.3%, and 380, respectively. The variation level of parameters as well as the results is presented in Table 5.

The ADU window exhibits the largest influence on all three outcomes. Reducing the window (more responsive ADU) increases average on – hand from 50 to 77 units (+27), increases fill rate from 98.1% to 100% (+1.9 pp), and reduces order count from 405 to 292 (–113). Conversely, lengthening the window smooths usage excessively, yielding lower inventory buffers (42), more frequent ordering (460), and lower service (90%). This indicates that ADU responsiveness is the primary service–inventory trade – off lever in the context of this study.

The upstream decoupled lead time DLT1 is the second – most influential factor. DLT1 was varied in buffer calculations, not in the actual timing of shipments, but effectively resulting in the replenishments arriving earlier or later than buffered for. Increasing DLT1 increased average on – hand to 57 (+7) and improved fill rate to 99.9% (+1.8 pp), while decreasing orders to 372 (–33). This is consistent with buffer sizing rules that scale with lead time, as longer replenishment exposure necessitates larger buffers, improving availability at the cost of higher inventory. Decreasing DLT1 in buffer calculations resulted in average on-hand of 45 (–5), fill rate of 94.2% (–3.9 pp), and 451 orders (+46).

The lead time factor, which affects the size of red and green zones, also has a moderate effect: lower LTF reduced on-hand to 44 (–6), fill rate to 95.5% (–2.6 pp), and increased orders to 462 (+57), while increasing LTF had more modest impact. The variability factor, affecting the size of red zone, shows a small effect with this dataset: lowering VF decreases on-hand to 49 (–1), fill rate to 97.9% (–0.2 pp), and orders to 403 (–2), while raising VF had even more marginal impact.

The results of the sensitivity analysis are visualised in Figure 8 against the control scenario. At baseline, DDMRP outperforms the control in service (98.12% vs 91.3%) and inventory efficiency (50 vs 64 units per component), though with more placed orders (405 vs 380). Under favourable conditions DDMRP clearly dominates in terms of average on-hand inventory and fill rate, only underperforming with low ADU window (+13 on-hand) and high ADU window (–1.3 pp in fill rate) with those KPIs. This indicates that DDMRP can cut excess buffers when demand is low, but also raise them in times of higher demand, as expected. Furthermore, as indicated by the baseline results, DDMRP tends to underperform in number of required replenishment orders, only outperforming control scenario when low ADU window (–88 orders) and high DLT (–8 orders) are used in buffer sizing. This behaviour can be explained by more accurate responses to demand spikes with lower ADU window, and higher buffers (although not as high as the control scenario) with higher DLT. Proportionally, number of orders is most parameter-dependent out of the measured KPIs. Changing VF and LTF by $\pm 25\%$ did not reverse the relative performance of DDMRP in any KPI. From these results, it can be said that DDMRP robustly outperforms the control scenario in inventory levels and fill rates under most conditions considered in this study. However, it is also important to note that, on average across the product portfolio, DDMRP only outperformed in all three KPIs simultaneously when DLT1 was raised above the actual DLT1 when calculating buffers, thereby preparing for replenishment delays.

5. Discussion

5.1. Interpretation of key findings

The findings of this study highlight the nuanced benefits of applying DDMRP at supplier level and underscore the importance of aligning inventory strategies with demand characteristics. The most notable improvement was the reduction of on-hand inventory, with weighted average reductions exceeding 20%, translating directly into lower holding costs and more efficient use

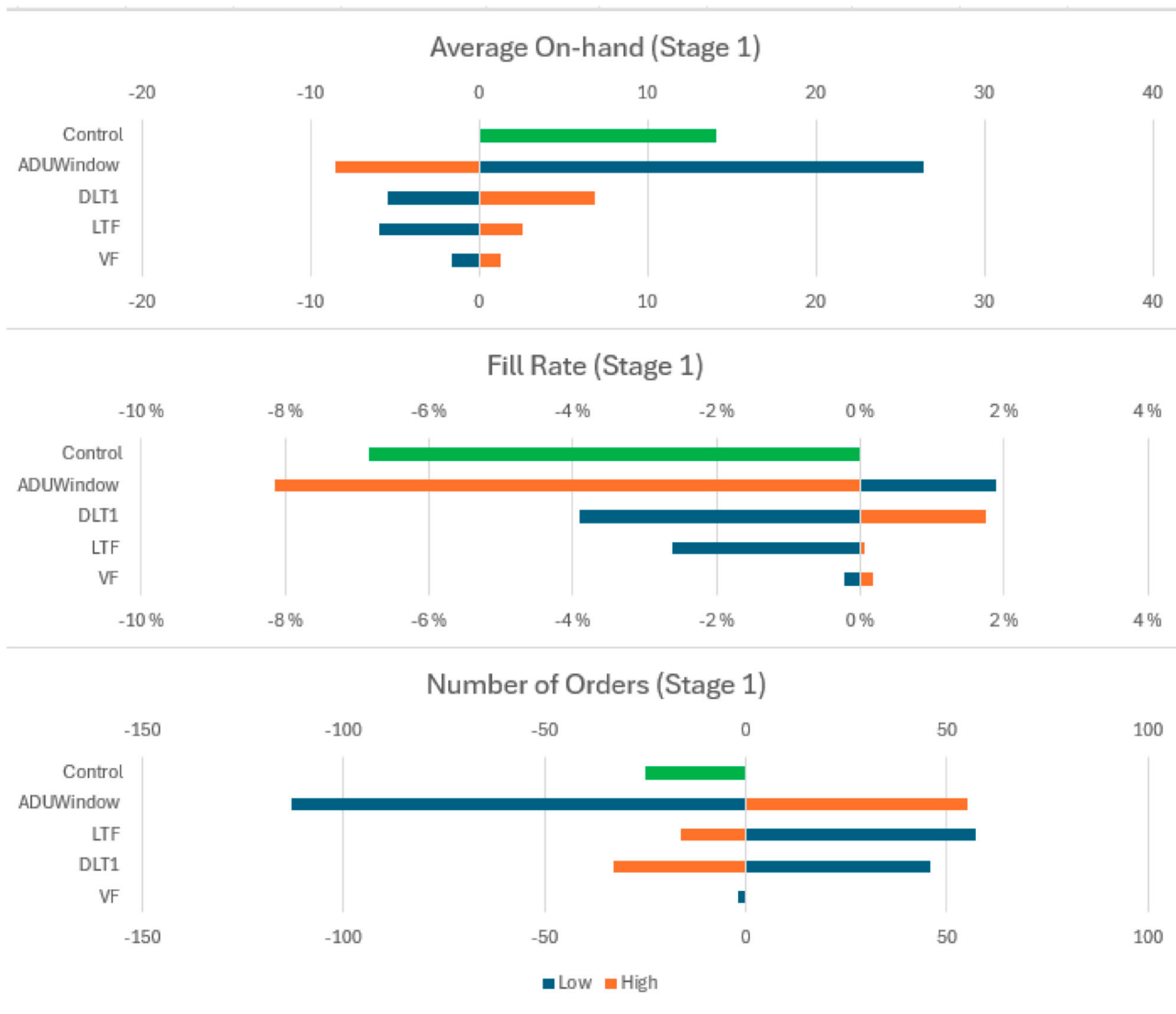


Figure 8. Sensitivity analysis with tornado charts.

of inventory space. Sensitivity analysis provides additional insight: inventory reduction was most pronounced when ADU windows were longer, although this resulted in unfilled orders. Higher DLT assumptions increased buffer size and partially offset inventory savings, further illustrating the trade-off between service assurance and inventory efficiency. These dynamics suggest that inventory efficiency under DDMRP can be highly parameter-dependent, reinforcing the need for careful calibration rather than default settings. This interpretation supports prior claims that DDMRP can reduce excess inventory in variable demand conditions (Azzamouri et al. 2021; Kortabarria et al. 2018; Miclo et al. 2019) while adding nuance on how parameter choices shape these benefits.

The most consistent improvement associated with the DDMRP scenario was fill rate, as it was improved for

every SKU that did not already hit 100% in the control scenario. Fill rate improvements were notable given the already high target levels (99%) in the control scenario. The sample exhibited substantial demand variability (average $CV^2 \approx 0.97$), which contributed to the control scenario falling short at around 91% average fill rate. Dynamic buffering not only raised overall fill rates but also reduced the depth and duration of shortages: per-item backorders decreased by 76%, and maximum stock-out depth by 81%. This result demonstrates DDMRP's ability to manage the depth and duration of shortages more effectively than static methods. Sensitivity analysis highlights that ADU window responsiveness is the primary lever for service performance, while adjusting DLT has a moderate effect. Overall, the fill rates were improved in the DDMRP scenario, which aligns with previous studies suggesting that DDMRP often maintains or increases

fill rates (Azzamouri et al. 2021; Kortabarria et al. 2018; Thüerer, Fernandes, and Stevenson 2022).

The mixed results for number of orders suggests that DDMRP's effectiveness on order reduction depends on the specific application case. On average, DDMRP increased the number of replenishment orders compared to control scenario, reflecting its emphasis on smaller, more frequent replenishments to maintain adaptive buffers. While this pattern improves responsiveness and reduces inventory exposure, it also implies higher administrative effort and ordering costs. Sensitivity analysis highlights that order frequency under DDMRP is highly parameter-dependent, and managers can influence this trade-off by adjusting ADU horizons and lead time assumptions to balance responsiveness with administrative effort. Although some studies, e.g. Kortabarria et al. (2018), report optimisation of order sizes, this metric has been underemphasised in previous comparative DDMRP studies (Butturi et al. 2021). As lowering the number or required replenishment orders can reduce administrative effort and ordering costs, this finding invites further exploration.

ADU window is the dominant lever and governs the service–inventory–workload frontier. Compared to other tested factors, decision on used window length is also more managerial, as it is less tied to frameworks or operational realities. Shorter ADU windows adjust buffers more rapidly to current demand, providing more accurate protection and consolidating replenishments; longer windows smooth and lag demand signals, compressing buffers, increasing order cadence, and impairing service under volatile demand. DLT shows moderate effects consistent with buffer logic. In DDMRP, buffers scale with $ADU \times (\text{expected})DLT$; longer lead times inflate buffer targets, improving service and smoothing ordering at the expense of inventory. LTF acts as a policy dial similar to lead time, with moderate impact. Unlike physical lead time, LTF is purely managerial and can be tuned to balance service vs holding cost and buyer workload. Tuning VF had minimal effects within the tested range. Raising VF had especially minimal effect, due to the already high demand variability within the sample. This suggests that the system is relatively robust to moderate variability scaling compared to the ADU window and lead – time – driven levers.

These parameterisation effects are shaped by the hybrid ETO context of the case. The presence of project-specific kits and design-penetrating orders places greater emphasis on service reliability and responsiveness, making shorter ADU windows more suitable for capturing irregular demand signals. Buffer placement was influenced by the modular structure, with shared components

managed as MTS upstream and configured piping sections treated as ETO downstream. This separation justified strategic decoupling at the component level, while LTF and VF tuning reflected the need to balance service against workload in a setting where demand variability is already high and engineering lead time is embedded in the total lead time.

A key insight from the simulation is that DDMRP's impact varies across categories. Components with lumpy demand and short lead times (20 samples) experienced a 26% reduction in average on-hand inventory and a 7.9% improvement in fill rate, indicating that dynamic buffering effectively absorbs irregular spikes without inflating stock. Similarly, intermittent items with short lead times (12 samples) showed moderate inventory reduction (−6.1%), with more variation between individual samples, and a notable fill rate gain (+7.8%). In contrast, intermittent items with moderate lead times (only 2 samples) exhibited an increase in inventory (+12.3%) alongside the largest fill rate improvement (+15.8%), suggesting that buffer sizing under longer lead times can trade off inventory for service. The single erratic item showed the most dramatic inventory decrease (−30.4%) with a 10.6% fill rate gain, though the small sample limits generalisation. These patterns underscore that DDMRP's benefits are not uniform: they depend on the interplay between demand variability and lead time exposure. This finding is relevant for environments, where demand profiles and lead times differ across components. It suggests that selective adoption of buffer policies may yield greater efficiency than blind implementation.

These insights also validate the study's decision to simplify the SKU portfolio through postponement by aggregating parts based on shared physical attributes. Even though the demand classification revealed that demand is overall highly volatile in this case even with aggregation, this allowed for greater visibility into demand behaviour at the component level, improving the applicability of DDMRP while reducing the complexity associated with managing a vast portfolio with great variation of demand across the items. Furthermore, representatives from the manufacturing company confirmed that this grouping reflects how the demand behaves from their supplier's perspective, which aligns with literature on the subject (Aviv and Federgruen 2001; Casado et al. 2020; Gosling and Naim 2009). This practical validation suggests the aggregation is not just a modelling simplification but a realistic way of viewing the upstream node. Nevertheless, the assumptions underlying this aggregation, such as using average lengths for variable-sized components, represent a trade-off between model simplicity and granularity.

Overall, the findings suggest that implementing DDMRP at supplier level can deliver notable benefits in modular ETO supply chains, particularly when paired with postponement strategies that consolidate demand. However, these benefits are not unconditional. Performance can depend strongly on demand profile and parameterisation choices, as shown by sensitivity analysis: factors such as ADU window length and lead time assumptions shape outcomes for inventory, service, and order frequency. Furthermore, relaxing some assumptions could alter outcomes: variable lead times might necessitate overestimation of DLT in buffering, increasing buffer sizes, while capacity constraints could reduce the effectiveness of dynamic buffering and affect replenishment timing. Findings reinforce that DDMRP is not a universal solution but a context-sensitive approach requiring careful calibration and selective application. These insights contribute to practical decision-making for managers seeking resilience under uncertainty and advance theoretical understanding of adaptive buffering in complex supply networks.

5.2. Theoretical contribution

This study derives generalised insights from simulation results and links them to established theoretical frameworks. Rather than viewing DDMRP solely as an operational technique, its mechanisms – adaptive buffering, temporal signal smoothing, and demand-driven planning – are conceptualised as dynamic control principles that contribute to resilience theory, control theory, contingency theory, and fit theory in operations management. Table 6 summarises these contributions by connecting empirical findings to underlying theoretical mechanisms, offering a foundation for future research on adaptive inventory systems under uncertainty.

Methodologically, this study contributes by adapting the demand categorisation framework of Syntetos, Boylan, and Croston (2005) from its original use in forecasting to the evaluation of planning methods. Linking demand categories and DDMRP performance allows the framework to be used as an analytical lens. This adaptation provides a structured way to assess how SKU-level demand characteristics influence the outcome. In doing so, the study demonstrates how demand categorisation can be extended beyond forecasting to guide the evaluation and application of inventory control policies.

5.3. Managerial implications

This study offers several actionable insights for managers considering DDMRP application, while operating in environments with high product variety and demand

variability. First, the results indicate that integrating DDMRP into decoupled modular supply chains can simultaneously improve inventory efficiency and service levels, particularly for SKUs with intermittent or lumpy demand and short lead times. Managers should anticipate a modest increase in order frequency as a trade-off for reduced inventory and improved responsiveness.

Second, the findings underscore the importance of demand profiling as a foundation for planning method selection. Blind application of DDMRP may lead to inefficiencies. Leveraging demand categorisation frameworks, such as proposed by Syntetos, Boylan, and Croston (2005), enables firms to tailor replenishment strategies to SKU-specific characteristics. This approach supports hybrid planning models and cautions against one-size-fits-all solutions, emphasising the need for investment in demand analytics.

Third, when implementing DDMRP, managers should prioritise tuning the ADU window and DLT parameters over lead time or variability factors. The ADU window strongly influences the responsiveness–efficiency trade-off: in volatile conditions, shorter windows improve service but raise inventory, while longer windows may reduce inventory at the cost of stockouts when demand spikes occur. Sensitivity analysis suggests that over-optimizing LTF and VF yields diminishing returns, making ADU window calibration the most impactful adjustment.

Fourth, the study provides practical guidance for parameter estimation under uncertainty. Slightly conservative estimates for DLT, LTF, and VF are safer, as underestimating these parameters can add noise in replenishment and cause service disruptions.

Finally, the results reinforce the value of simulation-based decision support tools for inventory policy design. Simulations allow organisations to test DDMRP configurations under realistic demand conditions, compare performance against traditional methods, and anticipate trade-offs before full-scale implementation. This capability reduces the risk of costly misalignment and supports more resilient planning decisions in volatile environments.

6. Conclusion

The research aimed to address the question: How does integrating DDMRP at supplier level impact the efficiency and resilience of inventory management in ETO supply chains? The results indicate that integrating DDMRP at supplier level in a two-echelon modular ETO supply chain can improve inventory management efficiency and resilience, particularly by reducing excess inventory and improving fill rates. Weighted

Table 6. Generalisations from the empirical study.

#	Implication	Empirical basis in the study	Underlying mechanism
1	Adaptive buffering enables both lower average stock levels and resilience to stochastic demand fluctuations.	The simulation showed DDMRP reduced on-hand inventory by c. 20%, while improving fill rates by c. 8pp, and cutting backorders by 76%. Sensitivity tests confirmed robustness across parameter variations.	Demonstrates that resilience can be achieved through adaptive response rather than static redundancy alone: dynamic buffer recalibration absorbs volatility without raising inventory costs. This extends resilience theory by quantifying adaptability as a dynamic state variable in inventory management.
2	Temporal demand signal smoothing governs the responsiveness – efficiency frontier.	The ADU window parameter had the strongest effect: shorter windows improved service but raised inventory, while longer windows lowered inventory but increased stockouts when demand spikes occurred.	Identifies signal averaging horizon as a key parameter affecting the balance between responsiveness and efficiency. This creates a theoretical bridge between DDMRP parameterisation and control theory principles of signal filtering, providing a conceptual framework for understanding how inventory systems can adapt dynamically through controlled signal processing.
3	Demand-driven planning is effective for intermittent and lumpy demand profiles, particularly when lead times are short.	Categorised simulation data showed most consistent performance gains for SKUs with intermittent or lumpy demand and short lead times. Other demand profiles exhibited mixed outcomes, while having limited sample size.	Refines the applicability of demand-driven control by linking its effectiveness to demand characteristics. Rather than positioning DDMRP as a universal solution, this contribution supports selective use, suggesting that demand-driven methods are especially suitable for environments with high uncertainty in demand timing, or both timing and quantity. This adds nuance to contingency and fit theories in operations management.

average on-hand inventory was reduced by 21.4%, fill rates improved by 7.5 percentage points, and backorders decreased by 76%, although order frequency increased slightly by 1.5%. These results align with previous literature that highlights the advantages of DDMRP in volatile demand environments (Damand, Lahrichi, and Barth 2023; Kortabarria et al. 2018; Miclo et al. 2019; Thüerer, Fernandes, and Stevenson 2022). The findings also suggest that DDMRP is particularly beneficial for items with intermittent or lumpy demand profiles and short lead times, while its effectiveness varies across demand profiles, reinforcing the need for selective adoption and careful parameter tuning. Sensitivity analysis identified the ADU window as the primary lever for balancing service and inventory, with lead time assumptions also exerting moderate influence.

The study assumed deterministic lead times, unlimited capacity, and continuous review, which simplifies real-world dynamics but enables controlled comparison of planning methods. The SKU set lacked smooth demand profiles, restricting generalizability to stable contexts. Sensitivity analysis was one-factor-at-a-time, meaning parameter interactions were not captured. Confidence intervals were also not reported; future work should include stochastic replications and design-of-experiments approaches to quantify uncertainty. Future research should evaluate DDMRP under lead time uncertainty, capacity constraints, and inter-SKU demand

correlation, as well as optimise parameter settings for cost, service, and space utilisation. Expanding the analysis across multiple industries and product categories would help generalise the findings and uncover potential boundary conditions for the effectiveness of DDMRP. Additionally, the role of supplier collaboration and information-sharing mechanisms could be further emphasised in future studies assessing the effectiveness of DDMRP implementation. Overall, this research contributes empirical evidence and practical guidance for managers seeking inventory efficiency and resilience under uncertainty, while advancing theoretical understanding of adaptive buffering in complex supply networks.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors



Oskari Huttunen is a doctoral researcher at the University of Vaasa, where he received his MSc (Econ) in Industrial Management in 2023, and has actively contributed to multiple research projects. His work focuses on simulation-based analysis of supply chain and production system resilience and efficiency. He studies how demand driven inventory planning, demand variability,

and production disruptions influence performance in complex manufacturing environments, using data-driven methods and discrete-event simulation to evaluate and design resilient systems. His broader interests include supply chain resilience analytics, simulation, data-driven planning, and the design of resilient production and supply networks.



Petri Helo is a full professor of Industrial Management (logistics systems) with the department of technology and innovations at the University of Vaasa. His research primarily focuses on supply chain management, operations management, logistics systems, and the digitalisation of industrial processes, addressing the management of logistics processes in supply demand networks, which take place in various industries. This research has developed new approaches on analytical modelling and use of computers solving the industrial management problems. He has authored and co-authored several articles in peer-reviewed scientific journals, several research reports, conference contributions and other scientific publications.

Data availability statement

The participants of this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research supporting data is not available.

ORCID

Oskari Huttunen  <http://orcid.org/0009-0006-2799-799X>

Petri Helo  <http://orcid.org/0000-0002-0501-2727>

References

- Aviv, Y., and A. Federgruen. 2001. "Capacitated Multi-item Inventory Systems with Random and Seasonally Fluctuating Demands: Implications for Postponement Strategies." *Management Science* 47 (4): 512–531. <https://doi.org/10.1287/mnsc.47.4.512.9829>.
- Azzamouri, A., P. Baptiste, G. Dessevre, and R. Pellerin. 2021. "Demand Driven Material Requirements Planning (DDMRP): A Systematic Review and Classification." *Journal of Industrial Engineering and Management* 14 (3): 439. <https://doi.org/10.3926/jiem.3331>.
- Azzamouri, A., P. Baptiste, R. Pellerin, and G. Dessevre. 2023. "Impact of the Continuous and Periodic Assessment of a Buffer Replenishment on the DDMRP Method." *International Journal of Production Research* 61 (16): 5637–5658. <https://doi.org/10.1080/00207543.2022.2109219>.
- Bagchi, S. S., and J. Gaur. 2018. "Optimization of Postponement Process for a Two Stage Modular Manufacturer." *Journal of Global Operations and Strategic Sourcing* 11 (1): 39–54. <https://doi.org/10.1108/JGOSS-03-2017-0009>.
- Boylan, J. E., and A. A. Syntetos. 2010. "Spare Parts Management: A Review of Forecasting Research and Extensions." *IMA Journal of Management Mathematics* 21 (3): 227–237. <https://doi.org/10.1093/imaman/dpp016>.
- Butturi, M., G. D. Rosa, E. Balugani, and R. Gamberini. 2021. "Understanding the Demand Driven Material Requirements Planning Scope of Application: A Critical Literature Review." Proceedings of the 32nd international DAAAM symposium 2021. <https://doi.org/10.2507/32nd.daaam.proceedings.067>.
- Calleja, G., Albert Corominas, Carme Martínez-Costa, and R. de la Torre. 2018. "Methodological Approaches to Supply Chain Design." *International Journal of Production Research* 56 (13): 4467–4489. <https://doi.org/10.1080/00207543.2017.1412526>.
- Casado, S., M. Laguna, J. Pacheco, and J. C. Puche. 2020. "Grouping Products for the Optimization of Production Processes: A Case in the Steel Manufacturing Industry." *European Journal of Operational Research* 286 (1): 190–202. <https://doi.org/10.1016/j.ejor.2020.03.010>.
- Damand, D., Y. Lahrichi, and M. Barth. 2023. "Parameterisation of Demand-Driven Material Requirements Planning: A Multi-objective Genetic Algorithm." *International Journal of Production Research* 61 (15): 5134–5155. <https://doi.org/10.1080/00207543.2022.2098074>.
- DDI. 2025. *Demand Driven Material Requirements Planning (DDMRP)*. DDI. <https://www.demanddriveninstitute.com/ddmrp>.
- Dessevre, G., Jacques Lamothe, Robert Pellerin, Maha Ben Ali, Pierre Baptiste, and V. Pomponne. 2023. "Comparison of Pull Management Policies for a Divergent Process with DDMRP Buffers: An Industrial Case Study." *International Journal of Production Research* 61 (23): 8022–8042. <https://doi.org/10.1080/00207543.2022.2162997>.
- García-Dastugue, S. J., and D. M. Lambert. 2007. "Interorganizational Time-Based Postponement in the Supply Chain." *Journal of Business Logistics* 28 (1): 57–81. <https://doi.org/10.1002/j.2158-1592.2007.tb00232.x>.
- Goldratt, E. M. (with Internet Archive). 1997. *Critical Chain*. Great Barrington, MA: North River Press. <http://archive.org/details/criticalchain0000gold>.
- Gosling, J., and M. Naim. 2009. "Engineer-to-order Supply Chain Management: A Literature Review and Research Agenda." *International Journal of Production Economics* 122:741–754. <https://doi.org/10.1016/j.ijpe.2009.07.002>.
- Graman, G. A. 2010. "A Partial-Postponement Decision Cost Model." *European Journal of Operational Research* 201 (1): 34–44. <https://doi.org/10.1016/j.ejor.2009.03.001>.
- Jalilibal, Z., A. Amiri, P. Castagliola, and M. Khoo. 2021. "Monitoring the Coefficient of Variation: A Literature Review." *Computers & Industrial Engineering* 161: 107600. <https://doi.org/10.1016/J.CIE.2021.107600>.
- Kortabarria, A., U. Apaolaza, A. Lizarralde, and I. Amorrtu. 2018. "Material Management without Forecasting: From MRP to Demand Driven MRP." *Journal of Industrial Engineering and Management* 11 (4): 632. <https://doi.org/10.3926/jiem.2654>.
- Li, J., Y. Chen, Y. Liao, V. Shi, and H. Zhang. 2025. "Managing Strategic Inventories in a Three-Echelon Supply Chain of Durable Goods." *Omega* 131:103204. <https://doi.org/10.1016/j.omega.2024.103204>.
- Lücker, F., A. Timonina-Farkas, and R. W. Seifert. 2025. "Balancing Resilience and Efficiency: A Literature Review on Overcoming Supply Chain Disruptions." *Production and Operations Management* 34(6): 1495–1511. <https://doi.org/10.1177/10591478241302735>.
- Miclo, R., M. Lauras, F. Fontanili, J. Lamothe, and S. A. Melnyk. 2019. "Demand Driven MRP: Assessment of a New Approach to Materials Management." *International Journal*

- of *Production Research* 57 (1): 166–181. <https://doi.org/10.1080/00207543.2018.1464230>.
- Ohta, H., R. Ikeno, and M. A. Rahim. 2009. “Utility of the Inventory Information Sharing in a Supply Chain.” *International Journal of Integrated Supply Management* 5 (2): 173. <https://doi.org/10.1504/IJISM.2009.029360>.
- Olhager, J. 2010. “The Role of the Customer Order Decoupling Point in Production and Supply Chain Management.” *Computers in Industry* 61:863–868. <https://doi.org/10.1016/j.compind.2010.07.011>.
- Ptak, C., and C. Smith. 2011. *Orlicky’s Material Requirements Planning*. 3rd ed. Columbus, Ohio: McGraw-Hill Education. <https://www.accessengineeringlibrary.com/content/book/9780071755634>.
- Ptak, C., and C. Smith. 2016. *Demand Driven Material Requirements Planning*. 1st ed. South Norwalk, Connecticut: Industrial Press, Inc.
- Ram, B., M. R. Naghshineh-Pour, and X. Yu. 2006. “Material Requirements Planning with Flexible Bills-of-Material.” *International Journal of Production Research* 44 (2): 399–415. <https://doi.org/10.1080/00207540500251505>.
- Rota, K., C. Thierry, and G. Bel. 2002. “Supply Chain Management: A Supplier Perspective.” *Production Planning & Control* 13 (4): 370–380. <https://doi.org/10.1080/09537280210130469>.
- Saghiri, S. S., and S. J. Barnes. 2016. “Supplier Flexibility and Postponement Implementation: An Empirical Analysis.” *International Journal of Production Economics* 173:170–183. <https://doi.org/10.1016/j.ijpe.2015.12.015>.
- Sbai, N., and A. Berrado. 2018. “A Literature Review on Multi-echelon Inventory Management: The Case of Pharmaceutical Supply Chain.” *Matec web of conferences* 200: 00013. <https://doi.org/10.1051/MATECCONF/201820000013>.
- Schmitt, T. G., S. Kumar, K. Stecke, F. Glover, and M. Ehlen. 2017. “Mitigating Disruptions in a Multi-echelon Supply Chain Using Adaptive Ordering.” *Omega* 68:185–198. <https://doi.org/10.1016/J.OMEGA.2016.07.004>.
- Smith, D. 1999. *The Measurement Nightmare: How the Theory of Constraints Can Resolve Conflicting Strategies, Policies, and Measures*. Boca Raton, FL: CRC Press.
- Syntetos, A. A., J. E. Boylan, and J. D. Croston. 2005. “On the Categorization of Demand Patterns.” *Journal of the Operational Research Society* 56 (5): 495–503. <https://doi.org/10.1057/palgrave.jors.2601841>.
- Thieuleux, E. 2025. *6 Best Safety Stock Formulas On Excel | Abc-SupplyChain*, April 7. <https://abcsupplychain.com/safety-stock-formula-calculation/>.
- Thürer, M., N. O. Fernandes, and M. Stevenson. 2022. “Production Planning and Control in Multi-stage Assembly Systems: An Assessment of Kanban, MRP, OPT (DBR) and DDMRP by Simulation.” *International Journal of Production Research* 60 (3): 1036–1050. <https://doi.org/10.1080/00207543.2020.1849847>.
- Umble, M. M. 1992. “Analyzing Manufacturing Problems Using V-A-t Analysis.” *Production and Inventory Management Journal* 33 (2): 55.
- Uzun Araz, O., M. A. Ilgin, O. Eski, and C. Araz. 2024. “Fuzzy Demand-Driven Material Requirements Planning: A Comprehensive Analysis of Fuzzy Logic Implementation in DDMRP.” *International Journal of Production Research* 62: 7793–7811. <https://doi.org/10.1080/00207543.2024.2328770>.
- Van Hoek, R. I. 2001. “The Rediscovery of Postponement a Literature Review and Directions for Research.” *Journal of Operations Management* 19:161–184. [https://doi.org/10.1016/S0272-6963\(00\)00057-7](https://doi.org/10.1016/S0272-6963(00)00057-7).
- van Jaarsveld, W., and A. Scheller-Wolf. 2015. “Optimization of Industrial-Scale Assemble-to-Order Systems.” *INFORMS Journal on Computing* 27 (3): 544–560. <https://doi.org/10.1287/ijoc.2015.0641>.
- Vanteddu, G., and R. B. Chinnam. 2014. “Supply Chain Focus Dependent Sensitivity of the Point of Product Differentiation.” *International Journal of Production Research*. 52 (17): 4984–5001. <https://doi.org/10.1080/00207543.2014.886026>
- Vicente, J. J., Susana Relvas, and Ana Paula Barbosa Póvoa. 2020. “Supply Chain Management under Product Demand and Lead Time Uncertainty.” *International Journal of Operational Research* 37 (4): 453–478. <https://doi.org/10.1504/IJOR.2020.105763>.
- Wang, Q. 2011. “Control Policies for Multi-echelon Inventory Systems with Stochastic Demand.” In *Supply Chain Coordination under Uncertainty. International Handbooks on Information Systems*, edited by T. M. Choi and T. Cheng, 83–108. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-19257-9_4.
- Yang, B., and N. Burns. 2003. “Implications of Postponement for the Supply Chain.” *International Journal of Production Research* 41 (9): 2075–2090. <https://doi.org/10.1080/00207544031000077284>.
- Zhao, Y., and D. Simchi-Levi. 2006. “Performance Analysis and Evaluation of Assemble-to-Order Systems with Stochastic Sequential Lead Times.” *Operations Research* 54 (4): 706–724. <https://doi.org/10.1287/opre.1060.0302>.
- Zinn, W. 1990. “Developing Heuristics to Estimate the Impact of Postponement on Safety Stock.” *The International Journal of Logistics Management* 1 (2): 11–16. <https://doi.org/10.1108/09574099010804554>.