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Systematic Review of DDMRP Parameterization: From Planner Judgment to Static and Dynamic Optimization

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Abstract

Demand-Driven Material Requirements Planning (DDMRP) is a hybrid push–pull strategy aimed at buffering variability and enhancing flow. The performance of DDMRP is determined by two interrelated choices: (i) the parameterization of buffer zones (e.g., variability and lead-time factors, MOQ, thresholds); and (ii) the strategic positioning of decoupling points. Traditionally, planners relied on their judgment instead of systematic approaches. This led to a divergence between theoretical potential and achievement. This paper presents a systematic review of the publication period from 2020 to 2025 within the context of transforming DDMRP via heuristics into optimization-based formulations. Two principal streams emerge. The parameter optimization models ranging from linear mixed integer programming to multi objective metaheuristics and fuzzy/statistical based designs consistently offer improvements over heuristics in reducing inventories and shortages while increasing service levels. The buffer positioning models focus on MILP/MINLP, graph-theoretic explorations, and hybrid heuristics to formalize decoupling decisions; this stream is less evolved and is typically not coupled with parameter tuning, with few studies addressing their integration, creating the largest gap. The findings from the review point to three principal conclusions: (1) optimization consistently outperforms heuristics; (2) achieving ideal service targets (100% on-time delivery) requires exponentially high inventories or capacities; and (3) parameter optimization appears to be more advanced than buffer positioning, which remains discrete and deterministic. We conclude with a future research agenda focused on the unifying and dynamic co-optimization of buffer positioning and parameters, considering uncertainty and capacity constraints. Thus, linking the models through a rolling horizon and adaptive methodology would be necessary to advance DDMRP from heuristics to optimization science.

Keywords
Demand Driven MRP, DDMRP, Decoupling Points, Customer Order Decoupling Point, Inventory buffer

1. Introduction
Worldwide, the rise of volatility, uncertainty, complexity, and ambiguity (VUCA) across various industries is changing market competitiveness and redefining the responsiveness of global supply chains (Bennett & Lemoine, 2014). In 1965, Material Requirements Planning (MRP) was first introduced by Joseph Orlicky (Ptak & Smith, 2016). MRP was originally designed as a push forecasting system in which operational stages are tightly linked to their predecessors. However, the inaccuracy of forecasts, coupled with constrained capacity, often tends to push variability upstream. That would translate bimodal changes in inventory into what is known as the bullwhip effect which in turn spawns excess inventory or stock out scenarios (Younespour et al., 2024; Ptak & Smith, 2016).

To overcome these constraints, a number of alternative methodologies have been suggested, such as lean pull systems, Kanban, and the Theory of Constraints (Azzamouri et al., 2021; Kortabarria et al., 2018). These strategies are mainly based on actual demand cues to effect replenishment and hence lessen but not eradicate reliance on forecasts. Although they have helped in increased stability in particular circumstances, they are not very reliable in unstable situations (Bennett & Lemoine, 2014). On that note, in 2011, co-founders of the Demand Driven Institute (DDI) Carol Ptak and Chad Smith unveiled what they termed Demand Driven Material Requirements Planning (DDMRP) in an attempt to eliminate dependency chains through integrating the visibility of Material Requirements Planning (MRP) with the responsiveness of pull systems (Demand Driven Institute, 2025). Nowadays, DDMRP is implemented in various industries.

In other sectors, including FMCG, textiles and apparel, automotive, and pharmaceutical products, industrial manufacturing, electronics and more, case applications and successes were reported by (Miclo et al., 2018). The Demand Driven Institute (DDI) (ddi cases) handled such cases. A number of reports have highlighted substantial inventory reductions (25–54%), As many as 75 % of lead-time savings and over 99 % of service level improvements have been reported (Miclo et al., n.d.; Demand Driven Institute, n.d.). On the other hand, these benefits have enhanced the effects of DDMRP on the upstream and downstream activities. DDMRP is supported by five fundamental components and is organized in such a way under *Position* –Protect–Pull logic (Figure 1) (Kortabarria et al., 2018; Martin et al., 2023).

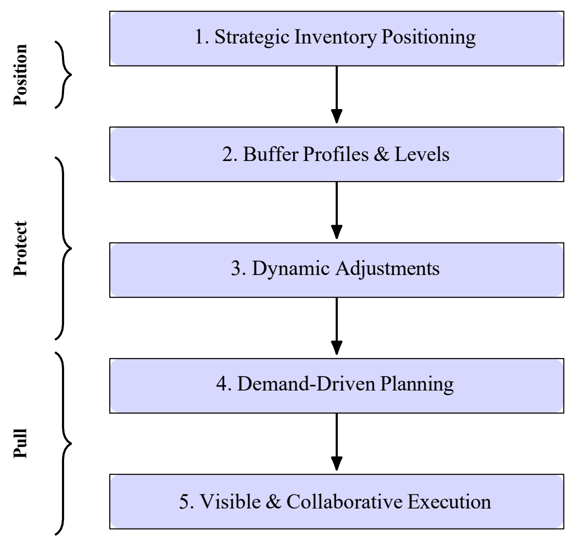

Figure 1: The five integrated components of Demand Driven MRP (Ptak & Smith, 2016).

The methodology is structured in the Position Protect Pull framework. The transition between the methodology of strategic decoupling (Position), buffer protection and dynamic adjustment (Protect) into flow-based execution (Pull) is demonstrated in the diagram.This mapping shows the conceptual framework, which links the different levels of operational decision-making in Dynamic
Demand-Driven Material Requirements Planning (DDMRP). . Mapping used here is canonical: (1) → Position; (2–3) → Protect; (4–5) → Pull.

Figure 1 Shows how the main principle of DDMRP works, i.e. the correlation between the speed and regularity of information and material movement and the performance of the supply chain is directly correlated with it. DDMRP is concerned with the five critical settings. In particular, *strategic inventory positioning* the analysis identifies the best locations where decoupling points can be located to help deal with variations and perturbation in the supply chain. In addition, *visible and collaborative execution* It also makes sure that open orders are prioritized and synchronized on the network. The parameters make up the set up of the Demand Driven Material Requirements Planning (DDMRP) (Benavente et al., 2023; Kortabarria et al., 2018; Martin et al., 2023).

In the past, DDMRP has had several heuristics in determining the decoupling points using qualitative information about customer tolerance time and market lead times. The location of dynamic buffers is determined by these decoupling points and these are divided into three segments of buffers which are Red, Yellow and Green whose sizes are defined by five general parameters namely: average daily use (ADU), decoupled lead time (DLT), variability factor (VF), lead time factor (LTF) and minimum order quantity (MOQ). The original DDMRP methodology is to have the Yellow Buffer segment cover the expected amount of material consumed during the decoupled lead time ($Y = ADU \times DLT$), the Red Buffer segment provide variability protection based on the product of lead time and demand variability factors ($R = ADU \times DLT \times LTF + ADU \times DLT \times LTF \times VF$), and the Green Buffer segment govern the frequency of orders and batch size requirements ($GZ = \max(ADU \times DLT \times LTF,\ ADU \times DOC,\ MOQ)$).

Practically speaking, the Demand Driven Institute (DDI) training documentation describes these segments through a set of indicative interval ranges — for example, the Yellow Segment could be roughly 0.5-1.5 times (ADU DLT), and the Red Segment could be roughly 0.2-1.0 times (ADU DLT), depending on the organization's selected profile settings (Low, Medium, or High). In opposition to this utilitarian use of the interval ranges, the formal DDMRP methodology does not specify definite numeric values of those ranges, but rather outlines these segments by using LTF and VF as parameters, thus enabling the companies to outline their specific ranges within their own, calibrated profiles. Figure 2 illustrates this standard three-zone configuration.

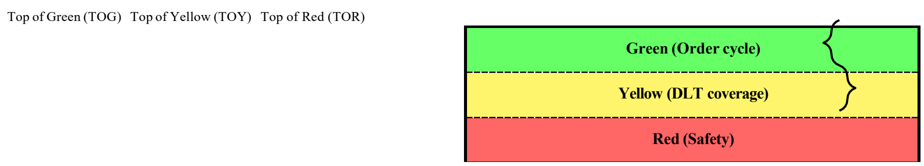

Figure 2: Schematic of the DDMRP buffer zones (adapted from Ptak & Smith, 2016).

The three-color model illustrates the logic behind stock protection: Red Zone is the safety stock which is aimed at addressing variability, the Yellow Zone is the usage within the decoupled lead time (DLT), and the Green Zone is the replenishment cycles. When the Net Flow Position (NFP) drops to the top of Yellow Zone (TOY) and resumes inventory to the top of Green Zone (TOG), then the replenishment process is activated. The three-color model depicts the rationale of the stock protection: the Red Zone is the inventory in the presence of variability, the Yellow Zone is the intake that can be anticipated during the decoupled lead time (DLT) and the Green Zone is the replenishment cycles. The replenishment process is stimulated when Net Flow Position (NFP) decreases to the top of Yellow (TOY) and replenishes inventory up to the top of Green (TOG).

The core metric for evaluating buffer status is the Net Flow Position (NFP), expressed in Equation 1:

$$\text{NFP}(t) = \text{On-hand}(t) + \text{On-order}(t) - \text{Qualified Demand}(t) \tag{1}$$

where:

- On-hand(t) is the physical inventory available at time t,
- On-order(t) represents firm supply orders pending receipt, and
- Qualified Demand(t) refers to confirmed and qualified demand within the decoupled lead time horizon (DLT).

The generation of a replenishment order occurs whenever NFP(t) when the inventory is lower than the Top of yellow (TOY), the replenishment quantity is enough to raise the inventory up to the Top of Green (TOG). In this regard, the dynamic, feedback-based replenishment decision process utilizes the daily demand information in determining the best time in which to replenish an inventory buffer, as illustrated in Figure 2.

According to (Ptak & Smith, 2016), the heuristic definition of the settings was made to maintain flexibility. Such subjectivity has frequently led to the inability to match theoretical models and real-life findings thus supporting the need of more systematic methodological solutions. As a result, researchers have made more and more attempts to parameterize DDMRP (not just parameterization by the size of buffers) by using mathematical optimization models to set the decoupling point positioning and adjustment rules.

2. Methodology

The research paper presents a systematic review of the recent research on the optimization of the Demand-Driven Material Requirements Planning (DDMRP) with a focus on buffer parameters and decoupling position. The multi-stage, structured approach was used in the analysis to cover and make results reproducible.

2.1 Data Sources and Search Strategy

Publications were collected from major scholarly databases (**Web of Science**, **Scopus**, and **Google Scholar**), complemented by AI-assisted platforms (**Connected Papers**, **Consensus**, and **Research Rabbit**) to extend citation-based discovery. Searches were restricted to the years **2020–2025** and limited to full-text, English-language studies. Earlier publications (prior to 2020) were reviewed only to provide historical context and to establish a foundational introduction; they were not included in the core body of the systematic literature analysis.
Core keywords were derived from the DDMRP body of knowledge and combined using Boolean logic, including: *"Demand Driven MRP" OR "DDMRP" OR "Demand Driven Material Requirements Planning" OR "Customer Order Decoupling Point" OR "Inventory Buffer" OR "Buffer Zones" OR "Decoupling Points"*, paired with optimization-related terms such as *"Optimization," "Mathematical Model," "Metaheuristic," "Static,"* and *"Dynamic."*

2.2 Screening and Selection

The initial search retrieved 5,180 records. Applying the *Science Citation Index Expanded (SCIE)* filter excluded 1,510 publications, leaving 3,670 records for screening. The addition of the *Supply Chain & Logistics* This number was further narrowed down to 867 by the topical filter. The limitation of the timeframes to 2020–2025 provided 208 studies. A final dataset of 43 studies was then obtained by evaluating titles, abstracts and where appropriate full texts in terms of relevance to DDMRP optimization. Based on them, 17 papers were chosen to be analyzed in detail: within these are five foundational and historical papers, seven papers that deal with parameter optimisation, and five articles that deal with the issue of buffer positioning(Figure 3).

2.3 Inclusion and Exclusion Criteria

Inclusion: Peer-reviewed journal articles, conference proceedings and doctoral dissertations in which a clear strategy of optimization methodologies was used in parameterization of DDMRP. **Exclusion:** Editorials, Case studies that solely focus on implementation and those that focus on generic MRP or lean systems that are not explicitly integrated with DDMRP.

2.4 Classification Framework

The 17 included studies were classified into three categories:
Foundational papers ($n = 5$): retained for context, not part of the systematic dataset.
Parameterization of buffers ($n = 7$): studies focusing on the optimization of buffer sizing and adjustment parameters through deterministic, stochastic, or metaheuristic approaches.
Buffer positioning and decoupling points ($n = 5$): studies addressing the strategic placement of decoupling points and inventory buffers to absorb variability and improve flow across supply chains.

2.5 Analysis

Every research was reviewed in the following dimensions: (1) the research question, goals, and variables of optimization; (2) quantitative results; (3) optimization tools and methodologies used; (4) reported limitations; and (5) the amount of novelty and contributions.
The use of these five categories helped to provide an overall assessment in terms of both quantity (breadth) and quality (depth) of the studies which were evaluated in order to synthesize methodological trends, as well as the trade offs between the results of optimization studies and the challenges that remain unsolved.

2.6 Study Quality and Risk of Bias

The methodological quality and the potential for bias within the compiled body of evidence from each of the studies incorporated into the synthesis were assessed using a framework developed by PRISMA 2020, which provides guidance for conducting critical appraisals. The assessment was based on four factors: (1) Clarity of objectives and formulation of the model; (2) Transparency regarding the data, assumptions, and/or constraints used within the model; (3) Validation and/or sensitivity testing of the optimization model; and (4) Reproducibility of the results presented and completeness of reporting. Those studies that provided clear descriptions of their objective function(s), decision variable(s), and validation procedures were deemed high-quality; whereas those studies that reported only partially on their methodologies or validation were deemed moderate-quality. Two studies were identified as being of low-quality based on the incomplete nature of their data and/or lack of experimental validation. However, no studies were eliminated from the review based solely on quality issues; rather, the quality assessments influenced how the results of the reviewed studies were interpreted in Section 4. Therefore, the interpretation of the results of the studies reviewed accounted for the strengths and weaknesses of the overall body of evidence. Overall, the collective body of evidence demonstrated an extremely high level of methodological consistency; however, many of the studies are simulation-based and have not been tested within a live industrial setting.

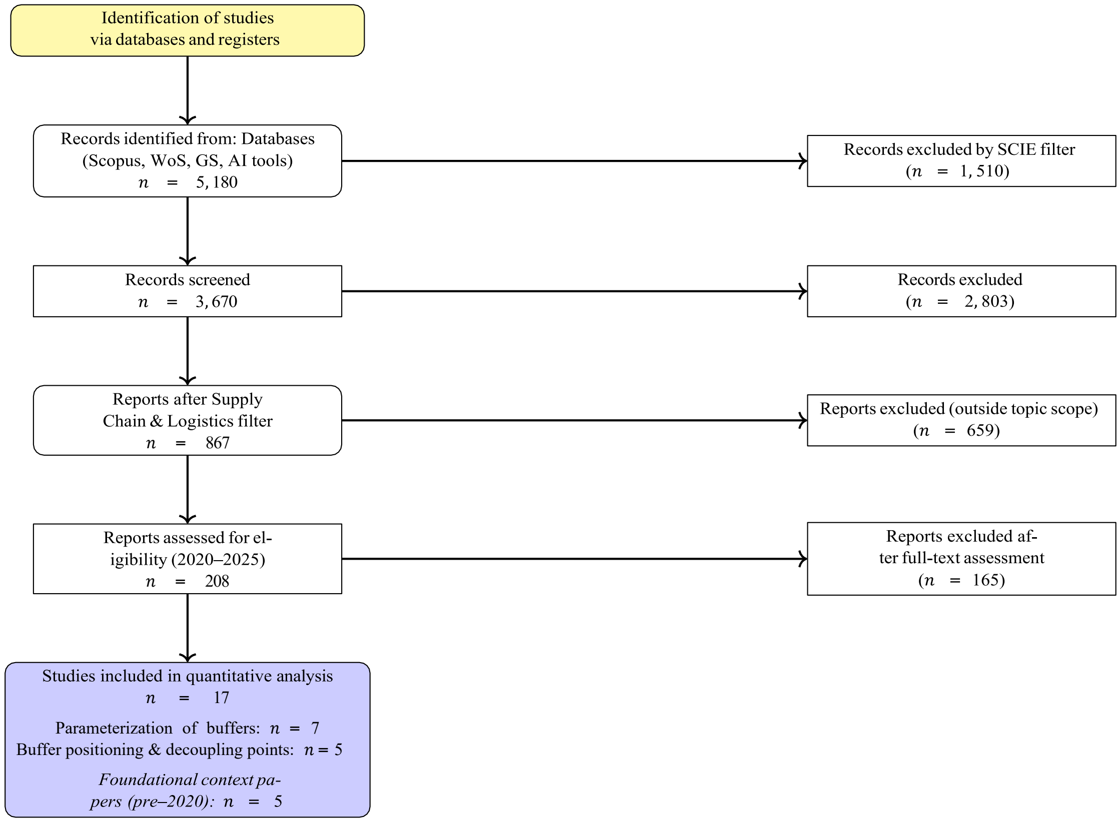

Figure 3: PRISMA 2020 flow diagram illustrating the sequential filtering process of identifying, screening and including literature in this review.

The diagram indicates that the 5,180 abstracts retrieved from Scopus, Web of Science, and Google Scholar were progressively reduced to a final data set of 17 key studies. For clarity and transparency, each level of exclusion was illustrated (abstract filtering using SCIE; filtering by topic; and full-text screening), as well as all levels of exclusion used to select studies within the last five years (2020-2025). All five foundation studies published before 2020 were identified separately to provide historical context.

3. Literature Review

This literature review examines studies published since 2020 that advance Demand-Driven Material Requirements Planning (DDMRP) from heuristic practice to a rigorous optimization discipline. Two primary research streams emerge:

Parameter Optimization — employing mixed-integer programming, metaheuristics, fuzzy logic, and statistical models to reduce inventory costs and stockouts while maintaining high service levels.

Buffer Positioning — using mixed-integer linear or nonlinear programming, graph theory, or hybrid heuristics to identify the optimal placement of inventory buffers within the supply chain.

Research Contributions These two streams mark a clear shift in DDMRP research. They replace traditional rule-of-thumb methods with systematic, model-driven approaches that improve cost efficiency, service reliability, and system robustness under real-world constraints.

The Original Qualitative Heuristic Process. Ptak & Smith (2016) outline a qualitative process for determining both the Variability Factor (VF) and the Lead Time Factor (LTF) through a three level classification system for each part (Low, Medium, High) based on the variability of demand and supply and decoupled lead time (DLT). Also, the placement of decoupling points was based on the variability of lead times. Consequently, the planner's subjective decision-making processes played a significant role in the placement of decoupling points. Researchers have stated that the subjectivity involved in this "intuitive" approach does not include objective procedures and, as such, can result in oversized buffers that increase costs, or insufficiently sized buffers that do not adequately protect against disruptions. This subjectivity has been identified as the key driver for moving toward the use of model based optimizations.

3.1 Parameter Optimization Models

The focal challenge of DDMRP is the setting of numerical parameters. Traditionally, it is guided according to interval ranges and managerial judgment for the key parameters, such as the Lead Time Factor (LTF), the Variability Factor (VF) (low, medium, and high), the spike threshold (T_{peak}), and the minimum order quantity (MOQ). Throughout this literature (Table 1), various optimization models are introduced based on varying objective functions, decision variables, and considerations of constraints, which aim to systematically determine parameter values while delivering better cost and service trade-offs.

Table 1: Comparison of DDMRP parameter optimization models published between 2020 and 2025.

Paper	**Problem (Objective + Decision Variables)**	**Key Quantitative Results**	**Approach/Tools**	**Methodological Theme**	**Novelty & Contribution**
(Lakrichi, et al., 2022)	Obj: Minimize inventory service-level constraints (100% OTD). DV: LTF, VF, peak threshold.	under 24 instances solved optimally within achieved an 8.1% average inventory reduction compared to GA heuristics	seconds; MILP solved with IBM ILOG CPLEX.	Mathematical Programming	First exact MILP benchmark for DDMRP parameterization.
(Damand et al., 2022)	Obj: Maximize OTD and minimize inventory. DV: Eight DDMRP parameters (e.g., LTF, VF, MOQ, ADU, spike horizon).	Identified 29 Pareto-efficient solutions for a detailed test instance, illustrating the trade-off between on-time delivery and average on-hand inventory.	NSGA-II metaheuristic + discrete-event simulation.	Metaheuristic Optimization	First comprehensive GA-based multi-objective parameterization establishing cost–service frontiers.
(Damand et al., 2025)	Obj: Extend (Damand et al., 2022) to a multi-product environment with finite capacity. DV: LTF, VF, T_{peak}	Found that achieving a 100% OTD (service level) required a minimum 30% capacity increase over the theoretical capacity.	Extended NSGA-II with capacity-constrained simulation.	Metaheuristic Optimization	First multi-product, finite-capacity parameterization model for DDMRP.
(Xu et al., 2023)	Obj: Optimize production planning and material control under resource constraints using DDMRP logic. DV: Inventory quantities and capacity allocation.	Improved supply reliability; reduced shortages; balanced utilization under four demand-volatility scenarios.	Grey Wolf Optimizer (Java).	Metaheuristic Optimization	First integration of DDMRP with a Grey Wolf Optimizer under explicit resource constraints.
(Younespour, et al., 2024)	Obj: Jointly minimize inventory cost and stockouts across strategic and operational levels. DV: Buffer positioning, LTF, VF.	The average inventory cost, stockout, and total cost are reduced by 21%, 68%, and 78% respectively.	Hybrid GA–PSO (MATLAB).	Hybrid Metaheuristic Optimization	First integration of strategic buffer placement with operational parameter tuning in one framework.
(Uzun Araz et al., 2024)	Obj: Dynamically adjust variability and lead-time factors under uncertainty. DV: VF, LTF (fuzzy).	utperformed baseline DDMRP by achieving superior outcomes in backorder rate and total cost. Demonstrated improvements in total cost by up to 10.9% and reduced backorder rates by up to 45.04% across experimental scenarios	Fuzzy-logic controller (triangular memberships).	Fuzzy Optimization Modeling	First fuzzy-logic-based DDMRP parameterization enabling adaptive tuning to variability.
(Kraic̆ovic̆ et al., 2024)	Obj: Replace subjective parameters (LTF, VF) with a statistical-analytical model to optimize buffer levels. DV: Buffer-zone sizes (red, yellow, green).	New statistical model increased service level (from 99.55% to 99.94%) and decreased average inventory by 8.9% compared to the standard DDMRP method.	Statistical analysis	simulation-based validation.	Analytical & Statistical & First data-driven buffer calibration (using classic inventory theory) to replace subjective DDMRP profile settings (LTF/VF).

Notes: Obj = Objective; DV = Decision Variables; OTD = On-Time Delivery; LTF = Lead-Time Factor; VF = Variability Factor; MOQ = Minimum Order Quantity; ADU = Average Daily Usage; MILP = Mixed-Integer Linear Programming; NSGA-II = Non-dominated Sorting Genetic Algorithm II; GWO = Grey Wolf Optimizer; GA = Genetic Algorithm; PSO = Particle Swarm Optimization.

Each study's objective, decision variables, quantitative results, tools, and contributions are summarized from the cited papers. While intuitive, such methods risk oversizing buffers and inflating costs or undersizing them and compromising service (Lahrichi et al., 2022). The optimization perspective treats these factors as a decision vector (Equation 2):

$$x = \{\text{LTF},\ \text{VF},\ T_{\text{peak}},\ \text{MOQ},\ \text{zone thresholds}, \ldots\}, \qquad x \in \mathbb{R}^n \tag{2}$$

Performance is assessed through expected inventory holding cost $C_{\text{inv}}(x)$, expected shortage cost $C_{\text{stockout}}(x)$, and a service measure such as on-time delivery (OTD) or fill rate ServiceLevel(x). In some formulations, production or resource limits are also included as capacity constraints β.
Three families of formulations dominate the literature. The first follows a constraint-driven form (Equation 3):

$$\min_x\ C_{\text{inv}}(x) \quad \text{s.t.} \quad \text{ServiceLevel}(x) \geq \alpha \tag{3}$$

Where inventory is minimized, subject to a minimum service requirement α. This was the structure adopted by (Lahrichi et al., 2022), who used a MILP to enforce 100% OTD while reducing inventory by 8.1% compared to GA heuristics.
The second family employs multi-objective optimization (Equation 4):

$$\min_x\ f_1(x) = C_{\text{inv}}(x) + C_{\text{stockout}}(x), \qquad \max_x\ f_2(x) = \text{OTD}(x) \tag{4}$$

explicitly balancing efficiency and reliability. (Damand et al., 2022) used NSGA-II on eight parameters and, in a detailed analysis of a single "worst-case" instance , generated 29 Pareto-efficient trade-offs. This analysis showed that 100% OTD required more than double the inventory of 86% OTD. (Xu et al., 2023) extended this idea by embedding capacity constraints into a Gray Wolf Optimizer, while (Younespour et al., 2024) coupled buffer placement with parameter tuning in a GA–PSO hybrid that cut the total cost by up to 78%. (Damand et al., 2025) further extended extended NSGA-II to a multi-product, finite-capacity setting, finding that achieving perfect 100% OTD required a minimum of 30% more capacity than the theoretical baseline.

The third family uses adaptive and AI-driven formulations (Equation 5):

$$x \sim \tilde{X}(\mu), \qquad \min\ \mathrm{E}[C_{\text{inv}}(x) + C_{\text{stockout}}(x)], \qquad \max\ \mathrm{E}[\text{ServiceLevel}(x)] \tag{5}$$

where decision variables are formulated as fuzzy or statistically driven values. (Uzun Araz et al., 2024) used triangular fuzzy sets for LTF and VF, varying parameters under uncertainty to minimize both backorders and costs. Likewise, (Krajcˇovicˇ et al., 2024)proposed a new statistical-analytical model to set buffer zones, replacing the subjective LTF and VF parameters. This new "optimisation" method improved service levels from 99.55% to 99.94% and reduced average inventory by 8.9% compared to the standard DDMRP settings.

All of these papers define a smooth transition between deterministic, mixed-integer linear programs (MILPs) that are used to determine the likelihood of feasibility, large-scale metaheuristics that trade-offs, and adaptive modeling schemes that accept uncertainty. Through these diverse structures, one structural concept is fixed, and that is the achievement of optimum levels of service. (OTD = 100%) This phenomenon absorbs skewed portions of inventory or capacity. At the same time, salient gaps are still unaddressed, with most models assuming deterministic demand and fixed lead times and only a few studies addressing the dynamic features of DDMRP, including spike honing and the use of simulation metrics as opposed to the results of industrial applications. As a result, parameter optimization model has a great potential *strategic and tactical tools for buffer loading*; however, their application in *real-time operational decision-making* represents an exciting avenue for future work. **Bridge to Findings:** Our conclusions about cost-service trade-offs (Finding 2), the surrogate role of the exact MILP instead of scalable metaheuristics (Finding 3), and the invariably high level of optimization over the heuristic methods are based on the literature on the parameter optimization.

3.2 Buffer Positioning Models

While parameter optimization focuses on tuning the numerical values within buffers, a complementary research stream addresses the *strategic placement of the buffers themselves*. Buffer positioning determines where along the bill of materials (BOM) or supply chain decoupling points should be established and, therefore, which stages are protected by stock and which rely on pull signals. In the original DDMRP guidelines (Ptak & Smith, 2016), buffer placement relied on qualitative criteria such as lead time variability, demand volatility, customer tolerance times, and managerial judgment.

Table 2: Comparison of buffer positioning and decoupling-point optimization models in DDMRP (2020–2025).

Paper	**Problem (Objective + Decision Variables)**	**Key Quantitative Re-sults**	**Approach/Tools**	**Methodological Theme**	**Novelty & Contribu-tion**
(Achergui et al., 2021)	Objective: Minimize inventory cost under service-time constraints. Decision variables: bi-nary buffer positions.	Efficiently solved BOM structures up to 160 parts after linearization; sig-nificant cost differences were observed across po-sitioning strategies.	INLP reformulated and linearized using IBM CPLEX.	Mathematical Pro-gramming	First INLP model for buffer positioning in hy-brid MTO/MTS systems.
(Haji Moham-mad et al., 2022)	Objective: Minimize holding costs in distri-bution networks. Deci-sion variables: buffer po-sitions, decoupled lead times, and mean inven-tory levels.	Holding cost reduced by 75% (from \$1331.8 to \$333.3); inventory re-duced by 67%.	MINLP implemented in GAMS/BARON.	Mathematical Pro-gramming	Pioneering optimization model for Demand-Driven Distribution Resource Planning (DDDRP).
(Jodlbauer et al., 2025)	Objective: Minimize to-tal inventory cost under service-level constraints. Decision variables: de-coupling point positions and reorder-point dimen-sioning.	Analytical results show that order variance in-creases with lot size and that upstream decou-pling (closer to suppli-ers) can reduce demand variability.	Graph-theoretic ana-lytical model.	Analytical & Statisti-cal	First analytical formula-tion of the decoupling-point setting problem.
(Habbadi et al., 2025)	Objective: Joint opti-mization of buffer po-sitioning and production control. Decision vari-ables: buffer location and replenishment pol-icy.	Improved service and in-ventory trade-offs across three experimental sce-narios.	GA + MIP hybrid model.	Metaheuristic & Hy-brid Optimization	First GA–MIP hybrid ap-proach for positioning and production control in an Industry 4.0 context.
(Younespour et al., 2024)	Objective: Joint strate-gic and operational opti-mization. Decision vari-ables: buffer placement, LTF, and VF.	Average inventory cost, stockout, and total cost were reduced by 21%, 68%, and 78%, respec-tively.	Hybrid GA–PSO (MATLAB).	Metaheuristic & Hy-brid Metaheuristic Optimization	Bridges strategic buffer positioning with opera-tional parameter tuning within a single optimiza-tion framework.

Notes: BOM = Bill of Materials; INLP = Integer Non-Linear Programming; MINLP = Mixed-Integer Non-Linear Programming; MIP = Mixed-Integer Programming; GA = Genetic Algorithm; PSO = Particle Swarm Optimization.

This table classifies studies according to their mathematical structure, decision variables, optimization techniques, and main contributions to formalizing the strategic placement of inventory buffers in supply chains. However, recent work reformulates buffer positioning as an optimization problem, seeking formal criteria that minimize system nervousness, stabilize flow, and improve service levels at minimal cost.

Formally, the problem can be expressed as choosing the set of decoupling points y (Equation 6):

$$y = \{0, 1\}^m \tag{6}$$

where each binary variable indicates whether a given node or product is buffered. The objective functions typically combine three terms (Equation 7):

$$\min_{y} f(y) = C_{\text{inv}}(y) + C_{\text{stockout}}(y) + C_{\text{delay}}(y) \tag{7}$$

subject to service level and capacity constraints. Here, $C_{\text{inv}}(y)$ is the cost of maintaining buffers at selected points, $C_{\text{stockout}}(y)$ is the penalty for unmet demand, and $C_{\text{delay}}(y)$ captures flow variability or lead-time amplification in unprotected segments.

Multiple optimization approaches have been developed. (Achergui et al., 2021) proposed a formal buffer positioning model (an INLP, which they also linearized) using CPLEX to identify buffer positions that minimize total inventories while satisfying a service-time constraint. Their results revealed that automated positioning leads to superior outcomes compared to using heuristic positioning rules, especially when the complexity of the BOM is incorporated. Demand-Driven Distribution Resource Planning (DDDRP) was first proposed by (Erraoui et al., 2019) as a derivation of demand-driven material resource planning theory into distribution environments. (Haji Mohammad et al., 2022) proposed the first optimization model for buffer placement in a multi-echelon DDDRP network. Their model demonstrated that this optimized placement led to more dependable flows, reducing total holding costs by 75%. (Jodlbauer et al., 2025) proposed a technical contribution that took a theoretical approach, modeling the decoupling points in a static, graph-theoretic conception. It was able to demonstrate analytically that buffer placement closer to the consumer dampens order variance and improves upstream flow more effectively. (Habbadi et al., 2025) took a hybrid metaheuristic approach and modeled both production and buffer placement, revealing that the joint optimization of placement and control parameters dramatically reduced inventory and stockouts within smart manufacturing capacities.

These contributions collectively indicate a growing recognition that the location of buffers is equally important to buffer sizing. Buffer positioning models expand the logic of DDMRP beyond the heuristic positioning decision making context, integrating modeled, optimized, or decision support for complex supply chains with multiple products, echelons, and stochastic variability. However, most models are static in nature, assuming static demand; or a simplified model of cost structures. Similar to parameter optimization, dynamic positioning could be the next threshold of proposed research; or research that will continue with an emphasis on repositioning buffers in real time as conditions change in the network. **Bridge to Findings:** The body of literature on buffer positioning forms the basis for our finding that it is comparatively immature (Finding 4), indicating that while there are optimization frameworks, there has not been integration with parameterization or dynamic positioning.

4. Results and Discussion

The evidence corpus from 2020 to 2025 culminated in five findings. The most significant finding is the balance lens: parameterization is now an active and well-developed research stream, while positioning remains comparatively immature and is only beginning to mature.

Table 3: Overview of included peer-reviewed DDMRP optimization studies (2020–2025).

Author (Year)	**Focus Area**	**Methodology**	**Optimization Tool / Platform**	**Industry / Case Context**	**Main Contribution**
(Lahrichi et al., 2022)	Parameterization	MILP formulation	IBM CPLEX	Generated data for a single reference case	First exact MILP bench-mark for DDMRP parame-terization
(Damand et al., 2022)	Parameterization	Multi-objective NSGA-II	JAVA	Synthetic test instances	Cost–service Pareto fron-tier for buffer optimization
(Damand et al., 2025)	Parameterization	Extended NSGA-II (finite capacity)	JAVA + simulation	Multi-product planning	Multi-objective optimiza-tion under capacity con-straints
(Xu et al., 2023)	Production Plan-ning	Grey Wolf Optimizer (GWO)	Java	Manufacturing network	Constrained planning opti-mization integrating capac-ity and flow stability
(Uzun Araz et al., 2024)	Parameterization	Fuzzy optimization	Fuzzy logic system	Mixed-demand environment	Adaptive tuning of variabil-ity and lead-time factors un-der uncertainty
(Krajc˘ovic˘ et al., 2024)	Parameterization	Statistical-analytical opti-mization + simulation	Simulation platform	Manufacturing context (simulation ex-periments)	Data-driven buffer calibra-tion replacing subjective settings
(Younespour et al., 2024)	Positioning + Pa-rameterization	Hybrid GA–PSO meta-heuristic	MATLAB	Assembly system	Joint optimization of buffer placement and parameter tuning
(Achergui et al., 2021)	Positioning	INLP reformulated as MILP	IBM CPLEX	Hybrid MTO/MTS	First formal optimization model for buffer position-ing in hybrid MTO/MTS systems
(Haji Mohammad et al., 2022)	Positioning	MINLP	GAMS/BARON	Distribution network	Optimization of Demand Driven Distribution Re-source Planning (DDDRP) buffers
(Habbadi et al., 2025)	Positioning	GA + MIP hybrid	.NET Core (C#)	Industry 4.0 produc-tion line	Integrated production con-trol and buffer positioning optimization
(Jodlbauer et al., 2025)	Positioning	Analytical / graph-theoretic model	Analytical deriva-tion	Generic supply chain	Analytical proof of decou-pling location effects on variance propagation

Notes: All studies are peer-reviewed journal or conference papers between 2020 and 2025 that explicitly model DDMRP parameterization or buffer positioning as an optimization problem.

The table summarizes each paper's methodological orientation, optimization tools, industrial context, and primary contribution. Only research papers published between 2020 and 2025 are included in accordance with the systematic review scope. Finding 1: Optimization shifts parameterization. For parameterization studies, structured optimization versus heuristic-based rules delivers substantial improvements in performance. Using exact MILP, (Lahrichi et al., 2022) found that optimal service could be achieved with 8.1% less inventory compared to GA heuristics. With this same structure, (Damand et al., 2022) first applied the NSGA-II framework to derive cost-service frontiers for a single product. (Damand et al., 2025) then extended that framework to address the more complex problem of multi-product, finite-capacity constraints. (Xu et al., 2023) demonstrated that production stability could be optimized under limited capacity. Similarly, (Younespour et al., 2024) reported reductions of 21% in inventory costs, 68% in stockouts, and 78% in total costs using GA–PSO hybrids. (Uzun Araz et al., 2024) further demonstrated that fuzzy DDMRP improved resilience in uncertainty by dynamically updating buffer parameters. In essence, moving from planner judgment to structured optimization consistently reduces inventories, stabilizes variability, and improves service performance. Discussion: These findings advance DDMRP from heuristic approaches to a field of formal optimization. Exact MILP models provide validated benchmarks, while metaheuristic and fuzzy implementations scale to stochastic and complex cases. This mirrors broader supply chain optimization trends, where hybrid approaches address high dimensionality and uncertainty.

Finding 2: Perfect service costs and has a structure. Research on service levels approaching perfection has revealed consistent insights. When on-time delivery reaches perfection (100%), the costs of improvement grow exponentially. For example, (Damand et al., 2022) found that reaching 100% OTD required more than double the inventory needed at 86% OTD. (Damand et al., 2025) showed that achieving perfect service required a 30% increase in additional capacity due to larger buffers. Likewise, (Krajcˇovicˇ et al., 2024) proposed a new statistical-analytical model that improved service levels from 99.55% to 99.94% while simultaneously reducing average inventory by 8.9%. (Jodlbauer et al., 2025) analytically derived that buffers closer to the supplier (upstream) can reduce demand variance and lower total inventory costs. Across these studies, a clear story emerges: inventory, service, and costs are structurally interdependent, and the last few percentage points toward perfection are disproportionately costly. Discussion: This supports the cost–service frontier in DDMRP. Optimization does not eliminate the frontier; it clarifies it, enabling planners to evaluate trade-offs through formal models rather than judgmental estimation.

Finding 3: At scale, metaheuristics dominate parameterization, MILP provides exact routes. MILP remains effective for small, tailored cases. (Lahrichi et al., 2022) argued that MILP could outperform heuristics when service levels are predefined. However, as variables, complexity, and uncertainty increase, metaheuristics become essential. (Damand et al., 2022, 2025) demonstrated that NSGA-II scaled across multiple parameters, providing Pareto-optimal trade-offs beyond the scope of MILP. (Xu et al., 2023) found Gray Wolf Optimizer satisfactory under bounded conditions, and (Younespour et al., 2024) showed GA–PSO hybrids as a practical approach for coordinating tuning and buffer placement. Overall, exact models validate structured cases, while metaheuristics enable feasible solutions for large-scale, uncertain DDMRP problems. Discussion: MILP validates optimality for structured cases; metaheuristics ensure computational feasibility for real- world complexity. This reflects a prevailing operations research trend where hybrid evolutionary methods balance rigor and scalability.

Finding 4: Positioning is developing compared to parameterization. While parameterization research has advanced significantly, positioning remains relatively underdeveloped. Early contributions (Achergui et al., 2021; Haji Mohammad et al., 2022) used deterministic binary formulations to create the first formal optimization models for buffer placement. More recent efforts show incremental progress. (Jodlbauer et al., 2025) employed graph-theoretic analysis with analytical proofs to optimize decoupling point locations. (Habbadi et al., 2025) introduced a hybrid GA–MIP approach integrating placement and production control in smart manufacturing. (Younespour et al., 2024) provided the first model to jointly optimize both placement and parameter tuning using a hybrid GA-PSO algorithm. To date, no integrated model has co-optimized buffer placement, sizing, and tuning under stochastic or limited capacity conditions. Discussion: The discrepancy is evident: parameterization has diversified into exact, heuristic, and adaptive approaches, while positioning remains deterministic. Fragmentation is a liability for external validity—poor placement can negate strong parameterization. The lack of integration between the two streams represents the greatest research gap.

Finding 5: The frontier continues to be adaptation and operational validation. Research is shifting toward adaptation and realism. (Uzun Araz et al., 2024) provided evidence that static tuning fails under contingency, while adaptive fuzzy tuning improves outcomes. (Damand et al., 2025) advanced optimization toward practical applicability. (Habbadi et al., 2025) contextualized DDMRP within Industry 4.0 environments. Yet, few studies validate models at an industrial scale. ERP providers have not embedded these advanced methods, leaving most research validated only in simulations or stylized settings. Discussion: Collectively, these findings point toward adaptation and realism; however, a gap remains between academic contributions and operational reality. Until advanced optimization models are validated in live supply chains, algorithmic progress will remain primarily a proof of concept. The critical next step is bridging simulation with industrial practice.

5. Conclusion

The review has shown that the studies of the optimization associated with DDMRP have undergone significant advances over 2020–2025, shifting towards the analysis of the models of optimization that are defined with rigor and no longer rely on the methods of heuristics. New algorithms such as genetic algorithms, mixed-integer linear programming (MILP), and fuzzy-logic optimization introduced into the literature on parameter-based studies, including those by (Lahrichi et al., 2022; Younespour et al., 2024; Uzun Araz et al., 2024; Damand et al., 2022, 2025; Krajcˇovicˇ et al., 2024) allow the optimization of the variability controls and size of buffers to be fine-tuned. In parallel, positioning studies (Achergui et al., 2021; Jodlbauer et al., 2025; Habbadi et al., 2025) formalized the location of buffers and decoupling points within complex Bills of Materials (BOM) structures, while (Haji Mohammad et al., 2022) extended this logic to multi-echelon distribution networks. Together, these two streams support the premise that DDMRP is not merely heuristic but can be rigorously formalized through mathematical and computational models.

Nonetheless, many of these models remain distinct, either in parameter tuning or buffer positioning, with very few attempts at combined integration. On the practitioner side, global ERP providers SAP (S/4HANA) and Microsoft (Dynamics 365) have incorporated the DDMRP module into their software (SAP SE, n.d.; Microsoft Corporation, n.d.); however, the improved advanced optimization models from recent studies have not yet been reported as being implemented in these commercial platforms. Therefore, industrial applications of such models remain limited and are typically delivered through custom or ad-hoc solutions rather than standardized ERP functionality.

In the studies reviewed, it is clear that juggling and managing the trade-offs among various service levels, inventory costs, and other decision variables is critical. Robust optimization models minimize these, reducing the jitters experienced by many planners and allowing their focus to remain on strategy instead of ‘wasting’ time making judgmental assumptions about trade-offs. Finally, tools and ERP integration will facilitate adoption and additional research investments. The ultimate goal of future researchers will be therefore to perfect joint model parameter tuning and buffer positioning in a single dynamic model that is able to handle all levels of uncertainty and throughput rates and be scaled to an ERP industrial environment.

All these remaining gaps require methodologies that are developed based on the stagnant, stand-alone systems and simulation-based validation. The use of rolling-horizon models, demand-shock sensitivity, and stochastic assumptions are to be used instead of the static assumptions. Synthetic approaches to reinforcement learning, with hybrids of mixed-integer programming and metaheuristics, may be of use in the finer details of flexibility and analytical precision. Similarly, the chosen tactics should be implemented in practical industrial practices, including the involvement of ERPs in the scopes that can be accepted by the academic research.

In case these limitations can be overcome, it is possible that the field will leave the status of an infantile research opportunity; and become a well-proven industry standard of DDMRP optimization. This benchmark would go beyond basic measures of service levels and cost-cutting, including the assessment of how DDMRP aligns with the overall supply-chain goals, like resilience, sustainability and the future implementation of digital twin technology. At the same time, this approach should be proved to be consistent with the strategic requirements of the modern supply-chain architectures.

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Appendix A. Search Documentation

Searches for research on optimizing Demand-Driven Material Requirements Planning (DDMRP) were performed in September 2025.
Three major databases were employed to provide breadth and depth to the research base:

1. **Scopus.** This was selected because it provides access to a vast number of publications across multiple disci-plines, including engineering, decision sciences, business, and computer science, thus enabling a comprehensive disciplinary reach.
2. **Web of Science (WoS).** The searches were limited to the Science Citation Index Expanded (SCIE) and the Emerging Sources Citation Index (ESCI) to exclude non-indexed and lower impact sources.
3. **Google Scholar (GS).** It was used to locate conference papers and gray literature not contained in Scopus or Web of Science.

The searches were conducted between 1 September and 10 September 2025, allowing all published works available through these databases prior to 31 August 2025 to be captured.

A2. Boolean Search Expression

Below are the Boolean expressions developed for use in the database queries; minor modifications were made to accommodate the specific query syntax of each database:

TITLE-ABS-KEY(

("Demand Driven MRP" OR "DDMRP" OR "Demand Driven Material Requirements Planning" OR
"Customer Order Decoupling Point" OR "Decoupling Point"
OR "Inventory Buffer" OR "Buffer Zone" OR "Buffer Positioning") AND
("optimization" OR "optimization model" OR "mathematical model" OR "metaheuristic" OR
"simulation-based optimization"
OR "MILP" OR "MINLP" OR "multi-objective optimization" OR "fuzzy optimization" OR "parameter optimization")
)

AND (LIMIT-TO (PUBYEAR, 2020-2025))

The query string was iteratively improved to achieve an optimal balance between maximizing the recovery of studies related to DDMRP optimization while minimizing the recovery of studies that focused on the description of DDMRP and/or the implementation of DDMRP.

A3. Screening and Eligibility Criteria

The selection and exclusion process followed the PRISMA 2020 guidelines.
The various stages of the screening and inclusion process are summarized in Table 4.

Table 4: *Summary of screening and inclusion process using PRISMA 2020 guidelines.*

Stage	Number of Records	Description
Initial retrieval (Scopus, WoS,	5,180	All records prior to any filtering. GS)
After SCIE/duplicate filtering	3,670	Removal of duplicates and non-indexed items. After topical filtering
	867	Focused on supply-chain and logistics subject areas.
After time-frame restriction	208	Temporal narrowing to recent studies. (2020–2025)
Eligibility screening	43	Assessment by relevance and study quality.
Final inclusion positioning.	17	Studies used in the analysis: 5 foundational, 7 parameterization, and 5

A4. Domain Expansion Rules

Only those studies that utilized terminology synonymous with or derived from the terms "DDDRP" and "Decoupling Inventory" were considered if they referred to the Demand Driven Institute (DDI) framework or followed the DDMRP methodology.
This was done to maintain consistency throughout the final dataset.

A5. Replication. The search history, screening comments, and bibliographic information were all documented in Zotero. Duplicate detection was turned on automatically to generate an electronic archive of all screenings and selection procedures. It is possible to replicate or verify the review process via this electronic archive that is an entire audit trail. The last verification search was carried out on 10 October 2025. No further studies of optimization with DDMRP were found after that date from this search. A completed reference list, exportable citation files and the documentation of the searches are available for independent validation by request.