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Research Article

Dynamic Replenishment Policies for Vendor-Managed Inventory under Stochastic Demand: A Simulation-Based Comparative Study

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Abstract: Vendor-Managed Inventory (VMI) is a pivotal strategy for optimizing supply chain performance, yet it poses a significant challenge in balancing operational costs against service levels under stochastic demand. While dynamic policies are gaining traction, the literature lacks a systematic comparison of the underlying trigger logic (reactive vs. proactive). This study addresses this gap by providing a rigorous comparative analysis of static versus dynamic inventory replenishment policies within a VMI framework for a pharmaceutical distribution network. We design and evaluate four distinct policies: a traditional static (s,S) policy and three novel dynamic policies—reactive, proactive, and inertial—that adapt replenishment triggers based on real-time, system-wide demand signals. The novelty of this work lies in the formal design and first systematic comparison of these distinct dynamic trigger mechanisms, particularly the "Inertial" policy, which utilizes a smoothed urgency signal to enhance resilience. A high-fidelity simulation-optimization framework is developed, where policy parameters are optimized via a Genetic Algorithm to ensure each strategy operates at its peak potential. The results, analysed using ANOVA and Tukey's HSD tests, reveal that while all policies can be optimized to a statistically similar total cost ($p = 0.782$), they differ significantly in their ability to maintain service levels. The proposed inertial policy, which utilizes a smoothed urgency signal, demonstrates superior performance, significantly reducing stockouts by 21.5% and 29.7% compared to the static and reactive policies, respectively, without incurring a statistically significant cost increase. This demonstrates that integrating anticipatory, smoothed demand signals offers a robust pathway to enhancing service resilience without sacrificing economic efficiency.

Keywords: Vendor-Managed Inventory (VMI); Inventory Routing Problem (IRP); Dynamic Replenishment; Simulation-Optimization; Genetic Algorithm; Supply Chain Resilience.

I. INTRODUCTION

In an era of increasing market volatility and customer expectations, collaborative supply chain strategies are paramount for achieving a competitive advantage. Vendor-Managed Inventory (VMI) has emerged as a cornerstone of such collaboration, enabling vendors to manage customer inventories directly, thereby mitigating the bullwhip effect, optimizing logistics, and enhancing product availability [1], [2]. The primary motivation for this research stems from the inherent vulnerability of traditional VMI systems to demand shocks in critical sectors like healthcare. Static reorder points often fail to account for the cumulative stress on a distribution network, leading to localized stockouts even when global inventory is sufficient. By investigating dynamic triggers that "sense" system-wide urgency, we seek to provide a more agile decision-making framework.

1. Problem Statement and Objectives

The operational core of VMI is the Inventory Routing Problem (IRP), a notoriously complex optimization challenge that integrates inventory control and vehicle routing decisions [3]. The central objective of this study is to determine which dynamic replenishment logic—reactive, proactive, or inertial—best balances the conflicting goals of cost minimization and high service levels under stochastic conditions. We specifically aim to quantify the benefits of signal smoothing in inventory decision-making.

Traditional IRP models often rely on static inventory policies, such as the fixed reorder point (s,S) policy. While analytically tractable, these policies lack the agility to adapt to real-time demand fluctuations [4]. This has motivated research into dynamic policies (e.g., [5], [6], [7]), yet no study to date has systematically compared the nature of the state-dependent signal—whether it is immediate, anticipatory, or smoothed—and its impact on the trade-off between cost and service level.

II. Literature Review

Research on the Inventory Routing Problem (IRP) seeks to integrate two of the most critical functions in logistics management. Comprehensive reviews by [8] and, more recently, [3] provide a thorough classification of IRP variants and solution methodologies, highlighting a persistent focus on balancing the cost-service trade-off.

1. Static vs. Dynamic Inventory Control in IRP

Static policies, particularly the Order-Up-To (OUT) or (s,S) policy, have long served as the benchmark in IRP literature due to their simplicity [9], [10], [11]. The effectiveness of these policies often depends on strategic logistical configurations; for example, selecting optimal logistic center locations through multi-criteria comparison is essential for balancing environmental and economic factors in regional distribution [12]. Furthermore, recent advancements in VMI practice demonstrate that breaking down the complex inventory routing problem into manageable phases—such as clustering and service sequencing—can significantly enhance delivery optimization and minimize stockouts [13]. Concurrently, the rise of Deep Reinforcement Learning (DRL) has shown promise [14], though these methods often require extensive training and can be difficult to interpret .To address such challenges, recent research emphasizes that improving decision robustness in IRP settings requires moving beyond purely algorithmic sophistication to incorporate hybrid fuzzy-neural decision models [15], [16].

2. Stochastic VMI and IRP

In a stochastic environment, which is the focus of this paper, the challenge is magnified. [17], [18] demonstrated that policies optimized for a deterministic scenario perform poorly when demand is uncertain. This has spurred research into robust optimization, noting that addressing inventory challenges in high-stakes environments, such as humanitarian supply chains, requires robust multi-criteria frameworks to manage coordination under uncertainty [19]. Furthermore, the application of reliability-centered maintenance and computerized management systems has shown that optimizing operational reliability can lead to a 30% improvement in inventory management efficiency [20].While prior work has established the value of adaptive systems (e.g., [21], [22], [23]), it has not systematically compared different architectures for the dynamic trigger itself.

3. Research Positioning and Contribution

This study bridges a critical gap between advanced IRP solution methods and the design of intelligent, state-dependent replenishment logic. The design of such triggers is increasingly influenced by the digital transformation of logistics, where Web 4.0 technologies enable the transition toward intelligent, data-driven replenishment processes [24]. Our focus on the "nature of the signal" aligns with recent findings in service supply chains, where the ability to utilize information to update processing capacity is identified as a top priority for system performance [25]. Additionally, our approach integrates strategic logistics considerations, such as the prioritization of transportation costs in sustainable supplier selection [26], into the operational logic of the IRP. Our use of a Genetic Algorithm for parameter tuning aligns with best practices for ensuring a fair comparison of heuristic policies [27], [28]. Furthermore, while complex adaptive models are often prioritized in academic literature, recent research suggests that a significant gap remains between theoretical complexity and managerial intuition. It has been demonstrated that a parsimonious, optimized urgency threshold (OUT) heuristic can sometimes outperform more intricate adaptive architectures, challenging the assumption that parametric complexity is a prerequisite for high performance in stochastic IRPs [29].

Table 1. *Comparative Summary of Recent and Relevant Literature*

Author(s) & Year	***Problem Context***	***Methodology***	***Key Contribution/Finding***
Archetti & Speranza (2022)	IRP Review	Literature Synthesis	Updates the state-of-the-art in IRP, noting trends in stochastic and dynamic models.
Afridi et al. (2020)	VMI in Semiconductors	Deep Reinforcement Learning	DRL-trained policy significantly improves inventory performance (from 43% to 95% compliance).
Mahjoob et al. (2021)	Multi-product IRP	Modified Adaptive Genetic Algorithm	Proposes an adaptive GA that outperforms benchmark heuristics for complex IRPs.
Lotfi et al. (2024)	VMI in Healthcare	Robust Stochastic Optimization	VMI with a consignment stock policy reduces costs by 14.8% in a viable supply chain model.
Charaf et al. (2024)	Two-Echelon IRP	Matheuristic (Tabu + MP)	Develops a highly effective matheuristic for solving large-scale two-echelon IRPs.
This Study	VMI / Stochastic IRP	**Simulation & Hybrid Metaheuristics (GA–NN–Tabu)**	**Designs and provides the first systematic comparison of reactive, proactive, and inertial dynamic replenishment triggers.**

The word count does not include the title, authors, affiliations, keywords, abstract, acknowledgements, author contributions, disclosure statement, OrcID, appendix and references.

III. Problem Formulation and Modeling Framework

This section details the formal problem definition and the components of our proposed solution methodology.

1. Mathematical Model

We model a multi-period IRP over a discrete time horizon *T*. A central depot (node 0) serves a set of *N* pharmacies.

Notation:

- I_{it} : Inventory level of pharmacy i at the end of day t.
- B_{it} : Backorder level (unmet demand) for pharmacy i at the end of day t.
- D_{it} : Stochastic demand at pharmacy i on day t, drawn from a distribution.
- C_h : Unit holding cost per day (€/unit/day).
- C_s : Unit stockout penalty (€/unit).
- C_t : Transportation cost per kilometer (€/km).
- ***dist(i, j)*** : Distance between locations i and j.
- Q : Vehicle capacity (units).
- $\sum_{i=1}^{n} \mu_i$: The total mean daily demand across all n pharmacies in the system (from i=1 to n).
- s_i^{base}: Base reorder point of pharmacy i.
- I: Indicator Function, which is 1 if the condition inside is true, and 0 otherwise.
- β: Sensitivity parameter (dimensionless, $0 < \beta < 1$).
- α : Smoothing factor for EWMA (dimensionless, $0 < \alpha < 1$).

Objective Function: The goal is to minimize the expected total system cost over the planning horizon, combining transportation, inventory holding, and stockout costs:

$$\text{Minimize } E[\text{Total Cost}] = E\left[\sum_{t=1}^{T}\left(\text{HoldingCost}_t + \text{TransportCost}_t + \text{StockoutCost}_t\right)\right] \quad (1)$$

where:

Holding Cost: The cost of carrying positive inventory at all pharmacies.

$$\text{Holding Cost}_t = C_h \times \sum_{i=1}^{N} I_{it}, \quad \text{where } I_{it} > 0 \quad (2)$$

Transportation Cost: The cost of delivery routes. On each day t, a set of pharmacies V_t is selected for replenishment. The routing problem is solved using a two-phase heuristic: a Nearest Neighbor algorithm for initial route construction, followed by a Tabu Search routine for improvement. The resulting total distance is multiplied by the unit cost.

$$\text{Transport Cost}_t = C_t \times \text{VRP\_Cost}(V_t, \text{dist}, Q) \quad (3)$$

Stockout Cost: A penalty is applied to any new backorders generated on day t. After demand D_{it} is realized, the inventory is updated. If $I_{i,t-1}$- D_{it} < 0, the magnitude of this negative value represents new backorders.

$$\text{Stockout Cost}_t = C_s \times \sum_{i=1}^{N} \max(0, D_{it} - I_{i,t-1}) \quad (4)$$

2. Policy Structures

The replenishment decision rules are represented through four policy architectures. A key construct is the Demand-Weighted Urgency Index (DWUI), $U_{t,dw}$:

$$U_{t,dw} = \frac{\sum_{i=1}^{n} \mu_i \cdot I(I_{i,t-1} < s_i^{\text{base}})}{\sum_{j=1}^{n} \mu_j} \quad (5)$$

A. Static (s,S) Policy (Baseline): The delivery decision a_{it} is triggered if inventory falls below a fixed threshold s_i.

$$a_{it} = I(I_{i,t-1} < s_i) \quad (6)$$

Parameter vector: $\theta_{\text{static}} = [s_1, s_2, \dots, s_n]$.

B. Dynamic Reactive Policy: The dynamic reorder point s_{it} is lowered during times of system stress.

$$s_{it} = s_i^{\text{base}} \times (1 - \beta \cdot U_{t,dw}) \quad (7)$$

Parameter vector:
$\theta_{\text{dynamic}} = [s_1^{\text{base}}, s_2^{\text{base}}, \dots, s_n^{\text{base}}, \beta]$.

C. Dynamic Proactive Policy: The dynamic reorder point s_{it} is raised during times of system stress.

$$s_{it} = s_i^{\text{base}} \times (1 + \beta \cdot U_{t,dw}) \quad (8)$$

Parameter vector:
$\theta_{\text{dynamic}} = [s_1^{\text{base}}, s_2^{\text{base}}, \dots, s_n^{\text{base}}, \beta]$.

D. Dynamic Inertial Policy (Proposed): This policy applies exponential smoothing to reduce noise in the urgency signal via an EWMA calculation:

$$U_t^{\text{smooth}} = \alpha \cdot U_{t,dw} + (1 - \alpha) \cdot U_{t-1}^{\text{smooth}} \quad (9)$$

The replenishment trigger is then based on this smoothed signal:

$$s_{it} = s_i^{\text{base}} \times (1 + \beta \cdot U_t^{\text{smooth}}) \quad (10)$$

Parameter vector:
$\theta_{\text{inertial}} = [s_1^{\text{base}}, s_2^{\text{base}}, \dots, s_n^{\text{base}}, \beta, \alpha]$.

The proposed methodology for the dynamic policies follows a systematic procedure: (1) Urgency Sensing, where system stress is calculated; (2) Signal Treatment, where the signal is smoothed (in the inertial case) or reacted to immediately; and (3) Trigger Adjustment, where reorder points $s_{it}$are modified. This is detailed in Algorithm 1.

Algorithm 1. Logic for Dynamic Inertial Replenishment

1: Initialize parameters:

$$s_i^{base}, \beta, \alpha, \text{ and } U_0^{smooth} = 0.$$

2: For each time step $t \in T$:
3: Calculate current system urgency:

$$U_{t,dw} = \frac{\sum \mu_i \cdot I(I_{i,t-1} < s_i^{base})}{\sum \mu_j}$$

4: Update smoothed urgency:

$$U_t^{smooth} = \alpha \cdot U_{t,dw} + (1 - \alpha) \cdot U_{t-1}^{smooth}$$

5: For each pharmacy i:
6: Update dynamic trigger:

$$s_{it} = s_i^{base} \times (1 + \beta \cdot U_t^{smooth})$$

7: If $I_{i,t-1} < s_{it}$ then add pharmacy i to daily visit list V_t.
8: End For
9: Pass $V_t$to VRP Solver (Algorithm 2) to generate optimal routes.
10: End For

3. Matheuristic Optimization Framework

The parameters **θ** of each policy are optimized using a Genetic Algorithm (GA). Each chromosome encodes the policy parameter vector. The fitness function evaluates the average total cost over multiple demand replications (R) to ensure the selection of robust, generalizable solutions.

Algorithm 2. Robust Ga for Policy Optimization

1: Initialize Population P with pop size random solutions θ.
2: for g = 1 to max _ generations do
3: for each individual $p \in P$ do
4: replication costs ← []
5: for r = 1 to R do
6: cost ← Run Simulation(p, seed=r)
7: Add cost to replication costs.
8: end for
9: fitness(p) ← Average(replication costs).
10: end for
11: Create P_{next} via elitism, tournament selection, crossover, and mutation.
12: $P \leftarrow P_{next}$
13: end for
14: return best individual θ* found across all generations.

IV. Methodology

The experimental methodology is designed for rigor and reproducibility, following the structured simulation-optimization process defined in Section 3. The entire framework, which integrates a Genetic

Algorithm (GA) for parameter optimization with a high-fidelity simulation environment for performance evaluation, is visualized in **Fig. 1**. The outer loop of this framework represents the GA's evolutionary process, which iteratively refines a population of candidate solutions. The inner loop details the fitness evaluation, where each candidate's performance is robustly assessed across multiple stochastic replications.

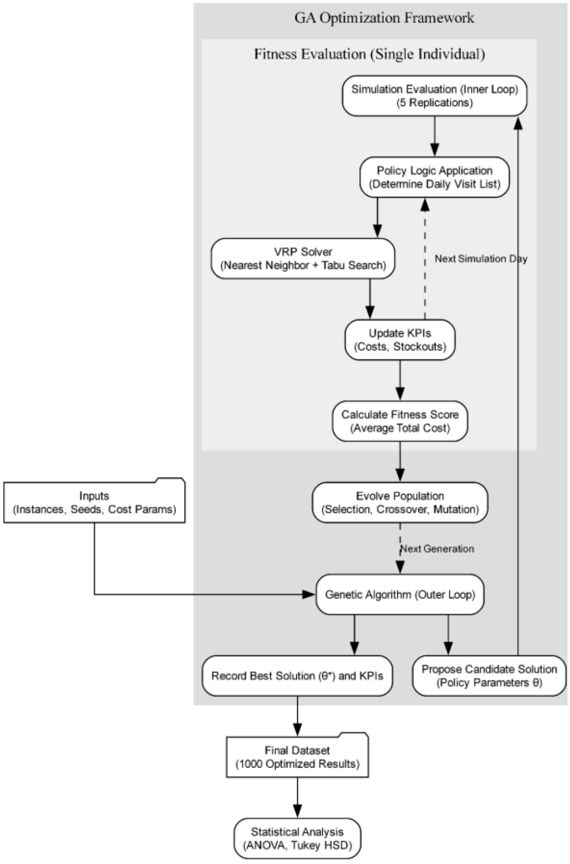

Figure 1. *Methodological flowchart of the simulation-optimization framework.*

1. Simulation Environment

A discrete-time simulation model was developed in Python 3.9. The model simulates a network of 50 pharmacies supplied by a single depot over a 30-day horizon. To ensure the robustness of our findings against stochastic demand, each candidate parameter set was evaluated over 5 distinct replications, each with a different random seed. Daily demand at each pharmacy is drawn from a truncated Gaussian distribution with unique mean and standard deviation parameters specific to that pharmacy. The main experimental campaign was conducted across 10 global random seeds and 5 distinct problem instances (network structures), resulting in a total of 1000 independent optimization runs.

2. Replenishment Policies

The four replenishment policies, formally defined by Equations (6-10) in Section 3, were implemented within the simulation. While all three dynamic policies utilize the same underlying Demand-Weighted Urgency Index (DWUI), their strategic responses to system stress are fundamentally different. The conceptual divergence of these policy triggers is illustrated in **Fig. 2.** The figure depicts a scenario where the system experiences a stress event (e.g., a sudden, sustained demand spike). The reactive policy responds by conservatively lowering its trigger to conserve inventory, whereas the proactive policy aggressively raises its trigger to push more stock into the network. The inertial policy, by smoothing the urgency signal, provides a more measured and stable proactive response.

The transient, exponential-like behavior of the inertial trigger seen in **Fig. 2** at the onset of the stress event is a direct result of the EWMA smoothing factor (α). This prevents the system from overreacting to instantaneous demand spikes, ensuring that replenishment thresholds only rise significantly if the system stress is sustained.

3. Optimization via Genetic Algorithm

A Genetic Algorithm was chosen to optimize the parameters for each policy due to its proven effectiveness in navigating complex, non-differentiable, and high-dimensional search spaces, which are characteristic of simulation-based optimization problems [30]. The GA is less prone to getting trapped in local optima compared to simpler gradient-based methods, making it well-suited for finding globally competitive policy parameters. The GA was configured with a population size of 50, tournament selection, uniform crossover, and a small mutation rate, running for 40 generations.

4. Statistical Analysis

The final dataset, containing 1000 optimized results (10 seeds × 5 instances × 4 policies × 5 replications), was analysed using one-way and two-way ANOVA to test for significant differences in mean performance. A Tukey HSD post-hoc test was conducted for all pairwise comparisons where the ANOVA F-test was significant ($p < 0.05$).

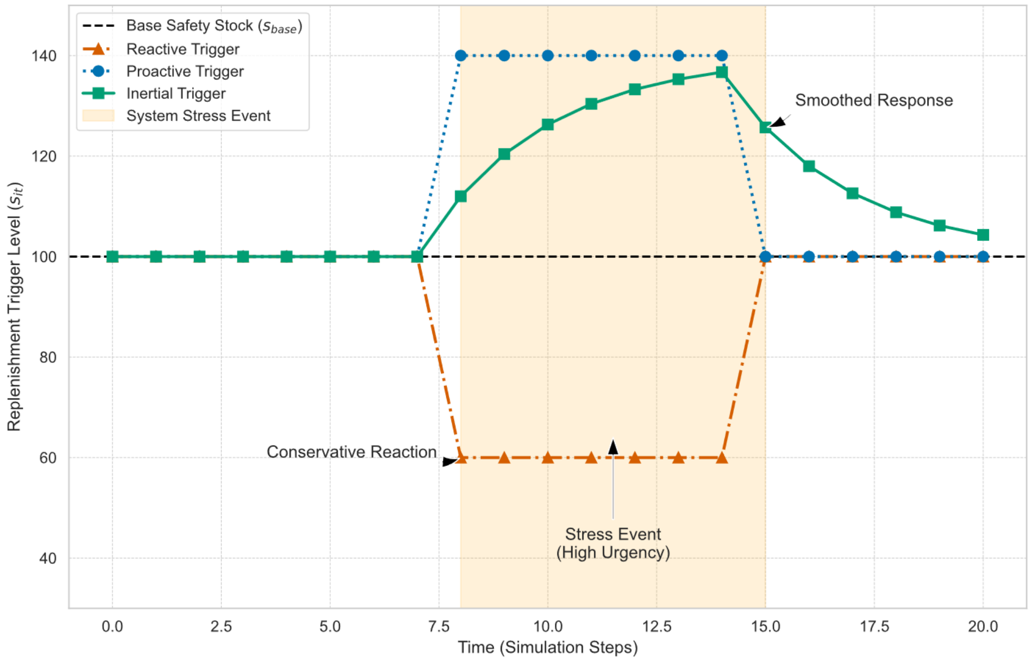

Figure 2. *Conceptual illustration of dynamic policy trigger adjustments.*

V. Results

The analysis of the 1000 optimized simulation runs yielded clear and statistically robust results.

1. Descriptive Statistics

Table 2 presents the grand mean performance of the four policies across all experimental runs. The dynamic (s, S) inertial policy achieved the lowest mean stockout quantity, while the dynamic (s, S) proactive policy achieved the lowest mean total cost.

2. Inferential Statistical Analysis

The one-way ANOVA for Final Optimized Cost yielded a p-value of 0.7821, indicating **no statistically significant difference** in the mean total cost among the four policies. Conversely, the ANOVA for Final Stockout Quantity was highly significant ($p < 0.001$). The Tukey HSD post-hoc test (**Table 3**) provides pairwise comparisons.

The results confirm that the inertial and proactive policies are statistically superior to reactive and static policies in reducing stockouts. To validate these results, we compared our results against the established (s,S) static baseline.
The observed 21.5% reduction in stockouts achieved by the Inertial policy exceeds the improvements reported in similar stochastic IRP studies, such as the 14.8% reduction noted by [31].

3. Visual Analysis of Performance

To provide a richer understanding of the performance differences, a series of visualizations were generated. **Fig. 3** presents the distributions of the two primary Key Performance Indicators (KPIs)—Total Cost and Stockout Quantity—for each of the four policies across all experimental runs.

Table 3. *Tukey HSD Results for Pairwise Comparison of Mean Stockout Quantity*

group1	*group2*	*Mean diff.*	*P-adj*	*lower*	*upper*	*reject*
dynamic (s, S) inertia	dynamic (s, S) proactive	9.556	0.6983	-13.236	32.348	False
dynamic (s, S) inertia	dynamic (s, S) reactive	48.356	0	25.564	71.148	True
dynamic (s, S) inertia	static (s, S)	32.088	0.0019	9.296	54.88	True
dynamic (s, S) proactive	dynamic (s, S) reactive	38.8	0.0001	16.008	61.592	True
dynamic (s, S) proactive	static (s, S)	22.532	0.054	-0.26	45.324	False
dynamic (s, S) reactive	static (s, S)	-16.268	0.2535	-39.06	6.524	False

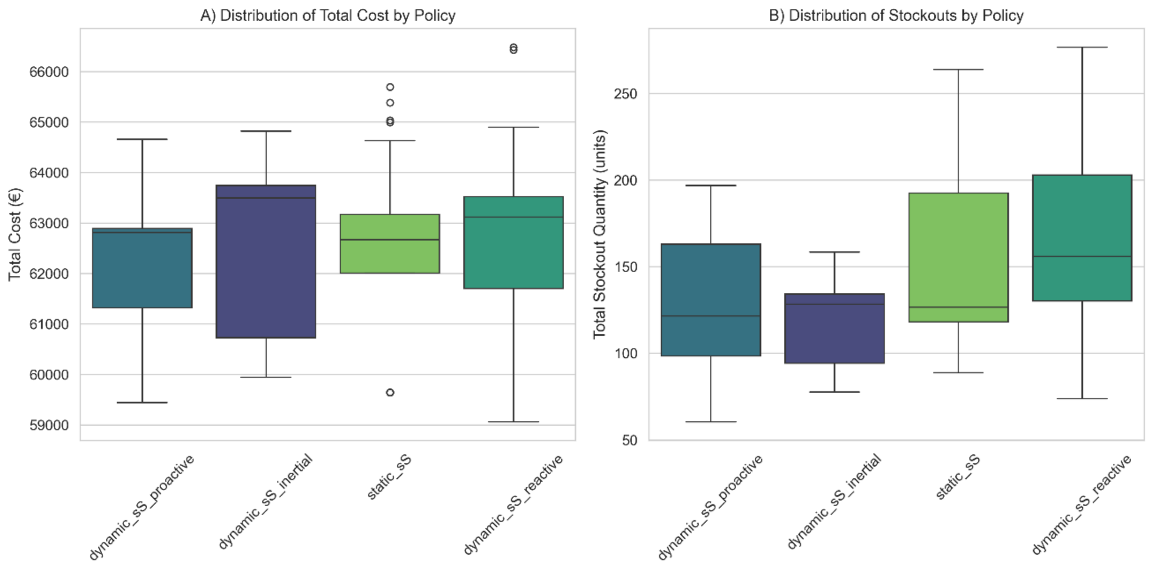

Figure 3. *Comparison of Key Performance Indicator (KPI) distributions across replenishment policies.*

The box plots for Total Cost (**Fig. 3A**) visually confirm the ANOVA result; the distributions are largely overlapping, with similar medians and interquartile ranges, indicating no clear cost advantage for any single policy. In stark contrast, the distributions for Stockout Quantity (**Fig. 3B**) show a distinct performance hierarchy.

The dynamic (s, S) inertial policy not only achieves

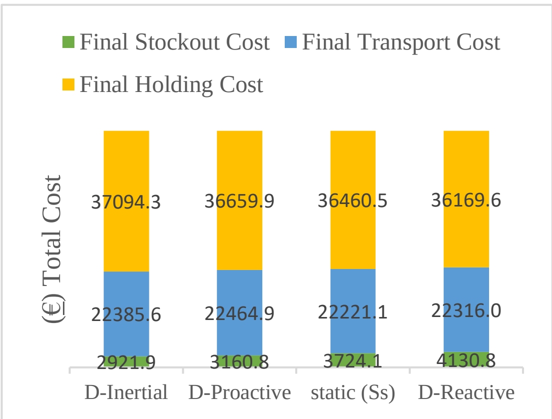

Figure 4. *Composition of average total cost by policy.*

the lowest median stockouts but also exhibits the tightest distribution, signifying consistent and reliable service level performance. To diagnose the drivers of total cost, the average cost for each policy was decomposed into its primary components: Transport, Holding, and Stockout Penalty costs, as shown in **Fig. 4**. This visualization clearly illustrates that the primary differentiator among the policies is not operational efficiency (transport and holding costs are remarkably stable across all four), but rather the ability to mitigate service failures. Specifically, the inertial policy achieves the lowest mean stockout penalty cost (€2,921.90), representing a significant reduction compared to the static policy (€3,724.10) and the reactive policy (€4,130.80). In contrast, transportation costs are virtually indistinguishable between models, averaging €22,346.89, while holding costs maintain a stable average of approximately €36,596.13. This empirical breakdown confirms that the economic value of the inertial approach is driven primarily by its resilience in minimizing high-penalty stockout events rather than through routing or holding efficiency.

Finally, the trade-off between the two primary KPIs is visualized in **Fig. 5**, which plots the mean cost against the mean stockout quantity for each policy. This places the policies in a two-dimensional performance space, allowing for an assessment of Pareto efficiency.

The dynamic (s, S) inertial policy is clearly positioned in the most favourable (bottom-left) quadrant, dominating the reactive and static policies

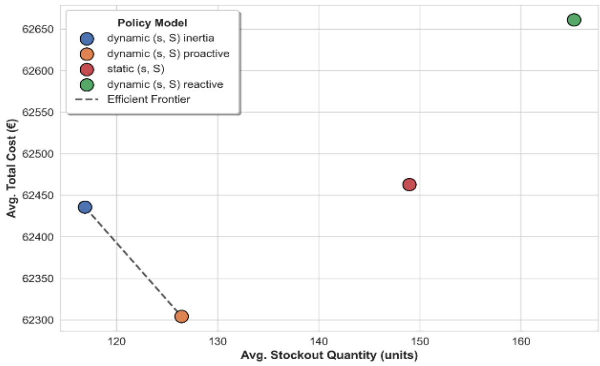

Figure 5. *Cost-stockout trade-off analysis and the efficient frontier.*

by being superior on both KPIs simultaneously. While the proactive policy achieves a slightly lower mean cost, the inertial policy provides a substantially better service level, positioning it as the most balanced and resilient strategy on the efficient frontier.

VI. DISCUSSION

The findings of this study reveal a critical insight: in a well-optimized VMI system, the value of sophisticated dynamic policies lies in dramatically improving service level resilience rather than just reducing total costs**.**

The Failure of a Reactive Stance: A key finding is the poor performance of the dynamic (s, S) reactive policy, which was statistically indistinguishable from the static (s, S) baseline in reducing stockouts. This result warrants a deeper explanation. The reactive policy's logic is to lower its replenishment triggers during times of system-wide stress. The intent is to conserve central inventory for only the most critical, already-low pharmacies. However, this logic is fundamentally flawed due to the inherent **lead time** in the system. The urgency signal U_{t} only becomes high *after* several pharmacies are already below their safety stock. By the time the policy reacts, a day has already passed. For a pharmacy that was just above its safety stock, a single day of high demand can easily deplete its inventory, but the reactive policy, having lowered its trigger, will fail to identify this new risk. In essence, the policy is always fighting yesterday's fire, leaving it vulnerable to today's demand uncertainty. This finding underscores a critical principle in inventory control: in systems with non-zero lead times, purely reactive measures are insufficient for ensuring high service levels.

The Benefit of Proactive and Inertial Approaches: In contrast, the proactive and inertial policies are anticipatory. By *raising* their replenishment triggers in response to system stress, they proactively push inventory into the network to buffer against potential future stockouts. From a control-theoretic perspective, dynamic supply chains can be modelled as state-space systems in which replenishment decisions act as control inputs influencing stability and system responsiveness. Recent optimal control formulations of dynamic supply chains highlight the importance of stability and sensitivity management when designing inventory–capacity interactions [32]. We demonstrate that adapting the inventory policy trigger itself provides a significant and complementary lever for performance improvement. The dynamic (s, S) inertial policy's superior performance, especially its low variance (as seen in **Fig. 3B**), suggests that smoothing the urgency signal with an exponential moving average (the α parameter) is highly beneficial. This prevents the policy from overreacting to daily demand "noise" and allows it to respond more effectively to persistent trends, a concept central to control theory. However, it is worth noting that while the Inertial policy shows superior stability in this study, the choice between adaptive complexity and optimized simplicity remains a critical decision for managers. Comparative studies have shown that rigorously optimized, time-based rules can achieve even higher resilience under extreme environmental shocks, suggesting that the effectiveness of the Inertial signal depends heavily on the specific nature of the demand volatility and capacity constraints [29].

Healthcare and Societal Implications: The implications for pharmaceutical supply chains are profound. Reducing stockouts from an average of nearly 149 units per month (static policy) to 117 (inertial policy) represents a 21.5% improvement in medicine availability. This directly contributes to the critical challenge of medicine shortage management, a topic of increasing global concern. In a real-world scenario, this translates to better patient access to critical treatments, improved public health outcomes, and enhanced community trust in the healthcare system, a goal supported by the integration of AI and VMI in modern hospitals [33]. The fact that this can be achieved without a statistically significant increase in cost makes a compelling business and ethical case for the adoption of such intelligent policies.

VII. CONCLUSION

This study is, to our knowledge, the first to systematically design, optimize, and compare reactive, proactive, and inertial replenishment triggers within a stochastic VMI framework. Our unique theoretical contribution lies in the empirical demonstration that integrating anticipatory, smoothed demand signals—rather than immediate reactive adjustments—offers a robust pathway to enhancing service resilience without sacrificing economic efficiency. Methodologically, this research contributes a high-fidelity simulation-optimization framework that allows for the isolation of trigger-logic performance, ensuring that the observed benefits are inherent to the policy architecture itself rather than sub-optimal parameterization.

The findings provide both academic insights into the design of dynamic inventory control systems and actionable strategies for pharmaceutical supply chains.

Managerial Implications: A primary insight revealed by this research is that in well-optimized VMI systems, the primary value of sophisticated dynamic policies lies in dramatically improving service level resilience. Achieving a 21.5% reduction in stockouts without a statistically significant cost increase (p=0.7821) provides a compelling business and ethical case for the adoption of intelligent replenishment triggers in critical distribution networks. Managerial implications are equally profound, as logistics providers can directly implement the proposed inertial logic into existing VMI systems. By monitoring system-wide inventory and applying simple exponential smoothing, managers can create a more adaptive strategy that improves patient outcomes without requiring a complete overhaul of their optimization software.

Limitations and Future Research: Despite these contributions, several limitations suggest fertile avenues for future research. The current demand model does not account for seasonality, and the reliance on a single-objective cost function with penalty terms may not fully capture the complexity of the cost-service trade-off. Consequently, subsequent studies should explore multi-objective metaheuristics to explicitly map the Pareto frontier. Additionally, further investigation is needed to compare these complex adaptive models against parsimonious, optimized heuristics to identify the limits of parametric complexity and determine under which conditions simplicity provides superior robustness [29]. Finally, integrating advanced forecasting models into the replenishment logic could uncover even more sophisticated, non-linear pathways to supply chain stability.

AUTHOR CONTRIBUTIONS

J. Musbah: Conceptualization, Methodology, Theoretical analysis, writing—original draft preparation.

I. Badi: Conceptualization, Review and editing, Validation.

D. Pamucar: Supervision, Review and editing.

DISCLOSURE STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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