Risk-Aware Inventory Management

Analyzing Reorder Policies Under Demand Uncertainty and Congestion

Fundamentals of Organization and Strategic Business Management
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Abstract

Modern supply chains operate under significant uncertainty arising from both stochastic customer demand and variable transportation lead times. Traditional inventory policies, based on fixed reorder points and deterministic lead times, often fail to capture the interaction between operational decisions and logistics constraints. This work presents an Agent-Based Modeling framework designed to compare three inventory replenishment strategies, Fixed Reorder Point (FRP), Adaptive Reorder Point (ARP) and Forecast-Based Reorder (FBR), under varying levels of demand variability and congestion sensitivity.

The model formalizes the relationship between ordering behavior and logistics congestion, highlighting how transportation delays can become an endogenous source of supply chain instability. The simulation environment implements a simplified version of the full analytical model to ensure computational tractability, while preserving the key mechanisms required to address the research questions.

Preliminary analyses indicate meaningful differences between the strategies in terms of stock-out risk, cost performance, and lead-time stability. The results derived from the simulation are processed with a Design of Experiments (DoE) framework and will provide quantitative insights into the trade-off between cost efficiency and operational resilience, supporting managerial decision-making in uncertain and capacity-constrained environments.

1 Introduction: The Imperative for Resilience in Inventory Management

1.1 Volatility and Risk in Modern Supply Chains

Effective inventory management requires balancing two conflicting objective, minimizing holding costs associated with excess stock and avoiding stock-outs, which generate lost sales, emergency transport expenses, and reputational damage. This balance has become increasingly difficult to achieve due to the growing volatility characterizing modern supply chains. Firms must regularly cope with uncertainty in both customer demand and supply lead time and also the latter often being influenced by transportation congestion, disruptions, or capacity constraints.

Classical inventory models rely on static assumptions such as deterministic lead time and stable demand. However, empirical evidence shows that real supply chains behave as complex systems exposed to shocks, variability, and nonlinear interactions. In such environments, operational decisions taken by firms can generate ripple effects through the logistics network, amplifying delays and instability. This underscores the need for modeling approaches capable of capturing dynamic, interdependent behaviors.

1.2 Problem Statement: Linking Inventory Decisions to Logistics Performance

Traditional Reorder Point (ROP) policies determine when to replenish stock based on expected demand during lead time and a buffer of Safety Stock (SS). These methods assume that lead time (LT) is exogenous and stable. In practice, however, LT is often endogenous—it depends on the collective load imposed by multiple actors on the logistics infrastructure.

When firms place orders more frequently or in larger quantities—whether due to demand spikes or aggressive replenishment strategies—this behavior increases the utilization of transportation resources (e.g., vehicle fleets). In capacity-constrained environments, high traffic can generate congestion, which increases LT and its variability. These longer and more uncertain lead times in turn force firms to hold higher safety stocks, creating a self-reinforcing feedback loop that links operational decisions to logistics performance. Understanding this feedback mechanism is essential, as inventory policies that appear optimal under static assumptions may become unstable or costly when LT is influenced by network congestion. This motivates the need for simulation-based approaches that explicitly represent interactions between inventory behavior and logistical constraints.

2 Research Objectives and Key Questions (RQ1–RQ4)

The project is structured around four interlinked research questions designed to assess the performance of the three inventory policies: Fixed Reorder Point (FRP), Adaptive Reorder Point (ARP), and Forecast-Based Reorder (FBR).

- **RQ1: How does demand variability affect stock-out probability under different reorder policies?**
  This question addresses the fundamental operational robustness of each policy. It assesses the policy's ability to maintain a target service level (i.e., minimize the probability of running out of stock) as the standard deviation of demand (σ) increases.

- **RQ2: Which policy minimizes total cost (holding, transport, stock-out)?**
  This is the core economic efficiency question. It requires a detailed comparison of the aggregated total cost (C_{tot}), ensuring that the comparison includes not only inventory costs (C_{hold}, C_{out}) but also the logistical expenses (C_{trans}) incurred by the policy's ordering behavior.[3]

- **RQ3: How does logistics congestion (fleet usage) influence lead time and system stability?**
  This is the resilience metric. It investigates the impact of the ordering strategies on the shared logistics infrastructure. Performance indicators include average lead time ($\bar{L}$), fleet saturation (Truck utilization), and, most importantly, the coefficient of variation of lead time (CV_L). Policies that generate large fluctuations in order frequency or size are expected to lead to higher CV_L in congested networks, increasing operational risk.[2]

- **RQ4: Which strategy offers the best trade-off between cost efficiency and operational resilience?**
  This strategic question synthesizes the findings from RQ1, RQ2, and RQ3 to provide a framework for decision-makers, guiding the optimal selection of inventory policy based on the organization's tolerance for cost versus its exposure to logistics risk.

3 Literature Review on Stochastic Inventory Control and Supply Chain Dynamics

3.1 Foundations of Inventory Control and Classical Models

Classical inventory theory focuses on determining when to reorder stock and in what quantity, typically through the Reorder Point (ROP) mechanism. The ROP is calculated as the expected demand during lead time plus a buffer of Safety Stock (SS), which protects against uncertainty in demand and delivery conditions [1]. Safety stock is commonly derived using a service-level factor multiplied by the standard deviation of demand during lead time, assuming that demand follows a stationary distribution.

Foundational works such as Silver, Pyke, and Peterson formalize these principles and provide closed-form expressions for computing optimal ROP and Economic Order Quantity under various assumptions regarding demand variability, replenishment frequency, and cost structures. However, these traditional frameworks typically assume constant or deterministic lead time (LT), which limits their ability to capture real-world volatility and dynamic logistics interactions.

3.2 Uncertainty, Lead-Time Variability and Adaptive Policies

Uncertainty in demand is a key driver of instability in supply chains, and the well-known *Bullwhip Effect* illustrates how small variations in downstream demand amplify as they propagate upstream, leading to excessive inventory, higher operating costs, and degraded service levels [3]. Factors such as forecast inaccuracies, batching policies, order synchronization, and information delays all contribute to this amplification mechanism.

Recent studies extinguished this view by emphasizing the role of lead-time (LT) variability as a risk multiplier. Although traditional sources of the Bullwhip Effect are rooted in demand-side factors, research has increasingly emphasized that transportation delays and congestion-driven LT variability can significantly amplify upstream volatility [3]. When LT becomes unpredictable, firms must increase SS to maintain service levels, which binds capital and can worsen the variability of order.

Importantly, several authors highlight that LT should not be treated as an exogenous parameter because operational decisions, such as frequent or over-the-top orders—can induce congestion in shared logistics systems, thereby increasing LT variability. This endogeneity of LT is crucial to understanding risk propagation in modern supply chains.

To address the limitations of fixed-parameter policies, adaptive inventory strategies update the reorder point (ROP) and safety stock (SS) based on observed demand. The Adaptive Reorder Point (ARP) policy, for example, recomputes expected demand and its variance using rolling-window estimators, improving responsiveness in volatile environments. These policies remain rooted in classical ROP logic but embed data-driven components to adjust to changing conditions. A more advanced class of strategies leverages demand forecasting to dynamically determine both the ROP and the replenishment quantity. Forecast-Based Reorder (FBR) policies use methods such as moving averages or time-series predictors to compute a target inventory position, akin to concepts employed in Material Requirements Planning.When forecasts are reliable and LT is stable, FBR typically outperforms simple ROP policies by reducing excess inventory while maintaining high service levels. However, recent research warns that the effectiveness of such advanced policies depends critically on logistics capacity and LT stability. Dynamic replenishment quantities, which are characteristic of FBR, can induce substantial variability in transportation demand. In capacity-constrained or congestion-sensitive logistics systems, this variability can increase LT volatility, undermine resilience, and erode the theoretical performance gains of forecasting-based methods. These insights motivate the comparative analysis developed in this paper, which examines how FRP, ARP, and FBR perform under different combinations of demand uncertainty and congestion sensitivity.

4 Simulation Methodology: Agent-Based Modeling

Agent-Based Modeling (ABM) represents heterogeneous supply chain actors with decentralized decision rules, whose local interactions generate emergent behaviors such as congestion, disruption propagation, and demand amplification. In Supply Chain Risk Management, ABM is used to model shock propagation, assess resilience, and test mitigation strategies under large-scale disruptions. By explicitly modeling behavioral heterogeneity, adaptive rules, and network structure, ABM is well suited to capture how inventory policies interact with logistics performance and capacity constraints, highlighting that resilience emerges from the joint behavior of inventory and logistics subsystems.

4.1 Rationale and Environment Setup

The proposed simulation adopts an Agent-Based Modeling (ABM) approach to capture the decentralized and interactive nature of supply chain operations. Unlike analytical models, which typically rely on simplifying assumptions such as stationary demand or deterministic lead time, ABM allows heterogeneous actors to operate autonomously and interact through shared logistical resources. This enables the emergence of system-level dynamics—such as congestion and lead-time variability—from simple local decision rules.

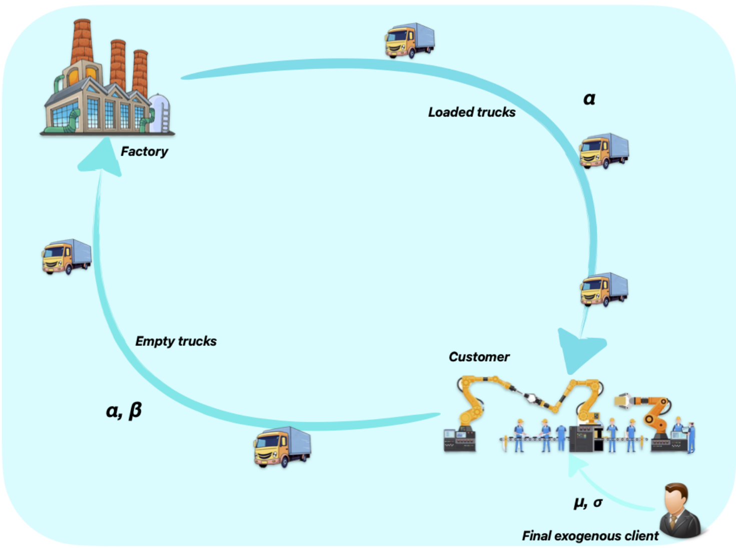

Figure 1: Structure of the ABM

The environment represents a simplified single-echelon supply chain consisting of a Factory, a single Customer, and a fleet of Truck agents responsible for transportation. Time progresses in discrete steps, each corresponding to one operational period (e.g.: a day). At each step, agents update their internal states and exchange information according to the rules defined by the inventory policies under evaluation: Fixed Reorder Point (FRP), Adaptive Reorder Point (ARP), and Forecast-Based Reorder

(FBR).

Demand is generated stochastically, either through a Normal or Poisson process, ensuring that the Customer agent operates under uncertainty. Transportation lead time is influenced by system congestion, which depends on the number of trucks simultaneously in transit. This mechanism establishes the endogenous link between ordering decisions and logistics performance.

All simulation experiments are run for a fixed time horizon to collect statistically meaningful data on inventory levels, stock-outs, transportation load, and system-wide cost.

4.2 Description of Agents and Interactions

The model consists of three main types of agents, each performing specific functions and contributing to the overall system dynamics:

1. **Customer Agent.** The Customer holds an inventory buffer used to satisfy external demand. Its state variables include the on-hand inventory, the historical demand data, and outstanding orders in transit. Based on the selected policy (FRP, ARP, or FBR), the Customer decides whether to place a replenishment order and, if so, computes the corresponding order quantity. The Customer is the primary driver of system activity, as its replenishment behavior determines transportation load and warehouse dynamics.

2. **Factory Agent.** The Factory maintains a stock of available goods and fulfills incoming orders when capacity allows. In accordance with the simplified simulation design, the Factory replenishes its warehouse deterministically each period, ensuring that production constraints do not overshadow the effects of transportation congestion. Once an order is accepted, the Factory dispatches one Truck to deliver the requested quantity.

3. **Truck Agents.** Trucks represent the transportation resources of the system. Each Truck has a maximum load capacity, a current position along the delivery route, and a boolean availability state. When assigned to a shipment, a Truck becomes unavailable, moves toward the Customer, and delivers its load upon arrival. The number of Trucks currently in transit determines the congestion level, which in turn affects the lead time experienced by all orders. After delivery, the Truck returns to availability and resets its position.

Interactions arise naturally through these mechanisms: the Customer's decision to order activates the Factory, which in turn activates Trucks. The cumulative number of active Trucks influences lead time, shaping future Customer decisions through stochastic delays.

4.3 Scenario Design and Performance Indicators

To evaluate the behavior of the replenishment policies under different operational conditions, the simulation explores a scenario matrix defined by two sources of uncertainty. The collected data allow comparative evaluation of FRP, ARP, and FBR across low-, medium-, and high-uncertainty environments. By systematically varying (σ, α), the simulation reveals how inventory policies interact with logistical constraints and how these interactions influence cost, resilience, and service-level performance.

Parameter Category	**Symbol**	**Description**	**Typical Range/Basis**
Demand	μ	Average daily demand	Constant across scenarios
Demand	σ	Standard deviation of demand	Low, Medium, High
Logistics	L_0	Base (free-flow) lead time	Constant (e.g., 3 days)
Logistics	α	Congestion sensitivity coefficient	Low (Resilient), High (Constrained)

Table 1: Fundamental hyperparameters

The simulation runs are designed to collect key performance indicators across all scenarios:

KPI	**Formulas/Metrics**	**Related RQ**	**Managerial relevance**
Stockout Probability	$\text{Prob}(S_t < 0)$	RQ1 (Robustness)	Customer Service Level, Revenue Loss Risk
Total Cost	$C_{tot} = \sum(C_{hold} + C_{out} + C_{trans})$	RQ2 (Efficiency)	Profitability, Working Capital Management
Lead Time Variability	$CV_L = \sigma_L/\mu_L$	RQ3 (Resilience)	Predictability of Supply Chain, Operational Risk
Fleet Saturation	$\left(\frac{\text{Busy Trucks}}{\text{TotalTrucks}}\right)$	RQ3 (Resilience)	Logistics Bottleneck Identification
Inventory Volatility	$CV_S = \sigma_S/\mu_S$	RQ4 (Trade-off)	Obsolescence Risk, Capital Exposure

Table 2: Key Performance Indicators

5 Quantitative Model Framework and Formulation

This section formalizes the mathematical structure underlying the agent-based simulation. The model integrates stochastic demand, inventory dynamics, replenishment policies, transportation congestion, and cost functions into a coherent step-by-step simulation executed for each time step t.

5.1 Demand and Inventory Dynamics

5.1.1 Demand Model

The stochastic demand D_t at time step t is drawn from a predefined statistical distribution $\mathcal{D}(\mu, \sigma)$.
Typical choices include: Poisson distribution, $D_t \sim Poisson(\lambda)$, or a Normal distribution truncated at zero to ensure non-negative integer demand, $D_t \sim \mathcal{N}(\mu, \sigma^2)$.

5.1.2 Inventory Evolution

The inventory level at step t, S_t changes based on consumption and incoming shipments. The stock dynamics are governed by the equation:

$$S_{t+1} = \max(0, S_t - D_t) + I_t \tag{1}$$

where I_t is the incoming shipment quantity, which is equal to the order quantity Q if an order was placed L periods prior, and zero otherwise.

5.2 Dynamic Lead Time

The critical feature of the model is the endogenous lead time L. This structure moves beyond simple stochastic variability by linking L directly to the system's operational load.

5.2.1 Congestion Function

The instantaneous lead time L experienced by a shipment is calculated as a function of the base, free-flow lead time L_0 and the current level of logistical traffic:

$$L = L_0 + \alpha \cdot \text{Traffic} \tag{2}$$

Traffic is defined as the total number of Truck agents simultaneously active in transport over the cardinality of the Truck set (that is a hyperparameter of the model). The coefficient α controls the network's sensitivity to congestion. A high α implies highly constrained logistics capacity.

5.3 Detailed Formalization of Reorders Policy

The three policies are implemented as decision rules for the Customer Agent.

5.3.1 Policy 1 – Fixed Reorder Point (FRP)

This policy represents the simplest, non-adaptive control. Reorder point ROP and order quantity Q are predetermined constants based on historical averages of μ and L_0:

$$\text{If: } S_t \leq ROP \Rightarrow \text{order } Q \tag{3}$$

5.3.2 Policy 2 – Adaptive ROP (ARP)

The ARP dynamically adjusts the ROP based on observed demand variability over a rolling window n.
There is also a safety stock level SS_t, determined by the desired service level factor k (that determines the security threshold) and the estimated standard deviation of demand during lead time ($\hat{\sigma}_L$):

$$SS_t = k \cdot \hat{\sigma}_L = k \cdot \hat{\sigma} \cdot \sqrt{L} \tag{4}$$

The adaptive reorder point is:

$$ROP_t = \hat{D}_t + SS_t \tag{5}$$

Where, D_t is calculated as the moving average of the n demands received n steps before the current step t. (n is a hyperparameter).
The order quantity Q remains fixed, stabilizing the demand on the logistics network compared to FBR.

5.3.3 Policy 3 – Forecast-Based Reorder (FBR)

The FBR policy uses a moving average to forecast demand $\hat{D}_t$ and calculates a dynamic order quantity Q_t designed to replenish stock up to a target level. The dynamic ROP remains sensitive to the current lead time:

$$ROP_t = \hat{D}_t \cdot L + k \cdot \sigma \cdot \sqrt{L} \tag{6}$$

D_t is again calculated as a moving average as before.

In this case also the reorder quantity Q_t is highly variable, aiming to cover expected demand during the lead time plus safety stock, minus current inventory and outstanding orders.

$$Q_t = \lambda \cdot ROP - S_t \tag{7}$$

Where λ is a safety hyperparameter, that ranges in $[0, 2]$.

5.4 Cost Model and Objective Function

The objective of the economic analysis (RQ2) is the minimization of the Total Cost C_{tot}, gien by the following factors.

1. **Holding Cost (C_{hold}):**

$$C_{hold} = h \cdot S_t \tag{8}$$

where h is the unit holding cost per period (simulation step).

2. **Stockout Cost (C_{out}):**

$$C_{out} = p \cdot \max(0, D_t - S_t) \tag{9}$$

   where p is the unit stock-out penalty.

3. **Transport Cost (C_{trans}):**

$$C_{trans} = c \cdot \text{shipment} \tag{10}$$

   where c is the unit transport cost per shipment, incorporating distance and handling costs.

The objective function to minimize over the simulation horizon T is:

$$C_{tot} = \sum_{t=1}^{T} (C_{hold,t} + C_{out,t} + C_{trans,t}) \tag{11}$$

5.5 Simulation Algorithm

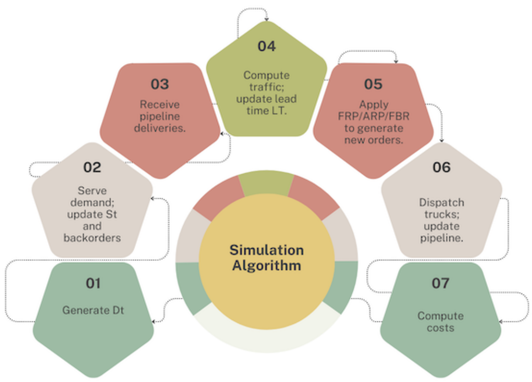

Figure 2: Sequence summary of operations performed at each step

5.6 Model Simplifications for Simulation Implementation

The mathematical framework presented in this chapter provides a complete formulation of stochastic demand, inventory dynamics, adaptive reorder policies, and congestion-driven lead-time variability. However, implementing the full model in an Agent-Based Model (ABM) would significantly increase computational complexity and reduce the transparency of the resulting dynamics. For these reasons, the simulation adopts a set of controlled simplifications that preserve the essential mechanisms required to address the research questions (RQ1–RQ4), while ensuring stability and interpretability.

The primary simplifications introduced in the implementation are the following:

1. **Linear congestion function.** Instead of the nonlinear Bureau of Public Roads (BPR) formulation for lead time, the simulation uses a linear approximation:

$$LT_t = L_0 + \alpha \cdot \text{traffic}_t$$

   This preserves the endogenous relationship between vehicle utilization and lead time while reducing computational overhead.

2. **Simplified ARP and FBR formulations.** While the analytical model defines ARP and FBR through complete expressions for adaptive reorder points and target inventory positions, the simulation computes these using moving averages of past demand:

$$\widehat{D}_t = \frac{1}{n} \cdot \sum_{i=0}^{n} D_i$$

   which is then used to approximate both the reorder point and, in the case of FBR, the replenishment quantity. This simplification preserves the adaptive behaviour of the policies without requiring full variance aggregation under stochastic lead times.

3. **Implicit representation of the order pipeline.** The theoretical model tracks pending orders as tuples (q, t_{arr}). The simulation instead represents incoming inventory through the spatial movement of Truck agents, which carry quantities and deliver them when reaching the Customer node. This maintains the timing logic of deliveries without explicitly modeling a formal queue.

4. **Constant production lead time at the Factory.** To focus the analysis on transportation congestion rather than upstream capacity constraints, the Factory agent replenishes its warehouse deterministically at each simulation step. This matches the single-echelon perspective adopted in classical inventory models.

5. **Discrete-time approximation.** All processes (demand generation, inventory updates, truck movement, and policy decisions) occur in synchronized discrete time steps, which is consistent with the agent-based paradigm implemented and sufficient for capturing the qualitative effects under study.

Despite these simplifications, the simulation environment retains the core feedback loop of interest: inventory decisions affect logistics congestion, which in turn generates lead-time variability and influences subsequent ordering behaviour. Therefore, the implemented model remains suitable for evaluating the comparative performance of FRP, ARP, and FBR under different levels of uncertainty and congestion, as required by the research questions.
As a result, the simulation is not intended to provide optimal policy parameters, but rather to compare the relative performance and stability of alternative replenishment strategies under controlled uncertainty and congestion scenarios.

6 Results: Comparative Performance Analysis of Reorder Policies

This section presents the results of the ABM across the demand variability and congestion scenarios defined in the experimental matrix. The simulation has been implemented in order to simulate a real scenario, with an average daily trucking range of 500 km, and a distance between the customer and factory firms is approximately three times this range, leading to a free-flow lead time of 3 days.

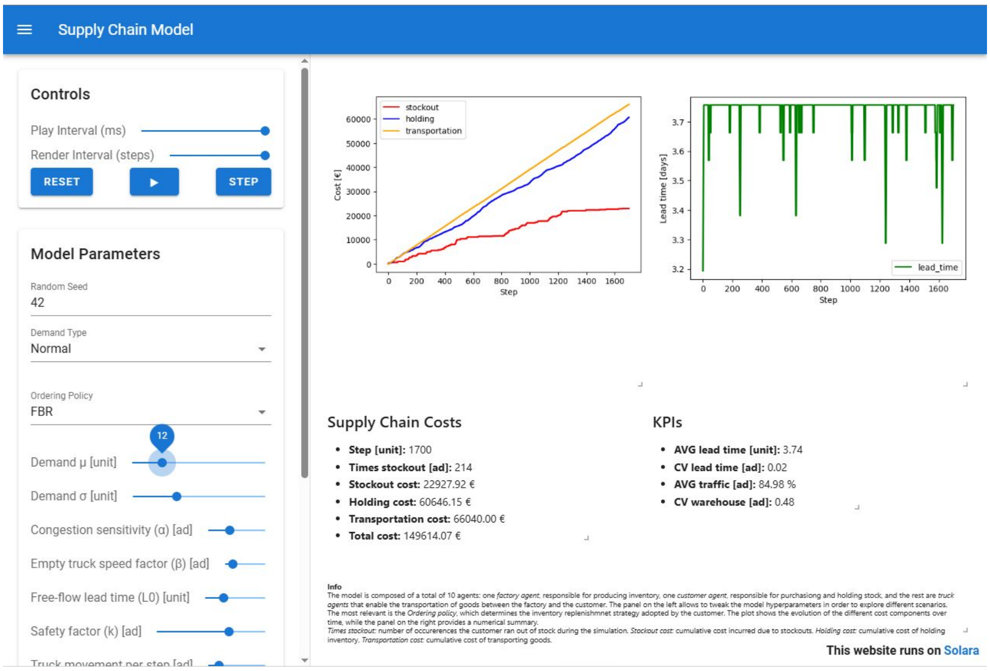

Figure 3: Dashboard interface

For each FRP, ARP, FBR we assess operational robustness economic efficiency and logistical stability.

The quantitative analysis is based on the KPIs introduced in Section 4.3. Simulation outcomes are reported using tables and graphical outputs, including time-series plots of lead-time variability, which provide a clear basis for comparing the three strategies under different operating conditions.

6.1 Design of Experiment

To answer our research question, we have implemented a Design of Experiments (DoE). We considered four scenarios, each defined by a different combination of the parameters α, σ (low/high traffic congestion versus demand variability) with other features that remain fixed.

The data gathered from the DoE are statistics coming from a total of five run per each scenario over the three distinct policies.

	S_1	S_2	S_3	S_4
σ	2	8	2	8
α	0.1	0.1	1.2	1.2

Table 3: Hyperparameters per scenario

The main aim of the DoE is to understand how the output will vary due to a slight or substantial change on the input.

Scenario	S_1			S_2			S_3			S_4		
Policy	FRP	ARP	FBR	FRP	ARP	FBR	FRP	ARP	FBR	FRP	ARP	FBR
total cost [€]	29 001.99	26 618.19	42 418.09	54 262.11	35 358.86	57 559.33	29 918.19	30 015.09	37 139.73	39 086.58	38 235.33	46 123.34
stockout probability [ad]	3.9%	9.2%	4.2%	7.9%	12.2%	5.8%	32.3%	31.0%	10.8%	25.8%	20.5%	13.2%
fleet saturation [ad]	9.2%	9.2%	3.4%	2.3%	8.9%	2.3%	11.0%	11.0%	4.3%	10.7%	10.8%	5.4%
AVG lead time [days]	3.17	3.17	3.13	3.13	3.17	3.12	4.16	4.16	3.56	4.13	4.13	3.47
CV leadtime [ad]	0	0	0.006	0	0	0	0.02	0.02	0.038	0.034	0.032	0.036
CV warehouse [ad]	0.39	0.32	0.49	0.51	0.52	0.48	0.35	0.36	0.474	0.63	0.59	0.57

Table 4: Results of DoE

6.2 Simulation Time-Series Analysis and Emergent Dynamics

While aggregated KPIs provide a static comparison of policy performance, time-series analysis enables investigation of the dynamic mechanisms through which system-level outcomes emerge. In particular, the temporal evolution of cost components and lead time reveals how inventory decisions interact with logistics congestion and how instability propagates over time.

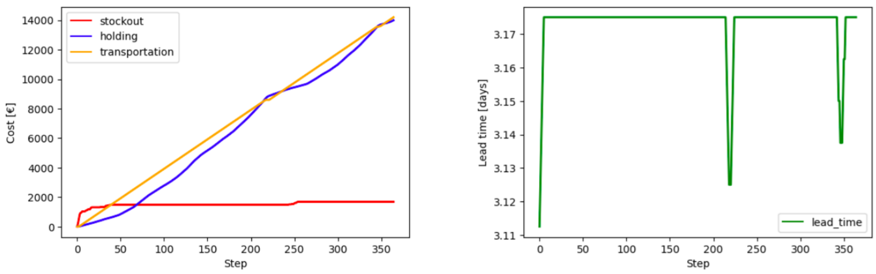

Figure 4: Scenario 1, Policy FRP

Figure 4 illustrates a representative low-uncertainty and low-congestion case (Scenario S1). Lead time remains close to the free-flow value, with only two lower-spikes, indicating absence of critical variance. Throughout the simulation horizon, the congestion effects are negligible. Cost components evolve smoothly and approximately linearly, with the stockout cost limited by an upper bound set by the low number of stockout times. This behavior characterizes a stable operating regime in which logistics capacity is not a binding constraint and policy differences remain marginal, consistent with the low stockout probabilities and low fleet saturation reported in Table 4.

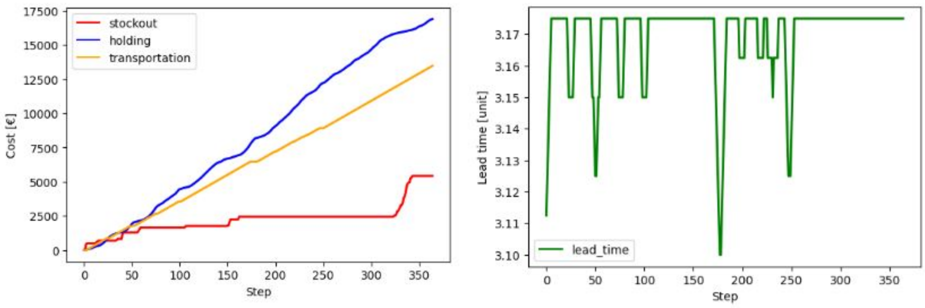

Figure 5: Scenario 2, Policy ARP

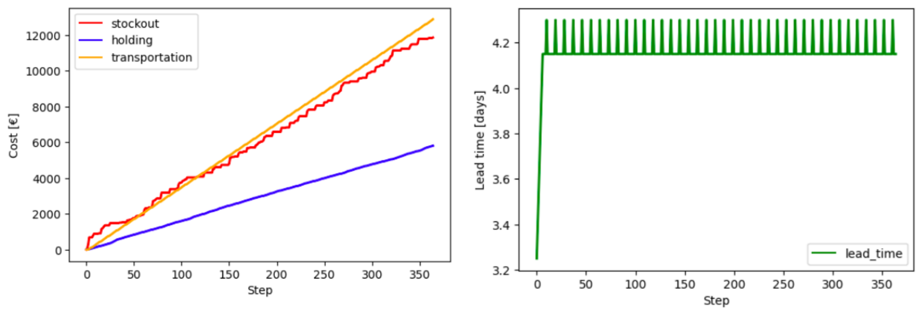

Figure 6: Scenario 3, Policy FRP

Figure 5 and Figure 6 focuses on a congestion-sensitive scenario (Scenario S2 and S3) and compare the FRP and ARP policies. Periodic oscillations emerge in lead time as a consequence of synchronized replenishment activity and fleet saturation. These oscillations propagate into inventory dynamics, producing bursts of stockout accumulation and increased variability in cumulative costs. This dynamic behavior explains the substantially higher stockout probabilities observed for FRP and ARP in Scenario S2 and S3 (above 30%, Table 4). The ARP policy partially mitigates these oscillations by adapting reorder thresholds based on observed demand, resulting in a much lower lead time and slightly adjusted trajectories with an improved control relative to FRP, although congestion effects remain significant.

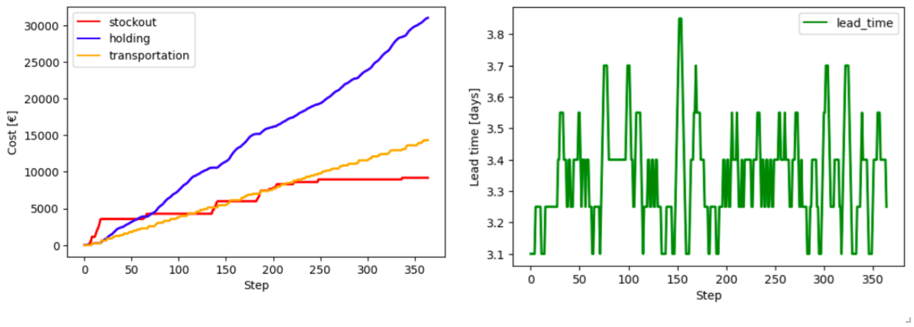

Figure 7: Scenario 4, Policy FBR

Figure 7 illustrates the behavior of the FBR policy under high uncertainty and congestion (Scenario S4). Stockout accumulation remains comparatively low, confirming the robustness of forecast-driven replenishment in maintaining service levels (approximately 13% stockout probability in Table 4). However, holding costs increase substantially due to higher safety stock levels and more aggressive replenishment behavior, which is reflected in the higher total cost observed for FBR.
Lead time exhibits high variability.

Overall, the time-series evidence confirms that congestion is not an exogenous disturbance but emerges endogenously from ordering behavior and fleet interactions. Inventory policies influence not only average performance levels but also the dynamic stability of the system. These dynamic patterns reinforce the resilience–cost trade-off identified in the aggregated indicators and highlight the importance of evaluating replenishment strategies within a systemic, congestion-sensitive framework.

6.3 RQ1: Robustness to Demand Variability

Demand variability has a clear and direct impact on stock-out probability. When comparing scenarios with low variability (S_1 and S_3, $\sigma = 2$) with those with high variability (S_2 and S_4, $\sigma = 8$), the probability of stock-out increases for all reorder policies.
However, this increase strongly depends on the policy adopted. FBR consistently shows the lowest stock-out probability in all scenarios. In high-variability conditions, FBR is able to limit stock-out to around 11-13%, while FRP and ARP exceed 20% and in some cases 30%.
A higher congestion sensitivity level ($\alpha = 1.2$) impacts the stock-out risk, worsening the effect of high demand variability.

Overall, the results indicate that **FBR is the most robust policy when demand uncertainty increases**

6.4 RQ2: Economic Efficiency

Total cost is influenced by both demand variability and reorder policy.
In low sensitive transportation networks ($\alpha = 0.1$), ARP achieves the lowest total cost. This is mainly due to lower holding costs, while transportation costs remain

similar across all policies.
When α increases to 1.2, total cost for FRP and ARP becomes more similar. In contrast, FBR consistently results in higher total cost, driven by higher holding cost, which is required to reduce stock-out risk.

From a **cost-oriented** perspective, **ARP is the most efficient policy** in most scenarios, especially when demand variability is limited.

6.5 RQ3: Resilience and Congestion Sensitivity

Fleet saturation provides useful insights into logistic congestion and into system performance.
Scenarios with high demand variability lead to higher fleet usage, with FRP and ARP often exceeding 10%. FBR leads to lower fleet saturation, which is reflected in shorter average lead time and more stable system behavior. In high-variability scenarios, FBR reduces lead time by 15-20% compared to the other policies.

Although lead time variability remains generally low across all cases, **lower congestion clearly improves predictability and operational stability** in supply chain.

6.6 RQ4: The Resilience–Cost Trade-Off

When cost efficiency and operational resilience are considered jointly, clear trade-offs emerge.
ARP minimizes total cost, but with the huge burden of a higher stock-out probability under volatile demand.
FRP shows moderate cost performance but limited robustness.
FBR, despite higher costs, significantly improves services level, reduces congestion and stabilizes lead time.

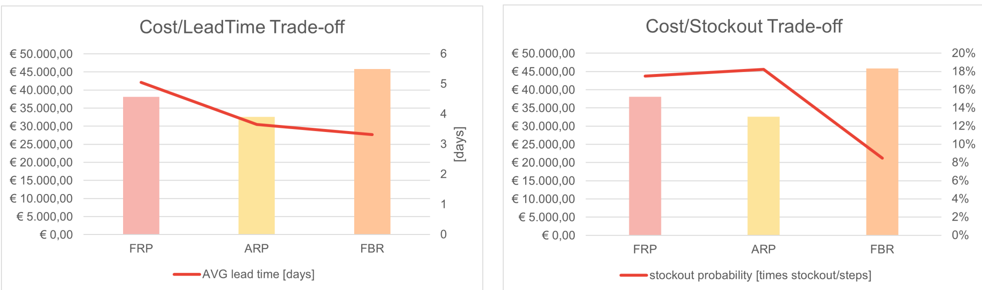

Figure 8: Trade-Offs from DoE

From a volatility perspective, the behaviors of the coefficient of variation, calculated for both lead time and the warehouse, has a similar pattern.
ARP is the policy that minimizes the variation of the warehouse and the lead time over the transportation network, while FBR is the policy bringing the highest variation, testified by the adaptability applied to both reorder point and reorder quantity.

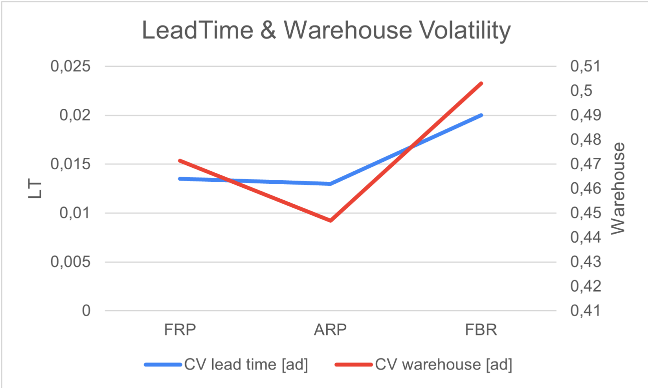

Figure 9: Lead time and Warehouse CV

Therefore, **FBR offers the best overall trade-off in high uncertainty environment**, while **ARP is preferable when demand is stable and cost minimization is the primary objective**.

7 Discussion, Managerial Implications, and Strategic Insights

The results obtained from the simulation offer several insights into how inventory policies interact with logistical constraints and operational uncertainty. This section interprets these findings, linking them to the research questions and to managerial decision-making.

7.1 Interpreting Policy Behavior Under Uncertainty and Risk Propagation

Adaptive policies behave very differently under uncertainty and congestion. Static FRP degrades as demand variability grows, confirming that fixed-parameter rules are ill-suited to dynamic environments.
ARP improves robustness by regularly updating reorder points based on observed demand, while FBR achieves high efficiency when congestion is low by closely aligning replenishment quantities with expected demand. However, highly responsive policies such as FBR can generate bursty orders that overload transport capacity, creating endogenous congestion, volatile lead times, higher safety stocks, and deteriorating service levels. ARP partially mitigates this congestion-driven risk propagation by stabilizing replenishment quantities and smoothing transportation demand, which explains its superior performance in highly congestion-sensitive scenarios.

7.2 Managerial Implications

From a decision-making perspective, the findings suggest several actionable principles:

- **Monitor logistics as closely as inventory.** Metrics such as lead-time variability (CV_{LT}) and fleet utilization offer early signals of systemic stress.
- **Match policy sophistication to logistics capacity.** Forecast-based policies are beneficial only if transportation resources can absorb fluctuations in order size; otherwise, they may destabilize the system.
- **Resilience requires stability as well as adaptivity.** ARP demonstrates that moderate adaptivity combined with low volatility in order quantities can outperform more sophisticated strategies in congested systems.

7.3 Strategic Insights

The results reinforce a key message for supply chain design: *operational policies should be evaluated not only for local efficiency but also for their systemic effects on shared resources.* Policies that appear optimal under classical inventory theory may underperform in congested environments where lead time becomes endogenous.

By explicitly modeling these complexities and emergent behaviors through ABM, this work highlights the strategic trade-offs firms must navigate when selecting inventory policies under uncertainty.

8 Conclusions, Limitations, and Future Research Directions

8.1 Summary of Key Findings

This study developed an Agent-Based Modeling (ABM) framework to evaluate the performance of three inventory replenishment strategies—Fixed Reorder Point (FRP), Adaptive Reorder Point (ARP), and Forecast-Based Reorder (FBR)—under different levels of demand uncertainty and logistics congestion. The results highlight the critical role of endogenously generated lead-time variability in shaping inventory performance and system-wide resilience.

Overall, the comparison reveals that:

- FRP, while simple to implement, is highly sensitive to demand volatility and increasingly prone to stockouts as uncertainty grows.
- ARP offers a robust balance between responsiveness, stability and costs, adjusting reorder decisions according to observed demand while avoiding the excessive variability associated with dynamic order quantities.
- FBR performs well in unconstrained environments, but its higher variability in replenishment behavior can trigger congestion, amplifying lead-time instability and undermining cost efficiency in capacity-limited systems.

These findings confirm that inventory policies cannot be evaluated in isolation from the logistical context in which they operate. Endogenous congestion mechanisms act as a multiplier of operational risk, altering the trade-offs between cost minimization and service-level reliability.

8.2 Model Limitations

To maintain tractability and focus, several simplifying assumptions were introduced in the simulation implementation:

- The nonlinear Bureau of Public Roads (BPR) congestion model was replaced by a linear approximation of lead time as a function of traffic.
- ARP and FBR policies were implemented using moving averages rather than the full analytical expressions based on variance aggregation under stochastic lead times.
- The Factory agent operates with deterministic production and without upstream capacity constraints, reflecting a single-echelon perspective.
- The pipeline of pending orders was represented implicitly through Truck movements rather than explicit scheduling tuples representing queues.

These simplifications do not alter the validity of the comparative analysis but should be considered when generalizing the results to more complex, real-world systems.

8.3 Future Research Directions

Several extensions could strengthen the model and broaden its applicability:

- **Incorporating multi-echelon structures.** Adding distributors, suppliers, more and distinct agents with their own intrinsic behaviors, would allow exploration of Bullwhip propagation and network-wide congestion effects.

- **Integrating more realistic congestion dynamics.** Implementing a full BPR function or microscopic traffic simulation could capture nonlinearities in lead-time behavior under heavy load.
  In this front, traffic could be modeled with Cellular Automata, as they are a simple and powerful tool that allow the integration of ABM.

- **Adaptive and intelligent decision-making though Reinforcement Learning.** Reinforcement Learning agents could replace static replenishment rules by learning policies that balance demand uncertainty and congestion risk in real time, leading to optimal policies.

- **Economic extensions.** Introducing price elasticity, lost-sales valuation, or substitution effects would enable a richer analysis of customer-facing impacts and cost structures.

By situating inventory policies within a dynamic, congestion-sensitive logistics system, this work provides a foundation for more comprehensive modeling of supply chain resilience and operational decision-making under uncertainty.

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A Appendix: code

To carry-out the simulation we use the MESA Python library for Agent Base Modeling.[10] All code is available on the GitHub repository with the instructions for installing the simulation software developed:

https://github.com/fraro01/Agent-Based-Modeling-for-Logistics

A.1 Agent in MESA

```python
class Factory(mesa.Agent):
    """An agent that produces a stochastic amount of goods per day"""

    def __init__(self, model, warehouse):
        #pass the parameters of the parent class
        super().__init__(model)
        self.warehouse = warehouse #number of stocks in the warehouse
        #since we do not model any queue upstream, this class is super easy

    def step(self):
        self.warehouse += self.model.mu #average production per step
```

Figure 10: Definition of Factory Agent

A.2 KPIs

```python
def compute_kpis(self):
        """Compute additional KPIs after the simulation ends"""
        #lead time avg and coefficient of variation
        AVG_L = float(np.mean(self.lead_time_history)) if len(self.lead_time_history) > 0 else 0
        CV_L = float(np.std(self.lead_time_history) / AVG_L) if AVG_L > 0 else 0
        #warehouse avg and coefficient of variation
        AVG_S = float(np.mean(self.customer_warehouse_history)) if len(self.customer_warehouse_history) > 0 else 0
        CV_S = float(np.std(self.customer_warehouse_history) / AVG_S) if AVG_S > 0 else 0
        #traffic avg
        AVG_T = float(np.mean(self.traffic_history)) if len(self.traffic_history) > 0 else 0
```

Figure 11: How KPIs are calculated