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Inventory Digital Twin: Simulation & Optimization Under Uncertainty

by

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Problem & System Overview

Inventory Digital Twin: Simulation & Optimization Under Uncertainty

1. Problem Context

Inventory management decisions must balance customer service levels against operational costs while operating under uncertainty. Variability in customer demand and supplier lead times makes deterministic planning approaches insufficient, often resulting in either excessive inventory or frequent stockouts.

Traditional inventory formulas rely on average demand and fixed lead times, which fail to capture the stochastic nature of real systems. As a result, decision-makers lack visibility into risk, variability, and the true cost–service trade-offs inherent in inventory control.

To address these limitations, simulation-based decision support enables organizations to evaluate inventory policies under realistic operating conditions before deploying them in live systems.

2. Project Objective

The objectives of this project are to:

- Build a **digital twin** of a warehouse inventory system
- Evaluate inventory performance under **stochastic demand and lead-time uncertainty**
- Compare policy performance across multiple operating scenarios
- Identify inventory policies that achieve **high service levels at minimal total cost**

The focus of this work is on **system-level trade-offs**, rather than optimizing a single metric in isolation.

3. System Overview

The modeled system represents a simplified but realistic warehouse environment:

- Single warehouse
- Single stock keeping unit (SKU)

- One upstream supplier
- Continuous review inventory control using an *(s, S)* policy

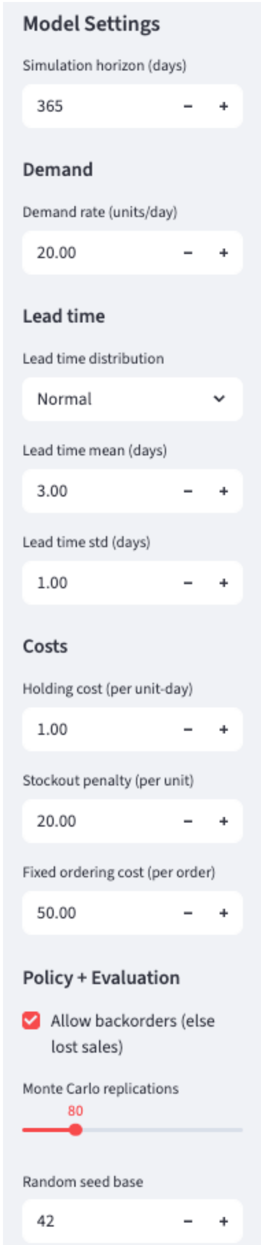
System flow:

Customer Demand → Inventory Consumption → Reorder Decision → Supplier Replenishment → Inventory Update

4. Key Assumptions

- Demand arrives randomly over time
- Inventory is reviewed continuously
- Replenishment orders arrive after a stochastic lead time
- Stockouts may result in backorders
- Costs are incurred for holding inventory, placing orders, and unmet demand

This simplified structure enables clear insight into uncertainty-driven dynamics while remaining computationally efficient.



Streamlit sidebar showing system inputs

Model & Baseline Simulation Results

1. Simulation Approach

A **discrete-event simulation** approach is used to model the inventory system. The system state changes only at event times, such as demand arrivals or replenishment arrivals, allowing accurate representation of real operational behavior.

Inventory control follows a standard **continuous review (s, S) policy**:

- When inventory position ≤ s, an order is placed
- The order raises the inventory position to S

2. Stochastic Modeling

To reflect real-world uncertainty:

- **Demand arrivals** are modeled as a Poisson process
- **Lead times** are modeled using random distributions (Uniform or Normal)
- Each simulation run produces a different outcome due to randomness

This ensures results are not driven by average-case assumptions.

3. Monte Carlo Evaluation

Each policy is evaluated using **Monte Carlo simulation** consisting of 100 independent replications. For each policy, mean performance metrics and **95% confidence intervals** are computed, enabling statistically meaningful comparisons.

4. Baseline Simulation Results

A baseline inventory policy with parameters **(s = 40, S = 120)** was evaluated under nominal demand and lead-time conditions.

Observed performance:

- **Service level (fill rate):** 70.41%
  (95% CI: 69.77% – 71.05%)
- **Total system cost:** 57,071
  (95% CI: 56,253 – 57,890)
- **Average orders placed:** 87.47 per year

Cost decomposition shows that **stockout penalties dominate total cost**, indicating insufficient inventory buffers under uncertainty.

Results

Service level (mean)	Total cost (mean)	Orders placed (avg)
70.41%	57071.3	87.47
↑ 95% CI: [69.77%…	↑ 95% CI: [56253.…	

	count	mean	std	min	25
service_level	100	0.7041	0.0328	0.6157	
total_cost	100	57071.3434	4174.4616	45363.123	54
holding_cost	100	9566.6434	751.3399	7750.5567	9
stockout_cost	100	43131.2	4875.0599	29760	
ordering_cost	100	4373.5	55.7116	4250	
orders_placed	100	87.47	1.1142	85	
total_demand	100	7287.13	80.4929	7034	
immediate_fills	100	5130.57	237.4762	4501	
ending_on_hand	100	26.57	26.7073	0	
ending_backorders	100	9.38	16.579	0	

Figure 2. Baseline Monte Carlo simulation results from the *Run Simulation* tab.

Key Insight:

Even under nominal operating conditions, the baseline policy delivers poor service performance, demonstrating that intuition-based or deterministic parameter selection is inadequate when uncertainty is explicitly modeled.

Scenario Analysis Results

1. Scenario Design

To evaluate system robustness, the same baseline inventory policy **(s = 40, S = 120)** was tested under multiple operating scenarios. Only environmental parameters were modified; the inventory policy itself remained fixed.

The following scenarios were evaluated:

Scenario	Description
Baseline	Nominal demand and lead time
Demand +30%	30% increase in demand rate
Lead-Time Disruption	Lead-time mean and variability increased by 50%

Each scenario was evaluated using Monte Carlo simulation with 95% confidence intervals.

2. Scenario Performance Summary

Scenario	Service Level (mean)	Total Cost (mean)
Baseline	70.41%	57,071
Demand +30%	46.56%	112,224
Lead Time ×1.5	35.16%	102,594

3. Observations

- A **30% demand increase** reduced service level by approximately **24 percentage points** and nearly **doubled total cost**
- Increased lead-time variability caused an even more severe degradation in service performance
- Cost escalation under stressed scenarios was driven primarily by **stockout penalties**, not holding costs

These results demonstrate that the baseline policy is **highly fragile** under realistic disruptions.

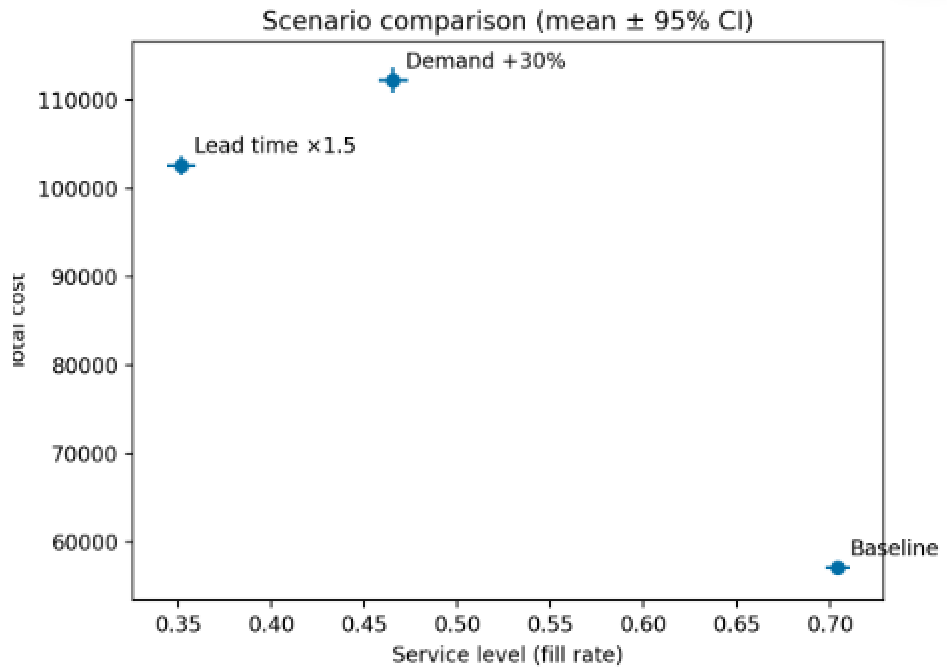


Figure 3. Scenario comparison plot showing service level vs total cost (mean ± 95% CI).

Key Insight

Policies that appear operationally acceptable under nominal conditions can fail catastrophically under stress, highlighting the necessity of scenario-based evaluation.

Optimization & Business Insights

1. Policy Optimization

Given the poor baseline performance and high sensitivity to uncertainty observed in scenario analysis, a **constrained policy optimization** was performed.

Optimization objective:

- Minimize total system cost

Constraint:

- Service level ≥ 98%

Method:

- Grid search over feasible *(s, S)* policies
- Monte Carlo evaluation (40 replications per policy)

Search space:

- s ∈ [20, 120], step 10
- S ∈ [120, 300], step 20

2. Optimization Results

The best feasible policy identified was:

- **(s, S) = (90, 180)**
- **Service level:** 98.59%
- **Total cost:** 33,571

Compared to the baseline policy, this represents:

- **+28.18 percentage point increase** in service level
- **≈ 41% reduction** in total system cost

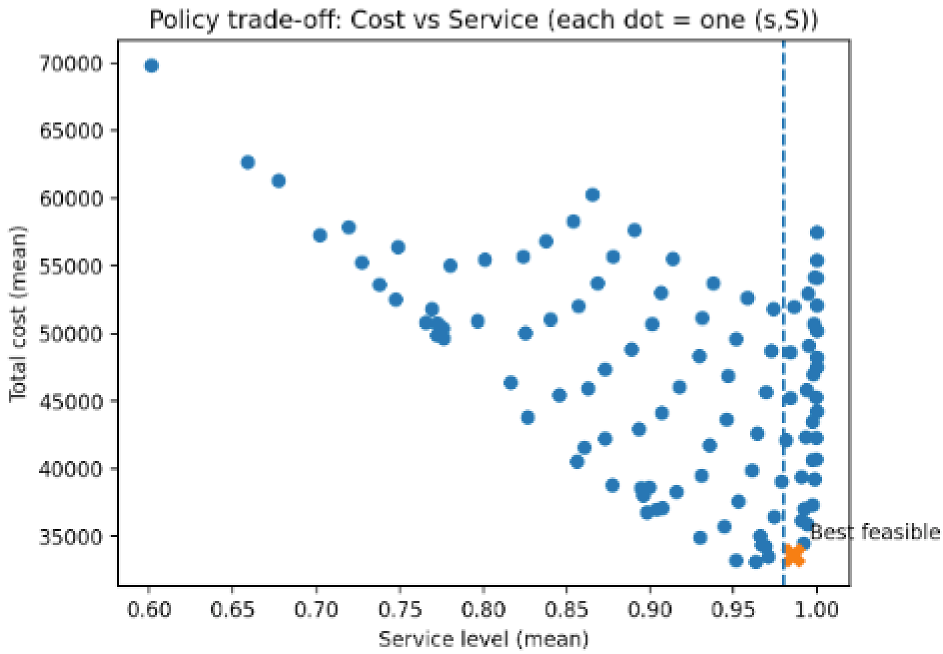


Figure 4. Cost vs service trade-off curve with the optimal policy highlighted.

Key Insight:

Increasing safety stock alone is not an effective strategy.
Jointly adjusting reorder points and order-up-to levels yields superior cost–service performance under uncertainty.

The optimal policy lies near the feasibility boundary, where further service improvements would require disproportionately higher inventory buffers.

Conclusion

This project demonstrates how **digital twins and simulation-based optimization** can support robust inventory decision-making.

Key takeaways:

- Inventory systems must be evaluated under uncertainty
- Simulation reveals risks hidden by average-case analysis
- Optimization enables cost-effective achievement of high service levels

The resulting Streamlit application serves as an **interactive decision-support tool**, rather than a static analytical exercise, and can be extended to multi-SKU or multi-echelon systems.