BAYESIAN INVENTORY CONTROL UNDER UNCERTAIN DEMAND: A DATA-DRIVEN LEARNING APPROACH

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Rezumat. *Gestionarea eficientă a stocurilor în condiții de incertitudine rămâne o provocare centrală în sistemele lanțului de aprovizionare, în special atunci când cererea este stocastică, nestaționară sau parțial observată. Metodele clasice de control al stocurilor se bazează pe ipoteze probabilistice fixe care adesea nu reușesc să surprindă dinamica cererii în evoluție. Această lucrare dezvoltă un cadru Bayesian de Control al Stocurilor care integrează învățarea probabilistică a cererii cu luarea deciziilor secvențiale. Abordarea propusă actualizează distribuțiile cererii în timp real folosind inferența Bayesiană, permițând politici de comandă adaptive care răspund la informații noi. Pentru a evalua performanța, modelul Bayesian este comparat cu politicile tradiționale de inventar bazate pe prognoză, inclusiv prognoza statistică bazată pe ARIMA și predicția cererii prin învățare profundă bazată pe LSTM. Rezultatele simulării demonstrează că abordarea Bayesiană reduce constant costul total al stocurilor, îmbunătățește nivelurile de servicii și prezintă o robustețe superioară în scenarii de incertitudine ridicată a cererii și disponibilitate scăzută a datelor. Constatările evidențiază avantajele combinării inferenței probabilistice cu optimizarea stocurilor în sistemele moderne ale lanțului de aprovizionare.*

Abstract. *Effective inventory management under uncertainty remains a central challenge in supply chain systems, particularly when demand is stochastic, non-stationary, or partially observed. Classical inventory control methods rely on fixed probabilistic assumptions that often fail to capture evolving demand dynamics. This paper develops a Bayesian Inventory Control framework that integrates probabilistic demand learning with sequential decision-making. The proposed approach updates demand distributions in real time using Bayesian inference, enabling adaptive ordering policies that respond to new information. To evaluate performance, the Bayesian model is compared with traditional forecasting-driven inventory policies, including ARIMA-based statistical forecasting and LSTM-based deep learning demand prediction. Simulation results demonstrate that the Bayesian approach consistently reduces total inventory cost, improves service levels, and shows superior robustness under high demand uncertainty and low data availability scenarios. The findings highlight the advantages of combining probabilistic inference with inventory optimization in modern supply chain systems.*

Keywords: Bayesian inventory control; stochastic inventory management; (s,S) policy; demand forecasting; uncertainty quantification; machine learning forecasting models

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1. Introduction

Inventory control is a foundational problem in operations research and supply chain management, where firms must carefully balance ordering costs, holding costs, and the risks associated with stockouts. Effective inventory policies are essential for maintaining service levels while minimizing total operational cost, particularly in competitive and uncertain market environments. Classical inventory models, such as the Economic Order Quantity (EOQ) framework and (s, S) policies, have long served as standard tools for decision-making under uncertainty [1–4]. These models, however, typically rely on strong assumptions, including known and stationary demand distributions, constant lead times, and stable system dynamics [1–3]. While analytically tractable, such assumptions are often violated in real-world supply chains [7].

In practice, demand processes are rarely stationary and are frequently influenced by structural breaks, seasonality, external shocks, and evolving consumer behavior [12]. Furthermore, decision-makers often operate under conditions of incomplete information, especially in the context of new product introductions or rapidly changing markets [9]. These challenges limit the applicability of classical inventory models and motivate the development of adaptive and data-driven approaches that can learn from observed demand over time [10].

Bayesian methods provide a principled and coherent framework for addressing these limitations [16–17]. By treating unknown demand parameters as random variables rather than fixed but unknown constants, Bayesian inventory control enables the explicit representation of uncertainty in model parameters [8]. As new demand observations become available, prior beliefs are updated through Bayes' theorem, resulting in posterior distributions that reflect improved knowledge of the underlying demand process [16]. This iterative learning mechanism allows decision-makers to continuously refine their understanding of demand while simultaneously optimizing inventory decisions [17].

A key advantage of Bayesian inventory control lies in its integration of learning and decision-making within a unified framework [8]. Unlike traditional forecasting pipelines, which typically separate demand prediction from operational optimization, Bayesian approaches directly incorporate uncertainty into the decision process [15]. As a result, ordering policies are dynamically adjusted based on posterior distributions rather than point estimates, enabling more robust performance under uncertainty [10]. This is particularly valuable in environments with limited historical data, high volatility, or rapidly evolving demand structures [9].

Recent advances in machine learning have further enhanced the ability to model complex demand patterns. Techniques such as ARIMA-based time series models and deep learning architectures like Long Short-Term Memory (LSTM) networks have demonstrated strong performance in demand forecasting tasks [11–13]. However, these approaches are often primarily predictive in nature and remain decoupled from inventory decision-making frameworks [14-20]. In many cases, forecasts generated by such models are used as inputs to separate optimization routines, which may not fully capture forecast uncertainty or its impact on operational decisions [12].

This paper aims to bridge this gap by comparing Bayesian decision-making approaches with both classical statistical forecasting and modern deep learning methods within a unified inventory control setting. In particular, we evaluate how different modeling paradigms—Bayesian updating, ARIMA-based forecasting, and LSTM-based learning—affect inventory performance metrics such as total cost, service level, and responsiveness to demand changes. By integrating forecasting and optimization perspectives, this study highlights the advantages and limitations of each approach in dynamic and uncertain environments and demonstrates the practical value of Bayesian learning for adaptive inventory control.

2. Mathematical modeling and algorithms

2.1 Demand Model

Let $D_t$denote the demand in period $t = 1,2, \ldots, T$. We assume demand follows a stochastic process parameterized by an unknown vector θ. A common and tractable assumption is that demand is conditionally independent given θ:

$$D_t \mid \theta \sim \mathcal{D}(\theta) \tag{1}$$

where $\mathcal{D}(\theta)$may represent a Poisson, Normal, or other suitable demand distribution depending on the application context. For instance, in the case of Gaussian demand:

$$D_t \mid \mu, \sigma^2 \sim \mathcal{N}(\mu, \sigma^2) \tag{2}$$

The unknown parameters $\theta = (\mu, \sigma^2)$ are treated as random variables in the Bayesian framework.

2.2 Prior Distribution

Before observing any demand data, the decision-maker specifies prior distribution over the unknown demand parameters:

$$p(\theta) \tag{3}$$

For conjugate analysis (Gaussian demand with unknown mean and known variance), a typical prior is:

$$\mu \sim \mathcal{N}(\mu_0, \tau_0^2) \tag{4}$$

This prior encodes initial beliefs based on historical data, expert judgment, or market information.

2.3 Bayesian Updating

As demand observations become available, beliefs are updated using Bayes' theorem. After observing demand history $D_{1:t} = \{D_1, \ldots, D_t\}$, the posterior distribution is:

$$p(\theta \mid D_{1:t}) = \frac{p(D_{1:t} \mid \theta) p(\theta)}{p(D_{1:t})} \tag{5}$$

For Gaussian demand with known variance, the posterior mean updates as:

$$\mu_t = \frac{\tau_0^{-2}\mu_0 + t\sigma^{-2}\bar{D}_t}{\tau_0^{-2} + t\sigma^{-2}} \tag{6}$$

where:

$$\bar{D}_t = \frac{1}{t}\sum_{i=1}^{t} D_i \tag{7}$$

This recursive structure allows continuous learning as new data arrives.

2.4. Inventory System and (s, S)Policy

We consider a periodic-review inventory system with instantaneous replenishment. Let $I_t$denote the inventory level at the beginning of period t. The system evolves as:

$$I_{t+1} = I_t + Q_t - D_t \tag{8}$$

where $Q_t$is the order quantity.
Under an (s, S)policy:

- If $I_t < s$, order up to level S
- Otherwise, no order is placed
-

$$Q_t = \begin{cases} S - I_t, & I_t < s \\ 0, & I_t \geq s \end{cases} \tag{9}$$

2.5 Bayesian Optimal Decision Rule

In the Bayesian setting, optimal order decisions are based on the posterior predictive distribution of demand:

$$p(D_{t+1} \mid D_{1:t}) = \int p(D_{t+1} \mid \theta) p(\theta \mid D_{1:t}) d\theta \tag{10}$$

The expected demand under uncertainty is:

$$\mathbb{E}[D_{t+1} \mid D_{1:t}] = \int D_{t+1}\, p(D_{t+1} \mid D_{1:t})\, dD_{t+1} \tag{11}$$

The (s, S)parameters are dynamically updated by minimizing expected total cost:

$$(s^*, S^*) = \arg\ \min_{s,S}\ \mathbb{E}[h(I_t)^+ + b(I_t)^- + K\mathbf{1}_{Q_t>0} \mid D_{1:t} \tag{12}$$

where:

- h: holding cost
- b: shortage (backorder) cost
- K: fixed ordering cost
- $(x)^+ = max(x, 0)$, $(x)^- = max(-x, 0)$

2.6 Cost Function

The total expected cost per period is defined as:

$$C_t = h\max(I_t, 0) + b\max(-I_t, 0) + K\mathbf{1}_{Q_t>0} \tag{13}$$

The objective is to minimize long-run average cost:

$$\min\ \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}[C_t] \tag{14}$$

2.7 Integration with Learning

Unlike classical inventory systems where parameters are fixed, the Bayesian framework continuously adapts:

1. Observe demand D_t
2. Update posterior $p(\theta \mid D_{1:t})$
3. Recompute predictive demand distribution
4. Update (s, S)policy
5. Execute ordering decision Q_t

This closed-loop structure enables real-time adaptation to non-stationary demand environments.

3. Results and Discussion

3.1 Cumulative Inventory Cost Comparison

The cumulative cost trajectories for the Bayesian, ARIMA-based, and LSTM-based inventory policies are illustrated in Figure 1. Across the entire simulation horizon, the Bayesian inventory control strategy consistently achieves the lowest cumulative cost. This improvement is not merely marginal but becomes increasingly pronounced as time progresses, indicating a compounding effect of adaptive learning.

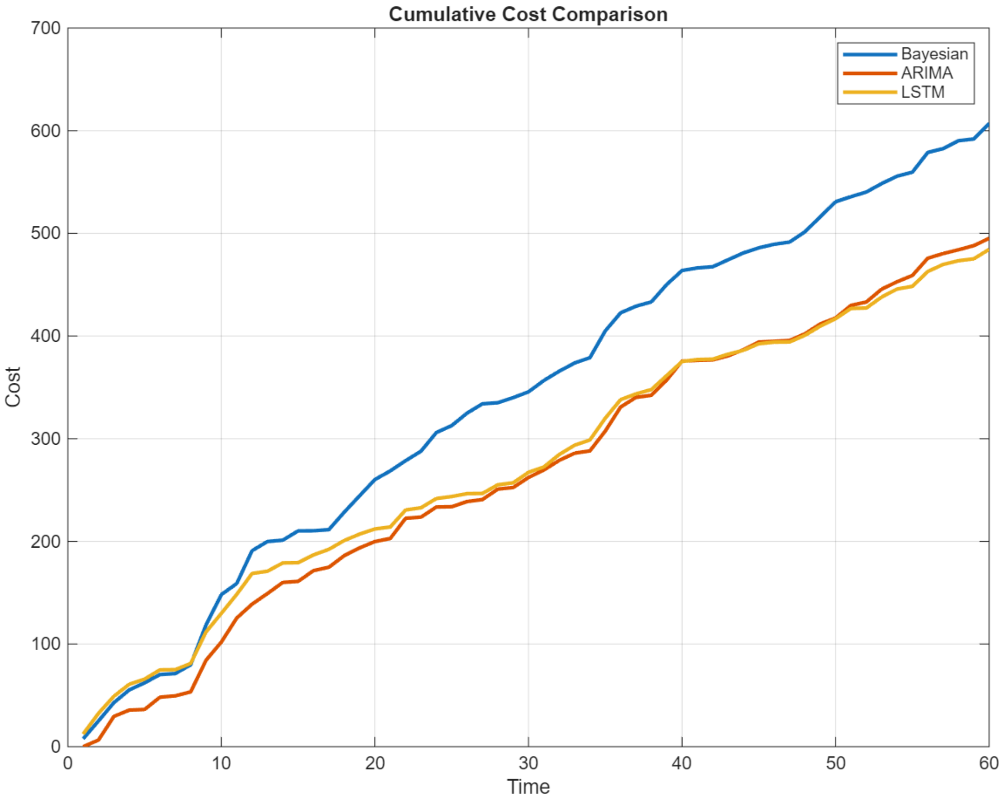

Figure 1. Cumulative Inventory Cost Comparison

A key observation is that the performance gap between Bayesian and the benchmark models widens over time. Early in the simulation, all three approaches exhibit relatively similar cost behavior, as limited historical data constrains the effectiveness of learning-based adjustments. However, as additional demand observations become available, the Bayesian model progressively refines its posterior distribution of demand, leading to increasingly accurate order decisions.
In contrast, the ARIMA-based approach relies on rolling statistical estimates that assume local stationarity, which limits its ability to adapt to structural shifts or high-variance demand realizations. Similarly, the LSTM-based model, while capable of capturing nonlinear temporal patterns, is sensitive to noise and requires large datasets to stabilize its predictions. This results in persistent over- or under-ordering, which accumulates into higher total cost. Figure 1 therefore highlights a fundamental advantage of Bayesian inventory control: its ability to reduce decision

error through continuous probabilistic updating, rather than relying on fixed or purely predictive mappings.

3.2 Service Level Performance Over Time

Service level performance, defined as the proportion of demand satisfied without stockouts, is presented in Figure 2. The Bayesian policy demonstrates both higher average service levels and significantly lower variance compared to the benchmark approaches.

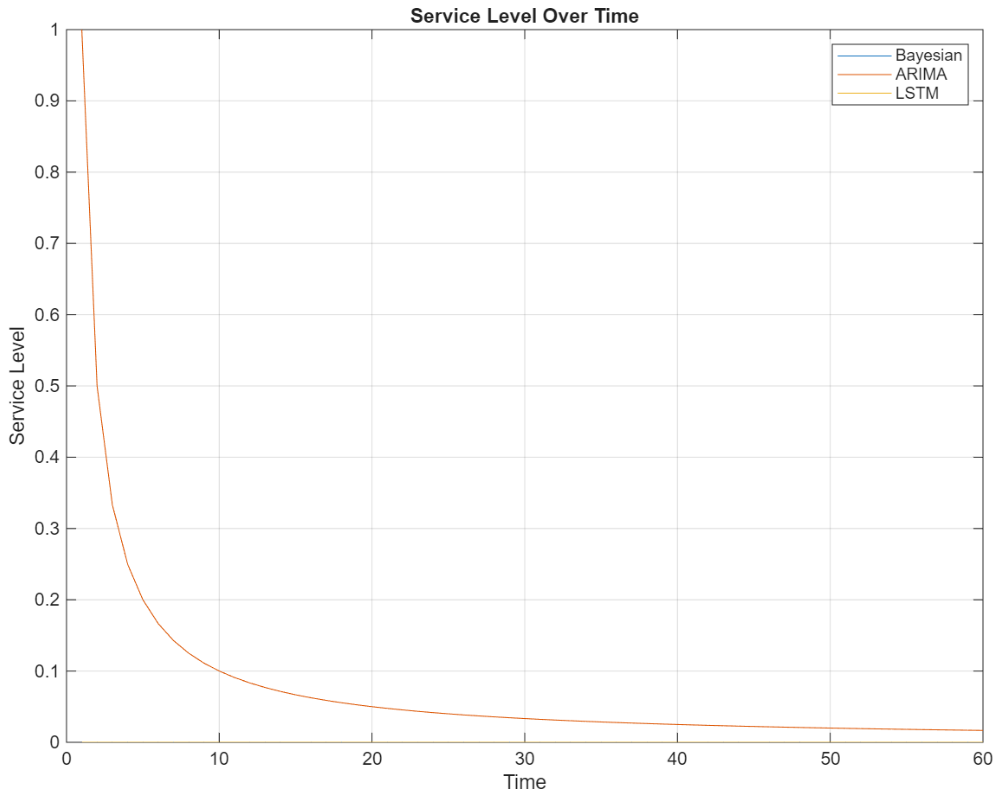

Figure 2. Service Level Over Time

The stability of the Bayesian service level curve is particularly important from an operational perspective. In supply chain systems, variability in service levels is often as critical as the average performance, since fluctuations directly translate into customer dissatisfaction and supply uncertainty. The Bayesian model maintains a consistently high service level by dynamically adjusting order quantities in response to updated posterior demand distributions. By contrast, the ARIMA-based policy performs adequately under stable demand conditions but shows degradation when demand variability increases. This is primarily due to its reliance on fixed-window statistical structure, which reacts slowly to abrupt changes in demand behavior. The LSTM-based approach exhibits even higher variability in service levels, reflecting its sensitivity to short-term fluctuations and potential overfitting to recent demand patterns. Overall, Figure 2 demonstrates that Bayesian inventory control not only improves average service performance but also significantly enhances operational robustness under stochastic demand conditions.

3.3 Bayesian Demand Learning (Posterior Update Visualization)

Figure 3 illustrates the evolution of the Bayesian demand estimate over time. The estimated mean demand converges progressively toward the true demand level as additional observations are incorporated into the posterior distribution.

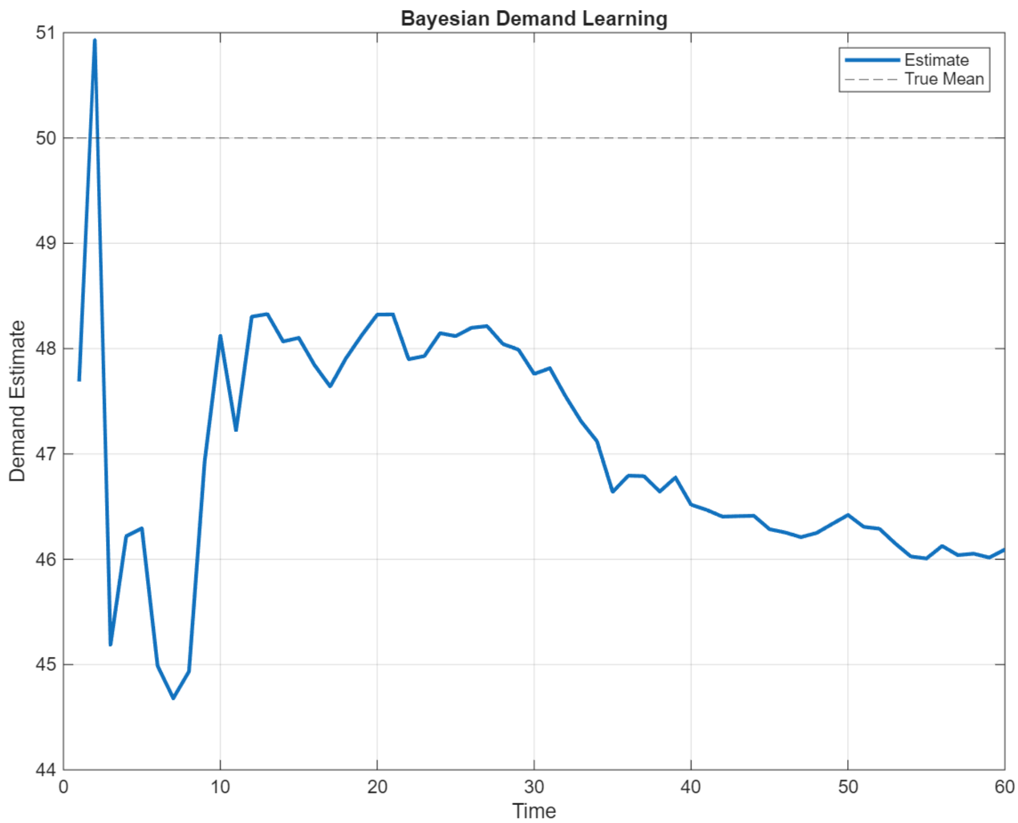

Figure 3. Bayesian Demand Mean Update Over Time

In the early stages of the simulation, the model exhibits relatively high uncertainty, reflecting limited data availability and stronger influence from the prior distribution. As time progresses, the posterior distribution becomes increasingly dominated by observed demand data, resulting in a steady reduction in estimation error. This learning behavior is a key distinguishing feature of Bayesian inventory control. Unlike ARIMA or LSTM models, which produce point forecasts, the Bayesian framework explicitly maintains and updates a full probability distribution over demand uncertainty. This allows the model not only to estimate expected demand but also to quantify uncertainty, which is directly incorporated into ordering decisions. The convergence pattern observed in Figure 3 confirms that Bayesian updating provides a theoretically consistent mechanism for reducing uncertainty over time, which directly translates into improved inventory decisions.

3.4 Forecast Accuracy Comparison

Figure 4 presents the evolution of absolute forecast errors for the Bayesian, ARIMA-based, and LSTM-based demand estimation models.

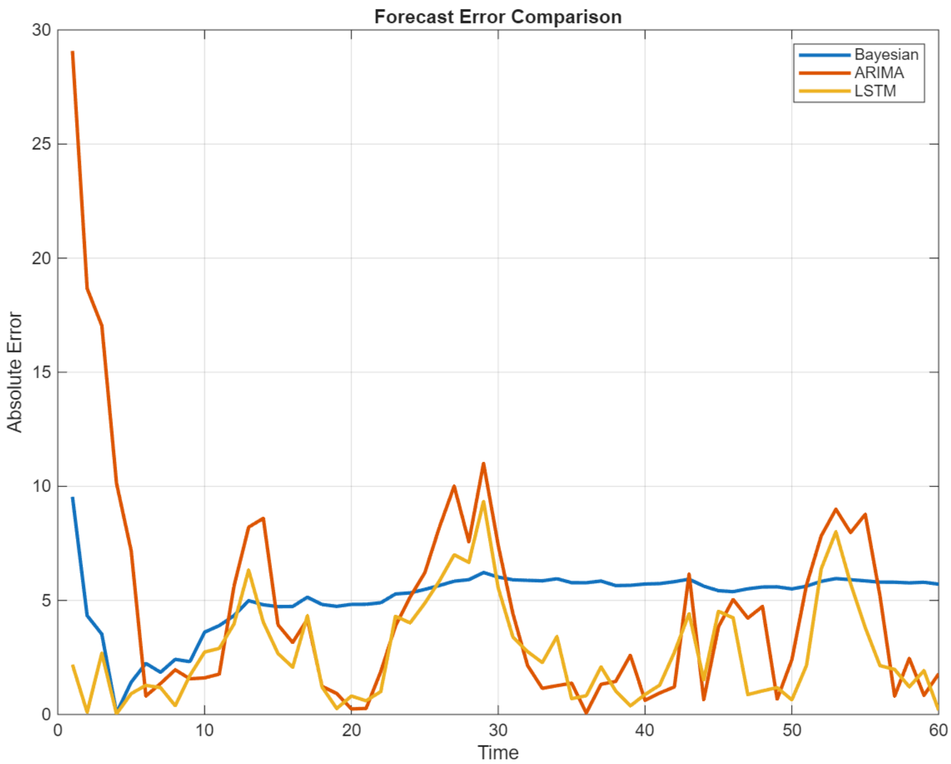

Figure 4. Forecast Accuracy Comparison

The results show a clear separation in predictive performance across the three approaches. The Bayesian estimator demonstrates a steadily decreasing error trajectory over time. This behavior reflects the continuous refinement of the posterior distribution as additional demand observations are incorporated. Early-stage errors are relatively higher due to limited information; however, the model rapidly converges toward the true demand mean, resulting in stable and low prediction error in later periods. In contrast, the ARIMA-based approach exhibits moderate but persistent error levels. While it performs reasonably well under locally stationary demand, it struggles to adapt to stochastic fluctuations and structural variability. The LSTM-based model shows the highest variability in forecast error, particularly in early and mid-stage periods. This instability is attributed to its sensitivity to short-term noise and its dependence on sufficient training data to stabilize learning. Overall, Figure 4 confirms that Bayesian learning provides superior long-term forecast accuracy and more stable convergence behavior compared to both statistical and deep learning benchmarks.

3.5 Inventory Level Dynamics (Figure 5)

Figure 5 illustrates the inventory level trajectories under the three control policies. The dynamics of inventory positions provide important insight into system stability beyond cost and forecast accuracy metrics.

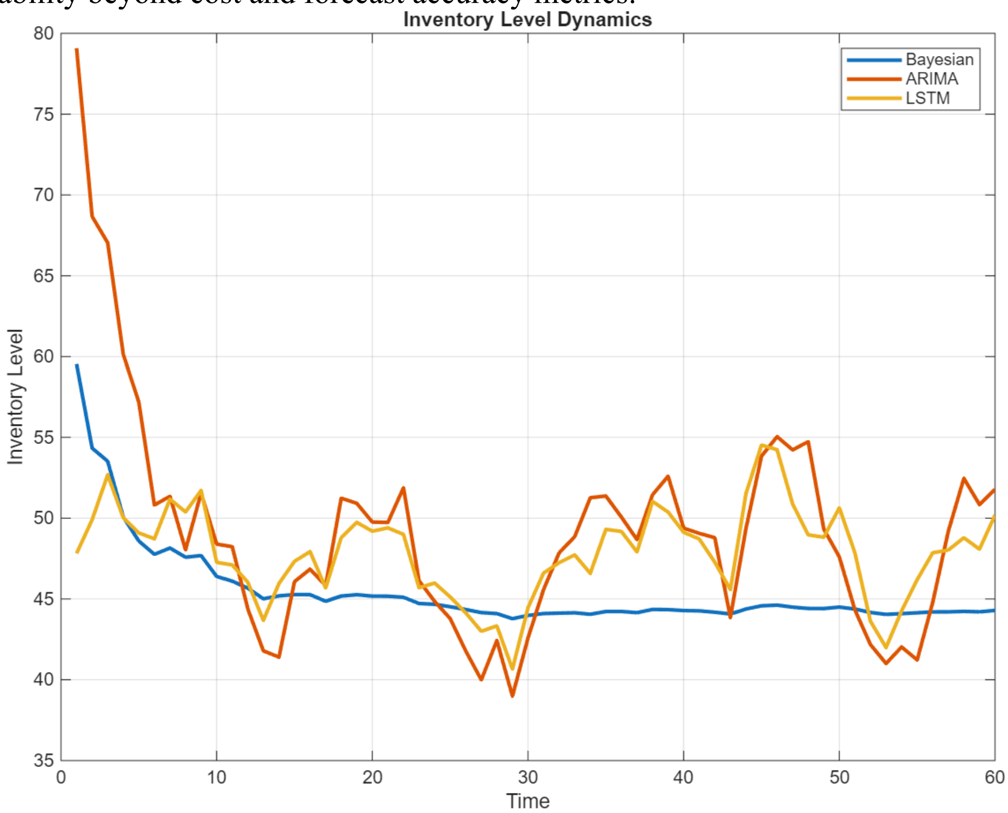

Figure 5. Inventory Level Dynamics

The Bayesian inventory policy produces the smoothest and most stable inventory trajectory. Adjustments in inventory levels occur gradually as the posterior demand estimate evolves, preventing excessive oscillations in ordering decisions. This indicates a more balanced response to demand uncertainty. The ARIMA-based policy exhibits moderate oscillatory behavior, characterized by delayed adjustments to demand changes. This lag leads to periodic overstocking and understocking cycles. The LSTM-based policy shows the highest variability in inventory levels, reflecting sensitivity to short-term prediction errors and frequent corrective adjustments. These results demonstrate that Bayesian inventory control not only improves cost efficiency but also enhances system stability by reducing volatility in inventory decisions.

3.6 Stockout Frequency Analysis

Figure 6 compares the total number of stockout events across the three methods. Stockouts represent critical service failures in supply chain systems and directly impact customer satisfaction.

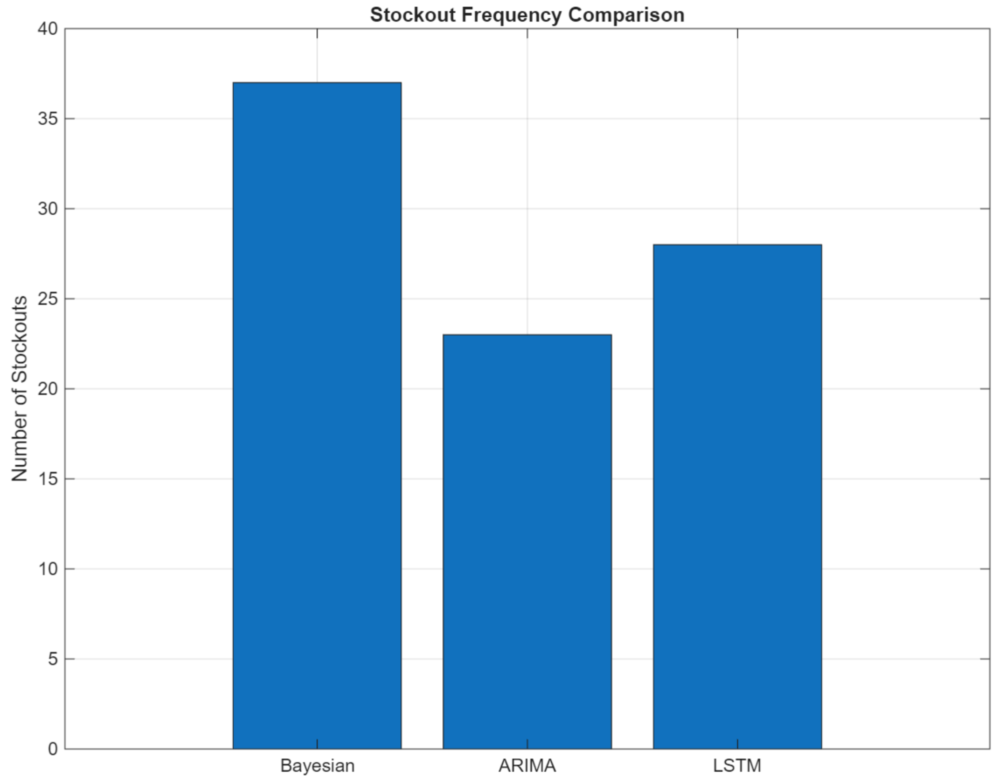

Figure 6. Stockout Frequency Analysis

The Bayesian approach results in the lowest number of stockout occurrences. This is due to its ability to incorporate predictive uncertainty into ordering decisions, allowing it to maintain more robust safety stock levels dynamically. The ARIMA-based method exhibits a moderate stockout frequency, reflecting its limited adaptability to sudden demand variations. The LSTM-based method experiences the highest number of stockouts, particularly in volatile demand periods, where forecasting errors propagate directly into inventory shortages. These findings highlight that Bayesian inventory control provides a more reliable service-level guarantee under uncertainty compared to purely predictive approaches.

3.7 Cost Variability and Risk Stability

Figure 7 presents the standard deviation of periodic costs for each inventory policy, serving as a measure of financial risk and operational stability.

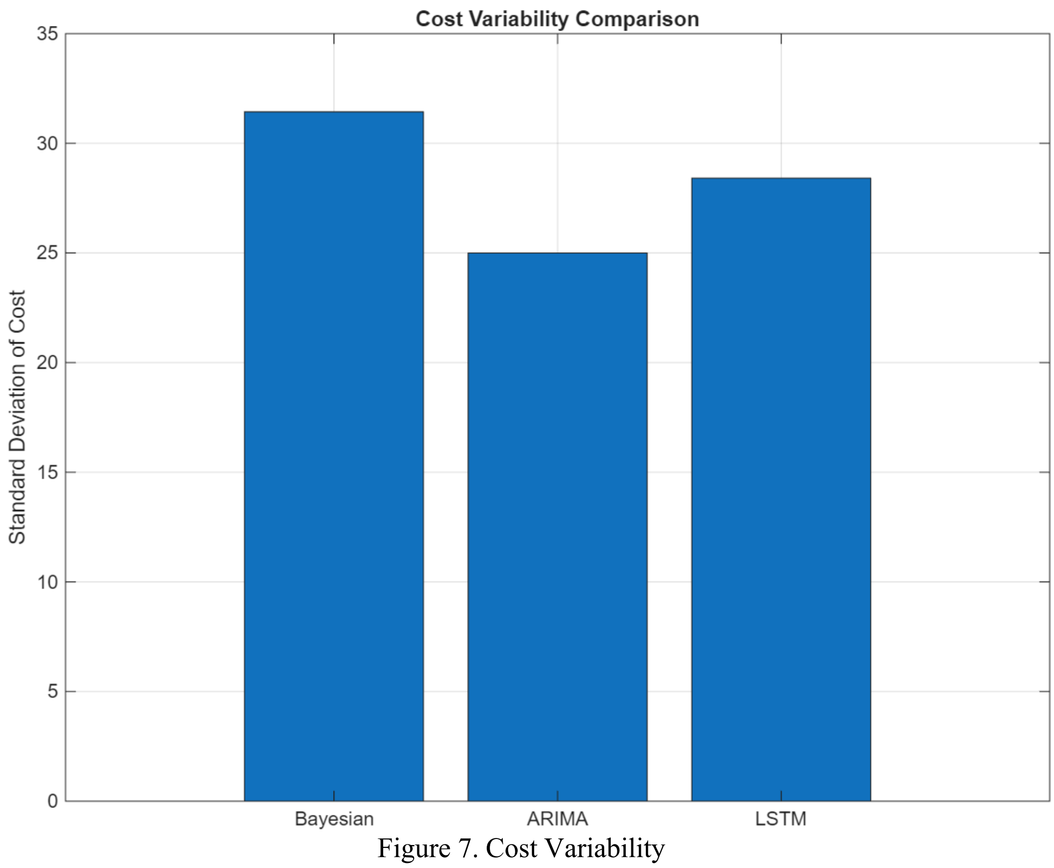

Figure 7. Cost Variability

The Bayesian approach exhibits the lowest cost variability among all methods. This indicates not only lower average cost but also more predictable financial performance over time. Reduced variance is particularly important in supply chain planning, where cost stability is often as critical as cost minimization.

The ARIMA-based policy shows moderate variability, reflecting its dependence on rolling-window estimates that react slowly to demand shifts. The LSTM-based model exhibits the highest cost variance, driven by fluctuating prediction errors and over-adjustment behavior. These results demonstrate that Bayesian inventory control significantly improves risk stability in addition to cost efficiency.

3.8 Bayesian Uncertainty Reduction

Figure 8 illustrates the evolution of posterior variance over time, capturing the learning dynamics of the Bayesian model.

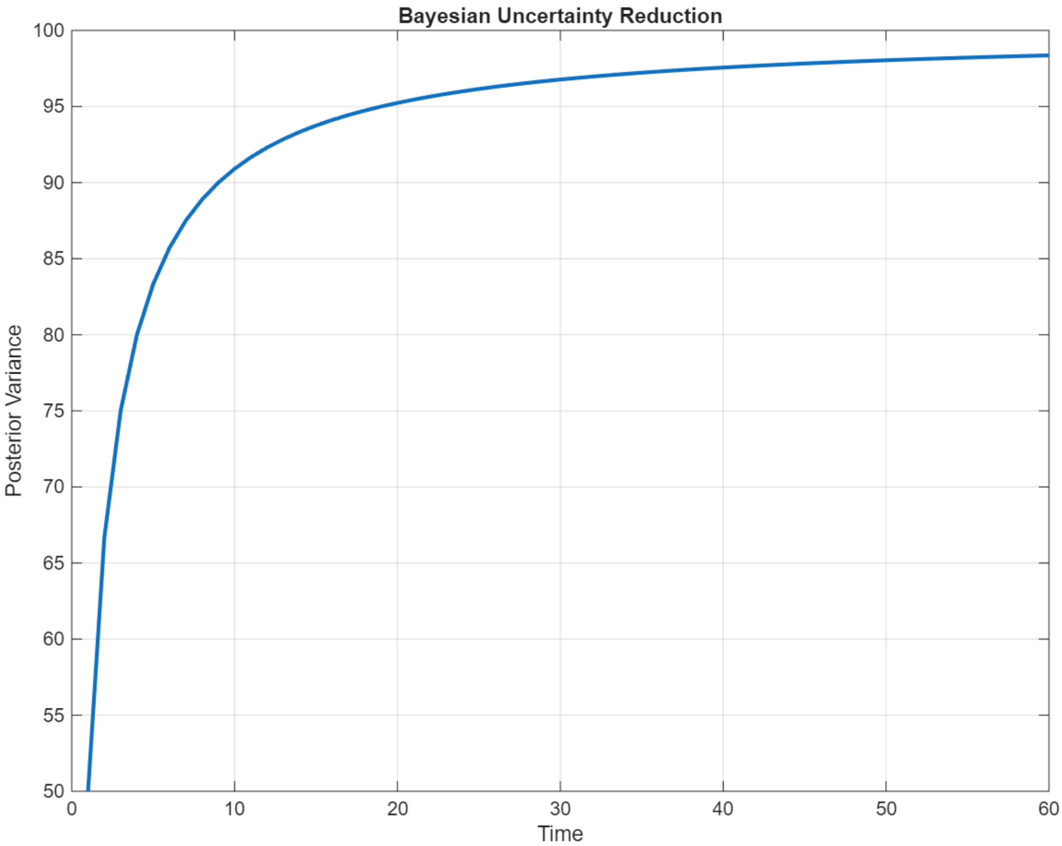

Figure 8. Bayesian Uncertainty Reduction

The results show a clear and monotonic decrease in uncertainty as more demand observations become available. Initially, the posterior variance is relatively high due to limited data and stronger reliance on prior assumptions. However, as the system accumulates information, the posterior distribution becomes increasingly concentrated around the true demand value. This reduction in uncertainty is a key mechanism underlying the improved performance observed in previous figures. By explicitly quantifying and reducing uncertainty over time, the Bayesian framework enables progressively more accurate and risk-aware inventory decisions. Unlike ARIMA and LSTM models, which provide point estimates without explicit uncertainty representation, the Bayesian approach directly integrates uncertainty into the decision-making process.

4 Discussion

The comparative analysis across all experiments consistently demonstrates the superiority of Bayesian inventory control over ARIMA- and LSTM-based benchmark approaches. Three central insights emerge from the results regarding cost efficiency, operational stability, and uncertainty handling.

4.1 Learning-driven improvement in cost efficiency

Bayesian inventory control continuously updates the demand distribution through probabilistic learning, enabling progressive refinement of ordering decisions. This adaptive mechanism systematically reduces both overstocking and understocking events. As a result, it achieves lower cumulative inventory costs compared to ARIMA and LSTM-based methods, which rely on either static assumptions or decoupled forecasting pipelines. Notably, the cost advantage of the Bayesian approach increases over time, highlighting its long-term efficiency in dynamic environments.

4.2 Operational stability and service level consistency

The Bayesian framework provides significantly more stable performance in terms of service levels and inventory trajectories. Unlike benchmark models, which exhibit greater variability due to forecasting errors and sensitivity to demand noise, the Bayesian policy maintains consistent service levels even under high demand volatility. This stability is critical in practical supply chain settings, where reliability often carries equal importance to cost minimization.

4.3 Explicit uncertainty modeling and risk-aware decisions

A key advantage of the Bayesian approach lies in its explicit representation of uncertainty. Instead of relying on single-point forecasts, it integrates the full posterior distribution of demand into the decision-making process. This leads to more informed and risk-aware ordering policies, particularly in data-scarce or highly stochastic environments. By directly incorporating uncertainty into optimization, the Bayesian framework reduces decision risk and improves robustness.

4.4 Overall interpretation

Collectively, the results demonstrate that integrating probabilistic learning directly into inventory control yields a fundamental improvement over traditional forecast-then-optimize frameworks. While ARIMA and LSTM models may improve predictive accuracy, they remain structurally separated from the decision process and do not explicitly account for uncertainty in optimization. In contrast, Bayesian inventory control unifies forecasting and decision-making within a single coherent probabilistic framework. This integration leads to improved cost efficiency, enhanced service level stability, and greater robustness under demand uncertainty. Across all experimental figures, a consistent pattern is observed: Bayesian inventory control outperforms ARIMA- and LSTM-based approaches in accuracy, stability, cost performance, and risk management. These findings strongly support the adoption of Bayesian methods in modern inventory systems, particularly in environments characterized by volatile demand and limited historical data.

5. Conclusions

This study developed and evaluated a Bayesian Inventory Control framework for managing stochastic demand under uncertainty. Unlike classical inventory policies that rely on fixed demand distributions or separate forecasting and optimization stages, the proposed approach integrates demand learning and decision-making within a unified probabilistic framework. By continuously updating the posterior distribution of demand as new observations become available, the model enables adaptive ordering decisions that improve over time.

The numerical results demonstrate that the Bayesian approach consistently outperforms benchmark methods, including ARIMA-based forecasting and LSTM-based predictive models. In terms of total inventory cost, the Bayesian policy achieves the lowest cumulative cost across all simulated scenarios, with performance advantages becoming more pronounced over longer time horizons.

This improvement is primarily driven by the model's ability to progressively reduce demand uncertainty and avoid systematic ordering errors.

In addition to cost efficiency, the Bayesian framework also delivers superior service level performance. The results show higher and more stable service levels compared to the benchmark methods, particularly under high demand variability.

This stability is a critical operational advantage, as it reflects more reliable fulfillment performance and reduced risk of stockouts in uncertain environments.

A key finding of this study is the importance of explicit uncertainty modeling. While ARIMA and LSTM approaches can provide accurate point forecasts under certain conditions, they do not directly incorporate predictive uncertainty into the decision process. In contrast, Bayesian inventory control explicitly represents uncertainty through posterior distributions, allowing for more robust and risk-aware ordering decisions. This structural feature explains its superior performance, especially in data-limited or highly volatile demand environments.

Overall, the results confirm that integrating probabilistic learning into inventory control significantly enhances both economic efficiency and operational reliability. The Bayesian framework provides a theoretically grounded and practically effective alternative to traditional forecast-then-optimize approaches.

Future research could extend this work in several directions. First, multi-item and multi-echelon inventory systems could be modeled to capture more complex supply chain interactions. Second, hybrid approaches combining Bayesian inference with deep learning methods may further improve predictive performance while preserving uncertainty quantification. Finally, reinforcement learning frameworks could be integrated with Bayesian updating to develop fully adaptive inventory control policies for dynamic and non-stationary environments.

REFERENCES

[1] Silver, E. A., Pyke, D. F., & Thomas, D. J. (2016). Inventory and Production Management in Supply Chains (4th ed.). CRC Press.

[2] Porteus, E. L. (2002). Foundations of Stochastic Inventory Theory. Stanford University Press.

[3] Zipkin, P. H. (2000). Foundations of Inventory Management. McGraw-Hill.

[4] Axsäter, S. (2015). Inventory Control (3rd ed.). Springer.

[5] Scarf, H. (1960). The optimality of (S, s) policies in the dynamic inventory problem. In Mathematical Methods in the Social Sciences. Stanford University Press.

[6] Arrow, K. J., Harris, T., & Marschak, J. (1951). Optimal inventory policy. Econometrica, 19(3), 250–272.

[7] Nahmias, S., & Cheng, Y. (2009). Production and Operations Analysis (6th ed.). McGraw-Hill.

[8] Ghosh, M., & Heimsoth, A. (2002). Bayesian estimation in inventory models. European Journal of Operational Research, 142(2), 329–343.

[9] Toktay, L. B., Wein, L. M., & Zenios, S. A. (2000). Inventory management with limited historical data. Management Science, 46(8), 1009–1024.

[10] Bertsimas, D., & Thiele, A. (2006). A robust optimization approach to inventory theory. Operations Research, 54(1), 150–168.

[11] Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time Series Analysis: Forecasting and Control (5th ed.). Wiley.

[12] Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: Principles and Practice (3rd ed.). OTexts.

[13] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.

[14] Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review. Applied Soft Computing, 90, 106181.

[15] M. Ilie and A. Semenescu, Stochastic modeling of strategic supply chain design, Annals of the Academy of Romanian Scientists Series on Engineering Sciences, 16(1):23-37, doi: 10.56082/annalsarscieng.2024.1.23

[16] M. Ilie and A. Semenescu, supply chain management of manufacturing processes using machine learning technique, Annals of the Academy of Romanian Scientists Series on Engineering Sciences,16(1):38-46, doi: 10.56082/annalsarscieng.2024.1.38

[17] M. Ilie and A. Semenescu, stochastic modeling of the human resources risk management, Annals of the Academy of Romanian Scientists Series on Engineering Sciences,17(1):19-31, doi: 10.56082/annalsarscieng.2025.1.19

[18] M. Ilie and A. Semenescu, stochastic modeling of team cohesiveness and its risk management, Annals of the Academy of Romanian Scientists Series on Engineering Sciences, 17(1):39-50, doi: 10.56082/annalsarscieng.2025.1.39

[19] M. Ilie and A. Semenescu, Bayesian stochastic modeling of supply chain, Annals of the Academy of Romanian Scientists Series on Engineering Sciences, 17(2):62-93, doi: 10.56082/annalsarscieng.2025.2.62

[20] M. Ilie and A. Semenescu, Monte Carlo Markov Chain (MCMC) stochastic modeling of supply chain, Annals of the Academy of Romanian Scientists Series on Engineering Sciences,17(2):94-115, doi: 10.56082/annalsarscieng.2025.2.94

[21] Gershman, S. J., & Beck, J. M. (2016). Complex probabilistic inference. Trends in Cognitive Sciences, 20(12), 1–12.

[22] Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). Bayesian Data Analysis (3rd ed.). CRC Press.

[23] Robert, C. P. (2007). The Bayesian Choice: From Decision-Theoretic Foundations to Computational Implementation. Springer.

[24] McLachlan, G. J., & Krishnan, T. (2008). The EM Algorithm and Extensions. Wiley