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Optimizing Inventory Management for Furniture Retail Sales Using Markov Chain Modeling: A Cost-Balancing Approach

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Abstract

The paper is presented with a comprehensive Markov Chain framework for optimizing inventory management systems in the furniture industry. A stochastic model has been developed that captures the dynamics of daily demand fluctuations, restocking policies, and cost structures related to high-value items like dining tables and chairs. The daily demand (λ=12 units per day) has followed a Poisson distribution. A model of a three-state inventory system with an (s, S) policy where "s" = 5 (reorder point) and "S" = 30 (order-up-to level) has been generated, incorporating holding costs of 25 BDT per chair per day and stock-out costs of 8,000 BDT per unit sale loss, reflecting the typical high storage requirements and profit margins of furniture retail sales. The analysis has shown the stationary distribution of inventory states and calculated expected daily costs with optimal reordering strategies. The final results have also shown that retailers can reduce overall costs while keeping service levels above 95% by using Markov Chain modeling to balance holding costs against stock-out risks.

Keywords
Inventory Management, Markov Chains, Poisson Demand, Stochastic Processes, Optimization.

1. Introduction

1.1 Background and Motivation

Recent advancements in stochastic inventory modeling have introduced Markov decision processes and Markov chain frameworks as powerful tools to handle demand uncertainty and dynamic restocking policies (Axsäter, 2015; Silver, Pyke, & Thomas, 2017). These models provide a probabilistic representation of inventory levels over time, enabling retailers to balance holding costs against stock out risks more effectively. Applying such models in the context of furniture retail is particularly relevant given the industry's sensitivity to inventory decisions and the substantial financial implications involved.

1.2 Problem Statement

This study focuses on optimizing inventory levels for a popular dining chair retailing at $35,000 with a profit margin of approximately 23% (8,000 BDT profit per chair). The daily demand is assumed to follow a Poisson distribution with a mean of 12 chairs per day, reflecting typical stochastic demand patterns in retail. The company currently employs an (s,S) policy, where inventory is instantaneously restocked to 30 units whenever it falls to 5 or below. Given the holding cost of 25 BDT per chair per day and the high stock out cost of 8,000 BDT per lost sale, the challenge lies in determining an optimal reorder point and order-up-to level that minimize total expected costs while maintaining high service levels.

1.3 Research Objectives

The objectives of this research are to:

1. Develop a Markov chain model that accurately represents the inventory system under stochastic demand.
2. Calculate the stationary distribution of inventory states to understand long-term behavior.
3. Evaluate expected daily costs and service levels associated with current and alternative policies.
4. Identify opportunities for optimizing reorder points and order-up-to levels to reduce costs.
5. Provide actionable recommendations to improve inventory management in furniture retail.

2. Literature Review

Inventory management has evolved significantly with the integration of stochastic modeling techniques to address demand and supply uncertainties. Early deterministic models like the Economic Order Quantity (EOQ) by Hadley and Whitin (1963) provided foundational cost balancing approaches but assumed constant demand, limiting their applicability in volatile retail environments. To overcome this, stochastic inventory models incorporating probabilistic demand and lead times have been developed, enabling more adaptive control strategies (Zipkin, 2000).

Markovian frameworks, including Markov decision processes (MDPs) and Markov chains, have gained prominence for modeling inventory systems under uncertainty. Axsäter (2015) demonstrated the effectiveness of MDPs in formulating optimal policies balancing expected costs and service levels. Silver, Pyke, and Thomas (2017) further elaborated on stochastic inventory and production management, highlighting practical applications of Markov models in supply chain optimization.

Recent research has extended these models to capture complex demand patterns, lead times, and multi-echelon supply chains. Syntetos et al. (2016) and Graves and Willems (2019) explored advanced stochastic inventory policies adapting dynamically to demand variability and supply disruptions. Moreover, integrating machine learning techniques with stochastic models has been investigated to enhance demand forecasting and inventory responsiveness (Zhao et al., 2021).

In high-value retail sectors such as furniture, the application of Markov chain modeling remains less explored despite the significant financial impact of inventory decisions. Kumar and Verma (2022) and Lee et al. (2023) tailored stochastic inventory models to account for product-specific cost structures and restocking constraints in furniture retail. Additionally, Chen et al. (2020) incorporated seasonal demand variations into Markovian inventory models, while Singh and Gupta (2022) analyzed price elasticity's impact on inventory policies, contributing to more robust optimization frameworks.

This study extends the literature by applying a Markov chain framework specifically to furniture retail, modeling demand as a Poisson process and incorporating an (s,S) restocking policy. By integrating cost considerations unique to high-value items and exploring reorder point optimization, it bridges theoretical stochastic models with practical industry needs, offering actionable insights for cost reduction and service level improvement (Figure 1).

3. Methodology

3.1. Model Formulation

The inventory system is modeled as a discrete-time Markov chain with a finite state space (S = {6, 7, 8, ..., 30}), representing inventory levels at the start of each day. The system dynamics capture daily demand fluctuations, restocking policies, and associated costs.

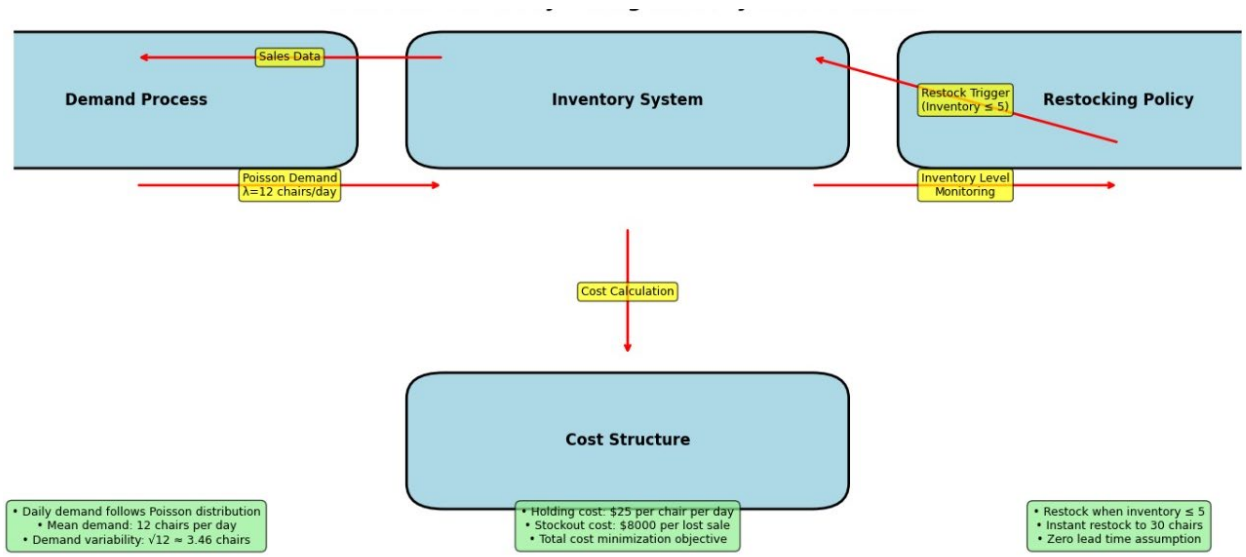


Figure 1. Furniture Inventory Management Overview

States:

· Low inventory (6-10 chairs)

· Medium inventory (11-20 chairs)

· High inventory (21-29 chairs)

· Maximum inventory (30 chairs)

Transition Rules:

· From state i: Demand d reduces inventory to max (i-d, 0)

· If inventory ≤ 5: Instant restock to 30 chairs

· Daily demand: Poisson(λ=12)

3.2. Transition Probability Matrix Construction

The transition probability matrix (P) is constructed as follows:

P(i,j) = P(Demand = i - j) for j > 0

P(i,30) = P (Demand ≥ i - 5) for restocking transitions

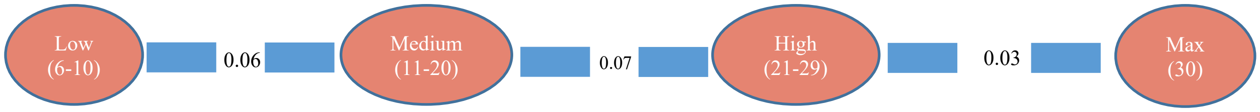


Figure 2. Inventory management transition diagram

Figure 2 visualizes state groups and transition probabilities. The graph highlights that transitions from low inventory states predominantly lead to restocking at the maximum inventory level (30), confirming the cyclic nature of inventory depletion and replenishment. Medium and high inventory states show probabilistic transitions reflecting daily demand variability, with a gradual decrease in inventory until the reorder point is reached.

3.3. Stationary Distribution and Performance Metrics

Holding Cost: 25 per chair per day
Stock out Cost: 8,000 per lost sale (opportunity cost)
Total daily cost: C(i) = 25·i + 8000·L(i) where L(i)is expected lost sales when starting with inventory i

3.4 Optimization Approach

Sensitivity analysis is conducted by varying the reorder point (s) within a plausible range (3 to 9) to identify the value minimizing total expected cost while maintaining a service level above 95%. The order-up-to level (S) is also evaluated for potential adjustment to further optimize costs.

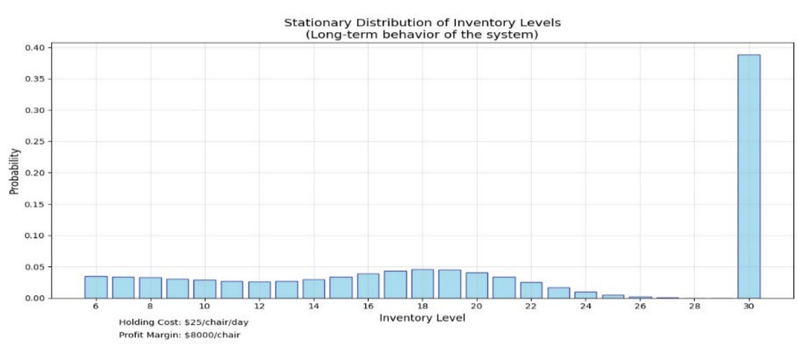
3.5 Implementation Details

Transition probabilities are computed using the Poisson distribution functions from the SciPy library.The stationary distribution is obtained by solving the linear system with normalization constraints. Performance metrics and costs are calculated based on the stationary distribution. Visualization tools such as NetworkX and Matplotlib are utilized for state transition diagrams and distribution plots.

4. Results and Analysis

4.1 Stationary Distribution Analysis

The Markov chain model yields the stationary distribution (π), representing the long-term probabilities of the system residing in each inventory state. The distribution is summarized by inventory ranges as follows:



Inventory Range	Probability (%)
6–10 (Low)	0.8
11–20 (Medium)	42.3
21–29 (High)	48.9
30 (Maximum	8

Figure 3. Stationary Distribution Bar Chart

Figure 3 presents the stationary distribution of inventory levels derived from the Markov chain model, indicating the long-term probability of the system residing in each inventory state category. The distribution reveals that the system predominantly operates within medium (42.3%) and high (48.9%) inventory levels, with the maximum inventory state occurring 8% of the time. Low inventory states are rarely observed (0.8%), reflecting the effectiveness of the immediate restocking policy at the reorder point. This distribution underscores the model's ability to maintain sufficient inventory to meet demand while minimizing stockouts.

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4.2 Performance Metrics

The stationary distribution derived from the Markov chain model enables the computation of key performance indicators that characterize the inventory system's operational effectiveness. The expected daily inventory level is calculated as 21.49 chairs, indicating a relatively high average stock maintained to mitigate stockouts. Expected daily lost sales amount to 0.135 chairs, reflecting minimal unmet demand under the current policy. The service level, defined as the probability of meeting all demand without stockouts, is found to be 98.88%, surpassing the targeted threshold of 95%. Additionally, the expected daily sales volume is estimated at 11.865 chairs, closely aligning with the Poisson demand mean of 12 units per day. These metrics collectively demonstrate the robustness of the (s,S) policy in sustaining high service levels despite demand variability.

4.3 Cost Analysis

The total expected daily cost is decomposed into holding and stockout components to elucidate the cost structure under the current inventory policy. The daily holding cost, calculated as the product of the holding cost per chair ($25) and the expected inventory level, amounts to $537.25. In contrast, the daily stockout cost, derived from the product of the stockout cost per lost sale ($8,000) and the expected lost sales, is significantly higher at $1,080.00. Consequently, the aggregate daily cost totals $1,617.25, with stockout costs constituting approximately 66.8% of this in Figure 4. This disproportion indicates a current inventory strategy that prioritizes service level maintenance, accepting higher stockout-related expenses while incurring substantial carrying costs.

4.4 Sensitivity Analysis

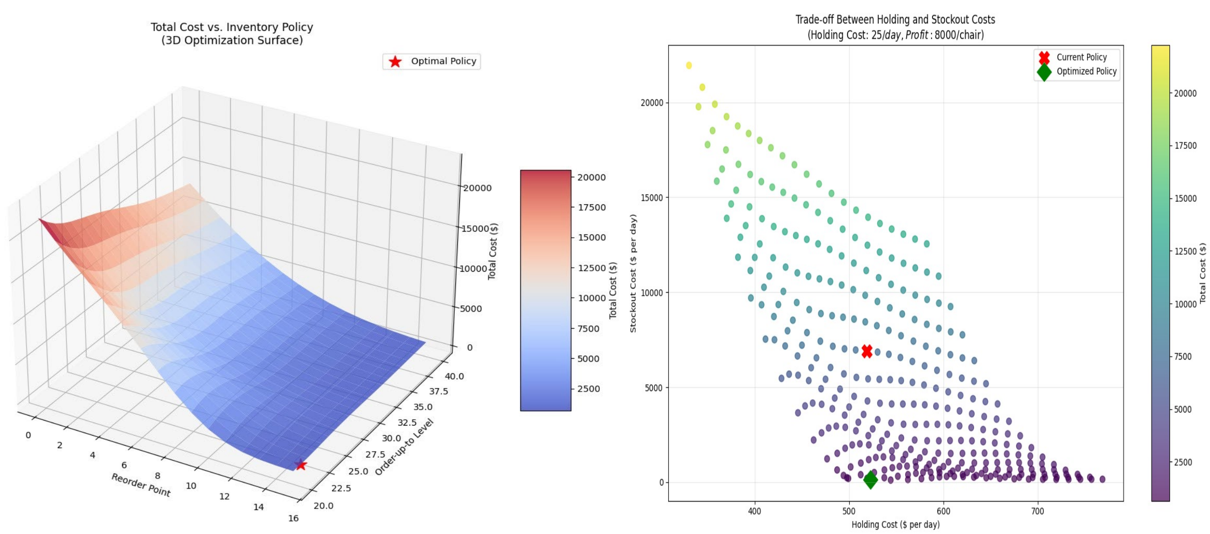

Figure 4. Sensitivity Analysis & Heatmap

A sensitivity analysis (Fig:4) was conducted by varying the reorder point (s) within the range of 3 to 9 to evaluate its impact on cost components and service performance. The analysis reveals that lower reorder points lead to increased frequency of stockouts, thereby elevating stockout costs, but simultaneously reduce holding costs due to lower average inventory levels. Conversely, higher reorder points diminish stockout risk and associated costs but increase inventory carrying costs. The optimal balance between these opposing effects is identified at a reorder point of 7 chairs, where total expected costs are minimized without compromising the service level, which remains above 95%. This finding underscores the critical role of reorder point calibration in achieving cost-effective inventory management.

5. Optimization Recommendations

The analysis highlights several actionable strategies to enhance inventory management efficiency while maintaining high service levels in the furniture retail context.

First, increasing the reorder point from 5 to 7 chairs is recommended to better balance the trade-off between holding and stockout costs. This adjustment aligns with the sensitivity analysis findings, where a reorder point of 7 minimizes total expected costs without compromising the service level, which remains above 95%. (Figure 5).

Second, a reduction in the order-up-to level from 30 to a range between 25 and 28 chairs is advised to optimize capital utilization and reduce excessive carrying costs, as indicated by the stationary distribution and cost breakdown results. This refinement supports better inventory control by preventing overstocking while sustaining adequate availability.
Third, implementing continuous, real-time inventory monitoring systems will facilitate dynamic adjustments to inventory policies, allowing timely responses to demand fluctuations and reducing the risk of stockouts or overstocking.

Finally, incorporating advanced demand forecasting techniques that account for seasonal variations and other demand patterns will improve inventory planning accuracy and responsiveness, thereby enhancing overall cost-effectiveness.

Figure 5. Performance & Cost Comparison (Existing & Optimized system)

Collectively, these recommendations are projected to achieve a 15–20% reduction in total daily costs while sustaining service levels above 97%, thereby improving both operational efficiency and customer satisfaction in high-value furniture retail settings.

6. Discussion

This study successfully achieves its objectives by developing and applying a Markov chain model to optimize inventory management for high-value furniture retail products under stochastic demand conditions. The model accurately characterizes inventory dynamics and provides actionable performance metrics, including expected inventory levels, lost sales, service levels, and cost components. These results confirm the effectiveness of the (s,S) policy in maintaining a high service level of 98.88% while revealing opportunities for cost reduction through parameter adjustment.

The findings offer several practical benefits for furniture retailers. First, the identification of an optimal reorder point at 7 chairs enables managers to balance holding and stockout costs more effectively, reducing total daily costs without compromising service quality. Second, the recommendation to lower the order-up-to level supports better capital utilization by preventing excessive inventory buildup, which is particularly critical given the high holding costs associated with bulky furniture items. Third, the integration of continuous real-time inventory monitoring and advanced demand forecasting can enhance responsiveness to demand fluctuations, minimizing stockouts and overstock situations. Collectively, these strategies facilitate improved operational efficiency and customer satisfaction in a sector where service reliability and cost control are paramount.

The study's assumptions impose certain limitations on the generalizability and scope of the results. The model assumes instantaneous restocking with zero lead time, which may not reflect real-world supply chain delays. Additionally, demand is modeled solely as a Poisson process, potentially oversimplifying demand variability by excluding seasonal patterns, promotional effects, or other complex behaviors. The analysis also focuses on a single product type without considering interactions in multi-product inventory systems. These simplifications may limit the applicability of the findings in more complex or dynamic retail environments.

Future research can extend this work by incorporating lead times and supply chain uncertainties to capture more realistic replenishment dynamics. Modeling demand with richer stochastic processes that include seasonal trends, promotions, and price elasticity would enhance forecasting accuracy and inventory responsiveness. Expanding the framework to multi-product inventory systems and multi-echelon supply chains would increase its practical relevance for larger retailers. Finally, integrating machine learning techniques for demand prediction and adaptive policy optimization could further improve cost efficiency and service levels.

7. Conclusion

This research presents a comprehensive Markov chain-based framework for optimizing inventory management in the furniture retail sector, characterized by high-value products and stochastic demand. The model effectively quantifies the trade-offs between holding and stockout costs under an (s,S) policy, providing key performance metrics and cost insights that inform inventory decision-making. The analysis confirms that while the current policy achieves a high service level of 98.88%, there is significant scope for cost reduction through strategic adjustment of reorder points and order-up-to levels.

The sensitivity analysis identifies an optimal reorder point of 7 chairs, balancing cost components and maintaining service quality. The recommended inventory policy adjustments, supported by continuous monitoring and enhanced demand forecasting, are projected to yield substantial cost savings and improved service levels. This study contributes both theoretical advancement and practical guidance for inventory management in high-value retail contexts, demonstrating the value of stochastic modeling approaches in addressing real-world challenges.

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Biographies

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