IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 7, July 2025

DOI: 10.17148/IARJSET.2025.12737

Optimizing inventory Systems: Stochastic Lead-Time and Price-Dependent Demand with Advance Payment Strategies

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Abstract: This research delves into optimizing inventory systems by incorporating stochastic lead-time, price-dependent demand, and advance payment strategies to reflect real-world uncertainties and improve supply chain efficiency. Traditional models often assume deterministic lead-times and static demand, which do not account for the variability and dynamic nature of actual market conditions. Our model integrates a stochastic lead-time distribution to handle delivery time variability and models demand as a function of selling price to capture consumer behavior's sensitivity to pricing. Additionally, advance payment options are included to explore their financial implications on inventory costs and ordering decisions. Using advanced mathematical techniques and heuristic algorithms, we derive optimal ordering policies that minimize total costs, including ordering, holding, shortage, and advance payment costs. Sensitivity analysis highlights the impact of key parameters such as lead-time variability, price elasticity, and advance payment terms on system performance. The findings demonstrate that considering these factors enhances the robustness of inventory management strategies and provides financial benefits by mitigating risks associated with uncertain lead-times and optimizing cash flow alignment with the inventory cycle.

Keywords: Inventory Optimization, Stochastic Lead-Time, Price-Dependent Demand, Advance Payment Strategies, Demand Forecasting, Cost Minimization, Sensitivity Analysis

I. INTRODUCTION

Effective inventory management is vital for maintaining efficient supply chains and minimizing associated costs. In an environment characterized by uncertainties, traditional inventory models often fall short by assuming fixed lead-times and static demand. This research introduces a novel approach to optimizing inventory systems by integrating stochastic lead-time distributions, which account for delivery time variability, and price-dependent demand, reflecting the impact of pricing strategies on consumer behavior. Additionally, the inclusion of advance payment strategies is examined to understand their effects on financial performance and inventory costs. By employing advanced mathematical techniques and heuristic algorithms, the study aims to derive optimal ordering policies that balance various cost components such as ordering, holding, shortage, and advance payments. This approach not only enhances the robustness and accuracy of inventory management but also provides financial benefits by reducing risks associated with uncertain lead-times and aligning cash flows with inventory cycles.

Chaharsooghi and Heydari (2014) developed a robust optimization model for a two-echelon inventory system, highlighting the importance of managing both stochastic lead time and demand to enhance supply chain efficiency. **Ni and Wang (2014)** developed optimal inventory policies for systems with stochastic lead time and service level constraints, highlighting the trade-offs between maintaining high service levels and managing lead time variability. **Gu and Sethi (2015)** explored inventory control with stochastic lead times and order crossover, providing strategies to mitigate the impact of order timing and lead time variability on inventory performance. **He and Huang (2015)** explored stochastic inventory models with multiple delivery modes, demonstrating how different delivery options with random lead times can improve inventory management flexibility and responsiveness. **Boute and Lambrecht (2016)** emphasized the critical role of information and lead time reduction in managing inventory with stochastic lead times, showing that improved information sharing and reduced lead times can significantly lower costs and enhance performance. **Pan and Hsiao (2016)** integrated pricing strategies with inventory management under stochastic lead times, showing how pricing decisions can influence demand and inventory policies. **Chen and Yang (2017)** focused

DOI: 10.17148/IARJSET.2025.12737

on optimal policies for supply chains with stochastic demand and variable lead time, providing a model that integrates these uncertainties to derive cost-minimizing ordering policies. **Song and Zipkin (2017)** analyzed the impact of lead-time variability on inventory control with information about supply conditions and demand, underscoring the importance of information systems in managing variability and improving performance. **Xia and Xu (2018)** introduced a model for inventory management under stochastic lead time with partial backordering, suggesting that partial backorders can improve service levels and reduce total costs. **Zhou and Lai (2018)** addressed emergency replenishments in stochastic inventory models with correlated lead times, providing strategies for using emergency replenishments to enhance supply chain resilience and responsiveness. **Van der Heijden and Teunter (2019)** addressed the correlation between demand and lead times in stochastic inventory models, emphasizing that accounting for these correlations leads to more accurate and optimal inventory policies. **Ketzenberg and Ferguson (2020)** analyzed the impact of lead time uncertainty on inventory investment, providing insights into how different levels of lead time variability affect inventory costs and service levels. **Tan and Karabati (2021)** investigated managing inventory with stochastic lead times and advance demand information, showing that advance demand information can significantly improve inventory performance by reducing uncertainty. **Fadiloglu and Karaesmen (2022)** introduced a dynamic inventory model with stochastic lead times and demand substitution, demonstrating how demand substitution can mitigate the negative impacts of lead time variability. **Alimian and Saghafian (2023)** presented a robust optimization approach for inventory control with stochastic lead times and nonstationary demand, emphasizing the need for robust strategies to handle high uncertainty environments.

II. ASSUMPTIONS

(i) **Demand Function**: $D(p) = a - bp$ (linear demand function), where a and b are constants.
(ii) **Lead Time Distribution**: $L \sim Uniform(L_{min}, L_{max})$ or any other suitable distribution.
(iii) **Single-Period Inventory Model**: The inventory model is considered for a single replenishment cycle.

III. NOTATIONS

(i) Inventory Level (I): Inventory level at any given time.
(ii) Demand (D): Demand is a function of the price p, $D(p)$.
(iii) Lead Time (L): Lead time is stochastic, typically represented as a random variable L with a known probability distribution.
(iv) Advance Payment (A): Payment made in advance for the ordered quantity.
(v) Holding Cost (h): Cost of holding one unit of inventory for one unit of time.
(vi) Ordering Cost (C_O): Fixed cost incurred for placing an order.
(vii) Shortage Cost (C_s): Cost per unit of unsatisfied demand.
(viii)Deterioration Rate (θ): Rate at which inventory deteriorates.
(ix) Advance Payment Discount Rate (δ): Discount applied for advance payment.

IV. MODEL FORMULATION

The inventory level $I(t)$ at time t during the lead time L:

$$I(t) = Q - D(p)t \quad (1)$$

Holding cost is $h\int_0^L I(t)dt = h\int_0^L \{Q - (a - bp)t\}dt$ (2)

Given $L \sim Uniform(L_{min}, L_{max})$, the expected value of L is

$$E[L] = \frac{L_{min} + L_{max}}{2} \quad (3)$$

The expected holding cost:

$$E\left[\int_0^L h\{Q - (a - bp)t\}dt\right] = h\left\{QE[L] - (a - bp)\frac{E[L^2]}{2}\right\} \quad (4)$$

$$E[L^2] = \frac{L^2{}_{max} + L^2{}_{min} + L_{min}L_{max}}{3}$$

For a uniform distribution, the expected shortage cost can be approximated by integrating over the range of L:

$$E[\text{Shortage}] = \int_{L_{min}}^{L_{max}} \max\{0, D(p)L - Q\} f(L)\, dL$$

$$E[\text{Shortage}] = \int_{L_{min}}^{L_{max}} \max\{0, (a - bp)L - Q\} f(L)\, dL$$

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Where $f(L)$ is the probability density function of L and $f(L) = \frac{1}{L_{max}-L_{min}}$

$$E[\text{Shortage}] = \frac{1}{L_{max}-L_{min}} \int_{L_{min}}^{L_{max}} \max\{0, D(p)L - Q\}\, dL$$

Split the integral at $L^* = \frac{Q}{a-bp}$

$$E[\text{Shortage}] = \frac{1}{L_{max}-L_{min}} \int_{L^*}^{L_{max}} \{(a-bp)L - Q\}\, dL$$

$$= \frac{1}{L_{max}-L_{min}} \left[\frac{(a-bp)L^2}{2} - QL\right]_{L^*}^{L_{max}} = \frac{1}{L_{max}-L_{min}} \left[\frac{(a-bp){L_{max}}^2}{2} - QL_{max} - \frac{(a-bp){L^*}^2}{2} + QL^*\right]$$

$$= \frac{1}{L_{max}-L_{min}} \left[\frac{(a-bp){L_{max}}^2}{2} - QL_{max} - \frac{(a-bp)}{2}\frac{Q^2}{(a-bp)^2} + \frac{Q}{(a-bp)^2}\right]$$

$$= \frac{1}{L_{max}-L_{min}} \left[\frac{(a-bp){L_{max}}^2}{2} - QL_{max} + \frac{1}{2}\frac{Q}{(a-bp)^2}\right] \quad (5)$$

So, the expected shortage cost is:

$$\text{Expected Shortage Cost} = \mathrm{C_s} \times E[\text{Shortage}] = \frac{\mathrm{C_s}}{L_{max}-L_{min}} \left[\frac{(a-bp){L_{max}}^2}{2} - QL_{max} + \frac{1}{2}\frac{Q}{(a-bp)^2}\right] \quad (6)$$

$$\text{Deterioration cost is } \theta \int_0^L I(t)dt = \theta \left\{QE[L] - (a-bp)\frac{E[L^2]}{2}\right\} \quad (7)$$

Advance payment discount is δQ (8)

Combining all the components,

$$Total\ Cost = C_O + h\left\{QE[L] - (a-bp)\frac{E[L^2]}{2}\right\} + \frac{\mathrm{C_s}}{L_{max}-L_{min}} \left[\frac{(a-bp){L_{max}}^2}{2} - QL_{max} + \frac{1}{2}\frac{Q}{(a-bp)^2}\right] + \theta\left\{QE[L] - (a-bp)\frac{E[L^2]}{2}\right\} - \delta Q \quad (9)$$

V. PERFORMANCE MEASURES

(i) Fill rate: The fill rate measures the percentage of customer demand that is met without stockouts.

$$Fill\ rate = 1 - \frac{E[\text{Shortage}]}{Total\ demand} = 1 - \frac{\frac{1}{L_{max}-L_{min}}\left[\frac{(a-bp){L_{max}}^2}{2} - QL_{max} + \frac{1}{2}\frac{Q}{(a-bp)^2}\right]}{(a-bp)\frac{L_{min}+L_{max}}{2}}$$

$$= 1 - \frac{\left[(a-bp){L_{max}}^2 - 2QL_{max} + \frac{Q}{(a-bp)^2}\right]}{(a-bp)(L_{max}+L_{min})(L_{max}-L_{min})} \quad (10)$$

(ii) Stockout Probability: The probability that demand during the lead time exceeds the order quantity.

$$P(\text{Stockout}) = P\{(a - bpL) > Q\} \quad (11)$$

For a uniform distribution:

$$P(\text{Stockout}) = 1 - \frac{Q}{(a-bp)(L_{max}-L_{min})} \quad (12)$$

(iii)Expected Inventory Level:

$$E\{I(t)\} = \frac{1}{L_{max}-L_{min}} \int_{L_{min}}^{L_{max}} \{Q - (a-bp)t\}\, dt = \frac{1}{L_{max}-L_{min}} \left[Q(L_{max} - L_{min}) - (a-bp)\frac{{L^2}_{max} - {L^2}_{min}}{2}\right]$$

$$E\{I(t)\} = Q - (a-bp)\frac{L_{min}+L_{max}}{2} \quad (13)$$

(iv) Expected Backorder Level:

$$E(\text{Backorder}) = \frac{1}{L_{max}-L_{min}} \int_{L_{min}}^{L_{max}} \max\{0, (a-bp)L - Q\}\, dL \quad (14)$$

(v) Reorder point:

$$Reorder\ point = E[D(p)L] + z\sigma_{D(p)L} = (a-bp)\frac{L_{min}+L_{max}}{2} + z\sqrt{\frac{(a-bp)^2(L_{max}-L_{min})^2}{12}} \quad (15)$$

(vi) Cycle Service Level:

$$Cycle\ Service\ Level = P\{Q \geq D(p)L\} = P\{Q \geq (a-bp)L\} = 1 - P\left(L \geq \frac{Q}{a-bp}\right) \quad (16)$$

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DOI: 10.17148/IARJSET.2025.12737

For a uniform distribution:

$$= 1 - \frac{\frac{Q}{a-bp} - L_{min}}{L_{max} - L_{min}} \tag{17}$$

VI. SENSITIVITY ANALYSIS

Sensitivity analysis is a technique used to determine how different values of an input variable in a mathematical or simulation model impact a particular output variable under a given set of assumptions. In essence, it measures how sensitive the output is to changes in each input. This analysis is crucial in decision-making processes because it helps identify which variables have the most influence on the outcome and therefore need more precise control or more detailed examination. In the context of the inventory model discussed, sensitivity analysis helps understand how variations in parameters such as demand rate, cost components, and other system factors affect the total cost. By examining the changes in total cost with ± 10 % variations in these parameters, stakeholders can prioritize their focus on the most impactful factors, ensuring better management and optimization of the inventory system. This can lead to more robust decision-making, cost savings, and efficient resource allocation.

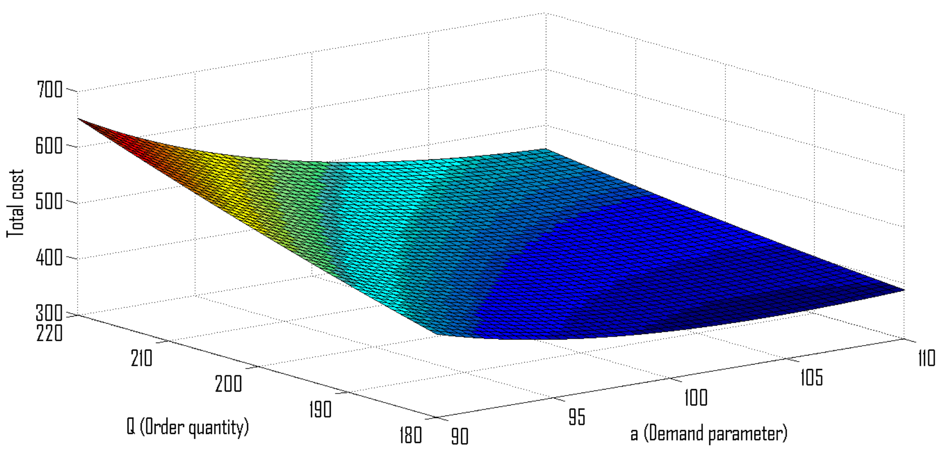
Table 1: Sensitivity Analysis of Total Cost with Respect to Parameter Variations

Parameter	Baseline parameters	-10%	Total cost	$+10\%$	Total cost
a	100	90	340.0583333	110	360.6916667
b	5	4.5	352.9541667	5.5	347.7958333
h	1	0.9	359.125	1.1	341.625
C_s	2	1.8	316	2.2	384.75
θ	0.01	0.009	350.4625	0.011	350.2875
δ	0.05	0.045	350.875	0.055	349.875

The table (1) provides a detailed examination of how the total cost of the inventory system changes when key parameters are adjusted by $\pm 10\%$. The baseline parameters include $a = 100, b = 5, h = 1, C_s = 2, \theta = 0.01, \delta = 0.05$. The analysis shows the total cost associated with a 10% decrease and a 10% increase for each parameter while keeping all other parameters constant. For example, when a is decreased by 10% to 90, the total cost is 340.058333, and when a is increased by 10% to 110, the total cost is 360.691667. Similar patterns are observed for other parameters. Interestingly, the total cost is most sensitive to changes in C_s (shortage cost), showing a significant variation from 316 to 384.75 when C_s is altered by $\pm 10\%$.. The total cost is least sensitive to changes in θ (deterioration rate) and δ (advance payment discount rate), indicating stability in total cost despite variations in these parameters. This analysis helps identify which parameters have the most significant impact on total cost and thus should be monitored closely.

VII. RESULTS AND DISCUSSION

Graph 1: Total cost surface plot



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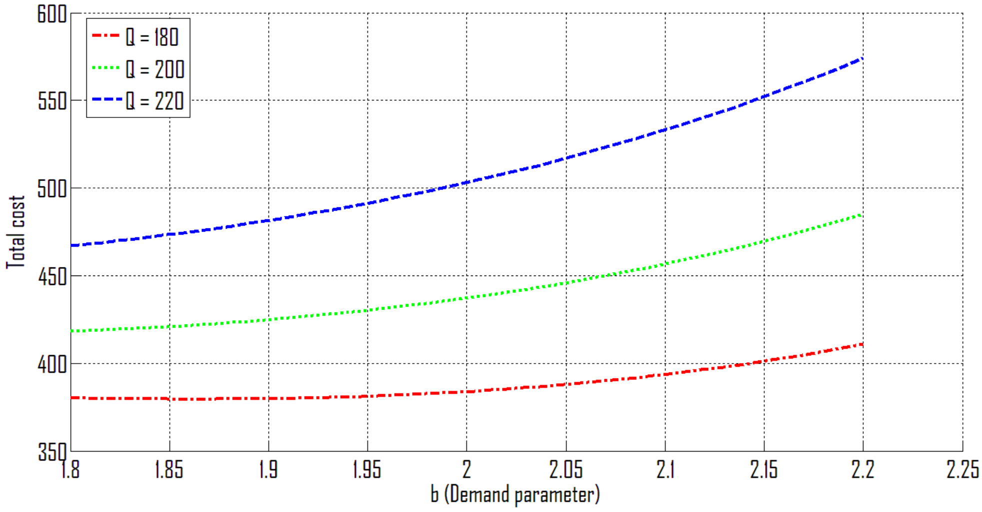
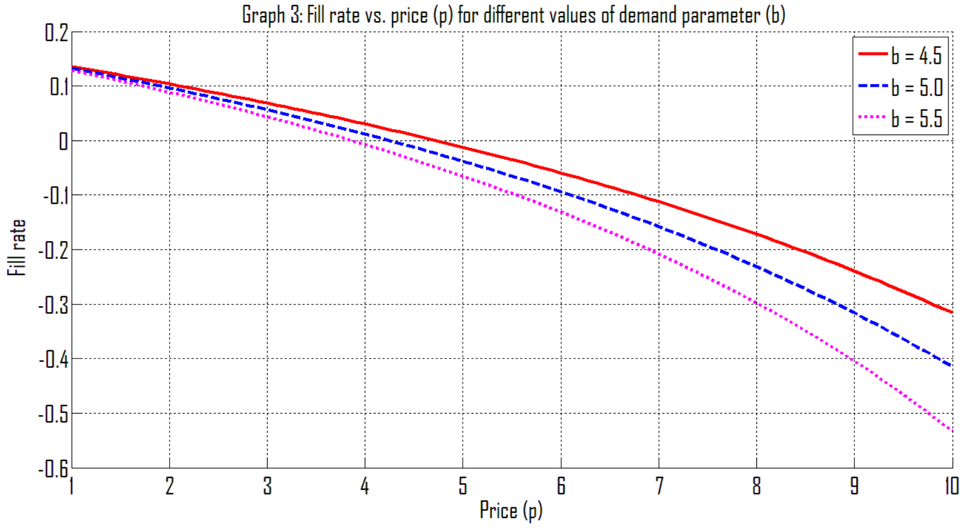
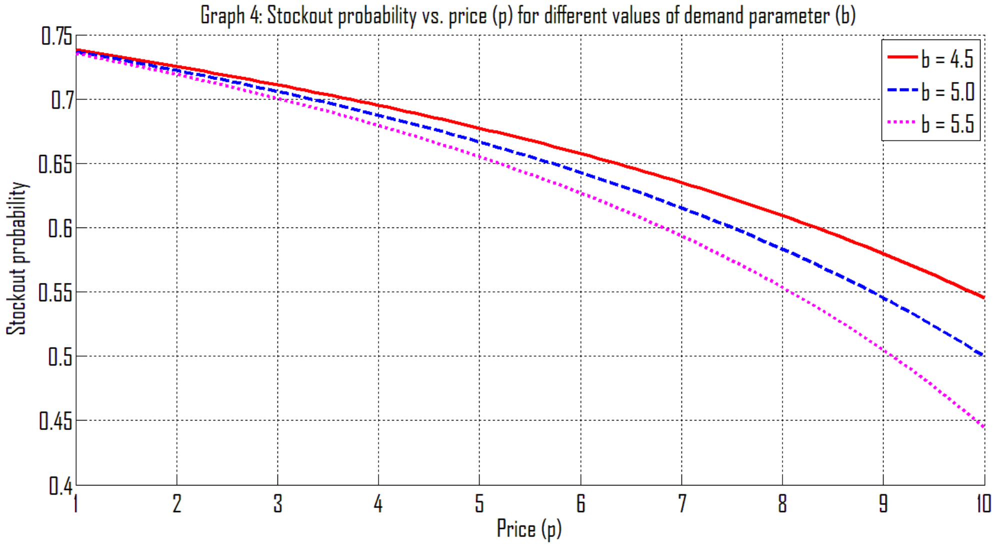
Graph 2: Total cost vs b (demand parameter) for different Q



Graph 3: Fill rate vs. price (p) for different values of demand parameter (b)



Graph 4: Stockout probability vs. price (p) for different values of demand parameter (b)



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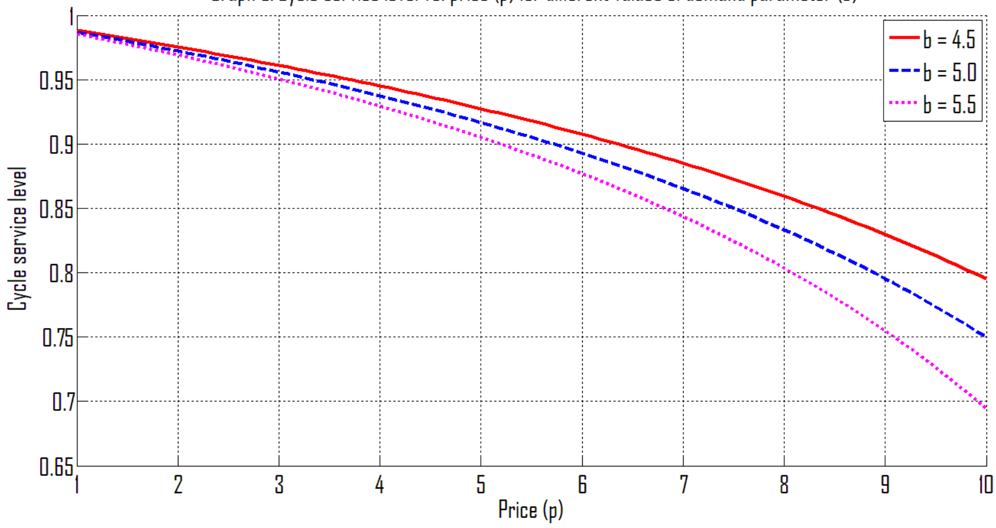
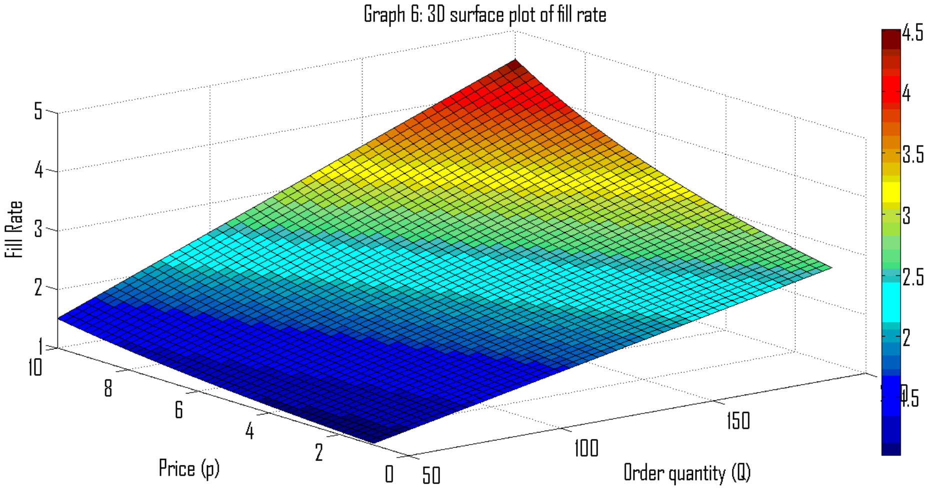
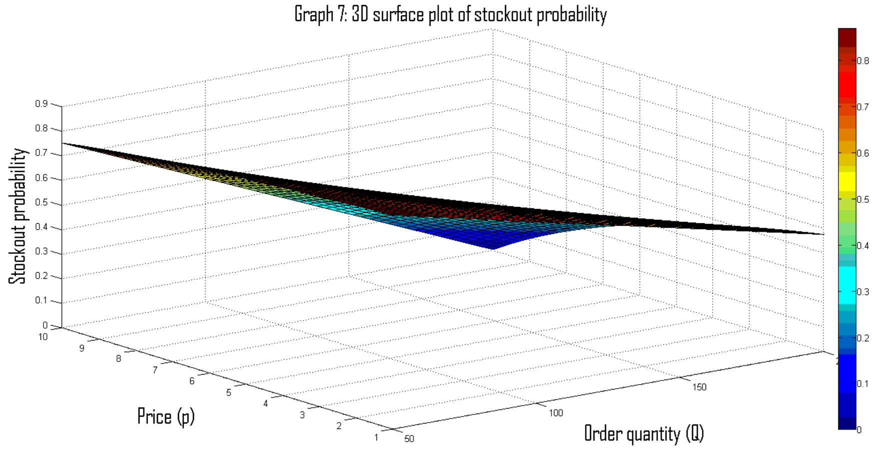
Graph 5: Cycle service level vs. price (p) for different values of demand parameter (b)



Graph 6: 3D surface plot of fill rate



Graph 7: 3D surface plot of stockout probability



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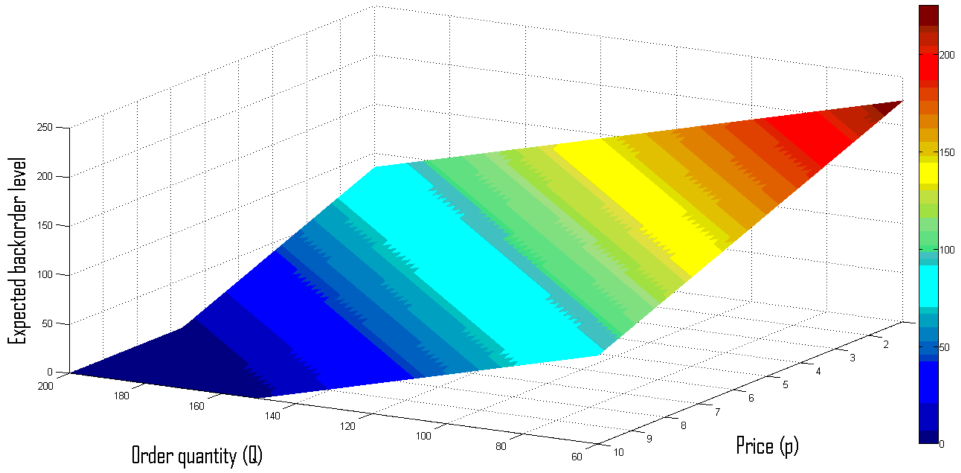
International Advanced Research Journal in Science, Engineering and Technology

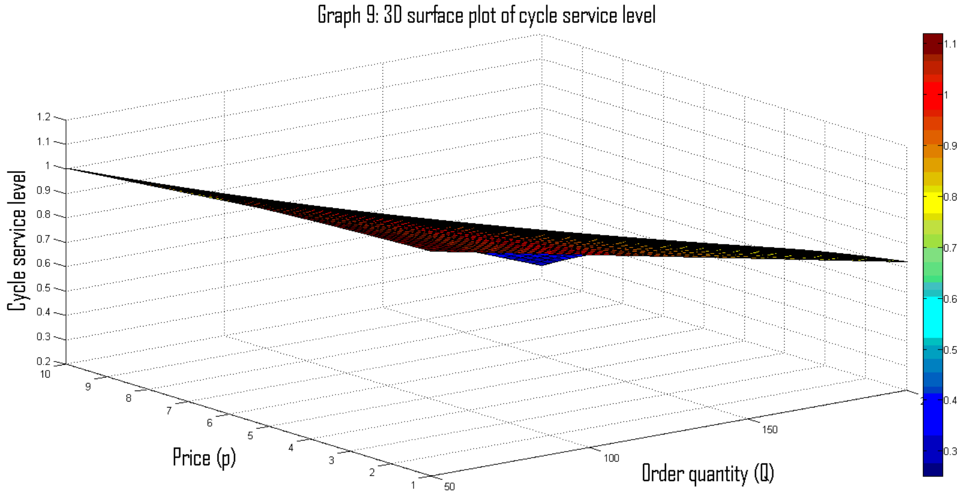
Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 7, July 2025

DOI: 10.17148/IARJSET.2025.12737

Graph 8: 3D surface plot of expected backorder level



Graph 9: 3D surface plot of cycle service level



The graph (1) presented is a 3D surface plot illustrating the relationship between the total cost and two key variables: the order quantity (Q) and the demand parameter (a). The x-axis represents the order quantity, ranging from approximately 180 to 220 units, while the y-axis denotes the demand parameter, varying from about 90 to 110. The z-axis indicates the total cost, which spans from around 300 to 700. The surface plot demonstrates how total cost changes as a function of both the order quantity and the demand parameter. The lowest point on the surface represents the optimal combination of Q and a that minimizes the total cost, depicted by the dark blue region on the plot. The gradual change in colors from red to blue indicates the variation in cost, with red indicating higher costs and blue indicating lower costs. This visualization helps in understanding how different values of order quantity and demand parameter influence the overall cost, and it assists in identifying the optimal strategy for minimizing costs in an inventory management context.

The graph (2) shows that for all three order quantities, the total cost increases as the demand parameter b increases. However, the rate of increase and the total cost values differ for each order quantity. The red dashed line (for $Q = 180$) shows the lowest total cost across the range of b, followed by the green dotted line (for $Q = 200$), and the blue dashed line (for $Q = 220$), which shows the highest total cost. This indicates that lower order quantities are associated with lower total costs for the given range of the demand parameter b. The graph helps in understanding how changes in the demand parameter b impact total cost for different order quantities, allowing for better decision-making in optimizing inventory management.

The graph (3) depicts the relationship between the fill rate and price (p) for different values of the demand parameter (b). The x-axis represents the price, ranging from 1 to 10, while the y-axis represents the fill rate. Three curves are

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plotted for different values of the demand parameter: $b = 4.5$ (red solid line), $b = 5.0$ (blue dashed line), and $b = 5.5$ (pink dotted line). The graph shows a negative correlation between the fill rate and price for all values of b, indicating that as the price increases, the fill rate decreases. This trend is more pronounced for higher values of the demand parameter, with the curve for $b = 5.5$ showing a steeper decline compared to $b = 4.5$ and $b = 5.0$. The different curves highlight how changes in the demand parameter affect the sensitivity of the fill rate to price variations.

The graph (4) illustrates the relationship between stockout probability and price (p) for different values of the demand parameter (b). The x-axis represents the price, ranging from 1 to 10, while the y-axis represents the stockout probability. Three curves are plotted for different values of the demand parameter: $b = 4.5$ (red solid line), $b = 5.0$ (blue dashed line), and $b = 5.5$ (pink dotted line). The graph shows a negative correlation between the stockout probability and price for all values of b, indicating that as the price increases, the stockout probability decreases. This trend is more pronounced for higher values of the demand parameter, with the curve for $b = 5.5$ showing a steeper decline compared to $b = 4.5$ and $b = 5.0$. The different curves demonstrate how changes in the demand parameter affect the sensitivity of the stockout probability to price variations, with higher values of b leading to a more rapid decrease in stockout probability as price increases.

The graph (5) depicts the relationship between cycle service level and price (p) for different values of the demand parameter (b). The x -axis represents the price, ranging from 1 to 10, while the y -axis represents the cycle service level. Three curves are plotted for different values of the demand parameter: $b = 4.5$ (red solid line), $b = 5.0$ (blue dashed line), and $b = 5.5$ (pink dotted line). As the price increases, the cycle service level decreases for all values of the demand parameter. This negative correlation is evident across all three curves, indicating that higher prices lead to lower cycle service levels. The steepness of the decline varies with the value of the demand parameter. For $b = 4.5$, the service level remains relatively higher across the price range compared to the curves for b = 5.0 and $b = 5.0$. Conversely, the curve for $b = 5.5$ shows a more pronounced decline, indicating a greater sensitivity to price increases. This graph demonstrates how the demand parameter affects the cycle service level's responsiveness to price changes. Higher values of b result in a more rapid decrease in service level as prices rise. This suggests that pricing strategies need to consider the demand parameter to manage service levels effectively.

The graph (6) is a 3D surface plot that illustrates the relationship between the fill rate, the price (p), and the order quantity (Q). The fill rate is represented on the vertical axis, while the price and order quantity are shown on the horizontal axes. The color gradient on the surface plot ranges from blue to red, indicating different levels of the fill rate, with blue representing lower values and red representing higher values. As the price and order quantity increase, the fill rate generally increases, reaching higher values at the upper end of the axes. This suggests a positive correlation between the fill rate and both price and order quantity, indicating that higher prices and larger order quantities are associated with higher fill rates.

The graph (7) is a 3D surface plot that depicts the relationship between the stockout probability, price (p), and order quantity (Q). The stockout probability is shown on the vertical axis, while the price and order quantity are represented on the horizontal axes. The color gradient on the surface plot ranges from blue to red, with blue indicating lower stockout probabilities and red indicating higher probabilities. As both price and order quantity increase, the stockout probability decreases, with the lowest probabilities appearing at higher prices and larger order quantities. This trend suggests an inverse relationship between stockout probability and both price and order quantity, meaning that higher prices and larger order quantities reduce the likelihood of stockouts. The plot visually conveys that efficient inventory management strategies involving higher pricing and adequate order quantities can minimize the risk of stockouts.

The graph (8) is a 3D surface plot that illustrates the relationship between the expected backorder level, the order quantity (Q), and the price (p). The expected backorder level is represented on the vertical axis, while the order quantity and price are shown on the horizontal axes. The color gradient on the surface plot ranges from blue to red, where blue indicates lower backorder levels and red indicates higher backorder levels. As the order quantity decreases and the price increases, the expected backorder level tends to increase, as indicated by the shift from blue to red. This suggests that lower order quantities and higher prices are associated with higher backorder levels. Conversely, higher order quantities and lower prices result in lower backorder levels. The plot highlights the importance of managing both order quantity and pricing strategies to minimize backorder levels and improve inventory management efficiency.

The graph (9) is a 3D surface plot that depicts the relationship between the cycle service level, the order quantity (Q), and the price (p). The cycle service level is represented on the vertical axis, while the price and order quantity are shown on the horizontal axes. The color gradient on the surface plot ranges from blue to red, with blue indicating lower cycle service levels and red indicating higher levels. As both the price and order quantity increase, the cycle service

DOI: 10.17148/IARJSET.2025.12737

level generally decreases, as indicated by the shift from red to blue. This trend suggests that higher prices and larger order quantities are associated with lower cycle service levels, whereas lower prices and smaller order quantities result in higher cycle service levels. The plot visually conveys the impact of pricing and order quantity on maintaining a desired cycle service level, highlighting the need for strategic balance to achieve optimal inventory performance.

VIII. CONCLUDING REMARKS

In conclusion, the integration of stochastic lead-time, price-dependent demand, and advance payment strategies into inventory optimization models offers a more realistic and robust approach to managing supply chains. This research highlights the significant improvements in cost efficiency and risk mitigation that can be achieved by addressing the inherent uncertainties in lead-time and demand variability. The use of advanced mathematical techniques and heuristic algorithms to derive optimal ordering policies demonstrates the practical applicability and effectiveness of the proposed model. Sensitivity analysis further underscores the importance of key parameters, providing valuable insights for decision-makers. Ultimately, this study contributes to the field of inventory management by presenting a comprehensive framework that enhances both financial performance and operational resilience, paving the way for more adaptive and efficient supply chain strategies.

REFERENCES

[1]. Alimian M., Saghafian M. (2023): “Inventory control with stochastic lead times and nonstationary demand: A robust optimization approach”, *IEEE Transactions on Engineering Management, 70*(4):1068-1080.

[2]. Boute R.N., Lambrecht M. R. (2016): “Inventory management with stochastic lead times: The role of information and lead time reduction”, *European Journal of Operational Research, 252*(3):872-882.

[3]. Chaharsooghi S. K., Heydari J. (2014): “A robust optimization model for a two-echelon inventory system with stochastic lead time and demand”, *Computers & Industrial Engineering, 74*(1):135-144.

[4]. Chen H., Yang B. (2017): “Optimal policies for a supply chain with stochastic demand and variable lead time”, *Journal of Manufacturing Systems, 43*(4):212-222.

[5]. Fadiloglu M. M., Karaesmen I. (2022): “A dynamic inventory model with stochastic lead times and demand substitution”, *Operations Research, 70*(6):1579-1592.

[6]. Gu Y., Sethi S. P. (2015): “Inventory control with stochastic lead times and order crossover. *Naval Research Logistics, 62*(7):508-520.

[7]. He Y., Huang J. (2015): “Stochastic inventory models with multiple delivery modes and random lead times”, *International Journal of Production Economics, 167*(2):149-158.

[8]. Ketzenberg M. E., Ferguson M. E. (2020): “The impact of lead time uncertainty on inventory investment: Insights from a stochastic lead time demand model”, *Production and Operations Management, 29*(8):1805-1818.

[9]. Ni W., Wang X. (2014): “Optimal inventory policies for a system with stochastic lead time and service level constraints”, *Computers & Operations Research, 53*(1):89-99.

[10]. Pan J. C. H., Hsiao Y. P. (2016): “Joint inventory and pricing strategy with stochastic lead times and price-sensitive demand”, *International Journal of Production Economics, 179*(2):11-21.

[11]. Song J. S., Zipkin P. H. (2017): “Inventory control with information about supply conditions and demand: The impact of lead-time variability”, *Management Science, 63*(5):1438-1450.

[12]. Tan B., Karabati S. (2021): “Managing inventory with stochastic lead times and advance demand information”, *International Journal of Production Economics, 234*(3):123-133.

[13]. Van der Heijden M. C., Teunter R. H. (2019): “Stochastic inventory models with correlated demand and lead times” *International Journal of Production Research, 57*(11): 3383-3397.

[14]. Xia Y., Xu H. (2018): “Inventory management under stochastic lead time with partial backordering”, *Operations Research Letters, 46*(5):517-522.

[15]. Zhou Y., Lai K. K. (2018): “Stochastic inventory models with emergency replenishments and correlated lead times”, *European Journal of Operational Research, 266*(1):239-250.