

Inventory Control Decision Support System Under Stochastic Demand: A Case Study of a Retail Warehouse

Husam Kaid, Yasir Almutairi, Mohammed Haysam, Shadi Mohammed, Talal Almohammdi and Khaled N. Alqahtani

Industrial Engineering Department, College of Engineering, Taibah University, Medina 41411,
Saudi Arabia

hkaid@taibahu.edu.sa, O8yasser8o@gmail.com, Mohammedtayp@gmail.com,
shadi979@hotmail.com, Talalalms55@gmail.com and knqahtani@taibahu.edu.sa

Abstract

Inventory management under stochastic demand poses significant challenges for retail warehouses, often leading to high holding costs, stockouts, and inefficient ordering practices. This study investigates the inventory control of Product A at the X Shopping Store Company's warehouse, where the existing system lacked a reorder point and predetermined order quantity, resulting in an annual cost of 2,803.79 SAR and 12.27 sacks of stockouts. To address these issues, a stochastic simulation–optimization model was developed using Arena, integrating historical demand data and EOQ-based inventory principles. A VBA-based interface was implemented to allow managers to dynamically adjust reorder points, maximum storage, and other parameters while instantly observing the impact on order quantities, shortages, and total cost. The simulation-optimization results demonstrate that an optimal policy—with a reorder point of 30 sacks, maximum storage of 65 sacks, and order quantity of 39 sacks—reduces annual stockouts to 5 sacks and lowers total cost to 2,115.72 SAR, achieving a 24.54% cost reduction. The proposed framework provides a practical and robust decision support system for inventory management under uncertainty, enabling cost-efficient, data-driven decision-making and improved warehouse performance.

Keywords

Inventory Management, Stochastic Demand, Simulation–Optimization, Arena, Decision Support System, Stockout Reduction.

1. Introduction

Inventory management is a crucial component of supply chain operations, especially in retail settings where warehouses must accommodate fluctuating customer demand across various locations. Efficient inventory management guarantees product availability when required, while reducing expenses related to storage, procurement, and stock shortages. In practice, attaining this equilibrium is difficult due to the unpredictable nature of demand, fluctuations in supplier lead times, and operational limitations such as storage capacity and financial constraints.

Due to its impact on cost efficiency and service levels, stochastic demand inventory management has garnered study attention. To evaluate inventory policies and assist data-driven decision-making under uncertainty, numerous research studies have used discrete-event simulation and simulation–optimization methods, such as Arena and OptQuest, to overcome deterministic model restrictions. The following studies demonstrate recent applications and advancements in this field. (Mitrović *et al.*, 2021) developed an Arena-based simulation model to determine optimal inventory reorder levels that minimize total costs. By analyzing the impact of different reorder points on holding, shortage, and ordering costs, the study identified an optimal stock level of 31 pallets, highlighting the usefulness of simulation for understanding inventory system behavior and cost trade-offs. (Sridhar, Vishnu and Sridharan, 2021) investigated an inventory management problem in a retail store using Arena simulation and OptQuest optimization. Through extensive experimentation, the proposed system significantly reduced inventory levels and lost sales compared to the traditional

approach. The study demonstrated that simulation-based optimization can substantially improve retail inventory performance and decision-making. (Antic, Milutinovic and Lisec, 2022) addressed inventory control in a centralized pharmaceutical distribution system using a dynamic discrete mathematical model that incorporated stochastic and deterministic demand, variable lead times, and multiple ordering policies. Using real-life data, the study developed a procedure to determine reorder points and delivery frequencies, showing improved stock availability and reduced shortages compared to traditional planning models. (Atakay *et al.*, 2022) proposed an integrated inventory control framework for automotive spare parts by combining Analytical Hierarchy Process (AHP)-based Multi-Criteria Decision Making (MCDM), ABC-VED classification, and Arena simulation with OptQuest optimization. Different inventory policies were assigned to classified spare parts, and a decision support system (DSS) was developed to support real-time inventory tracking and ordering decisions. Their results demonstrated the effectiveness of simulation-optimization in minimizing total inventory costs while supporting managerial decision-making. (Eren *et al.*, 2023) applied a simulation-based (R, S) inventory control model to a construction company facing probabilistic demand. By comparing the proposed model with the existing system, the study reported cost reductions and improved inventory performance, emphasizing the value of simulation for inventory decision-making under uncertainty. (Saracoglu, 2023) examined a multi-product, multi-period (s, S) inventory policy under stochastic demand and budget constraints. The study employed simulation-optimization to validate mathematical model results, demonstrating that simulation is an effective tool for determining reorder points and maximum inventory levels in complex inventory systems. (Gebreabzgi, Beyene and Aregawi, 2025) utilized Arena simulation integrated with OptQuest to optimize a multi-echelon supply chain under demand uncertainty. The optimized model improved customer service levels and significantly reduced inventory costs. The study highlighted the applicability of simulation-optimization as a robust decision-making tool for supply chains operating under resource and demand constraints. (Lukito *et al.*, 2025) improved an existing retail inventory simulation model by identifying and correcting critical design flaws through field interviews and Arena modeling. The enhanced model achieved significant reductions in lost customers and improved demand fulfillment, demonstrating the importance of accurate simulation logic for realistic inventory system analysis. (Oyedepo, 2025) explored the role of stochastic simulation in enhancing supply chain resilience under uncertain demand and supply conditions. The study emphasized the strategic value of simulation models for evaluating disruption scenarios, improving responsiveness, and supporting resilient inventory and supply chain decisions. (Arevalo *et al.*, 2025) proposed a discrete-event simulation framework to improve inventory control and demand satisfaction in an agricultural supply chain. The study demonstrated how simulation-based inventory policies can minimize costs and enhance system robustness in environments characterized by high demand and supply variability.

Despite the extensive application of simulation-optimization methods for inventory control under stochastic demand, limited attention has been given to the development of practical, user-oriented decision support systems, particularly those integrating VBA-based interactive interfaces within simulation environments. To address this gap, this study develops a DSS for inventory management in a retail warehouse operating under stochastic demand. The proposed approach analyzes the existing inventory system at X Shopping Store, develops a stochastic Arena simulation model using historical data, and applies OptQuest optimization to determine optimal reorder points, order quantities, and safety stock levels. A VBA-based interface is implemented to enable user-friendly interaction, scenario analysis, and performance visualization. The optimized policy is compared with the current system in terms of cost reduction, stockout minimization, and storage efficiency, demonstrating the effectiveness of the proposed framework for data-driven inventory decision-making under uncertainty.

2. Case Study Description and Problem Identification

The case study analyzes the central warehouse of X Shopping Store, which services five retail locations. The warehouse employs a centralized computerized system for inventory management, encompassing product identification, barcode scanning, and price registration. A five-week diagnostic assessment identified multiple significant deficiencies:

1. One employee conducts inventory management, thereby elevating operational risk.
2. The system does not compute holding or shortage costs.
3. Reorder points and safety stock levels remain undefined.
4. Product transfers to branches lack explicit documentation.
5. Periodic audits of inventories utilizing barcodes are omitted.

Replenishment choices are made manually, depending on visual inventory inspection and managerial judgment. This method results in irregular ordering behavior, increased storage requirements, and recurrent shortages.

The lack of a systematic inventory management policy and analytical decision-making assistance has led to: Increased total annual inventory expenditure (2,803.79 SAR).

1. Annual stockout totaling 12.27 sacks.
2. Insufficient use of storage capacity.
3. High workload and decision-making complexity.

3. Methodology

This section illustrates the study's methodology shown in Figure 1. The methodology combines modeling, optimization, and automation to provide a decision support system for inventory management in the context of unpredictable demand. The current system was evaluated, and historical demand data were gathered and organized. A discrete-event simulation model in Arena was constructed and validated, subsequently optimized with Arena OptQuest to determine the best reorder point, order quantity, and safety stock. A VBA-based interface was ultimately developed to facilitate interactive scenario analysis and visualization of system performance.

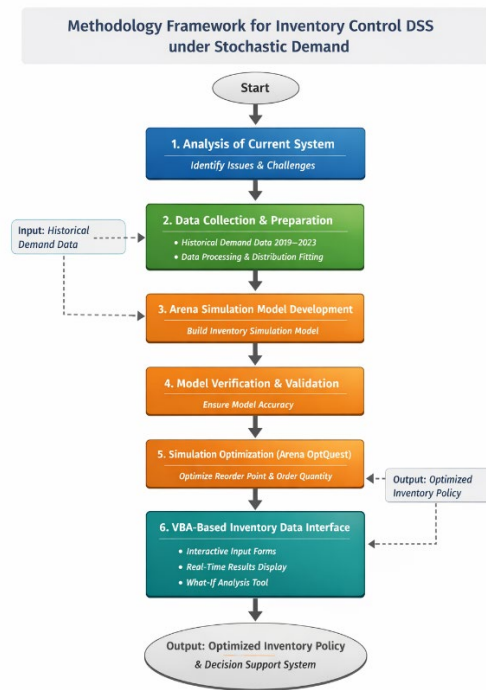


Figure 1. The methodology of the study.

3.1 Analysis of Current System

The company's inventory system in X shopping store is computerized software that facilitates the automated tracking and updating of inventory via a centralized database encompassing product information, barcodes, and prices. When new shipments arrive, they are recorded to ensure that inventory updates are accurate. A five-week examination of the primary warehouse uncovered numerous deficiencies. One worker oversees inventory management for the warehouse and its five branches, which exacerbates workload and increases the risk of data entry mistakes. The system fails to compute holding or shortage costs, hindering the evaluation of the financial implications of inventory choices. Furthermore, it does not establish reorder points, resulting in possible stockout or superfluous restocking. The system fails to document product transfers to branches and does not facilitate periodic barcode-based inventory audits, leading to potential inventory discrepancies. During the review of the procurement procedure, several issues were identified. Initially, a reordering point is not established. Secondly, there is no specified minimum order quantity. The two issues led to an excessively elevated overall storage cost for the product. The evaluation of the existing system indicated a significantly high total annual cost of 2803.79 SAR. The issue arose from deficient reordering procedures, in which the warehouse manager would manually assess inventory levels and, if found lacking, manually ascertain and place

orders to replenish stock to optimal levels. These measures led to an annual stockout of 12.27 sacks and generated significant storage expenses. Table 1 presents a summary of data associated with the existing inventory system.

Table 1. Summary of the cost-related data associated with the existing inventory system.

	Current System
Maximum Storage	100
Reorder Point	15
Quantity	89
Total Shortage Per Year	12.27
Total Cost Per Year (SAR)	2803.79

3.2 Data Collection and Preparation

The data utilized in this study was collected from the inventory records of X Shopping Store's central warehouse throughout a five-year span. The collection includes daily transaction records for the selected inventory product A and comprises:

1. Daily demand quantities
2. Replenishment order dates and quantities
3. Supplier lead times
4. Recorded stockout occurrences
5. Inventory on-hand levels

To accurately represent demand uncertainty in the simulation model, Arena's Input Analyzer was employed to fit probability distributions to the historical demand data collected from 2019 to 2023. The analysis was conducted separately for demand quantity per transaction and time between successive demand arrivals. The Input Analyzer results shown in Figure 2 indicate that the demand quantity follows a Lognormal distribution, which provided the best fit based on goodness-of-fit statistics and visual inspection. The fitted distribution is expressed in Arena syntax as:

$$\text{Demand}=0.5+\text{LOGN}(3.09,3.63).$$

The Lognormal distribution is particularly suitable for modeling retail demand because it ensures non-negative demand values and effectively captures right-skewed behavior commonly observed in real-world sales data. The additive constant (0.5) ensures numerical stability and avoids zero-demand artifacts in the simulation.

Similarly, the time between consecutive demand events was best represented by a Lognormal distribution, expressed as:

$$\text{Interarrival Time for demand}=-0.5 + \text{LOGN}(2.36, 1.13)$$

This distribution captures the variability in customer arrival patterns and reflects periods of high demand intensity as well as low activity. The subtraction constant (-0.5) corrects the distribution shift to better match observed data.

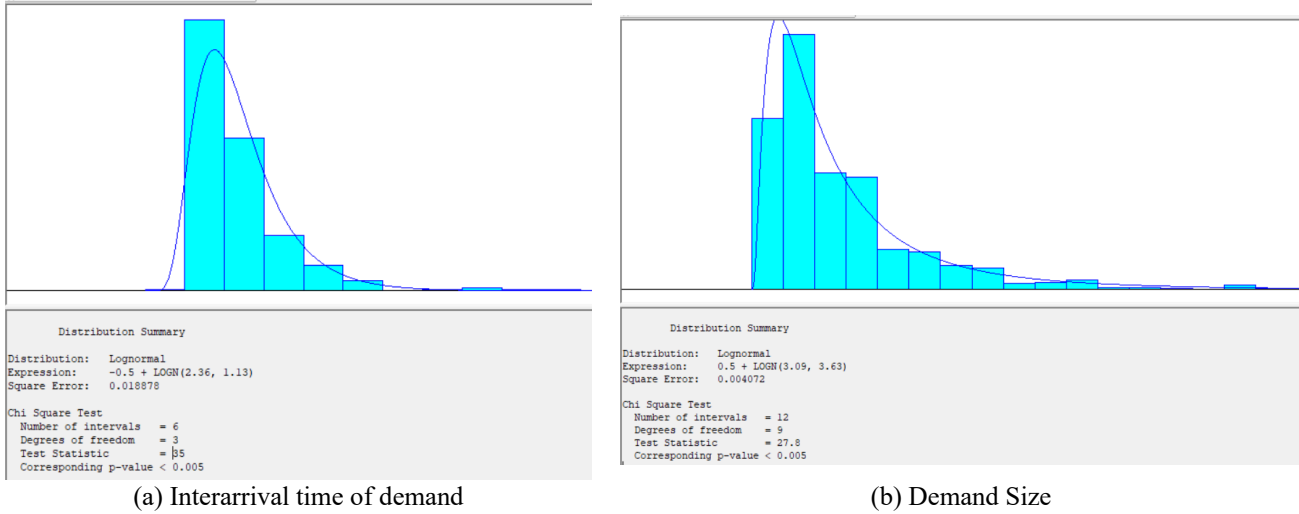


Figure 2. Input Analyzer results of size and interarrival time of demand for the X Shopping Store's central warehouse.

The Arena simulation model was initiated using a collection of system variables that depict the operational condition of the warehouse at the commencement of the simulation period. These variables were extracted from historical warehouse data and managerial practices to monitor inventory dynamics, costs, and system performance during the simulation period. Table 2 presents initial inventory, ordering parameters and cost parameters for X Shopping Store's central warehouse

Table 2. Initial inventory, ordering parameters and cost parameters demand for the X Shopping Store's central warehouse.

Variable	Initial Value	Description
Inventory on-hand level	68 units	Initial available stock at simulation start
Reorder point	15 units	Inventory level triggering replenishment
Order indicator	1	Binary variable indicating order placement
Maximum storage capacity	100 units	Physical storage limit of the warehouse
Total demand	0	Cumulative demand during simulation
Number of shortages	0	Number of stockout events
Total shortages	0 units	Total unmet demand quantity
Unit holding cost	0.14705882	SAR/unit/day
Unit shortage cost	10	SAR/unit
Days to run	306 days	Annual operational period
Total order quantity	0	Accumulated ordered units
Number of orders	0	Total number of replenishment orders

3.3 Arena Simulation Model Development

A model using Arena Simulation Software, shown in Figure 3, was developed to simulate the operational dynamics of the X Shopping Store's central warehouse under stochastic demand conditions.

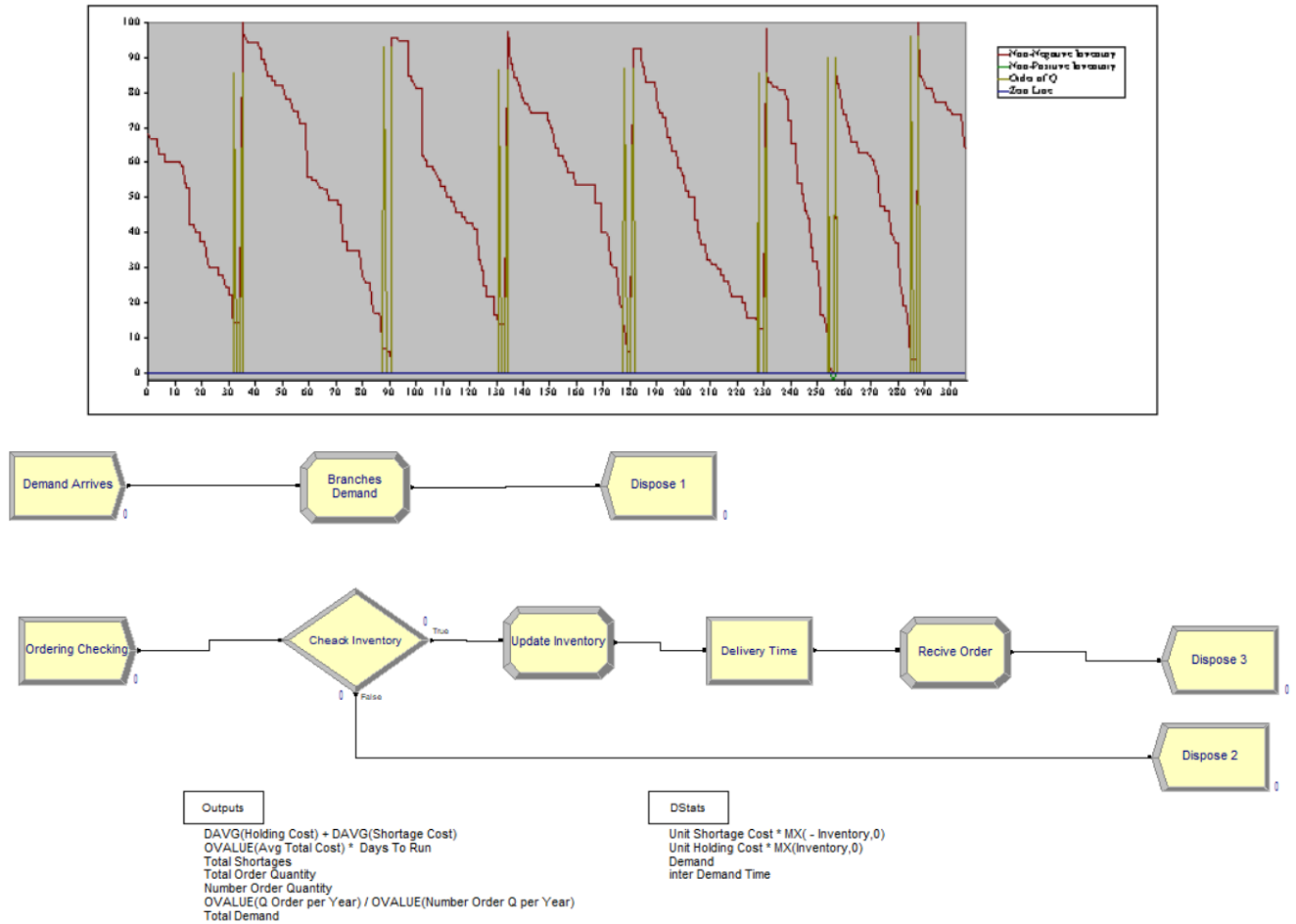


Figure 3. Arena model for the X Shopping Store's central warehouse.

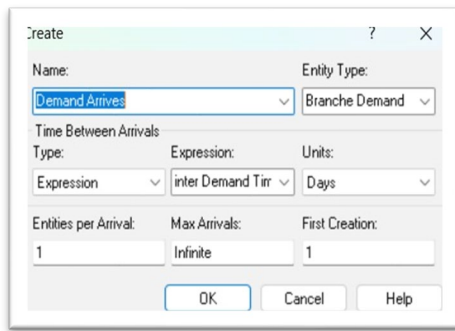
The Arena model consists of the following core components:

1. Create Module: Generates customer demand entities based on the fitted stochastic demand distribution as shown in Figure 4(a and b).
2. Assign Module: Updates inventory levels and records demand quantities as shown in Figure 4(c and d).
3. Decide Module: Checks inventory availability to determine whether demand can be fully satisfied or results in a stockout as shown in Figure 4(e).
4. Process Module: Represents order placement and replenishment lead time as shown in Figure 4(f).
5. DStats Module: This module will count and update the variable when the system detects change in the variable stat as shown in Figure 4(g).
6. Outputs Module: This Module will calculate and show the final desired output as shown in Figure 4(h).
7. Dispose Module: Terminates demand entities after fulfillment or stockout recording.

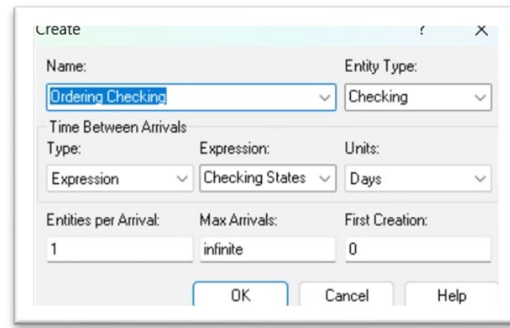
The following cost components were explicitly modeled within Arena:

1. Holding Cost: Accumulated based on average on-hand inventory and holding cost rate.
 2. Ordering Cost: Incurred each time a replenishment order is placed.
 3. Shortage Cost: Applied when customer demand cannot be satisfied due to insufficient inventory.
- Arena's Variables and Record Modules were used to track cumulative costs throughout the simulation run.

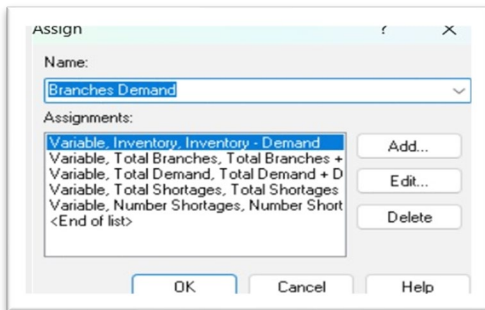
Inventory replenishment follows a continuous review (Q, R) policy, where inventory position is continuously monitored, and an order of size Q is placed whenever the inventory level reaches or falls below the reorder point R .



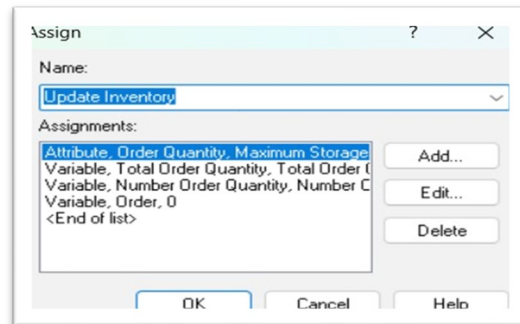
(a)



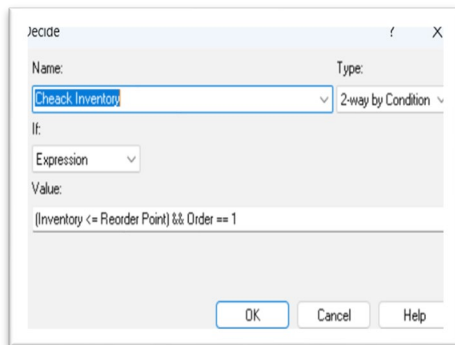
(b)



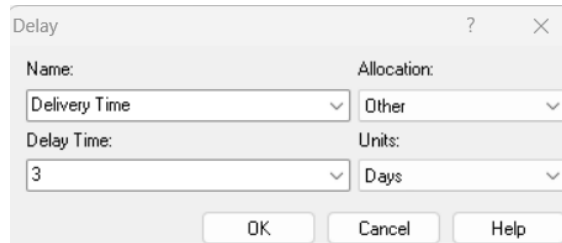
(c)



(d)



(e)



(f)

Outputs

DAVG(Holding Cost) + DAVG(Shortage Cost)
 OVALUE(Avg Total Cost) * Days To Run
 Total Shortages
 Total Order Quantity
 Number Order Quantity
 OVALUE(Q Order per Year) / OVALUE(Number Order Q per Year)
 Total Demand

(g)

DStats

Unit Shortage Cost * MX(- Inventory,0)
 Unit Holding Cost * MX(Inventory,0)
 Demand
 inter Demand Time

(h)

Figure 4. Core components of the Arena model shown in Figure 3.

3.4 Model Verification and Validation

Model verification was performed by a sequential animation review and logical flow assessment to ensure precise portrayal of warehouse operations. Validation was conducted by comparing simulation results under the existing inventory strategy with historical performance metrics, comprising average inventory levels and annual stockout

quantities. The simulation outcomes closely aligned with the observed behavior of the warehouse, hence validating the created model.

To guarantee statistical reliability and accuracy of the simulation outcomes, the Arena model was conducted for an adequate number of independent replications. The convergence study revealed that 580 replications were necessary to attain a specified error rate of 0.01 for the principal performance metrics. The resultant half-width of 0.08 at a 95% confidence level signifies a tight confidence interval, denoting great precision and minimal variability in the simulation results. This verifies that the chosen number of replications is sufficient for a stable and statistically significant performance assessment. The stated accuracy value of 0.009812219 illustrates the model's robust predictive capability while sustaining a consistently narrow error margin. This degree of precision instills assurance that the simulation outcomes are both dependable and resilient for decision-making and optimization objectives.

3.5 Simulation Optimization Using Arena OptQuest

To identify optimal inventory policy parameters, **Arena OptQuest** shown in Figure 5 was employed as the optimization engine.

Decision Variables

Order quantity (Q)

Reorder point (R)

Objective Function

$$\min TC = HC + OC + SC$$

Where:

TC : Total annual inventory cost, HC : Holding cost, OC : Ordering cost, and SC : Shortage cost

Constraints

$$Q > 0$$

$$R \geq 0$$

Service level \geq predefined target (e.g., 95%)

OptQuest iteratively evaluated multiple combinations of Q and R using simulation outputs to identify the policy that minimizes total cost while satisfying service level constraints.

Controls Summary									
Included	Category	Control /	Element Type	Type	Low Bound	Suggested Value	High Bound	Step	Description
<input type="checkbox"/>	User Specified	Days To Run	Variable	Continuous	275.4	306	336.6	N/A	
<input type="checkbox"/>	User Specified	Inventory	Variable	Continuous	61.2	68	74.8	N/A	
<input checked="" type="checkbox"/>	User Specified	Maximum Storage	Variable	Continuous	90	100	110	N/A	
<input type="checkbox"/>	User Specified	Number Order Quantity	Variable	Continuous	0	0	0	N/A	
<input type="checkbox"/>	User Specified	Number Shortages	Variable	Continuous	0	0	0	N/A	
<input type="checkbox"/>	User Specified	Order	Variable	Continuous	0.9	1	1.1	N/A	
<input checked="" type="checkbox"/>	User Specified	Reorder Point	Variable	Continuous	13.5	15	16.5	N/A	

Figure 5. Arena OptQuest of the model shown in Figure 3.

4. Results and Performance Analysis

The combination of Arena simulation with OptQuest optimization yielded an important enhancement in inventory performance. The best policy parameters were derived by minimizing the overall annual inventory cost while ensuring acceptable service levels under stochastic demand situations. Table 3 presents a comparison between the existing inventory system and the Arena-optimized policy.

Table 3. Comparison of inventory performance before and after optimization

Parameter	Current System	Arena-Optimized Policy
Maximum Storage	100	65
Order Quantity (Q)	89	39
Reorder Point (R)	15	30
Safety Stock	None	30
Cycle Time for Q	None	20.16 days
Annual Stockouts	12.27 sacks	5 sacks
Total Cost Per Year	2803.79	2115.72
Cost Reduction Percentage	-	24.54%

The improved inventory policy indicates a distinct transition to more frequent, smaller replenishment orders, as seen by the decreased order amount from 89 to 39 units and the associated cycle time of 20.16 days. This modification lowers surplus inventory buildup while ensuring sufficient availability to satisfy unpredictable demand. The reorder point increased from 15 to 30 units, including a designated safety supply of 30 units. This alteration markedly enhances service level performance by mitigating demand variability and lead-time unpredictability. Consequently, annual stockouts decreased from 12.27 to 5 sacks, signifying a reduction of nearly 59%. The optimized policy decreased the maximum necessary storage capacity from 100 items to 65 units, demonstrating enhanced warehouse space efficiency and reduced holding costs.

The overall annual inventory cost diminished from 2,803.79 SAR to 2,115.72 SAR, resulting in a cost savings of 24.54%. This enhancement underscores the efficacy of the suggested simulation-optimization-based decision support system in reconciling holding, ordering, and shortage costs amid stochastic demand scenarios. Finally, the Arena-based simulation-optimization approach effectively determined an inventory policy that concurrently minimizes overall costs, decreases stockouts, and enhances storage efficiency in the context of unpredictable demand.

5. VBA-Based Inventory Data Interface for Arena

To improve the usability and accessibility of the Arena simulation model, Visual Basic for Applications (VBA) was utilized to create a bespoke inventory data interface. The VBA interface facilitates smooth interaction among the simulation model, input data, and output reporting, ensuring efficient analysis and real-time result presentation.

5.1 Purpose and Advantages

The VBA integration serves several purposes:

1. **Streamlined Data Input:** Users can enter or update inventory parameters (e.g., reorder Point and maximum Storage) through a simple interface, eliminating the need to manually modify Arena modules.
2. **Automated Simulation Execution:** VBA scripts trigger simulation runs in Arena directly from the interface, allowing batch execution of multiple replications or scenario experiments without manual intervention.
3. **Real-Time Output Analysis:** Key performance metrics, including total cost, stockouts, and order quantity, are automatically extracted from Arena and displayed within the interface for immediate interpretation.
4. **Simplified Visualization:** Charts and tables are generated within the VBA interface to summarize results, enhancing managerial understanding and decision-making.

5.2 Interface Design

The interface shown in Figure 6 was structured as follows:

- **Input Section:** Users provide initial model variables, such as reorder points and maximum storage as shown in Figure 7.
- **Control Section:** Includes buttons for starting, pausing, or resetting the simulation and options for specifying the number of replications and confidence levels.
- **Output Section:** Displays key performance indicators, cost components, and stockout metrics. Results can also be exported to Excel for further analysis as shown in Figure 8.

VBA modules interact with Arena objects and variables via the **Arena Automation API**, enabling direct reading and writing of simulation parameters and outputs. Figure 9 presents a part of VBA code in arena.



Figure 6. VBA-based inventory data interface of the model shown in Figure 3.

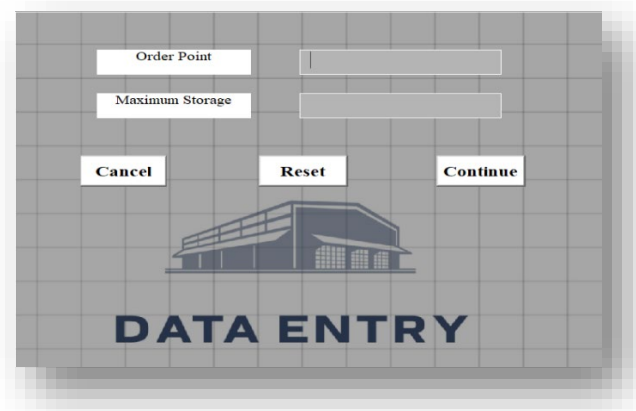


Figure 7. Input of the VBA-based inventory data interface shown in Figure 6.

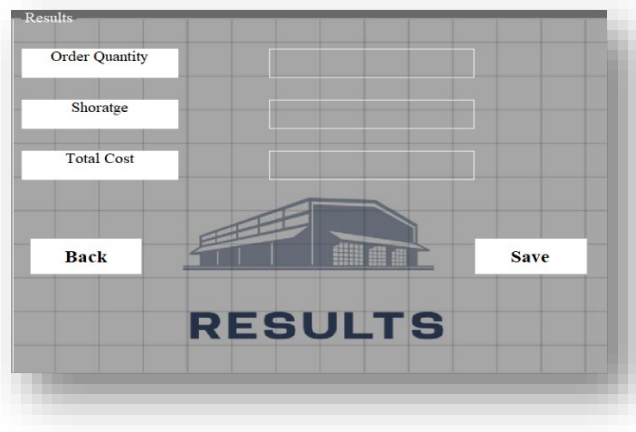


Figure 8. Output of the VBA-based inventory data interface shown in Figure 6.

```
' Code for ModelLogic_RunBeginSimulation subroutine
Private Sub ModelLogic_RunBeginSimulation()
    DataEntry.Show ' Show DataEntry form to input variables
End Sub

' Code for Continue button click event on DataEntry form
Private Sub ContinueButton_Click()
    ' Retrieve values for "Reorder Point" and "Maximum Storage"
from DataEntry form
    Dim reorderPoint As Double
    Dim maximumStorage As Double
    reorderPoint = DataEntry.Reorder_Box.value
    maximumStorage = DataEntry.TargetStock_Box.value

    ' Hide the Data Entry form
    DataEntry.Hide

    ' Show the Interface form
    Interface.Show
End Sub

Private Sub Start_Butoon_Click()

Interface.Hide 'When the button is clicked
                'remove the user form, and
                'continue with the run.

End Sub

Private Sub ModelLogic_RunEndReplication()
    Dim m As Model
    Dim s As SIMAN
    Set m = ThisDocument.Model
    Set s = m.SIMAN
    ' Retrieve values from the simulation results
    Dim totalOrderQuantity As Double
    Dim totalShortageCostPerYear As Double
    Dim totalCostPerYear As Double

    totalOrderQuantity = s.OutputStatisticValue(s.SymbolNumber("Q
Order"))
    totalShortageCostPerYear =
s.OutputStatisticValue(s.SymbolNumber("Total Shortages per year"))
    totalCostPerYear = s.OutputStatisticValue(s.SymbolNumber("Total
Cost Per Year"))
    ' Show the Results form
    Results.TextBox6.Text = totalOrderQuantity
    Results.TextBox1.Text = totalShortageCostPerYear
    Results.TextBox2.Text = totalCostPerYear
    Results.Show
End Sub
```

Figure 9. A part of the VBA code -based inventory data interface shown in Figure 6.

5.3 Benefits of VBA Integration

The VBA-based interface provides several practical benefits:

- **Efficiency:** Reduces model setup time and manual input errors.
- **Accessibility:** Enables non-technical users to run simulations and interpret results without in-depth knowledge of Arena.
- **Flexibility:** Supports rapid scenario analysis, sensitivity studies, and optimization experiments.
- **Decision Support:** Facilitates fast presentation of results for managerial decisions, aligning with the overall goal of a decision support system for inventory control.

6. Conclusion

This study was conducted at the X Shopping Store Company's warehouse to evaluate the effects of stochastic demand on the management of Product A. Analysis of the existing inventory system revealed critical deficiencies in the ordering process: the absence of a reorder point and the lack of a predetermined order quantity. These shortcomings led to an excessively high total storage cost, with the annual inventory cost reaching 2,803.79 SAR. Stock replenishment was performed manually by the warehouse manager, who assessed inventory levels and calculated replenishment quantities subjectively, resulting in an annual stockout of 12.27 sacks and significant holding costs.

To address these issues, a stochastic simulation–optimization model was developed in Arena, integrating historical demand data and EOQ-based inventory concepts. The model incorporated the existing warehouse operations and allowed for dynamic adjustment of reorder points and maximum storage capacity, while computing the resulting order

quantity, shortages, and total cost. A VBA-based interface was implemented to facilitate user-friendly interaction with the model, enabling managers to quickly test different scenarios and visualize system performance.

The simulation–optimization results demonstrate significant improvements over the existing system. By adopting a reorder point of 30 sacks, a maximum storage capacity of 65 sacks, and an order quantity of 39 sacks, the model reduced annual stockouts to 5 sacks and lowered the total annual inventory cost to 2,115.72 SAR, achieving a cost reduction of 24.54%. These results highlight the benefits of a structured, data-driven approach to inventory management under stochastic demand, improving service levels while reducing holding and shortage costs.

In conclusion, the integration of Arena simulation, OptQuest optimization, and a VBA-based decision interface provides a practical and robust decision support system for inventory management. It allows managers to make informed, cost-effective decisions under uncertainty, efficiently balance holding and shortage costs, and optimize warehouse capacity utilization. This framework is scalable and can be extended to other products or warehouses, supporting continuous improvement in retail inventory operations.

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Biographies

Husam Kaid is an associate professor in the Department of Industrial Engineering, College of Engineering, at Taibah University in Saudi Arabia. In 2021 and 2015, he received his PhD and MS in Industrial Engineering from King Saud University in Saudi Arabia, respectively. In 2010, he received a BS in Industrial Engineering from Taiz University in Yemen. His current research interests include Petri net theory and application, supervisory control of discrete event systems, workflow modeling and analysis, system reconfiguration, systems simulation, operations research, optimization of manufacturing operations, flexible manufacturing systems and cellular manufacturing systems, product design analysis, and applications of decision support systems in manufacturing.

Yasir Almutairi is a student in the Department of Industrial Engineering, College of Engineering, at Taibah University in Saudi Arabia. In 2024, he received a BS in Industrial Engineering from Taibah University in Saudi Arabia. His current research interests include systems simulation, operations research, optimization techniques, and manufacturing systems.

Mohammed Haysam is a student in the Department of Industrial Engineering, College of Engineering, at Taibah University in Saudi Arabia. In 2024, he received a BS in Industrial Engineering from Taibah University in Saudi Arabia. His current research interests include systems simulation, operations research, and applications of decision support systems in manufacturing.

Shadi Mohammed is a student in the Department of Industrial Engineering, College of Engineering, at Taibah University in Saudi Arabia. In 2024, he received a BS in Industrial Engineering from Taibah University in Saudi Arabia. His current research interests include systems simulation, operations research, optimization techniques, and flexible manufacturing systems and cellular manufacturing systems.

Talal Almohammdi is a student in the Department of Industrial Engineering, College of Engineering, at Taibah University in Saudi Arabia. In 2024, he received a BS in Industrial Engineering from Taibah University in Saudi Arabia. His current research interests include systems simulation, operations research, optimization techniques, and flexible manufacturing systems and cellular manufacturing systems.

Khaled N. Alqahtani is an associate professor who serves as chair of the Department of Industrial Engineering, College of Engineering, Taibah University, KSA. He earned his Ph.D. and B.Sc. degrees in Industrial Engineering from the University of Miami and received his MSc. degree in Industrial and Systems Engineering from the University of Central Florida. His current research interests include data-driven analytics and optimization, complex network theory, economic resilience, systems simulation, operations research, and manufacturing systems.