

Cairo University

Faculty of Computers and Artificial Intelligence

**Petrol Station Multi-Channel Queue**

**Hospital Inventory**

Department: Operations Research and Decision Support

Course Name: Systems Modeling and Simulation

Course Code: DS331/DS241

Instructor: Assoc. Prof. Ayman Ghoneim

Group members:

|  |  |
| --- | --- |
| **Name** | **ID** |
| Ghassan Elgendy | 20220239 |
| Rowan Ammar | 20220133 |
| Mohamed Osama | 20220477 |
| Ibrahim Zennary | 20221003 |

Table of Contents   
  
1. Problem Formulation and Objectives  
 1.1 Categorization of Vehicles  
 1.2 Dynamic Queuing Behavior  
 1.3 Performance Metrics to Estimate  
 1.4 Policy Decisions  
  
2. System Components  
 2.1 Entities (Cars and Their Behavior)  
 2.2 Resources (Fuel Pumps)  
 2.3 Queues  
  
3. System Analysis  
 3.1 Cumulative Distribution Simulation Table (20 Cars)  
 3.2 Statistical Distributions and Probabilities  
  
4. Experimental Design Parameters  
 4.1 Experiment 1: Medium-Scale Simulation  
 4.2 Experiment 2: Large-Scale Simulation  
  
5. Justification of Experiment Parameters  
 5.1 Rationale for Experiment 1  
 5.2 Rationale for Experiment 2  
  
6. Results Analysis  
 6.1 Findings from Experiment 1  
 6.2 Findings from Experiment 2  
  
7. Conclusion  
 7.1 Summary of Key Insights  
 7.2 Recommendations for System Improvements  
  
8. Hospital Inventory: Problem Formulation and Objectives  
 8.1 Goals and Challenges  
  
9. Hospital Inventory System Components  
 9.1 Entities (Inventories and Patient Rooms)  
 9.2 Attributes (Capacities and Demand)  
 9.3 Activities (Consumption, Replenishment, and Restocking)  
  
10. Hospital Inventory System Analysis  
 10.1 Cumulative Distribution Simulation Table (20 Days)  
  
11. Experimental Design Parameters  
 11.1 Experiment 1: Baseline Scenario  
 11.2 Experiment 2: Optimized Scenario  
  
12. Hospital Inventory Results Analysis  
 12.1 Findings from Experiment 1  
 12.2 Findings from Experiment 2  
  
13. Conclusion  
 13.1 Summary of Key Insights  
 13.2 Final Recommendations

## **1.0 Problem formulation & Objectives.**

The problem: To design a multi-channel queuing system to simulate a petrol station that has 3 types of pumps (95 Octane, 90 Octane, Gas) and serves 3 car categories (A, B, C) that arrives randomly

**1.1 Categorization of Vehicles**

Cars that arrive are:

* Category A with probability 0.2
* Category B with probability 0.35
* Category C with probability 0.45

Cars belong to one of three categories based on their fuel compatibility.

* Dynamic Queuing Behavior:

Categories B, C may opt for alternative pumps depending on the queue length:

* category B cars can opt for 95 pumps with probability 0.6 if the queue when arriving to the 90-octane has more than 3 cars
* category C cars can go for the 90-octane petrol pump with probability 0.4 if the queue when arriving to the gas has more than 4 cars
* Performance Metrics to Estimate:

-Average service times, waiting times, queue lengths, idle times, and probabilities of waiting for each pump.

* Policy Decisions:

-Give insight of the best type of pump to add to minimize overall waiting times.

# 2 System Components.

2.1. Entities

Entities are the moving parts of the system, primarily the cars that arrive and require service.

**Cars**:

Each car belongs to one of three categories:

* **Category A**: Requires 95 octane petrol.
* **Category B**: Can use either 90 octane or 95 octane petrol.
* **Category C**: Can use either 90 octane petrol or gas.

**Behavior:**

* **Category B** cars may switch to 95 octane if the 90-octane queue exceeds 3 cars (60% probability).
* **Category C** cars may switch to 90 octane if the gas queue exceeds 4 cars (40% probability).

2.2. Resources

Resources are the service points in the system.

**Pumps**:

* **Octane Pump**: Serves cars of categories A and B.
* **Octane Pump**: Serves cars of categories B and C.
* **Gas Pump**: Serves cars of category C.

2.3. Queues

Each pump has a queue to manage waiting cars.

* **95 Octane Queue**
* **90 Octane Queue**
* **Gas Queue**

Queues can grow as cars arrive and wait for service.

2.4. Events

Discrete events drive the system's state changes.

* **Arrival Events**:

Cars arrive at the petrol station based on the inter-arrival time distribution (Table 1).

* **Service Events**:

Cars are served based on service time distributions (Tables 2 and 3).

* **Queue Switching Events**:

Cars of categories B and C may switch to other queues based on queue lengths and their switching probabilities.

A table with numbers and a few black text

Description automatically generated2.5. Statistical Distributions

Used to model randomness in the system:

* **Inter-Arrival Times**

Time intervals between car arrivals follow a probability distribution.

* **Service Times**:

Service durations for each category follow their respective distributions

A table with numbers and text

Description automatically generated

2.6. State Variables

Variables that represent the system's state at any given time:

**Queue Lengths**: Current number of cars waiting at each pump.

**Idle Time**: Tracks when pumps are not in use.

**Waiting Times**: Time spent by cars in queues.

**Service Times**: Time spent by cars being served.

A number of numbers on a white background

Description automatically generated3. System analysis including cumulative distribution simulation table (For 20 cars).

|  |  |  |  |
| --- | --- | --- | --- |
| Inter-Arrival Time (minutes) | Probability | Cumulative Probability | Random No. |
| 0 | 0.17 | 0.17 | 0-17 |
| 1 | 0.23 | 0.40 | 18-40 |
| 2 | 0.25 | 0.65 | 41-65 |
| 3 | 0.35 | 1.00 | 66-100 |

|  |  |  |  |
| --- | --- | --- | --- |
| Service Time for Category A, B | | | |
| Service Time (minutes) | **Probability** | **Cumulative Probability** | **Random No.** |
| 1 | 0.20 | 0.20 | 0-20 |
| 2 | 0.30 | 0.50 | 21-50 |
| 3 | 0.50 | 1.00 | 51-100 |

|  |  |  |  |
| --- | --- | --- | --- |
| Category | Probability | Cumulative Probability | Random No. |
| A | 0.20 | 0.20 | 0-20 |
| B | 0.35 | 0.55 | 21-55 |
| C | 0.45 | 1.00 | 56-100 |

## 4. Experimental Design Parameters

**4.1 Experiment 1: Medium-Scale Simulation**

* **Number of Cars**: 1000
* **Number of Runs**: 30

**4.2 Experiment 2: Large-Scale Simulation**

* **Number of Cars (per day)**: 3000
* **Number of Days (runs)**: 50

## 5 Justification of experiment parameters

* **5.1 Experiment 1 justification:**
* **Number of Cars per Day**:  
  Simulating 1000 cars per day represents a typical workload for a petrol station during an average day. This provides enough data to observe common system behaviours without making the simulation too time-consuming.
* **Number of Days**:  
  Simulating 30 days (runs) allows the experiment to cover a full month of operation. This is sufficient to account for randomness in daily traffic and service times, ensuring the results represent a range of typical scenarios.
* **5.2 Experiment 2 Justification**:
* **Number of Cars per Day**:  
  Simulating 3000 cars per day tests the system under heavy traffic conditions. This helps evaluate its performance when demand is much higher, such as during peak periods or special events. It also allows rare cases, like very long queues, to appear more often in the results.
* **Number of Days**:  
  Simulating 50 days provides a more detailed analysis. This longer time frame helps reduce the effect of randomness, offering more reliable averages and confidence in the results, especially under extreme conditions.

## 6 Results Analysis: Using graphs & discussions stating the results for the 8 questions.

**6.1 Experiment 1**

All the answers are given after running the simulation 30 times with 1000 cars in each run.

6.1.1. Average Service Time per Category

* **Observations**:
* A: 2.29
* B: 2.31
* C: 5.21
* A graph of a service

  Description automatically generated**Graph**:
* **Discussion**:
* Cars in **Category C (Gas)** have significantly longer service times, likely due to the nature of their fuel requirements which are 60% Gas if the queue has more than 4 cars and 100% Gas if it’s less than or equal to 4 cars
* Categories A and B (95 and 90 octane, respectively) have similar service times, aligning with their theoretical averages.

6.1.2. Average Waiting Time in Queues

* **Per Pump**:
  + **95 Octane**: 4.18 minutes
  + **90 Octane**: 0.95 minutes
  + **Gas**: 7.36 minutes

**Overall Average**: 3.71 minutes

* A graph of a number of red squares

  Description automatically generated with medium confidence**Graph**:
* **Discussion**:
* The **Gas pump** has the highest waiting time, reflecting its longer service times and higher utilization.
* **95 Octane** has the least waiting time, suggesting underutilization or fewer cars requiring this fuel type.

6.1.3. Maximum Queue Length per Pump

* **Values**:
* **95 Octane**: 394 cars
* **90 Octane**: 337 cars
* **Gas**: 269 cars
* **Discussion**:
* The **95 Octane pump** shows the longest queues, indicating a bottleneck in the system.
* This aligns with its relatively high waiting probability

6.1.4. Probability That a Car Waits

* **Per Pump**:
* **95 Octane**: 39%
* **90 Octane**: 34%
* **Gas**: 27%
* **Discussion**:
* The **95 Octane pump** has the highest waiting probability, corroborating the findings of maximum queue lengths and waiting times.
* The **Gas pump** has a lower waiting probability despite higher waiting times, indicating variability in car arrivals and service.

6.1.5. Idle Time Ratios

* **Per Pump**:
* **95 Octane**: 3%
* **90 Octane**: 0%
* **Gas**: 1%
* **Discussion**:
* The **90 Octane pump** has no idle time, indicating it is either perfectly utilized or slightly overloaded since it’s the backup plan for category C cars if the queue length is more than 4 cars
* The **95 Octane pump** shows minimal idle time despite its high waiting probabilities, suggesting it operates near capacity.

6.1.6. Theoretical vs Experimental Average Service Time

* **Comparison**:
* **Category A**: Theoretical = 2.3, Experimental = 2.28
* **Category B**: Theoretical = 2.3, Experimental = 2.34
* **Category C**: Theoretical = 5.2, Experimental = 5.19
* **Graph**:

**A graph of a service time

Description automatically generatedA graph of a service time

Description automatically generated**

**A graph of gas pump service

Description automatically generated**

* **Discussion**:
* Experimental values approximately match theoretical ones, validating the simulation model.

6.1.7. Theoretical vs Experimental Average Inter-Arrival Time

**Comparison**:

* Theoretical = 1.78 minutes
* Experimental = 1.78 minutes

6.1.8. Recommendation for Adding an Extra Pump

* **Effect on Average Waiting Time**:
* Adding a **95 Octane pump**: Reduces to **3.68 minutes**
* Adding a **90 Octane pump**: Reduces to **3.57 minutes**
* Adding a **Gas pump**: Reduces to  **3.61 minutes**
* **Discussion**:
* Adding an extra **95 Octane pump** has the greatest impact on reducing average waiting time, aligning with its high queue length and waiting probability.
* This suggests that the **95 Octane pump** is the most strained resource in the current setup.

**6.2 Experiment 2**

All the answers are given after running the simulation 50 times with 3000 cars in each run.

6.2.1. Average Service Time per Category

* **Observations**:
* A: 2.3
* B: 2.3
* C: 5.2

A graph of a service

Description automatically generated**Graph**:

* **Discussion**:
* Same as experiment 1, Cars in **Category C (Gas)** have significantly longer service times, likely due to the nature of their fuel.
* Also, similar to the first experiment, Categories A and B (95 and 90 octane, respectively) have similar service times, aligning with their theoretical averages.

6.2.2. Average Waiting Time in Queues

* **Per Pump**:
* **90:**  4.49
* **95:**  0.94
* **Gas:** 8.41
* **Overall Average Waiting Time:** 4.09

A graph of a diagram

Description automatically generated with medium confidence**Graph**:

* **Discussion**:
* Similarly, the **Gas pump** has the highest waiting time, reflecting its longer service times and higher utilization.
* **95 Octane** has the least waiting time, suggesting underutilization or fewer cars requiring this fuel type.
* **Average waiting time** in this experiment is more than experiment 1, which may be closer to real life scenarios

6.2.3. Maximum Queue Length per Pump

* **Values**:
  + **95 Octane**: 1251 cars
  + **90 Octane**: 958 cars
  + **Gas**: 791 cars

**Discussion**:

* + When simulating a large number of cars, rare scenarios like very long queue lengths happen , like in this experiment the maximum queue is around **3x more** than the first experiment

6.2.4. Probability That a Car Waits

* **Per Pump**:
  + **95 Octane**: 42%
  + **90 Octane**: 32%
  + **Gas**: 26%
* **Discussion**:
  + Waiting probability in **Octane 95** is objectively higher than the first experiment due to its busy nature

6.2.5. Idle Time Ratios

* **Per Pump**:
  + **95 Octane**: 0.056%
  + **90 Octane**: 0.037%
  + **Gas**: 0.056%
* **Discussion**:
  + The idle ratios are **much lower** than in experiment 1 due to the rush of the cars and severe increase in demand

6.2.6. Theoretical vs Experimental Average Service Time

* **Comparison**:
* **Category A**: Theoretical = 2.3, Experimental = 2.29
* **Category B**: Theoretical = 2.3, Experimental = 2.33
  + **Category C**: Theoretical = 5.2, Experimental = 5.19

**Graph**:

**A graph of a service time

Description automatically generatedA graph of a service time

Description automatically generated**

**A graph of gas pump service time

Description automatically generated**

* **Discussion**:
* Similar to the first experiment, Experimental values closely match theoretical ones, validating the simulation model.

6.2.7. Theoretical vs Experimental Average Inter-Arrival Time

* **Comparison**:
  + Theoretical = 1.78
  + Experimental = 1.78

6.2.8. Recommendation for Adding an Extra Pump

* **Effect on Average Waiting Time**:
  + Adding a **95 Octane pump**: Reduces to **4.1 minutes**
  + Adding a **90 Octane pump**: Reduces to **4.05 minutes**
* Adding a **Gas pump**: Reduces to **4.08 minutes**
* **Discussion**:

Similar to experiment 1, Adding an extra **95 Octane pump** has the greatest impact on reducing average waiting time, which validates the suggestion **that the best course of action is adding an extra 95 Octane pump**

7 Conclusion

This project aims to model a petrol station using simulation, focusing on a multi-channel queuing system. The station has three pump types (95, 90 Octane, and Gas) serving three car categories (A, B, and C). Cars arrive randomly and have different fuel needs, sometimes switching queues based on length.

A simulation table was used to track the system over time, considering system components like:

* **Entities:** Cars, categorized by fuel type
* **Resources:** Pumps for each fuel type
* **Queues:** Lines at each pump
* **Events:** Car arrivals, service completion, queue switching
* **Distributions:** Probabilities for arrival times and service durations
* **State variables:** Queue lengths, pump idle times, waiting and service times

The experiment involved simulating a specific number of cars and running the simulation multiple times to ensure reliable results. Analysis focused on key performance indicators like average service/waiting times, queue lengths, and idle time ratios.

Results showed the 95 Octane pump was a bottleneck, with the longest waits and highest probability in queues. The 90 Octane pump had little idle time due to Category C cars using it as an alternative. Theoretical and experimental values were closely aligned, validating the model's accuracy.

* **Key recommendation:** Add another 95 Octane pump to reduce overall waiting time.

Hospital Inventory

8 Problem formulation & Objectives.

A hospital manages an inventory of medical supply boxes for patient rooms. The inventory system consists of two locations:

1. **First Floor Inventory:** Maximum capacity of 10 boxes, supplies consumed daily by patient rooms.
2. **Basement Inventory:** Maximum capacity of 30 boxes, used to replenish the first floor.

Daily demand is determined by the number of patient rooms occupied (Table 1), and restocking orders for the first floor are made when it runs out of boxes. These restocks depend on the availability of supplies in the basement. During the lead time (Table 2) for receiving new supplies, shortages may occur.

Key factors include:

* **Review period (N):** Time after which inventory levels are assessed and orders are placed.
* **Maximum capacity (M):** Capacity of the basement inventory to minimize shortages.

8.1 Objectives**:**

1. **Determine Average End Inventory:**
   * Calculate the average remaining inventory levels in both the first floor and basement after each review period.
2. **Analyze Shortage Days:**
   * Evaluate the number of days where a shortage of medical supply boxes occurs.
3. **Validate Theoretical vs. Experimental Averages:**
   * Compare the theoretical average daily demand for medical supplies with experimental outcomes.
   * Validate the theoretical and experimental average lead times.
4. **Optimize Review Period (N):**
   * Identify the optimal review period that minimizes shortages in medical supplies.
5. **Optimize Basement Capacity (M):**
   * Propose an ideal maximum capacity for the basement inventory to minimize shortages while maintaining cost efficiency.

9 System Components

**Entities:**

* **First Floor Inventory:** Tracks the daily usage of medical supply boxes for patient rooms.
* **Basement Inventory:** Stores medical supply boxes to replenish the first floor when needed.
* **Patient Rooms:** Each occupied room consumes one box of supplies per day(demand).

**Attributes:**

* **First Floor Inventory Attributes:**
  + Maximum capacity: 10 boxes.
  + Current inventory level.
* **Basement Inventory Attributes:**
  + Maximum capacity: 30 boxes.
  + Current inventory level.
* **Patient Room Attributes:**
  + Number of rooms occupied (1 to 5 based on Table 1).
  + Daily demand for supplies (1 box per room per day).
* **Order Attributes:**
  + Lead time for receiving orders (1 to 3 days, with probabilities in Table 2).
  + Quantity of boxes ordered.

**Activities:**

* **Consumption of Medical Supplies:** Daily depletion of boxes from the first floor inventory based on the number of rooms occupied.
* **Replenishment from Basement:** Transfer of boxes from the basement inventory to the first floor when the first floor inventory runs out of boxes.
* **Restocking Orders:** Placing and receiving restocking orders to refill the basement inventory to its maximum capacity.

**State:**

The system state is defined by the following variables:

1. Current number of boxes in the **first floor inventory**.
2. Current number of boxes in the **basement inventory**.
3. Number of **rooms occupied** (determining daily demand).
4. Status of **pending orders** (lead time remaining and quantity of boxes ordered).

**Events:**

* **End of Day:** Updates inventory levels after daily consumption and checks for shortages.
* **First Floor Inventory Depletion:** Triggers replenishment from the basement inventory.
* **Order Arrival:** Updates the basement inventory when a restocking order is received.
* **Review Period Trigger (N days):** Assesses inventory levels and places restocking orders if needed.

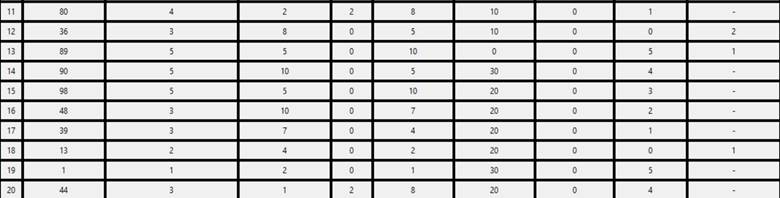
**Endogenous:**

* Daily consumption of medical supply boxes.
* Replenishment of the first floor from the basement.
* Restocking orders for the basement inventory.

**Exogenous:**

* **Random Number of Rooms Occupied:** Affects daily demand (Table 1).
* **Random Lead Time for Orders:** Affects the delay in replenishing the basement inventory (Table 2).

10. System analysis including cumulative distribution simulation table

(For 20 days).

|  |  |  |  |
| --- | --- | --- | --- |
| Lead Time | Probability | Cumulative Probability | Random No. |
| 1 | 0.40 | 0.40 | 0-40 |
| 2 | 0.35 | 0.75 | 41-75 |
| 3 | 0.25 | 1.00 | 76-100 |

|  |  |  |  |
| --- | --- | --- | --- |
| Number Of Rooms | Probability | Cumulative Probability | Random No. |
| 1 | 0.10 | 0.10 | 0-10 |
| 2 | 0.15 | 0.25 | 11-25 |
| 3 | 0.35 | 0.60 | 26-60 |
| 4 | 0.20 | 0.80 | 61-80 |
| 5 | 0.20 | 1.00 | 81-100 |

## 11. Experimental Design Parameters

Experiment 1: Baseline Scenario

* Days (Simulation Period): 30 days
* Maximum Basement Inventory (M): 30 boxes
* Review Period (N): 6 days

Experiment 2: Optimized Scenario

* Days (Simulation Period): 60 days
* Maximum Basement Inventory (M): 15 boxes
* Review Period (N): 8 days

## 11.1 Justification of experiment parameters

-Experiment 1

* A one-month period provides a sufficient timeline to observe patterns, detect shortages, and evaluate the system's behavior.
* Current maximum capacity of the basement inventory as given in the problem. It serves as a baseline to measure performance and compare alternative capacities.
* This is the current policy outlined in the problem. It reflects the time interval after which inventory is assessed and restocking orders are placed.

-Experiment 2

* A 60-day simulation exposes the system to a larger variety of demand fluctuations and lead times, providing deeper insights into its long-term performance.
* Testing with only 15 boxes in the basement highlights the system’s dependency on frequent resupplies and challenges its ability to avoid shortages under severe constraints.
* Increasing the review period introduces delays that amplify the risk of shortages, pushing the system to operate under less responsive conditions.

## 12. Results Analysis: Using graphs & discussions stating the results for the 5 questions.

Experiment 1

Single run

A person pointing at something

Description automatically generated

**1-The average ending units in the first floor inventory and the basement inventory:**

* **First Floor Inventory (FF):** The average ending inventory is **5 units**.
* **Basement Inventory:** The average ending inventory is **18 units**.
* **Analysis:** The first floor inventory consistently maintains about 50% of its capacity, while the basement inventory operates well below its maximum capacity of 30 boxes, suggesting adequate restocking policies.

**2-The number of days when a shortage condition occurs:**

* **Total Shortage Days:** **8 days**.
* A graph with a number of objects

  Description automatically generated with medium confidence**Analysis:** Shortages occur on approximately **27% of the 30-day simulation period**, which indicates room for improvement in inventory policies, particularly for the first floor.

3- **Does the theoretical average demand of boxes match the experimental one?**

* **Theoretical Average Demand:** **3.25 boxes/day**.
* **Experimental Average Demand:** **3.33 boxes/day**.
* **Analysis:** The experimental average demand closely matches the theoretical value, with only a small deviation of **2.46%**. This suggests that the simulation model accurately reflects real-world demand distributions.

**A graph of a bar graph

Description automatically generated**

**4-Does the theoretical average lead time of the lead time distribution match the experimental one?**

* **Theoretical Average Lead Time:** **1.85 days**.
* **Experimental Average Lead Time:** **1.60 days**.
* **Analysis:** There is a slight deviation of **13.5%**, with the experimental lead time being shorter than the theoretical average. This discrepancy might result from random sampling in the simulation or insufficient simulation duration.

**5-Is there a better value for the review period variable (N) to minimize the shortages of medical supplies boxes?**

* **Optimal Review Period (N):** **10 days**.
* **Analysis:**  After running the simulation for 500 times testing with review periods from 3 to 15 , we found that increasing the review period from the baseline of 6 days to 10 days minimizes shortages, as it aligns inventory replenishment with demand fluctuations and reduces unnecessary over-ordering.

**6- Is there a better value for the maximum capacity (M) of the basement inventory to minimize the shortages of medical supplies boxes?**

* **Optimal Maximum Basement Inventory (M):** **15 boxes**.
* **Analysis:** After running the simulation for 500 times testing with basement capacity from 10 to 40, we found that reducing the maximum basement inventory capacity to 15 boxes improves system efficiency without causing shortages. This value optimally balances storage costs and availability, indicating the current capacity of 30 boxes is unnecessarily high.
* When running the simulation to find the optimal for both simultaneously, we reached the conclusion that using an **N of 5 days** and **M of 13 boxes** offers the most efficient configuration, reducing shortages and storage overhead simultaneously.

Experiment 2

A screenshot of a computer

Description automatically generated

1. **The average ending units in the first floor inventory and the basement inventory:**
   * **First Floor Inventory (FF):** The average ending inventory is **0 units**.
   * **Basement Inventory:** The average ending inventory is **0 units**.
   * **Analysis:** Both inventories are completely depleted on average, indicating severe shortages and an inability to meet demand under the current configuration. This highlights significant deficiencies in the system's design.
2. **The number of days when a shortage condition occurs:**
   * **Total Shortage Days:** **58 days (out of 60).**
   * **Analysis:** Shortages occur on **96.7% of the simulation period**, which demonstrates that the system cannot sustain the demand. This configuration leads to almost constant shortages.
3. **Does the theoretical average demand of boxes match the experimental one?**
   * **Theoretical Average Demand:** **3.25 boxes/day**.
   * **Experimental Average Demand:** **3.27 boxes/day**.
   * **Analysis:** Similar to the first experiment , The experimental demand matches the theoretical value closely, with only a **0.6% deviation**.
4. **Does the theoretical average lead time of the lead time distribution match the experimental one?**
   * **Theoretical Average Lead Time:** **1.85 days**.
   * **Experimental Average Lead Time:** **1.71 days**.
   * **Analysis:** There is a slight deviation of **7.6%**, with the experimental lead time being shorter. This difference is less than what is in the first experiment , most likely due to the increase in the testing period

## 13 Conclusion

-The simulation provided valuable insights into the hospital's inventory system:

**Experiment 1: Baseline Scenario**

* **Average Inventory:**
  + First Floor: 5 units
  + Basement: 18 units
* **Shortage Days:** 8 out of 30 days (27%).
* **Demand and Lead Time:**
  + Experimental demand (3.33 boxes/day) and lead time (1.60 days) closely match theoretical values.
* **Optimization:**
  + Best review period (N): **10 days**
  + Best basement capacity (M): **15 boxes**

**Experiment 2: Extreme Scenario**

* **Average Inventory:**
  + First Floor: 0 units
  + Basement: 0 units
* **Shortage Days:** 58 out of 60 days (96.7%).
* **Observation:** Severe shortages highlight system limitations under constrained conditions.

**Optimal Configuration**

* **Review Period (N):** 5 days
* **Basement Capacity (M):** 13 boxes
* **Benefits:** Balances responsiveness, reduces shortages, and minimizes overstocking costs.

**-Key Takeaway:**

Optimizing inventory parameters is critical to ensuring a reliable supply chain while controlling costs. Future adjustments should account for demand fluctuations to improve resilience.