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

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Table of Contents

Hospital Inventory

1. 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

Cars: The primary moving parts in the system, requiring fuel service.

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.

2.2. 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).

2.3. Attributes

Car Attributes:

Category: Indicates whether the car is of Category A, B, or C.

Arrival Time: The time the car arrives at the station.

Service Time: The time required to serve the car based on its category.

Pump Attributes:

Type: Defines the type of pump: 95 Octane Pump, 90 Octane Pump, or Gas Pump.

Capacity: Maximum number of cars a pump can serve in each time.

Idle Time: The time when the pump is not in use.

Queue Attributes:

Length: The number of cars waiting in each queue (95 Octane, 90 Octane, Gas).

Waiting Time: Time cars spend waiting in a queue before being serviced.

2.4. Activities

Car Arrivals:

Cars arrive at the petrol station based on inter-arrival times, following a probability distribution.

Queue Management:

Cars join the appropriate queue based on their fuel type needs (95 Octane, 90 Octane, or Gas).

Service:

Cars are served at the pumps based on their service times, which are distributed according to their category.

Queue Switching:

> 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).

2.5. State

Queue Lengths:

The current number of cars waiting in each queue (95 Octane Queue, 90 Octane Queue, Gas Queue).

Idle Time: The time that each pump remains idle (not in use).

Waiting Times: The time each car spends waiting in queues before service.

Service Times: The time each car is served at the pump.

Discrete events drive the system's state changes:

> Arrival Events: Cars arrive at the petrol station based on inter-arrival time distributions
>
> Service Events: Cars are served based on their service time distributions

Queue Switching Events:

> 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).

2.7. Endogenous

Car Arrival: A car arrives based on the inter-arrival time distribution.

Car Service: Once at the pump, cars are served according to their service time distribution.

Queue Management: Cars are assigned to appropriate queues, and they wait for service.

Queue Switching: Cars of Category B and Category C may switch queues based on the conditions of the other queues.

2.8. Exogenous

Inter-Arrival Time: The time between the arrival of two consecutive cars is random and follows a specified distribution (e.g., exponential distribution).

Service Time Distribution: The time required to serve each car is random and follows a specified distribution based on the car's category (e.g., uniform, exponential).

Queue Length Thresholds: Cars of Category B and Category C may switch queues depending on the lengths of the other queues. These thresholds are fixed but may be influenced by real-world traffic patterns or external scheduling factors.

2.9. Statistical Distributions

Inter-Arrival Times

Time intervals between car arrivals follow a probability distribution.

Time between Arrivals (Minutes)	Probability
0	0.17
1	0.23
2	0.25
3	0.35

Service Times:

Service durations for each category follow their respective distributions

Category A & B Service Time (Minutes)	Probability	Category C Service Time (Minutes)	Probability
1	0.20	3	0.20
2	0.30	5	0.50
3	0.50	7	0.30

3. System analysis including cumulative distribution simulation table (For 20 cars).

Car	Category	Arrival Time	Service Time	Service Begins	Service Ends	Waiting Time	Pump
1	B	1	3	1	4	0	90
2	B	4	3	4	7	0	90
3	B	6	3	7	10	1	90
4	A	8	3	8	11	0	95
5	B	8	3	10	13	2	90
6	B	8	3	11	14	3	95
7	C	11	7	11	18	0	Gas
8	B	12	2	13	15	1	90
9	C	14	3	18	21	4	Gas
10	B	15	2	15	17	0	90
11	C	17	3	21	24	4	Gas
12	C	19	7	24	31	5	Gas
13	B	20	3	20	23	0	95
14	C	22	7	31	38	9	Gas
15	C	23	5	38	43	15	Gas
16	C	25	7	43	50	18	Gas
17	B	25	3	25	28	0	90
18	A	25	1	25	26	0	95
19	B	27	1	27	28	0	95
20	B	27	1	28	29	1	95

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

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

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

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.

    By using 30 days as duration we're making sure we're avoiding the overhead of starting the simulation and ensuring that we can use t-table for validation (it will follow the normal distribution) overcome the initial conditions
- **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.

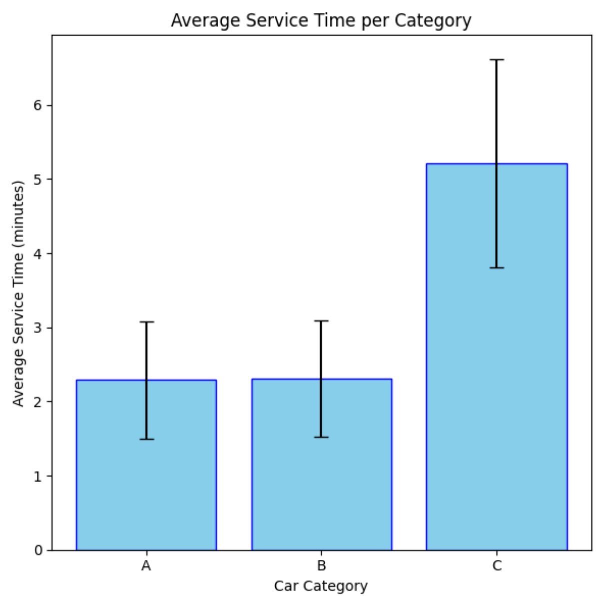
6 Results Analysis: Using graphs & discussions stating the results for the 8 questions.

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
- **Graph**:



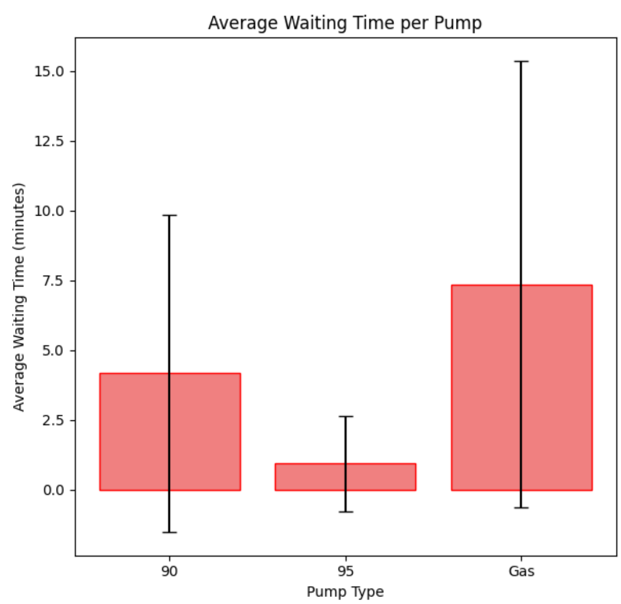
- **Discussion**:
  - Cars in **Category C (Gas)** have significantly longer service times, likely due to the nature of their fuel requirements which are 60% Gas if the queue has more than 4 cars and 100% Gas if it's less than or equal to 4 cars
  - Categories A and B (95 and 90 octane, respectively) 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

- **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.

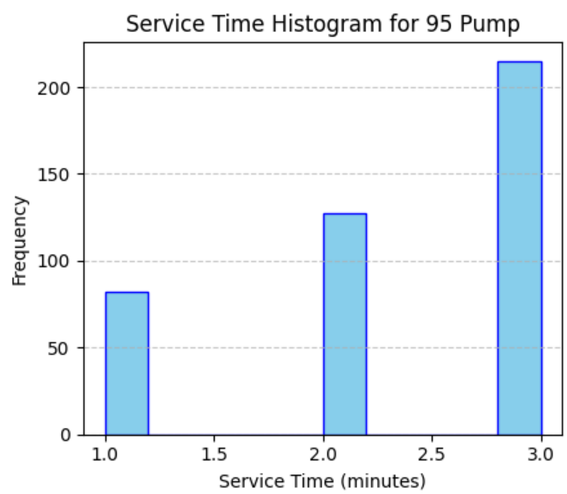
6.1.5. Idle Time

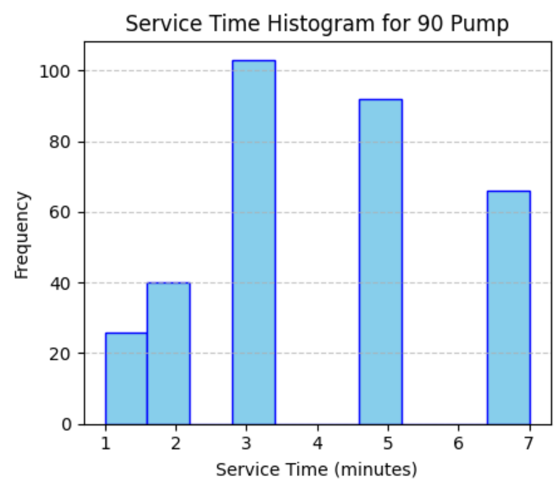
- **Per Pump**:
    - **95 Octane**: 810 (0.44%)
    - **90 Octane**: 612 (0.33%)
    - **Gas**: 436 (0.24%)
    - **Total simulation time :** 1804
- **Discussion**:
    - The **Gas pump** has lowest idle time, indicating it is either perfectly utilized or slightly overloaded .
    - The **95 Octane pump** shows maximum idle time, Most likely due to the limitation of the cars that can use it.

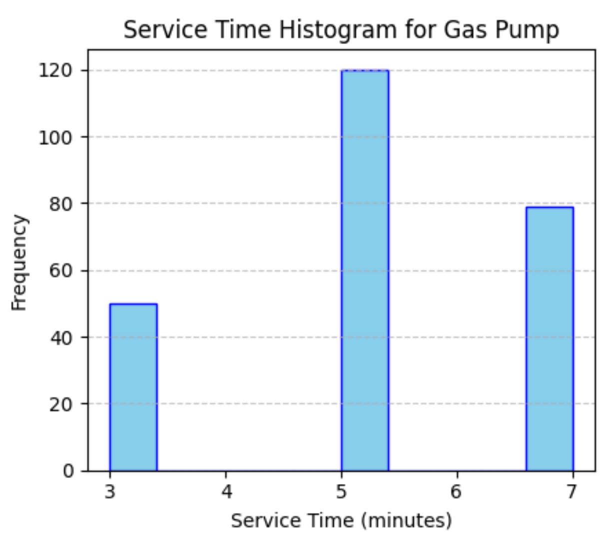
6.1.6. Theoretical vs Experimental Average Service Time

- **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**:







- **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

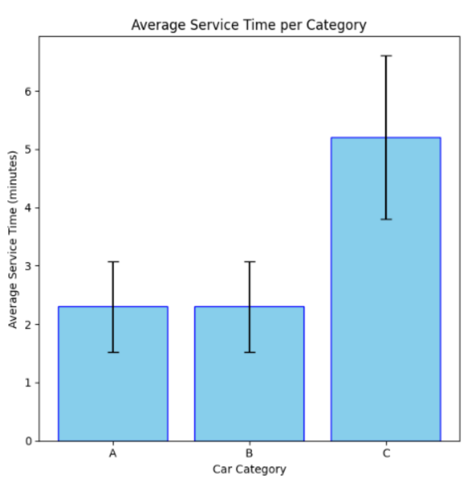
- **Effect on Average Waiting Time**:
  - Adding a **95 Octane pump**: Reduces to **3.68 minutes**
  - Adding a **90 Octane pump**: Reduces to **3.57 minutes**
  - Adding a **Gas pump**: Reduces to **3.61 minutes**
- **Discussion**:
  - Adding an extra **90 Octane pump** has the greatest impact on reducing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

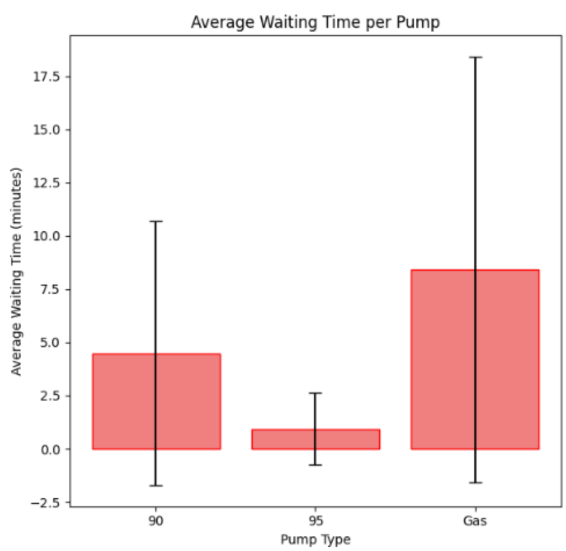


- **Discussion**:
  - Same as experiment 1, Cars in **Category C (Gas)** have significantly longer service times, likely due to the nature of their fuel.
  - Also, similar to the first experiment, Categories A and B (95 and 90 octane, respectively) have similar service times, aligning with their theoretical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

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

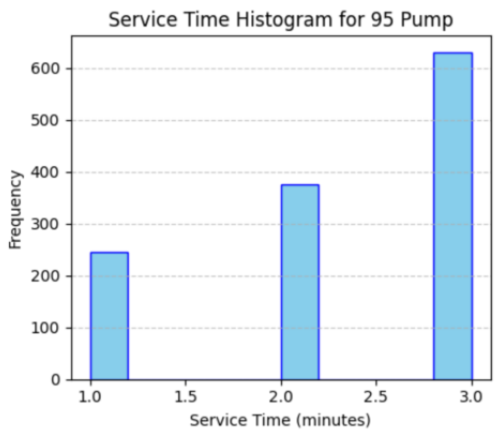
6.2.5. Idle Time

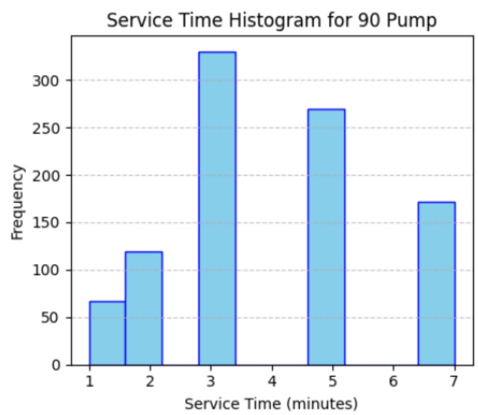
- **Per Pump**:
  - **95 Octane**: 2611 (0.49%)
  - **90 Octane**: 1511 (0.28%)
  - **Gas**: 1043(0.19%)
  - **Total simulation time**: 5319
- **Discussion**:
  - The idle ratios are **lower** than in experiment 1 due to the rush of the cars and increase in demand

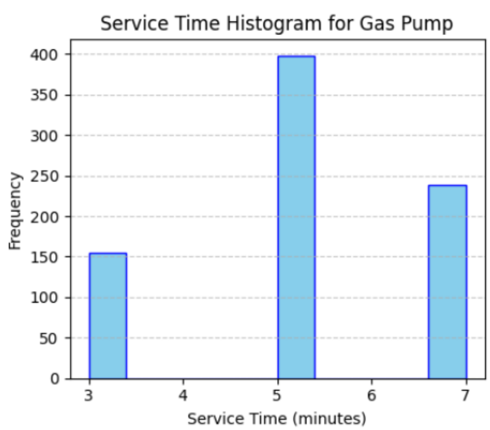
6.2.6. Theoretical vs Experimental Average Service Time

- **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:







- **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 **90 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 90 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:** Adding another 90 Octane pump will 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).

Day	NumOfRooms Rand	Rooms Occupied (Boxes Demand)	Beginning FF Inventory	Shortage	Ending FF Inventory	Basement Inventory	Basement Shortage	Days Until Review	Days Until Order Arrival
1	19	2	4	0	2	30	0	5	-
2	98	5	2	3	7	20	0	4	-
3	56	3	7	0	4	20	0	3	-
4	29	3	4	0	1	20	0	2	-
5	14	2	1	1	9	10	0	1	-
6	62	4	9	0	5	10	0	0	1
7	73	4	5	0	1	30	0	5	-
8	57	3	1	2	8	20	0	4	-
9	31	3	8	0	5	20	0	3	-
10	34	3	5	0	2	20	0	2	-
11	80	4	2	2	8	10	0	1	-
12	36	3	8	0	5	10	0	0	2
13	89	5	5	0	10	0	0	5	1
14	90	5	10	0	5	30	0	4	-
15	98	5	5	0	10	20	0	3	-
16	48	3	10	0	7	20	0	2	-
17	39	3	7	0	4	20	0	1	-
18	13	2	4	0	2	20	0	0	1
19	1	1	2	0	1	30	0	5	-
20	44	3	1	2	8	20	0	4	-

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

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

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): 20 boxes
- Review Period (N): 2 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.
- After running the simulation with different parameters many times , it was found that the optimal solution is having a basement capacity of 20 boxes and review period of 2 days, so this experiment serves to prove that.

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

Experiment 1

Single run

Simulation Statistics

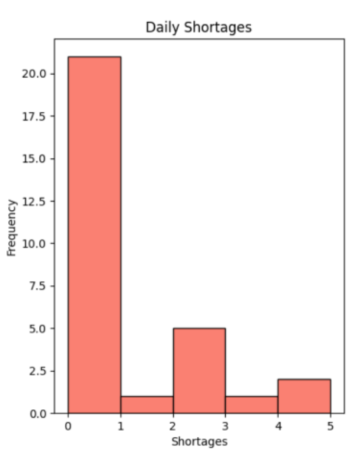
Average FF Inventory: 5
Average Basement Inventory: 18
Total Shortage Days: 7
Total Basement Shortage: 0
Experimental Avg Demand: 3.30
Experimental Avg Lead Time: 2.20
Theoretical Avg Demand: 3.25
Theoretical Avg Lead Time: 1.85
Optimal Max Basement: 20
Optimal Review Period: 10
Optimal Combination: (20, 2)

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.

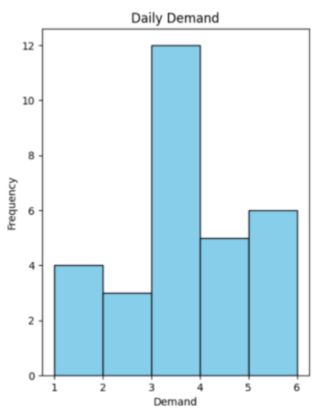
2-The number of days when a shortage condition occurs:

- **Total Shortage Days: 7 days**.
- **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: 3.30 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.



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: 2.20 days**.
- **Analysis:** There is a slight deviation of **13.5%**, with the experimental lead time being longer 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?

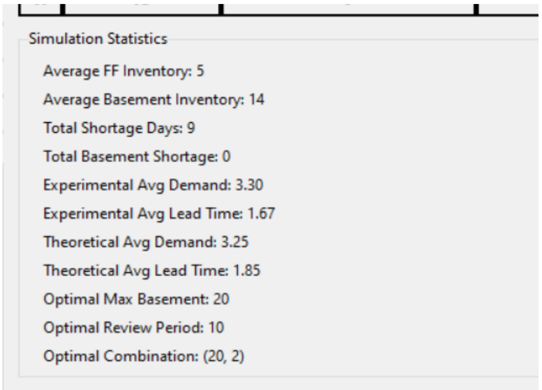
- **Optimal Review Period (N): 2 days**.
- **Analysis:** After running the simulation for 500 times testing with review periods from 2 to 10 , we found that decreasing the review period from the baseline of 6 days to 2 days minimizes shortages, as it aligns inventory replenishment with demand fluctuations .

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): 20 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 20 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 2 days** and **M of 20 boxes** offers the most efficient configuration, reducing shortages and storage overhead simultaneously.

Experiment 2



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 **14 units**.
   - **Analysis:** The first-floor inventory consistently maintains a low average inventory of 5 units, potentially indicating frequent replenishment. Meanwhile, the basement inventory operates well below its maximum capacity of 20 units, suggesting the inventory policies are appropriately matched to demand and restocking frequencies.
2. **The number of days when a shortage condition occurs:**
   - **Total Shortage Days: 9 days (out of 60).**
   - **Basement Shortage Days : 0**
   - **Analysis:** Shortages occur on 30% of the simulation period (9 out of 30 days) in the first floor, but no shortage occurs in the basement.
3. **Does the theoretical average demand of boxes match the experimental one?**
   - **Theoretical Average Demand: 3.25 boxes/day**.
   - **Experimental Average Demand: 3.30 boxes/day**.
   - **Analysis:** Similar to the first experiment, The experimental average demand closely aligns with the theoretical value, with a minimal deviation of 1.54%. This indicates that the simulation accurately reflects real-world demand patterns.

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: 1.67 days**.
    - **Analysis:** The experimental lead time is slightly shorter than the theoretical average, with a deviation of approximately 9.73%. This minor difference may result from randomness in the simulation or a need for a longer simulation run to stabilize the averages.

Multiple Runs

Analysis: Running the optimal values 1000 runs shows very low basement shortage (nearly zero) which proves those parameters to be the optimal solution.

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):** 2 days
- **Basement Capacity (M):** 20 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.