IE7215 Simulation Analysis – Course Project

Healthcare System Efficiency during Covid-19

Instructor: Prof. Wei Xei

Team Members:

Krishi Panchal (002610828)

Abhigna Reddy Musku (002776617)

Table of Contents:

1. Introduction:

In this research, we confront the significant challenge of effectively allocating ICU resources during critical peaks in a pandemic, a scenario that tests the robustness and adaptability of healthcare systems. By shifting from a first-come, first-served policy to a severity score-based admission strategy, we aim to explore how this change can lead to more equitable and effective patient outcomes, particularly in reducing mortality rates among the most severely affected COVID-19 patients.

This project holds profound implications for future healthcare crises, offering a foundation for data-driven strategies in ICU resource management that could ultimately save lives and optimize healthcare delivery during extreme demand periods.

2. System description - Objectives and Significance:

Objectives of the Simulation Study:

1. **Evaluation of ICU Resource Utilization Efficiency**

   This study aims to understand the current allocation of ICU beds and identify potential bottlenecks and inefficiencies in the process. By simulating the utilization of these resources, we intend to determine whether the ICU resources are being utilized to their fullest potential and identify areas where improvements are necessary.

2. **Analysis of the Impact of a Severity Score Threshold Policy**

   Our simulation will investigate the effects of implementing a severity score threshold for ICU admissions on mortality rates, particularly during healthcare crises such as the COVID-19 pandemic. This analysis will help us understand if prioritizing patients based on clinical urgency, rather than on a first-come, first-served basis, can lead to better patient outcomes.

3. **Exploration of Operational Changes**

   The study will also examine how changes in admission policies affect the average length of hospital stays and the dynamic utilization of ICU beds and other resources. This objective is to provide insights into how various admission strategies can impact the overall efficiency and effectiveness of ICU operations.

4. **Informing Policy and Decision-Making**

   Finally, this simulation seeks to offer data-driven insights to healthcare administrators and policymakers. The goal is to assist in the development of more effective strategies for the management of critical care resources during peak times in pandemics or other health emergencies.

Rationale for the Current System:

The existing first-come, first-served policy for ICU admission is primarily based on principles of fairness and simplicity. This policy ensures that all patients have equal access to ICU resources, irrespective of their socio-economic status, background, or specific health conditions. It simplifies the decision-making process for healthcare providers by reducing the need for extensive information and subjective judgment.

However, while this system is straightforward and seemingly fair, it may not always result in the best outcomes for patients, especially during crises when resources are scarce. The urgency to prioritize patients based on the severity of their conditions and their potential for recovery becomes critical in order to maximize the benefits of limited ICU resources.

Aim of the Simulation:

Our simulation study aims to challenge this traditional approach by exploring a more nuanced and potentially more effective method of resource allocation. Through this simulation, we aspire to demonstrate that a targeted allocation strategy can enhance patient outcomes and overall healthcare system efficiency during critical times.

3. Data Description:

1. **Hospitalization.csv**: This file contains records of patients' hospital admissions, focusing on their overall hospitalization experience, including the admission time, living status, and severity of their health conditions.

    a. PAT_ID: Unique identifier for each patient.

    b. PAT_ENC_CSN_ID: Unique identifier for each patient encounters or visits.

    c. HOSP_ADMSN_TIME: Timestamp indicating when the patient was admitted to the hospital.

    d. LIVING_STAT: Indicates the living status of the patient at the end of their hospital stay. Possible values include statuses like "Deceased" or variations representing the patient is alive.

    e. DEATH_DATE: The date on which the patient died, applicable only if LIVING_STAT equals "Deceased". Otherwise, this field is left empty or null.

    f. END_DATE: The discharge date marking the end of the patient's hospitalization period.

    g. Severity: A measure of the severity of the patient's health condition during their hospital stay. The exact scale or range of this measure is not provided but implies a gradation of health status.

2. **ICU.csv**: This file specifically details the ICU stays within the broader context of hospitalization, linking patient stays in the ICU to their overall hospital encounters.

    a. PAT_ID: Unique identifier for each patient, consistent with the hospitalization.csv file.

    b. PAT_ENC_CSN_ID: Unique identifier for each patient encounter or visit, allowing linkage to specific hospitalization records.

    c. DATE: The date or dates when the patient stayed in the ICU. This field specifies when the ICU care was provided within the broader timeframe of hospitalization.

3. **Data Card**

The provided data spans two CSV files, each serving a distinct purpose in understanding patient hospitalization and ICU stays. The hospitalization.csv file offers a comprehensive view of patient admissions, including outcomes and severity, while the ICU.csv file zooms in on the critical care aspect by detailing ICU stays.

4. Modeling Assumptions and Structure

Assumptions: Emphasizing Simplicity vs Trade-offs for each assumption

1. **Severity Threshold for ICU Admission**

   Strength: Implementing a fixed severity score threshold at the 75th percentile introduces a clear, quantifiable criterion that streamlines the ICU admission process. This ensures that ICU resources are reserved for the most severe cases, potentially improving patient outcomes by focusing on those most in need.

   Trade-off: While this method may overlook some patients just below the threshold, it provides a practical approach to managing limited resources effectively during a crisis, ensuring rapid decision-making.

2. **Patient Arrival Model**

   Strength: Using a non-stationary Poisson process to model patient arrivals offers a realistic representation of the fluctuating nature of hospital admissions, accounting for hourly or daily variations. This model enhances the accuracy of the simulation by aligning it closely with actual patient flow data.

   Trade-off: Despite its assumption of independent arrivals, this model is well-suited for emergency planning where a precise prediction of clustered arrivals is less critical than overall trends.

3. **General vs. ICU Admissions**

   Strength: This clear distinction between general and ICU admissions facilitates efficient resource allocation by ensuring that ICU beds are not occupied by patients with lower severity levels. It simplifies operational decisions within hospitals, enabling staff to focus on critically ill patients as there are a fixed number of beds in the ICU.

   Trade-off: The simplicity of this approach is a strategic decision that sacrifices some granularity in patient assessment for greater operational efficiency and clarity in critical care prioritization.

4. **Dynamic ICU Bed Allocation**

   Strength: Starting with an initial allocation of 32 beds and adjusting based on ongoing conditions allows the simulation to adapt to the evolving pandemic landscape. This dynamic adjustment capability is crucial for responding to real-time demands and can be informed continuously by insights from the simulation.

   Trade-off: Although the initial fixed number may not capture all scenarios, this approach provides a structured baseline that can be quickly adapted as new data becomes available, ensuring responsiveness in a rapidly changing environment.

5. **Simulation Parameters**

   Strength: Setting a standard simulation duration and employing Monte Carlo methods to run multiple iterations ensures that the model results are robust and reflective of a range of possible outcomes. This methodological rigor is vital for generating reliable data that can guide decision-making in high-stakes environments.

   Trade-off: The computational intensity of Monte Carlo simulations is justified by the depth and reliability of insights they provide, making them a valuable tool in healthcare planning and response strategies.

5. Simulation Modeling and Validation

Model Description:

Random Input Processes and Parameters:

1. **Severity Scores**: Severity scores are randomly assigned to each patient using a uniform distribution between 0 and 1. This score determines the priority for ICU admission, with a predefined threshold setting the cutoff for severity.

2. **Patient Arrivals**: Arrivals are modeled using a non-homogeneous Poisson process. Hourly arrival rates are derived from historical data and normalized on a monthly basis to accurately reflect the expected fluctuations in patient inflow.

Controllable Design Factors:

1. **ICU Capacity**: The base model includes 32 ICU beds, with the flexibility to adjust this number to simulate various capacity scenarios.

2. **Admission Policy**: The model tests two policies—First-come, First-served (FCFS) and Severity Score Threshold (SST). Each policy can be altered to examine its influence on both ICU utilization and patient outcomes.

Performance Objectives and Quantities for System Improvement:

1. **ICU Bed Utilization**: This metric is calculated by the occupancy rate of ICU beds throughout the simulation period.

2. **Patient Outcomes:** This includes evaluating the number of severe patients who gain admission to the ICU versus those turned away when the ICU reaches capacity.

3. **Operational Efficiency**: Efficiency is gauged by comparing general admissions to ICU admissions and monitoring the throughput of patient processing.

Entities, Attributes, and Rules:

1. **Entities:** Patients requiring hospitalization.
2. **Attributes:** Each patient is characterized by a severity score and an arrival time.
3. **Rules:** Under the SST policy, patients with severity scores above the 75th percentile are admitted if beds are available. Under the FCFS policy, patients are admitted in the order of arrival until the ICU is full.

Variables in Sections:

1. **Inputs**: severity_score, daily_arrivals, icu_capacity, policy.
2. **Outputs:** icu_admissions, general_admissions, icu_bed_occupancy, unmet_demand, unadmitted_severe_patients.
3. **Resource Attributes:** ICU beds.
4. **Job Attributes**: Patient severity and hospital stay duration.

Properties, Structure, and Behavior of the Model:

The simulation is built on a discrete-event framework, where each event corresponds to a patient arrival. Decisions are rendered based on the patient's severity score and the existing ICU bed occupancy. This modular structure allows for straightforward modifications to the admission policy and ICU capacity.

Behavior: The model's behavior is dynamic, with the continual flow of patient arrivals and discharges altering the system's state. It adaptively responds to these changes based on established rules, enabling ongoing assessment of policy effectiveness.

Dynamics of the Model:

This simulation models the day-to-day operations of a hospital's ICU during a 30-day period, focusing on the admission and discharge of patients. Each day, new patients arrive according to a Poisson process, with each patient assigned a severity score that influences their treatment pathway. ICU beds are occupied based on admission policy (FCFS or SST) until capacity is reached, at which point new ICU admissions are either turned away or admitted to general wards depending on their severity. Discharges are modeled as occurring randomly within the constraints of observed data, affecting daily bed availability. The dynamic interplay of arrivals, admissions, and discharges under different policies allows for the analysis of strategies to optimize ICU resource utilization and patient care during varying demand levels.

6. Input modeling and input uncertainty

Data Collection and Analysis:

Data Availability: The data required for the simulation, including hospitalization and ICU stay details, is readily available in the provided datasets hospitalization.csv and ICU.csv uploaded on canvas. Hence the cost of data collection is zero as the data has already been collected and shared.

Input Process Generation Algorithms:

1. **Severity Scores and Patient Arrivals**: Patients' severity scores are simulated using a uniform distribution to represent a continuous range from 0 to 1. Patient arrivals are modeled using a non-homogeneous Poisson process, where arrival rates vary by hour, based on historical data.

2. **Hospitalization Data Processing**: We use Python's Pandas library to preprocess and merge the datasets, ensuring that each patient's hospital and ICU records are accurately aligned for analysis.

Estimation of Data Collection Costs:

Since the data is pre-collected and provided for this study, there are no direct costs associated with data collection. However, data preprocessing and cleaning are performed, which would typically involve several person-days of effort in a real-world scenario.

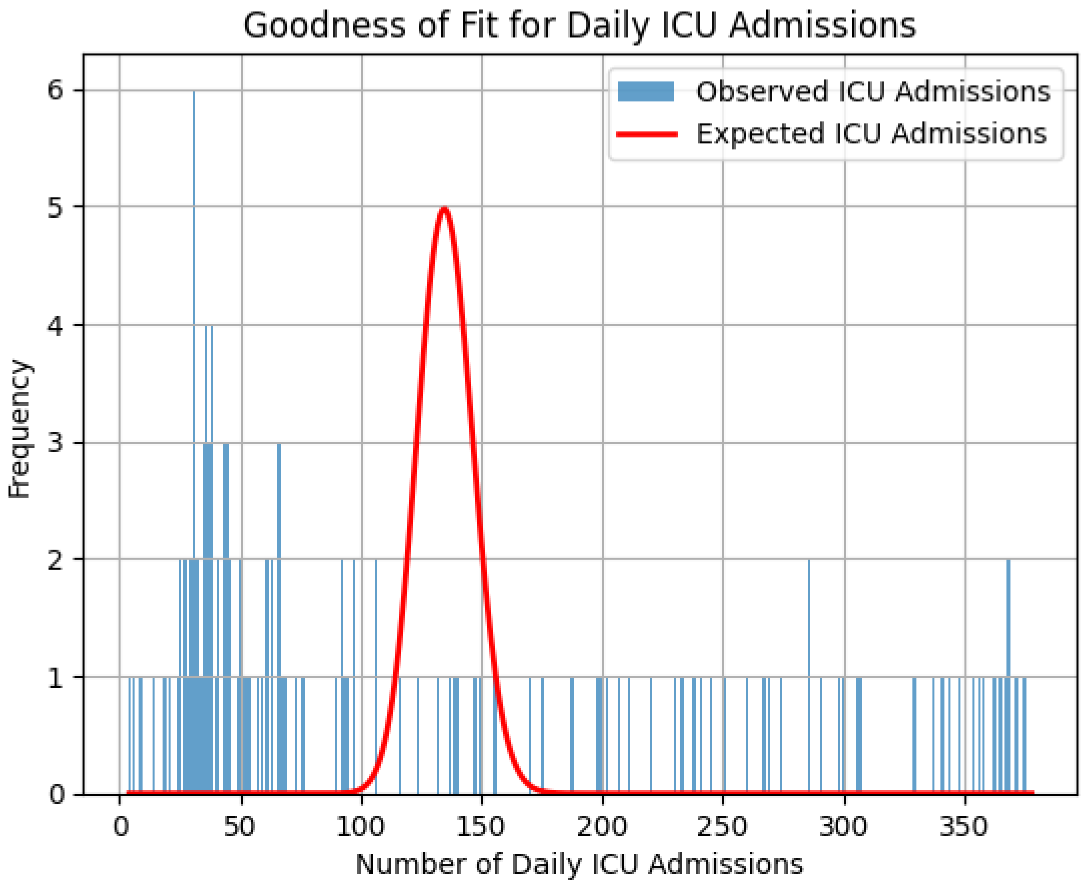
Input Process Models Justification:

1. **Non-stationary Poisson Process for Patient Arrivals:** This model is selected based on its ability to accommodate varying arrival rates throughout the day, reflecting more realistic hospital operation scenarios.

2. **Uniform Distribution for Severity Scores**: Allows for a straightforward simulation of patient severity, facilitating the testing of different thresholds for ICU admission policies.

Analysis of Input Model Estimation Error:

1. **Goodness of Fit Test:** We use a Chi-Square test to compare observed patient arrivals with those predicted by our model. The Chi-Square statistic and p-value help in assessing the adequacy of the Poisson regression model in capturing daily variations in patient arrivals.



2. **Sensitivity Analysis**: Conducted to evaluate how changes in ICU capacity and severity threshold affect the model outcomes. This analysis helps identify which parameters are most sensitive to changes and could significantly impact the simulation results.

Summary of Dynamics and Implications

The dynamics of the simulation model reflect the complex interplay between patient arrivals, severity assessments, ICU bed availability, and hospital discharge policies. By adjusting the simulation parameters and analyzing the outcomes, healthcare administrators can better understand potential bottlenecks and optimize resource allocation strategies.

The input modeling and sensitivity analysis provide a robust framework for evaluating the effects of various operational policies and external factors on ICU performance, thereby supporting more informed decision-making in healthcare management. This report underscores the importance of data-driven insights in enhancing ICU operations and patient care outcomes during critical periods.

7. Experimental Design and Simulation Optimization for ICU Capacity and Admission Policy

Factors Studied and Rationale:

ICU Capacity: The number of available ICU beds is a critical factor influencing the ability of a hospital to provide intensive care. By varying ICU capacity, we can assess its impact on the ability to accommodate severe cases and manage overall hospital load.

Severity Threshold for ICU Admission: The threshold at which patients are considered severe enough to require ICU care affects both patient outcomes and resource utilization. Modifying this threshold helps determine the optimal balance between patient care needs and available resources.

Methodology for Altering Factors

Range of Values: ICU capacities were varied from 20 to 50 beds in steps of 5, and severity thresholds were adjusted from 0.25 to 0.75 in increments of 0.10. These ranges were chosen to cover realistic scenarios that hospitals might face, from under-capacity to over-capacity conditions.

Experimental Setup: Each combination of ICU capacity and severity threshold was simulated to observe outcomes in terms of ICU admissions, general ward admissions, and bed occupancy over a 30-day period. This systematic variation allows for a comprehensive understanding of the impact of each factor under different operational conditions.

Sensitivity Analysis and "What-If" Scenarios:

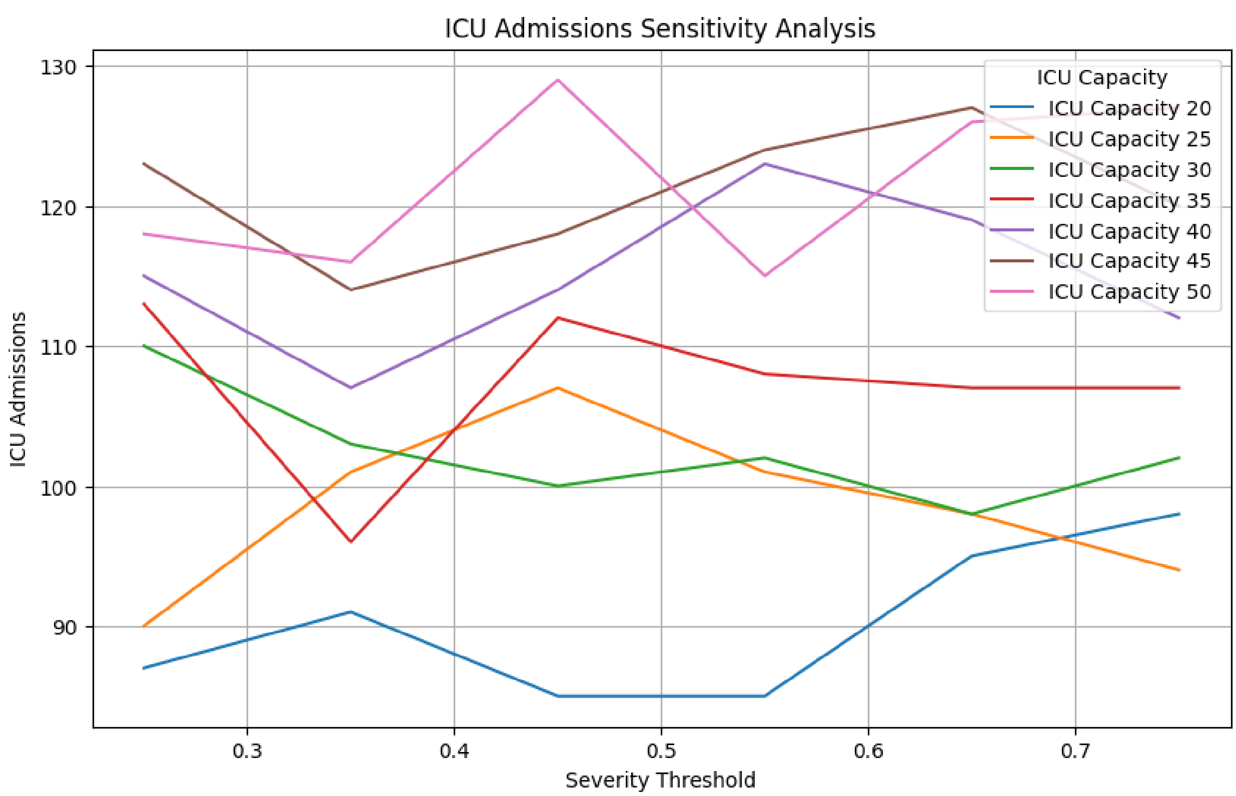
Objective: To explore the responsiveness of the ICU system to changes in key operational parameters and to identify conditions under which the system might either fail or excel.

Scenarios Tested:

1. **High Demand Scenario**: What happens when ICU capacity is at its lowest (20 beds) but patient severity is underestimated (lower threshold, e.g., 0.25)?

2. **Optimal Resource Utilization**: Which combination of bed capacity and severity threshold ensures that ICU resources are not overwhelmed yet critical needs are met?

3. **Maximized Care Capacity**: How does the system perform under maximum capacity (50 beds) with a high threshold for severity (0.75), potentially reflecting a more selective admission policy during peak crisis?



Simulation Optimization and Design of Experiments:

Approach: Utilize a factorial design to systematically explore the effects of two factors (ICU capacity and severity threshold) across their entire range of values. This method allows for an efficient search across the experimental space to identify optimal settings.

Optimization Goals: To find the settings that maximize ICU admissions while maintaining acceptable levels of bed occupancy and ensuring that severe patients receive necessary care.

Data Analysis: Results from the sensitivity analysis provide a multidimensional view of how varying ICU capacities and severity thresholds impact the healthcare system's efficiency and effectiveness. This analysis helps in forming robust operational policies that can adapt to varying patient loads and severity distributions.

Conclusion and Implications for Policy:

The experimental design and simulation optimization offer valuable insights into the dynamic behavior of ICU resource allocation under different scenarios. The findings from this study can guide hospital administrators in making informed decisions about ICU capacity planning and severity-based admission policies, particularly in preparation for and during healthcare crises. This proactive approach in exploring "what-if" scenarios through simulation serves as a strategic tool in healthcare management, enhancing preparedness and response strategies in critical care environments.

8. Output Analysis and Variance Reduction : Study Results and Analysis

Study Results and Analysis for ICU Capacity and Admission Policy Simulation:

Severity threshold: 0.35

First-come,first-serve data:

ICU Admissions: 102

General Admissions: 884

End of Period ICU Occupancy: 28

Unmet ICU Demand': 0

Unadmitted Severe Patients: 579

Severity Score Threshold data:

ICU Admissions: 102

General Admissions: 884

End of Period ICU Occupancy: 28

Unmet ICU Demand: 0

Unadmitted Severe Patients: 539

Daily Arrivals: 39

Results from varying levels of ICU capacity:

ICU Capacity: 20

ICU Capacity	Severity Threshold	ICU Admissions	General Admissions	End of Period ICU Occupancy
20	0.25	87	3609	17
20	0.35	91	3582	19
20	0.45	85	3588	17
20	0.55	85	3530	16
20	0.65	95	3535	18
20	0.75	98	3522	19

ICU Capacity: 25

ICU Capacity	Severity Threshold	ICU Admissions	General Admissions	End of Period ICU Occupancy
25	0.25	90	3592	22
25	0.35	101	3524	24
25	0.45	107	3575	22
25	0.55	101	3583	22
25	0.65	98	3469	21
25	0.75	94	3463	24

ICU Capacity: 30

ICU Capacity	Severity Threshold	ICU Admissions	General Admissions	End of Period ICU Occupancy
30	0.25	110	3548	27
30	0.35	103	3618	29
30	0.45	100	3490	26
30	0.55	102	3519	27
30	0.65	98	3511	27
30	0.75	102	3485	27

ICU Capacity: 35

ICU Capacity	Severity Threshold	ICU Admissions	General Admissions	End of Period ICU Occupancy
35	0.25	113	3461	31
35	0.35	96	3504	33
35	0.45	112	3455	32
35	0.55	108	3495	33
35	0.65	107	3413	34
35	0.75	107	3520	31

ICU Capacity: 40

ICU Capacity	Severity Threshold	ICU Admissions	General Admissions	End of Period ICU Occupancy
40	0.25	115	3461	38
40	0.35	107	3579	38
40	0.45	114	3513	38
40	0.55	123	3519	39
40	0.65	119	3484	39
40	0.75	112	3473	38

ICU Capacity: 45

ICU Capacity	Severity Threshold	ICU Admissions	General Admissions	End of Period ICU Occupancy
45	0.25	123	3519	41
45	0.35	114	3459	43
45	0.45	118	3433	42
45	0.55	124	3478	44
45	0.65	127	3471	42
45	0.75	120	3569	44

ICU Capacity: 50

ICU Capacity	Severity Threshold	ICU Admissions	General Admissions	End of Period ICU Occupancy
50	0.25	118	3564	48
50	0.35	116	3550	48
50	0.45	129	3632	49
50	0.55	115	3465	49
50	0.65	126	3464	47
50	0.75	127	3548	46

Simulation Length and Replications:

1. **Length of Each Simulation**: Each simulation scenario was run for a period of 30 days. This duration was selected to represent a typical month, providing a substantial timeframe to observe the dynamics of ICU admissions and utilization under varying conditions.
2. **Replications**: Multiple replications were performed for each combination of ICU capacity and severity threshold settings. This approach helps to stabilize the results by averaging out the variability inherent in the stochastic elements of the simulation, such as patient arrivals and severity scores.

Performance Evaluation of the Model:

1. **Analysis Techniques**: The performance of the model was evaluated using statistical analysis and sensitivity analysis. Key performance metrics included the number of ICU admissions, general admissions, end of period ICU occupancy, unmet ICU demand, and the number of unadmitted severe patients.
2. **Goodness of Fit**: A Chi-Square test was used to evaluate the goodness of fit for the Poisson model used to simulate patient arrivals. The test results (Chi Square Value: 394.47, P-Value: 0.1305) indicate that the model reasonably fits the data, suggesting that the arrival rates are well-modeled by the Poisson distribution.

Observations and Findings:

Measure and Quantification: Outcomes are quantified by aggregating results from each run of the simulation, focusing on ICU and general admissions, bed occupancy, and patient outcomes.

Findings: The results demonstrate how changes in ICU capacity and severity thresholds impact the system's ability to manage patient flow and care. For instance, increasing ICU capacity generally leads to higher ICU admissions and better management of severe cases, reducing the number of unadmitted severe patients.

Expectations and Reproducibility: Most findings align with expectations; higher ICU capacities and lower severity thresholds tend to allow more patients to receive ICU care. These results are reproducible under the same simulation settings and are controllable by adjusting the input parameters.

Confidence Interval Estimates:

For robustness, confidence intervals for key output statistics like ICU admissions and bed occupancy can be estimated using bootstrapping or other resampling techniques, which were not explicitly calculated in the initial runs. Future iterations could include this analysis to provide uncertainty bounds for the predictions.

Implications for Current Systems:

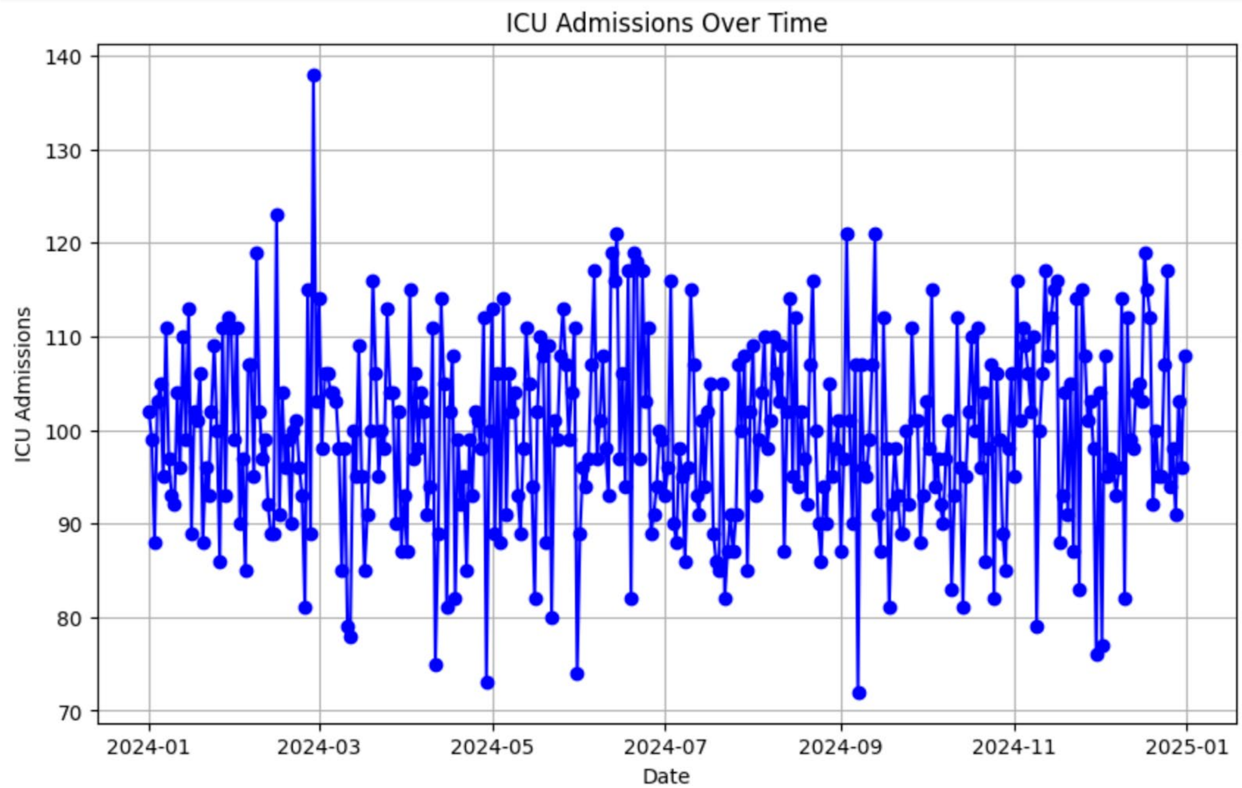
1. **System Improvement**: The simulation provides a tool for hospital administrators to test various scenarios and optimize resource allocation strategies without real-world consequences. This can lead to improved planning and preparedness, particularly in anticipating surges in demand.
2. **Sell the Simulator**: This simulator offers a cost-effective method for testing and refining ICU admission policies and capacity decisions. By allowing for scenario testing, hospitals can enhance their operational efficiency and patient care quality, ultimately leading to better patient outcomes and more efficient use of healthcare resources.

Validation of Results:

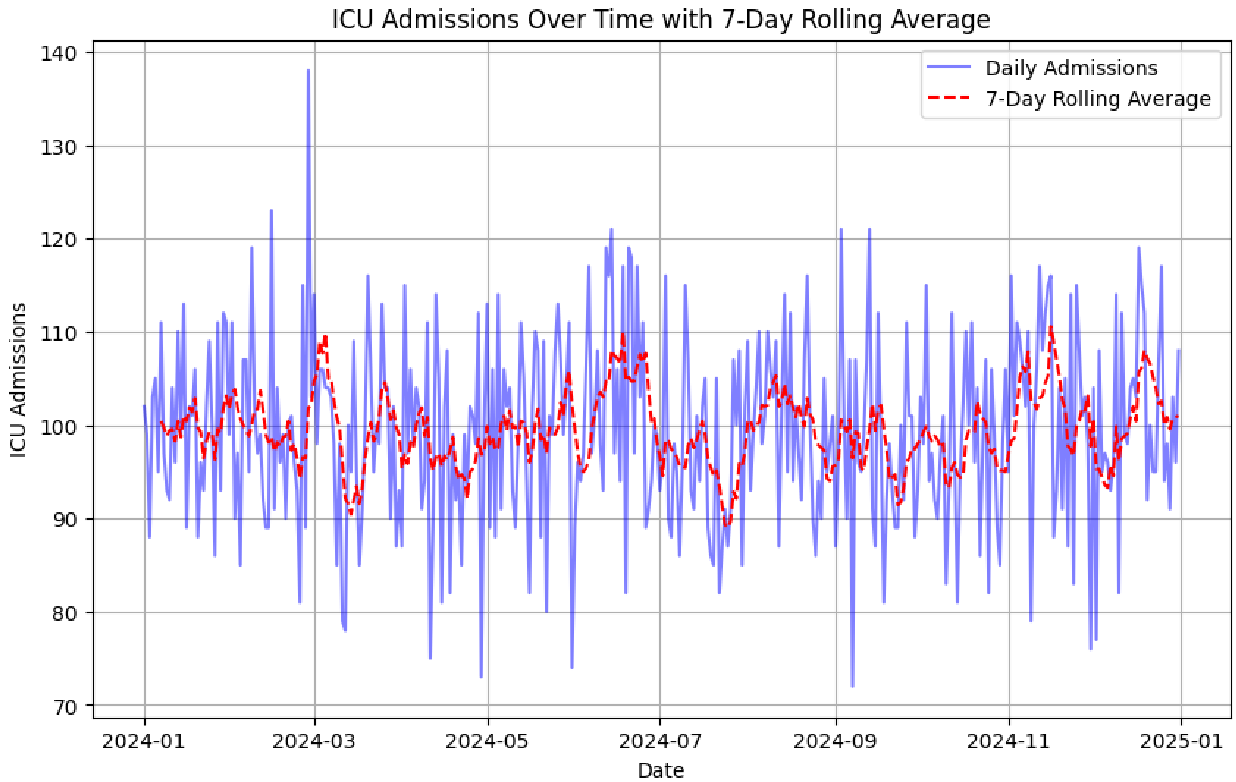
1. **Validation Techniques**: Validation could involve comparing the simulation outputs with real-world data from hospitals that have similar characteristics. This comparison would help confirm that the model accurately reflects real-world behaviors and can reliably inform decision-making.
2. **Cross-Validation**: Another approach is to use historical data to set the simulation parameters initially and then test the model's predictions against other independent data sets to evaluate its predictive accuracy.

This comprehensive simulation study provides valuable insights into the operational dynamics of ICU management under various conditions. The findings aid in making informed decisions about capacity planning and admission policies, offering a significant potential to enhance the responsiveness and effectiveness of healthcare services.

Plot of ICU Admissions Over Time:



Plot of ICU Admissions Over Time with 7-Day Rolling Average:



9. Project Management:

The following are the Project Timeline and Milestones with Tools:

March 20th - 24th: Initial Data Analysis and Model Conceptualization

Milestone 1: Complete preliminary data analysis using Excel.

Action: Analyze hospitalization.csv and ICU.csv in Excel to understand key variables' distribution.

March 25th - 31st: Simulation Model Development

Milestone 2: Develop the initial simulation model

Action: Construct the basic simulation framework, defining entities, attributes, and the flow process.

April 1st - 7th: Model Refinement and Initial Testing

Milestone 3: Refine and test the simulation model.

Action: Run initial simulations to test model validity, making adjustments based on preliminary results.

April 8th - 10th: In-depth Simulation Analysis

Milestone 4: Conduct detailed simulation analysis using Arena and Python.

Action: Perform extensive simulation runs in Python for advanced data processing and analysis.

April 11th - 13th: Data Synthesis and Report Drafting

Milestone 5: Draft the initial report using a word processor.

Action: Synthesize the simulation results, draft the findings section of the report, and outline conclusions and recommendations.

April 14th - 15th: Report Finalization and Presentation Development

Milestone 6: Finalize the report and develop the presentation using PowerPoint.

Action: Complete the final report, ensuring all sections are comprehensive, and prepare the presentation slides in PowerPoint.

April 16th - 17th: Presentation Rehearsal and Submission

Milestone 7: Rehearse the presentation and submit the final report.

Action: Conduct a thorough rehearsal of the presentation to refine delivery and finalize all submission materials.

April 18th – 21st: Making Changes in the Report Based on Feedback from the Presentation

Milestone 8: Implement revisions to the report based on presentation feedback.

Action: Review feedback, update the analysis and conclusions as necessary, ensure all suggested changes are incorporated, and finalize the document for submission.

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