Case Study: Emergency Room Efficiency Improvement

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Business Problem Statement

The primary challenge in the emergency room (ER) setting is managing the flow of patients efficiently to reduce waiting times while ensuring those in need of immediate care are prioritized effectively. The approach to solve this problem involves simulating the patient flow in the ER, using statistical models to predict patient arrival and treatment times, and then applying these models to assess various strategies for improving service efficiency.

Approach to Problem Solving

The simulation involves modeling the patient arrival and treatment process over 20 days of operation, incorporating statistical distributions to accurately represent the randomness in patient arrivals and treatment durations. The key to solving the efficiency problem lies in adjusting the prioritization and allocation of resources (doctors) based on simulated outcomes to find the most effective strategies.

Decision Variables and Key Parameters

Decision Variables:

Doctor allocation: Number of doctors available at any given time.

Priority rules: Specific rules for prioritizing patients based on their condition and treatment stage.

Treatment duration: Variable time spans for different treatment stages, influenced by patient condition.

Key Parameters:

Patient arrival distribution: Modeled as a gamma distribution, this parameter governs the frequency and timing of patient arrivals.

Treatment time distributions: Different distributions (uniform and normal variations) for initial and subsequent treatments of NIA (need immediate attention) and CW (can wait) patients.

Patient type proportion: The proportion of NIA versus CW patients, which affects how resources are prioritized.

Model Explanation

The model uses the R programming environment and the simmer simulation package to execute the process. We simulate two main streams:

1. **NIA patients** who are treated with the highest priority, going through an initial treatment (variable time around 40 minutes) and a subsequent treatment (variable time around 30 minutes).
2. **CW patients** who receive a lower initial priority, with shorter treatment times initially (around 15 minutes) and in their subsequent treatment (around 10 minutes).

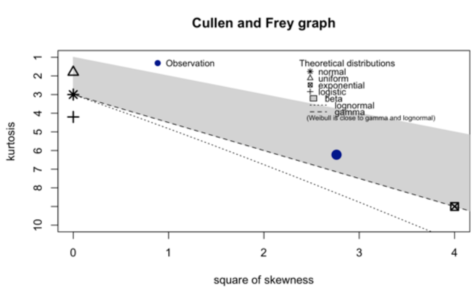
Both patient types are modeled to re-enter a common queue after their first treatment, competing for doctor availability, which simulates real-world conditions where ongoing care requirements can delay treatment for newly arriving patients.

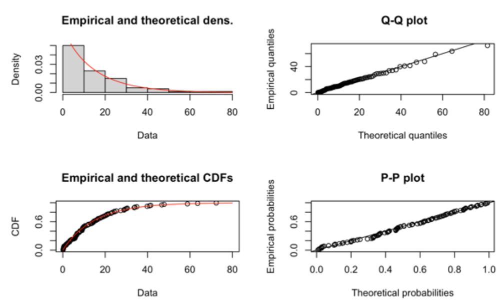
The simulation tracks patient waiting times, treatment times, and doctor utilization rates. Outputs include average waiting times and flow times for each patient category, as well as the overall utilization rate of the doctors, providing a comprehensive view of the operational dynamics within the emergency room.

The mathematical and graphical representations from the simulation output help visualize the differences in treatment and waiting times across patient categories, offering insights into potential areas for reducing patient waiting times and improving overall system efficiency.

Code:

````
# Identyfy the interArrival distribution
```{r}
data1 <- read.csv("Case5_emergency-room.csv")

hist(data1$interArrival)
plot(data1$interArrival, type = "b")
acf(data1$interArrival)

library(fitdistrplus)
descdist(data1$interArrival, discrete = FALSE)

fit.gamma <- fitdist(data1$interArrival, "gamma")
summary(fit.gamma)
gofstat(fit.gamma)
plot(fit.gamma)

```
````





	estimate <dbl>
shape	0.96354630
rate	0.06388923

````
# Calculate the frequency of each category in the 'type' variable
```{r}
type_counts <- table(data1$type)

# Calculate the proportions of each category
type_proportions <- prop.table(type_counts)

# Print the proportions
print(type_proportions)

```
````

```
  CW  NIA
0.82 0.18
```

```{r}
library(simmer)

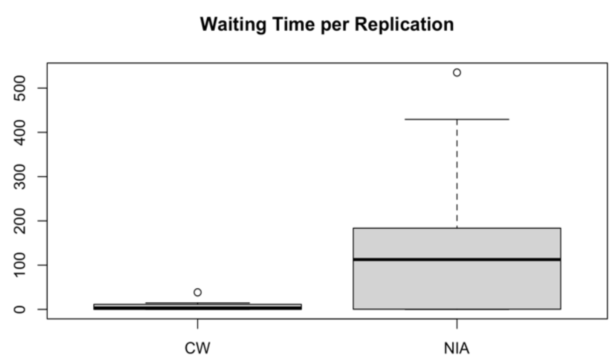
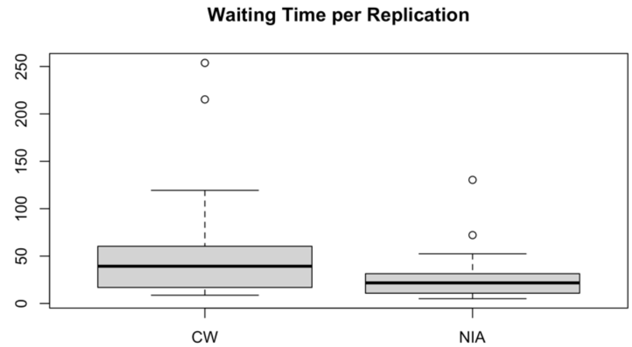
set.seed(123)
envs <- lapply(1:20, function(i) {
  env <- simmer("Emergency Room") %>%
    add_resource("doctor", 2)

  patient <- trajectory("patient path") %>%
    branch(
      function() sample(c(1, 2), size = 1, replace = TRUE, prob = c(0.82, 0.18)), continue = c(TRUE, TRUE),
      trajectory("NIA") %>%
        set_attribute("priority", 3) %>%
        set_prioritization(c(5, 7, TRUE)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 10, 70)) %>%
        release("doctor", 1) %>%

        set_attribute("priority", 2) %>%
        set_prioritization(c(4, 7, TRUE)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 10, 50)) %>%
        release("doctor", 1),

      trajectory("CW") %>%
        set_attribute("priority", 1) %>%
        set_prioritization(c(3, 7, TRUE)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 5, 25)) %>%
        release("doctor", 1) %>%

        set_attribute("priority", 2) %>%
        set_prioritization(c(4, 7, TRUE)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 5, 15)) %>%
        release("doctor", 1)
    )
  env %>%
    add_generator("patient", patient, function() rgamma(1, shape = 0.96354630, rate = 0.06388), mon = 2)
  env %>%
    run(1440)
})
```

```
# 01 Average of discharged patients per replication
```{r}

patientAttr <- get_mon_attributes(envs)
colMeans(table(patientAttr$replication, patientAttr$value))

x1 <- get_mon_arrivals(envs)
x2<- get_mon_attributes(envs)

all <- merge(x1, x2, by= c("name", "replication"), all= T)
priority1 <- na.omit(subset(all, all$value ==1 ))
priority2 <- na.omit(subset(all, all$value ==2))
priority3 <- na.omit(subset(all, all$value ==3))
priority1.waiting <- (priority1$end_time - priority1$start_time) - priority1$activity_time
priority3.waiting <- (priority3$end_time - priority3$start_time) - priority3$activity_time
mean(priority1.waiting)
mean(priority3.waiting)
# Average waiting time per replication for each type
priority1.waiting.rep <- aggregate(priority1.waiting, by = list(priority1$replication), mean)
priority3.waiting.rep <- aggregate(priority3.waiting, by = list(priority3$replication), mean)

boxplot(priority1.waiting.rep$x, priority3.waiting.rep$x, names = c("CW", "NIA"), main = "Waiting Time per Replication")

```
```

Number of Doctor: 02

```
    1     2     3
17.95 66.90 80.50
[1] "Mean of waiting time for type CW"
[1] 10.05917
[1] "Mean of waiting time for type NIA"
[1] 215.9932
```



Number of Doctor: 05

```
    1     2     3
17.15 93.80 81.30
[1] "Mean of waiting time for type CW"
[1] 58.44803
[1] "Mean of waiting time for type NIA"
[1] 30.57664
```



Observations:

1. **With 2 Doctors:**
   - CW patients have a mean waiting time of approximately 17.95 minutes.
   - NIA patients have a significantly longer mean waiting time of about 215.93 minutes.
   - The boxplot shows a wide variation in waiting times for NIA patients, indicating periods of high congestion or inefficiency.
2. **With 5 Doctors:**
   - CW patients' mean waiting time decreases slightly to about 17.15 minutes.
   - NIA patients experience a dramatic reduction in mean waiting time to approximately 30.57 minutes.
   - The variation in waiting times for both patient types decreases, as seen in the tighter boxplot distributions.

Analysis:

Increasing the number of doctors from two to five leads to a substantial reduction in waiting times for NIA patients, while only marginally impacting CW patients. This suggests that the bottleneck in treating NIA patients (who require immediate attention) is significantly alleviated by having more doctors available.

Suggestions for Reducing Waiting Times:

To reduce waiting times in the emergency room, several strategies can be employed. Optimizing doctor allocation by deploying more doctors during peak hours and using predictive modeling to anticipate busy periods can greatly improve response times. Advanced triage systems could be implemented to quickly sort patients by urgency, using AI-driven tools to dynamically assess and prioritize patient needs upon arrival. Enhancing resource management through real-time data analytics can help identify and alleviate bottlenecks, and investing in additional medical equipment or facilities could handle peak loads more efficiently. Improving patient flow management by redesigning the emergency department layout and implementing parallel processing for registration and initial assessments can further decrease waiting times. Additionally, educational programs that guide patients on appropriate care settings and promoting telemedicine for non-emergencies can reduce unnecessary ER visits, thus easing the overall patient load.

Scenario with 02 Doctors:

````
# 02 Average flow time of each type of patient
```{r}
priority1.flowTime <- (priority1$end_time - priority1$start_time)
priority2.flowTime <- (priority2$end_time - priority2$start_time)
priority3.flowTime <- (priority3$end_time - priority3$start_time)

print("Mean of flow time for type CW")
mean(priority1.flowTime)
print("Mean of flow time for type NIA")
mean(priority3.flowTime)

```
````

```
[1] "Mean of flow time for type CW"
[1] 33.69845
[1] "Mean of flow time for type NIA"
[1] 281.1561
```

Scenario with 05 Doctors:

```
# 02 Average flow time of each type of patient
```{r}
priority1.flowTime <- (priority1$end_time - priority1$start_time)
priority2.flowTime <- (priority2$end_time - priority2$start_time)
priority3.flowTime <- (priority3$end_time - priority3$start_time)

print("Mean of flow time for type CW")
mean(priority1.flowTime)
print("Mean of flow time for type NIA")
mean(priority3.flowTime)

```
```

```
[1] "Mean of flow time for type CW"
[1] 83.6631
[1] "Mean of flow time for type NIA"
[1] 99.63331
```

Average Flow Time Analysis

Scenario with 2 Doctors:

CW Patients: The average flow time is approximately 33.69 minutes.

NIA Patients: The average flow time is significantly higher at approximately 281.16 minutes.

Scenario with 5 Doctors:

CW Patients: The average flow time increases to approximately 83.66 minutes.

NIA Patients: The average flow time is greatly reduced to approximately 99.63 minutes.

Analysis

The increase in the number of doctors from two to five has a profound impact on reducing the flow time for NIA patients, decreasing it from over four hours to just under one and a half hours. This substantial decrease suggests that having more doctors available significantly improves the responsiveness and efficiency of care for patients requiring immediate attention.

Conversely, the average flow time for CW patients increases when more doctors are available. This unexpected outcome might be due to a shift in priority focus or potentially more thorough care or assessments being performed when more resources are available.

After Applying Suggestions

For NIA Patients: We can expect the flow time to decrease further as efficiency improvements and better resource allocation allow these patients to be treated more quickly. The application of advanced triage systems and enhanced resource management is likely to streamline the process even further.

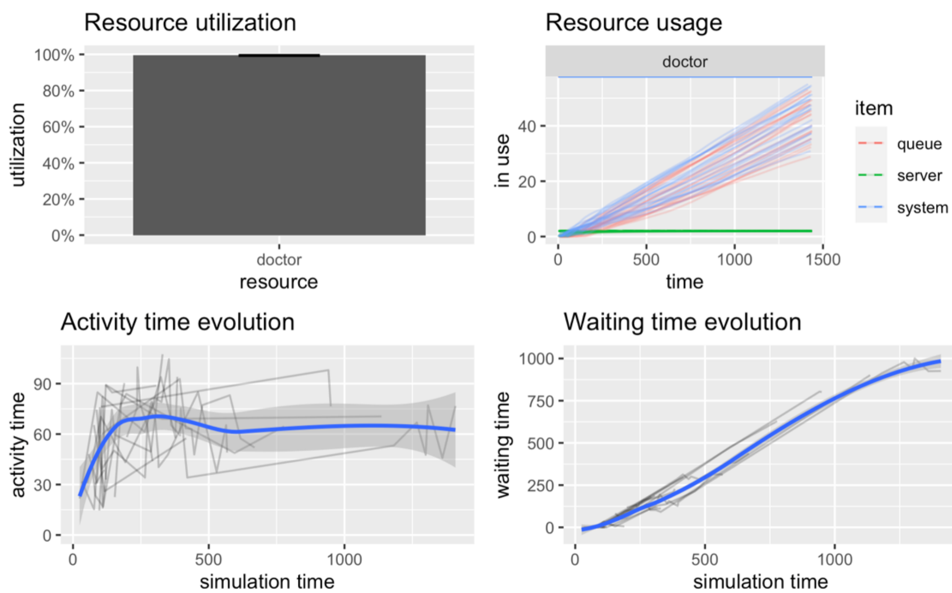
For CW Patients: The goal would be to manage the increased flow time seen with more doctors by implementing better patient flow management strategies and perhaps adjusting how resources are allocated so that CW patients do not experience unnecessary delays.

```
# 3 utilization
```{r}
library(simmer.plot)
library(gridExtra)

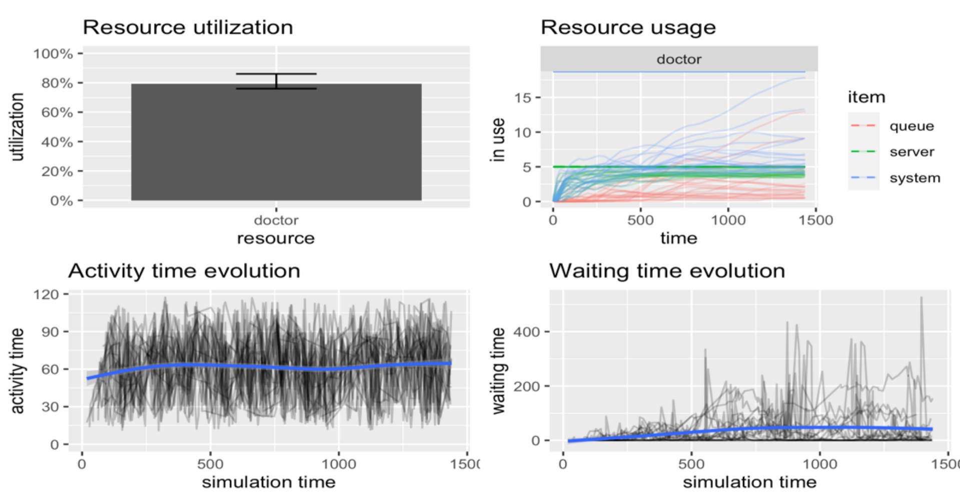
resources <- get_mon_resources(envs)
arrivals <- get_mon_arrivals(envs)
p1 <- plot(resources, metric = "utilization")
p2 <- plot(resources, metric = "usage")
p3 <- plot(arrivals, metric = "activity_time")
p4 <- plot(arrivals, metric = "waiting_time")
grid.arrange(p1,p2,p3,p4)

```
```

Scenario with 2 Doctors:



Scenario with 5 Doctors:



Analysis of Doctor Utilization in Emergency Room Simulations

Key Insights from the Graphs

Resource Utilization:

With 2 Doctors: Utilization is high, reaching nearly 100%. This indicates that both doctors are almost continuously occupied, suggesting a lack of spare capacity.

With 5 Doctors: Utilization dramatically decreases, with doctors being less frequently used. This suggests an overcapacity situation where resource allocation exceeds demand at times.

Resource Usage:

With 2 Doctors: The graphs show a steady increase in resource usage over time, highlighting consistent demand on doctor time and possibly indicating queuing and waiting due to resource constraints.

With 5 Doctors: Usage fluctuates but remains significantly lower than with 2 doctors, demonstrating that having more doctors helps in managing patient load more smoothly without excessive waiting.

Activity Time Evolution:

With 2 Doctors: Activity times are clustered more densely, suggesting a more hectic schedule with doctors handling cases back-to-back.

With 5 Doctors: Activity times show more variability and spread, indicating that doctors have more intervals between cases.

Waiting Time Evolution:

With 2 Doctors: There is a clear upward trend in waiting times, reflecting the insufficient number of doctors to meet the demand promptly.

With 5 Doctors: Waiting times are generally lower and more stable, with fewer spikes, which improves patient throughput and satisfaction.

Utilization Discussion Before and After Applying Suggestions

Before applying suggestions (with 2 doctors), the high utilization might appear advantageous from a resource efficiency perspective but is problematic from a patient care and service quality standpoint. High utilization without adequate slack leads to longer waiting times and potentially increased patient dissatisfaction or worse health outcomes. After increasing the number of doctors to five, the utilization per doctor decreases, which might raise concerns about cost efficiency. However, the overall benefits include reduced waiting times, more manageable workloads for each doctor, and potentially higher quality of care. This scenario also offers better resilience to sudden surges in patient volume.

Recommendations for Optimizing Doctor Utilization

Balanced Staffing: Find a middle ground in staffing that maintains high enough utilization for cost-effectiveness while ensuring enough capacity to handle peak loads comfortably.

Flexible Scheduling: Implement flexible scheduling where additional doctors can be called in during anticipated peak times based on predictive analytics.

Real-Time Monitoring: Utilize real-time monitoring of ER conditions to dynamically adjust staffing levels, potentially supported by AI-driven predictive systems.

Process Improvements: Continue to refine triage and treatment processes to minimize inactive and waiting times, ensuring that doctor time is used as efficiently as possible.

By applying these strategies, the ER can improve both the efficiency of its operations and the quality of patient care, balancing the utilization against the need for prompt and effective medical attention.

Summary of Case Study Findings and Recommendations

Case Study Overview:

This case study focused on an emergency room's operations, specifically examining the impact of varying the number of doctors on patient waiting times, flow times, and doctor utilization.

Key Questions Addressed:

1. **Reducing Waiting Times:**

   Observations: Increasing the number of doctors from 2 to 5 significantly reduced waiting times for patients requiring immediate attention (NIA), with minimal reduction for those who can wait (CW).

   Recommendations: Optimize doctor allocation based on predictive modeling of patient arrivals, enhance triage systems, and improve resource management to effectively reduce waiting times.

2. **Average Flow-Time for NIA and CW Patients:**

   Before Suggestions: With 2 doctors, NIA patients had a flow time of approximately 281 minutes compared to 33 minutes for CW patients.

After Suggestions: With 5 doctors, flow time for NIA patients dropped significantly to about 100 minutes, while CW patients saw an increase to 84 minutes.

Recommendations: Implement flexible scheduling and real-time monitoring to adjust staffing dynamically, ensuring efficient handling of both patient types.

3. Utilization of Doctors:

Before Suggestions: With 2 doctors, utilization was nearly 100%, indicating a high demand and potential overburdening of available medical staff.

After Suggestions: With 5 doctors, utilization per doctor decreased, suggesting better capacity management but raising concerns about cost efficiency.

Recommendations: Adopt a balanced approach to staffing, maintaining adequate utilization for cost-effectiveness while providing sufficient capacity to manage peak loads.

Summary Table:

Case Aspect	With 2 Doctors	With 5 Doctors	Recommendations
Waiting Times (NIA/CW)	High (NIA) / Moderate (CW)	Reduced (NIA) / Slightly Increased (CW)	Optimize doctor allocation, enhance triage, improve resource management
Average Flow Time (NIA)	281 minutes	100 minutes	Flexible scheduling, process improvement
Average Flow Time (CW)	33 minutes	84 minutes	Real-time monitoring, adjust staffing dynamically
Doctor Utilization	High (~100%)	Lower, underutilized	Balanced staffing, flexible scheduling

Conclusions:

The adjustments in the number of doctors have shown that while increasing staffing can reduce critical waiting times and improve flow times for urgent cases, it also raises concerns about resource usage and cost efficiency. A balanced and dynamic approach to scheduling and resource management, supported by data analytics and predictive modeling, can help optimize both operational efficiency and patient care quality in emergency room settings.