**Patient Admittance for Emergency Department System using Discrete Event Simulation**

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Simulation and Optimization ISQS Final Project

Table of Contents

## Abstract

**Background:** In recent times, there has been increase on the amount of waiting time patience experience in an emergency department (ED). In addition, the emergence of crowded situations and inefficient resource utilization in the EDs have led to prolonged patient service time and poor patient satisfaction on national surveys. Consequently, various studies have been done to analyze government health data for strategic solutions to the problem. Nonetheless, in this project we attempted to model the ED system and replicate multiple scenarios that will aid the optimization of the ED service through efficient resource utilization, solve overcrowding problem, and reduce average waiting and service time in the ED.

**Model Methodology:** While we could not precisely validate the model accuracy, simulation would inform us about the behavior and normal operating conditions of the system as simulation experiments are designed with the intent to model a real system scenario that enhances the capability of the end-users and managers to evaluate various strategies and decisions. Hence its always important to validate the model by comparing it with actual system behavior. However, in the case of this project, predetermined ED conditions from a sample case were subjected to a dynamic modeling technique that involved the stochastic behavior of a system. To run the analysis, Discrete event simulation modeling with the assumption of a uniform distribution of the population were executed with the aid of R-programming software. After initial results were obtained, possible suggestions by adding additional resource to the model were implemented to analyze the impact of the change between the 2 systems.

**Results:** After executing both models for a runtime of 1440mins (24hrs) with 20 replications, there were significant differences in the results, the average waiting time for system 1 (Normal sample conditions) was **"22.4372"** mins, while after adding additional resource in system2 the average waiting time was **"1.128757"** mins. Also, in system 1, 85 % resource utilization was when compared with system 2 which was 58% utilization. The queue size reduced from 8 patients in system 1 to less than 2 patients in system 2 except on few occasions when it was 3 during the early hours of run time.

**Conclusion:** In conclusion, employing additional doctor resources in system 2 appeared to be a better option, however most managers of the Eds are usually constrained on hiring additional resources. Possible solutions might be to recreate the model environment with a different simulation technique that is more focused on the resources – Agent Based Simulation Model (ABM) which is designed to find ways to optimize resources in the ED or system.

**Keywords:** *Flowtime, Waiting time, Emergency Department (ED), Object (Patients), Resources (Doctors), Discrete Event simulation (DES), Environment, Triage & Priority*

## Introduction

According to the CDC national center for health statistics, a survey was conducted on ambulatory medical care at 294 hospitals nationally, of which 131,297 patients visited the ED within a 4 -week period of the survey analysis. The survey highlighted the average waiting time it took a patient to see a physician was 28.4mins after registration. The least time spent receiving services at the ED was less than an hour which was only 9% of the sample size and the others spent over an hour to 14hours (*"National Hospital Ambulatory Medical Care"*, 2020). The survey did not categorically state the position on utilization of available resources but rather focused on the medical conditions of the patients that visited the ED.

The purpose of this project was to optimize the ED services with discrete event simulation (DES). This is a technique used to model real world system operations that can be decomposed into a set of logically separate sequences that exclusively progress through time. That is each event occurs separately at a particular instance in time. Among other resources used was software R programming packages simmer to create the ED environment, then set up the sequence of the patient's path within the ED environment. To achieve this, we used a Trajectory and chaining method. This is a technique used in the simmer function to set the patient attributes in the model after the environment has been created. The patient's movement and activity are usually random based on the patient's condition after an ED attendant (Triage Nurse) has performed a triage process. Triage is a medical process done on a patient's arrival at the ED used to determine the urgency of the patient's care to know which patient exhibits the most at-risk life-threatening condition. The assessment includes vitals, symptoms, obvious critical injuries, and damages to the body. In a recent study (by Rex. L Et al, 2020) on performance of three-level triage scale in live triage encounters in an ED, they identified the triage levels as category 1 (immediate), category 2 (urgent) and category 3 (non-urgent). In the case of this simulation experiment, the triage process was designed to meet 2 conditions a level 1 – need immediate attention consisting of 20% of patients arriving at the ED and level 2 – patient can wait after arrival. For context arrival is when the patient has done registration. In this project patient arrival and service flow was done with discrete uniform distribution in which patients had constant arrival probability and service time at the ED. To meet the condition of data normality Bootstrapping was done for estimating standard errors of sampled data; And finally, we simulated the model by running it for 1440mins in 20 replications to aid with visualization of different scenarios depending on available resources.

***Fig.1***

*Patient Flow Process at an ED. Source: Copyright 2011 by Kelton Et al.*

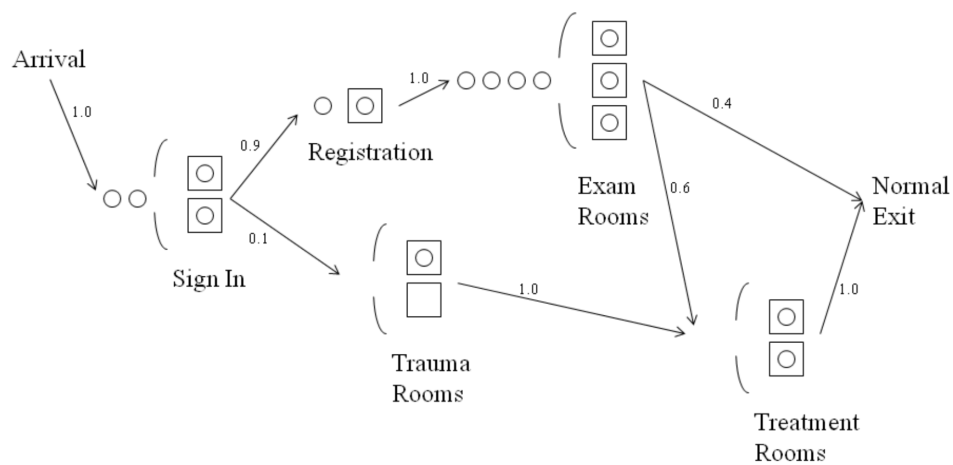



Fig.1 illustrates the flow of an example ED with the presence of several branches that affect the path of a patient's movement. On Arrival, the patient signs in and moves to registration and is accessed based on the triage process. Then proceeds to wait for care depending on the severity of the ailment. On the other hand, after patient arrival they are rushed to trauma room immediately for treatment, this is usually the case of life-threatening situations.

**Elements in Simulation Model**

- Entity – The entity is an object in the ED environment, in this case the patient because we are interested in the patient's movement in the model. In the project we used a random sampling generator with replacement. We also indicated earlier that patient's movement was discrete uniform distribution.

- Attributes – The patient's properties which defines the movement of the patient, and it is determined by the patient's priority (triage condition) after the patient's arrival.
- Resources – the resource in the system are usually limited, which could be doctors, nurses etc. They could either be in use or available to attend to a new patient. Here we focused on the doctor's utilization as a resource.
- Queue – The queuing system used was based on high value first criteria set at patient's priority.
- Event – This occurs when there is a change in the state of model.

**Understanding the Predetermined Conditions for the Sample Case**

The sample case is an extract from simulation modeling and arena exercise text (Rossetti M. 2015):

"Patient arrival at the ED is uniform distribution at about every 20 ± 10 minute (stream 1). The notation X ± Y means uniformly distributed with minimum X − Y and maximum X + Y. They will be treated by either of two doctors.

Twenty percent of the patients are classified as NIA (need immediate attention) and the rest as CW (can wait). NIA patients are given the highest priority, 3, see a doctor as soon as possible for 40 ± 37 minutes (stream 2), then have their priority reduced to 2 and wait until a doctor is free again, when they receive further treatment for 30 ± 25 minutes (stream 3) and are discharged. CW patients initially receive a priority of 1 and are treated (when their turn comes) for 15 ± 14 minutes (stream 4); their priority is then increased to 2, they wait again until a doctor is free, receive 10 ± 8 minutes (stream 5) of final treatment and are discharged.

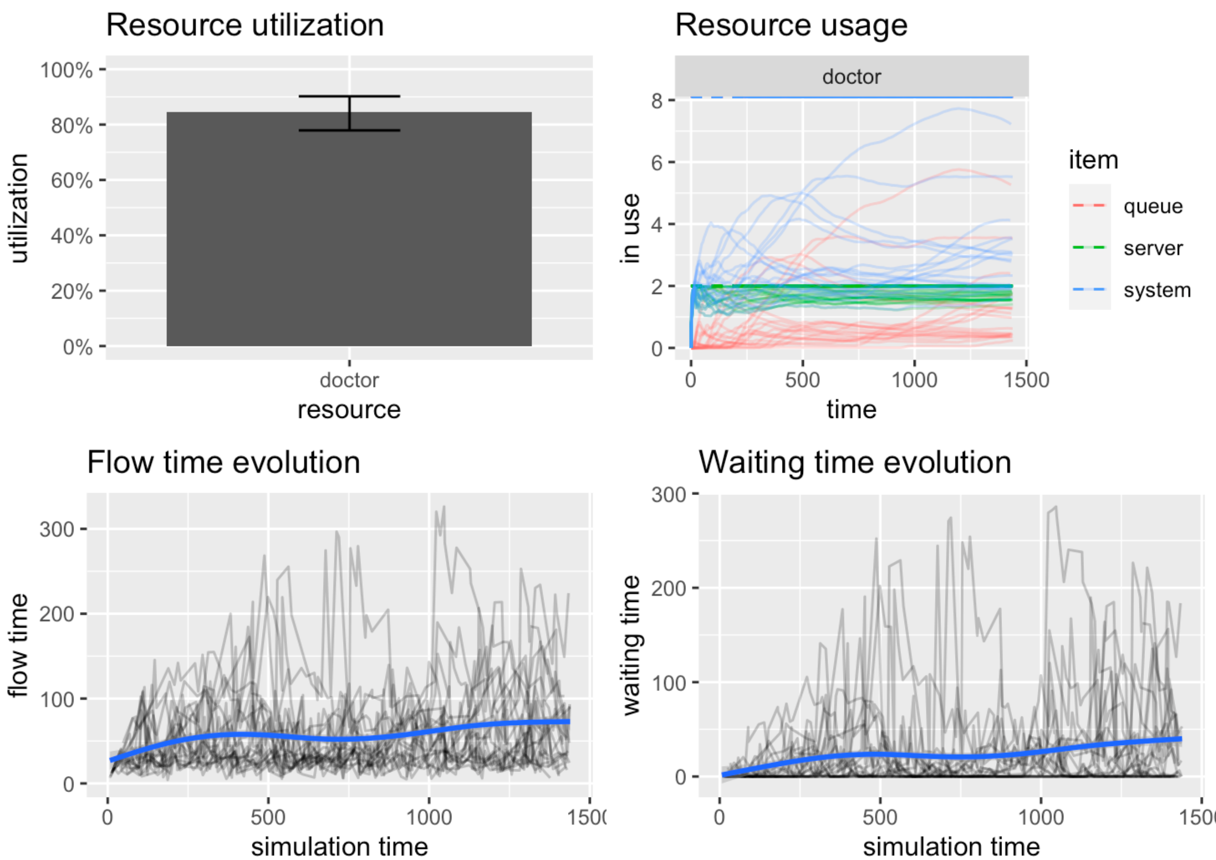
An important aspect of this system is that patients who have already seen the doctor once compete with newly arriving patients who need a doctor. As indicated, patients who have already seen the doctor once have a priority level of 2 (either increased from 1 to 2 or decreased from 3 to 2). Thus, there is one shared queue for the first treatment activity and the final treatment activity. In addition, we assume that the doctors are interchangeable. That is, it does not matter which of the two doctors performs the first or final treatment. Simulate for 20 days of continuous operation, 24 hours per day" (p. 476). With the subjected conditions, we analyzed the results and made inference on reducing the patients' waiting time. Review the average flowtime for NIA and CW patients before or after applying different suggestions to reduce resources. And finally, a discussion on the utilization of doctors before or after applying suggestions.

**Initial analysis under current Resource Conditions**

After running the simulation experiment at the set timeframe, we generated a visualization grid in ***Fig.2*** below. It consists of information that will help us understand the system's resource utilization and usage. It also highlights a breakdown of the patient's service (flowtime) and waiting time in the system.

***Fig.2***

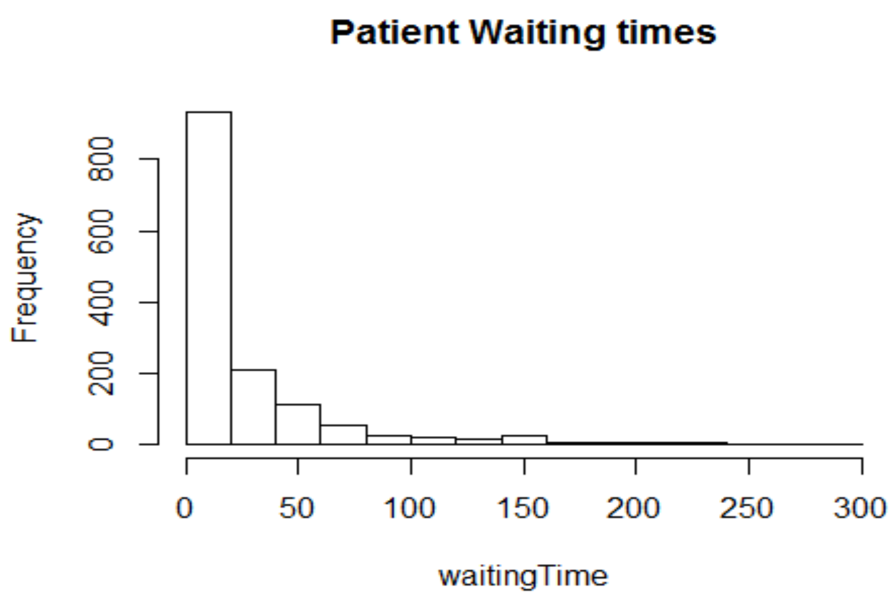
*Normal System Utilization Condition*




The initial system conditions are in line with the sample case, which details the number of resources to be only 2 doctors at the ED treating patients. The assumption here is either of the doctors would treat both patient priorities if they were available. In reviewing the grid, the resource utilization at the ED is 85%, close to its maximum, which exposed the wait time of patients at the ED to be at an elevated level during certain times of the day. The tick blue lines on the time evolution charts appear to rise as the day goes by on both flow and wait time. The waiting time for patients at the ED is between 0 and 40mins with the highest wait time at 290mins depending on the time at the day. The flowtime (Flow time evolution) shows patients entire service activity time and waiting time. It was within 10 and 70mins. but there are exceptional cases above 300mins based on the time of day. In Resource usage the serve is always busy, queuing size increases as we move through the day with highest of about up to 6 people during the day. The average flowtime spent by level 1 patients who need immediate attention is 16.66mins while that of level 2 patients who could wait was 40mins at the ED.

***Fig.3***

*Histogram of Patient Waiting Time with 2 Doctors*



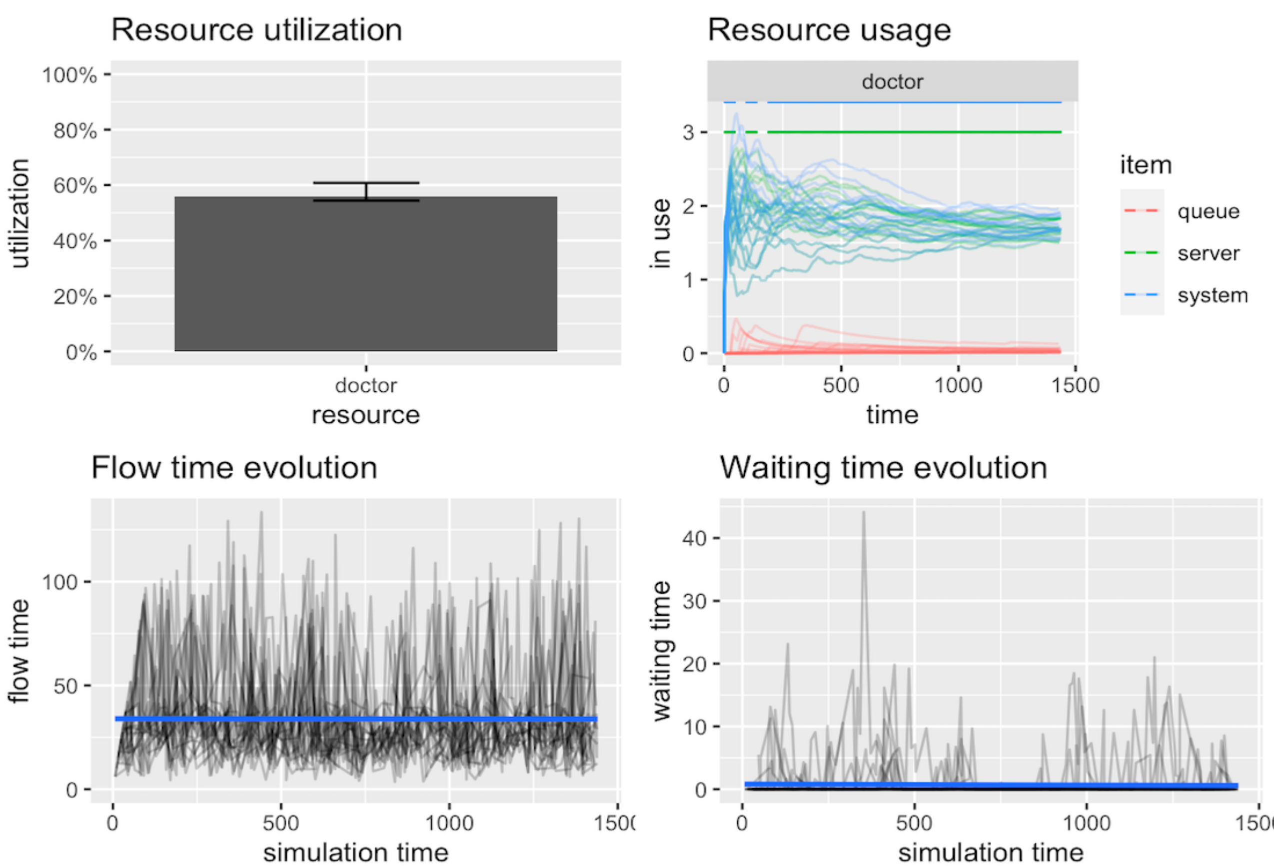

The histogram in ***Fig.3*** illustrates the patients waiting time before they got treatment from the doctor. It is left skewed with above 75% of the patients waiting not more than 50mins. The average waiting time of patients is 22mins while operating under current system condition with only 2 doctor resources at the ED.

**Analysis for Increasing Number of Doctor Resources**

While resources may be limited in the actual system environment, running a simulation by adding additional resources can help the ED managers to decide on hiring additional resources bearing in mind the cost implications and efficiency of the ED. After adding an additional resource to increase doctors at the ED from 2 to 3, the model was simulated for the same runtime and ***Fig.4*** below illustrates a revised grid of model.

***Fig.4***

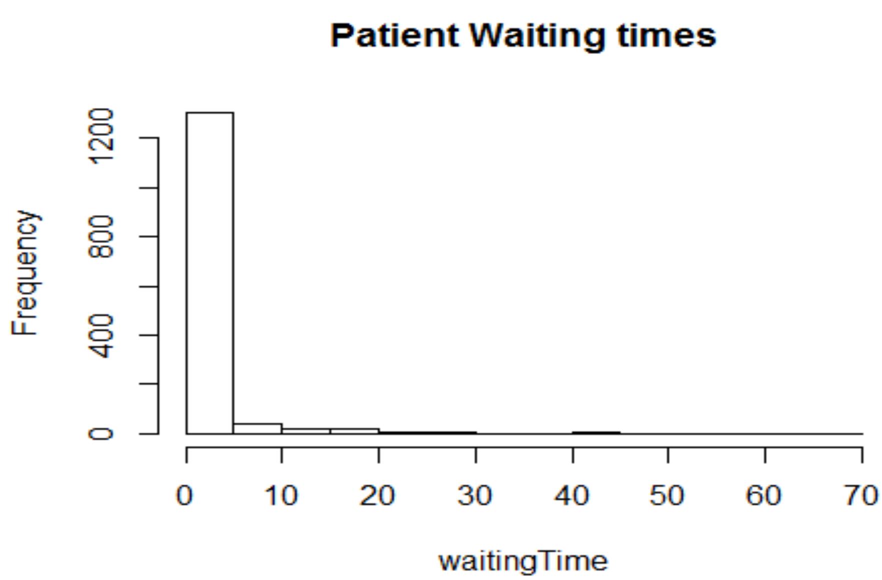
*Suggested System Utilization Condition*




From the grid result a general outlook of the system shows that by increasing doctors from 2 to 3, resource utilization capacity has reduced from 85% at the initial model conditions to 58%. When observing the resource usage at the ED, the server is busy, however not all through the day. The server is usually busy at the beginning of the day and 2 doctors at any point in time are always in use. The 3rd doctor is less active from midday. That resource can be hired part time basis at specific periods of the day. While queue size has dropped significantly, an indication that the ED system has improved for the better half of the day as patients in the queue is not more than 1 all through the day. The waiting time for patients at the ED is between 0 and 4mins throughout the day with some few occasions as high as 45mins based on the number on doctor availability. The flowtime of patients at the ED was within 25 and 30mins. but there were exceptional cases above 150mins probably due to extent of patient's treatment. The average waiting time of patients is 1.12min while operating under suggested system condition with additional resource increasing doctors available at the ED to 3. ***Fig.5*** illustrates the histogram of patient waiting time with additional resource

***Fig.5***

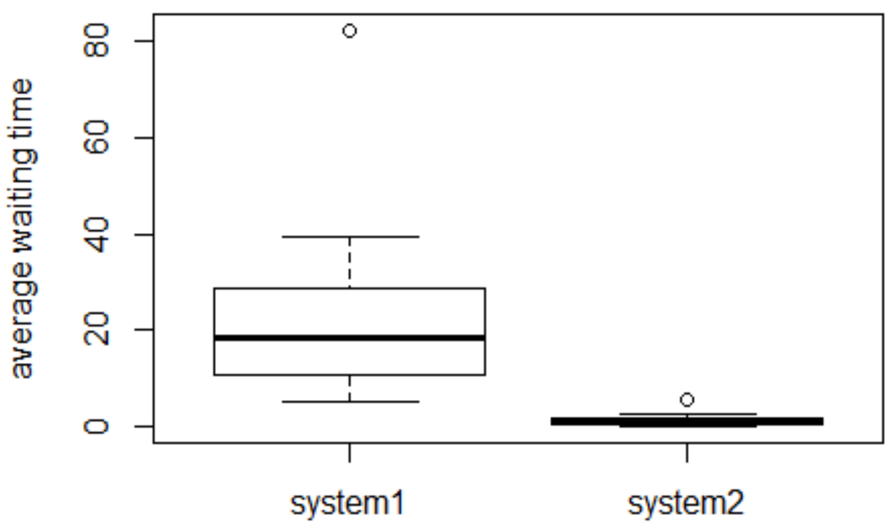
*Histogram of Patient Waiting Time with 3 Doctors*




From the illustration, above 90% of patients received service before 5mins as shown above. At a glance when comparing initial model with 2 resources, it is indicative that the system was over stressed leading to overcrowding with patients. In the suggested system, wait-time of patients reduced by 100% making the system more efficient and less crowded. As part of an illustration, a boxplot was created to visualize wait-times of patient in ***Fig.6.***

***Fig.6***

*Boxplot of Patient Waiting Time with 2 Systems*




From the plot the average waiting time was **"22.4372"** mins in system1 and after adding additional resource in system2 the mean average waiting time was **"1.128757"** mins. The boxplot above confirms this difference. System 1 represents the normal operating model conditions, while system 2 is the suggested operating condition with additional resources.

**Patient Time Metrics**

Flowtime refers to the total time a patient spends at the ED. It indicates patients' entire movement including activity time and waiting time, and it tells us how long each patient took to be processed in the system based on their priorities (Triage level). At the start of the project, we indicated 2 priority levels. Level 1 – Needs immediate attention (NIA) and level 2- Can wait (CW). Below table shows how data was captured in the model. The table also includes start and end time and activity time.

***Table.1***

*Random Sampling Data of Patient Priority and Wait time.*

| | name | start_time | end_time | activity_time | finished |
|---|---|---|---|---|---|
| 1 | Need immediate attention0 | 0.20000 | 15.38026 | 15.18026 | TRUE |
| 2 | patient0 | 15.75155 | 41.49757 | 25.74602 | TRUE |
| 3 | patient1 | 43.59993 | 139.22985 | 92.78040 | TRUE |
| 4 | Need immediate attention1 | 0.80000 | 146.21712 | 122.07154 | TRUE |
| 5 | patient2 | 62.66661 | 151.72114 | 38.68639 | TRUE |
| 6 | patient3 | 74.72511 | 180.66427 | 32.36346 | TRUE |

If you notice the table, patients with level 1 priority (Need Immediate attention), did not wait to see the doctor as they were giving immediate medical attention. The start time for this patient was within seconds, unlike level 2 priority patients who had start time values because they had waited to see the doctor. The average flowtime in system1 was 50min for NIA patients and 56mins for CW patients in the ED. While for system2 the average flow time was 26mins for NIA patients and 34mins for CW patients. The impact of additional resources had an impact and improved the average flowtime of patients in the system 2 the suggested operating condition when compared with the normal operating conditions.

*Activity time* is the patient timeout time, i.e., the time patient while receiving treatment from the doctor.

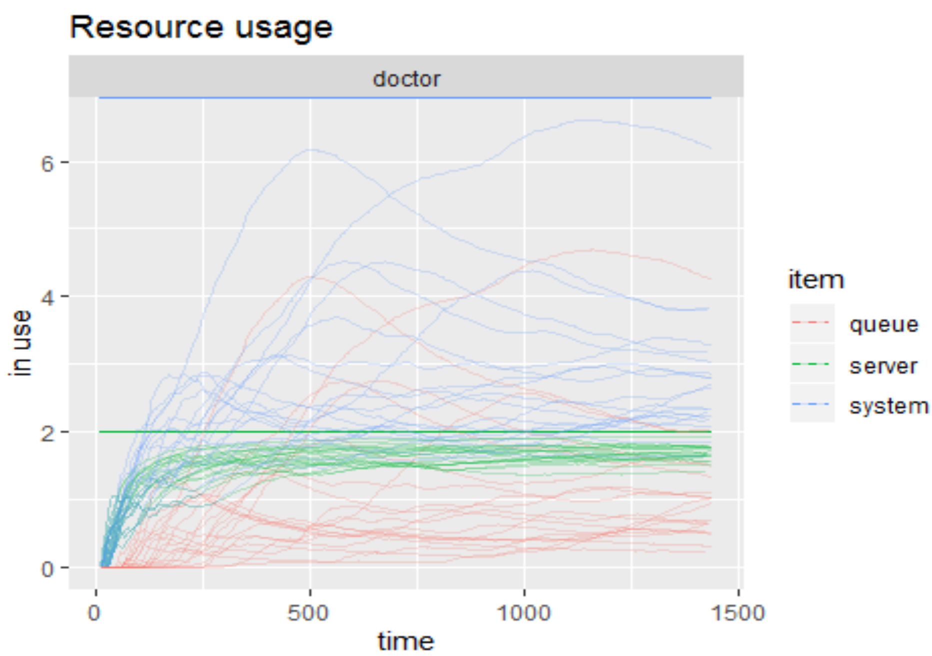
*Waiting time* is the time it takes the patients between activity times, i.e., the difference between the activity time from flow time.

**Resource Utilization on Model System**

While reviewing the ambulatory survey summary report from the National center for health statistics, there was an indication that more patients visited the ED after business hours, and this is the busiest time of the ED. Although the survey made no mention about the resource's efficiency and number of doctors available at each ED, we can assume that shortage of resources to accommodate patients care at the ED can be a reason. In the sample case we simulated, we were able to generate clear information about the resource usage. ***Fig.7*** below represents resource usage illustration from system 1 with normal operating conditions of 2 doctor resources at the ED.

***Fig.7***

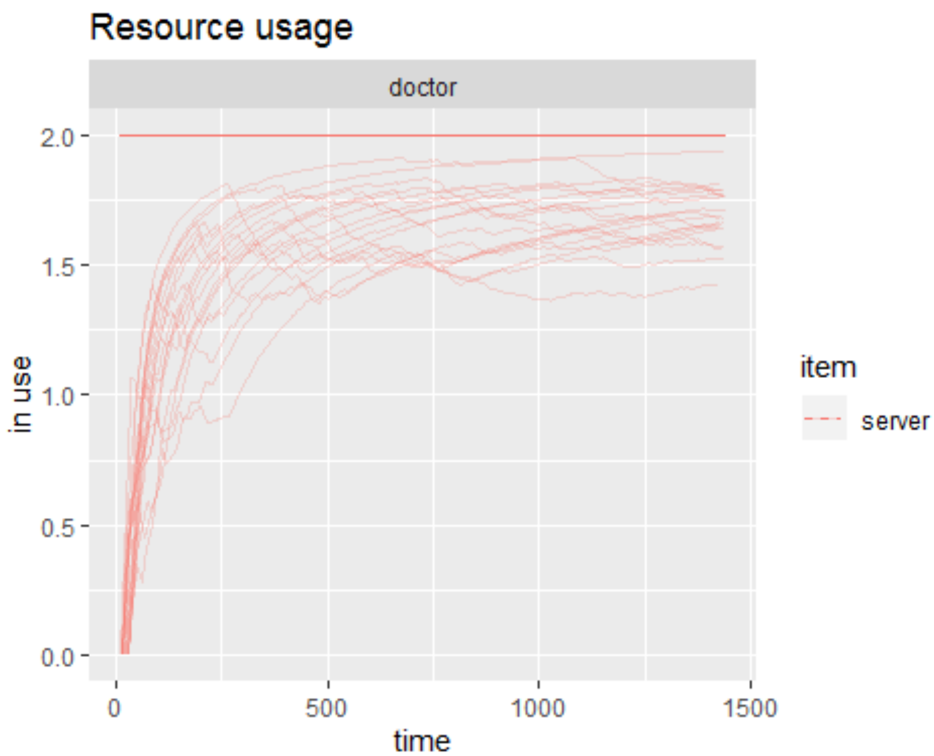
*Resource Usage – System 1*




After review, there was a clear indication that the system also appears to be very busy at the start of the mid-day till late after business hours. The blue lines represent the system usage, which went as high as 6 at some point, an indication of the number of resources the system would require to operate. The servers were also very busy and both doctors had a lot of patients waiting in the queue to receive treatment. In ***Fig.8*** we can see doctor usage within the server at max capacity from brunch period till the end of the day.

***Fig.8***

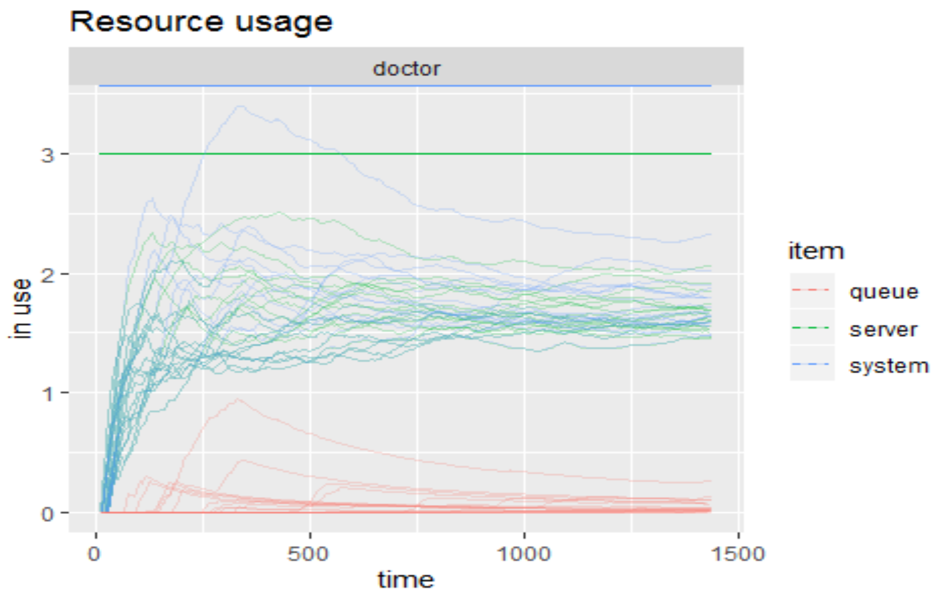
*Doctor Usage – System 1*




In the case of the suggested system, there seems to be no queue in the system, except on a few occasions when the queue was created with a single doctor resource as shown in Fig.9 below. General the system is operating optimally with additional doctor resource as not all doctors were in use at the latter half of the day. The 3rd doctor could be a part-time resource allocation.

***Fig.9***

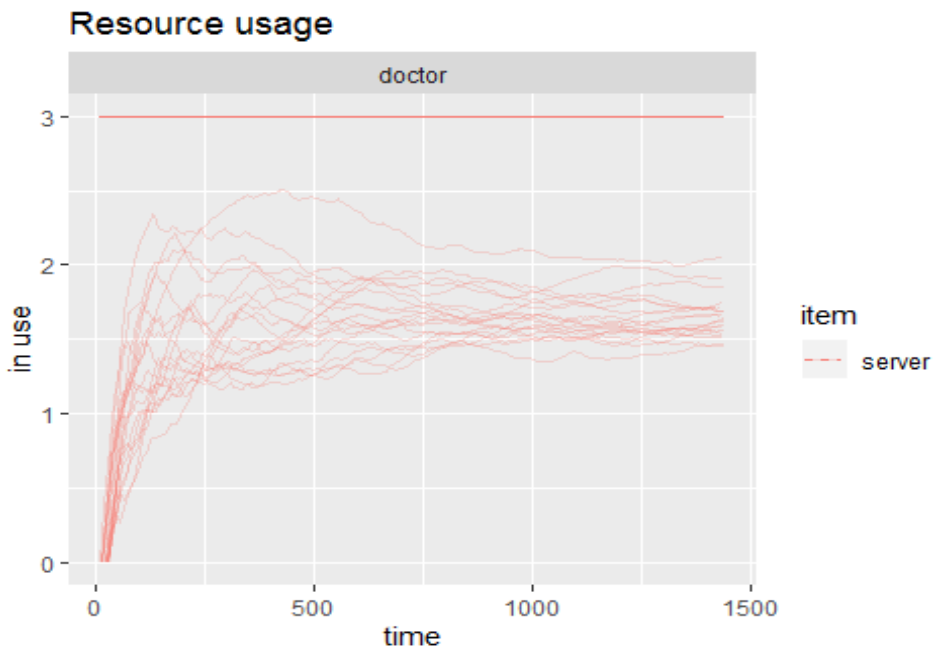
*Resource Usage – System 2*




The Doctor usuage in the system is also within acceptable tolerance as the additional doctor resource made the system more efficient. ***Fig.10*** below illustrates the effectiveness of hiring an additional resource in the system. The server is less busy with only 2 doctors in use at most times of the day.

***Fig.10***

*Doctor Usage – System 2*




**Conclusion**

For resource usage in the ED, the queuing size dropped for the better half of the day as patients in the queue was not more than 1 during the day. The server is usually busy at the beginning of the day and 2 doctors at any point in time are always in use. The 3rd doctor is less active from mid-day. That resource can be hired part time at specific periods of the day.

Hence this provides a clear picture of the resourcefulness of simulation in real world business decisions. Its's less expensive than performing live experiments on the ground. The only drawback to simulation lies in the user's capability to create the actual model that represents the real systems behavior. In the sample case we were able to create the real system environment through R-programming software and ran several replications to help with applying strategies and suggestions to improve the actual sample case through the model.

Other suggestions when applying simulation might be to try different simulation techniques if the users and managers of the ED focus on available resources in the system. One such simulation model technique is Agent based, designed to find ways to optimize resources in the ED or system.

**References and sources of the article are listed below:**

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# R-programing Code

**Analyzing results and explaining suggestions for reducing the waiting time of the patients.**

```
#install.packages("simmer")
library(simmer)
set.seed(123)
env <- simmer("emmergency room")
patient <- trajectory("patients' path") %>%
  branch(function() sample(1:2, size = 1, prob = c(0.20,0.80), replace = T), continue = c(T,T),
        trajectory("NIA Priority") %>%
        set_attribute("priority", 3) %>%
        set_prioritization(values = c(3,7,T)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 3, 77)) %>%
        release("doctor", 1) %>%

        set_attribute("wait", 2) %>%
        set_prioritization(c(2, 7, T), mod="+") %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 5, 55)) %>%
        release("doctor", 1),

        trajectory("CW Priority") %>%
        set_attribute("priority", 1) %>%
        set_prioritization(values = c(1,7,T)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 1, 29)) %>%
        release("doctor", 1) %>%

        set_attribute("wait", 2) %>%
        set_prioritization(values = c(2,7,T), mod="+") %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 2, 18)) %>%
        release("doctor", 1)
)
library(simmer.plot)
#plot(patient , verbose = T)
envs <- lapply(1:20, function(i) {
 simmer("emmergency room") %>%
 add_resource("doctor", 2) %>%
 add_generator("patient", patient, function() runif(1, 10, 30), mon = 2) %>%
 run(1440)
})
resources <- get_mon_resources(envs)
arrivals <- get_mon_arrivals(envs)
library(gridExtra)
p1 = plot(resources, metric = "utilization")
p2 = plot(resources, metric = "usage")
p3 = plot(arrivals, metric = "flow_time")
p4 = plot(arrivals, metric = "waiting_time")
grid.arrange(p1,p2,p3,p4)
```

Average waiting time

```
# Average waiting time
waitingTime = (arrivals$end_time - arrivals$start_time) - arrivals$activity_time
system1 <- mean(waitingTime)
system1
## [1] 22.4372
hist(waitingTime, main = "Patient Waiting times")
# Mean wait time
arrivalsmultiple = cbind(arrivals, waitingTime)
xbar1 = aggregate(arrivalsmultiple$waitingTime, by = list(arrivalsmultiple$replication),
FUN=mean)
```

Suggestion to reduce waiting time by increasing the number of resources (doctors)

```
# Increasing the number of resources (doctors) from 2 to 3
library(simmer)
set.seed(123)
env <- simmer("emmergency room")
patient <- trajectory("patients' path") %>%
  branch(function() sample(1:2, size = 1, prob = c(0.20,0.80), replace = T), continue = c(T,T),
        trajectory("NIA Priority") %>%
        set_attribute("priority", 3) %>%
        set_prioritization(values = c(3,7,T)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 3, 77)) %>%
        release("doctor", 1) %>%

        set_attribute("wait", 2) %>%
        set_prioritization(c(2, 7, T), mod="+") %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 5, 55)) %>%
        release("doctor", 1),

        trajectory("CW Priority") %>%
        set_attribute("priority", 1) %>%
        set_prioritization(values = c(1,7,T)) %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 1, 29)) %>%
        release("doctor", 1) %>%

        set_attribute("wait", 2) %>%
        set_prioritization(values = c(2,7,T), mod="+") %>%
        seize("doctor", 1) %>%
        timeout(function() runif(1, 2, 18)) %>%
        release("doctor", 1)
)
library(simmer.plot)
#plot(patient , verbose = T)
envs2 <- lapply(1:20, function(i) {
 simmer("emmergency room") %>%
 add_resource("doctor", 3) %>%
 add_generator("patient", patient, function() runif(1, 10, 30), mon = 2) %>%
 run(1440)
})
resources <- get_mon_resources(envs2)
arrivals <- get_mon_arrivals(envs2)
library(gridExtra)
p1 = plot(resources, metric = "utilization")
p2 = plot(resources, metric = "usage")
p3 = plot(arrivals, metric = "flow_time")
p4 = plot(arrivals, metric = "waiting_time")
grid.arrange(p1,p2,p3,p4)
```

Box plot

```
boxplot(xbar1$x, xbar2$x, names = c("system1", "system2"), ylab =
"average waiting time")
# system 1
x1 <- get_mon_arrivals(envs)
x2 <- get_mon_attributes(envs)
all <- merge(x1, x2, by=c("name", "replication"), all = T)
NIA <- subset(all, all$value == 1)
CW <- subset(all, all$value == 2)
NIA.flowTime = (NIA$end_time-NIA$start_time)
CW.flowTime = (CW$end_time-CW$start_time)
# Average
mean(NIA.flowTime, na.rm = T)
## [1] 50.43305
mean(CW.flowTime, na.rm = T)
## [1] 56.56924
# system 2
x1 <- get_mon_arrivals(envs2)
x2 <- get_mon_attributes(envs2)
all <- merge(x1, x2, by=c("name", "replication"), all = T)
NIA <- subset(all, all$value == 1)
CW <- subset(all, all$value == 2)
NIA.flowTime = (NIA$end_time-NIA$start_time)
CW.flowTime = (CW$end_time-CW$start_time)
```

```r
# Average
mean(NIA.flowTime, na.rm = T)
## [1] 26.053
mean(CW.flowTime, na.rm = T)
## [1] 34.63424
# system2 usuage and utilization
resources <- get_mon_resources(envs)
plot(resources, metric = "usage")

plot(resources, metric = "usage", c("doctor"), items = "server", "queue")
```