



A DISCRETE EVENT SIMULATION (DES) BASED APPROACH TO MAXIMIZE THE PATIENT THROUGHPUT IN OUTPATIENT CLINIC

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Article Received: 15-04-19

Accepted: 15-07-19

Published: 05-08-19

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ABSTRACT

The healthcare system is a complex system which exhibits conditions of uncertainty, ambiguity emergence that incurs incoming patient congestion. Discrete event simulation (FlexSim) is considered as a viable decision support tool in analyzing a system for improvement. Using a data-driven discrete event simulation approach, this paper portrays a comprehensive analysis to maximize the number of patients in an on-campus clinic, located at Mississippi State University. The outcome of the analysis of current system exhibits that deploying a few nurse practitioners results in bottlenecks which decreases the systems' throughput substantially due to the overall longer patients' waiting time. Access to the laboratory is characterized through multi-server queuing network, arrival process is followed discrete distributions, and batch sizes and arrival times are stochastic in nature. In an effort to plummet inpatient congestion at the outpatient clinic, by using empirically calibrated simulation model, we will figure out the best balance

between the number of the lab technician and incoming patient during working hour. An analysis of optimal solutions is demonstrated, which is followed by recommendation and avenues for future research.

Keywords: Healthcare, System Simulation, Discrete Event Simulation (DES), Patient Throughput, Waiting Time.

INTRODUCTION AND PROBLEM DESCRIPTION

Because of the increasing number of students and faculty, on-campus health centers are some of the most demanding outpatient clinics. Campus health centers are a convenient, and usually affordable, location for college students to obtain quick, effective health care service, so they can maintain an active academic schedule. On-campus Mississippi State University health center is under increasing pressure to reduce waste, eliminate unnecessary costs and redundant efforts, thereby improving the quality and consistency of healthcare delivery. Lack of automation is a critical factor that can help improving process efficiency. Recently, many research has been conducted related to healthcare simulation. Various models and techniques have been developed and analyzed to determine the optimal solution of various healthcare system problems. De Vasconcelos et al. (2018), Moon et al. (2015), Prodel et al. (2014), Nagahisarchoghaei et al. (2018), Abutabenjeh et al. (2019), Ahmadi et al. (2014a, 2014b), Raunak et al. (2009), Hossain et al. (2017) used simulation techniques in emergency healthcare systems. Chuang et al. (2018), Roh et al. (2013), Marmor et al. (2013), Soleimani et al. (2018) Nagahi et al. (2018), Hossain and Jaradat (2018), and Tyler et al. (2003) developed other models to provide better resource management solutions for the healthcare sector, and Kabaso et al. (2015), Montañola-Sales et al. (2015), and Adams et al. (1998) developed varied simulation models to circumvent the severity of pandemic diseases. Chen et al. (2018), Norouzzadeh et al. (2015), Jin et al. (2013), and Jacobson et al. (2006) focused on improving the healthcare system's performance by dint of reducing patient waiting time. Monahan and Fabbri (2018), Turkcan et al. (2014), Hossain et al. (2019), and Kaandorp and Koole (2007) concentrate on improving appointment scheduling techniques. Other than the healthcare simulation models, Ma et al. (2019) have developed a Virtual Reality based teaching module to provide more immersive experience to the users in a simulated way.

Because of the dynamic and emergent nature of healthcare systems, the patient wait time is still a big issue in today's healthcare systems. Thus there is an need to employ a "system approach" to better handle the intricacies stemming from any kind of complex system (Alfaqiri, 2019; Hossain & Jaradat, 2016, 2018; Lawrence et al., 2019; Nagahi, Hossain, & Jaradat, 2019; Nagahi & Jaradat, 2019; Nagahi et al., 2019; Stirgus et al., 2019). Therefore, we used a discrete event simulation –FlexSim to find optimal ways to reduce patient wait time in this paper and select the John C. Longest Student Health Center (LSHC) at Msstate as a case study to reduce patient wait time for the X-ray laboratory. LSHC employs physicians and nurses who are qualified to treat patients from most illnesses and capable of handling most medical emergencies including x-rays, shots, blood work, and trauma (UHS, 2019). The health center hours are from 8 am to 5 pm

during the week, and during those hours the health center is capable of assisting up to 200 patients. Most patients are treated adequately with a short amount of time. However, patients in need of X-rays usually need more time to go through the process of treatment. Only one technician handle the X-ray work process (taking picture) which takes around 5-15 minutes per patient. Our objective is to reduce bottlenecks that are created in the X-ray lab, and reduce patient's service time in the X-ray lab. By achieving this objective, more LSHC patients will be treated with a better quality of treatment. These objectives will be met by using Flexsim software to build a model and simulate the system under different variables that affect service utilization and work in process time.

In the current system, X-ray patients are routed in three ways, normal route and 2 reroute routes. The normal route requires patients to wait in the initial queue, enter the X-ray lab till technician take their picture, wait in a second queue to see the doctor (main processor), see the doctor and then exit the system (see Figure 1). The second and third reroute route requires patients to wait in the initial queue, enter the X-ray lab, see the subsidiary doctors (second and third processors) and then leave the system. The current system (LSHC) has 70% of patients routed through the normal route and 15% rerouted in second and third routs, respectively. We hypothesize that increasing the percentage of patients who are rerouted will decrease waiting times and increase the throughput of the entire system. Observations and data have been collected and inserted into the developed simulation model (see Figure 1). To show the real system, we developed a simulation model by using FlexSim software. According to the data collection, we manipulated and analyzed different percentages of X-ray patients in each route to obtain an optimal solution for patient routing, to reduce wait time, and to increase system throughput without actual changes in the current system.

The objectives of the paper are:

- To evaluate why bottlenecks are created in the X-ray Lab.
- To come up with potential recommendations to reduce patient's waiting time in the X-ray Lab.
- To observe how manipulating patient routing might impact the wait time and throughput of the system in the X-ray lab.

Following the introduction, the second section illustrates the developed simulation model in detail, and the third section shows the experimental design analysis, and the fourth section validates the proposed simulation model. The fifth section presents an analysis of the model output. Finally, the last section gives some recommendations based on the analysis results.

SIMULATION MODEL

To propose a simulation model for the study, this section is divided to four parts including, modeling assumption, key performance measures, key decision variables, and system description.

Modeling Assumptions

Following assumptions are considered to create the simulated model:

- (1) All patients entering the system will necessitate x-ray work. No other patient type will be considered in the system. Patients will only be able to enter the system from 8pm-4pm.
- (2) The first patient to enter the system will be the first patient to exit the system
- (3) The system will operate for nine consecutive hours to represent the normal operation hours of 8 am to 5 pm. However, the source will close one hour before the rest of the system to allow all patients to travel the length of the system (The actual system does not always abide by this and fluctuates its closing hours. This will likely impact the throughput of the system which will be explored in the validation results.)
- (4) Physicians, nurses, and technicians will always be available when the processors are empty of previous patients.
- (5) There will be no bulking or renegeing.
- (6) Arrival rate will follow a Triangular Distribution (because of lack of data, the distribution is not certain) and service time will be independent (exponential distribution).
- (7) For the Qu_X-Ray and the Qu_Doctor1 have a maximum capacity of 5 and 3 patients respectively.

Key Performance Measure

The performance measures of the system are presented as follows:

- The average wait time of patients in the second Queue (Qu-report)
- The throughput of the X-ray lab (entire system).

Key Decision Variables

The decision variable of the system is the percentage of patients that move through the normal route and two rerouted routes. Currently, the system flows 70% of the patients through the normal route and 30% of patients through the rerouted routes. Other than X-ray patients, no other patients entered the system for any case. The time that the system open for patients is from 8 a.m. to 4 p.m.

System Description

The simulation model presented is initiated by the arrival of patients in the system. Patients are then required to wait in the X-ray queue labeled Qu_X_ray in figure 1. Patients would wait to be processed in the X-ray room in order to take X-rays as specified. Once patients have been processed they are sent to the normal route which is the Qu_report, and follows is the Pr_Doctor who is a doctor that explains the X-rays and results. The normal route is taken by 70% of patients. The other 30% of patients are divided equally by two other doctors (Pr_Doctor_2_Reroute and Pr_Doctor_3_Reroute). The 30% are immediately seen by a doctor after they have been processed in the X-ray room (Pr_X_ray) and then sent to the sink which is exiting the system. Using this system, we have eliminated two queues for doctor 2 and 3. Figure

1 is a snapshot of the model using Flexsim, and Figure 2 is the object flow diagram (OFD) of the system. Both figures are presented below.

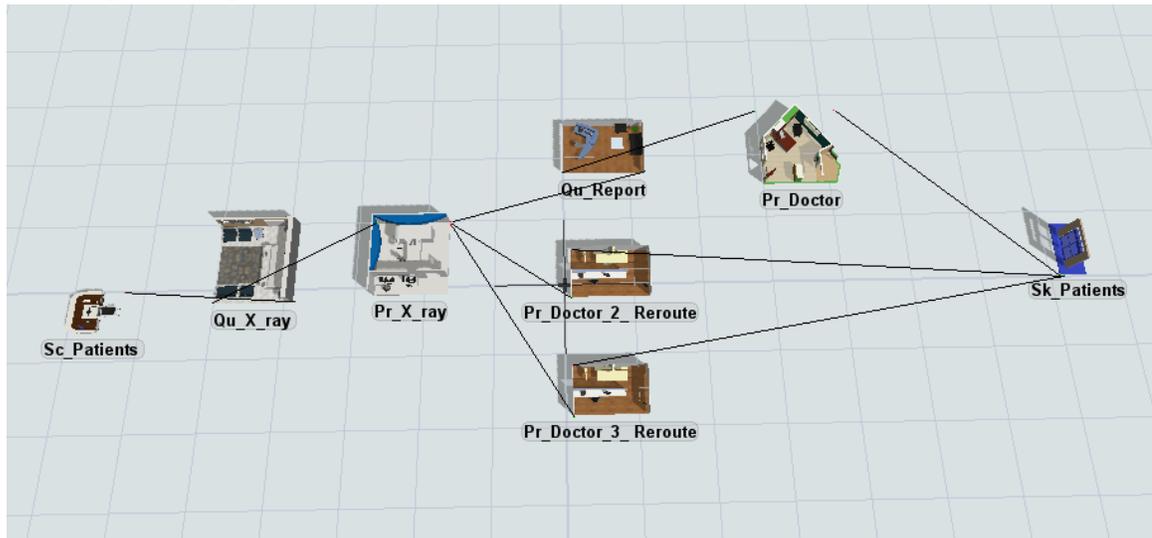


Figure 1. Model view in FlexSim interface

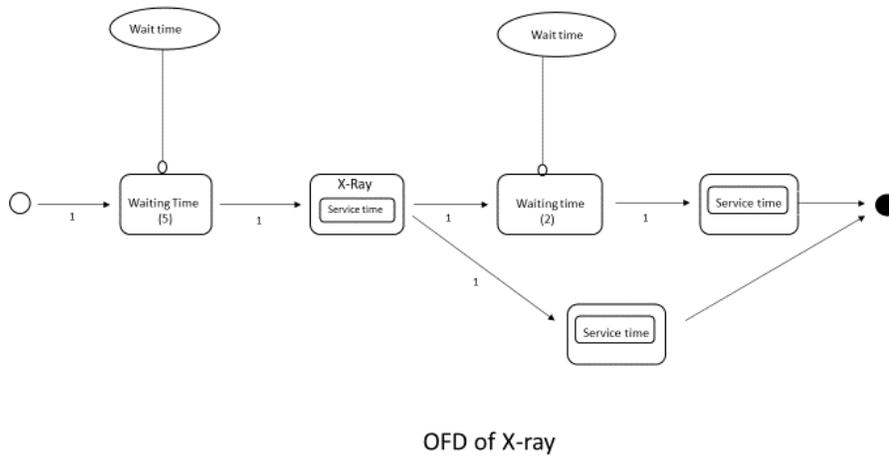


Figure 2. Object flow diagram (OFD) of X-ray Laboratory

The Basic properties of fixed resources are as follows:

Table 1: Basic properties of fixed resources

Object name	Description	Capacity	Downtime	Process Time
Sc_Patients	Source	---	4pm-9am	---
Qu_X-ray	Queue for X-ray	5	5pm-9am	---
Pr_X-ray	X-ray processor	1	5pm-9am	4 min
Qu_Report	Queue for Doctor	3	5pm-9am	---
Pr_Doctor_1	Doctor 1 processor	1	5pm-9am	15 min
Pr_Doctor_2_	Doctor 2 processor	1	5pm-9am	15 min

Reroute				
Pr_Doctor_3_	Doctor 3 reroute	1	5pm-9am	15 min
Reroute	processor			
Sk_Patients	Sink	---	5pm-9am	---

MODEL VALIDATION

The Student health center provides services to approximately 20,000 patients in 9 month time period when the university is in session. The implemented model with initial condition results in 24,563 patients over the same period. The reason for the discrepancy is no doctor (processors) dedicated only for X-ray lab. Those three doctors examine patients with different kinds of issues from the cold, flu, X-ray, and so on. The second reason is that the changes in health center opening and closing time affect the operation hours.

EXPERIMENTAL DESIGN

The source (Sc_Patients) follows a Triangular (5, 7, and 6) distribution to uphold entering six patients per hour to the system. The capacity of the Queue (Qu_X-ray) is 5, and all patients wait there before receiving the service. A global table is created with initial conditions of 70% of Route I, 15% of Route II, and 15% of Route III. Processor (Pr_X-ray) uses to send to port by case with Route I sent to Qu_Report (normal route), Route II sent to Pr_Doctor_2_ Reroute (Doctor 2 reroute), and Route III sent to Pr_Doctor_3_ Reroute (Doctor 3 reroute). The model runs for 259,200 minutes. The time is based on 180 working days with 9 hours of each day over 9 month period. To account for variance between separate replications, the model is set to run ten replications. A warm-up period is not included as no patients are waiting in line at the beginning of each day. The experiments details are summarized in Table 2.

Table 2: Experiments details

Scenario	Variables			Performance Measures	
	Global Table Row 1/Col 1 (Route I)	Global Table Row 2/Col 2 (Route II)	Global Table Row 3/Col 3 (Route III)	Qu_Report Wait Time min (Mean)	System Throughput (Patients/9 months)
1	70	15	15	43	24563
2	80	10	10	45	21532
3	90	5	5	45	19191
4	60	20	20	40	28309
5	50	25	25	34	32462
6	40	30	30	22	34312

Figure 3 represents the Qu_Report wait time for the six scenarios and Figure 4 shows the throughput of the system for the same scenarios.

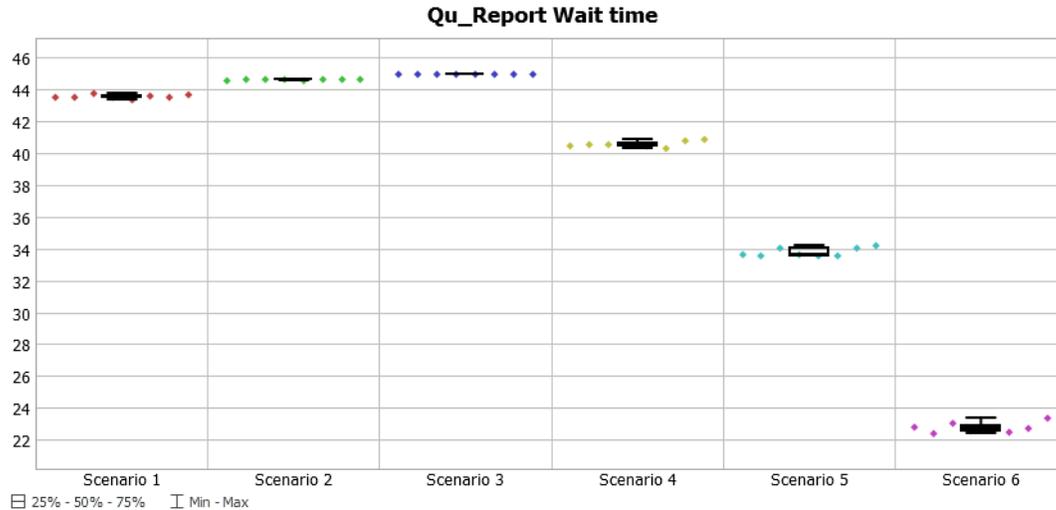


Figure 3. Qu_Report Wait time analysis under six scenarios

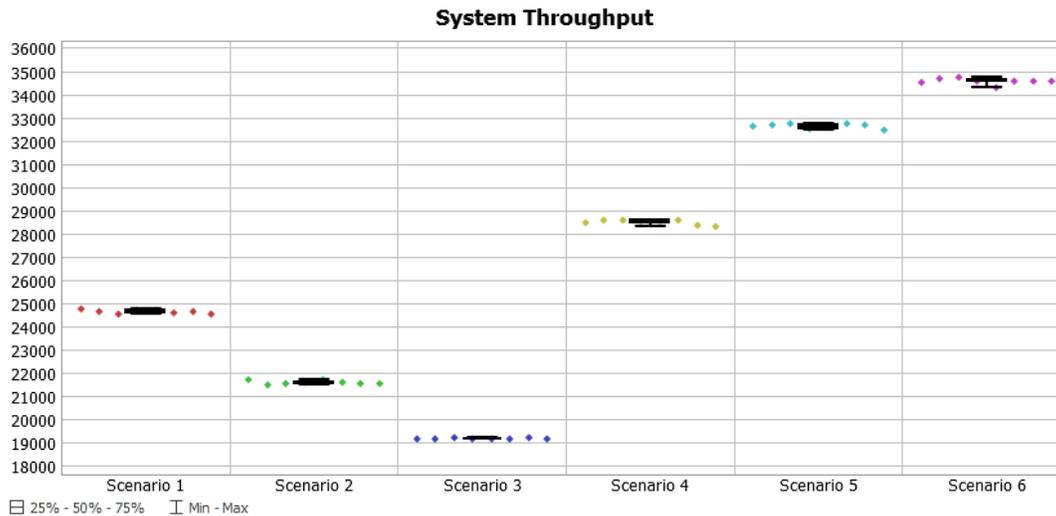


Figure 4. System throughput analysis under various scenarios

RESULT OF ANALYSIS

The system is designed to manipulate the actual X-ray lab system in LSHC as closely as possible with stated assumptions. A bottleneck is identified in the queue (Qu_Report) through a system run with initial conditions. The global table is used to define the percentages of patients labeled Route I (Sc_Patients- Qu_X-ray- Pr_X-ray- Qu_Report- Pr_Doctor - Sk_Paitents), Route II (Sc_Patients- Qu_X-ray- Pr_X-ray- Pr_Doctor_2_Reroute- Sk_Patients), and Route III (Sc_Patients- Qu_X-ray- Pr_X-ray- Pr_Doctor_3_Reroute- Sk_Patients) and manipulate the percentages to check the normal route and reroute routes. In Flexim, the Experimenter option under the Statistics tab is used to analyze different scenarios. For each scenario, Qu_Report Wait Time and System Throughput were calculated to analyze the system. Based on the results above,

a ratio of 40% Route I, 30% Route II, and 30% route III showed the lowest mean wait time (22 min) in Qu_Report and greatest System Throughput (34312 patients/9months).

CONCLUSIONS AND RECOMMENDATIONS

The current system rerouting 30% of patients (15% each) to Doctor 2 and Doctor 3 has created the bottleneck in the queue which results in higher waiting time. The results of this study suggest 40% of patients should follow the normal route in the x-ray lab, and 30% should be rerouted directly to Doctor 2, and the other 30% should be rerouted to Doctor 3. The increasing percentages in reroutes decrease waiting time and increase the throughput of the system by ~40%. Based on the results, it is recommended that John C. Longest Student Health Center should increase the percentage of rerouting from 30% to 60%.

ACKNOWLEDGMENT

Authors would like to express their appreciation to Dr. Raed Jaradat, assistant professor, and Niamat Ullah Ibne Hossain, doctoral student, from the Department of Industrial and Systems Engineering at Mississippi State University, for their constructive guidance.

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