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Development of a Simulation Model for Analyzing Outpatients' Waiting Time in a Health Center

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Abstract—Healthcare centers constantly experience a high influx of people seeking health services and facilities. Outpatients often have to wait in long queues at different sections of the facility being serviced. This study analyzed the patients' waiting time in a university healthcare center in Nigeria using a discrete event simulation technique. The movements of people within the system were studied to collect data. Queuing parameters of arrival and service rates for each department were derived from the probability distributions. A discrete event of the system model was built and simulated for 24 hours. The result shows that the patient arrival pattern follows a Poisson distribution with an average arrival rate of 11 patients per minute. Consultation rooms 1, 2, 3, and 4 have arrival rates of 15,4,10, and 4 patients per minute respectively. The simulated and optimized system ouputs indicated drastic reduction of 38-60% in patients' average waiting times. The study suggested an additional consultation room and a server added to the records and laboratory units.

Index Terms—Discrete Event Simulation, Healthcare, Outpatients, Queuing Pattern, Waiting Time.

I INTRODUCTION

The operation of a health facility is closely related to the job shop scheduling problem with several jobs (patients) and job processing centers (units, doctors, wards). The healthcare industry, comprising health centers, hospitals, pharmacies, and other outlets, has become indispensable in societies with a constant influx of people in need of care. In hospitals and health centers, departments that take in outpatients often experience long queues, resulting in long waiting periods, especially in underdeveloped countries with limited health facilities [1, 2]. The arrival pattern of patients at the facility is unpredictable with a high degree of uncertainty [3]. In addition, the period of the day, weekdays, seasonal variations (harmattan), and epidemics may also impact patients' influx. Maintaining orderliness within the facility requires the introduction of queuing mechanisms while patients wait for their turns to be attended to. Queues are often encountered in all units, from outpatients to inpatient wards and specialized units. The scheduling problem demands that servers follow certain priority rules during servicing for fairness [4]. With the arrival of patients to access healthcare services, each patient follows a different route in the facility based on the nature of the illness, while each of the units within the health facility (arrival, consultation room, laboratory, pharmacy, etc) is a processing center. The challenge is in the procedures of assigning and sequencing each patient since each patient needs to be treated one at a time per center. In the facility, the problem of assigning patients increases as the number of arrivals increases for a fixed number of processing centers. Analyzing patient flow is complex owing to the randomness of arrival times, the criticality of the illness, cases of emergencies, and the various departments involved, especially in the facility [5]. To reduce the mean waiting time of patients, clinic scheduling is often introduced, and appointments are given to patients [6]. However, the effectiveness of these appointments is based on the clinician at each processing center.

Spending time in queues, no matter how small, is quite undesirable since useful time could be spent doing other things. Also, a patient's health condition may worsen while waiting to be attended to by the doctor. Some patients are often fatigued resulting in low productivity for the rest of the day due to prolonged waiting in the hospital facilities. Studies have shown that extended waiting times result in some patients leaving the queue [7]. Time may be translated to money, and the possibility of fatality if a critically ill patient is not promptly attended to is higher; thus, a solution to this problem is highly desirable. However, it is expedient to ensure that patients' waiting time is not reduced at the expense of the quality of service rendered [8].

Simulation imitates real-world events, processes, or systems over time [9]. Several studies exist and authors have adopted the simulation approach to solve different problems in the health sector. Based on the classical perspective, these three categories of simulation are widely used: the discrete event, continuous event, and the Monte Carlo simulation techniques. Queuing theory is the basic model used in such studies, although some have resorted to employing the virtual simulation approach using the Discrete Event Simulation (DES) technique [10, 11, 12]. DES is used to study the behavior of dynamic systems over time [13]. DES is a powerful tool used to predict and analyze the performance of complex systems for improvement [14]. It is based on discrete events occurring randomly, such as entity arrival and departure times in a system. Studies show various integrations of DES and other optimization techniques to improve its applicability and output accuracy. For instance, DES models introduced into a queueing-theoretic framework simplify the simulation procedures, resulting in runtime savings [15].

DES is commonly used to model physical systems that change behavior over the simulation time [16]. DES relies on statistical distributions to model variability and randomness in systems. The appropriate selection of statistical techniques impacts the accuracy of simulating patients' behavior in healthcare and validation with significant improvements with suitable choices [17]. The inter-arrival times, service times, processing times, and patient queuing behavior are highly randomized and complex. Using DES tools helps healthcare providers gain insight into the system's performance. Without additional resources, simulating the impact of adjusting consultation start times with patient arrivals in a dual practice outpatient clinic using DES drastically reduced patients' turnaround times by up to 40% [18]. In the simulation of the Emergency Department performance in a hospital, DES approaches were utilized to assess resource allocation and patient flow.

In the healthcare sector, the application of DES extends into various categories comprising behavior, disease progression, operations, consultation, laboratory testing, and screening modeling [19]. The discrete event simulation was adopted to optimize the allocation of constrained hospital resources for glaucoma [20]. DES modeling is expected to draw increasing attention globally, owing to the need to improve system performance and improvements in computing capabilities. Several researchers have used DES models to reduce the waiting time of hospital outpatients using a single queuing discipline [21]. For instance, a discrete-event simulation of healthcare systems was developed to minimize delays in healthcare delivery using the system parameters of queuing [22]. However, DES models often assume static patient behavior, this may not entirely replicate the complexities of human decision-making [23]. To address this limitation, DES was integrated with Agent-Based Simulation (ABS) to model the system processes and individual patient behaviors in an orthopedic department, reducing total waiting time [24]. In emergency departments, the integration of DES and Agent-Based Simulation (ABS) was reported to streamline healthcare processes and care efficiency [25]. Combining DES with Data Envelopment Analysis (DEA) improved outpatient clinic performance [26]. This framework offers a basis for evaluating the performance of clinics, identifying improvement opportunities, and optimizing resources. DES integrated with Digital Twins (DTs) was adopted to analyze warehouse logistics [27]. The result shows improvements in real-time decision-making and system responsiveness

Although DES offers a valuable platform for assessing the effects of various configurations of resources on system performance by replicating facility behaviors and structures. Studies incorporate the dynamics of patient and staff behavioral responses to system changes in simulation modeling. This may bridge the gap between reality and the simulation outputs. Troubleshooting healthcare processes using DES models requires significant time. Studies reveal that only 50% of these models were entirely reproducible, posing substantial hindrances in application to solve real-world problems [28]. Studies may be tailored towards low-resource environments, specifically in the healthcare sector, where patients face the largest waiting time due to resource constraints.

In the observed health facility, preparatory activities (setup) are performed before patients are allowed to access the doctor or consultant. Patients have to wait for long hours to eventually get access to their records, see the doctor, or take their samples to the laboratory to be tested. In these sections, patients frequently encounter queues that they must join to access the service. This is an extremely undesirable situation because it demands that patients spend a significant amount of the day in queues, preventing them from carrying out other activities. Oftentimes, the duration of service is usually small compared to the amount of time patients wait in line. Given the daily influx of people to access health facilities, the issue of waiting in queues for service is quite inevitable [29]. Hence, a need to reduce patients' prolonged waiting time in the health facility without compromising the quality of service provided. This study developed and simulated a discrete event simulation (DES) model of the operations of a health facility, intending to minimize outpatients' waiting time using simulation software. In achieving this, the objectives of the study include evaluation of the current practices of the selected system, developing a discrete event simulation (DES) model to minimize the waiting time of outpatients in the health center, and evaluating the model to deduce relevant insight about the outpatients' movements in a health facility.

II THEORETICAL FRAMEWORK

The healthcare system is replete with several variables requiring optimization for better performance and efficient operation of the system. Some of these variables include the waiting time of the patients, the service time, patient scheduling problem, optimal allocation of ward rounds among medical personnel, the shift problem among nurses, allocation of medical facilities among patients, micro-machining of clinical equipment at optimal cost, the budgetary problem in healthcare pharmaceutical stores, planning geographical locations of new health care services taking into account proximity to patients in need of it, etc. [30, 31]. This requires the application of operations research techniques to minimize waste and eliminate non-value-adding processes. The use of discrete event simulation techniques for resource allocation of scarce resources, especially in cases where patients' arrival times are irregular, has caught the attention of several researchers [22, 30, 32]. The use of a multi-criteria decision approach for both resource allocation and patient satisfaction was demonstrated using the framework in Figure 1.

Simulation models the operation of a system to study the system's behavior and to determine the relationship between its components [33]. Simulation is often adopted to investigate the set of parameters that optimizes the system's performance or characteristics [34, 35]. Optimization by simulation process often follows the general form of Equation 1;

$$Min\,\{g(x) = E_X\,[\,Y(X)]\}\,, X \in \ominus \subset \Re^d \tag{1}$$

Where X is the vector of decision variables often referred to as solution.

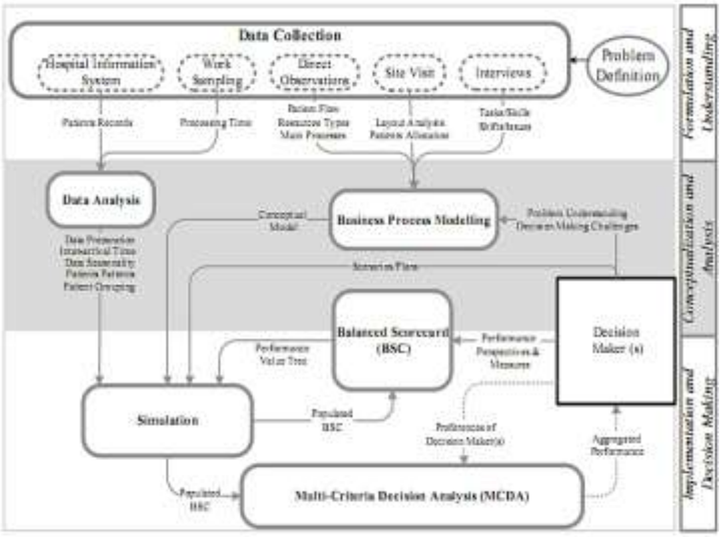


Figure 1 Multi-criteria Decision Framework [30]

The expression minimizes the objective function as a function of the expected value of a random variable whose distribution depends on the random decision variable X. The function represents the feasible region. ⊖. Discrete-event simulation applies to systems whose states change at discrete instants of time, having a limited number of changes occurring within any finite time interval [36]. The entities of the DES models consist of *attributes* that describe specific features of the system. These features include entity type, priority, dimensions, weight, order number, and time in the system [37, 38]. The attribute values vary from entity to entity, these attributes may be to determine the system's logic. For instance, the attributes of a system include the time individual entities spend performing an activity, the priority of an individual in a queue, or its route through the system. DES empowers simulators to easily model the details of individual entities of the system with a high degree of precision [39].

The multi-server, single-phase queuing system is popular within the outpatient departments of most healthcare facilities. This system is characterized as composed of more than one service facility providing identical services, drawing from a single waiting line [10]. Each unit of the facility (e.g., consultation, pharmacy) is considered a separate phase and an independent unit with its own queue. Since the population is unrestricted, the queue is infinite. The queuing system is described as a *M/M/C* model known as a multi-channel system. Some characteristics of this type of system observed show that patients awaiting service join a single queue with a service discipline of first-come, first-served (FCFS); patients proceed to any of the variable servers, and all servers are assumed to operate at the same rate. Arrival is supposed to follow a Poisson distribution, while service rates are exponentially distributed [10].

Similar studies of using a discreet event simulation approach in reducing waiting time exist including solving the problem of resource utilization [40], improving out-patient waiting time using simulation [41], and simulating patient flow in healthcare systems to reduce delay in healthcare delivery [37], analyzing waiting lists based on prioritization system for cataract surgery [42], determining the optimal times for treating patients with acute stroke [43], and optimizing the allocation of constrained hospital resources for glaucoma patients [20] among others. These studies examined several appointment times and compared them with current practice. Critical factors that influence long queues and prolonged waiting time were identified including service order, resource availability, and type of patient (whether a new patient, a follow-up patient, or a scheduled patient).

III METHODOLOGY

A The Outpatient Department

The outpatient department of the University of Ibadan Health Center was chosen as a case study. The current practice of the system was investigated. Personal observations of the system were carried out, aided by the use of questionnaires. The hospital consists of several departments which include the medical records department; medical laboratory department; radiology department; eye clinic; Consultation, and pharmacy. These departments were covered except the eye clinic, owing to little or no queue observed in this department.

B The Human Flow Process in a Health Facility

Figures 3 and 4 depict the hospital layout and the flow of patients within the facility. The arrows (Figure 2) depict the movement of patients across the system and C1 to C12 are consultation rooms. Upon arrival, patients register their presence by writing their identification numbers in a logbook in the waiting room. A single queue is maintained, and patients are served by a single server (M/M/1). During this process, the patient's physiological data are taken, including blood pressure and weight. Medical records of the patients are retrieved from the records department and brought to the waiting room. Balking often occurs (a situation whereby patients decide not to enter a queue probably due to the length of the queue). Patients are called into another set of queues that serve the consultation rooms in the order in which they arrived, a first-come first first-served (FCFS) discipline. The service system in the consultation room is characterized by the M/M/1 model. At this stage of the process, reneging seldom occurs (a situation whereby patients decide to exit the queue before being served). However, jockeying was not allowed. From the waiting room, the patients are led to the consultation rooms where they are diagnosed. The hospital has three blocks of consultation rooms each with three rooms (Figure 2). Each consultation room has an average of one doctor. Patients are distributed into waiting lines located outside these rooms (another queue), maintaining the FCFS discipline. Here, reneging, balking, or jockeying were not observed. Upon diagnosis, patients are either referred to the pharmacy, the laboratory, or the X-ray department. Patients referred to the laboratory and radiology departments for medical investigations often return to the clinician for final examination of test results and then to the pharmacy. From the pharmacy, patients exit the system. The layout of the clinic and the process described above are illustrated in Figures 2 and 3 respectively.

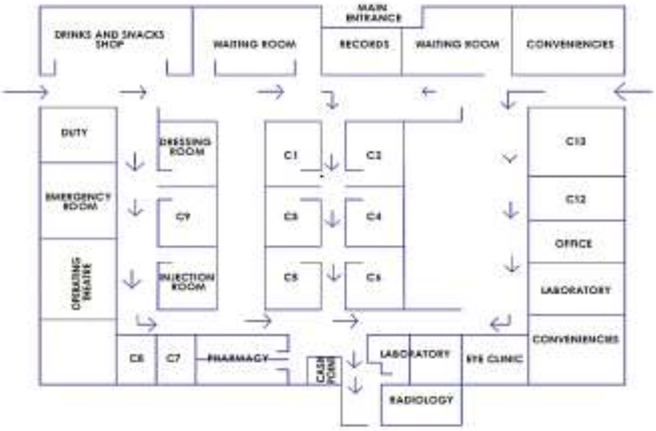


Figure 2 Hospital Layout and Patient Flow Pattern

C Model Development

The model incorporates the activities in the various units and their interactions with activities in other units. Model parameters were obtained from the data collected. This model was made to represent the system as much as possible. Simulink blocks were developed to form the whole system. Activities in each department are modeled to form subsystems (Figure 3).

1. Definition of Terms

The following terms were used during the model development and are defined: ***Entities-*** These are physical items of interest, the patients. ***Entity Generator-*** Simulink blocks generate the system inputs based on intergeneration time, specific generation times, or random generation frequencies. ***Queues-*** Queues hold entities for storage for a particular period until they are served. ***Servers-*** Blocks that distribute resources to entities released from a queue. Certain departments have a single server like the pharmacy, while others have multiple servers, like the consultation room. ***Attributes-*** Individual characteristics of each entity within a system. ***Time-Out Blocks-*** Simulink blocks are used to model impatient customers. ***Entity Splitter-*** This block splits out entities from a server into two or more queues such that they wait to access a resource. ***Entity Combiner-*** This block combines several entities already split into a single queue to jointly access a resource. ***Signal Scope-*** This block displays the expected output statistic of interest. ***Entity Sink-*** Entities generated from the entity generators are made to terminate at the entity sinks.

2. Model Assumptions

a. *Statistically, patients' arrival rate follows a Poisson distribution while the service rate assumes an exponential distribution.*

b. *There is no preemption in the server, i.e., a patient is fully attended to before the next.*

c. *The first-come-first-served (FCFS) queue discipline is obeyed.*

d. *Patients returning from the laboratory and other supporting departments are attended to next without having to rejoin the queue.*

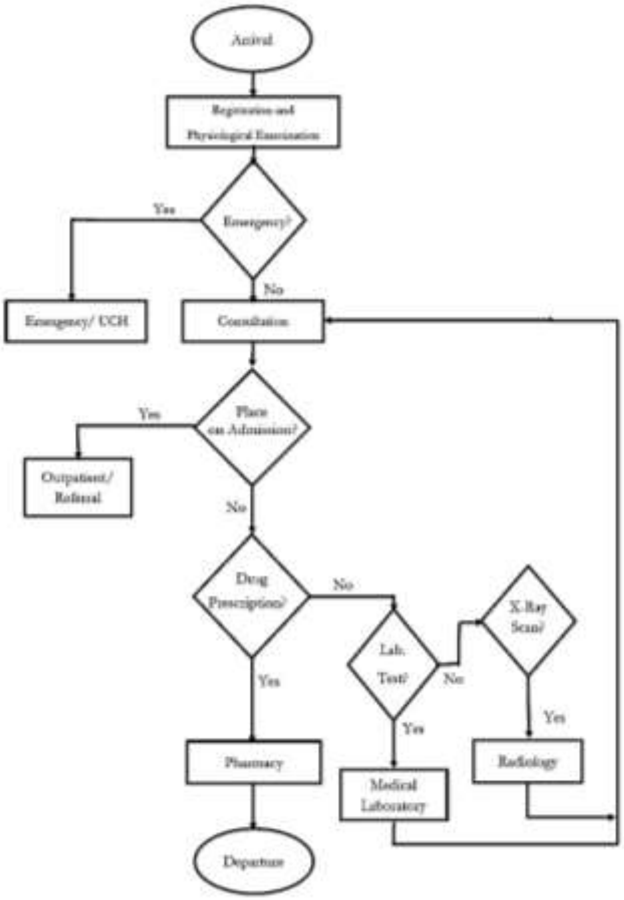


Figure 3 Process Flow Diagram

3. System Characteristics

The service system is characterized by a multi-server, single-queue. Prevalently, the system operates under this system such that a single queue is observed in the medical records department, with a single server, a single queue is observed in the consultation units, however, with multiple servers and varying service times and service rates. Let the average arrival rate = λ, and average service rate = μ, Number of servers = s, service utilization ratio (one server)

$$= p = \frac{\lambda}{\mu} \tag{2}$$

The average number of patients in the system

$$= \frac{\lambda}{\mu - \lambda} \tag{3}$$

The average number of patients waiting in the line (W)

$$= pL \tag{4}$$

The average time patients spend waiting in the system, including service periods, is

$$W = \frac{1}{\mu - \lambda} \tag{5}$$

Average time spent in the waiting line

$$W_0 = pW \tag{6}$$

The above holds for the single-server departments, however, for the multi-server departments like the consultation room, we have the following equations used in the system model.

Average System Utilization

$$p = \frac{\lambda}{s\mu} \tag{7}$$

The probability that there is no patient in the system is

$$P_0 = \left[\sum_{n=0}^{s-1} \frac{\left(\frac{\lambda}{\mu}\right)^n}{n!} + \frac{\left(\frac{\lambda}{\mu}\right)^s}{s!} \left(\frac{1}{1-p}\right) \right]^{-1} \tag{8}$$

Average Number of patients in the queue

$$L_Q = \frac{P_0 \left(\frac{\lambda}{\mu}\right)^s p}{s!\,(1-p)^2} \tag{9}$$

Average time spent in the queue

$$W_Q = \frac{L_Q}{\mu} \tag{10}$$

Average time spent in the system including the service period (W)

$$= W_Q + \frac{1}{\mu} \tag{11}$$

Average number of patients in the service system =

$$L = \lambda W \tag{12}$$

4 SimEvents Model

SimEvents is a discrete events simulation tool that enables the construction of simulation models. It provides a discrete-event simulation environment and component library to accurately model the system with customized routing, prioritization, and other operations. The SimEvents library contains predefined blocks, such as generators, queues, servers, and switches.

5 Modeling Procedures

The Simulink library consists of blocks as objects. These objects are pre-coded to perform specific tasks and thus the process is referred to as object-oriented programming. The model in Figure 4 was developed using the following procedures;

i. Launch the Simulink model library and open the SimEvent library for discrete event simulation.
ii. Select relevant blocks to model the problem to be modeled in the blank Simulink interface. Join blocks together using arrows.
iii. Configured parameters in each block.
iv. Create subsystems. Each subsystem highlights the constituent blocks.
v. Simulate the model for a period (1440 seconds in this study). Observe oscilloscopes (graphical representations) displaying the system dynamics and properties
vi. Report the results.

The SimEvents blocks were used to depict each activity in the system. Figure 5 represents the Simulink model from arrival to departure from the system.

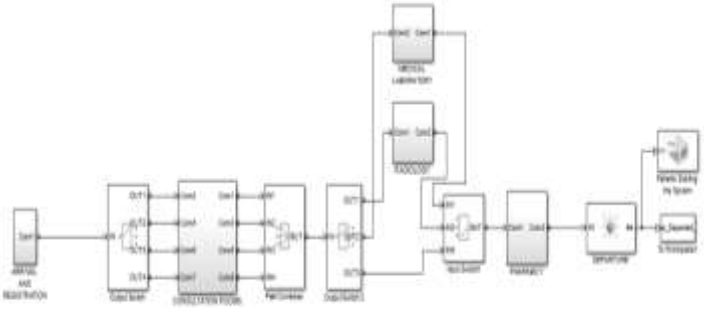


Figure 4 System Simulink Model

D Simulink Model Subsystems

1 Arrival and Registration

Figure 5 represents what happens at the patients' arrival and registration stage. The arrival time entity is generated by a random number generator using the Poisson distribution. Parameters (queuing discipline, average service rate) are obtained from the data collected. Entities (patients) wait in a queue in the waiting room to be served. Each server possesses an attribute called the service time. Statistics of patients taken to the consultation room (entities served) are recorded as an output using the entity scope.

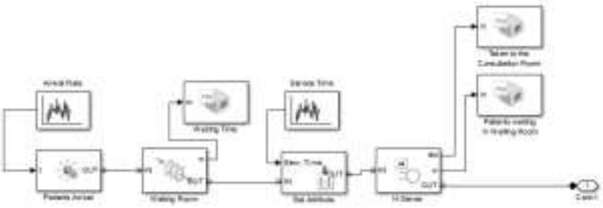


Figure 5 Arrival and Registration

2 Consultation Room

Patients wait outside the consultation rooms to be served by the doctors. There were 13 consultation rooms in the system, but only four consultation rooms were modeled (being actively used due to resource constraints), shown in Figure 2. Typically, 3 consultation rooms are used during off-peak periods, while an average of 5 rooms are used during peak periods. The service time of the servers is modeled using a random number generator with an exponential distribution.

3 Other Subsystems

The other subsystems were modeled similarly. Patients required to carry out medical tests or X-rays are referred to a medical laboratory or radiology department respectively. These patients also wait in a queue. The order of service is also first-come-first-served (FCFS). Equally, patients go to the pharmacy department to receive drugs prescribed by the doctor.

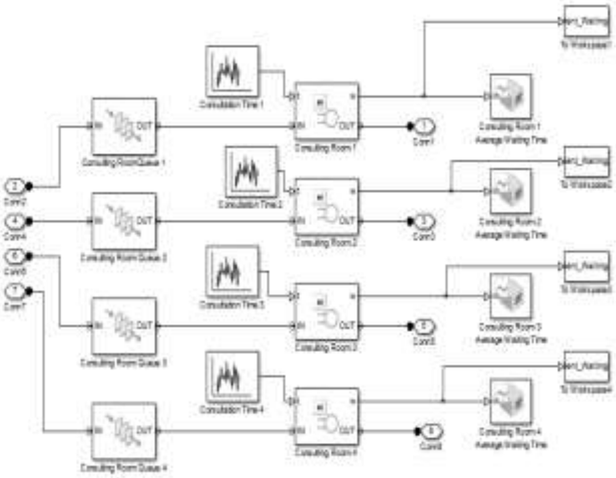


Figure 6 Consultation Room

E Model Simulation

Parameters from the data collected were used for the simulation process. A discrete event simulation process was used for the system. For the simulation process, the SimEvents toolbox in MATLAB was used. Statistics of simulation output in terms of average waiting time, average service time, number of entities served, etc. were also evaluated in the simulation.

F Model Evaluation and Testing

The model was tested for efficiency and effectiveness by comparing the values of the average waiting time of the current working condition to the model result. During the study, only the four active consultancy rooms were observed and modelled. Each room has a doctor (server).

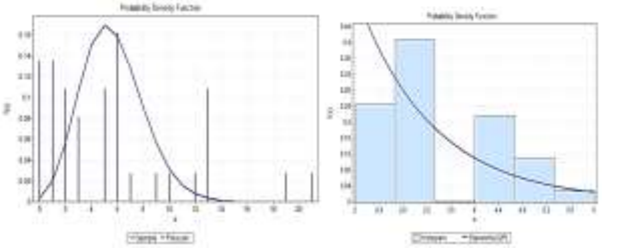
G Data Collection

The study of the system revealed that the arrival of patients can be categorised into two periods – the peak period and the off-peak period. Peak periods occur when students are in session, in the morning between the hours of 9:00 am to 2:00 pm, between the hours of 3:00 pm to 5:00 pm and also during school examinations. The off-peak periods occur when the students are on holidays, from 2:00 pm to 2:59 pm as well as at midnight. Data on arrival time, service time and the duration of service of patients were collected in selected peak and off-peak periods using a data collection form.

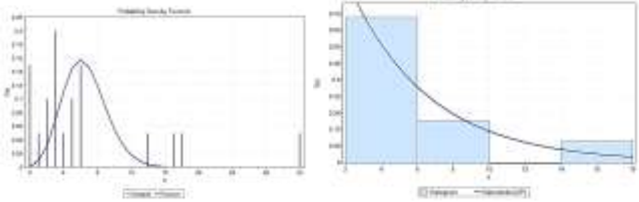
In collecting the data, patients' arrival times were observed and their departure times in each department. The time the patient gets to each department within the system is noted and recorded by each of the observers stationed at each of these departments. Inter arrival times, service rates, length of queue and duration of time for which the patient waits to be served were calculated from the data collected

H Probability Distribution

Data collected from each workstation were analyzed using EasyFit software to determine the statistical distribution of the patients. The arrival rate of patients at the Arrival and Registration desk was observed to follow the Poisson distribution (Figure 7a). The service rate of patients follows the exponential probability distribution (Figure 7b).



(a) Arrival: Patients' Inter-arrival time (b) Arrival: Service Rate



(c) Lab: Patients' Inter-arrival time (d) Lab: Service Rate

Figure 7 Probability Distribution of Patients' arrival and service times

The inter-arrival time of patients at the laboratory follows a Poisson distribution while the service rate follows the exponential distribution (Figure 7c&d). Similarly, the inter-arrival time of the radiology unit follows a Poisson distribution while the service rate follows an exponential distribution.

IV RESULTS AND DISCUSSION

A Simulation Result

The simulation was run for 1440 minutes with the parameters obtained from the data collected (Table 1). The arrival and service rates were obtained from the probability distributions of each decision unit corresponding to the Poisson and exponential distributions respectively. These were calculated as shown in equations (13) and (14). 5 observations were carried out for a total of 300 minutes.

$$Arrival\ Rate\ (\lambda) = \frac{Total\ time\ of\ Study}{Mean\ interarrival\ Time} \tag{13}$$

$$= \frac{(300)/5}{5.62} = 10.67 \cong 11 \frac{patients}{minute}$$

The service time was calculated using the equation 14.

$$Service\ Rate\ (\lambda) = \frac{Total\ time\ of\ Study}{Mean\ interservice\ Time} \tag{14}$$

$$= \frac{(300)/5}{3.27} = 18.35 \cong 18 \frac{minutes}{patients}$$

These calculations were repeated for all departments to obtain the parameters shown in Table 1.

TABLE 1: Simulation Parameters

Department	**Arrival Rate**	**Service Rate**

Consultation Room 1	15.40	9.46
Consultation Room 2	4.48	4.73
Consultation Room 3	9.90	9.60
Consultation Room 4	3.64	7.06
X-Ray Room	12.77	9.23
Laboratory	9.23	9.52
Waiting Room	10.67	18.35

1 Registration and Arrival

Shown in Figure 4 is the plot of patients that came for registration at the instance of time.

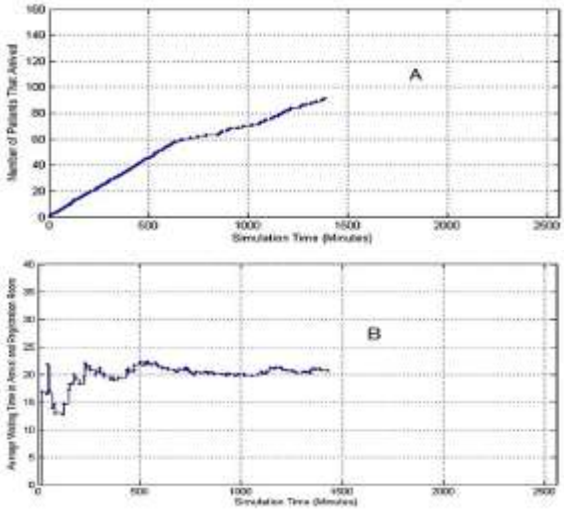


Figure 8 (A) Patient Arrival and (B)Average Waiting Time at the Registration Desk

Figure 8A shows that about 90 patients arrived at the registration desk in the course of the whole day. Figure 8B is a plot of the cumulative average waiting time of patients at the registration unit waiting for physiological tests. The average waiting time of each patient is cumulated for all patients who patronized the system for the period of study. The average waiting time of about 21 minutes for the whole day.

2 Consultation Rooms

The following figures describe the needful properties of interest in the four consultation rooms considered.

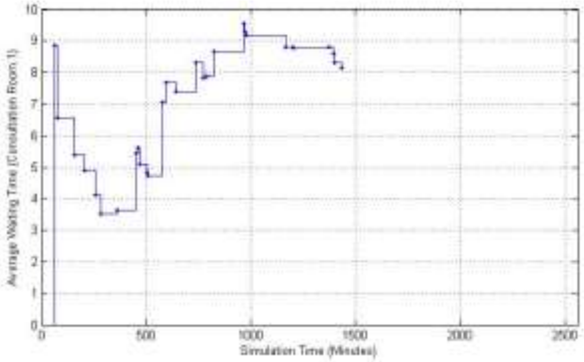


Figure 9 Average Waiting Time of Patients (Consultation Room 1)

An average waiting time of 8.1 minutes was recorded from the simulation (Figure 9). The graph shows a drastic reduction in the average waiting time for the first 500 minutes to a record low of 3.50 minutes. Similarly, the average waiting times of patients in consultation rooms 2, 3, and 4 were observed to be 5.5, 8.7, and 6.8 minutes respectively. The service rate of the doctor in the consultation room 2 was observed to be higher than the others. However, this could be a result of the cases of illness he/she handled or working relatively faster than the others.

3 Medical Laboratory

Figure 10 shows the plot of the average waiting time of the patients who patronized the medical laboratory throughout the study. The average waiting time is about 78 minutes for the whole day. The graph shows reduced average waiting for the first 700 minutes. The service rate of workers in this unit can be said to be relatively low as the day progresses. Reducing this waiting time is highly necessary for the system.

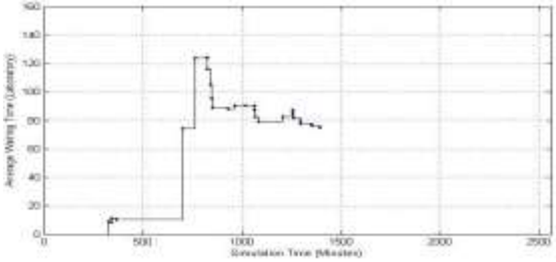


Figure 10 Average Waiting Time of Patients in the Laboratory

4 Radiology

Shown in Figure 11 is the average waiting time of patients in the radiology department. The average waiting time in this department cumulatively amounts to 97 minutes for a whole day. Similar results show a very low average waiting time for the first 700 minutes. This could be related to the practice of this department to schedule patients to a time zone for patronage. This was so because the model assumes that patients get referrals to the department daily. However, in practice, patients are scheduled to the days when X-rays are to be taken, mostly twice a week.

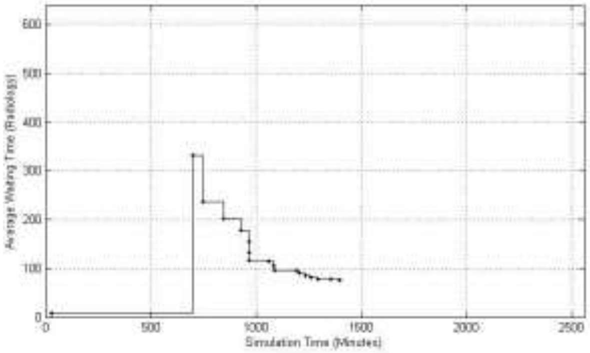


Figure 11 Average Waiting Time of Patients in the Radiology

5 Pharmacy

The average waiting time of patients in the pharmacy unit is shown in Figure 12 which tends to remain constant for the whole day. This department records an average waiting time of 2.8 minutes. This reveals that patients are attended to in less than 3 minutes. In the data collected, this department records the least waiting time which validates the simulation.

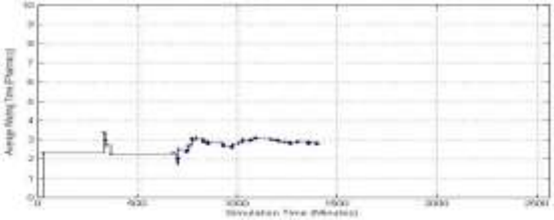


Figure 12 Average Waiting Time of Patients in the Pharmacy

B System Optimization

One of the primary objectives of this study is to reduce waiting time in the observed system. The observed times in Table 2 were determined by random sampling of patients using time study. We reasoned that a reduction in the maximum waiting time of one department may lead to an increased waiting time in another. To forestall this and achieve a near-optimal system structure, two variables were optimized to reduce the waiting time in the system: increasing the service time as well as the number of servers. However, the system inputs are human components that require careful attention, the servers also have a stress level. Instead of this, the service rate may not be increased, but rather the number of servers in departments with higher waiting times.

Consequently, the number of servers in the arrival and records was increased from 4 to 5 (Table 2). It is expected that there be an increased number of patients in the consultation rooms. Another consultation room was added to the simulation which makes a total of 5 consultation rooms. An appreciable number of patients are made to carry out one laboratory test or the other. A server was added in the laboratory. These parameters were used to simulate the new system. The result of the waiting time of the optimized system as well as the current practice was recorded as shown in Table 2.

TABLE 2 Optimized System Parameters

Dept.	**Observed Times (Mins)**	**Simulated System**		**Optimized System**		**% Reduction**
		Server	**Waiting Time (Mins)**	**Server**	**Waiting Time (Mins)**	
Arrival & Rec.	35.23	4	21	5	20.68	41%
Consult. Rm 1	15.32	1	8.1	1	9.2	40%
Consult. Rm 2	10.23	1	5.5	1	4.7	54%
Consult. Rm 3	12.22	1	8.7	1	8.5	30%
Consult. Rm 4	11.12	1	6.8	1	6.87	38%
Radiology	185	1	97	1	76.8	58%
Lab.	137	2	78	3	74.8	45%
Pharm.	7	2	2.8	2	2.79	60%
Consult. Rm 5	-	-	-	1	4.87	-

In Table 2, there exists a decrease in the waiting time in the arrivals and records department, the consultation rooms 1 and 2 as well as the radiology, medical laboratory, and pharmacy departments.

1 Arrival and Records

The optimized result indicated a reduction in average waiting time to 20.68 minutes upon simulation for a day (Figure 13), representing 41% reduction in observed patient waiting time. A digital record-keeping system could be used in this case too to reduce search duration. Shown in Figure 9 is the result of the 5 servers assumed to be working at the same rate.

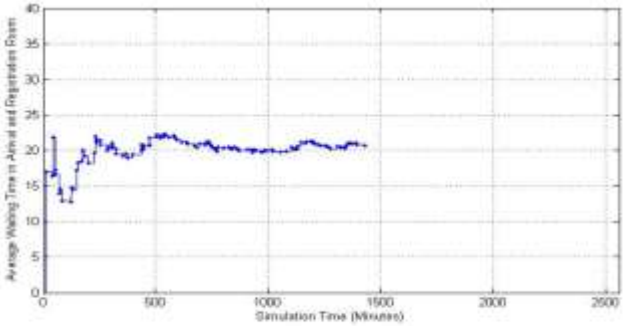


Figure 13 Optimised Waiting Time in Arrival and Registration

2 Consultation Rooms

The following are the results obtained from the consultation room 1 to 5. Shown in Figure 14 is the plot of the average waiting time of patients in consultation room 1 across the time of simulation. An average waiting time of 9.2 minutes (indicating 40% reduction in the observed waiting time) was obtained when the system was simulated for 24 hours. Similarly, average waiting times of 4.7, 8.5, 6.87, and 4.87 minutes were obtained for Consultation Rooms 2, 3, 4, and 5 when the system was simulated for 24 hours. The average waiting time of patients increases until a decrease is observed across the simulation. This fluctuation is due to the exponential distribution to which the service rate belongs.

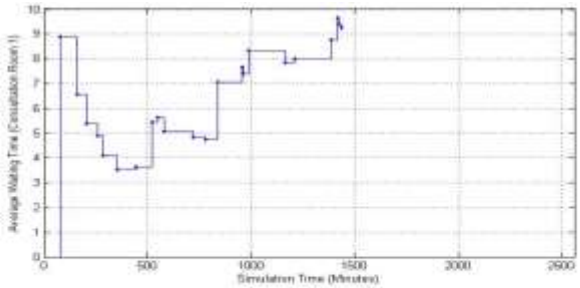


Figure 14 Consultation Room 1

3 Other Departments

Among all the departments, radiology shows a significant reduction in average waiting time from 97 minutes to 76.8 minutes when the system was simulated for optimization in a duration of 24 hours. There exists a zero-waiting time in this department until a simulation time of 603 is reached. A sharp increase was observed and the waiting time in the system gradually decreased until an average waiting time of 76.8 was reached. At the Medical Laboratory, increasing the number of servers in this department from 2 to 3 revealed about 5 minutes of waiting time until a simulation time of 603 minutes. The average waiting time in this period increased to a peak of 164 minutes. A decrease in average waiting time of up to 74.8 minutes was observed in the department. Patients at the Pharmacy were observed to have been on queue for about 2.8 minutes right from the beginning of the simulation. The average waiting time in this department did not exceed 2.79 minutes. This is relatively low compared to other departments in the hospital.

The study reveals that the pharmacy department having two staff recorded the lowest average waiting time both in the optimized system as well as the current hospital system. The consultation room 2 records the lowest average waiting time of patients, which is 3.5 minutes. This reveals that the service rate of the doctor in this room is average higher than the others. However, during the system optimization process, its average waiting time rather than reducing increased to 5.5 minutes. The third (3) consultation room recorded the highest average waiting time of patients which is 8.7 minutes in the current system. In the quest to reduce the average waiting time of the system, the first consultation room recorded the highest average waiting time of 9.2 minutes among the consultation rooms. The arrival and record section recorded an average waiting time of 21 minutes in the current system but a reduction was observed when one more server was added to the department. This brought the average waiting time from 21 minutes to 20.68 minutes but a sigbificant reduction from the observed average waiting time. The time savings between the simulated and observed waiting times appear insignificant but are sufficient to rescue a dying patient. The laboratory and the radiology department recorded the highest average waiting time of 78 and 97 minutes respectively for the current system and 74.8 and 76.8 minutes respectively for the optimized system.

In comparison, studies reported similar results. A modified integer linear programming model and a rescheduling algorithm developed using the DES framework for both outpatient and emergency patient scheduling in a hemodialysis unit show improvement in the system to accommodate emergency patients without delaying outpatient treatments [44]. Our findings suggest improvement in patients' flow from reducing patients' average waiting times (some departments experience no waiting time at early scheduling periods). In addition, the findings support adding personnel or equipment support services for patients, such as radiology, laboratory tests, and pharmacy could result in a decrease in patients' delay and total duration of treatment, but with a correlating increase in expenses. The typical increase in consultation rooms is in response to the reality of an increase in resources for improved services. Similarly, Using the DES model, a recent study suggested that the addition of two volunteers to escort patients decreased patients' queue times to see a physician by 33.9% (morning shift) and 65.2% (afternoon shift) [45]. The optimized DES model indicates the optimal number of such resources to be allocated. A similar study adopted the DES model to optimize the allocation of physicians between surgical units and outpatient clinics in a pediatric hospital, resulting in optimal resource distribution and minimized total patient wait times [46].

V CONCLUSION

Patients accessing limited resources could be competitive and so a queue is needed for orderliness. The concept of a queuing system as observed in hospitals and their integral units was considered in this study. Patients spending ample time accessing medical services most especially in university health services could lead to several devastating negative effects. The use of simulation to predict system behavior could help in the proper management of patient flow within the system and its supporting departments to minimize patients' waiting time.

The simulation procedures highlighted sections of the hospital with bottlenecks in patient flow, enabling the implementation of approaches to reduce patient waiting times and improve patient healthcare and satisfaction. Proper simulation offers efficient patient flow minimizing the likelihood of overcrowding and the need for emergency set-ups of the provision of additional infrastructure. Management can guarantee optimal utilization of hospital resources such as personnel, consultation rooms, laboratory equipment, and waiting areas. The result obtained from the reduced waiting times could ensure patients receive appropriate medical care resulting in better health outcomes. Simulation models offer cheap alternative quantitative data for making informed and accurate decisions. Hospitals could efficiently evaluate various scheduling policies through simulation modeling, such as appointment and allocation of resources before implementation.

From the study, the system was observed to unnecessarily delay patients. It is recommended that the file retrieving system in the arrival and records department be digitalized. The manual retrieval system takes time and delays patients. A user interface that enables the users to type their user identity digitally could be employed. Upon clicking an enter key, the patient's file could immediately be located and transferred to the nurses at the desk. These nurses then take the physiological data of the patient, log this data into the patient's medical history, and schedule the patient in real time for the next available consultation room. This system reduces the redundancy of the file-retrieving staff, minimizes space as well as enables patients to access medical services in record time. This proposed system attracts more nurses for physiological tests. The radiology and laboratory recorded the highest average waiting time both in the current and optimized system. The use of patient-specific time schedules can be adapted for patients patronizing the radiology department for efficiency. Instead of the single schedule per week system in operation, two schedules per week could be the result based on patronage. The development of standardized frameworks for integrating DES with emerging technologies like Iot and AI is undergoing rapid evolution. This is driven by the need to leverage current practices to improve decision-making accuracy.

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