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Application of Simulation and Response Surface to Optimize Hospital Resources

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***Abstract*—**This paper presents a case study that uses process-oriented simulation to identify bottlenecks in the service delivery system in an emergency department of a hospital in the United Arab Emirates. Using results of the simulation, response surface models were developed to explain patient waiting time and the total time patients spend in the hospital system. Results of the study could be used as a service improvement tool to help hospital management in improving patient throughput and service quality in the hospital system.

***Keywords*—**Simulation, Hospital Service, Resource Utilization, United Arab Emirates.

I. Introduction

A hospital in the United Arab Emirates (UAE) serves a population that comprises of various demographic groups. The patients are divided into three separate categories (A, B, and C) based on the severity of their medical conditions [5]. Since this is a public hospital subsidized by the government, there are usually a high number of patients using the emergency department because they cannot afford the high costs of private clinics. The high volume of patients who use the emergency department, as well as the limited human and material resources available to the hospital, cause bottlenecks in the efficient delivery of hospital services. The net result is that patients who use the hospital's emergency department experience long wait before receiving medical care.

The emergency department is the location where patients with acute and immediate life-threatening conditions are first examined by medical staff. The medical condition of the patient may relate to any specialty in any of the other departments in the hospital. Patients visiting the emergency department go through the following stages:

1. At the reception area, patient information is recorded
2. Experienced medical staff administers a quick examination and determine the patient's immediate medical needs.
3. Critically ill patients are given priority over non-urgent patients. The patients are classified as Category-A, B, or C, depending on the severity of the medical condition.
4. The medical staff sends the patient to any of the medical clinic most appropriate to treat the patient.
5. At the clinic, a doctor treats the patient.
6. After treatment, the patient is either recommended for discharge or referred to a specialist to decide the next course of action.

In this paper, a case study is undertaken to investigate the service delivery system of the emergency department of the hospital by using a simulation model. From the simulation study, response surfaces were developed to identify how to use competing resources in the hospital, such that bottlenecks in service delivery are alleviated. .

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II. Literature Review

A. Healthcare Resource Management

A number of studies have been conducted on how to improve the deployment of hospital resources and enhance service quality. Most of the studies used various analytical techniques to identify measures to improve the operating efficiency of healthcare facilities. Reference [2] used logical framework analysis to project the planning and management of hospital quality in the areas of operating room utilization, accident and emergency, and intensive care. Their results show great improvement in the quality assurance of hospital management when compared to traditional quality management tools.

Reference [9] examined the advantages and disadvantages of shrinkage and non-shrinkage estimators used in quality reports of hospitals and health plans. Their studies indicate that although shrinkage estimators may be preferred if the objective is to increase the accuracy of predicted mortality across all providers, non-shrinkage estimators provide better quality measures for patients who are making a choice among local healthcare providers. Reference [4] used visual analytics simulation model to identify solutions that would improve the efficiency of a hospital. Data used in the analysis include room capacity, room use, patient scheduling practices, staff capacity, and equipment availability. The model was able to identify bottleneck areas, and simulate viable options to improve the bottlenecks.

Reference [1] applied discrete-event simulation to evaluate multiple critical pathways in medical processes in a Belgian hospital. The resources of the hospital were modeled and examined by means of scenario and sensitivity analyses. The study was able to identify measures to increase patients' throughput and improve the hospital's operating efficiency. Green et al. (2007) used a modified queuing theory model to set staffing requirements in service systems where customer demand varies in an unpredictable pattern over the day. While the modified queuing model is typically used in telephone call centers, the same model can be applied to accident and emergency departments of hospitals.

Reference [8] used multi-class open queuing network model to analyze patient flow in a hospital. Results of the study indicate that parallelization can reduce cycle time for patients who require more than one diagnostic and/or treatment interventions, while there would be little improvement for other classes of patients.

Reference [12] investigated how to improve the quality of service at a hospital emergency department by using simulation and genetic algorithm to appropriately adjust nurses' schedules without hiring additional staff. The simulation model was developed to cover the complete flow of patients through the emergency department. Genetic algorithm was then applied to find a near-optimal nurse schedule based on minimizing the patients' queue time. Results of the study indicate that by making appropriate adjustments to the nurses' schedules, the patients queue time could be shortened by 43 percent without increasing the number of nurses in the system.

Reference [11] also used queuing theory and simulation to investigate the waiting time in a healthcare facility in Taiwan by incorporating sources and methods of prevention of human errors into the model. By categorizing and prioritizing the levels of care as critical, serious, and stable, the model reduced expected waiting time by 50 percent, without employing additional staff. Finally, [3] designed a simulation model to support the scheduling of patients waiting for surgery in the Australia public hospital system. Patients were categorized by urgency and type of operation. Results of the study indicate that urgent and semi-urgent cases were being coped with adequately, while routine cases needed some improvement. Such evidence aided hospital administrators in investigating alternative configurations and deployment of resources. These findings suggest that several analytical techniques can aid hospital management in implementing operational strategies that would reduce patient waiting time, and improve quality of care [7], [10].

III. THE SIMULATION

The simulation model is used to analyze the patient flow through the emergency department, the time to finish consultations and treatment, resources utilization, waiting time due to scheduling of doctors, nurses and equipment facilities, and queue length at any time inside the emergency department. The simulation approach is based on the description of the series of events that occur in sequence, in order to replicate the system behavior. The resources are the clinic's premises, waiting room, administrative staff, nurses, doctors, emergency equipments, and other necessary inventories. In addition, the system is governed by other important system parameters. Some of these parameters can be listed as: total time a patient is spending in the clinics to go through the healthcare phases, the waiting time, the idle time of the resources, and busy time of the paramedics and doctors, including nurses. Essentially, the simulation should run for a long period of time to avert the unbiased estimate of the system performances.

Fig. 1 shows the patient flow network at the emergency department. Patient arrival is simulated using uniform distribution. The time a patient arrives in the hospital is recorded in ATRIB (1) the CREATE node is labeled A1 and the time of first arrival of zero implies that the first patient arrived according to uniform distribution. The QUEUE node is QI and keeps the patient in waiting area according to the capacity of the room or service area. The patient waits for the records and the nurses update medical histories.

The COLCT node is labeled CL1. This is where treatment time in the clinic is recorded from the time the patient entered the clinic. ATRIB (1) records the time a patient entered the hospital and TNOW is the time when statistics is created. In order to utilize the resources, such as, doctors and nurses, RESOURCE node is introduced. This node models the number of doctors available in the hospital for patients. The purpose of this node is to record the number of doctors in the hospital at a given time.

The AWAIT node is used to allocate one or more resources. FREE node is used to release a resource previously allocated at an AWAIT node. It also checks the list of the AWAIT node to see if reallocation is possible. Once the doctor has treated the patient, the doctor is free to be reassigned to the next patient. The RESOURCE node along with AWAIT and FREE nodes replicates the patients engagement pattern as long as patients need the services of a doctor.

To develop clear and unambiguous model, the GOON node (G1) is used. Its purpose is to differentiate two successive events. This node makes it convenient to create a model that is easy to interpret. The TERMINATE node (T1) is used to end the simulation. It destroys the system entities and is used to remove the patient from the system once the patient's treatment is completed.

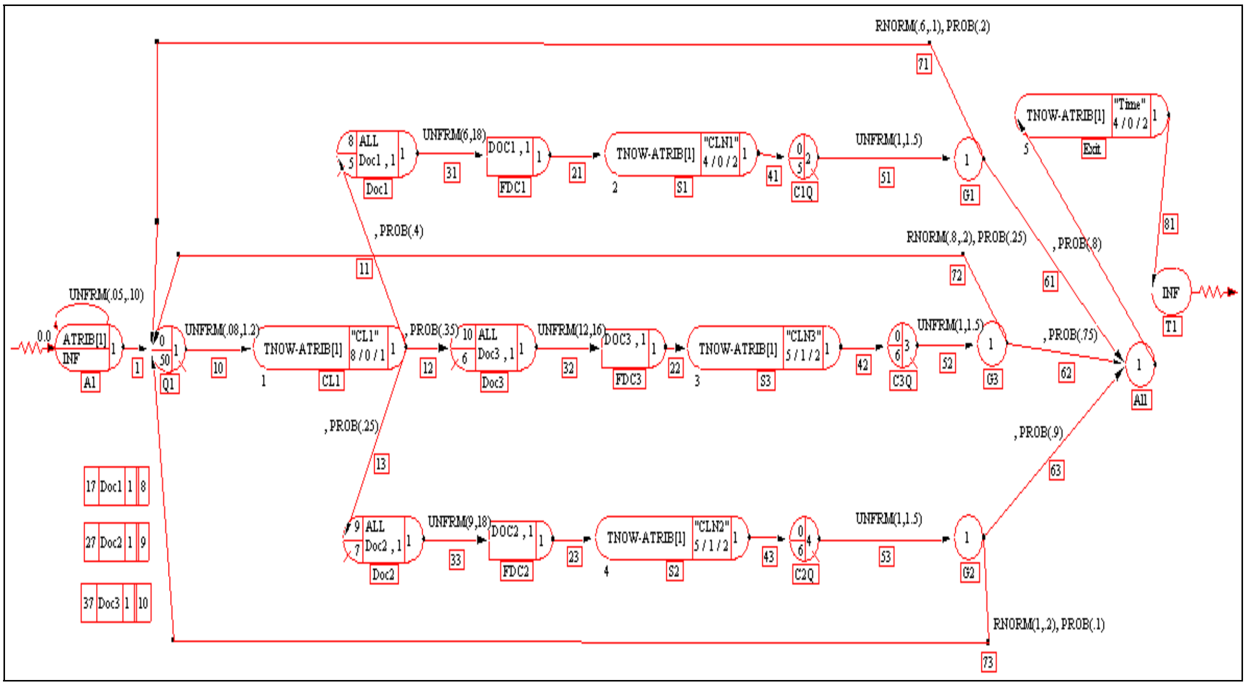

Fig. 1 Patient flow network

IV. RESULTS AND ANALYSIS

Table I reports the steady-state hospital system performance. For robust analysis, we perform 16 simulation rounds. In particular, average time for patients in Categories-A, B, C and average queue length in clinics 1, 2, and 3 are reported. It is noticed that on average a Category-A patient takes almost 118 minutes to be processed (see Table II). Also, Table II reports average queue length, treatment consultation time inside hospital. There are about 55 patients waiting for service in Clinic 1, while there are 84.5 and 75 .2 patients waiting in Clinics 2 and 3 respectively. It implies there is a backlog of patients waiting for treatment.

Table II shows the mean values and the corresponding standard deviations for steady-state behavior. The simulated results show consistent pattern in all system parameters, since the standard deviations are not high. To explain the overall hospital resources utilizations, the simulated results are taken into considerations to construct experimental design model. The multivariate regression model as shown in Table III combines the hospital resources to explain the cause and effect relationships. The contributions of the model parameters are significant. The ANOVA analysis in Table IV suggests that the F-values are acceptable to validate the regression model. Therefore, it implies that by reducing the treatment time for Category types A, B, and C patients, the expected overall time to provide care to the patient can be reduced. From the model it can be estimated that if the overall patient treatment time is about 98.5 time units, then corresponding patient treatment time for Categories A, B, and C are 80, 90, and 110 time units respectively.

Additionally, the queue length for Categories A, B, and C patients are 40, 65, and 60 time units respectively. This can be realized by employing more resources in clinic type A, B, and C, such as additional paramedical staff and another doctor. This might require reorganization of patient care management, and redeployment of resources for patient care. The predictability of the patient treatment time is accurate using this model.

For instance Fig. 2 explains treatment time of Category-A patient as a consequence of queue formation for doctor providing service to Category-A patient, and the overall time a patient spends in the hospital. It implies that if management would like to reduce the overall expected patient treatment time and adjust the queue or waiting time of a particular patient's category, it can influence the patient treatment time in a complex way, as the model explains or predicts. The complex relationship is enumerated by the following expression.

Treatment Time $_{\text{Category A-Patient}}$ = 111.67-0.676(Average System Time)-0.324(Category-A Patient

If we maintain 102 time units as overall patient treatment time with 49 time units as queue length for Category-A patient, then the expected time to complete treatment for Category-A patient is 90 time units (Fig. 2). Using sensitivity analysis, if we maintain an average of 80 time units as overall time for all patient treatment time, with the same queue length of 49 time units, the expected time to complete treatment for Category-A patient would be 158 time units. Finally, if we maintain the overall patient treatment time of 120 units, with 49 units of queue length as before, Category-A patient treatment time would be 116 time units. Hence, the sensitivity analysis shows the effect of patient treatment time on queue length.

TABLE I
SIMULATION OBSERVATIONS

#	All System Time	T1 System Time	DQ1 Queue	T2 System Time	T3 System Time	DQ2 Queue	DQ3 Queue
1	102.3	90.5	47.7	105.6	110	68.9	60.9
2	109.6	93.8	50.5	111.7	118.2	74.4	65.7
3	112.3	95	51.3	115.7	122.4	78.2	70.4
4	114.2	96.6	51.7	118	125.2	79.4	70.6
5	116	97	52.8	119	128	83.1	72.4
6	118.8	98.5	55.2	121.5	132.2	84.8	74.7
7	119.62	99.4	55.55	122.9	132.4	85.9	75.4
8	120.2	99.5	55.3	123.2	133.4	86.7	76.5
9	121.2	100.4	55.9	124.6	133.99	87.1	77.8
10	121.5	100.8	56.7	124.5	133.99	87.4	77.8
11	122	101.6	57.2	125	134.3	88.3	77.9
12	122.6	102.7	58	126.2	134.4	88	79.4
13	123.3	103.4	58.6	127	134.7	88.7	79.9
14	123.8	104	58.9	127.5	135.3	89.2	80.7
15	124	103.6	58.73	128.4	136.6	90.52	81.53
16	124	103	58.74	128.5	137	90.73	81.6

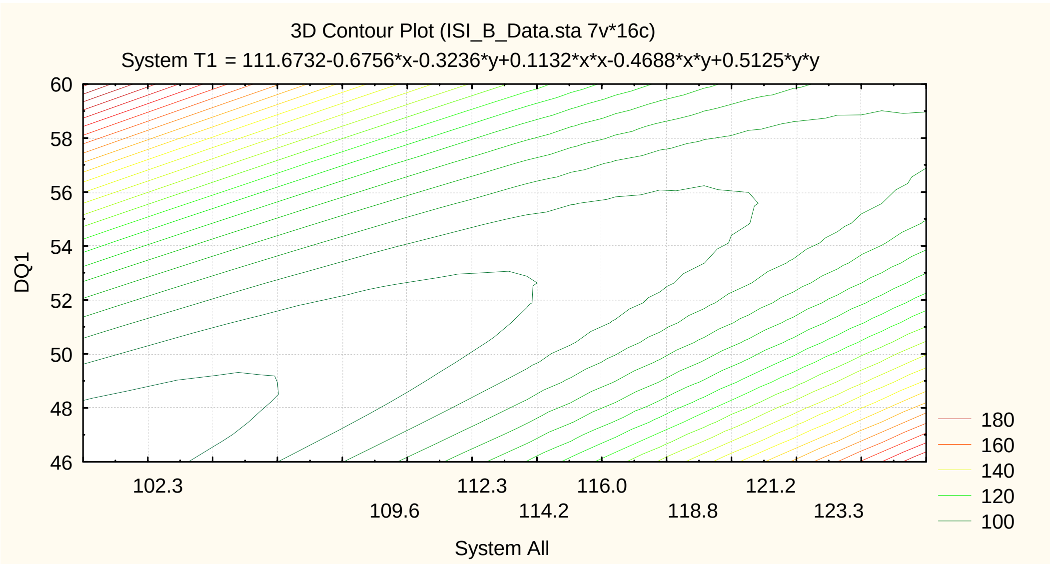

Fig. 2 3D contour plot (Category-A patients)

TABLE II SYSTEM PARAMETERS

Parameters	Mean	Std. Dev.
T1 System Time	99.3625	3.922393
T2 System Time	121.8313	6.428553
T3 System Time	130.1300	7.564654
DQ1 Queue	55.1762	3.430316
DQ2 Queue	84.4594	6.199661
DQ3 Queue	75.2019	5.891117
System All	118.4638	6.142873

Queue)+0.113(Average System Time^2)-0.469(Average System Time)(Category-A Patient Queue)+0.513(Category-A Patient Queue^2)

TABLE III
REGRESSION SUMMARY FOR DEPENDENT VARIABLE

Parameters	B	Std. Err.	t-value	p-level
Intercept	-9.308	10.0105	-0.929841	0.376720
System T1	0.675	0.34541	1.953718	0.082473
System T2	-0.106	0.37459	-0.282211	0.784164
System T3	0.634	0.17418	3.641063	0.005392
DQ1	-0.098	0.27437	-0.356377	0.729770
DQ2	-0.142	0.20681	-0.688899	0.508255
DQ3	0.113	0.24712	0.457220	0.658349

Regression Summary for Dependent Variable: System All
R= .99916157 R^2= .99832384 Adjusted R^2= .99720639
F (6,9)=893.40 p<. 00000 Std. Error of estimate: .32468

TABLE IV
ANALYSIS OF VARIANCE

	Sums of Sq	df	Mean	F	Significance F
Regress.	565.08	6	94.18	893.40	5.76E-12
Residual	0.9487	9	0.105		
Total	566.023				

V. CONCLUSION

This study uses a simulation model to investigate patient's throughput time in a hospital system's emergency department. The statistics gathered from the simulation include queue length, standard deviation of queue length, average patient waiting time in the clinics, and current queue length at the time of simulation. Using design of experiment, system time is developed as a function of patient waiting time and server idle time. In this analysis, three response surface models were developed for Clinics 1, 2, and 3. The system time in either of the clinic would have implications for the overall patient treatment tine in the entire hospital. The metric of overall system time is dependent on individual Clinic system time. Therefore, adjustment of common resources within the three clinics would determine overall system time. A hospital must optimize its material and human resources in order to reduce the total time patients spend in the system. The ability to configure system time with such combinations would improve the overall performance of the emergency department from management and patients' viewpoint.

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