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REDUCING TIME IN AN EMERGENCY ROOM VIA A FAST-TRACK

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ABSTRACT

Queues at emergency rooms (ER) are prioritized based on the patient's sickness level. As a consequence, patients with low priority frequently have to wait excessively long. At Mercy Hospital, we began to study means by which such time would be reduced, without putting in jeopardy the life of critical patients. As an initial effort, we studied the flow of patients at the Emergency Department (ED) and decided to model it with and without a fast track lane. A simulation study revealed that indeed a fast track lane reduces by almost 25% the time in the system for patients with low priority without negatively affecting the times of patients with higher priority.

1 INTRODUCTION

Queues at ER are prioritized based on the patient's sickness level: a patient with an open wound has a higher priority over a patient with a vesicular bladder pain (provided that no other symptoms are present). As a consequence, patients with low priority many a times have to wait excessively long. In times when the health care facilities are being forced to compete with less and less resources, it is of the utmost importance to service ***all*** types of patients as expeditiously as possible. An ER is perceived by its customers as a good one if the patient is given courteous and professional service relatively fast. Patients with the lowest priority (least sick) are the ones that are well enough to qualify the service being received; thus, it seems natural to closely monitor the time spent in the system by these customers.

Mercy Hospital, member of the American Hospital Association, is a nonprofit organization founded in 1950. Throughout the years, Mercy Hospital has managed to stay competitive in a field where quality of service is the driving force. However, recent trends in the ED's finances indicated the need for an operations improvement analysis. This analysis would seek to identify candidate areas for improvement and the means to realize such improvements. In the end, Mercy Hospital should see an increase in quality levels of the services provided. As an initial effort, we studied the flow of patients at the ED and decided to model it with and without a fast track lane. A fast track lane is a lane dedicated to service a particular type of patient with the sole intent of reducing their waiting time; thus, reducing their total time in the system. In this particular case, the *fast lane* was dedicated to serve non-urgent patients (type 3 and 4). The simulation study revealed that patients type 3 (headaches, abrasions, etc.) and patients type 4 (wound checks) have the longest stay in the system (2 to 3 hours on the average), but most of this time is spent waiting for service. However, using a fast track the length of stay of these patients is reduced by almost 25%, without increasing the length of stay of patients type 1 (cardiac, open wounds, etc.) and of patients type 2 (abdominal pain, chronic back pain, etc.).

Section 2 of this paper gives the background of the problem and other relevant work. Section 3 discusses the analysis of input models, the simulation model and the experimental conditions. Section 4 discusses the results of this on-going experimentation, and it sets directions for future enhancement. Only sample summaries of the extensive statistical analyses done is given in this paper.

2 CURRENT OPERATIONS AT THE ER

Patients arriving to Mercy Hospital's ER follow a process as depicted in Figure 1. The arriving patient goes through the registration clerk who records the time the patient came in and locates/creates his/her file. This file is then taken to the "triage" area, where a nurse picks it and calls the patient up for "triage care." Triage care consists of taking vital signs and determining, through direct and external contact, the acuity of the illness. In some instances, patients arrive in an ambulance; thus, they begin their process at the ER bed area, with the registration clerk service paralleling emergency care service. In general, once the acuity of the illness has been determined, the patient is either rush to the ER bed area or is told to wait for an empty bed. As soon as a bed becomes available, and using a priority queue discipline (FIFO within priority), the triage nurse takes the patient inside where actual medical treatment begins. Inside the ER bed area, the necessary tests are ordered and, once the results are obtained from the laboratory, a decision is made on whether the patient needs to be admitted or not. If the decision is to admit the patient, s/he is given emergency stabilizing care and is assigned to the appropriate care unit in the hospital. If the decision is not to admit the patient, the patient receives therapeutic care in ER and is sent home. Regardless of the outcome of the decision, the primary physician of the patient (if any) is always notified by the ER physician. Furthermore, any decisions concerning the patient is made by the ER physician in conjunction with the patient's primary physician.

A patient occupies a bed in ER for as long as s/he needs to either recover and go home or be admitted and go to a specific floor. If the patient is to be admitted, the patient waits in the ER area for a floor bed assignment. Once the assignment is made, a report is given to the designated care unit, and an escort for the patient is requested.

There are four categories that can be assigned to a patient as they pass through the triage nurse. These categories are assigned according to the patient's condition. Table 1 summarizes the levels of acuity and identifies what conditions determined these levels. In addition to those four categories, we had to create an additional category to identify those patients coming in ambulance. We gave these patients the highest priority since they skip the triage area. These categories determine the priority of the patient; thus, they determine how fast a patient takes a bed. Category 0 and 1 patients never wait for a bed for every time they come in, a bed is made available immediately. Patients type 3 and 4, on the other hand, wait an excessive amount of time for an available bed since they do not need immediate care.

The complexities of this process led us to use simulation modeling to analyze it. Simulation has been used widely in health care systems for medical research as well as for planning and management. Many practitioners and researchers have look into the operations of a hospital, in general, including the emergency room. For example, Singh, Chandran, and Dey (1990) conducted a study to estimate the number of ambulances required at a hospital in Pune, India. They utilized standard multi-channel queueing to describe the ambulance service at the hospital. A special queuing model was used simultaneously to accommodate the lack of steady state conditions of the system.

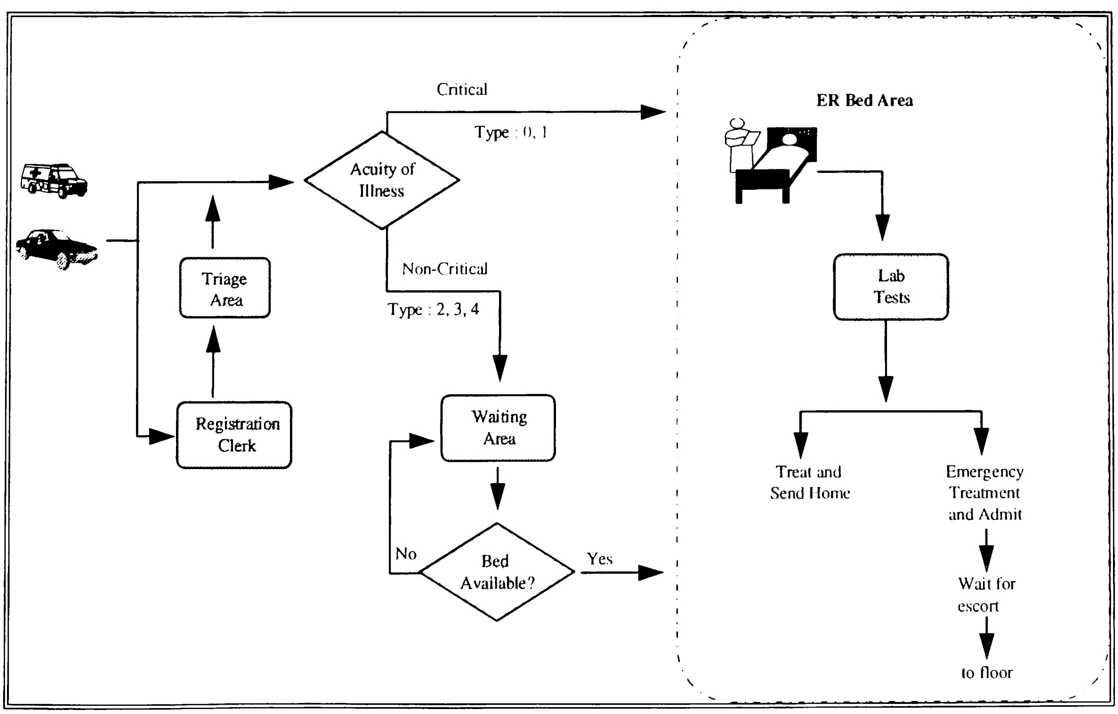

Figure 1: Flow of Patients

Table 1: Patients Categories

Patient Category	Condition
Ambulance - Category 0	Cardiac, Hemorrhage, Respiratory, Neural, ortho, Trauma, Psyche, etc.
Emergent - Category 1	Cardiac, Hemorrhage, Respiratory, Neural, ortho, Trauma, Psyche, etc.
Urgent -Category 2	Abdominal pain, Emotionally disrupted behavior, Acute back pain, etc.
Non-Urgent -Category 3	Chronic Headache, Nerves, Sprains, Eye Infection, Abrasion, etc.
Stable -Category 4	Wound checks

Kleckley et al. (1991) proposed the use of simulation modeling as part of strategic planning system for a 500+ bed medical center. Schellenberger, et al. (1992) reported on the second phase of the framework proposed by Kleckley et al. (1991). The main idea behind the framework is to have a decision support tool, with simulation as one of the component, to analyze the various interdependencies in hospital care. We believe that a similar, smaller scale, approach should be used to improve the operations at Mercy Hospital's ER.

Other researchers have focused on a particular component of a hospital health care system. For example, Bodtker, Wilson, and Godolphin (1992) used simulation to study the effects on throughput and staff utilization of new procedures on laboratory activities. A future comprehensive effort at Mercy Hospital would include a similar study as that conducted by these researchers.

Similar studies as the one reported in this paper were done by Kraitsik and Bossmeyer (1992) and by McGuire (1994). Kraitsik and Bossmeyer used simulation to study how to renovate the ER at a Humana Hospital and how to improve the turn-around times. In their study, they also studied the impact of a fast track lane in length of time in the system. McGuire reports an effort with similar objectives as ours. He also discusses the political issues of using simulation in this context.

3 THE SIMULATION MODEL

Preliminary studies done at the ED yielded information concerning the *total* turnaround time in the ER, the service time at the registration clerk, and the service time at the triage station. Based on this preliminary studies, we established several alternatives for further studies, including implementation of a fast track area, a study of volume Trends (total and by acuity level), staffing by skill level, work sampling by skill level, patient satisfaction and operational implications, turnaround time from support areas, and turnaround time from on call staff. We also found that two areas perceived as the source of delays are the lab and the admitting processes.

After having collected additional data (extracted from the original nurse's charts), we used UNIFIT II to find the corresponding arrival and service distributions. Table 2 summarizes our findings. All the units are in minutes. Noticed that ER nurse service times for patients type 0 and 1 are not defined. This is due to the fact that the ER nurse must be with these patients at all times; therefore, the ER nurse service time for these type of patients is the same as the patient's *total* ER time.

Table 2 gives us distributions to model the ER when there is no fast track implemented. Thus, these distributions reflect the excessive waiting time that patients type 3 and 4 are currently experiencing. We adjusted these distributions to better reflect the *total* ER time for patient type 3 and 4 (fast track patients), using relationship (1)

$$Y = \sum_{i=2}^{k} \left[E[X(i)] \times NIQ \times Pr[T = i] \right] \quad (1)$$

where

Y = Average excess time due to non fast track
$X(i)$ = Total time in ER, no fast track, type i
NIQ = Average number in queue
T = Patient type
$Pr[T=i]$ = Probability of a patient being of type i

which resulted in two new distributions for *total time* in ER for patients type 3 and 4. For type 3, it was a Weibull(141.71,1.5), whereas for type 4 it was a Gamma(1.82,18.26). It must be noted the that summation in (1) starts at two because patients type 0 and type 1 do not have to wait at all; thus, they do not experience excess time due to non fast track.

A histogram of the average inter-arrival time showed that the mean arrival time changes depending on the time of the day (Figure 2). To account for this situation in the model, a series of ASSIGN and BRANCH blocks were used to change the arrival distribution. In the case of the service times, the majority followed a Uniform distribution except for the *total* in ER service time. The doctor's service times were not recorded in the nurses' charts; therefore, We had to interview one of the ER doctors to obtain an empirical estimate.

Table 2: Input Distributions

Event	Distribution	Tools Used
Arrivals between 8 am & 10 pm	Exponential (17.88)	Goodness of fit test
Arrivals between 10 pm & 8 am	Exponential (49.08)	Goodness of fit test
Registration Service time	Uniform (5,15)	Time studies
Triage service times pat. type 2	Uniform (5,10)	Time studies and Interview
Triage service times pat. type 3 & 4	Uniform (5,15)	Time studies and Interview
ER Nurse service times pat. type 2	Uniform (30,40)	Hospital Policy
ER Nurse service times pat. type 3	Uniform (30,60)	Hospital Policy
ER Nurse service times pat. type 4	Uniform (0,30)	Hospital Policy
Doctor service times pat. type 1	Uniform (10,20)	Interviewing ER Doctor
Doctor service times pat. type 2	Uniform (10,15)	Interviewing ER Doctor
Doctor service times pat. type 3 & 4	Uniform (1,5)	Interviewing ER Doctor
Total ER service time pat. type 1	Uniform (84,408)	Goodness of fit test
Total ER service time pat. type 2	Normal (263,134)	Goodness of fit test
Total ER service time pat. type 3	Weibull(207.4,1.744)	Goodness of fit test
Total ER service time pat. type 4	Weibull(62.6,1.467)	Goodness of fit test
Total ER service time pat. type 0	Normal(232,90.5)	Goodness of fit test

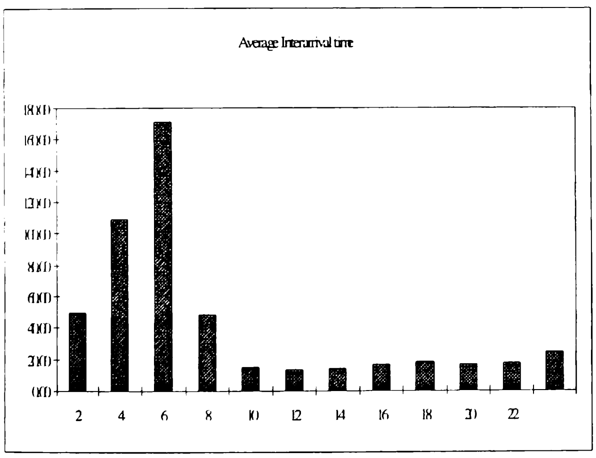

Figure 2: Histogram of inter arrival times

After various statistical analyses, it was concluded that indeed the fast track area within the emergency room was an appealing alternative. Thus, we proceeded to simulate the process in the ER with and without the fast track lane. The variables used in determining the performance of the fast track lane were cost of implementation, effect on other patients within the emergency room, and patient's length of stay (both fast track users and other patients).

We expected to determine 1) minimum resources allocation for the fast track lane, 2) personnel scheduling based on peak hours of operation, 3) percent reduction on length of stay of fast track users and other patients, and 4) cost and savings for fast track lane implementation. The simulation model was developed using SIMAN. The system under study was restricted to the areas of Registration, Triage, and Inside the ER.

Different attributes were used to establish levels for different measures of performance. These measures of performance included total time in the system, time spent waiting in the queue, time spent waiting for service, total time spent in ER, as well as resources utilization. Table 3 gives a summary of the major components of the simulated system. It is worth mentioning that the fast track was implemented, so that patients type 3 and 4 are routed to the fast track (FT) area, but they proceed to the regular ER if resources in FT were busy and ER had available resources.

Table 3: Components of Simulation Model

Dynamic Entity:	Patient.
Resources:	doctors, nurses, beds, and registrations clerk.
Attributes:	**Ptype** is the patient type. **TimeIn** is the time of creation. **InER** is the time an entity seizes a bed.
Inputs:	Inter arrival times, service times, percentages for each patient type.
Outputs:	Flow time of patients through the system and in ER, time spent in queues, utilization of resources, number of patients served by type.
Type of System	Non-Terminating.

Verification of the model was done by *walking through* the model, and by using the SIMAN debugging facility, in conjunction with the TRACE element. Validation of the model was done empirically by testing the *reasonableness* of the outputs from a trial run. We also estimated the values of the measures of performance under a deterministic setting (the values of Δt were set to constant values). We observed if the *proportion* of change in the outputs, as we changed the various Δt from constant values to probability functions, was reasonable. We also check if the model was creating the various types of customers, based on the given user-defined discrete function. During the validation process, we discovered that we had not implemented the fast track correctly. The logical expression being used in the SCAN block to route FT patients to either the FT area or the ER area was evaluating true in one too many instances. This was a very subtle error in logic that was discovered only because we noticed that FT patients were not being routed to ER even though we had put the logic for it. We tracked the error down by extensive use of COUNTERS. The key to the discovery of this error was our continuously questioning of the simulation outputs.

4 RESULTS AND RECOMMENDATIONS

Once we had exhaustively tracked the flow of entities, we performed several runs with the model under a variety of conditions, including two more different runs to establish the warm up times and the run length for the single replication of this non-terminating system (fast track and non fast track). For the warm up time of the non fast track (NFT), we found that the lag was 750 observations (warm up time = 525,600), whereas the lag for fast track (FT) was 575 observations. The estimated batch size was 750 for NFT and 300 for FT. However, in order to compare the results of both alternatives under the same framework, we decided to use a batch size of 750 for both (ensuring statistical independence) and a warm up time of 525,600 minutes. The total useful run length was 975,000 minutes, which allowed us to have 50 batches. During our analysis, we graphed correlograms on several measures of performance to confirm that we had reached steady state conditions.

Mercy Hospital gave us a fixed set of FT scenarios to consider (Table 4). There are 15 beds, so when FT is open, there are either 13 or 14 beds in regular ER. The FT nurse is taken out of the pool of ER nurses, so when FT is open the ER nurses decreases by one. Nurses capacity are as follows: 3 from 7 am to 11 am, 5 from 11 am to 11 pm, 3 from 11 pm to 7 am.

Table 4: FT Scenarios

Operating Times	Number of Beds	Number of Nurses	Number of Doctors
10 am-8 pm	1	1	0
	2	1	0
11 am-9 pm	1	1	0
	2	1	0
12 noon-10 pm	1	1	0
	2	1	0

We computed confidence intervals for the various average flow times and the number in the queues. We then proceeded to perform one-tailed tests on the mean values for FT and NFT (significance level = 0.05), per patient type. We were interested in detecting whether or not fast track was worth pursuing; in other words, we wanted to find out if the average flow times under FT were less than the average flow times under existing conditions (NFT). Therefore, our hypotheses were of the form

$$H_0 = \mu_{iFT} \geq \mu_{iNFT}$$
$$H_1 = \mu_{iFT} < \mu_{iNFT}$$

where

μ_{iNFT} = Average flow time for patient type *i* without fast track

μ_{iFT} = Average flow time for patient type *i* with fast track

These tests of hypotheses confirmed that indeed patients type 3 and type 4 greatly benefit from fast track implementation, without negatively impacting the other types of patients. Table 5 gives a sample summary of the computed confidence intervals, whereas Table 6 partly summarizes the results of the hypothesis tests.

Looking at the various results, we concluded that the best case scenario was to use one bed and one nurse for fast track, between the hours of 10 am and 8 pm. The other times gave slightly worse conditions. An appealing factor to our recommendation is that FT resources can be taken away from current resource; therefore, there is no additional cost of hiring new personnel. Moreover, the inclusion of a fast track area does not required any modification of the layout because there is a fast track bed that has never being used before.

Based at the utilization of the resources, it seemed that Mercy Hospital has no major problem if the involved personnel operates "by the book". Reality shows a "lack of resources", but the company's pre-established times for the various tasks say otherwise. We strongly recommend that more reliable data be collected, so that times to fill out forms (by the nurses and doctors) can be included in the model. We believe that most of nurses' and doctors' time is being spent filling out forms and charts. But the lack of data regarding these activities prevented us from including them in the model.

Table 5: Sample Confidence Intervals ($\alpha = 0.05$)

Measure of Performance	Type 3 flow time	Type 4 flow time
10 - 8 : 1 bed	159 ± 2.2	66.7 ± 3.8
10 - 8 : 2 beds	159 ± 2.2	66.7 ± 3.8
11 - 9 : 1 bed	159 ± 2.17	66.7 ± 3.8
11 - 9 : 2 beds	159 ± 2.09	68.2 ± 5.6
12 - 10 : 1 bed	159 ± 2.2	66.7 ± 3.8
12 - 10 : 2 beds	161 ± 1.94	70.9 ± 4.2

Table 6: Sample Test of Hypotheses

Measure of Performance	Combined flow time	Type 3 flow time	Type 4 flow time
NFT X-bar	240	206	91.1
FT X-bar	223	159	66.7
STD	4.8	4.42	5.39
Rejection Region	<-1.64	<-1.64	<-1.64
Decision	Reject H_0	Reject H_0	Reject H_0

Further enhancements to the model are under way based on management policies that Mercy Hospital is willing to consider. Our recommendations to them include establishing a pre-empting policy. At present, Mercy Hospital does not accept ambulance patients unless there is an empty bed. Even if one of the beds is occupied by a low priority patient, the hospital will not move the lower priority patient out the bed to accommodate the ambulance (high priority) patient. Other enhancements to the model are dependent on the collection of new data.

REFERENCES

Kleckley, J. W., B. L. Killingsworth, and M. G. Kletke. 1991. Simulation Model for Estimating Health Care Service Demand: A Knowledge-Based System Approach. *Simulation in Health Care*, ed. J. G. Anderson, 194-201.

Kraitsik, M. J. and A. Bossmeyer. 1992. Simulation Applied to Planning an Emergency Department Expansion. In *Proceedings of the 1992 Western Simulation Multi conference: Simulation in Health Care and Social Services*, ed. J. G. Anderson, 19-27.

Pegden, C. D., R. E. Shannon, and R. P. Sadowski. 1990. *Introduction to Simulation Using SIMAN*, McGraw-Hill, Inc. New Jersey.

Vincent, S. G., and A. M. Law. 1993. UNIFIT II: Total Support for Simulation Input Modeling. In *Proceedings of the 1993 Winter Simulation Conference*, ed. G. W. Evans, M. Mollaghasemi, E. C. Russell, W. E. Biles, 199-204.

Schellenberger, R. E., B. L. Killingsworth, and J. W. Kleckley. 1992. A Medical Market Share Simulation: Methodology and Results. In *Proceedings of the 1992 Western Simulation Multi conference: Simulation in Health Care and Social Services*, ed. J. G. Anderson, 3-7.

Singh, V. K., A. J. Chandran, and B. R. Dey. 1990. Operation Research for Estimation of Ambulance Requirement in a Hospital. *Computer Methods and Programs in Biomedicine*, 59-63.

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