Forecast Driven Simulation Model for Service Quality Improvement of the Emergency Department in the Moses H. Cone Memorial Hospital*

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Abstract

Patient satisfaction with the Emergency Department(ED) in a hospital is related to the length of stay, and especially to the amount of waiting time for medical treatments. ED overcrowding decreases quality and efficiency, therefore affecting hospitals' profitability. This paper presents a forecasting and simulation model for resource management of the ED at Moses H. Cone Memorial Hospital. A linear regression forecasting model is proposed to predict the number of ED patient arrivals, and then a simulation model is provided to estimate the length of stay of ED patients, system throughput, and the utilization of resources such as triage nurses, patient beds, registered nurses, and medical doctors. The near future load level of each resource is presented using the proposed models.

Key Words: Service Quality, Emergency Department, Forecast, Resource Management, Simulation Model

1. Introduction

Overcrowding in an Emergency Department (ED) is a common phenomenon in the United States.

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Almost half of U.S. hospitals have reported that their ED is at or over capacity. Overcrowding decreases the quality of health care and the efficiency of ED operations. Demand for EDs increased from 1995 to 2005, whereas supply of EDs decreased during the same period. It was estimated that 93.1 million patients visited EDs in 1995, and 114.8 million visited in 2005-approximately a 20 percent increase. At the same time, the supply of EDs decreased by 5 percent (4,884 in 1995, to 4,611 in 2005) (AHA, 2007). In addition, ED overcrowding affects the profitability of hospital since approximately 40 percent of all hospital charges come from ED patients(Evans and Unger, 1996). Therefore, it is critical to reduce the length of stay of patients in the ED for the improvement of ED processes because having patients wait is a non-value added activity for patients as well as hospitals.

ED overcrowding should be treated as a long term issue and policy changes such as financial assistance to hospital facilities and incentives for training ED staff resources should be considered (Schafermeyer and Asplin, 2003). Increasing the number of ED staff and beds and improving the efficiency of the ED process have been successful in dealing with the overcrowding of EDs (Schnneider *et al*., 2001). The length of stay in the ED affects the satisfaction of ED patients (Boudreaux *et al*., 2004). The number of patients who leave without being seen by a physician in the ED is related to the duration of the stay of the patients (Brand *et al*., 2005).

There are several works about forecasting patient arrivals in ED since estimation of unscheduled patient arrivals may increase the quality of health-care and reduce patients' length of stay by allocating proper ED staff resources. Times-series models tracking the relationship between the number of visits and the length of time have been found to be statistically significant (Champion *et al*., 2007). Time-series methods have also been used to assess the process of ED flow and the efficiency of ED process intervals; main ED process intervals between triage and patient discharge have been calculated and administrative intervention has been shown to be effective in reducing the length of stays (Kyriacou, *et al*., 1999). The number of ED patient arrivals has been analyzed using a large amount of patient data from 2000 to 2003 for Richmond area hospitals. Hourly, daily, and event trends of patient load were analyzed in this research. For example, (i) ED patient arrivals began to increase at 9:00 in the morning, (ii) a high number of ED patients arrived on Mondays, and (iii) inclement weather, such as snowfall or a hurricane, also affected the number of ED patient arrivals (Tawney, 2005).

Simulation modeling has been used to identify the delay area of ED process and improve it. Kolb (2007) analyzed the relationship between ED overcrowding and inpatient unit capacity where the assumption was that the main cause of ED crowding is the number of ED patients with high severity levels and the inpatient unit capacity. It was shown that ED overcrowding is closely related with inpatient unit utilization. Centeno and Ismail (2003) used a combined simulation method and linear programming to minimize the number of ED staff. Other simulation studies have applied Six Sigma principles to improve the ED process in the simulation model (Miller *et al*., 2003) and a simulation model of each ED process to analyze patient flows in ED and reduce the length of stay in ED has also been establish (Takakuwa and Shiozaki, 2004); (Samaha, *et al*., 2003); (White, 2005); (McGuire, 1994). Draeger (1992) used a simulation method to improve the allocation of staff resources.

This paper presents two models for service quality improvement of ED processes; a forecasting model for the in-coming number of patients; and a simulation model for managing resources of the ED in the Moses H. Cone Memorial (MCM) Hospital in Greensboro, North Carolina, USA. An accurate estimate of the number of patient arrivals at the ED is important to its efficient operation and the quality of healthcare it delivers. In-coming patient load is the key factor in determining ED resource level. A linear regression forecasting model is proposed to analyze ED patient arrival trends and predict the number of ED patient arrivals by day of the week. A simulation model is also provided to estimate the length of stay of ED patients, system throughput, and the utilization of resources such as triage nurses, patient beds, registered nurse, and medical doctors.

2. Emergency Department of the Moses H. Cone Memorial Hospital

Moses H. Cone Memorial (MCM) Hospital, founded in 1953, is the largest medical center in Greensboro, North Carolina, delivering high-quality healthcare to the community at large. It is part of the Moses Cone Hospital System that also includes Wesley Long Community Hospital, the Women's Hospital of Greensboro, Anne Penn Hospital, the Behavioral Health Center, the Health Services Division and several outpatient services. Moses Cone Hospital System has 1,408 licensed beds and more than 7,000 staff. Among them, MCM Hospital has 535 licensed beds and specializes in heart and vascular, rehabilitation, neuroscience, and level II trauma. The ED is a hospital facility for the provision of unscheduled outpatient services to patients whose conditions require immediate care and it is staffed 24 hours a day, 7 days a week.

The MCM Hospital is currently experiencing an overcrowding of ED patients. The growth of ED demands has not been solely due to the general increase of the patient population. Other growth factors have included the increased number of patients who do not have medical insurance and the increased number of elderly people. Overcrowding of EDs may lead to treatment delays for ED patients, which results in ED patients having to spend longer wait times to see medical staff such as registered nurses or physicians.

Figure 1 shows the ED process of MCM Hospital. Patients usually arrive at an ED by their private vehicles or by ambulance, although a small percentage of total ED patients is transferred from other hospitals. Patients arriving at an ED are evaluated by triage staff. Evaluations in triage are usually handled by a nurse. At this stage, the emergency severity conditions of patients are evaluated and categorized using a five-level severity index as follows: life-threatening; emergent; urgent; non-urgent; and express care. Approximately 80 percent of ED patients at MCM Hospital are categorized as at the urgent, non-urgent, or express-care severity level. Some patients are admitted to hospital inpatient beds if further medical treatment is required. If the hospital has an inpatient bed available, patients are discharged to inpatient beds from the ED. Otherwise, patients remain in an ED room until inpatient beds are made available to them.

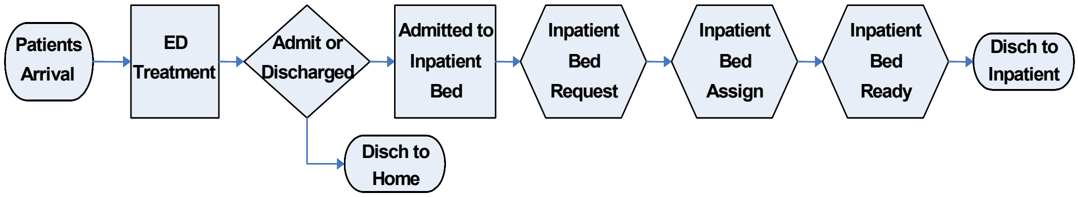

Figure 1. The ED process of MCM hospital

Overcrowding of EDs may lead to treatment delays of ED patients, meaning that ED patients have to spend longer wait times to see medical staff, such as registered Nurses or physicians. Patients admitted to hospitals through the ED, after medical emergency care, are also held in ED rooms while inpatient beds re readied to accommodate them. The wait and holding times of ED patients do not generate value to hospitals or to patients. Overcrowding of the ED decreases the quality of healthcare and the satisfaction of ED patients, and it is related to the percentage of patients who leave without seeing registered nurses or physicians in ED. Patient satisfaction increases if EDs use physician assistants to assist physicians in the ED. Figure 2 shows the various causes related to patients' lengthy stay times at the ED.

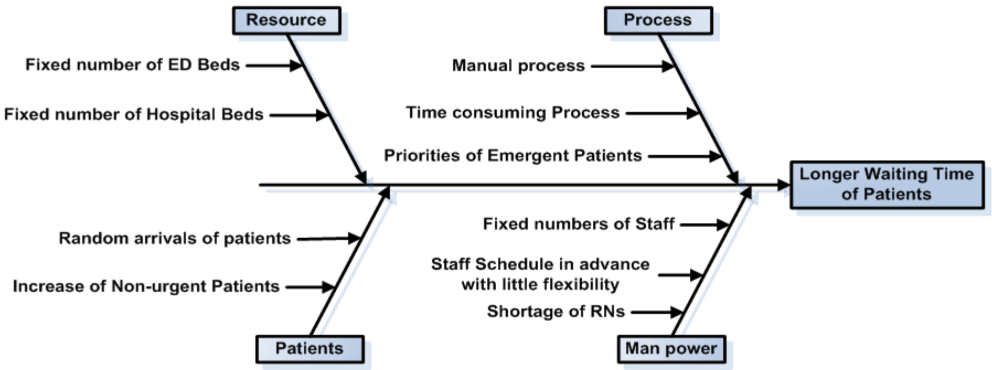

Figure 2. The cause and effect diagram of patients' lengthy waiting times

The ED of the MCM hospital operates with a fixed number of staff and beds. The number of ED staff is scheduled in advance with little flexibility, whereas patients arrive at separate points in time with a great deal of ebb and flow. If the ED encounters an unforeseen sharp increase of ED patient arrivals, there could be an unforeseen increase in demand for the nurses and physicians from the other hospital departments. However, it is not unusual for the same number of ED staff to see more patients, even if the number of ED patients arriving at the ED run over its resource capacity. Therefore, the predictability of patient arrivals at the ED is very important to allocating and scheduling ED staff.

3. Forecast Driven Simulation Model

Simulation is a useful tool to analyze the flow of the ED process in the real world. A simulation model demonstrates how to work the ED process simulation in the model and identifies the delay stage of ED processes, It then is able to help determine how to reduce the waiting time of ED patients by adjusting the number of staff necessary at different points in time. Two main steps are taken to analyze the performance of the ED in the MCM Hospital. The first one is to predict the number of patients arriving at the ED. A linear regression forecasting model is developed using the SAS statistics analysis package. Next patient flows are simulated, system throughput is determined, and resource allocation is tracked in the ED process. ARENA simulation software (version 10.0) is used for this process.

3.1 Forecasting Model for Patient Load

It is difficult to know exactly how many patients will arrive at an ED per day of the week or per hour of any day. However, patterns of patient arrivals from past electronic ED records may be analyzed for greater discernment. In this study, a linear regression method is used to analyze ED patient arrival trends and predict the number of ED patient arrivals by day.

The data used in this study are the electronic record data of ED patients at MCM Hospital from January 1, 2005 to September 30, 2007. The yearly number of ED patient arrivals is approximately 65,000. The average number of ED patient arrivals during the period is 5,450 per month. The number of patient arrivals tends to fluctuate by month but is higher in January and March each year. Figure 3 shows the monthly arrival pattern of the ED patient. The number of patient arrivals per day of the week does evidence a significant trend as shown in Figure 4. The number of patient arrivals on Sunday and Monday is high and Saturday is the day with the least number of patient arrivals. However, the difference between the maximum and minimum number of patients is not large on any day of the week. Another notable trend of patient arrivals is evidenced in the hourly arrival times of ED patients. The number of patient arrivals begins to increase at 7 : 00 in the morning and continues for 16 hours. The number of patients discharged from ED begins to increase from 7 : 00 am to 3 : 00 pm, even though it is far below that of patient arrivals.

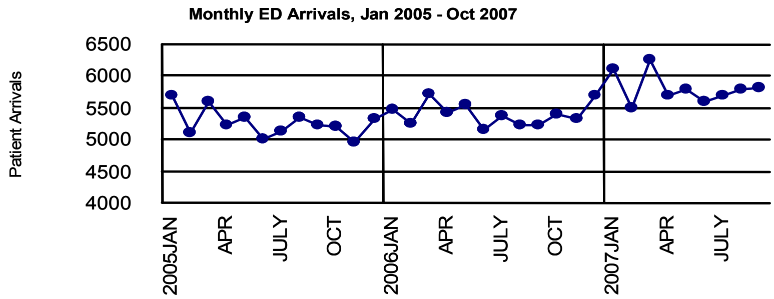

Figure 3. Monthly ED patient arrivals

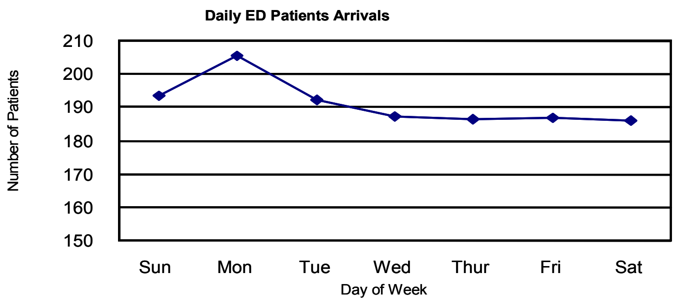

Figure 4. Trend of ED patient arrivals by day of week

The number of patient arrivals fluctuates by month and year. This means that the year, the month, and the day of the week all have effects on patient arrivals. It is assumed that the yearly effect and the daily effect are a linear function of the year and the day of the week, respectively. Therefore, the linear regression model is as follows;

$$P_t = \alpha + \beta \sum_{k=2005} kY_{t,k} + \sum_{j=Jan}^{Dec} \sum_{i=Sun}^{Sat} \delta_{i,j} X_{t,i,j} + e_t \tag{1}$$

P_t is observation t, i.e., the number of patient arrivals on the day i of the week in month j of year k, and α, β, $\delta_{i,j}$ are constants, and e_t is residuals, and $X_{t,i,j}$ is day i of week in month of j, (e.g., Sunday in January or Monday in January). $X_{t,i,j}$ is 1 if observation t is on the ith day of the week in the jth month of the year and 0 otherwise. $Y_{t,k}$ is 1 if observation t is on the kth year and 0 otherwise. It is assumed that residuals, e_t, are independent and identically distributed and have a normal distribution with mean of 0 and equal variances. The coefficients of the linear regression model are estimated using n = 231 observations from January 1, 2005 to September 30, 2007.

A significant effect of day of week and year was found for patient arrivals, $F = 6.43$, $p < 0.0001$, and R square = 0.7492. Hypothesis test on residuals' normality shows that residuals are distributed normally with mean = 0. The results are easy to use in predicting the number of patient arrivals if ED managers know the day of the week and the year. For example, the number of patient arrivals on Friday Oct 26, 2007 would be 173 according to the forecasting model (α = -16,863, β = 8.4905, $\delta_{Fri,Oct}$ = -12.9442).

3.2 ARENA Simulation Model

To estimate the length of stay of ED patients, system throughput, and the utilization of resources, a simulation model is used. There are four types of resources at the ED: triage nurses or physician assistants, patient beds, registered nurses, and medical doctors. It was assumed that the ED staff had three shifts per day. The number of ED staff changes according to the hour of day. More ED staff works between 7 : 00am and 3 : 00pm than during the other hours of the day because the patient load is high during that time. The data used for this simulation was the electronic records of ED patients between January 1, 2007 and September 30, 2007.

A discrete simulation model was programmed in ARENA. The overall structure of the simulation model consisted of four parts as shown in Figure 5. The first part is the Patient Arrival module, which explains the entity data of patient arrivals at ED. The Patient Arrival module is very important model because the ED processes are subject to random arrivals of ED patients that varied from hour to hour. The second part is the Triage Stage. Acuity degree of patient arrived at the ED is evaluated by a triage nurse. Patients wait to obtain triage assessment if a triage nurse is occupied with another patient. Some patients leave ED without being seen by a triage nurse if they feel they would wait for a long time. The third stage is ED Treatment Stage. After assessment by a triage nurse, a patient waits for ED treatment by ED staff if ED beds, nurses or medical doctors are not available. The fourth stage is Discharge Stage. Some patients leave ED after triage assessment if they believe they can not wait for ED treatment. After completion of ED treatment, patients are discharged to home if medical doctors decide patients do not need any further treatment. However, some patients are admitted to the hospital if the physicians decide they need further treatment. Patients admitted as hospital inpatients wait in the ED if hospital beds are not available for them. ED staff requests hospital beds for the admitted patients and then assign hospital beds if hospital beds are available. In this case, patients still occupy nurse and ED bed resources until they are moved into the hospital by ED staff. A few of the patients leave ED against medical doctor's advice that they need further treatment.

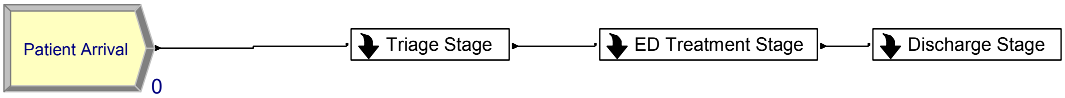

Figure 5. Overall structure of simulation model

The entity of this simulation model is the patients arriving at the ED (Not sure if this needs to be reworded). There are two types of arrival modes of ED patients; patients usually arrive at ED by their own vehicles or by ambulance. Table 1 shows the main attributes and input data studied in this paper. The distributions of input data are analyzed and fitted by the Input Analyzer of ARENA software.

Table 1. Model attributes and input data for simulation

Type of Model Inputs	Input data or Distribution
Mode of Arrivals (%)	Private Vehicle : 69.5, Ambulance: 28.8
Sex (%)	Female : 52.8, Male : 47.2
Age (%)	Adult(≥ 20) : 76.9 , Minor(< 20) : 23.1
Acuity (%)	Life-threat : 2.1, Emergent : 17.7, Urgent : 50.0, Non-urgent : 25.8, Express-care : 3.4
Patient Arrivals	Number of patients per hour
Triage duration	TRIA (3, 12, 20)
Percentage of leaving without being seen at each stage	Percentage of leave pre-triage, leave post-triage, post-RN/pre-MD, and AMA
Treatment duration by Registered Nurse	TRIA (3, 60, 152)
Treatment duration by Medical Doctor	TRIA (5, 8, 15)
Percentage of Patients admitted to hospital	Adult by Ambulance/by Private vehicle : 45.80%/18.19% Minor by Ambulance/by Private Vehicle : 12.03%/3.63%
Percentage of patients discharged to their homes	Adult by Ambulance/by Private vehicle : 50.65%/74.70% Minor by Ambulance/by Private Vehicle : 83.44%/90.00%
Duration between Inpatient Bed Request and Bed Assignment	Adult by Ambulance : 0.999 + WEIB(131, 0.707) Adult by Private vehicle : 0.999 + 1.36e + 003 * BETA(0.796, 7.52) Minor by Ambulance : 0.999 + ERLA(3.41, 11) Minor by Private Vehicle : 0.999 + EXPO(15.6)
Duration between Bed Assignment and Patient Discharge to hospital	Adult by Ambulance : 0.999 + WEIB(92.3, 1.08) Adult by Private vehicle : 0.999 + ERLA(38.4, 2) Minor by Ambulance : 0.999 + WEIB(92.3, 1.08) Minor by Private Vehicle : 0.999 + WEIB(56.2, 0.956)

Outputs of simulation model represent the operations and performances of the actual ED process. The proposed simulation model was validated with pilot simulations. The outputs obtained from these simulations were compared to the real data in the research.

4. Performance Evaluation

The ED manager of the MCM Hospital wants to reduce the waiting time of patients. The near future load level of each resource was determined using the proposed simulation model. Regression models were used to estimate the daily average number of patient arrivals in 2008. The results showed that the expected daily average number of patient arrivals in 2008 would increase by 3% compared to the number of arrivals in 2007.

4.1 Experimental conditions

Four types of main resources were chosen for the experimental conditions: number of triage nurses and physician assistants (NTN); number of patient beds (NBD); number of registered nurses (NRN); and number of medical doctors(NMD). Through interviews with the manager of ED, possible experimental levels of each resource were set as follows; 1) NTN level 1 : 1 nurse, NTN level 2 : 1 nurse + 1 physician assistant, NTN level 3 : 2 nurses, NTN level 4 : 2 nurse + 1 physician assistant, NTN level 5 : 3 nurses, 2) NBD level 1 : 53 beds, NBD level 2 : 5% increase, NBD level 3 : 10% increase, 3) NRN level 1 : 3 shift 22/29/26 nurses, NRN level 2 : 5% increase, NRN level 3 : 10% increase, 4) NMD level 1 : 4 doctors, NMD level 2 : 4 doctors, NMD level 3 : 6 doctors.

4.2 Performance evaluation

Through interviews with the manager of ED and pilot simulation studies, the following 6 alternatives were adopted in this paper; Alt. A-EXP(1, 1, 1, 1), Alt. B-EXP(2, 1, 1, 1), Alt. C-EXP(1, 2, 1, 1), Alt. D-EXP(1, 1, 2, 1), Alt. E -EXP(1, 1, 1, 2), Alt. F-EXP(3, 1, 1, 1) (e.g., EXP(1, 2, 1, 1) means the experiment having the condition combination of NTN level 1, NBD level 2, NRN level 1, NMD level 1). The patient load was set to + 3% of current load based on the proposed forecasting mode l(Refer to (1). It is necessary to reset the experimental alternatives according to the investment environment and the focused resource. Under Alt. A, all type of resources were used at current usage, (i.e. level 1). Alt. B used 2 nurses at the triage stage. In Alt. C, the number of patient beds was increased by 5% of the number of current beds. A 5% increase in the number of registered nurses was applied in Alt. E. The triage stage of Alt. F was operated with 1 nurse and physician assistant.

The average length of stay of patients (ALSP) was adopted as the major evaluation criterion of service quality. The length of stay of a patient begins when a patient arrives at ED and ends when he(she) is discharged from ED. Leave or transfer to another hospital occurs when a patient is not satisfied because of various reasons. System throughput (SYST), utilization of resources (UTLR), average waiting time of patients (AWPT), average number of waiting patients (ANWP), and number of patients departed or transferred (NRTP) were also measured. Throughput is defined as the total number of patients completed and discharged from the ED during a unit period of time.

To evaluate the system performance on steady-state, pilot simulation runs were made. To reduce the bias caused by system initialization, the test results for the first 4 days were discarded. The results of the simulation experiments were obtained with 10 replications per alternative at each level of the experimental condition. Each replication was observed over one unit time (24 hours) at steady state.

Table 2 shows the results of simulation experiments under various combination of the resource level. The table entries are the average and standard deviation of ALSP, SYST, UTLR, AWPT, ANWP, and NRTP. Alt. B and Alt. F performed relatively well in the performance criterion of ALSP and ANWP. Alt. A, C, D, and E had similar values in all criteria. Alt. F showed substantial improvements in the average waiting time of patients (AWPT) at the triage stage.

Table 2. The performance of each alternative

Alternative	ALSP (min)	SYST (No.)	UTLR(ratio)				AWTP(min)				ANWP(No.)				NRTP (No.)
			TN[c]	BD[c]	RN[c]	MD[c]	TN	BD	RN	MD	TN	BD	RN	MD	
Alt. A	202.39[a]	142.40	0.84	0.27	0.55	0.23	118.59	0	0.62	0.09	12.16	0	0.07	0.01	7.80
	(28.25)[b]	(9.58)	(0.04)	(0.03)	(0.05)	(0.01)	(46.39)	(0)	(1.26)	(0.09)	(6.01)	(0)	(0.16)	(0.01)	(1.32)
Alt. B	138.25	142.70	0.61	0.24	0.48	0.20	16.42	0	0.71	0.03	0.95	0	0.08	0	5.50
	(11.68)	(12.39)	(0.08)	(0.04)	(0.08)	(0.02)	(9.06)	(0)	(1.92)	(0.04)	(0.63)	(0)	(0.24)	(0)	(3.21)
Alt. C	202.39	142.40	0.84	0.25	0.55	0.23	118.59	0	0.62	0.09	12.16	0	0.07	0.01	7.80
	(28.25)	(9.58)	(0.04)	(0.02)	(0.05)	(0.01)	(46.39)	(0)	(1.26)	(0.09)	(6.01)	(0)	(0.16)	(0.01)	(1.32)
Alt. D	202.38	141.60	0.84	0.25	0.52	0.23	118.62	0	0.12	0.07	12.18	0	0.01	0.01	8.60
	(27.70)	(9.62)	(0.04)	(0.02)	(0.04)	(0.02)	(46.19)	(0)	(0.27)	(0.07)	(5.95)	(0)	(0.03)	(0.01)	(2.12)
Alt. E	200.15	140.60	0.84	0.25	0.54	0.19	118.13	0	0.46	0.01	12.02	0	0.06	0	7.70
	(24.21)	(9.65)	(0.04)	(0.02)	(0.04)	(0.01)	(40.11)	(0)	(1.18)	(0.02)	(5.59)	(0)	(0.15)	(0)	(2.06)
Alt. F	144.27	172.20	0.58	0.33	0.65	0.29	9.62	0.07	12.10	0.13	1.00	0.01	2.06	0.02	10.20
	(12.34)	(13.88)	(0.05)	(0.06)	(0.05)	(0.02)	(7.87)	(0.23)	(10.81)	(0.10)	(0.85)	(0.03)	(2.23)	(0.01)	(2.70)

Note: [a]Average, bStandard deviation.
[c]TN: triage nurse, BD: patient bed, RN: registered nurse, MD: medical doctor.

To analyze the relative performance of each alternative, the equality of the sample means were tested via the method of analysis of variance. The General Linear Model Procedure of SAS, a statistical analysis package, was used and the following hypothesis was tested.

$H_0 : \mu_{Alt.A} = \mu_{Alt.B} = \mu_{Alt.C} = \mu_{Alt.D} = \mu_{Alt.E} = \mu_{Alt.F}$
$H_1 :$ at least two of each means are unequal

where μ_i = mean of alternative i, $i = Alt.A, \cdots Alt.F$

First of all, the equality of the sample means of the ALSP criterion was investigated. At the test level of $\alpha = 0.05$ and with degrees of freedom of 5 and 54, the computed F-statistic of 18.20 and p-value < 0.0001 was significant. This indicated that the mean ALSP of the six alternatives were not the same. Through Duncan's Multiple Range Test, two Duncan groups were subsequently established. Alternative A, C, D, and E were in the higher value group. Alternative B and F belonged to the lower value group. Alternative B and F performed equally well in the criterion ALSP.

To choose the best alternative, the equality of the sample means of the SYST criterion was additionally tested. At the test level of $\alpha = 0.05$ and degrees of freedom of 5 and 54, the computed F-statistic of 12.85 and p-value < 0.0001 was significant. Through Duncan's Multiple Range Test, it was subsequently established that the system throughput for Alternative F, (i.e., EXP(3, 1, 1, 1)-2 triage nurses, 53 beds, 22/29/26 3 shift registered nurses, and 4 doctors) gave the highest performance.

The effect of the level of NTN was also investigated and the results are shown in Figure 6. The NBD, NRN, and NMD level were set at 1 in the experiments. Throughput performance was increased as NTN level increased from 1 to 3.

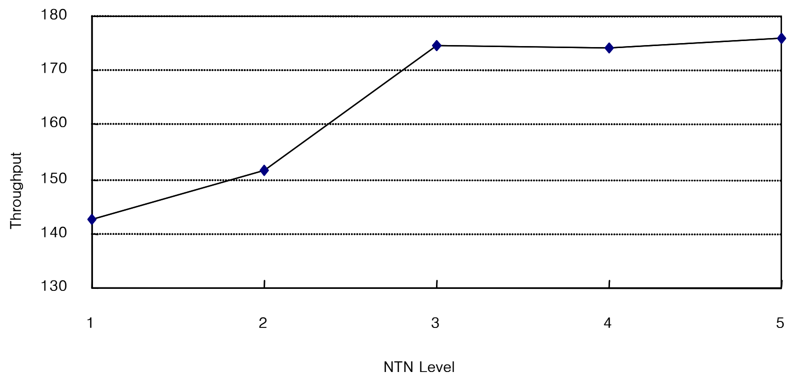

Figure 6. System throughput under various NTN

Other simulation results with various NBDs, NRNs, and NMDs are shown in Figure 7. When the effect of the number of NBDs was investigated, remain resources' level were set to 1, (i.e., NTN = 1, NRN = 1, NMD = 1). This experimental condition was applied similarly to the investigation of the effect of the number of NRNs and NMDs. The figure shows that the increasing rate in throughput was not substantial. This means that the patient beds, registered nurses, and the medical doctors are not bottlenecks in current ED situation.

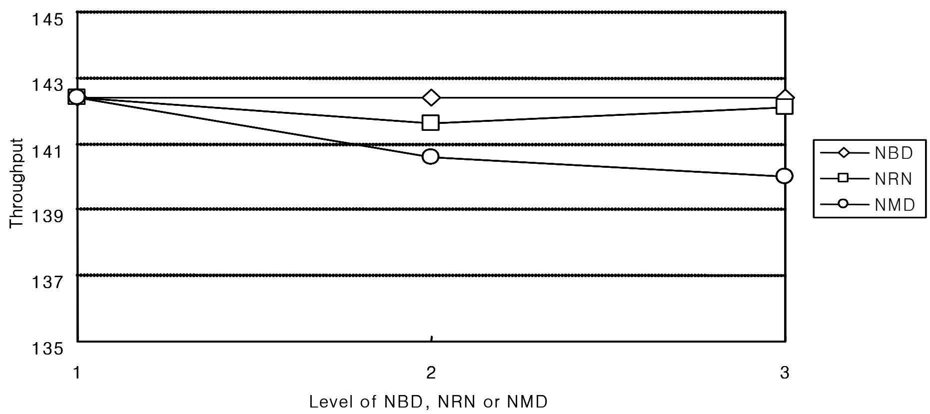

Figure 7. System throughput under various NBDs, NRNs, NMDs

5. Conclusion

To improve service quality of the ED in the Moses H. Cone Memorial Hospital, a forecasting and simulation model were proposed. Through experimental execution with the proposed models, the near future load level of each resource was presented. This study will help to establish efficient ED staff scheduling to decrease non-value added patient waiting time and increase the quality of patient healthcare.

The ED staff members of the MCM hospital know from past experiences that ED patient arrivals are affected by weather conditions, sport activities in the community, Thanksgiving Day and other holidays, paydays, or special community events such as the Homecoming Day of a local school or college. Further research is needed to enhance the predictability of the forecasting model. There is also a need for further on how to integrate the proposed forecasting model and the simulation model for more convenient simulation purposes.

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