Proceedings of the 2004 Winter Simulation Conference
R .G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, eds.

A SIMPLE AND INTUITIVE SIMULATION TOOL FOR ANALYZING EMERGENCY DEPARTMENT OPERATIONS

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ABSTRACT

In recent years hospitals have been vigorously searching for ways to reduce costs and improve productivity. One tool, simulation, is now widely accepted as an effective method for assisting management in evaluating different operational alternatives. It can help improve existing Emergency Departments (EDs) and assist in planning and designing new EDs. In order to increase the acceptance of simulation in healthcare systems in general and EDs in particular, hospital management should be directly involved in the development of these projects. Such involvement will also bolster the model's credibility. In addition, it is important to simplify simulation processes as much as is reasonably possible and use visual aids or animation that will heighten users' confidence in the model's ability. This study lays the foundation for the development of a simulation tool which is general, flexible, intuitive, simple to use and contains default values for most of the system's parameters.

1 INTRODUCTION

The annual U.S. expenditure on healthcare in 2003 was estimated at $1.5 trillion. This expenditure is expected to almost double and reach $2.8 trillion by the year 2011. Healthcare spending takes up a considerable portion of the total U.S. Gross Domestic Product (GDP). In the year 2000 healthcare accounted for 13.2% of the GDP and by 2011 may reach 17% of the GDP (Health Affairs 2002). Hospitals, which are the single largest item on this budget, are expected to account for 27% of the total projected healthcare expenditure by 2012. This estimation represents a decrease in this expenditure, down from 31.7% in 2001 (Price Waterhouse and Coopers 2003).

As a result, managers and other healthcare policy makers are pressured to come up with ways to improve the productivity of hospital operations. Cost reduction and waste elimination are generally the directions in which management heads.

Emergency Departments (EDs) play a crucial role in these operations. The ED acts as the hospital's 'gate keeper', determining if a patient needs to be admitted or can be discharged. At the same time the ED is required to treat efficiently and effectively a large variety of patients types, each with distinct needs. Hence, the ED has to be versatile and highly dynamic, and therefore, it is obvious that discrete-event simulation tools are particularly suitable for modeling these systems (Davies and Davies 1994). Simulation models can provide management with a reasonable assessment of the ED's efficiency, resource needs, utilizations and other performance measures in face of dynamic changes in the different system settings. Rakich et al. (1991) state that simulation can assist hospital management develop and enhance their decision-making skills for evaluating different operational alternatives in order to improve existing EDs or assist in designing and planning new EDs.

These facts have been recognized by a large number of researchers and consequently, a growing number of studies used simulation in modeling and analyzing ED performance. Jun, Jacobson, Swisher (1999) present a comprehensive literature review on the use of simulation in healthcare systems. Although this paper lists over one hundred simulation studies, simulation is still not widely accepted as a viable modeling tool in these systems. Hence, only a few successful implementations are reported.

One major stumbling block is the reluctance of hospital management, and especially the physicians in charge, to accept change, particularly if the suggestions come from a 'black-box' type of tool. Washington and Khator (1997) state that the reason simulation models are not used more often in healthcare settings is management's lack of incentive to do so. Management often does not realize the benefits to be gained by using simulation-based analysis tools when faced by the time and cost that have to be invested in building detailed simulation models. In a recent article entitled "Hospitals biased against optimization" Carter (2003) claims that there is an attitude among healthcare policy makers that spending money to improve systems only diverts funds from patient care.

In order to accelerate the proliferation and acceptance of simulation in healthcare systems and EDs, Lowery (1994) suggests that hospital management should be directly involved in the development of simulation projects in order to build up the models' credibility. In addition, it is important to simplify the simulation processes as much as possible and use visual aids or animation to instill more confidence in the model's ability. In conclusion, the desired simulation tool has to be based on the following principles:

1. The simulation tool has to be general and flexible enough to model different possible ED settings**.**
2. The tool has to be intuitive and simple to use. This way hospital managers, engineers and other non-professional simulation modelers can run simulation models with very little effort.
3. The tool has to include default values for all (or most) of the system parameters. This will reduce the need for comprehensive, costly and time-consuming time studies, which are usually among the first steps in building any simulation model.

By incorporating these principles, management's involvement in developing simulation models will increase, and as a result, management's confidence in the models will increase as well. At the same time, due to a decrease in the effort required to develop new simulation models, management's incentive to use simulation will hopefully grow.

The simulation tool has to include several modules in order for it meet all the requirements described earlier. The tool has to have a Graphical User Interface (GUI) that is intuitive and simple to use. Through it the user will input system characteristics and other required data and receive system operational results. Based on the user input, and with aid of several mathematical models, a simulation model of the system is designed. This process, illustrated in Figure 1, is entirely transparent to the user who only has to be know the system's operations and familiarize himself with a simple and intuitive GUI.

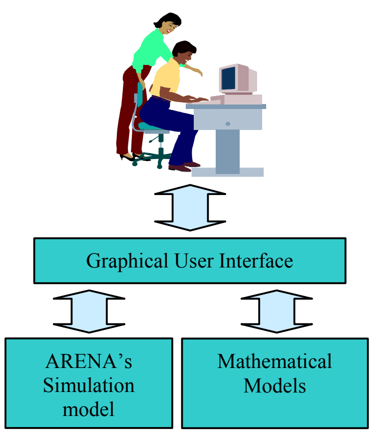


Figure 1: A Schematic Description of the Simulation Tool

Finding such a tool is not a simple task. Commercial simulation packages offer considerable flexibility in modeling any type of industrial or service system as well as any ED setting. In these packages flexibility is achieved through the use of generic activities as the basic building blocks of the model. However, due to a high abstraction level, developing simulation models using these generic activities is a complex, tedious and time-consuming task that requires specific knowledge and experience. In contrast, a dedicated simulation model of a specific system offers much greater simplicity and clarity in analyzing different options and scenarios of the system and can be easily used by nonprofessional programmers. In these custom-fitted models, simplicity is achieved through the use of fixed and rigid operation processes, which is also the reason why no other system can be modeled using this simulation. Between these two extreme points lies a range of possible intermediate modeling options, each with a different abstraction level, as illustrated in Figure 2.

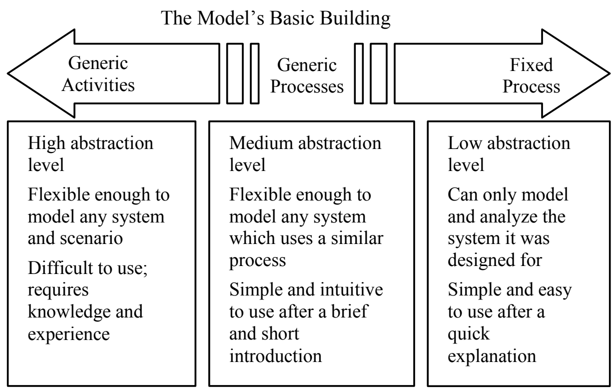


Figure 2: The Range of Modeling Options and the Building Blocks Used in Each Case

In order to maintain a reasonable level of abstraction, which is an essential requirement in an efficient and flexible modeling tool, while at the same time achieving simplicity, a generic process was selected to serve as the simulation model's basic building block. The first question raised is: Can a single generic process capture the distinctiveness of different EDs and serve as a basic operational structure upon which each ED is going to be modeled? A positive answer to this question is given in the following sections. We will also show that the processes patients go through when visiting an ED are better characterized by type (Internal, Surgical or Orthopedic) rather than by the hospital visited. This finding will form the foundation for the use of generic processes in the development of a general ED simulation tool which is not hospital or setting dependent.

2 GATHERING THE DATA

The first step is to study the different structures and work processes routinely used in different hospital EDs to see if some similarities can be detected. If these exist, these common processes and parameters will serve as base values in the simulation tool

Hospital EDs can be classified into four basic types according to two major characteristics as shown in Figure 1. The first characteristic is the ED physician type. ED physicians can be specialists in ED medicine, denoted hereafter as ED physicians, or specialists in specific disciplines such as internal, surgical or orthopedic medicine, denoted hereafter as professional physicians. The second characteristic is based on the patient's condition. Some EDs distinguish between acute and ambulatory patients and run each patient type through a different process, denoted hereafter as Separation. Other EDs run all patient types through the same processes regardless of their condition, denoted hereafter as No Separation.

In order to conduct the study, five hospitals were chosen and classified based on these two characteristics. The first class includes EDs 2 and 4, which operate with professional physicians and have no separation between acute and ambulatory patients. However, in ED 2 there is a physical separation between internal and trauma patients, while in ED 4 all patients are situated in one physical space. The second class includes EDs 1, 3 and 5 which also employ professional physicians; however, patients are classified based on their condition severity. In EDs 1 and 5, only the internal patients are separated, while in ED 3 both internal and trauma patients are separated.

The first step in the study included meetings with the senior physicians and head nurses of each ED to learn about the specific procedures routinely performed by the ED staff. Next, teams of supervised students equipped with standardized code lists of the different process elements conducted time and motion studies in the selected hospitals. An element is defined as a unique operation a patient goes through or one which a member of the hospital staff performs, such as patient administrative admission processing, E.C.G check etc. A total sample size of 16,250 elements was gathered by the teams in the different hospitals, 2951 in hospital 1, 3596 in hospital 2, 4195 in hospital 3, 1879 in hospital 4 and 3629 in hospital 5.

Based on the interviews and the time studies, eight patient types emerged: Fast-Track, Internal, Surgical, Orthopedic, Trauma, Walk-In Surgical, Walk-in Orthopedic and Internal/Surgical. Some types are more prevalent than others as they appear in all or most EDs. Table 1 lists the different patient types that were identified (including their acronyms in bold). In addition to the data gathered through the time study, hospitals (except hospitals 3 and 5) provided us with historical patient data (about 24 months) from their computerized information systems. The data covered the three main sites that handle patients at each hospital: the ED, the imaging centers and the labs. The data provided included:

Table 1: Patient Types at the Different EDs

Hospital	Type of Patients Defined
1	Fast-Track, Internal, Surgical, Orthopedic
2	Internal, Surgical, Orthopedic
3	Walk-In Internal, Walk-In Orthopedic, Walk-In Surgical, Internal, Trauma
4	Internal Acute, Internal/Surgical Minor, Orthopedic
5	Fast-Track, Internal, Surgical Orthopedic

1. The ED – patient ID number, admission/discharge date and time, the ED type to which the patient was admitted, the patient's complaints, age, gender, referring party, checks and tests (specialists, X-rays, urine, blood etc.) treatment (casts, stitches, medication etc.) and finally, hospital admission or discharge.
2. Imaging Center – patient ID number, type of lab (X-ray, ultrasound or CT), arrival date and time, referring unit (ED or hospital), complaint, number of X-rays performed.
3. Blood and Urine Labs - patient ID number, type of test, arrival date and time.

Based on the data gathered, a unique process chart was developed for each patient type at each of the five EDs observed. These charts include the duration (mean and variance) of each of the elements in the process and the frequencies of each of the connections between the different elements. Since all the process charts are very similar, a unified process chart, comprising all the different elements and transitions, was constructed, as shown in Figure 3. The individual charts for the 19 patient types including the time and frequency values of the different numbered elements and transitions can be obtained upon request from the authors.

3 ANALYZING THE GATHERED DATA

3.1 Classifying the Process Charts

According to the criteria listed in Section 3, the developed tool has to be general and flexible enough to model any ED and its processes. For this to be possible, we have to show that the processes patients go through when visiting an ED are mostly determined by the patient type (Internal, Orthopedic, Surgical etc.) rather than by the hospital in which they are performed. To do so, the different patient types need to be classified into clusters based on some similarity measure among them. The similarity values between the 19 different patient process charts were calculated using the similarity measure s_{ij} suggested in Sinreich et al. (2003). The s_{ij} similarity measure values range between 0 and 1, where higher values indicate a greater process similarity (the similarity values obtained in this study were in the range of 0.37 to 0.84). Next, the similarity values were normalized using (1) in order to enhance the distinction among the different processes.

$$\tilde{s}_{ij} = \frac{s_{ij} - s_{ij}^{\min}}{s_{ij}^{\max} - s_{ij}^{\min}}, \qquad (1)$$

where $s_{ij}^{\max}$, $s_{ij}^{\min}$ denote the largest and smallest similarity values, respectively.

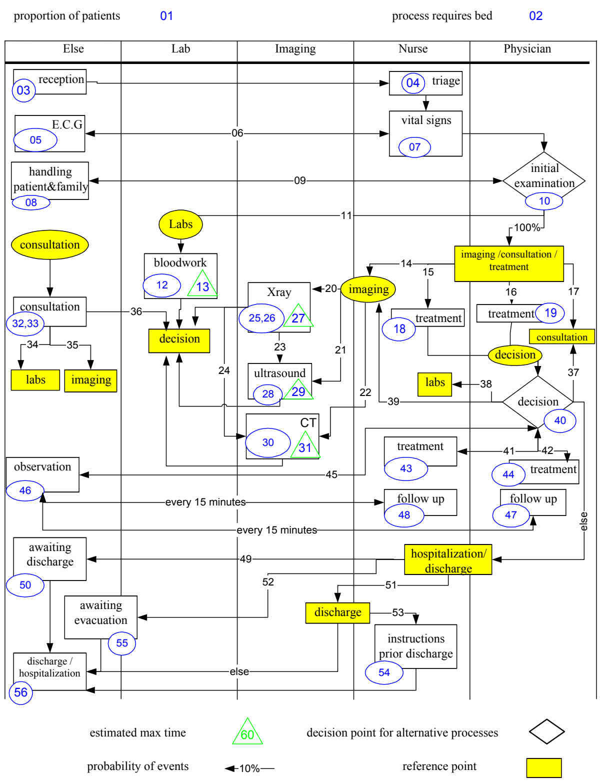


Figure 3: The Unified Process Chart

The overall average and standard deviation of the values listed in Table 2 are 0.44 and 0.22, respectively.

Since three major patient types appear in all the hospitals (Internal, Surgical and Orthopedic), we divided the 19 different patient types listed in Table 2 into three clusters, thereby maximizing (2):

$$\max \sum_{\forall i} \sum_{\forall j} \sum_{\forall k} \tilde{s}_{ij} \cdot I_{ik} \cdot I_{jk}, \qquad (2)$$

where I_{ik} and I_{jk} are indicators that are set to 1 if processes i and j, respectively, are included in cluster k; otherwise they are set to 0.

The problem at hand is being used only for evaluation purposes, we decided to enumerate all the different clustering options (approximately $3^{19}/3!$ options). The different clustering options were ranked based on an ascending order of the averages of the different similarity values. The optimal clustering option was not quite acceptable from a practical point of view. Therefore, we chose a different clustering option that was very close to the optimal value. This is a classical case where "good is better than best" (Petroski 1994).

Table 2: The Calculated Relative Precision Value

	Patient Type					
Element	Internal	Surgical	Orthop	Trauma	Fast-Track	Overall Precision $d_{i\bullet}$
Vital Signs	3.6%	5.7%	8.9%	6.7%	3.2%	**2.2%**
E.C.G Check	3.6%	11.3%	16.0%	13.1%	9.7%	**3.0%**
Treatment Nurse	5.5%	12.6%	11.1%	10.8%	15.6%	**3.9%**
Follow up Nurse	10.1%	47.5%	43.0%	19.7%	50.1%	**7.9%**
Instructions Prior to Discharge	16.5%	30.7%	29.1%	25.2%	43.2%	**11.9%**
First Examination	4.6%	6.3%	4.4%	7.4%	10.2%	**2.8%**
Second or Third Examination	6.7%	11.4%	8.0%	11.8%	30.2%	**4.3%**
Follow Up Physician	5.9%	27.8%	26.0%	32.9%	----	**5.4%**
Admission/Discharge	11.0%	13.0%	19.3%	32.9%	15.0%	**7.5%**
Handling Patient and Family	6.5%	15.9%	9.3%	9.5%	18.4%	**4.6%**
Treatment Physician	11.3%	12.9%	15.4%	21.2%	49.9%	**7.1%**
Patient Precision $d_{\bullet p}$	**5.2%**	**9.4%**	**8.1%**	**9.5 %**	**7.6%**	

The first cluster in this option comprises eight patient types that represent the Internal and Fast-Track patients in all five EDs, except for the Internal Walk-In patients from hospital 3. The average of the similarity values in the first cluster was 0.66. The second cluster comprises four patient types that represent the Orthopedic patients in all five EDs except for the Orthopedic Walk-Ins from hospital 3. The average of the similarity values in the second cluster was 0.75.The third cluster is comprises seven patient types that represent the Surgical patients in all five EDs, including the Walk-In patients from hospital 3. The average of the similarity values in the third cluster was 0.54. The overall average of this clustering option is 0.62 - only 0.015 away from the optimal average similarity value but much higher compared to the average of all similarity values before the patient types were divided into clusters (0.44) or any other random selected clustering option was used. Accordingly, it would be safe to argue that in the hospitals that participated in this study patient type has a higher impact in defining the process through which patients go compared to the specific hospital in which the patients are treated, as we hypothesized.

3.2 Analyzing the Precision of the Different Time Elements

Since a time study is basically a statistical sampling process, it is important to estimate the precision of the gathered data. The precision as a proportion of the true value can be calculated using the following formula, which is based on normal distribution.

$$d_{ip} = \frac{z(1-\alpha/2)\cdot\hat{\sigma}_{ip}}{\sqrt{m_{ip}}\cdot\hat{\mu}_{ip}}, \tag{3}$$

where $\hat{\mu}_{ip}$ and $\hat{\sigma}_{ip}$ are the average duration and standard deviation over all observed elements of type i for patient type p at all the hospitals participating in the study; m_{ip} denotes the number of times this element was observed for each specific patient, and z denotes the $1-\alpha/2$ standard normal quantile. Based on these observations the relative precision level d_{ip} of each element for each patient can be calculated.

Using the previously calculated element precision values, the relative precision value $d_{\bullet p}$ of patient type p, regardless of the hospital in which this patient type is treated, can be calculated via (4):

$$d_{\bullet p} = \sum_{\forall i} d_{ip}\cdot w_{ip} \tag{4}$$

where w_{ip} is defined as the relative weight of a specific element i of patient type p, regardless of hospital type. These weights can be calculated via (5):

$$w_{ip} = \frac{\tilde{t}_{ip}}{\sum_{\forall i}\tilde{t}_{ip}} \tag{5}$$

where $\tilde{t}_{ip}$ denotes the contribution each element i has to the total process time of patient p regardless of hospital type.

These values can be calculated via (6):

$$\tilde{t}_{ip} = \frac{\hat{\mu}_{ip}\cdot m_{ip}}{\vartheta_p} \tag{6}$$

where ϑ_p is defined as the maximum number of times patient type p goes through an element that is only performed once during the ED process, regardless of the hospital in which this patient is treated.

Table 2 lists the calculated d_{ip} relative precision values for the different elements that were directly observed in the time study at the different EDs for the five most significant (out of eight) patient types that appear in all or most EDs. All the elements with relative precision levels smaller than 10% are highlighted. Combining all the d_{ip} values (based on equations 4 - 6) produces the patient's process duration relative precision $d_{\bullet p}$, while the relative precision for each element $d_{i\bullet}$ can be calculated via (7):

$$d_{i\bullet} = \frac{z(1-\alpha/2)\cdot\hat{\sigma}_{i}}{\sqrt{m_{i}}\cdot\hat{\mu}_{i}} \tag{7}$$

where m_i denotes the number of times element i was observed over all patients types and hospitals

The combined precision values indicate that aggregating element duration according to patient type, regardless of the hospital in which they are treated, does not impact significantly on the precision levels of these elements. Furthermore, aggregating improves the precision levels of all the different elements, as the overall precision column shows. Both these analyses indicate that it is possible to aggregate patient process charts according to patient type, disregarding the hospital in which the patient is treated. Consequently, it follows that a general simulation tool based on a unified process can be developed.

4 DEVELOPING GENERAL PATIENT ARRIVAL MODELS

In order for the simulation tool to be as general and flexible as possible while at the same time simple and easy to use, patient arrival models have been developed. These mathematical models are based on at least 24 months of data obtained from the hospital's information systems.

4.1 Patient Arrival Model to the ED

The data from the hospital's computerized systems revealed that the number of patients arriving at the ED differs from hour to hour (evening hours are much busier than early morning hours), and from day to day (weekends - Friday and Saturday - are much slower than to the rest of the week). Statistical tests reveal that the square-root of the patients' arrival process (that means the number of arrivals per period of time) can be described by a normal distribution. Let X_{pihd} be a random variable normally distributed with a mean of μ_{pihd}, which represents the square-root of the number of patients of type *p* who arrive at the ED of hospital *i* at hour *h* on day *d*. Sinreich and Marmor (2004a) suggest a model to estimating the parameters of the above normal distribution:

$$\hat{\mu}_{pihd} = \hat{\mu}_{phd} \cdot \hat{F}_{pi} .$$

We can estimate the normal random variable X_{pihd} 's mean $\hat{\mu}_{pihd}$ and its standard deviation by 0.6; the latter standard deviation estimate turns out to follow the gathered data. The number of patients θ_{pihd} of type *p* who arrive at hospital *i* at hour *h* on day *d*, to be used in the simulation, can be estimated using a random realization x_{pihd} from the above distribution as follows:

$$\theta_{pihd} = \left\langle \left(x_{pihd} \right)^2 \right\rangle$$

where $\langle x \rangle$ represents the closest integer value of *x*. Once the number of patients is determined, the actual arrivals in the simulation are evenly distributing throughout each hour. For example, if the estimated number of arriving patients of type surgical at hospital 1 between 11:00 AM – 12:00 noon on Monday is three, the first patient is scheduled to arrive at 11:00 AM the second patient is scheduled to arrive at 11:20 AM and the third patient is scheduled to arrive at 11:40AM.

Using the hospital records, the $\hat{F}_{pi}$ factors for the different patient types in the different hospital were calculated as shown in Table 3. It is clear from these factors that hospital 1 is larger (as it acceptance more patients) compared to the other two hospitals.

Table 3: The Calculated F_{pi} Factors

	Patient Type		
Hospital	**Internal**	**Surgical**	**Orthopedic**
1	1.180649	1.292876	1.186829
2	0.957457	1.038417	0.83959
4	0.861894	0.668707	0.973586

The first step in validating this model was to compare the estimated patient arrival against the actual patient arrivals as gathered from the hospital records. The comparisons for the Internal patients are shown in Figures 4 and 5. The solid lines represent the actual arrivals and the dashed lines represent the model's estimations. It is clear from these figures that the arrival process estimation realistically reflects the actual arrivals.

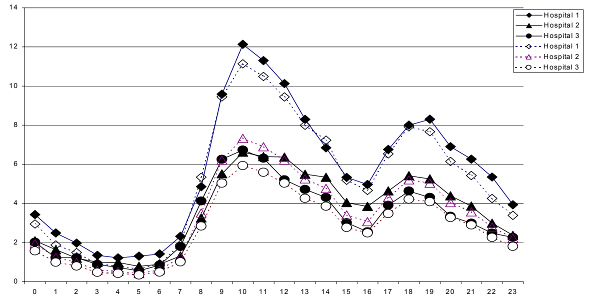


Figure 4: Patient Arrival Process Comparison for Internal Patients During 24 Hours on a Monday (weekday)

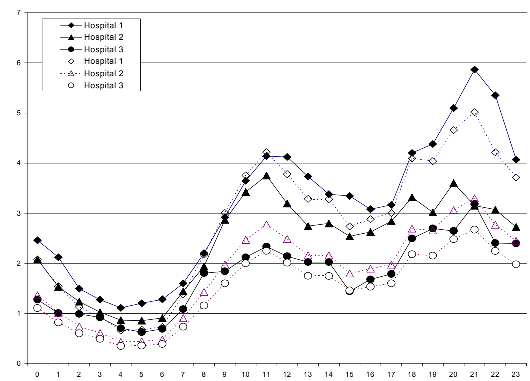


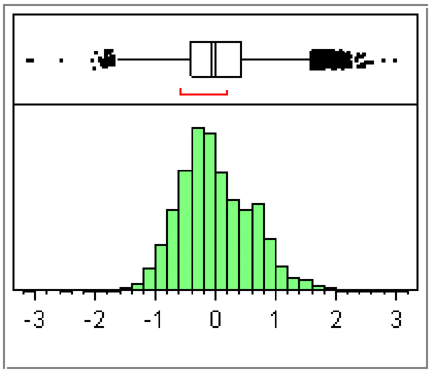
Figure 5: Patient Arrival Process Comparison for Internal Patients During 24 Hours on a Saturday (weekend)

Another step in verifying this model was to check the distribution of the residual values of the predicted patient arrivals versus the actual patient arrivals. The analysis using JMP (Sall et al. 2001) is illustrated in Figure 6.

Shapiro-Wilk goodness of fit tests reveal that the residuals can be described by a normal distribution with a mean close to 0, and as expected, a standard deviation of 0.6. All these values point to the adequacy of the arrival estimation model.

4.2 Patient Arrival Model to the Imaging Center

Imaging centers (X-ray, CT and ultrasound) are not always ED-dedicated. In some cases these centers as serve the entire hospital patient population. Therefore, from the ED simulation standpoint there are two different streams of patients for which we must account: ED patients and hospital patients. These two streams interact and interfere with each other. In order to accurately estimate the service time including the waiting time ED patients experience when sent to the imaging center, it is imperative to estimate the hospital's patient arrival process. The hospital's computerized records revealed that the number of patients coming from the hospital to the imaging center differs from hour to



Moments

Mean	0.0000844
Std Dev	0.6003367
Std Err Mean	0.0025241
upper 95% Mean	0.0050316
lower 95% Mean	-0.004863
N	56571

Figure 6: Distribution of the Residual Values for Internal Patients

hour, from day to day and from month to month. Statistical tests reveal that the square-root of the number of patients arriving from the hospital to the imaging center can be described by a normal distribution. Sinreich and Marmor (2004a) suggest the following linear regression model to estimate the square-root number of hospital patients arriving at the imaging center:

$$\hat{\varphi}_{ihdm} = \hat{\mu} + \alpha_i + \beta_h + \gamma_d + \delta_m + \varepsilon$$

where $\hat{\mu}$ denotes the square-root of the average number of patients arriving to the imaging center and $\alpha_i, \beta_h, \gamma_d, \delta_m$ denote the hospital effect, the hour effect, the day effect and the month effect respectively. All these parameters were found to be significant. Based on this linear regression the number of patients π_{ihdm} who arrive at the imaging center in hospital i at hour h on day d and on month m, can be estimated as follows:

$$\pi_{ihdm} = \left\langle \left(\hat{\varphi}_{ihdm}\right)^2 \right\rangle$$

where $\langle x \rangle$ represents the closest integer value of x).

The first step in validating this model was to compare the estimated patient arrival process against the actual patient arrivals as gathered from the hospital data. This comparison is shown in Figure 7. The different colors represent the different hospitals; while the solid lines represent the actual arrivals and the dashed lines represent the model's estimations.

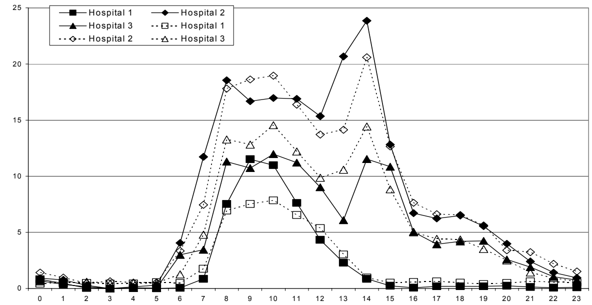
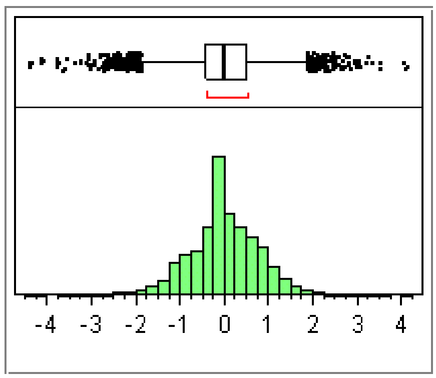


Figure 7: Patient Arrival Process Comparison - Tuesday

The comparison reveals a realistic fit between the estimated hospital patient arrivals and the actual arrivals of these patients. The last step in validating this model was to check the distribution of the residual values of the predicted hospital patient arrivals versus the actual arrivals of these patients. The analysis using JMP (Sall, Lehman and Creighton 2001) is illustrated in Figure 8.



Moments

Mean	-1.62e-14
Std Dev	0.8030956
Std Err Mean	0.0075429
upper 95% Mean	0.0147854
lower 95% Mean	-0.014785
N	11336

Figure 8: Distribution of the Residual Values

Shapiro-Wilk goodness of fit tests reveal that the residuals can be described by a normal distribution with a mean close to 0, and as expected, a standard deviation of 0.8. Again, these results point to the adequacy of the model for the estimation of the hospital patient arrivals to the imaging center.

4.3 Staff's Walking Model

From the observations made in the five hospitals it was clear that the medical staff spends a considerable amount of time, during each shift, walking between the different activity points in the ED. This includes walking to and from patient beds, medicine cabinet, nurse's station, ED counter etc. Therefore, walking time is important in the accurate estimation of the staff workload. Based on the data gathered during the observations the following physicians' and nurses' walking time estimation models (8) and (9) respectively were developed

$$T_p^D = [-461.37127 + 0.50041 \cdot W + 0.12628 \cdot d_c + 0.13354 \cdot d_r + 0.00047 \cdot (d_c - 703.5) \cdot (W - 596.5) + 0.00034 \cdot (d_r - 2043.8125) \cdot (W - 596.5) + \varepsilon(0,150^2)] / N \quad (8)$$

$$T_p^N = [-7695.81994 + 6.61123 \cdot W + 5.1936 \cdot d_s + 1.50267 \cdot d_m + 0.02921 \cdot (d_m - 499.44444) \cdot (W - 806.66667) + 0.00875 \cdot (d_m - 1176.66667) \cdot (W - 806.66667) + \varepsilon(0,150^2)] / [N \cdot L/W] \quad (9)$$

where W and L represent the width and length of the room in which the medical staff member operates, d_c represents the walking distance to the ED counter, d_r represents the walking distance to the stitching room, d_m represents the walking distance to the medicine cabinet, d_s represents the walking distance to the nurse's station and N represents the number of beds in the ED room.

The fit of the above models as indicated by R^2 is 0.737 and 0.675 for the physician's and nurse's walking models, respectively A full description of the model is given in Sinreich and Marmor (2004b).

5 CONCLUSIONS AND FINAL REMARKS

This study lays the foundation for developing a simulation tool for analyzing ED performance that is general yet simple, intuitive and easy to use. This study addresses the first objective listed in Section 3 and shows that the processes patients go through when visiting an ED are better characterized by type (Internal, Surgical or Orthopedic) than by the specific hospital visited. This enables the development of a general tool that is neither hospital nor setting dependent. The duration of the basic elements in the patient's process were also determined, to be used later in the simulation tool as default values that can reduce the need, in some cases, for elaborate time and motion studies in the future. In addition, the basic patient streams that trigger the different processes were identified and estimation models were developed to be used by the simulation tool. The main operation screen of the simulation tool is shown in Figure 9. This screen shows the process a patient goes through at the ED, including the different elements that can be adjusted to fit each patient type in each individual hospital.

ACKNOWLEDGMENTS

This research was supported by the Israel National Institute for Health Policy and Health Services Research NIHP under grants number 2000/7/a and 2000/7/b.

We would like to thank the Research Center for Work Safety and Human Engineering at the Technion and all the student teams who assisted us in the field study.

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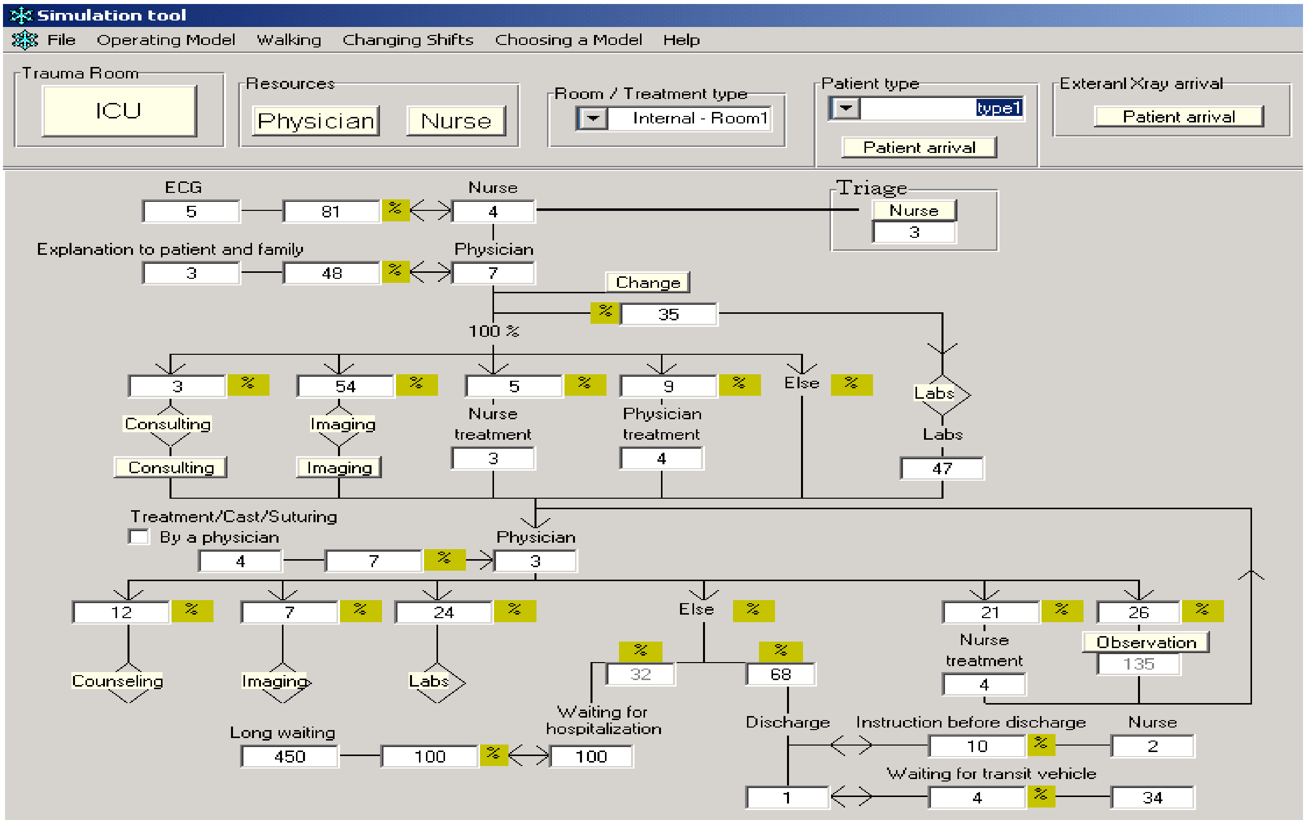

Figure 9: The Main Screen of the Simulation Tool

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