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Publisher: Taylor & Francis
Informa Ltd Registered in England and Wales Registered Number: 1072954
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IIE Transactions

Publication details, including instructions for authors and subscription information:
<http://www.informaworld.com/smpp/title~content=t713772245>

Emergency department operations: The basis for developing a simulation tool

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Online Publication Date: 02 February 2005

To cite this Article: Sinreich, David and Marmor, Yariv (2005) 'Emergency department operations: The basis for developing a simulation tool', IIE Transactions, 37:3, 233 - 245

To link to this article: DOI: 10.1080/07408170590899625

URL: <http://dx.doi.org/10.1080/07408170590899625>

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Emergency department operations: The basis for developing a simulation tool

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Received February 2003 and accepted August 2004

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 to assist 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 simulation'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

Until a few decades ago, service industries used simple methods, if any, to design, analyze and operate systems. However, in recent years, in light of the increased demand on these industries, coupled with the rising cost of providing services, management has been trying to better utilize existing resources and create more efficient systems. Consequently, service industries are changing, introducing modern design and evaluation techniques based on data gathering and information technology.

The healthcare industry, as part of the service industry, is also feeling the pressure to change. Throughout the last decade, hospitals have been struggling with scarce funds, shortages in nursing staff, limited resident hours (Wright *et al.*, 1992) and an increase in the number of patients who seek medical care. As a result, Emergency Departments (EDs), which serve as their hospitals' "gate keepers" suffer from overcrowding (Gallagher and Lynn, 1990). This is now an acute problem in many large urban hospitals. Faced with these problems, hospital managers and other healthcare policy makers are being forced to search for ways to reduce costs and improve productivity.

There are two basic types of modeling techniques that can be used to describe and analyze systems using computerized mathematical tools:

1. Prescriptive models: such as linear or nonlinear programming models. These models provide a prescription for how to set the decision variables in order to achieve optimal performance of a predefined objective function.
2. Descriptive models: such as queuing models, Markov chains or discrete-event simulation models. These models provide a detailed report on the system's operational behavior based on its description.

Similar to prescriptive models, queuing models and Markov chains, which often rely on closed-form mathematical solutions, are very sensitive to the size, complexity and level-of-detail required by the system under study. Discrete-event simulation models, on the other hand, are much less sensitive to these parameters. However, simulation demands a considerable investment of time, especially if detailed modeling is required.

Since EDs are large, complex, and highly dynamic, it is obvious that discrete-event simulation tools are particularly suitable for modeling them (Davies and Davies, 1994). Simulation models can provide a reasonable assessment of an ED's efficiency, resource needs, utilizations and other performance measures as changes are made in the different system settings. Rakich *et al.* (1991) state that simulation can assist hospital management develop and enhance their decision-making skills when evaluating different operational alternatives in order to improve existing EDs or to assist in designing and planning new ones.

The rest of the paper is organized as follows: Section 2 presents a literature review on the use of discrete-event

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simulation in ED design and operation. Section 3 lists the capabilities a simulation tool needs in order to be widely useable. Next, Section 4 describes the time and motion study data gathered for use in the current paper. The analysis of the gathered data is presented in Section 5. Section 6 describes the development of patient arrival models; and finally, our conclusions are presented in Section 7.

2. Literature review

A growing number of studies use simulation in modeling ED performance. Gonzalez *et al.* (1997) used a detailed simulation of an ED and showed how ED service quality can be improved through the evaluation of different alternatives that were generated by the simulation. Kraitsik and Bossmeyer (1993) used simulation to evaluate the establishment of a fast-track lane adjacent to the main ED and a large capacity lab in order to improve patient flow at the University of Louisville Hospital. Blake and Carter (1996) came to a similar conclusion when simulating the operation of the Children's Hospital of Eastern Ontario. McGuire (1994) used MedModel by the ProModel Corporation (Anon, 2002) to set appropriate staffing levels and check other operational alternatives in order to reduce patients' length-of-stay in an ED at SunHealth Alliance Hospital. Staffing was also a concern in the simulation study Bardi and Hollingsworth (1993) conducted at the Rashid Hospital in the United Arab Emirates. Liyanage and Gale (1995) used an $M/M/n$ model to ascertain the patients' arrival time, waiting time and service time distributions. These were later used in a simulation model of the Campbelltown Hospital ED to determine the required number of physicians and their utilization.

A comprehensive literature review on the use of simulation in healthcare clinics can be found in Jun *et al.* (1999). The vast majority of these studies modeled specific hospital EDs and did not attempt to develop a generic tool flexible enough to model any hospital ED. The exceptions to these are Altobelli *et al.* (1989) and Bergman (1990) who developed simulation tools to create scenarios that are used to test and train ED staff handling a mock mass casualty incident.

Although Jun *et al.* (1999) list over 100 simulation studies, only a few successful implementations are reported. This leads to the conclusion that simulation is still not widely accepted as a viable modeling tool in healthcare systems. One major stumbling block is the reluctance of hospital management, and especially the senior physicians in charge, to accept change, particularly if the suggestions come from a "black-box" type of tool. To overcome this resistance, Lowery (1994) suggests that hospital management should be directly involved in the development of the simulation project in order to bolster the model's credibility, and should incorporate in it visual aids or animation that will heighten users' confidence in the model's ability. 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, because they only consider the time and cost that have to be invested in order to build a detailed simulation tool. In light of the above mentioned opposition, a different approach to healthcare and ED simulation is needed.

3. Research objectives

The new approach has to address 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 managers, hospital engineers and other nonprofessional simulation modelers can run the simulation tool with very little effort.
3. The tool has to include *reasonable default values for many of the system parameters*. This will reduce the need for comprehensive, costly and time-consuming time and motion studies, which are usually among the first steps taken when building any simulation model.

By incorporating these three principles, management's involvement and confidence in the models will increase. At the same time, the effort required to develop new simulation models will decrease, and management's incentive to use simulation should increase accordingly.

The main objective of this study is to advance this approach. Therefore, the first step was 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 default values in the simulation tool.

4. Gathering the data

Hospital EDs can be classified into four basic types according to two major characteristics as shown in Fig. 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 as shown in Fig. 1. The first class includes EDs 2 and 4, which operate with professional physicians

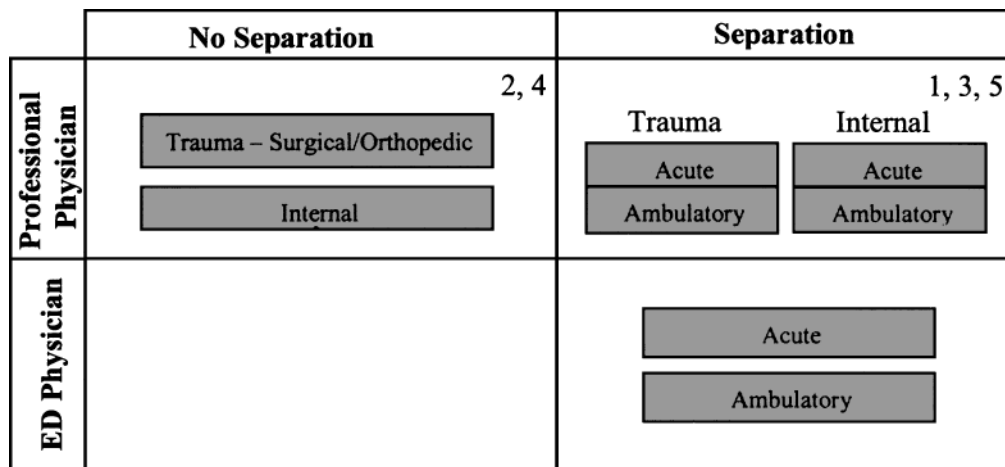


Fig. 1. Hospital ED classification.

and have no separation between acute and ambulatory patients. However, in ED 2 there is a physical separation between internal and trauma patients, whereas 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, here patients are classified based on their condition severity. In EDs 1 and 5, only the internal patients are separated, whereas in ED 3 both internal and trauma patients are separated. At this point in time, there is no hospital in Israel that is fully staffed by ED physicians and operates accordingly.

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. A total of 1325 man-hours were invested in gathering the data and an additional 2000 hours were invested in its analysis.

Different patient types were identified through the interviews with the senior staff and the conducted time studies. Table 1 lists the different patient types (including their acronyms), as defined by the hospital staff. Some of these definitions overlap, e.g., fast-track is the same as internal walk-in, and internal acute is the same as internal. As a result eight unique patient types emerged: (i) fast-track; (ii) internal; (iii) surgical; (iv) orthopedic; (v) trauma; (vi) walk-in surgical; (vii) walk-in orthopedic, and (viii) internal/surgical. Some types are more prevalent than others as they appear in all or most EDs. In addition to the data gathered through the time and motion study, hospitals (ex-

cept 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:

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

Table 1. Types of patients defined at the different EDs

Hospital	Types of patients defined
1	fast-track (1FT), internal (1I), surgical (1S), orthopedic (1O)
2	internal (2I), surgical (2S), orthopedic (2O)
3	walk-in internal (3I_W), walk-in orthopedic (3O_W), walk-in surgical (3S_W), internal (3I), trauma (3T)
4	internal acute (4I_A), internal/surgical (4I_S), orthopedic (4O)
5	fast-track (5FT), internal (5I), surgical (5S), orthopedic (5O)

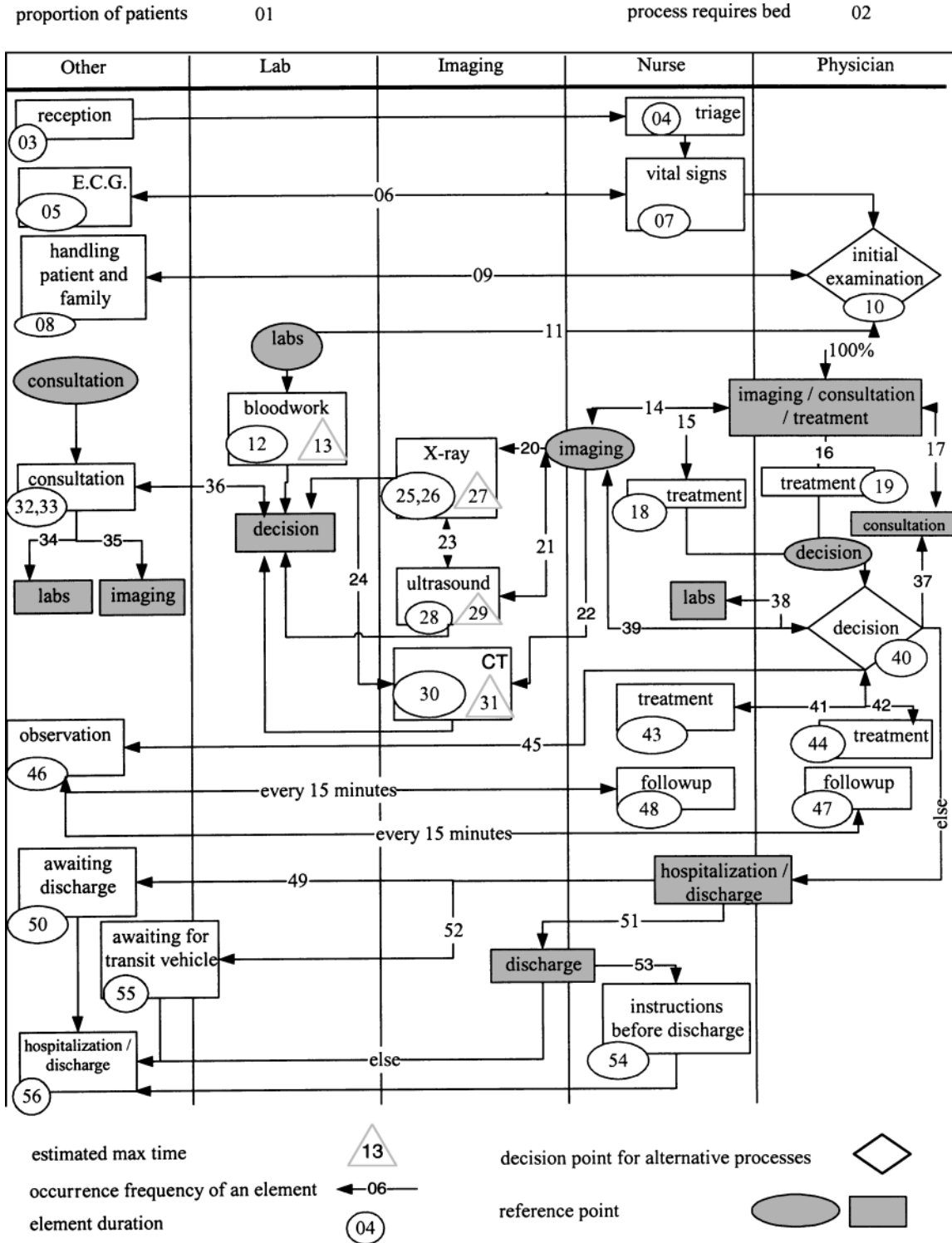


Fig. 2. The unified patient process chart.

process chart, comprising all the different elements and transitions, was constructed, as shown in Fig. 2. 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.

5. Analyzing the gathered data

5.1. Classifying the process charts

According to the criteria listed in Section 3, the developed tool has to be general and flexible enough to model different

5 FT	5 S	5 O	5 I	4 I_A	4 O	4 I_S	3 T	3 I_W	3 S_W	3 O_W	3 I	2 S	2 O	2 I	1 FT	1 S	1 O	1 I	
88	55	24	66	70	46	89	43	32	23	32	59	52	33	64	80	52	43		1 I
53	62	77	32	36	86	35	59	12	37	60	14	74	89	40	40	66			1 O
79	89	42	37	39	61	58	68	31	47	58	31	74	59	49	61				1 S
94	56	23	48	43	57	67	45	28	29	37	44	51	32	56					1 FT
66	40	23	89	73	25	59	38	39	18	25	63	53	44						2 I
46	51	72	32	50	71	30	45	6	23	43	9	67							2 O
64	71	51	37	45	55	46	62	32	38	45	31								2 S
52	23	1	53	51	7	57	27	27	9	10									3 I
46	51	25	14	15	52	28	88	16	84										3 O_W
37	41	2	5	5	31	16	100	30											3 S_W
45	19	0	23	26	3	29	36												3 I_W
54	64	22	23	24	46	34													3 T
79	54	27	61	72	39														4 I_S
57	56	53	18	26															4 O
59	27	32	77																4 I_A
55	25	16																	5 I
32	52																		5 O
65																			5 S
																			5 FT

Fig. 3. Similarity values ($\times 100$) among the different patient process charts.

EDs and their 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 zero and one, 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 the following equation in order to enhance the distinction among the different processes:

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

where s_{ij}^{\max} , s_{ij}^{\min} denote the largest and smallest similarity values, respectively. The normalized similarity values among all the different patient process charts (indicated by the acronyms listed in Table 1) are shown in Fig. 3. The overall average and standard deviation of the values shown in Fig. 3 are 0.44 and 0.22, respectively.

In all the hospitals analyzed we can find the following three patient types: internal, orthopedic and surgical. Therefore, we divided the 19 different patient types shown in Fig. 3 (symmetric about the diagonal) into three clusters,

thereby maximizing:

$$\max \sum_{\forall i} \sum_{\forall j} \sum_{\forall k} \tilde{s}_{ij} I_{ik} I_{jk},$$

where I_{ik} and I_{jk} are indicators that are set to one if processes i and j , respectively, are included in cluster k , $k = 1, 2, 3$; otherwise they are set to zero.

Different clustering methods are listed in Sato *et al.* (1997). However, since 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. For example, the average similarity value of the cluster that includes patient types 1O, 2O, 3O_W, 4O and 5O is 0.628. Omitting patient type 3O_W from this cluster increases the average similarity value of the cluster to 0.75. On the other hand, 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).

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 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.

On the one hand, the overall average of the above mentioned clustering option is 0.62: only 0.015 away from the optimal average similarity. On the other hand, this value is much higher than the average of all similarity values before the patient types were divided into clusters (0.44) or before any other randomly 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, than does the specific hospital in which the patients are treated: as we hypothesized.

5.2. Analyzing the relative precision of the different time elements

Since a time and motion study is basically a statistical sampling process, it is important to determine the precision of the gathered data. The precision as a proportion of the estimated average value can be calculated using the following formula, which is based on the normal distribution (Krajewski and Ritzman, 1998):

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

where \hat{v}_{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.

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:

$$d_{\bullet p} = \sum_{\forall i} d_{ip} w_{ip}, \quad (1)$$

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 in turn be calculated via:

$$w_{ip} = \tilde{t}_{ip} / \sum_{\forall i} \tilde{t}_{ip}, \quad (2)$$

where \tilde{t}_{ip} denotes the contribution each element i makes to the total process time of patient type p regardless of hospital type. This contribution can be calculated via:

$$\tilde{t}_{ip} = \frac{\hat{v}_{ip} m_{ip}}{\vartheta_p}, \quad (3)$$

where ϑ_p is defined as the maximum number of times an element that is performed only once, during the process of patient type p , was observed. For example, a patient may go through several physician examinations; however, discharge or hospital admission is performed once during each patient process. Using the proportion m_{ip}/ϑ_p we can estimate how many times on average each element is performed.

Table 2 lists the calculated d_{ip} relative precision values for the different elements that were directly observed in the time and motion 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 in bold type. Combining all the d_{ip} values (based on Equations (1)–(3)) produces the patient's process duration relative precision $d_{\bullet p}$, while the relative

Table 2. The calculated relative precision values in percent for d_{ip} , $d_{\bullet p}$, d_{\bullet} .

Element	Patient types					Element precision d_i (%)
	Internal (%)	Surgical (%)	Orthopedic (%)	Trauma (%)	Fast-track (%)	
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	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
Hospitalization/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	

precision for each element $d_{i\bullet}$ can be calculated via:

$$d_{i\bullet} = \frac{z(1 - \alpha/2)\hat{\sigma}_i}{\sqrt{m_i}\hat{v}_i},$$

where m_i denotes the number of times element i was observed over all patient types and hospitals, and \hat{v}_i and $\hat{\sigma}_i$ are the average duration and standard deviation over all observed elements of type i regardless of patient type.

The combined precision values indicate, as the overall precision column shows, that aggregating element duration according to patient type, regardless of the hospital in which the patients are treated, actually improves the precision levels of all the different elements. Consequently, it makes sense to develop a general simulation tool based on a unified process.

6. 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 to be developed. These models will be developed based on the ED data supplied by three out of the five hospitals that participated in the study. Hospital 3 provided us with partial data and hospital 5 did not provide any data.

6.1. Patient arrival model

As indicated earlier, the hospitals provided us with 24 months of data from their information systems. This data 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 (weekend, Friday and Saturday, are much slower than the rest of the week). Statistical tests indicate that the square root of the patients' arrival process (i.e., 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 . We introduce some notation that is used to determine the distribution's mean estimator.

- $1, \dots, p, \dots, P$ is the patient index;
- $1, \dots, i, \dots, H$ is the hospital index;
- $1, \dots, h, \dots, 24$ is the hour index;
- $1, \dots, d, \dots, 7$ is the day index;
- $1, \dots, w, \dots, W$ is the week index.

Let n_{pihdw} denote 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 in week w as collected from the hospitals' information systems.

The average square-root estimator $\hat{\mu}_{pi}$ of the number of patients of type p arriving at hospital i per hour can be

calculated as follows:

$$\hat{\mu}_{pi} = \frac{\sum_{w=1}^W \sum_{d=1}^7 \sum_{h=1}^{24} n_{pihdw}}{W \times 7 \times 24}.$$

These values are used to calculate the patient arrival factor \hat{F}_{pi} for each hospital. This factor indicates the relative volume of patients of type p arriving at a specific hospital with respect to the other hospitals:

$$\hat{F}_{pi} = \frac{\hat{\mu}_{pi}}{\sum_i \hat{\mu}_{pi}} H. \quad (4)$$

The above factor is now used to adjust the values of the arrival data gathered from the hospital's information systems for each patient type p in each hospital i . Namely, we let:

$$\hat{n}_{pihdw}^a = \frac{n_{pihdw}}{\hat{F}_{pi}}, \quad (5)$$

where \hat{n}_{pihdw}^a denotes the estimated adjusted arrival data values of patients of type p who arrive at hospital i at hour h on day d in week w .

The estimated adjusted values are used to calculate the average square-root estimator $\hat{\mu}_{phd}$ of the number of patients of type p who arrive during hour h on day d :

$$\hat{\mu}_{phd} = \frac{\sum_{i=1}^H \sum_{w=1}^W \hat{n}_{pihdw}^a}{HW}. \quad (6)$$

Finally, we calculate the mean square-root estimator $\hat{\mu}_{pihd}$ of the number of patients of type p who arrive at hospital i at hour h on day d as follows:

$$\hat{\mu}_{pihd} = \hat{\mu}_{phd} \hat{F}_{pi}. \quad (7)$$

The list of the 168 (7 days \times 24 hours) calculated $\hat{\mu}_{pihd}$ values for each patient type can be obtained upon request from the authors.

At this point we can estimate the normal random variable X_{pihd} 's mean by $\hat{\mu}_{pihd}$ and its standard deviation by 0.6; the latter standard deviation estimate turns out to follow from the gathered sample 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:

$$\theta_{pihd} = \langle x_{pihd}^2 \rangle, \quad (8)$$

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

The initial database and factors were determined using the data obtained from the three hospitals that participated in the study. If a hospital that did not participate in the study wishes to use the simulation tool, all that is needed are the n_{pihdw} values which can be obtained from the hospital's computerized information systems. The rest of the process, which includes calculating Equations (4)–(8), is performed automatically by our simulation tool.

Table 3. The calculated \hat{F}_{pi} factors

Hospital	Patient type		
	Internal	Surgical	Orthopedic
1	1.180	1.293	1.187
2	0.958	1.038	0.840
4	0.862	0.669	0.974

6.2. Validating the patient arrival model

The hospitals' computerized records recognized only the three major patient types. Therefore, we sorted all patient records accordingly.

The \hat{F}_{pi} factors for the different patient types in the different hospitals were calculated as shown in Table 3. It is clear from these factors that hospital 1 is larger (as it accepts more patients) than the other two hospitals.

The patient arrival models were developed from these factors and Equations (5)–(8). The first step in validating these models was to compare the estimated patient arrivals against the actual patient arrivals as gathered from the hospital records. The comparisons for the internal patients are shown in Figs. 4 and 5. The solid lines represent the actual arrivals and the dashed lines represent the model's estimates.

It is clear from these figures that the estimated arrival process realistically reflects the actual arrivals. The next step in

validating the model was to test the model using data from three hospitals that were not part of this study. The comparison for the surgical patients is shown in Fig. 6 where the different tick marks represent the different hospitals. The filled-in tick marks and corresponding solid lines represent the actual mean numbers of patient arrivals, while the open tick marks and dashed lines represent the estimated model.

Once again these figures show that the estimated arrival process accurately follows the actual arrivals. The last step in validating this model was to check the distribution of the residual values of the predicted patient arrivals against the actual patient arrivals. The analysis using JMP (Sall *et al.*, 2001) is illustrated in Fig. 7.

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

6.3. Patient arrivals at the imaging center

Imaging centers (X-ray, CT and ultrasound) are not always ED-dedicated. In some cases these centers serve the entire hospital patient population. Therefore, from the ED simulation standpoint there are two different streams of patients that are sent for service to the imaging center, namely, patients who are sent from the ED and patients who are sent from all other hospital wards. These two streams interact

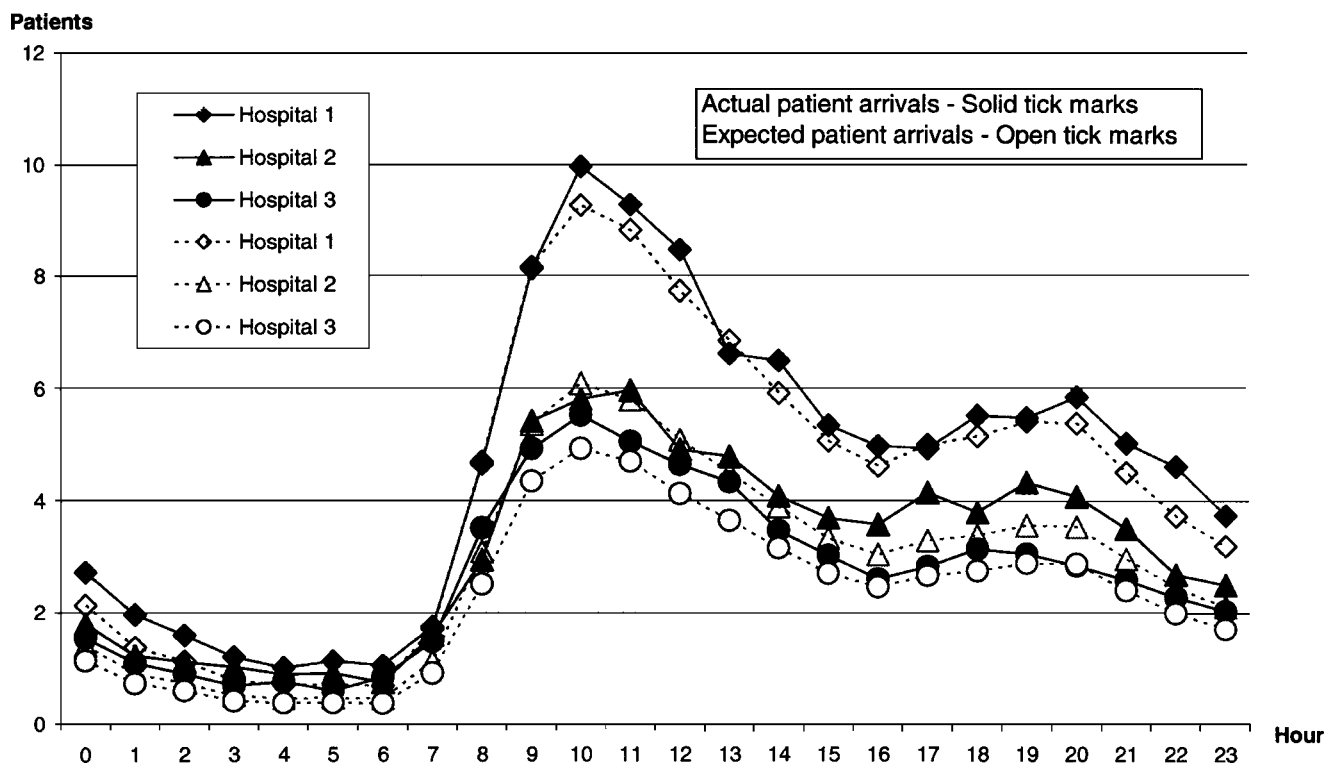


Fig. 4. Patient arrival process comparison for internal patients during 24 hours (Monday).

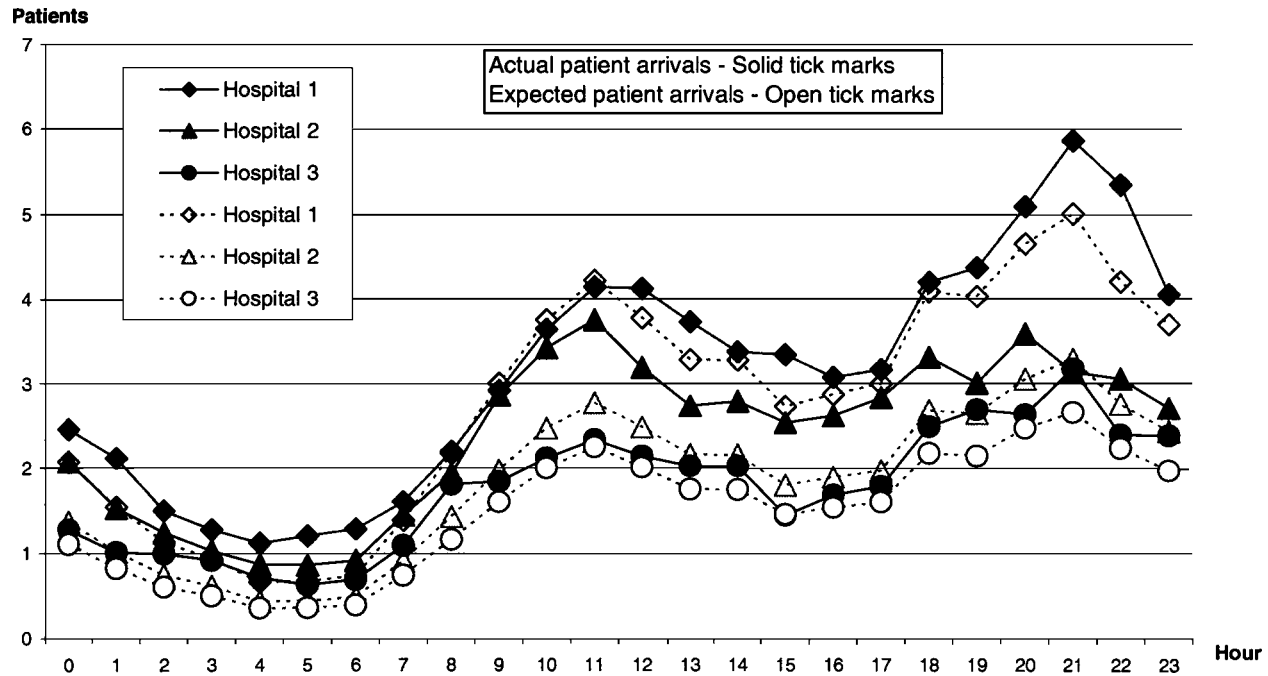


Fig. 5. Patient arrival process comparison for internal patients during 24 hours (Saturday).

and interfere with each other and compete for the same resources. In order to accurately estimate the waiting time ED patients experience when sent to the imaging center, we have observed the patients' walking time, the time it takes to perform an X-ray, and the time it takes the radi-

ologist at the imaging center to view the X-ray to return a diagnosis. These parameters were later used in the simulation tool. However, in the case that both ED patients and other hospital patients (not from the ED) are sent to the same imaging center, one must also estimate the hospital

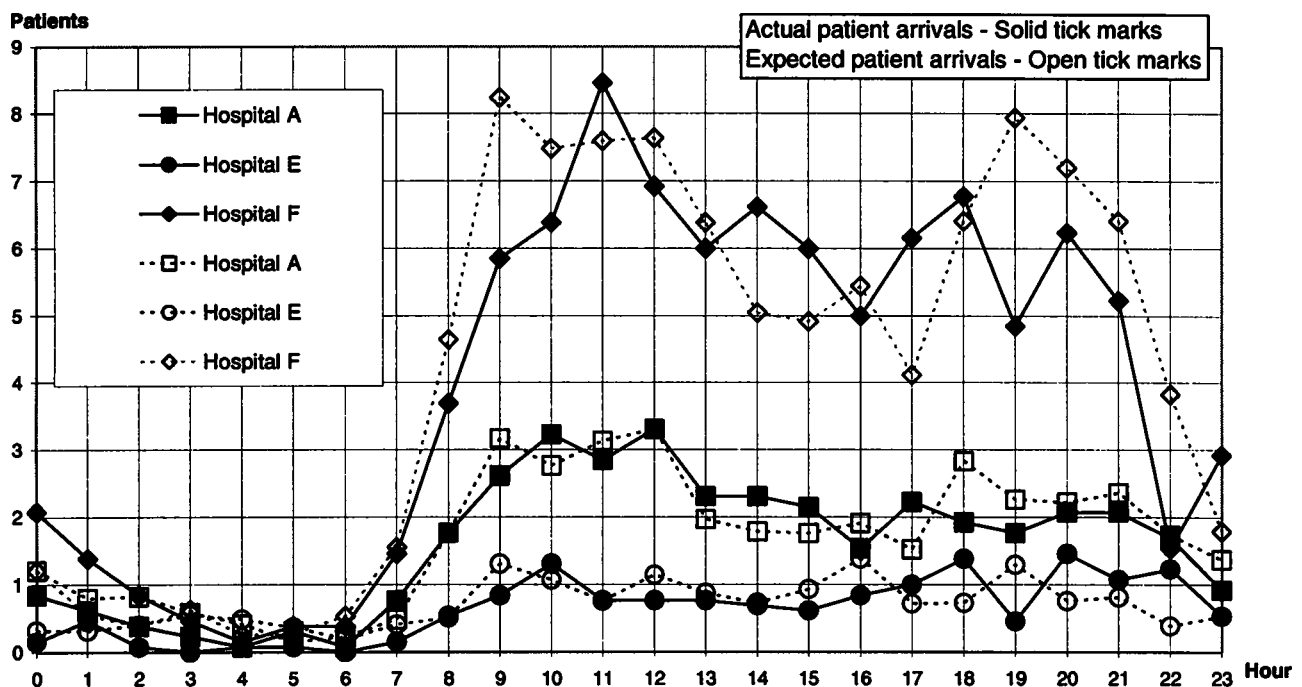


Fig. 6. Patient arrival process comparison for surgical patients during 24 hours in hospitals which were not part of the initial analysis (Wednesday).

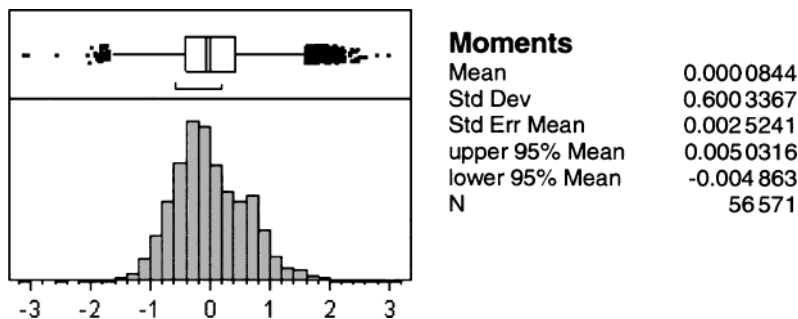


Fig. 7. Distribution of the residual values for internal patients.

patient arrival process. Furthermore, different hospitals operate their imaging centers differently. Some hospitals have dedicated ED imaging centers that operate during the entire day whereas others operate these centers only during part of the day; and there are those that do not have dedicated centers at all. The following models are used only in the case that the hospital operates a combined imaging center.

The hospital's computerized records reveal that the number of patients arriving at the imaging center from the hospital differs from hour to hour, from day to day and from month to month. As before, statistical tests reveal that the square root of the patients' arrival process (number of arrivals) to the imaging center can be described by a normal distribution.

The hospital-patient arrival-estimation model in this case is a linear regression model. In order to maintain the model's linearity, four separate regression sub-models were developed. Each of these sub-models is used to capture different modes of operation as found in the examined hospitals. Three of these sub-models were used to estimate the hospital patient arrival process when a combined imaging center operates around the clock. The first sub-model is used to estimate hospital patient arrivals between 6 am and 12 midnight on weekdays. The second sub-model is used to estimate hospital patient arrivals between 12 midnight and 6 am on weekdays and weekends. The third sub-model is used to estimate hospital patient arrivals between 6 am and 12 midnight on weekends. For the case where the imaging

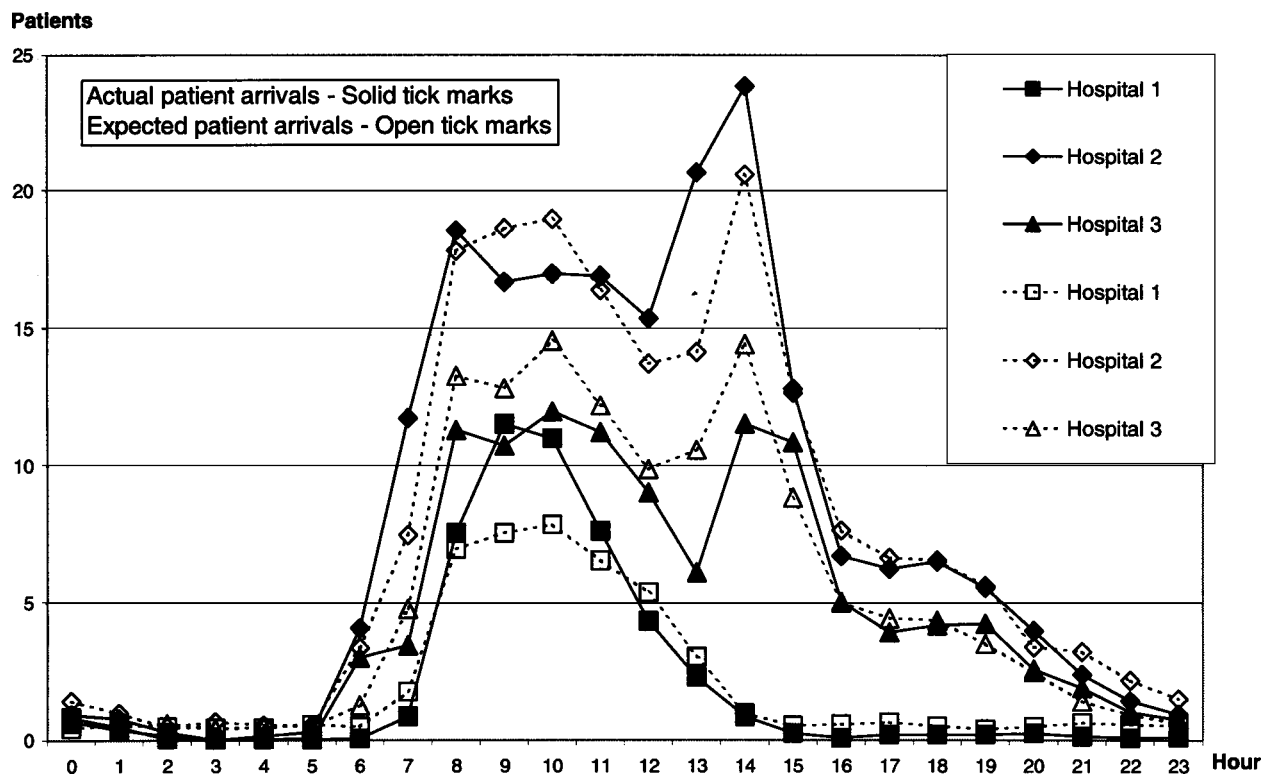


Fig. 8. A comparison of the actual and expected hospital patient arrivals to the imaging center (Tuesday).

center services both ED and other hospital wards only part of the day, an additional sub-model is needed. In our case hospital 4 operates a combined imaging center only between 6 am and 12 noon. Therefore, the first sub-model is used to describe the hospital's patient arrival process during these hours and the fourth sub-model is used to estimate the arrivals between 12 noon to 5 pm. At 5 pm the external arrivals are reduced to a minimum, similar to the conditions which exist at other hospitals during night hours and weekends. Therefore, the third sub-model is used to estimate the patient arrivals in hospital 4 between 5 pm and 6 am.

The linear regression model used to estimate the square root of the number of hospital patients arriving to the ED is:

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

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, hour, day, and the month effects, respectively. All of these parameters were found to be significant. The interaction between the hours and days was also found to be significant. This interaction is captured indirectly through the use of the four different estimation models, each for a different time and day combination as explained earlier. The complete list of the effect values used in the four regression models can be obtained upon request from the authors.

The estimated number of hospital patients π_{ihdm} who arrive at the imaging center in hospital i at hour h on day d and on month m , can be determined via

$$\pi_{ihdm} = \langle \hat{\varphi}_{ihdm}^2 \rangle.$$

For purposes of validating this model, we compared the estimated patient arrival process against the actual patient arrivals as gathered from the hospital data (see Fig. 8). The different tick marks represent the different hospitals,

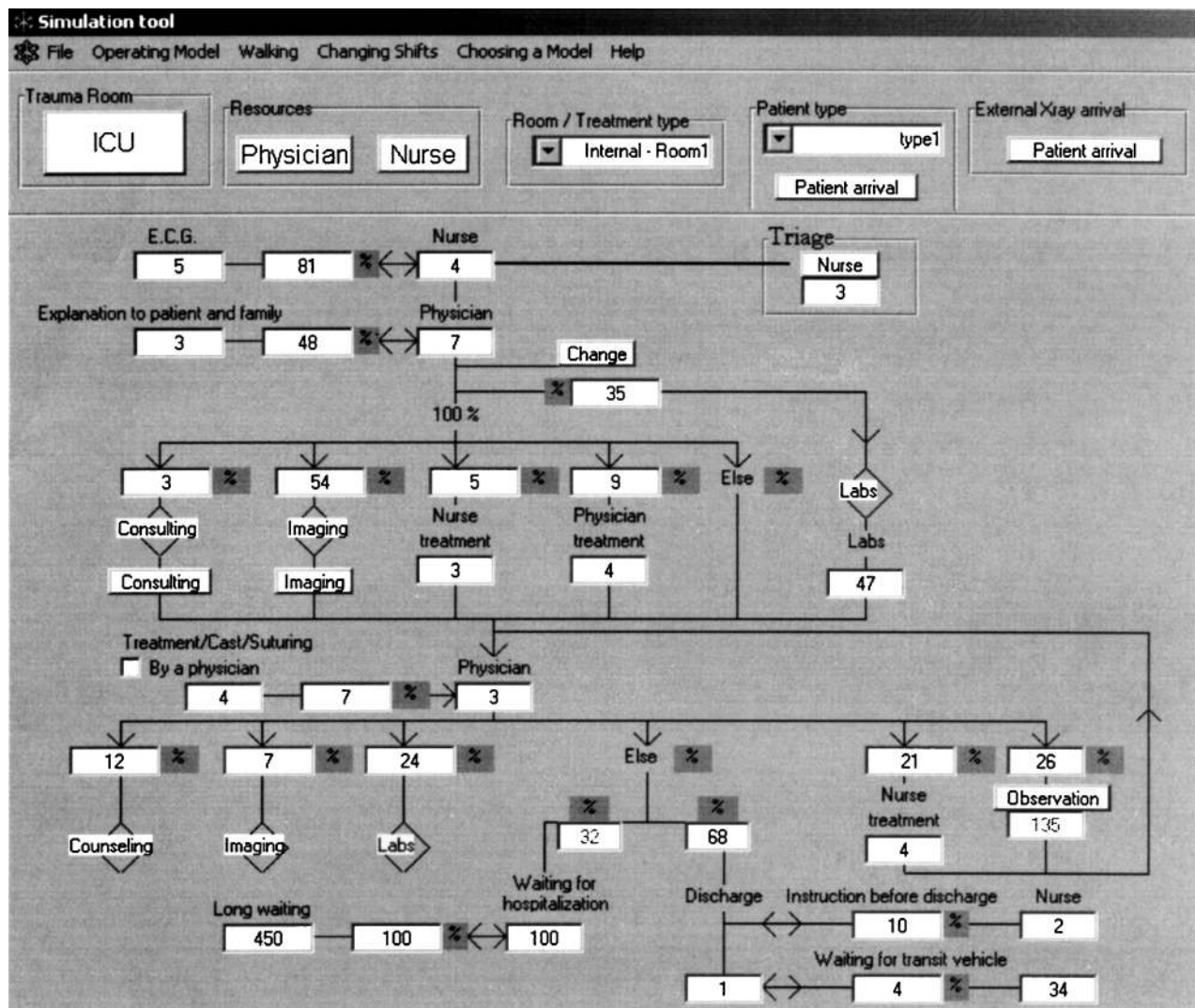


Fig. 9. The main screen of the simulation tool.

whereas the solid lines represent the actual arrivals and the dashed lines represent the estimated model.

The comparison reveals a realistic fit between the estimated hospital patient arrivals and the actual arrivals of these patients. Also, as before, Shapiro-Wilk goodness-of-fit tests show that the residuals can be described by a normal distribution with a mean close to zero. Again, these results point to the adequacy of the model to estimate the hospital patients' arrivals to the imaging center.

7. 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 in the five hospitals which participated in the study, 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 average durations 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 Fig. 9. This screen illustrates 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.

Acknowledgements

This research was supported by the Israel National Institute for Health Policy and Health Services Research NIHP under grants 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. Final thanks go to the editor and anonymous referees whose suggestions had a valuable impact on the paper.

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