# EMERGENCY DEPARTMENTS' OPERATIONS: A SIMPLE AND INTUITIVE SIMULATION TOOL BASED ON THE GENERIC PROCESS APPROACH

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## ABSTRACT

The Emergency Department (ED) operates in a highly dynamic environment since it is required to treat efficiently and effectively a large variety of patient types, each with its own distinct needs. Therefore, it is obvious that discrete-event simulation tools are particularly suitable for modeling these systems. However, simulation is still not widely accepted as a viable modeling tool by the systems' establishment. Management's reluctance to embrace these modeling tools often comes from not realizing the benefits that can be gained by using simulation-based analysis tools as compared to the time and cost that have to be invested in building detailed simulation models. The general consensus is that simulation tools used in healthcare settings, need to be general, flexible, intuitive and simple to use. In order to maintain a reasonable level of abstraction, essential for having a general 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 present study will describe a simulation tool that was developed around such a process and test its performance.

**Key Words:** Emergency Department Operations, Healthcare Simulation, Generic Processes, Modeling Emergency Departments

## 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). Similar results were obtained from the Israeli Central Bureau of Statistics (ICBS). According to the ICBS the expenditure on hospitals accounted for 36% of the total annual healthcare budget which reached 43 billion NIS in 2001 (8.8% of the GDP).

According to the American College of Emergency Physicians (June 2003), the cost of Emergency Department (ED) operations amounted to 5% of the total US healthcare expenditure (close to 16% of the total budget allocated to hospital operations). As a result, managers and other healthcare policy makers are pressured to come up with ways to improve the productivity of hospital and ED operations. Cost reduction and waste elimination are generally the directions in which management heads.

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 et al. (1999) present a comprehensive literature review on the use of simulation in healthcare systems. Although Jun et al. (1999) list 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 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 healthcare policy makers feel that spending money to improve systems' operations 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 to instill more confidence in the model's ability.

Based on these observations, it can be concluded that the acceptance of simulation as a viable modeling tool by healthcare policy makers relays on the simulation tool being general, simple, intuitive which in addition allows for efficient cost effective modeling.

By incorporating these principals, management's involvement in developing simulation models will increase, and as a result, the confidence in the model's ability will grow 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.

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 exactly the reason why these models can't be reused to model other systems. Between these two extreme points lies a variety of possible intermediate modeling options, each with a different abstraction level, as illustrated in Figure 1.

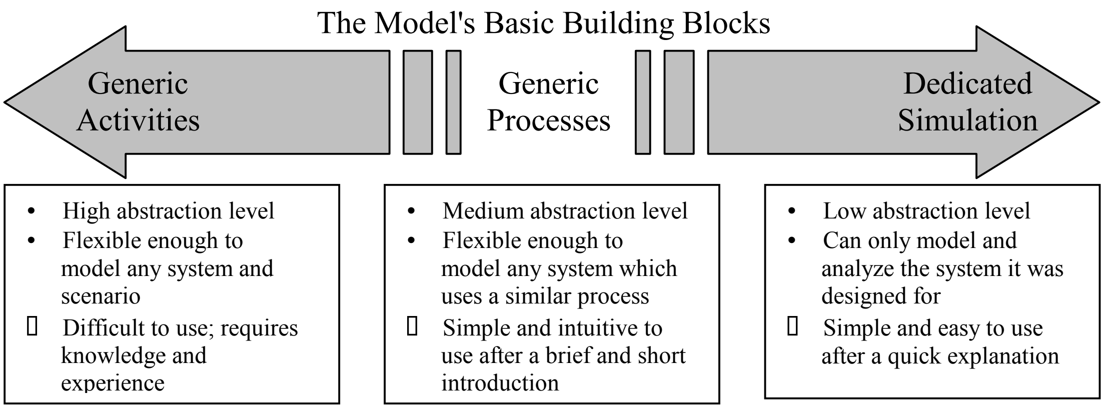


Figure 1. The Range of Modeling Options and the Building Blocks Used in Each Case

In order to maintain a reasonable level of abstraction, which is an essential requirement from a general modeling tool, while at the same time also promote simplicity; a generic process was selected to serve as the simulation model's basic building block. The generic process represents a class of systems each of which uses some derivative of this process. Developing a new model, using this approach, means customizing the generic process to meet specific system requirements, rather than developing a new model from the ground up. Herrmann *et al.* (2000) suggest an adaptability index to assess whether it is worth to modify an existing model or develop a new one from scratch while Robinson *et al*. (2004) propose a measure to asses the customization cost of a model.

Sinreich and Marmor (2005) show that the process each patient goes through when visiting the ED is better characterized by the patient type (Internal, Surgical or Orthopedic) rather than by the hospital visited. Based on this observation Sinreich and Marmor (2005) develop a single process (as illustrated in Figure 2) that is capable of capturing the distinctiveness of different EDs and serve as a basic operational structure upon which different EDs can be modeled. Figure 2 illustrates the activity elements which, when combined, describe all possible clinical pathways performed in the ED. The numbers next to the different elements and transitions represent pointers to data that is stored in an element duration and occurrence frequency database that characterizes the different patient types which where observed in several hospital EDs (Sinreich and Marmor, 2005).

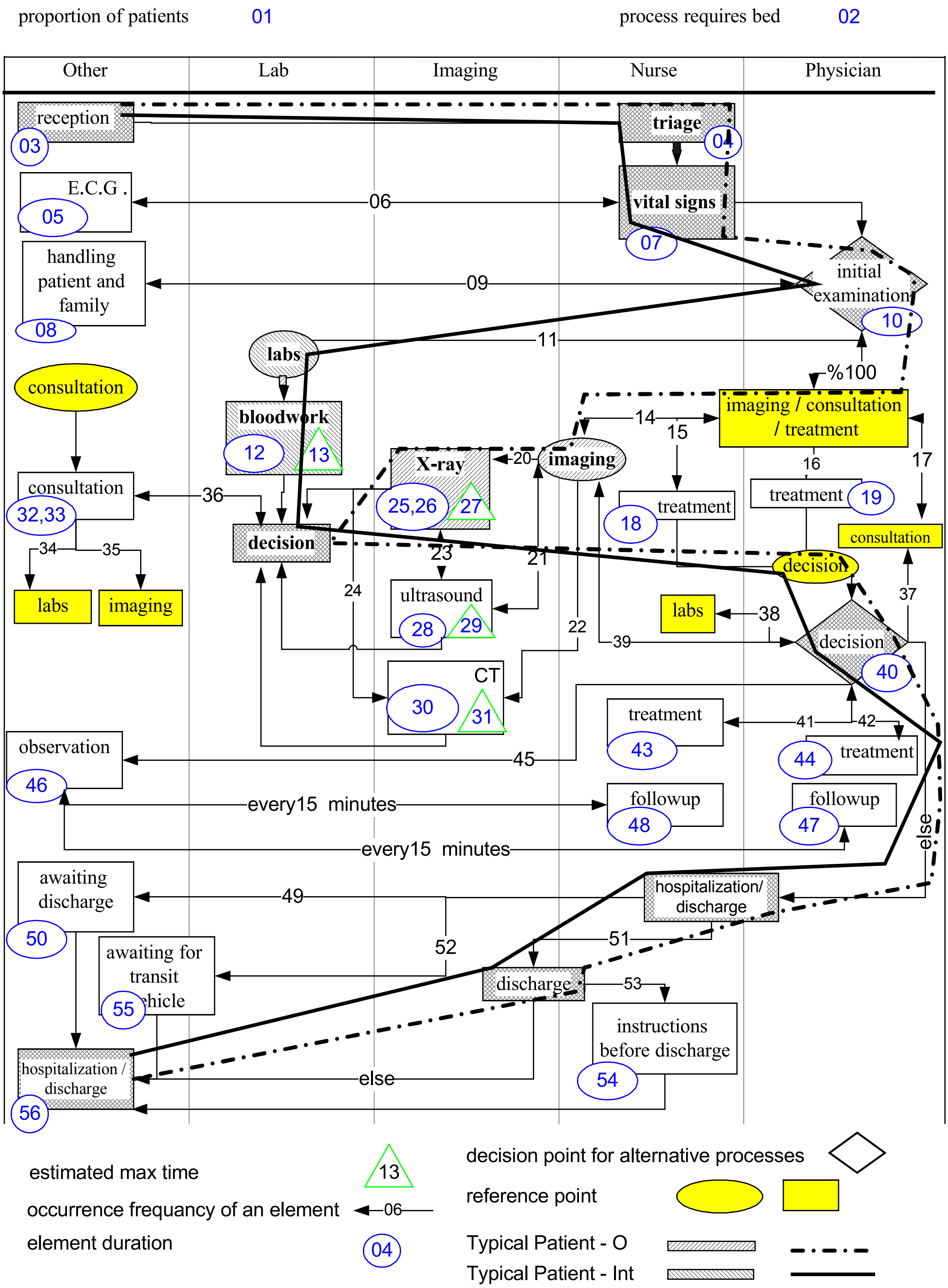


Figure 2. The Unified Patient Process Chart

The two arrows in Figure 2 represent the most common clinical pathways two of the three major patient types (Internal versus Orthopedic) go through when visiting the ED.

The rest of the study will describe and test the performance of a simulation tool that uses the general processes approach. Section 2 describes the modules that make up the ED dedicated simulation tool, the Graphical User Interface (GUI), the Staff's walking time estimation model and the simulation model. Section 3 describes the tool validation process and final remarks and conclusions are listed in Section 4.

## 2. The Simulation Tool - General Description

The simulation tool is comprised of several modules as illustrated in Figure 3.

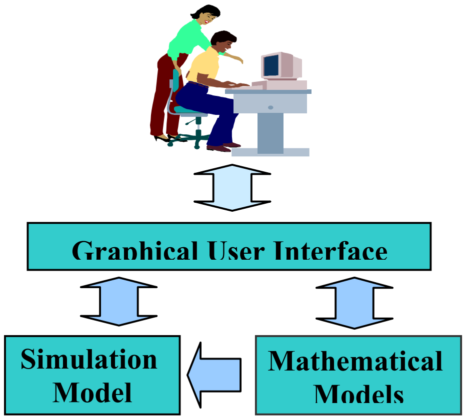


Figure 3. A Schematic Description of the Simulation Tool

1. The first module is a Graphical User Interface (GUI) that describes the general unified process illustrated in Figure 2. Through the GUI, the user can input data and customize the general process to fit the specific ED modeled and receive operational results from the ED after running the simulation.
2. The second module includes two mathematical models that are used to estimate patient arrivals and staff's walking time. The simulation tool uses the patient arrival estimation models that were developed in Sinreich and Marmor (2005). These models estimate the two major patient streams - the patient arrival process to the ED and the patient arrival process to the hospital imaging center. A summary of these two models is given in the appendix.
3. The third and final module is the simulation model itself. This model receives data from both the GUI and the mathematical models. The simulation is updated and

customized automatically to fit a specific ED based on data and information the user passes on to the GUI. The simulation model is transparent to the user who is only required to interacts with a user friendly GUI without the need to learn a simulation language syntax.

## 2.1 The Graphical User Interface

The Graphical User Interface was developed based on the general unified process plan illustrated in Figure 2. The rational for developing an interface between the user and the simulation is the attempt to make simulation more accessible to users that are not necessarily simulation experts but rather familiar with the system's operations and processes.

The first screen the user encounters, shown in Figure 4, requires the user to choose the ED operational mode. The ED operational mode indicates whether patients are separated by type (internal versus trauma) or by condition severity (acute versus ambulatory). Next the user is asked to define the data required to run the simulation model. Data can be entered through the different operational screens that will be described next or can come from either an existing or a new database.

The main simulation screen, shown in Figure 5, allows the user to reach all the simulation features. This screen illustrates the general unified process, (Sinreich and Marmor, 2005) each patient type goes through, starting from the patient's arrival to the ED reception area and ending with the patient's discharged or admission to the hospital. This includes the duration and frequencies of all the activity elements that turn the general process into a process that describes the operations of a specific ED.

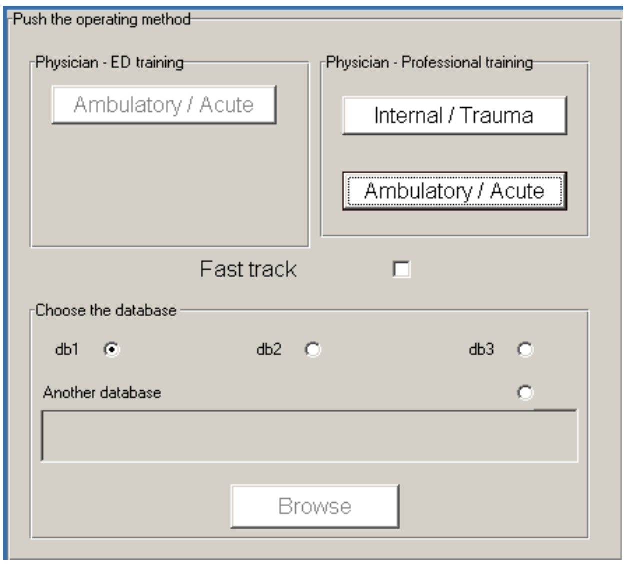

Figure 4. The Screen Used to Choose the ED Operational Mode

The main screen allows the user to invoke all other functional screens through which the rest of the simulation features are determined (The percentages associated with the different branches always add up to 100% using the branch "Else"). The resource screen, shown in Figure 6, can be reached by clicking on the desired resource, nurse or physician. This screen allows the user to determine shift lengths and number of physicians and nurses working in each shift. The user can also invoke the imaging center screen, shown in Figure 7, where all the activity durations and frequencies related to CT, X-ray and Ultrasound operations are determined. Another screen that can be reached from the main process screen is the consulting physician screen, shown in Figure 8. This screen is used to determine the duration and frequency of all activities related to the summon of a specialist to examine ED patients and consult with the ED physicians regarding specific patients being treated in the ED.

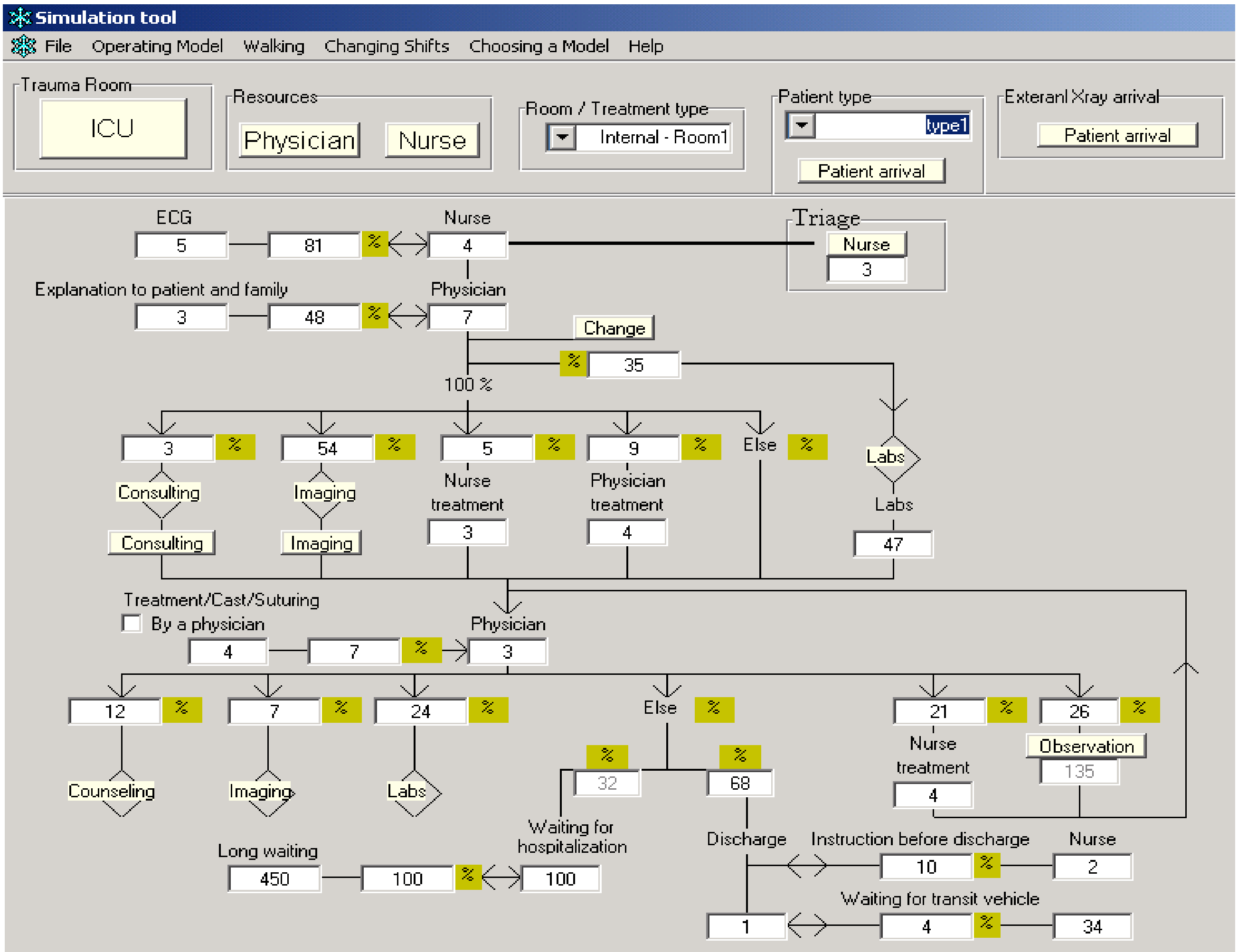


Figure 5. The Simulation Tool Main Screen Illustrating the Embedded Generic Process

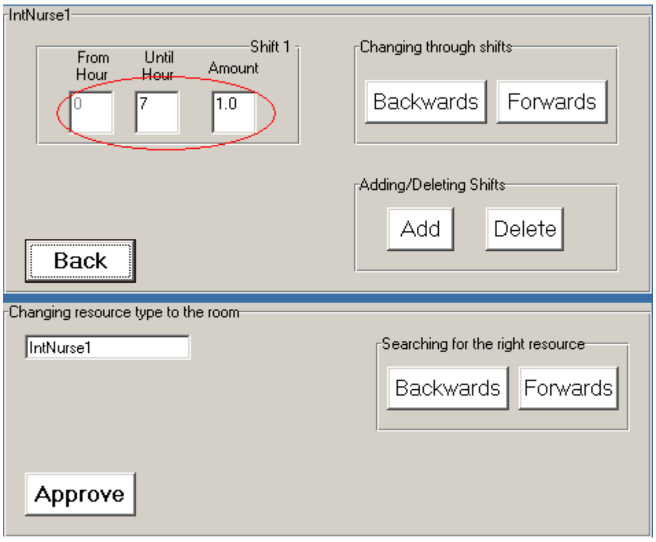


Figure 6. Resource Screen for Determining Length of Shifts and Medical Staff Size

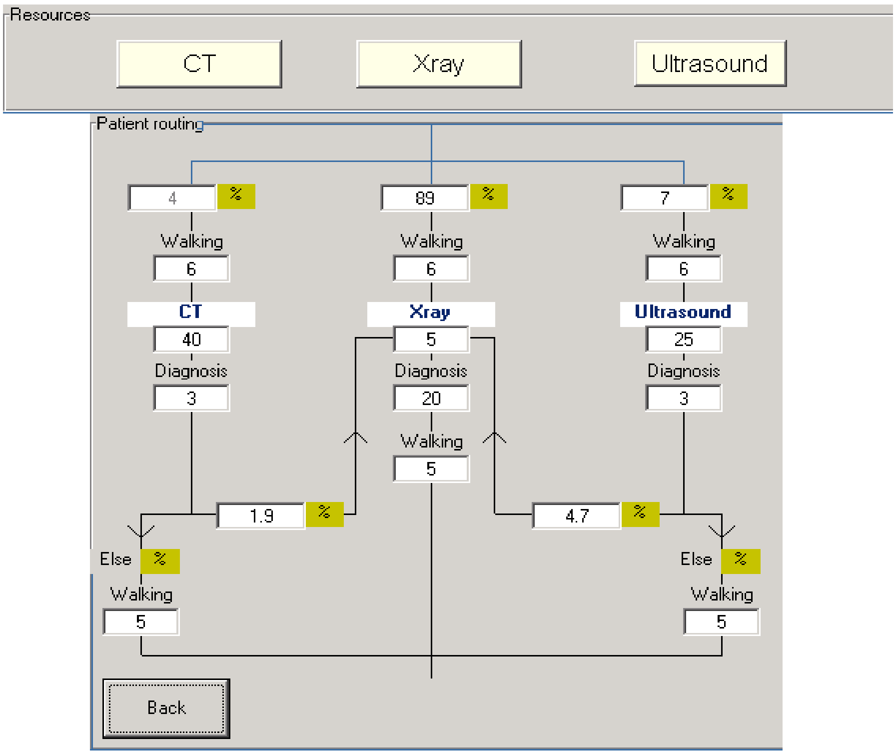


Figure 7. Imaging Center Screen to Determine CT, X-ray and Ultrasound Operations

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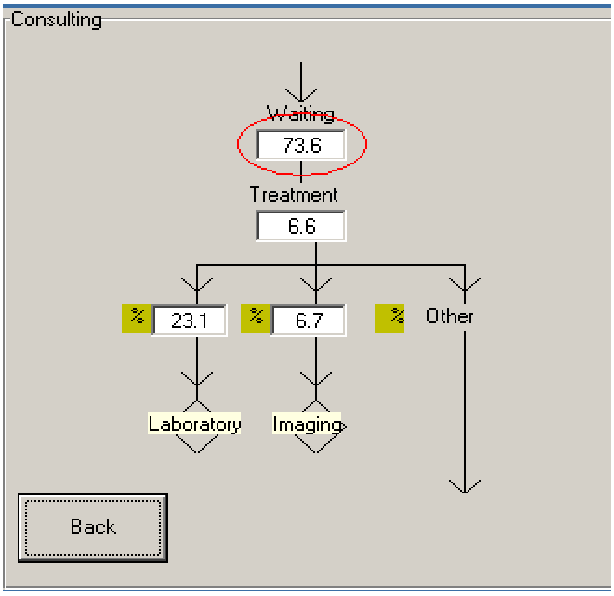



Figure 8. The Screen that Describes the Consultation Process

Once all the data has been obtained and incorporated in the simulation tool, the user can then run the simulation. Since the users are not expected to be simulation experts, it is imperative to provide them with a simple tool for displaying the simulation results. Nevertheless, the results have to capture the dynamic nature of the ED, especially since the users are expected to be experts in the different ED operations. Therefore, the results need to be illustrated in graphical form. The screen shown in Figure 9, enables the users to choose which graphs from a wide array of display options they wish to study and analyze. For example, the graphs currently chosen illustrate the max and average number of internal patients (type P1) during weekdays and weekends.

All the simulation parameters, illustrated in the different screens shown in Figures 4 – 8, are used to customize the general process to fit a large variety of different ED settings. However, only a few of these parameters actually need to be determined and updated so that the model will fit a specific ED. The rest of the parameters, such as the duration of the nurse's first examination, the duration of the physician's first treatment and others, were found to be similar enough from one ED to the next (Sinreich and Marmor 2005). Consequently, averages were calculated and used as suggested default values in the simulation tool for all the EDs analyzed.

### 2.2 Staff's Walking Time Estimation Models

Walking time is one of the major factors that contribute to the workload of the ED medical staff and is often a major source for fatigue related complaints. The medical staff spends a considerable amount of time during each shift, walking between the different activity points in the ED (according to the data gathered in this study the staff's walking time amounts to 15% of the treatment time). This includes walking to and from patient beds, medicine cabinet, nurse's station, ED counter etc.

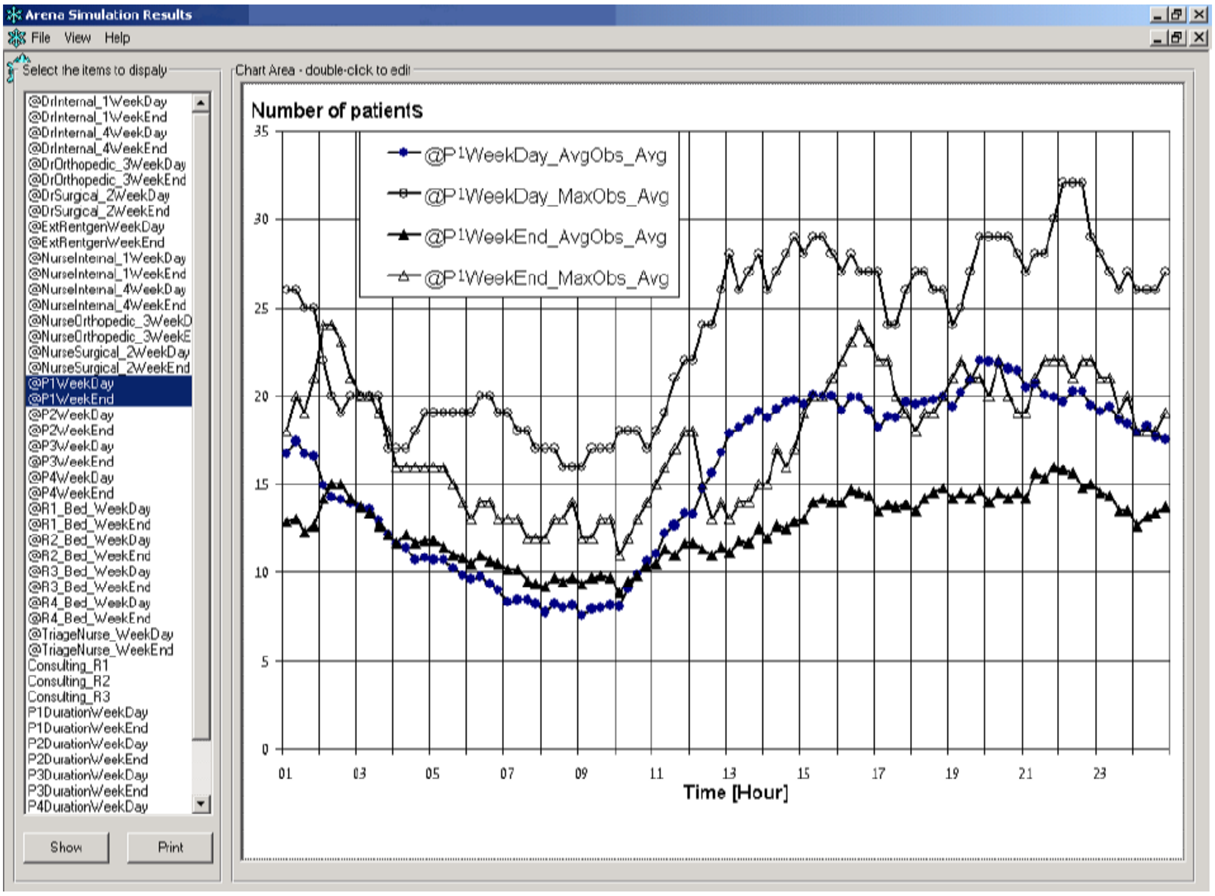



Figure 9. The Simulation Result Display Tool

In order to estimate the medical staff's walking time we requested five hospitals out of the 25 general hospitals operating in Israel, to participate in the study. These hospitals vary in size, location and capability. Two of the five hospitals (hospitals 1 and 4) are large (over 700 beds), one (hospital 3) is medium (400 - 700 beds) and rest are small (less than 400 beds). Hospital 3 is a regional hospital and the rest are inner-city hospitals. Hospitals 1 and 4 are level 1 trauma centers and the rest are level 2 centers[1].

The first step in the study included interviews with the senior physicians and head nurses of each of the participating EDs to learn what specific procedures are routinely performed by ED staff. Next a field study which included observations and a time and motion study were conducted by supervised student teams in all five hospitals. The

[1] A level 2 trauma center usually can not handle neurosurgical patients.

teams invested 104 man-hours and 70 man-hours observing the physicians and nurses respectively monitoring among others their walking activities. Based on the data gathered during these observations the following estimation models for physicians and nurses were developed. Following is the notation used by these models:

$\hat{T}_p^D$ **-** Physician's **mean** estimated walking time when treating patient type $p$ (seconds)

$\hat{T}_p^N$ - Nurse's **mean** estimated walking time when treating patient type $p$ (seconds)

$W, L$ - Width and Length of the space in which the medical staff operates (cm)

$d_c$ - Walking distance from the area's centroid to the ED counter (cm)

$d_r$ - Walking distance from the area's centroid to the procedure room (cm)

$d_m$ - Walking distance from the area's centroid to the medicine cabinet (cm)

$d_s$ - Walking distance from the area's centroid to the nurse's station (cm)

$N$ - Number of patient beds in the ED room

$\varepsilon(0{,}150^2)$ - Error adjustment

<u>Estimating the Physician's Walking Time</u>

$$\hat{T}_p^D = \Big[-461.371 + 0.5\cdot W + 0.126\cdot d_c + 0.134\cdot d_r + 0.00047\cdot(d_c - 703.5)\cdot(W - 596.5) \\ + 0.00034\cdot(d_r - 2043.813)\cdot(W - 596.5) + \varepsilon(0{,}150^2)\Big]\Big/N$$

The interactions in the above model indicate that if both dimensions $d_c$ and $W$ are smaller or greater than the threshold values 703.5, 596.5 respectively the walking time estimation is increased. However, if only one of these dimensions is greater than the threshold value while the other is smaller, the estimated walking time is reduced. The same is true for the interaction between $d_r$ and $W$.

<u>Estimating the Nurse's Walking Time</u>

$$\hat{T}_p^N = \Big[-7695.82 + 6.611\cdot W + 5.194\cdot d_s + 1.503\cdot d_m + 0.029\cdot(d_s - 499.444)\cdot(W - 806.667) \\ + 0.00875\cdot(d_m - 1176.667)\cdot(W - 806.667) + \varepsilon(0{,}150^2)\Big]\Big/[N\cdot L/W]$$

The interactions in the above model indicate that if both dimensions $d_s$ and $W$ are smaller or greater than the threshold values 499.444, 806.667 respectively the walking time estimation is increased. However, if only one of these dimensions is greater than the threshold value while the other is smaller, the estimated walking time is reduced. The same is true for the interaction between $d_m$ and $W$.

One conclusion from these models is that if the ED is relatively wide it is essential to position the ED counter or the nurses station as close as possible to the patient beds. However, if the ED is relatively narrow it is better to position the counter further away

The fit of the physicians' and nurses' walking time estimation models as indicated by $R^2$ is 0.737 and 0.675 respectively (The data upon which these models were developed can be obtained from the authors). Moreover, the variance analyses, illustrated in Tables 1 and 2 reveal that both models and all the parameters used are significant.

Table 1. Variance Analysis of the Physician's Walking Time Estimation Model

| **Analysis of Variance** | | | | |
|---|---|---|---|---|
| **Source** | **DF** | **Sum of Squares** | **Mean Square** | **F Ratio** |
| Model | 5 | 2439976.3 | 487995 | 19.0191 |
| Error | 34 | 872376.1 | 25658 | Prob>0 |
| C. Total | 39 | 3312352.4 | | <0.0001 |

| **Parameter Estimates** | | | | |
|---|---|---|---|---|
| **Term** | **Estimate** | **Std Error** | **t.Ratio** | **Prob > \|t\|** |
| Intercept | -461.371 | 96.385 | -4.79 | <0.0001 |
| $W$ | 0.5 | 0.15 | 3.34 | <0.0021 |
| $d_c$ | 0.126 | 0.0576 | 2.19 | <0.0353 |
| $d_r$ | 0.134 | 0.038 | 3.52 | <0.0013 |
| $(d_c - 703.5) \cdot (W - 596.5)$ | 0.00047 | 0.00018 | 2.63 | <0.0127 |
| $(d_r - 2043.813) \cdot (W - 596.5)$ | 0.00034 | 0.000113 | 2.99 | <0.0051 |

Table 2. Variance Analysis of the Nurse's Walking Time Estimation Model

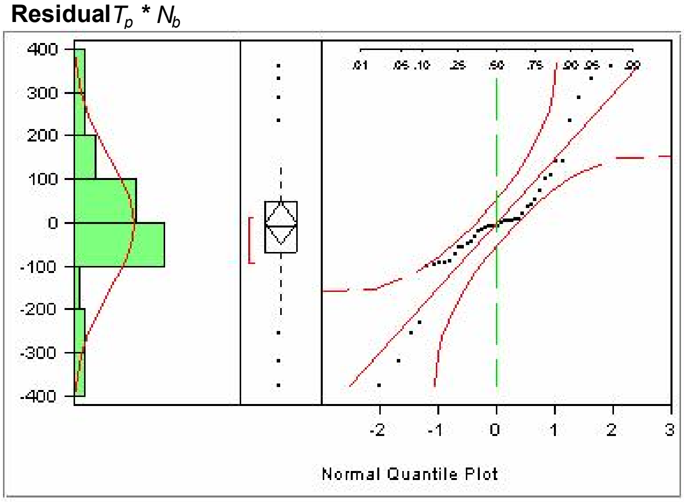
| **Analysis of Variance** | | | | |
|---|---|---|---|---|
| **Source** | **DF** | **Sum of Squares** | **Mean Square** | **F Ratio** |
| Model | 5 | 9273724 | 1854745 | 8.7164 |
| Error | 21 | 4468533 | 212787 | Prob>0 |
| C. Total | 26 | 13742257 | | <0.0001 |

| **Parameter Estimates** | | | | |
|---|---|---|---|---|
| **Term** | **Estimate** | **Std Error** | **t.Ratio** | **Prob > \|t\|** |
| Intercept | -7695.82 | 1362.764 | -5.65 | <0.0001 |
| $W$ | 6.611 | 1.16 | 5.70 | <0.0001 |
| $d_s$ | 5.194 | 0.822 | 6.32 | <0.0001 |
| $d_m$ | 1.503 | 0.248 | 6.06 | <0.0001 |
| $(d_m - 499.444) \cdot (W - 806.667)$ | 0.029 | 0.00516 | 5.66 | <0.0001 |
| $(d_m - 1176.667) \cdot (W - 806.667)$ | 0.00875 | 0.00189 | 4.62 | <0.0001 |

The first step in validating both models was to compare the results obtained to the actual waking time as observed in the field study of the five hospitals. The residual analyses of the physicians' and nurses' estimation walking models are illustrated in Figures 10 and 11, respectively. The analyses reveal that in both cases residuals are normally distributed with a mean of zero.

The next step in validating these models was to use them in a setting different from the ones that were used in the initial development stages. To do that, a sixth hospital was chosen. This hospital is a regional, medium size level 2 trauma center. The time and motion study included 20 hours of observations over the physicians' walking activities and 13 hours of observation over the nurses' waking activities. Next averages were calculated for each observation hour and compared with the results obtained from the two walking time estimation models and analyzed using a single factor ANOVA as illustrated in Tables 3 and 4.

**Distributions**
**Residual** $T_p * N_b$




**Quantiles**

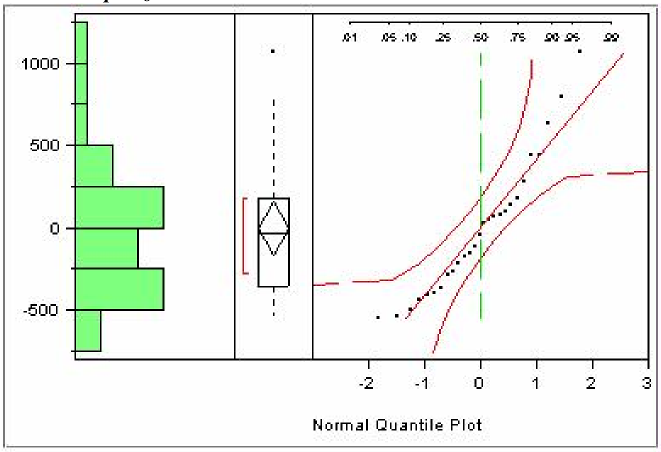
| | | |
|---|---|---|
| 100.0% | maximum | 363.0 |
| 99.5% | | 363.0 |
| 97.5% | | 362.2 |
| 90.0% | | 226.0 |
| 75.0% | quartile | 50.5 |
| 50.0% | median | -6.5 |
| 25.0% | quartile | -67.4 |
| 10.0% | | -216.1 |
| 2.5% | | -371.6 |
| 0.5% | | -373.0 |
| 0.0% | minimum | -373.0 |

**Moments**

| | |
|---|---|
| Mean | 1.918e-14 |
| Std Dev | 149.56142 |
| Std Err Mean | 23.647737 |
| upper 95% Mean | 47.832063 |
| lower 95% Mean | -47.83206 |
| N | 40 |

Figure 10. The Residual Analysis of the Physician's Walking Time Estimation Model

**Distributions**
**Residual $Tp*N_b*W/L$**




**Quantiles**

| | | |
|---|---|---|
| 100.0% | maximum | 1074 |
| 99.5% | | 1074 |
| 97.5% | | 1074 |
| 90.0% | | 670 |
| 75.0% | quartile | 183 |
| 50.0% | median | -34 |
| 25.0% | quartile | -358 |
| 10.0% | | -502 |
| 2.5% | | -542 |
| 0.5% | | -542 |
| 0.0% | minimum | -542 |

**Moments**

| | |
|---|---|
| Mean | -6.25e-12 |
| Std Dev | 414.56803 |
| Std Err Mean | 79.783654 |
| upper 95% Mean | 163.99765 |
| lower 95% Mean | -163.9976 |
| N | 27 |

Figure 11. The Residual Analysis of the Nurse's Walking Time Estimation Model

Table 3. Analyzing the Differences between the Physician's Walking Time Estimation Model Results and the Observation Data from Hospital 6

| **ANOVA: Single Factor - Summary** | | | | |
|---|---|---|---|---|
| **Groups** | **Count** | **Sum** | **Average** | **Variance** |
| Observation | 20 | 727 | 36.35 | 472.03 |
| Model | 20 | 898.55 | 44.93 | 754.39 |

| **Source of Variation** | **DF** | **SS** | **MS** | **F** | **P-Value** | **F-crit** |
|---|---|---|---|---|---|---|
| Between Groups | 1 | 735.74 | 735.74 | 1.2 | 0.28 | 4.1 |
| Within Groups | 38 | 23301.98 | 613.21 | | | |
| Total | 39 | 24037.72 | | | | |

Table 4. Analyzing the Differences between the Nurse's Walking Time Estimation Model Results and the Observation Data from Hospital 6

| **ANOVA: Single Factor - Summary** | | | | |
|---|---|---|---|---|
| **Groups** | **Count** | **Sum** | **Average** | **Variance** |
| Observation | 13 | 514 | 39.54 | 374.94 |
| Model | 13 | 478.5 | 36.8 | 494.85 |

| **Source of Variation** | **DF** | **SS** | **MS** | **F** | **P-Value** | **F-crit** |
|---|---|---|---|---|---|---|
| Between Groups | 1 | 48.62 | 48.62 | 0.112 | 0.741 | 4.26 |
| Within Groups | 24 | 10437.44 | 434.89 | | | |
| Total | 25 | 10486.06 | | | | |

The analyses in both cases reveal that the null hypothesis, (there is no statistical difference between the model and observation results) can not be rejected.

### 2.2.1 An Example to the Use of the Walking Time Estimation Models

To illustrate the use of the staff's walking time estimation model we chose the ED of hospital 5. Figure 12 illustrates the physical layout of the ED including all the activity points that are relevant to both models. The ED is divided into two major sections. The top one is the area where the internal and surgical patients are treated and the bottom area is where the orthopedic patients are treated. Based on this structure the appropriate walking distances for the physicians and nurses, listed in Table 5, were extracted. Using these distances the estimated mean walking time for the physicians and nurses in both ED sections were calculated. In the orthopedic section of the ED each physician's walking time was estimated to be 18 seconds (there is no nurse assigned to the orthopedic section in this ED). In comparison, the nurses and physicians who operate in the internal-surgical section of the ED need to cover a larger area and therefore, their walking times were estimated to be 31 seconds and 38 seconds respectively.

Table 5. The Parameters of the Walking Model

| | System Parameters | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Patient Type | $T_p^D$ | $T_p^N$ | $W$ | $L$ | $d_c$ | $d_r$ | $d_m$ | $d_s$ | $N$ |
| Orthopedic | 18 | --- | 255 | 570 | 233 | 653 | 3975 | --- | 1 |
| Internal-Surgical | 31 | 38 | 780 | 2820 | 1320 | 2862 | 1320 | 750 | 18 |

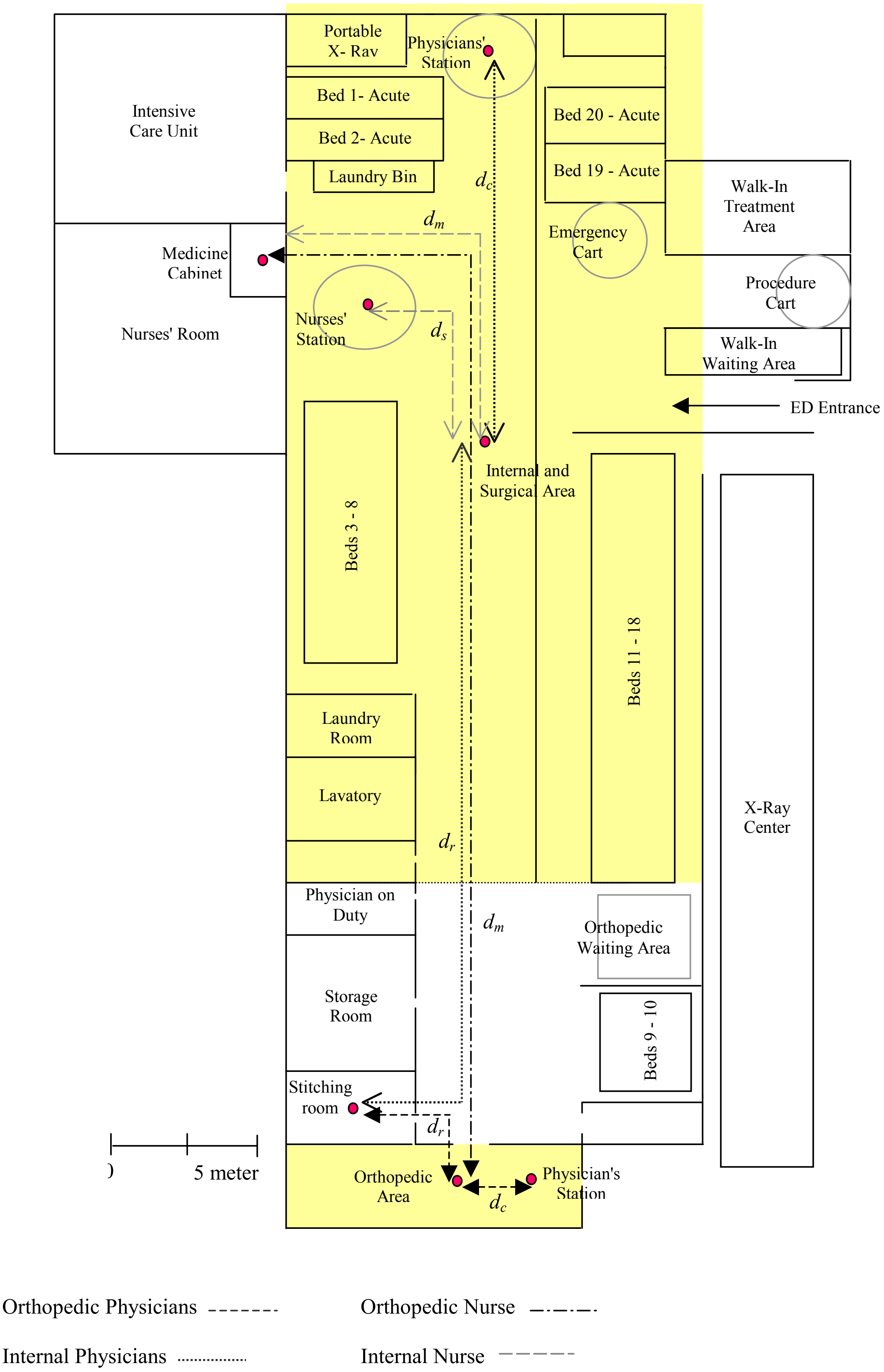



Figure 12. The Physical Layout of an ED

These times are then embedded in the processes each patient type goes through when visiting the ED and inserted before and after each element the nurses and physicians perform.

## 3. The Simulation Model

The operation process described by the simulation model starts with the reception followed by the nurse taking the patient's vital signs. Next the physician examines and treats the patient or orders a bank of lab exams, imaging scans and/or summons a specialist. These activities can be repeated several times until the patient is discharged or admitted to one of the hospital wards. The entire process follows several principals:

- The medical staff can operate on one patient at a time.
- Before and after each of these activities, delays are inserted to represent the medical staff's walking time. In addition to the activities directly performed on the patients the physician and nurses spent time reading lab results, filling in medical forms and consulting with specialists and with their peers. Based on the observations and field study conducted at the five hospitals, the sum of these activities is almost equal to time the medical staff spends with the patients.
- ED patients sent to the imaging center encounter patients from the other hospital wards. Both patient streams compete for the available resource and as a result ED patients experience additional delays beyond walking time and service time.
- The service time at the imaging center depends on the amount of equipment or technicians operating at the center.
- If lab exams are ordered or the patient is sent to the imaging center, the next physician exam for this patient is scheduled only after all the results and the patient are back at the ED.
- During the patients' stay at the ED routine observations are performed by the physicians and nurses.

### 3.1 Validating the Simulation Tool

The last step in every model development is the validation process. In this case the validation process was comprised of two stages. In the first stage, a simulation model was created, using the developed tool in conjunction with the suggested default values and the other specific values, for each of the five EDs that participated in the study. Ten 60-day simulation runs were performed for each of the five EDs. Tables 6 – 10 summarize, for each of the three basic patient types (internal, surgical and orthopedic), the length of stay in minutes (averages and standard deviations) as obtained from the simulation runs (10 runs) as well as the averages obtained from the hospitals' information systems (on average 258,000 data entries were received from each hospital which represent around two and a half years of data). Two steps were needed in order to compare the performance of each of the simulation models to the actual data obtained from each of five hospital's information systems. The first was to test whether the differences between the simulation results and the averages obtained from the hospital's information system, as illustrated in Figure 13 are statistically significant. The second was to analyze the practical significance of the differences between the information system's and simulation averages, as illustrated in Figure 13.

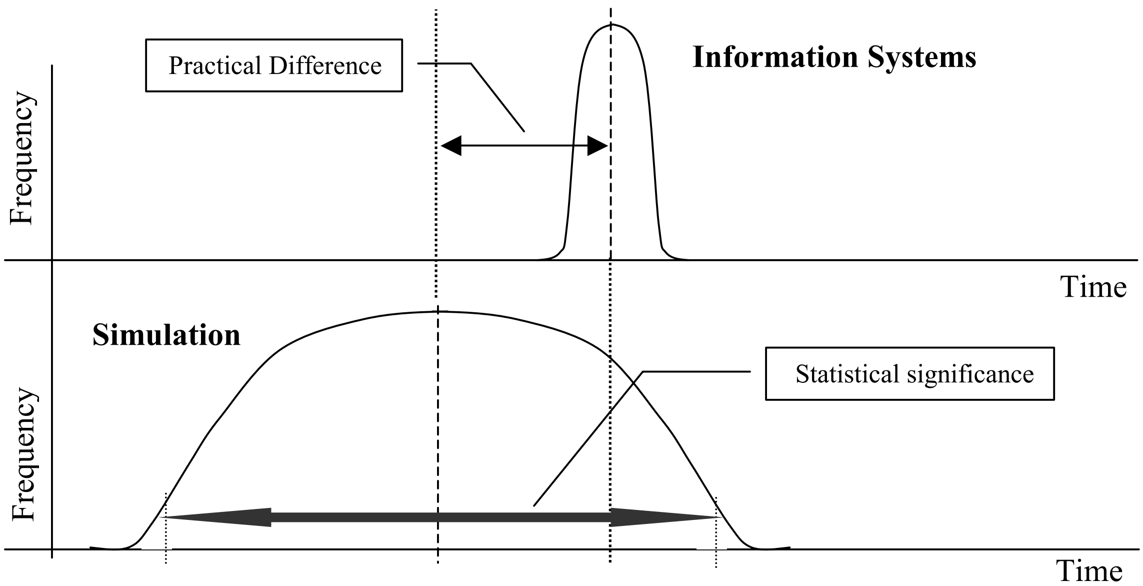



Figure 13. A graphical Representation of the Two Phase Comparison Process

Table 6. Comparison of the Results Obtained for the ED in Hospital 1

| Patient Type | Database Average [min.] (2 years) | Simulation Average [min.] (10 runs) | Simulation Std. | Practical Difference | P-Value |
|---|---|---|---|---|---|
| Internal | 195 | 182 | 13 | 6.7% | 0.33 |
| Surgical | 198 | 211 | 10 | 6.6% | 0.18 |
| Orthopedic | 157 | 150 | 7 | 4.5% | 0.28 |

Table 7. Comparison of the Results Obtained for the ED in Hospital 2

| Patient Type | Database Average [min.] (2 years) | Simulation Average [min.] (10 runs) | Simulation Std. | Practical Difference | P-Value |
|---|---|---|---|---|---|
| Internal | 408 | 399 | 20 | 2.2% | 0.67 |
| Surgical | 236 | 240 | 11 | 1.7% | 0.75 |
| Orthopedic | 166 | 156 | 9 | 6.1% | 0.28 |

Table 8. Comparison of the Results Obtained for the ED in Hospital 3

| Patient Type | Database Average [min.] (2 years) | Simulation Average [min.] (10 runs) | Simulation Std. | Practical Difference | P-Value |
|---|---|---|---|---|---|
| Fast-Track | 134 | 143 | 13 | 6.7% | 0.48 |
| Internal | 172 | 197 | 19 | 14.5% | 0.14 |
| Surgical | 95 | 103 | 8 | 8.4% | 0.06 |
| Orthopedic | 81 | 93 | 6 | 14.8% | 0.32 |

Table 9. Comparison of the Results Obtained for the ED in Hospital 4

| Patient Type | Database Average [min.] (2 years) | Simulation Average [min.] (10 runs) | Simulation Std. | Practical Difference | P-Value |
|---|---|---|---|---|---|
| Internal | 279 | 261 | 18 | 6.5 % | 0.31 |
| Surgical | 146 | 125 | 13 | 14.4% | 0.09 |
| Orthopedic | 134 | 142 | 15 | 6.0% | 0.59 |

Table 10. Comparison of the Results Obtained for the ED in Hospital 5

| Patient Type | Database Average [min.] (2 years) | Simulation Average [min.] (10 runs) | Simulation Std. | Practical Difference | P-Value |
|---|---|---|---|---|---|
| Internal | 161 | 178 | 17 | 10.6% | 0.32 |
| Surgical | 158 | 149 | 16 | 5.7% | 0.59 |
| Orthopedic | 125 | 127 | 6 | 1.6% | 0.68 |

Based on the P-values calculated in Tables 6 – 10 the hypothesis that both the averages obtained from the simulation results and the averages obtained from the hospitals' databases are the same can't be rejected. The average difference in the results obtained for hospitals 1 to 5 was 5.9%, 3.3%, 11.1%, 9% and 6% respectively. The practical differences in 12 out of the 16 comparisons was less than 8.5% (5.2% on average); while the largest practical difference was less than 15%.

The next step in this stage was to compare the number of patients in the ED using the hospital records and the simulation models that were developed for each ED. Figures 14 – 16 illustrate the changes in the number of the patients of a specific type in the ED during the 24 hours as obtained from the simulation (including the 95% confidence intervals) and the hospitals' information system. Figures 14 - 16 show a good fit between the simulation results (thin line) and the actual data (dark line) as obtained from the hospitals' information systems. This line also follows the upper and lower bounds set by the simulation. Similar results were obtained for the rest of the comparisons that are based on the different hospitals, the different patient types, and weekday and weekend combinations.

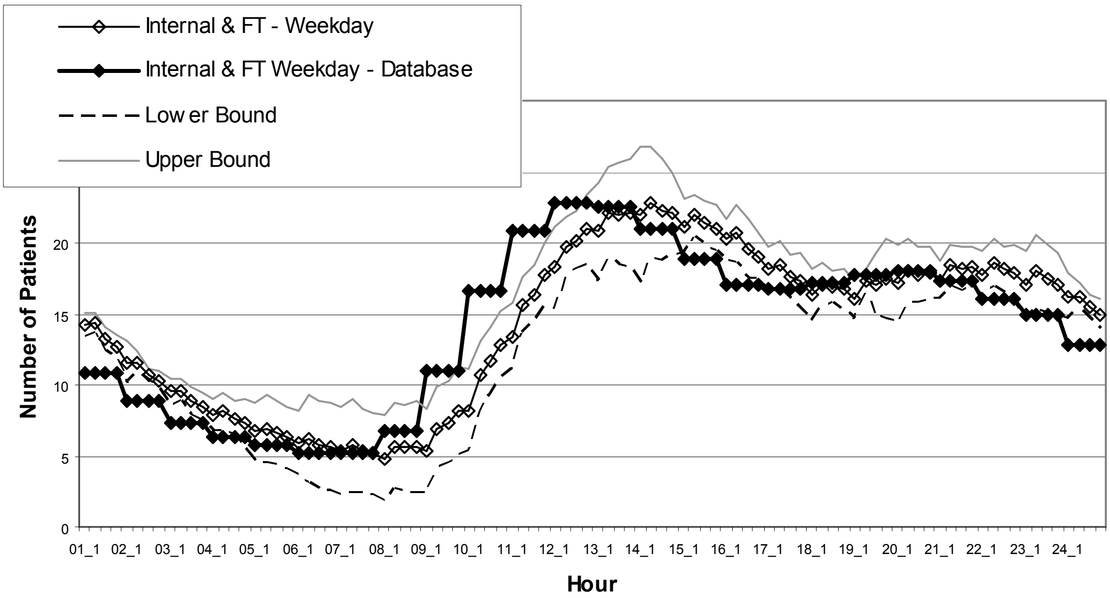



Figure 14. The Average Number of Internal Patients during a Weekday in the ED of Hospital 1

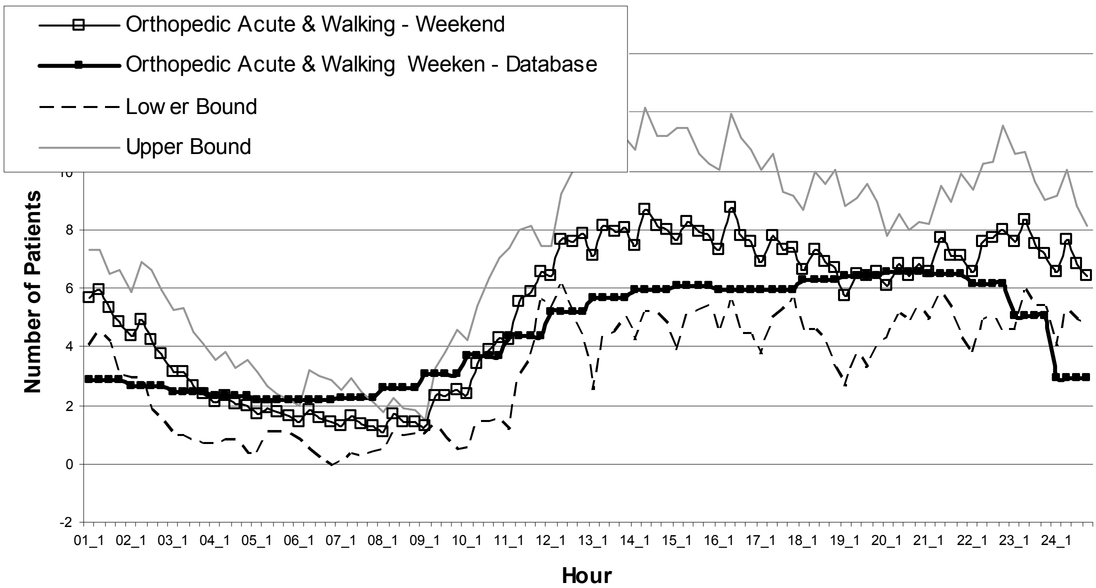



Figure 15. The Average Number of Orthopedic Patients during a Weekend in the ED of Hospital 4

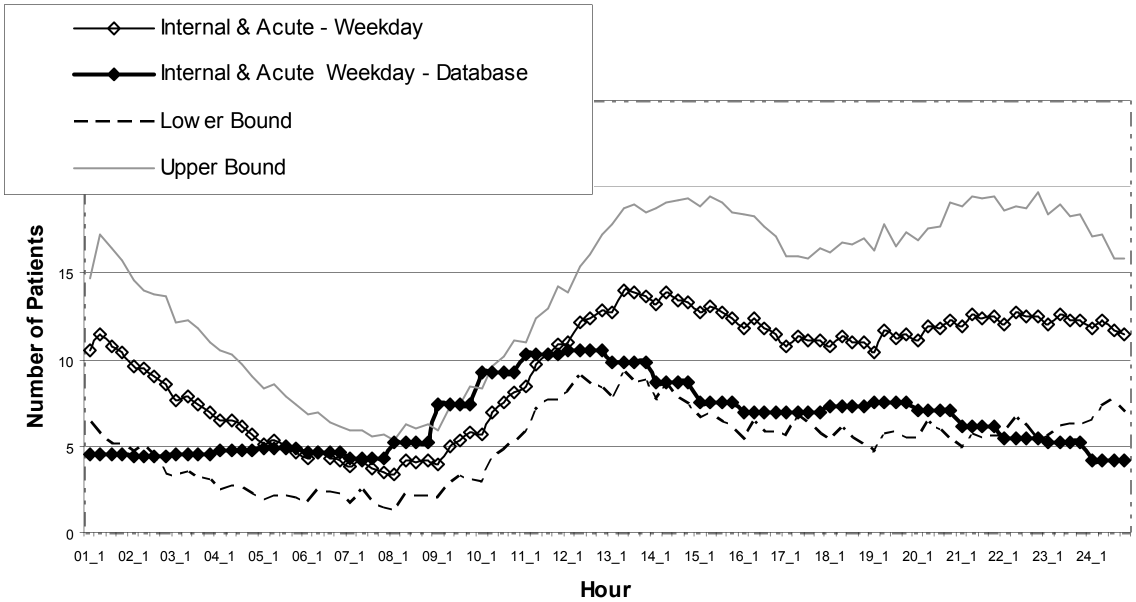



Figure 16. The Average Number of Internal Patients during a Weekday in the ED of Hospital 5

In the second stage a sixth ED was chosen and data on its operations was gathered from the hospital's information systems and through observations (Initially, this data was not incorporated in the developed simulation tool in order not to affect the validation process). Next, a simulation model was created using the tool's default values augmented by some of the gathered data (as indicated earlier). Again, ten 60-day simulation runs were performed. Table 11 summarizes the patients' length of stay in minutes as obtained from the simulation runs (10 runs) and the hospitals' information systems (two years of data) for each of the three basic patient types (internal, surgical and orthopedic). Again, based on the P-value calculated the hypothesis that both the averages obtained from the simulation results and the averages obtained from the hospitals' databases are similar can't be rejected.

Table 11. Comparison Results for the ED in Hospital 6

| Patient Type | Database Average [min.] (2 years) | Simulation Average [min.] (10 runs) | Simulation Std | Practical Difference | P-Value |
|---|---|---|---|---|---|
| Internal | 147 | 161 | 16 | 9.5% | 0.36 |
| Surgical | 154 | 149 | 11 | 3.2% | 0.67 |
| Orthopedic | 116 | 132 | 7 | 13.8% | 0.09 |

The next step in this stage was to compare the number of patients in the ED using the hospital records and the simulation model that was developed for this ED. Figures 17 and 18 illustrate the changes in the number of surgical and internal patients in the ED during the 24 hours as obtained from the simulation (including the 95% confidence intervals) and the hospitals' information system. These figures again show a good fit between the simulation results (thin line) and the actual data (dark line) as obtained from the hospital's information system. This line also follows the upper and lower bounds set by the simulation. The same is true for orthopedic patients as well.

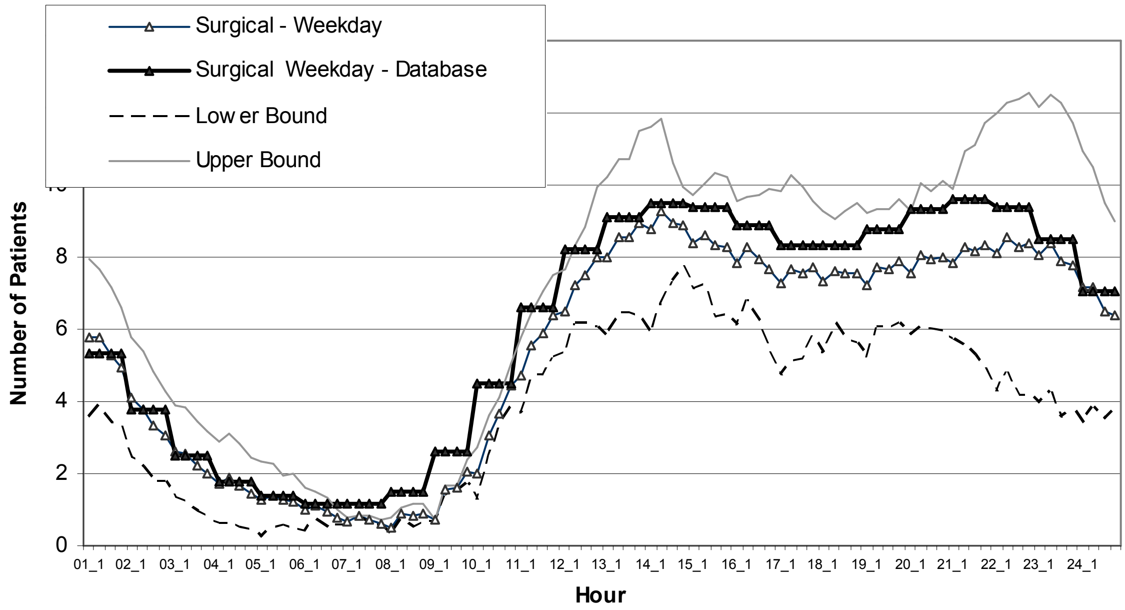



Figure 17. The Average Number of Surgical Patients during a Weekday in the ED of Hospital 6

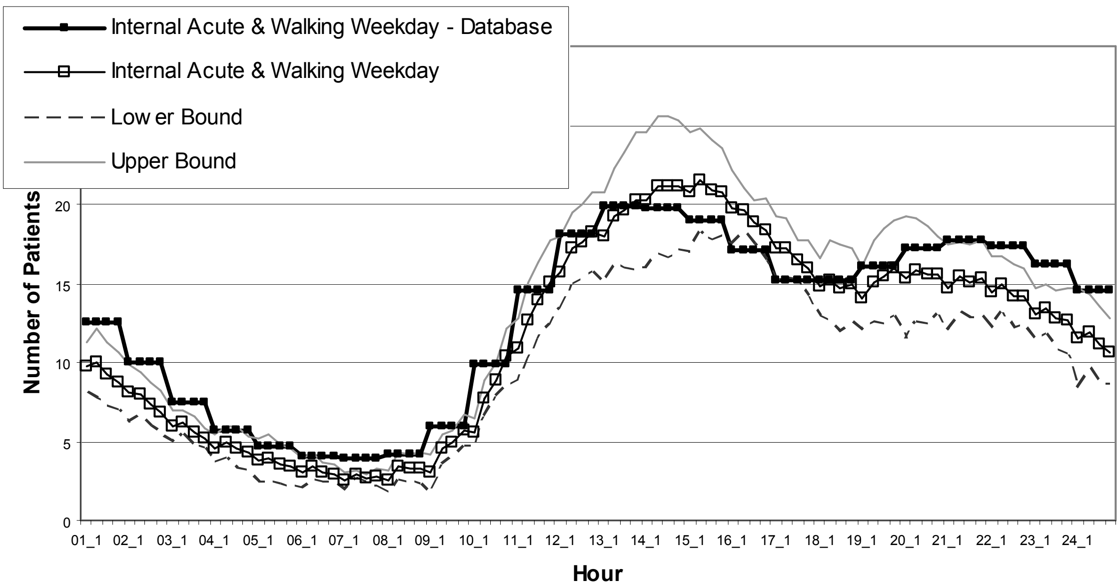



Figure 18. The Average Number of Internal Patients during a Weekday in the ED of Hospital 6

## 4. Final remarks

The objective of this study was to explore the possibility of developing an intuitive simple-to-use simulation tool that can model the operations of Emergency Departments and assist practitioners in making more sound decisions. A modeling technique, based on a general process rather than on generic activities, was used to achieve this goal. The built-in general process reduces the modeling degrees of freedom and provides simplicity and ease of use.

If we use the statement "the suggested general process can be used to model any arbitrary ED" as a scientific hypothesis and try to find a system for which the statement is not true, each failure increases our confidence in the model. So far we have failed to reject the statement six times (25% out of the general hospitals in Israel).

It is possible that a dedicated simulation model for each of the six hospitals would have achieved more accurate results. However, this improved accuracy would come at a price. As explained earlier, dedicated simulation models are much more difficult and expensive to develop. As a matter of fact, these difficulties and costs may cause management in some instances to abandon simulation altogether. Even though, accuracy was compromised using our simulation tool, the validation process revealed its ability to predict quite accurately different system parameters such as the patient's length-of-stay, number of patients in the system.

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## Appendix - Patient Arrival Estimation Models

### The Patient Arrival Process to the ED

The hospital's computerized records revealed that the number of patients arriving to the ED differs from hour to hour (evening hours are much busier compared to early morning hours), from day to day (weekends - Friday and Saturday - are much slower compared to the rest of the week). Statistical tests reveal that the square-root of the patient's arrival rate can be described by a normal distribution. Let $X_{pihd}$ be a random variable normally distributed with a mean of $\mu_{pihd}$ 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 (2005) suggest a model to estimate the number of patients $\theta_{pihd}$ of type *p* who arrive at hospital *i* at hour *h* on day *d*, to be used in the simulation. Following, is the model which is used to determine the distribution's mean estimator.

$1,..., p,..., P$ - patient index
$1,..., i,..., H$ - hospital index
$1,..., h,...,24$ - hour index
$1,..., d,...,7$ - day index
$1,..., w,..., W$ - 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 hospital's information systems.

Based on these values and using (1), 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,

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

where $W$ indicates the number of data weeks received from the hospitals' information system.

Using these values, a patient arrival factor $\hat{F}_{pi}$ can be calculated for each hospital. This factor indicates the relative volume of patients arriving at a specific hospital with respect to the other hospitals.

$$\hat{F}_{pi} = \frac{\hat{\mu}_{pi}}{\sum_i \hat{\mu}_{pi}} \cdot H \tag{2}$$

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 $i$.

$$\hat{n}^{a}_{pihdw} = \frac{n_{pihdw}}{\hat{F}_{pi}} \tag{3}$$

where $\hat{n}^{a}_{pihdw}$ 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 $w$.

Based on the estimated adjusted values and using (4), the average square-root estimator $\hat{\mu}_{phd}$ of the number of patients of type $p$ who arrive during hour $h$ on day $d$ can be calculated.

$$\hat{\mu}_{phd} = \frac{\sum_{i=1}^{H} \sum_{w=1}^{W} \hat{n}^{a}_{pihdw}}{H \cdot W} \tag{4}$$

Using these values and the factor calculated earlier, 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 $d$ can be calculated via (5). 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.

$$\hat{\mu}_{pihd} = \hat{\mu}_{phd} \cdot \hat{F}_{pi} \tag{5}$$

At this point we can estimate the random variable's normal distribution parameters as $X_{pihd} \sim N(\hat{\mu}_{pihd}, 0.6)$, where 0.6 denotes standard deviation of the residuals as verified by the gathered data. The number of patients $\theta_{pihd}$ of type $p$ who arrive at hospital $i$ at hour $h$ on day $d$, to be used in the simulation, can be can be estimated using a random sample $x_{pihd}$ from the above distribution as shown in (6).

$$\theta_{pihd} = \left\lceil (x_{pihd})^2 \right\rceil \tag{6}$$

where $\lceil x \rceil$ 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.

**The Hospital Patient Arrival Process to the Imaging Center**

The 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 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 (2004) 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 $\pi_{ihdm}$ who arrive at the imaging center in hospital *i* at hour *h* on day *d* and on month *m*, can be estimated as follows:

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

where $\lceil x \rceil$ represents the closest integer value of *x*.