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A simulation analysis of the impact of FAHP–MAUT triage algorithm on the Emergency Department performance measures

Omar M. Ashour [a], Gül E. Okudan Kremer [a,b,*]

[a] Department of Industrial and Manufacturing Engineering, The Pennsylvania State University, University Park, PA 16802, USA
[b] School of Engineering Design, The Pennsylvania State University, University Park, PA 16802, USA

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ABSTRACT

Emergency Department (ED) crowding is a major problem in the U.S. like in many other countries worldwide. This problem is adversely affecting the safety of the patients who rely on receiving a timely treatment in EDs. As a part of solving this problem, a triage process is utilized. Triage is a pre-hospital process by which patients are sorted according to the severity of their illnesses or injuries. Improvements to this process would affect the patient flow positively, and in turn would enhance patient satisfaction and quality of care. In a previous study, we developed a triage algorithm that uses Fuzzy Analytic Hierarchy Process (FAHP) and Multi-Attribute Utility Theory (MAUT) to rank the patients according to their characteristics: chief complaint, age, gender, pain level, and vital signs. The main purpose of this study is to compare two triage systems using Discrete Event Simulation (DES); one system uses the typical Emergency Severity Index (ESI), and the other uses the FAHP and MAUT algorithm. Overall, there was no strong statistical evidence that either system would do better than the other for all the performance measures when the average is taken across all ESI levels. On the other hand, the collected simulated data by each ESI level showed that the FAHP–MAUT algorithm tends to balance the time-to-bed (TTB) and length of stay (LOS) for ESI levels 2–5. In terms of the percentage of tardy patients, FAHP–MAUT system significantly outperforms the ESI system for ESI levels 4 and 5; 34% vs. 61% and 25% vs. 70%, respectively. Both systems were performing about equally for ESI level 1 and level 3 patients; 25% vs. 26% and 64% vs. 67%, respectively. While ESI system slightly outperforms FAHP–MAUT system for ESI level 2 patients, 56% vs. 66%. Based on these results, we recommend using FAHP–MAUT not only because it performs better in terms of minimizing the number of patients with longer than the allotted upper limits of wait times, but also it reduces potential bias and errors in decision making in clinical settings; and thus, it can be used as the basis of an expert system to advise triage nurses.

1. Introduction

Emergency Department (ED) is a healthcare facility that provides medical treatments for patients with usually acute injuries or illnesses who come to the department without prior appointment, by either themselves or by ambulance. ED setting is unique in that patients arrive to ED without planned appointments, with various injuries or illnesses, with various health insurance plans or even without insurance. Some of these patients come with life-threatening status, and thus need immediate treatment, while others come with non-urgent status and can wait. In US, EDs are considered as vital components of the nation's health care safety net (Richardson & Hwang, 2001), which are responsible for 45–65% of hospital admissions (Mahapatra et al., 2003).

EDs in most hospitals operate 24/7. In 2006, there were 119.2 million visits to EDs (Pitts, Niska, Xu, & Burt, 2008). Fig. 1 shows the trends in ED visits, number of hospitals, and the number of EDs in the US. (Kellermann, 2006). As observed in the figure, during the period from 1994 to 2004, although ED visits have increased by 26%, the number of EDs has decreased by 9%, and the number of beds in the hospitals has been reduced by 198,000 beds (Kellermann, 2006).

Emergency rooms are extremely complex. Complexity in health care settings, such as Operating Room (OR), Intensive Care Unit (ICU), and Emergency Room (ER), is obvious not only in the patient and treatment protocols, but also due to the high level of automation and instrumentation, huge volume of information, and interdisciplinary coordination that is necessary (Christian et al., 2006). Many U.S. EDs are exceedingly busy or crowded; thus, they are characterized with increased service pressures, which prompt researchers to study the complexity and inefficiency factors of the ED system and the ED-hospital interfaces (France & Levin, 2006).

* Corresponding author at: Department of Industrial and Manufacturing Engineering, The Pennsylvania State University, University Park, PA 16802, USA.
E-mail address: gkremer@psu.edu (G.E. Okudan Kremer).

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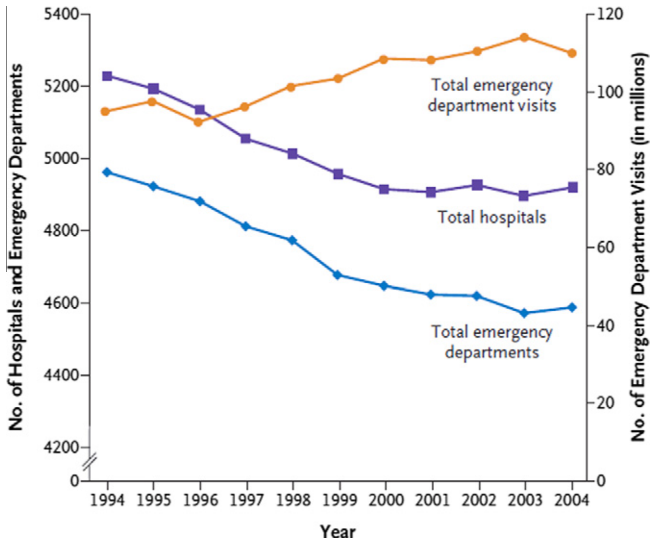


Fig. 1. Trends in Emergency Department Visits, Number of Hospitals, and Number of Emergency Departments in the United States, 1994–2004 (Adopted from Kellermann, 2006).

Every minute in the ED can make a big difference for patients. EDs usually implement a triage algorithm to assign a priority level for the coming patients. Triage is a pre-hospital process by which the triage nurse sorts the patients according to the severity of their illness or injury. The purpose of the triage interview is to place the patient in one of several queues, each having an associated maximum time until the patient sees a physician (Guterman, Mankovich, & Hiller, 1993).

In this paper, we present our investigation of the impact of using the Fuzzy Analytic Hierarchy Process (FAHP) and Multi-Attribute Utility Theory (MAUT) triage algorithm, and compare the ED performance measures under the conditions of using the aforementioned algorithm and the widely used Emergency Severity Index (ESI) algorithm. As explained later in the paper, although widely used, the ESI algorithm heavily relies on the judgment of the triage nurse, whereas the FAHP–MAUT triage algorithm makes use of quantitative triage knowledge in arriving at patient prioritization, and thus, if FAHP–MAUT algorithm is found to perform as good or better in realistic conditions, it will be conceivable to develop an expert system to aid nurse decision making. With these thoughts, we compare the algorithms based on system performance measures, i.e., time-to-bed (TTB), length of stay (LOS), throughput, time in ER, and percentage of tardy patients.

The paper is organized as follows: Section 2 describes the findings of key papers from the pertinent literature. Section 3 presents the problem and the methodology that was followed to draw our conclusions. Section 4 shows the experimental design and the results. Section 5 summarizes the findings.

2. Literature review

One of the most commonly used triage systems in the US, the five-level Emergency Severity Index (ESI), sorts the patients into five clinically distinct groups. These five levels are different with respect to resource and operational needs (Gilboy, Tanabe, Travers, Rosenau, & Eitel, 2005). The most acutely ill patient gets ESI level 1 (the highest acuity level), or 2. The ESI levels 3, 4, and 5 (the lower acuity levels) are assigned based on the number of needed resources (Gilboy et al., 2005). The algorithm flow chart is provided in Fig. 2. For example, a patient with ESI level 1 or 2 could be taken immediately to the treatment area, while patients with ESI levels 3, 4, or 5 can wait (Gilboy et al., 2005). During triage process, the nurse records the patient's vital signs as well as all the information about his/her current illness, past medical history, and any other needed information such as allergies and immunization status. Then, the nurse decides whether the patient needs immediate evaluation and treatment or he/she can wait (Claudio & Okudan, 2010).

Several attempts have been made to improve the ED care services, such as minimizing waiting time intervals and improving patient satisfaction (Spaite et al., 2002). Others have focused on developing a reliable decision support system in order to improve the patient waiting times and service quality problems (Mahapatra et al., 2003), and developing expert systems to aid the triage nurse in assigning patient's category (Padmanabhan et al., 2006), etc. The challenge in triage for nurses is to prioritize and rank non-urgent patients in order to recognize who is most in need of care (Claudio & Okudan, 2010). Some hospitals in the US use a three-level triage, which sorts the patients based on the question: "How long can this patient wait to be seen?" (Mahapatra et al., 2003). On the other hand, the five-level triage instrument has been developed and validated, which is based on not only on "Who should be seen first?" but also: "What will this patient need?" (Tanabe, Gimbel, Yarnold, Kyriacou, & Adams, 2004). Despite the fact that this system sorts the patients and prioritize them based on severity of the illness and/or injury (Tanabe et al., 2004), the patients' waiting period or the order of treating them, especially for the patients with the same acuity level, is rarely investigated (Claudio & Okudan, 2010). Tanabe et al. (2005) stated that the physician and nurses face a serious limitation of the ESI version 3; that is, they could not determine how acutely ill these level 2 patients in the waiting room are, when they deal with the scenario of "there are six level 2 patients in the waiting room". Moreover, two levels of the ESI level 2 patients have been identified in the clinical experience; those who can safely wait for physician evaluation for at least 10 minutes without clinical deterioration, and those who cannot wait (Tanabe et al., 2005).

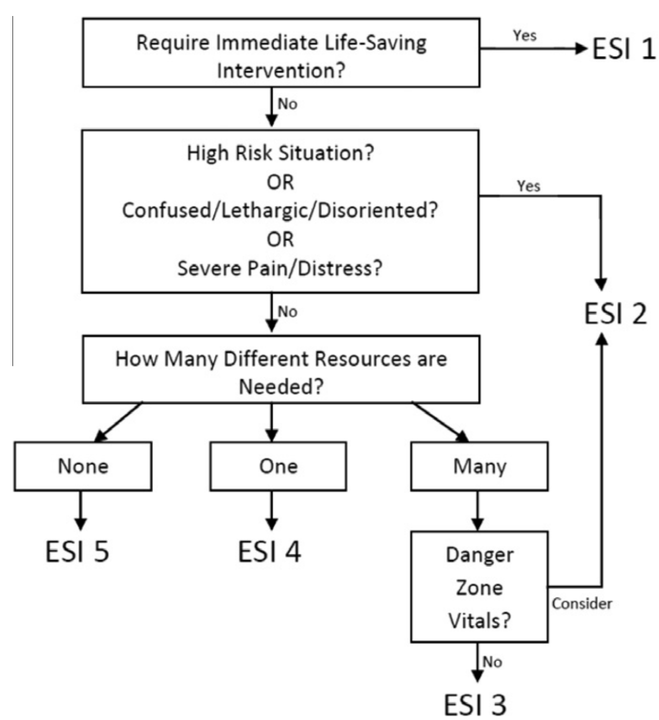


Fig. 2. ESI Triage Algorithm, version 4 (Modified from Gilboy et al., 2005).

The prioritization of time-to-be-seen is essential to the patient and is related to his safety, especially when the ED crowding delays evaluation (Cooper, 2004). Recent research utilized the utility theory to prioritize the patients with the same acuity level in EDs (Claudio & Okudan, 2010). In this study, the authors demonstrated the use of utility theory in patient prioritization with a hypothetical example. They explained the choice of utility theory due to the inherent uncertainty in ED settings, and that the utility theory accounts for uncertainty. Ashour and Okudan (2010a) also present a solution to the problem of patient prioritization in EDs using utility theory. A major difference from prior work is that in this study patients are ranked based on their age, gender, pain level, and as well as the assigned ESI. While vital signs (temperature, pulse, respiration rate and blood pressure) were considered for patient ranking in the Claudio and Okudan (2010) study, patient age, gender and pain level information were neglected. Further, these variables were not considered explicitly in the ESI algorithm either.

Even though Ashour and Okudan (2010a) have contributed to the triage decision-making problem, this solution has shortcomings. For example, while physiological variables influence patient symptoms (and hence the nurse decisions made during triage) they were not considered explicitly; they were implicitly covered within the ESI level. Patel, Gutnik, Karlin, and Pusic (2008) studied the decision making process of nurses in the general ED and concluded that nurses' decisions are based on a generated hypothesis related to both the information given by the patient and to the awareness of single symptoms believed to be a characteristic of the diagnosis. Further, based on our interviews at clinical settings, it is essential to note that while we have ascertained that the relative importance of vital signs may change across different complaints, neither the complaints nor the relative importance shifts have previously been considered. Therefore, FAHP–MAUT algorithm has extended the utility function algorithm in Ashour and Okudan (2010a) to incorporate the relation between the patient complaints and the vital signs as well as the descriptive variables.

The relation between the vital signs and the complaints is operationalized as the changing relative importance of vital signs. What we mean by the "relation" is that a nurse might differently interpret the vital signs of two patients if one has chest pain and the other has a headache (i.e., the relative importance of vital signs might change depending on the patient's complaint). Consequently, the vital signs might contribute different weights to the overall utility value. The overall utility function aggregates the utilities of descriptive variables (age, gender, and pain level) and the "pre-treated" values of the physiological variables (blood pressure, pulse, respiration rate, temperature, and oxygen saturation level). The values of the vital signs are treated using the FAHP, and the FAHP output is used in the overall utility function. The objective of the utility function is to quantify and minimize the associated clinical risk, and hence to arrive at an appropriate patient priority ranking.

It should be emphasized that the developed approach by Ashour and Okudan (2010b) aims to help triage nurses make the decisions more efficiently and easier taking into account their intuitive judgment and preferences but still minimizing potential bias. Their approach aggregates patient's chief complaint, age, gender and pain level along with the vital signs to create a clear ranking among waiting ED patients. The proposed decision algorithm starts by identifying the patient status as one would in the current ESI algorithm (Gilboy et al., 2005). Then, if the patient requires any immediate intervention, he is considered to be in "Critical State". After this stage, the procedure progresses as follows, see Fig. 3:

(1) Is the patient in need of immediate intervention? If the response is affirmative, he is a "Critical State" patient. If no, he goes to Step 2.
(2) The triage nurse asks the patient about his complaint, pain level, age, and gender, and takes his/her vital signs.
(3) The complaint and the vital signs data are treated using the FAHP to yield what we referred to as "pre-treated" data.
(4) The data from Steps 2 and 3 are processed by the overall utility function to give the utility value for each patient.
(5) Patients with high utility values go to the treatment area first, and the others with the lower values can wait in the waiting room. They are treated in descending order of priority based on the overall utility values.

This algorithm was applied to a sample of clinical data set from Susquehanna Health's Williamsport Hospital (Ashour and Okudan, 2010a, 2010b). In order to get the FAHP–MAUT score the health care provider should record the following inputs: (1) patient's chief complaint; (2) vital signs; (3) patient age; (4) patient gender; and (5) pain level.

Every patient who comes to the ED has a chief complaint. These complaints are classified according to Claudio, Ricondo, Freivalds, and Okudan (2009) into 17 categories as follows: (1) Neurological Complaints; (2) Chest Pain Complaints; (3) Abdomen/Male; (4) Abdomen/Female; (5) Seizure; (6) Headache; (7) Psychiatric Complaints/Suicide Attempt; (8) Head/Face Trauma; (9) General Medicine Complaints; (10) Respiratory Complaints; (11) Alleged Assault; (12) Multiple Trauma; (13) Motor Vehicle Crash; (14) Extremity Complaint/Trauma; (15) Back Pain/Injury; (16) Skin Rash/Abscess; (17) Eye, Ear, Nose, Throat and Dental Complaints.

Ashour and Okudan (2010b) study provides the detailed procedure to calculate the FAHP–MAUT score. The overall utility function is (Ashour & Okudan, 2010b):

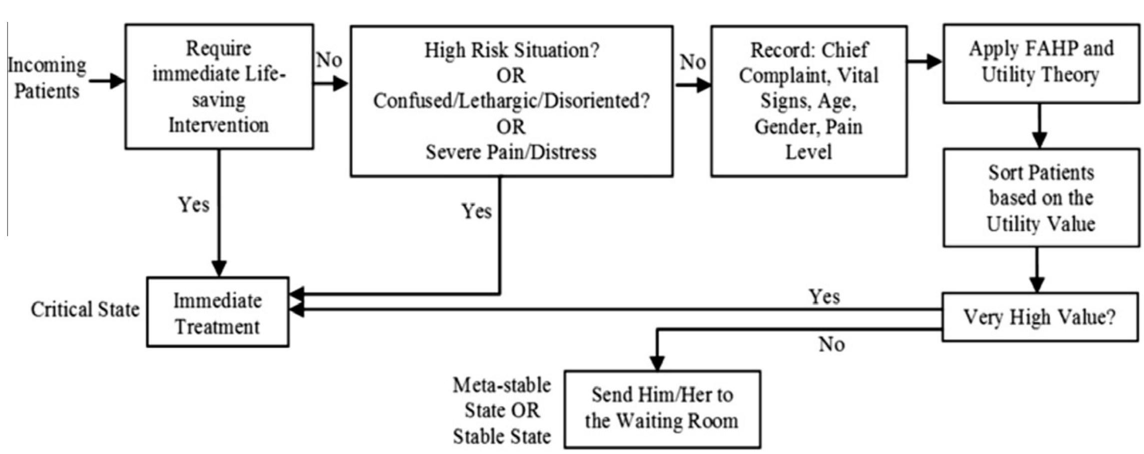


Fig. 3. FAHP–MAUT Triage Algorithm.

$$U(x_1,x_2,x_3,x_4) = \left(\frac{1}{-0.9804}\right) * \left(\left\{\left[-0.9804 * 0.756 * \left(-0.1149 + 0.0991 * exp\left(\frac{x_1}{147.898}\right)\right) + 1\right] * \left[-0.9804 * 0.587 * \left(-0.0252 + 0.0100 * \exp\left(\frac{x_2}{19.437}\right)\right) + 1\right] * [-0.9804 * 0.182 * (x_3 - 1) + 1] * \left[-0.9804 * 0.8000 * \left(-0.0957 + 0.0957 * \exp\left(\frac{x_4}{4.102}\right)\right) + 1\right]\right\} - 1\right) \quad (1)$$

where, x_1: mean value (the FAHP output); x_2: patient age; x_3: patient gender; x_4: pain level.

Although, it was shown that FAHP–MAUT based triage algorithm performs well, its comparison in a dynamic scenario has not been done; this paper fills this gap. Due to the high cost and the difficulty of trying new changes and new algorithms during real time, clinical operations which might endanger patient's life, Discrete Event Simulation (DES) is chosen as an effective tool to compare the triage algorithms. The next section presents the problem and the methodology that has been followed to investigate the study objectives.

3. Problem and methodology

3.1. Problem definition

As discussed above, in EDs, the triage nurse receives patients with different illnesses and/or injuries, and then based on several factors (i.e., vital signs, complaints, and pain level, etc.) he/she assigns the ESI level. Then, the nurse decides which patient will be treated first. The most widely used five-level ESI algorithm takes into account most vital signs in assessment of the acuity level (e.g., respiration rate, oxygen saturation and blood pressure, etc.). Only about 3% of the patients get the highest acuity level (Wuerz, Milne, Eitel, Travers, & Gilboy, 2000), and thus receive immediate service; the rest of patients would have to wait. Among the waiting patients, patients with lower ESI levels (which show a higher acuity level) will precede the others in receiving care. However, for conditions where several patients wait with the same ESI level, there are no clear differentiators to establish a prioritization. Clinical observations attest to the difficulty of this situation (e.g., (Tanabe et al., 2005)). Due to the dynamic and uncertain nature of the overall triage process in addition to the differentiation difficulty, methods are needed to help the triage nurse to be efficient (without increasing potential bias) in making prioritization among the patients with the same acuity classification. George et al. (1993) pointed out that triage could be the reason for long waiting times for all patients who visit the ED, more specifically for the patients with urgent needs. In another study by George et al. (1992), it was shown that the queuing problems after triage cause delays and not the triage process itself.

Ashour and Okudan (2010b) have built an FAHP and MAUT algorithm to help ED nurses in making triage decisions. There is a need to investigate the effects of using this algorithm on system performance, such as, waiting times, resource utilization, etc. Discrete Event Simulation (DES) is an appropriate tool to compare systems based on their performance measures. Thus, this paper undertakes this investigation, and compares the performance measures of two systems; one that uses the widely used ESI triage algorithm and the other using the FAHP and MAUT triage algorithm. Table 1 shows the independent and dependent variables included as part of this investigation.

Table 1
Independent and dependent variables.

Independent variables	Dependent variables (performance measures)
Current triage algorithm (ESI)	-Time-to-bed (TTB) -Length of stay (LOS)
FAHP and MAUT algorithm	-Time in ED -Throughput -Percentage of tardy patients

3.2. Conceptual model and process flow

In previous literature, Peck (2008) has utilized DES to analyze patient flow in the Emergency Department (ED) to study the effect of operational changes of the Fast Track (FT) on the patient flow. His simulation model was built and validated based on his observations at the Newton-Wellesley Hospital (NWH), and thus reflects a realistic scenario. His conceptual model of the observed ED is adopted for this study.

Fig. 4 shows the NWH's ED layout. The ED has three Emergency Rooms (ERs). The main ER has two sides; one side has 12 beds and is open 24 h (side A), while the other side has 12 beds and is open from 10am to 2am (side B). The pediatric ER has 8 beds and is open from 10am to 2am. The Fast Track (FT) ER has 4 beds and is open from 3pm to 11pm. The ED has 3 triage rooms, two of them are open 24 h and the third one is open from 10am to 2am. The incoming patients firstly approach the greeter's desk and provide basic information and their chief complaint. Greeters pass the information to a triage nurse who works on a First Come First Served (FCFS) basis unless the severity of the patient injury/illness requires immediate attention. Then, the triage nurse does a preliminary examination for the patient, assign the ESI level, and send the patient to the waiting room. Patients under 18 years old are sent to the pediatric ER.

In any ER room, patients may undergo a nurse examination, nurse treatment, doctor examination, doctor treatment, testing, and consultation. Patients experience one or more of these processes based on their needs. The patient then is either discharged to home or hospital, to another hospital, or to some other location. Fig. 5 describes the process flow diagram of the ED at hand.

3.3. Model assumptions and simplifications

To design the DES experiment, the following assumptions and simplifications were made:

3.3.1. ED input/output assumptions

(1) Walk-in and ambulance-in arrivals are combined in patients' arrival.
(2) Patients leave the ED by discharging them from the ED; the inpatient unit delays (boarding times are not considered), death, and transfer to any other location are not considered.
(3) No scheduled appointments are allowed.

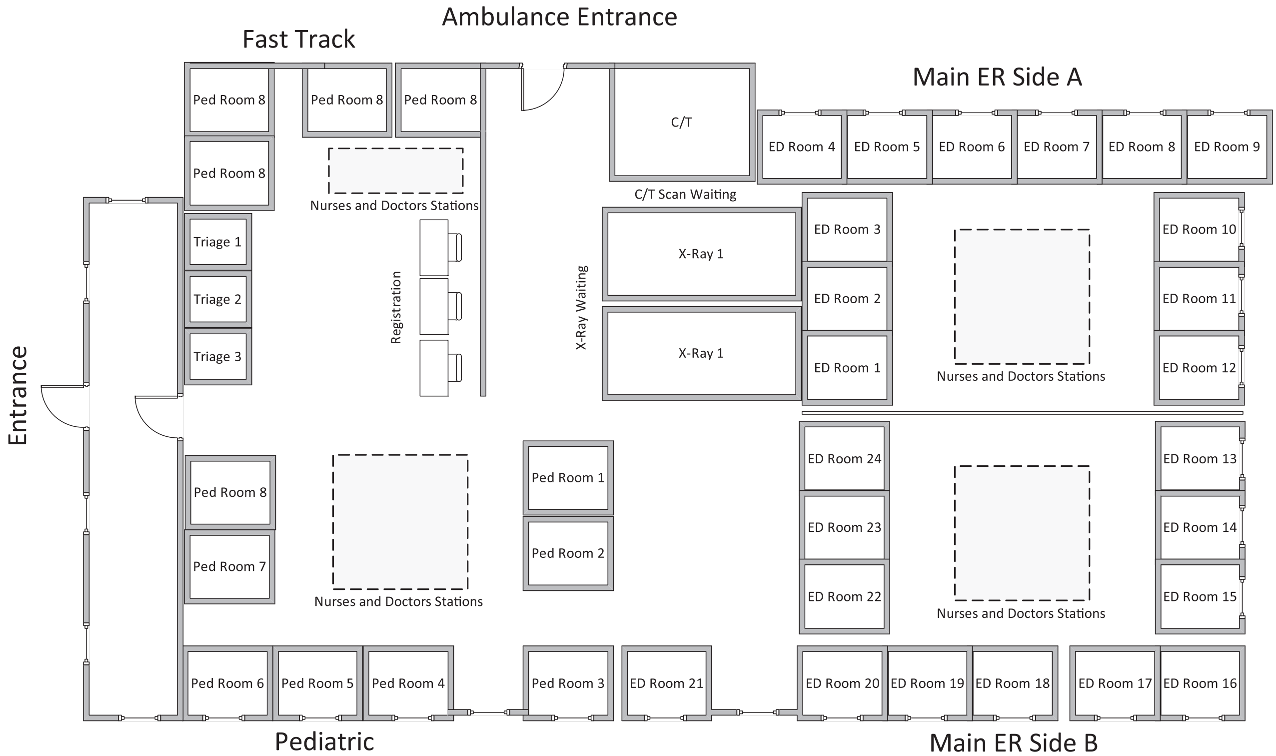


Fig. 4. ED Layout (Modified from Peck, 2008).

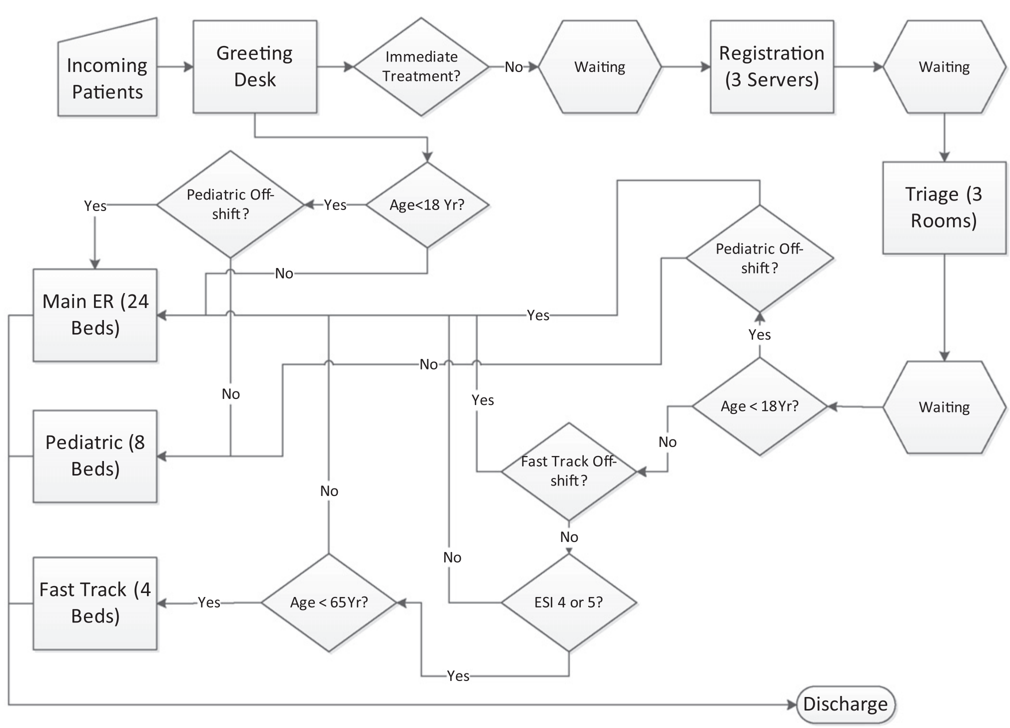


Fig. 5. ED Process Flow.

3.3.2. ED capacity assumptions

(1) The ED has three main departments; Main, Fast Track and Pediatric.

(2) The total number of beds in ED is n_b, and n_b^i is the number of beds in department i, where $i \in$ {Main, Fast Track, Pediatric}.

(3) The number of doctors, nurses and equipment in ED are not considered in the model.

(4) The greeting and registration desks have an infinite waiting capacity.
(5) There is no limit for waiting times.

3.3.3. Operations assumptions

(1) The bed processing times are exponentially distributed and varied based on patient's ESI level.
(2) The greeter desk has an exponentially distributed service time.
(3) The patients' arrival process is a non-stationary Poisson process.

3.4. Input/Output

The system variables used in the simulation model include inter-arrival times, treatment times, delay times (greeting). In order to count for variability, the input variables are modeled as random variables with appropriate probability distribution functions. System input variables are shown in Fig. 6 and Table 2. We adopted a set of hourly patient arrival rates from Williams (2006) and the number of NWH ED visits to estimate the hourly arrival rates. The percentages based on ESI level and age categories were estimated using a two-week worth patient dataset from Williamsport Regional Medical Center, Williamsport, Pennsylvania. Patient treatment times in the ER were estimated based on Fig. 7 from Peck et al. (2008). Since time in ER includes treatment time, testing, waiting, etc. the treatment times were estimated to be one third of the time in ER (Peck et al., 2008). Table 2 presents the treatment times by ESI level.

The Fast Track accepts patients with the following criteria: (1) Younger than 65 years but not pediatric, (2) ESI 4 or 5, and (3) entered the ED during the FT hours. The main ER would accept all ESI levels during the off-shift time of the FT and pediatric ERs. ESI level 1 patients go directly to the main ER or the pediatric ER (if they are under 18 and it is open).

Fig. 8 defines the time metrics that describe patient flow: (1) ***Average Length Of Stay*** (LOS), which is the length of time from the moment a patient steps into the ED after being greeted to when he is discharged from the ED system; (2) ***Average throughput,*** defined as the number of patients who are discharged from the ED per hour; (3) ***Average time in ER***, which is the length of time from the moment a patient steps into the bed up to when he is discharged from the ED system; (4) ***Average Time-To-Bed (TTB)***, described as the length of time from the moment a patient leaves the triage station up to when his treatment starts in an ER bed; and the last one which is not shown in Fig. 8 is; (5) ***Percentage of tardy patients***. In the scheduling literature tardiness is defined as (Pinedo, 2002):

$$T_j = max\{C_j - d_j, 0\} = max\{L_j, 0\} \tag{2}$$

Where, T_j is the tardiness of job j; C_j is the completion time of job j; and d_j is the due date of job j. L_j is called the lateness of job j.

The difference between lateness and tardiness is that tardiness can never be negative. There is one more relevant concept that is used in scheduling literature which is called unit penalty of job j. Unit penalty can be defined as:

$$U_j = \begin{cases} 1, & \text{if } C_j > d_j \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

In other words, when the tardiness is greater than 0, we assign 1. Otherwise, we assign 0. In our case, we are using the same analogy.

The Canadian Triage and Acuity Scale (CTAS) is used to setup the upper limits of waiting times for each ESI level: (1) Level I patients should have continuous nursing care; (2) Level IIs in every15 min; (3) Level IIIs in every 30 min; (4) Level IVs in every 60 min; and (5) Level Vs in every 120 min (CTAS, 2012). Thus, these limits represent the due dates for each ESI level, and the actual TTB values represent the completion times. Therefore, in our case, the definitions of the lateness, tardiness, and the unit penalty function would be as follows:

$$T'_j = \max\{TTB_j - UB_j, 0\} = \max\{L'_j, 0\} \tag{4}$$

$$U'_j = \begin{cases} 1, & \text{if } TTB_j > UB_j \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Where, T'_j is the tardiness of patient j; TTB_j is the time-to-bed of patient j; UB_j is the above mentioned upper bound of the waiting time for patient j; L'_j is the lateness of patient j; and U'_j is the unit penalty of job j. Unit penalty is used to calculate the percentage of tardy patients for each ESI level as follows:

$$\text{Percentage of Tardy patients}_i = \frac{\sum_j U'_{ij}}{N_i} \tag{6}$$

Where, i represents the ESI level (1, 2, 3, 4, and 5); and N_i is the total number of patients who have ESI level i.

3.5. Computer simulation model

The computer model was built using Simio version 4, and is based on the logic that has been covered in Section 3.2 and shown in Fig. 5. Fig. 9 represents a snapshot of the ED. The model has one source (Incoming) that creates patient entities according to a rate table shown in Fig. 10. The percentages of different patient groups would be generated based on a data table. The source assigns the ESI level, the FAHP score, and the picture for each patient entity. The greeter desk is a regular server with an infinite input buffer, zero output buffer, and infinite capacity. The registration station is also a regular server with infinite input and output buffers and capacity equals three. Patients with ESI level 1 do not go to the registration server. They either go to the main ER (age ⩾ 18) or to the pediatric ER (age < 18). Patients leave the registration server to the waiting area before triage, which is a regular server with infinite capacity, infinite input buffer, and zero output buffer. Patients leave this area and go to triage when it is available. Triage is a regular server with zero input buffer, infinite output buffer, and capacity equals 3, and is varied according to a work schedule. Then, patients leave triage to the waiting area after triage. Waiting area

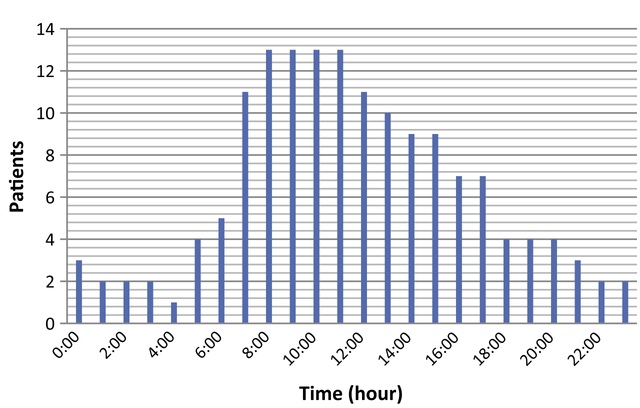


Fig. 6. Patient Arrival.

Table 2
Processing times by ESI level.

ESI level	Greeting time (Min)	Registration time (Min)	Triage time (Min)	Treatment time (Min)
1	Random.uniform (1,3)	0	0	Random.exponential (55)
2	Random.uniform (2,5)	Random.uniform (5,10)	Random.uniform (15,20)	Random.exponential (65)
3	Random.uniform (2,5)	Random.uniform (5,10)	Random.uniform (15,20)	Random.exponential (60)
4	Random.uniform (2,5)	Random.uniform (5,10)	Random.uniform (15,20)	Random.exponential (25)
5	Random.uniform (2,5)	Random.uniform (5,10)	Random.uniform (15,20)	Random.exponential (20)

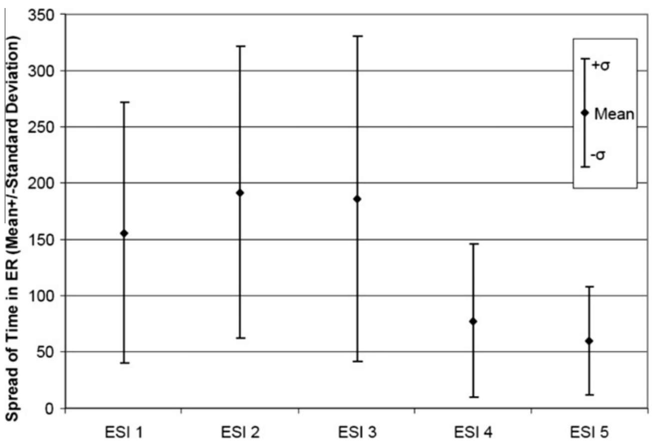


Fig. 7. Time in ER by ESI Level (Adopted from Peck (2008)).

after triage is a regular server with infinite capacity, infinite input buffer, and zero output buffer. When a bed is available, patient leaves the waiting area and is directed according to the work schedule, ESI, and age group. Main, pediatric, and FT ERs are regular servers with zero input buffers, and infinite output buffers.

The FAHP scores are sampled uniformly from data tables. These tables include FAHP scores that are calculated by using real patients' information from Williamsport Regional Medical Center.

4. Experimentation and results

Two alternatives are considered: (1) ED system that utilizes the ESI algorithm and (2) ED system that utilizes the FAHP–MAUT algorithm. The alternatives were simulated for 74 days including 18 days as a warm up period, and the runs were replicated 20 times.

4.1. Results

The results tables are shown in Appendix A. This section presents the comparisons between the alternatives based on four performance measures: average TTB, average LOS, average throughput, average time in ER, and percentage of tardy patients. The alternatives have been compared using confidence intervals of differences in performance measures. The following equations have been used to calculate confidence intervals:

$$(\overline{Y}_1 - \overline{Y}_2) \pm t_{\frac{\alpha}{2},v} * s.e.(\overline{Y}_1 - \overline{Y}_2) \tag{7}$$

$$s.e.(\overline{Y}_1 - \overline{Y}_2) = \sqrt{\frac{s_1^2}{R_1} + \frac{s_2^2}{R_2}} \tag{8}$$

$$v = \frac{\left(\frac{s_1^2}{R_1} + \frac{s_2^2}{R_2}\right)^2}{\frac{\left(\frac{s_1^2}{R_1}\right)^2}{R_1 - 1} + \frac{\left(\frac{s_2^2}{R_2}\right)^2}{R_2 - 1}} \tag{9}$$

Where; R_1 and R_2 are number of replications for system one and two, respectively; *s.e.* is the standard error; s_1 and s_2 are the standard deviations for system one and two, respectively; and v is the degrees of freedom.

The following table shows the resultant confidence intervals for each performance measure.

According to Table 3, all the confidence intervals have zero; therefore, there is no strong statistical evidence that one system would do better than the other in terms of these performance measures. We also reviewed collected simulated data by ESI level for the average LOS and the average TTB performance measures. During this review, we noticed that these times are distributed almost uniformly across the ESI levels 2–5 in the case of FAHP–MAUT system. On the other hand, ESI level 5 experiences a very high average LOS and average TTB compared to the other ESI levels (2–4) in the case of the ESI system.

The calculated confidence interval of average TTB for each ESI level is presented in Table 4. As expected, the two systems are similar in terms TTB with regard to ESI level 1. On the other hand, they are different for the rest of ESI levels. The intervals for ESI levels 2, 3, 4, and 5 do not have zeros; thus, we have a strong statistical difference between the two systems. Thus, ESI system has shorter TTB than FAHP–MAUT system for ESI levels 2 and 3, while the opposite happens for ESI levels 4 and 5. This conclusion should be

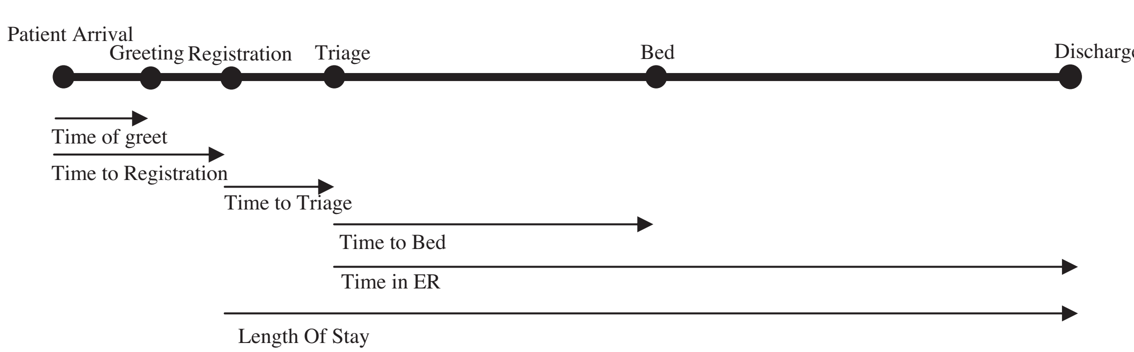


Fig. 8. Time metrics to describe patient flow.

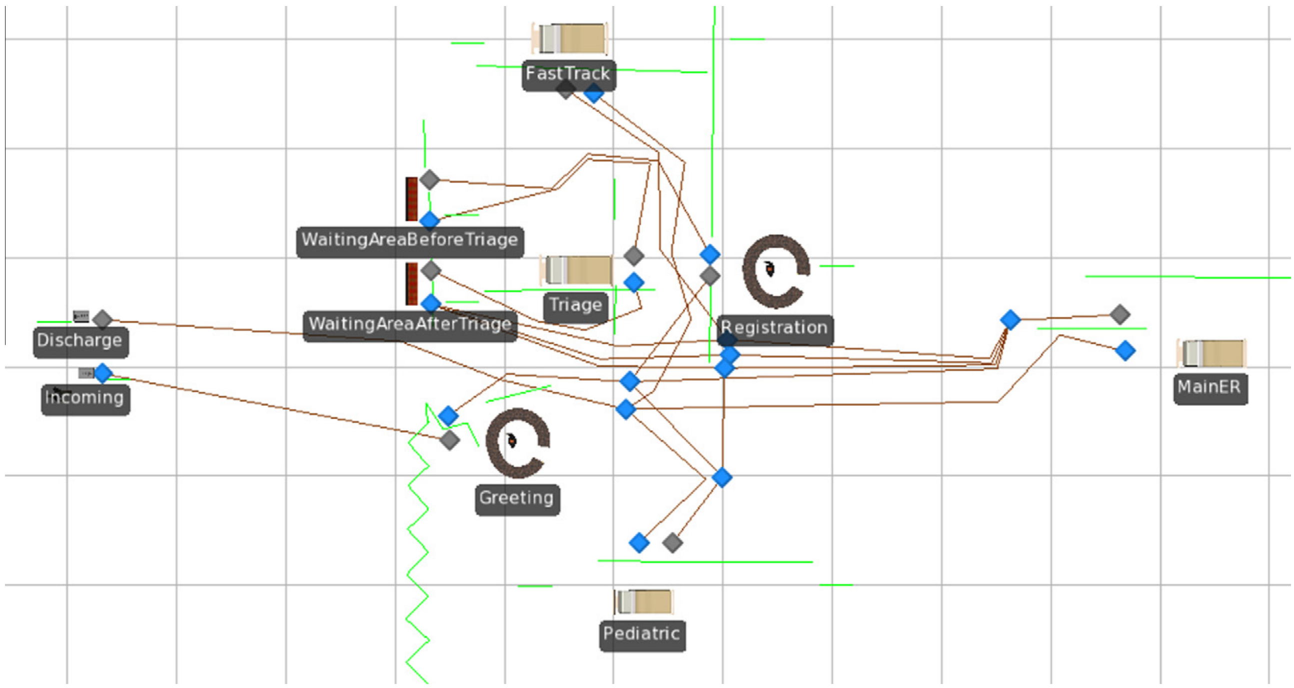
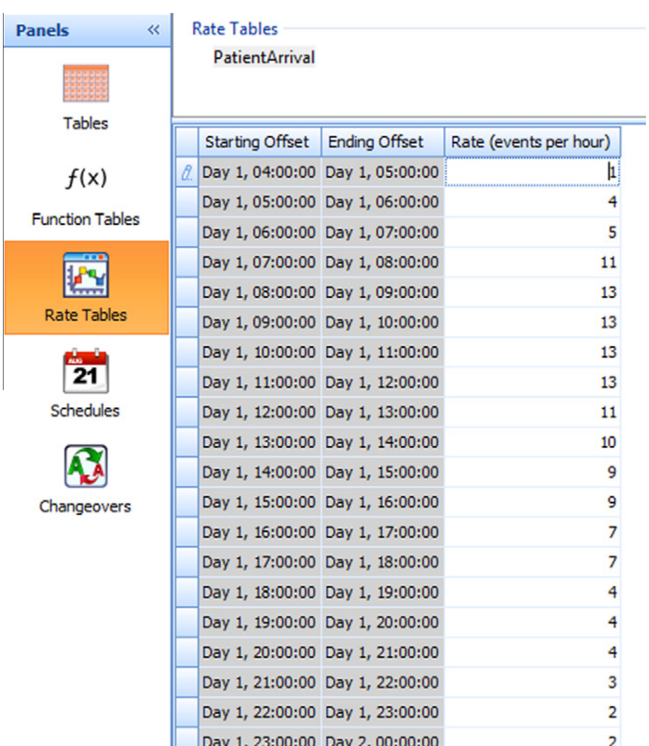


Fig. 9. ED computer model in Simio's facility window.



Starting Offset	Ending Offset	Rate (events per hour)
Day 1, 04:00:00	Day 1, 05:00:00	1
Day 1, 05:00:00	Day 1, 06:00:00	4
Day 1, 06:00:00	Day 1, 07:00:00	5
Day 1, 07:00:00	Day 1, 08:00:00	11
Day 1, 08:00:00	Day 1, 09:00:00	13
Day 1, 09:00:00	Day 1, 10:00:00	13
Day 1, 10:00:00	Day 1, 11:00:00	13
Day 1, 11:00:00	Day 1, 12:00:00	13
Day 1, 12:00:00	Day 1, 13:00:00	11
Day 1, 13:00:00	Day 1, 14:00:00	10
Day 1, 14:00:00	Day 1, 15:00:00	9
Day 1, 15:00:00	Day 1, 16:00:00	9
Day 1, 16:00:00	Day 1, 17:00:00	7
Day 1, 17:00:00	Day 1, 18:00:00	7
Day 1, 18:00:00	Day 1, 19:00:00	4
Day 1, 19:00:00	Day 1, 20:00:00	4
Day 1, 20:00:00	Day 1, 21:00:00	4
Day 1, 21:00:00	Day 1, 22:00:00	3
Day 1, 22:00:00	Day 1, 23:00:00	2
Day 1, 23:00:00	Day 2, 00:00:00	2

Fig. 10. Patients' arrival rate table.

Table 3
Confidence intervals of system differences.

Performance measure	ESI system vs. FAHP–MAUT
Avg. LOS	(−1.46, 4.33) min
Throughput	(−36.23, 84.03) patients
Time in ER	(−0.34, 0.36) min
Avg. TTB	(−1.57, 4.35) min

Table 4
Confidence intervals of TTB by ESI level.

ESI Level	ESI System vs. FAHP–MAUT
1	(−0.22, 0.12) min
2	(−81.85, −76.20) min
3	(−90.20, −86.23) min
4	(5.89, 14.20) min
5	(207.19, 223.80) min

Table 5
Percentages of tardy patients.

Percentage of patients who were serviced	ESI 1 (ESI/FAHP–MAUT)	ESI 2 (ESI/FAHP–MAUT)	ESI 3 (ESI/FAHP–MAUT)	ESI 4 (ESI/FAHP–MAUT)	ESI 5 (ESI/FAHP–MAUT)
<0.5 min	25/26	–	–	–	–
<15 min	–	100/100	–	–	–
<30 min	–	56/66	64/67	–	–
<60 min	–	–	–	61/34	–
<120 min	–	–	–	–	70/25

interpreted carefully, because any patient who is waiting longer than they should as per their acuity level will be adversely affected. Accordingly, we re-evaluated the comparison after setting an upper limit to the TTB using the limits from the Canadian Triage and Acuity Scale (CTAS, 2012). Then, the percentages of tardy patients are calculated by ESI level to provide a more explicit comparison on the prioritization algorithms. It was noticed that for ESI level 2 patients, the TTB for all patients were higher than 15 min for both systems; thus, a new limit was set as 30 min. Table 5 presents these proportions.

Table 5 shows that the FAHP–MAUT system outperforms the ESI system for ESI levels 4 and 5; 34% vs. 61% and 25% vs. 70%, respectively. Moreover, as expected, both systems were performing about equally for ESI level 1 and level 3 patients; 25% vs. 26% and 64% vs.

67%, respectively. While ESI system slightly outperforms FAHP–MAUT system for ESI level 2 patients, 56% vs. 66%.

5. Summary and conclusions

DES has been used as a tool to compare two ED systems: one system uses the current ESI while the other system uses FAHP–MAUT to prioritize ED patients. Because of the fact that the new system would lower the cognitive stress and load on the triage nurse, and would aid nurses to make better decisions, i.e. accurate and repeatable decisions for the same scenarios that they might face, we investigated the effect of using this algorithm on other system performance measures and compared it with the ESI system in terms of these measures (TTB, LOS, throughput, time in ER, and percentage of tardy patients).

In reviewing the averages of the performance measures, the results showed that there is no strong statistical evidence that one system would do better than the other in terms of these performance measures. However, when the simulated data was reviewed by each ESI level, we found that the new algorithm balances the length of stay and the time-to-bed for ESI levels while the previous algorithm (ESI) showed huge differences in terms of these measures, for example, between ESI level 4 and Level 5. Statistical significance has been conducted for the time-to-bed as a performance measure; the conclusion is that the two systems are statistically different from each other, and the new algorithm outperforms the previous one for ESI levels 4 and 5, but the ESI system outperforms FAHP–MAUT system for ESI levels 2 and 3. Finally, both system are not statistically different for ESI level 1.

Waiting time limits were established based on CTAS to measure the percentage of tardy patients whose TTB times are greater than these limits. FAHP–MAUT system outperforms the ESI system for ESI levels 4 and 5. Both systems almost perform equally for ESI level 1 and 3. On the other hand, ESI system slightly outperforms FAHP–MAUT system for ESI level 2. In view of all these results collectively, we recommend using FAHP–MAUT as it performs better in terms of minimizing the number of patients with waiting times longer than the allotted upper limits.

Overall, the paper has presented the comparison of two triage algorithms in a dynamic and realistic situation. Given the patient and system related performance results, we recommend the use of FAHP–MAUT algorithm. This recommendation is also impacted by the fact that the typical ESI algorithm heavily relies on nurse judgments whereas FAHP–MAUT uses quantitative measures to arrive at a priority for each patient, making it possible for an expert system to be generated to propose prioritization to nurses; indeed, the work presented herein is considered as a step in this direction.

Appendix A

This appendix includes the tables of the results. Table A1 shows the results of running the current ED system; the system that uses ESI as the patient ranking rule.

Table A2 shows the results of running the modified ED system; the system that uses FAHP–MAUT as a ranking rule.

(See Tables A1–A6 for various performance results).

Table A1
Performance measures for the current ED system.

Scenario	Replication	LengthOfStay (Min)	Throughput (Patients)	TimeInER (Min)	TimeToBed (Min)
ESI	1	162.6	8467.0	41.0	121.6
ESI	2	172.9	8740.0	40.8	132.1
ESI	3	166.9	8672.0	41.9	124.9
ESI	4	163.8	8605.0	41.5	122.4
ESI	5	163.5	8610.0	40.7	122.8
ESI	6	166.7	8684.0	41.1	125.6
ESI	7	156.0	8622.0	42.4	113.6
ESI	8	170.7	8719.0	40.9	129.8
ESI	9	170.5	8791.0	40.6	129.9
ESI	10	163.3	8622.0	39.6	123.7
ESI	11	165.7	8767.0	41.0	124.7
ESI	12	152.4	8452.0	41.4	111.1
ESI	13	172.5	8770.0	40.8	131.7
ESI	14	168.2	8667.0	41.1	127.1
ESI	15	171.3	8789.0	40.5	130.8
ESI	16	166.7	8697.0	41.6	125.0
ESI	17	159.5	8516.0	40.6	118.9
ESI	18	164.8	8588.0	41.2	123.6
ESI	19	172.6	8798.0	40.9	131.5
ESI	20	166.4	8703.0	41.7	124.7

Table A2
Performance measures for the modified ED system.

Scenario	Replication	LengthOfStay (Min)	Throughput (Patients)	TimeInER (Min)	TimeToBed (Min)
FAHP	1	168.8	8758.0	41.0	127.8
FAHP	2	165.2	8617.0	41.1	124.2
FAHP	3	164.6	8739.0	40.6	123.7
FAHP	4	164.6	8692.0	41.4	123.2
FAHP	5	166.7	8613.0	41.2	125.5
FAHP	6	162.0	8570.0	40.4	121.6
FAHP	7	168.0	8766.0	40.5	127.5
FAHP	8	168.0	8623.0	40.7	127.3
FAHP	9	164.9	8721.0	41.2	123.6
FAHP	10	164.4	8563.0	41.4	122.8
FAHP	11	159.9	8484.0	40.6	119.6
FAHP	12	160.5	8580.0	40.7	119.7
FAHP	13	165.5	8659.0	41.9	123.5
FAHP	14	161.9	8601.0	41.0	120.8
FAHP	15	163.1	8650.0	40.6	123.0
FAHP	16	156.7	8510.0	41.2	115.5
FAHP	17	169.7	8786.0	41.1	128.6
FAHP	18	163.9	8625.0	40.4	123.6
FAHP	19	166.9	8651.0	41.8	125.1
FAHP	20	163.2	8593.0	42.1	121.2

Table A3
Length of stay by ESI level for the current system.

LengthOfStay_ESI1	LengthOfStay_ESI2	LengthOfStay_ESI3	LengthOfStay_ESI4	LengthOfStay_ESI5
58.69	98.93	97.29	165.12	366.75
57.84	95.23	97.88	181.79	391.93
59.67	99.71	98.52	174.72	366.49
56.48	96.48	99.20	169.19	372.50
56.21	100.57	96.54	166.05	366.18
56.22	96.31	97.66	166.66	380.27
61.41	99.76	97.74	153.94	357.43
60.12	97.16	96.89	179.36	386.42
54.66	97.12	96.29	168.23	402.24
56.80	95.09	96.06	161.87	378.52
59.07	99.87	96.38	170.16	380.91
57.09	97.30	97.28	151.07	331.93
58.09	95.96	97.21	178.97	393.90
61.50	97.25	98.86	173.43	369.54
57.86	95.01	96.13	185.23	378.29
57.17	97.70	98.06	169.77	379.66
55.74	96.62	96.38	163.73	354.01
58.78	94.29	97.94	172.77	365.92
58.35	96.90	96.93	177.86	398.36
57.04	95.22	99.15	173.55	371.50

Table A4
Length of stay by ESI level for the FAHP–MAUT system.

LengthOfStay_ESI1	LengthOfStay_ESI2	LengthOfStay_ESI3	LengthOfStay_ESI4	LengthOfStay_ESI5
58.71	173.49	190.13	169.78	157.10
59.83	179.21	190.83	158.63	155.53
60.73	178.15	185.98	158.17	161.82
62.17	180.78	182.91	160.14	162.26
60.42	185.56	188.20	159.03	168.55
56.12	179.55	180.00	158.51	156.54
56.55	176.70	186.29	168.32	163.64
57.23	179.33	193.34	160.96	163.49
55.61	167.73	185.90	161.80	162.86
63.38	182.49	187.82	158.29	155.26
59.23	163.18	182.37	154.86	161.18
55.23	172.51	181.63	157.83	153.85
60.96	169.99	184.27	162.04	166.41
52.47	170.96	182.99	158.12	158.19
60.71	165.95	188.50	161.50	150.36
57.91	165.25	174.21	153.16	160.66
57.38	188.16	185.99	170.22	159.84
56.47	171.61	189.22	160.16	155.28
62.30	182.17	185.76	163.40	161.16
59.42	178.71	187.33	157.07	152.72

Table A5
Time-To-Bed by ESI level for the current system.

TimeToBed_ESI1	TimeToBed_ESI2	TimeToBed_ESI3	TimeToBed_ESI4	TimeToBed_ESI5
2.03	31.60	35.94	140.48	343.53
2.19	31.37	36.38	156.34	372.33
2.16	31.52	36.55	148.73	347.63
2.11	31.46	37.76	143.40	352.89
2.10	31.49	36.06	140.60	345.58
2.26	31.82	35.96	140.78	359.83
2.25	31.38	35.15	128.16	335.26
2.25	31.95	37.14	153.27	367.45
2.14	31.47	36.55	142.00	384.03
2.55	31.58	36.73	136.62	361.36
2.54	32.00	36.61	144.84	360.23
2.19	31.37	35.71	125.61	307.96
2.21	31.59	37.30	153.03	373.54
2.17	31.53	37.04	147.22	350.26
1.78	31.48	36.88	160.22	357.94
2.14	31.75	37.10	143.32	356.28
1.71	31.31	35.98	137.98	332.85
2.20	31.52	36.65	146.84	345.70
2.25	31.39	36.82	151.80	376.76
2.21	31.98	36.72	148.09	350.34

Table A6
Time-To-Bed by ESI level for the FAHP system.

TimeToBed_ESI1	TimeToBed_ESI2	TimeToBed_ESI3	TimeToBed_ESI4	TimeToBed_ESI5
1.99	111.44	128.57	144.04	137.03
2.40	114.04	128.50	133.54	135.56
2.35	114.92	125.37	132.23	141.49
2.11	114.64	124.08	133.17	140.49
2.11	116.54	127.86	133.17	147.47
2.57	113.57	122.23	132.80	134.54
2.21	113.77	127.80	142.41	141.86
2.08	113.57	133.23	135.54	142.95
2.51	100.10	125.64	135.97	141.87
2.05	113.39	126.64	132.97	133.72
2.33	97.05	123.87	129.59	141.25
2.51	106.32	120.95	132.01	133.98
1.83	104.44	121.56	136.44	145.61
2.05	103.70	122.52	132.70	136.75
3.40	100.82	130.49	135.32	129.07
2.15	99.50	113.14	127.51	140.98
2.32	122.91	125.54	144.06	139.59
2.38	107.91	129.73	133.96	134.62
2.30	115.21	124.75	137.76	140.42
2.27	112.14	124.94	130.98	132.63

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