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Developing a Correction Factor to Modify the FAHP and Utility Theory based Triage Algorithm

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Abstract

Triage is a pre-hospital decision making process which involves assigning a priority level for coming patients to emergency departments (EDs). The accuracy of assessing patient acuity and the prioritization of patient flow are the central issues in triage process. Inaccurate and/or inefficient triage might affect the patient safety and/or waiting times (e.g., increasing waiting time for patients with critical status or decreasing it for non-urgent patient). In order to improve the decision making in healthcare systems, many researchers have implemented different tools and models from various fields. In a previous study, we used the Fuzzy Analytic Hierarchy Process (FAHP) and utility theory to rank patients based on the following attributes: chief complaint, vital signs, age, gender, and pain level. In this paper, a modification for the FAHP and utility theory model has been proposed. The modification involves developing of a correction factor that adjusts the priority of the patient based on the estimated average length of time the patient remains urgent when he becomes urgent given his chief complaint. The average length of time will be estimated based on the patient's status sample path. A hypothetical example is used to illustrate the proposed method.

Keywords

Emergency Severity Index (ESI); Age; Gender; Pain-level; Triage; Sample Path

1. Introduction

Emergency Departments (EDs) are considered as vital components of the nation's health care safety net [1], which are responsible for 45%-65% of hospital admissions [2]. Thus, the ED performance is a very critical issue. Most EDs in major areas are often overcrowded, and hence, hospitals utilize a triage system to sort patients according to the severity of the illness/injuries [3].

Many hospitals in the United States utilize the five-level emergency severity index (ESI) to sort patients into five groups with clinically meaningful differences in projected resource needs and associated operational needs. The ESI designates the most acutely ill patients as level 1 (highest level) or 2, and uses the number of resources a patient needs to determine levels 3 to 5 (lowest level) [4]. Level 1 and 2 patients can be taken directly to the treatment area for rapid evaluation and treatment, while level 3 to 5 are sent to the waiting area [5]. This system does not consider prioritization of patients who are sent to wait (i.e., ESI levels 3 to 5); it assumes a first come first served routine.

Even though the number of resources is the primary decision rule to determine levels 3 to 5, physiological and descriptive variables can be used to determine a priority order for patients [6]. The physiological variables include heart rate, systolic and diastolic pressure, respiration rate, body temperature, and oxygen level. Indeed, Claudio and Okudan [6] presented a utility theory based patient prioritization, which takes into account the patient vital signs. The descriptive variables include age, gender, primary patient complaint, and pain level as described by the patient. In a preliminary study [7], Fuzzy Analytic Hierarchy Process (FAHP) and utility theory based approach has been used to rank the patients based on their vital signs, gender, age, and the pain level taking into account the chief complaint.

In general, patient prioritization is a decision making problem. Decisions in EDs involve a lot of uncertainty with respect to what a patient's illness and/or injuries are [6]. In addition, a study done by Fields et al. [8] investigated the discrepancies in decisions made across nurses in three clinical settings: Susquehanna Health Williamsport Hospital (SHWH), Mount Nittany Medical Center (MNMC), and Hershey Medical Center (HMC). In this study, Spearman's rank correlation comparison method was used. The results show that there are differences in patient rankings among nurses at different hospitals, and even within the same hospital. To accommodate for this uncertainty, FAHP and utility theory have been applied in unison [6, 7, 9].

Prioritization of the patients according to their medical condition and the chance of survival on arrival at the ED makes the triage process a dynamic decision making problem [6]. Moreover, Beveridge et al. [10] mentioned in the guidelines of the Canadian Emergency Department Triage & Acuity Scale (CTAS) that "Triage is a dynamic process: A patient's condition may improve or deteriorate during the wait for entry to the treatment area". Accordingly, we believe that the patient status might change in time, in other words, there is a chance that a non-urgent patient might become an urgent patient or vice versa.

This paper presents a modification for the FAHP and MAUT triage algorithm in which the patient's status sample path is used to estimate the average time the patient remains in an urgent status when he becomes urgent. This average time will be the base to develop a factor to adjust the patient priority.

2. Literature Review

In our preliminary work [7, 9], we used the utility theory and Fuzzy Analytic Hierarchy Process (FAHP) to prioritize patients at the EDs. A clinical data set, from Susquehanna Health's Williamsport Hospital, was used to build the overall utility function. Patients' age range varied between 18 and 92. In both studies, various patient attributes have been used to rank patients at EDs; chief complaint, emergency severity index (ESI), and three descriptive variables (age, gender and pain level) are among these. FAHP and utility theory take into account the uncertainty that comes from the subjectivity in the decision making process. For example, the recorded pain levels might be different even when expected to be similar (i.e., two patients might have the same symptoms and have the same illness/injury but one of them gives 5 and the other 8 out of ten for the pain level).

Patel et al. [11] studied the decision making process of nurses in the general ED and concluded that nurses' decisions are based on generated hypotheses according to both the information given by the patient, and on single symptoms perceived as being characteristic of the diagnosis. Further as per our interviews at clinical settings, we have ascertained that the relative importance of vital signs changes across different complaints, our previous work [7] has considered the chief complaints and the relative importance shifts.

In ED settings, it is generally difficult to ascertain the patient information because of the dynamic nature of the patient status [10]. For example, the vital signs change over time, and assessment of certain variables, such as pain level, are subjective [8]. The use of fuzzy set theory allows the decision makers to incorporate unquantifiable information, incomplete information, non-obtainable information and partially ignorant facts into a decision model [12], and hence, it is appropriate for such settings. Moreover, patient status might change during waiting, for example, a patient who comes to the ED with a chest pain complaint might be assigned ESI level 3, but after half hour his status might change from ESI level 3 (not-urgent) to ESI level 2 (urgent), due to the deterioration of his vital signs [6]. The sample path of the patient status over time can be used to estimate the average length of time the patient remains in an urgent status when he becomes urgent. This value is used to develop a correction factor to adjust the priority of the patient which is calculated by the FAHP and MAUT triage algorithm.

Sample path analysis which is also known as theory of level crossing has been developed to derive the steady state probability density function (pdf) and the cumulative distribution function (cdf) of the waiting time in M/M/c queues with service time depending on waiting time [13]. The level crossing method has been applied in many stochastic models, such as queues, inventories, dams, etc. The following section describes the sample path analysis in the case of triage process.

3. Sample Path Analysis

Sample path analysis can be applied to stochastic phenomena in ED settings. For example, a patient's status might change during waiting, and it is assumed that such changes would be according to an irreducible, positive recurrent

Markov chain with transition probabilities of P_{ij} , $i, j = 1, 2, 3, 4, 5$. From these, it is assumed that states 1 and 2 are urgent states (unacceptable, i.e. patient cannot wait) while 3, 4, and 5 are non-urgent states (acceptable, i.e. patient can wait). Patient status given his chief complaint might jump from an acceptable state (3, 4, 5) to an unacceptable state (1, 2) with a downward rate or vice versa with an upward rate. It is assumed that the patient state has been monitored, with a specific chief complaint, for a long time, and his/her states were recorded at observation epochs.

The main idea of the level crossing method is to establish a typical sample path of the stochastic process at hand [13]. As shown in Figures 2 and 3, the sample path is a tracing of the state random variable over time. Sample path can be used to solve the problem of obtaining the pdf. The level crossing approach is considered as a generalization of the rate in = rate out principle. This principle is usually used to calculate the steady state distribution of the state variable continuous time Markov chains with discrete state spaces [13]. Thus, in our case, we are using the sample path to estimate the average length of time the patient remains in an urgent state when he becomes urgent, as illustrated in the coming section.

The following section presents a hypothetical example showing how the proposed algorithm works.

4. Hypothetical Example

From the previous study [7], the proposed decision algorithm, given in Figure 1, starts by identifying the patient status. Then, if the patient requires any immediate intervention, he/she is considered to be in “Critical State”. After this stage, the procedure progresses as follows: 1) Is the patient in need of immediate intervention? If the response is affirmative, he/she is a “Critical State” patient. If not, he/she goes to Step 2; 2) The triage nurse asks the patient about his complaint, pain level, age, and gender, and takes vital signs; 3) The complaint and the vital signs data are treated using the FAHP; 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 value can wait in the waiting room. Then, they are sequenced in descending priority based on their overall utility values. The modification to this algorithm would be in step 5, where the patient priority (utility value) is multiplied by a correction factor that is based on the average length of time the patient remains in an urgent status when he becomes urgent.

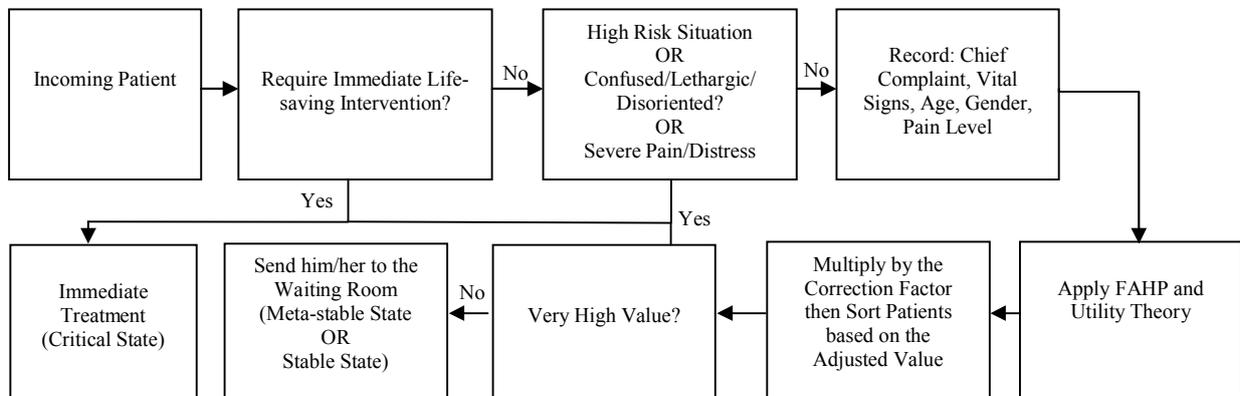


Figure 1: Modified Triage Algorithm from [7]

Every patient who comes to the ED has a chief complaint. These complaints are classified into 17 categories as follows [14]: 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 & Dental Complaints.

As shown in Step 2 (of Figure 1), the nurse records the patient complaint, and the physiological and descriptive variables. After that the nurse assigns the ESI level for the patient. Beyond what is commonly applied during triage as prescribed by Gilboy et al. [5], there is no systematic way to assign the ESI levels. Due to the presence of the

uncertainty in making such decisions we adopt the FAHP approach [7]. Our selection of this approach stems from the interviews we conducted with expert triage nurses. As per these interviews, we have identified the relative importance of vital signs changes given the patient’s complaint. In other words, the triage nurse assigns weights to the vital signs unequally based on the patient complaint, and then identifies the ESI level based on that weighting. In order to ascertain how the relative importance weights of vital signs changes, we have conducted further interviews with expert triage nurses, where nurses rated each vital sign for their importance with respect to the patient complaint using the fuzzy number scale: Low (L), Relatively Low (RL), Medium (M), Relatively High (RH), and High (H), these linguistic terms associated with $\tilde{1}$, $\tilde{3}$, $\tilde{5}$, $\tilde{7}$, and $\tilde{9}$, respectively. The hierarchy of this problem would be the complaint type in the first level and the vital signs in the second level. In the FAHP, vital signs get different weights. In addition, each patient’s vital signs are rated based on tables extracted with the aid of expert triage nurses. Then, the final score for each patient is calculated using the FAHP as illustrated by Lee et al. [15]. These scores are later converted via a utility function into utility values in order to calculate the overall utility value (or priority ranking) for each patient.

It is assumed that the patient changes states in accordance with an irreducible, positive recurrent Markov chain having transition probabilities P_{ij} , $i, j = 1, 2, 3, 4, 5$; and it is assumed that state 1 and 2 are urgent states (unacceptable, cannot wait) while 3, 4, and 5 are non-urgent states (acceptable, can wait). In order to calculate the average length of time the patient remains urgent when he becomes urgent, we need to start observing the patient when he/she comes to the ED with a chief complaint and record his/her state at the observation epochs.

Table 1 shows a hypothetical data for two patients, one of them has a neurological complaint and the other has a chest pain complaint. Assume that the time interval between observation epochs is 30 minutes. These transitions can be represented in graphs as shown in Figure 2 and 3. If both patients have the same age (53 years), gender (male), pain level (10 out of 20), and same set of vital signs (Sys. BP = 131, Dia. BP = 85, Pulse = 85, RR = 20, Temp. = 36.7°C, and SaO₂ = 99) they will get the same priority value based on the FAHP and MAUT algorithm, which is equal to 0.279.

Table 1: Hypothetical Data

Time of the Observation	Neurological Complaints		Chest Pain Complaints	
	State	Group	State	Group
0	4	‘Not Urgent’	3	‘Not Urgent’
1	5	‘Not Urgent’	3	‘Not Urgent’
2	5	‘Not Urgent’	3	‘Not Urgent’
3	5	‘Not Urgent’	2	‘Urgent’
4	5	‘Not Urgent’	2	‘Urgent’
5	2	‘Urgent’	2	‘Urgent’
6	3	‘Not Urgent’	2	‘Urgent’
7	3	‘Not Urgent’	2	‘Urgent’
8	4	‘Not Urgent’	2	‘Urgent’
9	4	‘Not Urgent’	2	‘Urgent’
10	4	‘Not Urgent’	2	‘Urgent’

Based on these observations and the sample path, the average length of time the patient remains urgent when he becomes urgent can be estimated. Note that in the following equations, down crossing means going from non-urgent state to urgent state.

The average length of time for patient #1 is urgent when his status becomes urgent (Time₁):

$$Time_1 = P(\text{patient in urgent state}) / \text{Rate of down crossing} = (1/10)/(1/10) = 1$$

The average length of time the patient #2 is urgent when his status becomes urgent (Time₂):

$$Time_2 = P(\text{patient in urgent state}) / \text{Rate of down crossing} = (7/10)/(1/10) = 7$$

Hence, the correction factor for patient #1 (neurological complaint) and patient #2 (chest pain complaint) equal 1 and 7, respectively. Then, the adjusted priority would be $0.279 \times 1 = 0.279$ and $0.279 \times 7 = 1.953$ for patients #1 and #2, respectively. Based on the adjusted scores, patient #2 should be treated before patient #1; because he has a much higher score.

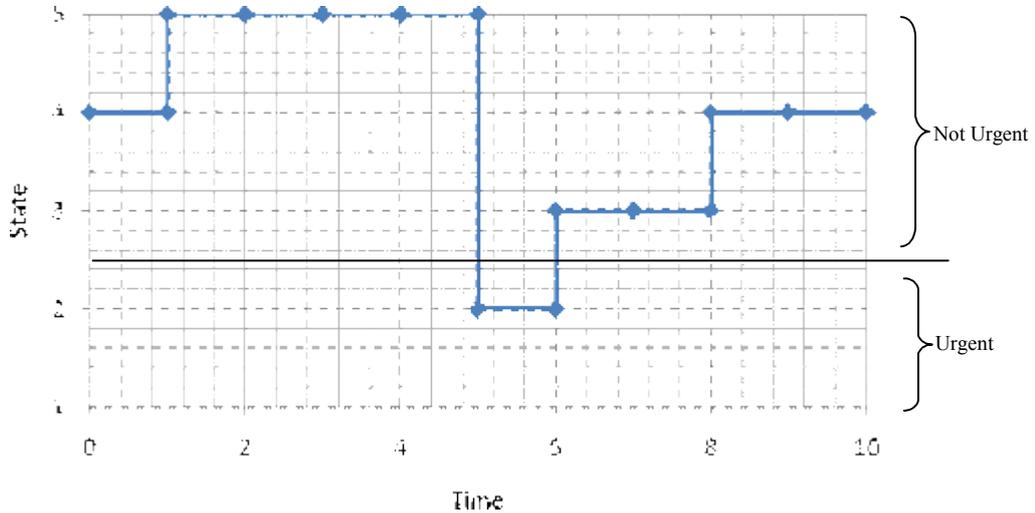


Figure 2: Sample Path of Patient #1

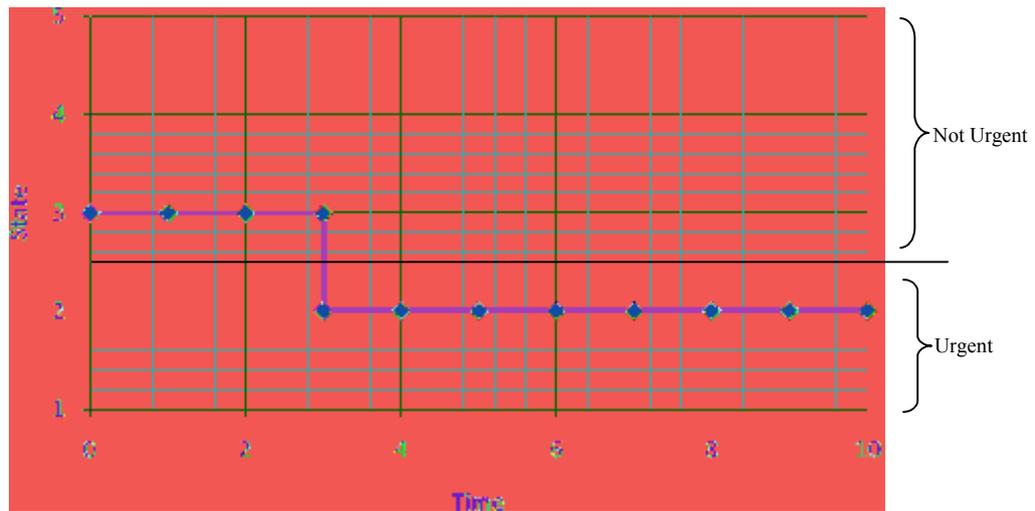


Figure 3: Sample Path of Patient #2

5. Conclusions

Sorting patients in EDs is a decision making problem. On one hand, this problem involves a lot of uncertainty as it depends on the nurse's knowledge, experience, intuition and on the subjectivity of patient's attributes, such as, pain level. To accommodate for uncertainty, FAHP and the MAUT were selected in our previous study. On the other hand, the dynamic nature of the patient status makes the decision more difficult. A correction factor has been developed to adjust the patient priority by using the principle of level crossing theory.

FAHP and MAUT coupled with the use of the correction factor helps DM to improve his consistency, reliability, and repeatability; which means the same decision can be suggested for the same scenario. The full model involves the physiological, the descriptive variables, and the estimated average length of time the patient remains urgent when he becomes urgent given his chief complaint. The model can reduce the stress and the strain on triage nurses and improve service quality for patients. It should be acknowledged that real patients with a specific chief complaint

should be monitored to develop a valid correction factor for each chief complaint and the results should be verified in a real emergency department setting. Moreover, the presented model should be considered as an aid to help the nurse making complex triage decision, and hence reduce the cognitive stress, improve productivity, the quality of the healthcare delivery in the EDs and not to make decisions without the benefit of the nurse's experience.

References

1. Weinick, R.M. and Burstin, H., 2001, "Monitoring the safety net: data challenges for emergency departments," *Academic Emergency Medicine*, 8, 1019–1021.
2. Mahapatra, S., Koelling, C.P., Patvivatsiri, L., Fraticelli, B., Eitel, D., and Grove, L., 2003, "Pairing emergency severity index5-level triage data with computer aided system design to improve emergency department access and throughput," *Proc. of the Winter Simulation Conference*, OMNIPRESS, Madison, WI, 1917-1925.
3. Andersson, A.K., Omberg, M., and Svedlund, M., 2006, "Triage in the emergency department-a qualitative study of the factors which nurses consider when making decisions," *Nursing in Critical Care*, 11(3), 136-145.
4. Tanabe, P., Gimbel, R., Yarnold, P.R., Kyriacou, D.N., and Adams, J.G., 2004, "Reliability and Validity of Scores on the Emergency Severity Index Version 3," *Academic Emergency Medicine*, 11, 59-65.
5. Gilboy, N., Tanabe, P., Travers, D.A., Rosenau, A.M., Eitel, D.R., 2005, "Emergency severity index, Version 4: Implementation Handbook," AHRQ Publication No. 05-0046-2, Rockville, MD: Agency for Healthcare Research and Quality.
6. Claudio, D., and Okudan, G. E., 2010, "Utility function based patient prioritization in the emergency department," *European J. Industrial Engineering*, 4(1), 59-77.
7. Ashour, O.M., Okudan, G.E., and Smith C.A., 2010, "An improved triage algorithm for emergency departments based on fuzzy AHP and utility theory," *Proc. of the IIE Annual Conference and Expo 2010, (IERC 2010)*, June 05- June 09, Cancun, Mexico.
8. Fields, E., Claudio, D., Okudan, G., Smith, C., and Freivalds, A., 2009, "Triage Decision Making: Discrepancies in Assigning the Emergency Severity Index," *Proc. of the IIE Annual Conference and Expo 2009, (IERC 2009)*, May 30- Jun 3, Miami, FL.
9. Ashour, O.M., and Okudan, G.E., 2010, "Patient Sorting Through Emergency Severity Index and Descriptive Variables' Utility," *Proc. of the IIE Annual Conference and Expo 2010, (IERC 2010)*, June 05- June 09, Cancun, Mexico.
10. Beveridge R., Clarke B., Janes L., et al., 1998, *Implementation guidelines for the Canadian Emergency Department Triage and Acuity Scale (CTAS)*, Canadian Association of Emergency Physicians
11. Patel, V.L., Gutnik, L.A., Karlin, D.R, and Pusic, M., 2008, "Calibrating urgency: Triage decision making in a pediatric emergency department," *Advances in Health Sciences Education*, 13, 503-520.
12. Kulak O., Durmusoglu, M.B. and Tufekci, S., 2005, "A complete cellular manufacturing system design methodology based on axiomatic design principles," *Computers & Industrial Engineering*, 48(4), 765–78.
13. Brill, P. H., 2000, "A brief outline of the level crossing method in stochastic models," *Canadian Operations Research Society Bulletin*, 34, 1-8.
14. Claudio, D., Ricondo, L., Freivalds, A., and Okudan, G. E., 2009, "Physiological and Descriptive Variables as Predictors for Emergency Severity Index," *Proc. of the IIE Annual Conference and Expo 2009, (IERC 2009)*, May 30- Jun 3, 2009, Miami, FL.
15. Lee, W. B., Lau, H., Liu, Z., and Tam, S., 2001, "A fuzzy analytic hierarchy process approach in modular product design," *Expert Systems*, 18(1), 32-42.

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