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Designing patient flow in emergency departments

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Emergency Department (ED) managers can choose from several operational models, for example, Triage or Fast-Track. The following questions thus naturally arise: why does a hospital choose to work with its particular operational model rather than another? Or what is the best model to operate under? More specifically, how to fit an operational model to an ED's uncontrollable (environmental) parameters? To address such questions, we develop a methodology for ED Design (EDD): we apply it to data collected over a period of two to four years from eight hospitals, of various sizes and deploying various ED operational models. (To cover all size-model combinations, we enrich our data via accurate ED simulation.) The EDD methodology first feeds the data into a Data Envelopment Analysis (DEA) program, which determines the relative efficiency of each month of the different operational models of each hospital. Then, after taking into account the individual hospitals effect, we identify the operational model that is dominant under each set of uncontrollable parameters. We discovered that different operational models dominate others over different combinations of uncontrollable parameters. For example, a hospital catering to an aging population is best served by a fast-track operational model.

Keywords: Patient flow, emergency department (ED), discrete-event simulation, data envelopment analysis (DEA), efficiency, Fast-Track, Triage, operational model

1. Introduction

The health care industry is constantly being challenged by new regulations (such as standard LD.3.15, which the Joint Commission on Accreditation of Hospital Organizations (JCAHO) set in early 2005 for patient flow leadership), new technology (e.g., introducing Picture Archiving and Communication System (PACS) which replaced the old X-ray films), and structural changes due to public policy. For example, when reimbursements from Medicare patients in the United States started to decrease in 1983, the health care industry found itself first in a retrenchment stage, but later on it was realized that improving performance is the only way to reach a viable financial condition. These phenomena motivated the use of DEA (Data Envelopment Analysis) as a benchmark tool to achieve health care institutional goals (Ozcan, 2008).

1.1. *The ED design problem*

Priority queues in EDs are based on patients' urgency and illness (García *et al*., 1995). This implies that operational aspects, such as Length of Stay (LOS), are rarely accounted for when staff are treating their patients. Therefore, hospital management teams have come up with various ways to incorporate their operational agendas, specifically through the ED structure and its operational models. We focus here on the most prevalent operational models that are being used in EDs: Triage, Fast-Track, Walking-Acute, and Illness-based approach. These models are graphically summarized in Fig. 1.

Triage: an operational model that was designed to ensure that patients are receiving appropriate attention at the right location with the right degree of urgency (George *et al*., 1993). Triage was originally meant to be a clinically-based approach. As seen in Fig. 1(a), in the Triage model patient arrivals to the ED are immediately classified by the Triage function, before entering the ED areas. When used just as a prioritizing tool, the benefits of Triage are not clear, because adding queues for a staff member (to prioritize the patients) could increase the total waiting times (for more details see George *et al*., 1993). Others found that Triage helps reduce Average LOS (ALOS) when used as a hospital gatekeeper (e.g., Derlet *et al*., 1992, and Badri and Hollingsworth, 1993, who suggest referring non-urgent patients to clinics), or when Triage nurses are empowered to initiate lab tests (e.g., blood or urine) or X-rays so that the results arrive when a physician is ready to evaluate the patient (e.g., Macleod and Freeland, 1992). Of course,

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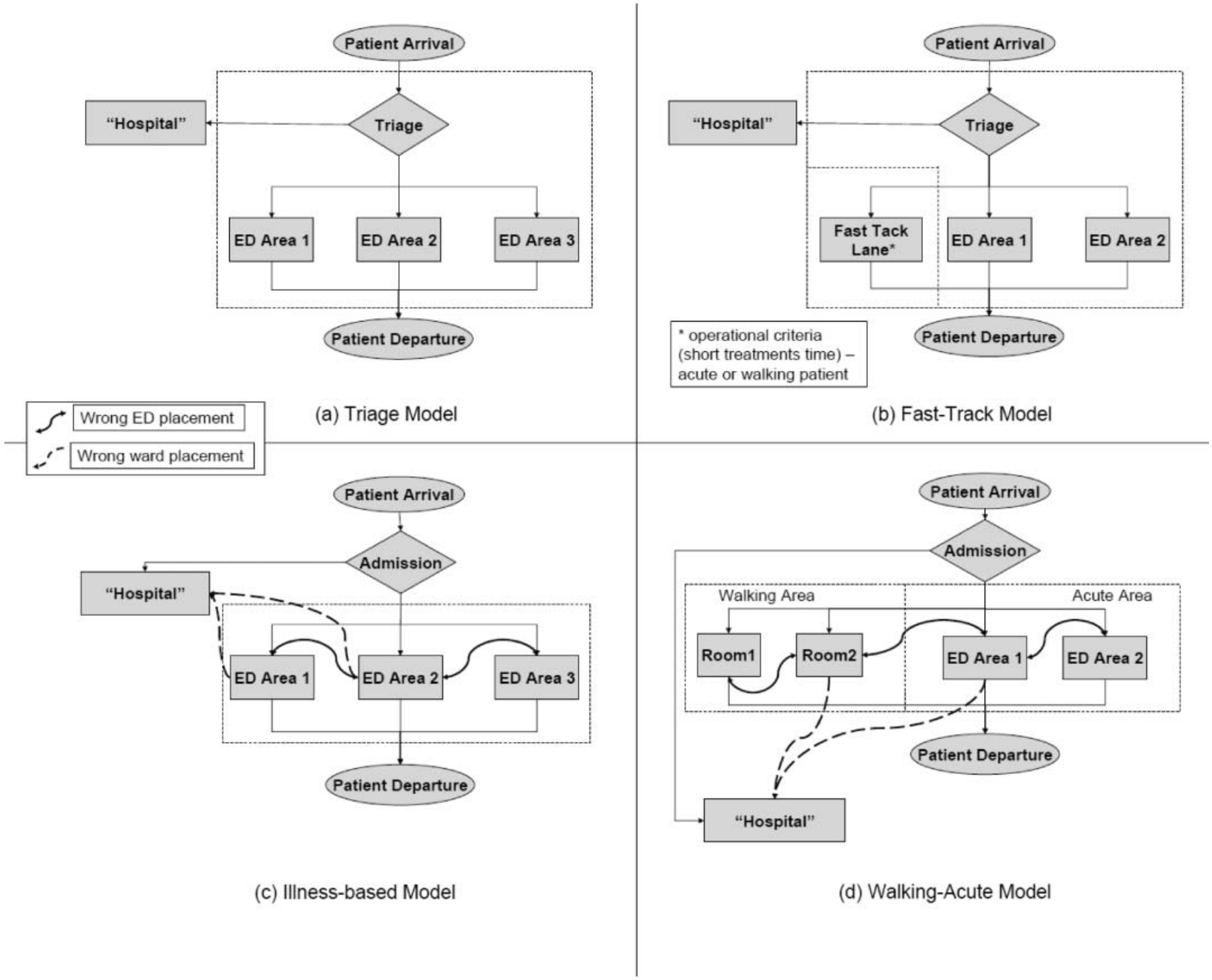

Fig. 1. Emergency Department (simplified) design of the common operational models.

identifying appropriate staffing levels of physicians (Wong *et al*., 1994) can reduce unnecessary queues and consequently reduce ALOS.

Fast-Track (FT): "A lane dedicated to serve a particular type of patient with the sole intent of reducing their waiting time; thus, reducing their total time in the system" (García *et al*., 1995). For example, FT lane may be needed for acute patients, e.g., patients with myocardial infarction (Pell *et al*., 1992) or evolving STEMI (Heath *et al*., 2003). FT is a mixture of a clinical and operational-based approach, since it aims both at saving lives and at reducing LOS for those who really need it. In Fig. 1(b), we see that the Triage and the FT models are very similar except for the special FT lane, which gave the model its name.

Illness-based (ISO): This operational model is based on the type of ED physician involved. ED physicians can be specialists in ED medicine, denoted hereafter as ED physicians, or specialists in specific disciplines such as Internal, Surgical or Orthopedic (ISO) medicine, denoted hereafter as professional physicians (Sinreich and Marmor, 2005). When an ED is operating with a special lane for each specialist, we call this approach "ISO," an abbreviation of its specialist physicians (Internal, Surgical and Orthopedic). From Fig. 1a, and Fig. 1c, we notice that the main difference between the Triage and the ISO models is the use of a Triage function, which could lead to misclassifications and to patients moving unnecessarily among areas in the ED, or out of the ED and into a hospital ward. The operational advantages of the ISO model over the Triage model could be the use of fewer staff members (due to staff pooling, which is not present in the Triage function).

Walking-Acute (WA): This is a special case of the "Fast-Track" model which is directed at the practice of reducing bed load by dedicating a separate lane for patients with minor illnesses or injuries (e.g., Docimo *et al*., 2000). Since such patients are commonly called "Walking Patients (WA)" (Falvo *et al*., 2007), we shall use the term WA for this approach instead of FT. Another difference between the WA and the FT models is that the latter employs the Triage function after patients enter the ED (see Fig. 1d and Fig. 1b). Being admitted without Triage, as in the ISO model, could lead to miss-classifications and, hence, later in the process patients moving from one area to another in the ED, or finding after a while that a patient's problem is not relevant to the ED, for example when the patient should have been admitted directly to one of the hospital wards.

1.2. *Prevalent limitations that we overcome*

As reflected by existing research, simulation methodology has been the leading methodology for planning healthcare systems. Notably, however, only a few works report actual implementation (Brailsford *et al*., 2009). Van Lent *et al.* (2012) offer two reasons why applying a simulation model across more than one healthcare setting is rare: (1) researchers are too involved with solving problems of a specific system; hence the models turn out "inappropriate" for others to use; and (2) simulation strength as a detailed descriptive tool works against the researchers when trying to generalize its finding. Some work, such as Sinreich and Marmor (2005) and Fletcher and Worthington (2009), analyze the differences between specific systems and therefore offer generic models or tools that can be used more broadly, in more than a single location. Pitt *et al.* (2009) argue that "as in the case of competing clinical investigations, alternative configurations of healthcare delivery need to be assessed using evidence-based methods."

Considering the lack of implementation and the limitations of simulation models when dealing with multiple healthcare settings, we chose to focus in this work on an evidenced-based methodology. This entails the evaluation of ED operational models, based on real data from several hospitals (Section 2.2) and further enriched with outcomes of well-validated simulation models (Section 2.3).

1.3. *DEA - basic principles*

DEA is a mathematical programming methodology dealing with performance evaluation, namely the efficiency of organizations, e.g., hospitals, government agencies, and firms in various business sectors. An example of measuring efficiency would be the cost (output) per unit (input), profit (output) per unit (input), and so on, which is manifested by the ratio Output/Input (Cooper and Seiford., 2000). Charnes *et al.* (1978) introduced the basic model, referred to in the literature as CCR (an abbreviation of the authors' names), which finds the efficiency of Decision Making Units (DMUs) operating in multiple input-output environments:

$$\max \quad h_0 = \frac{\sum_{r=1}^{R} w_r y_{r0}}{\sum_{i=1}^{I} v_i x_{i0}}; \quad s.t. \frac{\sum_{r=1}^{R} w_r y_{rj}}{\sum_{i=1}^{I} v_i x_{ij}} \le 1, \qquad (1)$$
$$w_r, v_i > 0, \quad j = 1, \ldots, J.$$

where x_{ij} represents the volume of input i (out of I inputs) utilized by DMU_j , while $y_{rj} > 0$ represents the volume of output r (out of R outputs) produced by DMU_j (out of J DMUs); v_i is the weight given to input i, and w_r is the weight given to output r. For each DMU rated both in the function as well in the constrains, with the index 0, the optimal solution $h_0^* = \max h_0$ will always satisfy $0 \le h_0^* \le 1$ with the appropriate $w_r^*, v_r^* > 0$. For solving Problem (1) we use linear programming with the following formulation:

$$\begin{aligned} \max \quad & \sum_{r=1}^{R} w_r y_{r0} \\ s.t. \quad & \sum_{i=1}^{I} v_i x_{i0} = 1, \quad \sum_{r=1}^{R} w_r y_{rj} - \sum_{i=1}^{I} v_i x_{ij} \le 0, \\ & j = 1, \ldots, J, \quad w_r, v_i > 0, \quad r = 1, \ldots, R, \\ & i = 1, \ldots, I. \end{aligned} \qquad (2)$$

1.4. *DEA - including uncontrollable elements*

It is often the case that some environmental parameters are uncontrollable (for example, weather conditions, or the inflation rate), so there is the need to extend (1) to account for uncontrollable inputs (Banker and Morey, 1986):

$$\max \quad \frac{\sum_{r=1}^{R} w_r y_{r0} - \sum_{k=1}^{K} u_k z_{k0}}{\sum_{i=1}^{I} v_i x_{i0}}$$

$$s.t. \quad 1 \ge \frac{\sum_{r=1}^{R} w_r y_{rj} - \sum_{k=1}^{K} u_k z_{kj}}{\sum_{i=1}^{I} v_i x_{ij}}, \; j = 1, \ldots J, \qquad (3)$$

$w_r > 0, \; r = 1, \ldots, R$, (weights for outputs),

$v_i > 0, \; i = 1, \ldots, I$, (weights for controllable intputs),

$u_k > 0, \; k = 1, \ldots, K$, (weights for uncontrollable intputs)

where Z_{kj} represents the volume of uncontrollable input k (out of K uncontrollable inputs) utilized by $\text{DMU}_\text{j.}$

1.5. *DEA – comparisons between groups of DMUs*

There are many reasons for using DEA. The main one is to identify the sources and the extent of relative inefficiency in each of the compared DMUs (for more reasons see Golany and Roll, 1989). Brockett and Golany (1996) introduced a new approach that analyzes data by groups rather than by individual DMUs. If the DMUs are grouped by their operational characteristics, their approach can assist management in evaluating what should be the best policy from the available options doing the following (originally s = 2):

I. Split the group of all DMUs (j = 1,...,J) into s programs consisting of $n_{1,} \ldots, n_s$ DMU_s ($n_1 + n_2 + \ldots + n_s = n$). Run DEA separately (e.g., Equation (3)).
II. In each of the s groups separately, adjust inefficient DMUs to their "level of efficiency" value by projecting each inefficient DMU onto the efficiency frontier of its group (e.g., by changing the controllable inputs in Equation (3)).
III. Run a pooled (or "inter-enveloped") DEA with all the n DMUs at their adjusted efficient level (again like in Equation (3)).
IV. Apply a statistical test to the results of III to determine if the s groups have the same distribution of efficiency values within the pooled DEA set (or does it vary over different uncontrollable parameters sets).

1.6. *Employing DEA in the health care industry*

In the last two decades, DEA has often been used to measure performance efficiency in the health care industry (for an extensive review see Hollingsworth *et al*., 1999). DEA was used to evaluate efficiency of hospitals (e.g., Ozcan *et al*., 1992), physicians (e.g., Chilingerian, 1995), and health maintenance organizations (e.g., Draper *et al*., 2000). Although many articles used quantitative outcomes as outputs, a few have tried to incorporate quality measures as well (Nayar and Ozcan, 2008).

2. Methods

Our work focuses on analyzing ED efficiency. Using an extensive database collected from eight hospitals, that employ different operational models, we investigate why each hospital chose to work with its specific operational model rather than another? In other words, we ask: can one identify which uncontrollable parameters should influence the choice of the operational model made by ED managers?

We start by introducing the ED Design (EDD) methodology to identify which operational model should be used to operate the ED, and implement the methodology on data collected at several hospital; we then display the results, and conclude with a summary and a description of some planned future work.

2.1. *EDD methodology*

The EDD methodology, for recommending an efficient ED operational model, consists of the following steps (based mainly on Golany and Roll, 1989, and Brockett and Golany, 1996):

- Prepare the model data:
  - Select DMUs to be compared.
  - List relevant efficient measurements, operational elements, and uncontrollable elements influencing ED performance.
  - Choose the measurements and elements that would enter the DEA model by:
    - Judgmental approach (I).
    - Statistical (correlation) approach (II).
- Evaluate the model:
  - Use the methodology suggested by Brockett and Golany (1996) to compare the different methods.
  - Find which uncontrollable elements may compel changing operational methods to reach an efficient system.

2.2. *Available data*

Our data was collected from the EDs of eight hospitals, of various sizes and employing different operational models (see Table 1). Hospitals 2, 6, and 7 have small EDs (around 4,000 patient arrivals per month). Hospitals 1, 3, 4, and 8 have medium-size EDs (around 6,000 patient arrivals per month) and Hospital 5 is a Level 1 Trauma hospital, which is also the largest ED in our sample (above 7,000 arrivals per month).

Hospital 2 uses separate locations in the ED for Internal, Surgical and Orthopedic patients (ISO method). In each location, a different physician type treats the patients. Hospitals 1, 3, and 6 adopted the FT model, which uses a dedicated area, physicians, and nurses (that functions also as a Triage nurse) for treatment of Internal patients considered to be less resource consuming (fast diagnosis process, no treatment needed—somewhat like a clinic) while the rest of the ED operates as ISO (for more details see García *et al*., 1995, Kraitsik and Bossmeyer, 1992, and Samaha *et al*., 2003). Hospitals 4 and 5 use the WA method, separating the sites into a Walking area (where patients are seated on chairs), and an Acute area (where patients are put in beds). The last two hospitals (7 and 8) use a Triage nurse to screen unrelated patients (those who need a specialist who is not available in the ED) and give priorities to acute patients (e.g., Badri and Hollingsworth, 1993).

2.3. *Enriching the data with simulation*

As seen in Table 2, we do not have a representation of each operational model in each size, which might hinder a fair comparison at the last step of the EDD methodology (see Section 2.1). We thus used the simulation model developed by Sinreich and Marmor (2005), which already validated their model on the relevant hospitals, to extend the scope of our analysis. The simulation enriched the data by using different arrival volumes with the same types of patients. For example, Hospital 1 is a medium hospital which gets an average of 5,700 patients per month. We use Hospital 1 simulation in order to get the results of applying the same procedures (e.g., patient flow), but with different volumes

Table 1. Overview of hospital data

Hospital	Start Date [Month-Year]	End Date [Month-Year]	Operational Model	Average Monthly Patient Arrivals	ED Scope
1	Apr-1999	Nov-2000	Fast-Track	5,700	Medium
2	Apr-1999	Sep-2001	ISO	4,200	Small
3	Apr-1999	Jun-2003	Fast-Track	6,400	Medium
4	Jan-2000	Dec-2002	WA	6,100	Medium
5	Jan-2004	Oct-2007	WA	7,600	Big
6	Mar-2004	Feb-2005	Fast-Track	3,200	Small
7	Apr-1999	Sep-2001	Triage	3,400	Small
8	Aug-2003	Mar-2005	Triage	5,500	Medium

of arrivals. For Hospital 1 we use 0.64*5700 patient arrivals per month (and 64% of the original staff) in order to simulate a smaller hospital working and 1.34*5,700 patient arrivals per month (and 134% of the original staff) in order to simulate a larger hospital. We also explore changes in the operational model by adjusting Hospital 3 and Hospital 5 so their patient will be grouped by physician type (ISO model) without changing their treatment flow.

2.4. *Choosing DMUs and parameters to enter the model*

We have chosen a month as the base period for measuring the performance of the DMUs. The reason for this choice was the need to control the variations influencing the ED performance on a daily basis and to average out the impact that mass casualties episodes have on patient arrival patterns and staff load. From Table 1 we see that there are 245 DMUs from the eight hospitals. We use the simulation to add four DMUs (for months with 28, 29, 30, and 31 days) for each ratio in Table 2. That adds up to 325 DMUs. (For Hospital 6 we did not have a simulation model in Sinreich and Marmor, 2005.) Exploring the ISO model on Hospitals 3 and 5, adds DMU for each magnitude and month type (2 hospitals * 3 magnitudes * 4 months type = total of 24 DMUs).

The parameters we obtained from the databases of each hospital were limited to what hospitals collect routinely. We narrowed the list down to the ones we thought would influence efficiency. Some of the parameters should be further eliminated since they comprised complementary information (e.g., number of arrivals by ambulance, and the number of arrivals not by ambulance). The parameters were divided into uncontrollable input parameters, controllable inputs, and output parameters. In the brackets we put the min, max, and average of each parameter value (min - max; average).

- Outputs (per month/DMU):
  - Countable1W: Number of patients that exit the ED without abandoning, who do not die, or do not return to the ED after less than one week. This parameter is the equivalent to "good" parts that exit from a factory line (2,699 - 7,576; 5,091).
  - Countable2W: Number of patients that exit the ED without abandoning, who do not die, or do not return to the ED after less than two weeks. This parameter is the equivalent to "good" parts that exit from a factory line (2,586 - 7,306; 4,906).
  - Q_LOS_Less6Hours: Total number of patients whose length of stay is reasonable (less than 6 hours) (2,684 - 8,579; 5,580).

Table 2. Hospital ratios and operational models

Hospital	Monthly Arrivals	Ratio for each unrepresented magnitude			Represented operational models			
		3,000–5,000	5,000–7,000	7000+	FT	Triage	WA	ISO
1	5,700	0.64	*	1.34	*			
2	4,200	*	1.45	1.81				*
3	6,400	0.57	*	1.19	*			**
4	6,100	0.6	*	1.25			*	
5	7,600	0.48	0.8	*			*	**
6	3,200	*	—	—	*			
7	3,400	*	1.79	2.24		*		
8	5,500	0.66	*	1.9		*		
Average		3,600	6,066.67	7,600				

*Original data.
**Exploring new operational model using simulation.

- Q_ALOS_P_Minus1: Average length of stay (ALOS). Since we wish to get a high level of output corresponding to high efficiency, we have taken the reciprocal ALOS (power of -1), multiplied by the average number of hours in a month: 30*24*ALOS^{-1} (119 - 445; 276).
- Q_notOverCrowded: Total number of patients who arrived to the ED when the ED was not overcrowded (more patients than beds and chairs) (2,388 - 8,368; 5,290).

- Controllable inputs (per month/DMU):
  - Beds: Number of bed days available per month (e.g., if ED has 10 available beds, and the month consists of 30 days, the total number of bed days should be 10 × 30 = 300) (840 - 2,573; 1,669).
  - WorkForce: Number of "cost hours." An hour of a physician costs the hospitals 2.5 times the hour of a nurse. We then summarized the number of hours nurses worked in a month and added the number of hours spent by physicians multiplied by 2.5 (10,900 - 35,914; 18,447).
  - PatientsIn: Total number of patient arrivals to the General ED. This parameter is considered to be a controllable one because hospitals can block patients from entering the ED once the place is overloaded (though it is used rarely) (2,976 - 8,579; 5,717).
  - Hospitalized: Total number of patients hospitalized after being admitted to the ED. We are aware that some hospitals use hospitalization as a way to relieve ED congestion by moving patients to the hospital wards possibly unnecessarily. The main reason is that more patients can be then admitted to the ED. Another reason could be a deliberate continuous approach for shortening the ALOS of ED patients (541 - 2,709; 1,496).
  - Imaging: Total Imaging "cost" examination ordered for ED patients per month. Imaging is a costly examination in the ED. The three main examinations are X-Ray, CT, and ultrasound (US). Rarely are patients sent from the ED for an MRI since this is an expensive test, and ED tests are not necessarily all covered by insurance.

    We weighted the different examinations by their relative cost (see Grisi *et al*., 2000) as follows: US = 1.8*X-Ray, CT = 4.4*X-Ray and MRI = 6.1*X-Ray (1,312 - 14,860; 2,709).
- Uncontrollable inputs (per month/DMU):
  - Age:
    - Child: Number of patients under the age of 18 who arrive at the ED during a month (95 - 1,742; 611).
    - Adult: Number of patients under the age of 55 and over 18 who arrive at the ED during a month (1,429 - 5,728; 3,178).
    - Elderly: Number of patients over the age of 55 who arrive at the ED during a month (728 - 3,598; 1,914).
  - Admission reason:
    - Illness: Number of patients with admission reason related to illness who arrive at the ED during a month (1,853 - 6,153; 3,775).
    - Injury: Number of patients with admission reason related to injury who arrive at the ED during a month (779 - 3,438; 1,849).
    - Pregnancy: Number of patients with admission reason related to pregnancy who arrive at the ED in a month (most patients with pregnancy reasons are directed to the relevant wards without entering the ED) (0 - 16; 3).
  - Arrivals mode:
    - Ambulance: Number of patients arriving at the ED during a month by ambulance (157 - 1,887; 795).
    - WithoutAmbulance: Number of patients arriving at the ED during a month without an ambulance (2,679 - 7,416; 4,921).
  - Additional information:
    - WithLetter: Number of patients arriving at the ED during a month with a reference letter from their physician (1,624 - 6,536; 3,741).
    - WithoutLetter: Number of patients arriving at the ED during a month without a reference letter from their physician (803 - 3,651; 1,976).
    - OnTheirOwn: Number of patients arriving at the ED during a month on their own (786 - 3,579; 1,952).
    - notOnTheirOwn: Number of patients arriving at the ED during a month not on their own (1,744 - 6,576; 3,765).
  - Type of treatment:
    - Int: Number of patients arriving at the ED during a month needing Internal type of treatment (1,431 - 5,176; 3,062).
    - Trauma: Number of patients arriving at the ED during a month needing Trauma type of treatment (378 - 4,490; 2,655).

Our next step is to identify which of those initial parameters will participate in our DEA model.

2.5. *Choosing the parameters to enter the DEA model by correlation*

Table 3 presents the correlation between every two parameters. Removing one of each pair of parameters with a correlation higher than 0.9 leaves us with the following parameters (see Table 4 for their correlation):

- Outputs: Countable1W, Q_notOverCrowded, and Q_ALOS_P_Minus1.
- Controllable inputs: WorkForce, Hospitalized, and Imaging.
- Uncontrollable inputs: Child, Elderly, Illness, Injury, Ambulance, WithoutLetter.

Table 3. Correlation between any (initial) two parameters

	Beds	WorkForce	PatientsIn	Hospitalized	Imaging	Child	Adult	Elderly	Illness	Injury	Pregnancy	Ambulance	WithoutAmbulance	WithoutLetter	WithLetter	OnHisOwn	notOnHisOwn	Int	Trauma	Countable1W	Countable2W	Q_LOS_Less6Hours	Q_notOverCrowded	Q_ALOS_P_Minus1
Beds	1																							
WorkForce	0.73	1																						
PatientsIn	0.95	0.78	1																					
Hospitalized	0.80	0.63	0.78	1																				
Imaging	0.82	0.64	0.88	0.70	1																			
Child	0.56	0.26	0.57	0.14	0.40	1																		
Adult	0.89	0.67	0.95	0.78	0.88	0.52	1																	
Elderly	0.59	0.73	0.61	0.60	0.52	−0.02	0.39	1																
Illness	0.85	0.78	0.89	0.74	0.73	0.37	0.78	0.75	1															
Injury	0.84	0.58	0.87	0.53	0.69	0.85	0.85	0.25	0.71	1														
Pregnancy	−0.04	0.11	−0.04	0.21	−0.05	−0.34	−0.13	0.35	0.11	−0.29	1													
Ambulance	0.62	0.50	0.69	0.68	0.61	0.28	0.65	0.51	0.65	0.52	0.31	1												
WithoutAmbulance	0.94	0.77	0.98	0.74	0.87	0.59	0.93	0.58	0.87	0.87	−0.12	0.55	1											
WithoutLetter	0.74	0.65	0.74	0.70	0.69	0.28	0.72	0.50	0.70	0.59	−0.03	0.24	0.80	1										
WithLetter	0.88	0.70	0.94	0.68	0.81	0.61	0.88	0.56	0.82	0.84	−0.04	0.78	0.90	0.48	1									
OnHisOwn	0.78	0.62	0.78	0.75	0.74	0.30	0.81	0.44	0.72	0.63	−0.02	0.33	0.82	0.97	0.55	1								
notOnHisOwn	0.86	0.72	0.94	0.66	0.80	0.62	0.85	0.60	0.82	0.84	−0.05	0.77	0.89	0.47	0.99	0.51	1							
Int	0.90	0.75	0.93	0.86	0.88	0.32	0.93	0.59	0.85	0.70	0.02	0.59	0.93	0.82	0.81	0.87	0.79	1						
Trauma	0.84	0.68	0.91	0.57	0.74	0.75	0.81	0.53	0.78	0.90	−0.10	0.68	0.89	0.54	0.93	0.56	0.94	0.70	1					
Countable1W	0.95	0.79	0.99	0.77	0.86	0.61	0.92	0.63	0.89	0.88	−0.05	0.68	0.98	0.75	0.93	0.78	0.93	0.91	0.93	1				
Countable2W	0.95	0.79	0.99	0.77	0.86	0.61	0.93	0.62	0.89	0.88	−0.04	0.68	0.98	0.75	0.93	0.78	0.93	0.91	0.92	1.00	1			
Q_LOS_Less6Hours	0.93	0.72	0.98	0.78	0.87	0.55	0.94	0.58	0.86	0.85	−0.01	0.74	0.95	0.66	0.96	0.72	0.95	0.91	0.90	0.97	0.97	1		
Q_notOverCrowded	0.82	0.68	0.82	0.60	0.66	0.68	0.73	0.49	0.65	0.82	−0.09	0.56	0.81	0.59	0.79	0.58	0.81	0.68	0.85	0.85	0.85	0.79	1	
Q_ALOS_P_Minus1	0.19	0.05	0.16	−0.01	−0.03	0.56	0.18	−0.25	0.02	0.46	−0.27	0.28	0.12	−0.14	0.29	−0.14	0.31	−0.05	0.37	0.20	0.20	0.21	0.40	1

Although Pregnancy had a low correlation with other parameters (see Table 3), we have chosen to remove it from the model. The reason was that pregnancy arrival to the ED is a rare event (most hospitals have a separate location for pregnancy admissions).

Table 5 presents the chosen parameters for each hospital, where each parameter is divided by the number of arrivals (PatientIn) (e.g., WorkForce_Ratio means the average number of weighted staff hours per patient, and Imaging_Ratio means the number of weighted imaging examination per patient; %Child gives us the percentage of patients under age of 18 in the data). The ALOS parameter is presented, instead of Q_ALOS_P_Minus1, since it is more intuitive to grasp.

Figure 2 presents the hospitals efficiency using the original data after "normalization." The least efficient hospital by far is number '2'; its parameters are not so extreme compared to others, although its output (%Q_notOverCrowded) is quite low (which can explain the second least effective hospital '5,' as it has the same low parameter). It should be noted that there is no single ratio that affects the efficiency of all hospitals.

Table 5 and Figure 2 were created using only the original data (245 DMUs, based on Table 1) to give a summary overview by hospital. As mentioned before, the main focus of this work is to compare between operational models, not hospitals.

2.6. *"Normalizing" the data, and adding constraints on the weights*

After choosing which of the parameters would participate in our model, we implemented the following two steps (Roll and Golany, 1993): (1) "Normalizing" the data so that the magnitude of the parameter would not influence the model (see Equation (4)); (2) Setting restrictions on the weights of the model (see Equation (5)).

$$\begin{aligned}
&\tilde{P}_{mj} = \frac{100 * P_{mj}}{\tilde{P}_{m\bullet}} \\
&\tilde{P}_{mj} - \text{Normilized parameter } i \text{ of } DMU_j \\
&P_{mj} - \text{Parameter } i \text{ of } DMU_j \\
&P_{m\bullet} - \text{Average of parameter } i \text{ over all } DMUs \\
&m = 1, \ldots, M;\ M \text{ - number of parameters} \\
&j = 1, \ldots, J; J\ ; \text{- number of } DMUs
\end{aligned} \tag{4}$$

The rationale behind the following bound constraints is to try and maintain reasonable weights. We find it unreasonable to exclude input or output parameters from the model at this point; hence we forced them to not differ by more than one order of magnitude from each other. For the (6) uncontrollable inputs, we just wanted their total to have a representation at most one fifth of the total (3) controllable inputs (as recommended in Roll and Golany, 1993):

$$\begin{aligned}
&v_i/v_{\tilde{i}} > 0.1; \quad i, \tilde{i} = 1., \ldots, I; \\
&\quad v_i, v_{\tilde{i}} \text{ - weights of controllable parameters} \\
&w_r/w_{\tilde{r}} > 0.1; \quad r, \tilde{r} = 1, \ldots, R; \\
&\quad w_r, w_{\tilde{r}} \text{ - weights of outpute parameters} \\
&\frac{5\sum v_i}{\sum u_k} > 1; \quad k = 1, \ldots, K; \\
&\quad u_k \text{ - weights of uncontrollable parameters}
\end{aligned} \tag{5}$$

3. Results

The EMS software (Scheel, 2000) was used to run the data and get the efficiency of each DMU. We present the results in the following two subsections. In the first section

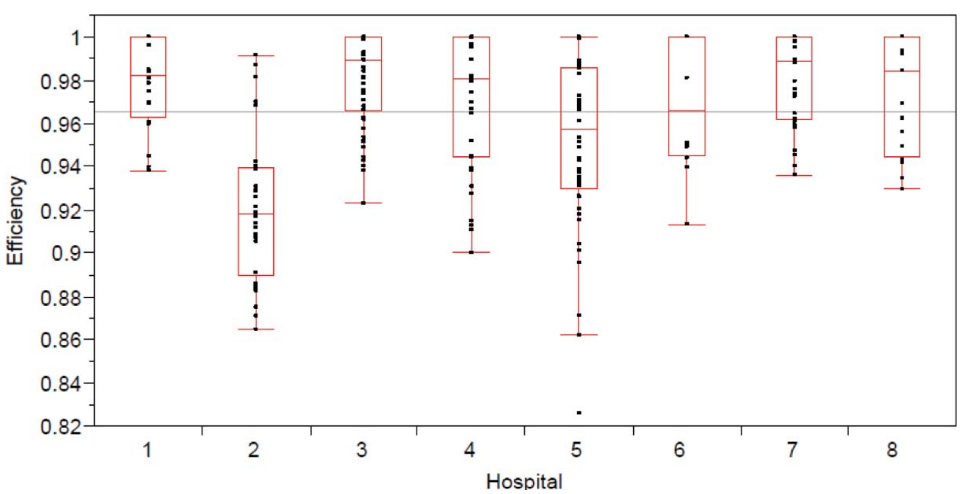

Fig. 2. Efficiency by hospital for the original data (without simulation). (Color figure available online.)

Table 4. Correlation between model parameters

	WorkForce	Hospitalized	Imaging	Child	Elderly	Illness	Injury	Ambulance	WithoutLetter	Countable1W	Q_notOverCrowded	Q_ALOS_P_Minus1
WorkForce	1											
Hospitalized	0.63	1										
Imaging	0.64	0.70	1									
Child	0.26	0.14	0.40	1								
Elderly	0.73	0.60	0.52	−0.02	1							
Illness	0.78	0.74	0.73	0.37	0.75	1						
Injury	0.58	0.53	0.69	0.85	0.25	0.71	1					
Ambulance	0.50	0.68	0.61	0.28	0.51	0.65	0.52	1				
WithoutLetter	0.65	0.70	0.69	0.28	0.50	0.70	0.59	0.24	1			
Countable1W	0.79	0.77	0.86	0.61	0.63	0.89	0.88	0.68	0.75	1		
Q_notOverCrowded	0.68	0.60	0.66	0.68	0.49	0.65	0.82	0.56	0.59	0.85	1	
Q_ALOS_P_Minus1	0.05	−0.01	−0.03	0.56	−0.25	0.02	0.46	0.28	−0.14	0.20	0.40	1

Table 5. Hospital parameters ratio (from the database without simulation) and average length of stay

		Controllable Inputs			Uncontrollable Inputs						Outputs			
Hospital	Operational Model	WorkForce_Ratio	Imaging_Ratio	%Hospitalized	%Child	%Elderly	%Illness	%Injury	%Ambulance	%WithoutLetter	%Countable1W	%Q_notOverCrowded	ALOS [minutes]	avgEfficiency
1	FT	3.37	1.06	29%	8%	41%	69%	31%	6%	42%	91%	98%	188	98%
2	ISO	3.53	1.2	22%	10%	45%	74%	26%	13%	39%	90%	75%	307	92%
3	FT	2.91	1.14	18%	18%	25%	60%	40%	12%	27%	90%	100%	119	98%
4	WA	2.98	1.13	30%	11%	38%	68%	32%	20%	29%	91%	100%	140	97%
5	WA	2.83	1.38	29%	7%	28%	63%	30%	15%	33%	85%	76%	188	95%
6	FT	4.67	0.56	41%	10%	37%	71%	29%	8%	41%	93%	100%	191	97%
7	Triage	4.47	0.93	29%	4%	46%	74%	26%	15%	40%	92%	97%	151	98%
8	Triage	2.79	1.36	26%	14%	27%	62%	38%	11%	44%	92%	100%	131	97%

we present the efficiency by operational model over all DMUs, while in the last section we present the influence of uncontrolled data on efficiency and identify the leading operational models.

Table 6. Mann-Whitney rank test *P* value between any two operational models

	FT	ISO	Triage
ISO	<0.001	-	-
Triage	0.506	<0.001	-
WA	<0.001	<0.001	<0.001

3.1. *Results over all DMUs*

First, we wish to see if there is a dominant operational model over the whole data. To this end, we used the Mann-Whitney rank test (as suggested by Brockett and Golany, 1996). Table 6 represents the *p* value for comparisons between any two methods. It seems that FT and Triage are the dominant operational methods at a significance level of 0.01. From Fig. 3, which represents the efficiency of each method ranked (the order of efficiency from the smallest ('1') to the highest, which depends on the number of DMUs in each category – see the table in the figure); we see that there are segments in which different operational models are taking the lead over others (though Triage and FT are switching the role for the best operational model throughout the whole data). The same result is attained when we compare the efficiency quantiles of the different models (Fig. 4). In Figs. 3 and 4 we added a summary table comparing the number of DMUs and the average and the median efficiency for each model.

3.2. *Results by uncontrolled parameters*

At first, we plotted the average efficiency vs. each **H**igh (more than the average) and **L**ow (less than the average) value for each uncontrolled parameter, by the operational models. Our uncontrolled data were the monthly children arrivals (Fig. 5), monthly elderly arrivals (Fig. 6), monthly arrivals with illness (Fig. 7), monthly arrivals with injury (Fig. 8), monthly arrivals with ambulance (Fig. 9), and number of arrivals without letter (Fig. 10).

From Fig. 5 to Fig. 10 we cannot identify an operational model that is superior over the entire range of parameters. What we do see from those figures is that FT and Triage methods efficiency is being influenced greatly by the parameters' magnitude. FT increases while uncontrollable parameters increase, while Triage decreases at the same time. That motivated us to try and analyze the impact of the parameters (using stepwise GLM) on the efficiency of each operational model (Linear Regression):

- FT ($R^2 = 0.66$, $p < 0.0001$): the parameters Illness and Injury, and the interactions Elderly*Injury, Child*Ambulance, Child*WithoutLetter, Elderly*WithoutLetter and Illness*Ambulance have positive statistical-significance influence on the efficiency; the parameters Elderly and Ambulance, and the interactions Child*Illness, Elderly*Injury, Injury*WithoutLetter and Injury*Ambulance have negative statistical-significance influence.
- ISO ($R^2 = 0.75$, $p < 0.0001$): the parameter Illness, and the interaction Elderly*Ambulance have positive statistical-significance influence on the efficiency; the parameters Child, Elderly and Ambulance have negative statistical-significance influence.

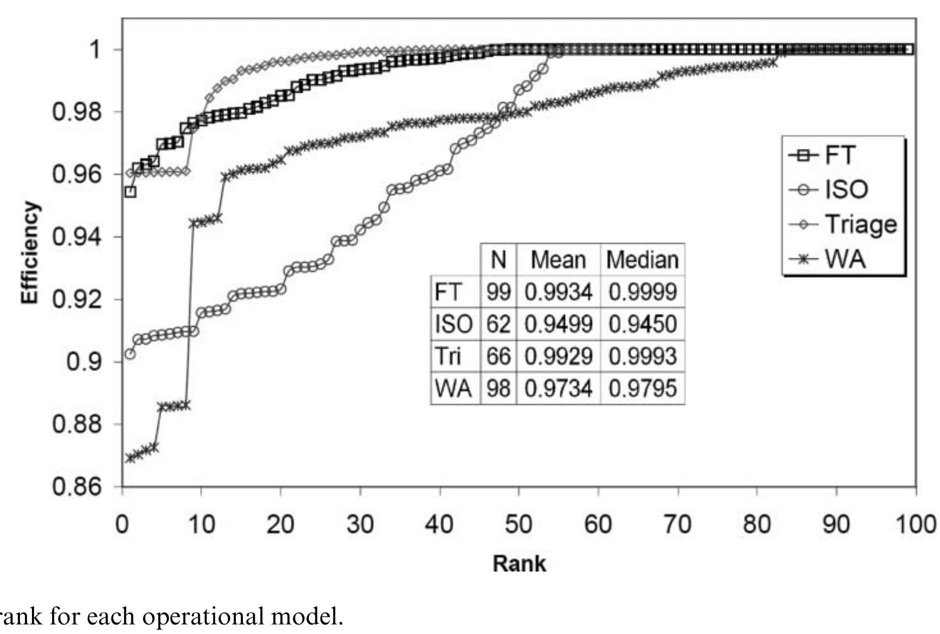

Fig. 3. Efficiency by rank for each operational model.

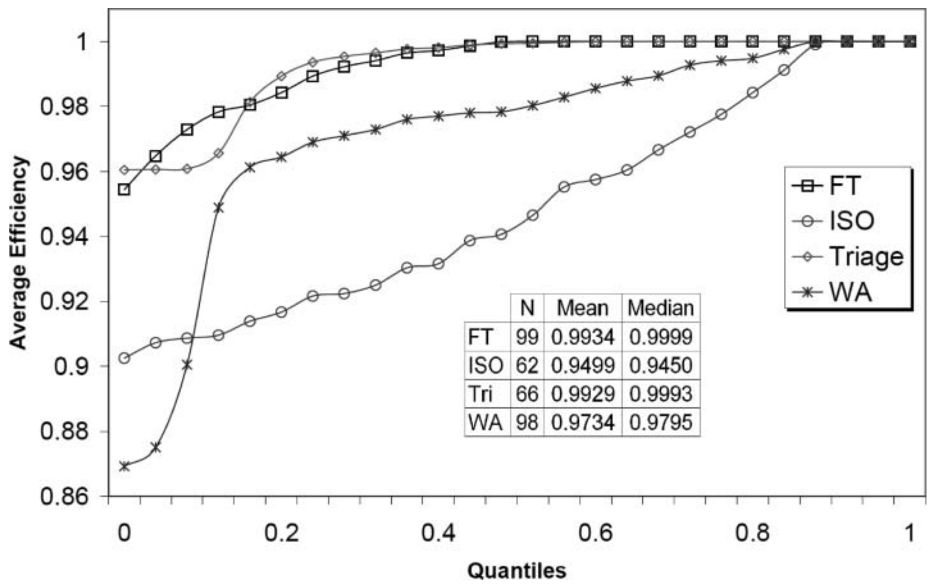

Fig. 4. Efficiency by Quantiles for each operational model.

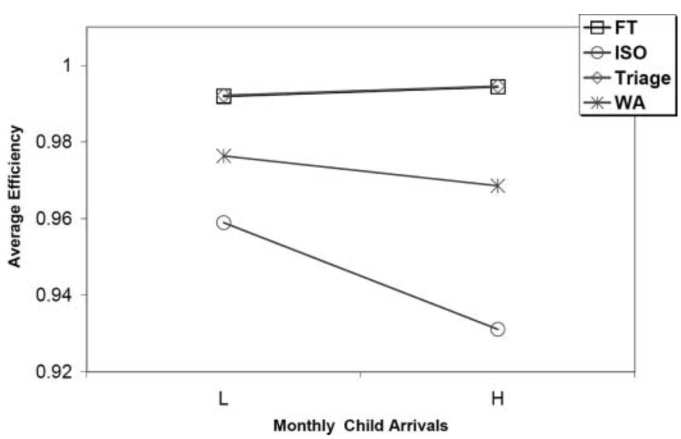

Fig. 5. Average efficiency by monthly child arrivals.

- Triage ($R^2 = 0.85$, $p < 0.0001$): the interactions Child*Illness and Elderly*Illness have positive statistical -significance influence on the efficiency; the parameters Elderly and Injury have negative statistical-significance influence.
- WA ($R^2 = 0.91$, $p < 0.0001$): parameters Elderly and Illness, and the interactions Child*Ambulance and Illness*Ambulance have positive statistical-significance influence on the efficiency; the parameter Child and the interaction Elderly*Illness have negative statistical-significance influence.

Another statistical technique that we used to identify environments in which there is a dominant operational model is Classification and Regression Tree (CART) (Breiman *et al.*, 1984), as implemented in JMP (SAS Institute Staff, 1996). The outcome of this analysis is as follows: FT and Triage are the preferable operational models for the ED

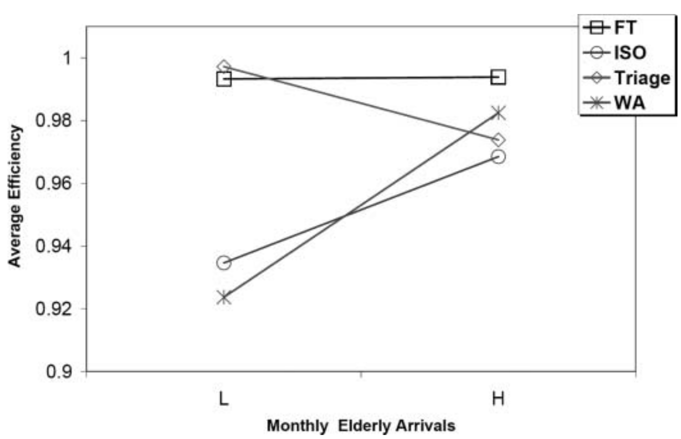

Fig. 6. Average efficiency by monthly elderly arrivals.

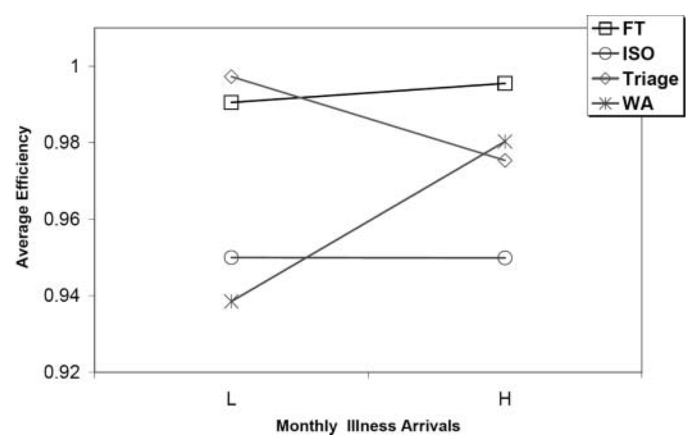

Fig. 7. Average efficiency by monthly illness arrivals.

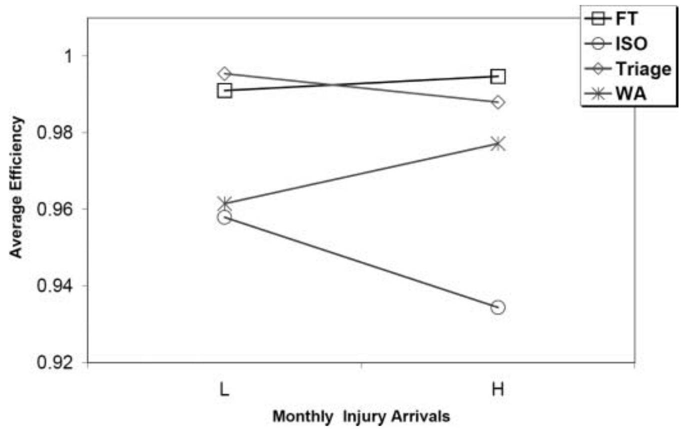

Fig. 8. Average efficiency by monthly injury arrivals.

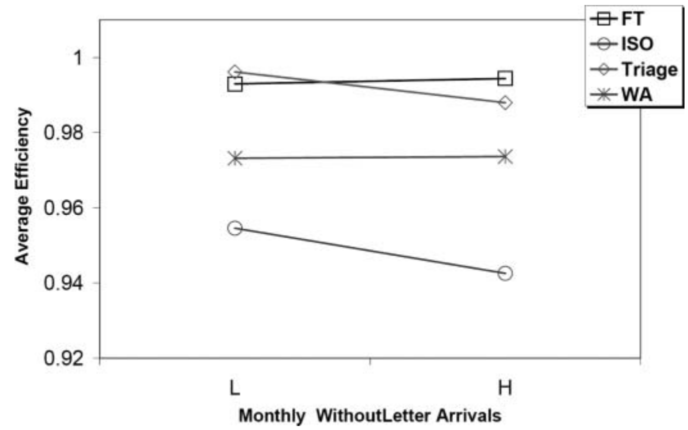

Fig. 10. Average efficiency by monthly arrivals without letter.

($p < 0.001$). When the number of Elderly arrivals is higher than average, choose FT ($p < 0.001$), while when Elderly arrivals is less than average choosing Triage over FT is not significant ($p = 0.42$). When Triage and FT are not feasible, choose WA ($p = 0.02$) when the number of Elderly arrivals is higher than average, but when the number of Elderly arrivals is low, there is no significant difference between the models ($p = 0.26$).

4. Discussion

Our EDD methodology searched for an efficient operational model out of four common ED models (Fast-Track, Triage, ISO Based, and Walking-Acute; see Badri and Hollingsworth, 1993, García *et al*., 1995). We investigate the influence of uncontrolled variables on the ability of the ED to utilize better results given its available resources.

The main strength of our methodology derives from its use of real data incorporated with simulation and combined with our use of mathematical models. Other researchers analyzed alternative operational ED designs (e.g., García *et al*., 1995; King *et al*., 2006; Liyanage and Gale, 1995), but are mostly based on one specific location and are using simulation and not real data.

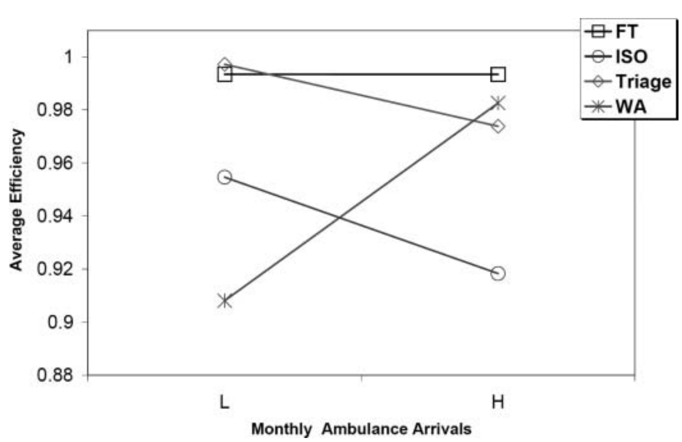

Fig. 9. Average efficiency by monthly arrivals by ambulance.

Our present work is unique in that it is based on data from several EDs, develops simulations that are customized to those EDs and offers a methodology that supports design decisions, for example by identifying circumstances that favor one design over the others.

5. Limitations

Although the results are conclusive, one must keep in mind that the DEA methodology could be sensitive to parameters choice (Pedraja-Chaparro *et al*., 1999). Thus, our results and conclusions are most relevant to stakeholders that enjoy the same values (parameters) as we do, although others can still follow our methodology and choose their own parameters to enter into the model.

We could have further investigated whether there is room to choose an Output-based approach (see King *et al*., 2006), as well as to answer what would happen if hospitals would prefer to specialize by admitting and treating only one type (or just a few types) of patients (e.g., Internal, Surgical, or Orthopedic), or use a flexible operational models, which allow on-line changes and adjustment to the primary architecture (see Docimo *et al*., 2000).

Also, in our work we incorporate different aspects of the ED performances, but we ignored, among other things, the patient satisfaction aspect (Graff *et al*., 2002). Again, one can easily include additional such parameters in the model in order to take patient satisfaction into account.

A comment on our data-age is in order. The present data was gathered in support of Sinreich and Marmor (2005), in the past decade. This data is rather unique in its scope and accuracy, which took then huge efforts to reach. Thus, before venturing into a new data-collection effort, towards the present article, we checked our present data against present practice. We then discovered that our EDs have kept working under the same operating models and environmental parameters, with minor changes relative to the time of the original data set. We have thus opted to using the original data, judging it to be as relevant today as it was when collected.

6. Conclusions

We presented the EDD methodology, which identifies a dominant operational model in an ED. Although we did not find a uniformly dominant model, we did discover that different operational models have weaknesses and strengths over various uncontrollable parameters. Hospitals which get a high volume (more than average) of elderly patients should prefer to dedicate a separate lane for high priority patients (FT model), while others can use a priority rule without the need for a separate space for high priority patients (Triage model). When Triage and FT are not a feasible option (e.g., lack of space or staff), using a different lane for Walking and Acute patients (WA) was found as the most effective operational model (mostly when the number of elderly arrivals to the ED is high).

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