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REAL-TIME SIMULATION AS A WAY TO IMPROVE DAILY OPERATIONS IN AN EMERGENCY ROOM

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ABSTRACT

Emergency Rooms (ER) are resource constrained systems that demand efficient management in order to fulfill their care and service objectives. This article explores the use of real-time simulation to improve daily operations at an ER where unplanned events may occur. Such a simulation model must adequately portray the current state of the system; however ER workflow management systems often provide only limited information for this purpose. This paper studies the impact of the model's ability to predict ER performance with a limited amount of input information, such that what-if questions may be asked to guide decision making. Towards this end, two input data scenarios are compared to a case of perfect information. One scenario considers only patient arrival times and the other assumes additional knowledge of patient care pathways. Although both generate similar performance measures, the case with least information yields a slightly worse estimate of patient care pathway composition.

1 INTRODUCTION

For over three decades, simulation has been an important tool for operations planning and long term facility design. Building a detailed simulation model of a given system, to be used for example in improving layout design, is often a time and resource-intensive task. Although such a model is usually discarded after its initial design purpose, it may be reused for short term decision making, as it is done in manufacturing shop control (Son and Wysk 2001).

Real-time decision making is an instantaneous response to a system event (Son, Rodriguez-River, and Wysk 1999) that has high impact on the system's performance. Examples of such events are the arrival of an urgent order that requires changing the production schedule, the call in sick of two physicians, the announcement of a bus accident that will overflow an emergency room, or a delay in the arrival of critical spare parts. In general, these events require immediate compensating actions that may be assessed with a simulation model.

A simulation-based decision model, initialized with current information on the state of the system, may be useful in short term evaluation of several alterative solutions or alternative operational strategies.

In general, real-time simulation, also referred to as online simulation, attempts to represent, in real time, the current state of a system on a validated simulation model. Such a representation of the current state of the system allows a modeler to ask what-if questions, at a particular decision point in time, regarding the future performance of the system. This involves testing new policies, rescheduling resources, or changing production plans, among other modifications to the system, and evaluating which changes affect the system most favorably.

Until now, most simulation-based real-time decision making articles in the literature relate to manufacturing systems, where significant improvements in operating performance indicators have been reported (Dalal, Groel, and Prieditis 2003). Application examples include the rerouting of parts in a flexible manufacturing shop given changes in demand (Saygin, Cheng, and Singh 2001), dynamic production planning (Frantzén, Ng, and Moore 2011), or a real time route recommendation for drivers (Ben-Akiva et al. 1998), among others. Real-rime applications in healthcare are practically non-existent (Tavakoli, Mousavi, and Komashie 2008).

Simulation has been used extensively within healthcare. General surveys (Mielczarek and Uzialko-Mydlikowska 2012, Barjis 2011, Rais and Viana 2011, Brailsford 2007) identify simulation applications in areas such as disease prevention, healthcare systems operation (e.g., resource allocation, staff scheduling, admissions management), optimization (Steins, Persson, and Holmer 2010) or design (e.g., capacity planning, layout, and process redesign), medical decision making (Hamrock et al. 2013; Thorwarth and Arisha 2012), and extreme events planning (Xiao et al. 2012; Rico, Salari, and Centeno 2007).

A recent and detailed literature review of specific simulation applications in Emergency Rooms (ER) is presented in Chonde, Parra and Chang (2013), who also discuss different patient flow models to minimize the time to first medical evaluation and the total length of stay of discharged patients. The use of Object Oriented Simulation to design an ER is presented in Ramis, Neriz, and Sepúlveda (2013). Improvements in patient flow –to minimize long waiting times and decrease patient unnoticed departures– are important because they often do not require physical modifications of the ER (He, Lei and Kremer 2013). Tan, Lau and Lee (2013) discuss comprehensive dynamic patient prioritization strategies to manage the demand, concurrently with dynamic resource adjustments to manage supply at an ER. Weng et al. (2011) present a simulation model for optimal allocation of resources in an ER while minimizing patient waiting time.

In Chile's healthcare system, the Center for Advanced Process Simulation (CAPS), has pioneered the use of simulation to improve layout, scheduling and planning of medical units (Ramis, Neriz, and Sepúlveda 2013; Ramis, Neriz, and Sepúlveda 2008; Ramis et al. 2002). Their work has led to the development of several healthcare related simulation models that could be useful in setting real-time decision making support systems.

While there is scholarly work on real-time simulation of manufacturing systems, healthcare literature seldom addresses this issue (Mousavi, Komashie, and Tavakoli 2011). It should be noted, additionally, that several differences exist between modeling a manufacturing process and an ER treatment process. In a manufacturing setting, jobs move through the process awaiting service at one or more work stations (the resources being typically stationary). The variables describing the current state of the system at any given time include the length of waiting lines at each work station, the state of resources and the expected remaining process time of jobs under work (Hotz, Hanisch, and Schulze 2006). These variables are easily obtained from a Workflow Management System (WfMS) if control technology, such as Rradio Frequency Monitoring (RFID) devices, are in place at the shop. Therefore, an important component for the successful use of real-time simulation is the integration of the information system (Gaba 2004), which stores information dynamically, with a simulation model that can be executed whenever a decision must be made (Rozinat et al. 2009).

In an ER, however, data collection has been reported as the main challenge in healthcare simulation development (Barjis 2011). In this kind of model, patients are mostly stationary. For example, they arrive, get prioritized and wait for an available examination room. Once at an examination room, patients typically stay there until discharged or admitted to the hospital. Movable resources such as physicians and nurses visit the patient to exam and define medical treatment.

The motivation for this research comes from observing ER managers in their short term operational decision activities; often times they need, for example, to reallocate staff in a particular ER shift because they have been informed that a key staff member has taken time off, or that food-poison cases are arriving from a nearby school. We refer to these incidents as the system event that triggers the need for decision making. Real-time simulation would be useful as a tool to evaluate alternative courses of actions in anticipation of short term needs. To provide input for such a simulation model, real-time information is needed regarding patient location and defined care pathway (associated to their prescribed medical treatment); however this kind of information is rarely fully captured by a patient WfMS in a manner useful to the model. Additionally, resource states (such as the current position or activity of a physician) are not available nor can be fully monitored through technology (Kuo, Leung, and Graham 2012).

An important issue in our work is to define the minimal type and amount of information needed in a patient WfMS so that a simulation model could have realistic input data to aid in real-time decision making at an ER. Hence, the work reported here contrasts simulated ER performance measures, given different input information scenarios. The input information refers to the data, about the patient, that is stored in the WfMS. A hypothesis driving this work is that the more input data is available, the more realistic is the simulated representation of the current state of the system, and the better is the expected quality of the decision making process. To test it, two input scenarios are evaluated: one with least information where only patient arrival times are available in the WfMS (Case A), and another, with more information, where care pathways are also available for patients that have received their first medical evaluation (Case P).

2 MODELING AND SIMULATION STUDY

This study develops a simulation model based on a real and paperless ER from a Chilean public hospital, which treats adult patients with general medicine, surgery and traumatology health issues. The ER has all the resources needed for urgent care, although often also treats non-urgent patients that generate unnecessarily long waiting times in the system. In the following sections we present the modeling methodology, the patient care pathway descriptions and the scenarios defined to test the simulator's initial conditions.

2.1 Modeling Methodology

In order to develop the simulation study, the seven step model proposed by Law (2014) was applied. This process includes the following steps: (1) problem definition, (2) conceptual modeling and data gathering, (3) validation of conceptual model, (4) computational model construction, (5) verification and validation of computational model, (6) experimental design and replication, and (7) results implementation and documentation.

The design of the conceptual model was based on in depth interviews with doctors and nurses of the ER unit, information that was complemented with a literature review. All the activities, decisions and relationships were modeled using standard UML notation and activity service times were fit to probability distributions using Experfit software (Law 2014).

The ER model of the system under study was built in FlexsimHC, an object oriented discrete event simulation software designed for healthcare and patient flow modeling. An important departure from traditional modeling when using FlexsimHC is that it requires the definition of care pathways or patient treatment sequences (called tracks), which are defined as the sequence of activities that a patient experiments as he passes through the ER, as explained in section 2.2.

The validation of the computer model was done using historical ER information for the system under study, where patient throughput and cycle time statistics were compared to real system performance, failing to reject the hypothesis that they were different. Also, the opinion of experienced health care professionals was elicited to validate performance measures for the ER.

2.2 Patient Care Pathway

In Chile, there are six processes common to any patient arriving at an ER: 1) Admissions, 2) Triage, 3) First Medical Examination, 4) Exams & Procedures, 5) Second Medical Examination and 6) Discharge. Upon arrival, the patient provides his personal information to a receptionist and then is sent to Triage, where he is categorized based on the acuity of his condition. The patient then waits until called into an examination room for the first medical exam. Here the list of required exams and treatments are prescribed, determining his care pathway through the ER. For the ER under study, 14 different care pathways have been identified (shown in Table 1), which are also called treatment sequences or tracks. Care pathways and their relative frequency were identified after analyzing a year's worth of ER data, information that was later validated with unit nurses and doctors.

Table 1: Patient care pathways in the ER, after diagnosis.

Pathway	Activities
1	EKG + Hydration + Sampling + Observation
2	Nebulization
3	Intramuscular Treatment + Hydration + Sampling
4	EKG + Observation
5	Hydration + Sampling
6	Imaging + Cast
7	Hydration + Minor Surgery + Imaging
8	Hydration + Minor Surgery
9	Minor Surgery + Nurse Procedure
10	Imaging + Nurse Procedure
11	Hydration
12	Medical Procedure + Wound Treatment
13	Sampling + Imaging
14	Nurse Procedure

2.3 Real-Time Data Collection

As the patient goes through his care pathway, the patient WfMS collects data at several stages: (1) Admissions counter, (2) Triage room, (3) Examination room, (4) Procedure room, (5) Lab and imaging units, (6) Observation room and (7) Discharge. All the information recorded specifies both the medical personnel tending the patient and a time stamp (typically recorded either at the beginning of an activity or at the end of an activity). These workflow systems, however, do not account for personnel activities not directly related with patient care, and might only provide partial information of their whereabouts. For a nurse, for example, the WfMS might store the sequence of patients she has visited during her ER shift, and the time she finished typing each report will be stored in the system. Neither nurses, nor doctors nor patients carry RFID tags or monitoring devices such as those used in manufacturing systems to collect data on the flow of components through a system. Additionally, the WfMS collects service times with hidden waiting times and travel times. Thus, the digital information available regarding patient flow in an ER is incomplete, and this becomes an important issue when planning for real-time simulation data input.

2.4 Model Initialization

In order to run the models that will evaluate the cases depicted in sections 2.7 and 2.8, two types of input are necessary to ensure an adequate model initialization: real-time or recent information obtained prior to the system event that triggers the need for a decision; and probability distributions for process times and other random variables (fitted from historical data), to represent or predict possible future states of the system.

Real time information at the system event time (hereafter referred to as T_0), allows for the representation of the current state of the system. The simulated period after T_0 is run to evaluate performance measures of interest (Figure 1) up to a near future T_f. The short term period between T_0 and T_f is relevant first to predict the "status quo" future state of the system (where no decisions are made at T_0). What-if questions are then evaluated through simulation of this same period to measure the relative impact of corrective actions to be implemented at decision event time T_0.

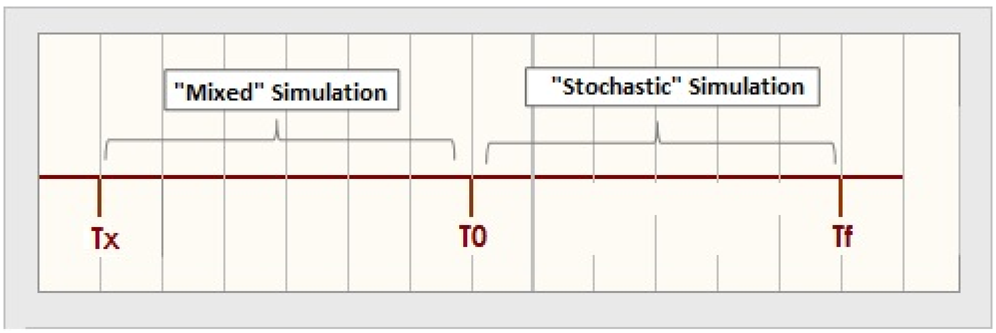

Figure 1: Timeline of relevant instances in the real-time simulation run.

Providing an accurate representation of the current state of the system at time T_0 is a challenging task due to imperfect system information availability. Given this handicap, the elapsed time between instants T_x and T_0 is simulated to provide an appropriate warm up period that will realistically reconstruct the state of the system. The input instant T_x is defined as the moment of least congestion immediately before the arrival of the first patient present in the system at time T_0 (i.e., the patient that arrived earliest among those known to be in the system at T_0). Because incomplete information is used in the two cases analyzed, some missing information will be randomly generated (e.g., process times) and this will be combined with real-time retrieved data. We refer to this as a "mixed" input simulation, and the main purpose of this simulation is to accurately represent the real state of the system at instant T_0, time after which predictive system performance statistics are of interest. The patients (entities) in the system at T_0 continue their flow until they finish their service process based on a realistic operation of the hospital ("stochastic" simulation), and statistics are collected until simulation finish time T_f (typically a few hours or days after T_0).

2.5 Demand Scenarios

The congestion level of a typical week varies over time but follows a similar daily cycle pattern: arrival rates are low after 11 PM, dramatically increase after 7 AM and are moderate after 3 PM. Since congestion and resource availability vary significantly during any given day, the analysis of a system event should depend on the instant it occurs, thus three different 8-hour time intervals are studied separately, according to the system's congestion level during a 24-hour period. Specifically, these intervals may be classified as high, medium and low demand scenarios for ER service (see Table 2 and Figure 2 for specifications). The system is least congested around 4 AM.

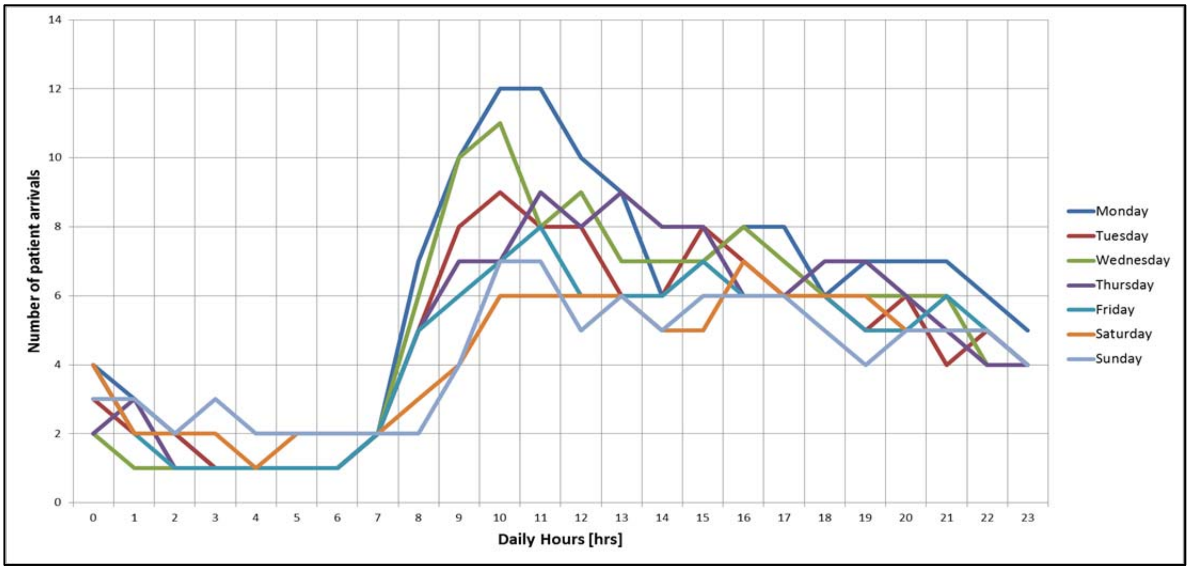

Figure 2: Hourly arrival rates of patients throughout a day.

The scenarios evaluated consider that T_0 is defined around the beginning of the scenario interval, and the simulation is run for 8 hours. For example, T_0 is set at 8:00 AM and T_f at 4:00 PM for the high demand scenario.

Table 2: Selected representative demand scenarios under study.

Demand scenarios	Representative day	Time Interval T_0 - T_f
High demand	Friday	08:00 hrs. to 16:00 hrs.
Medium demand	Saturday	16:00 hrs. to 00:00 hrs.
Low demand	Wednesday	00:00 hrs. to 08:00 hrs.

2.6 Baseline – Case (B)

The baseline represents the ideal case in which the workflow provides all the real-time information that the simulation model needs as input data (arrival times, process times, care pathway assigned to every patient, discharge times, medical staff state, etc.).

The importance of this case is that it describes the perfect information situation. For example this implementation assumes that physicians use the concept of a standardized care pathway or track and record a specific pathway number in the WfMS as a patient receives his or her first medical examination. It also assumes all resource states are known.

Although, as described above, this situation is not realistic, it allows for the establishment of a best case against which other cases are evaluated. This case is a deterministic case, where the history of what has occurred before T_0 is known and completely specified, and where system states after T_0 will be known as they occur in time.

2.7 Arrival Times – Case (A)

This case considers minimal real input data, where only patient arrival times to the system (for all patients that have arrived before T_0) are extracted from the WfMS.

The implementation of this case requires the generation of all missing input variables as random variables from fitted probability distributions (e.g., patient care pathways and process times). With this information, the simulation runs from T_x to T_0 in order to provide a realistic representation of the current state of the system at that instant.

2.8 Arrival Times and Care Pathways – Case (P)

In this case the workflow provides more information to simulate the time interval from the initial input time T_x to the trigger event time T_0. Specifically, real-time data is obtained for the arrival instants of every patient entering the system after T_x, and it is assumed that information about the care pathway followed by a patient can be inferred (and is available in the workflow) once the patient has received first medical evaluation.

The care pathway is assigned deterministically (from real data) for all those patients that have experienced their first medical evaluation before T_0. All other patients in the system at T_0 (that have arrived but haven't yet experienced their first medical evaluation) will be assigned a care pathway randomly (from probability distributions fitted to historical data).

2.9 Experimentation

Experiments are designed to compare system performance measures in order to determine if the input data used by each scenario generates a realistic enough representation of the ER under study. The purpose is to evaluate the quality of the simulation representation under different amounts of input information. These experiments are not an evaluation of the impact of an unplanned event for which a decision must be made, but rather show how a simulated input case performs in comparison to a perfect information case.

Three performance measures are assessed (Tables 3 and 4): (1) Time to first medical exam (elapsed time between patient arrival and their first medical evaluation), (2) medicine cycle time (elapsed time between arrival and departure of general medicine type patients) and (3) surgery cycle time (elapsed time between arrival and departure of trauma/surgery type patients). In addition, two characteristics of the state of the system at event time T_0 are evaluated (Table 5): (4) patient census at the ER (total count) and (5) composition of care pathways for ER patients (rate of current count per pathway).

Cases A and P were simulated for all three demand scenarios (high, medium and low) and results were compared to those of base Case (B). The average experimentation time for 20 replications was 158 seconds for each case/demand scenario.

3 RESULTS AND DISCUSSION

Results from the two input cases are presented in Table 3, where mean and standard deviation for each scenario are shown. Table 4 compares output differences between the baseline Case (B) and the two input scenarios, Cases (A) and (P) respectively. For each difference between base and input cases, estimates for the mean difference and for 95% confidence intervals are also provided, considering high, medium and low demand scenarios.

As shown in Table 4, for these performance measures there is no significant evidence that Cases (A) and (P) are different than the full information case represented by the baseline Case (B).

The census statistic (Table 5) refers to the number of patients in the ER at T_0. These results include mean estimates and 95% confidence intervals for the mean of each case (A) and (P), considering high, medium and low demand scenarios. Results reported for Case (B) are not an average census for the scenario as this data is provided by the workflow of the real system at instant T_0, thus there is only one value to compare to all replications of Cases (A) and (P). For a case to adequately represent patient census at T_0, a confidence interval for its mean should contain the value of the base case. Note that in the high demand scenario, for example, the base case census of 5 patients is measured at T_0=8 when, as depicted in Figure 2, the low demand scenario is ending and the high demand is beginning.

For the care pathway composition statistic in Table 5, fourteen confidence intervals are created, one for each possible pathway. Each of these confidence intervals is compared to the T_0 baseline patient count

Table 3: Average and standard deviation results for Input Cases (A) and (P).

	Demand Scenario	**(A)** Average	**(A)** St. Dev.	**(P)** Average	**(P)** St. Dev.
TIME TO FIRST MEDICAL EXAM (minutes)	HIGH	37.133	12.223	26.901	7.293
	MED	37.647	31.062	18.085	6.158
	LOW	10.628	1.122	13.675	9.071
MEDICINE CYCLE TIME (minutes)	HIGH	155.535	9.817	150.865	18.153
	MED	159.037	33.545	142.416	19.066
	LOW	137.304	25.42	140.259	26.947
SURGERY CYCLE TIME (minutes)	HIGH	134.191	25.608	124.741	9.611
	MED	148.704	47.010	121.064	15.953
	LOW	113.392	23.566	93.718	33.804

Table 4: Input Cases compared against a Base Case of perfect information.

	Demand Scenario	**(A) - (B)** Average [95% Conf. Int.]	**(P) - (B)** Average [95% Conf. Int.]
TIME TO FIRST MEDICAL EXAM (minutes)	HIGH	-12.195 [-25.671, 1.281]	1.963 [-5.494, 9.419]
	MED	22.785 [-4.672, 50.243]	3.223 [-2.455, 8.902]
	LOW	-0.962 [-2.507, 0.584]	3.110 [-2.784, 9.005]
MEDICINE CYCLE TIME (minutes)	HIGH	12.726 [-4.903, 30.354]	8.056 [-8.190, 24.302]
	MED	24.418 [-17.547, 66.382]	7.796 [-15.023, 30.616]
	LOW	10.282 [-16.330, 36.894]	3.485 [-21.217, 28.187]
SURGERY CYCLE TIME (minutes)	HIGH	15.766 [-4.915, 36.446]	6.316 [-3.572, 16.203]
	MED	30.279 [-7.910, 68.469]	10.353 [-11.892, 32.598]
	LOW	16.107 [-3.724, 35.939]	1.602 [-22.029, 25.234]

per care pathway (not shown). The percentage number presented for this statistic indicates the proportion, out of 14 confidence intervals, that include the baseline patient-count for its corresponding pathway. For example, 8 out of 14 (57%) confidence intervals, for Case (A) high demand scenario, include Case (B) patient-count observed value for the care pathway (not shown).

Table 5: Cases compared at event time T_0.

	Demand Scenario	**Case (A)** Average [95% Conf. Int.]	**Case (P)** Average [95% Conf. Int.]	**Case (B)** (Deterministic)
CENSUS (number of patients)	HIGH	6.000 [4.125, 7.875]	5.600 [5.020, 6.180]	5
	MED	29.600 [25.888, 33.312]	28.300 [24.410, 31.190]	31
	LOW	21.059 [19.469, 22.649]	25.432 [23.183, 27.682]	26
		Current count per pathway (rate)		
COMPOSITION of CARE PATHWAYS	HIGH	57%	78%	--
	MED	50%	78%	--
	LOW	57%	78%	--

Regarding patient census at T_0, the baseline value is contained in all confidence intervals except in the low demand scenario for Case (A) and the high demand scenario for Case (P).

The current count for the care pathway composition statistic is higher (78%) for Case (P), in all demand scenarios, when compared to Case (A), where the rate is between 50% and 57%.

It is interesting to note that, although some difference is found when comparing cases (A) and (P) for the care pathway composition statistic, this difference is not significant in the performance measures described in Table 4.

4 CONCLUSIONS AND FUTURE WORK

Emergency rooms are complex systems that may gain from discrete event simulation modeling when seeking improvements in their operations. The development of hospital management tools based on process modeling and information systems technology is a recent tendency in health care. This project studies two different cases of real-time data obtained from an ER patient workflow, each representing less or more information useful to feed a discrete event simulation model of an emergency room.

Three demand scenarios were studied to test how well the input Case (A), with less information, and (P), with more information, performed when compared to a baseline case that assumes full knowledge of the true state of the system at some event time of interest. No significant difference was detected, which is an encouraging finding when considering that not all healthcare facilities are equipped with sophisticated patient workflow systems, especially in the developing world.

It is important to keep improving a workflow's ability to record information for all relevant system variables, mostly because information such as arrival times, process times and patient care pathway rates are required to construct valid simulation models of an ER. However, if this data were to be obtained elsewhere, the preliminary results of this study indicate that even a simple WfMS is useful for representing a realistic state of the system in order to aid, in real-time, the decision making process given an unplanned event.

To further validate these conclusions an extensive study must be performed in two dimensions: (1) for the ER system under study, several other scenarios must be tested, performance measures should be compared at different time frames other than T_0 and T_f, and longer term simulations should be run; and (2) other systems of similar and different complexity (ER size and variety of care pathways) should be studied. The authors of this article are currently working on such extensions.

In the long run, applications that run comparative analyses over a real-time simulation model are needed. Furthermore, tools that aid decision makers in developing the alternatives that they wish to compare through simulation are also necessary.

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