Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. D. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

A COMPREHENSIVE SIMULATION MODELING OF AN EMERGENCY DEPARTMENT: A CASE STUDY FOR SIMULATION OPTIMIZATION OF STAFFING LEVELS

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ABSTRACT

We propose a Discrete Event Simulation (DES) model for an emergency department (ED). The model is developed in close collaboration with the French hospital Saint Camille, and is validated using real data. The objective of this model is to help ED managers better understand the behavior of the system and to improve the ED operations performance. The most essential features of an ED are considered in the model. A case study is conducted in order to allow decision makers select the most relevant investment in the human staffing budget. A simulation-based optimization algorithm is adopted to minimize the average Length of Stay (LOS) under a budget constraint. We conduct a sensitivity analysis on the optimal average LOS as a function of the staffing budget, and derive useful recommendations to managers on how the budget can impact the performance of the system.

1 INTRODUCTION

The Emergency Department (ED) is the service within hospitals responsible for providing care to life-threatening and other emergency cases over 24 hours daily, 7 days a week. Therefore, such departments are highly frequented by patients and this frequency is continuously increasing (Weng et al. 2011; Trzeciak and Rivers 2003; Saghafian et al. 2012). As a result, the performance of emergency departments is facing a recurrent problem nowadays, namely overcrowding.

Overcrowding or congestion in EDs occurs when the available caring capacity cannot meet the demand represented by patients' flow, and it can manifest itself through different ways. For instance, an excessive number of patients present in the ED, long patient stays and waiting times, and treatment in hallways, are all overcrowding signs. Congestion in emergency departments leads to negative effects such as decreased physician productivity, miscommunication between working staff, ambulance diversions (Paul, Reddy, and DeFlitch 2010), and dissatisfaction of patients who may sometimes leave without treatment (Saghafian et al. 2012). Moreover, it leads to high levels of stress, violence, decreased morals among ED staff, increased medical errors, higher mortality rates and high staff turnovers (Trzeciak and Rivers 2003; Kuo, Leung, and Graham 2012). For these reasons, solving the problem of overcrowding has become of great interest for both healthcare emergency practitioners and researchers in operations management.

In current practices, several methods are used to improve ED performance. The simplest method which is used frequently by ED managers is to make some intuitive decisions such as modifying staffing levels or process design. However, such intuitive methods are inconvenient and still costly and time consuming. For this reason, healthcare practitioners have resorted to researchers in operations management in order to develop scientific approaches to optimize ED performance. In the literature, a number of such approaches exist where the two major adopted streams are either analytical methods (Huang, Carmeli, and Mandelbaum 2012) or simulation models. Past experience shows that analytical methods reveal some shortcomings when dealing with real-world complex systems. Analytic models represent simplified versions of the ED or focus on a specific part of it. As explained in Saghafian et al. (2012), it is impossible to catch the complexity of ED in a single analytic model. Computer-aided simulation tools are more adapted for addressing such problems (Fitzpatrick et al. 1993; Kuo, Leung, and Graham 2012).

ED simulation models have been abundantly addressed in the literature. The earliest efforts date back to the 1960s and most of these studies were conducted in the two last decades (Paul, Reddy, and DeFlitch 2010). A wide number of authors designed ED simulation models such as (Saunders, Makens, and Leblanc 1989) and (Sinreich and Marmor 2005). These models can be classified according to several metrics. First, they are different in terms of included ED characteristics and detail level. This issue will be addressed in section 2.6. (Paul, Reddy, and DeFlitch 2010) classified experiments that used ED simulation models into three types: *Resource-related* experiments that consist on assessing the effect of changing staffing levels and allocations on ED performance (see Duguay and Chetouane 2007); *Process-related* experiments that consist on modifying some protocols and organizational aspects in the process (see Pallin and Kittel 1990) and *Environment-related* experiments that focused on variables external to the ED (see Hannan, Giglio and Sadowski 1974). Besides, EDs' performance is measured using different Key Performance Indicators (KPI). Among these, Length of Stay (LOS) that refers to the total time period spent by the patient in the ED is a major KPI in the literature and in practice as well (see Evans, Gor and Unger 1996; Samaha, Armel, and Starks 2003).

The main contributions of this paper can be summarized as follows. We propose a realistic simulation model of an ED. The proposed model is based on a comprehensive understanding of the real-world functioning of emergency departments. A field study was conducted for this purpose through a close collaboration with ED staff of a Parisian Hospital, Saint Camille. This enabled us to take the most important features of an ED into account making thus our model more realistic. Given the complexity of the system, Discrete Event Simulation (DES) is adopted. In fact DES has largely proven its worth in complex systems in several industries and in healthcare systems particularly (Sinreich and Marmor 2005; Günal and Pidd 2010). Real data and expert judgments are used for constructing the model. For the validation, the model's outputs are compared with historical data or judged by experts. The model is close to the real system and can be used by ED managers to face their organizational problems through a scientific management approach. Besides, in order to alleviate the congestion in the ED, the question under consideration for decision makers (DMs) is "By how much should the current staffing budget be increased and how should this additional budget be used in the allocation of human resources?" We make a sensitivity analysis on a stochastic model that we solve using Simulation Optimization. By studying the effect of Staffing budget on LOS, we show that it has a diminishing marginal effect. These experiments allowed DMs to choose an increase of 10% in the current staffing budget that corresponds to a reduction of 33% in the average LOS.

Although the modeling is based on a specific ED, qualitative conclusions still hold. Besides, the framework can be easily adapted to other emergency departments, mainly in France, by means of few appropriate changes in the model process and, obviously, in input data. In fact, an ED in another French hospital (Bichat) will be addressed in a future case study using the model introduced in the present paper.

The paper is organized as follows: In section 2, we describe our model and the different steps from the data collection to the validation of the computerized model, and then we highlight the detailed level of modeling and compare it with several related papers by taking some important features as reference. Section 3 presents a case study where we assess the effect of staffing budget on LOS with the use of Simulation optimization applied on the model developed in the previous section.

Finally, our conclusions are presented in section 4, as well as the limitations of our study and some interesting perspectives for future works.

2 BUILDING A REALISTIC ED MODEL

We used Saint Camille hospital's ED as a main reference to build our model. In this section we give a brief overview of the service, and then we explain the methodology adopted for modeling the ED. Finally, we address the problem of level of detail in the literature and compare the granularity of our model with previous works.

2.1 Emergency department overview

Saint Camille hospital is a teaching hospital situated in the Eastern Parisian suburb. This hospital has almost 300 beds and covers most of the medical and surgical specialties. Its ED is open 24 hours a day and serves more than 60 000 patients a year.

There are seven different zones that we will consider inside the ED: The external waiting room for walk-in patient arrival (0), the Registration and Triage zone (1), A Shock room (SR) for acute ill patients (2), Examination Rooms (ER) also called boxes (3), an inside Waiting room with stretchers for lying patients (4), an inside Waiting room for sitting patients (5) and the Observation Unit called in France the Short term hospitalization unit (*Unité d'hospitalisation de courte durée*, UHCD) (6).

In addition, the ED includes an ambulance arrival area and a central operation room where all the tasks that don't require the presence of the patient are made, such as reporting on computer, interpretation of diagnostic tests, discussions with juniors and specialists, preparation of material, etc.

Arrivals are assumed to follow a Non-homogenous Poisson Process (λ_t). The time dependent arrival pattern is quite typical for most EDs in the world. Monday is usually the day that records the most arrivals, and higher arrival rates are found in the period between 10 am and 10 pm for any given day. Arrivals were modeled with an average arrival rate $\hat{\lambda}$(t) for each hour of the day (7*24 rates). These 168 rates are estimated based on a database of 103 weeks in Saint Camille ED from September 2011 to September 2013.

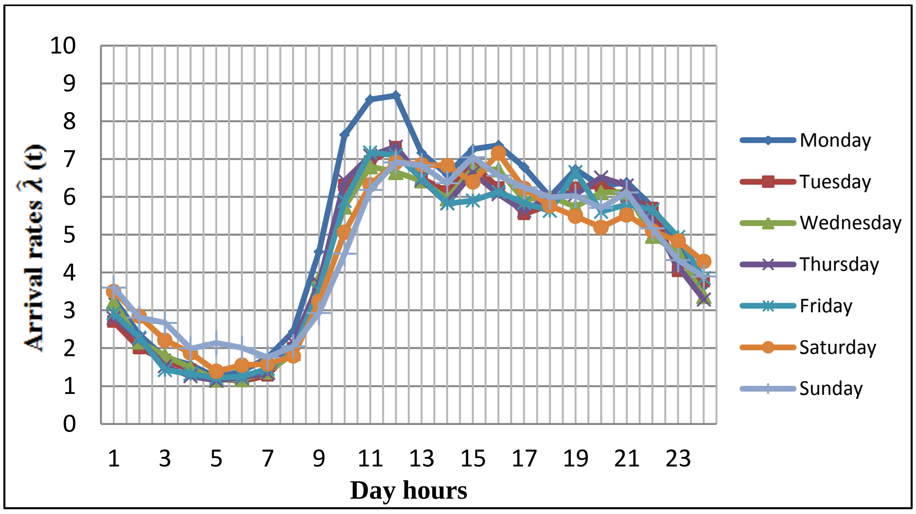

Figure 1: Estimated hourly patients' arrival rate $\hat{\lambda}$(t) per day

Patients arriving to the ED are heterogeneous. Since the ED has a limited capacity of resources, and the health status of a patient is likely to deteriorate without a medical intervention, the most serious cases should be treated immediately, and the less serious ones as soon as possible. Therefore, at the beginning of the process, patients are categorized by a triage nurse, according to their condition, into five degrees of seriousness, called the Emergency Severity Index (ESI). As explained in (Tanabe et al. 2007), Triage level 1 is the highest priority and reserved for immediate life-threatening situations. Level 5 indicates the lowest priority.

During the stay, patients flow over a multitude of stages that involve different type of resources. Every single resource that can generate waiting times (WT) for the patient in the ED should be included in the model. As shown in Table 1, these resources are split into subcategories. In fact, a physician for instance can be either Senior or Junior, where juniors can be responsible only for a combination of ESI_3, ESI_4 and ESI_5. There are also two different types of nurses: The first one called Triage Nurse is dedicated to the triage. The other nurses are inside the ED and are in charge of in-process patients.

In addition, some resources are dedicated to specific ESIs with different staffings for each group. In fact ESI_1, ESI_2 and ESI_3 belong to a group of patients called *Long Circuit* (LC) and are treated by dedicated Physicians and nurses. ESI_4 and ESI_5 are part of a group called Short Circuit (SC) and are also treated by resources dedicated to this group. Examination Rooms are also assigned to certain ESIs but with a different subdivision. The Shock room is dedicated to ESI_1 patients and a part of ESI_2 and ESI_3. The Shock room is also known as trauma and resuscitation room (Kuo, Leung, and Graham 2012). Examination rooms are divided in three: Medium Boxes for ESI_2 and ESI_3, General Boxes for ESI_4, and a *Fast Track* for ESI_5.

The ED contains an Observation Unit (UHCD). It is a part of the ED that admits, for a short stay (generally one night spent), patients waiting for a bed elsewhere (in another service of the hospital or another hospital) or requiring observation before to be released. The Observation Unit disposes of a medical presence 24 hours a day. However, we will not take these resources into consideration in our model since they don't interact with the rest of the ED. In fact, UHCD doctor and nurse are dedicated to this area and besides, the availability of the UHCD is above all conditioned by free beds. Thus, among all UHCD's resources, only the beds are considered in the model.

Table 1: List of the resources included in the model with appropriate assignments

		Assigned to ESI:					Actual Min	Actual Max
		1	2	3	4	5	Staffing level	Staffing level
Doctors	**Senior LC**	x	x	x			1	2
	Senior SC				x	x	0	1
	Senior LSC	x	x	x	x	x	0	1
	Junior 3			x			0	2
	Junior 4, 5				x	x	0	1
	Junior 3,4,5			x	x	x	0	1
Nurses	**Triage Nurse**	x	x	x	x	x	1	1
	Nurse LC	x	x	x			2	3
	Nurse SC				x	x	1	1
Stretcher bearer		x	x	x			1	2
Shock room places		x					3	3
Examination Rooms	**Medium Boxes**		x	x			9	9
	General Boxes				x		6	6
	Fast Track					x	1	1
Waiting Rooms	**Int and Ext sit**		x	x	x	x	Considered infinite	
	Intern lying		x				7	7
UHCD beds		x	x	x	x	x	12	12

In the current situation, different shift lengths can go from 4h to 24 hours and can overlap. However, the ED mostly uses two different shifts, a first one from 9:30 am to 6:30 pm that we will call later day shift, and another one from 6:30 pm to 9:30 am that we will call night shift.

The current Staffing levels were made in an intuitive way by the head of the ED based on experience. The objective is to use combinations of resources staffing that allows matching the capacity with different demand categories. Doctors staffing levels are the same during the week but changes on Saturday and Sunday. On the other hand, other resources like nurses or stretcher bearers have the same Staffing levels every day. Note that we decided not to include some resources in our model such as janitorial staff because they generate negligible waiting times.

2.2 Proposed methodology

Similarly to other related papers (see for example Rossetti, Trzcinski, and Syverud 1999), (Centeno et al. 2003), Duguay and Chetouane 2007), our methodology is based on assessing the effect of some staff changes on key performance indicators. We considered Human and space resources in the model. Human resources will used as control variables in the experimentation part.

Because of the size of the system, and the complexity of its process, simulation seemed to be the most appropriate technique to build a realistic model of the ED. We selected Discrete Event simulation (DES) as a tool to build our simulation model. Model development was made using Arena Simulation software from Rockwell Automation.

We chose to follow the fundamental steps of a simulation study used in the literature (Law and McComas 2001; Baldwin, Eldabi, and Paul 2004) which are: formulation of the problem, data collection and model design, model verification and validation, and finally experimentation and analysis of results.

2.3 Data collection and analysis

It is well known that the quality of output data relies on the accuracy of input parameters. Therefore, data collection and analysis must be undertaken carefully. The first step consisted on collecting the different types of data. In the second step, we modeled these data with statistical distributions in order to use them as input parameters for the model. Our simulation model requires three kinds of data: (*i*) the Arrival pattern, (*ii*) Routing probabilities and (*iii*) Processing times.

(Kuo, Leung, and Graham 2012) addressed the problem of data scarcity in EDs. In fact, depending on their type, ED data are more or less easy to collect. Thus, we relied on the wide variety of data sources commonly used in similar studies and summarized in (Paul, Reddy, and DeFlitch 2010): Records from databases, interviews with experts and decision makers, and on-site observations; in addition to comparison with other hospitals' ED. Arrival pattern and some routing probabilities are relatively easy to collect since the corresponding data are systematically recorded and stored in the ED database. On the other hand, processing times and some process information are not recorded. They can be collected by on-site observations but that technique is time-consuming and can be quite complicated because of its intrusive aspect. That's why we used it only for data that we could not obtain from any other source. Other hospitals' records have been useful to complete some missing data. In fact we used data that was recorded, by on-site observations on a representative sample of patients, for a study conducted in the ED of VU University medical center in Amsterdam. Then, the values have been submitted to the medical staff of Saint Camille's ED in order to be validated, completed or adjusted.

Table 2: Sources, characteristics and inventory of the different inputs of the model

Inputs' category	Source	Features	Inputs
Arrivals	-ED database	-Depends on the day of the week and the hour of the day	-An arrival rate per hour/day (7*24 arrival rates) -Which ESI mix?
Routing probabilities	-ED database -Other databases -Interviews with experts	-The probabilities depend generally on the patient's ESI: Proba= f (ESI)	-Diagnosis test? -Abandonment? -Which tests? - Which Radiology? - Need for specialist opinion? - Which outcome? - Remake tests? - UHCD outcome?
Processing Times	-Other databases -Interviews with experts -On-site observations	-Junior doctors are slower than Seniors -Critical patients take more time	26 different Service Times

As mentioned before, the arrival rates depend on the day of the week and the hour of the day. Routing probabilities indicate the chance that a patient has to pass a certain step of the process. They are used after each decision in the process and the probabilities differ from one ESI to another. Note that service times depend on both the resource and the patient's type. In fact, senior doctors are faster than juniors, and processing a critical patient is longer than processing a non-critical one. Finally, using Arena software's Input Analyzer, we fitted distributions for processing times (all P-values > 0.07) in order to use it as inputs for the simulation model.

2.4 The conceptual model

The ED is a large system which involves several resources and heterogeneous patient types within a complex and well organized process. Building and validating an ED model is a long and iterative task. To reach a good understanding of the system, many interviews and on site observations were necessary. From the arrival to the ED, the patient undergoes a series of assessments in order to take the appropriate decisions. Obviously, because of the variety of the cases, the process varies from patient to patient. However, the typical complete patient stay in an ED can be divided into five principal parts.

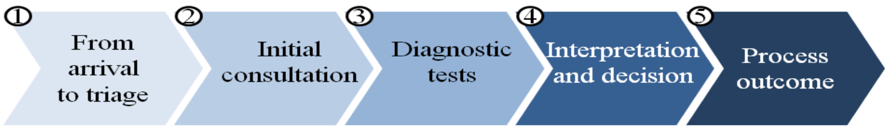

Figure 2: The five typical stages of an ED Process

(1) From arrival to triage:

When a patient arrives at the ED, he is first registered at the reception and then he is being triaged by the triage nurse in a dedicated box at the entry of the ED. As explained before, triage levels are assigned to patients using the Emergency Severity Index (ESI) triage system. This step of the process plays a critical role in determining how quickly patients must be seen (Tanabe et al. 2007) and how to route them to the appropriate resources throughout the process. When the triage nurse is busy, patients must wait in the external waiting room. The red code patients (ESI_1) generally arrive by ambulance; they must be stabilized immediately and skip the triage.

(2) The initial consultation:

After the patient has been triaged, he waits in the waiting room (sitting or on a stretcher depending on the severity) until the appropriate box gets free. Then, he is transported and installed in the box by an appropriate nurse. ESI_5 don't need to be transported or installed. The consultation starts when the right doctor becomes available. The doctor makes a first assessment and may decide, if necessary, to request tests in order to confirm or refine his diagnosis. If not, the patient is discharged to go home. After the consultation, the doctor reports the diagnosis and the decisions taken on computer in the operations room. Besides, some important organizational aspects in the model are to be mentioned:

- ESI_1 patients have the priority over other patients throughout the whole process.
- Each decision taken by a junior doctor must be validated by a senior.
- Each patient must be treated by the same doctor and the same nurse all along the process. The "*same patient-same staff*" rule, mentioned in (Saghafian et al. 2012) and (Saunders, Makens, and Leblanc 1989), is a strong constraint with a significant Impact on the system behavior.
- Among any given ESI level and for any doctor, arriving patients have the priority upon already seen patients (called in-process patients by (Huang, Carmeli, and Mandelbaum 2012)).

(3) Diagnosis tests :

According to the decision of the doctor, many types of diagnosis tests can follow the consultation. The doctor can order an electrocardiogram (ECG) which is generally performed by a nurse in the box. Blood tests can be ordered; the nurse is responsible of the sampling in the box. Then, the sample is sent to the laboratory to be analyzed. During this time, the patient can wait in his box or can be put if possible in an internal waiting room (sitting or on a stretcher) in order to make the box available for other patients. This decision depends on the patient's condition and we translated it in our model with a certain probability for each ESI. The duration of blood tests starts at this moment and finishes when results are ready. It represents one of the longest delays in the ED. Radiology tests can also be ordered with different combinations of X-Ray, CT-Scan, Echo and MRI. In this case, the Stretcher Bearer transports LC patients to the Radiology department and leave them there. Later, he is informed when imaging is completed and goes to bring them back to the ED. SC patients can present to Radiology and come back alone. When both are ordered, radiology and lab tests periods generally overlap. Analgesics can also be requested by the doctor. In the case of perfusion, it will be done at the same time with the sampling (if there is any), but it presents an additional delay anyway because it requires a preparation before.

Diagnosis tests are undergone by resources located in another department and shared with other services of the hospital. Therefore, the durations that we fitted don't represent only processing times but the total wait for the results. In fact, we included in this duration waiting times outside the ED. Consequently, reducing waiting times for extern activities (Radiology and Laboratory) will not belong to our improvement scope and will be considered as incompressible.

(4) Results' interpretation and decision of the outcome:
Once all the tests are completed, the doctor responsible of the patient examines the results, makes an interpretation and decides what to do with the patient. It is possible that the doctor requires additional tests or decides to redo some. The doctor can also request with a certain probability a specialist for his opinion. Since the specialist belongs to another department, his intervention implies three additional durations: The time that the ED doctor spends to call the specialist by phone, the time necessary for the specialist to arrive, and the discussion with the ED doctor when he arrives. The last duration is longer when the ED doctor is a junior because of the learning part of the discussion.

(5) The process outcome:
As mentioned before, the patient can be transferred to another service of the hospital, transferred to another hospital, admitted in the observation unit (UHCD) or discharged. When a patient is transferred to another department to be hospitalized, the responsible doctor must organize the transfer by phone. Then, the stretcher bearer is responsible for transporting the patient to the destination department and installing him. When a patient is transferred to another hospital, the responsible doctor must also call the hospital to organize the transfer. In this case, the transportation to the ambulance is not done by the stretcher bearer but by the ambulance crew.

The UHCD has a limited capacity of beds and admits and releases patients only during specific periods of the day. Generally, patients can spend at most one night in the UHCD until the UHCD doctor takes a final decision (as we said before, we will not consider the UHCD human staff in our model). After the UHCD, the potential outcomes are: transfer to another department, transfer to another hospital, discharge or death. Observation units are generally neglected in ED models in the literature, and yet it is very important to include it because it interacts with the rest of the ED and has an impact on its performance. In fact, in Saint Camille's ED, when the UHCD is full, patients supposed to be admitted are kept in the ED, laid in boxes or in the internal WR. In this case, a nurse from the ED must control these patients regularly like in (Weng et al. 2011).

2.5 Verification and validation

As explained in Law and McComas (2001), if the model is not a "close" approximation of the current system, any conclusions derived from the model are likely to be erroneous and may result in costly decisions being made. For this reason, we had to validate our conceptual model with experts and make sure that it is an accurate representation of the system. Feeding gradually the model, this step was long and contained many iterations.

For the verification of the conceptual model, we ensured that the designed model describes the ED truthfully and mirrors the reality of the process. Then, in order to validate the computerized model, we made sure that it corresponds to the conceptual model and behaves as we intended. In other words, we confirmed that "the code" corresponds to the model. To this end, we referred to three indicators:

(1) LOS per ESI (without counting the sojourn in the UHCD), (2) Resources workload and (3) The durations of the five stages represented in figure 2 (including the corresponding WT for each one). These reference indicators were either compared to real system values using descriptive statistics or judged by experts. Validation allowed improving the quality of the model by figuring out some missing characteristics, by looking for mistakes and correcting them until the model fits with reality. Figure 3 represents a boxplot where the current LOS of 37986 patients is compared to the LOS given by simulation for 7604 patients. The outliers represent less than 5% for both real and simulated values. After these two steps, the model was considered reliable and apt to support experiments.

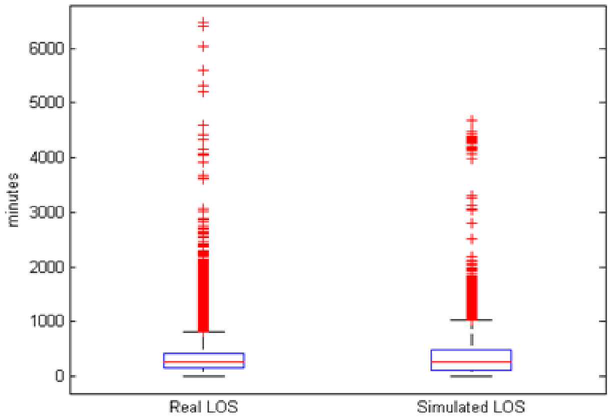

Figure 3: Comparison between Real and simulated LOS

2.6 The models' granularity

It is admitted that EDs are such complex systems that it is impossible to take all their features into consideration. Robinson (1994) has shown that in most cases, 80% of model accuracy is obtained from only 20% of the model's detail. However, ED models in literature generally use many assumptions where important characteristics of the system are neglected.

Building a realistic and credible model in the eyes of ED professionals requires choosing properly the model's level of detail which is characterized by some features that have a strong impact on the system's behavior. Table 3 synthesizes most features included in our model compared to previous studies. For instance, the feature *Resources Subdivisions* refers to the differentiation of the staff members. As explained in (Sinreich and Marmor 2005), some EDs distinguish between acute and ambulatory patients and allocate doctors accordingly. Another possible subdivision is the difference between seniors and juniors (generally neglected), and this is included in *Expertise based processing times* and *teaching aspects* features. Besides, some crucial features like the *same patient same staff* constraint that do not appear in the table are almost never mentioned in the literature.

3 EXPERIMENTS: A CASE STUDY USING SIMULATION OPTIMIZATION

In order to alleviate the congestion in the ED, ED managers and the general management of the hospital intend to invest in Human Staffing. Their objective is to improve the average LOS by increasing resources staffing levels. The question facing the DMs is: By how much should the current staffing budget be increased and how should this additional budget be used in the allocation of human resources?

Many papers conducted their experiments intuitively by testing various scenarios and comparing their performance in order to find the most efficient configuration of staffing levels such as (Rossetti, Trzcinski, and Syverud 1999), (Komashie and Mousavi 2005), (Duguay and Chetouane 2007). However, this approach can be very tedious and time-consuming even for small problems. In fact, a complete enumeration of the feasible solutions would be too long and an intuitive experimentation by designing different alternatives, even based on experience, will not guarantee to obtain an optimal combination of parameters. For this reason, we used Simulation Optimization that overcomes this problem. Simulation Optimization consists on searching for optimal solutions automatically within the simulation model.

Table 3: Comparison of previous works and the present study in terms of model's granularity

	Centeno et al. 2003	Komashie and Mousavi 2005	Duguay and Chetouane 2007	Ahmed and Alkhamis 2009	Weng et al. 2011	Present study
Arrival Process	Depends on Periods of the day	Depends on week days	Depends on week days	Depends on day hours	Depends on the period of the day	Depends on week days and day hours
Patients' categories	Yes (4)	Yes (2)	Yes (5)	Yes (3)	Yes (4)	Yes (5)
Included resources	Doctors, Nurses, boxes (called beds)	Doctors, Nurses, Boxes (cubicles)	Doctors, Nurses, Boxes	Receptionists, Doctors, Nurses, Lab technicians, Boxes (ER), Beds	Doctors, Nurses, SickBeds (SR)	Doctors, Nurses, Stretcher bearer, SR, Boxes, beds
Resources subdivisions	No	Yes	No	No	Yes	Yes
Severity and/or expertise based processing times	Yes, based on severity	Yes, based on severity	Yes, based on severity	No	No	Yes, based on both
Lab tests/Radiology	Yes	No	Yes	Yes	Yes	Yes
Transportation times	No	No	No	No	No	Yes, for patients, not for staff
Staff Shifts	Yes	No	Yes	No	No	Yes
Teaching aspects	No	No	No	No	No	Yes
Specialist	No	No	No	No	No	Yes
Abandonment	Yes	No	No	No	No	Yes
Observation Unit	No	Yes	No	Yes	Yes	Yes
Experiments	Simulation combined with Integer Linear Programming	Intuitive What-if scenarios	Intuitive What-if scenarios	Simulation Optimization	Simulation Optimization	Simulation Optimization
Control variables in the experiments	Nurses	All included resources	All included resources	Doctors, Nurses, Lab technicians	Doctors and Nurses	All included Human resources

We define a problem that seeks to minimize the average LOS under a budgetary constraint. The problem is solved with Simulation Optimization using OptQuest for Arena applied on the simulation model developed in Section 2.

Let I = {Senior, Junior, Nurse, Triage nurse, Stretcher bearer} be the set of considered resources in our problem. Let J = {Day shift, Night shift} be the set of considered shifts. The objective function seeks to minimize the average LOS under a deterministic constraint of labor cost. The real salaries of the ED staff have been used. The objective function doesn't have an analytic form and can be evaluated only through simulation. The control variables represent the amount of a certain resource during a given shift. For practical reasons, the staffing levels for doctors during weekends will remain unchanged. The problem is expressed as follows:

$$\text{Minimize} \qquad f(X_{ij}) = \overline{LOS}$$

Subject to

$$\sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij} X_{ij} \leq \mathrm{C}\,(1+\alpha) \qquad \forall\, i \in I, \forall\, j \in J$$

$$X_{ij} \text{ is integer} \qquad \forall\, i \in I, \forall\, j \in J$$

Where:

$\overline{LOS}$ = Average Length of Stay of the system

X_{ij} = Amount of resource *i* during shift *j*
C_{ij}= Salary cost for resource *i* during shift *j*
C = Current staffing budget
α = Percentage of additional staffing budget

We make a sensitivity analysis on the budgetary constraint in order to allow the decision makers to choose the most efficient investment. By varying α, we analyzed the impact on $\overline{LOS}$. Since the results of the optimization can slightly vary according to the initial solution, we made each optimization several times with varying starting parameters.

Table 4: Optimal solutions according to the additional staffing budget

Additional Staffing budget (α)	**Optimal $\overline{LOS}$ (minutes)**	**Improvement of $\overline{LOS}$**	**Optimal solution**
5%	323	12%	One additional Senior SC during Day shift
10%	246	33%	One additional Senior LC during Night shift
20%	205	44%	One additional Senior LC during Night shift Two additional nurses LC during Night shift
30%	182	50%	Two additional Seniors LC during Night shift One additional Senior SC during Day shift One additional Nurse LC during Night shift One additional Triage Nurse during Day shift One additional Junior ESI_{45} during Day shift

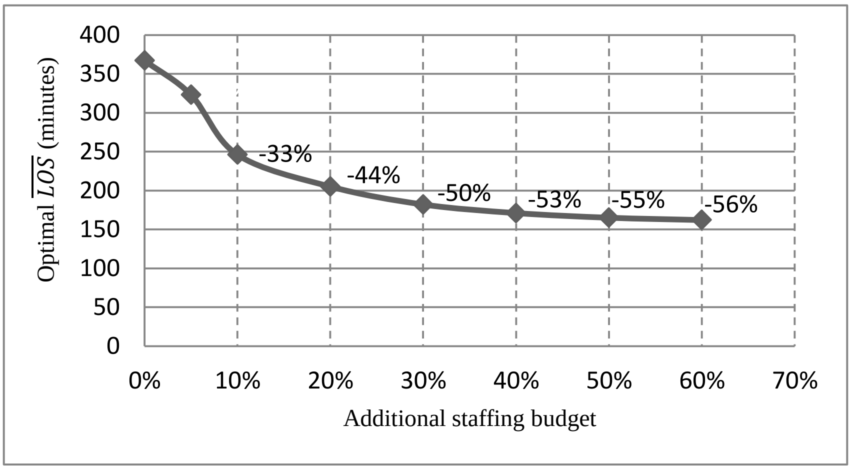

Figure 4: Sensitivity analysis of $\overline{LOS}$ as function of α

The first observation is that the optimal solution corresponding to the current budget is very close to the current staffing in the ED. In other words, the experience of ED managers allowed them to shape intuitively a nearly optimal human resource allocation. Moreover, the sensitivity analysis revealed that the highest marginal effect of α on the $\overline{LOS}$ corresponds to an investment of 10% of the current budget. This result allowed the ED managers with the general management of Saint Camille hospital to take an important tactical decision that consists on increasing the current Staffing budget by 10% in order to reduce the current average LOS by 33%. Finally, as a remark, we are convinced that a larger set of possible shifts *J* (which actually contains only two types) would be beneficial. The current shifts cross both congested and empty periods of the day and that does not allow enough flexibility to adapt staffing levels to demand variation.

4 CONCLUSIONS AND FUTURE RESEARCH

We have built a realistic ED model using DES in Arena software. Thanks to a close collaboration with ED Staff, modeling was performed taking into account all common structural and functional characteristics of at least French EDs. One of the main difficulties that we encountered in this modeling task was the formalization of a process where many procedures are based on *tacit knowledge*. Moreover, we point out a set of important ED features that are frequently ignored in the related literature. Obviously, a simulation model can't be an exact imitation of the real system; but in our opinion, the mentioned characteristics should preferably be taken into consideration in EDs' models given their impact on the system behavior. Our experiments focused on Human staffing levels and provided useful insights to decision makers. With the use of a stochastic program that we solved with Simulation Optimization, we made a sensitivity analysis of the optimal average LOS as a function of the Staffing budget. Two main conclusions can be drawn. First, the Staffing configuration applied currently in the ED is close to the optimal solution. It can thus be deduced that experience of decision makers, with the current shifts' configuration, can allow them to shape a nearly optimal Human resources allocation. Secondly, the sensitivity analysis showed that the staffing budget reveals a decreasing marginal effect on the ED's performance. For instance, an increase of 10%, 20% and 30% in the staffing budget can generate respectively an improvement of 33%, 44% and 50% in the optimal LOS. This last result gave decision makers a better insight on how budget can impact system's performance, and consequently allowed them to choose the most relevant investment.

However, the present study contains some limits that can be divided into two different types: The first type is related to input data. For instance, we considered routing probabilities and processing times as a function of the patient severity. However, in practice, some of these data depend also on the patient's age or the medical specialty required. Even if there are some correlations like between ESI and age, we think that this represents a shortcoming. Besides, we used an abandonment probability for patients as input while this parameter should be an output that depends on waiting time. Unfortunately, the data about abandonment time is not reliable since it is not registered in the database when the patient leaves the ED, but only once his absence is noticed by the staff. The second type of limit is related to the designed process. We assumed that the health status of a patient does not deteriorate during his sojourn in the ED, which could not be the case in general. Since this parameter determines the tracking of the patient in the ED, the simulation model can present a lack of accuracy. Finally, "preemption" is a strong characteristic of human ED staff's tasks that is difficult to model. This shortcoming can generate longer waiting times in simulation than reality. For instance, in the real system, senior doctors can interrupt some tasks to control and validate junior doctors' decisions, while in the simulation, juniors have to wait and thus patients as well.

According to the classification made in (Paul, Reddy, and DeFlitch 2010), experiments in the present paper are *Human resource-related*. It would be interesting as an extension to our case study to carry similar experiments on ED's *Space resources* such as boxes and Observation unit's beds. Besides, a plan is under consideration as future work to undertake *Process-related* experiments using the same framework. As demonstrated in (Samaha, Armel, and Starks 2003), EDs' problems can stem from the process itself, not the staffing levels. *Process-related* experiments consist on assessing the impact of modifying the process or changing some protocols and organizational rules on the ED's performance. Among these changes, we aim to test the effect of some "anticipation methods" like allowing triage nurse to order tests and treatments or initiate search for a bed earlier. In addition, the *Same patient Same staff* rule would be a very interesting issue to explore. Finally, in addition to LOS, it would be useful to consider other key performance indicators such as Time to first see (TTFS), Left without being seen (LWBS) or simply to adapt the LOS target according to the ESI in the experiments.

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