A Discrete Event Simulation Model to Support Bed Management

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Abstract: In recent years, due to the overcrowding of Emergency Department (ED) and the growing concern in reducing the number of inpatient ward beds, it has become crucial to improve the capacity planning and control activities, which manage the patient flows from EDs to hospital wards. Bed Management has a key role in this context. This study starts by a collaboration with the Local Health Government (LHG) of the Liguria region aimed at studying the impact of supporting bed management with some operational strategies without increasing the bed capacity. A large amount of data was collected over a one-year period at public hospital in Genova and a preliminary observational analysis was conducted to get the main information about the flow of emergency and elective patients from ED to inpatient wards. A Discrete Event Simulation (DES) model has been then developed in order to represent the real system. A scenarios analysis is proposed to assess the best strategy to improve the system performance without increasing bed capacity, by simply synchronizing bed supply and demand. The model can be used as a decision support tool to optimise the use of the available resources as well as to improve the quality of the patient pathway inside the hospital.

1 INTRODUCTION AND PROBLEM ADRESSED

In recent years, in order to increase clinical outcomes and citizens' satisfaction, there has been a growing concern to reduce overcrowding in Emergency Department (ED). Two main interventions are usually suggested (Bagust et al, 1999). Firstly, reducing the number of patients which inappropriately addressees the EDs. Secondly, facilitating early discharges from inpatient wards to facilitate on time emergent admissions in inpatient departments.

In Italy, regional decision makers tackled the first intervention encouraging general practitioners to give appropriate pathways for their patients, by giving more non-hospital options available and imposing a co-payment for non-appropriate admissions. Indeed in one year access to ED has been reduced by about 1 million (Agenas, 2012). In spite of that, EDs are always overcrowded. This is mainly due to both a public budget unbalance and the reduction, in the same period, of the number of inpatient ward beds available, which has been reduced drastically, from 6.1 to 4.3 per thousand population in ten years ranking below the European average (Istat, 2011).

Nowadays hospitals are focusing on the second intervention trying to facilitate early discharges from inpatient beds and get more beds available for emergent patients to be admitted. This entails to recognize that the so-called "ED problem," is actually a "system problem". ED is simply a step in the patient flow through the hospital and increasing capacity in the ED without facilitating a smooth exit, can worsen the problem (IHI, 2003). In the past the problem has been already addressed extensively in many health systems, mainly North American and UK (Audit Commission, 1992; Audit Commission, 1993; IHI, 2003). A solution suggested is the introduction of the so-called Bed Manager (BM). It's main task is to report at given interval time slots during the day the volume, census, and occupancy rates of the available ward stay beds in order to synchronize the expected discharges, i.e. bed supply, with the expected admissions from ED, i.e. bed demand, (Haraden et al., 2004).

The BM is not a new concept. Indeed, twenty years ago, it has already been defined as the way of "keeping a balance between flexibility for admitting emergency patients and high bed occupancy, which

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is an indicator of good hospital management" (Green and Armstrong, 1994).

The bed manager function has been proved to be effective. For instance, Howell et al. (2008) report an increase of the ED throughput, substantially due to the reduction of about 25% (approximately one hour and half) of the time spent inside ED. This effect was still larger in transferring patients from ED to Intensive Care Units (Howell et al., 2010).

Efficient patient throughput, however, requires a high degree of coordination and communication among the different staff and health care facilities involved. The control of the whole set of patient flows, is obviously possible only with the help of an on-line system able to identify earlier information about pending admissions to the acute beds available (Tortorella et al., 2013). This can be done, for instance, visualizing the on time patient flows by means of a tool which collects and filters the information from the ED and inpatient ward thus supporting hospital bed managers in their daily decision making (Jensen et al., 2012).

Of course BM should be supplemented by other techniques generally intended to reduce the patient flows variability inside the hospital, developing all activities and tools to allow supply matching demand in a dynamic situation. Many operations research and management science methods such as queuing theory, supply chain models, optimization and simulation, can be used study this problem. In fact, the analysis of patient flows and clinical pathways are a key issue in the recent operational research literature (see, for instance, Vanberkel et al, 2009; Vissers et al., 2005). In addition, many other methods from industrial and business process modelling have been also used, such as lean health care or six sigma (Young et al., 2004).

Health Foundation (2013) provides an extensive collection of empirical research studies aimed at improving patient flow across pathways, not only through BM. From the analysis of the literature it appears that the scope, responsibility and role of bed manager is not clearly defined and it is actually rather different in practical applications: medical, nursing or managerial staff can perform the bed manager function and even tasks or levels may be different (Proudlove et al., 2007). The non-existence of standards of bed management practice is taken to reflect a lack of systematic attention paid to this role (Boaden et al, 1999). In the operative scenario of the Italian Health System herein studied, the bed management has been only recently introduced in hospitals and no systematic results are until now available (Simeu, 2011).

This study starts by a collaboration with the Local Health Government (LHG) of the Liguria region aimed at studying the impact of supporting bed management with some operational strategies without increasing the bed capacity. At least to the authors knowledge, this is the first attempt to give some quantitative insights in this field.

The specific objective of this paper is to develop a Discrete Event Simulation (DES) model to study the interrelation of the flows of emergent and elective admissions into inpatient departments and show how the model can help in supporting the bed management decisions. The advantage to use a DES model is mainly related to its ability to give a deep analysis of the dynamic flows of patients throughout different time windows. It is not sufficient to consider the average distribution pattern. Capacity and demand may match on average, and it may look as though the system ought to flow smoothly. However, even when capacity and demand match on average, the degree of variation in the timing of the patient arrivals (demand) and the ability of beds to absorb that demand can results in admission delays and cancellations.

Simulation has been already utilized in bed management literature. Bagust (1999) applies a stochastic simulation model to determine which is the optimal level of spare capacity in presence of flows by their nature stochastic and difficult to predict, resulting in 85% bed occupancy at most. Harper et al. (2002) utilize a DES model not only to manage but also to plan the bed capacity, with particular regard to the trade-off between bed occupancy and refusals. Schmidt et al. (2013) implement a DES model to assess a decision support system for bed management in a context where there is inherent uncertainty in length of stay and ED patients to be admitted.

In this paper, we focus on studying the flow variability in order to manage the on-line decisions to be taken at a given set of time windows. The effect of different BM rules is evaluated by means of a set of performance indexes. They are chosen to take into consideration both the hospital point of view (bed occupancy, turnover interval, additional beds) and the patient point of view (misallocation, cancellations of elective admissions already scheduled, excessive waits). The BM rule are defined assuming a flow process where emergent patients are "pushed" through the system from the ED to the acute wards and "pulled" towards anticipated discharge (Proudlove et al., 2003).

The paper is organized as follow. In Section 2 the description of the simulation model structure and performance metrics to be used for the analysis are given. In Section 3 the case study is introduced together with the data collection and analysis performed with the collaboration of the Local Health Government (LHG) of the Liguria region. Section 4 is devoted to the model validation and experiment settings, while in Section 5 the preliminary results of the scenarios analysis tests are given. Conclusions and future direction of the research end the paper.

2 SIMULATION MODEL DESCRIPTION

The main aim of the model herein developed is to study the interrelation and synchronization of the patient flows between an emergency department and a set of inpatient hospital wards. A discrete-event simulation model has been developed adopting a patient-centred approach. From an operational point of view, this means considering the patient characteristics regarding their clinical need (medical, surgical, orthopaedics or others) and the timing of the care process from their entrance into the system until their exit.

The overview of the system under study, main elements and patient flows involved is reported in Figure 1.

Both emergent and elective patients flow across the system made up of one ED and a given set of hospital inpatients wards.

Hospital wards are divided into a set of *n* groups (in the case study reported in Section 3 they are: medical, surgery, orthopaedic and other wards). Emergent patients exiting from the ED with a decision to admit and the elective ones compete for the same beds available in the wards. The elective patients are previously registered in a waiting list and the date of admissions is fixed a priori. This means that this flow can be controlled and indeed this can be a way to smooth the demand for beds. Obviously, emergent patients can be admitted into a ward if and only if there is a free bed available. Note that for both emergent and elective patient arrivals, a detailed shift pattern is created to simulate the different arrival distribution during the day and week. For each emergent patient who arrives in the system four attributes are generated. The attribute "to_admit" can assume the value 1 or 0, if respectively, the patient must be admitted into an hospital ward and 0 if is discharged. The Attribute "ward" gives the ward where the patients to be admitted should be allocated. The "Time_in_ED" is the time spent by the patient within the ED. These attributes are generated with different distributions depending on the slot time of arrival. Besides, for both elective patients and emergent to be admitted, the Length of Stay (LOS) is also generated with a different pattern depending on the type of patient (emergent or elective) and the ward they are assigned to. When the elective patients have spent in the emergency department their "Time_in_ED", they become ready and are then processed by a machine which verifies if they must be admitted into ~~a~~ hospital ward or not. In the positive case they are pushed into one of the buffers "To_be_admitted" depending on the ward they are assigned to.

Afterwards at a priori determined time windows during each day the "bed manager", verifies the consistency of available ward beds and decides the emergent patients allocation to them. The number of beds available in each ward is known as well as the average number of elective arrivals during the following time slots in the same day as well as the transferrals of patients among inpatient wards. After the admission the patients stay in the inpatient ward accordingly to the assigned "LOS" attribute.

Different rules and levels of timing and look ahead policies can be applied to simulate the bed manager decisions. The set of performance metrics used to test and compare the impact of different BM rules and hospital ward organizational strategies is reported in the next section, while the preliminary results of the scenario analysis performed are given in Section 5.

2.1 Performance Metrics

The impact of applying alternative bed management rules is assessed by means of the following main indicators:

1. Misallocation index: percentage of patients admitted in a ward different from the one assigned to them at the ED decision to admit. In a baseline scenario patients can be placed in the first available bed, but this is not always appropriate. It is important, for instance, to limit the number of medical ward beds occupied by surgical patients and, vice versa. (Audit commission, 1993).
2. Average number of patients waiting to be admitted for each ward, time slot/day (additional beds or trolley in ED)
3. Waiting times before admission for emergent patients into inpatient wards. Note that national guidelines give a maximum time of 4 hours for UK Proudlove et al., 2003) and 8 hours in Italy (Simeu, 2011).

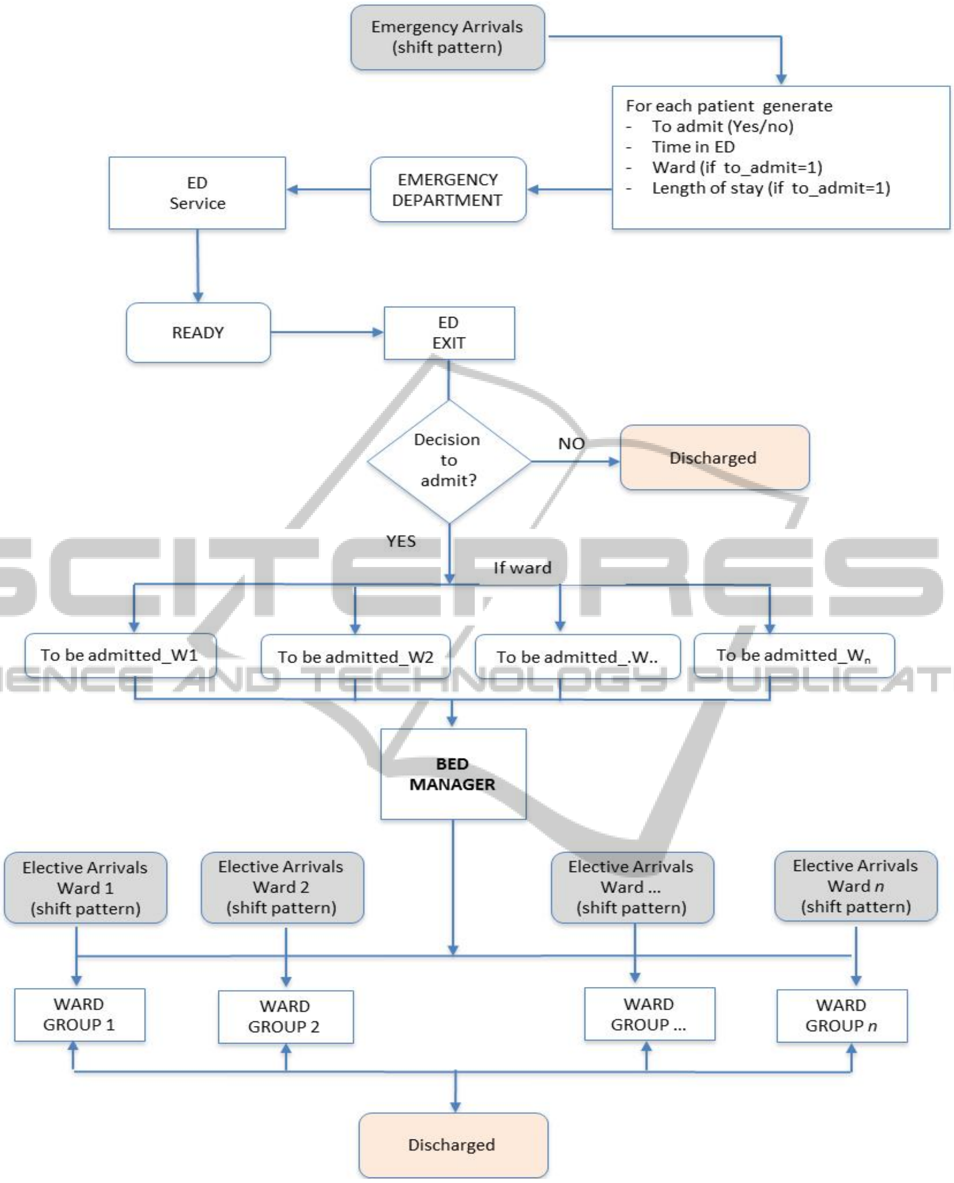

Figure 1: Overview of the system and flows of patients under study.

4. Number of elective patients postponed for the unavailability of a free bed in the day a priori fixed for their admission .
5. Bed utilization rate: bed occupancy of stay beds for each ward (total, emergent and elective ones).

3 CASE STUDY

Our case study refers to a large hospital in the city of Genova. The data has been provided by the Local Health Government of Liguria (Agenzia Regionale Sanitaria). In 2012, the number of patients arrivals at the ED was 84,781. As shown in Table 1, approximately one out of four (24.7%), i.e. 20,942, were subsequently admitted to an inpatient ward. In the same period 24,696 elective patients were admitted into the same wards.

The total number of beds available in the wards is 1256, distributed among 79 wards. The wards have been grouped into four main groups, i.e. Medicine, Surgery, Orthopaedics and other wards, respectively. For each ward group the number of beds available, the average time spent in the ED and the average length of stay are reported.

Table 1: Case study descriptive analysis.

# of ED admissions	84,781
% discharged without admissions	(75.3%)
% transferred to inpatient wards	(24.7%)
# of inpatient ward admission	45,638
elective	24,696
coming from ED	20,942
Average time spent in ED (in hours)	
patients discharged without admission	2.92
patients transferred to inpatient wards	4.45
Average LOS (in days)	
Medicine	3.14
Surgery	6.87
Orthopaedics	9.00
Other	8.73
# of ward beds	1,141
Medicine	332
Surgery	157
Orthopaedics	80
Other	569

Table 2: Time slots and shift pattern.

Slot	Day	Time	Slot	Day	Time
1	Mon	0-7	22	Thurs	13-16
2	Mon	7-10	23	Thurs	16-19
3	Mon	10-13	24	Thurs	19-24
4	Mon	13-16	25	Fri	0-7
5	Mon	16-19	26	Fri	7-10
6	Mon	19-24	27	Fri	10-13
7	Tues	0-7	28	Fri	13-16
8	Tues	7-10	29	Fri	16-19
9	Tues	10-13	30	Fri	19-24
10	Tues	13-16	31	Sat	0-7
11	Tues	16-19	32	Sat	7-10
12	Tues	19-24	33	Sat	10-13
13	Wed.	0-7	34	Sat	13-16
14	Wed.	7-10	35	Sat	16-19
15	Wed.	10-13	36	Sat	19-24
16	Wed.	13-16	37	Sun	0-7
17	Wed.	16-19	38	Sun	7-10
18	Wed.	19-24	39	Sun	10-13
19	Thurs	7-10	40	Sun	13-16
20	Thurs	10-13	41	Sun	16-19
21	Thurs	13-16	42	Sun	19-24

Table 3: Emergent patients ward admissions.

Ward Group	%
Medicine	62.47
Surgery	4,80
Orthopaedics	5,93
Other	26,80

3.1 Data Collection and Analysis

During a one year period, January 2012- December 2012, data have been collected from two database sources which refer to the flow of patient within the emergency department and hospital wards, respectively. From the first, we get the day and time of arrival and the exit decision from the ED (to be admitted into an hospital ward or not). From the second, we collected for both elective and emergent patients the date and time of admission; the ward of admission, the eventual transferral information to other wards and the date and time of discharge from the hospital.

A deepest analysis has been devoted to estimate the inter-arrival and service rates for both emergent and elective patients. They are, apparently, very variables. Indeed, there is a large difference in arrivals between weekdays and weekends, working and resting time. Their variance, however, can be reduced when particular time slots are considered. Therefore, with the help of the medical staff 42 time slots have been chosen to cover each week time period (Table 2).

For each emergent patient the value of the attribute "ward" has been generated using the empirical distribution reported in Table 3.

In Figure 2 the overall trend of patient flows during the 42 slots time is given. In particular, for each timeslot the number of patient discharged and admitted is given. The number of patients admitted is also splitinto emergency and elective flows.

These flows represent for each slot the supply of beds, which consists of the patients discharged that are leaving a bed free for a new admission, and the demand for ward beds, composed by emergent patients to be admitted from the ED and elective patients already scheduled to be admitted into inpatient wards.

A grayed area also highlights the internal flow of patient transferred from one ward to another. It does not affect the admission/discharges flows but has a significant impact over ward occupancy rates. Two main remarks can be outlined. The most of the discharges are concentrated in the days before the weekend, while the admissions are mainly concentrated in the first days of the week. This effect is mainly due to the internal hospital organization and can have great impact over the bed occupancy flows and allocation. Looking at the internal distribution of arrival flows it is clear how the elective patients are admitted on regular frequency, mostly at the beginning of the week,

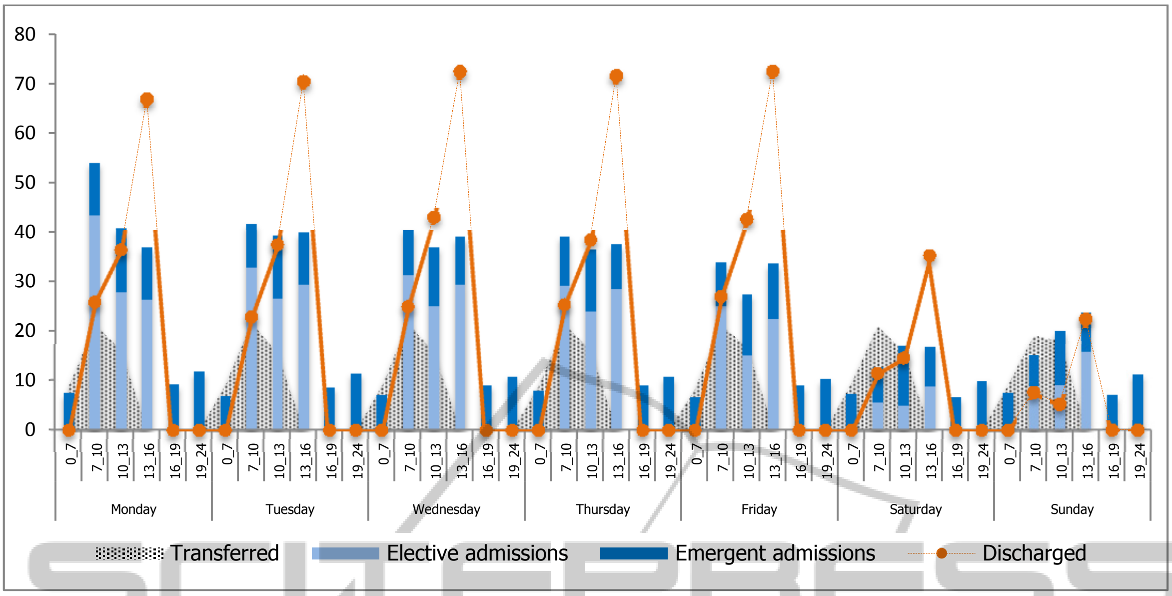

Figure 2: Distribution of inpatient ward input-output flows.

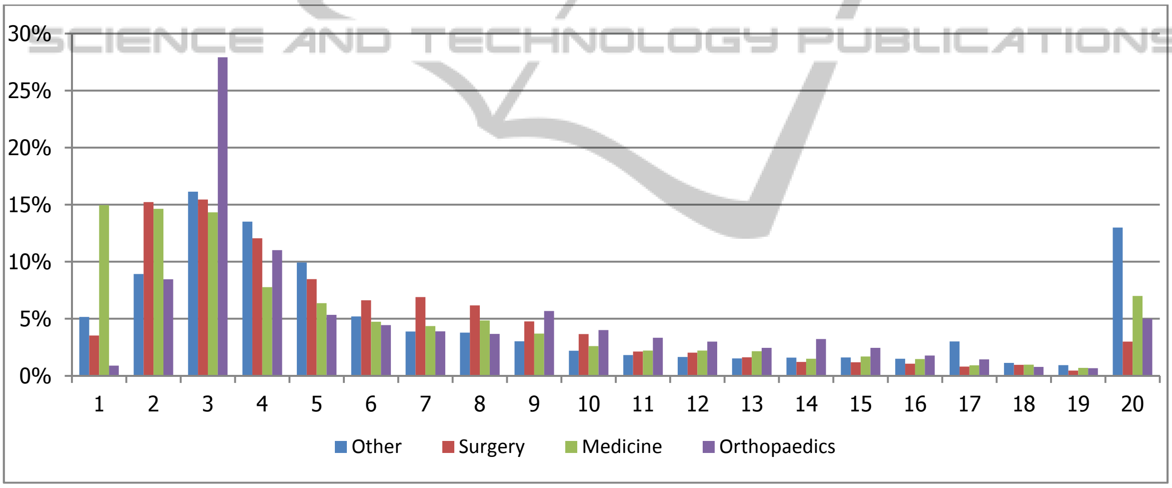

Figure 3: LOS distributions (in days) in the inpatient wards- elective patients.

while emergent ones are more equally distributed. This phenomenon is quite reasonable and must be taken into account to effectively plan the bed allocation. Discharges are distributed in three slots (i.e. 7_10, 10_13, 13_16). The most of discharges are placed in the last slot of the day (13-16), just after the launch and after the ward rounds.

Figure 3 and Figure 4 show the distribution of the length of stay (LOS) for each ward, for elective and emergent patients, respectively. On the x-axis, the length of stays in days are represented, while on y-axis the % of patients is reported for each ward where they have been admitted.

The largest number of emergent patients exits the ED with a decision to be admitted into one of the medicine wards and their stay is quite short (the largest number remain for no more than 3 days). The elective patients are more equally distributed over different wards, in fact the most stay in the "other" group which contains all the wards but medicine, orthopaedics and surgery. The average length of stay is greater in this case. More elective patients are admitted into surgery wards with respect to the emergent ones and the length of stay is on average greater.

The data analysis highlights some phenomena which can be addressed by the model to simulate different bed manager rules (i.e. decision about the ward where an emergency patient should be admitted) and hospital organizations (i.e. slots and frequencies of patients discharge and elective admissions).

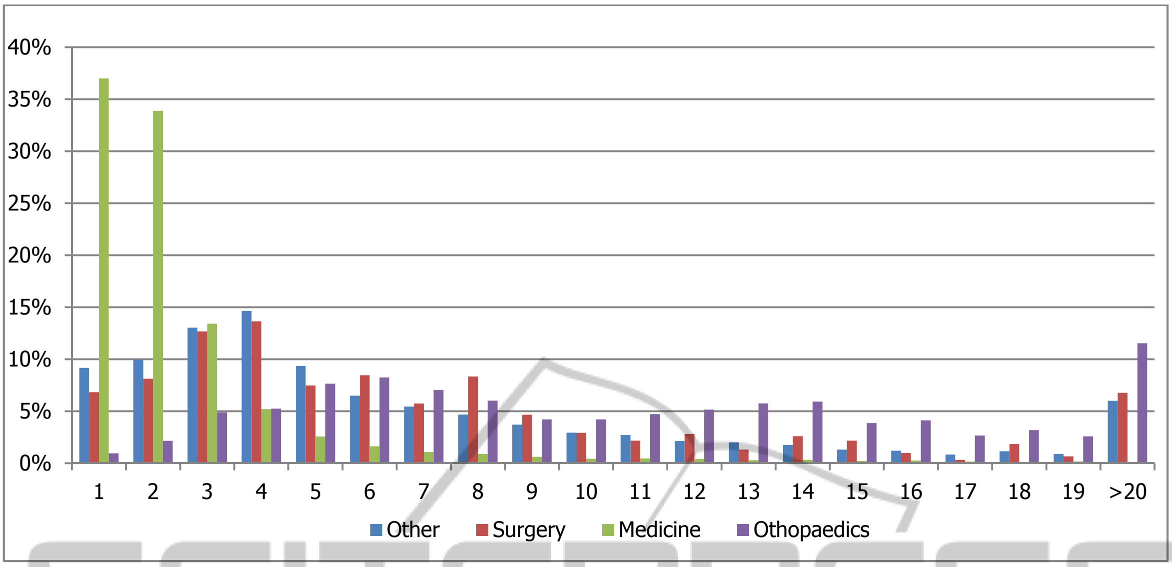

Figure 4: LOS distributions (in days) in the inpatient wards - emergent patients.

4 MODEL VALIDATION AND STEADY STATE CONDITIONS

The DES model has been implemented using the simulation software environment Witness (Witness, 2013) and has been be validated to ensure that the simulation outputs adequately represented the real data of the system under investigation by adopting appropriate statistical tests (Law, 2007). There are numerous techniques for validating a simulation model; some of them are based on subjective graphical analysis, some others on mathematical statistics to obtain quantitative data about the quality of the simulation model.

Firstly, the model validation has been performed to verify if and to which extent the model is able to represent the real flows of elective and emergent patients within the system under investigation. Referring to the logic and rules implemented to simulate the bed manager decisions a face validation (Law, 2007) has been firstly performed with the hospital managers and clinicians which gave us many insights to adapt the model to the current practice and render it a truer representation of the real system. Besides, the simulation outputs have been compared to the real data using a classical parametric statistical test, i.e. the T-test (Law, 2007).

In particular, we compared two output measures, i.e. number of emergent patients to be admitted and number of total patient admissions (for each inpatient ward). Note that the last metric includes the emergent and elective admissions as well as the transferrals among different inpatient wards. The simulated output measures were obtained through 20 IID replications and then compared against the same real measures for the reference time period, i.e. one year. We decided to test the null hypothesis H_0 under a probability of rejecting the model fixed to the α=0.05 level. The corresponding critical value of the test is $t_{n-1,1-\alpha/2} = t_{19,\ 0.975} = 2.093$; from Table 4 we can see that $t_{(19)} \leq 2.093$ for all values and hence our simulation model has been proved to represent the real behaviour with a low probability of error.

Table 4: Comparison between real data and simulated output.

	# of emergent admissions			
	W1	W2	W3	W4
Real measures	12349	948	1173	5299
Simul. outputs	12382	954	1162	5321
Δ_{opt}	0.27%	0.63%	0.94%	0.42%
T-test (t_{24})	1.932	2.065	2.088	1.989

Since the aim of our simulation study is to derive a set of performance indices able to evaluate the efficiency of the system under study, it is important to choose the conditions under which a steady state behaviour in the simulation is reached (Law, 2007).

To obtain the steady state conditions we have used the batch means method, based on a single run of data collection, which has been divided into 10 batches. The decision of using 10 sampling batches is due to the results of the initial experimentation

with the simulation model, that revealed a relatively small variance in the system output.
The first run begun at time $t_0 = 0$ corresponding to the empty initial state of the system; therefore, a preliminary simulation time was needed to clean out the transient simulation period. After this initial warm-up fixed to 90 days, we reset the statistics of the model and run it starting by the new initial time t_0=2160 (hours) until the ending time condition t_f=88560, so that each batch represents 360 days of steady-state simulation. The results presented in the next section are the average of the performance indices sampled for the 10 batches.

5 SCENARIOS ANALYSIS AND PRELIMINARY RESULTS

Once validated, the discrete event simulation model has been used to analyze the effects on system behavior of different bed management rules and inpatient ward organization and verify their effectiveness to face the bed allocation problem.

For the output analysis we used the set of performance metrics reported in Section 2.1 which allow to assess the performance of the system from both the patient point of view (waiting time before admission and elective admission postponements) and the hospital point of view (bed utilization rate and misallocation indexes).

Three set of scenarios and related results are herein presented (Table 5).

In the first set of scenarios (Scenarios 0-3) the system rules of the bed management are modified with respect to the number and timing of the evaluation of available beds and ability to look ahead. In particular, in the baseline scenario (Scenario 0) the bed manager simply verifies, for each emergent patient to be admitted in the inpatient wards, if there is a free bed available in the ward assigned to her/him, if not it checks the bed availability in the other wards and when it finds a free bed sends the patient to the first ward with a free bed available even if misallocated. Including the “timing” characteristic (Scenario 1) gives the bed manager the ability to postpone at most 4 times the assignment of a patient to a “wrong” ward in order to verify if after a short time (usually half an hour) some beds will be available. The number of times the BM can postpone its decision as well as the period between the re-evaluations are also key parameters. In the preliminary tests herein presented they are set at 4 re-evaluation, every 30 minutes, i.e. at least the bed manager can postpone its decision to admit for 2 hours. The ability to long-ahead (Scenario 2 and 3) allows the BM to consider in each time slot not only the number of beds available but also the expected number of elective patients to be admitted during the day.

Table 5: Scenarios analysis.

Scenario	Bed manager timing	Bed manager look ahead	Elective admiss. blocking	New discharge policy
Scenario0				
Scenario1	x			
Scenario2		x		
Scenario3	x	x		
Scenario4	x	x	x	
Scenario5	x	x		x

In the second series of results (Scenario 4 and 5) the idea is to block (not schedule) or reduce the elective admission during the days and slots where peaks in the ED admissions are expected, for instance on Monday, slot 7-10, (see Figure 2 and Figure 5). These is scenario tries to manage the inpatient demand flow in order to smoothing the flow of emergent patients coming from the ED.

Finally, the third analysis is intended to manage the supply flow, i.e. to change the discharge policy to shortening as much as possible the length of stay (Scenario 6 and 7). The usual proposal is to transfer patients likely to be discharged during the day and (waiting only for the next visit by the consultant), in a dedicated room (referred as discharge room or lounge). This allows freeing in advance some beds since the morning, instead of the first afternoon as it usually happens in the current practice observed. This analysis can also be designed to verify the impact of removing some administrative barriers or modifying the work shifts and roastering of the inpatient ward staff, thus allowing discharges on Saturday and Sunday, or late evening, thus smoothing the in and out flows during the day and avoid useless stays.

The results are reported in Table 6. For each scenario the resulting values of the performance indexes reported in Section 2.1 are given.

Introducing the re-evaluation in the BM behaviour reduces the number of misallocated patients. Moving from scenario 0 to scenario 1 and from scenario 2 to 3, the total number of patients misallocated is reduced of about 61% and 83%, respectively, thus resulting in a reduction of the

Table 6: Scenarios analysis results.

Indexes	Scenario 0	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
# of patients misallocated (W1)	376	175	1133	227	163	138
# of patients misallocated (W2)	0	0	38	0	0	1
# of patients misallocated (W3)	5	0	29	0	1	3
# of patients misallocated (W4)	238	64	1070	141	25	87
Total # of patients misallocated	*619*	*239*	*2270*	*368*	*189*	*229*
Misallocation index (W1)	2,959	1,3973	9,0351	1,814	1,2944	1,0980
Misallocation index (W2)	0,000	0,0000	3,7924	0,000	0,0000	0,1067
Misallocation index (W3)	0,419	0,0000	2,3829	0,000	0,0853	0,2555
Misallocation index (W4)	4,163	1,1140	18,8646	2,497	0,4365	1,5029
Avg. Misallocation index	*3,005*	*1,1706*	*11,1106*	*1,805*	*0,9252*	*1,1188*
Avg. # of ED patients to be admit. in W1	2,933	2,667	2,200	1,133	2,000	1,584
Avg. # of ED patients to be admit. in W2	0,200	0,067	0,467	0,000	0,600	0,234
Avg. # of ED patients to be admit. in W3	0,067	0,400	0,467	0,800	0,000	0,200
Avg. # of ED patients to be admit. in W4	0,933	1,533	1,000	2,667	1,600	1,800
Avg. # of ED patients to be admitted	*1,033*	*1,167*	*1,033*	*1,150*	*1,050*	*0,955*
Waiting time before admission (W1)	1,799	2,560	2,584	2,986	2,828	2,528
Waiting time before admission (W2)	1,576	1,603	1,673	1,667	1,700	1,600
Waiting time before admission (W3)	1,564	1,751	1,736	1,677	1,681	1,681
Waiting time before admission (W4)	1,705	2,228	2,063	2,543	2,286	2,342
Avg. waiting time before admission	*1,661*	*2,035*	*2,014*	*2,218*	*2,124*	*2,038*
# postponed elective admissions (W1)	73	126	8	93	54	66
# postponed elective admissions (W2)	0	0	23	0	0	0
# postponed elective admissions (W3)	4	0	11	0	0	0
# postponed elective admissions (W4)	627	616	41	211	72	101
Total # postponed elective admissions	*704*	*742*	*83*	*304*	*126*	*167*
Bed utilization rate (W1)	92,350	92,520	92,420	92,320	91,680	92,380
Bed utilization rate (W2)	67,210	66,310	79,660	68,060	66,730	67,730
Bed utilization rate (W3)	73,490	70,020	75,930	71,250	70,010	72,230
Bed utilization rate (W4)	92,690	92,490	90,710	92,750	89,280	91,450
Avg. bed utilization rate	*81,435*	*80,335*	*84,680*	*81,095*	*79,425*	*80,948*

misallocation indexes as well. This is correlated with an increase of the number of patients waiting to be admitted and their average waiting time. Beside the waiting time to be admitted never grows of more than one hour. The introduction of the look-ahead characteristics (Scenario 2 and 3) has a major impact on reducing the number of postponed elective admissions. By including both the decision postponements and the look-ahead in the BM rules (Scenario 3) the number of patients misallocated and the number of elective patients postponements is reduced of about 40%.

Looking at the detailed slot time results a major problem is shown in some shifts where the number of patients to be admitted grows since no bed are available in the inpatient wards, for example on the afternoon slots of Monday (Figure 5). Moving o this direction, Scenario 4 and Scenario 5 are directed to manage the flow of elective admissions and discharges, respectively, in order of smoothing the flow of emergent patients coming from the ED and better synchronize them with the inpatient ward flows.

The first strategy (i.e. reducing the elective admissions of the slots where peaks in the emergent admissions are observed) shows to be more effective in reducing the number of misallocations and the number f elective patients postponements, while the

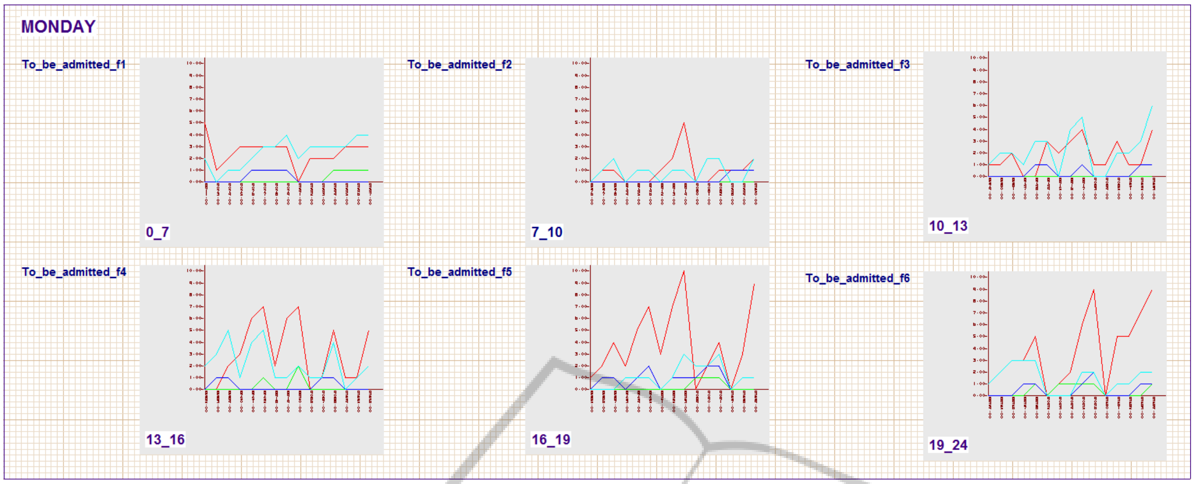

Figure 5: Number of ED waiting patients to be admitted on Monday for each time slot.

second performs better in reducing the number of patients waiting in ED to be admitted and their waiting time.

Finally, it must be noticed a problem related to the bed capacity of ward group 1 and 4. The utilization rate of those ward group are more than 90% and all the scenarios tested little impact on these performance metrics.

Future direction of the research will be also devoted to verify the impact of an alternative assignment of the beds among the ward groups on the system performance.

Note that the three kinds of analysis entail different tactical and organizational decisions to be taken from the hospital management.

There are, of course, many other possibilities, not herein taken into consideration, which imply strategic decisions. For example, facilitating the discharge of elderly patients by improving the continuity of care and linking the discharge coordinator with the social services; extending the hours of community nurse team by increasing the home assistance and the transferrals to the intermediate care ward, i.e. lower intensity ward, (Boaden et al, 1999).

It should be pointed out that the second and third groups of scenarios entail additional costs, even not necessarily financial costs. Blocking the elective admissions in some days, for instance, generates a lengthening of waiting lists for elective patients (social cost) or cancelations (financial cost); the supply side scenarios assume to set up a dedicated room (organizational cost) and/or requires higher staff costs to manage the discharges in different and enlarged time periods.

Besides determining the impact and benefits of alternative scenarios by means of the chosen set of performance metrics, costs should also be estimated and taken into account.

6 CONCLUSIONS AND FUTURE WORKS

In this paper we developed a decision support framework for analysing the patient flows between an hospital Emergency Department and the inpatient stay wards of the same hospital.

The framework has been applied to a real case study of the teaching hospital San Martino sited in the city of Genova Surgery (Italy).

The main conclusion is that, in principle, a decision tool cannot individuate the best solution, but rather can help in assessing the direct and indirect impact of different BM working rules as well as of alternative organizations of the stay wards aimed at facilitating the integration and synchronization of the flows between ED and inpatient wards.

The model underlying the bed manager decisions affects how other hospital resources, such as operating theatres and elective inpatients wards perform since all hospital services are dependent on bed availability. In turn, other hospital department inefficient performance, mainly lengthening hospital stays, can impact, upon ED crowding. This study has recognised this effect in line with the literature findings.

The so-called "bed management" is a business function that allows increasing the efficient use of beds, in order to optimize the flow of patients within the hospital. It is a crucial function within an organization based on process activities. Improving patient flow is a way of improving health services.

The model herein developed could be used as a decision support tool for a priori verifying the effects of different bed management rules both by a patient and hospital point of view.

Of course the model could include other patient characteristics and patient flows also versus other hospital facilities and can easily be adapted to simulate other case studies, changing the system constraints and the organizational models of the ED and hospital wards.

Future work will be directed to perform an extensive scenario analysis and compare the results with a larger amount of real data and performance indexes.

Moreover, future research are going to explore the potentiality of applying the optimization module integrated in the simulation software environment, in order to determine the optimal decision pertaining the number of beds to be assigned to each ward group, able to optimize ad hoc chosen objective functions, such as maximizing the bed utilization rate, minimizing the number of postponed patients or the overall misallocation index.

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