Simulation and Optimization for Bed Re-organization at a Surgery Department

Paolo Landa, Elena Tànfani and Angela Testi
Department of Economics and Business Studies, University of Genova, Via Vivaldi 5, Genova, Italy

Keywords: Discrete Event Simulation, Simulation Optimization, Patient Flow, Bed Reconfiguration, Surgery Department.

Abstract: In this paper we focus our analysis on patient flows inside a hospital surgery department, with the aim of supporting the bed re-configuration following an "intensity of care" paradigm. The main contribution of this paper is to develop a Discrete Event Simulation (DES) model which describes the elective and emergent patient flows in a Surgery Department, and is able to evaluate the impact of re-organizing hospital resources within the Department. The model has been applied to reproduce a case study of a General Surgery Department sited in Genova (Italy). Firstly, the model has been used to quantify the impact on a set of performance indicators of the re-organization of a "traditional" stay area into an "intensity of care" one. Following this re-organization the available beds capacity is no longer divided into operating units based on the pathology and medical discipline, but into three different stay areas homogeneous with respect of the complexity of care to be delivered. Secondly, by using the "Optimizer" module, embedded in the Witness simulation software, the best number of beds to be assigned to each Intensity of Care Level (ICL) is determined in order to maximize the number of patients operated. The model development is presented and preliminary results are analyzed and discussed.

1 INTRODUCTION

Worldwide, aging of population, more demanding consumers and, above all, fast technological progress able to diagnose and solve more and more health problems, are threatening the sustainability of public health systems. The situation is worsened by the current economic crisis and the stringent public budget constraints.

If we agree that coverage should not be reduced, the only way of ensuring the health systems survival is reducing costs. There are many potential ways of doing it (Berwick and Hackbarth, 2012). Here we focus on what can be done by re-organizing patient flows through hospital surgical facilities.

From the analysis of the literature it appears that simulation has been extensively used for evaluating the impact of resource availability and organizational setting, since direct experimentation is too costly and almost impossible to pursue (Jacobson et al., 2006); (Lagergren, 1998); (Gunal, 2012).

All phases of patient flow have been studied. In particular, some authors use simulation to improve the waiting list management and scheduling patient admission in hospitals (Sciomachen et al., 2005); (Vissers et al., 2007). Tuft and Gallivan (2001) use simulation to compare different strategies for determining admission dates for patients awaiting cataract extraction, while Ratcliffe et al. (2001) evaluate alternative allocation policies for the management of waiting list for liver transplantation.

Other works deal with the use of simulation for Operating Room (OR) planning and scheduling. Among them, a practical and efficient simulation model to support OR scheduling decisions concerning patients waiting for elective surgery is proposed in Everett (2002), while in Bowers and Mould (2004) simulation is used to assess proposals for improving the utilisation of orthopaedic trauma theatre sessions. In Testi et al. (2007) a discrete event simulation model has been developed in order to compare different sequencing of patients inside ORs.

Simulation has been used also for planning bed capacity (Harper and Shanani, 2002) and for balancing bed unit utilizations (Cochran and Bharti, 2006), while Akkerman and Knip (2004) use

Landa P., Tànfani E. and Testi A..
Simulation and Optimization for Bed Re-organization at a Surgery Department .
DOI: 10.5220/0004635805840594
In *Proceedings of the 3rd International Conference on Simulation and Modeling Methodologies, Technologies and Applications* (HA-2013), pages 584-594
ISBN: 978-989-8565-69-3

simulation to reallocate hospital beds, taking into account the relationship between patient length of stay, bed availability, and hospital waiting lists.

From a more "holistic" point of view, Harper and Shanani (2002) develop an integrated simulation model for planning and managing operating theatre, beds and workforce needs, while VanBerkel and Blake (2007) propose a discrete event simulation model to support capacity planning and wait time reduction in a general surgery department.

Other authors investigate the global flow of patients belonging to different paths, focusing on hospital or ambulatory facilities (Cardoen and Demeulemeester, 2008); (Swisher et al., 2001), while Maliapen and Dangerfield (2010) use a system dynamics-based simulation approach to examine clinical pathways in an Australian hospital.

In this paper we use simulation adopting a patient-centered approach. From an operational point of view this means considering the patient clinical characteristics (i.e. their pathology, which can be proxied by the so called Clinical Pathway (De Blaser, 2006), as well as their demand of services (that is, for instance, operating room time, nurse assistance, monitored post-intervention assistance, stay bed time, and so on).

The first objective of our study is to evaluate the impact of re-organizing the "traditional" stay area into an "intensity of care" one. This means that the available stay beds are no longer grouped by operating units, based on the pathology and medical discipline, but into homogeneous stay areas with respect of the complexity of care, not necessarily coincident with the medical severity of the case. The second objective is to determine the best bed capacity re-configuration able to maximize the number of patients operated by the surgical department.

This first objective is achieved by developing a Discrete Event Simulation (DES) model reproducing a case study of a General Surgery Department sited in Genova (Italy).

Afterwards, the optimization module integrated in the simulation software environment (Witness, 2012) has been used in order to identify the "best scenario", i.e. the optimal number of beds to be assigned to different Intensity of Care Level (ICL) areas in order to maximize the patient throughput.

The paper is organized as follows. In Section 2, we introduce the DES models developed to represent the traditional and the intensity of care Department organization. In Section 3 the data collection and characteristics of the case study are given, while in Section 4 the preliminary results of the scenario analysis and optimization phase are reported. Finally, some conclusions and directions on future research are given in Section 5.

2 DES SIMULATION MODELS

Patients flowing across a surgical department can be identified by many attributes, describing both their clinical characteristics as well as resource requirement (Tànfani and Testi, 2012).

In this framework we consider the following relevant attributes:

- Pathology-related Clinical Pathway which is related to the Surgical Specialty assigned to the patient;
- Urgency coefficient (URG);
- Expected Operating Time (EOT);
- Length of Stay (LOS);
- Intensity of Care Level (ICL).

The first two attributes refer to the clinical characteristics of the patient, whereas the other three to the individual resource requirement. Moreover, we can use the number of beds and OR blocks as proxies of department resource capacity, assuming that their amount includes all necessary inputs, such as staff, materials, drugs, etc.

In our framework, both elective surgery pathways, as well as emergent patients coming from the Emergency Department (ED) are considered and the above reported attributes manage the patient flows through the system.

In particular, two simulation models have been developed in order to analyze how the department stay areas can be organized and what is the impact of different settings on patient flows. The first refers to the system as it is in the current practice, whereas the second reproduces the system after re-organizing beds into the so-called "intensity of care" levels. From literature analysis, the latter proved to be a better setting engendering not only beneficial effects on patient, but also hospital costs reduction (Major, 2007).

In the "intensity of care" model patients are grouped into 3 ICLs: i.e. high, medium and low. These groups embody the patient clinical conditions and complexity level of assistance.

Patients following a CP that requires particular complexity of care (advanced nurse control, specific monitoring activity and so on) are defined as "high ICL" patients. The correspondent high intensity area is high technology equipped and staff is usually more skilled and abundant.

Patients following a CP requiring a LOS between

1 and 5 days are defined as "low ICL". If they are appropriately scheduled, they can be admitted and dismissed within the same week. The low ICL area is standard equipped and can be closed during the weekends, engendering a consistent cost saving for the hospital. For this reason it is usually named also as "week surgery area". Note that not only patients with LOS less than five days are classified as low ICL. There is the possibility that some patients, with an expected LOS less than 5 days, are classified as into high ICL, depending on the level of assistance needed and the specific CP they are following.

All other patients, not classified as high or low ICL, are admitted into the “medium ICL” area. These patients are more heterogeneous with respect to the ones admitted into the other two areas.

Patients coming from ED first stay in the medium ICL area and, after being diagnosed and possibly operated, could also change their ICL following the pathology assessment.

In Figure 1 and 2 chart overviews of the DES models are reported, identifying the main elements of the system and the functional relationship among them. In particular, Figure 1 depicts the current system which follows the traditional organization of the department in surgical specialties, while Figure 2 reproduces the system behaviour that should come from the “intensity of care” re-organization.

2.1 Traditional Model

Elective patients begin the care process by a consultation visit when the clinician decides if a surgical intervention is needed. In the first case, the surgeon assigns the patients to a surgical specialty i and registers them in the corresponding waiting list (WL_i).

The queue discipline of the WLs which determines the order by which patients are admitted to be operated on is based on an already validated prioritization system (Valente et al., 2009). When a patient is registered in an elective waiting list, the surgeon assigns him/her an urgency coefficient depending on the maximum time allowed before the treatment. The urgency coefficient (URG) gives the speed at which the clinical need of the patient increases along with time passing. Patients proceed in the list according to their urgency and gain different relative priorities, given the same time spent in the list. In our model the queue discipline is, therefore, based on the individual priority score computed multiplying the already waited time for the URG coefficient.

Elective patients exit the waiting list to be admitted and operated in an OR block assigned to the specialty they belong to (block scheduling strategy). We assume the tactical decisions pertaining the number of OR block times (usually one half to one full day in length) assigned to each surgical specialty as input data. We assume as given also the cyclic timetable, denoted as Master Surgical Schedule (MSS), which gives the assignment of surgical specialties to each OR and day of the planning horizon.

In our model, MSS is assumed to be given on a historical basis and the planning horizon is set to a week. Alternatively MSS can be obtained from ad hoc optimization models (Cardoen et al., 2010).

At the beginning of the week, the model reads the MSS. Afterwards, before including a patient in the “Preoperation list” of a given OR block assigned to the specialty to which the patient belongs to, the model, firstly, verifies if there is a free bed and after if the EOT is not larger than the left time available in the assigned OR block. If the time is not enough to include the patient in the operation list, the patient returns to the waiting list to be scheduled in the next OR block assigned to the specialty. The model then goes on trying to fill the operation list as much as possible, until the sum of the EOT of the patients included does not exceed the block time capacity. The ORs are modelled as machines with service times given by the duration of the intervention. Note that, the surgery duration can be different by the EOT. If the surgery durations of some operated patients exceed their EOT, the left time in a block could not be enough to start the intervention of some other patients. In this case, patients are shifted, i.e. their operation is postponed to another day.

Emergent patients are directly admitted from the Emergency Department (ED) and enter the stay area of a specific specialty to be diagnosed and operated on if intervention is needed. After few days if they do not need any intervention, or if their intervention may be postponed, they go back home and may re-enter the system as elective patients in the future. On the contrary, if they need immediate intervention, they will be pushed to the “Emergent to operated” buffer and scheduled to be operated on in the first OR block assigned to the specialty they have been associated to.

In order to create the operation lists, emergent and shifted patients have pre-emption with respect to the elective ones. In particular, firstly the model checks if there are patients in the “Emergent to operate” buffer, then it checks if there are patients previously shifted waiting for the surgical operation (“Shifted WL”) and just afterwards elective patients in the waiting lists are selected.

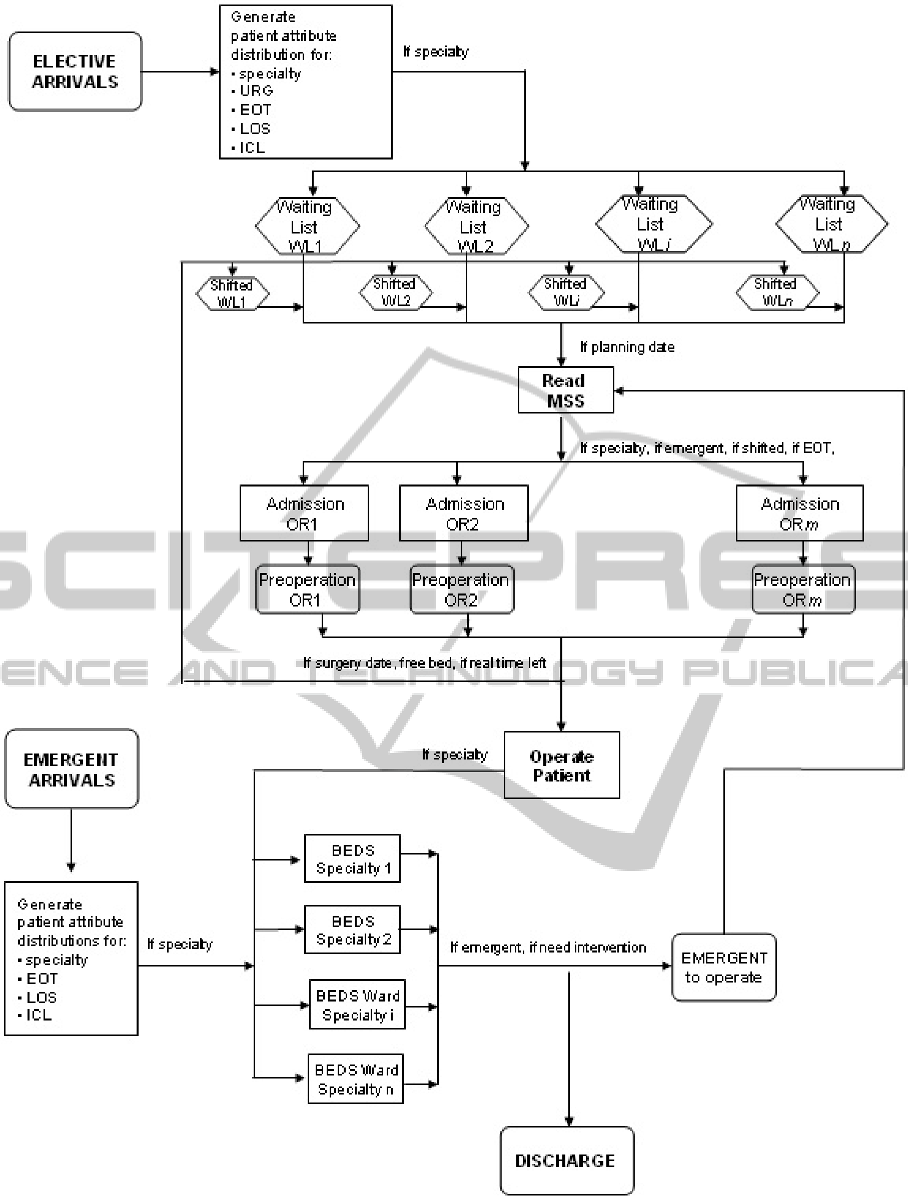

Figure 1: Traditional (“per specialty”) model.

Finally, after the intervention both elective and emergent patients stay in a bed for a given number of days, according to their length of stay, before being discharged.

2.2 Intensity of Care Model

Figure 2 shows the ICL model representing an alternative organization of the stay area with respect to the traditional model. This organization represents an important contribution to surgical therapeutic strategies, allowing an excellent compromise among safety, convenience for the patient, nurse workload organization and economic savings for health care structures.

The modifications with respect to the traditional model are intended to exploit all possible benefits coming from the “intensity of care” re-organization.

Elective patients arriving from outside world are registered into two different waiting lists created for low (WL low) and medium-high (WL M-H) patients, respectively.

The admission machine rules allow operating low ICL patients in the first days of the week to be able to discharge them before the week end. Both

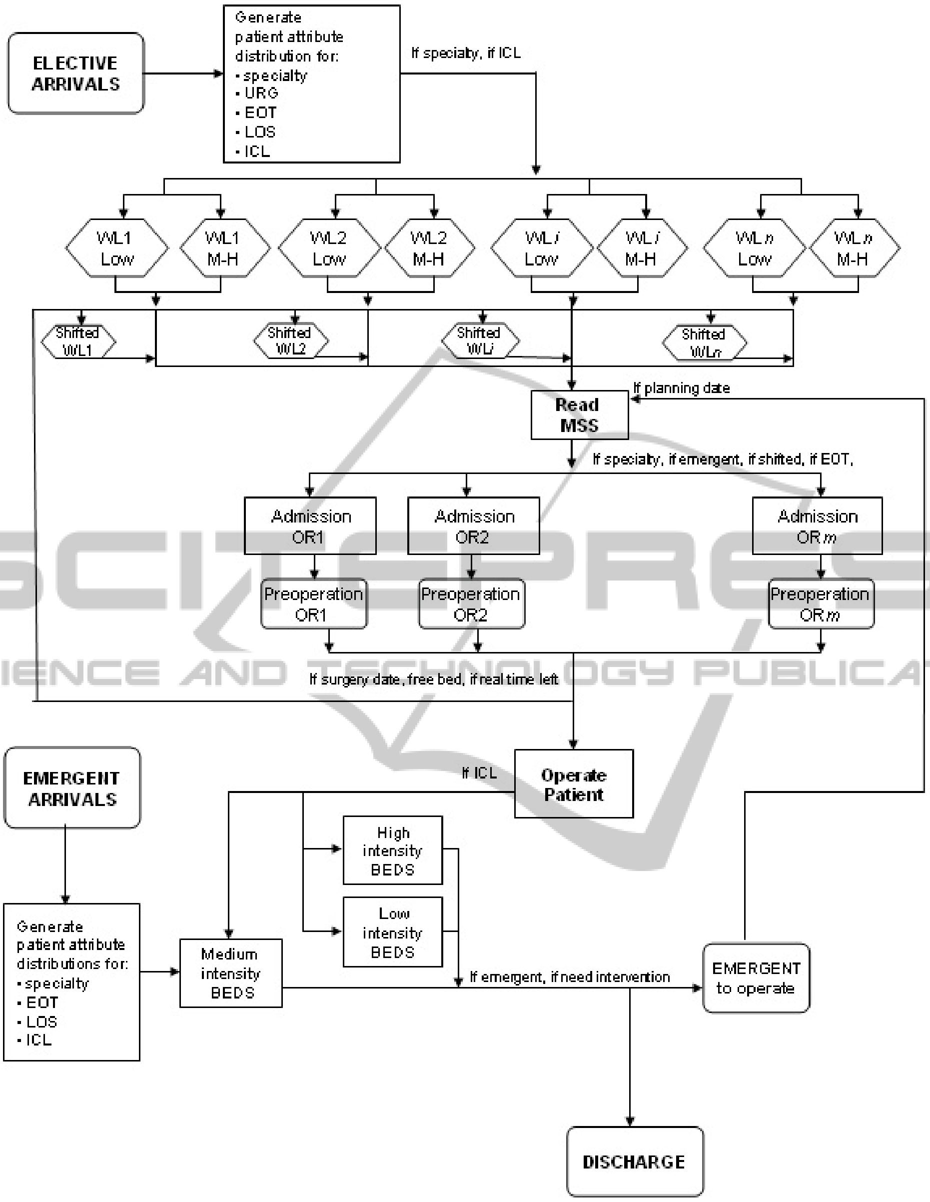

Figure 2: "Intensity of Care" (ICL) Model.

lists are ordered following the same prioritisation system of the traditional model. In the first two days of the week (Monday and Tuesday) the admission machines read the MSS and first check for each OR and day if there are emergent or shifted patients to be operated on. After, they verify if patients from the low ICL waiting list are present and only if there not patients belonging to the above described classes, medium-high patients are selected. In the other days of the week, patients with the highest priority among low, medium and high ICL patients are selected to be included in the Preoperation list of each OR block.

In the ICL model emergent patients coming from the ED stay into a medium ICL bed (pre-intervention stay) and, after being diagnosed, can be dismissed or included into the "Emergent to operated" buffer. Note that, have to be operated, they could change their ICL following the pathology assessment.

The main modification of the system behaviour regards the organization of the stay area. Beds are grouped into low, medium and high ICL areas. This organization impacts on the rule which manages the flow of patients (both elective and emergent) in the stay area after the surgical intervention. In particular, low ICL patients are directed to a Low Intensity bed, while patients that have a medium and high ICL are moved respectively to Medium and High Intensity beds. Note that, the Low ICL area closes during the week end and patients that are not dismissed before Saturday morning are moved into a medium ICL bed.

3 CASE STUDY AND DATA COLLECTION

The simulation model has been applied to analyse the patient flows into a General Surgery Department of the San Martino University hospital sited in Genova, Italy. In the department under study 7 specialties share the hospital resources, i.e. operating theatre and hospital stay beds. In particular, the operating theatre includes 6 ORs open, from 8 a.m. to 2 p.m., 5 days a week, for a total of 30 OR blocks available for surgery each week.

The OR scheduling strategy herein utilized is based on block scheduling, where the entire time slot belongs to the specialty which OR session is assigned by the MSS. The historical MSS is reported in Figure 3.

With reference to the stay area 105 beds are available for the post-intervention stay of patients and also for the pre-intervention stay of the emergent ones.

Day/OR	Mon	Tue	Wed	Thu	Fri
OR1	SS 1	SS 2	SS 4	SS 3	SS 2
OR2	SS 2	SS 1	SS 3	SS 2	SS 5
OR3	SS 3	SS 5	SS 1	SS 7	SS 4
OR4	SS 6	SS 4	SS 2	SS 3	SS 3
OR5	SS 4	SS 3	SS 3	SS 6	SS 1
OR6	SS 1	SS 7	SS 1	SS 4	SS 1

Figure 3: The Master Surgical Schedule.

The distribution of beds among surgical specialties is reported in Table 1.

One year of patient data collection has been carried out, through the collaboration of the hospital department under study. For all patients we collected the whole set of characteristics necessary to generate the distribution functions to manage the flow of patients through the system.

Table 1: Number of beds available for each surgical specialty.

Surgical specialty	# Beds available
SS1	19
SS2	21
SS3	25
SS4	18
SS5	7
SS6	9
SS7	6
TOTAL	105

The collected data were sorted and various statistics were derived using statistical modelling package, such as SAS System, to estimate the inter-arrival time distribution function for each specialty and to obtain the empirical distributions of SS, EOT, LOS and ICL attributes.

The patient inter-arrival times of each surgical specialty are generated following NegExp distributions with mean value defined in Table 2.

Table 2: Mean values inter-arrival times.

Surgical specialty	Mean
SS1	9.2
SS2	12.0
SS3	10.5
SS4	12.7
SS5	30.0
SS6	33.3
SS7	40.0

The patient distribution of the ICL attribute among the specialties is shown in Figure 4.

Note that, the highest percentage of patients belongs to medium and low ICL, while high intensity patients represent a small ratio.

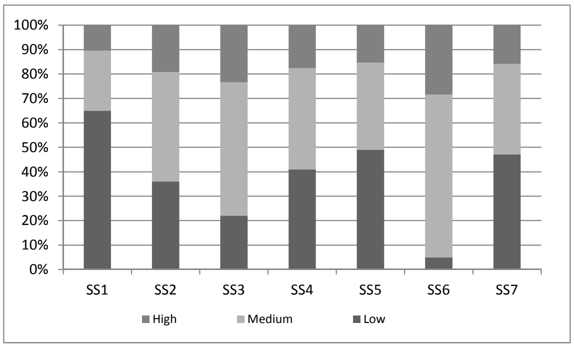

Figure 4: Distribution of High, Medium and Low ICL patients for each specialty.

In Figure 5 are depicted the LOS empirical frequency distributions for the elective patients belonging to the three ICLs. Low ICL patients usually have a LOS less to five days and rarely consume few days outside the first week. High and medium ICL patients have longer LOS (between one week and two weeks), with most likely values of 10 and 11 days, respectively.

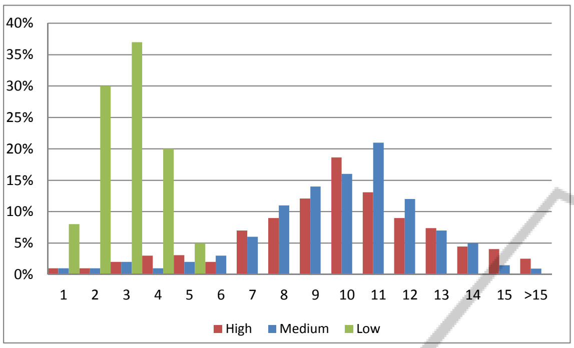

Figure 5: Elective LOS distributions (in days) by each ICL.

Emergent patients have different LOS distributions from the elective ones and they occupy a bed also before the intervention (pre-operation stay). The rationale of this behaviour becomes from the clinical need of surgeons to perform preliminary diagnosis evaluation in order to assess if they need or not an intervention.

The histograms depicted in Figure 6 show the empirical distributions of the LOS for emergent patients operated and not operated. Usually if the patient should not be operated, he/she is dismissed by the hospital within 5 or 6 days, otherwise he/she occupies a bed for at maximum two weeks.

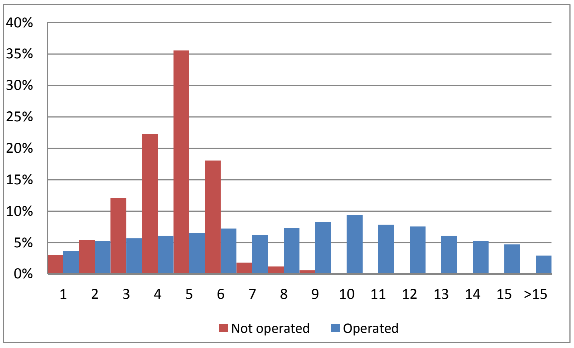

Figure 6: LOS distributions (in days) for emergent patients operated and not operated.

Finally, the distributions of the patient EOT and URG are shown in Figure 7 and 8. Also for these attributes the distributions used differ with respect to the specialty to which patients belong to, even if some similarities among specialties have been observed.

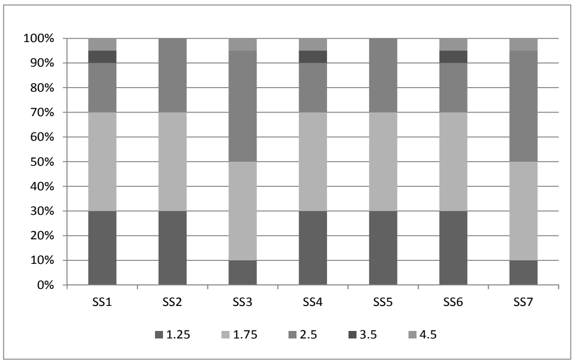

Figure 7: Patient EOT distributions (in hours) for each surgical specialty.

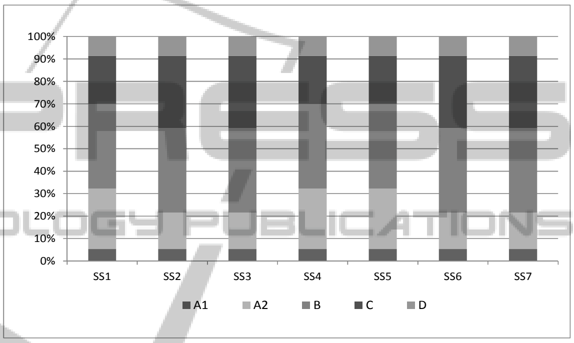

Figure 8: Patient urgency distributions for each surgical specialty.

4 VALIDATION AND SCENARIOS ANALYSIS

Once the discrete event simulation model has been implemented in WITNESS simulation software (Witness, 2012), it has been validated to ensure its ability to represent the real system case study under investigation.

During the models development and after their implementation and running a face validation (Law 2007) has been performed with the clinicians and nurses of the department to verify the overall behaviour and the rules introduced for both the traditional and ICL model. The personnel involved gave us many insights to adapt the model to the current practice and render it a truer representation of the real system. Afterwards, the "traditional" simulation outputs have been compared to the real measures under investigation by adopting appropriate validation tests (Law, 2007). After a one year warm up, we compare the number of patients operated by each specialty simulation output, obtained by 10 IID replications one year length, with the real collected values. We used the t-Test for testing the null hypothesis H_0 under a probability of rejecting the model fixed to the α=0.05 level, obtaining for all specialties a value inferior to the critical value.

The discrete event simulation models have been used to analyze the effects on system behavior of the proposed re-organization of the stay area. Besides, the optimization module integrated in the simulation software environment has been applied in order to determine the optimal decision pertaining the number of beds to assign to each ICL area following the intensity of care re-organization.

For the output analysis we used a set of performance indexes able to assess the performance of the system and the resource (OR and beds) utilizations and bottlenecks by different point of views.

The ORs activity is measured by the number of patients operated during the period. The OR utilization rate measures whether OR blocks, which are the most costly resources of the hospital, are exploited as much as possible. The index is computed as the average ratio between the real occupation and the OR block length for all blocks. The number of shifted patients, could be considered, in some sense, an index of equity of the OR activity measuring the percentage of patients planned to be operated on and then shifted, i.e. rescheduled in other days.

Finally, the stay area performance is assessed by the bed utilization rate. Note that in the ICL model the utilization rate is computed separately for beds devoted to low, medium and high intensity stay and as average for the whole department (overall).

4.1 Optimization Settings and Results

In order to run the ICL model a decision must be taken about how many beds, among the 105 currently available in the Department, should be assigned to each ICL area. To find the best combination of these variables we run the "Optimizer" module, embedded in Witness, using as objective function the number of patients operated.

Two optimization settings have been evaluated which differ on the range of values fixed for each variable, i.e. lower and upper bounds on the number of beds for each ICL area (Table 3). At this stage we just take the preliminary hypothesis under study at the Department which provides us the data, but many other range value combinations could be tested and compared. A total capacity constraint has been included which forces the total number of beds used to be less than, or equal to, the maximum number of beds available.

To carry out the optimization process we choose the "Adaptive Thermostatistical Simulated Annealing (SA)" algorithm. This algorithm is based on traditional simulated annealing methodology and incorporates adaptive cooling and reactive thermostatistical search. We set the maximum number of consecutive moves without improvement at 300, thus obtaining the maximum number of constrained scenarios to be evaluated reported in the last row of Table 3.

Table 3: Optimization parameters settings and scenarios.

	ICL Model [Setting 1]	ICL Model [Setting 2]
# beds LOW	[15-35]	[15-35]
# beds MEDIUM	[55-75]	[45-65]
# beds HIGH	[15-35]	[15-35]
Total beds	<=105	<=105
# of constr. scenarios to be evaluated	286	711

The one-year length steady state computational results, obtained with a one-year warm up and 10 IID replication runs, are reported in Tables 4 and 5.

Table 4: Optimization results.

	ICL Model [Setting 1]	ICL Model [Setting 2]
Best scenario	27-55-23	27-51-23
Total number of beds	105	101

In particular, in Table 4 the best scenario, i.e. the number of beds for each ICL level, and the total number of beds used are reported, while in Table 5 the output measures obtained with the traditional model and the ICL ones, are reported and compared.

The best scenario has been obtained by using the optimization setting 2 and corresponds to assign, respectively, 27, 51 and 23 beds to high, medium and low ICL stay areas.

Moreover, for both optimization settings herein evaluated, the ICL model overlaps the traditional one with respect to all performance measures computed. Introducing the "intensity of care" organization improves the activity indexes, not only for the number of patients operated and OR utilization rate, as expected, but also improves the performance of the stay area. Dismissed patients and bed utilization rates increase as a consequence of the

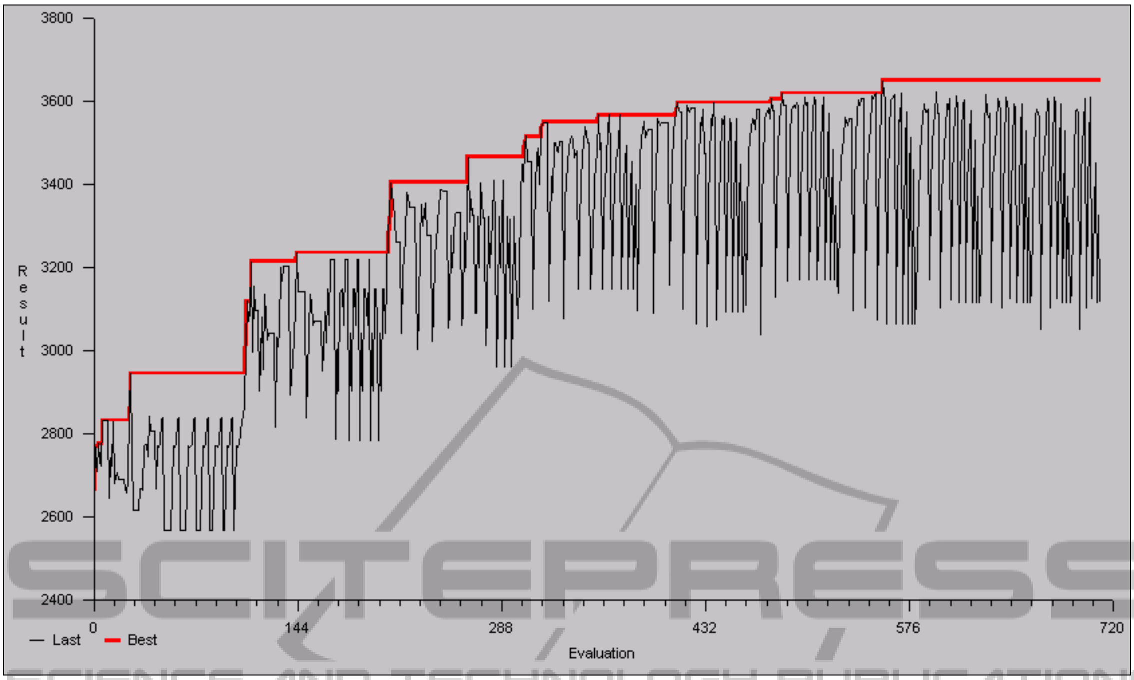

Figure 9: Objective function value obtained during the optimization run.

Table 5: Traditional and ICL models comparison.

	Tradit. Model	ICL Model [Setting 1]	ICL Model [Setting 2]
# operated .	3244	3619	3649
# shifted	869	735	717
OR utiliz. rate	75.6	85.9	84.8
# dismissed	3418	3793	3821
Bed utiliz. rate (high ICL)	/	63.5	63.4
Bed utiliz. rate (medium ICL)	/	69.6	72.1
Bed utiliz. rate (low ICL)	/	71.9	74.3
Bed utiliz. rate (overall)	64.8	66.8	68.5

performance of the stay area. Dismissed patients and bed utilization rates increase as a consequence of the increased throughput. Note that the overall utilization rate passes from 64.8 (traditional model) to 68.5 (ICL model [Setting 2]) as a direct effect of this re-organization. More importantly the bed utilization of the different ICL areas are balanced, thus allowing an efficient human resources workload organization within the stay areas. In addition, the number of shifted patients decreases.

As a further analysis, in Figure 9 the values of the objective function for each evaluation of the ICL model [setting 2] are plotted, while in Table 6 the performance measures of the best 20 scenarios are reported and compared.

The SA optimization algorithm starts to explore the scenarios with less high ICL beds and for each value of this variable, changes the number of medium and low beds, respectively. Note that, by increasing the number of high ICL beds until 27 greater objective function values are obtained. The best solution is reached at evaluation 557 and corresponds to 3649 operated patients, afterwards no more improvement can be obtained.

From the analysis of the set of output measures of the 20 best solutions, it appears that the decision tool here presented allows quantifying the performance of the system for several scenarios by means of a multidimensional evaluation. In fact looking at the total number of beds used it can be noted that comparing the best scenario with scenarios 486, 549 and 630, only 99 beds are used instead of 101, even if less patients are operated. While, if we focus on the beds utilization rates, the scenarios with 25 high ICL beds (502, 509 and 515) allow a better bed balancing utilization even if 3609 patients are operated instead of 3649.

The DES models, together with the use of some optimization methods, allow assessing how the re-organization can impact on system behaviour as well as finding a set of “good” solutions with respect to different performance measures. The optimal solution greatly depends on the case study analysed.

Table 6: Best 20 scenarios output analysis.

Evaluat.	Obj_funct (operated patients)	Total # of beds used	High ICL beds	Medium ICL Beds	Low ICL beds	# dismissed patients	# shifted patients	OR utilization rate (%)	Bed utiliz. rate % (High)	Bed utiliz. Rate % (Medium	Bed utiliz. rate % (Low)
486	3619	99	25	49	25	3768	745	84.439	65.945	75.894	68.002
502	3609	101	25	53	23	3765	746	84.020	70.986	69.634	70.901
509	3609	103	25	55	23	3765	746	84.020	70.986	67.102	70.901
515	3609	105	25	57	23	3765	746	84.020	70.986	64.747	70.901
549	3611	99	27	49	23	3785	749	84.159	61.357	75.653	72.419
551	3615	103	27	49	27	3772	735	84.321	62.401	78.405	60.382
552	3619	105	27	49	29	3776	741	84.272	63.209	76.405	56.297
557	3649	101	27	51	23	3821	717	84.810	63.332	71.841	74.399
558	3618	103	27	51	25	3784	698	84.393	68.364	70.466	67.558
565	3614	105	27	53	25	3794	723	84.180	63.32	70.044	67.277
570	3619	105	27	55	23	3793	735	84.252	62.969	69.42	71.933
595	3623	101	29	47	25	3782	705	84.641	58.045	79.229	65.374
604	3607	105	29	49	27	3758	753	84.005	57.611	75.212	62.13
609	3613	103	29	51	23	3781	759	84.107	57.494	73.268	73.208
630	3614	99	31	45	23	3761	764	84.330	57.782	78.821	72.181
638	3607	101	31	47	23	3774	740	83.963	54.096	80.1	71.228
644	3608	101	31	49	21	3796	696	84.257	57.308	76.587	75.867
673	3607	103	33	47	23	3774	740	83.963	50.818	80.1	71.228
678	3609	103	33	49	21	3765	757	83.890	52.077	74.104	80.994
700	3607	105	35	47	23	3774	740	83.963	47.914	80.1	71.228
704	3609	105	35	49	21	3765	757	83.890	49.101	74.104	80.994

Moreover, the framework could be used as a decision support system, to quantify the costs and benefits of different re-organization strategies and their impact on system performance.

5 CONCLUSIONS

In this paper we develop a decision support framework to analyze patient flows inside a hospital surgery department, taking advantage both from simulation and optimization ability to support decisions. The framework has been applied to a real case study of a Surgery Department sited in Genova (Italy).

The main aim is to evaluate the effects on the department system performance of differentiating stay areas with respect to the level of assistance needed by patients. In this organization, which follows the so called "intensity of care" paradigm, stay beds should be grouped by complexity of assistance, rather than be associated to specialties as it is in the current practice.

The results of the optimization analysis performed with the "Optimizer" module are presented.

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 each re-organizational strategy.

Of course the model is quite general and other patient characteristics and flows, as well as structure and system constraints implying different organizational models, could be included.

Future research can be devoted to explore the effects of introducing different objective functions, such as maximizing the utilization bed rate, minimizing shifted patients or detecting the best mix between bed and OR availability. Moreover, a deeper analysis is still necessary in order to compare a larger set of variable combinations as well as quantify the sensitivity of the solutions to parameter settings.

ACKNOWLEDGEMENTS

The authors acknowledge support from the Italian Ministry of Education, University and Research (MIUR), under the grand FIRB n. RBFR081KSB. The authors wish to thank the staff of General Surgery Department of the San Martino and in particular, Giancarlo Torre, Gianluca Ansaldo and Emanuela Varaldo, for providing data and helping in model implementation and validation.

REFERENCES

Akkerman R., Knip M., 2004. Reallocation of beds to reduce waiting time for cardiac surgery. *Health Care Management Science* 7(2), 119-126.

Berwick D. M., Hackbarth A. D., 2012. Eliminating Waste in US Health Care, *JAMA* 307(14), 1513-151.

Bowers J., Mould G., 2004. Managing uncertainty in orthopaedic trauma theatres. *European Journal of Operational Research* 154, 599-608.

Cardoen B., Demeulemeester E., 2008. Capacity of Clinical Pathways - A Strategic Multi-level Evaluation Tool. *Journal of Medical Systems* 32(6), 443-452.

Cochran J. K., Bharti A., 2006. Stochastic bed balancing of an obstetrics hospital. *Health Care Management Science* 9(1), 31-45.

Cardoen B., Demeulemeester E., Beliën J., 2010. Operating room planning and scheduling: A literature review. *European Journal of Operational Research* 201(3), 921-932.

De Blaser L., Depreitere R., De Waele K., vanhaecht K., Vlayen J., Sermeus W., 2006. Defining pathways. *Journal of Nursing Management* 14, 553-563.

Everett J. E., 2002. A decision Support Simulation model for the management of an elective surgery waiting system. *Health Care Management Science 5, 89-95.*

Gunal M. M., 2012. A guide for building hospital simulation models. *Health Systems* 1, 17–25

Harper P. R., Shanani A. K., 2002. Modelling for the planning and management of bed capacities in hospitals. *The Journal of the Operational Research Society* 53(1), 11-18.

Harper P. R., 2002. A framework for operational modeling of hospital resources. *Health Care Management Science* 5(3), 165-173.

Jacobson S. H., Hall S. N., Swisher J. R., 2006. Discrete Event Simulation of Health Care Systems. In *Hall R.W. (eds.) Patient Flow: Reducing Delay in Healthcare Delivery, pp. 211-252. International Series in Operations Research and Management Science,* Vol. 91. Springer, New York.

Lagergren M., 1998. What is the contribution of models to management and research in health services? A view from Europe. *European Journal of Operations Research* 105(2), 257-266.

Law M. A., 2007. Simulation Modeling & Analysis. *McGraw-Hill*, 4th ed.

Major S., 2007. New approach to surgical care aims to improve recovery and reduce length of hospital stay. *British Medical Journal* 334(7598), 816-817.

Maliapen M., Dangerfield B. C., 2010. A system dynamics-based simulation study for managing clinical governance and pathways in a hospital. *Journal of the Operational Research Society 61, 255–264*.

Ratcliffe J., Young T., Buxton M., Eldabi T., Paul R., Burroughs A., Papatheodoridis G., Rolles K., 2001. A simulation Modelling Approach to evaluating alternative policies for the management of the waiting lists for liver transplantation. *Health Care Management Science* 4, 117-124.

Sciomachen A., Tanfani E., Testi A., 2005. Simulation models for optimal schedules of operating theatres. *International Journal of Simulation* 6, 26-34.

Swisher J., Jacobson S., Jun J., Balci O., 2001. Modeling and analyzing a physician clinic environment using discrete event-event (visual) simulation. *Computers & Operations Research* 28, 105-125.

Tànfani E., Testi A., 2012. A decision support tool to analyze Clinical Pathways in hospital. In *Advanced decision making methods applied to Health Services – Series on Operations Research and Management Science*, pp. 191-211, Vol. 173. Springer- Verlang, Milano

Testi A., Tànfani E. Torre G., 2007. A three-phase approach for operating theatre schedules. *Health Care Management Science* 10,163–172.

Testi A., Tanfani E., Valente R., Ansaldo G., Torre G.C., 2008. Prioritising surgical waiting list. *Journal of Evaluation in Clinical Practice* 14(1), 59-64.

Tuft S., Gallivan S., 2001. Computer modelling of a cataract waiting list. *British Journal of Ophthamology* 85, 582-585.

Valente R., Testi A., Tanfani E., Fato M., Porro I., Santori G., Santo M., Ansaldo G., Torre G.C., 2009. A model to prioritize access to elective surgery on the base of clinical urgency and waiting time. *BMC, Health Services Research* 9(1). doi: 10.1186/1472-6963-9-1.

VanBerkel P. T., Blake J. T., 2007. A comprensive simulation for wait time reduction and capacity planning applied in general surgery. *Health Care Management Science* 10(4), 373-85.

Vissers J. M., Adan I. J., Dellaert N. P., 2007. Developing a platform for comparison of hospital admission systems: An illustration. *European Journal of Operations Research* 180(3), 1290-301.

Witness (2012). User guide. Lanner Group, London, UK