SIMULATION MODELS FOR OPTIMAL SCHEDULES OF OPERATING THEATRES

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Abstract: In this work discrete event simulation models developed in Witness are discussed and used to evaluate performance indices of interest related to the scheduling of operating theatre activities for surgical departments; in particular the attention is focused on the wards' productivity in terms of utilization rate, throughput and overruns. The first model reproduces the behaviour of the operating theatre and tunes the parameters. Subsequently, alternative operative scenarios are proposed by comparing the actual time table and schedule with that obtained by using a blocked booking criterion for the weekly scheduling of the surgery rooms. The sequencings of the surgical activities are analysed according to different priority rules, derived from the classical scheduling theory. In the analysis the possibility of introducing the so-called "pre" and "post" recovery room is considered with respect to the activity level of the department. The computational results presented in the paper are related to a one-year simulation horizon for the surgical department of a hospital located in Genoa, Italy.

Keywords: Discrete event simulation, performance evaluation, scheduling, operating theatre.

1. INTRODUCTION AND PROBLEM DEFINITION

In the recent literature on operations management and decision science, discrete event simulation has been well recognized to be the most suitable tool for the evaluation of healthcare systems management, particularly those related to hospitals, where direct experimentation is too costly and almost impossible to pursue [Jun et al., 1999].

An important advantage of simulation in the healthcare area concerns the potential of models to be used as a discussion and communication tool among the different actors involved in the decision-making and planning processes. Moreover, simulation offers the opportunity of evaluating whether the reallocation of the existing resources or changes in the organisation can result in a performance improvement, while examining alternative scenarios for the effective application of additional resources.

In particular, discrete event simulation has been largely used in studies dealing with capacity planning in healthcare services and management [Groothuis et al., 2001; Kim et al., 1999; Ratcliffe et al., 2001]. Some researchers have used simulation to compare different strategies to schedule patients admission dates [Tuft and Gallivan, 2001], or to calculate how future activity levels may affect waiting list behaviours [Cromwell and Mays, 1999].

However, to the authors' knowledge, only few works dealing with the use of simulation for operating theatres are reported in the recent literature. Among them, a practical and efficient simulation model to support scheduling decisions concerning patients' waiting time 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. Harper (2002) develops an integrated simulation model for the planning and management of operating theatres, beds and workforce needs, and Davies (1994) uses simulation to compare scheduling policies in a cardiovascular disease clinic.

In this work the simulation package Witness 2004 [Witness, 2004], which is a flexible and visual-interactive software environment, is used to model the behaviour of the operating theatre of an university surgical department of a public hospital located in Genoa, Italy. More precisely, discrete event simulation models are developed to assess alternative operative scenarios having in mind the maximization of the operating theatre productivity; the aim is to evaluate different performance indices of interest, such as surgery rooms utilization rate, average number of operations carried out and number of overruns.

Since the aim of a schedule for the operating theatre is to optimally manage the time assigned to every surgeon, in this work the reduction of the costs due to both unused operating time and delays are taken into proper consideration; note that the scheduled operations performed outside the allocated time greatly impact the cost for staff overtime.

In the present analysis the actual timetable is compared to the one obtained by solving the Integer Programming (IP) model proposed in [Sciomachen et al., 2005] and, subsequently, the sequences of surgical activities arising from different scheduling rules are analysed; in particular: a) the longest waiting time (LWT), b) the longest processing time (LPT) and c) the shortest processing time (SPT) rules are considered. In the proposed scheduling procedure a blocked booking criterion for the surgery room allocation is used, and a fixed weekly timetable, denoted master schedule, is defined, which is considered and applied, whenever it is possible, over the entire simulation horizon, i.e. a one-year period. Moreover, in the evaluation of the alternative scheduling policies, the changes in performance resulting from the introduction of the so-called "pre" and "post" recovery room, with respect to the activity level of the department, are analysed.

This paper is organised as follows. Section 2 is devoted to the description of the surgical department under investigation, together with the design and implementation of the simulation models. In Section 3 the experimentation framework is presented, while in Section 4 the steady state simulation results relative to a one-year simulation horizon are reported. Finally, some conclusions and an outline for future work are presented.

2. DESCRIPTION OF THE SYSTEM AND SIMULATION MODEL CONSTRUCTION

The department under consideration consists of five wards that share the same operating theatre, including three surgery rooms. For confidentiality, let w_1, w_2, w_3, w_4 and w_5, respectively, denote such wards. The surgical department organizes its working time according to a weekly time schedule; in particular, ward w_i (i = 1, .., 4) has access to one of the three surgery rooms for two to five mornings per week, depending on the number of patients in the corresponding waiting list. Since a surgery room is assigned to ward w_5 every afternoon, in the following only the organisation and planning of the morning sessions, from 8 a.m. to 2 p.m. will be considered, without taking into account the requirements of w_5. Note that, the morning operating sessions of each surgery room last for at least six hours, but can become longer as a consequence of possible complications arising during the scheduled operations. Due to the pre-assignment of a surgery room to ward w_5 in the afternoon, the delays of the morning sessions, referred to as overruns, have to be reduced and, consequently, some operations may need to be shifted to a later day. Note that in this paper non-elective patients are not considered since they are treated separately as they follow an urgent procedure in a dedicated operating theatre.

In order to develop the simulation models, the layout of the department is first analysed to reproduce its dynamics into the Witness environment and graphically represent it in the display window, as it is shown in Figure 1.

Patients are considered as entities of the simulation models. Each patient entity has three attributes associated with it representing its clinical status, denoted as *c*, its expected length of operating time, denoted as EOT, and its updated waiting time *t*.

In all the simulation models the surgery rooms have been represented by three identical machines, denoted SR_1, SR_2 and SR_3, respectively, which are characterised by the same input / output rules; the pre and post recovery room that will be considered for the scenario analysis is represented as a buffer of unit capacity.

The waiting list is modelled by a buffer of infinite capacity, while the operation list is a buffer of maximum capacity fixed to 7. Wards w_1, w_2, w_3 and w_4 are modelled as machines and move patients from the waiting list to the operation list; machines are displayed together with their associated icons representing the corresponding patients.

Staff and personnel (e.g. nurses) are also modelled as machines that move patients from the operation list to the surgery room. Before a patient is drawn from the operation waiting list the model verifies whether the expected length of operating time for the first patient to be admitted is larger than the time available for the programmed operating session; if that is the case the patient is rejected and the operation is delayed until a later day, i.e. he/she returns to the waiting list and his/her operation will be scheduled for a later session.

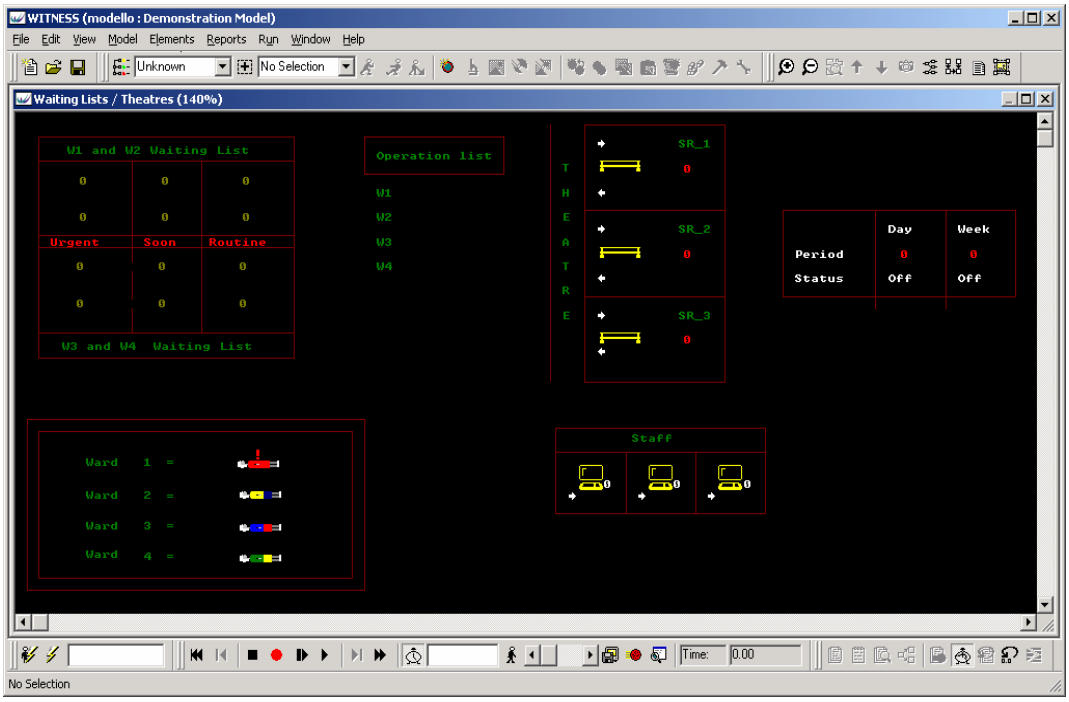

Figure 1. Witness implementation of the surgical department

To give an idea of how the patient admissions are managed in the proposed simulation models, an example of how the rules that regulate the admissions to surgery room SR_1 are implemented in the Witness environment is reported below.

IF SRav ≥0 AND ISTATE (SR_1)=0
MATCH/CONDITION (SRav + EOT ≤ 6)
Operation_list_1 #(1)
ELSE
Push to Waiting_list1
Shift = Shif +1
ENDIF

where "SRav" indicates the hourly capacity of the programmed operating session, and "ISTATE" is a function expressing the status of the machine, such that, for instance, if ISTATE is equal to zero it means that the machine, i.e. the surgery room, is empty; finally, "Shift" is an integer variable tracking the number of patients shifted to later sessions.

Note that the queuing discipline of the waiting list is based on clinical prioritisation, which allows to establish an explicit admission rule distinguishing between "urgency" and "priority" [Kee et al., 1998]. In particular, the attribute "urgency" is attached to a single patient according to his/her clinical condition at the time of referral; the urgency status is hence an attribute assigned when the patient joins the list and remains constant over time, unless the patient's conditions worsen, thus changing his/her clinical status. The attribute "priority", instead, is a value that represents the relative position of each patient in a given surgical waiting list at any moment. As in [Testi and Tanfani, 2004], in this paper it is assumed that patients should be admitted with the highest value of the priority score P, that is determined for each patient by equation (1) on the basis of the urgency status c and the elapsed waiting time t, expressed in days.

$$P = c \cdot t \qquad (1)$$

In particular, the urgency status c is given by the sum of the numerical values of three clinical criteria, i.e. progress of disease (α), pain or dysfunction (β) and disability (γ). Note that t must be included in order to avoid that lower-urgency cases could become first in the queue list even if higher urgency cases are still waiting [Mullen, 2003].
Each clinical criterion may assume values ranging from 0 to 4, according to the evaluation scale stated by the Department's surgeons, while the weights given to each criterion reflect the relative contribution of each criterion to the total priority score, i.e. 3, 0.5, 0.5 for progress of disease, pain or dysfunction and disability, respectively. The clinical status c is hence given by:

$$c = 3 \cdot \alpha + 0.5 \cdot \beta + 0.5 \cdot \gamma \qquad (2)$$

From (2) it follows that the value of *c* ranges from 0 to 16, while the priority score value ranges from 0 to sixteen times the elapsed waiting time of the longest waiting patient. Moreover, the priority score increases proportionally with time and the speed at which the priority score increases depends on the urgency status *c*; this allows patients to proceed in the list according to the urgency of their condition and gain different relative priorities even when the waiting time is the same.
Consequently, the queue discipline is not based either on the waiting time, that is the FIFO logic, or on its clinical status, that is the Urgency logic, but on how much each day spent in the list affects its clinical conditions, that is the Pioritisation lofic. Since the chosen queue discipline is based on the maximum value of P, computed according to equation (1), the first patient in the waiting list to be operated will be that having with the highest value of priority score.

When a patient is called by the ward to be operated he/she leaves the corresponding waiting list and joins the operation list. The sequencing rule adopted to create the operation list is based on the processing time of each patient. In particular, in the actual clinical practice the longest surgical operations are performed first, that is the LPT rule is applied. Note that this queuing rule allows to reduce the overtime for each overrun, that is the average overrun time is reduced; however, as shown later, it results in a larger number of overruns and operations that have to be delayed and moved to a later day.

The data used to develop the simulation models have been collected through the hospital (theatre) information system and are representative of the total working time of all wards for a whole year. Let T be such a twelve- month period. More precisely, the input data collected for this work are:

1- arrival time of patients joining the waiting list of ward w_i, i = 1, …, 4;
2- number and types of monthly operations performed in ward w_i, i = 1, …, 4;
3- clinical status c and expected operating time EOT of each operation performed in ward w_i, i = 1, …, 4;
4- duration of each operation performed in ward w_i, i = 1, …, 4, including the pre and post surgical operation time, i.e. anaesthesia and awakening;
5- surgical waiting list of ward w_i, i = 1, …, 4, at the starting point of period T.

The patient inter-arrival times in all wards are exponentially distributed with means varying depending on the day and season. Moreover, the probability density function of the urgency status *c* for the patients belonging to each ward has been observed to follow the normal distribution, as it is depicted in Figure 2 in the case of ward 3.

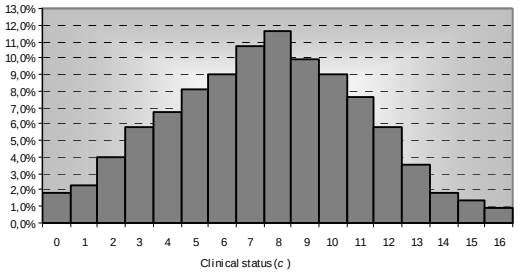

Figure 2. Clinical status (c) probability density function of patients belonging to ward 3

Data related to patients' arrivals of each ward are preprocessed in such a way that they are grouped into homogeneous classes according to the estimated length of operation time. For instance, in ward w_3 there are 15 classes having EOT of 20, 40, 60, 80, 100, 120, 140, 160, 180, 200, 220, 240, 260, 280 and 300 minutes, respectively. Starting from the number of operations belonging to each class of duration for a particular ward their relative frequencies are calculated to build a distribution, as shown in Figure 2 for ward 3; The resulting distributions have been represented as empirical probability distributions available in the Witness software environment as "Elements" of the model (Figure 3).

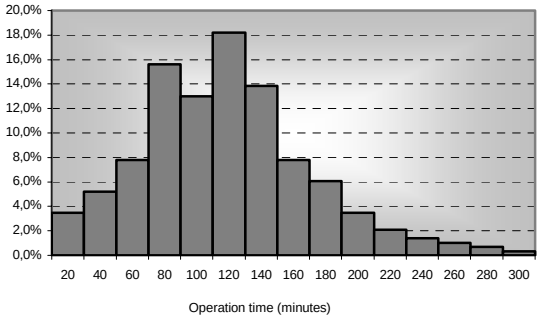

Figure 2. Expected operation time (EOT) distribution of patients belonging to ward 3

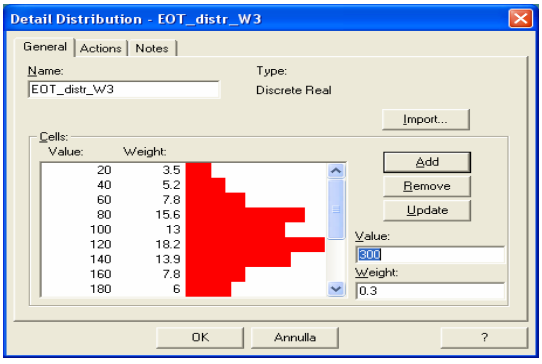

Figure 3. Witness implementation of the EOT distribution

The effective processing time of the patient entities includes the actual duration of the surgical operation, the preparation, the anaesthesia and the awakening times together with the room cleaning and set-up times. This represents the total duration of the operation performed and is indicated as LOT. Starting from the available data related to the time period T, for each list it is possible to derive the effective processing time of the patients (see Figure 4).

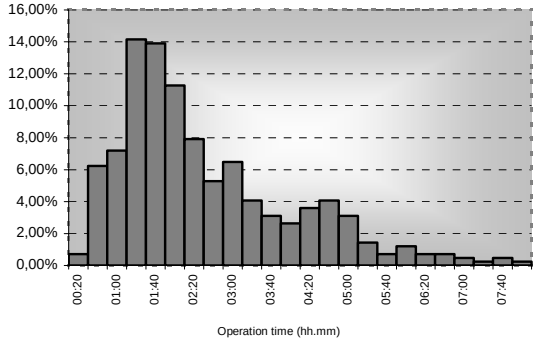

Figure 4. Effective operating time (LOT) distribution of patients belonging to ward 3

In particular, for each ward the list of all operations and their effective duration, LOT, are considered; then, the probability density function of the variations in operation time with respect to the corresponding EOT is determined according to a best-fit approach. More precisely, different distribution functions have been evaluated by applying the classical Chi-square and Kolmogorov - Smirnov tests and, subsequently, for each case the one that best reproduces the observed behaviour has been chosen [Law and Kelton, 2000]. Note that this implies that different distribution functions are obtained depending on both the ward and the class.
An example of distribution function for the variations in operating time is reported in Table 1, where the 32 operations belonging to the fifth EOT class (i.e. 120 minutes) of ward w_2 and the corresponding LOT are considered together with their deviations from the expected values (in minutes see Figure 5).

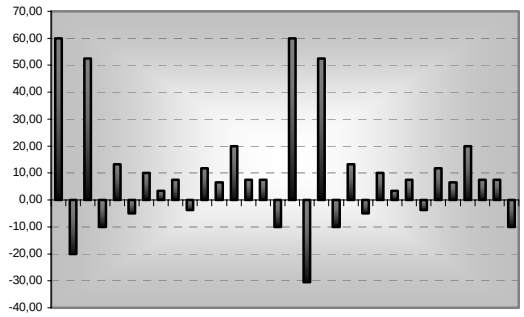

Figure 5. Example of distribution of the operating time variations

W2 - EOT class 120: Input data					
Patient ID	LOT	Variation	Patient ID	LOT	Variation
1	180,00	60,00	17	180,00	60,00
2	100,00	-20,00	18	89,50	-30,50
3	172,50	52,50	19	172,50	52,50
4	110,00	-10,00	20	110,00	-10,00
5	133,30	13,30	21	133,30	13,30
6	115,00	-5,00	22	115,00	-5,00
7	130,00	10,00	23	130,00	10,00
8	123,30	3,30	24	123,30	3,30
9	127,50	7,50	25	127,50	7,50
10	116,25	-3,75	26	116,25	-3,75
11	131,66	11,66	27	131,66	11,66
12	126,60	6,60	28	126,60	6,60
13	140,00	20,00	29	140,00	20,00
14	127,50	7,50	30	127,50	7,50
15	127,50	7,50	31	127,50	7,50
16	110,00	-10,00	32	110,00	-10,00

Table 1. Variations between expected and effective operating time

3. SCENARIO ANALYSIS

For the purposes of the present research four different discrete-event simulation models have been developed. The first model, denoted Mod.1, has been implemented to reproduce the actual behaviour of the surgical department, including the morning time schedule (from 8 a.m. to 2 p.m.) that is reported in Table 2; Mod.1 could hence be considered as a test bed for the correctness of the model. Subsequently, Mod.2 has been developed from Mod.1 to represent the behaviour of the department when a new proposed Master Surgical Schedule (MSS) - derived from Sciomachen et al. (2005), also reported in Table 4 - is applied. Finally, Mod.3 and Mod.4 consider the above hypothesis of master schedules in the presence of a pre and post recovery room.

	Mod.1 and Mod.3				
Room	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**
SR1	W2	W2	W2	W3	W3
SR2	W1	W1	W1	W1	W1
SR3	W3	W4	W3	W4	W2
	Mod.2 and Mod.4				
Room	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**
SR1	W3	W4	W3	W4	W3
SR2	W1	W1	W1	W1	W1
SR3	W2	W1	W4	W2	W2

Table 2. Morning time table for Mod.1 , Mod.2., Mod.3 and Mod.4.

Note that, the proposed MSS solution is based on a two-phase approach aimed at assigning more sessions to the wards having bigger "relative demand" of operating sessions. In particular, the relative demands of each ward are updated each week based on previous allocations to the waiting list.

The MSS reported in Table 2 are related in all cases, that is for Mod.1-Mod.4, to the system configuration with respect to the input data collected for the simulation models. In particular, while the schedule used in Mod.1 and Mod.3 is fixed and iteratively used on a weekly basis, the proposed MSS used for Mod.2 and Mod.4 refers only to the first simulated week and it is updated and modified depending on the size of the waiting lists of the corresponding wards during the simulation run.

Further analysis has been focused on testing different scheduling rules applied to the above mentioned models, such as: a) the longest waiting time (LWT), b) the longest processing time (LPT) and c) the shortest processing time (SPT). Note that, in the Witness environment it is possible to manage the queue discipline directly by the "detail" window of the operation list; in particular, it is possible to use as output rule either the default one, that is FIFO, or a rule based on the maximum or minimum value of the EOT attribute.

Because the aim of the present simulation study is to compare the performance indices of interest for the examined scenarios in the steady-state condition, a preliminary simulation run to clean out the transient period has been executed [Rubinstein and Melamed, 1999; Kleijnen, 1995]. More precisely, the warm-up time has been fixed to T = one year. To obtain the steady state conditions the batch means method [El-Darzi et al. 1998] has been used, based on a 10 years single run of data collection, which has been divided into 10 batches of length T (one-year). In particular, each batch represents 360 days of steady state simulation. After the warm-up period, i.e. transient simulation, the statistics of the model have been cleaned and, without resetting the clock, the model has been run starting from the end of the warm-up period for 10 years. The output variables for each batch have been sampled and the mean of the performance indices obtained in the 10 batches has been calculated. The decision of using 10 sampling batches is due to the results of the initial simulation experiments, that revealed a relatively small variance in the system output.

The indices used to evaluate the scenarios are:

- number of operations performed in time T (i.e. one year);
- number of patients in the waiting list at the end of the study period T;
- number of delayed operations;
- number of overruns;
- utilization rate of the operating theatre by the wards.

Some indices, such as the number of operations performed and the number of patients in the waiting list at the end of the study period, i.e. the simulation run, are automatically averaged and computed by the model and reported onto an output file named "steady-state statistics". In order to be able to derive the number of overruns and delayed operations two integer variables have been created. The first variable is interactively updated when the surgery room, that is the machine, works overtime to terminate an operation; the other variable records the number of delayed operations and increases if at the end of the shift some of the scheduled patients are still waiting in the operation list.

Finally, with respect to the last index, only the real utilization rate of the operating theatre by each ward has been computed with respect to its assigned time, that is established by the given time table. This performance index is hence given by:

$$\sigma_i = \frac{\overline{Z_i}}{Z_i} 100 \qquad \forall i \tag{3}$$

where $\overline{Z_i}$ and Z_i are the total effective time used by ward w_i (computed in the simulation runs) and the total time available to w_i during time period T derived according to the master surgical schedule.

4. COMPUTATIONAL RESULTS

The first comparison has been performed between models Mod.1 and Mod.2. The values of the performance indices in both cases are reported in the left side of Table 3. As it can be observed, Mod.2 gives better results in terms of number of operations performed and number of overruns. In particular, by using the flexible MSS proposed in [Sciomachen et al., 2005] the size of the waiting list for the whole department is reduced to 187 patients, instead of 242, while the average number of overruns during the same period is 184, instead of 205. However, it is worth mentioning that following the LPT sequencing rule used by the department under investigation in both cases the utilization rate is very high, that is 89,8% and 89,5%, respectively.

Ward	*# Operations*	*Waiting list*	*# Overruns*	*Utilisation rate*	*Ward*	*# Operations*	*Waiting list*	*# Overruns*	*Utilisation rate*
Mod.1					**Mod.3**				
W1	652	126	85	93%	W1	714	61	64	80%
W2	320	25	44	85%	W2	345	0	33	72%
W3	390	56	50	92%	W3	429	17	38	76%
W4	257	35	26	89%	W4	293	2	20	75%
TOT	*1619*	*242*	*205*	*89,8%*	*TOT*	*1781*	*80*	*154*	*75,8%*
Mod.2					**Mod.4**				
W1	685	90	80	92%	W1	754	22	60	78%
W2	310	35	48	88%	W2	345	0	36	76%
W3	408	38	41	90%	W3	446	0	31	74%
W4	271	24	15	88%	W4	295	0	11	74%
TOT	*1674*	*187*	*184*	*89,5%*	*TOT*	*1839*	*22*	*138*	*75,5%*

Table 3. Performance indices

The results reported in the right part of Table 3 are related to Mod.3 and Mod. 4 and are obtained by introducing a recovery room where patients stay before and after their operation. It can be easily observed that in these cases the number of operations performed improves noticeably: it increases from 1619 to 1781 in Mod.1 and Mod.3 and from 1674 to 1839 in Mod. 2 and Mod 4, respectively. Moreover, the waiting list at the end of the examined period decreases in all wards (Mod.3).

As a further improvement it can be noted that when the proposed MSS is adopted (Mod.4) it is also possible to empty the waiting lists in w_2, w_3 and w_4; in fact, the MSS reported in Table 2 and used in Mod.2 and Mod.4 is designed to give higher priority to the wards having greater queue length. Such results come together with a reduction of the average utilization rate of the operating theatre from 89.8% to 75.8% and from 89.5 % to 75.5%, respectively, as it is shown in Figure 6.

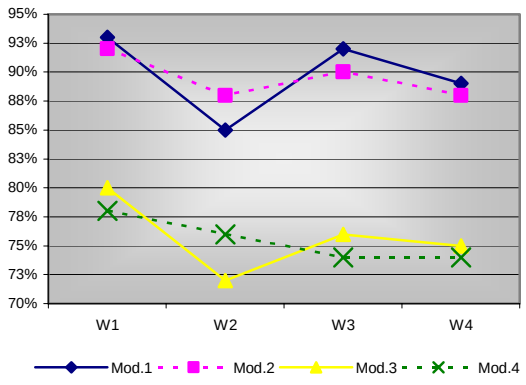

Figure 6. Comparison of the ward utilisation rate

Moreover, note that the average yearly number of overruns, that in the first model is 205, is reduced to 138 in model Mod.4, that is the last one, thus resulting in noticeable cost savings for the hospital department as shown in Figure 7.

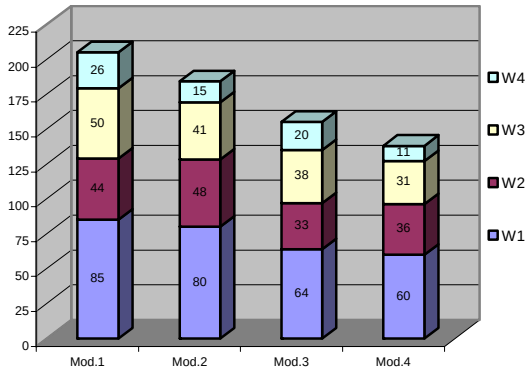

Figure 7. Comparison of the number of overruns

Note that the introduction of the recovery room implies on one side a reduction of the costs due to the overruns, while, on the other a reduction of the operating theatre utilisation rate and, consequently, a cost for the unused operating theatre time. Moreover, starting from Mod.4 it could be possible to think of a new surgery rooms' allocation strategy aimed at reducing their under utilisation.

Finally, further analysis has been performed aimed at evaluating the impact of different sequencing rules on the above performance indices. On the basis of the steady state simulation results related to ward 1 as reported in Table 4, it is possible to conclude that the chosen sequencing rule does not substantially change either the number of operations or the average waiting time.

Rule	*# Operations*	*# Overruns*	*Overruns' time*	*# Shifted*	*Ultilisation rate*	*Rule*	*# Operations*	*# Overruns*	*Overruns' time*	*# Shifted*	*Ultilisation rate*
Mod.1						**Mod.3**					
LWT	620	83	2010	334	94%	LWT	679	62	1513	227	81%
LPT	652	85	2384	235	93%	LPT	714	64	1795	160	80%
SPT	662	37	1676	208	82%	SPT	725	28	1262	142	71%
Random	648	81	2261	242	91%	Random	710	61	1702	165	78%
Mod.2						**Mod.4**					
LWT	651	78	1892	270	93%	LWT	717	59	1419	171	79%
LPT	685	80	2244	190	92%	LPT	754	60	1683	120	78%
SPT	696	35	1577	168	81%	SPT	765	26	1183	106	69%
Random	681	76	2128	196	90%	Random	749	57	1596	124	76%

Table 4. Comparison of different sequencing rules applied to Ward 1.

On the contrary, the sequencing rule affects the completion times of the weekly operations scheduled and consequently the number of operations that have to be delayed until the next day. In fact, as it has already been pointed out, the LPT rule actually applied in the department under observation allows to reduce the overtime for each overrun but on the other side increases the number of overruns and operations that have to be shifted with respect to the SPT rule. Moreover, the selection of the SPT rule results in a noticeable reduction of the number of operations to be completed overtime and hence gives better performance as far as the number of completed operations.
Note that the application of the SPT rule in the actual operative scenario (Mod.1) results in a 54% reduction of the number of overruns that move from 85 to 37 and of the total overruns' time that is reduced to 1676 minutes. Moreover the reduction of the average utilisation rate is only about 10%.

5. CONCLUSION

In this paper discrete event simulation models have been developed to reproduce the behaviour of an university surgical department and compare alternative operative scenarios in terms of surgery rooms utilization rate, average number of operations and number of overruns. In particular, a blocked booking criterion for the weekly scheduling of the surgery rooms is compared to the actual time schedule considering the impact of the presence of the so-called "pre" and "post" recovery room.

The results of steady state simulation experiments show that by using the flexible master surgery schedule the size of the waiting list for the whole department and the average number of overruns are reduced by about 25% and 10%, respectively.

Moreover, the introduction of the recovery room seems to be very very promising since a noticeable improvement in terms of overruns reduction and number of operations performed has been observed.

In a second set of computational experiments different sequencings of the surgical activities are analysed according to alternative classical priority rules. As a first comment, it is possible to say that the longest processing time (LPT) rule results in a larger reduction of the overtime for each overrun than that obtained by using the shortest processing time (SPT) rule; however, the LPT increases the number of overruns and operations that have to be delayed. The selection of the SPT rule increases the number of completed operations. Note that the selection of the SPT rule in the actual operative scenario allows to reduce the number of overruns by approximately 54% and the total overrun time by 30% with against the LPT rule, while the reduction of the average utilisation rate is only about 10%.

On the basis of the proposed results it seems that further investigation is still required, especially aimed at verifying different timetables that could consider, for instance, a blocked booking shorter than one week, for instance two days, which is expected to provide greater flexibility in the utilization of the surgery rooms by the different wards.

Future directions of the research will be focused on studying the possible re-allocation strategies of the surgery rooms with the aim of reducing the cost for the unused operating theatre time (reduction of the average utilisation rate) when the recovery room is introduced.

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