A Hybrid Model for the Analysis of a Surgical Pathway

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Abstract: In this paper we focus our attention on the analysis of a surgical pathway from a patient-centred point of view. The main concern of this work is the introduction of some optimization modules in the management of the most critical resources in a surgical pathway, that is the stay beds and the operating rooms, and to evaluate their impact with respect to a set of patient– and facility– centred indices. We propose a hybrid simulation and optimization model: simulation is used in order to generate a real situation with respect to the inherent stochasticity of the problem while optimization is used to take the best decisions in different points of the surgical pathway.

1 INTRODUCTION

The current development of the health care systems is aimed to recognize the central role of the patient as opposed to the one of the health care providers. In this context, Clinical Pathways (CPs) shift the attention from a single health benefit to the health care chain that starts to resolve the illness episode. They can be defined as "health-care structured multidisciplinary plans that describe spatial and temporal sequences of activities to be performed, based on the scientific and technical knowledge and the organizational, professional and technological available resources" (Campbell et al., 1998).

The aim of a care pathway is to enhance the quality of care by improving patient outcomes, promoting patient safety, increasing patient satisfaction, and optimizing the use of resources as stated by the European Pathway Association. Moreover, while many papers show that, appropriately implemented, CPs have the potential to increase patient outcome, reduce patient length of stay and limit variability in care, thereby yielding cost savings (Rotter et al., 2010), little attention has been dedicated to study how CP can optimize the use of resources.

In this paper we focus our attention on the analysis of a surgical pathway from a patient-centred point of view. The main concern of this work is the introduction of some optimization modules in the management of the most critical resources in a surgical pathway, that is the stay beds and the operating rooms, and to evaluate their impact with respect to a set of patient- and facility- centred indices.

Our approach is a hybrid simulation and optimization model. Simulation is used in order to generate a real situation with respect to the inherent stochasticity of the problem while optimization is used to take the best decisions in different points of the surgical pathway. Accordingly to (Magerlein and Martin, 1978), we consider the operative decisions concerning the advanced scheduling and allocation scheduling of patients. Furthermore we consider the real time management of the operating room planning.

The aims are to reduce the waiting list according to a prioritized admission system, to operate patients within a given time limit depending on their level of urgency, to improve the utilization of the above critical resources and to minimize the number of cancellations. The results show an evident improvement of the patient-centred indicators without deteriorating the facility-centred ones.

The paper is organized as follow. Section 2 briefly review the literature regarding the problem under consideration. The problem is depicted in Section 3 while the integrated simulation and optimization model is discussed in Section 4. Model validation and its main results are discussed in Section 5 and Section 6, respectively. Section 7 closes the paper.

2 LITERATURE REVIEW

A CP can be conceived as an algorithm based on a flow chart that details all decisions, treatments, and

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reports related to a patient with a given pathology, with a logic based on sequential stages (De Bleser et al., 2006). A CP is therefore ”the path” that a patient suffering from a disease walks in the National Health System. This pathway can be analysed at a single, local level of care (a single hospital, or a single region) or globally, taking into account every level of health-care from education and prevention, to diagnosis of diseases, treatment and recovery. CPs are specifically tailored to stimulate continuity and coordination among the treatments given to the patient through different disciplines and clinical environments. For this reason, they can be considered an operational tool in the clinical treatment of diseases, from a patient-focused point of view (Panella et al., 2003).

As already discussed in the introduction, little attention has been dedicated to study how CP can optimize the use of resources. The few papers dealing with the CP resource optimization are reviewed in (Aringhieri et al., 2012) to which the reader can refer to deepen this topic. In the remaining of the section, we briefly report the literature concerning the optimization solutions applied to the operating room planning.

In the international literature there is a large number of papers dealing with the OR planning problem. (Cardoen et al., 2010; Guerriero and Guido, 2011) have recently published exhaustive literature reviews on the operating room planning and scheduling problem classes, analysing in detail multiple fields related to the problem settings and summarizing significant trends in research areas of future interest.

Problems arising in the OR planning and scheduling are usually classified into three phases corresponding to three decision levels, that is strategic (long term), tactical (medium term) and operational (short term) (Testi et al., 2007). Here, we take into account the last phase – “surgery process scheduling” – which is generally separated into two sub-problems referred to as “advanced scheduling” and “allocation scheduling” (Magerlein and Martin, 1978). The first sub-problem consists in assigning a specific surgery and OR time block to each patient over the planning horizon, which can range from one week to one month (Ozkarahan, 2000; Guinet and Chaabane, 2003; Lamiri et al., 2008; Fei et al., 2008; Hans et al., 2008; Marques et al., 2012; Rizk and Arnaout, 2012). Given this advanced schedule, the second subproblem then determines the precise sequence of surgical procedures and the allocation of resources for each OR time block and day combination (Pham and Klinkert, 2008; Cardoen et al., 2009; Roland et al., 2010; Riise and Burke, 2011; Herring and Herrmann, 2012; Meskens et al., 2013) in order to implement it as efficiently as possible. Approaches dealing with more than one planning level simultaneously are quite rare (Jebali et al., 2006; Testi et al., 2007; Tànfani and Testi, 2010).

When dealing with uncertainty, literature usually considers three main issues, that is the arrival of patients (see, e.g.,(Lamiri et al., 2008; M et al., 2009)), the variability of patient length of stays (see, e.g., (Beliën and Demeulemeester, 2007; Adan et al., 2011; Herring and Herrmann, 2011)) and the variability of patient operating times (see, e.g., (Hans et al., 2008; Min and Yih, 2010; Tànfani et al., 2010; Batun et al., 2011; Shylo et al., 2013)). Methodologies adopted ranges from montecarlo simulation to sample average approximation, from probabilistic and chance constraints programming to stochastic programming with recourse. Some authors use simulation to compare different scheduling and sequencing strategies and test the solution robustness against the randomness of surgery duration (Testi et al., 2007; Persson and Persson, 2010; Sobolev et al., 2011).

3 PROBLEM STATEMENT

We consider the problem of managing a single surgical pathway taking into account the optimization problems arising when dealing with the decision levels concerning the advanced and the allocation scheduling. In order to guarantee the execution of such decisions, we deal with the real time management of an operating room planning. It consists in a sort of centralized surveillance system whose main task is to supervise the execution of the planning and, in the case of delays, to take a decision regarding the patient cancellation or the overtime assignment.

The definition of the surgical pathway is inspired to that presented and analysed in (Ozcan et al., 2011) for the thyroid surgical treatment. The reader can refer to this paper for further details. From a management point of view, a surgical pathway can be seen as made up of three phases.

The first phase concerns the *pre-admission phase* and it is related to all the activities regarding the patients before the admission as depicted in Figure 1.

A Diagnosis Related Groups (DRG) defines a general time limit before which the patient should be operated on. In our context, a *Urgency Related Group* (URG) is assigned to each patient belonging to the same DRG: the URG states a more accurate time limit. In other word, URG allows to define a partition of the patients in such a way to prioritize their surgical intervention. The optimization problem arising in this

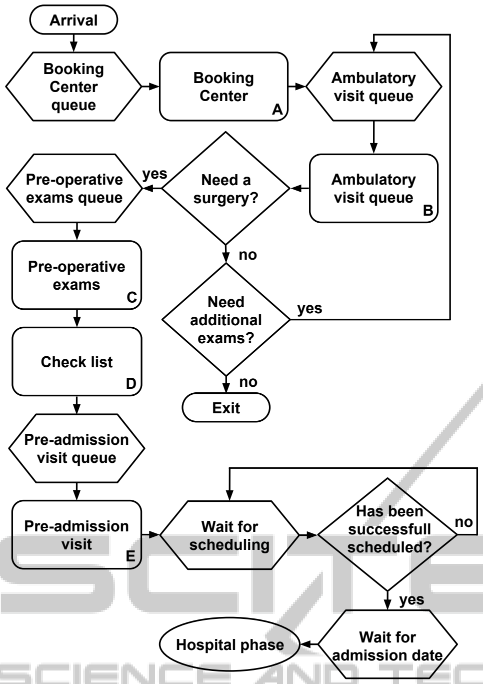

Figure 1: Pre-admission phase flowchart.

phase – the advanced scheduling problem – is that of selecting patients from the (usually long) waiting list and to assign them to an *OR session* (i.e., an operating room on a given day) in such a way to satisfy several operative constraints (number of beds available during the patient stay, total time available for the OR session, and so on). Our objective is to maximize the utilization of the operating rooms in each day in such a way to guarantee that each patient is operated within the time limit defined by the URG. This problem is well known in literature as Surgical Case Assignment Problem (SCAP) (Tànfani and Testi, 2010).

The *hospital phase* is concerned with all the activities involving the admitted patient stay except for those related to the operating theatre as depicted in Figure 2. The relevant information in this phase is the Length Of Stay (LOS) of each patient, that is the number of days required before the discharge. The optimization problem arising in this phase – the allocation scheduling problem – is that of finding a sequence of patients to decide the order in which they are operated on. The objective is to minimize the risk of cancellation according to their assigned position in the sequence taking into account a patient-centred point of view (considering waiting time, class of urgency, possible previous referrals) with respect to the available operating time.

Figure 3 depicts the *operating theatre phase* which is a component of the hospital phase – as highlighted in Figure 2. Due to its importance in a surgical pathway, it requires to be treated separately. Patients assigned to a given OR session will be operated on following the sequence previously defined unless delays imposes to define a new sequence. Patient not operated on will be rescheduled. The optimization problem arising in this phase is the real time management of the operating room planning. When the *Estimated Operating Time* (EOT) differs from the *Real Operating Time* (ROT), we could have a delays. If such delays become significant, that is exceeding the total operating time allowed, the real time management should deal with the following possible decision to be taken every time a patient finish its intervention:

- to use some overtime reducing the total amount weekly available;
- to cancel 1 or more patients and to re-schedule them, if possible;
- to change the sequence of the remaining patients in order to minimize the number of cancellations.

The first two choices are generally non-trivial and alternatives requiring to consider several aspects. For instance, the decision of postponing a patient could violate the so called `Maximum Time Before Treatment` (MTBT) determined by its URG. Further, it determines an increased patient stay lowering the patient satisfaction and, by consequence, the quality of the service. These decisions have to take into account the inherent uncertainty. On the other side, overtime is a scarce resource. So, it seems crucial to establish some criteria driving the decisions of using it to avoid cancellations.

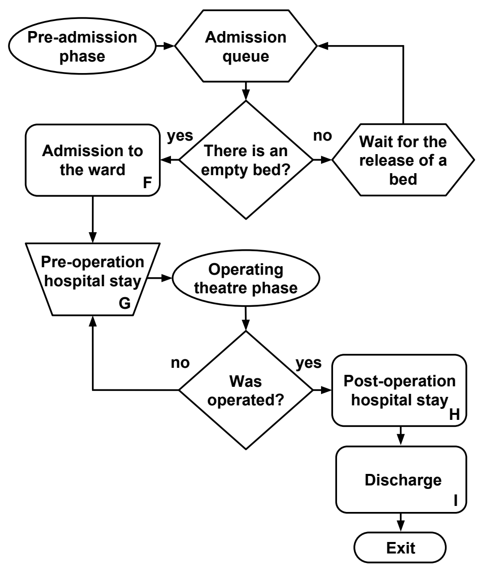

Figure 2: Hospital phase flowchart.

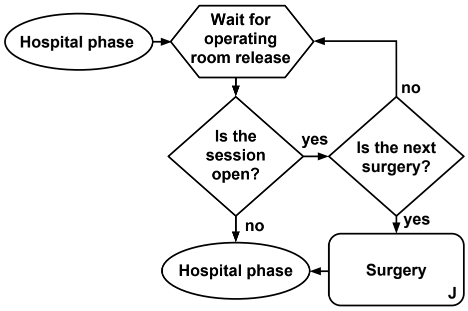

Figure 3: Operating theatre phase flowchart.

3.1 Notation

Let us introduce the notation of the problem used hereafter in the paper.

N: number of OR sessions,
S_j: duration of j-th OR session,
d_j: day of the week (from Monday to Friday) of the j-th OR session,
B_k: number of beds available the k-th day of the week ($k = 1, \ldots, 7$ such that $k = 1$ is Monday, $k = 5$ is Friday, $k = 7$ is Sunday),
I: set of patients in the pre-admission waiting list,
L: set of scheduled patients,
$L^{(j)}$: set of patients scheduled into the j-th OR session,
t_i: waiting time of the i-th patient,
M_i: MTBT of patient i,
e_i: EOT of patient i,
r_i: ROT of patient i,
ℓ_i: LOS of patient i,
Ω: weekly overtime available.

4 THE HYBRID MODEL

This section discusses the hybrid simulation optimization model proposed in this paper. Simulation allows to deal with the inherent stochasticity of the problem while optimization allows to deal with the three problems arising in the three phases depicted in Section 3. In the following, we will briefly describe the hybrid model through the description of its main components, that is the Discrete Event Simulation (DES) simulation framework and the three optimization modules.

Note that the hybrid model is implemented using AnyLogic 6.9 (Borshchev, 2013). The Enterprise Library is exploited for the implementation of the DES simulation framework whilst the optimization modules are implemented from scratch using Java exploiting the fact that AnyLogic is build on the top of an Eclipse platform.

4.1 The Simulation Framework

The simulation framework is based on a DES methodology. It is a straightforward implementation of the surgical pathway depicted in Figures 1, 2 and 3. The main parameters of the simulation model and their distribution are depicted in the Appendix.

4.2 The Advanced Scheduling Problem

As reported in Section 2, several approaches have been proposed. Here, we proposed a simple metaheuristic based on a greedy construction of an initial solution and then a local search to improve that solution. Note that we should take into account the fact that the resources available can be reduced since patients admitted the previous week are already in the hospital phase, usually waiting for the discharge but also for their surgical intervention.

4.2.1 Constructive Greedy Algorithm

The algorithm associates to each patient $i \in I$ the following values

$$w_i = \frac{t_i + \min_{1 \le j \le N} d_j}{M_i}, \quad (1)$$

$$\tilde{w}_i = \frac{t_i + \min_{1 \le j \le N} d_j + 7}{M_i} = w_i + \frac{7}{M_i}. \quad (2)$$

w_i measures the ratio of the time elapsed before the surgical intervention and the MTBT associated to the URG of the patient $i \in I$ whilst $\tilde{w}_i$ is the same meaning but referred to the next week.

Patients are ordered by decreasing value of w_i in such a way to promote the scheduling of those patients which are close to their MTBT. Then, each patient is considered for the scheduling. A patient will be inserted in the current schedule if there exist an OR session available with enough free operating time in such a way to satisfy the operative constraints regarding the bed occupation and the operating time S_j.

Among different possible OR sessions, the algorithm tries to schedule the patient first in a day k such that $k + \ell_i \le 5$. If it is not possible, the algorithm tries the insertion in a day k such that $k + \ell_i > 5$. The rationale here is to avoid the use of the weekend stay beds which are usually a limited resource. This rule can be overridden when $\tilde{w}_i \ge 1$ assigning the patient to the first day $k = 1$, if possible, or to the second day $k = 2$, and so on. In this case, we would like to reduce the probability to do not satisfy the URG requirements in case of cancellation.

Finally, if a patient cannot be scheduled, the algorithm will consider the next patient. The algorithm terminates when all patient are considered for the insertion in the schedule.

4.2.2 Improvement Local Search Algorithm

The Local Search tries to improve the solution computed by the greedy exchanging pairs of patients already scheduled in such a way to cluster them in a reduced number of OR sessions and, by consequence, to allow the insertion of new patients previously not scheduled. Le us consider the OR session j^* having the maximum operating time yet available, that is the one having the minimal utilization. The Local Search algorithm follows these criteria to select a new solution when exploring the neighbourhood:

- the new solution will be that providing the maximal increase of the time yet available of j^*;
- otherwise, if the two schedules are equivalent in j^*, the algorithm will considers the second one less utilized OR session, and so on;
- otherwise, if the two schedules are equivalent in all OR sessions, the algorithm selects those solutions having OR sessions less utilized at the end of the week.

4.3 The Allocation Scheduling Problem

In our settings, the allocation scheduling problem consists in establishing the order in which patients $i \in L^{(j)}$ will be operated on. For this reason, it is also called sequencing problem. The main objective is to minimize the inefficiency due to possible cancellations. Note that the real time management – depicted in Section 4.4 – will be devoted to the minimization of the number of cancellations, that is to minimize the number of patients re-scheduled due to a delay.

Considering a given schedule, there is a set of patients for which is better to avoid the cancellation of their surgical intervention, that is those patients whose $\tilde{w}_i$ is greater than or equal to 1 and those patients whose their intervention was already postponed. To deal with these special cases, let us introduce the following values:

$$W_i = \begin{cases} \tilde{w}_i & \text{if } \tilde{w}_i > 1 \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$

and $D_i > 0$ is the number of days elapsed after a cancellation, 0 otherwise. Finally, we define the value

$$s_i = \alpha_1 W_i + \alpha_2 D_i + \alpha_3 e_i \tag{4}$$

for each $i \in L^{(j)}$ where α are parameters. Setting

$$\alpha_1 \gg \alpha_2 \gg \alpha_3 = \begin{cases} 1 & \text{case (A)} \\ 0 & \text{case (B)} \end{cases},$$

the sequencing of patients $i \in L^{(j)}$ is simply obtained by ordering them by the decreasing order of the associated s_i.

The use of α imposes a three levels of priorities. First we schedule patients whose intervention was previously postponed, and then the others. Among those postponed, first we schedule those close to their MTBT and, in case of same value, those waiting for more days after the previous cancellation. Finally. when the first two components of s_i, that is $\alpha_1 W_i$ and $\alpha_2 D_i$, yield to the same value for two different patients, we break ties by ordering them following a LPT or a SPT policy (with respect to EOT) in the case (A) and in the case (B), respectively.

4.4 Operating Room Real Time Management

During the execution of the operating room plan, it could be happen that the EOT differs from ROT. When $r_i > e_i$, for a patient $i \in L^{(j)}$, the whole plan will be delayed. When the overall delay could determine the exceeding of the jth OR session duration S_j, the operating room real time management should deal with the problem of postponing an intervention or to use a part of the available overtime. Such a decision poses the problem of evaluating the impact of consuming overtime or to have a cancellation.

Let us consider the jth OR session on day $k = d_j$ having duration S_j and a list $L^{(j)}$ of scheduled and sequenced patients. We suppose that $m < \left|L^{(j)}\right|$ patients are already operated on. Let ρ_m the effective time elapsed to operate on the m patients, that is

$$\rho_m = \sum_{i=i_1,\ldots,i_m} r_i. \tag{5}$$

Setting $\rho_m = t$, let us introduce the following parameter:

$$\beta_{kt}^{j} = \left(1 + \frac{N_k}{N} - \frac{\Omega_{kt}^{j}}{\Omega}\right) \tag{6}$$

where N_k is the number of OR sessions from the day after k and Ω_{kt}^{j} is the remaining overtime after the intervention of patient i_m.

The value β_{kt}^{j} would like to measure the overtime still available with respect to the number of OR sessions to be still performed. Actually, β_{kt}^{j} is closed to 1 when the overtime has been used proportionally; it is between 0 and 1 or it is greater than 1 when it is underused or overused, respectively. Because of N_k is equal to 0, we remark that the last day of the week it is always less than or equal to 1 hence promoting the use of overtime.

The real time management is activated whenever

$$\rho_m > \sum_{i=i_1,\ldots,i_m} e_i$$

after operating the last patient. After checking the sequencing of the remaining patients, the decision of postponing or assigning overtime could be taken.

The sequencing is checked in such a way to ensure that (i) all the remaining patients having $\tilde{w}_i > 1$ are scheduled prior to the other patients and (ii) those having $\tilde{w}_i > 1$ are ordered by decreasing value of $\tilde{w}_i$.

Let i_{m+1} be the next patient in the schedule. Then, if

$$e_{i_{m+1}} > S_j - \rho_m\,,$$

the patient i_{m+1} could incur in a cancellation. Therefore, the real time management algorithm checks if

$$\beta^j_{d_j,\rho_m}\left(\frac{e_{i_{m+1}}+\rho_m}{S_j}\right) \leq 1 \qquad (7)$$

and if (7) is satisfied, the required overtime is assigned to patient i_{m+1}.

Finally, we implemented an algorithm that runs at the end of the day and it is responsible to reschedule the next day all the postponed surgical interventions. The algorithm tries to insert an intervention with EOT e_i in the jth OR session planned in the next days in such a way to minimize the difference between S_j and the sum of the EOTs of the already assigned patients plus e_i. If an insertion is not possible, the patient will be scheduled next week.

5 MODEL VALIDATION

The validation of a simulation model requires a quite complex analysis. In our case, we are interested in the logical correctness of the simulation model representing the surgical pathway while we are not interested in the replication of a real system.

To this purpose, we adapted our simulation model to represent the inspiring case, that is that reported in (Ozcan et al., 2011). In that paper, the proposed model dealt with two patient flows having similar EOT but different LOS. Note that the LOS of the second flow is roughly the double of the first one while the number of patients in the first flow is roughly the double of the second flow. Since our model deals with only one patient flow, we adapted our patient flow generator in such a way to have, on average, the same number of patients having the LOS of the first flow which is the most numerous. Furthermore, we turn off all the optimization during the three phases. The other parameters are reported in the Appendix.

Let us introduce the following performance indices: u_{bed} is the bed utilization whilst u_{OR} is the OR session utilization. Table 1 reports the results of the comparisons with respect to the measures [1] of the system modelled in (Ozcan et al., 2011). Our results are the average value over those obtained by running the hybrid model 30 times with different starting conditions. Each of these computational experiments runs for a time horizon of 2 years but collecting data only in the second year.

Table 1: Model validation: comparison with real measures.

	$u_{\textbf{bed}}$	$u_{\textbf{OR}}$
Real measures	51.10%	77.33%
Simulation model	49.10%	80.82%
Difference	2.00%	3.49%

The differences in the two performance indices can be accounted to the different composition of the patient flow as depicted above. For instances, the gap of 3.49% for u_{OR} expressed in minutes corresponds to the execution of an intervention having average duration. On the basis of these considerations, the comparison is satisfactory with respect to our objective, that is the validation of the logical correctness of our simulation model.

6 IMPACT OF THE OPTIMIZATION

In this Section we would like to evaluate the impact of the optimization modules integrated in the simulation model. To this purpose, we need to define a *baseline configuration* with respect to the three phases as follows:

Phase 1: advanced scheduling performed by a first-fit algorithm, that is (i) consider patients by decreasing order of w_i, (ii) place a patient in the first OR session available from Monday to Friday;

Phase 2: patients are sequenced in a random order;

Phase 3: overtime is assigned *a priori* uniformly to all OR sessions;

Phase 3: interventions rescheduled only at the end of the day using a first-fit algorithm.

The simulation parameters are depicted in the Appendix.

[1] Taken from the presentation made by the authors at the ORAHS 2012 conference.

Table 2: Performance indices for each test configurations.

Option(s)							Performance indices							
id	1	2	3	seq.	A	B	C	$f_{\mathbf{MTBT}}$	$I_{\mathbf{avg}}$	$t_{\mathbf{avg}}$	$U_{\mathbf{bed}}$	$U_{\mathbf{OR}}$	$w_{\mathbf{avg}}$	$w_{\mathbf{max}}$
(0)	baseline configuration						234 (2348)	32.63%	338	55	63.61%	89.88%	1.17	4.05
(1)	$\surd$						235 (2347)	31.85%	346	56	60.20%	89.78%	1.11	3.29
(2)	$\surd$	$\surd$					226 (2340)	25.97%	360	58	60.57%	89.32%	1.16	3.27
(3)			$\surd$				252 (2346)	35.95%	324	52	60.35%	89.60%	1.12	3.61
(4)	$\surd$		$\surd$				246 (2349)	35.34%	330	53	60.26%	89.78%	1.06	3.41
(5)	$\surd$	$\surd$	$\surd$				230 (2338)	27.17%	355	58	60.79%	89.55%	1.17	3.10
(6)				LPT			236 (2367)	47.85%	292	48	60.52%	90.76%	1.03	3.79
(7)				SPT			240 (2261)	12.14%	452	72	58.57%	86.35%	1.51	4.91
(8)					$\surd$		197 (2384)	74.62%	213	35	59.26%	91.34%	0.80	2.64
(9)						$\surd$	236 (2315)	30.70%	339	55	72.56%	88.79%	1.18	3.79
(10)					$\surd$	$\surd$	222 (2372)	72.97%	223	37	64.16%	90.65%	0.83	2.68
(11)			$\surd$	LPT	$\surd$		239 (2389)	79.91%	192	32	60.27%	91.75%	0.73	2.62
(12)	$\surd$		$\surd$	LPT	$\surd$		248 (2390)	85.53%	207	34	60.58%	91.78%	0.71	1.87

6.1 Test Configurations and Performance Indices

Here we define the various configurations we used to evaluate the impact of the optimization tools. Each configuration is defined with respect to the baseline configuration previously defined.

- **Phase 1**:
  option 1: computing w_i w.r.t Monday instead of the previous Friday;
  option 2: adopting the greedy depicted in Section 4.2.1 (instead of the first-fit algorithm);
  option 3: adopting the Local Search depicted in Section 4.2.2;
- **Phase 2**:
  LPT/SPT: use LPT or SPT rules in sequencing (case (A) or (B) in Section 4.3);
- **Phase 3**:
  option A: adopting real time management after each interventions;
  option B: adopting the algorithm depicted in Section 4.4 for rescheduling patients at the end of the day (instead of the first-fit algorithm).

Finally, we introduce all the performance indices used in the following analysis, that is the patient-centred indices:

C: number of cancellations,
$f_{\mathbf{MTBT}}$: percentage of patients operated within the MTBT,
$I_{\mathbf{avg}}$: average length (number of patients) of the waiting list,
$t_{\mathbf{avg}}$: average waiting time spent in the waiting list,
$w_{\mathbf{avg}}$: average value of patient's w_i at the time of their surgery,
$w_{\mathbf{max}}$: maximum value of patient's w_i at the time of their surgery,

and the facility-centred indices:

$u_{\mathbf{bed}}$: bed utilization,
$u_{\mathbf{OR}}$: OR session utilization.

It is quite evident that different indices can affect each other. For instance, the increase of the number of cancellations can affect the bed utilization and, in its turn, can reduce the percentage of patients operated within the MTBT. Our aim is to identify a test configuration which increases the patient-centred indices without deteriorating the facility-centred ones.

6.2 Quantitative Analysis

As reported for the model validation, the reported results are the average value among those obtained by running the hybrid model 30 times on a given configuration and, each time, starting from a different initial condition.

First, the impact of each optimization modules is evaluated through the quantitative analysis. Based on these results, two further configurations are studied. The results of such analysis are summarized in Table 2 which reports the value of the performance indices for each test configurations denoted by the value in the first column "id". Note that the column reporting the number of cancellations also reports in brackets the total number of patients operated on. All the analysis are compared with the baseline configuration.

Regarding the impact of the advanced scheduling optimization module, we can observe a lower waiting time in the waiting list and an improvement of the performance indices related to MTBT in test configurations (3) and (4). On the other side, the minimal number of cancellations is obtained with configuration (2) but, at the same time, the percentage of patients operated on before their MTBT decreases consistently. Note that the use of Local Search allows to insert more patients determining the improvement measured in (3) and (4).

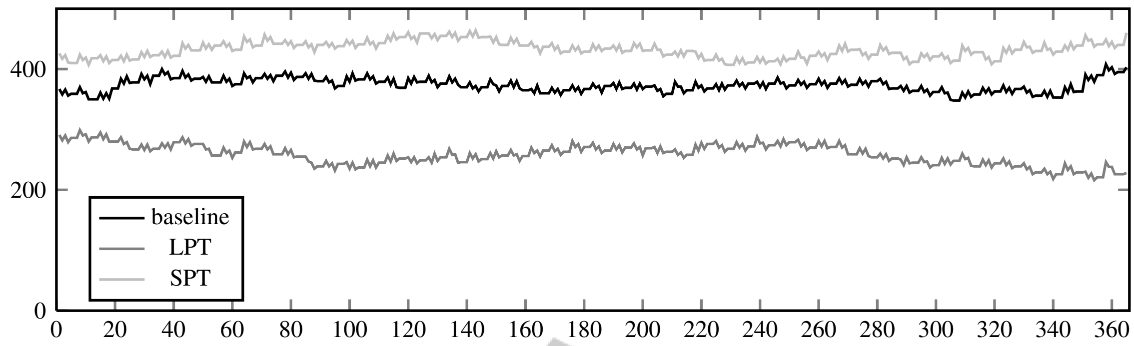

Figure 4: Trend of I_{avg} (data referred to the 2nd year, days on x-axis, patients on y-axis).

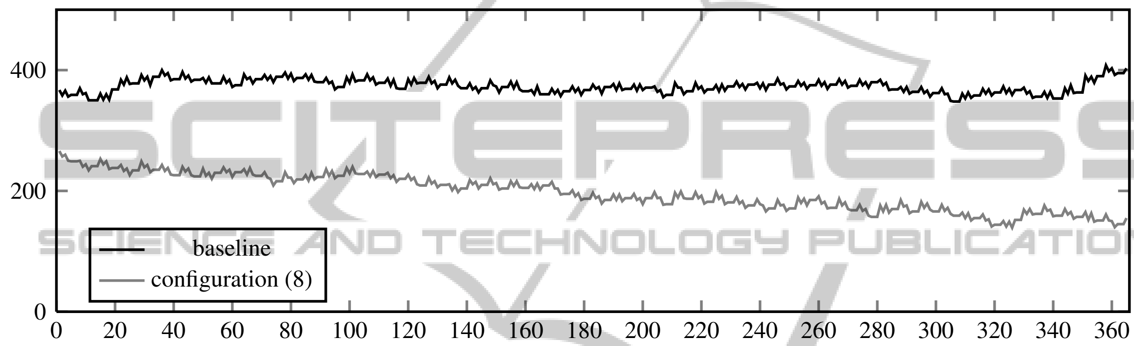

Figure 5: Trend of I_{avg} (data referred to the 2nd year, days on x-axis, patients on y-axis).

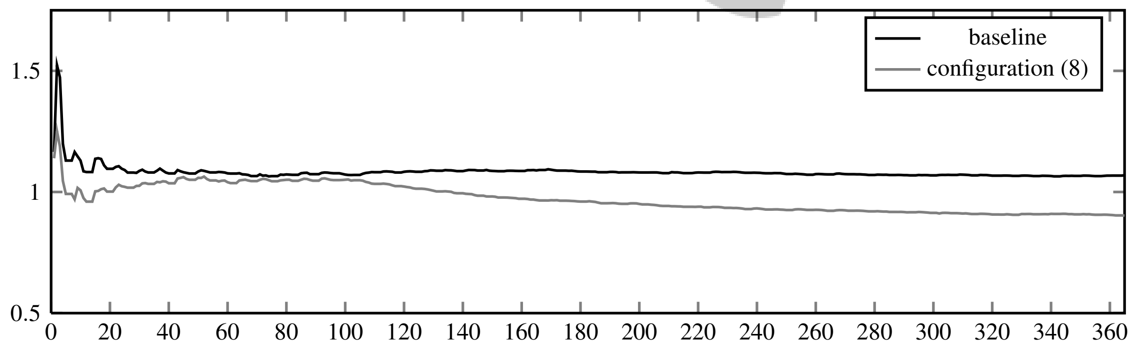

Figure 6: Trend of w_{avg} (data referred to the 2nd year, days on x-axis, patients on y-axis).

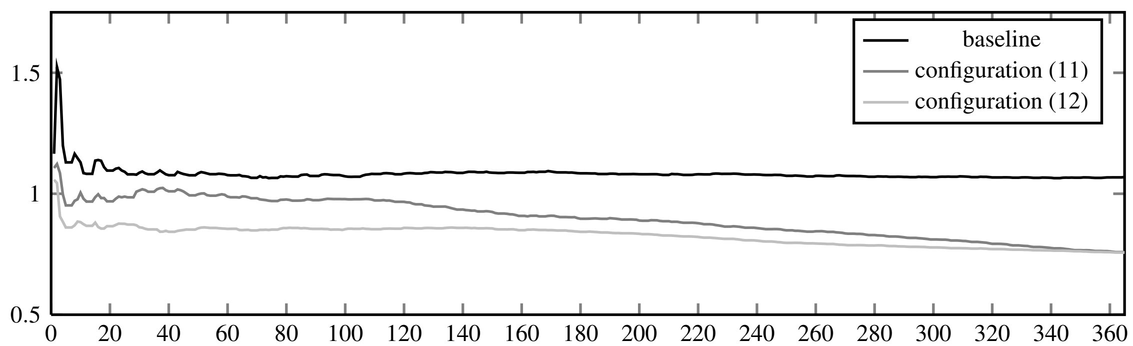

Figure 7: Trend of w_{avg} (data referred to the 2nd year, days on x-axis, patients on y-axis).

Regarding the impact of the allocation schedule optimization module, we can observe a significant better performances when LPT policy is adopted. Figure 4 shows the trend of I_{avg} under the baseline, (6) and (7) configurations.

Regarding the impact of the operating room real time management module, we observe a remarkable improvement of all the performance indices (see configurations (8) and in particular f_{MTBT}). On the other side, we observe the negligible impact of the algorithm for the rescheduling postponed patients at the end of the day (see configurations (9) and (10)). Figure 5 and 6 show respectively the trend of I_{avg} and w_{avg} under the baseline and (8) configurations. Note that it is positive when $w_{\text{avg}} < 1$ which means that, on average, all the patients are operated on before their MTBT.

Finally, configurations (11) and (12) report about the combination of the different options. We note a further improvement of the performance indices except for that related to the number of cancellations if compared with configuration (8). This is due to the fact that Local Search allows to insert more patients in the advanced scheduling thus reducing the waiting time in the waiting list but increasing the probability of incurring in a cancellation. Figure 7 shows the trend of w_{avg} under the baseline, (11) and (12) configurations. While baseline configuration shows a value of w_{avg} always greater than 1, we remark that both configurations (11) and (12) tend to be less than 1. Further, configuration (12) seems more stable and powerful in reducing this indices.

7 CONCLUSIONS

In this paper we proposed a hybrid simulation and optimization model for the analysis of a surgical pathway from a patient-centred point of view: simulation is used to generate a real situation with respect to the inherent stochasticity of the problem while optimization is used to take the best decisions in different points of the surgical pathway.

The quantitative analysis discussed in Section 6 shown the positive impact of the optimization in the management of the surgical pathway. In particular, the most effective optimization module is the operating room real time management determining a general improvement of all the performance indices with respect to a baseline configuration of the surgical pathway.

Comparing the baseline configuration with configurations (11) and (12) we can observe a great improvement of the performance indices related to the waiting list in terms of its length and the waiting time. This allow to double (at least) the percentage of the patients operated on before their MTBT time limit. These improvements can determine a general improvement of the quality of service from a patient-centred point of view without deteriorating the facility-centred performance indices.

The quantitative analysis confirms the trade-off between the number of cancellations and the number of operated patients (or, equivalently, the OR session utilization) as discussed in (Beaulieu et al., 2012). From this point of view, the proposed hybrid model could help the hospital management in the evaluation of this trade-off.

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APPENDIX

In this appendix, we report the parameters of the simulation framework and their setting for the model validation (Section 5) and for the quantitative analysis (Section 6). In brackets, the unit of measure.

Flow and patient characteristics:

r_0**:** patient interarrival rate [patients/minutes],

R_0**:** initial length of the pre-admission waiting list [patients],

p_1**:** patient probability to require a surgical treatment during the ambulatory visit (see Fig. 1),

p_2**:** patient probability to do not require a surgical treatment but requiring further exams during the ambulatory visit (see Fig. 1),

$p_{\mathbf{A}}, \ldots, p_{\mathbf{G}}$**:** patient probability to belong into the urgency class A,. . .,G.

Duration of activities:

$T^{min,avg,mod}_{\mathbf{A},\ldots,\mathbf{F},\mathbf{I}}$**:** minimum, average and modal time for the execution of A,. . .,F,I [minutes] (see Figures 1–3),

$\ell_{\mathbf{min,\,max,\,mod;\,A,\ldots,G}}$**:** minimum, maximum and modal LOS for patients belonging to the urgency class A,. . .,G [days],

$\bar{\varepsilon}_{\mathbf{A},\ldots,\mathbf{G}}$**:** average EOT for the surgical intervention of a patient belonging to the urgency class A,. . .,G [minutes],

$e_{\mathbf{max}}$**:** maximum duration of a surgery [minutes],

$\sigma_{\mathbf{A},\ldots,\mathbf{G}}$**:** EOT standard deviation [minutes],

σ**:** ROT standard deviation for each patient [minutes],

τ**:** tolerance time within which the surgical team operates a patient at the end of OR session without resorting to the overtime [minutes].

Table 3 shows the distributions used to generate the required time for the execution of the activities A,. . .,J. Table 4 reports the values assigned to the parameters for the model validation and for the quantitative analysis.

The parameters k and ϑ for the Gamma distributions (see Table 3) were obtained from the empirical data reported (Ozcan et al., 2011), requiring that the expected and the modal values of these distributions coincide with the empirical values reported in that paper. Further, we compute the value of the survival function on the maximum time for the execution of activities (always reported in the paper), obtaining a value less than 10%.

The choice to use a lognormal distribution derives from the literature (see, e.g., (Strum et al., 2000; May et al., 2000; Spangler et al., 2004)).

Table 3: Distribution of the activity durations.

Activities	Durations	Parameters
A,..., F, I	$T_{\min}^{\mathrm{A},\ldots,\mathrm{F,I}}+T$, $T \sim \mathrm{Gamma}(k,\vartheta)$	$k = T_{avg}^{\mathrm{A},\ldots,\mathrm{F,I}} - T_{mod}^{\mathrm{A},\ldots,\mathrm{F,I}}$, $\vartheta = \frac{T_{avg}^{\mathrm{A},\ldots,\mathrm{F,I}} - T_{min}^{\mathrm{A},\ldots,\mathrm{F,I}}}{T_{avg}^{\mathrm{A},\ldots,\mathrm{F,I}} - T_{mod}^{\mathrm{A},\ldots,\mathrm{F,I}}}$
H (LOS)	$\lfloor \mathrm{Triangular}(l_{\mathrm{min;\,A,\ldots,G}}, l_{\mathrm{max;\,A,\ldots,G}}, l_{\mathrm{mod;\,A,\ldots,G}}) + \frac{1}{2} \rfloor$	
J (EOT)	$\min\left\{\max\left\{\lfloor \frac{T}{u} + \frac{1}{2} \rfloor u, 0\right\}, e_{\max}\right\}$, $T \sim \mathrm{Lognormal}(\mu, s^2)$	$\mu = \log \varepsilon_{\mathrm{A,\ldots,G}} - \frac{1}{2}\log\left(\frac{\sigma^2_{A,\ldots,G}}{\varepsilon^2_{A,\ldots,G}} + 1\right)$, $s = \sqrt{\log\left(\frac{\sigma^2_{A,\ldots,G}}{\varepsilon^2_{A,\ldots,G}} + 1\right)}$
J (ROT)	$\min\{\max\{0, T\}, e_{\max}\}$, $T \sim \mathrm{Gaussian}(\mathrm{EOT}, \sigma^2)$	

Table 4: Parameters used in the simulation framework.

Parameters	unit of measure	Validation	Quantitative analysis
r_0	patients/minutes	$5.8 \cdot 10^{-3}$	$2.0 \cdot 10^{-2}$
R_0	patients	140	420
p_1, p_2		0.2, 0.1	0.2, 0.1
$p_{\mathrm{A}}, \ldots, p_{\mathrm{G}}$		$0.0245, 0.1401, 0.4136, 0.1785$ $0.1140, 0.0749, 0.0544$	$0.0245, 0.1401, 0.4136, 0.1785$ $0.1140, 0.0749, 0.0544$
$T_{min}^{\mathrm{A},\ldots,\mathrm{F,I}}$	minutes	$5, 25, 25, 25, 40, 25, 35$	$5, 25, 25, 25, 40, 25, 35$
$T_{avg}^{\mathrm{A},\ldots,\mathrm{F,I}}$	minutes	$7.5, 31.5, 31, 28, 62.5, 32, 41$	$7.5, 31.5, 31, 28, 62.5, 32, 41$
$T_{mod}^{\mathrm{A},\ldots,\mathrm{F,I}}$	minutes	$6, 30, 26, 25, 50, 30, 40$	$6, 30, 26, 25, 50, 30, 40$
$\ell_{\mathrm{min;\,A,\ldots,G}}$	days	$2, 1, 1, 1, 1, 1, 1$	$2, 1, 1, 1, 1, 1, 1$
$\ell_{\mathrm{max;\,A,\ldots,G}}$	days	$29, 16, 7, 9, 5, 5, 5$	$29, 16, 7, 9, 5, 5, 5$
$\ell_{\mathrm{mod;\,A,\ldots,G}}$	days	$3, 2, 2, 2, 2, 2, 2$	$3, 2, 2, 2, 2, 2, 2$
$e_{\max}$	minutes	360	420
$\bar{\varepsilon}_{\mathrm{A,\ldots,G}}$	minutes	$145, 171, 149, 153, 171, 164, 166$	$145, 171, 149, 153, 171, 164, 166$
$\sigma_{\mathrm{A,\ldots,G}}$	minutes	$85, 85, 66, 60, 61, 51, 60$	$85, 85, 66, 60, 61, 51, 60$
σ	minutes	0	30
τ	minutes	30	10
Ω	minutes	0	300
u	minutes	30	30
N		7	21
$S_1, \ldots, S_N$	minutes	$360, 360, 360, 360, 360, 360, 360$	$300, 360, 420, 420, 420, 300, 360$ $420, 420, 300, 360, 420, 300, 360$ $420, 420, 420, 300, 360, 420, 420$
$d_1, \ldots, d_N$		$2, 2, 3, 3, 4, 4, 5$	$1, 1, 1, 1, 1, 2, 2, 2, 2, 3, 3, 3$ $4, 4, 4, 4, 4, 5, 5, 5, 5$
$B_1, \ldots, B_7$	beds	$18, 18, 18, 18, 18, 18, 18$	$50, 50, 50, 50, 50, 35, 35$
$M_{\mathrm{URG\ A,\ldots,URG\ G}}$	days	$8, 15, 30, 60, 90, 120, 180$	$8, 15, 30, 60, 90, 120, 180$