Incorporation of different objectives in surgical patients management: Optimisation and simulation of the scheduling process

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In the operating room context, different stakeholders can be identified and grouped according to their individual interests, which may reflect different planning goals for the surgical system operating processes. This way, this paper proposes a multi-objective approach to optimise and simulate the surgical scheduling process, which incorporates the different perspectives and interests of the stakeholders involved. This approach can be decomposed into two main phases, one of optimisation and the other of simulation. Thus, for the first phase, an optimisation model was developed in order to obtain an optimised weekly scheduling solution. For the second phase, a simulation model of the surgical process was developed in order to analyse the optimised solution, obtained in the first phase, and compare the respective results with a solution considered to be representative of a real schedule. The methodology is tested in a case study context concerning a Portuguese public hospital.

***Index Terms*—Operating theatre, stakeholders, multi-objective, optimisation and simulation.**

I. Introduction

Hospitals face increasingly complex challenges in managing scarce resources and providing high service levels to patients due to growing demand for health services, the ageing of the world population and the development of new and expensive methods and equipment. Along with hospitals' restrictive budgets, managers are forced to promote and increase efficiency in the use of resources that can be human or material, which may involve different approaches. Particularly, operating rooms involve many stakeholders and restrictive constraints and can have a great impact in hospital budgets. This way, it is not surprising the increasing contribution of research work applied to the surgical context over the last few years (Cardoen et al. 2010*a*). It turns out that most of these papers, present in the literature, have had a certain tendency to focus on the more technical issues of the problems that researchers aim to solve (such as resource-related data, demand estimates and many other parameters) and somehow omitting the individuals, the problem owners and the OR (operational Research) experts, who are engaged in the real processes (Franco & Hämäläinen 2016). This has resulted in solutions that suggest the implementation of procedures that often ignore both interests and other behavioural characteristics of the stakeholders involved, disregarding the influence this may have, either in the system or in the implementation of solutions proposed by models developed by OR researchers (Hämäläinen et al. 2013). For that reason, and based on some literature regarding BOR and also some operational research on healthcare systems, a simulation model was developed in order to complement an optimisation one, modelled with the purpose of finding an optimised schedule for elective surgeries for a time planning horizon of one week, having in account 3 distinct objectives, reducing both the total number of cancelled surgeries (associated with efficiency KPI (Key Performance Index)) and workload (associated with utilisation rate as KPI) while maximising the total number of scheduled surgeries, considering each one as representative of the interest of the 3 main stakeholders directly involved in the surgical system, which are patients, staff and OR managers respectively.

Using the simulation model allows to try and evaluate distinct scheduling solutions in a more communicative and interactive way rather than only using the optimisation model. The idea of using simulation in this work, was mainly to analyse and compare the outcomes of two different solutions, the optimised one, after running the optimisation model, and another one considered as representative of the actual schedule solution of a real scheduling process based on HESE (Hospital Espírito Santo de Évora) given data and information. This approach aims to enable a better understanding of the impact of scheduling solutions over the operational process and also to promote a greater acceptance on implementing optimised solutions, in case it verifies better running results for a validated and verified simulation model.

Through simulation it was also possible to include uncertainty that may lead to operational process disruption. It was considered mainly 2 different causes of disruption in elective process, one internal and another external. The first cause was associated with uncertainty regarding surgical real time duration, which may differ from planned duration and can compromise the elective process in an internal way. This duration variability was included in the simulated process as an adjusted random distribution function, based on surgical duration's data grouped by surgical type. The second cause is associated with surgical system disturbing events arrivals, such as urgency´s arrivals that may interfere in the elective process in an external way. This second cause of disruption was included differently in a two-phase approach, the first was called "usual regime" and the second was called "variable regime". The "usual regime" refers to the first phase of simulation, in which results were collected under usual operational conditions regarding this arrivals of disturbing events, according to HESE given data about real time blocks cancellations verified over 2 months of surgical process operation. Regarding the "variable regime" simulation phase, a sensibility analysis was preformed over the so-called disruption level variation, which means that results were collected, for both considered scheduling solutions, by varying the disruption level associated to disturbing events arrivals in the system.

After running both scheduling solutions for each phase, it was verified that the optimised solution had better running results, under the simulation conditions, for the KPI´s considered as measures of stakeholders goals included in this work. This does not mean the optimised one is better nor worst than the actual schedule, since the model was preformed under certain assumptions and the context of the problem was simplified and more objectives could be involved as more stakeholders too, it just mean that for the considered stakeholder´s goals and under the operation process conditions assumed it has shown better results. Therefore, future work should include a more collaborative and interactive methodology, as much as possible, with those involved in the process.

II. Literature Review

In order to cope with behavioural aspects, some literature review was gathered on the *BOR* concept. Two distinct frameworks were identified, one proposed by Franco & Hämäläinen (2016) (subsection II-A) and another by Kunc et al. (2020) (subsection II-B), in order to structure this concept. Also some techniques to simplify multi-objective modelling were presented in subsection II-C, highlighting some authors that have develop and used multi-objective approaches to address conflicts of interest between different stakeholders, that may occur in the surgical system. Finally, this section ends with some examples of works applied to the surgical system context, which served as one of the main basis for the elaboration of this work (subsection II-D).

A. A two stream BOR framework

Franco & Hämäläinen (2016) describe two main streams of work within BOR. The first stream, with more history in the discipline of operational research (OR), focuses on using typical operations research techniques to model human behaviour in complex scenarios. This stream can be considered as a passive way of BOR proceeding, with no intention of promoting changes in that behaviour, only having it in account within models. The second stream investigates how human behaviour affects or is affected by OR model–supported processes in individual, group and organisational contexts. This stream can be considered as an active way of BOR proceeding, when measures are applied with the intention of promoting changes in the system human agents way of acting in processes.

Taking into account the work carried out by Franco & Hämäläinen (2016), the simulation model development with this work included human behaviour according to the first stream (in a passive way), in the sense that many behavioural aspects were included in the model in order to represent the real behaviours of the human actors in the system, specially some behaviours related with patients and staff, for example, the path of patients through the surgery process or the way human resources operate in the system were modelled in order to represent the real behaviour of these agents in the system simulation, without any intention to promote changes in their way of acting. It is also possible to relate the second stream (active way) mainly with the OR manager behavioural characteristics that may have influence over decision making process such as cognitive abilities and resistance to change (Giannoccaro 2013), since the simulation model allows the decision maker to interact with it, testing different solutions and drawing his on conclusions, enabling a better understanding of different solutions impact on operational process results, which can be seen as a potential way for active contribution to a better decision performance, as Cardoen et al. (2010*b*) also had suggested before.

B. A three area BOR framework

Kunc et al. (2020) propose a division of BOR concept in three different research areas: behaviour in models (the most covered in this work), behaviour with models, and behaviour beyond models (the least covered in this work).

The first area evaluates the representation of behaviour in OR models. Human behaviour can be included in models in many different ways depending on the assumptions of the modellers. According to Greasley & Owen (2016), the inclusion of human behaviour in models can be external or internal. Approaches that include behaviour in an external form correspond to methods that simplify models by eliminating the behaviour of the model formulation, being able to disregard the behavioural aspects or include them in an external way, just like the decision maker possibility of interacting with the simulation model as this work proposes. Approaches that include human behaviour in an internal way, can represent it as a flow (assuming a generalised behaviour, flowing along the system), an entity (modelling people as a single entity, obeying to particular rules of procedure, just like an industrial machine), a task (modelling their response action to a sequence of tasks that can be associated with performance measures) or it can be modelled as an individual (modelling human behaviour based on individual characteristics as well as interactions with third parties) (Greasley & Owen 2016). Having in account the 3 main stakeholders considered in this work, it is possible to differentiate the way they were represented in the proposed simulation model. The decision maker's behaviour (in this case, the OR manager) was modelled externally, that is, through the possibility of interaction with the simulator, in which the decision alternatives are an input into the model simulation. Patients were modelled internally, as a flow of working items throughout the system. Finally, staff was also modelled internally, but as an entity obeying to specific rules according to surgical process requirements.

The second area is related to the way in which models are used by decision makers, that can differ from the modeller´s expectations due to their behavioural characteristics. Thus, the focus is on the way how people use models to make decisions, mainly in the type of information they use and the way they process it. Mantel et al. (2006) describe some behaviours that can have influence over decisions, and also can be associated to the way people use models, for example, people´s tendency to avoid additional information, that may lead to decisions that are not necessarily based on all available information provided (by models). This research area is less covered in this work than the first one, since there was no direct interaction with any stakeholder directly involved in the system this work aims to approach. The only thing it is possible to highlight regarding this BOR area is the possibility of interaction between a decision maker and the simulations model, that was modelled in a tailored way, according to some surgical process characteristics based on HESE information provided. The simulation model allows the decision maker to try the optimised solution and make his conclusions, which can be seen as a way of enabling understanding and acceptance of new solutions provided by models.

The last area is concerned with the impact on behaviour beyond the use of models, since models can be more than mere mathematical or problem structuring techniques, models are created to have an impact beyond the results they suggest, they are also instruments of thought and a way to better understand real systems (or part of it) (Kunc et al. 2020). This area is more difficult to relate with the developed work, at this stage, as it requires a post-implementation observation of the model which, by now, is not possible to attend.

C. *Multi-objective optimisation models*

A multi-objective approach was preformed in this work in order to include different and conflicting goals that may represent stakeholders considered interests in surgical context. There is a considerable literature regarding multi-objective models applied to surgical system case studies, just like, Marques & Captivo (2017), Cappanera et al. (2016), Rachuba & Werners (2014), Meskens et al. (2013). For this work, the most relevant literature was mainly theoretical support about some techniques to deal with the complexity associated to multi-objective models formulation, since "considering multiple objectives while addressing jointly decisions at multiple levels, can result in problems characterised by high computational complexity and, thus, in models that might not be solved on real instances" (Cappanera et al. 2016). Cappanera et al. (2016) suggest 3 main procedures: treating one or more of the criteria as constraints; reducing the length of the planning horizon in which the decisions have to be taken; and trading-off the type of decisions to take into account and the number of objectives to consider.

The first procedure was applied to staff considered objective, that means that the work load was include as a restriction in both developed models. Even so, comparisons were made regarding the KPI, associated with this goal (utilisation rate), between the analysed solutions in this work. The second procedure was applied by reducing the decision of scheduling time horizon to only one week, limiting this decision to the operation level. Finally, the third procedure was also applied by only considering the surgical scheduling decision in this work, reducing the scope of decision to a simpler problem.

D. *Works applied to the context of the surgical system*

Similar to the work developed by Roure et al. (2015), a simulation model was modelled and used in order to test and analyse solutions with the goal of improving patient flow (or maximising both number of surgeries and process efficiency) throughout the operational surgical process, benefiting from the advantages of using simulation vs real experimentation. Unlike Roure et al. (2015), the work developed in this dissertation analysed and compared different scheduling solutions (optimised vs non-optimised solution) for identical scenarios, varying the scenarios only with respect to the occurrence of system disruption caused by arrival of destabilising events, for a constant resource level (unlike Roure et al. (2015)), only aiming to improve the current surgical area serving elective patients (outpatient or inpatient), while Roure et al. (2015) aimed to scale a new surgery area deployed specifically for outpatients. Another difference between the two works resided in the type of interaction with the hospital's employees, in which Roure et al. (2015) presented a more direct interaction, which allowed a greater proximity and level of knowledge of the system, allowing the elaboration of a personalised risk analysis for the implementation of the proposed solution in the context of the operational process.

As in the work developed by Banditori et al. (2013), an optimization-simulation approach was used with respect to surgical scheduling concerning elective patient surgeries, whose surgical planning was performed by surgical groups rather than individual cases, assuming that surgeries of the same group have similar expected operation duration, as well as length of stay (LOS) (although LOS was not considered in this work). Banditori et al. (2013) defined the groups according to the type of resources needed for the preparation of the respective surgeries, similarly to what was done in this work in which the type of surgery was grouped according to the surgical speciality (involving, for example, dedicated operating rooms and specialised surgical teams for the purpose). Like Banditori et al. (2013), an analysis regarding the impact of varying the level of disruption of the system was included, the main difference between the approach of Banditori et al. (2013) and this work, lies mainly in the type of origin of the disruption caused, since Banditori et al. (2013) analyses the impact of variations in surgical duration LOS, while this work proposes a sensitivity analysis regarding the occurrence of destabilising events (in an external way of the elective surgery process). The objective of Banditori et al. (2013) with this analysis is to evaluate the robustness of the optimised solution, while the objective of the sensitivity analysis of this work is to compare the variation of the performance levels between the optimised solution and the representative solution of the hospital (not optimised by the model), as a function of the variation of the system disruption level.

Fügener et al. (2017) analysed the impact (in this case negative) of some behavioural aspects on the outcome of the system, namely regarding the planning of surgical duration time by surgeons. Taking this into account and in order to avoid this kind of inefficiencies caused by the fact that decision makers are not purely rational, as suggested by Simon (1979), in this work a stochastic approach was adopted, based on historical records of surgery times, in order to simulate the respective duration and thus the number of surgeries planned for a given room time was planned for a 95% confidence level.

Just like Denton et al. (2007), this work also compared performance levels of optimised schedules with non-optimised schedules, including the uncertainty of surgical duration, based on real data about duration and performance results. The main difference between both approaches was the fact that this work has not included the impact of different process sequencing rules nor developed a cost sensitivity analysis. Also in terms of time horizon, the focus of this work was a week instead of just one day, and also taking into account several operating rooms in the scheduling decision (contemplating one of the recommendations proposed by Denton et al. (2007)).

Similarly to the work developed by Tancrez et al. (2009), in this work the disruption of patient flow, throughout the surgical process, was included in a stochastic way, having as main causes the uncertainty associated with surgical duration and the randomness of the arrival of disruptive events as well, which in the case of the work developed by Tancrez et al. (2009) concerns only the arrival of urgent patients, while in this work it represents everything that was not directly included in the model and that may cause disruption in the process, such as the various aspects highlighted by Wiegmann et al. (2007) (as for example, technical failures in equipment), thus covering a little more disruptive aspects than Tancrez et al. (2009). The main difference lies in the fact that the variation of the disruptive level (variation of the daily rate of disruptive events), was used in the sensitivity analysis of the solutions tested in this work, analysing the impact on the results of the KPIs considered and comparing them between different scheduling solutions (operational level), unlike the work developed by Tancrez et al. (2009) that took into account the disruption in order to assist in the tactical-strategic level decision, concerning the proportion of service allocated to urgencies, which in this work was considered previously taken.

III. Problem description: HESE Case study

The new early 20s Portuguese National Health Plan (PNHP 2021-2030) focus mainly on building sustainable development highlighting 10 recommendations, including: "Sustainable Health: from all to all", "The valorisation of information, communication, science, knowledge and innovation" and "The construction of a "Social Pact for the Decade", focused on sustainable health and the reduction of health inequities" (https://www.sns.gov.pt/noticias/2022/04/08/plano-nacional-de-saude-2021-2030-2/). Having these PNHP directives in mind, this work aims to promote sustainability by following these mentioned recommendations to a real case study, that means using communication, science, knowledge and innovation to seek for optimised and sustainable solutions while reducing inequalities and promoting the inclusion of different perspectives of those directly involved in the process.

HESE (Hospital Espírito Santo de Évora) is one of the main public hospitals in Portugal, which annually provides medical care to a considerable percentage of the population, mainly from Alentejo. Within the national context of growing surgical demand (Marques & Captivo 2017), HESE is no exception, and the long waiting lists for surgery are one of the main problems detected (http://tempos.min-saude.pt/#/instituicao/233, 28/04/2022). These lists are characterised not only by their size (number of patients waiting) but also by their considerable average waiting time, from the time a patient is entered on the waiting list until the date on which the surgery is actually performed.

Some decisions may be considered critical in this process. Throughout this work, only operational decisions will be considered, in order to simplify the context of the problem by reducing the time horizon of action to just one week, as previously suggested in subsection II-C, as well as to facilitate its possible practical implementation, that is, an implementation that does not require revolutionary changes that may affect the pre-existing structure (like changes at a strategic level).

This way, the decision regarding surgical scheduling was identified as one of the critical points in the surgical process both in literature and HESE, in this case referring to the surgical area assigned to surgeries for elective patients, whose surgery can be well planned in advance (Cardoen et al. 2010*b*). According to HESE provided information, for the elective surgery unit was assigned 5 rooms, operating over 5 working days a week (Monday to Friday) in 2 daily shifts (morning and afternoon shifts) with the necessary equipment and staff to preform 13 different surgical specialities. This way, assuming this elective unit dimensions as fixed and with no intention of changing these taken decisions at tactical-strategic level (Guerriero & Guido 2011), the main focus of this work is to find a better way of using this previous dimensioned unit (at operational level), including different stakeholders views. Unfortunately it was not possible to interact directly with HESE OR main stakeholders (Patients, Staff and OR manager), for that reason, the 3 objectives (efficiency, utilisation and the total number of scheduled surgeries) included as representing their interests were based in some literature (mainly Cappanera et al. (2016), Banditori et al. (2013)).

The next section proposes a method which aims to optimise the weekly surgery scheduling in a communicative way, facilitating its understanding in the context of the surgical system and its human actors.

IV. Methodology and solution approach

A MILP optimisation model (subsectin IV-A) and a Descret Event Simulation (DES) model (subsection IV-B) were developed based on general information highlighted in the literature review (section II) as well as specific information regarding HESE elective surgery unit. The purpose of the optimisation model is to support the OR manager's decision consisting in assigning times to surgical specialities, in order to maximise the number of surgeries that can be scheduled for a 95% service level under resource conditions (engaging staff requirements). The simulation model aims to represent the surgical operational process itself, from the moment a patient is admitted to the service until he/she is referred to recovery, so that results can be collected to preform analyses and comparison between both HESE representing solution and the optimised solution (extracted from the optimisation model).

A. Optimisation model

In order to include an optimised solution in this work, a mathematical model representing the scheduling problem was formulated and, using Solver (a tool provided by Excel), which, through a MILP (Mixed Linear Programming) search method, allowed to find an optimised solution for the elective surgical scheduling problem over a week. Subsection IV-A1 describes how the model formulation was developed.

1) Mathematical formulation

Indexes: Given the context of the problem described in section III, 3 indexes were defined, i, j and t, referring respectively to surgical specialities, rooms and daily time blocks for the morning and afternoon shifts.

- Surgical specialities (i) available at the Hospital service: Ophthalmology (i_1), General surgery (i_2), Obstetrics gynecology (i_3), ORL surgery (i_4), Urology (i_5), Plastic surgery (i_6), Orthopedics (i_7), PED surgery (i_8) and Others (i_9).
- Rooms allocated for elective patient surgeries (j): Room 1 (j_1) ; Room 2 (j_2); Room 4 (j_3) ; Room 5 (j_4) and BOMI (j_5).
- Operating rooms working time blocks (t): Morning shift (8:00-14:00 H) (t_1) and Afternoon shift (14:00-20:00 H) (t_2).

Speciality i_9 referring to "Other" surgeries represents a set of 5 different surgery types (Stomatology, Neurosurgery, Vascular surgery, Breast surgery and Gastrosurgery), which data records were not enough and their weekly frequency was less than one surgery by week. This way, gathering these 5 specialities together in one group, allowed to obtain a greater sample of data and also a frequency around one surgery a week, which facilitated its inclusion in both models development.

Parameters: In order to develop a model tailored to the real case of HESE, the following parameters where included based on HESE provided data and information:

- Number of surgeries expected by OR time block, for each speciality: D_i.
- Maximum weekly capacity of times per room: $Cmax_{j,t}$.
- Minimum service level by speciality: $Nmin_i$.

The number of surgeries expected by time block for each specialty "D_i", was obtained according to surgical time duration records, which were assume to fit a log-distribution (Fügener et al. 2017) and the number of surgeries for a time block was calculated for a 95% confidence interval, that means this parameter represents the number of surgeries that is possible to preform in a 6 hours shift, for each speciality type i, covering 95% of the real cases. The maximum weekly capacity of time blocks per room "$Cmax_{j,t}$" was also obtain according to HESE given data, knowing that each room j operates in a two daily shift t over 5 working days of an operational week. Finally, the minimum service level by speciality "$Nmin_i$" was based on previous time blocks assigned to each speciality decisions, according to HESE given data, assuming these decisions translate properly the complex context of each speciality requirements.

Variables:

- Number of time blocks assigned to each speciality in each room at each time: $X_{i,j,t}$.

A set of decision variables was defined as an *output* of the model, representing the weekly amount of time blocks assigned to each speciality in each room (X_{ijt}). The values return by *Solver* for this variable constitute the solution suggested by the model in order to achieve the maximum number of scheduled surgeries over a week.

Constraints:

- X_{ijt} is non-negative and integer 1

$$X_{ijt} \in Z \wedge X_{ijt} \geq 0 \tag{1}$$

- Rooms and specialities Compatibility 2

This set of constraints 2, composed by 7 restrictions, takes into account compatibility issues between rooms and specialities. It was verified, by observing HESE provided data, that some rooms (j) only had records of surgeries performed or planned for a certain type of specialities (i). This way, the hypothesis was raised that, for example, due to technical equipment issues, some rooms could not attend to some surgical specialities and thus, in order to include this type of requirements, it was assumed that if a speciality is not included in any register that has been carried out in a given room, then the respective value $X_{i,j,t}$ must be null as no time can be assigned in that room to the respective speciality.

$$X_{ijt} = 0, \ \ \forall ijt : (i = i_1 \wedge j \neq j_4) \tag{2a}$$

$$X_{ijt} = 0, \ \ \forall ijt : (i \in \ \{i_2, i_6\} \wedge j \in \ \{j_4, j_5\}) \tag{2b}$$

$$X_{ijt} = 0, \ \ \forall ijt : (i = i_3 \wedge j \neq j5) \tag{2c}$$

$$X_{ijt} = 0, \ \ \forall ijt : (i = i_4 \wedge j \in \ \{j_3, j_4, j_5\}) \tag{2d}$$

$$X_{ijt} = 0, \ \ \forall ijt : (i \in \ \{i_5, i_8\} \wedge j \neq j_2) \tag{2e}$$

$$X_{ijt} = 0, \ \ \forall ijt : (i = i_7 \wedge j \neq j_3) \tag{2f}$$

$$X_{ijt} = 0, \ \ \forall ijt : (i = i_9 \wedge j = j_5) \tag{2g}$$

- Maximum capacity of available room time 3

Constraint 3 was included in the model in order to take into account weekly operating time blocks (t) limitations for each room (j). In order words, this constrain was included to ensure that the sum of times assigned to each speciality for a certain room ($X_{i,j,t}$) is not superior than the weekly amount of available room time ($Cmax_{j,t}$).

$$\sum_i X_{ijt} \leq Cmax_{jt}, \forall j, t \tag{3}$$

- Minimum weekly assigned time block level for each speciality 4

Constraint 4 was included in the model to guarantee that each speciality is properly satisfied by the weekly time block distribution. This is to avoid that the model penalises some specialities just because they do not contribute as much to the objective as others.

$$\sum_j \sum_t X_{ijt} \geq Nmin_i, \forall i \tag{4}$$

Auxiliary functions:

Finally, 2 functions were created to enable the objective definition and also to facilitate the model verification and monitoring, defined as follows.

- Total number of time blocks assigned per week by the returned solution 5

"Tot.Times" 5 returns the sum of all times assigned to all specialities for all rooms, as a function of the decision variable $X_{i,j,t}$, allowing to check whether the model has assigned all available times for the considered surgical area.

$$Tot.T.Blocks = \sum_i \sum_j \sum_t X_{ijt} \tag{5}$$

- Total number of surgeries planned per week by the solution found 6

"Tot.Cir" 6, returns the sum of the number of surgeries expected for all time blocks assigned to all specialities for all rooms, as a function of D_i and $X_{i,j,t}$, corresponding to the total number of surgeries expected for a week of operation.

$$Tot.Surg = \sum_i \sum_j \sum_t D_i.X_{ijt} \tag{6}$$

Objective function:

- Maximising the number of planned surgeries per week 6

The objective function consists in maximising the total number of surgeries planned per week, which means maximising "Tot.Surg" 6 function.

$$Max\{Tot.Surg\}(6)$$

2) Results and solution application

After only 0.062 seconds of running time, using the Solver LP Simplex search method, in a computer equipped with 6 GB RAM processor, the model returned the solution expressed in figure 1 as a possible distribution of time blocks for each speciality (i) for an operational week ($X_{i,j,t}$ variable expressed in light blue cells).

As it is possible to verify, $X_{i,j,t}$ is always non-negative integer respecting constraint 1. Also, the red cells expressed in figure 1 represent all the mandatory null values for $X_{i,j,t}$ according to constraints 2, respecting compatibility requirements between rooms (j) and specialities (i). The maximum capacity of available time blocks (t) for each room (j) was not exceeded, since the second last row ("Total"), representing the sum of the weekly amount of time blocks (t) assigned for each room (j), has equal values to the last row ("Cmax(j,t)"). This suggests that constraint 3 was respected and also that the solution proposes the use of all available time blocks which make sense having in account the objective of maximising planned surgeries over the week. Finally, constraint 4 was also satisfied, since the values in column "Time blocks to speciality (i)", representing the sum of the weekly amount of time blocks assigned to each speciality (i), are not smaller than the corresponding values in column "Nmin(i)". The green cells, expressed along the column "Time blocks to speciality (i)", correspond to the specialities for which the total time blocks assigned by the model solution was higher than the minimum level defined by the corresponding $Nmin_i$ parameter value. This way, all restrictions imposed by the constraints in section IV-A1 were respected while assigning time blocks according to the model solution.

There can be many ways of applying this obtained solution, since the model only returns the total amount of time blocks (t) to assign to each speciality (i) in each room (j), not mentioning any particular weekday. For instance, according to the 7^{th} column and 1^{th} row, the solution leaves no choice but to assign every room 5 (j_4) weekly morning shifts (t_1) to ophthalmology speciality (i_1), since the maximum amount of time blocks over a week was achieved. But regarding the 8^{th} column values (expressing the amount of room 5 (j_4) assigned afternoon shifts (t_2)), the solution do not specify in which day "room 5" (j_4) should preform "other" surgeries (i_9) rather than ophthalmology (i_1). Figure 2 suggests a possible weekly elective surgery scheduling respecting the model returned solution, which is assumed to represent the Solver solution in further simulation analyses.

B. Simulation model

The simulation model was developed using a simulation software, known as *Simul8* (https://www.simul8.com/software/), according to HESE provided data and system information and also based on some literature highlighted in section II.

This way, 9 starting points were created in order to include patients arrivals according to surgical speciality type (i). Also an activity of patient receiving in service was included, which allowed to root out patients to 5 surgical activities according to compatibility issues between specialities (i) and operating rooms (j) (expressed by constraint 2). Each one of these 5 surgical activities was associated with a required resource, which represents all the required resources to preform surgical activities grouped by rooms (j) (representing rooms and also any required resource, such as staff or equipment). Queues were created before any activity mainly to facilitate the process, avoiding activities to block the system flow. Finally, two end points were included in the model in order to differentiate patient preformed surgeries from cancelled surgeries.

The model was tested and it verified all the process requirements considered within this work, like work items (patients) arrivals and roots, or surgery duration according to each speciality. In order to validate the model, a considered HESE scheduling solution, based on surgery real data records, was introduced as an input. After running the model, results were collected for efficiency and utilisation rates and then compared with HESE historical results. In general, the difference between both solutions regarding efficiency results were around 2% and 7% for the global utilisation rate. It was assumed that these differences were not significant and that the model is capable of proceeding with solution analyses and comparisons.

	Weekly amount of time blocks assigned to each speciality X(i,j,t)													
	Room 1 (j1)		Room 2 (j2)		Room 4 (j3)		Room 5 (j4)		BOMI (j5)					
	t1 (8:00-14:00)	t2 (14:00-20:00)	t1 (8:00-14:00)	t2 (14:00-20:00)	t1 (8:00-14:00)	t2 (14:00-20:00)	t1 (8:00-14:00)	t2 (14:00-20:00)	t1 (8:00-14:00)	t2 (14:00-20:00)	Time blocks to speciality (i)	Weekly surgeries by speciality	Nmin(i)	D(i)
Ophthalmology (i1)							5	4			9	18	6	2
Gen. surgery (i2)	5	2	0	0	0	5					12	12	12	1
Obs. gynecology (i3)									5	5	10	20	4	2
ORL (i4)	0	3	0	0							3	9	2	3
Urology (i5)			0	2							2	4	2	2
Plastic surgery (i6)	0	0	0	2	0	0					2	4	2	2
Orthopedics (i7)					5	0					5	10	5	2
PED (i8)			5	1							6	18	1	3
Others (i9)	0	0	0	0	0	0	0	1			1	1	1	1
Total	5	5	5	5	5	5	5	5	5	5	total	96		
Cmax(j,t)	5	5	5	5	5	5	5	5	5	5	50			

Fig. 1: Weekly distribution of time blocks by speciality obtained by the optimisation model.

Day	Time blocks (t)	Room 1 (j1)		Room 2 (j2)		Room 4 (j3)		Room 5 (j4)		BOMI (j5)	
		Speciality (i)	D(i)	Speciality (i)	D(i)	Speciality (i)	D(i)	Speciality (i)	D(i)	Speciality (i)	D(i)
Mon.	08:00 14:00 (t1)	Gen.surg (i2)	1	PED (i8)	3	Ortop (i7)	2	Ophthal (i1)	2	Gynec (i3)	2
	14:00 20:00 (t2)	Gen.surg (i2)	1	PED (i8)	3	Gen.surg (i2)	1	Ophthal (i1)	2	Gynec (i3)	2
Tues.	08:00 14:00 (t1)	Gen.surg (i2)	1	PED (i8)	3	Ortop (i7)	2	Ophthal (i1)	2	Gynec (i3)	2
	14:00 20:00 (t2)	Gen.surg (i2)	1	Urol (i5)	2	Gen.surg (i2)	1	Ophthal (i1)	2	Gynec (i3)	2
Wed.	08:00 14:00 (t1)	Gen.surg (i2)	1	PED (i8)	3	Ortop (i7)	2	Ophthal (i1)	2	Gynec (i3)	2
	14:00 20:00 (t2)	ORL (i4)	3	Urol (i5)	2	Gen.surg (i2)	1	Ophthal (i1)	2	Gynec (i3)	2
Thurs.	08:00 14:00 (t1)	Gen.surg (i2)	1	PED (i8)	3	Ortop (i7)	2	Ophthal (i1)	2	Gynec (i3)	2
	14:00 20:00 (t2)	ORL (i4)	3	Plast.surg (i6)	2	Gen.surg (i2)	1	Ophthal (i1)	2	Gynec (i3)	2
Fri.	08:00 14:00 (t1)	Gen.surg (i2)	1	PED (i8)	3	Ortop (i7)	2	Ophthal (i1)	2	Gynec (i3)	2
	14:00 20:00 (t2)	ORL (i4)	3	Plast.surg (i6)	2	Gen.surg (i2)	1	Others (i9)	1	Gynec (i3)	2

Fig. 2: Suggestion of weekly elective surgery scheduling, taking into account the solution of the optimisation model.

Simulation length was fixed to one week (5 working days) and did not require any warm-up period, since the system is reset each day. The number of replications was calculated using a Simul8 tool (Trial calculator), for a 95% confidence interval for the total number of surgeries preformed results, so that the numerical values correspond to the mid half-width of that interval (similar to Roure et al. (2015) presented work).

1) Disruptor inclusion

A disruptor was modelled in order to include the disruption phenomenon in the simulation model, mainly caused by uncertain events that may occur in the real context of the system. This distruptor was modelled in an external way to the elective surgical process, by adding an extra starting point with the propose of simulating external disruptive events random arrivals (such as, urgent patients arrivals (Tancrez et al. 2009) or malfunction of technologic equipment (Wiegmann et al. 2007)), fitted to a Poisson distribution arrival rate (similar to Tancrez et al. (2009) developed work). A sub-activity (zero time duration activity) was included after this starting point, in order to root out these events to one of the 5 following activities that determine which of 5 resource groups will be allocated to deal with this event, over 6 hours (corresponding to the time duration of a working time block). These 5 activities have priority over the previous mentioned 5 surgical activities, interfering with the elective process described in the previous section IV-B (causing process disruption). This sub-activity rooting out follows a probability function, in which each exit root probability is inversely proportional to the usual efficiency rate of the room associated to the destination activity (according to HESE provided data). After this 5 "disturbing" activities, an end point was included, enabling the disturbing event to exit the system. Just like in the elective process simulation (section IV-B), queues were included before any activity to facilitate the process.

2) Results

The analyses and comparisons between both considered solutions (HESE representative solution vs optimised solution) were preformed under two different contexts of operating conditions, the "usual regime" and the "variable regime".

The "usual regime" refers to the regular operating conditions context, in which the obtained efficiency rate parameter, based on HESE records about room cancellation time blocks,

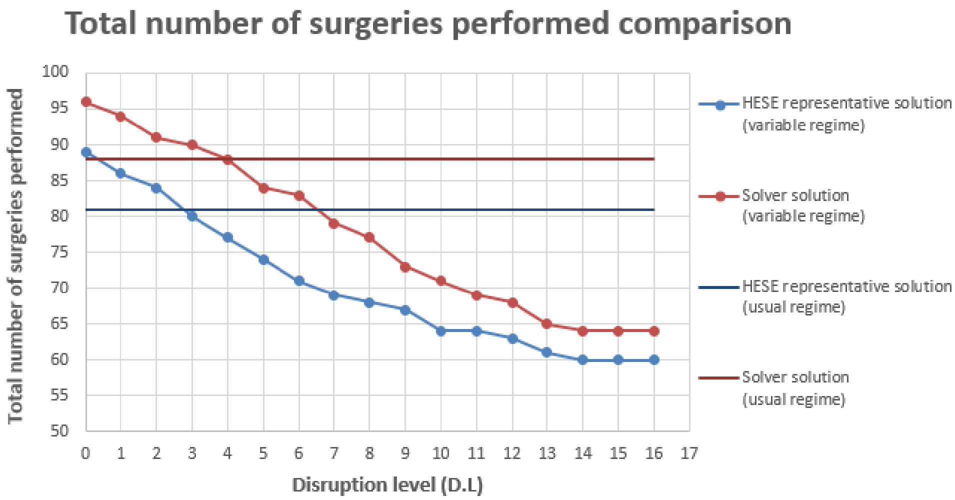

Fig. 3: Comparison of the simulation results for the total amount of surgeries performed of HESE representative solution with the scheduling solution results proposed by the solver, while varying the disruptive level.

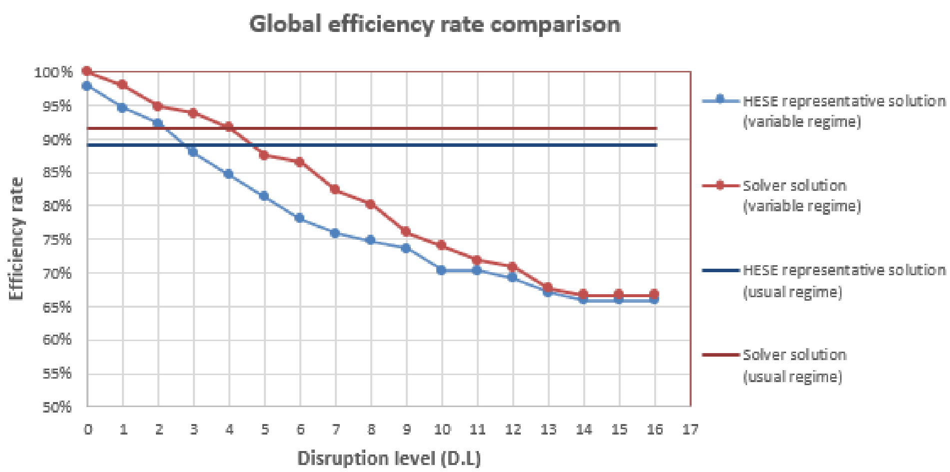

Fig. 4: Comparison of the global efficiency rate simulation results of HESE representative solution with the scheduling solution results proposed by the solver, while varying the level of disruption.

was assumed as representative of usual operating conditions regarding process disruption. Under this regime, the efficiency parameter is associated to each surgical activity associated with each resource group (grouped by room (j) as mention in section IV-B) and the disruptor (defined in section IV-B1) is turned off, by setting work items (disruptive events) arrivals in the corresponding starting point to zero, while running the simulation.

Under the "variable regime" simulation conditions, the efficiency parameter was associated with the probability of a disruptive event to involve each resource group (as previously mentioned in section IV-B1). After that, the simulation was executed for 17 different disruption levels, which are proportionally associated with the number of disruptive events arrival rate, starting the analyses at level zero, that means zero disruptive events arrival rate (or in other words, no external disruption), and ending at level 16 (corresponding to a 16 disruptive events a day on average).

The simulation results were collected under both regimes, according to the defined objectives, considering as representative of the interests of the 3 main stakeholders directly involved in the process, OR manager, patients and staff. This way, 3 KPIs were considered in the analysis, "total number of surgeries performed" (referring to OR manager considered goal), "Efficiency rate" (referring to patients considered goal) and "Utilisation rate" (referring to staff considered goal), which global results are expressed in figure 3, figure 4 and figure 5 respectively.

As it is possible to verify by checking figure 3, the total number of surgeries preformed results obtained for solver solution were always above HESE representative solution results under both "variable" and "usual" (parallel horizontal lines in figure 3) regimes, which suggests better results regarding this considered objective (in an OR manager prespective).

The same happened regarding global efficiency rate results (expressed in figure 4), which also suggests better results for patients considered objective, within the model limitations that may differ from the real context. It may be also relevant to notice that "HESE representative solution (usual regime)" line intercept "HESE representative solution (variable regime)"

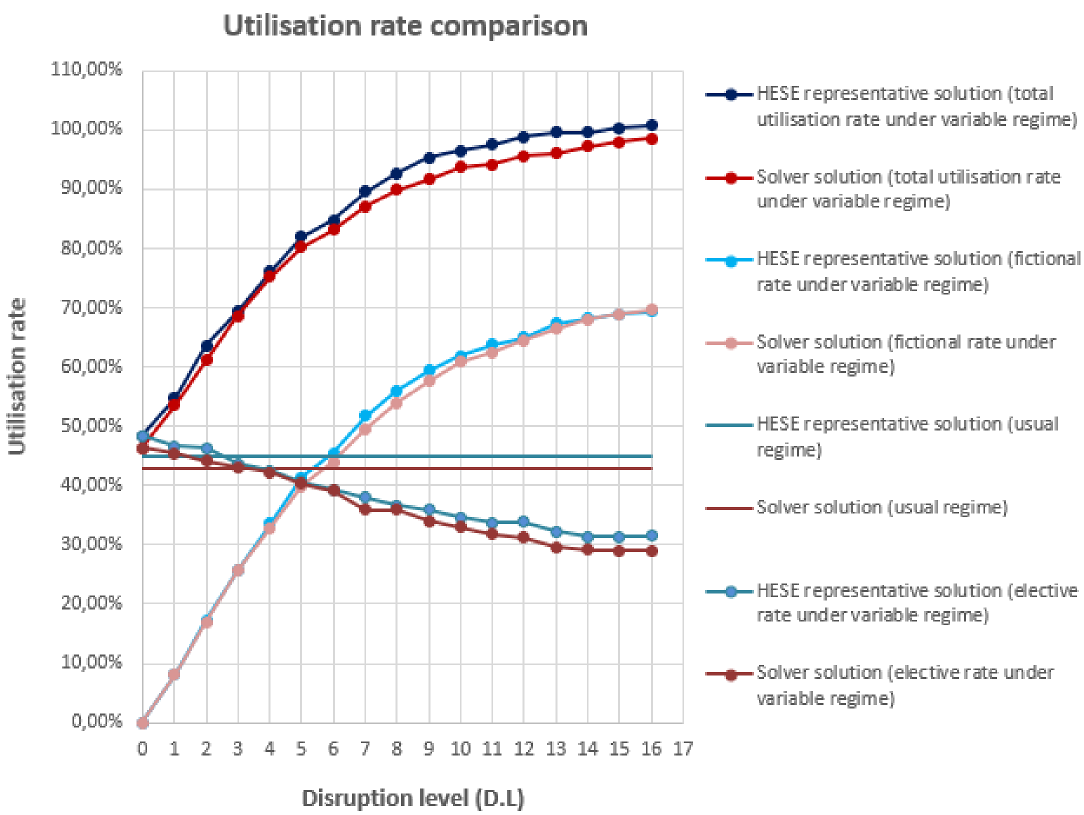

Fig. 5: Comparison of the global resource utilisation rate simulation results, of HESE representative solution with the scheduling solution proposed by the solver, while varying the level of disruption.

curve for a corresponding disruption level (D.L) around 3, for both considered KPIs results expressed in figure 3 and figure 4. The "Solver solution (usual regime)" line intercept "Solver solution (variable regime)" curve around level 4 of disruption for both respective KPIs results. This may suggest that solver solution is more robust than HESE representative solution, since it takes a greater level of disruption to incur in worse results than usual regime (under a usual operating context).

As it is possible to check in figure 5, 3 different resource utilisation rates were included in "variable regime" analyses. The "elective rate" represents the utilisation rate results of the elective process modelled area (described in section IV-B), while the "fictional rate" represents the utilisation outside the elective process, that means resource utilisation taking care of the disturbing activities included in the disruptor (described in section IV-B1). The "total utilisation rate" correspond to the sum of both "elective" and "fictional" utilisation rates, representing the total resource utilisation, or the total work load from the staff point of view. As its possible to observe in figure 5, HESE representative solution results for "total utilisation rate" under variable regime were slightly higher than solver solution "total utilisation rate" results for all disruptive levels. This may suggest that solver solution presented better results regarding this KPI, considering the staff objective included in this work.

Regarding the "usual regime" analyses, only one utilisation rate was considered, representing the resource utilisation in the elective process operation (similar to the "elective utilisation" considered in the "variable regime"). Also, under the "usual regime" HESE representative solution utilisation rate was slightly higher than solver solution, suggesting that solver solution had better results according to staff perspective.

As it is possible to verify in figure 3, once again, "HESE representative solution (usual regime)" line intercept "HESE representative solution (elective rate under variable regime)" curve around disruptive level 3 and "Solver solution (usual regime)" line intercept "Solver solution (elective rate under variable regime)" curve around level 4 of disruption. This may suggest that solver solution is also more robust having in account this KPI.

V. Conclusions and Future Research

Although the results of this work had suggested that Solver´s solution is better than HESE representative solution, as previously mentioned in section IV-B2, it is relevant to notice that the developed models only represent part of the real system in a simplified way. More objectives could have been included as more human stakeholders, or more specified groups. Also more system details could have been included in both models, to better level the complexity of real context. Both models would have benefited with a more interactive modelling with HESE human agents. Even so, both models results appeared to verify real system outcomes considered in this work. Furthermore, it was possible to test and analyse different weekly scheduling solutions enabling interaction with an hypothetical decision maker, which can provide a better understanding of solutions and their impacts on the system. It can also promote a better acceptance by those involved in the system regarding implementation of new solutions. Also, the fact that it allowed to test and analyse different solutions without having to carry out practical experimentation tests, avoids incurring unnecessary costs or risks associated with possible inefficiencies caused in the system.

Further analyses could be carried out as future work, such as the implementation of different time duration priority rules included in the optimisation model and testing their impact through simulation model, for example, to compare LPT (Longest Processing Time) with SPT (Shortest Processing Time) results regarding elective patient surgical scheduling. Also, it would be interesting to try to develop a more specified urgent patient inclusion in both models, after gather some real data support, since urgent patients can have a great impact on daily operations and are less covered in the literature.

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