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THREE-STAGE OPTIMIZATION APPROACH USING NONLINEAR PROGRAMMING AND SIMULATION

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Abstract

Problems involving patient scheduling and resource sizing are common in healthcare environments. Since the variability is higher in healthcare processes, procedure times, patient arrivals, and recovery times are critical factors for decision-making. Therefore, we propose an Operating Room scheduling optimization and resource management in a Surgical Centre (SC). Then, it aims daily scheduling planning to better assist patients linked to decrease SC's overtime and increase the financial results. For this, a three-stage approach was proposed to split the problem due to its high complexity. Firstly, Nonlinear Programming was used to prioritize the procedures to be performed, since it was not possible to perform all of them due to time constraints. Moreover, a Discrete Event Simulation model of the SC was built, and through the Simulation-based Optimization approach, we carried out other two-optimization stages, aiming to obtain the optimal procedure scheduling and the optimal resources sizing, respectively. It was possible to analyse the SC performance considering different decisions about overtime.

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Key Words: Operation Room Scheduling, Nonlinear Programming, Simulation-Based Optimization, Discrete Event Simulation

1. INTRODUCTION

The health industry is one of the largest in the world and it seeks for improving service quality because it directly impacts patient satisfaction and safety [1]. In this context, health clinics and hospitals look for increasingly efficient decisions, improving processes and reducing costs without affecting the minimum requirements for patient care. Moreover, one of the major problems faced by the healthcare environment refers to appointment scheduling, procedures, and operating rooms (ORs) since they present high process variability [2].

Scheduling procedures increases hospital facilities' utilization and provides timely access to health services. However, in shared environments, procedures may suffer delays and changes due to emergencies, requiring constant scheduling re-planning [3]. A shared hospital that presents patients with different priorities and characteristics demands efficient tools and techniques to help managers in decision-making. Thereby, there are several approaches in the literature aiming to obtain better answers regarding the scheduling of the procedures [2-5].

Furthermore, clinical-hospital systems also have to ensure that processes operate in the most efficient way. Then, they need to reduce the number of staff and physical resources and, at the same time, allow the minimum requirement of care to patients. Although this challenge is not exclusive to the health area, the search for dimensioning and allocating resources (financial, structural, and labour) in an efficient way has been increasing [6]. Therefore, stakeholders are using management, analysis, optimization, and process improvement tools. They support forecasting, restructuring, and cost reduction integrated by efficient patient care strategies [6-8].

Although there are many techniques, Brailsford et al. [9] state that unique approaches are hardly able to provide good guidelines. In this sense, it is necessary to integrate techniques and

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tools to provide efficient and timely responses, such as optimization methods and computer simulation. Optimization methods address techniques for solving problems that involve one or more objective functions, satisfying some constraints [10]. Computer simulation allows to evaluate behaviours, test scenarios, and perform "what if " experiments without real interventions in the systems [11, 12].

Both techniques present advantages and disadvantages when used to model complex systems. Computer simulation provides several output performance measures creating an easy way to evaluate problems that are hard to be modelled by optimization techniques, e.g. services priorities, appointment scheduling, and service routings. However, many optimization techniques use only one round of experiments to obtain the best solution while simulation needs to run more replications, consequently, more time to provide good results. On the other hand, optimization requires too many assumptions that may not be feasible to the systems. Then, when they are used together, it is possible to combine both advantages and give more precise results [13]. When the simulation results are used to find a system's optimal parameters based on optimization criteria it is called the Simulation-based Optimization (SBO) approach [14]. In this case, we highlight several SBO applications in health environments, such as [15].

Therefore, this work aims to use optimization techniques, more precisely the Nonlinear Programming (NLP), to obtain better decisions regarding procedures prioritization in a Surgical Centre (SC). In this first stage, the problem looks to reach the largest number of patients considering the best SC's net revenue. NLP is one of the main optimization approaches adopted in this context [16, 17] and it is composed of one or more nonlinear functions that aim to maximize or minimize them [18]. For Rao [10], the problems may be written in a generic way, as shown in Eq. (1).

$$\begin{gathered} Min \text{ or } Max\ [f_1(x_1, x_2, \ldots, x_n), f_2(x_1, x_2, \ldots, x_n), \ldots, f_i(x_1, x_2, \ldots, x_n)] \\ \text{S.t.: } [g_1(x_1, x_2, \ldots, x_n), g_2(x_1, x_2, \ldots, x_n), \ldots, g_j(x_1, x_2, \ldots, x_n)] \end{gathered} \tag{1}$$

where f_i represents the objective function i of the problem, g_j are the constraints j, and x_n denotes the decision variables, which we want to obtain the optimal values. There may be problems with constraints and without constraints.

Some possible objective functions in the health context would be to maximize the number of patients that received completed care and resource utilization and/or minimize waiting times, Length of Stay (LOS), and processes cost. Moreover, some problems need to cope with constraints such as limited resources and limited budget [19].

Two other optimization steps were performed using the SBO approach. For this purpose, we built a Discrete Event Simulation (DES) model. The second problem aims to maximize the total number of patients that have a procedure in a day, minimize SC overtime and maximize total earnings. Finally, in the third round, the problem formulation goals to minimize staff without compromise the metrics optimized in the second stage. We repeated the steps in eight scenarios. Moreover, we opted to divide the optimization problem into three stages because it is a highly complex problem. It presents a large number of possible solutions, making it very hard to address the whole problem in a single analysis step. In addition, the proposed approach may serve as an alternative for managers and researchers to deal with scheduling problems.

2. PROBLEM DESCRIPTION

We explored a SC that shares the unit with a hospital. It presents three ORs, a Pre-Operative (PreOp) area (four beds), and a Post-Anaesthesia Care Unit (PACU) area (nine beds). Moreover, it is available five Anaesthesiologists, three PreOp Nurses (PON), three PACU Nurses (PACUN), five Circulating Nurses (CN), five Scrub Nurses (SN), and three Maintenance Tech (MT). The SC offers services related to orthopaedic, ophthalmology, vascular, obstetrics and gynaecology, and general surgery procedures, which are performed by ten doctors.

Doctor A performs only orthopaedic procedures. Doctor B is responsible for some specific ophthalmology surgeries, however, if he is not available, Doctor I can carry out it. Doctor C must perform some procedures related to vascular and general surgery. Nevertheless, if he is not available, Doctor G and Doctor H may care for general surgery and vascular patients, respectively. Doctor D takes care of patients that need an orthopaedic procedure. If he is in another activity, Doctor J may replace him. Finally, Doctor E is responsible for obstetrics and gynaecology surgeries; however, he may be replaced by Doctor F.

Some patients may come from the hospital (Inpatients) and others may come just to make a procedure (Outpatients). If it is an Outpatient, he goes to registration, changes clothes, and waits until PON transports him to PreOp area. Inpatients arrive at the hospital with a Unit Nurse (UN) in a gurney and go to the PreOp area. After this point, both patients have the same flow. In PreOp area, the responsible doctor and an anaesthesiologist make a pre-surgery procedure. Then, a PON and a CN transport the patient to a pre-defined OR. Surgeries need a responsible doctor, an anaesthesiologist, a CN, and a SN. At the end of the surgery, PACUN and the anaesthesiologist transfer patients to PACU area, and the OR is cleaned by a MT. Patients are monitored by a PACUN every 15 minutes until they are recovered.

Surgeries start at 06:00 AM and finish at 05:00 PM. In other words, ORs are available for 11 hours. There is a possibility of ORs' overtime; however, it implies more cost. In addition, from 35 planned surgeries in one day, some constraints must be considered: Block cases (8 patients) should take priority to AddOn cases, since they require specific surgeon groups; also, four procedures (gynaecology) have to be performed in OR1 due to equipment constraints.

3. DISCRETE EVENT SIMULATION

A DES model was developed using FlexSim® software. Since there are a lot of variability processes, we incorporated them into the model using probability distributions. These variabilities are in patient arrival time, dressing time (Outpatients), PreOp process, in three procedures performed in the ORs (wheels in to incision, incision to closure, and closure to wheels out), and in recovery time. As described before, when patients leave the ORs, a MT cleans and prepares them for another surgery. Moreover, we made some assumptions in the model. Doctors that perform the surgeries are available from 05:45 AM to 12:00 PM and we did not consider break time individually, since they do not carry out procedures all day. The same was considered to the anaesthesiologist group. Fig. 1 shows the SC structure in the DES model.

Figure 1: SC DES model through FlexSim®.

After building the model, we performed model verification and validation. According to Sargent [20], verification needs to be performed to ensure that the computer model implementation corresponds to the real system while validation aims to evaluate if the model presents a satisfactory range of accuracy. In this sense, we performed the verification stage using face-to-face technique. The team analysed inpatient and outpatient flows, and they agreed that the model was close to the real process. We used sensitivity analysis in the model validation stage. In sensitivity analysis, we change value on the input model to determine the influence in outputs [20]. The same should occur in the real system. We define the patients that would be attended (22 patients) and varied all processing time in -50 %, -25 %, 0 %, +25 %, and +50 %. As validation outputs, we collected overtime spent in SC to perform all surgeries and recovery the last patient and the total earnings obtained by it. Each minute added in overtime costs US$ 40.00, reducing total earnings. Fig. 2 shows the sensitivity analysis results and, as expected, by varying processes' times, the overtime would increase or decrease proportionally. Then, we considered the model validated.

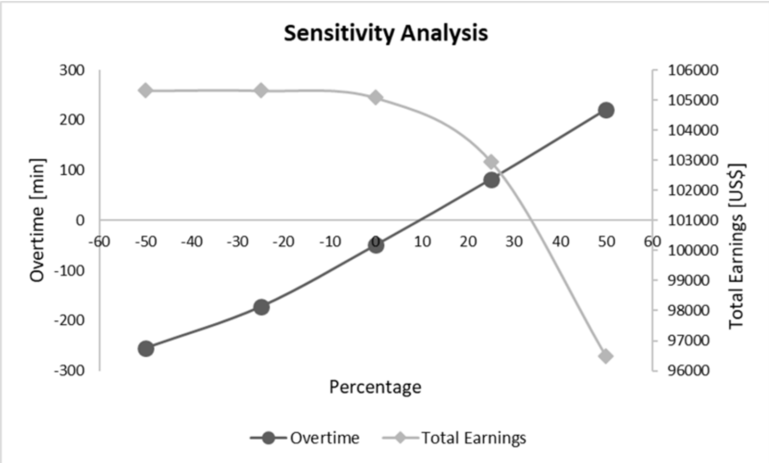

Figure 2: Sensitivity analysis for DES model validation.

4. PROBLEM FORMULATION

4.1 Model notation

We consider a set of I patients, indexed by i that can be attended in one day. These patients may use a set of J ORs, indexed by j. Each surgery returns an amount to the SC; however, we considered the net revenue w per minute in each case. Moreover, the total minutes available in each OR is represented by T_i that varies in each scenario ω. A set of Ω scenarios, indexed by ω was considered. Then, the first round of optimization is given by the optimization of w_{total}, considering how many patients will be attended in a day and defining which OR the procedure will be carried out.

In the second round of optimization, we should consider the total number of completed cases cc in one day, the overtime ot and the total earnings te received. Total earnings are calculated by obtaining the total tps received by carrying out all surgeries in a day minus total minutes in overtime m_o cost and the total cost with MT group n_{MT} and nurses n_N. In addition, we set a number of permutations π in arrival patients, indexed by $\pi_a \in \langle \pi_1, \dots, \pi_m \rangle$. In this stage, using SBO, the algorithm test different combinations of arrival patients to minimize ot and, consequently, maximize te.

Finally, the third-optimization problem aims to maximize cc and te and, at the same time, minimize ot and the total number of staff t_{ns} available in SC that do not compromise care quality. It is represented by the total number of PreOp Nurses n_{PON}, PACU Nurses n_{PACUN}, Circulating

Nurses n_{CN}, Scrub Nurses n_{SN}, and Maintenance Tech n_{MT}. The number of staff for CN and SN is in a set of K, indexed by k and the other staff is indexed in a set of P, indexed by p. In this round, we also used SBO approach. Table I summarizes the notation used in all stages.

Table I: Model notations.

Symbol	Description
Sets	
I	Set of patients scheduled in a day, indexed by $i \in I$, $I \in [1, 35]$.
J	Set of available ORs, indexed by $j \in J$, $J \in [1, 3]$.
Ω	Set of scenarios, indexed by $\omega \in \Omega$.
π	Set of arrival patient sequence, indexed by π_a, $\pi \in [1, 35]$.
K	Set of available Circulating and Scrub nurses, indexed by $k \in K$, $K \in [1, 5]$.
P	Set of available PreOp and PACU nurses, and Maintenance Tech, indexed by $p \in P$, $P \in [1, 3]$.
Model parameters:	
w_i	Net revenue per minute [US$/min] from surgery i.
w_{total}	Total net revenue per minute [US$/min].
T_i	Available minutes in OR j.
tps	Total paid by all surgeries.
m_o	Minutes spent in overtime.
π_a	Permutation order that a patient arrives in the model.
n_N	Number of staff used among all nurses.
n_{PON}	Number of PreOp nurses.
n_{PACUN}	Number of PACU nurses.
n_{CN}	Number of Circulating nurses.
n_{SN}	Number of Scrub nurses.
n_{MT}	Number of Maintenance techs.
First-optimization variables	
x_i	Patient i that needs a surgery procedure; 1 if the surgery is performed; 0 otherwise.
y_j	OR j which the procedure will be done; 1 if the surgery is performed in OR j; 0 otherwise.
Second-optimization variables	
cc	Completed case in one day.
ot	Overtime.
te	Total earnings.
Third-optimization variables	
cc	Completed case in one day.
ot	Overtime.
te	Total earnings.
t_{ns}	Total number of staff.

4.2 OR's optimization

Hillier and Lieberman [18] define three steps in a NLP optimization: decision variables, objective function, and constraints. In OR's optimization, the decision variables are: x_i = patient i that needs a surgery procedure, and y_j = OR j which the procedure will be done. In this case, $1 \leq i \leq 35$ and i is each patient. Moreover, $1 \leq j \leq 3$ and j is each OR.

The main objective is to reach the largest number of patients considering the best SC's net revenue. The rate between the surgery price and the time that an OR is occupied, considering total surgery time and cleaning routines, represents SC's net revenue per minute. Since all procedures have a normal distribution time, we considered the mean plus two standard deviations to carry out the optimization. In this sense, the problem aims to maximize the total net revenue (w_{total}) per minute [US$/min] for each patient *i* procedure. Eqs. (2) to (12) show the optimization problem:

$$max(w_{total}) = \sum_{i=1}^{35}\sum_{j=1}^{3} w_i x_i y_j \tag{2}$$

s.t.:

$$x_i,\ y_j = bin \tag{3}$$

$$x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8 = 1 \tag{4}$$

$$x_8 \cdot y_1 = 1 \tag{5}$$

$$\text{if } x_{22} = 1; \text{then } x_{22} \cdot y_1 = 1 \tag{6}$$

$$\text{if } x_{23} = 1; \text{then } x_{23} \cdot y_1 = 1 \tag{7}$$

$$\text{if } x_{24} = 1; \text{then } x_{24} \cdot y_1 = 1 \tag{8}$$

$$\sum\nolimits_{i=1}^{35} t_i \cdot y_1 \le T_i \tag{9}$$

$$\sum\nolimits_{i=1}^{35} t_i \cdot y_2 \le T_i \tag{10}$$

$$\sum\nolimits_{i=1}^{35} t_i \cdot y_1 \le T_i \tag{11}$$

4.3 Patients' arrival order optimization

In the second round of optimization, we used SBO approach. The optimization problem has three functions: (i) maximize the total number of patients that have a procedure in a day; (ii) minimize overtime; and (iii) maximize total earnings. Each minute in overtime costs US$ 40.00, each MT receives US$ 1,000.00, while each nurse receives US$ 1,200.00. In this sense, total earnings (*te*) is given by Eq. (12):

$$te = tps - 40 \cdot (m_o) - 1000(n_{MT}) - 1200(n_N) \tag{12}$$

Moreover, Eqs. (13) to (14) show the problem optimization:

$$\min\,[cc \quad ot \quad te] \tag{13}$$

s.t.:

$$\pi_a \in \langle \pi_1, \dots, \pi_m \rangle \tag{14}$$

We considered all staff available in the SC because we focused on the order that patients arrive. We used Optquest package from FlexSim® to perform the optimization. The solution presents the best arrival patient sequence that minimizes OR idleness.

4.4 Resource optimization

The last stage comprises Resource optimization since total earnings depend on the number of staff working in SC. The third optimization aims to minimize the total number of staff and, at the same time maximize (i) and (iii) and minimize (ii), as described before. The total number of staff is represented in Eq. (15):

$$t_{ns} = n_{PON} + n_{PACUN} + n_{CN} + n_{SN} + n_{MT} \tag{15}$$

Eqs. (16) to (21) present the problem optimization:

$$min\,[cc \quad ot \quad te \quad t_{ns}] \tag{16}$$

s.t.:

$$1 \leq n_{PON} \leq 3 \tag{17}$$

$$1 \leq n_{PACUN} \leq 3 \tag{18}$$

$$1 \leq n_{CN} \leq 5 \tag{19}$$

$$1 \leq n_{SN} \leq 5 \tag{20}$$

$$1 \leq n_{MT} \leq 3 \tag{21}$$

We also used the Optquest package in this stage, since we considered SBO approach. When using Optquest, in stages 2 and 3, the software provided a Pareto frontier to analyse the best results. Moreover, we used Amazon Web Service® (AWS) – Cloud Compute Service that gave us faster responses in both stages. The computer was set as a Windows with 32 core, 2.80 GHz, and 63.3 GB RAM.

5. RESULTS AND DISCUSSIONS

5.1 OR optimization

We planned eight scenarios to analyse the best sequence of procedures and define the ORs for each patient. In Eqs. (9) to 11), as mentioned in Table I, T_i represents the available minutes in each OR, considering: (a) Scenario 1: Patients require a maximum of 180 minutes for recovery. No overtime is considered, so the last procedure must finish 180 minutes before shift end, leaving 480 available minutes; (b) Scenario 2: With an average recovery time of 110 minutes and no overtime, the last procedure must finish 110 minutes before shift end, providing 550 available minutes; (c) Scenario 3: Recovery time is not considered, and the last procedure ends with the shift, allowing 660 available minutes; and (d) Scenarios 4–8: Each adds one hour of overtime. Scenario 4 offers 720 available minutes, Scenario 5 provides 780 minutes, and so forth.

We used the Evolutionary algorithm in Excel® to solve the problem. Since it is an NLP problem, we set 10 different starter points and each optimization round was solved around 20.000 sub problems. Table II shows the best result of Eq. (1) for each scenario.

Table II: Best result for each scenario.

Scenario	Number of surgeries completed				w_{total} [US$/min]
	OR1	OR2	OR3	Total	
1	6	8	8	22	2,381.27
2	6	9	9	24	2,554.38
3	8	10	10	28	2,787.82
4	8	10	11	29	2,838.25
5	10	10	11	31	2,926.40
6	10	11	11	32	2,969.24
7	10	11	12	33	3,004.79
8	10	12	13	35	3,067.75

Table II presents the results of net revenue by minutes considering only the available minutes in ORs. OR1, in all scenarios, presents fewer procedures than others ORs, since obstetrics and gynaecology surgeries need to be done in it and they spend more time than other procedures. Some procedures may be carried out in different ORs depending on their availability (available minutes represented in scenario 1 to 8).

5.2 Arrival order

In the second round of optimization, Eq. (14) represents the constraint related to patients' arrival order. We are aware that a permutation problem has many possible solutions, e.g. the first scenario presents more than 1.12×10^{21} results. To reduce the feasible region, we added the patient arrival order using criteria. Then, patients that present a higher LOS need to be attended first, they arrive at each minute and wait until be attended. We set this criterion because we know that patient that needs more time to recovery would increase *ot* if they would be attended at the end of the ORs' shift. In this sense, it would not be the best solution and we avoided testing not suitable responses.

In addition, we added a label in each patient in the DES model. This label record what time each one enters the ORs and it helps in the scheduling problem. For example, if the surgery starts at 9:00 AM, the patient should be scheduled to arrive at 8:10 AM. In other words, patients should arrive at least 50 minutes before starting the procedures. Moreover, we considered variability in the patient arrival time using DES model.

As mentioned before, the model was optimized using Optquest provided by FlexSim® through AWS. We set for each optimization round 5 replications and we limited the solution to 5,000, and we spend around 200 minutes to obtain the solutions. The best solution was selected and we got the best sequence to perform the surgeries and what time each patient need to arrive in the SC. The procedure was repeated for the eight scenarios.

5.3 Resource optimization

As in the second round, we used OptQuest to test 675 solutions, running 30 replications per round. Using AWS with the same configuration, each scenario took about 120 minutes to reach a solution. Being a multi-objective problem, the software produced a Pareto Frontier. However, in all scenario, the best combination of staff was 1 PON, 2 PACUNs, 3 CNs, 3 SNs, and 2 MTs. We did not aim to minimize doctors' utilization but designed the model to determine their availability in the SC. It identifies when doctors start and finish their shifts based on patient needs. The earliest start time ensures all patients are attended, while the latest finish time defines the shift end.

5.4 Confirmation runs

After the three optimization steps, we conducted 100 confirmation runs for each of the eight scenarios, collecting data on daily case completions, SC overtime, total earnings, OR and staff utilization, and doctors' required availability.

All programmed patients in the first-round optimization were attended according to confirmation runs. We have exceptions on scenario 7 and 8, which attends, on average, 32.94 and 34.63 of patients, respectively. In scenario 7, it was planned to assist 33 patients, while in scenario 8, it was planned 35. It occurs because ORs close at 00:00 AM and some surgeries may not be finished or even started in some replications.

Overtime may be a problem since the SC works more than 8.5 hours to finish all surgeries in scenario 8. In this sense, the staff needs to work until 01:30 AM. However, if the SC decides to perform all surgeries, it receives around US$ 164,642.40 in a workday. Fig. 3 shows the relation between overtime and total earnings for each scenario. We added a polynomial trend line of order 2, with R^2 of 99.35 % and it shows that there is an inflection point around 565 minutes in overtime. Moreover, Table III shows the results found in each scenario with a confidence interval of 95.0 % for *cc*, *ot*, and *te*.

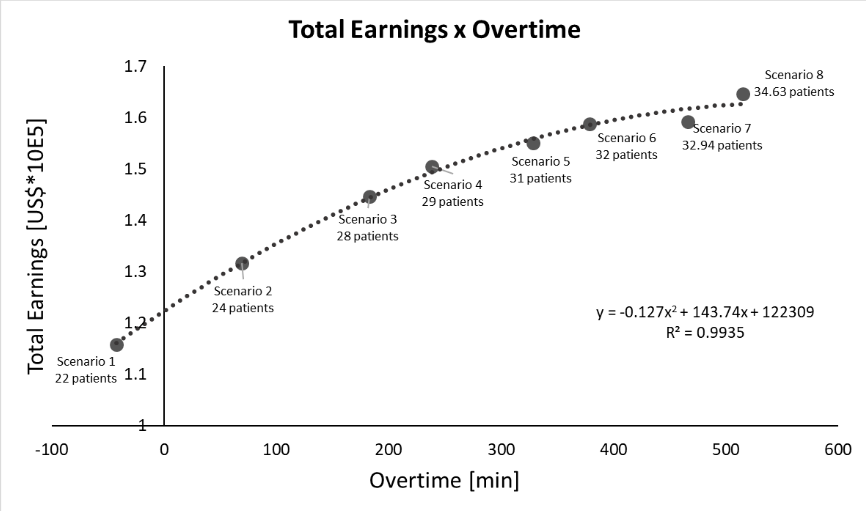

Figure 3: Total Earnings × Overtime – 8 scenarios.

Table III: Final results.

Scenario	Completed cases		Overtime [min]		Total earnings [US$]	
	Mean	*CI*	Mean	*CI*	Mean	*CI*
1	22	-	-42.0	(-49.3; -34.8)	115,758.8	(115,664.0; 115,853.6)
2	24	-	69.1	(60.2; 78.1)	131,691.0	(131,348.4; 132,033.6)
3	28	-	183.1	(176.5; 189.7)	144,566.6	(144,302.7; 144,830.4)
4	29	-	238.6	(229.5; 247.7)	150,518.1	(150,153.6; 150,882.7)
5	31	-	328.3	(320.7; 336.0)	154,991.5	(154,684.1; 155,298.9)
6	32	-	378.6	(369.3; 388.0)	158,762.7	(158,387.6; 159,137.8)
7	32.9	(32.9; 33.0)	466.0	(455.1; 476.9)	159,221.5	(158,612.6;159,830.4)
8	34.6	(34.5; 34.8)	515.0	(503.4; 526.5)	164,642.4	(163,530.6; 165,754.3)

The ORs' utilization is around 75.5 % for all scenarios, on average. In other words, the ORs operate around 53.2 % of the time and it is cleaned by the MTs around 22.3 %. The idleness is acceptable since there is variability between times in each surgery. According to the results, ORs utilization is balanced, since they are occupied by the surgery or been cleaned in 75.3 %, 76.8 %, and 74.3 % of the time, for OR1, OR2, and OR3, respectively. Fig. 4 presents the average utilization in each scenario for the group.

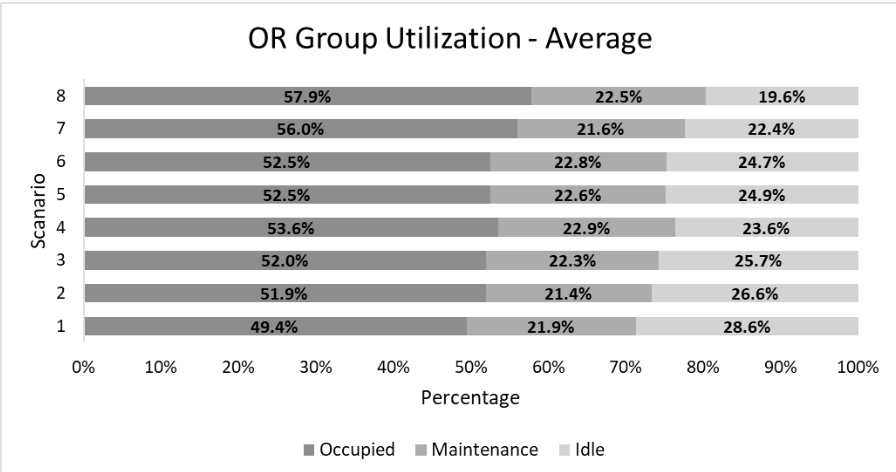

Figure 4: OR group utilization.

According to staff utilization, PON presents the least idleness among all. Since there is only one PON in the SC, the average idleness for all scenarios is around 6.8 %. They spend most of the time in transit because its main function is to escort patients from PreOp to ORs and transport them after the surgery to the PACU area. PACUNs have idleness around 64.6 % of the time. However, if we remove one of them, *ot* starts to increase and, consequently, *te* decreases. They are needed to monitor patients every 15 minutes, spending about 4 minutes per round, as multiple patients may require attention simultaneously.

SNs and CNs have similar idleness rates of 54.4 % and 54.2 %, as they are always needed together during surgeries, with three required simultaneously. Removing one increases *ot* by about 120 minutes in scenario 1, with similar effects in other scenarios. MTs are 65.6 % idle but are essential for cleaning multiple ORs simultaneously. Operating with one MT increases *ot*. Only PONs have no idleness across scenarios. Other groups can perform non-patient-related tasks during idle periods. Fig. 5 illustrates idleness rates for all groups across eight scenarios.

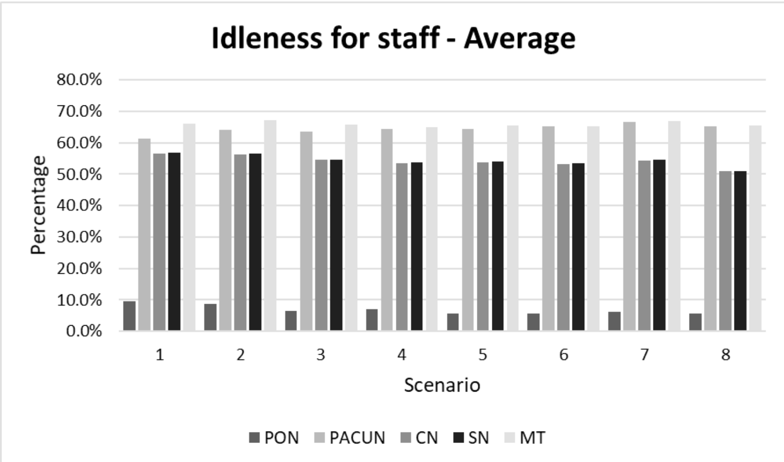

Figure 5: Idleness rate for staff.

Although the study does not aim to study the best shift for doctors, the DES model resulted in how many hours they need to be available in the SC. Doctors do not need to start all of them at the same hours since some of them are requested only part of the day. Fig. 6 shows how many hours each doctor needs to be available in the centre.

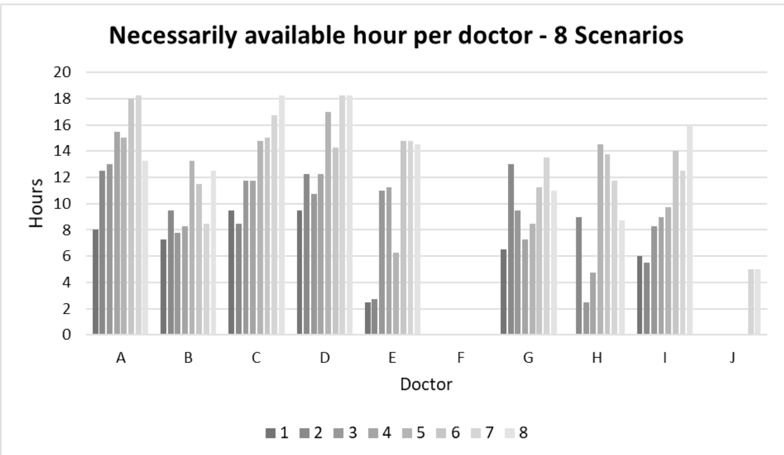

Figure 6: Necessarily available hours per doctor.

According to the results, Doctor F does not perform surgeries as Doctor E is always available for his patients, allowing Doctor F to handle other SC activities. Similarly, Doctor J, assisting with orthopaedic surgeries alongside Doctor D, is only needed in scenarios 7 and 8, working 47.1 % and 39.3 % of the time, respectively, over a 5-hour availability. Critical situations arise for Doctor A in most scenarios and for Doctors C and D, who must be available for over 12 hours in scenarios 5 to 8 but work only 42.6 % (A), 40.9 % (C), and 30.4 % (D) of the time. This is due to performing surgeries early, staying idle, and then performing the final surgery late in the shift. While doctors' shifts are a study limitation, this could be explored in future research.

In general, all ORs and staff utilizations remain the same percentage in the eight scenarios. Doctors' utilization is different because depends on scheduling patient time. In addition, using the method with the AWS technology it is possible to get efficient results in a small time and can be used as an operational strategy every day in centres with high variability processes by the stakeholders.

6. CONCLUSIONS

OR scheduling is an important and difficult problem that many healthcare systems face. It is difficult to optimize it because there are involved many variables, such as patient arrival time, ORs that the surgery will be performed, number of staff, and doctors' availability. In order to cope with it, the paper proposed a three-optimization problem approach to decrease the number of tested solutions. In the first stage, we used NLP to maximize the total net revenue per minute considering the time that each OR is used to carry out the surgeries and clean it. We used the Evolutionary algorithm in this stage and proposed eight scenarios.

The second and third stages applied the SBO approach. A DES model was built and validated via sensitivity analysis. The second stage optimized *cc*, *ot*, and *et* for each scenario by varying patient arrival order. Given the permutation complexity, patients with longer LOS were prioritized, identifying the best arrival sequence and schedule. The third stage optimized the same metrics plus total SC staff. The best setup across scenarios was 1 PON, 2 PACUNs, 3 CNs, 3 SNs, and 2 MTs. After all phases, the SC handled about 34.6 of 35 scheduled patients in critical scenarios, with balanced staff and OR utilization. SC operated 515.0 overtime minutes, generating $164,642.40 in net revenue.

We are aware that the problem has a great number of solutions and in SBO approach, each tested round was run 5 times in the second stage and 30 times in the third. Moreover, to obtain fast responses we used AWS technology that provides solutions in a small amount of time. Finally, the study has limitations: doctor shifts and anaesthesiologist optimization were not considered, and variability was not tested in the first stage despite using mean OR time plus two standard deviations. In the second stage, solutions were reduced due to the problem's complexity (over 1.12×10^{21} possibilities). Future work should explore staff shifts, especially for doctors with low utilization but long availability, and test variability using stochastic methods in the first stage.

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