Author/s:
Zadeh, HS;Anjomshoa, H;Zhang, L;Fackrell, M

Title:
A data-driven preventive surgery scheduling in flexible operating rooms using stochastic optimization

Date:
2023

Citation:
Zadeh, H. S., Anjomshoa, H., Zhang, L. & Fackrell, M. (2023). A data-driven preventive surgery scheduling in flexible operating rooms using stochastic optimization. Proceedings of the International Congress on Modelling and Simulation Modsim, pp.795-801. Modelling and Simulation Society of Australia and New Zealand Inc.. https://doi.org/10.36334/modsim.2023.sadeghzadeh.

Persistent Link:
https://hdl.handle.net/11343/362904

25th International Congress on Modelling and Simulation, Darwin, NT, Australia, 9 to 14 July 2023
mssanz.org.au/modsim2023

# A data-driven preventive surgery scheduling in flexible operating rooms using stochastic optimization

**H. Sadegh Zadeh**, **H. Anjomshoa, L. Zhang and M. Fackrell**

*ARC Training Centre in Optimisation Technologies, Integrated Methodologies, and Applications, School of Mathematics and Statistics, The University of Melbourne, Australia*
*Email: h.sadeghzadeh@student.unimelb.edu.au*

**Abstract:** Planning operating theatres and scheduling surgeries play a crucial role in hospital management. Operating theatres generate the most revenue for hospitals while demanding significant resources. This study investigates the optimal plan for flexible operating rooms (ORs) as a shared resource between elective and emergency patients. Elective operations might be planned weeks or months in advance. An emergency operation, on the other hand, must be performed as soon as possible. In this study, the uncertainty in parameters, such as emergency arrivals and surgery durations, has been considered. Based on the historical data obtained from a local hospital in Australia, we fitted lognormal distributions to surgery durations and Poisson distributions to emergency case arrivals. A stochastic programming model is developed to optimise the assignment of selected elective patients to surgical blocks considering the emergency arrivals with the objective of minimising the total cost of conducting or postponing surgeries and overtime. The surgical blocks are obtained from a master surgery schedule (MSS) which is determined at the tactical level of OR scheduling for several months. Each block is combinations of weekday/time, surgical specialty, and ORs. To distinguish the patients on the waiting list, a priority factor has been determined for each patient considering their surgical specialty, their actual waiting time, and their urgency level. Emergency patients have higher priority compared to the elective case with the same attributes. To preventively manage the random arrivals of emergency cases, most of the literature applied a Break-In-Moment (BIM) methodology in which finish times of surgeries in blocks are distributed in a way that maximises the insertion opportunities for emergency case arrivals. However, this methodology cannot be considered as a highly responsive-preventive methodology when the lengths of surgeries appear to be long as it may reduce opportunities for emergency case insertions.

The proposed solution in this paper considers buffer time in each surgical block as a preventive methodology for emergency case arrivals. These buffer times can be divided into several parts and can be inserted into the plan every few hours, or they can be used as a whole time at the end of block time. In this paper, at first, we run the model deterministically to obtain good estimates of buffer time for each block. Then we run the model stochastically using the buffer times from the deterministic model and the random data obtained from distribution functions of the random parameters. By considering this scenario as a base, varying the buffer times and solving each scenario stochastically, we found that increasing the amounts of buffer times did not change the objective function significantly, however reducing them changed the objective function noticeably. Based on this, solving the model deterministically at first can give us a good estimation of buffer time for preventive scheduling for emergency case in flexible ORs.

***Keywords:*** *Surgery planning, flexible ORs, stochastic programming, emergency case arrivals, buffer time*

## 1. INTRODUCTION

Hospitals worldwide are under pressure to provide the best medical services to an increasing number of patients in reasonable lengths of time and with a limited set of resources (Fugener et al. 2014). Operating rooms (ORs). often constitute the majority of patient flow and are perhaps one of the most profitable areas of the hospital. OR scheduling problems are determined by a variety of objectives, constraints, and uncertainty linked to various parameters (Jebali and Diabat 2015; Marques and Captiva 2017; Neyshabouri and Berg 2017; Calegari et al. 2020). In reality, OR scheduling problems are frequently far more complex than many of the models proposed in the literature. Previously discussed problems are frequently simplified versions of real-world problems, while several constraints and functional objectives have been neglected. For example, uncertainty, which is inherent inreal-world problems, has been often neglected (Molina-Pariente et al. 2015). These challenges demonstrate the need to use high-level methodologies in solving real-world OR scheduling problems. In this paper, we solve an elective surgery planning problem in flexible ORs. By flexible ORs, we mean that the OR can be shared between elective cases and emergency cases whenever they show up. The scheduling of elective cases may begin from weeks or months in advance. However, emergency cases who arrive randomly, must undergo surgery, often on the same day. In this study, we assume that at the beginning of each week the OR manager ranks the patients on the waiting list, with the help of surgeons, based on their needed specialty, their urgency level, and their time spent on the waiting list. Then he/she allocates the highest ranked patients to their needed specialty blocks (that is, combinations of ORs, specialties and date/time slots) to undergo surgery during the next week considering the buffer time which has been previously reserved for random arrivals of emergency cases in each block. Our objective in solving this problem is to minimise the total cost caused by performing or postponing surgeries and over-utilisation of surgical blocks. The inherent randomness in lengths of surgeries and emergency cases arrivals are also considered. The problem studied in this paper is surgery scheduling at the operational level with the assumption that the Master Surgery Schedule (MSS) from tactical level is already available.

## 2. LITERATURE GAP

The literature on relevant studies shows that in most similar surgery scheduling problems, the initial elective surgery schedule is developed without any preparations for future emergency arrivals. Emergency surgery patients should be operated on in a limited time, depending on their urgency category. Nevertheless, without any preparations, there will be no guarantee that delayed access to ORs can be completely avoided due to the unpredictable nature of emergency arrival patterns and the uncertain length of surgeries. As a result, it is critical to proactively prepare for possible future emergency arrivals. In preventive planning, some of the studies considered developing an initial schedule, in which completion times of elective surgeries are distributed in a way that maximises opportunities for emergency case insertions. After a certain elective surgery is completed, an emergency OR access is possible. This method is called Break-In-Moment (BIM) (Vandenberghe et al. 2019). However, this type of scheduling is insufficient for some specialities if all elective surgeries are anticipated to take a long time. As can be seen in Figure 1, there are circumstances in which BIM-based preventive scheduling will not respond quickly enough. Even though the emergency surgery is scheduled to be inserted in the first available operating room (OR) once it arrives, as shown in Figure 1 (b), the waiting time limit can be easily violated, and it may get the situation more severe for emergency cases with higher urgency level who have shorter waiting time limits to undergo surgery. In this situation, it is recommended that on the day of surgery, some buffer times be reserved in initial schedule to make it easier for ORs to accommodate emergency arrivals. The consideration of these buffer times will help minimise the risk of surgical delays due to emergency patient arrivals. Creating and distributing buffers in the original schedule allows us to construct a schedule that is both practical and very responsive. The buffer times can be divided into several parts and be inserted every few hours (Figure 2) or they can be used as a whole part at the end of each block times.

Based on Figure 2, if the buffer time is distributed in the blocks and the operating room is empty during the buffer times, this provides an opportunity for emergency patients to enter faster and reduces their waiting time compared to Figure 1 (b) (The red horizontal line indicates the waiting time for emergency patients.) This is beneficial for situations where surgeries are too lengthy.

As in our case study the number of emergency cases cancelled due to lack of OR time is high. On the other hand, since the most urgent category of emergency cases required treatment within the first hour after arrival, it was necessary to consider buffer time in at least one surgical block every hour to ensure timely treatment. In this case, the total buffer time obtained can be distributed during the OR opening period. The BIM methodology may provide enough insertion opportunities in some cases, eliminating the need for dividing buffer time. However, determining these, requires further study.

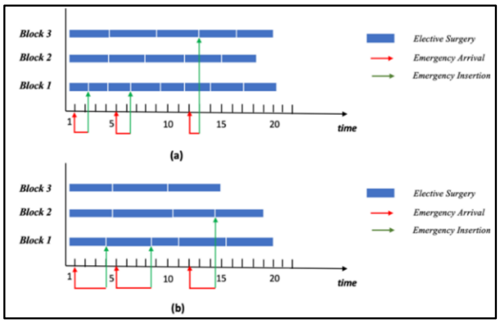


**Figure 1.** The shortcoming of preventive schedules based on only BIMs

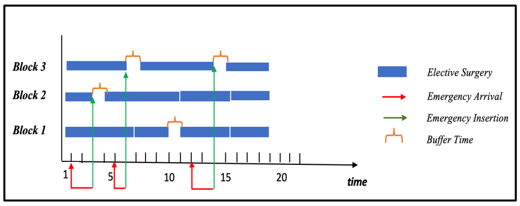


**Figure 2.** The preventive schedules based on using buffer times every few hours

## 3. PROBLEM DESCRIPTION

This study aims to find the optimal surgery schedule at a hospital that has $B \in \{1,2,\dots\}$ available surgery blocks over the planning horizon of $T$ days (here $T = 5$ representing a week without the weekend). The MSS has each surgical block $b \in [B] := \{1,\dots,B\}$ allocated to an OR and to one surgical speciality with a regular length of time $(Rl_b)$. The time length of $RL_b$ for each block $b$ is normally long enough that several operations can be conducted during that time. It should be noted that for the same speciality, several blocks may exist within a cycle of the OR plan (a week). The operating room capacity is divided between two competing surgery categories: a known number $(I_{elec})$ of elective procedures that must be scheduled beforehand (for example, at the beginning of the week) and a random number of emergency cases that must be conducted on the day of arrival. Each elective case $(i \in I_{elec})$ has a specific surgery specialty, and throughout the planning horizon, it is possible to allocate them to any of the blocks pre-assigned to their specific surgical specialty. There are costs related to conducting or postponing surgery for each elective and emergency case (that is, cost of postponing the surgery to the next available cycle). We imagine that patients are allocated to a dummy block $(b' \notin [B])$ if they are not scheduled for any of the surgery blocks within the current cycle.

Let the costs of conducting and postponing surgery be denoted by $c_{ib}$ and $c_{ib'}$, respectively. Hence, we assume that for any $b \in [B]$, $c_{ib'} > c_{ib}$ . Also, the cost of allocating a surgery to a block is dependant to its specialty type. The length of an elective procedure $(d_i)$ is a random parameter which depends on its specialty type. Emergency surgeries arrive randomly, and their durations are also random. The costs and lengths of emergency surgery cases are also dependent on their surgical specialty. To compare the costs of emergency and elective surgery cases, the emergency cases often have higher costs (for both conducting and postponing) (Haider et al. 2015). To make a highly preventive schedule for emergency arrivals, we consider a predefined buffer time capacity for emergency cases besides the capacity for elective cases in each block (denoted by $Bf_b$). The exact determination of buffer time is highly important, since overestimation of it may reduce the capacity for elective cases, and in contrast, underestimation of it could result in emergency case cancellations. We also assume priority factors for each elective patient on the waiting list and each emergency case which are defined based on their needed specialty, their urgency level, and their actual waiting time. It is obvious that in most of the circumstances, emergency cases have higher priorities compared to the elective cases of the same specialty. Considering a waiting list of elective surgeries $(I_{elec})$ and their types, we aim to create a plan that designates: ***(a)*** buffer time length for emergency cases, and ***(b)*** the number (or subset) of elective and emergency surgeries to schedule in each surgery block based on their needed specialty (equivalently, surgery assignments to available surgical blocks). The objective of the plan is to minimise the total cost of conducting or postponing elective and emergency cases and the costs of OR overtime. When operations allocated to block $b$ are not finished within $[0, Rl_b]$, overtime is incurred. The time (in terms of days) that the patient has been added to the waiting list is considered as waiting time.

## 4. MODEL FORMULATION

The notations used in the model are shown in Table 1. To express the uncertainty in this problem, we defined a scenario $\phi \in \Phi$ to represent a vector of stochastic parameters (which is determined based on different surgery durations in various situations), then the surgical time for patient $i \in I$ in each scenario $\phi \in \Phi$ can be shown by $d_i^{\phi}$. Let $Pr(\phi)$ represents the probability of scenario $\phi$, therewith, $\sum_{\phi \in \Phi} Pr(\phi) = 1$.

**Table 1.** Notations used in the model development

| Type | Notations | Definitions |
|---|---|---|
| Indices | $I$ | Set of all patients waiting for surgery |
| | $I_{elec}$ | Set of elective patients |
| | $I_{emer}$ | Set of emergency patients |
| | $B$ | Set of surgical blocks |
| | $\{b'\}$ | Set of dummy blocks (not surgical blocks) |
| | $\Phi$ | Set of scenarios (based on different surgery durations) |
| Functions | $Pr(\phi)$ | Probability density function of scenario $\phi$ |
| Decision variables | $x_{ib}$ | 1, if patient $i$ is allocated to block $b$; 0 otherwise |
| | $x_{ib'}$ | 1, if patient $i$ is allocated to dummy block $b'$; 0 otherwise |
| | $o1_b^{\phi}$ | Overtime of surgical block $b$ in scenario $\phi$ (of elective cases) |
| | $o2_b^{\phi}$ | Overtime of surgical block $b$ in scenario $\phi$ (of emergency cases) |
| | $o_b^{\phi}$ | Total overtime of surgical block $b$ in scenario $\phi$ |
| | $Bf_b$ | Buffer time of block $b$ |
| Parameters | $p_i$ | Priority of patient $i$ |
| | $a_{ib}$ | 1, if patient $i$ can be assigned to block $b$; 0, otherwise |
| | $c_b^o$ | Unit overtime cost of block $b$ per minute |
| | $c_{ib}$ | Cost of allocating patient $i$ to block $b$ |
| | $c_{ib'}$ | Cost of postponing surgery to dummy block $b'$ |
| | $Rl_b$ | The regular open duration of surgical block $b$ |
| | $O_{max}$ | The maximum permitted overtime |
| | $d_i^{\phi}$ | Surgery duration of elective patient $i$ in the scenario $\phi$ |
| | $\tilde{d}$ | Uncertain surgery duration |
| | $K$ | Number of scenarios (based on different surgery durations) |
| | $S$ | Number of scenarios (based on buffer time amounts) |

In the objective function (1), the fixed initial terms represent the costs of conducting or postponing elective and emergency surgeries, while the last term $E(Q(x,\tilde{d}))$ shows the expected objective value of a recourse problem which captures overtime costs under the impact of uncertainties in all the scenarios. Constraints (2), (3) guarantee that each of the patients are assigned to exactly one surgical block or are postponed (are assigned to a dummy block). Constraints (4) and (5) guarantee that each surgery is allocated to one of its pre-allocated blocks to its corresponding specialty. The variables $x_{ib}$ are defined as binary decision variables in constraints (6).

$$\boldsymbol{Min}\left(\sum_{i=1}^{I_{elec}}\sum_{b\in B} p_i\, c_{ib}x_{ib} + \sum_{i=1}^{I_{elec}}\sum_{b'\in\{b'\}} p_i\, c_{ib'}x_{ib'} + \sum_{i=1}^{I_{emer}}\sum_{b\in B} p_i\, c_{ib}x_{ib} + \sum_{i=1}^{I_{emer}}\sum_{b'\in\{b\prime\}} p_i\, c_{ib'}x_{ib'} + E(Q(x,\tilde{d}))\right) \quad (1)$$

$$\sum_{b\in B} x_{ib} + \sum\nolimits_{b'\in\{db\}} x_{ib'} = 1 \qquad \forall i \in I_{elec} \quad (2)$$

$$\sum_{b\in B} x_{ib} + \sum\nolimits_{b'\in\{db\}} x_{ib'} = 1 \qquad \forall i \in I_{emerg} \quad (3)$$

$$x_{ib} \le a_{ib} \qquad \forall i \in I_{elec}\,, b \in B \quad (4)$$

$$x_{ib} \le a_{ib} \qquad \forall i \in I_{emer}\,, b \in B \quad (5)$$

$$x_{ib} \in \{0,1\}, \qquad \forall i \in I\,, b \in B \quad (6)$$

$E\left(Q(x,\tilde{d})\right)$ represents the objective value of the following recourse problem:

$$Min \sum_{\phi\in\Phi} Pr(\phi)\left(\sum_{b\in B} c_b^o\, O_b^{\phi}\right) \quad (7)$$

$$O1_b^{\phi} \ge \sum_{i\in I} x_{ib}\, d_i^{\phi} - (Rl_b - Bf_b), \quad \forall i \in I_{elec}\,, b\in B, \phi \in \Phi \quad (8)$$

$$O2_b^{\phi} \ge \sum_{i\in I} x_{ib}\, d_i^{\phi} - Bf_b, \quad \forall i \in I_{elec}\,, b\in B, \phi \in \Phi \quad (9)$$

$$O_b^{\phi} = O1_b^{\phi} + O2_b^{\phi} \quad \forall\, b \in B, \phi \in \Phi \quad (10)$$

$$0 \le O_b^{\phi} \le O_{max} \quad \forall\, b \in B, \phi \in \Phi \quad (11)$$

The objective function (7) aims to minimise overtime costs in different scenarios. Constraint (8) calculates the overtime of each surgical block in each scenario for elective cases based on random surgery durations, the regular length of each surgical block and the amount of buffer time for each block. Constraint (9) calculates the overtime of each surgical block in each scenario for emergency cases based on random surgery durations and amount of buffer time for each block. Constraint (10) calculates the total overtime of each surgical block in each scenario. Constraint (11) guarantees that total overtime of each surgical blocks is between 0 and the maximum permitted overtime. The priority factors of patients *($p_i$)* in the waiting list are defined based on their needed specialty, their waiting time, and their clinical urgency level.

## 5. CASE STUDY

Inspired by real data from the surgery departments in hospitals, we considered a waiting list of 1172 elective patients from different specialties who have been ranked and will undergo surgery during the next week considering the random number of emergency case arrivals in flexible ORs. We considered an operating theatre with 3 ORs and 15 surgical blocks for 5 working days. Table 2 shows the master surgery schedule that was been determined at the tactical level for several months. To make it clearer, as an example, the combination of OR1, Monday and GASTRO specialty comprise a surgical block (here, block 1).

**Table 2**. The master surgery schedule*

| ORs\Days | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| OR 1 | GASTRO | GASTRO | GYN | GEN | VASC |
| OR 2 | ENT | ORTH | GEN | GYN | URO |
| OR 3 | GEN | ENT | URO | VASC | GASTRO |

* GASTRO=Gastroenterology, GYN=Gynaecology, VASC=Vascular, GEN=General, ORTH=Orthopaedic, URO=Urology, ENT=Ear, nose & throat

Each block has a different length (for example, 480 minutes), and each surgery can be allocated to any of its related pre-assigned specialty blocks during the planning cycle (here a week). Surgery duration is among one of the important surgical uncertainties. It is commonly assumed that surgery durations in stochastic programming models will also be lognormally distributed since the lognormal distribution provides the best fit for OR data (Marques and Captivo; 2017, Zhang, 2020). Moreover, the patients from the same specialty are usually assumed to have the same probability distribution function (Jebali and Diabat, 2015; Neyshabouri and Berg, 2017). Based on these, using historical data, we fitted lognormal distributions to our different surgical specialties. Table 3 shows the parameters of elective surgery duration lognormal distribution functions based on each surgery type obtained from our data analysis.

**Table 3**. The surgical blocks information (obtained from analysis of our data)

| Block number | Surgery types | Weekday | Block duration (min) | Mean surgery duration (min) | Surgery duration distribution function* |
|---|---|---|---|---|---|
| b1 | GASTRO | Monday | 435 | 25.33 | lognormal(3.15, 0.39, K) |
| b2 | ENT | Monday | 540 | 79.13 | lognormal(4.24, 0.49, K) |
| b3 | GEN | Monday | 435 | 63.82 | lognormal(4.00, 0.54, K) |
| b4 | GASTRO | Tuesday | 480 | 25.33 | lognormal(3.15, 0.39, K) |
| b5 | ORTH | Tuesday | 555 | 102.72 | lognormal(4.42, 0.64, K) |
| b6 | ENT | Tuesday | 540 | 79.13837 | lognormal(4.24, 0.49, K) |
| b7 | GYN | Wednesday | 555 | 60.07304 | lognormal(3.94, 0.55, K) |
| b8 | GEN | Wednesday | 435 | 63.82435 | lognormal(4.00, 0.54, K) |
| b9 | URO | Wednesday | 450 | 48.75474 | lognormal(3.70, 0.60, K) |
| b10 | GEN | Thursday | 435 | 63.82435 | lognormal(4.00, 0.54, K) |
| b11 | GYN | Thursday | 555 | 60.07304 | lognormal(3.94, 0.55, K) |
| b12 | VASC | Thursday | 540 | 88.52627 | lognormal(4.37, 0.46, K) |
| b13 | VASC | Friday | 540 | 88.52627 | lognormal(4.37, 0.46, K) |
| b14 | URO | Friday | 450 | 48.75474 | lognormal(3.70, 0.60, K) |
| b15 | GASTRO | Friday | 435 | 25.33276 | lognormal(3.15, 0.39, K) |

* K in this column shows the number of stochastic scenarios we aim the model to be run.

Another random parameter is the emergency arrivals. Some authors discussed that the arrivals of emergency cases follow a Poisson process (Samudra et al., 2016; Jebali and Diabat, 2017). Using historical data, the Poisson distribution functions of the number of emergency cases from each specialty group, which showed up on each weekday has been shown in Table 4. We assume that emergency surgeries can only be performed in their needed specialty blocks (within their urgency waiting time limit).

**Table 4**. The distribution of emergency case arrivals in each specialty-weekday

| Specialty\Weekday | Monday* | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| ENT | Poisson (0,S) | Poisson (0,S) | Poisson (0,S) | Poisson (0,S) | Poisson (0,S) |
| GASTRO | Poisson (4,S) | Poisson (2,S) | Poisson (1,S) | Poisson (3,S) | Poisson (2,S) |
| GEN | Poisson (1,S) | Poisson (3,S) | Poisson (1,S) | Poisson (3,S) | Poisson (2,S) |
| GYN | Poisson (0,S) | Poisson (0,S) | Poisson (0,S) | Poisson (0,S) | Poisson (1,S) |
| ORTH | Poisson (6,S) | Poisson (11,S) | Poisson (6,S) | Poisson (7,S) | Poisson (7,S) |
| URO | Poisson (1,S) | Poisson (0,S) | Poisson (2,S) | Poisson (0,S) | Poisson (1,S) |
| VASC | Poisson (1,S) | Poisson (0,S) | Poisson (1,S) | Poisson (1,S) | Poisson (0,S) |

*S in this table refers to the value of Poisson distribution.

As an example, Figure 3 shows the probability distributions of GASTRO surgical specialty (surgery duration and the number of emergency case arrivals on Monday).

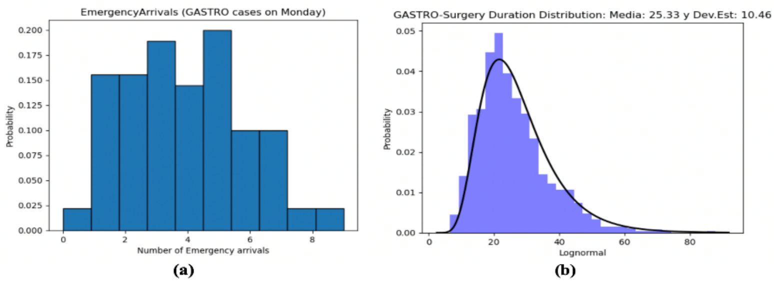


**Figure 3**. Probability distributions of GASTRO surgical specialty

The proposed mathematical model has been solved stochastically using the Gurobi package in Python. Every cost parameter for the performance measures (such as overtime $(c_o)$, scheduling $(c_{ib})$ and postponing $(c_{ib'})$) in the objective function is supported by relevant healthcare references. They are generated using data that are publicly accessible (Carlo et al 2010). Priority factors have been defined using historical data for each elective patient on the list considering their needed specialty, their waiting time, and their urgency level. In our case study, elective patients in the waiting list have been divided into three main urgency categories based on their urgency level (A=Required admission within 30 days, B=Required admission within 90 days, C=Required admission within 365 days). Emergency cases also have different urgency levels based on their waiting time limit (A=1hr Life threatening, B= 2hrs Highly critical organ/limb threat, C=4hrs Critical, D= 8hrs Urgent, E=24hrs Semi-Urgent, F=72hrs non-Urgent).

## 6. NUMERICAL RESULTS

We solved and ran our model for $S = 5$ different scenarios based on various buffer time amounts in each block. The number of emergency case arrivals per specialty per weekday in each of these buffer time scenarios, have been defined randomly using their specific Poisson distribution function (Also the value of Poisson distribution functions equal to 5). In each of these 5 scenarios, the model has been run $K = 10$ times (i.e., $K$ shows the number of surgery duration scenarios). At first, we ran the model deterministically to acquire a good estimation of the buffer time optimal value. Then we used the buffer times from the deterministic model to solve the problem stochastically. We consider it as the base scenario. Then we changed the amounts of buffer time in each scenario and ran it several time stochastically. At the same time with changing buffer times, we changed the number of emergency case arrivals per specialty per weekday. Table 5 and Table 6 represent the number of emergency cases and the buffer times obtained from solving the model in the base scenario (*stochastic model with buffer time from deterministic model*), respectively. The results of objective function sensitivity analysis in different buffer time scenarios have been summarised in Figure 4. The model has been coded and run with Gurobi package in Python.

**Table 5.** The number of emergency patients in base scenario

| Specialty | Monday* | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| ENT | 0 | 0 | 0 | 0 | 0 |
| GASTRO | 4 | 2 | 1 | 3 | 2 |
| GEN | 1 | 3 | 1 | 3 | 2 |
| GYN | 0 | 0 | 0 | 0 | 1 |
| ORTH | 6 | 11 | 6 | 7 | 7 |
| URO | 1 | 0 | 2 | 0 | 1 |
| VASC | 1 | 0 | 1 | 1 | 0 |

**Table 6.** Buffer times obtained from the base scenario

| Block number | b1 | b2 | b3 | b4 | b5 | b6 | b7 | b8 | b9 | b10 | b11 | b12 | b13 | b14 | b15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Buffer time (min) | 435.0 | 63.8 | 0.0 | 279.5 | 452.3 | 205.4 | 50.7 | 0.0 | 285.9 | 54.7 | 128.1 | 480.0 | 0.0 | 102.7 | 333.4 |

## 7. CONCLUSIONS

Cancellation, postponement or not treating the emergency case surgeries within their permitted waiting time, due to a lack of enough OR time capacity, are so costly to hospitals and result in potentially dangerous situations for patients. One of the methods in the literature is using BIM methodology as a preventive methodology against emergency case random arrivals in flexible ORs, however there are some shortcomings for this methodology. According to Figure 1, when the surgeries are too long, it may reduce the opportunities for emergency patients' insertions who have limited waiting time to be under treatment. It is suggested to consider buffer time for emergency cases. The length of each buffer time is important as it cannot be too long or too short. Based on Figure 3, the base scenario of solving the stochastic model with buffer time from the deterministic model can provide a good estimate of buffer time for emergency cases. After increasing the amounts of the base scenario, the objective does not change much, however by reducing the base scenario amounts, the objective function increases significantly.

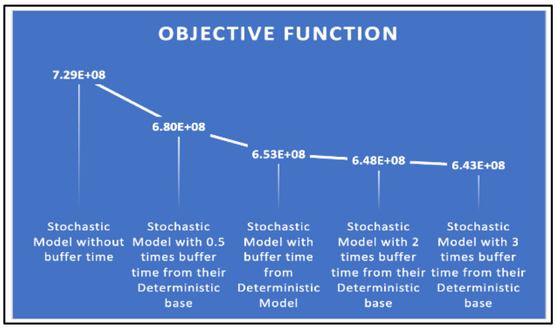


**Figure 4**. Objective function amounts based on different buffer time scenarios

## ACKNOWLEDGEMENTS

We are grateful to everyone who assisted us during this project, especially Ms Karen Berry from Central Coast Local Health District for sharing data and providing a thorough problem description, and the MISG team at Monash University for their valuable assistance.

## REFERENCES

Calegari, R., Fogliatto FS., Lucini FR., Anzanello MJ., Schaan BD., 2020, Surgery scheduling heuristic considering OR downstream and upstream facilities and resources. BMC Health Serv Res. 20(1):684.

Carlo, M., Eivind J N., and Tomas E N., 2010: Mss-adjusts surgery data. [WWW] Available from: https://www.sintef.no/Projectweb/Health-care-optimization/Testbed/

Fugener, A., Hans, E. W., Kolisch, R., Kortbeek, N., 2014, Master surgery scheduling with consideration of multiple downstream units. European Journal of Operational Research, 239(1), 227-236.

Haider, AH., Obirieze A., Velopulos CG., Richard P, Latif A, Scott VK, Zogg CK, Haut ER, Cornwell, 2015, EE 3rd, MacKenzie EJ, Gaskin DJ. Incremental Cost of Emergency Versus Elective Surgery, Annals of Surgery, 262(2):260-6.

Jebali, A., and Diabat, A. ,2015, A stochastic model for operating room planning under capacity constraints. International Journal of Production Research, 53(24):7252–7270.

Jebali, A., and Diabat, A. ,2017, A chance-constrained operating room planning with elective and emergency cases under downstream capacity constraints. Computers and Industrial Engineering, 114:329–344.

Marques, I., and Captivo, M. E. ,2017, Different stakeholders' perspectives for a surgical case assignment problem: Deterministic and robust approaches. European Journal of Operational Research, 261(1):260–278

Molina-Pariente, J. M., Fernandez-Viagas, V., and Framinan, J. M. ,2015, Integrated operating room planning and scheduling problems with assistant surgeon-dependent surgery durations. Computers and Industrial Engineering, 82:8–20.

Neyshabouri, S., and Berg, B. P. ,2017, A two-stage robust optimization approach to elective surgery and downstream capacity planning. European Journal of Operational Research, 260(1):21–40.

Samudra, M., Van Riet, C., Demeulemeester, E., Cardoen, B., Vansteenkiste, N., 2016, Scheduling operating rooms: Achievements, challenges, and pitfalls. Journal of Scheduling, 19(5):493–525.

Vandenberghe, M., De Vuyst, S., Aghezzaf, E. H,2019, Surgery sequencing to minimize the expected maximum waiting time of emergent patients. European Journal of Operational Research, 275(3), 971–982.

Zhang, J., Dridi M., Moudni A., 2020, Column-generation-based heuristic approaches to stochastic surgery scheduling with downstream capacity constraints, International Journal of Production Economics, 229: 107-764.