# A Two-Step Stochastic Optimization and Simulation Approach for Scheduling Operating Rooms in an Ophthalmology Surgery Department 

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#### Abstract

In this study, a two-step method for the daily priority-based surgical case scheduling of elective patient of non-identical Operating Rooms (OR) is presented. In the first step, we present a mixed integer programming model to select patients from the waiting list and to assign the selected patients to the operating room. The objectives are to minimize the makespan, undertime and overtime costs simultaneously and maximize the weighted sum priority of selected surgeries. After assigning the patients to the ORs, in the second phase, the sequence of selected surgeries in the operating room assigned them has been determined by discrete event simulation by two dispatching rules including the Shortest Surgery Time based on priority (SST), and the Longest Surgery Time based on priority (LST). Also, the schedules obtained by these two dispatching rules are compared with the head surgeon schedule. This research has been performed in one of the surgical departments of a public hospital located in Iran.


## Keywords

Dispatching sequencing rules, Mathematical model, OR scheduling, Simulation-based optimization

## 1. Introduction

The management of Healthcare was changed in the past decade. For example, the age of the patient population and their number is growing. In addition, a considerable number of patients is not able to be treated instantly or has a long time to wait due to technological restrictions as well as human resource limitations in hospitals. Whereas on another side, State Hospital suffers from many financial debts. The manager of the hospital strives to enhance healthcare performance and to reduce the cost of healthcare to equilibrate the finances (Wang, 2012, Hamid et al., 2018b).

The operating room management is important due to the fact that surgeries typically generate around $67 \%$ of hospital revenues and at least most of the patient visit the department of surgery one time. Therefore, a good organization of the day surgery is necessary for the planning and scheduling of the operating room (van Essen et al., 2012). According to the literature on operating room planning and scheduling provided by Cardoen et al. (2010), in the planning problem, the surgeries are firstly assigned to a day and operating room. Then, the sequence of surgeries is determined in the assigned day-operating room.

The duration of surgery involves significant uncertainty. One way to tackle this challenge is the use of the simulation. However, simulation by itself is not able to provide many plausible solutions, simulation and optimization together can dominate on this constraint. In this study, a mixed method of simulation-based optimization has been used in two stages. In the first phase, the planning of the operating rooms is determined by using a mathematical
model. Then in the second phase, the scheduling of each operating room has been determined by discrete event simulation using compare several dispatching rules.

The remainder of the article is organized as follows: The Literature review is presented in Section 2. The description of the problem is reviewed in Section 3. A mixed integer mathematical model proposed in Section 4. Using simulation to compare three dispatching rules is represented in Section 5. Finally, the conclusion is drawn in Section 6.

## 2. Literature review

The operating room scheduling can be studied from different aspects which can be found in the study conducted by Cardoen et al. (2010). Mainly, the aspects can be classified into different fields which are as follows; performance measures, decision delineation, patient characteristics, research methodology, uncertainty and applicability of research.
There are several functionality measures in order to assess the operating room planning and scheduling methods such as Waiting time, Cost, Financial criteria, Length of surgery, Length of stay, Makespan, OR efficiency, OR utilization, Overtime, Patient priority, Revenue, and Surgery cancellations (Guerriero and Guido, 2011). Researchers sometimes have used one of these criteria to evaluate the operating room scheduling. However, it is possible to formulate the OR model as a multi-objective. Fei et al. (2010) performed operating room scheduling weekly to aim at maximizing the efficiency of the operating room and minimizing the costs of the operating room and unemployment time between two successive surgeries. Hamid et al. (2017b) developed a comprehensive model to address the operating room scheduling. They considered various constrain such as the availability of PACU beds, operating rooms, human resources, and disposal material. Molina-Pariente et al. (2015) assumed that surgery groups contained one or two surgeons in which surgical procedures length was based on their knowledge and abilities. The objectives were to maximize the number of patients scheduled, to minimize the tardiness and to minimize surgeons' waiting time. Vijayakumar et al. (2013) described the model that the objective was to maximize the utilization. Hamid et al. (2019) developed a multi-objective programming model to address the scheduling problem of inpatients incorporating decision making styles of surgical staff. They considered various factors in their study, including the availability of material resources (i.e., operating rooms, post-anesthesia beds, and equipment), priorities of patients, and availability, skills, and competencies of the surgical personnel.

The uncertainty has occurred in the operating room due to various sources such as characterized the duration of activities related to the intake process recovery processes, surgeries, emergency patient arrivals, and medical staff available (Guerriero and Guido, 2011). A reasonable estimate of the duration of the surgery is necessary for the planning of the operation room. This duration follows the random nature, which depends on the patient, the type of surgery and the personality of the surgeon (Riise and Burke, 2011). Herring and Herrmann (2012) presented the singleday surgery scheduling according to the block scheduling formulated the dynamic programming in which they assumed that the entrance of the patient was probabilistic. Mancilla and Storer (2009) described Benders algorithms for a stochastic appointment sequencing and a scheduling problem with waiting times, idle time, and overtime costs. Fei et al. (2009) focused on maximizing utilization of operating rooms and minimizing overtime cost obtained by an explicit column generation (CG) procedure.

Elective and non-elective patient's classes are considered in the literature on the operating room planning and scheduling. Wullink et al. (2007) tested the operating room, which should specifically be allocated to emergency surgery, or the part of the operating room capacity of elective patients should be dedicated to emergency cases. van Essen et al. (2012) considered emergency surgeries in an elective operating room. Break-in-moments’ (BIMs) method was applied to minimize the waiting list. Vermeulen et al. (2009) deliberated urgencies cases and preferences on hospital resources with constrained capacity. Marcon and Dexter (2006) evaluated seven sequencing rules in the postanesthesia care unit (PACU) where the elective and the noun elective patient were considered.

The literature on the operating room planning and scheduling explain a wide range of methods to solve. Mathematical modeling is widely used in operating room planning and scheduling. Persson and Persson (2009) presented the scheduling of elective patients. They conducted the simulation method to minimize the cost. Saremi et al. (2013) described the scheduling of outpatient surgeries to reduce the total waiting time. In doing so, the simulationbased tabu search (STS) was applied. Yin and Xiang (2012) determined the sources of the hospital, which included the operating room, surgeons and surgical sequence to minimize makespan by using the ant colony algorithm. Marques et al. (2015) considered the elective surgery scheduling to maximize the surgical suite occupation and to maximize the number of surgeries scheduled. The genetic algorithm was proposed to obtain those objectives. Aringhieri et al. (2015) developed a model for the allocation of surgeons and patients within each time block. A heuristic two-step
method was applied to reduce waiting-time costs and production costs.

## 3. Problem description

Surgeries are executed through the primary five days of the week. For a week ending up in the ophthalmology surgeons, the medical condition of patients will be outlined. The head medical expert scheduler research checks the elective patients' list and estimates the duration of surgeries, which are determined by historical information and other technological healthcare details. The head surgeon has used the Longest Processing Time (LPT) first sequencing rule for determining the patient sequence in the operating room. This rule sorts surgeries based on descending surgery duration. The operating rooms are open from 6:00 am until 5:00 pm in which overtime may not exceed one hour. Surgeries are performed in four no identical operating rooms in the ophthalmology department. With respect to the complexity of the surgery and patients' status, the surgeries are divided into two priority levels (the high level=10, the low level $=1$, see Table 3).

The goal of this study is to help the head surgeon to create a daily surgical procedure schedule regarding the overall accessible capability of working by considering the stochastic part of operations length. Longer than average surgery durations result in late starts not only for the next surgery in the schedule but also potentially for the rest of the surgeries in the day as well. Late starts also result in indirect costs associated with overtime staffing when the last surgery of the day finishes later than the scheduled shift end time. To take the variability of the operation's length into account, we propose the use of percentile. Because the planning of surgery durations near to the 100th percentile might cause a below utilization of the operating room, as well as the lower percentile, could lead to overtime. The 70th percentile can be applied to be a feasible approximate of the duration of surgeries in which it may control the two opposites (Wang, 2012).

In this study, the planning of the ORs has been addressed for elective patients. This study aims to use a mathematical model for planning of elective patients of the ophthalmology Surgery department. Afterward, we use simulation to compare schedules obtained by the mathematical model and two dispatching sequence rules (Shortest Surgery Time (SST) and Longest Surgery Time (LST)) with the current schedule suggested by the head surgeon scheduler.

### 3.1. Mathematical model

The problem under study in this paper is based on the open strategy. Our objectives are to minimize the makespan (Cmax), undertime and overtime costs simultaneously and to maximize the weighted sum priority of assigning surgery. The notation and decision variables of the problem and the mathematical model is presented as:

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Notation
i the index of a patient, i=1, 2, 3\ldotsI
r the index of an operating room, r=1,2,3\ldotsR
\mp@subsup{\boldsymbol{h}}{\boldsymbol{r}}{}}\quad\mathrm{ the regular opening time in a minute of operating room r
\mp@subsup{\boldsymbol{f}}{i,r}{}}\quad\mathrm{ if patient i can be operated in operating room r, it takes 1; otherwise, 0.
\mp@subsup{\boldsymbol{p}}{\boldsymbol{i}}{}\quad\mathrm{ the 70th percentile of the operating time of patient i}
\mp@subsup{o}{r}{}
pir the cost of idleness for operating room r
porr the cost of overtime for operating room r
\mp@subsup{w}{i}{}}\mathrm{ the priority of patient i
\mp@subsup{y}{r}{}}\quad\mathrm{ overtime for room r
Z\mp@subsup{z}{r}{}}\quad\mathrm{ idle time for room r
\mp@subsup{c}{r}{}}\mathrm{ the makespan for operating room r
Variable
\mp@subsup{x}{i,r}{}}\quad1\mathrm{ if operation i is assigned to room r}\textrm{r}\mathrm{ , else 0
CMAX the maximum completion time of surgeries
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$\operatorname{Max} \sum_{i=1}^{I} \sum_{r=1}^{\boldsymbol{R}} \boldsymbol{x}_{i, r}{ }^{*} \boldsymbol{w}_{\boldsymbol{i}}$
$\operatorname{Min} \sum_{r=1}^{R} \boldsymbol{y}_{r} * \boldsymbol{p o} \boldsymbol{o}_{\boldsymbol{r}}+\boldsymbol{z z _ { r }} * \boldsymbol{p} \boldsymbol{i}_{\boldsymbol{r}}$
Min $\boldsymbol{C M A X}$

$$
\begin{array}{lc}
\sum_{r=1}^{R} \boldsymbol{x}_{i, r} \leq \mathbf{1} & \forall i \\
\boldsymbol{x}_{\boldsymbol{i}, \boldsymbol{r}} \leq \boldsymbol{f}_{i, r} & \forall i, r \\
\sum_{i=1}^{I} \boldsymbol{x}_{\boldsymbol{i}, r} * \boldsymbol{p}_{\boldsymbol{i}} \leq \boldsymbol{h}_{\boldsymbol{r}}+\boldsymbol{o}_{\boldsymbol{r}} & \forall r \\
\sum_{i=1}^{I} \boldsymbol{x}_{\boldsymbol{i}, \boldsymbol{r}} * \boldsymbol{p}_{\boldsymbol{i}}-\boldsymbol{h}_{r} \leq \boldsymbol{y}_{r} & \forall r \\
\boldsymbol{h}_{r}-\sum_{i=1}^{I} \boldsymbol{x}_{\boldsymbol{i}, r} * \boldsymbol{p}_{\boldsymbol{i}} \leq \mathbf{z z}_{\boldsymbol{r}} & \forall r \\
\boldsymbol{c}_{\boldsymbol{r}} \geq \sum_{i=\mathbf{1}}^{I} \boldsymbol{x}_{\boldsymbol{i}, \boldsymbol{r}} * \boldsymbol{p}_{\boldsymbol{i}} & \forall r  \tag{9}\\
\boldsymbol{C M A X} \geq \boldsymbol{c}_{\boldsymbol{r}} & \forall r
\end{array}
$$

$\boldsymbol{x}_{i, r} \in\{0,1\}$

The objective function (1) maximizes the weighted sum priority of assigning surgery. The objective function (2) and (3) minimizes underutilization and overtime for each operating room and minimizes the maximum of completion time of surgeries (Cmax), respectively. Eq. 4 determines that the patient can be assigned to only one operating room. Eq. 5 assigns the patient to an operating room where the required equipment is available. Eq. 6 determines that the total duration of surgical procedures dedicated to each operating room should not go beyond the total regular and overtime opening length of operating rooms. Eq. 7 and Eq. 8 show overtime and idle time for each room, respectively. The makespan for each operating room is reflected in the Eq. 9 and Eq.10. Eq. 11 is known as a binary restriction.

## 4. Solution approach

In the previous section, an integer linear programming (ILP) model has been proposed for the multi-objective scheduling of elective surgery ophthalmology surgery department. This model is coded in GAMS. Several approaches are presented to solve multi-objective mathematical models in the literature such as goal programming, multiple response optimization (Salmasnia et al., 2012), epsilon-constraint method (Hamid et al., 2018a, Jamili et al., 2018, Rabbani et al., 2018, Hamid et al., 2018c, Zhalechian et al., 2018, Hamid et al., 2017a), weighted sum method (Hejazi et al., 2013, Rezaei-Malek et al., 2017), game theory approach (Zhalechian et al., 2016), Tchebycheff-based methods and fuzzy programming approaches (Rabbani et al., 2018). We used the weighted sum method to solve the proposed multi-objective model. To solve the problem, The Weighted-Sum Method is applied to a real example of a typical day in the ophthalmology surgery department with four operating rooms $(\mathrm{R}=4)$ and 57 patients with different priorities (See Table 3). The surgeries B, C, D, E, F, and H, can be performed in ORs 1, 2 and 3 and other surgeries can be done in all ORs. Details are given in Table 1.

Table 1. The assignment of selected patients to operating rooms

| OR1 | $32-36-34-49-51-1-9-18-19-20$ |
| :--- | :--- |
| OR2 | $33-35-37-14-39-43-44-46-47-28-21-29$ |
| OR3 | $15-53-52-4-6-22-24-25-26-27$ |
| OR4 | $15-53-52-4-6-22-24-25-26-27$ |

Compared to the actual schedule provided by the head surgeon scheduler (See Figure 1), the performance of the result of the mathematical model is shown in Table 2. The proposed model provides an improvement concerning the

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objectives of makespan, priority, idle time, and overtime.

Table 2. Performance of the mathematical model

|  | Cmax | Priority | Idle time | Overtime |
| :---: | :---: | :---: | :---: | :---: |
| Current model | 651.864 | 161 | 0 | 171.69 |
| Our model | 600.252 | 186.000 | 0 | 0.288 |


|  | 80 | 160 | 240 | 320 |  | 400 | 480 |  |  | 600 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Op 53 | Op52 | Op54 | Op29 | Op18 | Op14 | Op22 | Op2 |  | Op24 | Op |  |
| Op51 | Op54 | Op30 | Op19 | Op21 | Op15 | Op24 | O |  | Op10 | Op11 | Op38 |
| Op50 | Op56 | Op31 | Op20 | Op16 | Op17 | Op27 | Op2 |  | Op12 | Op13 | Op39 |
| Op49 | Op57 | Opl | Op2 | Op3 | Op4 | Op5 | Op6 | Op7 | Op8 | Op40 | Op41 |

Figure 1. The current schedule provided by head surgeon scheduler.

## 5. Simulation

All data were obtained by personal visits to the ophthalmology surgery department and by getting relevant information from records to avoid the missing data. The data were collected over one year the primary five days of the week from 6 am until 5 pm . The collected data included surgery duration, number of operatives assigned to the patient. Historical data was used to fit a distribution to the duration of surgeries. The distribution of surgical procedure time was determined by using Input Analyzer in ARENA 14Rockwell software (Table 4). Also, Table 3 illustrates the different types of surgery.

Table 3. Surgery type and priority

| Surgery type | Surgery | Priority |
| :---: | :---: | :---: |
| A | $1-2-3-4-5-6-7-8$ | 1 |
| B | $9-10-11-12-13$ | 1 |
| C | $14-15-16-17$ | 10 |
| D | $18-19-20-21$ | 1 |
| E | $22-23-24-25-26-27-28$ | 1 |
| F | $29-30-31$ | 1 |
| G | $32-33-34-35-36-37$ | 10 |
| H | $38-39-40-41-42-43-44-45-46-47-48$ | 1 |
| L | $49-50-51-52$ | 10 |
| M | $53-54-55-56-57$ | 10 |

Table 4. Surgery category and priority

| Surgery category | Surgery distributions |
| :---: | :---: |
| A | GAMMA $(3.71,0.0793)+0.54$ |
| B | GAMMA $(3.74,0.0644)+0.64$ |
| C | WEIB $(0.172,6.22)+0.79$ |
| D | GAMMA $(10,0.0316)+0.61$ |
| E | BETA $(2.45,4.63) * 0.46+0.76$ |
| G | LOGNORM $(0.003,0.009)$ |
| H | WEIB $(0.241,4.45)+0.68$ |
| L | BETA $(3.31,2.55) * 0.33+0.43$ |
| M | BETA $(1.35,3.57) * 0.55+1$ |
|  | GAMMA $(3.78,0.0523)+1.2$ |

The simulation model was created by ARENA14 Rockwell software. A preliminary simulation to eliminate the transient period was run in order to obtain steady-state conditions. As Figure 2, the warm-up period was determined to be 300 minutes to obtain steady-state results.


Figure 2. Shown steady state

### 5.1. Validation and verification

For verification, the proposed model represented the expert, and then, he accepted this model. Once a model was constructed and implemented, it should be validated to ensure that it adequately represented the system under investigation and to what extent (Yazdanparast et al., 2018, Habibifar et al., 2019, Gharoun et al., 2019). The current schedule and our model were run 100 times. We chose a comparison parameter with a known pattern of variation, the total waiting time, for comparison purposes. Simulation results should be compared with actual data. For total waiting time, Independent two-tailed t-tests were used to compare the performance of the outcomes of the current schedule with the actual system. In $95 \%$ significance level, there was no reason to reject the null hypothesis. The sample size of our model was $n=100$. Therefore, the critical points of the hypothesis test were less than the critical value of 1.97. The result is shown in Table 5.

Table 5. Result in the t -test and total waiting time

|  | Total waiting time |
| :--- | :---: |
| The head surgeon | 231.3369 |
| Average current schedule | 231.6728 |
| T-test | 1.503 |

### 5.2. Scenario

We designed three sequencing rules in an attempt to minimize the total waiting time. (Shortest Surgery Time) This rule ranked the surgeries in order of the priority in an ascending their duration. The patient had a higher priority (in our case 10) scheduled first, and then the patient had a lower priority (in our case 1) scheduled. (Longest Surgery Time) This heuristic rule sorted the surgeries which had the same priority in decreasing their duration. The third sequence was the head surgeon schedule (which was set by using LPT rule).

### 5.3. Results

The results for the total waiting time indicator expressed in hours for three scheduling methods (current schedule provided by the head surgeon scheduler and two schedules obtained by the model and SST and LST rules) is shown in Figure 3. Figure 3 shows that the schedule obtained by the model. SPT rule is the best, and the actual schedule provided by the head scheduler is the worst. The simulation results show that it is possible to reduce the total waiting time required to process patients by $8 \%$ when the SST rule is used instead of the current schedule. The second Scenario, which is the LST rule, can improve $4 \%$ compared with the current schedule.

## Interval Plot of Current scheduling, LPT, SPT

$95 \%$ CI for the Mean


Figure 3. The current schedule provided by the head surgeon scheduler and two schedules obtained by the model and SST and LST rules.

## 6. Conclusion

In this paper, we illustrated a two-step approach to address the daily operating room scheduling problem. The first step consisted of assigning the surgical operation to the operating rooms. The second step consisted of sequencing operations, which were assigned to an operating room in the previous step. Given the assigning step have been presented the mixed model programming. The multi-objective functions were to minimize the makespan, idle \& over time and to maximize the priority. The second-step considered three Heuristic sequencing rules, which were applied to the discrete event simulation model. The simulation model compared the total waiting time of the three heuristics. The results showed SST and LST rules outperformed the current schedule which is proposed by the head surgeon.

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