# Operating Room Scheduling by Considering Surgical Inventory, Post Anesthesia Beds, and Emergency Surgeries to Improve Efficiency During the COVID-19 Outbreak with Machine Learning

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## Abstract

Surgical operating rooms are critical in the total hospital costs, while surgical care accounts for one-third of hospital costs. Thus, successful and improve operating room management and scheduling can bring significant benefits. In this study, we develop Operating Room (OR) scheduling problem integrated with a Post-Anesthesia Care Unit (PACU) by considering emergency surgeries during the COVID-19 outbreak. Accurate prediction of surgery duration and required PACU time for each surgery are critical for operating room scheduling. Due to the inherent uncertainty in surgery duration and PACU time, we develop supervised machine learning to estimate surgery duration and PACU time. Finally, based on discrete event simulation, we compare our proposed surgery scheduling model to the available scheduling by using statics and data from Montreal's hospitals. We could show that our scheduling model can significantly increase operating room utilization with the issue of PACU congestion.

## Keywords

Operating Room Scheduling, Post Anesthesia Care Unit, Logistic Regression, Machine Learning, COVID-19

## 1. Introduction

As one of the most sensitive and expensive hospital resources, the operating room significantly affects both costs and revenues (Zhao et al. 2019 , Macario 2010). According to the conducted studies, about 40% of the hospital costs are related to the operating rooms(Denton et al. 2010), while the surgeries usually raise 67% of the hospital's revenues (Hamdan 2017). Maximizing the efficiency of the operating room to improve performance in health care has become a necessity. Effective management and exact and heuristic scheduling for operating rooms can significantly benefit the hospital (Fairley et al. 2019). Also, operating room performance improvement leads to increased patient service and satisfaction (Dexter et al. 2019.).

To allocate rooms in hospitals to patients with Coronavirus (COVID-19 ) in the first wave of COVID-19 outbreaks, hospitals had to reduce their medical care as much as possible, including surgery in operating rooms. In the first wave of COVID-19 disease, hospitals had to perform only emergency and semi-urgent surgeries. With accurate scheduling and planning, this downsizing may be prevented in the future. Operating room capacity may not need to be reduced as much as before (the first wave of COVID- 19 outbreaks). But deciding to what extent the operating room capacity should be reduced is a difficult one. So far, no suitable solution has been proposed to reduce the waiting list of patients for surgery. In addition to the limitations and uncertainties were earlier and before COVID-19 outbreak, the meaning of the operating room has become much more challenging than before, given the variables associated with COVID-19. Therefore, it is necessary to help the surgical ward through careful planning and scheduling, considering the variables related to COVID-19 to cope with all the limitations in the intensive care unit and other hospital wards so it is able to perform emergency and semi-urgent surgeries as much as possible.

The operating room's efficiency and equipment utilization due to COVID-19 decreased compared to previous years. Therefore, it is necessary to provide an accurate operating room scheduling model for patients' surgery in COVID- 19 conditions.
Many factors affect the operating room's efficiency and inefficiencies, such as human and non-human resources, surgery room constraints, schedule variations, disruption in patients' flow in hospital wards, different types of hospitalization (inpatients or outpatients), and surgeons (Lee et al. 2019). However, the researcher could employ several proposed metrics to measure the efficiency of surgery scheduling. Common measures include:

### 1.1 Patient's waiting time

The long waiting for surgery in hospitals is among the most frequent complaints among healthcare providers (Rothstein and Raval 2018). Because prolonged waiting times for medical care in hospitals, including surgery - in addition to potentially injuring the patient because of the urgent need for treatment, it could lead to the patient to refrain from treatment and leave the hospital to another and subsequently aggravate the problem. Therefore, decreasing waiting times represent the efficiency of operating room scheduling. The importance of waiting times for emergency patients is so much more significant than for elective patients. Therefore, surgery room staff should consider these patients in scheduling, and minimizing their waiting time should be the main object.

### 1.2 Operating room overtime

The hospital management must pay for all hours when the operating room and surgical resources are available for surgery (Childers and Maggard-Gibbons 2018). Therefore, every idle time or overtime of the operating room is an extra cost. Ideally, these costs could minimize idle time and overtime through detailed and accurate planning and scheduling, and invest this saved money in other hospital wards. For example, hospital managers could reduce patients' waiting times by increasing capacity in the emergency department.

### 1.3 Emergency Surgeries

Since emergency patients' arrival time to the operating room is unpredictable, planners should schedule other surgeries in such a way that surgeons could operate on these emergency patients on time to irreparable injuries, and even death prevented (Heng and Wright 2013).

### 1.4 Humanitarian goals

The humanitarian goals are to save the lives of as many patients as possible. In the COVID-19 disease, when planning the operating room, if there are not enough resources in the operating room, priority should be given to emergency patients. Surgeons should operate them first, and the surgery of patients with more stable conditions should be postponed. The process of deciding who should be treated early is called triage. If the operating rooms' capacity needs to be reduced due to COVID- 19 disease and fewer surgeries are performed, triage may be required. Surgeons should prioritize patients on the waiting list for surgery because emergency surgeries must be performed anyway, even if the operating rooms' capacity is reduced.

### 1.5 Leveling

Leveling means keeping the number of surgeries per day constant. During COVID-19, most ICU capacities include available nurses, and beds are assigned to Coronavirus patients. So there is less capacity for other patients. Therefore, patients who need intensive care after surgery should be admitted to the ICU less than usual.

### 1.6 The start time of the first surgery

Delay in the first surgery's starting time results in inefficiency in multiple operating rooms and decreases the operating room's productivity (Marjamaa et al. 2008). The operating room scheduling and planning's primary goal is to improve the operating room's efficiency by minimizing unnecessary costs. A review of studies shows that hospitals receive 1 to 5 percent of primary care patients in the intensive care unit by approximately 5 minutes delay, indicating a preventable cost (Phieffer et al. 2017). The most common reasons for the delay are lack of access to surgeons, personnel, delay in patient registration, transportation problems, etc. (Overdyk et al. 1998).

### 1.7 Surgeries duration and PACU accuracy

The prediction of surgery duration for both elective patients and emergency patients cannot be accurate, and this uncertainty, besides imposes costs on the system, affect times simultaneously. If the surgery time exceeds the anticipated duration for surgery, it will cause the next remaining surgeries to start later. These delays lead to overtime costs for operation room management (Haldar et al. 2019). Therefore, planners should take into account these metrics planning and scheduling model of the operating room.surgery duration is defined as "The total minutes from patient entry into the OR to exit." (Bartek et al. 2018). Uncertainty in the surgery duration means "The difference between the actual surgery duration and the estimated surgery duration." Uncertainty in the surgery duration is a crucial factor in the operating room's planning and scheduling problems, affected by many factors such as patient condition, surgeon skill, and other factors mentioned in Table 2.

Accurate estimation of the surgery duration can increase operating room efficiency by properly allocating human and non-human resources and patient satisfaction (Zeng et al. 2018). Most studies use two methods to predict surgery's duration: Surgeon prediction and historical surgery duration (Zhao et al. 2019). However, many studies have demonstrated that surgeons surgery duration is not reliable because there are multiple patients, anesthetic, and system factors that might not be considered in the surgeon estimation (Pandit and Carey 2006, Olkkonen et al. 2008). After surgery, most patients are transferred to the post-anesthesia care unit (PACU) to recover from anesthesia (Fairley et al. 2019).

By COVID-19 outbreak, it is sometimes impossible to move patients to the PACU ward after surgery due to the unavailability of resources such as nurses and beds in the PACU. Patients with coronavirus due to their physical condition need to be hospitalized in an intensive care unit to get back their regular physicians. The intensification of coronavirus leads to an increase in COVID-19 patients in the hospital who need to be admitted to the intensive care unit (Li et al. 2020). Therefore, due to the lack of physical infrastructure and hospital beds in hospitals' PACU and the allocation of anesthesia and intensive care teams to corona patients, it causes disruptions in hospital systems, including delays in providing timely surgery services such as timely surgery. It sometimes leads to the cancellation of surgeries on elective patients that have been planned in advance (Philouze et al. 2020). The PACU crowding harms operating room scheduling since it delays the subsequent surgeries. One way to prevent this problem is to increase the PACU's capacity, such as the number of beds and staff, but improving these capacities is usually costly and impractical.

Researchers recently use big data and up-to-date data science methods such as machine learning because of their ability to predict postoperative events and provide medical decision makers with suggested medical operations (Bartek et al. 2018).

We could develop a complete and integrated model. An exact scheduling model for optimizing the operating room is not easy because the surgery room environment faces many uncertainties. For example, as mentioned above, the surgery duration may be prolonged and lead to disorder and scheduling changes.

Given that our output variable is of continuous type, we must use regression algorithms in this paper. These algorithms can be used as approaches to predict surgery's duration and help us understand the relationships between variables. One of these algorithms is XGboost, which can examine the relationships between multiple variables and provide us with all possible nonlinear answers efficiently, which is very suitable for understanding the problem's complexity.

In our surgery sequencing and scheduling model, we address several challenges and uncertainties in the operating room by a combination of machine learning and integer programming.

We overcome these challenges and uncertainties to increase operating room efficiency through using machine learning models to predict the delayed input parameters, namely surgery duration and PACU duration required for scheduling (section3.1), Estimate the hospital requirement for the ICU beds for COVID-19 Patients(section 3.2), and develop a scheduling optimization model with an integer programming that uses predicted inputs for determining the sequence of patients in the operating room (section 3.3).

## 2. Literature Review

The research literature has covered a wide range of varied subjects in different planning and scheduling of operating rooms that can be studied to review the relevant papers in greater detail. We will point out some papers in the present section where that are related to our study.

Recently, Eun et al. (2019) have proposed a mixed-integer linear programming model to schedule elective surgical by taking into account patients' health status and operating room overtime. They solved their model using three meta heuristics approximation methods, local search, and Tabu search. Ballestín and Quintanilla (2019) have proposed a two-stage scheduling model for scheduling elective surgery in the operating room. In the first phase, two weeks before the planning period, they define a tentative schedule to minimize surgery delay. The second and final phase is proposed based on changes in the available information in the few days before the planning period is proposed. Computational experiments have been performed through simulating cases randomly generated according to the data of a Spanish hospital.One of the common reasons for the daily operating rooms rescheduling is an emergency operation. Ceschia and medicine (2012) Proposed a dynamic Patient Admission Scheduling by developing a meta-heuristic method for static scheduling (with a predictive approach) and dynamic scheduling (rescheduling daily) for the operations. They compared two concentration and flexibility policies to strike a balance between emergency and non-emergency surgeries. Wullink et al. (2007) examine whether it is better to allocate a specific operating room to the emergency operations or not. They concluded that the overtime and the efficiency of the operating room improved when reserved capacity was divided among the versatile rooms. Marcon and Dexter (2006) examined the effect of sequence on the patients' waiting time in PACU. They discussed the sequence pattern that significantly affects the number of patients who receive healthcare services in PACU. Stepaniak et al. (2016) used simulation to evaluate the operating rooms allocated to the emergency operations in terms of operation duration, equipment, and beds. Jittamai et al. (2019) proposed an operating room scheduling approach to improves the operating room's performance by minimizing its consumable resources. Hooshmand and MirHassani (2018) proposed a daily model to schedule the operating rooms where each patient's operation time was considered the uncertain parameters and considered a rescheduling model. Noorizadegan and Seifi (2018) have proposed an efficient method for the operating room scheduling and planning problem by considering the surgeons and uncertainty in the surgeries duration. They attempted to allocate the patients to the surgeons and operating rooms and determine their operating rooms' admission. Kumar and Fackrell (2018) have developed a mixed-integer planning model for operating room scheduling. We have reviewed several articles in the field of surgery scheduling in recent years. We list the results in the table1.

Table 1. review of scheduling research

| **Authors** | Year | patients | Objective Function | Model | Solving Method | Uncertainty |
|---|---|---|---|---|---|---|
| Serhat Gul (Gul 2018) | 2018 | Elective | Minimize the patient waiting time and operating room idle time | Surgery Scheduling | stochastic integer programming | Surgery duration |
| Bowen Pang ( Pang et al. 2019) | 2018 | Elective | Cost of health care providers and patients | Surgery scheduling | stochastic integer programming | Case cancellation and surgery duration |
| Ashwani Kumar (Kumar et al. 2019) | 2018 | Elective | Maximize the utilization | Surgery scheduling | stochastic mixed-integer programming | patients' length of stay |
| Ines Marques (Marques et al. 2019) | 2019 | Elective | Allocate OR time blocks to the surgical specialty with the highest number of surgeons available | Surgery planning and scheduling | mixed-integer linear programming | - |
| Mahdi Hamid (Hamid et al. 2019) | 2019 | Elective | minimize the total waiting time and the maximum completion time of surgeries | Surgery Scheduling | Optimization and simulation approach | - |
| Reza Behmanesh (Behmanesh and Zandieh 2019) | 2019 | Elective | minimize makespan and number of unscheduled surgery | Surgery scheduling | Job shop problem | Service times |

| | | | | | | |
|---|---|---|---|---|---|---|
| Sung Jung (Jung et al. 2019) | 2019 | Elective and Emergency | minimize the total cost of the ORs' expected operating time, idle time | Surgery Scheduling | mathematical programming | arrivals of patients requiring emergent surgery |
| Amirhossein Najjarbashi (Najjarbashi 2019) | 2019 | Elective | minimize the CVAR of overtime and idle time costs | Surgery scheduling | stochastic mixed-integer linear programming | Surgery duration |
| Yu Zhang (Y.Zhang et al. 2020) | 2020 | Elective | mitigating the overtime risk | Surgery scheduling | exact hill-climbing algorithm | Surgical durations |
| Clavel (Clavel et al. 2020) | 2020 | Elective | improving the efficiency of medical teams' work | Surgery scheduling | mathematical programming | Surgery duration |
| Thiago Silva(Silva and de Souza 2020) | 2020 | Elective and Emergency | minimize the total expected cost | Surgery scheduling | Approximate dynamic programming with the integer programming model. | Surgery duration and arrival of the emergency patient to the hospital |
| Jian Zhang(J. Zhang et al. 2020) | 2020 | Elective | minimize the patient-related cost as well as the hospital-related cost | Advance surgery scheduling | Stochastic programming and column-generation-based heuristic approaches | surgery durations and postoperative length-of-stays |

## 3. Methods

In this study, we have integrated the operating room with PACU. We developed a three-stage model for scheduling operating rooms to minimize the patient's waiting time and operating room overtime.
In the first stage, we used machine learning to estimate surgery duration. We required PACU time for each surgery as uncertainty parameters in our scheduling model. In the second stage, we have developed deterministic integer programs for operating room scheduling for a block time that use predicted inputs in the first stage. The proposed model includes decisions at the operational level, determining the operation day, starting time, and operating room. In the third stage, we used discrete event simulation to compare our optimized surgery scheduling to the existing schedule using data from one of Montreal's hospitals and showing that an accurate scheduling model can significantly improve operating rooms' efficiency.

### 3.1 Surgery and PACU Duration prediction

Surgery duration and PACU duration are uncertain and can be affected by many factors included the type of surgery, the patient's age, the surgeon's capability, and the hospital system's state. Data scientists could employ a list of predictor variables for predictive modeling surgery, and PACU durations are presented respectively in Table 2 and Table 3. As the machine learning (ML) approaches are very applicant for estimating the surgeries duration and PACU duration because it can consider many factors that affect these durations, we potentially develop accurate estimation through machine learning as an advanced predictive tool.

Table 2. Description of the predictors used for surgery duration estimation(Shahabi et al. 2014)

| **Predictors** | **Description** |
|---|---|
| Category | "Urgent category of the patient (Nominal)" |
| Age | "Age of patient (Numeric)" |
| Gender | "Patient gender (Nominal)" |

| | |
|---|---|
| BMI | "a person's weight in kilograms divided by the square of height in meters." |
| Classification | "Patient payment class (Nominal)" |
| CCI | "Charlson Comorbidity Index (Nominal)" |
| Referral Centre | "Center patient referred to (Nominal)" |
| Procedure indicator | "Planned procedure." |
| Unit | "Hospital unit (Nominal)" |
| Specialty | "Hospital specialty (Nominal)" |
| Theatre | "Operating room number (Nominal)" |
| Order | "Operation order in session (Nominal)" |
| Ward | "Hospital ward (Nominal)" |
| Sub Specialty | "Subspecialty code (Nominal)" |
| Procedure | "Procedure code (Nominal)" |
| Primary | "Is it the primary procedure? (Binary)" |
| Session | "Morning/Afternoon session (Nominal)" |
| Session Type | "Type of the session (Nominal)" |
| Consultant | "The doctor who visited the patient (Nominal)" |
| Con.Category | "Professional category of consultant (Nominal)" |
| Surgeon | "Surgeon in charge of the operation (Nominal)" |
| Surgeon Category | "Professional category of the surgeon (Nominal)" |
| Surgeon Consultant | "Is a surgeon the same as a consultant?" |
| Surgeons | "Number of the surgeon involved (Nominal)" |
| Anesthetists | "Number of anesthetists involved." |
| Team Size | "Total number of people involved (Nominal)" |

Table3. Feature considered for recovery length prediction

| **Feature** | **Type** | **Description** |
|---|---|---|
| Procedure | Categorical | The type of procedure (e.g., adenotonsillectomy) |
| Weight | Categorical | The patient's weight |
| Age | Categorical | The patient's age |
| Scheduled postop destination | Categorical | In the hospital unit, the patient will go after PAC recovery |
| Service | Categorical | The surgical service performing the procedure |
| Scheduled procedure length | Categorical | The scheduled duration of the procedure |
| Patient Class | Categorical | The patient admission class (e.g., inpatient, outpatient) |
| Sex | Binary | The patient's sex |
| Location | Categorical | Where the procedure will be performed (e.g., main operating room or ambulatory procedure unit) |

### 3.1.1 Linear Regression

The regression algorithm can estimate the relationships among variables. Generally, Linear Regression models the relationship between a dependent variable(objective) and one or more independent variables (predictors). In the regression model, there are three variables:

$$\mathcal{F}(x) = \beta_0 + \sum_{j=1}^{n} x_j \beta_j \tag{1}$$

According to the regression function's specific form, regression algorithms are classified as Linear Regression, Logistic Regression, Ridge Regression, Polynomial Regression, and Lasso Regression.

### 3.1.2 Logistic regression

Logistic regression models the probability of an event that depends on the values of independent variables.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{2}$$

The dependent variable in a logistic regression obeys Bernoulli's distribution. the Bernoulli's distribution:

$$g(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

$$g(y) = \frac{1}{1 + e^{-(\beta^T x)}} \tag{4}$$

The Bernoulli distribution, the probability distribution of the dependent variables is unknown. Hence, we could express the probability of P as a standard logistic function.

$$logit(p) = \log\left(\frac{p(x)}{1-p(x)}\right) = \frac{\frac{e^{\beta^T x}}{1+e^{\beta^T x}}}{1-\frac{e^{\beta^T x}}{1+e^{\beta^T x}}} = \log\left(e^{\beta^T x}\right) = \beta^T x = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n = y \tag{5}$$

The logit (p) represents the probability that the component fails. It is the ratio of "Success" to "non-success." The antilog of the logit (p) is equal to Eq. (6):

$$e^y = \frac{p}{1-p} \tag{6}$$

From Eq. (5) and (6), the probability of the risk of failure "P" is Eq. (7):

$$P = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n}} \tag{7}$$

### 3.1.3 Random Forest

Decision trees are a hierarchical structure consisting of beginning and ending points. This algorithm connects these points through branches. Tree construction begins with the root node, which contains all the data in the training set. The CART algorithm recursively searches for all possible predictions and points with the best binary value to obtain the lowest node impurity value.

Each division creates two descending groups: the left contains data that provides the test's logical value, and the right contains information that does not provide this value. These nodes are the criteria for deciding on the next descending areas that binary testing evaluates. After reaching a criterion stop in the splitting process, the final partition splits the main predictor structure of the decision forest presented by Bbeiman is as follows(Bbeiman 1996):

1. B independent bootstrap samples of fixed size from the training data L randomly drawn.
2. A tree Tb should be fitted for each bootstrapped data. At each internal node, choose m predictors randomly from the p available predictors to split (m $\leq p$). The number of variables is constant. In classification problems, usually suggested the m value is equal to $\lfloor\sqrt{p}\rfloor$ with least possible node size equal to one and for regression M=$\lfloor p/3 \rfloor$With a minimum node size equal to five (Raposo et al. 2020).

$$\Delta i(s,t) = i(t) - pr_L i(t_L) - pr_R i(t_R) \tag{8}$$

$pr_L = n_{tl}/n$ and $pr_R = n_{tl}/n$ and $i(t)$ (impurity criterion) could be calculated through a model called the Gini index.

$$G(t) = 1 - \sum_{c=1}^{C} Pr_c \tag{9}$$

While C is equal to the number of classifications and $Pr_c$ is the probability that observations of the node belonging to class c

3. Gathering data from the B trees to predict new data using unweighted voting for classification and unweighted averaging for regression.

### 3.1.4 XG Boosting

The objective function in the XG model usually consists of two parts (Nguyen et al. 2019):

$$\mathrm{F}(\Theta) = L(\Theta) + \Omega(\Theta) \tag{10}$$

Where L is the training loss function, and Ω is the regularization term. The training loss is employed to assess the model performance on training data. The regularization term aims at reducing the complexity of the model and avoiding overfitting. There are several ways to define complexity. However, researchers often use the following equation to calculate the structural complexity of each tree:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2 \tag{11}$$

Where T is the number of leaves and $\omega$ is the vector of scores on leaves. The objective function of XGBoost is calculated as follows:

$$obj = \sum_{j=1}^{T} \left[\!\left[ G_j\omega_j + \frac{1}{2}\left(H_j + \lambda\right)\omega_j^2 \right]\!\right] + \gamma T \tag{12}$$

### 3.1.5 Support Vector Machine (SVM):

Support Vector Machine is a powerful tool for data classification and regression(Abd 2017). In this method, we have training data with inputs $\{(x_1.y_1).(x_2.y_2) \dots \dots .(x_n.y_n)\}$ in $R^n$ where our outputs are binary $y \in \{-1.1\}$ .The SVM looks for a hyperplane with the most significant possible distance from the training samples to separate the two classes of $x_n$ associated with $y_n$ =1 and $y_n = -1$. The hyperplane is represented by:

$$w^T x + b = 0 \tag{13}$$

Moreover, we assume having the correct classification:

$$\text{If } y_n = 1 \quad \rightarrow \quad w^T x + b \geq 1 \tag{14}$$
$$\text{If } y_n = -1 \quad \rightarrow \quad w^T x + b \geq -1 \tag{15}$$

The distance between the above two lines is equal to $d_1 + d_2$, which is $d_1 = d_2$.

(16)

$$x_0 = \mathrm{t}w$$

$$w^T x_0 + b = 0 \quad \rightarrow \quad \mathrm{t}w^T w + b =$$

$$\mathrm{t}\|w\|^2 + b = 0 \quad \rightarrow \quad \mathrm{t} = -\frac{b}{\|w\|^2} = -\frac{b}{w^T w}$$

$$\|x_0\| = t\|w\| = -\frac{b}{\|w\|^2}\|w\| = -\frac{b}{\|w\|}$$

Therefore, the distance of the hyperplane from the origin is equal $-\frac{b}{\|w\|}$.

If we consider the distance between $w^T x + b \geq -1$ and $w^T x + b = 0$ (hyperplane) equal to $d_1$:

$$d_1 = \left| \frac{|b-1|}{\|w\|} - \frac{|b|}{\|w\|} \right| = \frac{1}{\|w\|} \rightarrow \quad d_1 = d_2 = \frac{1}{\|w\|} \tag{17}$$

Our object function:

$$\text{Max } d_1 + d_2 = \frac{1}{\|w\|} + \frac{1}{\|w\|} = \frac{2}{\|w\|} \tag{18}$$

So we must minimize the $\|w\|$:

$$\text{Min } \|w\| \quad \rightarrow \quad min \frac{1}{2} \|w\|^2 = \frac{1}{2} w^T w \tag{19}$$

### 3.1.6 Model Evaluation

We could use the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R Squared ($R^2$) to assess and compare our machine learning models concerning one another and an exsiting current hospital estimation method for surgery duration.
RMSE calculates the difference between the values predicted by the model ($f(x_i)$)and the actual values of estimated variable ($y_i$).

$$\text{RMSE}=\sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - f(x_i))^2} \tag{20}$$

MAPE expresses forecast accurately and can be used for measuring the accuracy of a model(Kim and Kim 2016).

$$\text{MAPE}=\frac{1}{n} \left( \sum_{i=1}^{n} \frac{|y_i - f(x_i)|}{y_i} \right) \tag{21}$$

($R^2$) measures of goodness of fit

$$\mathrm{R}^2 = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{Y_i} - \mathrm{f}(\mathrm{x_i}))^2}{\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{Y_i} - \overline{\mathrm{Y}})^2} \tag{22}$$

## 3.2 Estimating demand for PACU beds for COVID-2019

To estimate the number of beds needed on the intensive care unit to treat COVID-19 patients, we can consider one of the world cities heavily involved in COVID-19 and has performed well in controlling it. We should extract information from their health system in at least two weeks to simulate their condition. For this purpose, we first need to identify and estimate the number of patients whose coronation has been approved. Coronary patients have experienced at least one case of shortness of breath, irregular breathing, pneumonia, etc., in 24 hours. Among these coronary patients, there are patients with critical conditions who need a ventilator to breathe due to respiratory diseases. The function of some parts of their body is impaired. For this reason, they need intensive care and must be hospitalized.
We can extract data related to COVID-19, such as improved patients, mortality rate, and patients with critical conditions in the desired period. We could use statistical calculations through mini-tab software to predict how many beds are available in PACU for the surgical department to plan surgeries to prevent delays or cancellations in surgeries.

## 3.3 Surgery Scheduling model

Regarding the explanations given about the affective processes in planning and scheduling the operating room, we now attempt to develop a model for allocating the operating rooms to the patients to minimize the operating room's overtime costs and patient's waiting time. Therefore, we propose our scheduling and planning surgery model in three steps. We determine the elective patients' day and operating room regarding their waiting times in the first stage. The next phase of the model is related to the elective patients' daily scheduling that the sequence of their surgeries in any operating room is determined. Finally, if the emergency patients arrived at the hospital during the day while requiring an immediate operation, they are considered in the third phase of the model. The patients are also hospitalized in PACU.

## 4. Conclusion

Operating room scheduling during the COVID-19 outbreak is very important and requires a lot of research. Planners should develop operating room scheduling model for the hospital to surgery on more urgent and semi-urgent patients while not having a shortage of beds in the intensive care unit (ICU). In our scheduling model, we consider variables related to COVID-19 diseases such as different levels of patients, humanitarian goals, leveling, patient waiting time, and constraints and uncertainties in the operating room to meet operating room managers' needs in COVID-19 prevalence.

We attempt to develop a model for distributing the operating rooms to the patients to decrease the operating room's overtime costs and the patient's waiting time as much as possible by considering the CoronaVirus (COVID-19) outbreak and the fact that hospitals should allocate a number of their beds in the ICU to these patients. To develop an accurate surgery scheduling, estimation of surgery duration is necessary. Before we develop our scheduling model, we use machine learning algorithms such as linear regression, decision tree, etc., to predict patients 'surgery duration and the duration of patients' hospitalization in the Post Anthesia Care Unit (PACU). To evaluate the performance of these methods, we use Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R Squared ($R^2$) criteria.Therefore, the model for scheduling and planning problems developed in three phases. We determine the elective patients' day and operating room regarding their waiting times at the first stage. The second phase of the model is related to the daily scheduling of the elected patients that the sequence of their surgeries in any operating room is determined.

We finally use discrete event simulation to compare our optimized scheduling model to the available schedule using data from by using statics and data from Montreal's hospitals. We could show that our scheduling model can significantly increase operating room utilization with the issue of PACU congestion.

Concluding, This model helps our patients enter the operating room on a priority basis to not run out of resources in the operating room and other areas such as the ICU while maintaining operating room efficiency. Our model also gives managers an overview of patient status and operating rooms to plan more surgery.

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