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EVALUATION OF OPTIMAL SCHEDULING POLICY FOR ACCOMMODATING ELECTIVE AND NON-ELECTIVE SURGERY VIA SIMULATION

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ABSTRACT

There are two main types of surgeries within an operating room (OR) suite, namely elective (or scheduled) and non-elective (or non-scheduled) surgeries. Non-elective surgeries count for a considerable proportion of surgery demand and often have a priority for begin served in a timely manner. Accommodating this type of surgery can be a challenging task on the day of surgery. This is mainly a result of the uncertain demand for non-elective surgeries, which discourages hospitals from reserving sufficient capacity for these surgeries. Using simulation, we evaluate an optimal policy for accommodating elective and non-elective surgeries that minimizes waiting time of patients, overtime, and number of patients turned away. We carry out the analysis on a stylized, two-room study where one room is dedicated to non-elective cases and the other room contains elective cases but can accept a non-elective case if necessary. The optimal policy is originally found by using a Markov decision process (MDP). However, since Markov modeling has an exponential arrival rate and steady state assumptions, which may not always be true in a surgical environment, the evaluation through simulation allows these assumptions to be relaxed.

1 INTRODUCTION

The operating room (OR) is well known to be the most profitable and critical hospital resource (Macario et al. 1995). Coupled with increasing healthcare costs and increasing patient expectations, it is imperative that hospitals manage their ORs effectively (i.e., reducing cost of care while maintaining the highest quality of care). Managing ORs becomes even more difficult when a facility serves several types of cases.

Surgeries in an operating room often can be grouped into two broad categories: elective and non-elective. Elective cases are typically those that enter into the schedule by the end of the day before surgery. Non-elective cases (such as add-on and urgent cases) are those that have not been scheduled in advance. These patients could also be inpatients that require surgery without prior notice, previously canceled surgeries due to some unsatisfied medical condition or lab result, or walk-in patients that need surgery within the same day. Considering these two surgery types, three potential types of ORs are possible with an OR suite: dedicated OR to non-elective, dedicated OR to elective, and versatile OR. The dedicated OR to elective and dedicated OR to non-elective as their names imply could solely be used by one type of surgery. On the other hand, a versatile OR is filled with elective surgeries, yet it could also be used to perform non-elective surgeries. In other words, the versatile OR (which is a shared resource between elective and non-elective surgeries) can be completely scheduled with elective cases, yet still be used on the day of surgery for performing non-elective surgery (with some penalty to the already scheduled elective surgeries in the form of cancellation or delay). With the three types of ORs described, the total of five OR configurations could be defined within OR suite. Each hospital chooses one of these configurations based on their need and financial goals. One of these configurations is when OR suite has only the two OR types of dedicated to non-elective and versatile ORs. In such configuration there is still need for non-elective surgeries to use versatile ORs mainly because of the uncertain demand of non-elective cases that causes OR managers not to dedicate enough capacity to them. Therefore, it is important to have a policy that under that policy, non-elective surgeries can use versatile OR. Currently some hospitals use extreme policies such as delaying non-elective cases until the regular close time of OR to perform surgery on these cases. Some others have the policy of blocking elective surgeries to perform non-elective surgeries. These extreme policies usually are in favor of certain type of cases, creating imbalance system in terms of waiting time of patients and number of cancellations causing a lot of direct and indirect costs to systems.

The problem of finding an optimal policy (for described OR configuration with one dedicated OR to non-electives and one versatile OR) for how to distribute non-elective patients between the two types of versatile and dedicated OR to non-elective on the day of the surgery has been studied in Hosseini et al. (2014) through modeling with MDP. The objective of the MDP is to minimize the overall cost of the system from waiting time of patients, turn away costs, and overtime. The approach used in MDP has limited assumptions related to the distribution of arrivals of patients and the steady state assumptions that are less common in healthcare. In this research considering the same system, we use simulation optimization to find an optimal policy for accommodating patients. We use the same objective as considered in Hosseini et al. (2014), however we relax steady state and exponential assumptions. We note that since the focus of the research is only on configuration with dedicated OR to non-elective, the dedicated OR implies dedicated OR to non-elective. We minimize the cost associated to the waiting time of patients for surgery (from check in to surgery start time) and the number of cases that are turned away to find a balanced policy for accommodating non-elective cases on the day of surgery as was considered in MDP model in Hosseini et al. (2014).

To summarize the research problem, we are considering a system with two types of servers (dedicated and versatile ORs) and two types of customers (elective and non-elective patients). At arrival, an elective case can use the versatile OR if the room is idle and there is no other elective case waiting. A non-elective case will use the dedicated OR first. However, if the dedicated OR is busy, the non-elective case will either be assigned to the versatile OR or be placed in the non-elective queue. The sizes of non-elective and elective queues are finite, implying that cases may be turned away. When a case finishes in the versatile OR, the decision must be made as to which type of case will be performed next in the versatile OR. We note that the problem studied in this paper is based on only two ORs however this could be extended to larger systems. The authors in Hosseini et al. (2014) solved the MDP model for only two ORs (one dedicated and one versatile) noting that the output policy could be seen visually best when there are two ORs in the system. They however note that the problem could be expanded for higher number of ORs. It is also noted that two ORs could represent the demand of surgery in hospital. Therefore, we use the same number of ORs for sake of comparison.

2 LITRITURE REVIEW

Several research conducted in the different areas of surgical scheduling. Decisions related to the strategic (Cardoen and Demeulemeester 2008; Adan and Vissers 2002; Dexter et al. 2002; Dexter and Macario 2002; Hosseini and Taaffe 2014), and operational planning (Belien and Demeulemeester 2007; Belien and Demeulemeester 2008; Blake et al. 2002; Cardoen and Demeulemeester 2008) have been studied in several research. Some studies considered only elective cases (Belien et al. 2006; Cardoen et al. 2009) while others considered both types of elective and non-elective cases (Mulholland et al. 2005; Lamiri et al. 2008a; Lamiri et al. 2008b). Although the stochastic demand of non-elective cases has been considered in strategic-level and tactical-level research, operational decisions related to the management of patients on the day of surgery are not often addressed. Lans et al. (2006) found a sequence for elective surgeries so that the waiting time of emergencies was minimized on the day of surgery. More similar to our problem, Green et al. (2006) represented the problem of accommodating inpatient, outpatient, and emergency patients in a MRI suite. In their model, no resource has been dedicated to any type of patient. Similar problems have been studied in non-healthcare environments. Gong and Betta (2006) addressed a two-priority, preemptive, single-server system with a queue-length cutoff. In their model, work ceases on high-priority jobs once the number of low-priority jobs reaches some threshold. This assumption is unrealistic when relating this to patients and surgery as the surgeries cannot be interrupted. Xiong and Altiok (2009) introduced a multi-server queuing system in which the customers leave if they wait more than some time or if the length of the queue exceeds a threshold. They estimated the waiting time of customers in queue. In both Xiong and Altiok (2009) and Gong and Betta (2006), all customer types can be served by any server and none of the customers are dedicated to a specific server. Frank and Zhang (2003) studied a periodic inventory system with two priority classes of stochastic demands in which one class needs to be fully satisfied within the period while demand in the other class might be lost if it cannot be satisfied by the end of the period. Our research differs from these examples in that we have two customer types with one shared resource and one dedicated resource. Moreover, we use a fixed set of resources and cannot adjust our supply across periods.

3 METHODS

3.1 Problem Description

Consider a facility with two operating rooms that admits two classes of patients for surgery, elective patients and non-elective patients. Patients arrive one at a time based on their class (the arrival of patient is depend on the approach used and is explained more in this section). There are two types of rooms available to perform surgery, a dedicated and a versatile room. The dedicated room may only be used to serve non-elective patients, while the versatile room may be used to serve either class of patients. The length of surgery depends on the patient class and not on the room. The flow of surgeries upon arrival and departure of cases are shown in Figures 1-3. An arriving patient who is not served immediately will join a queue for their class and incur a waiting cost in dollars per unit time of c_{el} and c_{em} for elective and non-elective patients, respectively. Waiting cost could be described as patient dissatisfaction cost, the cost of patient health (which may be critical for non-elective patients), or cost related with surgeon idle time. We make no assumptions concerning the relative magnitude of waiting costs for elective and non-elective patients.

Upon arrival, an elective patient can use the versatile room if the room is idle and there is no other elective patient waiting. Otherwise, the patient will join the elective patient queue. An arriving non-elective patient will use the dedicated room if he finds the room idle and there is no other non-elective patient waiting. If the dedicated room is busy and the versatile room is idle, this patient will either use the versatile room or join the non-elective queue. If both rooms are busy, the patient must join the non-elective queue. We assume that there is a finite queue for each patient class of size max_{el} and max_{em} for elective and non-elective patients, respectively. If a patient arrives to the system and the queue for his class is full, he will leave the system and a one-time turn-away cost will be incurred, which depends on the patient class; cc_{el} (for elective) and cc_{em} (for non-elective). To understand why the turn-away costs may depend on patient class, consider a non-elective surgery that arrives to a full queue; if there are several hospitals in the area, the non-elective patient could be rerouted to a sister hospital even before he arrives to the primary facility (resulting in a very low turn-away cost). On the other hand, if this facility is the only medical service in the region, the cost of turning away a non-elective case could be very high as it may risk the patient's health. Unlike non-elective patients, the turn-away costs for elective patients may not be related to the location of the hospital. The turn-away cost of elective cases could be comprised of dissatisfaction of the surgeon and the patient due to rescheduling the case or lost revenue (if the case does not get rescheduled). In either scenario we expect that turn-away costs associated with elective cases will be high.

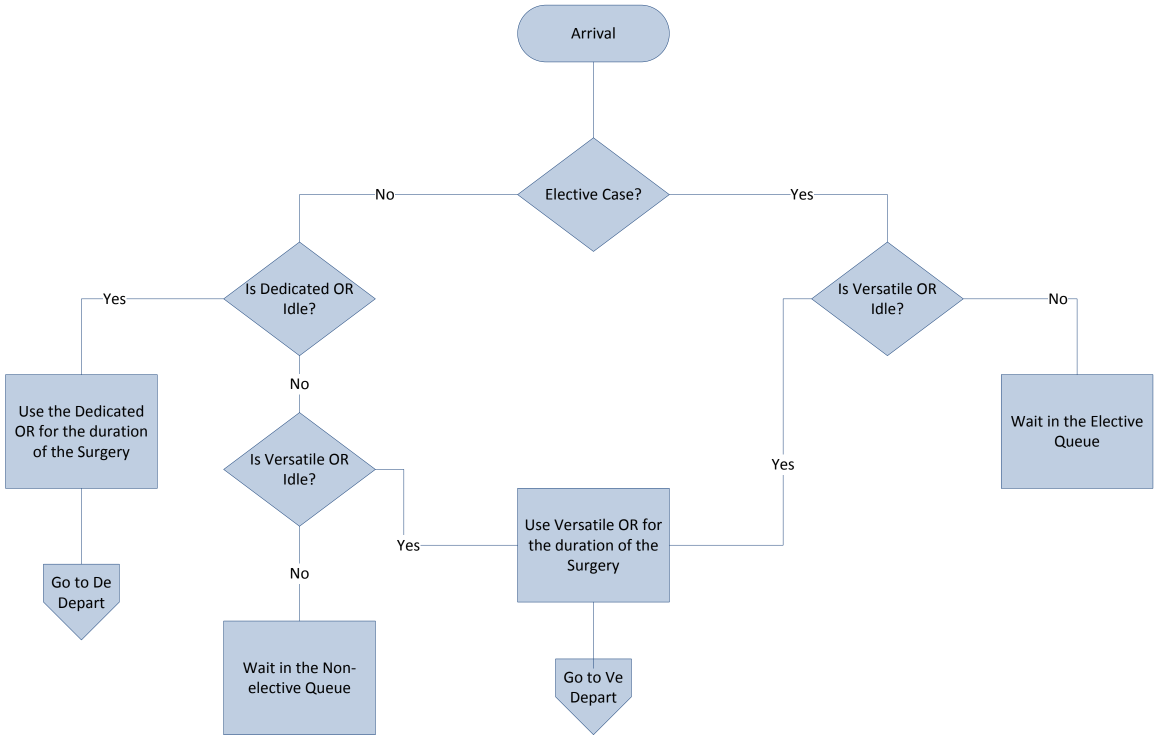

Figure 1: Flow of cases upon arrival.

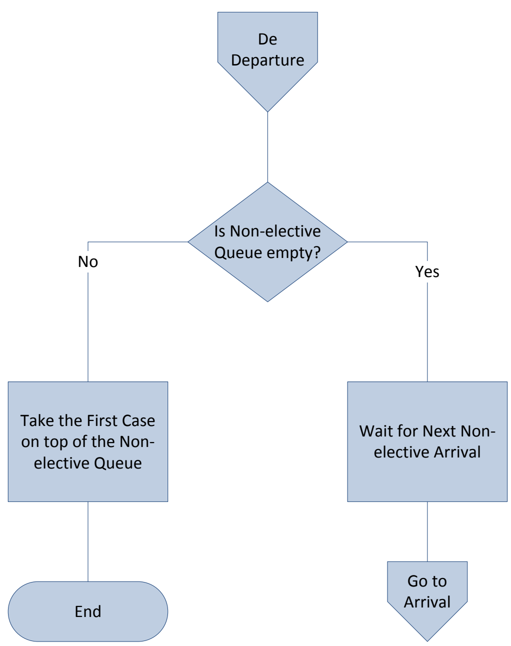

Figure 2: Departure from Dedicated OR.

Lastly, we consider that when a non-elective patient is served in the versatile room, he may cause some overtime to versatile OR which costs W dollar per hours. We point out that any possible costs associated with idle times or under-utilization are not considered. We believe this is reasonable because on the day of surgery, staff are already scheduled and considered a sunk cost. This assumption has also been used and justified by Dexter (2002).

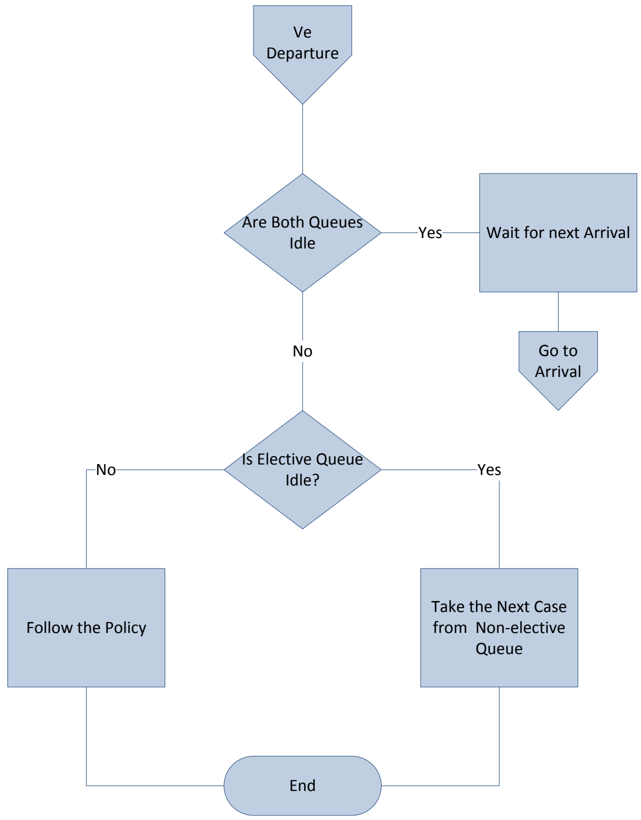

Figure 3: Departure from Versatile OR.

As explained when a case leaves the versatile OR, the decision needs to be made about what type of case to perform in versatile OR next, if both elective and non-elective queues are non-empty. In other word, there is need for a policy that specifies the type of patient that next enters the versatile OR for surgery. Two approaches has been used to solve this problem; one approach is using MDP (this approach has been studied in Hosseini et al. (2014) and the other approach is simulation optimization; however, we only discuss the simulation approach in details here. Although both approaches follow the same basics but they are different in terms of the way solution is carried. Also assumptions of the two approaches are different. One of the differences between the two models is that in the MDP model, arrival of patients and surgery times are considered to be exponential. These assumptions are relaxed in simulation model in sense that we do not consider any distribution for arrival and surgery times. In fact in the simulation model, we consider stream of patient arrival and surgery times as they historically happened. MDP also considers steady state assumption. With the simulation model, this assumption also is relaxed by considering actual start and stop time of OR times as historically happened. MDP approach provides an optimal solution to the problem while it considers arrival and surgery times to be exponentially distributed. Although limited assumptions of MDP are relaxed in simulation model and more realistic arrival and surgery times are considered, there is no guarantee for simulation model to lead to an optimal solution. We discuss this issue further in the paper. One motivation for use of MDP over the simulation model for finding policy is the time it takes to find a solution. While MDP finds a solution to this problem in seconds, optimization through simulation takes hours to run to guarantee a good solution. MDP offers an optimal solution to the problem quickly, however as mentioned it has limited assumptions. These assumptions may not be true in healthcare applications however, we can verify whether these assumptions affect the solution through relaxing assumptions in simulation model. To do so we create a simulation model for this problem using Arena software, when these assumptions are relaxed. We then use OptQuest within the simulation to find a policy which is depend on the current status of the versatile OR and number of cases waiting in each queue. The optimization through OptQuest is to minimize the overall costs of waiting, turn away and overtime. We then compare the policy obtained from simulation under more realistic assumptions with the one obtained from MDP model. We again note that the goal of this paper is to focus on the simulation part and show how simulation can be used as a validation tool.

We use surgical data from a local hospital as part of the comparison between the two approaches. We also use randomly generated data to perform similar comparison.

3.2 Simulation Model Output Policy

For ease of discussion, we present the output policy in three separate decision matrices based on the status of the ORs and the number of cases of each patient type waiting queues. These three matrices are: R_{ne}, R_{nn}, and R_{ni}. The reason for considering three matrices is that the decision or policy is depending on the current status of the versatile OR. The versatile OR could be occupied by an elective case, by a non-elective cases, or it could be ideal. The indices of matrices represent the status of the dedicated OR and versatile OR respectively (where the first indices shows the status of the dedicated OR and the second indices shows the status of the versatile OR; letters *n*, *e*, and *i* identify the current status of the OR as whether occupied with a non-elective, *e*, occupied with an elective, *n,* or being idle respectively, *i*). For all three matrices R_{ne}, R_{nn} and R_{ni}, an element in the matrix equal to 1 implies the optimal action is to serve a non-elective case next in the versatile OR, whereas a value of 2 implies it is best to serve an elective patient next in the versatile OR. A value of 0 implies that the versatile OR should remain idle. Also Rows and columns of the matrices represent the number of patients waiting in each of the elective and non-elective queues.

For example, when the dedicated OR is busy with a non-elective case and the versatile OR is busy with an elective case, then $R_{ne}(k,l)$ denotes the type of patient (elective or non-elective) to be served next in the versatile OR when k (k is in $\{1,\ldots, max_{em}\}$) cases are waiting in the non-elective queue and l (l is in $\{0,\ldots, max_{el}\}$) cases are waiting in the elective queue. When both versatile and dedicated *ORs* are busy with non-elective cases and there are k non-elective patients in the non-elective queue and l elective patients in the elective queue, we denote $R_{nn}(k,l)$ to be the type of patient to be served next in the versatile OR. Note that for both R_{ne} and R_{nn}, k starts from 1 since there are no decisions to be made when $k=0$. When the versatile OR is idle (implying the elective queue is empty) and the dedicated OR is busy with a non-elective case, the versatile OR can stay idle or could be filled with a non-elective case. For k in $\{1,\ldots, max_{em}\}$, $R_{ni}(k)$ indicates whether the versatile OR needs to stay idle or should be filled with a non-elective case.

R_{ne} and R_{nn} are both max_{em} by $max_{el}+1$ matrices, while R_{ni} is a max_{em} size matrix. It is clear that the first column of matrices R_{ne} and R_{nn} will only take on values of 0 or 1 (since there is no elective patient in the queue to be served) whereas other elements of these two matrices could take on values of 1 or 2 (with both queues nonempty, the versatile OR will not remain idle). Matrix R_{ni} will take on values of 0 or 1 only (as there is no elective patient in the queue). In the following example we explain briefly how the policy could be read from the output matrices.

4 RESULTS

4.1 A Case Study

As previously noted, certain assumptions used in the MDP model may not be strongly supported in a surgical environment. In order to further substantiate the use of the MDP results in practice, we must illustrate how the MDP policy compares to that generated from a simulation with actual surgical data. In this section we relax the steady-state and exponential distribution assumptions and develop a model for a local surgical care facility based on 30 days worth of historical data from a local hospital. We designed policy matrixes as described in Section 3.2 as variables in the model allowing OptQuest to change the values of these variables while evaluating the objective which is to minimize the total cost of waiting, turn away and overtime. OptQuest changes the values of elements of policy matrices over the possible candidates for each element as was described in Section 3.2 to obtain an optimal solution. Even when each queue is limited to two patients, there are 2^{14} or 16384 scenarios to test to find the optimal solution for this problem (there are total of 14 elements in the three matrices R_{ne}, R_{nn}, and R_{ni} in this situation). OptQuest, a simulation-optimization product that works in combination with Arena, searches from available simulation settings for an optimal course of action or inputs (while restricted to some policy structure, stationarity, deterministic, and state dependent assumptions).

The data provided by the local hospital does not suggest an exponential distribution as a close fit for the arrival and service times available. However, to compare the solution from OptQuest with the optimal solution from the MDP, the historical average arrival and service rates are calculated and used as parameters for the respective exponential distributions to use in the MDP model. The data shows that average arrival and service rates for elective cases are 1/2.41 and 1/2.18 per hour, respectively, whereas for non-elective cases these values are 1/3.02 and 1/1.93 per hour, respectively. In the simulation model however, we used the stream of arrival and surgery times as they historically happened to generate the policy. Other cost assumptions are c_{em}*=800 \$/hr*, c_{el}*=500 \$/hr*, cc_{em}*=\$2500*, and cc_{el}*=\$3000*, and *W=600 \$/hr* (These cost assumptions are based upon interviewing OR managers regarding the relative costs of waiting and turn away. We note that the policy is not sensitive to the cost rather to the relative costs of waiting and turn away for elective and non-elective patients). Using the above rates for interarrival and service times, we have the following policy generated from the MDP model:

$$R_{ne} = \begin{pmatrix} 1 & 2 & 2 \\ 1 & 1 & 1 \end{pmatrix}, \quad R_{nn} = \begin{pmatrix} 1 & 2 & 2 \\ 1 & 2 & 2 \end{pmatrix}, \quad R_{ni} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}.$$

OptQuest is run for about 2.5 hours with over 15,000 simulations (each with 30 days as replications) being tested. After running these simulations, OptQuest finds the same results that are suggested by the MDP, providing support for the use of the MDP policies and further research using this modeling approach. In addition, OptQuest finds several other alternate solutions with identical cost. Over the 30 days of the schedule, some of the states of the policy are never visited, resulting in no difference in the simulated performance cost which results in getting alternative solution. For example, both queues never become full at the same time, so the decision to make when both queues are full is never used or needed. Table 1 shows some alternate solutions reported by OptQuest.

The average cost per hour by using the MDP optimal policy is \$309, however this cost in the simulation model is only \$254. This could be because historical surgery times have low variability; this fact was also shown when we tested continuous exponential arrival and surgery rates in simulation model to find the times that model reaches steady state. One other reason for the difference in costs might be that the simulation model uses a discrete schedule while the MDP is using continuous arrival and surgery rates. Given the actual arrival and surgery times, the simulation model does not actually create situations when more cases arrive than can be accommodated. Thus, the only reason for patients to be turned away is if non-elective cases use the versatile OR.

Table 1: Alternate solutions from OptQuest.

Alternate Solution	R_{en}	R_{nn}	R_{ni}
1	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 2 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 1 \end{pmatrix}$
2	$\begin{pmatrix} 1 & 2 & 2 \\ 0 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 2 \\ 0 & 2 & 2 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 0 \end{pmatrix}$
3	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 1 & 2 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 1 \\ 1 & 2 & 2 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 1 \end{pmatrix}$
4	$\begin{pmatrix} 1 & 2 & 2 \\ 0 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 1 & 2 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 0 \end{pmatrix}$
5	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 2 \\ 0 & 2 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 0 \end{pmatrix}$
6	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 2 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 1 \end{pmatrix}$

4.2 Other Examples

In order to provide stronger support for the results of this study, in addition to the case study, we developed two different sets of random schedules to examine our model. In both sets 30 days of arrival and surgery time schedules for both elective and non-electives were randomly created. Neither arrival nor surgery times in these two sets of data are not following exponential distribution however we calculated the average service and interarrival rates to be used in MDP model assuming that these distributions are exponential. The information regarding rates are provided in Table 2. For simulation model we directly used the discrete random schedule to counter for more realistic representation of surgery day.

Table 2: Randomly generated rates.

Set	Elective arrival rate	Elective surgery rate	Non-elective arrival rate	Non-elective surgery rate
1	1/2.71	1/2.85	1/2.26	1/3.04
2	1/2.61	1/2.44	1/2.54	1/2.31

Our results show that for both random schedules tested, the MDP model and simulation model suggest the same policy. The average costs from simulation model are lower than the costs from MDP model for both sets of data. These policies and their corresponding average costs are presented in Table 3.

Table 3: Optimal Policies.

Set	R_{en}	R_{nn}	R_{ni}	MDP average cost	Simulation average cost
1	$\begin{pmatrix} 1 & 2 & 1 \\ 1 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 2 & 2 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 1 \end{pmatrix}$	1280	750
2	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 1 & 1 \end{pmatrix}$	$\begin{pmatrix} 1 & 2 & 2 \\ 1 & 2 & 2 \end{pmatrix}$	$\begin{pmatrix} 1 \\ 1 \end{pmatrix}$	699	554

Both approaches provided with the same policy as solution however the average cost per hour for set 2 is higher. This increase could be due to faster arrival and longer surgeries of non-electives in addition to the continuous arrival of them.

5 DISCUSSION

We note that although the MDP has the ability to obtain an optimal policy (and finds it quickly), the simulation model provides alternate solutions and performance data, which in some situations can be an important factor. The alternate solutions may be easier to explain and implement in practice, which could be the main advantage of the solution found through simulation. The simulation is also able to measure performance criteria such as waiting time of patients and queue lengths (cases waiting) at any point in time, testing the generated policy. The MDP model, however, is unable to capture such measures and needs to be accompanied by other tools such as simulation if looking at these measures is the goal.

Typically, the policy put in place would not require updating frequently, since it would consider historical surgery arrival rates and service times. If there is a shift in either of these, however, the policy could easily be updated by running either the MDP or the simulation model. In fact, it would be a further validation to run both to continue to assess the appropriateness for using an MDP with its assumptions. With expanding the model and considering more than two ORs, the number of variables in simulation optimization increases drastically, causing simulation to run much longer that it was ran for two ORs. This change however may not affect the run time of MDP by more than few seconds.

6 CONCLUSION

In this research we created a simulation optimization to find policies for accommodating elective and non-elective surgeries in a OR setting with a dedicated OR to non-elective and a versatile OR for both elective and non-elective. We compared the result of this model with the optimal policy from the MDP. The MDP approach finds an optimal solution to this problem but it has limiting assumptions. Using simulation optimization, we solved the problem by relaxing certain assumptions. The simulation and MDP solutions are the same for both the case study as well as the analysis using randomly generated data, indicating that the assumptions applied in the MDP are not adversely affecting the policy generated by the MDP. Although we consider only two operating rooms, this problem could be extended to larger number of ORs, which is part of the future research plan.

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