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SURGERY RESCHEDULING USING DISCRETE EVENT SIMULATION: A CASE STUDY

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ABSTRACT

Operating room (OR) rescheduling is the process of adjusting the surgery schedule when the current schedule is subjected to disruptions on the day of surgery. The decision to make a schedule adjustment will impact patient safety, patient satisfaction, hospital costs, as well as surgeon satisfaction. Of particular importance is when, and how frequently, to update the scheduling and tracking systems. These questions and their impact on maintaining schedule accuracy and minimizing room overtime are explored. Discrete event simulation was used to simulate surgical cases in the OR and to test different "right shifting" and case updating policies for their effectiveness. Results and staff experience indicate that ten minutes is the preferred delay in which an update should be made; otherwise staff satisfaction or schedule accuracy will suffer.

1 INTRODUCTION

During the course of a day in a hospital, surgery schedules set at the beginning of the day may undergo disruptions. These disruptions can include the addition of add-on elective, urgent or emergent cases, case cancellations, and deviations from scheduled case duration. This paper focuses on the latter. Deviations from scheduled case durations can be caused by unpredictable complications during surgery, patient health issues before surgery, surgeon availability and many other reasons. These deviations create a need for nurses and core coordinators to reschedule cases during the course of the day. In this paper we focus on the impact of right-shift rescheduling cases when disruptions occur. Right-shifting is the process of delaying cases by visually moving them to the right on the posted schedule. The decision that core coordinators will need to make are those related to when and by how much time to delay the rescheduled cases. This is the question that this research aims to answer using simulation.

Currently the hospital will rarely reschedule a room because of case delay. They will, however, make updates to surgeries that have moved to another room. Any changes made to the schedule are communicated through phone and pager to the involved staff (e.g. surgeon, pre-op coordinators, and nurses). If the tracking board could be kept more routinely and automatically updated, the loss of work due to unnecessary communication could be minimized.

These decisions on the day of surgery can impact OR utilization, equipment availability, surgeon availability, surgeon satisfaction, staffing levels, patient satisfaction, and costs (patient and hospital). OR managers are required to make rescheduling decisions every day. Interviews with Greenville Memorial Hospital (GMH) staff in Greenville, SC have confirmed that communication in the OR and across all activities within perioperative services are important to making good decisions. Hence, the motivation for this research comes primarily from research questions posed by perioperative management at GMH. They ask under what conditions they should update the tracking boards in the OR with a new schedule.

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There is a fine balance between providing useful information about case status and overwhelming the staff with too much information.

In order to study this balance, GMH perioperative management have agreed to trial the automatic updating of the surgery schedule for one room in the OR suite. We have modeled this trial OR in an effort to fine tune the rescheduling parameters to use in the actual system as well as to validate our initial rescheduling approach. Since the trial study is just being implemented this paper focuses on the modeling and initial results of our simulation for the trial OR. In future work we will validate our model with the study of the trial room and fine tune the model for a more accurate estimating of the important parameters to be discussed. Our contributions to surgery rescheduling, although exploratory, are an important step to tackle more difficult problems.

2 LITERATURE REVIEW

The timely incorporation of surgical equipment, hospital staff, surgeon groups, ORs, preop rooms, post anesthesia care unit rooms and the patients are all important. The scheduling of all of these interconnected parts creates a complex problem and falls under the general research area of OR scheduling. Although extensive research has been performed under the umbrella of OR scheduling, there is comparatively few research papers and journal articles regarding decision making on the day of surgery.

Cardoen, Demeulemeester, and Beliën (2010) provide an extensive literature review and survey of OR planning and scheduling. A base knowledge of OR scheduling would include block scheduling, elective case scheduling, case duration estimation, and surgery capacity planning. Block scheduling is a scheduling system in which OR managers schedule "block time" to ORs, which belong to a specific surgical group or surgeon. A paper by Fei, Meskens, and Chu (2010) also discusses block scheduling as opposed to an open scheduling strategy.

Elective case scheduling is the act of scheduling an elective case. By definition, elective cases are those that are scheduled ahead of time and are not urgent or emergent in nature. Elective cases are usually scheduled in days or weeks in advance of the surgery, but it is possible for cases to be rescheduled to take place with very little notice (especially for inpatient cases) if the schedule permits. This is also known as scheduling of an add-on case. Add-on cases are added on to the day's schedule in addition to the schedule posted at the beginning of the day (Dexter and Traub 2002). In addition to elective add-on cases there are also non-elective add-on cases. The cancellation or postponement of an elective case is common when procuring OR time to accommodate non-elective case add-on surgeries (Hosseini 2012). Li, Gupta, and Potthoff (2013) show that we can improve OR schedules by rescheduling ORs before the day of surgery to minimize the staffing costs.

OR scheduling techniques include a wide range of solution methodologies. Such methodologies predominately involve mathematical programming techniques or simulation (Cardoen, Demeulemeester, and Beliën 2010). Such mathematical programming techniques include mixed integer programming and column generation to solve these problems (Fei, Meskens, and Chu 2010; Brunner and Edenharter 2011). For example, the objective may be to minimize the total staff in a hospital OR suite where the variables may be levels of experience among staff (Brunner and Edenharter 2011). In a paper by Fei, Meskens, and Chu (2010), they use mixed integer programming to minimize the amount of idle time between surgeries. Branch-and-price strategies have been used to minimize the number of staff needed over a particular work-day to meet coverage constraints (Belien and Demeulemeester 2008). There are many articles that discuss linear programing or threshold-based statistics as a means to schedule OR cases (Denton, Viapiano, and Vogl 2007; Herring and Herrman 2012).

Simulation has also been a widely used tool in OR scheduling. Discrete event simulations have been used to analyze management policies, determine OR schedules, and increase OR utilization (Denton et al. 2006; Persson and Persson 2010; Steins, Persson, and Holmer 2010). Monte Carlo simulations based on Markov Decision Processes and discrete event simulations have also been used to generate policies for accommodating elective and non-elective surgeries (Hosseini 2012).

To thoroughly review methodologies in OR scheduling and rescheduling, it is important to look past methodologies proven in healthcare and also look at other industries such as manufacturing or project management. The stochastic job shop scheduling problem in manufacturing is similar in nature to the surgery scheduling problem in healthcare. They are similar in that jobs are like the surgeries to be scheduled and that both problems have stochastic processing times. In a paper by Jones and Rabelo (1998) solution methodologies to the job shop scheduling problem include mixed-integer programming, dynamic programming, branch and bound, Lagrangian relaxation, discrete event simulation, neural networks, and a variety of meta-heuristics. Vieira, Herrmann, and Lin (2003) provide a framework of strategies, policies and methods for rescheduling manufacturing systems. They discuss practical rescheduling methods that include right-shift rescheduling, partial rescheduling, and complete regeneration. The similarities between these two problems will prompt further research into which solution methodologies may be able to bridge the gap to the healthcare scheduling problem.

With regards to OR rescheduling, there is comparatively little literature amongst the general research in OR scheduling. One paper addresses the human factors element on the day of surgery, which can include how visual presentation of the OR status can affect decision making (Dexter et al. 2007). The literature on day of surgery case scheduling focuses mostly on how to optimally accommodate add-on cases, whether they are elective or non-elective (Hosseini 2012; Li, Gupta, and Potthoff 2013), while some literature focuses on case duration as a driver for the scheduling process (Dexter 2000; Zhou and Dexter 1998). There is some literature that discusses decision making on the day of surgery (Dexter et al. 2007). Dexter (2000) has also provided advantages and disadvantages to moving a case to another room at the end of the day to minimize OR over-utilization costs. Van Essen et al. (2012) discuss rescheduling of ORs due to case delay and addition of emergency surgeries. They employ an integer linear program to minimize the deviation from the preference of the stakeholders (e.g. surgeon, hospital, patient). Van Essen et al. (2012) found that the "preferences mainly lead to shifting a surgery and scheduling a break between two surgeries."

Examples of using any type of quantitative method (math model, simulation, or fixed policy based on model findings) in real time to replace gut-feeling decisions, judgment calls, and experience-based decisions on the day of surgery are non-existent. Quantitative methods being used in real time have been discussed briefly in a few instances of the literature, but have not been implemented nor documented (Baumgart et al. 2007). There appears to be an opportunity to investigate the value of using such methods for making decisions on the day of surgery.

3 METHODOLOGY

In this section, we present the OR rescheduling problem as well as introduce the simulation model used to generate new schedules throughout the day. We will use the model to test varying parameters and to create generalized policies. We use 100 simulation replications to obtain the results that are discussed in section 4. We choose 100 replications because the system is quite variable and a large number of replications were needed to get higher confidence in our output measures.

3.1 Terminology

We briefly introduce the following terms that are used in this paper: scheduled case duration, setup, induction, procedure, reversal, clean up, and case lateness. Scheduled case duration is the time between scheduled case start and scheduled case end times. Setup is the time spent preparing the room for the patient and surgery. Induction is the time during which the patient is prepared for the procedure. The procedure is the time that the surgeon is working and is usually started with first incision (procedure start) and completed with closing the patient (procedure finish). Reversal is the time between the end of the procedure and patient out of room. This is the time spent waking the patient up. Clean up refers to the time spent cleaning the OR from the previous surgery. Cases rarely start on their scheduled start times and tend to either start a little early or late regardless of any other constraint on the room. Case lateness refers to the difference between the scheduled start time and the actual start time for any given case.

3.2 Data Input

The input for our simulation model was developed from 18 months of case data (301 cases / data-points) from one OR at GMH and was used to create distributions for scheduled and actual case durations. Case data has been broken up into five different stages while case milestones indicate the start and end times of each stage. This is indicated in Figure 1. Although the reasons for case delays are known by the coordinating staff, they are difficult to see in case data collected at the hospital. Therefore, we can only make decisions on the times certain events occur during the course of the day. Since we are not considering add-on cases (e.g. urgent and emergent cases), our model data was taken from historical data on elective outpatient cases only. This is a limitation that we plan to address in future work. Empirical distributions were created from the data for scheduled case durations, reversal time, and case lateness. Arena's Input Analyzer was used to find the best fit for the remaining distributions. Scheduled gaps were sampled from a gamma distribution. Actual durations of case stages were fit to a mixture of Triangular, Lognormal, Exponential, Normal and Gamma distributions. Every distribution fit the respective data according to a chi-squared goodness of fit test. In our analysis, we are assuming that case duration is not affected by rescheduling and that the actual duration of each case stage is independent of the next. We are mimicking how the hospital handles delays of rescheduled cases by simply using offsets, but there may be a better way estimate how case delay affects remaining case time.

3.3 Model Development

This simulation model has been developed to study the rescheduling problem for one OR. Arena modeling software was used for input analysis as well as for generating the random schedules because it was both familiar and available to us. A random schedule is generated by sampling case times and scheduled gaps from probability distributions. The logic for creating random schedules is shown in the left part of Figure 2. Once the day has a full schedule, the cases are then played out according to distributions created from the historical data. The actual duration of case stages are sampled from individual distributions for each part. Starting from the beginning of the day sampled stage times are played out according to the logic shown below in the right part of Figure 2. Keep in mind that the logic will be slightly different when triggering the reschedule event based on a different milestone. As the day progresses, cases begin to get ahead or fall behind. As an example, if a procedure has not yet finished and is running late by more than the allowable amount, a reschedule event is triggered. This allowable amount is also known as the criterion amount. During this reschedule event, the remaining cases in the room are adjusted by the reschedule amount. Then the process continues and the rest of the day is played out. It is possible that multiple reschedule events will happen on the same day.

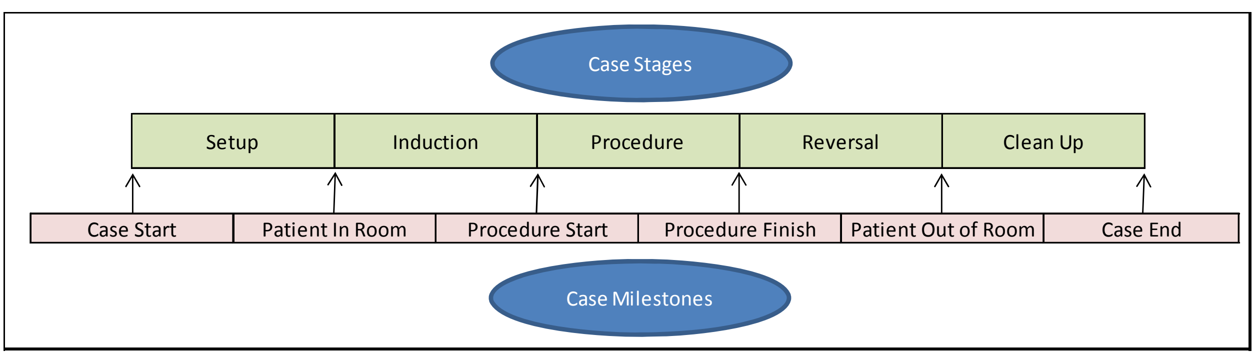

Figure 1: Terminology for case stages and case milestones.

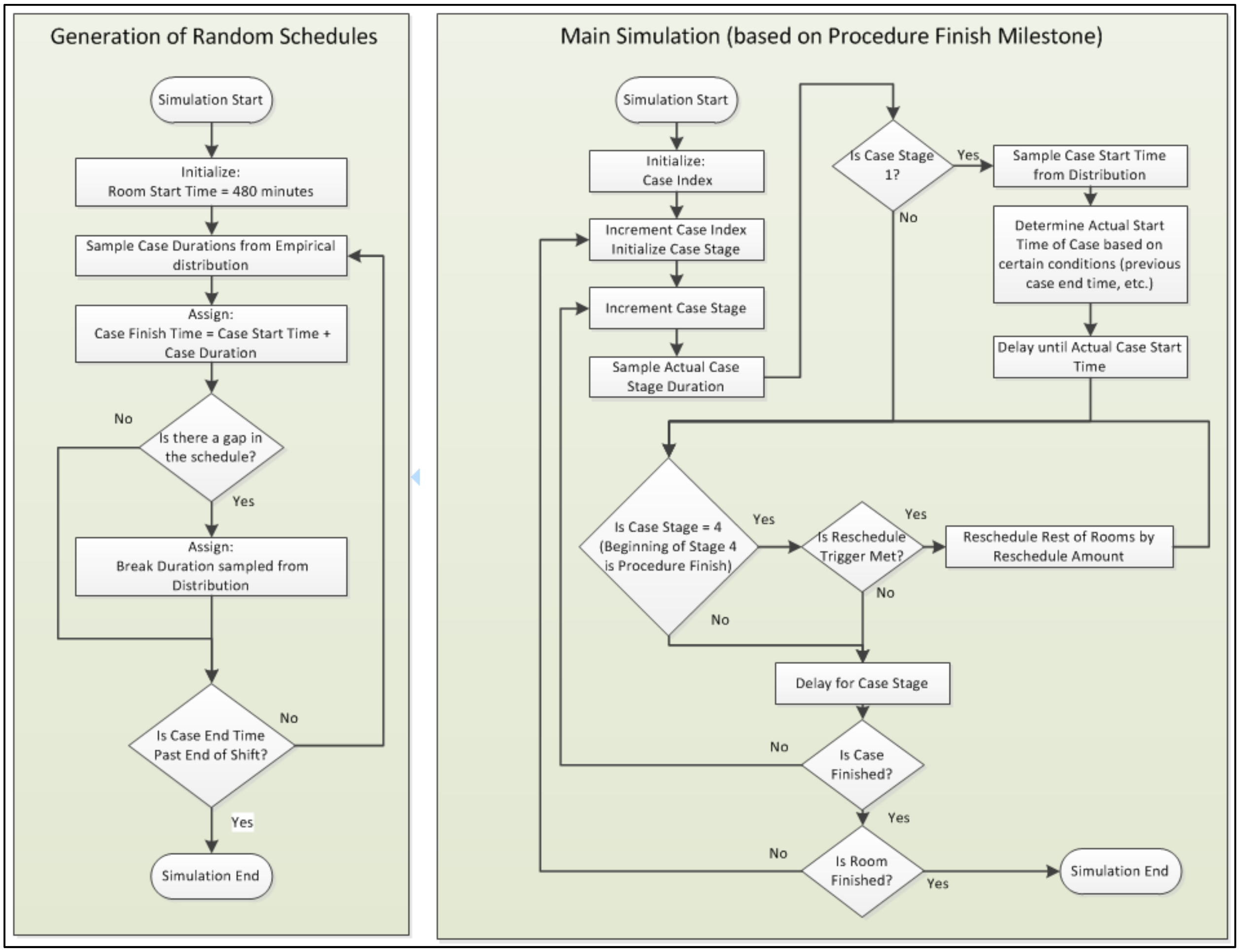

Figure 2: Simulation flow charts.

During the reschedule event, the current schedule is right-shifted or delayed by the reschedule amount (which in all experiments will be equal to the criterion amount). After the triggering milestone has been delayed by a certain number of minutes, the amount that the schedule is right-shifted is dependent on whether or not there is a gap in the schedule between the delayed case and the potentially affected case. If there is no gap between the cases then the next case is rescheduled by the reschedule amount. However, if there is a scheduled gap between cases and the first case is delayed, the gap will be used up before delaying the start of the next case.

3.4 Model Output

During the course of a simulation run, the model records important information as the room's cases are played out. First, we look at the average start time offsets and average end time offsets. Start time offsets refer to the difference between the actual start time and scheduled start time of an individual case, where end time offsets refer to the difference between the actual end time and scheduled end time. Note that reschedule events will change the scheduled start and end times for all the remaining surgeries. Second, we look at the number of reschedule events and the number of surgeries affected by rescheduling. This is important because there is a tradeoff between communicating accurate case start and end times and overwhelming the users of the hospital tracking boards with information. For now, we will use the experience of GMH perioperative management to define the limits of the rescheduling events. Last, we consider accuracy of shift end predictions. It is important to accurately schedule and manage nurses in perioperative services, and having accurate case end times (and, thus, the room completion time) is an advantage for the core coordinators.

3.5 Scenarios and Parameters

For the first part of our analysis, three scenarios were modeled to test different milestones with which to trigger the reschedule event. The three milestones are case start (*Scenario 1*), procedure start (*Scenario 2*), and procedure finish (*Scenario 3*). These milestones are the point during the case where the model decides whether or not the case is running late. We are testing these different parameters because these three milestones were determined by hospital management to be the most likely candidates to be used in the trial study discussed previously.

For each of the scenarios listed above, experiments were run with varying parameter values. The parameter, criterion amount, is varied between 5 and 60 minutes in increments of 5 minutes. This range encompasses all of the practical values that this parameter could take on.

Second, we considered how under-posting of cases affects the rescheduling policy suggested by looking at end of day prediction accuracies. Under-posting is when OR managers schedule rooms for less time then they will actually take (and this is how the historical data from the hospital actually behaves). This is a common occurrence because hospitals and surgeons try to fit as many cases into their scheduled block time as possible, and it causes more rescheduling to take place. It also begs the question, "How different would the rescheduling policy behave if cases were not under-posted?" We considered two additional surgery schedules – accurate(neither under-posted or over-posted) and over-posted. For both cases the variability of the schedules resemble the original scenario and historical data. Average scheduled durations are scaled to mimic more accurate scheduling.

Lastly, we considered accuracy of our scheduled procedure finish as a parameter to explore how its accuracy affects the rescheduling policy. The scheduled procedure finish milestone is estimated based on historical case data. Since cases are routinely under-posted, this estimation is not always a good indicator of the actual procedure end time. We estimate procedure finish time as an offset from the case end time. We explore the range from 10-40 minutes in increments of 5 minutes.

4 RESULTS

Considering the range of parameter values, there was a common theme between all three scenarios. On one hand, we found that the number of reschedules decrease as we increase the criterion amount, but on the other hand, the start time offsets and end time offsets also increase. This was not a surprising outcome, however the staff and researchers desired more insight into the magnitude of the trend, especially as it pertains to each scenario. The results for each scenario can be seen in Figures 3, 4 and 5 below. In these graphs, the start and end time offsets use the left vertical axis in minutes while the reschedule events and rescheduled cases use the right vertical axis in number of reschedule events and rescheduled cases respectively. It is desirable for the start and end time offsets to be close to zero, which indicates a smaller difference between scheduled and actual start and end time offsets. In addition, it is also desirable for there to be a smaller number of reschedule events and rescheduled cases because there is some cost involved with each. In all three scenarios, the number of reschedule events becomes very large as you decrease the parameter values, but the start and end time offsets only get marginally smaller. The only exception is that the end time offset for Scenario 3 (procedure finish is the trigger milestone) approaches zero as you increase the number of reschedule events and rescheduled cases. In addition, the number of reschedule events / rescheduled cases is also much higher for Scenario 3.

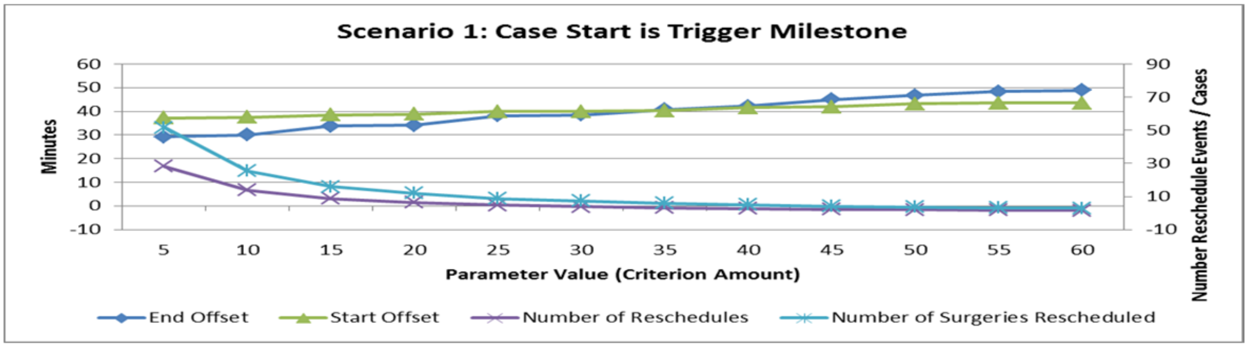

Figure 3: Scenario 1 (Case start trigger), Offset and rescheduling statistics.

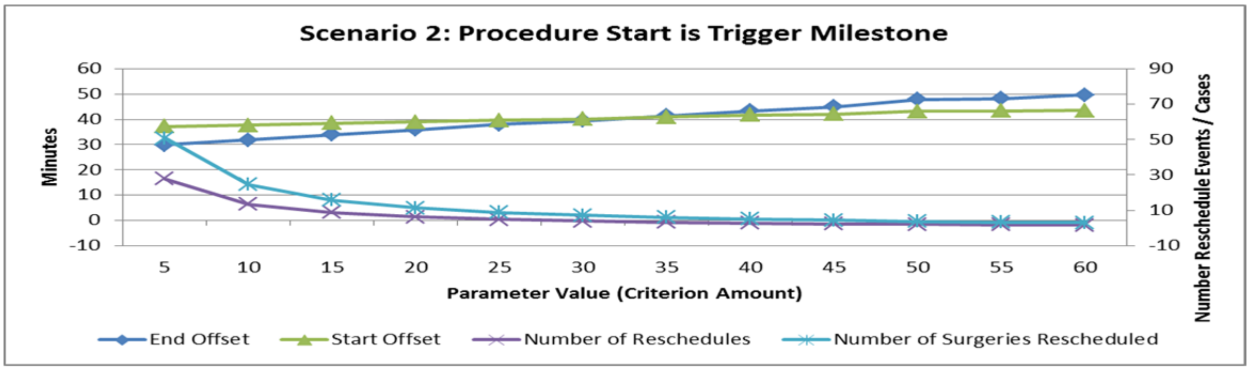

Figure 4: Scenario 2 (Procedure start trigger), Offset and rescheduling statistics.

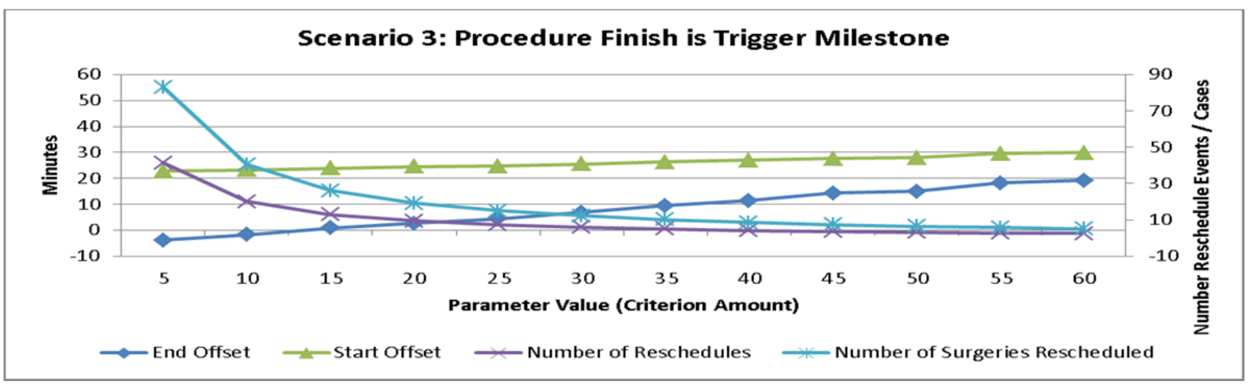

Figure 5: Scenario 3 (Procedure finish trigger), Offset and rescheduling statistics.

In conclusion, depending on the cost of the reschedule event and the cost of not starting a case on time, the optimal parameter values can be found somewhere on the total cost curve. Generally speaking, managers at GMH believe that the reschedule event will have a very low cost since the tracking boards can be updated automatically when a reschedule event occurs. The more subjective cost to a reschedule event is the cost to the stakeholders of the information. The more often we reschedule cases the more burdening it is for the surgeons and nurses to keep up-to-date with the latest information. Experts in perioperative management have suggested that reschedule events more than every 10 minutes will be interpreted as just noise. Therefor we assume that a criterion amount of 10 minutes is preferred. Further research needs to be conducted to quantify the subjective costs of rescheduling.

As we continue to explore the trends above we find that there is little difference between Scenarios 1 and 2. However, there is a notable difference between Scenarios 1 and 2 and Scenario 3. In Scenarios 1 and 2, we are triggering a rescheduling event based on how late the case or procedure is starting. In both of these scenarios, we are not considering the variability in length of the procedure duration in determining the likely case end time. Scenario 3 is unique because we wait until the procedure finish is running late before triggering a reschedule event. Since Scenario 3 is considering the length of the procedure which is commonly the most variable process in the OR schedule, we find that Scenario 3 out performs the other two scenarios in terms of start and end time offsets. On the other hand, we find that the number of reschedule events and rescheduled cases are much higher for the lower parameter values than Scenarios 1 and 2.

We have found that there is no difference between the performance of Scenarios 1 and 2. As you can see in the following graphs (Figures 6-9) the confidence intervals for Scenarios 1 and 2 are overlapping, which indicates that there is no significant statistical difference between the two scenarios. However, you can see that there is a statistical difference between Scenarios 1 and 2 and Scenario 3. In addition to non-overlapping 95% confidence intervals, paired t-tests confirm statistical significance for every parameter value (p-values less than 0.05).

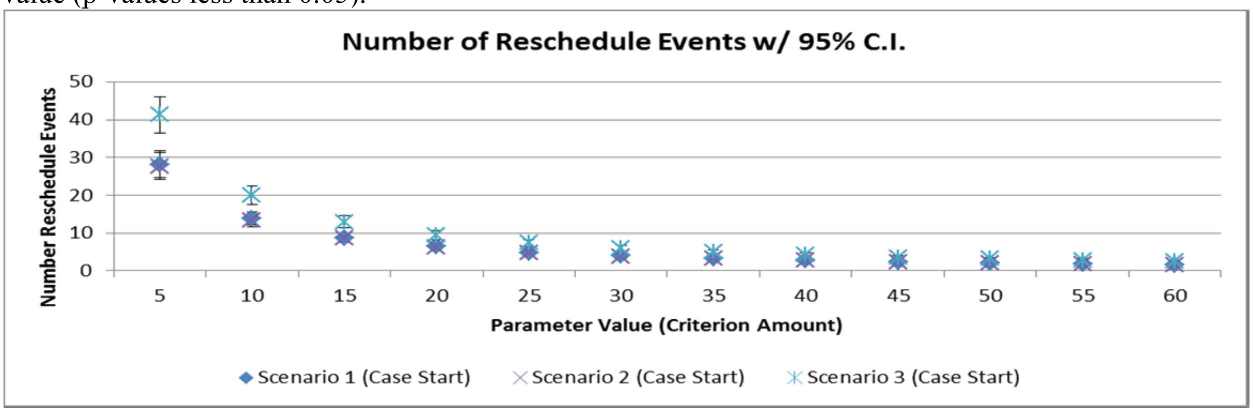

Figure 6: Number of reschedule events w/ 95% C.I.

In Figures 6 and 7, we find that Scenario 3 had many more reschedule events and rescheduled surgeries than the other scenarios (1 and 2). We also found that there is a significant statistical difference between the Scenarios 1 and 2 and Scenario 3. Overall we find that Scenario 3 has approximately 50% more reschedule events and rescheduled surgeries than the other two scenarios.

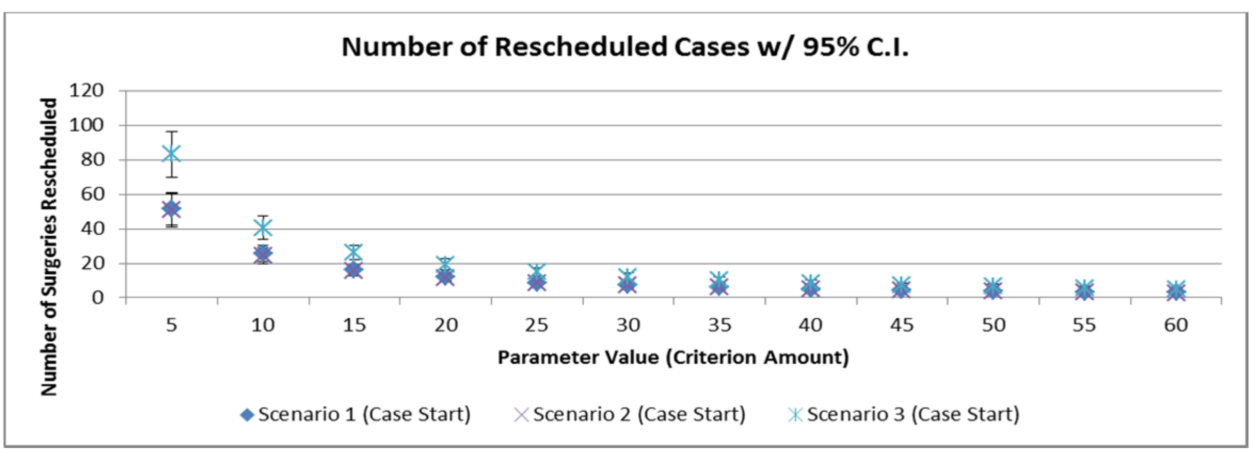

Figure 7: Number of reschedule cases w/ 95% C.I.

In Figure 8 we can see that Scenario 3 has an average start time offset of approximately 14 minutes smaller than Scenarios 1 and 2. We also see that there is a significant statistical difference between Scenarios 1 and 2 and Scenario 3. In Figure 9, we see that the same trend applies to the end time offset. We can see that end time offset for Scenario 3 actually reaches and passes zero for smaller criterion amount values indicating that surgery end times are being predicted accurately.

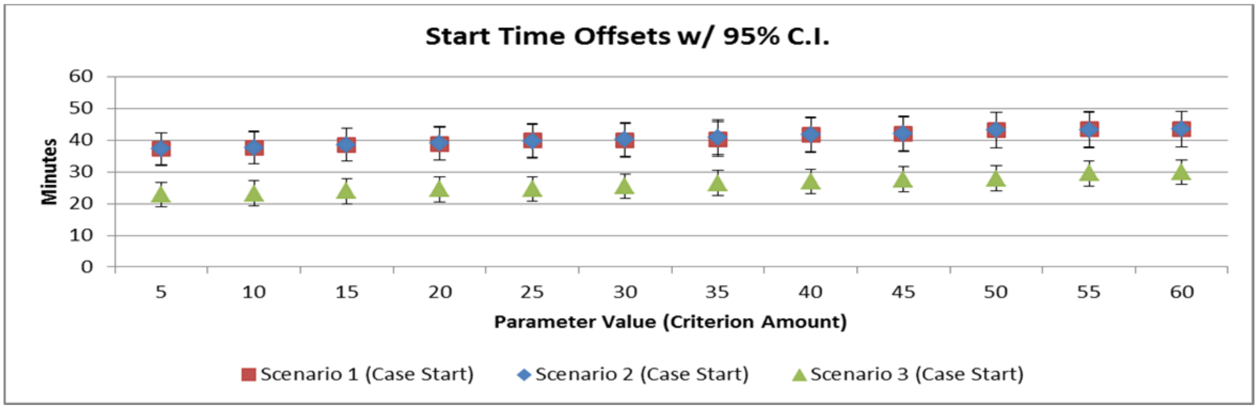

Figure 8: Start time offsets w/ 95% C.I.

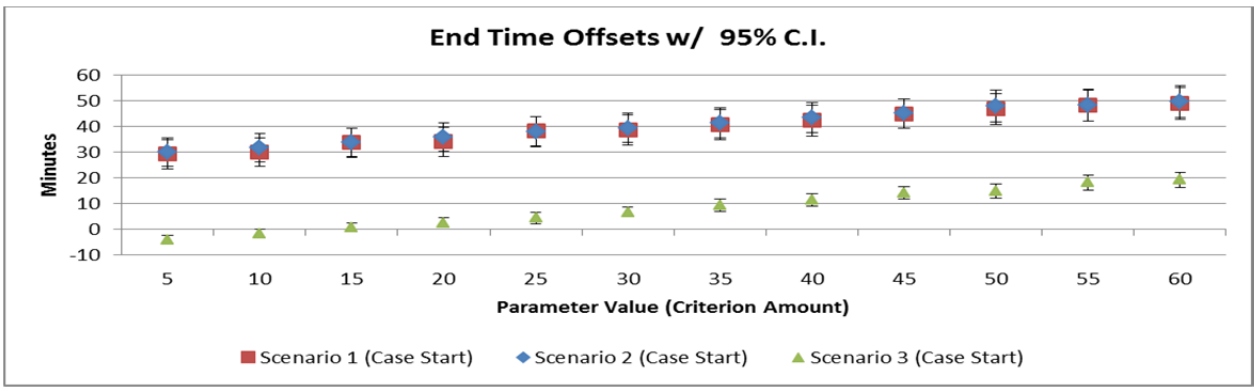

Figure 9: End time offsets w/ 95% C.I.

We also found that there is not a notable difference between scenarios when looking at end of day prediction accuracies. This can be attributed to the routine under-posting of cases at GMH. Instead, we look at how three different under-posting scenarios affect our output measures.

Next we considered end of day prediction accuracies for the three different under-posting scenarios. The under-posting scenario is the same scenario as above where cases are routinely posted for 30% less time than they actually take. The normal scenario schedules cases for how long they actually take, while the over-posting scenario schedules cases for 30% longer than they actually take. In both of the new cases, scheduled durations from the data were scaled up to represent a more accurate duration and over-posted scenario respectively. We use 30% because we achieve symmetry in our analysis (real data is 30% under-posted while the over-posted scenario is 30% over-posted). This way we can explore the entire spectrum. We used a criterion amount of 30 minutes for our reschedule policy and found that end of day prediction accuracy is best for the normal scenario. Results are shown in Figures 10 and 11 below. For Figure 10, each data point on the chart marks a reschedule event. We find the initial predictions (points along the y-axis, t=480 minutes) to average below the line marking 100% for the under-posted scenario, where points along the 100% line are desirable (this means that we are accurately rescheduling). We find for the over-posted scenario that although reschedule events are much less common and end time offset are much better (see Figure 11), our end of day predictions get worse closer to the end of the day.

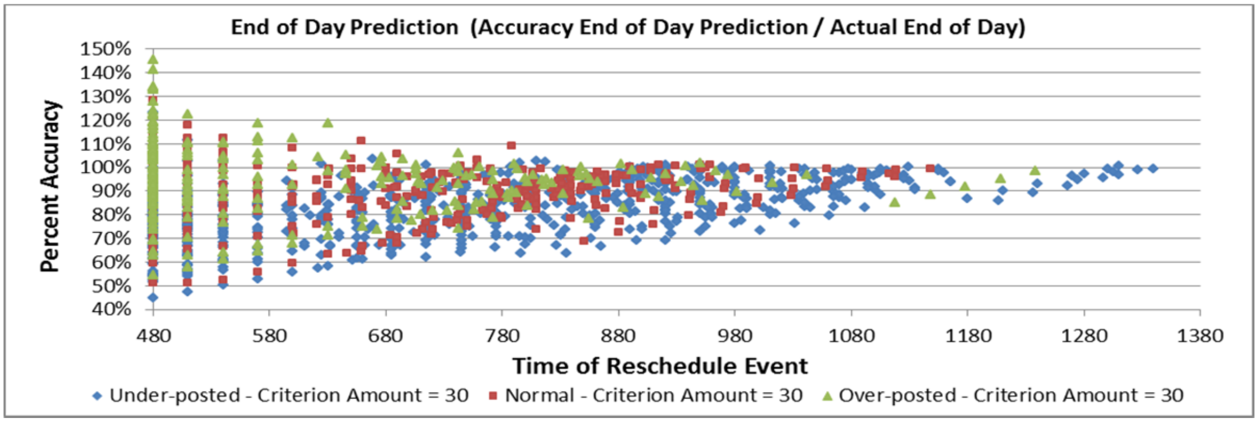

Figure 10: End of day prediction accuracy for under-posted, normal and over-posted cases.

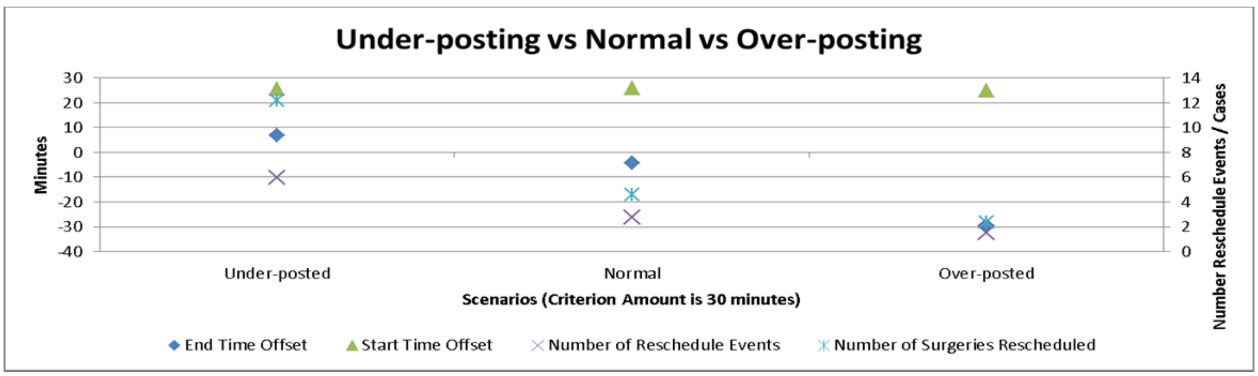

Figure 11: Under-posting vs. normal vs. over-posting cases.

Last we considered accuracy of our scheduled procedure finish as a parameter to explore how its accuracy affects the rescheduling policy. We found that the value of start time offsets, number of reschedule events and number of rescheduled cases stays approximately the same while end time offset decreases dramatically (Figure 12). End time offset starts at about 15 minutes and reduces to zero (the goal) around 30 minutes before continuing into the negative values.

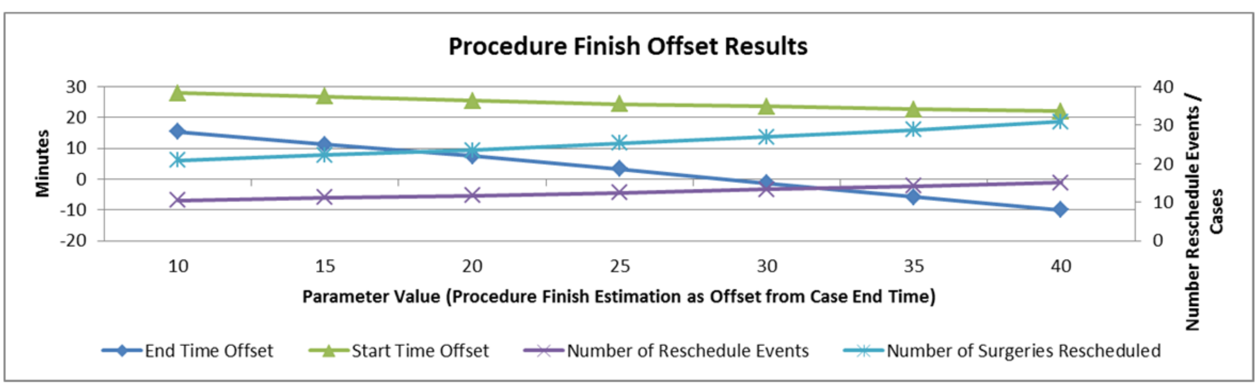

Figure 12: System output for different procedure finish offsets.

We conducted a paired t-test for each parameter value for the end time offsets and found that the mean end time offsets were statistically different for each parameter value (p-values less than 0.05).

5 CONCLUSIONS AND FUTURE RESEARCH

In conclusion, we have developed a discrete event simulation model that was used to simulate regular days in an OR being trialed to test different rescheduling policies. We explored different right-shift rescheduling policies by changing two parameters, criterion amount and reschedule amount. We confirmed the notion that as we increase the criterion amount, we have fewer reschedule events and larger start and end time offsets. Scenario 3 resulted in the lowest start and end time offset, even though it also had the most reschedule events. We propose that the trial OR is setup to automatically update according to offset from the procedure finish milestone. In addition, we propose that the hospital use a criterion amount of 10 minutes in order to trigger reschedule events. However, we would like to use data from the trial study to validate our model and fine tune it for future work.

Although under posting is common at many hospitals, it is an underlying problem that may be skewing results. Therefore, future work may include OR rescheduling for rooms that are not under posted. In addition, conditional probability models could be used to provide a more accurate estimation for our remaining time in each case instead of assuming that case duration is unaffected by rescheduling.

In the future, we plan to explore scenarios including consideration of two or more rooms, the addition of surgeon constraints, and the addition of add-on cases. In addition, we would like to begin testing more policies including left-shifting, partial regeneration, and complete regeneration of the surgery schedule. As our simulation model implements more complex constraints and logic, we will be able to use this modeling approach to gather performance data on more complicated hospital rescheduling policies.

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