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# A SIMULATION OF VARIABILITY-ORIENTED SEQUENCING RULES ON BLOCK SURGICAL SCHEDULING

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## ABSTRACT

Surgery scheduling has received considerable attention in recent years. Block schedules, in which surgeon groups utilize the OR for whatever surgeries they have scheduled for the day, present additional challenges to schedulers. While mean operation times are often used as the primary factor in scheduling strategies, the variability of these operations is not. Recent research suggests that sequencing surgeries based on their variation may decrease the number of late surgery starts. This article builds upon this emerging methodology of variability-oriented sequencing rules for block schedules. Discrete event simulation was used to examine the effectiveness of different sequencing algorithms in reducing the number of behind schedule surgeries and their magnitude. The number and magnitude of tardy surgeries and the patient waiting time were significantly improved by an average of 40% with the proposed scheduling strategies. Additional simulations explored several variations of the variability-based scheduling methodology.

## 1 INTRODUCTION

The scheduling problem has received considerable attention from industrial engineering and operations research fields. The ever-growing healthcare system, which represents 18% of the nation's GDP (Chandra, Holmes, and Skinner 2013), is a prime candidate for researchers to apply scheduling strategies in an effort to decrease costs. Within the healthcare field, Operating Rooms (ORs) in hospitals often consume a large proportion of hospital resources and attention (Fügener et al. 2014; Niu et al. 2011). Discrete event simulation (DES) is an effective tool for these complex systems and allows researchers to explore alternative methods or strategies without impacting patients or providers (Santibáñez et al. 2009).

While many different scheduling strategies have been explored through simulation, few focus on incorporating the variability of surgical procedures into sequencing strategies (Schultz and Claudio 2014). This study extends upon this burdgeoning methodology and applies a different variability-oriented sequencing rule to a multi-OR suite that uses block scheduling and examines their effect on patient waiting time and the number and magnitude of late surgeries.

## 2 RELATED WORK

A considerable amount of recent research has focused on improving healthcare systems. This study is primarily interested in the use of DES models as a technique to achieve more efficient operating room scheduling in a hospital. Simulation is one of the most popular and widely used techniques by healthcare

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researchers because it is cheap, fast, and simple; it allows researchers to alter and compare different scenarios or solution methods and their effect on certain variables of interest or performance metrics (Alhaag, Aziz, and Alharkan 2015; Azari-Rad et al. 2014; Chakravarthy 2012; Coelli et al. 2007; Huggins, Claudio, and Waliullah 2014; Huggins et al. 2012; Konrad et al. 2013; Lin, Sir, and Pasupathy 2013; Ramis, Palma, and Baesler 2001; Shi, Peng, and Erdem 2014; Venkatadri et al. 2011).

Simulation also allows researchers to model very complex processes. For example, Huggins et al. (2014) developed a DES model to evaluate different scheduling policies in an oncology clinic with the aim of increasing the patient output while maintaining the same wait time, patient's total time in the system, and the system's service level. Their model considered the interactions between patients, information, and resources and the relationship between these parameters with the patient's time in the clinic (Huggins et al. 2014).

Another advantage of simulation in the healthcare system is that it allows researchers to change different variables such as resource allocation, patient scheduling, surgical duration, patient arrival and departure rates, staff scheduling, etc., without compromising the life and health of patients (Niu et al. 2011). This is especially relevant to certain aspects of the healthcare system, such as Emergency Medical Services, where researchers can explore "what if" scenarios and their impacts without harming patients. (Knight, Harper, and Smith 2012; Maxwell, Henderson, and Topaloglu 2009; Yang et al. 2009; Yue, Marla, and Krishnan 2012)

Within healthcare operations, the operating room (OR) is an important component of services offered in a hospital and is also one of the most expensive and demanding resources in the system (Fügener et al. 2014; Niu et al. 2011). Operating room managers face the complex decision of what strategies for surgical scheduling should be used to assign surgeries to maintain a certain level of service and maximize efficiency and equipment and personnel utilization (Bennis et al. 2013; Cardoen, Demeulemeester, and Beliën 2010; Erdogan and Denton 2011). Since there is limited availability of surgery rooms, the use of sophisticated analytical and mathematical tools as well as simulation have been used to design new methodologies and conduct studies for surgical scheduling. (Azari-Rad et al. 2014; Bennis et al. 2013; Cappanera, Visintin, and Banditori 2014; Choi and Wilhelm 2014; Denton et al. 2006; M'Hallah and Al-Roomi 2014; Persson and Persson 2010; Ramis et al. 2001; Schultz & Claudio 2014). Not all ORs have the same method of operations. Roland et al. (2009) notes that most researchers agree that there are three main assignment models for an OR:

- Open scheduling: A blank schedule is filled on a first-come-first-serve order, by a negotiation process, or as more important information arises.
- Block scheduling: schedules are based on area of surgery or particular surgeons reserving the same day of week, time slot, and OR. Portions of on OR are given to a particular surgeon group or surgery on the same day/hour time slot each week.
- Modified block scheduling: reallocates unused time to other surgeries not previously included in the block. It is a more flexible method as it provides the opportunity to rearrange or to free previously allotted slots in the operating schedule. Unused surgery time within blocks can be given to other surgeries or surgical groups. It is more flexible than the block scheduling model.

Open scheduling used to be more common in the 1960's and 1970's but has been replaced by block scheduling because it makes better use of surgeons' times (Blake, Dexter, and Donald 2002). Recent literature reviews of surgical scheduling articles consolidate, analyze, and organize the developments made in this field and discuss how this may lead to future research. Cardoen et al. (2010) present a literature review organized by six different categories, while Erdogan and Denton (2011) structure their review by type of operations research methodology. These studies demonstrate simulation's effectiveness in improving performance or defining ideal operating room conditions.

The variability of a process is a very critical element in a stochastic setting and has a large role in the behavior of a system. Choi and Wilhelm (2014) prove that the smallest-variance-first rule is the optimal way to sequence surgical blocks assuming that surgeries are independent and normally distributed and that a surgery will start immediately after the previous one even if it finishes ahead of schedule. A recent study by Schultz et al. (2014) used simulation to examine a variability-oriented surgery sequencing technique in a multi-OR suite that uses block scheduling. Procedures were categorized into low or high variability. After calculating an adjusted mean and standard deviation, a sequencing rule was proposed in which low variability procedures were performed prior to high variability procedures. The performance metrics of interest were tardiness and average lateness for each group. The variability oriented model achieved significant improvements, decreasing the number of surgeries that start late by 18% and the number of surgeries with more than a thirty-minute delay by 11%. This study showed the importance of including variability in order to account for uncertainty into the simulation model.

Similarly, Smith et al. (2013) proved that considering the variability of the patient flow through the OR can improve the system both operationally and financially. The authors worked with a variability methodology which implicates separate cases according the nature of the variability (either artificial or natural). The results obtained in the study were considerably encouraging: a decrease in staff overtime by 27%, a decrease in the day-to-day variability of the number of cases by 20% and a 22% decrease in time, and a staff turnover decrease of 41%. The hospital achieved an overall better performance while maintaining enough operating rooms for emergency cases and increased the number of surgical cases performed.

The simulation model we describe in this article is built upon this emerging variability-oriented methodology in a multi-OR setting with block scheduling by focusing on variability by surgical procedure versus a more general classification system. Furthermore, this article examines what would happen if surgical blocks were rearranged according to historical variability, all the while trying to maintain realistic assumptions such as surgeries not starting early if the previous surgery finished ahead of schedule.

## 3 METHODOLOGY

The DES model in this paper used the same database as Schultz and Claudio (2014). The database contained three years of historical data to include 18,071 unique surgeries and 567 different types of surgical procedures. Schultz and Claudio (2014) examined ten specific weeks that had a higher number of surgeries than average. Weeks are referred to by sequential number (1-156). This study examined the same ten weeks. These busier weeks often had 5 to 6 surgeries per day per OR and 4 to 5 different surgery types per day per OR. While these 10 weeks did not necessarily represent a typical week in this hospital, the intent was to test the algorithm under the most stressful conditions. Furthermore, given the growing population and demand the hospital faces, these busier weeks may start becoming more frequent.

Of the 567 different types of surgical procedures, 242 occurred at least once during the weeks examined in the study. The mean duration, standard deviation, and squared coefficient of variation ($CV^2$) were calculated for each of the 242 surgical procedure types. Probability distributions were fitted to each of the surgical procedure types. In the case where a surgical procedure only occurred once during the entire three year period, the duration of the sole surgery was used in lieu of a probability distribution. In the case where a surgical procedure occurred only two or three times, the average duration was used if the standard deviation was relatively small. If a surgery occurred only two or three times during the three year period and the standard deviation was not small, then the duration of the surgery that occurred during the examined ten weeks was used.

A surgery turnover distribution was calculated using the entire three year period of data. Turnovers greater than one hour were excluded because the dataset did not contain enough information to determine if the time between the end of a surgery and the beginning of the next surgery was caused by an excessively long turnover or other factors. Weeks with unusually high or low turnovers were assigned a unique probability distribution. Of the ten weeks examined, five used the general turnover distribution and five used distributions unique to that week.

There were six different ORs in the suite. Surgeries generally started at 07:30 with the final surgery scheduled no later than 16:30, though there were some exceptions. If a surgery started before its scheduled time, then it was adjusted to start at its scheduled time. The model recorded the number of tardy surgeries and the magnitude of the tardiness. The total number of surgeries with lateness greater than 30 minutes was also recorded. If a surgery was the first scheduled surgery in an OR for the day and it started late, it was not counted as late because the model would not capture such an event. Subsequent surgeries that were tardy because the first surgery was tardy were not counted if the amount of lateness was less than the original. For example, a surgery scheduled for 7:30 that started at 7:35 was not counted as late and a second surgery starting at 9:30 was not counted as late if it started prior to 9:35. It would be counted as late if it started after 9:35.

A model was built using Arena version 14.7 to represent the OR suite. The model was run so that the half width percentage of the average number of tardy surgeries per week would be no more than 10% from the mean. A significance level of 0.05 was used in the number of replications, resulting in 50 replications in each iteration. Figure 1 illustrates the conceptual model for one OR. Individual surgeries are created through the read file and assigned a scheduled start time, surgery procedure type, and OR. After seizing the OR, the surgery is delayed according to the surgical procedure distribution and then the turnover distribution. Then, the OR is released and statistics about whether the surgery had a tardy start and the magnitude of the tardiness are recorded.

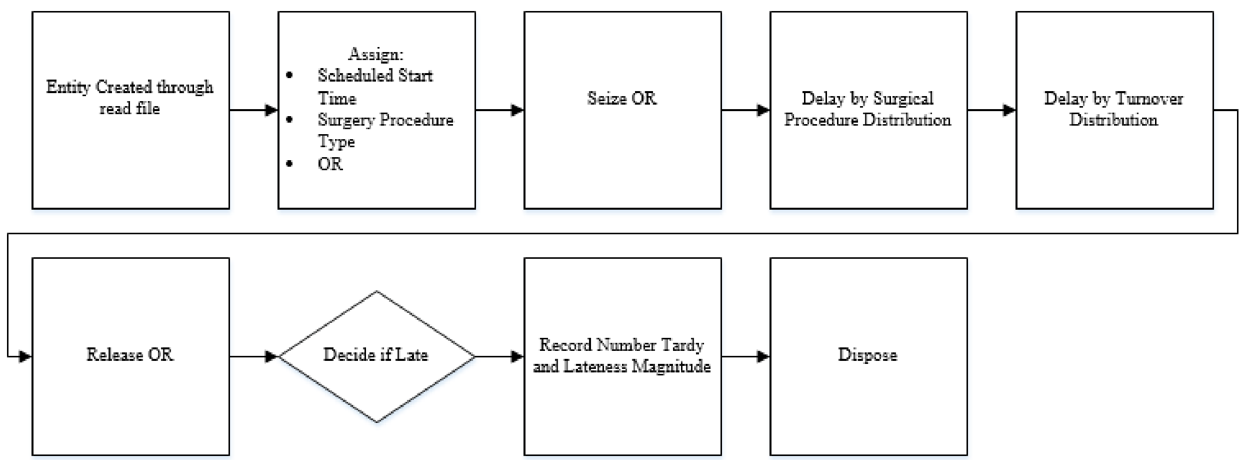


Figure 1: Conceptual Model of a Single OR.

To validate the model, the actual number of tardy surgeries was compared to the average number of tardy surgeries in the model for each of the ten weeks using the schedule from the dataset. Table 1 summarizes the validation statistics for the model. In eight of the ten weeks the actual number fell within the 95% confidence interval of the model, as did the aggregated average. The other two weeks saw a lower number of tardy surgeries in the model than the actual number. Much like Schultz and Claudio (2014), the model's underestimating of some weeks was anticipated because the dataset did not contain other information that may contribute to late surgeries (e.g. low number of staff for the day).

After the model was validated, a new scheduling algorithm that incorporated the variability of a surgical procedure was used. Variability was defined as the squared coefficient of variation ($CV^2$), which is equal to the square of the standard deviation divided by the square of the mean (Hopp and Spearman 2008).

A surgery could only be scheduled on the same day and same OR that it actually occurred. Within those restrictions, surgeries were then ranked according to variability by surgical procedure. Surgeries with a low variability were scheduled first. Generally, the first surgery of the day was scheduled at the same time as the original first surgery of the day. Ties between surgeries of the same procedure type were broken randomly.

Table 1: Validation of Current State.

| Week | Current state Original # Tardy Surgeries | Current state Simulation Model # Tardy Surgeries | 95% Confidence Interval for # Tardy Surgeries |
|---|---|---|---|
| 62 | 35 | 34.68 | (31.21 , 38.15) |
| 91 | 47 | 36.34 | (32.71 , 39.97) |
| 100 | 35 | 35.76 | (32.18 , 39.34) |
| 101 | 40 | 38.20 | (34.38 , 42.02) |
| 102 | 43 | 39.74 | (35.77 , 43.71) |
| 110 | 37 | 37.12 | (33.41 , 40.83) |
| 129 | 49 | 42.72 | (38.45, 46.99) |
| 137 | 34 | 37.64 | (33.88 , 41.40) |
| 143 | 40 | 37.48 | (33.73 , 41.23) |
| 150 | 42 | 46.30 | (41.67 , 50.93) |
| **Average** | **40.2** | **38.60** | **(34.74 , 42.46)** |

In addition to surgery sequencing, variability was also factored into calculating the length of time that occurs between surgeries, or scheduled buffer time. This buffer time plays an important role. Surgeries scheduled too close together will result in numerous late starts and patient frustration while surgeries scheduled too far apart will reduce late starts but may result in too much overtime or an unsustainable schedule that does not contain enough surgeries in a day given a certain demand. The scheduled buffer time that would occur between successive surgeries was calculated according to the surgical procedure mean, variability, and the turnover distribution. Surgeries were given a different buffer to account for their variability. Low variability procedures ($CV^2<0.3$) were given a 10% buffer to the expected duration, medium variability procedures ($0.3<CV^2<0.6$) were given a 20% buffer to the expected duration, and high variability procedures ($CV^2>0.6$) were given a 30% buffer to the expected duration. The mean turnover time plus approximately one standard deviation was added to scheduled buffer time regardless of the category of variability. The addition of one standard deviation is to allow for variability. Figure 2 displays the sequencing algorithm.

After the proposed algorithm was simulated, two variations of the methods were run to determine what aspects of the proposed algorithm contributed most to the performance metric improvement. The proposed algorithm is essentially composed of two parts: the in-between time buffer and the shortest variability first rule. To determine the contribution of the first, a simulation of the current baseline order of surgeries with the proposed in-between buffer rule was conducted (second method). In this simulation, the exact same order of surgeries was kept as the current state (baseline) and the starting time of the first surgery of the day remained the same. The only aspect that changed was the starting time of the subsequent surgeries of the day, which was calculated using the in-between buffer rule of the proposed algorithm. To determine the contribution of the shortest variability first rule, a simulation of the proposed algorithm modified to do the largest variability first was conducted (third approach). Essentially, this simulation followed the same procedures as figure 2 except for the third step, in which the surgeries were scheduled with the largest variability first. The results from these two additional methods were then compared to the shortest variability simulation (initial proposed algorithm).

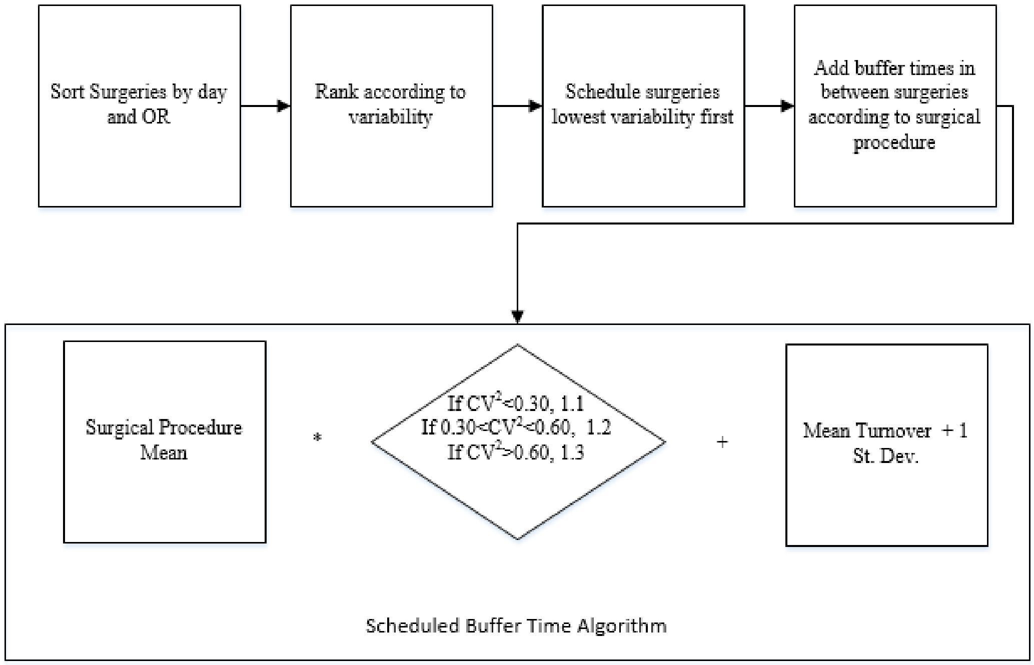


Figure 2: Sequencing Algorithm.

## 4 RESULTS

Similar to the validation portion, each week was run for 50 replications, which was the value that gave, with 95% confidence, a half width no greater than 10% from the mean of the total number of tardy surgeries. With the proposed sequencing algorithm, the total number of tardy surgeries, total number of surgeries that were tardy by more than 30 minutes, and the average lateness of tardy surgeries all significantly decreased in each of the ten weeks. The total average number of late surgeries decreased by approximately 45%, the number of surgeries tardy by more than 30 minutes decreased by approximately 55%, and the average lateness of tardy surgeries decreased by approximately 31%. Average waiting time in the system was also reduced by approximately 16 minutes compared to approximately 42 minutes in the current state model while keeping the same percentage of OR utilization. These results were greater than those reported in Smith et al. (2013) and Schultz and Claudio (2014), where the proposed strategies improved the system by at most 35%. It was also possible to identify the surgery categories with a greater number of tardy surgeries such as general surgery, orthopedic, and urology.

A confidence interval was calculated to compare the two system configurations (Baseline vs. Shortest variability first) and check if improvements by the proposed schedule were statistically significant. Table 2 presents a complete summary of the simulation results in which it can be seen that all the total number of tardy surgeries, total number of surgeries with lateness greater than 30 minutes, and the average lateness magnitude were significantly lower with the new proposed algorithm.

The results suggest that sequencing surgeries based on lowest variability first and factoring in the variability when calculating times between surgeries is a methodology that should be considered in generating the surgery schedule in hospitals. This methodology results in a decrease in the number of tardy surgeries, their magnitude, and waiting time in the system and increases the efficiency of the system as well as the quality of service offered by hospitals. Although only ten weeks were simulated, these ten weeks represented some of the highest demand weeks in the three year period.

Table 2: Simulation Results.

| | **Total number tardy** | | | **Number Tardy > 30 min** | | | **Avg. Lateness Magnitude (min)** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Week** | **Baseline** | **Proposed** | **95% Confidence Interval on difference** | **Baseline** | **Proposed** | **Confidence Interval on difference** | **Baseline** | **Proposed** | **95% Confidence Interval on difference** |
| 62 | 34.68 | 18.86 | (14.10, 17.54) | 25.70 | 11.06 | (12.89, 16.39) | 90.43 | 69.37 | (12.36, 29.75) |
| 91 | 36.34 | 20.26 | (14.31, 17.85) | 27.42 | 12.60 | (13.35, 16.29) | 96.44 | 70.75 | (16.85, 34.53) |
| 100 | 35.78 | 18.8 | (15.34, 18.62) | 24.64 | 10.30 | (12.80, 15.88) | 79.63 | 60.03 | (11.43, 27.77) |
| 101 | 38.20 | 21.18 | (15.17, 18.87) | 28.50 | 13.72 | (13.12, 16.44) | 102.88 | 70.07 | (23.96, 41.66) |
| 102 | 40.22 | 23.92 | (14.49, 18.11) | 30.16 | 15.42 | (12.95, 16.53) | 98.29 | 76.73 | (12.15, 30.97) |
| 110 | 34.20 | 20.36 | (12.25, 15.43) | 24.80 | 12.52 | (10.73, 13.83) | 96.80 | 68.28 | (19.80, 37.34) |
| 129 | 42.72 | 21.72 | (19.30, 22.70) | 34.02 | 13.66 | (18.71, 22.01) | 100.43 | 63.77 | (30.27, 43.05) |
| 137 | 37.64 | 19.76 | (16.18, 19.58) | 29.12 | 12.84 | (14.58, 17.98) | 128.79 | 79.52 | (37.31, 61.23) |
| 143 | 37.58 | 20.66 | (15.24, 18.60) | 28.68 | 13.60 | (13.36, 16.80) | 116.23 | 81.14 | (23.17, 47.01) |
| 150 | 42.62 | 23.00 | (17.79, 21.45) | 33.70 | 14.72 | (17.11, 20.85) | 126.38 | 76.65 | (39.08, 60.38) |
| Avg. | 37.99 | 20.85 | (16.18, 18.12) | 28.67 | 13.04 | (14.60, 16.65) | 103.63 | 71.63 | (27.19, 36.81) |

The two additional simulations helped to provide insight into the contribution of the two aspects of the proposed algorithm. When compared to the baseline, the second method significantly improved the three performance metrics in all ten weeks. The smallest-variability first with in-between buffer rule (proposed approach) had a significantly better average number of tardy surgeries in 5 of the 10 weeks when compared to the second method. The smallest variability first was significantly better than the largest variability first in eight of the ten weeks for average lateness, three of the ten weeks for average number of late surgeries, and one of the ten weeks for number of surgeries later than 30 minutes. Interestingly, the largest variability first simulation (or third method) did perform significantly better in one of the ten weeks for average lateness and number of surgeries later than 30 minutes.

These results suggests two things. First, the variability oriented in-between buffer rule plays a role in system improvement. Second, the smallest variability first rule does appear to perform better than the largest variability first rule, but its contribution to overall performance in this situation was not as large as the variability oriented in-between buffer rule. This may have resulted for a couple of reasons. First, because the same type of surgery was repeatedly performed multiple times on the same day in the same OR, the actual difference between the shortest variability first schedule and the largest variability first schedule was often not very large. Second, the variability oriented in-between buffer rule helps mitigate the chain reaction of late surgeries that may start at the beginning of the day. In other words, because the variability is already being incorporated into the buffer time between surgeries, the actual effect of having the variability in the order of the surgeries may not be as significant. To test this theory, the in-between buffer rule could be reduced or eliminated and then the smallest variability first and largest variability first rules could be compared to one another.

There are a few shortcomings with the model. While unscheduled, add-on surgeries that occurred in a certain OR had to occur at the same time and OR, there were no constraints on scheduled surgeries for only certain parts of a day. For example, a surgery may have had to occur at a certain time of the day due to patient or surgeon availability, but the dataset did not include that level of detail and thus this could not be considered.

The proposed model also did not take into account other constraints such as instrument availability. For example, the hospital may only have one of a certain specialized instrument that precludes certain surgeries from being scheduled on or near the same date and time. Again, the dataset did not have this level of detail. Similarly, the staffing schedule was not known, which may contribute to the turnover distributions. Five of the ten weeks displayed a turnover distribution that deviated from the average enough so that the model could not validate these weeks at first. The model could only be validated after fitting specific turnover distributions to those five weeks. Finally, future research could also examine the balance between having enough scheduled buffer time to reduce late surgery starts while also minimizing the amount of overtime.

## 5 CONCLUSIONS

The proposed scheduling strategy, which is a combination of a sequencing algorithm and a variability buffer algorithm, resulted in an improvement over the current system. The proposed model significantly reduced the number of tardy surgeries, number of surgeries tardy by more than 30 minutes, the average lateness of tardy surgeries, as well as the average waiting time. Two more algorithms were generated to examine the impact that the two aspects of the proposed scheduling strategy had on system improvement. While both aspects played a role in the improvement, the in-between buffer rule appeared to have a larger effect. Because of the characteristics of the data set and the number and of types of surgeries that occurred, however, this cannot be known for certain. Further research lies in reducing or eliminating the in-between buffer rule and comparing the smallest variability first rule against the largest variability first rule. Comparing these results would help determine this dynamic of what aspect contributed most to the overall improvement.

As was previously mentioned, there are a number of factors that must be considered to develop a more realistic model. These include:

- Incorporating the staffing schedule which may affect surgery time availability and turnover distributions
- Accounting for unique instruments or other resources that my affect certain surgeries from occurring within a certain time of one another
- Taking into account the surgeon's preferences for surgery times. Although the model maintains blocking surgeries into a specific OR, it focuses solely on improving the system through the patient perspective. The proposed model also may not be realistic to implement if it gives too much padding into the schedule, which may result in the surgery schedule being increasingly backed up and ultimately unsustainable.
- Exploring the balance between having enough scheduled buffer time to reduce late surgery starts while minimizing the amount of overtime and maintaining a sustainable surgery schedule given a certain demand.

Finally, implementing such a change in scheduling strategy requires organization buy-in from all members. The human factors element in optimization is an important consideration, and further research in this area is needed.

## REFERENCES


Alhaag, M. H., Aziz, T., & Alharkan, I. M. 2015. "A queuing model for health care pharmacy using software Arena." In *Proceedings of the 2015 International Conference on Industrial Engineering and Operations Management,* 1-11. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Azari-Rad, S., Yontef, A., Aleman, D. M., & Urbach, D. R. 2014. "A simulation model for perioperative process improvement." *Operations Research for Health Care* 3:22-30.

Bennis, F., Amghar, M., Sbiti, N., & Elouadi, A. 2013. "Modeling and Performance Evaluation of the Operating Room in a Hospital." *International Journal of Emerging Science and Engineering* 1:69-73.

Blake, J. T., Dexter, F., & Donald, J. 2002. "Operating room managers' use of integer programming for assigning block time to surgical groups: a case study." *Anesthesia & Analgesia* 94:143-148.

Cappanera, P., Visintin, F., & Banditori, C. 2014. "Comparing resource balancing criteria in master surgical scheduling: A combined optimisation-simulation approach." *International Journal of Production Economics* 158:179-196.

Cardoen, B., Demeulemeester, E., & Beliën, J. 2010. "Operating room planning and scheduling: A literature review." *European Journal of Operational Research* 201:921-932.

Chandra, A., Holmes, J., & Skinner, J. 2013. "Is this time different? The slowdown in healthcare spending." *Brookings Papers on Economic Activity* 47: 261-302.

Chakravarthy, S. R. 2012. "Reliability, health care, and simulation." *Simulation Modelling Practice and Theory* 29: 44-51.

Choi, S., & Wilhelm, W. E. 2014. "An approach to optimize block surgical schedules." *European Journal of Operational Research* 235:138-148.

Coelli, F. C., Ferreira, R. B., Almeida, R. M. V., & Pereira, W. C. A. 2007. "Computer simulation and discrete-event models in the analysis of a mammography clinic patient flow." *Computer methods and programs in biomedicine* 87:201-207.

Denton, B. T., Rahman, A. S., Nelson, H., & Bailey, A. C. 2006. "Simulation of a multiple operating room surgical suite." In *Proceedings of the 2006 Winter Simulation Conference*, edited by L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto, 414-424. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Erdogan, S. A., & Denton, B. T. 2011. "Surgery planning and scheduling." *Wiley Encyclopedia of Operations Research and Management Science*, edited by J. J. Cochran, 1-13. John Wiley & Sons, Inc.

Fügener, A., Hans, E. W., Kolisch, R., Kortbeek, N., & Vanberkel, P. T. 2014. "Master surgery scheduling with consideration of multiple downstream units." *European Journal of Operational Research* 239:227-236.

Hopp, W. J., and M. L. Spearman. 2008. *Factory Physics: Foundations of Manufacturing Management.* 3rd ed. New York: IRWIN/McGraw-Hill.

Huggins, A., Claudio, D., & Waliullah, M. 2014. "A detailed simulation model of an infusion treatment center." In *Proceedings of the 2012 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1198-1209. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Huggins, A., Lovejoy, M., Page, L., Rahman, M., Lommatsch, G., Miller, A., . . . Green, S. D. 2012. "A complete methodology to simulate a complex healthcare system." In *Proceedings of the 2012 Industrial and Systems Engineering Research Conference,* edited by G. Lim and J.W. Herrmann, 1226-1234. Institute of Industrial Engineers-Publisher.

Knight, V. A., Harper, P. R., & Smith, L. 2012. "Ambulance allocation for maximal survival with heterogeneous outcome measures." *Omega* 40:918-926.

Konrad, R., DeSotto, K., Grocela, A., McAuley, P., Wang, J., Lyons, J., & Bruin, M. 2013. "Modeling the impact of changing patient flow processes in an emergency department: Insights from a computer simulation study." *Operations Research for Health Care* 2:66-74.

Lin, R.-C., Sir, M. Y., & Pasupathy, K. S. 2013. "Multi-objective simulation optimization using data envelopment analysis and genetic algorithm: Specific application to determining optimal resource levels in surgical services." *Omega* 41:881-892.

M'Hallah, R., & Al-Roomi, A. 2014. "The planning and scheduling of operating rooms: A simulation approach." *Computers & Industrial Engineering* 78:235-248.

Maxwell, M. S., Henderson, S. G., & Topaloglu, H. 2009. "Ambulance redeployment: An approximate dynamic programming approach." In *Proceedings of the 2009 Winter Simulation Conference*, edited by M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, and R. G. Ingalls, 1850-1860. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Niu, Q., Peng, Q., El Mekkawy, T., Tan, Y. Y., Bruant, H., & Bernaerdt, L. 2007. "Performance analysis of the operating room using simulation." *Proceedings of the Canadian Engineering Education Association*.

Persson, M., & Persson, J. 2010. "Analysing management policies for operating room planning using simulation." *Health Care Management Science* 13:182-191.

Ramis, F. J., Palma, J. L., & Baesler, F. F. 2001. "The use of simulation for process improvement at an ambulatory surgery center." In *Proceedings of the 2001 Winter Simulation Conference*, edited by B. A. Peters, J. S. Smith, D. J. Medeiros, and M. W. Rohrer, 1401-1404. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Roland, B., Di Martinelly, C., Riane, F., & Pochet, Y. 2010. "Scheduling an operating theatre under human resource constraints." *Computers & Industrial Engineering* 58:212-220.

Santibáñez, P., Chow, V. S., French, J., Puterman, M. L., & Tyldesley, S. 2009. "Reducing patient wait times and improving resource utilization at British Columbia Cancer Agency's ambulatory care unit through simulation." *Health care management science* 12:392-407.

Schultz, J., & Claudio, D. 2014. "Variability based surgical scheduling: a simulation approach." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 1353-1364. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Shi, J., Peng, Y., & Erdem, E. 2014. "Simulation analysis on patient visit efficiency of a typical VA primary care clinic with complex characteristics." *Simulation Modelling Practice and Theory* 47:165-181.

Smith, C. D., Spackman, T., Brommer, K., Stewart, M. W., Vizzini, M., Frye, J., & Rupp, W. C. 2013. "Re-engineering the operating room using variability methodology to improve health care value." *Journal of the American College of Surgeons* 216:559-568.

Venkatadri, V., Raghavan, V. A., Kesavakumaran, V., Lam, S. S., & Srihari, K. 2011. "Simulation based alternatives for overall process improvement at the cardiac catheterization lab." *Simulation Modelling Practice and Theory* 19:1544-1557.

Yang, W., Guo, T., Liu, T., & Huang, J. 2009. "Multi-period allocation of ambulances to casualty cluster in a disaster relief operation with uncertain demand." In *2009 International Conference on Industrial Engineering and Engineering Management*, 1632-1636. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Yue, Y., Marla, L., & Krishnan, R. 2012. "An Efficient Simulation-Based Approach to Ambulance Fleet Allocation and Dynamic Redeployment." In *Proceedings of 2012 AAAI Conference of Artificial Intelligence,* edited by Hoffmann, Jorg and Selman, Bart. Canada: AAAI Press.

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