

Simulating a sterilization processing department to evaluate block schedules and tray configurations

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Abstract

Discrete event simulation is a well-established tool for examining the effect of different operating room (OR) block schedules on various performance metrics within the OR suite and adjacent units. However, one unit that has rarely been studied is the sterilization processing department (SPD), which cleans and assembles reusable OR instruments. As part of a larger research study, we developed a series of OR block assignment models that sought to reduce the workload of the SPD and developed a tray optimization model to reduce the number of instruments on increasingly bloated instrument trays. While initial numerical experiments were promising, a comprehensive simulation model of the OR and SPD was needed to more thoroughly examine how potential changes to the block schedule and/or more efficient tray configurations could improve SPD processing times. In this article, we incorporate the SPD into an existing simulation model of an OR suite, which is the first of its kind, and examine the effect that different block schedules and tray configurations have on SPD processing times. Simulation results confirm earlier numerical computations. Furthermore, simulation results suggest that more efficient instrument tray configurations are a much better and more viable method for improving SPD processing time than reconfiguring block schedules.

KEYWORDS

block scheduling, discrete event simulation, operating room, sterilization processing department, tray optimization problem

1 | INTRODUCTION

Operating room (OR) suites are usually the largest generator of revenues and costs within a hospital.¹ The OR scheduling problem has been well studied by researchers over the past two decades.^{2–4} Discrete event simulation (DES) is a common tool for testing different OR scheduling models.⁴ The simulation models often include upstream and downstream units such as the Pre-Surgery Ward, Post Anesthesia

Care Unit, Intensive Care Unit, and Recovery Ward. The sterilization processing department (SPD), however, is rarely considered when modeling the OR suite. In addition to servicing other departments in a hospital, the SPD sterilizes reusable OR instruments and packs the instruments into trays that are used for upcoming surgical cases.

The SPD plays a critical role in patient health and often services several hospital departments, with the majority of volume usually coming from the OR suite. Overworked or improperly trained staff can make

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errors when cleaning instruments. These errors present a significant risk to patient safety through surgical site infections. Surgical site infections can result in up to \$10 billion in annual direct and indirect medical costs.⁵ If errors in the sterilization process are detected prior to being used, those instruments still need to be re-sterilized, which results in additional workload for the SPD and longer turnaround times. If surgical instruments are not available in the OR due to excessively long turnaround time in the SPD, then the OR surgical schedule can be adversely impacted. But despite its importance, managers often overlook the SPD because it does not generate revenue.⁶ Perhaps Swanson,⁶ in the article “Shifting the sterile processing department paradigm: a mandate for change”, describes this challenge best:

“Until recent years, some health care administrators held the private and rarely expressed belief that staff members in the sterile processing department...were “nothing more than glorified dish washers.” ... It is generally understood that SPDs have a significant role in supporting the surgical department, which typically is the dominant revenue generating department in the hospital. The importance of the SPD, however, can be overlooked because it does not produce its own revenue. When considering the role the SPD plays in supporting the emergency department, intensive care unit, and labor and delivery, however, the volume of resources passing through the SPD is staggering.”

1.1 | Motivation

This article describes a DES model developed as part of a larger research study motivated by a workflow improvement project for an actual SPD.⁷ During initial observations of the SPD, it was apparent that an uneven block schedule and bloated instrument trays had a large impact on the SPD's daily caseload. The excessive caseload was beginning to overwhelm the SPD staff, resulting in increased instrument processing and turnaround times. Sterilization error rates were starting to increase, and while these errors were identified through quality checks and did not affect patient health, it resulted in an even higher workload because they needed to go through the sterilization process a second time. This was increasing the number of instances in which an OR case was starting soon and some of the requested instruments were still going through the SPD. This caused the OR staff to send more high priority job requests down to the SPD, meaning the SPD staff had to stop regularly scheduled jobs and sterilize the high priority job as quickly as possible. These high priority jobs often were sent through the sterilization machines by themselves, further delaying the other jobs. While buying more instruments could alleviate this issue to some extent in the short term, there were budget and storage space constraints that management was facing. Furthermore, process-based solutions were a more sustainable solution to this emerging problem.

At the time that these problems were arising, OR management was in the process of its annual block schedule evaluation, where it consid-

Significance and Practitioner Points

To our knowledge, we developed the first comprehensive simulation model of an operating room (OR) suite and its sterilization processing department (SPD), in which the entity arrival rate is stochastic and directly linked to the actual OR system. We simulated a series of block schedules generated by mathematical models and more efficient instrument tray configurations to better understand their effect on SPD processing times. For practitioners, a key takeaway from this study is that reducing the number of unused instruments is a more effective and practical method to improve SPD performance than rearranging the block schedule.

ers making changes to the existing block schedule based on anticipated surgical group demand for the upcoming year and surgical group preferences for different block times, among other considerations. An opportunity arose to examine how potential block schedules would affect the SPD. Certain block schedules may help alleviate the excessive workload and subsequent issues that were emerging in the SPD and starting to adversely impact the OR suite.

In addition to the potential changes in the OR block schedule, another opportunity arose in re-examining the current instrument tray configurations. Anecdotal feedback from staff suggested that the instrument trays used for surgical procedures had steadily grown over time, resulting in extremely low instrument utilization. This dynamic was understandable, as it was quite easy to add instruments to tray configurations as they became available or new surgeons arrived with their own preferences. However, there had not been a tray configuration reevaluation in several years that removed instruments with excessively low utilization rates. Furthermore, the trays exceeded the recommended maximum weight, and all instruments on the tray had to go through the sterilization process even if they had not been used.

OR instrument tray configuration is a complex problem that is outside the scope of this paper, but there is a general tradeoff between custom tray configurations for specific procedures which result in high utilization and lower flexibility and more general tray configurations that can be used in several different types of procedures which result in low instrument utilization. Furthermore, a conservative approach of having more instruments is favored because the potential occurrence of a certain instrument being needed but not on hand is more consequential than a more efficient tray configuration. Nevertheless, the instrument trays had become quite excessive, and management was interested if more efficient tray configurations were possible and to what extent that could help alleviate the excessive workload the SPD was facing.

To assist with the block schedule reevaluation, we developed a series of mathematical block assignment models that rearranged the block schedule of surgical groups to decrease the expected workload of the SPD while maintaining surgical group preferences for their most

desired block times.⁸ For the bloated instrument tray issue, we developed a goal programming model for the tray optimization problem (TOP) that sought to reduce the number of unused instruments on the instrument trays.⁹ While the initial numerical results from these models were promising, a comprehensive simulation model was needed to more thoroughly examine how potential changes to the block schedule and/or more efficient tray configurations could improve the SPD processing times. This article focuses on the development of that comprehensive simulation model of the OR suite and SPD, how the simulation model was used to simulate the results of the mathematical models, and how the simulation model allowed for drawing conclusions about the larger research study.

1.2 | Literature review

There are numerous research articles on the OR scheduling problem. Cardoen et al.,² Demeulemeester et al.,³ and Samudra et al.,⁴ wrote literature reviews that classified OR scheduling articles into different categories, such as operations research methodology used and performance metrics used, among others. DES is a common tool for examining OR scheduling strategies.^{10–14} DES was used in approximately 40% of all operations research-based OR scheduling papers from 2004 to 2014.⁴ As a part of a larger study, we reviewed 246 OR scheduling papers from 2015 to 2020, of which 67 (27%) used a simulation model.¹⁵ However, none of these simulation models incorporated the SPD.¹⁵

There are a handful of papers that developed simulation models of an SPD. These papers used simulation to improve process efficiency or explore alternative workflow and design configurations within the SPD. Di Mascolo et al.¹⁶ developed a DES model to examine how smoothing the container arrival rate into a French hospital's SPD improved the system's overall performance. Lin et al.,¹⁷ Rupnik et al.,¹⁸ and Haseeb¹⁹ all built SPD simulation models to help with operational decisions, such as staffing, equipment, and inventory levels, during SPD expansion and redesign projects. Casati²⁰ used an Erlang-C queueing system to determine the optimal number of SPD staff required per tray type for every 30-min block. Di Mascolo and Gouin²¹ developed a generic DES model that fellow researchers and practitioners can use to model their SPD using either local or global data.

Cassettari et al.²² developed a simulation model of a medium-sized Italian hospital's SPD to help identify process inefficiencies and test an alternative future state layout and workflow process. Similarly, Hachicha et al.²³ used a simulation model of an SPD in Tunisia to test different autoclave configurations. Ghiyasinasab et al.²⁴ developed an SPD simulation model to examine the effect that automating certain steps of the sterilization process with automated guided vehicles would have on case turnaround times.

The primary difference between previous research articles and the simulation model in this study is that the entity arrival rate is linked to the actual OR system and is not a parameter. In other words, our simulation model incorporates both the OR suite and its SPD as stochastic elements. While most SPD simulation models focus on process effi-

ciency or alternative configurations, the model in this study is used to evaluate the impact that different OR block schedules or tray configurations have on the SPD. Thus, to the best of our knowledge, this is the first comprehensive simulation model of an OR suite and its SPD. In other words, this is the first simulation model that views the OR and SPD as one system. This model allowed us to more thoroughly examine how potential changes to the block schedule and/or more efficient tray configurations could improve the SPD turnaround time, which would in turn alleviate emerging problems that this was causing the OR suite.

2 | PREVIOUS WORK

2.1 | Mathematical models

The motivation for this study began with a workflow improvement project for an SPD in a medium-sized hospital in the state of Montana.⁷ The SPD services a seven-room OR suite that sees about 6000 patients annually, a dedicated OBGYN delivery room, and approximately 20 other departments within the hospital. The OR suite utilizes a block schedule in which surgical groups are allocated OR time throughout the week and may schedule surgeries within their designated block time. Initial observations revealed sizeable variation in daily SPD workload depending on which surgical groups were operating that day.

To help assist OR management with the reevaluation of the existing block schedule, we developed three different surgical group block assignment mathematical models that rearranged the OR block schedule to reduce the expected SPD instrument processing time while considering surgical group preferences for different block times and ORs.⁸ The planning horizon for the models was 1 week. The specific formulations of these models are outside the scope of this paper, but Figure 1 displays the pseudo-code. They are summarized as follows:

- Model 1: A mixed-integer programming (MIP) model with a quadratic objective function and linear constraints. The expected SPD processing time was calculated using one of four different techniques, referred to in this paper as techniques A–D. Thus, these models will be referred to as 1A, 1B, 1C, and 1D.
- Model 2: A goal programming model with a linear objective function and linear constraints. In this model, the expected SPD processing time is minimized by leveling the expected SPD workload across each day as much as possible.
- Model 3: A two-phase version of model 2 in which the SPD expected workload is considered in the first phase and surgical group preferences are considered in the second phase. While model 3 is not as practical as model 2, it provided an effective lower bound on the expected SPD processing time.

In addition to the existing block schedule potentially having an adverse impact on the SPD, the instrument trays used for surgical procedures had steadily grown over time, resulting in extremely low instrument utilization. The trays exceeded the recommended maximum weight, and all instruments on the tray had to go through the

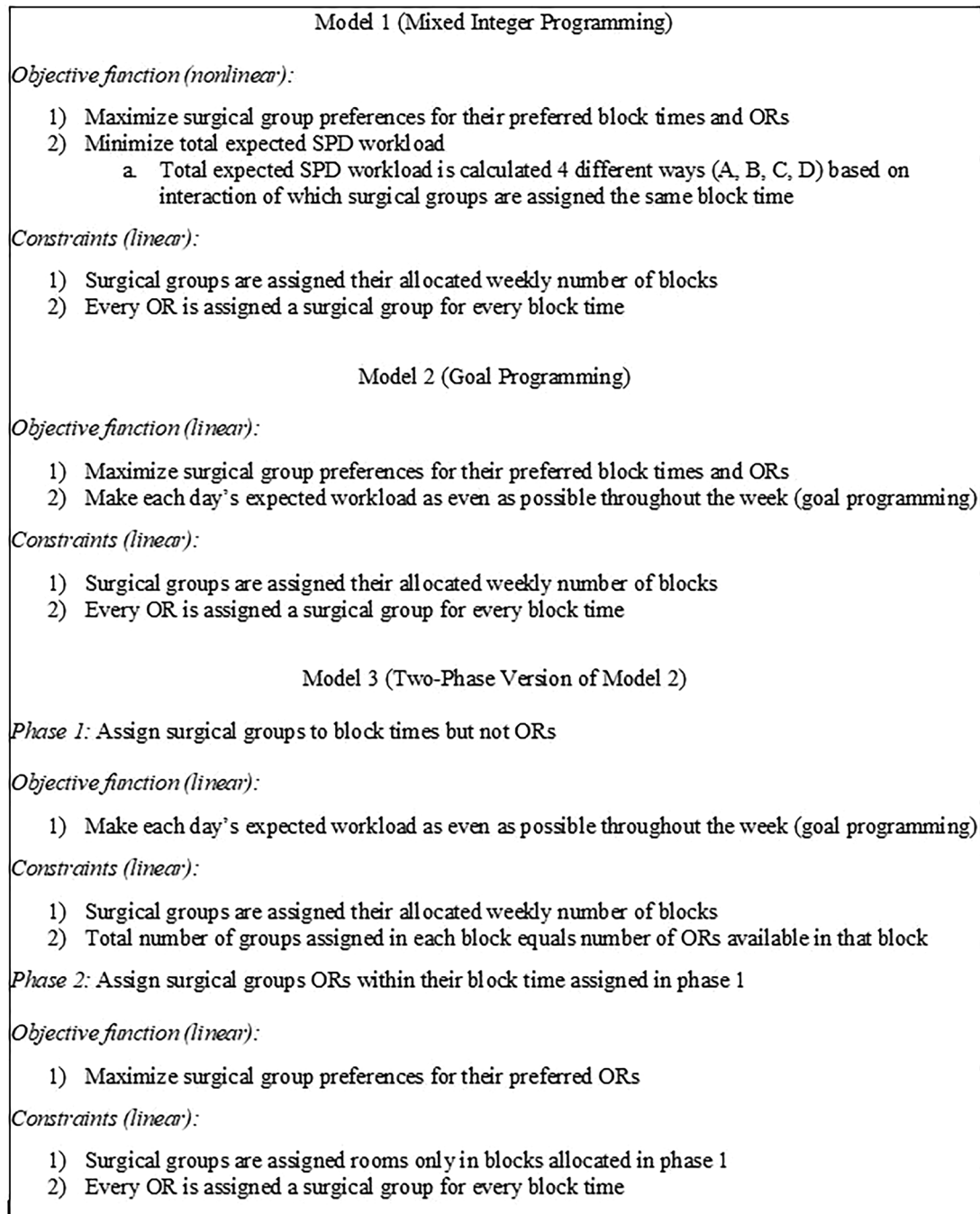


FIGURE 1 Block assignment model pseudo code.

sterilization process even if they had not been used. This increased workload was further stressing the SPD. To help combat this growing problem, we developed a goal programming formulation for the TOP, in which instruments were assigned to trays, and trays were assigned to surgical procedures.⁹ The objectives of this tray optimization model (TOM) were to minimize the expected number of unused instruments, minimize the total amount that trays exceeded their desired weight limit, and minimize the number of instruments that were requested by the surgeon but not assigned to surgical cases.

2.2 | Need for comprehensive simulation model

Based on the numerical computations for the block assignment models, the goal programming models (models 2 and 3) were superior to the nonlinear MIP models 1A–1D.⁸ For the bloated instrument trays, the TOM did appear to reduce the number of instruments per tray.⁹ While these numerical results were all based on historical data, a simulation model was needed to test the schedules in a stochastic setting and translate the models input into SPD processing times, a metric

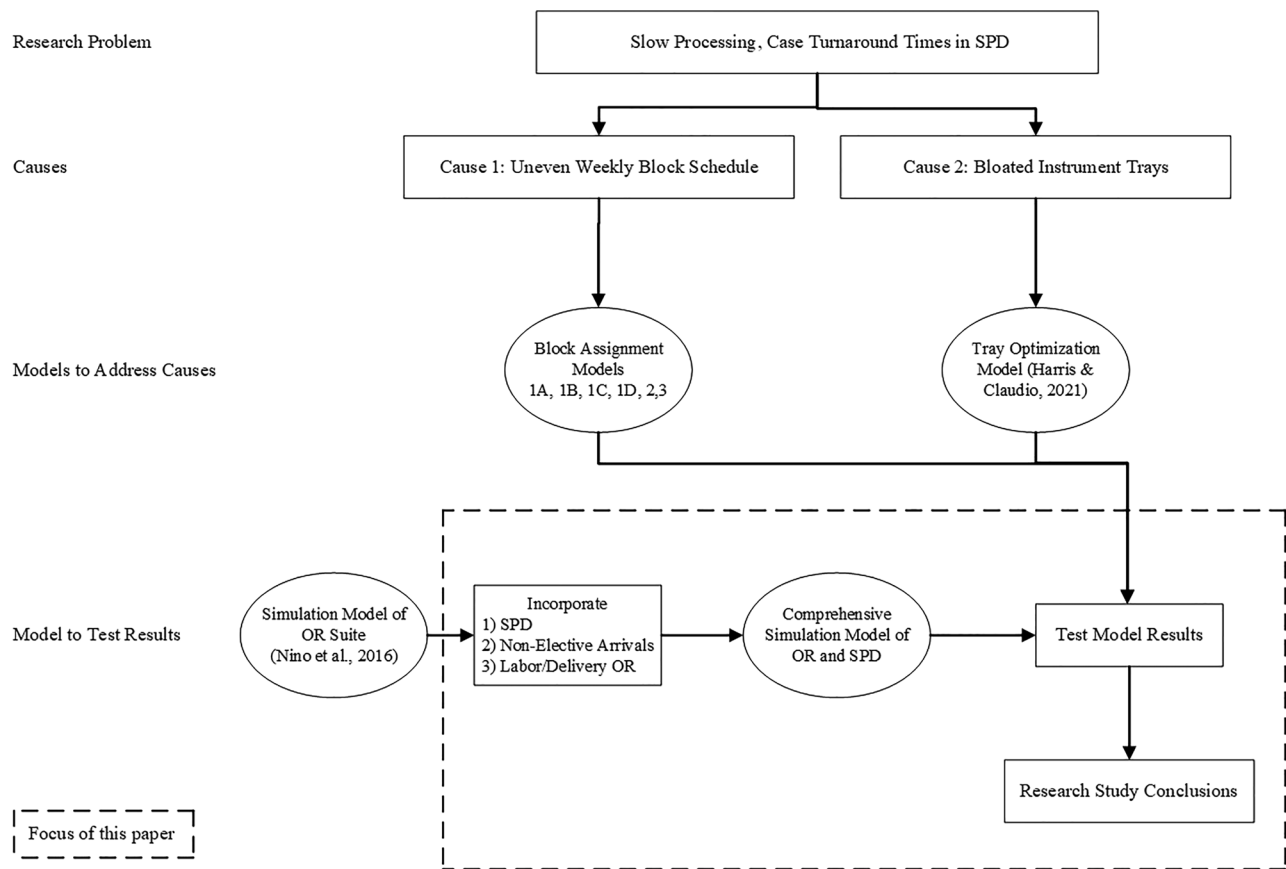


FIGURE 2 Research study summary.

that management could more easily understand and use to help inform decision making.

We had developed a simulation model of the OR suite as part of an earlier study to explore how different variability-oriented sequencing rules affected the number and magnitude of tardy surgeries.²⁵ The SPD had to then be incorporated into this simulation model. The comprehensive simulation model of the OR and SPD was then used to simulate the mathematical model results. The dashed rectangle in Figure 2 summarizes where this paper fits into the larger research study. The objectives of the simulation study were to simulate the results of the mathematical models. This allowed us to gain insights into which models were most effective and which strategies would be most effective and practical in reducing the SPD's slow processing and case turnaround times.

3 | MODEL DEVELOPMENT

3.1 | Data collection

The first step in developing the comprehensive simulation model was data collection. The SPD was observed for approximately 8 weeks. The observation and input from SPD staff allowed the authors to gain a thorough understanding of the SPD workflow, described in

the next section. During the observation, the authors recorded the times to rinse and assemble surgical cases. A wide variation existed in these processing times. For example, a spine case or robotic knee case could take over 2 h to rinse and assemble, while a simple tonsillectomy case could take under 20 min. The other stages in the sterilization process, such as the dirty side washing machine and clean side autoclave machine, are identical regardless of case type. However, larger cases consume more machine capacity than smaller cases.

After the rinse and assembly processing times were collected, probability distributions for both rinse and assembly times were fitted. The Kolmogorov–Smirnov test²⁶ was used for goodness of fit, with a minimum *p*-value of .05 required to use the distribution. If a case occurred only once or twice during the data collection period, then a deterministic duration was used for both rinse and assembly processing times. For the rinse processing times, distributions were fitted by surgical case type. For example, a total knee case that consisted of several trays may take 35 min. For the assembly process, however, cases often are not assembled at once. For example, the same total knee case may be composed of one Ortho Major tray, one Arthrex vendor tray, three wraps, and six peel packs. This required the assembly process to be captured at the subcomponent level. A total assembly time distribution was then calculated as the sum of the individual subcomponent assembly distributions.

In addition to direct observation, this research study utilized three datasets from the hospital. The first dataset contained records for every OR surgery performed over a 3-year period, totaling 18,071 unique surgeries and 567 different surgical procedures. This dataset was used to fit the probability distributions for the surgical case durations for the OR suite portion of the simulation model.²⁵ The same information was used for most of the case types in the comprehensive simulation model of the OR and SPD. This dataset was also used to calculate the historical non-elective case arrival rate. The five most common types of non-elective cases and their approximate frequencies were used for the simulation model.

A second, more recent dataset containing every OR surgery for 6 months was also used for the research study. This dataset, which contained approximately 6268 unique surgeries, was used to generate the baseline weeklong surgical schedule. As will be discussed in section six, the baseline schedule was simulated, and the results were compared with the simulation results of the schedules generated by the block assignment models. Additionally, there were approximately 21 surgical case types that were not in the previous data set that occurred in the generated baseline schedule. Probability distributions for these surgical case times were fitted using the same methodology as the SPD rinse and assembly processing times.

The final dataset was an SPD productivity report. During the direct observation period, the non-OR suite case arrival rate to the SPD was calculated to follow an exponential distribution. However, SPD case volume was lower than average during the observation period. Therefore, the productivity dataset was used to calculate the mean number of non-OR suite case arrivals to the SPD for a typical weekday.

3.2 | Sterilization workflow and conceptual model

The 8 weeks of in-depth observations allowed us to model the sterilization process. The sterilization process requires several steps. Instruments arrive at the SPD's dirty room through two different means depending on their origin. OR instruments arrive via the dirty elevator from the OR suite that is one floor above the SPD. Non-OR instruments are dropped off by non-OR department staff at the door that leads into the dirty room from the external hallway. Instruments are first manually rinsed by an SPD staff. Then, they are placed in one of three washing machines. When the washing machine cycle is complete, the SPD staff unloads the instruments through the backside of the washing machine into the clean side of the SPD. After drying, SPD staff assemble the instruments into a tray, wrap, or peel pack. Next, the assembled item is put into an autoclave machine for sterilization. Finally, the item must cool down to room temperature after sterilization and is then sent back to the OR via the clean elevator or placed in a pick-up area where non-OR department staff retrieves the item.

Recall from Figure 2 that this article focuses on the development of comprehensive simulation model of the SPD. The SPD process described in the previous paragraph was incorporated into an existing simulation model of the OR suite to examine how different block schedules and instrument tray configurations would affect SPD pro-

cessing times. The simulation model began with the existing simulation model from Nino et al.²⁵ Figure 3 displays the conceptual model. Entities (surgical cases) are created through a read file that depicts the OR schedule. Each entity seizes its assigned OR at its scheduled case time if the OR is currently available. The OR is delayed by the surgical case's probability distribution, then a general turnover distribution, and then released. The metrics of interest in Nino et al.²⁵ were the number and magnitude of tardy surgeries, and the simulation recorded this information after each case was complete.

This research study then developed the simulation logic for the SPD after a surgical case is completed. Figure 4 displays the comprehensive OR and SPD simulation model. Elements of the OR simulation model from Nino et al.²⁵ are italicized to illustrate the additions made to develop the comprehensive simulation model. The primary addition to the original simulation model is the right half of Figure 4, which represents the SPD. The SPD portion of the simulation model follows from the previously described sterilization process at the beginning of this section. Two SPD staff are available to manually rinse cases at the two sinks in the dirty room. The model assumed no staff breaks during the day, and the staff had similar proficiency in rinsing cases. During the observation period, SPD staff swapped out with one another throughout the day, resulting in a continuously staffed rinsing station.

Three washing machines processed the rinsed cases. The simulation model utilized the separate and adjustable batch functions in Arena to represent how cases fit into washing machines. Certain surgical cases, such as spine procedures, had more trays and instruments that required more space in washing machines than smaller cases such as tonsillectomies. After the rinsing station, cases are cloned according to their case size. An adjustable batch module then batched the cases according to the washing machine capacity. After the batched groups finish drying, they are re-batched back into their original surgical cases.

After drying, the cases seized one of three SPD staff for assembly into the trays, wraps, and peel packs that compose the case. The model assumed the SPD staff have similar proficiency in assembling cases. The model also assumed three continuous staff are available for assembly throughout the day for the same reason as the manual rinsing station. The autoclave sterilization process logic followed the washing machine logic. Cases are cloned according to how much space they consume in the autoclave. An adjustable batch module then batched the cases for the autoclave machine. After sterilization and cool down, the group cases are separated and re-batched back into their original surgical cases.

In addition to the SPD, other changes were made to the OR suite portion of the simulation model. First, the read file now contained washing and autoclave machine sizes for surgical cases in addition to the start times. This information played a role in the batching logic for the washing and autoclave machines. Second, the model now included a dedicated labor and delivery room, which the original model did not. Finally, non-elective cases now arrived as separate entities. In the original model, the non-elective cases were scheduled according to when they had arrived and in what OR they were assigned to for the given week.²⁵ In the new model, non-elective cases arrived according to their historical arrival rate. The non-elective cases have priority over all

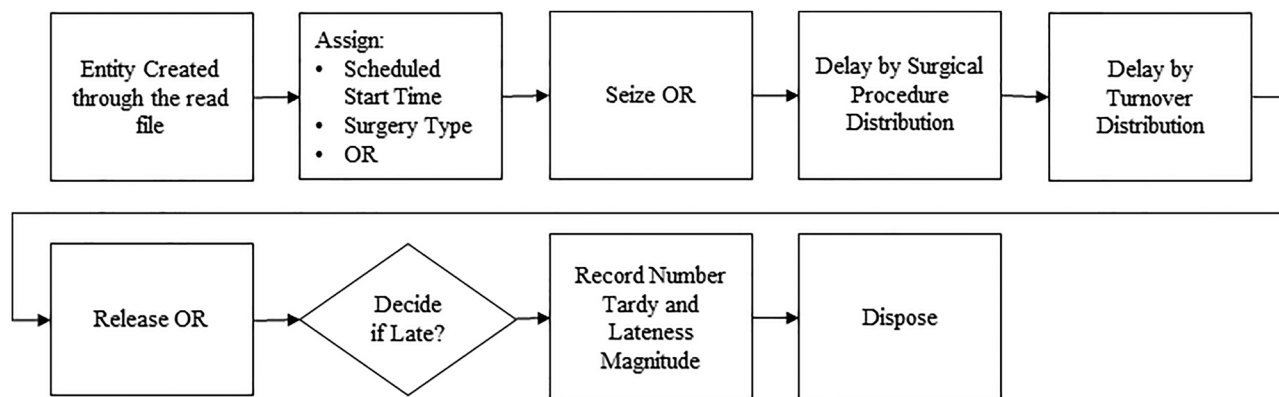


FIGURE 3 OR conceptual model.

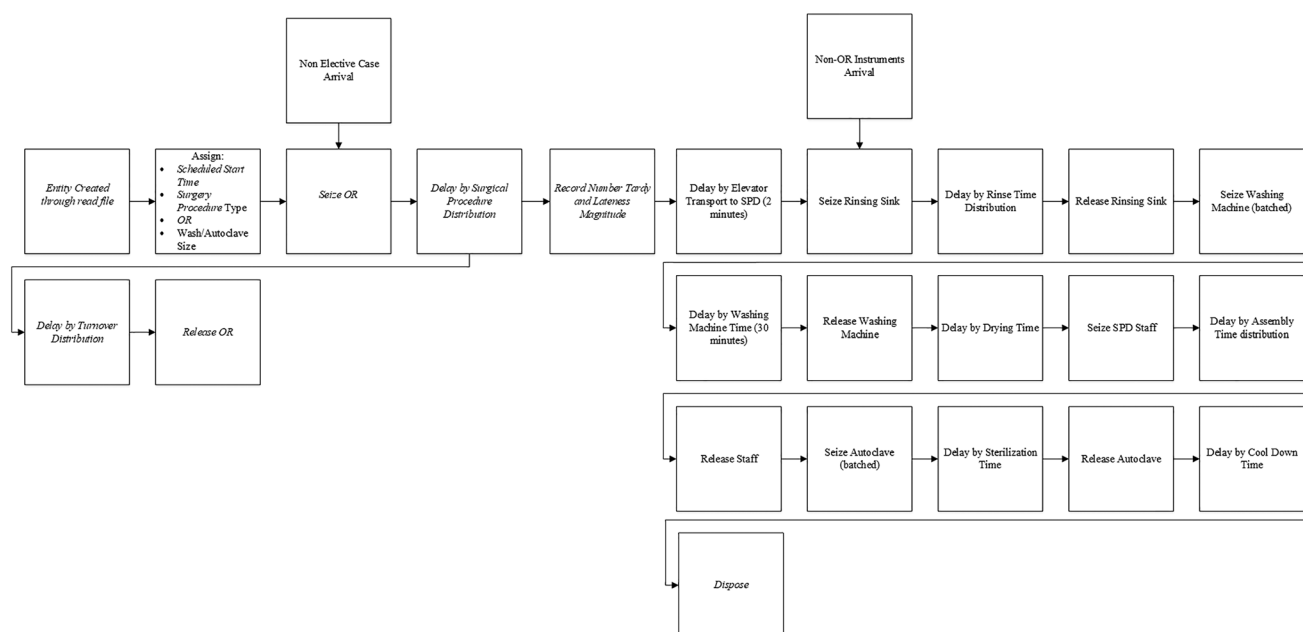


FIGURE 4 Comprehensive OR and SPD simulation model (elements from Nino et al. in italics).

elective cases but do not interrupt any elective cases that have already started (non-preemptive priority). In other words, a non-elective case moved to the front of the OR queue and seized the first OR that became available. Non-elective labor and delivery cases were only allowed to go to the designated labor and delivery room.

In addition to the original OR-related metrics, the new simulation model recorded several SPD metrics of interest. For the dirty side of the SPD, the model recorded the number of cases that wait to be rinsed, the number of cases that do not wait to be rinsed, the rinse wait time for cases that wait to be rinsed, and the total rinse station time (wait time plus rinse processing time). For the clean side of the SPD, the model recorded the number of cases that wait to be assembled, the number of cases that do not wait to be assembled, the assembly wait time for cases that wait to be assembled, and the total case assembly station time (wait time plus assembly processing time). The model

also recorded the total case turnaround time, which starts when a case arrives in the dirty room and ends when the case has finished cooling down after the autoclave. Table 1 summarizes the simulation model metrics of interest. Each of the nine metrics is also recorded by what day the case occurs. Appendix A contains screenshots of the simulation model in Arena (v. 15.1).

4 | VERIFICATION AND VALIDATION

4.1 | Simulation model verification

Once the comprehensive simulation model was developed, we employed functional testing²⁷ to verify the simulation model worked correctly. The verification plan systematically tested the different

TABLE 1 Simulation model metrics of interest.

Simulation model metrics of interest	
1	Average rinse station time
2	Average assembly station time
3	Average case turnaround time
4	Average rinse wait time for those who wait
5	Average assembly wait time for those who wait
6	Average number who wait for assembly
7	Average number who wait for rinse
8	Average number who do not wait for assembly
9	Average number who do not wait for rinse
10–54	The above 9 metrics for each weekday

elements of the new simulation model. Table 2 summarizes the first 19 verification tests, which primarily address entity flow, batching/separate functions, and metric calculations. The surgery procedure time, turnover time, SPD rinse time, and SPD assembly time were fixed to 10 min for these tests. Arrival time refers to the number of minutes into the simulation time. For example, 0 corresponds to 7:30 a.m. Monday and 1440 to 7:30 a.m. Tuesday. The elevator to the SPD and post-washing machine dry time was 5 min, and the washing machine, autoclave, and post autoclave cool down times were 30 min. The metric used to verify tests 1–16 was the average case turnaround time. Tests 17–19 were run by time step with animation to verify the non-elective cases successfully moved to the front of their respective OR queue. Tests 1–19 were successfully verified.

Table 3 summarizes tests 20–24. These tests involved multiple entities going through the SPD at once and checks that the wait time metrics were successfully calculated. Tests 20–24 used the same fixed parameters as tests 1–19, except the drying time was 25 min for tests 20–23, and the washing machine time was 10 min for test 20. These tests were run by time step with animation to verify correct flow. All tests were successfully verified.

4.2 | Simulation model validation

After model verification, we proceeded to model validation. The initial OR portion of the simulation model was validated in Nino et al.²⁵ via predictive validation,²⁷ in which the average number of tardy surgeries from the model was compared to the actual number of tardy surgeries from the historical dataset. The SPD portion of the simulation model was validated via face validation²⁷ based on discussion with SPD staff and 2 months of in-depth observations. The SPD portion of the comprehensive simulation model was not validated based on observed metrics (predictive validation) for several reasons. SPD staff did not assemble the cases using any systemic structure or sequencing rule that can be modeled. SPD staff could not identify the original case for an item they were currently processing. In general, SPD staff randomly chose

an item from the assembly queue to assemble based on their personal preference. There ended up being a wide range in rinsing and assembling proficiency based on how experienced the staff member was. This randomness would be incredibly difficult to model and validate based on observed data. Furthermore, subcomponent items did not maintain case integrity after the rinsing station, making tracking the progress of a case virtually impossible. There is no bar code system within the SPD that tracked the status of items.

Validating the SPD portion of the model using face validation is consistent with previous SPD simulation studies. Of the previous research articles that built an SPD simulation model, only Di Mascolo and Gouin²¹ and Hachicha et al.²³ validated the model based on observed metrics. However, the metrics used for model validation were the mean number of washing cycles, autoclave cycles, and the number of entities processed. The mean number of washing and autoclave cycles only conveys how many items are processed by the SPD. They do not relate to the stochastic nature of the sterilization process like metrics such as case turnaround time do. Additionally, Hachicha et al.²³ stated that their primary method for model validation was extensive discussions with hospital managers (face validation). Lin et al.¹⁷ also relied on face validation, using extensive observations and discussions with SPD staff to validate case turnaround times.

The purpose of the simulation model was to test the results of block scheduling models and the TOM, compare them to the current baseline, and determine if the different schedules would affect SPD performance. The schedules generated by the research models and the current baseline schedule were simulated under identical conditions, allowing for a fair comparison in accordance with the research objectives.

5 | EVALUATING THE SCHEDULES FROM THE MATHEMATICAL MODELS

After the simulation model was validated, we proceeded to simulate the results of the mathematical models from our previous works. The baseline schedule and the block assignment model schedules were run in Arena version 15.1 on Windows 10. To test the TOM results, the baseline schedule was simulated with decreased SPD rinsing and assembly processing times to mimic the effect of trays with fewer instruments. Figure 5 summarizes the simulation testing methodology. The only change between the baseline schedule and schedules generated by the block assignment models (1A–D, 2,3) was which surgical groups had which block times in the different ORs. The surgical schedule (start time and case type) of each surgical group remained the same.

The simulation model was run such that the number of replications yielded a half-width percentage for the average assembly wait time for those who wait within 5% of the mean. Using a significance level of 0.05, this resulted in 200 replications per run. Randomly sampling nine of the simulation run times yielded an average run time of 178.22 s with a standard deviation of 9.93 s.

TABLE 2 Verification plan for entity flow, batch/separate functions, and metrics.

Test #	Test description	Entities in system	Autoclave size	Wash size	Arrival time	Expected result
1	Elective case flow, testing batching/separate functions, day metric calcs	1, OR 1	48	36	0 (Monday)	Avg case turnaround time of 175
2		1, OR 2	48	36	1440 (Tuesday)	Avg case turnaround time of 175
3		1, OR 3	48	36	2880 (Wednesday)	Avg case turnaround time of 175
4		1, OR 4	48	36	4320 (Thursday)	Avg case turnaround time of 175
5		1, OR 5	48	36	5760 (Friday)	Avg case turnaround time of 175
6		1, OR 6	48	36	0	Avg case turnaround time of 175
7		1, OR 7	48	36	0	Avg case turnaround time of 175
8		1, OR P2	48	36	0	Avg case turnaround time of 175
9	Adjustable batch function	2, OR 1	6	3	0,120	Avg case turnaround time of 155
10		2, OR 2	6	3	0,120	Avg case turnaround time of 155
11		2, OR 3	6	3	0,120	Avg case turnaround time of 155
12		2, OR 4	6	3	0,120	Avg case turnaround time of 155
13		2, OR 5	6	3	0,120	Avg case turnaround time of 155
14		2, OR 6	6	3	0,120	Avg case turnaround time of 155
15		2, OR 7	6	3	0,120	Avg case turnaround time of 155
16		2, OR P2	6	3	0,120	Avg case turnaround time of 155
17	Non-elective OR 1 flow seize OR priority	2 OR 1, 1 NE OR 1	12	18	0, 5, NE-6	The non-elective OR 1 case should jump in front of the 2nd OR 1 elective case and be processed first once the turnover in OR 1 is complete.
18	Non-elective OR flow seize OR priority	2 each OR 2-P2, 8 NE general	12	18	0,5, NE-6	The non-elective OR cases should jump in front of the 2nd elective cases and be processed first.
19	Combined non-elective case flow	2 each OR 1-P2, 8 NE general, 2 NE OR 1			0,5, NE-6	The non-elective OR cases should jump in front of the 2nd elective cases and be processed first. The NE OR 1 cases should jump in front of the OR case and be processed first. The NE OR 1 case should go to OR 1, and the general NE cases should go to any OR except OR 1

6 | RESULTS

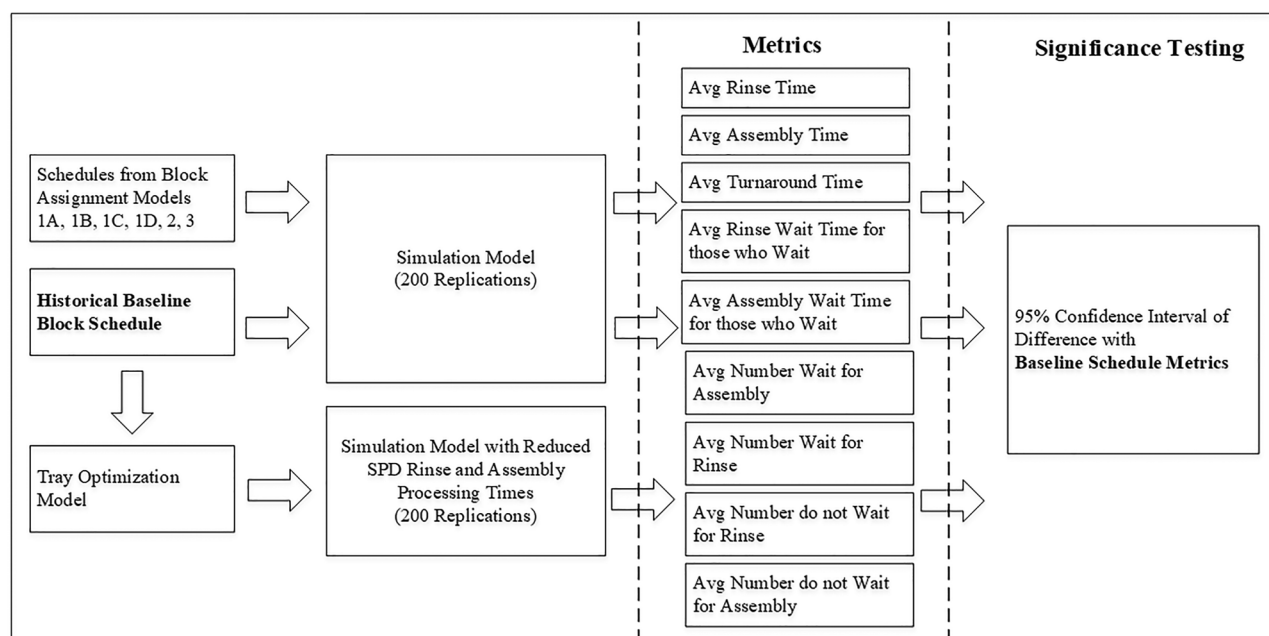
6.1 | Block assignment model results

There was a systematic evaluation plan for the block assignment models that altered the run times and weights for the two components in the objective function, resulting in 24 total instances for models 1A–1D and model 2.⁸ Model 3 only had nine instances due the two phase formulation reducing the ways parameters could be varied.⁸ In each instance, the block schedule produced by the model was simulated, and the number of metrics that significantly improved upon the baseline schedule was recorded. Table 4 summarizes the total number of instances in which the metric was significantly improved across all instances (“Ratio of Significant Improvement”) and the best value for each metric (“Best Value”), along with the metrics for the baseline historical schedule for context. All times

are in minutes. The “Overall Improvement Percentage Rate” column in Table 4 gives the overall percentage for the number of metric improvements across all instances produced by the model runs. According to the results, Model 2 yielded more metric improvements than the four variants of Model 1 combined. This confirms the results from the numerical computations that suggested Model 2 is more effective. Additionally, the simulation model provided insight into how much actual time would be saved by the alternative block schedules. The lowest average case turnaround time amongst all the simulated schedules was 197.61 min, which was 4.64 min less than the baseline schedule’s average case turnaround time. While an improvement of 4.64 min may seem small, consider that the SPD processes approximately 234 cases during a normal workweek. This would result in approximately 1085.76 min, or about 2.26 SPD staff shifts, less than the SPD currently spent processing cases each week.

TABLE 3 Verification plan for entity flow and metrics.

Test #	Test description	Entities in system	Autoclave size	Wash size	Arrival time	Expected result
20	SPD rinse, assemble calcs	1 × OR 1–4	8	2	0,0,0,5	Change assembly staff to two instead of four. Checks SPD Wait and avg rinse, assembly metrics. One waits for rinse for 5 min, one waits for rinse for 10 min, one wait for assembly at 10 min. Avg Rinse time for those who wait is 7.5, avg assemble wait time for those who wait is 10
21	SPD rinse, assemble calcs multiple days	1 × OR 1–4	8	2	0,0,0,4 1440 × 3 and 1445	Change assembly staff to two instead of four. Checks SPD Wait and avg rinse, assembly metrics. For Mond one waits for rinse for 6 min, one waits for rinse for 10 min, 1 wait for assembly at 10 min. AVG Rinse time for those who wait is eight, avg assemble wait time for those who wait is 10. For Tuesday, avg rinse wait time for those who wait is 7.5, avg assemble wait time for those who wait is 10. Overall, rinse wait time for those who wait is 7.75, assembly 10. Also, run this test for Wednesday and Thursday, Friday and Friday to confirm metrics work for each day.
22	Re-batching functions	1 × OR 1–3	4	2	0	The three cases should successfully re-batch back to their original entity after washing machine and autoclave. Turnaround time of 145
23	SPD non OR arrival flow	1 × SPD non-OR	48	36	0	Average turnaround time of 195. Also checks the day calc functions.
24	SPD non OR arrival re-batching functions	3 × SPD non-OR	4	2	0	The three cases should successfully re-batch back to their original entity after washing machine and autoclave. Turnaround time of 145

**FIGURE 5** Simulation testing methodology.

One factor that was not accounted for in the block assignment models was the schedule of each surgical group. The models did not account for the expected timing of OR case arrivals to the SPD for different surgical group combinations. As an extreme example, consider two dif-

ferent schedules. In schedule one, the cases for the seven ORs happen to have the same duration, resulting in seven cases arriving at the SPD at approximately the same time. This would result in significant delays in SPD case processing. Contrast that with schedule two, in which the

TABLE 4 Block assignment model simulation results.

	Avg. rinse station time	Avg. assembly station time	Avg. turnaround time	Avg. rinse wait time for those who wait	Avg. assembly wait time for those who wait	Avg. number Wait for assembly	Avg. number wait for rinse	Avg. number do not wait for assembly	Avg. number do not wait for rinse	Overall improvement percentage rate
Baseline	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38	
Model 1A										
Ratio of significant improvement	10/24	4/24	6/24	5/24	0/24	5/24	7/24	9/24	8/24	25%
Best value	23.84	48.86	198.94	15.25	29.01	96.37	77.29	129.67	114.97	
Model 1B										
Ratio of significant improvement	7/24	0/24	3/24	6/24	0/24	3/24	7/24	7/24	7/24	19%
Best value	23.99	49.66	200.05	15.26	29.73	97.89	79.83	132.71	113.97	
Model 1C										
Ratio of significant improvement	3/24	0/24	2/24	3/24	0/24	1/24	4/24	4/24	1/24	8%
Best value	23.80	49.53	199.71	15.13	29.61	99.55	78.95	132.52	111.32	
Model 1D										
Ratio of significant improvement	1/24	0/24	0/24	0/24	0/24	1/24	5/24	4/24	2/24	6%
Best value	24.24	49.86	200.93	15.86	30.06	102.52	80.85	131.42	109.73	
Model 2										
Ratio of significant improvement	23/24	20/24	21/24	20/24	4/24	19/24	24/24	24/24	24/24	83%
Best value	23.67	47.67	197.61	14.68	27.03	98.25	76.33	134.61	114.21	
Model 3										
Ratio of significant improvement	0/3	0/3	0/3	0/3	0/3	0/3	3/3	3/3	3/3	33%
Best value	24.49	49.44	200.21	16.59	29.37	101.12	80.12	132.60	111.36	

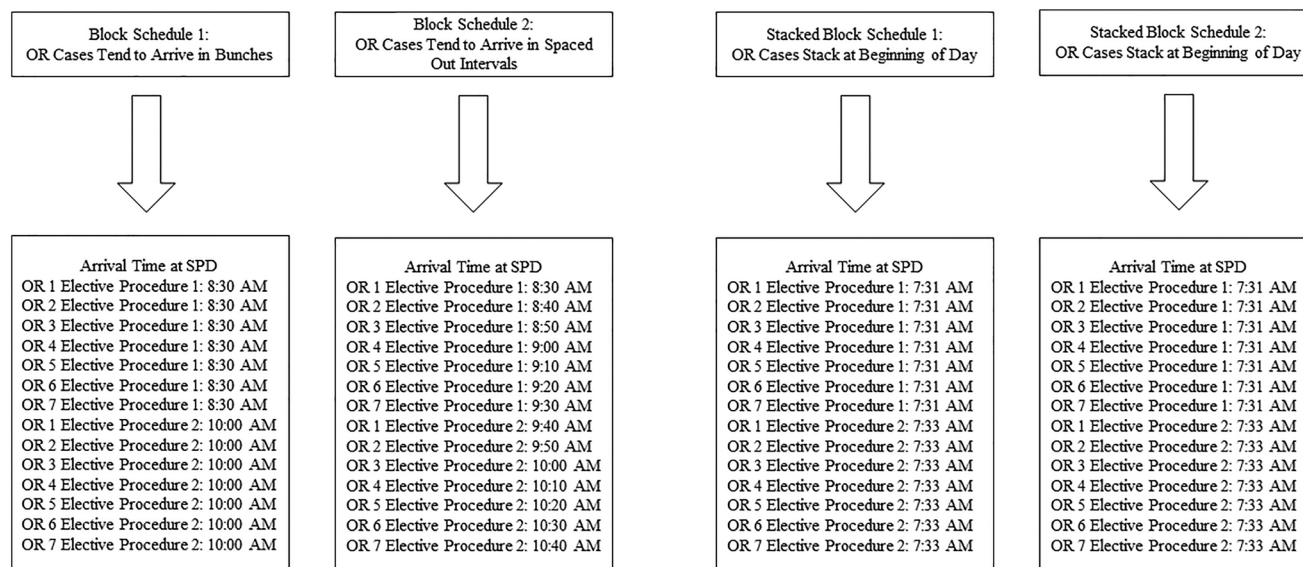


FIGURE 6 Stack schedule concept.

cases for the seven ORs happen to have evenly spaced-out durations, resulting in a nice even arrival rate to the SPD. This schedule is much easier for the SPD to process and would have fewer cases waiting in line than the first schedule. The left half of Figure 6 illustrates this dynamic.

Although the larger number of simulation replications helps reduce the effect of this noise on the simulation results, an additional set of schedules was created and simulated to control for this effect. These schedules, referred to as “stack” schedules, were created for each schedule generated from the block assignment models along with the historical baseline schedule. Within each surgical group, surgeries are scheduled to start 1 min after the preceding surgery’s scheduled start time. Each surgical case takes 1 min for the OR to complete, and the OR turnover time is also 1 min. Essentially, all the surgical cases for the day are processed within the first 10–15 min and “stack” on top of one another at the SPD entrance. The right half of Figure 6 shows what the “stack schedules” look like. Additionally, non-elective cases and non-OR cases do not exist in the stack schedules. Thus, the stack schedules are a truer version of what the block assignment models specifically address in the objective function. Theoretically, the block assignment models should show better improvement with the stack schedules.

Table 5 displays the number of statistically significant metric improvements by the model with the stack schedules. For the stack schedules, the four metrics relating to the number of cases that wait and do not wait at the rinse and assembly queues are going to be high regardless of schedule and were not counted. Essentially, the same methodology as Figure 5 was followed except the bottom four metrics were not measured. Therefore, there were only five metrics for each simulation run. All the models performed better with the stacked schedules. This result makes sense because the stack schedules are a more accurate depiction of what the block assignment models address. This does not mean the models are any more effective in practice because the concept of a stacked schedule is not realistic. Further-

TABLE 5 Percentage of statistically significant metric improvements by model, stack schedules.

Model	% rate
Model 1A	77.00%
Model 1B	85.00%
Model 1C	83.00%
Model 1D	77.00%
Model 2	95.00%
Model 3	60.00%

more, it would be difficult for a block assignment model to address the expected timing of cases to the SPD. However, it is encouraging to see the models performed better (as they should) with the stack schedules, which is something the simulation model showed that numerical computations could not. Additionally, Model 2 still emerged as the best model.

6.2 | Tray optimization model (TOM) results

The nature of the TOM prevented a direct simulation comparison like the block assignment models. While there was a baseline expected annual instrument utilization rate that compared to the TOM results, there was no baseline schedule that could be compared within the simulation model. The TOM resulted in instrument trays that had fewer instruments and a higher proportion of instruments that were used for each case. Thus, this study investigated the potential impact these more “efficient” instrument trays could have on SPD performance.

Efficient instrument trays decrease the number of unused instruments that SPD staff sterilize. This decrease in workload would affect the rinsing and assembly stations in the SPD. Thus, we conducted a

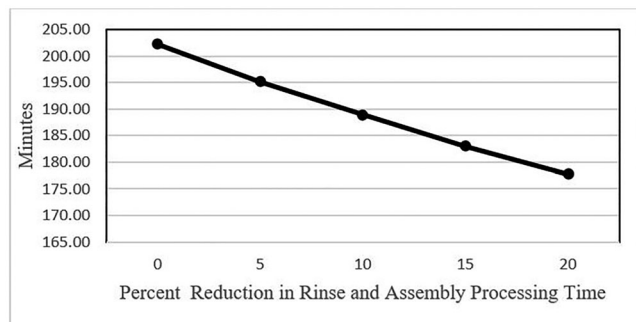


FIGURE 7 SPD case turnaround time versus reduction in rinse and assembly time.

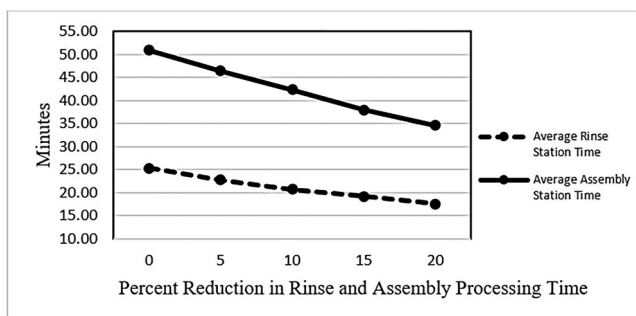


FIGURE 8 Average rinse and assembly station time versus reduction in rinse and assembly time.

systematic testing plan in which all the rinsing and assembly processing times were decreased by 5%–20%, incrementing every 5%. Table 6 displays these results, along with the original baseline simulation metrics. All times are in minutes. Like the block assignment model schedule simulations, a 95% confidence interval of the metric difference was calculated to determine statistical significance. All the results in Table 6 are statistically significant improvements over the baseline historical schedule.

Figures 7 and 8 display the linear relationship between the percentage reduction and SPD turnaround, rinse, and assembly time metrics. Figure 8 shows a larger decrease in the assembly time versus rinse time as the percentage reduction increases. This result agrees with the direct observations of the SPD, in which SPD staff in the rinse station often did not scrub unused instruments. During the assembly process, SPD staff did handle all the instruments regardless of whether they were used. Therefore, reducing the number of unused instruments would have a larger impact on the assembly process than the rinsing process.

7 | DISCUSSION

The TOM simulation results suggest that, given the structure of the observed SPD and the estimated parameters for this research study, reducing the number of unused instruments is a more effective way to improve SPD performance than rearranging the block schedule.

TABLE 6 Effect of reduction in rinse and assembly times on SPD performance.

	Avg rinse station time	Avg assembly station time	Avg turnaround time	Avg rinse wait time for those who wait	Avg assembly wait time for those who wait	Avg number wait for assembly	Avg number wait for rinse	Avg number do not wait for assembly	Avg number do not wait for rinse
Baseline schedule	25.28	50.90	202.25	17.22	30.87	105.34	85.66	126.09	106.38
5% reduction	22.74	46.35	195.15	14.76	27.25	97.94	78.20	133.90	114.16
10% reduction	20.65	42.29	188.91	12.83	24.41	89.33	70.71	140.83	122.20
15% reduction	19.17	37.94	183.02	11.70	20.64	80.29	66.28	145.58	131.58
20% reduction	17.49	34.55	177.76	10.53	18.16	72.39	58.93	153.80	140.33

A relatively small percentage reduction in the rinsing and assembly processing times yielded a larger improvement in the SPD simulation metrics than the best block schedule. For example, a 5% reduction in rinse and assembly processing time produced an average case turnaround time of 195.15 min, compared to the 197.61 min from the best performing block schedule. As previously discussed, instrument tray configurations tend to be more conservative to reduce the probability that an instrument is needed for a case but not on hand. But, given the extent to which the instrument trays had become bloated, this was a feasible objective that could be accomplished without presenting a risk to patient safety. Furthermore, this insight was valuable to management because rearranging the block schedule for the SPD would have been a hard sell for several stakeholders. Conversely, conducting a long overdue tray configuration reevaluation was much more feasible, especially since it would have a larger positive impact on the OR system.

The simulation model assumed that SPD staff had similar proficiency in the manual rinsing and assembly stages of the sterilization process. However, during the SPD observations, a new SPD staff member was in the training process of rinsing and assembling cases. This new SPD staff member often took twice as long to process cases than more experienced staff. Though it was outside the scope of this research study, there was a clear learning curve associated with rinsing and assembling the several types of cases and trays. Furthermore, it appeared that it would take several weeks, if not months, before a new SPD staff member could process all types of cases and trays as quickly as more experienced staff. Time limitations unfortunately prevented us from going back and adding this dynamic into the study. But this would not have affected the general findings because all of the block schedules and more efficient tray configurations were simulated under identical conditions in the simulation model and the focus was on the difference in SPD processing times, not the raw numbers. If staff processing heterogeneity would have been incorporated into the simulation models, then the raw numbers may have been different, but the differences between the numbers would have been relatively similar. Regardless of the proficiency of a particular staff, it would take less time to process a tray with fewer instruments. Incorporating SPD staff learning curves and heterogeneity in processing times is an exciting opportunity for future research.

The staff heterogeneity dynamic also presented another insight that, while outside the scope of the original problem, was quite useful to management. The SPD had historically experienced high staff turnover. This was not surprising, given the relatively low compensation SPD staff received compared to other positions within the OR system and the perceived lack of value the SPD has relative to other departments. If small reductions in staff processing times were more effective in improving turnaround time than rearranging the block schedule, then it would stand to reason reducing staff turnover could have a similar effect. Lower staff turnover would result in less instances of having staff with significantly longer processing times as they go through daunting task of learning how to rinse and assemble hundreds of instruments and dozens of tray configurations. Again, this would

need to be proved with a rigorous data-driven study but based on our observations we believe that this would more likely than not to be the case.

8 | CONCLUSION

A simulation model of an OR suite and its SPD was developed, verified, and validated. A baseline schedule based on historical data was generated. Then, block assignment model schedules were simulated along with the baseline historical schedule. Nine metrics of interest from the simulation results of the baseline and research model schedules were compared for statistical significance. "Stack" schedules were then generated to control for differences within surgical group schedules, and five of the original nine metrics of interest were compared for statistical significance with the baseline stack schedule. The simulation results closely follow the findings from numerical experiments of the models. Key findings include:

- Goal programming model 2 is more effective than nonlinear models 1A–1D. Model 2 schedules see a significant improvement in the metrics of interest when compared to the baseline schedule 83% of the time, compared to only 25% for the best of the model 1 variants.
- Within Model 1, variants 1A and 1B were more effective than 1C and 1D (25% and 19% improvement rates versus 8% and 6% improvement rates, respectively). This also agreed with numerical experiments.
- When controlling for potential noise in the simulation (stack schedules), Models 1A–1D did perform much better, though Model 2 still had the best percentage improvement rate (95% compared to a maximum of 85% with model 1B).

The TOM did not produce schedules comparable to the historical baseline like the block assignment. Instead, the TOM reduced the number of instruments per case. This should reduce SPD rinsing and assembly processing times. These processing times were systemically decreased, and the baseline schedule was then simulated with the decreased processing times. The results were compared for statistical significance to the baseline schedule simulation with the original processing times. Key findings include:

- A mere 5% reduction in processing times significantly improved all nine metrics more than the best of all the block schedules from models 1, 2, and 3.
- A linear relationship emerged between percentage reduction in processing time and improvement in SPD case turnaround time.
- The same percentage reduction had a larger impact on assembly processing time compared to rinse processing time, which agreed with direct observation of the SPD.
- Over the course of the study, it was apparent that staff heterogeneity in processing times, particularly for new employees, was present. While time limitations prevented us from incorporating this into the research study, these observations do suggest that reducing SPD

staff turnover could, like more efficient instrument tray configurations, be a more effective and practical method for improving SPD performance than rearranging the OR block schedule.

Several opportunities for future research surrounding the simulation model exist. The staff processing learning curve and associated heterogeneity could be incorporated into the simulation model to quantify the impact of reduced staff turnover. The variability-oriented sequencing rules from Nino et al.²⁵ could be simulated again to determine their impact on the SPD. The variability-oriented sequencing rules could also be applied to the block schedules to determine the effect on patient-centered OR metrics (number and magnitude of late starts) and SPD metrics. More generally, the simulation model could be used to examine the impact any schedule has on patient-centered metrics and SPD metrics. Downstream units such as the Post Anesthesia Care Unit could also be incorporated into the model.

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CONFLICT OF INTEREST STATEMENT

No conflicts of interest exist.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions

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APPENDIX A: Simulation Model Screenshots

Figure A-1 shows a screenshot of the entire simulation model in Arena. The five subsections will be shown in more detail in the following figures.

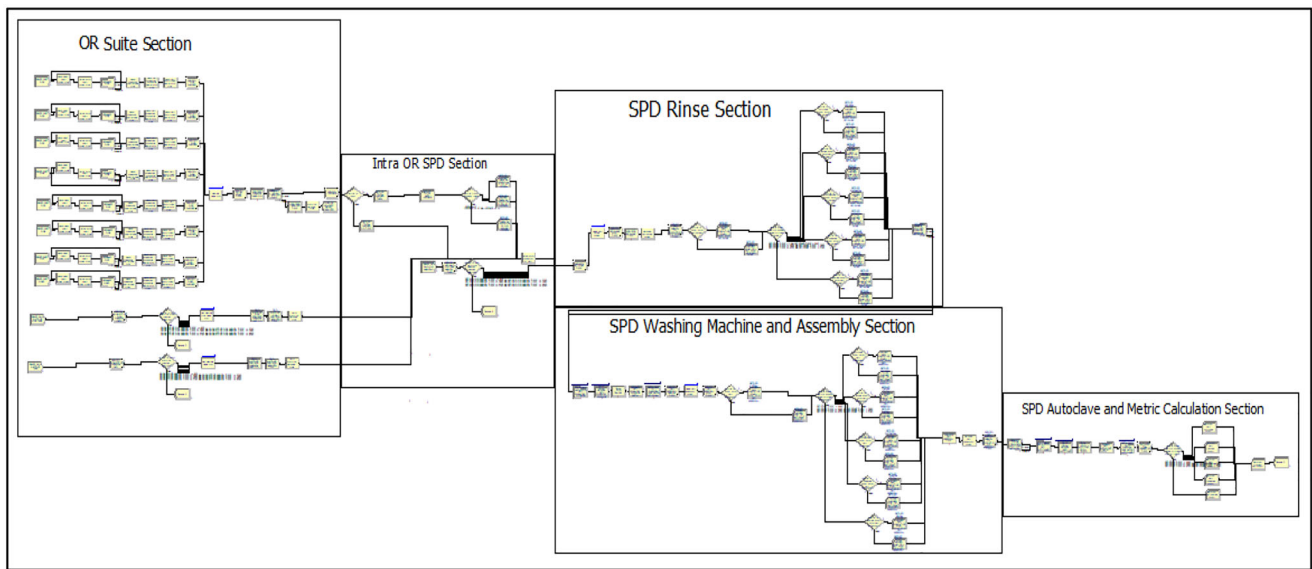


FIGURE A1 Comprehensive Simulation Model

Figure A-2 displays the OR suite subsection. In this section, the surgical case entities are created from the excel schedule file (elective cases) or generated according to their historical arrival rate (non-elective cases). Non-elective cases that occur outside of normal working hours are immediately disposed of, while the cases that occur during work hours are put in the OR queue with a higher priority than elective cases. Non-elective labor and delivery cases can only be processed by OR 1. After a surgical case is processed, one cloned entity is created to account for the OR turnover while the original entity proceeds to the SPD.

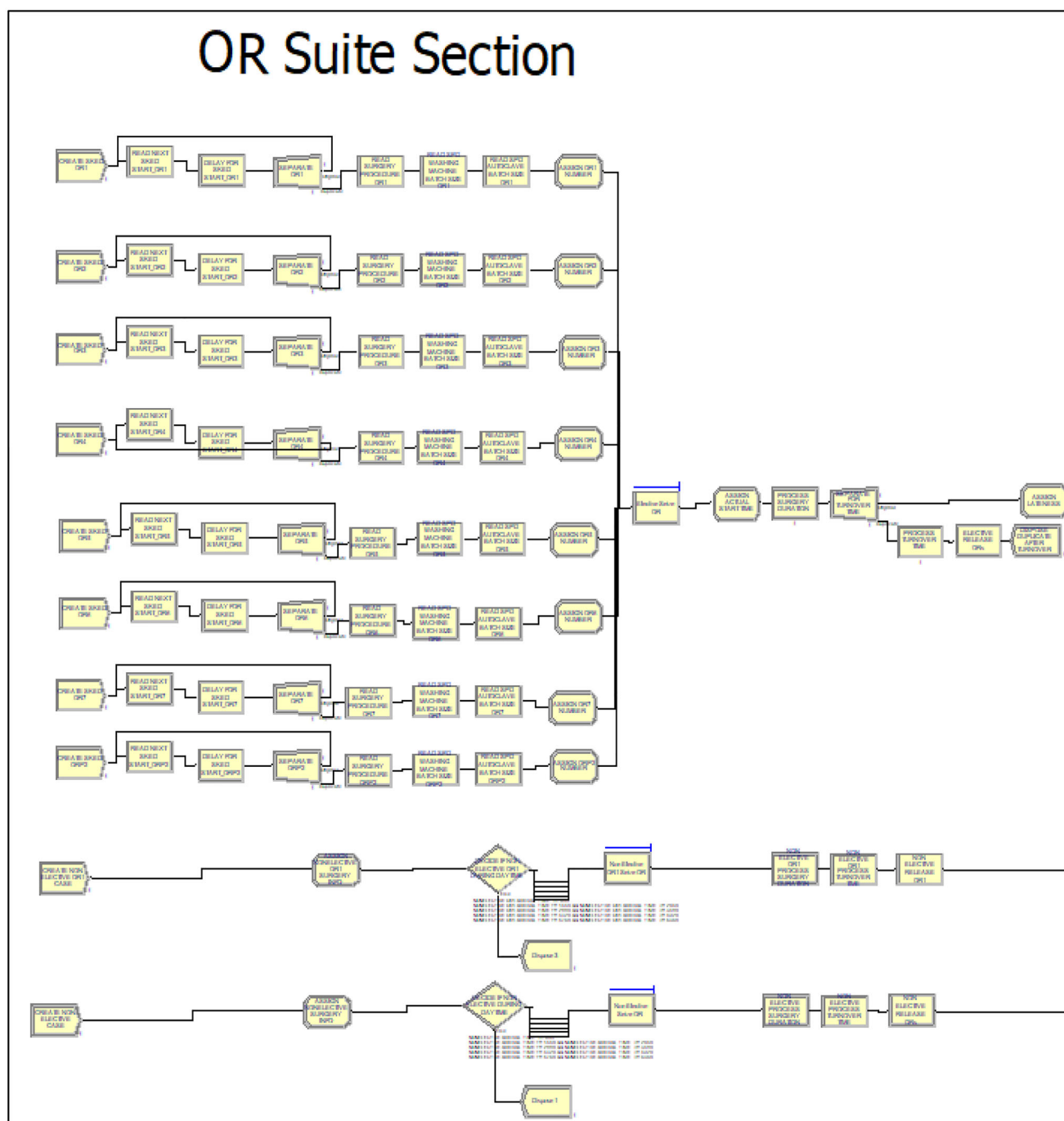


FIGURE A2 OR Suite Subsection

Figure A-3 displays the intra SPD OR section. The original model's metric calculations for the number and magnitude of tardy surgeries remain in the new model. After which, elective cases are sent to the elevator to the SPD. Non-OR SPD cases are generated according to their historical arrival rate. Non-OR SPD cases arriving outside normal work hours are immediately disposed of.

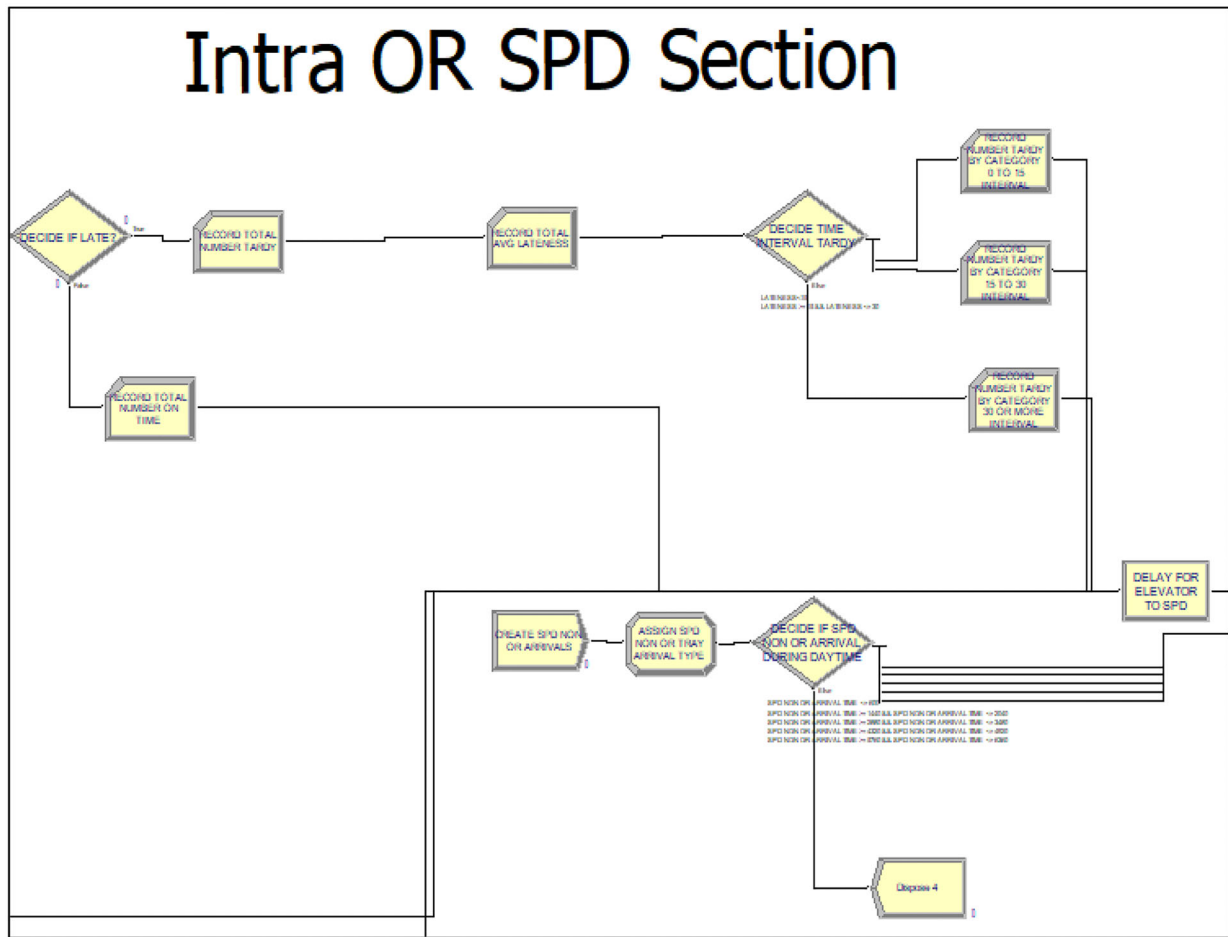


FIGURE A3 Intra OR SPD Section

Figure A-4 displays the SPD rinse section. Cases seize one of two SPD staff for manually rinsing. SPD rinse-related metrics are calculated globally and by separate weekday, after which the cases are cloned for the washing machine batching.

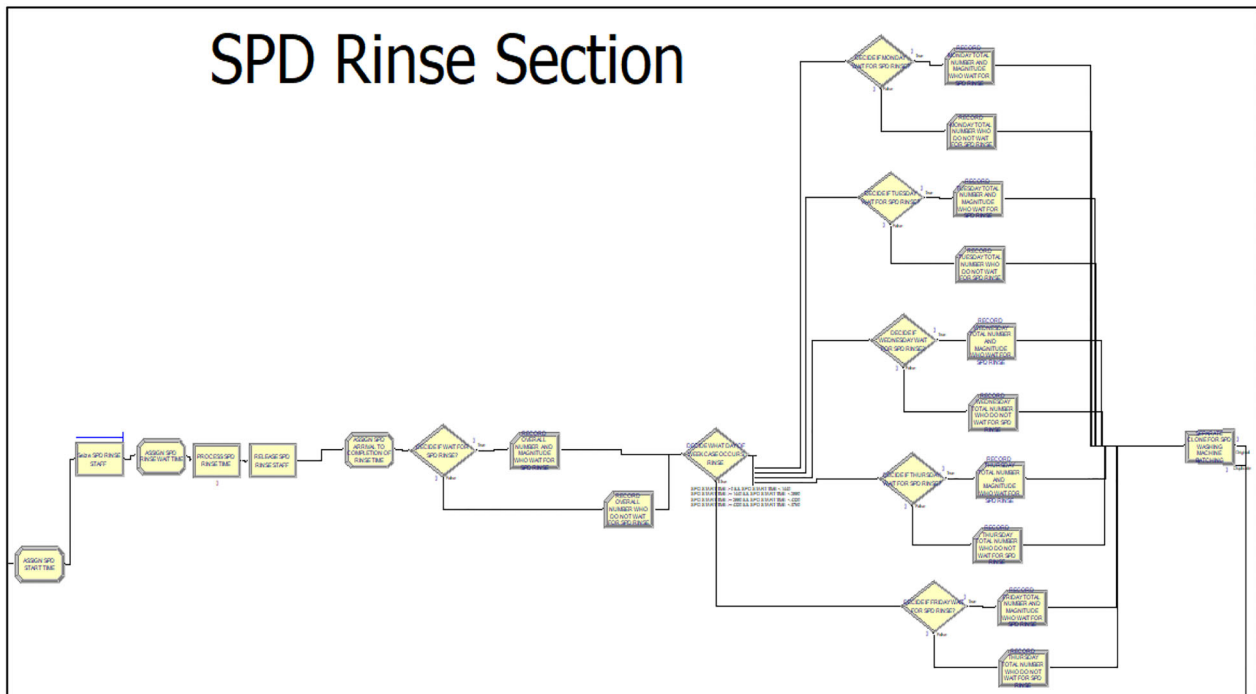


FIGURE A4 SPD Rinse Section

Figure A-5 displays the SPD washing machine and assembly section. Cases are batched and sent through the washing machine, dry, re-batch back into their original cases, and then seize one of three SPD staff for assembly. The corresponding assembly metrics are calculated globally and by weekday.

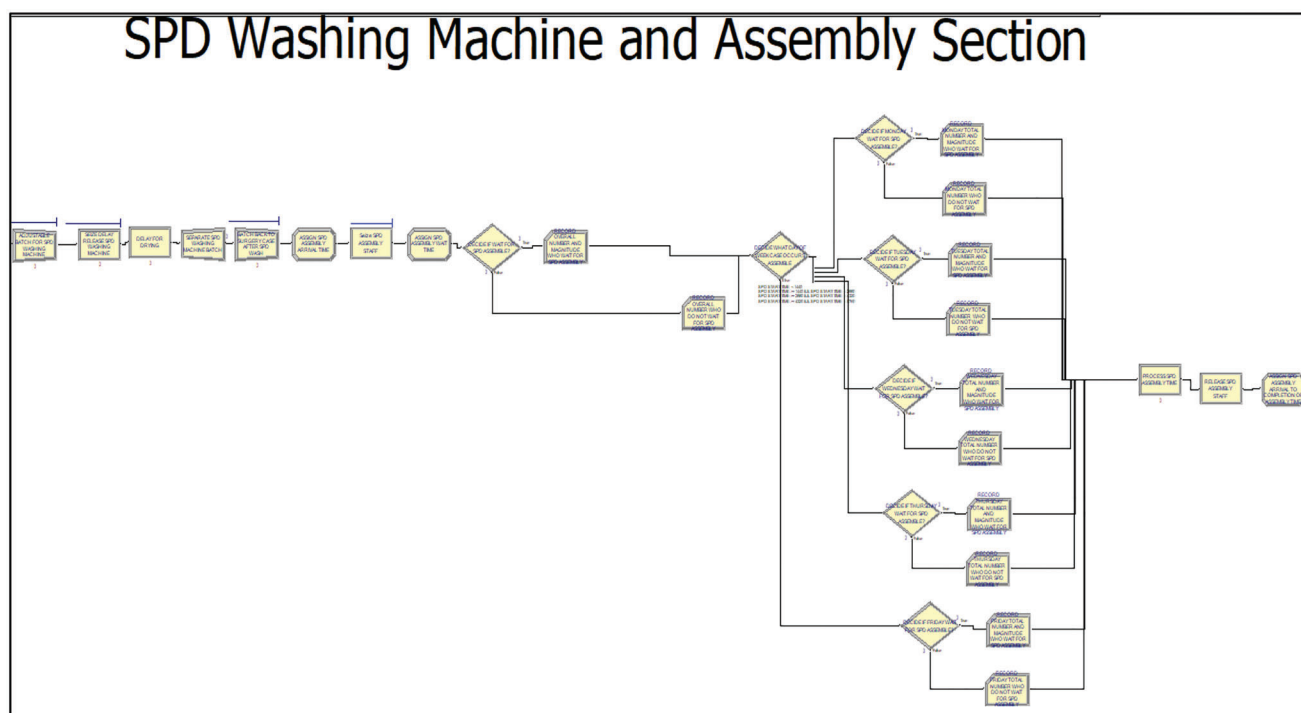


FIGURE A5 SPD Washing Machine and Assembly Section

Figure A-6 displays the autoclave and metric calculation section. Cases are cloned according to the autoclave bath size, batch and seize three autoclave machines, cool down after the autoclave, and then re-batch back to their original case. The case turnaround metric is then calculated globally and by weekday before the cases are disposed of.

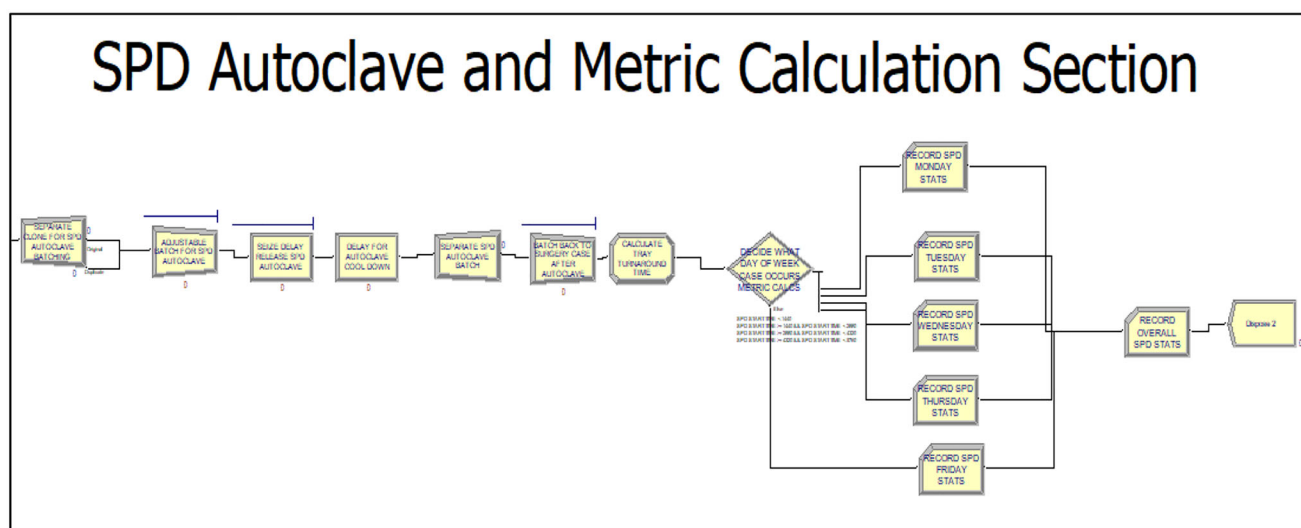


FIGURE A6 Autoclave and Metric Calculation Section

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