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IMPLEMENTATION SCIENCE & OPERATIONS MANAGEMENT

Coordination of Intraoperative Neurophysiologic Monitoring Technologist and Surgery Schedules

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Abstract

Resource coordination in surgical scheduling remains challenging in health care delivery systems. This is especially the case in highly-specialized settings such as coordinating Intraoperative Neurophysiologic Monitoring (IONM) resources. Inefficient coordination yields higher costs, limited access to care, and creates constraints to surgical quality and outcomes. To maximize utilization of IONM resources, optimization-based algorithms are proposed to effectively schedule IONM surgical cases and technologists and evaluate staffing needs. Data with 10 days of case volumes, their surgery durations, and technologist staffing was used to demonstrate method effectiveness. An iterative optimization-based model that determines both optimal surgery and technologist start time (operational scenario 4) was built in an Excel spreadsheet along with Excel's Solver settings. It was compared with current practice (operational scenario 1) and optimization solution on only surgery start time (operational scenario 2) or technologist start time (operational scenario 3). Comparisons are made with respect to technologist overtime and under-utilization time. The results conclude that scenario 4 significantly reduces overtime by 74% and under-utilization time by 86% as well as technologist needs by 10%. For practices that do not have flexibility to alter surgeon preference on surgery start time or IONM technologist staffing levels, both scenarios 2 and 3 also result in substantial reductions in technologist overtime and under-utilization. Moreover, IONM technologist staffing options are discussed to accommodate technologist preferences and set constraints for surgical case scheduling. All optimization-based approaches presented in this paper are able to improve utilization of IONM resources and ultimately improve the coordination and efficiency of highly-specialized resources.

Keywords Intraoperative Neurophysiologic Monitoring · Resource Coordination · Surgery Scheduling · Surgery Staff Scheduling · Optimization

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Introduction

Coordination of resources, both human and physical, within health care delivery systems is challenging [1, 2]. If ill-managed, uncoordinated inefficiencies can lead to waste, increased costs, delays in patient access, frustrated staff, and patient safety challenges [3–5]. This is particularly true in quaternary care systems where highly-specialized resources are limited, demand may be high, and patients have often experienced extensive barriers to obtaining care such as travel and appointment coordination. This paper considers a scheduling coordination setting where patients are scheduled for complex procedures which are highly uncertain in their duration and technologists supporting the procedures need to be scheduled in an efficient manner while maintaining high service levels for patient access.

Intraoperative Neurophysiologic Monitoring (IONM) measures neural function and integrity as per an established strategy to reduce the risk of injury during surgery [6]. IONM services requested for complicated neurosurgical procedures has steadily increased [7]. In general, IONM is extensively used in spinal, cranial, and brainstem types of surgeries and is commonly utilized by various specialties including Orthopedics, Cardiovascular Surgery, Neurologic Surgery, and Otorhinolaryngology. IONM is performed by highly trained technologists and is monitored by a neurophysiologist on-site.

An IONM technologist monitors different modalities that can give real time information regarding the integrity of different neural pathways during surgery including motor evoked potentials (MEP), somatosensory evoked potentials (SSEP), electroencephalography (EEG), and electromyography (EMG) and is usually required throughout the duration of specific surgeries. In our practice, the daily average number of IONM surgeries, i.e., surgeries that require IONM, is 8.2 and ranges from 5 to 15. To ensure adequate coverage, 8 IONM technologists may be scheduled in a typical day. As the duration of IONM surgeries ranges from 60 to 810 min with an average of 400 min, the variability in the volume of IONM cases and their duration create substantial challenges for IONM scheduling decisions.

Most of the quality improvement efforts in IONM contexts have primarily focused on surgery outcomes [8] and staffing studies mostly center around neurologists and other neurophysiologists in IONM volume, case type, duration, numbers of concurrent cases, and physical location of the monitoring [9]. While the ultimate decision making is dependent on the interpreting neurophysiologist, it is the IONM technologist that is typically performing the physical monitoring in the operating room with practice guidelines published to assist increasing their capability [10]. In most spine surgeries that require instrumentation, IONM monitoring is considered the standard of care, reflecting the importance of IONM technologists' role and responsibility. This paper proposes multiple scheduling methods for IONM technologists which meet the demand of IONM surgeries. As per the current practice, the schedules of IONM surgeries are asynchronous with the IONM technologists' schedules, which significantly adds to their overtime and low utilization. Therefore, this study aims to propose scheduling methods which meet the demand for IONM technologists while simultaneously reducing their overtime and increasing their planned staff utilization and potentially reduces the number of concurrent IONM cases. The scheduling methods or operational scenarios proposed attempt to improve upon these goals by either (1) adjusting the IONM surgery schedules, (2) adjusting the IONM technologists' schedules, or (3) simultaneously adjusting both in a coordinated fashion. In the next section, we describe the optimization approaches undergirding the proposed methods.

Methods

Four scheduling operational scenarios (3 proposed and 1 current practice) are presented in this section that define the IONM technologists' schedule such that the demand of IONM surgeries is satisfied and the total overtime and under-utilization time of IONM technologists is reduced with respect to the current practice. Overtime is defined as the time (in minutes) spent on monitoring surgery by the IONM technologists beyond their scheduled shift end time while the under-utilization is defined as the total time (in minutes) in their scheduled shift when IONM technologists are not in surgery.

Our practice uses the OpTime module within Epic for Operating Room (OR) scheduling. When someone lists a surgery, they simply add an IONM technologist to the list of staffing resources needed for the case. When the case is scheduled in a specific OR on a specific date and time the Epic system runs a concurrency check to verify that the number of concurrent cases requesting IONM resources does not exceed resource availability. The system also checks the total number of cases requesting IONM resources for the day and verifies the daily limit is not exceeded. The combination of these two checks ensures that the neuro-physiologist on-site is not overwhelmed with too many cases at the same time and that IONM technologists are not overwhelmed with too many cases in a day.

An example based on a typical surgery day is selected to describe and demonstrate all four operational scenarios. This particular day consists of five IONM surgeries with durations of 360, 390, 390, 420, and 600 min, respectively. The example day had five IONM technologists assigned since

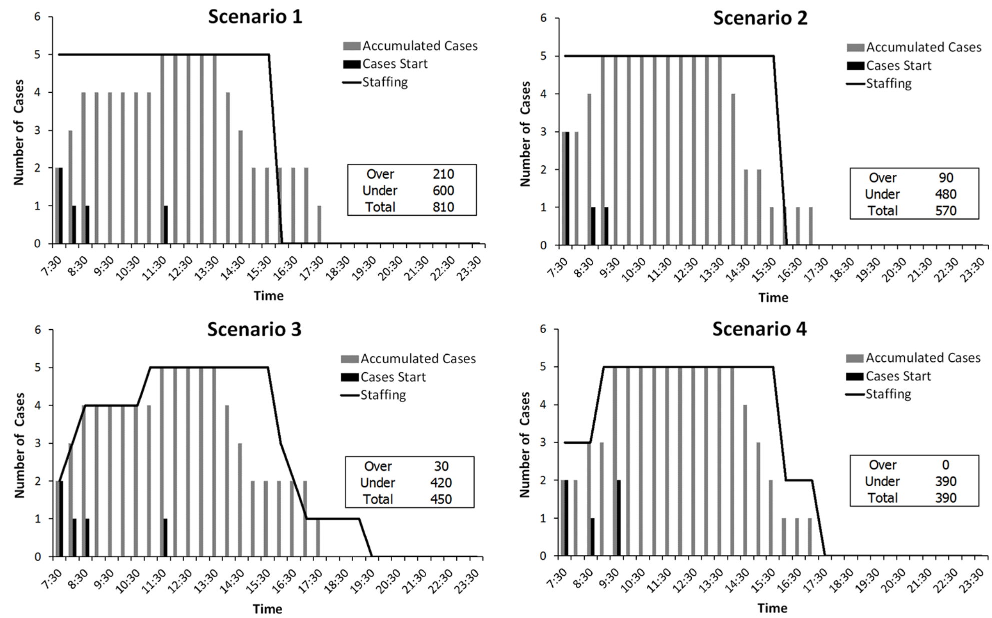

Fig. 1 The four scheduling operational scenarios are illustrated based on an example for a day with 5 surgical cases and 5 IONM technologists. Overtime and under-utilization time are presented for each scenario

all five surgeries were scheduled concurrently at some point in time. Figure 1 shows the resulting schedule for IONM technologists and surgeries under all four operational scenarios along with the accumulated surgeries at any given 30-minute time interval. The total overtime (the grey bar outside the staffing line in Fig. 1) and under-utilization (the white area within the staffing line in Fig. 1) for all IONM technologists is also shown. The subsequent descriptions of the scheduling operational scenarios will refer to Fig. 1 and its example for illustrative purposes and each scenario's description. A larger set of test cases is later used in the Results section to demonstrate the performance of the proposed operational scenarios.

Operational Scenario 1: Current Practice

This scenario represents the current practice where all IONM technologists start in the beginning of the day while the start times of IONM surgeries depend on surgeons' preferences. IONM technologists generally prefer the shift starting from 7:00 am to 4:00 pm with a 30-minute preparation time from 7:00 to 7:30 am. Operational scenario 1 in Fig. 1 gives the schedule of five IONM surgeries. Two surgeries (420 and 600 min) start at 7:30 am and one each starting at 8:00 am (390 min), 8:30 am (360 min), and 11:30 am (390 min). As all five IONM technologists start monitoring at 7:30 am, their scheduled coverage ends at 4:00 pm which leads to 210 min of total overtime and 600 min of total under-utilization; a total of 810 min.

Operational scenario 2: Determine Optimal Surgery Schedule

This scenario assumes that IONM surgeries can be scheduled according to IONM technologists' schedule. An optimization-based approach is adopted. The objective is to minimize the total overtime and under-utilization time. The decisions are to determine the start time of each IONM surgery. The constraints include IONM staffing at any given time, number of IONM surgeries, number of operating rooms, operating hours, and how surgeries can be overlaid for the same surgeon.

In general, for a given IONM technologist's schedule, an IONM surgery is allocated to available IONM technologists in the order of their surgery times such that surgeries with longer surgery times are started as early as possible. This is to avoid overtime resulting from delayed starting of longer surgeries. In the example, as all five IONM technologists start their shift at 7:00 am, the optimization model decision for scenario 2 in Fig. 1 schedules three IONM surgeries (360, 390, and 600 min) to start at 7:30 am and one each starting at 8:30 am (390 min) and 9:00 am (420 min). This schedule generates 90 min of total overtime and 480 min of total under-utilization for IONM technologists with a total of 570 min, yielding a reduction of 57% total overtime, 20% total under-utilization time, and 30% in total over scenario 1 (current practice). The 600-minute IONM surgery is the only case that exceeds technologist availability.

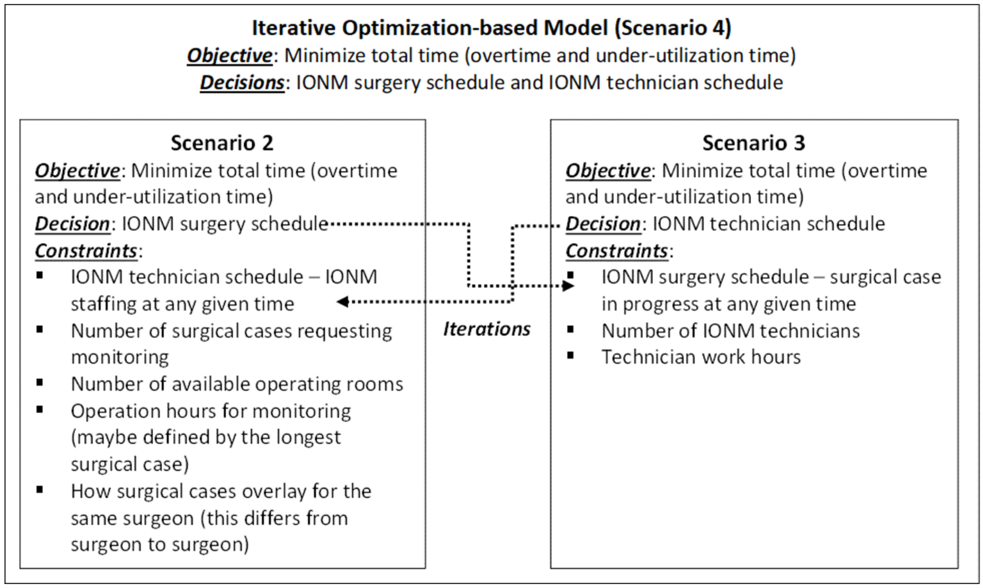

Fig. 2 The algorithm for iterative optimization-based model (operational scenario 4) is illustrated as iterating between the decision on surgery (operational scenario 2) and technologist schedule (operational scenario 3)

Operational Scenario 3: Determine Optimal Technologist Schedule

This scenario determines the IONM technologists' schedules for a given IONM surgery schedule. An optimization-based approach is also used. The objective is to minimize the total overtime and under-utilization time. The decision is to determine the start time of each IONM technologist. The constraints include the number IONM surgeries at any given time, the number of IONM technologists, and IONM technologist work hours.

The number of IONM technologists required by a surgery schedule is determined by the maximum number of concurrent surgeries at any point of time. In the current practice, these IONM technologists are allocated to the surgeries randomly such that the same IONM technologist is not allocated to multiple surgeries at any point of time. In the example, for the IONM surgery schedule stated in scenario 1, scenario 3 in Fig. 1 shows that the optimization-based decision schedules two IONM technologists to start at 7:30 am, and one each at 8:00 am, 8:30 am, and 11:00 am. This results in 30 min of total overtime and 420 min of total under-utilization for IONM technologists yielding a reduction of 86% in total overtime, 30% in total under-utilization time, and 44% in total as compared to scenario 1.

Operational Scenario 4: Determine Optimal Surgery and Technologist Schedule

Figure 2 outlines operational scenario 4. Here, we assume flexible start times for both IONM technologists and surgical cases. An iterative optimization-based approach is adopted since two scheduling decisions (IONM technologists and IONM surgeries) are required. The objective is, again, to minimize the total overtime and under-utilization time. The optimization-based algorithm iterates between scenario 2 and scenario 3 until the objective converges and no longer improves between iterations. This method is initialized using a given IONM technologists' schedule from current practice and is assumed to be the current best IONM technologists' schedule. The optimization starts with the decision on the current best IONM surgery schedule for the current best IONM technologists' schedule (operational scenario 2). Then the current best IONM technologists' schedule is updated with the current best IONM surgery schedule (operational scenario 3). The algorithm continues to iterate and terminates when scheduling decisions and the objective values show no change between iterations. The current best IONM technologists' and IONM surgery schedule after termination are considered as the final schedules.

Figure 3 demonstrates three iterations of scenario 4 in the aforementioned example involving five IONM surgeries and five IONM technologists. Scenario 4 is initialized with all five IONM technologists starting their shift at 7:30 am as in Method (1) In Iteration 1, this IONM technologists' schedule (considered as current best IONM technologist schedule) acts as the input to scenario 2 yielding the current best IONM surgery schedule with 570 min of total overtime and under-utilization for IONM technologists. In Iteration 2, the current best IONM surgery schedule from Iteration 1 acts as the input for scenario 3 which outputs the updated current best IONM technologist schedule, leading to a total of 390 min of overtime and under-utilization time. As total overtime and under-utilization time from Iteration 1 is not equal to the one resulting from Iteration 2, scenario 4 executes Iteration 3 where the current best IONM technologists' schedule from scenario 3 is again provided as

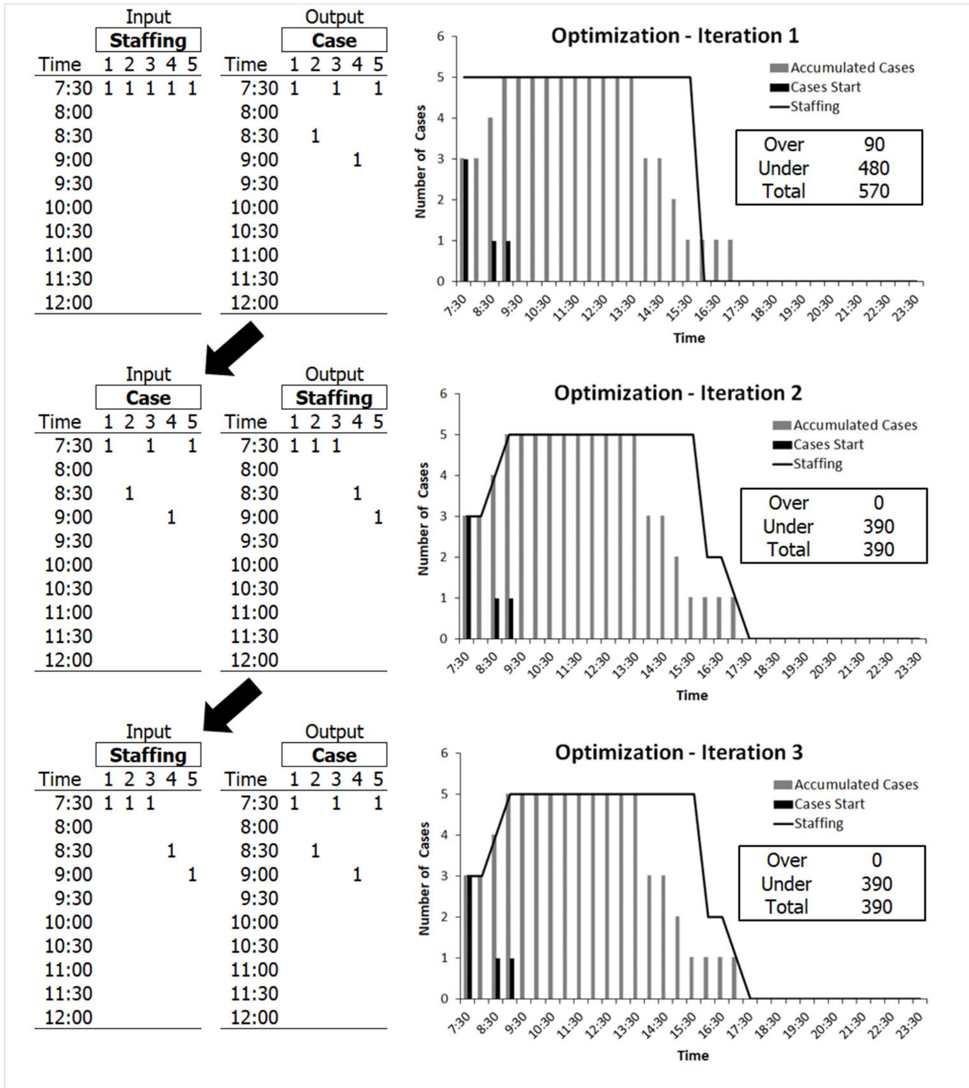

Fig. 3 Three iterations of operational scenario 4 are presented for an example of 5 IONM surgeries with 5 IONM technologists. The optimization iterations are terminated at the iteration 3 since overtime and under-utilization time remain the same between iteration 2 and 3

input to scenario (2) This iteration yields the same results as Iteration 2, so scenario 4 terminates with the current best IONM technologists' and surgery sched- ule as the final schedules. To be noted, each iteration improves the objective (total overtime and under-utilization time). Since the total time of 390 min all comes from under-utilization time, the IONM technologists are adjusted from five to four; see Fig. 4. We then rerun scenario 4. After three iterations, the method terminates and yields a result of 360 min total time (240 min overtime and 120 min under-utilization time), which improves the objective. However, the scheduled IONM technologist hours need to be extended for two hours to accommodate this resource reduction.

A Note on the Optimization-based Methods

The optimization-based methods described in this section draw from the math programming discipline within operations research [11]. Optimization methods have been applied in a range of health care delivery settings such as optimal treatment design, patient scheduling, resource allocation, and pharmacy inventory management [12–14]. Much of the literature using optimization methods applied to coordinating staff and resources in surgery or procedure settings has been in the context of nurse scheduling in operating suites [15, 16]. While most surgery scheduling optimization models are focused on surgery-to-room assignments or developing block-based schedule structures, there have also been optimization-based approaches on scheduling staff who are integral to the surgeries or procedures [17]. The authors' model simultaneously develops a master surgery schedule and nurse staffing schedule based on various workload requirements. However, simultaneously obtaining such schedules is shown to be computationally burdensome and the authors propose a column generation approach that is shown to be able to solve the model in reasonable time.

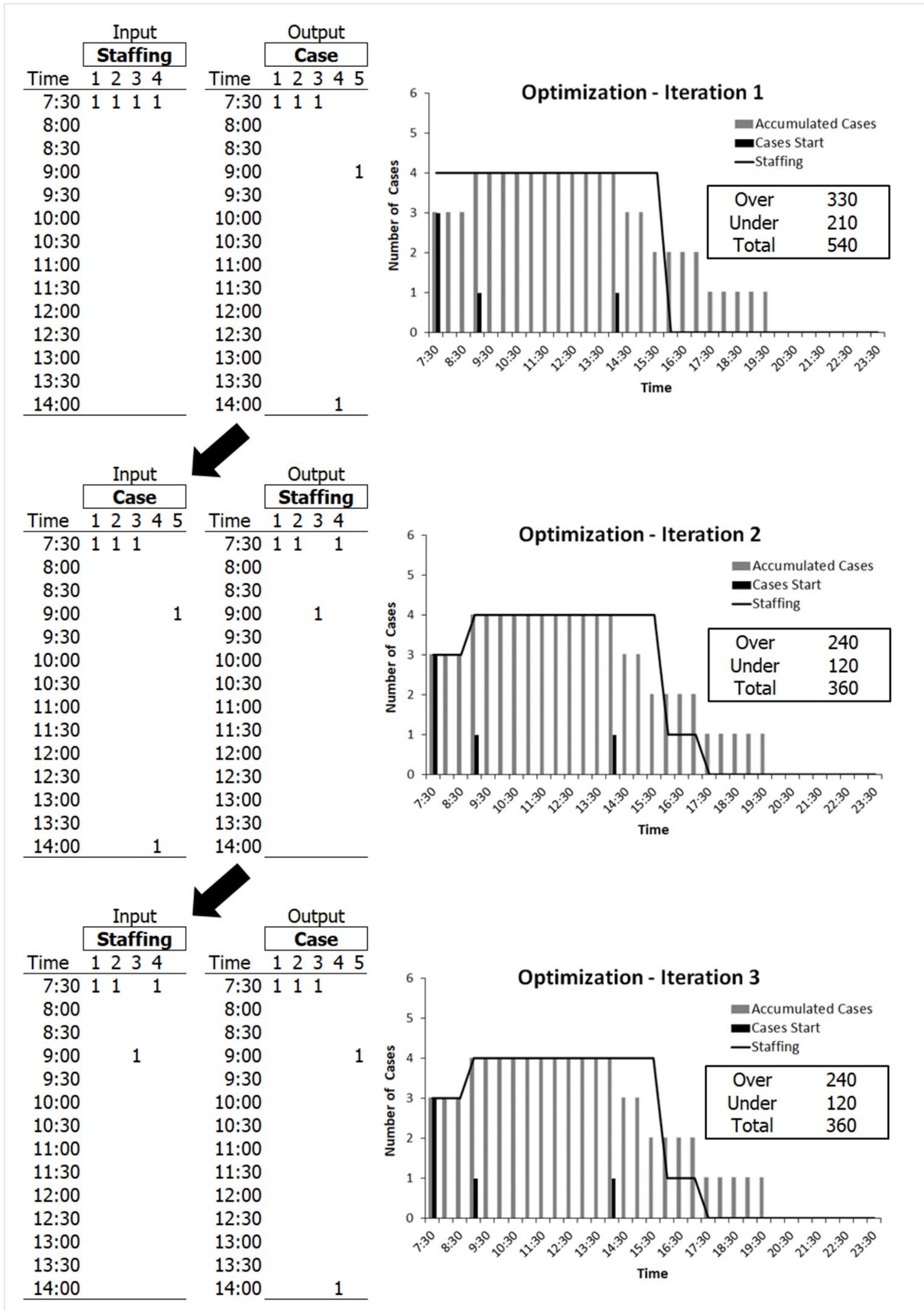

Fig. 4 Three iterations of operational scenario 4 are presented for an example of 5 IONM surgeries with 4 IONM technologists. The optimization iterations are terminated at the iteration 3 since overtime and under-utilization time remain the same between iteration 2 and 3

Column generation was also used to mitigate computational challenges in [18] where the authors include a multi-objective model to which schedules nurses to surgeries based on specialty and competency. The scope of surgery scheduling models continues to broaden, notably in the incorporation of upstream and downstream capacity considerations [19–21] and in the use of implementable heuristics [22, 23]. Yet, the scheduling of auxiliary staff in surgical planning requires further investigation.

The optimization-based methods in this paper were implemented in Microsoft Excel Solver [24], which is a spreadsheet-based solver with a user interface within Microsoft Excel. Excel Solver was chosen due to it being widely available for implementation without the use of sophisticated commercial solvers. However, Excel Solver is also limited by the number of variables and constraints in a model. As a result, instead of combining the two objectives into a single model which is too large for Excel Solver, the

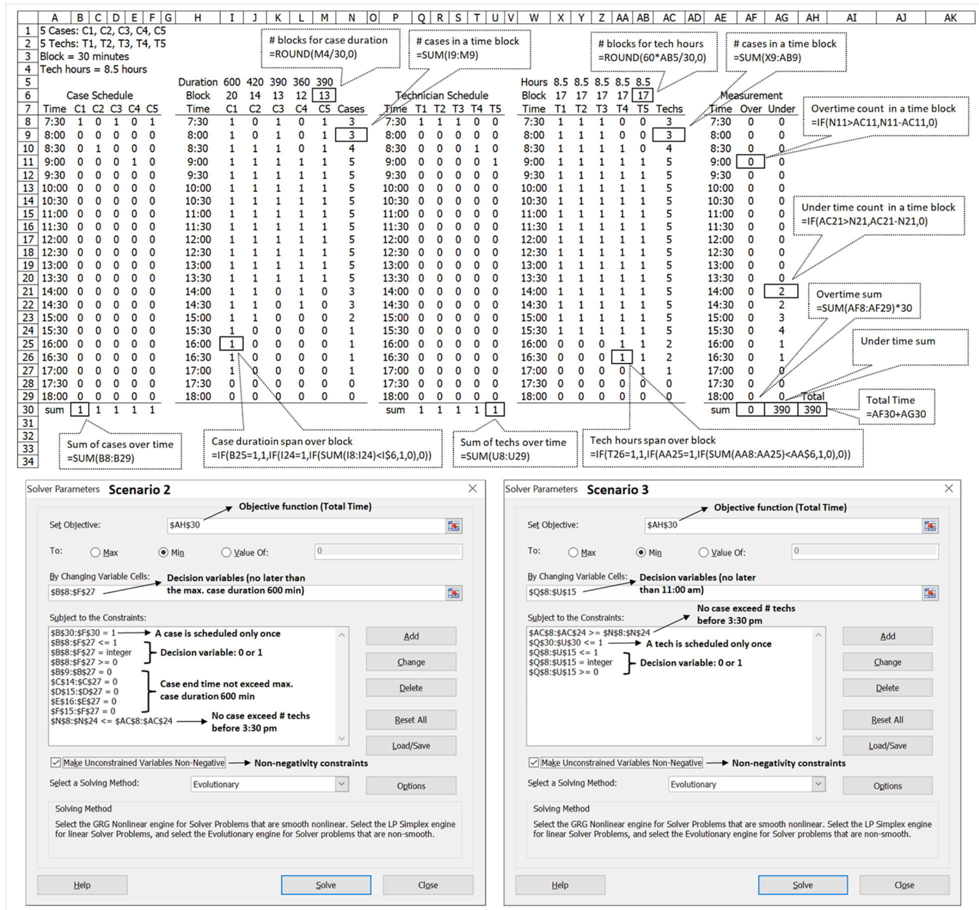

Fig. 5 A screenshot of the implementation of iterative optimization model using Excel Solver illustrates how excel functions and solvers are set up. The top portion presents how spreadsheet is arranged and modeled. The bottom portion demonstrates how solver is set up in relation to spreadsheet

iterative approaches were developed to ensure their usability by the partnering practice as well as for broader uptake in other organizations. The software allows for inputs from different databases and can run on most personal computers, making its implementation transition within the practice setting simple. An example screenshot of the program is included in the Fig. 5 with explanation on spreadsheet modeling and setting up solvers.

Results

The four scheduling methods are compared using 10 test case days from our practice. The test cases' data are summarized in Table 1. Results are shown in Table 2 where each row gives compares the total overtime and under-utilization time for IONM technologists and the number (under the heading staff) scheduled each day. Operational scenario 2, which matches the IONM surgery schedule to a given IONM technologist schedule, outperforms the current practice (operational scenario 1) by reducing the total overtime by 49% and total under-utilization time by 29%, on average. Operational Scenario 3, on the other hand, matches the IONM technologist schedule to a given IONM surgery schedule and outperforms scenario 1 by improving the total overtime by 63% and total under-utilization time by 37% on average. Operational scenario 4 which implements scenario 2 and scenario 3 iteratively reduces the total overtime by 74%, total under-utilization by 86%, and the number of IONM technologists scheduled by 10% as compared to the current practice. Table 2 also shows that, on average, scenario 2 is outperformed by scenario 3, which is outperformed by scenario 4. Note that Test Cases 3 and 10 using scenario 4 extend IONM technologist schedule by two hours and one hour, respectively. The other eight days are able to complete the day within the longest surgery duration. Based on internal discussions and practice feedback, a two-hour delay is reasonable as long as overtime and under-utilization time are improved significantly.

Discussion

Surgery scheduling has received significant attention in the literature [25–27]. In addition, the impact on surgery sequencing and scheduling on operational performance measures such as staffing, operating room over/under utilization, and costs have been studied [28–31]. However,

Day	IONM Cases	Mean Duration (min)	Max Duration (min)	IONM technologists
1	8	450	780	8
2	10	330	630	9
3	5	430	600	5
4	15	360	810	12
5	8	340	570	7
6	11	420	600	10
7	5	470	600	4
8	10	450	780	8
9	9	440	690	8
10	7	420	690	6

Table 1 Summary Statistics of 10-day Data Set (rounded to the nearest ten for duration)

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
Days	Over	Under	Staff	Over	Under	Staff	Over	Under	Staff	Over	Under	Staff
1	630	1140	8	360	870	8	120	630	8	120	120	7
2	210	1500	9	180	1470	9	0	1290	9	0	270	7
3	210	600	5	90	480	5	30	420	5	240	120	4
4	690	1410	12	540	1260	12	480	1200	12	30	240	11
5	120	1020	7	60	960	7	30	930	7	180	60	5
6	990	1500	10	210	720	10	60	570	10	120	120	9
7	960	690	4	300	30	4	360	90	4	300	30	4
8	1230	840	8	570	180	8	570	180	8	420	30	8
9	390	510	8	330	480	8	300	420	8	60	210	8
10	210	330	6	210	330	6	150	270	6	0	120	6
Average	**564**	**954**	**7.7**	**285**	**678**	**7.7**	**210**	**600**	**7.7**	**147**	**132**	**6.9**
Improvement	-	-	-	***49%***	***29%***	***0%***	***63%***	***37%***	***0%***	***74%***	***86%***	***10%***

Table 2 Four Scheduling Operational Scenarios Comparison across 10 Test Instances for Overtime, Under- utilization, and Staffing level

less is understood regarding methods to coordinate highly-specialized procedure staff and resources and surgery schedules. In this paper, we presented and evaluated four methods for coordinating IONM technologists and surgeries.

The results in the previous section illustrate the improvements in overtime and under-utilization of IONM resources associated with the optimization-based approaches presented in this paper. Operational scenario 4 significantly reduces the total overtime and under-utilization of IONM technologists as compared to all other scenarios, including the current practice. However, the assumption of flexible start times of both IONM surgeries and technologists may not be reasonable for some health care organizations. As surgery start times are often driven by surgeons' preferences and are difficult to be altered, scenario 3 seems to be the most preferable among the proposed methods. Hence, distributing IONM technologists start times throughout a day is a potential solution to reduce IONM staff overtime and under-utilization rather than all technologists starting at 7:00 am. However, this may lead to IONM technologist schedules which may violate some of the working constraints such as the latest hour by which the technologists are willing to start their shift, maximum number of desired shifts in a day, the time difference between shifts, and the maximum number of technologists in each shift. Thus, to resolve this problem we develop four IONM technologist staffing levels that satisfy these working constraints. These are illustrated in Fig. 6. Once the staffing level is decided, the IONM surgery schedule is constrained by it when using scenario 2.

For our practice, the latest shift start time preferred by IONM technologists is 11:00 am and the maximum time difference between shifts is upper-bounded at 90 min. Hence, in Fig. 6, we consider IONM staffing with one (Staffing 1), two (Staffing 2), three (Staffing 3), and four (Staffing 4) technologists per shift with the start time of each shift uniformly distributed between 7:30 am to 11:00 am. Table 3 compares the performance of the four IONM staffing patterns proposed in Fig. 6 over the 10-day data set stated in Table 1. As seen in Table 3, Staffing 1 yields the minimum

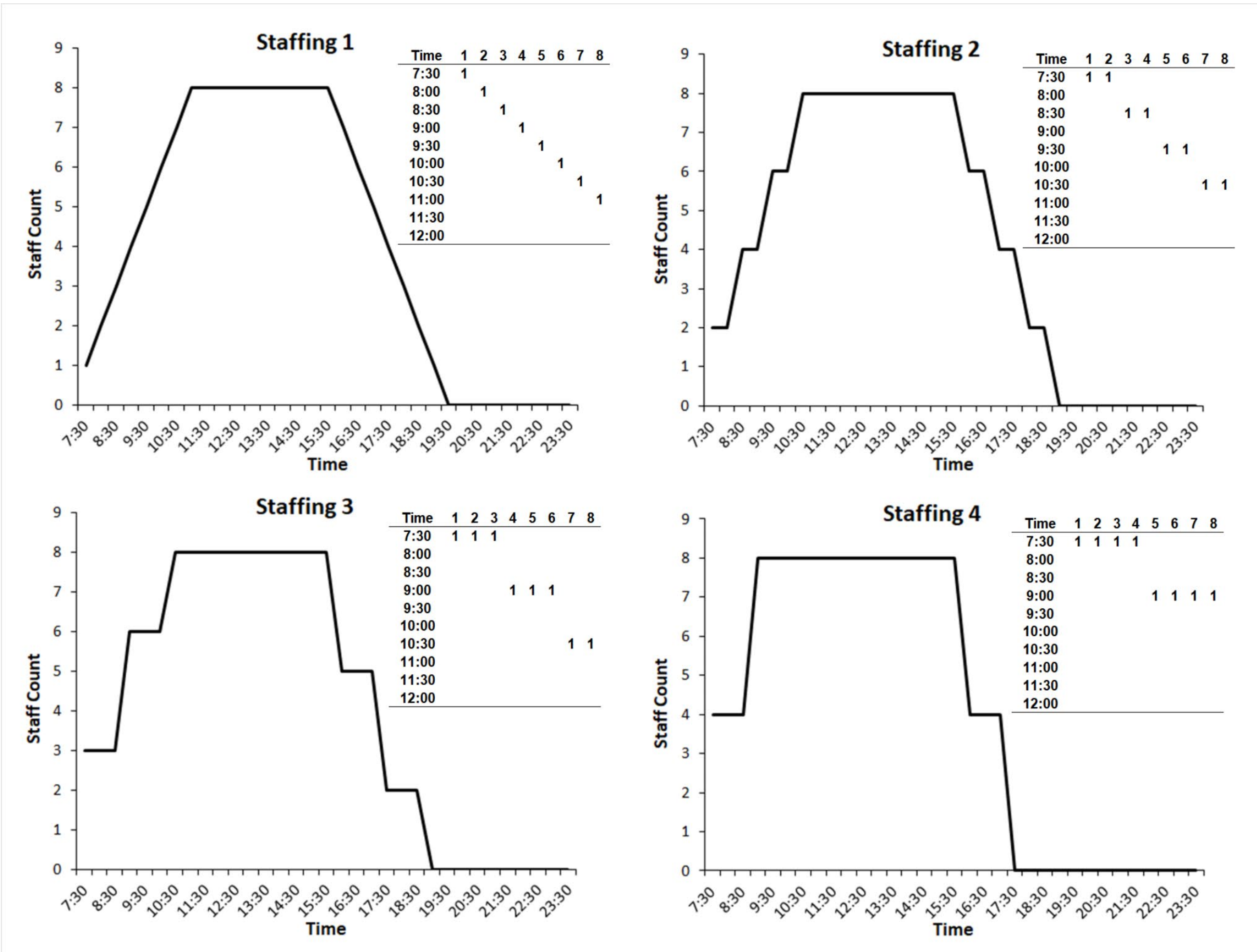

Fig. 6 Four possible schedule structures for eight IONM technologists: one starts every 30-minute from 7:30 to 11:00 am (Staffing 1), two start every hour from 7:30 to 10:30 am (Staffing 2), three start every 90-minute from 7:30 to 10:30 am (Staffing 3), four start at 7:30 am and at 9:00 am (Staffing 4)

average total overtime and under-utilization for IONM technologists among all four staffing patterns. Moreover, Staffing 1, Staffing 2, Staffing 3, and Staffing 4 give improvement of 41%, 38%, 37%, and 28%, respectively, over scenario 2 in Table 2 where all IONM staff start at 7:00 am. Note that although Staffing 1 is the best choice among the feasible alternatives, the choice is still left with individual practices.

Conclusion

Resource coordination in surgical scheduling remains challenging in health care delivery system due to surgeon preference, especially in requesting a highly-specialized resource such as IONM technologists. Limited access to this type of resource creates constraints to surgical quality and outcomes. To maximize the efficiency in utilizing IONM resources, we adopted optimization-based approaches to most effectively schedule IONM surgical cases and technologists. Three scheduling operational scenarios are presented and compared with current practice with respect to technologist overtime and under-utilization time. Our results show that scenario 4, which uses an iterative optimization approach for scheduling between surgical cases (operational scenario 2) and IONM technologists (operational scenario 3), significantly reduces overtime by 74% and under-under-utilization time by 86% as well as technologist needs by 10%. For practices that do not have flexibility to alter surgeon preference or IONM technologist staffing levels, they can select either scenario 2 or scenario 3 according to their objectives. Both these methods also result in substantial reduction in technologist overtime and under-utilization time. While intended to achieve balance between surgical case preferences and IONM technologist schedules, one can develop a reasonable technologist staffing levels similar to the ones discussed in the Discussion section and use

Days	IOM Techs	Staffing 1			Staffing 2			Staffing 3			Staffing 4		
		Over	Under	Total	Over	Under	Total	Over	Under	Total	Over	Under	Total
1	8	60	570	630	90	600	690	90	600	690	180	690	870
2	9	0	1290	1290	0	1290	1290	0	1290	1290	30	1320	1350
3	5	0	390	390	0	390	390	0	390	390	0	390	390
4	12	120	840	960	150	870	1020	150	870	1020	330	1050	1380
5	7	0	900	900	0	900	900	0	900	900	0	900	900
6	10	0	510	510	0	510	510	30	540	570	0	510	510
7	4	270	0	270	270	0	270	270	0	270	300	30	330
8	8	390	0	390	390	0	390	390	0	390	420	30	450
9	8	0	150	150	60	210	270	30	180	210	150	300	450
10	6	30	150	180	60	180	240	90	210	300	90	210	300
Average		**87**	**480**	**567**	**102**	**495**	**597**	**105**	**498**	**603**	**150**	**543**	**693**

Table 3 Four Staffing Structure Comparison across 10 Test Instances for Overtime, Under- utilization Time, and Total Time

them as a constraint when scheduling surgical cases. All optimization-based approaches presented in this paper are able to maximize utilization of IONM resources and have the potential to reduce costs significantly.

Declarations

Declaration of Competing Interest This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors have no conflicts of interest regarding this study.

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