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Optimization and Simulation of Orthopedic Spine Surgery Cases at Mayo Clinic

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Spine surgeries tend to be lengthy (mean time of 4 hours) and highly variable (with some surgeries lasting 18 hours or more). This variability along with patient preferences driving scheduling decisions resulted in both low operating room (OR) utilization and significant overtime for surgical teams at Mayo Clinic. In this paper we discuss the development of an improved scheduling approach for spine surgeries over a rolling planning horizon. First, data mining and statistical analysis was performed using a large data set to identify categories of surgeries that could be grouped together based on surgical time distributions and could be categorized at the time of case scheduling. These surgical categories are then used in a hierarchical optimization approach with the objective of maximizing a weighted combination of OR utilization and net profit. The optimization model is explored to consider trade-offs and relationships among utilization levels, financial performance, overtime allowance, and case mix. The new scheduling approach was implemented via a custom Web-based application that allowed the surgeons and schedulers to interactively identify best surgical days with patients. A pilot implementation resulted in a utilization increase of 19% and a reduction in overtime by 10%.

Keywords: operating room scheduling; surgery scheduling; mixed-integer program
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1. Introduction

For spine surgeries, large medical centers like Mayo Clinic generally face more patient demand than available capacity. One reason is the relatively long surgical times for spine patients. Data from Mayo Clinic shows that 50% of spine surgeries are over four hours in length. Thus, on most days a spine surgeon is able to do only one or at most two surgeries (within regular working hours).

The length and variability of spine surgeries adversely impact patient access, effective operations, and financial performance (Dexter et al. 2010). At Mayo Clinic, 38% of surgical days went past the desired end time of 5 P.M. At the same time, operating room (OR) utilization during normal hours was less than desired, limiting patient access and reducing potential financial performance. Overtime is a concern at Mayo Clinic due to the importance of quality of life for the surgeons and the surgical teams. In addition, as noted in Espin et al. (2006), safety for both the patient and surgical staff may be an issue if surgical days run long. Emergency cases, short-term cancellations, teaching requirements for surgeons on specific weekdays, and complex cases that require more than one surgery per patient further complicate scheduling and OR management.

In this paper, we describe a data-driven hierarchical modeling approach for scheduling spine surgeries that tackles multiple aspects such as surgery variability (by better classification), OR utilization, overtime, payer mix, and financial performance. We use a seven-year data set consisting of 2,500 spine surgeries to parameterize our models. We also quantify how this scheduling approach performed in a pilot implementation. Many of the concepts and approaches discussed in this research are relevant to other surgical practices and particularly those in spine surgery. Nonetheless, the orthopedic spine surgery practice at

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Mayo Clinic has many unique characteristics. In what follows, we discuss the specific problem setting.

1.1. Mayo Clinic Spine Surgery Scheduling Approach

Mayo Clinic's core value is the "needs of the patients come first." This influences surgical scheduling because patient timing preferences are important to final scheduling decisions. This is in contrast to many surgical settings where patients are simply told when to show up. Thus, at Mayo Clinic the patient negotiates with the surgeon and their team, when to schedule their surgery. This is also in part because spine surgeries often have significant impact on patients' lives for extended periods and a lengthy recovery process.

However, this approach leads to problems in daily surgical loads; for example, when a patient requests to have their surgery on a particular day when several other surgeries are already scheduled. This is due to the difficulty in simply "squeezing in" another spine surgery because of their length and variability. Conversely, other days and weeks are underutilized. In the absence of good information regarding the current status of their schedule, surgeons and schedulers are often driven to make decisions influenced too much by patient preferences.

Scheduling surgeries at Mayo Clinic is further complicated by the fact that dedicated OR time is available to most surgeons, thus there is a specific time preallocated to each surgeon. This is a positive in that it allows the surgeons a great deal of autonomy in managing their cases both in the OR and the clinic. However, it is problematic in that the organization cannot pool OR time and balance loads across all ORs. Rather each surgeon's load must be balanced across their surgical days. These surgical days are assigned via the "blue and orange" system at Mayo Clinic. This harkens back to the system developed by the Mayo brothers, Dr's. Will and Charlie, who performed surgeries every other day, in complementary fashion. In the first week, one surgeon ("blue") performs surgeries on Mondays, Wednesdays and Fridays, while the other surgeon ("orange") is active on Tuesdays and Thursdays. In the next week, the orange surgeon performs surgeries on Monday, Wednesday, and Friday while the blue surgeon does so on Tuesday and Thursday. This alternating cycle is then repeated. On days that surgeons are not operating, they have clinical consultations with patients. This creates a simple management system for clinic and surgery days that continues today, but results in some restrictions in scheduling flexibility and can make short-term case load imbalances worse as some surgeons get overloaded and others underutilized. A nontrivial 10% of spine patients require multiple surgeries that need to be scheduled within days of each other. Furthermore, even on surgical days, surgeons have teaching and seminar responsibilities, leading to a late start for surgeries. Thus weekdays get characterized as "early start" or "late start" days, which has an impact on access as well as overtime.

Although Mayo Clinic is a nonprofit organization, financial viability and sustainability are still important considerations. Profits from clinical practice support research, education, and ongoing improvement initiatives, all of which are important to Mayo Clinic's mission. With limited capacity to allocate to the high demand for spine surgeries, some control of which surgeries are performed and when, can be important to net operating income (NOI). Given specific revenue reimbursements and Mayo's cost structure, some types of spine surgeries are more profitable than others, for example patients with government payers (e.g., Medicare and Medicaid) generally have lower profitability. However, there is no desire to reduce the number of such patients.

Furthermore, the overall patient profitability to Mayo Clinic, including their hospital stay, is affected by the timing of surgeries, specifically the day of week (DOW) that the surgery is performed. Thirty-four percent of spine surgery patients require discharge to a skilled nursing facility (SNF). These facilities generally do not accept patients on weekends and therefore if a patient requires a SNF and their planned discharge is on a weekend, Mayo often incurs the additional costs without compensating revenue. This is due to the fact that government insurance payers generally have a fixed reimbursement for each procedure type. Even though it may be difficult to a priori determine the probability of a patient requiring a SNF at discharge, it is known that older patients have a higher risk. Because such patients are generally covered by Medicare, special attention is paid to when these patients are scheduled. In general they are scheduled on Mondays and Fridays with the assumption that this results in the least number of delayed discharges. Although all the above factors are important when scheduling patients, the Mayo system needs to have the flexibility to ensure that the needs of the patients always come first.

1.2. Objectives and Approach

The primary objective of our research is to create schedules that improve patient access as a result of increased utilization of surgical capacity, while keeping the practice financially sustainable. It is also important to ensure that overtime levels are not too high, the proportion of government payer patients remains at historical levels, and Mayo-specific DOW constraints discussed above are met. To address this problem, the following research approach was used (see Figure 1 in §3).

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• Data mining and statistical analysis were performed using Mayo Clinic's database. Surgeries were categorized based on surgical time distributions, using patient characteristics known in advance of scheduling.

• Using the surgical categories, Simulation Model 1 was used to identify combinations of surgeries that can feasibly be performed within one surgical day and to calculate the outcomes (overtime, utilization, and NOI). Since spine surgeries are long and highly variable, only combinations consisting of one or at most two surgeries need to be considered. The simulation uses the relevant time distributions derived from the data set.

• The feasible surgical combinations and their outputs are used as an input to the hierarchical optimization approach, consisting of three stages:

a. Optimization Model 1: A mathematical program was formulated and implemented to maximize a weighted function of OR utilization and NOI, considering changes to surgical case mix, limiting overtime, and downstream inpatient length of stay (LOS). The surgical combinations and their outcomes are used as inputs. This stage generates the optimal case mix over a planning horizon.

b. Optimization Model 2: The second-stage optimization model creates the optimal schedule for each day in the horizon using the results of the first-stage model and maximizes available slots for patients who need to have multiple surgeries within a short period, typically two days.

c. Optimization Model 3: The last stage of the optimization creates a surgeon schedule by incorporating Mayo Clinic specific scheduling requirements (the blue–orange surgical template).

• Another simulation model (Simulation Model 2 in Figure 1) is used to test the impact of urgent surgeries and cancellations on the optimal schedule.

• As a last step, our optimization framework was implemented in Mayo Clinic and the results of the intervention were evaluated in a controlled pilot, with a pre and post evaluation as well as using a control group (with two surgeons) and a test group (with two surgeons).

2. Literature Review

Surgical scheduling is an extensively studied area, and a full review is beyond the scope of this paper. Instead, we split up our literature review into two parts: literature on prediction of surgical times and a short review on surgical scheduling. These two parts broadly revolve around our two major contributions: a new method for classifying spine surgeries based on their durations, and the pilot implementation.

2.1. Literature on Prediction of Surgical Times

Accurately estimating surgical durations is crucial for surgical case scheduling (May et al. 2011). Currently, the surgical duration in Mayo Clinic spine practice is estimated using historical data based on the last five similar surgeries—a widely used estimation tool called the "last 5 case estimate" (Macario and Dexter 1999). This is a poor estimation tool especially when there are too few historical cases, as it is very surgeon specific (Zhou et al. 1999). In fact, a recent study has shown that OR times for similar surgeries in eight different hospitals vary significantly from each other (Dexter et al. 2006). Other common methods for surgical duration estimation are surgeon estimates, historical averages, a combination of historical average with surgeon estimate, adjustments with case complexities, and regression models to develop predictive models (Schult et al. 2011).

There are many factors that impact the surgical duration, like type of anesthesia, age, gender, surgeon, and American Society of Anesthesiologists (ASA) risk class (Strum et al. 2000). We investigate all of the factors that are known in advance of surgery to find the best categorization that is also clinically relevant. Lognormal distribution is typically the best fit and is often used in the literature to represent highly variable procedure times (Spangler et al. 2004). However, besides estimating a single surgery, for scheduling purposes, it is essential to predict an entire surgical day or an OR block's duration (Dexter et al. 1999). This is why, as discussed in Strum et al. (2003, p. 232) we then use the surgery duration predictors "...for building simulation models of surgical environments and for decision analysis based on such simulations."

Surgery durations exhibit high variability and when multiple cases are performed back to back this variability accumulates. Research in this field has proposed various ways to estimate the end of day (EOD) in the face of high variability. Wang and Yang (2014) suggest using Type 4 Pearson distribution to approximate the EOD distribution for a list of cases.

Alvarez et al. (2010) develop a method to accurately determine the EOD for multiple cardiovascular operations, considering the turnover times as well. The authors suggest using the sum of the average case durations from historical cases and turnover times to estimate the time to complete a series of surgical cases, supporting Dexter et al. (1999).

We have analyzed the convolution of lognormal variables to predict the EOD distributions for different surgical combinations. For instance, Gao et al. (2009) study the asymptotic behavior of a probability density function for the sum of two lognormally distributed random variables. They approximate both the left and right tails with simple functions. However, these models get intractable when we are considering the tail probability density function of more

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than two lognormally distributed random variables (which is the case when we are characterizing each of the surgical steps with a lognormal distribution). Thus, we have turned our focus to using simulation models that mimic the ORs in Mayo Clinic based on sampling from historical data. And instead of directly using the empirical values for the surgical combinations, we have created a simulation model due to the fact that not all of the combinations were represented in the data-set. We were able to derive the results of interest (overtime, normalized NOI, utilization) using a simulation model for all feasible surgical combinations.

2.2. Literature on Surgical Scheduling

Surgical suites' management impacts costs, the patient flow, and resource utilization throughout the whole hospital (Nan and Li 2011). Various approaches have been used to optimally schedule surgeries to ORs like, integer programming (Blake and Donald 2002; Denton et al. 2007, 2010; Vissers et al. 2005; Adan et al. 2009), stochastic optimization models (Denton et al. 2010, Batun et al. 2011, Oostrum et al. 2008, Testi et al. 2007), goal programming (Rohleder et al. 2005), discrete event simulation (Adan et al. 2009), and heuristics (Denton et al. 2010, Oostrum et al. 2008, Testi et al. 2007). For detailed reviews on surgical scheduling, we refer to May et al. (2011), Guerriero and Guido (2011), and Cardoen et al. (2013). Here, we only emphasize studies that are relevant to the unique features of our study.

Although there has been research on addressing the financial implications of surgical scheduling (Wachtel et al. 2005, Dexter et al. 2002), we not only consider the financial differences between patient groups, but also the profitability of patients' entire encounter related to their surgery. This would include post-surgery hospitalization and the effects of unnecessary hospital stays (and associated costs) for patients likely to require a SNF upon discharge. In addition, it was a vital part of our project that there was no deterioration in care, thus we did not limit access to OR time, inpatient beds, or surgical expenses to reduce our costs as suggested in some papers (Dexter et al. 2002).

A major shortcoming in the literature is the lack of research on implementations. To the best of our knowledge, Blake and Donald (2002) is one of the few papers that mention the implementation of a deterministic model without considering the variability in surgical durations. Recently, Turner et al. (2013) discuss how operations research was used to improve the education and training of surgical trainees at the Northwestern University Feinberg School of Medicine. Cardoen et al. (2013, p. 142) note in their detailed review of the surgical scheduling literature that "even if implementation of research can be assumed, authors hardly provide details on the process of implementation." A major missing piece, the paper notes, are "the behavioral factors that coincide with the actual implementation" (p. 142). Furthermore, it notes that "identifying the causes of failure or the reasons that lead to success, may be of great value to the research community" (p. 143). We attempt to fill this crucial gap in surgical scheduling research.

2.3. Contributions

In summary, our paper contributes to the literature in multiple ways. The suggested approach is applicable to any institution with surgical specialties that have long and variable durations, such as spine, cardiothoracic, neurosurgery, and plastic surgery. The classification of surgeries based on time required for surgery using clinical information known at the time of case scheduling is also unique and can be applicable to other surgical areas. We consider various aspects of surgery scheduling such as costs of the downstream hospital stay, payer type, and DOW effects. These are questions surgical specialties in all large academic medical centers have to grapple with. The specific details may differ. For example, the idea of surgical days and consultation days (which in Mayo results in the blue–orange system) may exhibit a different pattern; or the teaching responsibilities, which result in late start surgery days, may occur differently; or the payer mix may follow a different proportion. This is why we have kept the formulations and indices as general as possible.

Finally, by creating a scheduling interface based on our optimization models, implementing it in a pilot, and measuring the outcomes of the implementation, this research provides a template that other institutions could adapt based on their own specific requirements. The combination of objectives and constraints considered in our models, supported by an actual pre/post implementation and test and control group comparison, and a discussion of the lessons learned from the pilot implementation, sets the paper apart from other purely modeling-based efforts in the literature.

3. Optimization Models

As described in §1.2, we follow a hierarchical optimization approach; if all stages are considered together as an integrated model, tractability becomes an issue. The interactions between different stages is visualized in Figure 1. The first stage decides on the optimal patient case mix in a time horizon to maximize a weighted function of utilization and estimated profitability (via NOI). With this optimal surgery mix as input, the second stage allocates cases to specific

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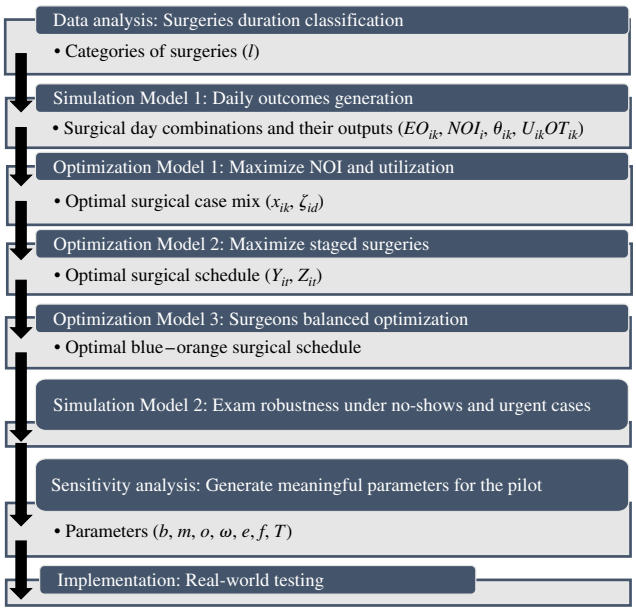
Figure 1 **(Color online) Research Approach**



days in the time horizon, while ensuring that multiple surgeries performed on the same patient can be carried out within a few days. The third stage determines which exact days the surgeons will work and the specific surgical combinations they will perform.

Before describing the three stages, we define indices and parameters used in the model. The index l refers to surgery category. Surgeries are statistically categorized based on the length of their durations. In our case study, there are 10 surgical categories ($l = 1..10$). The index r indicates payer type: "1" for government (G), in our case typically Medicare; and "2" for private (P).

The index i refers to a surgical combination. A surgical combination is a set of surgeries, and each surgery in the set is defined by: (a) the category it belongs to, and (b) the payer or insurance type. For example, $(1P, 6G)$ is a two-surgery combination: the first is a surgery from category 1 with a private payer; and the second is a surgery from category 6 with a government payer. Other examples of surgical combinations are as follows: $(4P)$, a combination that contains only one privately insured category 4 surgery; and $(3G, 3G)$, a combination that contains two government insured category 3 surgeries.

Because spine surgery durations are long, we need to consider only combinations involving one or two surgeries for a given day. By linking surgery categories and payer type we get a finite number of feasible surgical combinations, which are indexed by i. The operational consequences of scheduling a particular combination on a surgical day are precalculated by simulation. For example, the combination $(1P, 6G)$ scheduled on a particular day will result in a certain amount of average operating room utilization, create some probability of overtime, and produce a certain average NOI. These parameters become inputs to the first stage of the optimization model.

In the formulations, the parameter M_{ilr} denotes the number of category l surgeries insured by payer type r in combination i. For the combination $i = (1P, 6G)$, $l = 1$, and $r = P$, the value M_{ilr} will be equal to 1. For the combination $i = (3G, 3G)$, $l = 3$ and $r = G$, the value M_{ilr} will be equal to 2; for the same combination, if $l = 3$ and $r = P$, M_{ilr} will be equal to 0 since there are no privately paid category 3 surgeries in the combination. We use M_{ilr} in constraints relevant to the number of surgeries in each category and the number of Medicare surgeries.

Additionally, we note that there are three sets of indices for days in the formulation: k, d, and t. Each index serves a unique function. Index k represents whether a particular weekday is a late or a regular start day. Late starts happen because of teaching responsibilities on specific weekdays, which influences overtime and utilization if a certain surgical combination i is scheduled on a late start day. DOW (M, T, W, T, F), which is important for scheduling Medicare surgeries is represented with d. In our formulations, we impose that Medicare surgeries are scheduled on specific days of the week, since this minimizes downstream LOS costs by reducing unnecessary weekend stays. The DOW also helps differentiating hospital-specific dynamics such as blue–orange surgical days (described in §1.1). Parameter D_{kd}, connects the DOW index d with the start of the day indices, k in the formulation. Finally, the index $t = 1, 2, \ldots, T$ is for days in the time horizon (in our case study, 120 days), which is required to schedule the surgeries to specific days in the rolling horizon.

3.1. First Stage: Maximizing Utilization and Net Operating Income

The main decision variable in this stage is the total number of surgical combinations of type i to be performed on day type k in a time horizon consisting of T days. The decision variable thus gives us the case mix for the time horizon. The objective is to maximize a weighted combination of normalized NOI and utilization with Equation (1). This is constrained by: (a) number of surgeries from each category (minimum and maximum limits determined by the practice); (b) minimum number of Medicare surgeries; (c) overtime limit; (d) available number of operating rooms; and (e) DOW in which Medicare surgeries can be performed. Recall that average NOI, average operating room utilization, and probability of overflow for each surgical combination performed on a particular day are precalculated via simulation, and serve as an

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input to this optimization model. The formulation is as follows.

Indices

$l(1,\ldots,L)$: Surgery category index

$r(1,\ldots,R)$: Payer index (where 1 is for Medicare or government; and 2 is for non-Medicare or privately insured patients)

$i(1,\ldots,I)$: Combination of surgeries.

$k(1,\ldots,K)$: OR-weekday category (where 1 means a regular weekday; and 2 is a late start day)

$d(1,\ldots,5)$: DOW (Monday, Tuesday, Wednesday, Thursday, and Friday)

$w(0,1,\ldots,W-1)$: Where W is the number of weeks in the time horizon

$t(1,\ldots,T)$: Days in the planning horizon

Parameters Obtained from the Simulation

OT_{ik}: Simulation derived parameter representing the average probability of finishing after the EOD (5 P.M.) when surgery combination i is performed on day group k.

EO_{ik}: Simulation derived parameter for average overtime after EOD (5 P.M.) when the surgery combination i is performed on day group k.

θ_{ik}: Simulation derived parameter for the average overtime probability after 11 P.M. for surgery combination i on day group k. (Variable costs start to be incurred after 11 P.M. because of the shift change.)

U_{ik}: Simulation derived parameter for the average OR utilization for surgery combination i on day group k.

NOI_i: Simulation based average NOI for surgery combination i. NOI is a measure of the projected revenue less operating and fixed allocated costs.

Parameters Determined by the Practice

o: Practice imposed limit on the proportion of overtime after 5 P.M.

e: Practice imposed limit on the expected overtime after 5 P.M.

f: Practice imposed limit on the percentage of overtime after 11 P.M.

b: The case-mix bound width represented as a fraction between 0 and 1 (i.e., allowed flexibility in changing the case mix).

m: Minimum percentage of Medicare surgeries to be performed.

P_l: Average number of surgeries from surgical category l, calculated per OR room.

T: Number of working days in the planning horizon.

J_t: The open number of ORs on day t.

ω: Weight assigned to utilization in the objective function (i.e., relative importance of utilization in comparison to NOI).

Parameters that Link Indices

F_{ld}: Binary parameter with a value of 1 if DOW d is the best surgical day for category l Medicare patients; 0 otherwise. $\sum_d F_{ld}=1$ and F_{ld} binary $\forall\, l, d$.

D_{kd}: Binary parameter with a value of 1 if DOW d is a type k day (i.e., if it is a regular start or late start day); 0 otherwise. $\sum_k D_{kd}=1\ \forall\, d$ and D_{kd} binary $\forall\, k, d$.

M_{ilr}: The number of category l surgeries in each surgical combination i with payer r.

Decision Variables

x_{ik}: Total number of surgery combinations of type i performed on day group k over the time horizon T.

ζ_{ld}: Output variable representing the number of Medicare surgeries from surgical category l scheduled on DOW d.

First-Stage Model

$$\max\left\{\omega\cdot\sum_k\sum_i U_{ik}\cdot x_{ik}+(1-\omega)\cdot\sum_k\sum_i \mathrm{NOI}_i\cdot x_{ik}\right\} \tag{1}$$

$$\text{s.t}\ \sum_t P_l\cdot(1-b)\cdot J_t \le \sum_k\sum_i\sum_r M_{ilr}\cdot x_{ik} \le \sum_t P_l\cdot(1+b)\cdot J_t,\quad \forall\, l, \tag{2}$$

$$\sum_k\sum_i x_{ik}\cdot M_{il1} \ge \sum_i\sum_k\sum_r x_{ik}\cdot M_{ilr}\cdot m,\quad \forall\, l, \tag{3}$$

$$\sum_k\sum_i x_{ik}\cdot M_{il1} \le \sum_t P_l\cdot(1+b)\cdot J_t\cdot m,\quad \forall\, l, \tag{4}$$

$$\sum_i\sum_k \frac{\mathrm{OT}_{ik}\cdot x_{ik}}{\sum_t J_t} \le o, \tag{5}$$

$$\sum_i\sum_k \frac{\mathrm{EO}_{ik}\cdot x_{ik}}{\sum_t J_t} \le e, \tag{6}$$

$$\sum_i\sum_k \frac{\theta_{ik}\cdot x_{ik}}{\sum_t J_t} \le f, \tag{7}$$

$$\sum_i\sum_k D_{kd}\cdot x_{ik} = \sum_w J_{5\cdot w+d},\quad \forall\, d, \tag{8}$$

$$\zeta_{ld} = \sum_i\sum_k x_{ik}\cdot M_{il1}\cdot F_{ld}\cdot D_{kd},\quad \forall\, l, d, \tag{9}$$

$$\sum_i\sum_k x_{ik}\cdot D_{kd}\cdot M_{il1} \le B\cdot F_{ld},\quad \forall\, l, d, \tag{10}$$

$$x_{ik}\in\mathbb{Z}_{\ge 0},\quad \forall\, i, k. \tag{11}$$

There are four main groups of constraints in this stage: case-mix and payer-mix calculations (Equations (2)–(4)), overtime restrictions (Equations (5)–(7)),

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open OR restrictions (Equation (8)), and DOW restrictions for Medicare surgeries to minimize the number of weekend discharges (Equations (9)–(10)). We explain these in more detail below.

To build a realistic model, the surgical schedule needs to create a surgical case mix that is similar to observed levels in the current practice. Thus, Equation (2) ensures that number of patients from surgical categories $(1, \ldots, L)$ deviates from the current case mix within a prespecified bound width, b. Medicare surgeries are enforced to constitute at least $m\%$ of the overall number of surgeries with Equation (3). Sum of Medicare patients from each surgical category is within the $\pm m\%$ range of the empirically observed number of these patients (Equation (4)).

The percentage of overtime (after 5 P.M.) is enforced to be less than the overtime limit based on the clinic's threshold, "o" (Equation (5)). Expected hours of overtime after 5 P.M. is kept less than the observed average overtime hours, "e" (Equation (7)). Similarly, the proportion of days with overtime after 11 P.M. is forced to be less than the historical average, "f" (Equation (6)).

Equation (8) ensures that the total number of surgeries that will be performed on each DOW d in the horizon must be equal to the total number of operating rooms available on such weekdays in the horizon.

In Equation (9), ζ_{ld} represents the number of Medicare surgeries from category l scheduled on DOW d, that is the product of the binary variable that indicates the best day to perform category l Medicare surgery and the sum of all Medicare surgeries for that specific surgery category. With Equation (10), Medicare patients are assigned to their best day of surgery, based on their category so that the Medicare weekend stay is minimized. This has financial impact, which will be discussed later in the case study.

3.2. Second Stage: Maximizing Multiple Days Staged Surgeries

In the first stage the surgery combinations are not yet tied to a specific day t in the time horizon consisting of T days. The second stage assigns surgery combinations to each day t in the horizon, while meeting constraints imposed by the first-stage outputs. Note that this stage has no impact on NOI or utilization, since they have already been optimized in the first stage.

The objective in the second stage is to maximize the ability of the spine practice to accommodate surgeries on the *same* patient conducted over multiple days. We call such surgeries on the same patient "multiple days staged surgeries" (MDSS). MDSS result when some of the very long surgeries are broken down into two or more surgeries with feasible durations by the surgeons. The components of surgeries need to be carried out within two to five days.

For example, a patient may need to undergo a category 6 surgery followed by a category 8 surgery within two days. This would be the MDSS pair 6_8, where MDSS are indexed with s. If t is the day of the first surgery on the patient, then this means that a combination containing surgery 6 must be scheduled on day t and a combination containing surgery 8 on day $t+2$. One of the ways this would be possible is if combination 1_6 is scheduled on day t and combination 1_8 is scheduled on day $t+2$; thus MDSS pair 6_8 spans two days. To ensure MDSS constraints are met in the formulation, we use a binary parameter δ_{ics} that takes on the value of 1 if for surgery combination $i =$ (1_6) contains one element of the MDSS pair $s =$ (6_8) in cth position; for this example if $c = 1$, $\delta_{ics} = 0$, but if $c = 2$, $\delta_{ics} = 1$.

Indices

- $i(1, \ldots, I)$: Combination of surgeries
- $s(1, \ldots, S)$: MDSS pair index
- $c(1, \ldots, C)$: Position in the sequence in which the MDSS pair is performed
- $w(0, \ldots, W-1)$: Weeks in the planning horizon

Parameters

- ζ_{ld}: Number of Medicare surgeries from surgery category l scheduled on DOW d. (Derived from the first stage.)
- β_s: Weight of MDSS pair s in the objective function, based on the empirically observed proportion of pair s.
- α: Coefficient for balancing the workload over the weekdays.
- δ_{ics}: Binary parameter that takes on the value 1, if surgery combination i contains one element of the MDSS s in cth position; 0 otherwise.

Decision Variables

- Y_{it}: Integer decision variable representing the number of surgery combination i's performed on day t as a part of MDSS pair.
- Z_{it}: Integer decision variable denoting the number of surgery combination i's performed on day t not as a part of MDSS (rather as a single stand-alone surgery combination).
- L_{ts}: Integer decision variable denoting the number of surgeries on day t performed as the first component of the MDSS pair s.
- Q_{id}: Number of surgery combination i's to be performed on DOW d.

Second-Stage Model

$$\max \sum_t \sum_s (\beta_s \cdot L_{ts}) \tag{12}$$

$$\text{s.t} \sum_d Q_{id} D_{kd} = x_{ik}, \quad \forall i, k, \tag{13}$$

$$\sum_w (Y_{i(5w+d)} + Z_{i(5w+d)}) = Q_{id}, \quad \forall i, d, \tag{14}$$

$$\sum_i Q_{id} \cdot M_{il1} = \zeta_{ld}, \quad \forall l, d, \tag{15}$$

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$$\sum_i (Y_{it} + Z_{it}) = J_t, \quad \forall t, \tag{16}$$

$$L_{ts} \le \sum_i \delta_{i1s} \cdot Y_{it}, \quad \forall t, s, \tag{17}$$

$$L_{ts} \le \sum_i \delta_{i2s} \cdot Y_{i(t+2)}, \quad \forall t, s, \tag{18}$$

$$\sum_w \sum_s L_{(5w+d)s} \ge 5\alpha \sum_t \sum_s L_{ts}, \quad \forall d, \tag{19}$$

$$Y_{it}, Z_{it} \in \mathbb{Z}_{\ge 0}, \quad \forall i, t, \tag{20}$$

$$L_{ts} \in \mathbb{Z}_{\ge 0}, \quad \forall t, s, \tag{21}$$

$$Q_{id} \in \mathbb{Z}_{\ge 0}, \quad \forall i, d. \tag{22}$$

The objective function maximizes the weighted sum of MDSS performed (Equation (12)). Detailed analysis is presented in §4.1.2.

Constraints. Equation (13) links the first-stage output (the optimal surgery case mix), to the second-stage decision variable (number of surgeries scheduled from each surgery category on specific days of week). Equation (14) ensures that number of combination i surgeries performed on each DOW matches with the first-stage results, via the Q_{id} decision variable. Next, Equation (15) enforces that the Medicare surgeries are performed on the right DOW.

There can be at most J_t number of combinations scheduled each day (Equation (16)); recall that J_t is the number of open/available operating rooms on day t. Equations (17) and (18) ensure that for a MDSS pair s to take place, the second surgery of MDSS pair needs to be arranged within two working days after the first surgery. Equation (19) spreads MDSS evenly over the workdays, using a lower bound α. This ensures that not all of the MDSS pairs, which place significant burden on the surgical team, are performed on the same days of the week.

3.3. Third Stage: Determining Surgeon Schedules

At the end of the second stage, surgical combinations have been assigned to specific days in the time horizon. In this last stage, each surgeon in the practice is assigned the exact days when they will operate and the surgical combinations they will perform. In our pilot implementation, we only had two spine surgeons with predetermined alternating schedules (the blue–orange alternating template discussed earlier). Since spine surgeries tend to be long and variable, an operating room is dedicated to each surgeon on each day that he/she operates. Thus the two surgeons create an alternating schedule that covers surgical cases assigned to each each day in the horizon. See Table 3 in §4.3.3 for an example. Other hospitals may have more surgeons in the practice and greater flexibility in assigning surgical days to cover their cases during a horizon. This in itself is an optimization question. For such a general case, we provide a formulation to balance the workload across surgeons for different surgery types and payer mix.

Only the additional relevant indices are described here. The main decision variable ϕ_{hit} is a binary variable denoting if surgeon h performs combination i on day t (1 if yes, 0 otherwise). The objective is to balance the workload between the surgeons so that the absolute difference in the surgery categories and payer types performed by surgeons relative to the practice average is minimized.

Indices

$h(1, \ldots, H)$: Surgeon index

Decision Variables

ϕ_{hit}: Binary decision variable denoting if surgeon h performs combination i on day t.

τ_{lhr}: Absolute difference in workload for surgeon h, from the average number of category l surgeries scheduled over the planning horizon with payer r.

W_{lhr}: Number of category l surgeries with payer r scheduled for surgeon h over all weeks.

Third-Stage Model

$$\min \sum_l \sum_h \sum_r \tau_{lhr} \tag{23}$$

$$\text{s.t} \quad W_{lhr} = \sum_t \sum_i \phi_{hit} M_{ilr}, \quad \forall h, l, r, \tag{24}$$

$$\tau_{lhr} \ge W_{lhr} - \frac{\sum_{h'=1}^{H} W_{lh'r}}{H}, \quad \forall l, h, r, \tag{25}$$

$$\tau_{lhr} \ge \frac{\sum_{h'=1}^{H} W_{lh'r}}{H} - W_{lhr}, \quad \forall l, h, r, \tag{26}$$

$$\sum_h \phi_{hit} = Y_{it} + Z_{it}, \quad \forall i, t, \tag{27}$$

$$\sum_i \phi_{hit} \le 1, \quad \forall h, t, \tag{28}$$

$$\phi_{hit} \in 0, 1, \quad \forall h, i, t, \tag{29}$$

$$\tau_{lhr} \ge 0, \quad \forall l, h, r, \tag{30}$$

$$W_{lhr} \in \mathbb{Z}_{\ge 0}, \quad \forall l, h, r. \tag{31}$$

Constraints. Each surgeon's workload over the planning horizon is calculated using Equation (24). τ_{lhr} is calculated as the absolute difference between the workload of each surgeon and the average number of surgeries from each surgical category, in a linear fashion with Equations (25) and (26). Equation (28) ensures that combinations scheduled on a particular day t are covered by the surgeons in the practice. Equation (29) ensures that each surgeon has at most one combination scheduled on a particular day t. This constraint can be relaxed for specialties where a surgeon may perform more than one case per day.

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4. Case Study

The optimization model was developed and evaluated based on the operations and data from the orthopedic spine practice at Mayo Clinic, Rochester, MN. Model development and evaluation occurred over much of 2012 with a live implementation target set as December 2012. We have set the planning horizon T to 120 days, with a surgical day length of 10 hours. This is a sufficiently large horizon to represent all the surgery categories, including those that are sparsely observed. We consider two types of surgical days: regular and late start days. The latter occurs on Mondays to allow for teaching seminar, resulting in reduction of the surgery day by one hour. As discussed in §1.1, we follow the "blue and orange" system.

4.1. Data and Model Assumptions

Spine surgery related data involves two primary OR rooms with five surgeons performing more than 2,500 surgeries over seven years from 2005 to 2011. Data available include patient-related (age, gender, geographical location, ASA scores of patient physical condition before surgery, initial diagnosis (ICD9 code), and LOS), surgery-related (surgeon name, OR room, long description of the surgery provided by the surgeons, surgery durations broken down into OR enter to incision time, incision to closure time, and closure time to OR exit time), and financial information (procedures performed, cost and revenue for each case) at a very detailed level.

Some of the baseline characteristics of the data set are as follows: average patient age was 57.6, with 45% female patients. Hospital LOS is on average 5.9 days with a standard deviation of 6.5 days. The average OR enter to incision time is 1.5 hours with a standard deviation of 0.4, the average incision to closure time is 4.6 hours with a standard deviation of 2.5 hours. The average closure to OR exit time is 0.5 hours with a standard deviation of 0.3 hours.

4.1.1. Surgery Type. We classified the entire patient population into 10 surgery categories using Classification and Regression Tree (CART) analysis in JMP (version 9.01, SAS Institute, 2010). This data mining analysis enabled us to accurately predict how long each surgery will take and therefore better plan the surgery days. Table A.1 in the appendix illustrates the properties of the surgical categories generated as a result of this analysis. The clinical characteristics used in this categorization is also explained in the appendix.

Figure 2 shows the cumulative distributions for the surgical categories and highlights the difference between the categories. For example, surgeries from category 1 always take less than four hours to complete, although on average only 50% of all cases take less than four hours to complete.

4.1.2. MDSS Patients. As explained previously, some of the very long surgeries are split on individual patients into two or more procedures with feasible durations. Such surgeries constitute 10% of the all surgeries and need to be performed within a certain number of days (ideally in two days).

Whether a patient will be undergoing a MDSS or not depends on the ASA scores, anatomical location, surgical approach, and other factors. We also analyzed which surgical categories are generally divided into multiple segments. Table A.2 in the appendix summarizes the most commonly observed MDSS pairs. For instance, a surgery category 6 followed by an 8 constitutes the biggest percentage. These percentages are

Figure 2 Cumulative Distribution of the Surgery Time by Each Patient Category

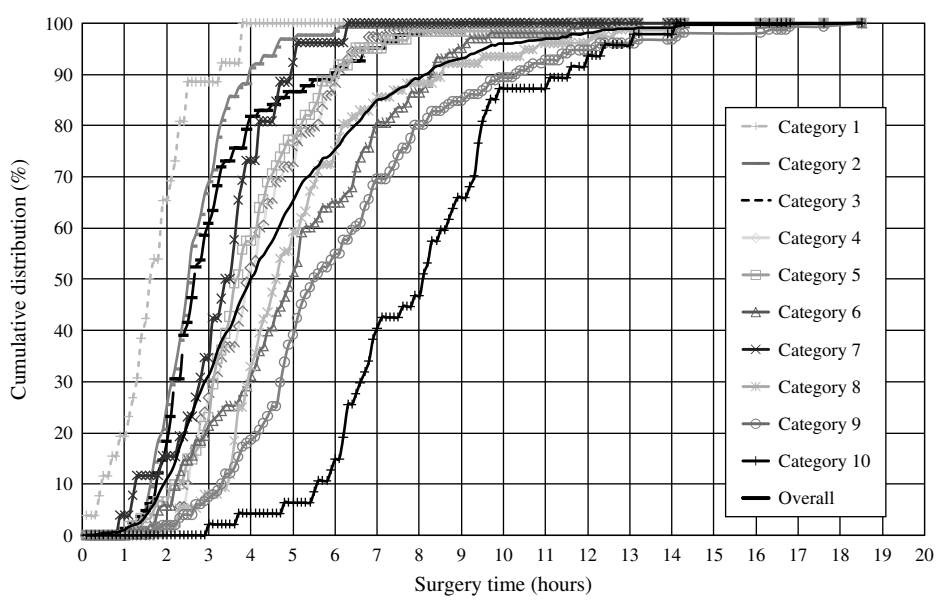

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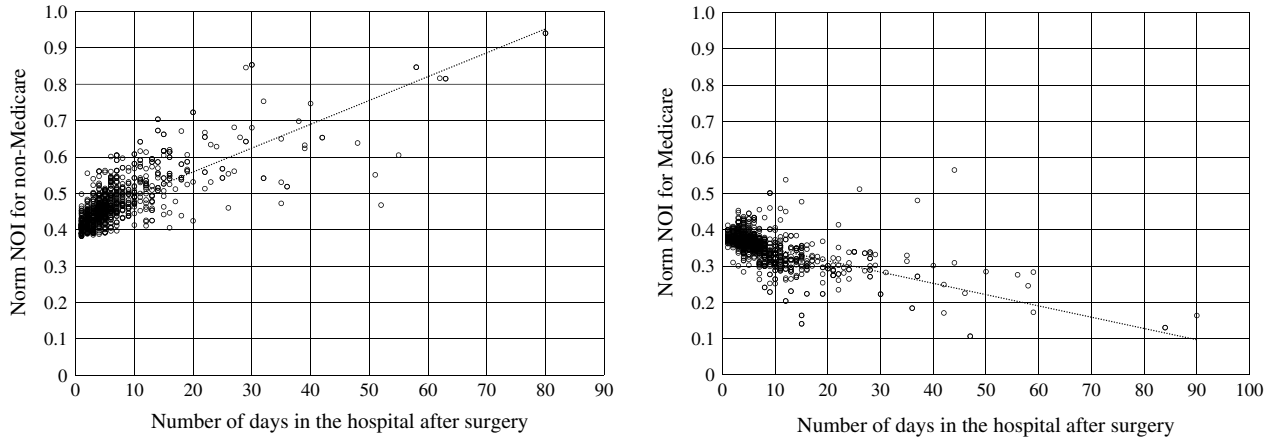
Figure 3 **Relationship Between NOI and LOS for Medicare and Non-Medicare Patients**



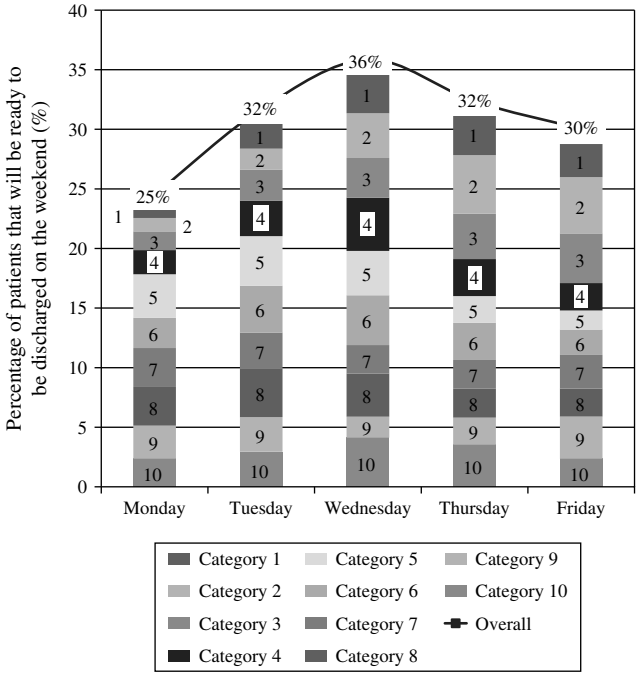
then used as weights in the objective function of the second stage (β_s).

4.1.3. Financial Analysis and LOS. Our financial analysis is based on the reported NOI values. Data mining was used to derive the cost drivers for the clinic. NOI values are driven by the LOS of the patients, i.e., the hospitalization period in an inpatient unit post surgery. As well as the LOS, the characteristics of surgery like the equipment used (such as microscope and CT scanner), fusion and number of vertebrae segments are an important predictor of NOI (see the appendix for terminology).

We performed the analysis for Medicare and non-Medicare patients separately, because of the difference in reimbursement policies (Figure 3). Regardless of their hospitalization period, Medicare patients only get reimbursed for four days and the hospital almost always loses money for Medicare surgeries. However, for non-Medicare patients, the hospital is reimbursed based on the number of hospitalization days. Thus, as seen in Figure 3 as the LOS increases for non-Medicare patients so does the NOI. However, the opposite is true for Medicare patients. Only some of the patients with small LOS indicate a potential gain, the majority of patients result in loss of NOI. In performing this analysis, we only considered first surgeries of the day, to ensure that the effect of overtime costs are discarded.

Since Medicare patients often require discharge to aSNF that does not accept patients on weekends, it was important to schedule surgeries to avoid unnecessary weekend stays in the hospital. We calculated LOS in base 7 to analyze their discharge day of the week after the surgery. For example, a LOS value of 8 was equal to 1, meaning the discharge happened on the following DOW of the surgery. Figure 4 represents the percentage of weekend overflow (patients who are ready to be discharged on the weekend) if they have their surgery on that DOW. This shows

Figure 4 **The Percentage of Weekend Overflow by Each Patient Category and Surgery DOW**



that Mondays and Fridays are generally the best days to schedule surgeries, when it is important to avoid unnecessary weekend stays. However, this is not true for all surgery categories. In particular, some of the more complex surgeries were better to schedule in mid-week because of specific LOS distributions.

We integrate the optimal day of Medicare surgeries into the first part of our optimization model using the F_{ld} parameter, to minimize the weekend overflows in the optimal solution. Using the results of the data analysis, this binary parameter takes on a value of 1 if the best DOW to perform category l Medicare surgery is d and 0 otherwise.

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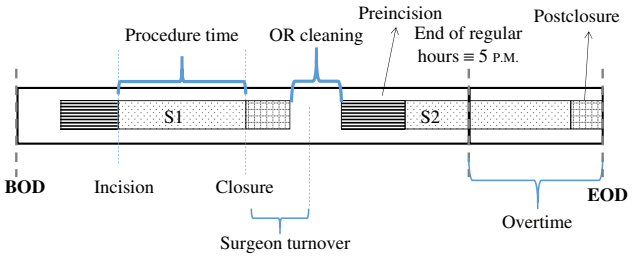
4.2. Simulation for Scenario Generation

4.2.1. Surgery Steps and Times. Similar to Batun et al. (2011) we divide the surgery durations into three components: preincision, incision to closure, and postclosure activities. Preincision time involves preparing the patient for surgery, incision to closure time is the actual procedure time, and the postclosure is required to close up the incision and prepare the patient for recovery. Surgeons only need to be present in the OR for incision to closure; the other activities can be performed by other surgical staff.

In addition to the preincision, incision to closure, and postclosure time, we analyzed the surgeon turnover, OR cleaning, and beginning of day (BOD) time distributions as well (see Figure 5). Table 1 summarizes the best theoretical distribution fit for the empirical data. The lognormal function typically fits the best and is commonly used in the literature to represent similar highly variable procedure times (Spangler et al. 2004, Choi and Wilhelm 2012). However, in our research we have chosen to use the empirical distributions and not theoretical distributions.

The simulation used data for the time distributions of the 10 surgery categories. The distributions are derived for: BOD, preincision, incision to closure, postclosure, surgeon turnover, and OR cleaning for the 10 categories.

Figure 5 (Color online) Stages in OR Time



4.2.2. Inputs to the Optimization Model. Table 2 illustrates the simulation-based outputs for a sample of surgery combinations. These outputs in turn become inputs to the first-stage optimization. The measures of interest are overtime percentage after 5 P.M. and 11 P.M., expected hours of overtime after 5 P.M., OR utilization, and normalized NOI for Medicare and non-Medicare surgeries. The values in the parentheses represent the Monday outputs, as Mondays have different outcomes as a result of late starts.

Table 1 Distributions for the Relevant Durations

	25% quartile	Median	75% quartile	Mean	Std. dev.	Best fit
BOD (hrs)	8:18 (8:34)	8:22 (8:40)	8:28 (8:51)	8:27 (8:52)	0:22 (0:41)	Normal 2 mixture
OR enter to incision (hrs)	1.1	1.4	1.7	1.4	0.47	Johnson Su
Incision to closure (hrs)	2.2	3.7	5.7	4.2	2.77	Weibull
Closure to OR exit (hrs)	0.3	0.45	0.6	0.5	0.29	Johnson Su
OR turnover time (mins)	37	44	55	48.5	18.3	Normal 2
Surgeon turnover time (hrs)	2.4	2.3	2.7	2.1	0.6	Johnson Su

Note. The values in parentheses represent the Monday outputs.

Table 2 Simulation Inputs to the Optimization Model

Combination	Duration	EOD	% OT after 5 P.M.	Hours after 5 P.M.	% OT after 11 P.M.	Utilization	NNOI for Medicare (%)	NNOI for non-Medicare (%)
1	3.99	10:18 A.M.	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	21.6 (31.6)	22	41
2	4.71	12:18 P.M.	0.9 (1.2)	0.0 (0.1)	0.1 (0.4)	40.7 (50.9)	25	38
5	5.79	2:54 P.M.	16.2 (29.8)	0.2 (0.4)	0.0 (0.1)	67.1 (76.5)	22	45
3	5.88	1:24 P.M.	1.7 (4.4)	0.1 (0.1)	0.0 (0.2)	52.8 (62.8)	23	42
8	6.22	4:00 P.M.	23.8 (37.5)	0.7 (0.9)	3.9 (3.6)	74.6 (83.1)	19	65
7	6.47	4:06 P.M.	34.6 (44.3)	0.7 (1.0)	0.9 (1.8)	76.1 (82.3)	6	87
6	6.71	2:42 P.M.	12.1 (16.8)	0.3 (0.4)	2.0 (1.6)	64.0 (73.0)	20	56
4	7.00	1:30 P.M.	5.2 (9.6)	0.1 (0.1)	0.0 (0.1)	53.9 (63.3)	20	48
9	8.14	6:06 P.M.	59.1 (74.4)	1.6 (2.2)	7.8 (8.8)	89.0 (94.0)	10	77
1_1	8.51	2:18 P.M.	5.2 (14.0)	2.2 (1.5)	0.1 (0.6)	68.9 (78.4)	16	54
2_1	9.17	4:12 P.M.	18.6 (68.0)	2.0 (1.6)	1.7 (2.1)	85.5 (94.5)	19	51
2_2	10.04	6:06 P.M.	61.4 (96.8)	2.0 (2.8)	4.0 (4.9)	96.6 (99.6)	22	47
1_5	10.19	6:48 P.M.	70.4 (94.0)	2.8 (3.4)	5.6 (14.6)	96.1 (98.8)	16	58
1_3	10.22	5:24 P.M.	42.9 (90.7)	1.8 (2.2)	2.6 (3.1)	93.5 (98.7)	17	55
10	10.24	6:30 P.M.	66.6 (76.9)	2.0 (2.5)	2.1 (6.3)	90.9 (94.5)	13	75
1_7	10.88	8:18 P.M.	86.7 (99.2)	4.1 (4.3)	21.3 (18.2)	98.3 (99.9)	0	100
1_8	10.90	7:54 P.M.	84.0 (94.9)	3.5 (4.1)	13.7 (16.7)	98.3 (99.3)	13	78
1_6	10.98	6:42 P.M.	66.3 (97.6)	2.7 (3.5)	7.5 (13.3)	96.9 (99.7)	14	69
1_4	11.34	5:24 P.M.	43.4 (80.5)	2.2 (2.9)	3.3 (5.3)	91.1 (96.6)	13	61
2_4	12.31	7:30 P.M.	81.7 (97.8)	3.2 (3.6)	10.8 (14.0)	98.4 (99.7)	16	58

Note. The values in parentheses represent the Monday outputs and NNOI stands for normalized net operating income.

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Note that sequencing does not play a role in our models. A category 1 surgery followed by a category 2 surgery performed in the same OR will produce identical results compared to a category 2 surgery performed after a category 1 surgery in the same operating room. Certain combinations result in 100% overtime and were therefore infeasible; this left us with 55 feasible combinations. We compared the empirical EOD collected over seven years with the results of the simulation model. The simulation model accurately predicts the EOD values of the empirical distribution, with 95% confidence.

4.3. Example Optimization Results

The outputs of the simulation model were used to test and evaluate the optimization model. In addition, the optimization model was explored to consider tradeoffs and relationships among utilization levels, financial performance, overtime allowance, and case mix.

4.3.1. First-Stage Optimization. An example of the optimal surgery mix for a 120 day horizon can be observed in Figure 6. The figure displays the optimal number of surgeries from each combination (y-axis) performed on different day groups. The shorter surgeries (which are the lower numbered categories) are performed on Mondays. Fridays are heavily loaded with longer Medicare procedures. This results from late start Mondays and to prevent excessive overtime, long Medicare surgeries are left to Fridays, leading to greater burden. Note that for profitability reasons, Medicare surgeries are generally best scheduled on Mondays and Fridays, however this is not true for all surgery types.

4.3.2. Second-Stage Optimization. The second stage creates the optimal 12 week schedule with the focus on maximizing the availability for MDSS. The schedule assigns more priority to surgeries that have a greater empirically observed percentage (Table A.2 in the appendix). The schedule repeats itself every 12 weeks.

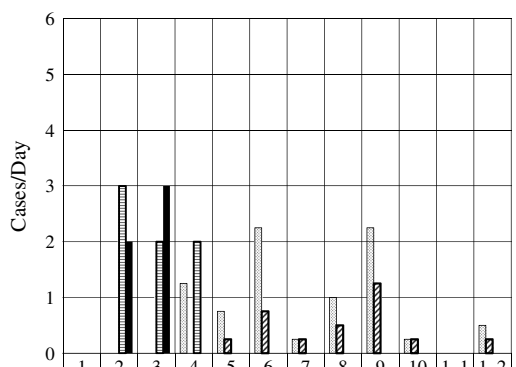
4.3.3. Third-Stage Optimization. Table 3 is an illustration of the final output of the optimization model, for one set of parameter values. Values in each cell indicate the surgical combination assigned to that day. This specific schedule is created so that it follows the blue–orange schedule template of Mayo Clinic. This stage ensures there is a balanced workload between the blue and orange surgeons.

4.3.4. Simulation for Testing Robustness. Even though most of the spine surgeries are scheduled in advance, there are also some urgent cases. Six percent of the patients present infections, which need to be operated quickly (within 24 hours). These surgeries generally result in overtime, because infection patients need to be operated as the last surgery of the day to prevent the spread of infections. These urgent cases typically take much shorter than regular surgeries (with an average length of 2 hours). Also, anecdotally 5% of the time last minute cancellations happen when the insurance company declines the surgery or when the health of the patient deteriorates.

We developed a second simulation model to test the impact of unplanned surgeries (infections) and cancellations. We analyzed the impact of these on EOD when utilizing the optimal schedule. We conclude that the simulation models and the results of our optimization model are robust and are not statistically different when compared with a year's worth of data (with a confidence interval of 99%).

4.3.5. Sensitivity Analysis. We performed sensitivity analysis to test the impact of parameters and

Figure 6 Optimal Surgery Mix



	1	2	3	4	5	6	7	8	9	10	1_1	1_2
Tue-Fri non-Med all	0	0	0	1.25	0.75	2.25	0.25	1	2.25	0.25	0	0.5
Fri Med all	0	0	0	0	0.25	0.75	0.25	0.5	1.25	0.25	0	0.25
Mon Med all	0	3	2	2	0	0	0	0	0	0	0	0
Mon non-Med all	0	2	3	0	0	0	0	0	0	0	0	0

Table 3 (Color online) Optimal 12-Week Alternating Blue–Orange Schedule for Two Surgeons

Week number	Type of week	Monday	Tuesday	Wednesday	Thursday	Friday
W01	Blue week	**2**	9	**9**	6	**7**
W02	Orange week	3	**5**	8	**2_1**	6
W03	Blue week	**3**	6	**4**	9	**6**
W04	Orange week	2	**9**	2_1	**6**	2_1
W05	Blue week	**2**	5	**4**	8	**6**
W06	Orange week	4	**9**	4	**9**	10
W07	Blue week	**2**	8	**8**	4	**6**
W08	Orange week	3	**10**	7	**5**	9
W09	Blue week	**4**	6	**9**	9	**8**
W10	Orange week	2	**6**	9	**9**	6
W11	Blue week	**3**	9	**9**	4	**5**
W12	Orange week	3	**6**	9	**8**	6

Note. The numbers indicate the surgical combination recommended on each day. Numbers in bold indicate the combinations for the first surgeon while numbers not in bold indicate combinations for the second surgeon.

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constraints, including the weight assigned to utilization in the objective function, case-mix bound width, limit on overtime, and length of the planning horizon. We analyzed the impact on optimal case mix, NOI, expected overtime, total number of surgeries, and utilization, using a multivariate analysis. Since planning horizon did not have a statistically significant impact on any of the output measures, we focused on bound width, overtime limit, and weight assigned to utilization.

To understand the trade-off between NOI and utilization, we generated an efficient frontier (as can be seen in Figure A.1 in the appendix). We altered the weights assigned to these two output measures for different boundwidths and overtime limits. This analysis points to potential gains with the same OR utilization, but with a different patient mix. The initial flat line in the curve shows the potential gain in NOI without sacrificing from utilization. The underlying reason is that the surgeries that are creating high utilization levels do not necessarily result in higher revenue (like long Medicare surgeries).

This sensitivity analysis was used to set the parameter values used in the optimization model for the pilot study implementation. Some of the main parameter values used in the pilot are as follows: w (weight assigned to utilization) = 80%, o (overtime percentage after 5 P.M.) = 25%, e (number of hours past 5 P.M.) = 5 hours, f (percentage of days that end after 11 P.M.) = 5%, m (Medicare patient proportion) = 30%.

5. Implementation

The optimized scheduling approach was implemented via a custom designed Web-based application that partially integrates with Mayo Clinic's existing surgical planning systems. The application, Spine Surgery Scheduling Optimization (SSSO), provides visual cues to promote scheduling surgeries on the appropriate days identified by the optimization model. If a surgeon or their delegated scheduler needs to schedule a case on a "nonoptimal" day, the tool provides visual information as to the case load and the likelihood of going overtime. The application can be used on any office or tablet computer and is therefore easy to use in an interactive way with the patient. Figures 7–9 are screenshots from the Web-based application.

To evaluate the effectiveness of the optimization model and SSSO application, a pilot study was run from December 2012 to June 2013. Two of the four orthopedic spine surgeons participated in the study. It should be noted that other initiatives were going on at the same time as the pilot. In particular the orthopedic spine practice was working to increase case volumes and improve work processes related to on-time case starts and room turnover. Therefore, as in an intervention to an ongoing process, it is difficult to determine the precise benefit or cost of the implementation. In the following section we will describe the results of the pilot and how we attempted to account for process effects not due to SSSO.

5.1. Results of the Pilot Implementation

In evaluating the results, the first month of the pilot data was removed, because surgical cases during this period were primarily scheduled using the old approach. Figure 10 shows the results for the key performance measures during the evaluated pilot period. For all measures we eliminated empty days that were due to holidays, vacations, and on-call duties. For utilization, this was evaluated as the busy percentage of the prime time period of 7:30 A.M. to 5:00 P.M. Overtime is defined as the percentage of days that went over 5 P.M.

Figure 10 shows that, in general, the implementation of the SSSO system provided the desired results. Patient access and utilization were higher and overtime lower for the surgeons participating in the pilot, during the pilot period. In particular, it is interesting to note the significant increase in cases per day for the

Figure 7 (Color online) SSSO Screenshots

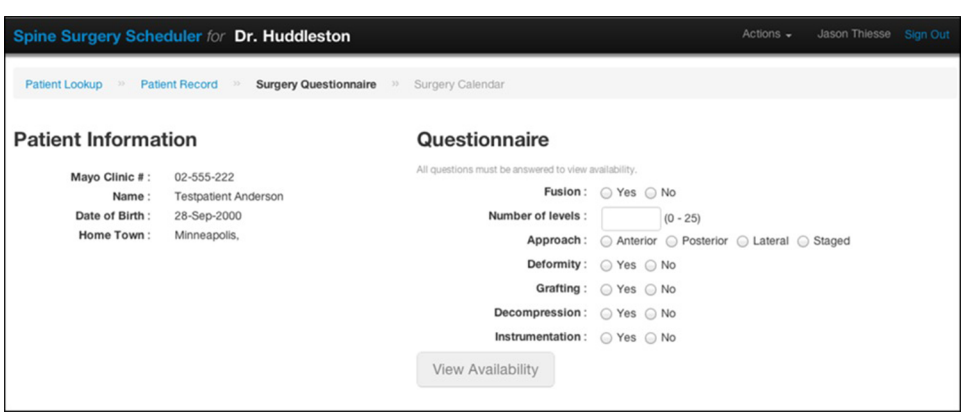

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Figure 8 (Color online) Question Screen to Categorize Surgical Case

Figure 9 (Color online) Initial Screen that Identifies Optimal Days

surgeons participating in the pilot. It is also important to note that this was not done by using more overtime.

Since it may be that the surgeons participating in the pilot had practices that performed better before the pilot, we also compared the pre- and postimplementation results for all surgeons in Table 3. It is gratifying to identify that the overall efforts of the practice to improve patient access were achieved because all surgeons increased their number of cases per day during the pilot evaluation period. The two surgeons participating in the SSSO pilot together increased their access by a higher percentage (30.1%) versus the nonparticipating surgeons (24.6%). The improvement in number of cases per day and utilization during the pilot period was statistically significant compared to the prepilot period for the SSSO group, whereas the improvement in the same two measures for the two surgeons that did not use the tool was not statistically significant. The increase in overtime was not statistically significant for the SSSO surgeons or for the non-SSSO group. We now discuss results specific to each surgeon.

In our study, as observed in Table 4, Surgeon 1 achieved the kind of results the optimization method was intended to return: an increase in cases per

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Figure 10 Comparison of Output Measures Evaluated During the Pilot

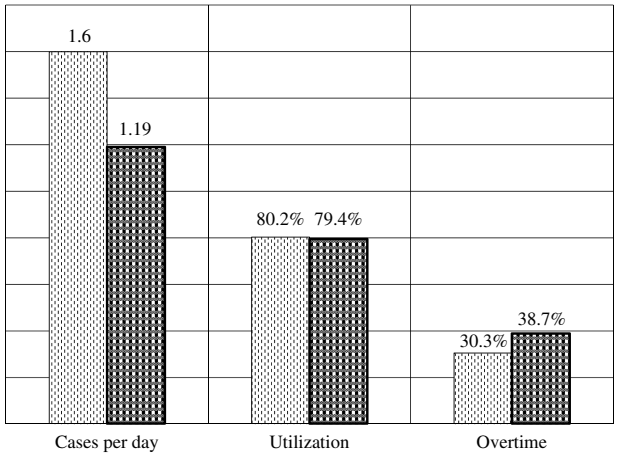
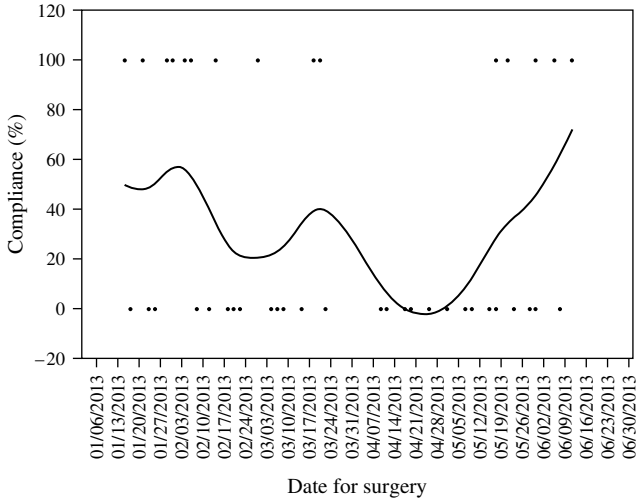


Figure 11 Compliance Rate of Surgeon 1



day, prime-time utilization, and a decrease in days going to overtime. However, only the increase in the number of cases per day was statistically significant. Surgeon 2, who was also involved in the pilot increased access and utilization, but also had a statistically significant increase in days with overtime. Thus, we would say that Surgeon 1 used a "working smarter" approach and Surgeon 2 a "working harder" approach. Surgeons 3 and 4 also increased their access and utilization, however, like Surgeon 2, they also increased their overtime. Working hard is, of course, commendable, but the continued strain on the surgeons and the surgical teams working in this mode may not be sustainable or safe in the long run. In summary, improvements in comparison to the prepilot period were noticed in all surgeons, however, it was only Surgeon 1 that improved in all measures.

These results also correlate well with the observed compliance to the SSSO suggested optimal schedule. Surgeon 1 complied exactly with the suggested SSSO schedule on 15 of 42 surgery days during the pilot while Surgeon 2 complied exactly on 7 of the 43 surgery days during the pilot. Note that this does not mean that the surgeons did not use the SSSO on other surgery days: the interface allowed surgeons to look at the overtime probabilities if they chose to override the suggested schedule with their own choices, and also the ideal day to schedule Medicare surgeries.

Figure 11 demonstrates Surgeon 1's compliance rate, where x axis is the day of the surgery and the y axis represents either full compliance to the schedule (100%) or a lack of compliance (0%) on each surgical day during the pilot. Note that partial compliance counts as 0% in the graph. Although compliance itself is binary, the curve shows a weighted moving average of the percent compliance. The drop in the month of April represents the detection of a slight error in the interface (one surgery category was misclassified), which resulted in surgeons not using the interface until it was fixed at the end of April. After this minor error was fixed and surgeons were urged to restart using the interface, the compliance rate once again increased.

Table 5 shows the (normalized) average NOI per case from July 2012 to June 2013, for the four surgeons six months before the pilot and during the pilot, split by the four insurance groups. Numbers in the parentheses indicate the standard deviation. During the pilot, S1 and S2 performed 138 total cases, compared to 84 by S3 and S4. S1 and S2 performed 53 commercial cases and 65 Medicare/Medicaid cases, compared

Table 4 Pre- and Postimplementation Results for All Surgeons (Mean and Standard Deviation of the Mean for the Biweekly Data)

	Cases per day		Utilization (%)		Overtime (%)	
Surgeon	Preimp.	Postimp.	Preimp.	Postimp.	Preimp.	Postimp.
S1	**1.30 (0.02)**	**1.57 (0.04)**	72 (1)	77 (1)	30 (1)	24 (4)
S2	**1.16 (0.02)**	**1.63 (0.05)**	70 (1)	83 (2)	**21 (1)**	**37 (4)**
S3	**1.07 (0.02)**	**1.30 (0.04)**	75 (1)	83 (1)	33 (2)	48 (4)
S4	0.85 (0.03)	1.09 (0.06)	61 (2)	76 (4)	25 (2)	29 (3)

Notes. Surgeons 1 and 2 participated in the SSSO pilot implementation. Bold values show statistical difference at 0.05 significance level.

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Table 5 **Pre and Post Daily Normalized NOI**

	S1 (%)		S2 (%)		S3 (%)		S4 (%)	
Payor group	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Commercial	49 (4)	53 (10)	54 (13)	60 (14)	55 (10)	58 (12)	57 (12)	53 (8)
Employee	36 (4)	36 (3)	32 (5)	38 (2)	31 (9)	32 (10)	38 (0)	37 (2)
No insurance	45 (8)	52 (7)	47 (1)	60 (9)	44 (0)	48 (0)	0 (0)	50 (2)
Goverment	40 (2)	40 (2)	38 (4)	40 (5)	37 (6)	40 (3)	33 (13)	37 (7)

Note. The values in parentheses represent the standard deviation.

to 22 commercial and 50 Medicare/Medicaid cases by S3 and S4. For the surgeons participating in the SSSO pilot there was a small overall drop in the proportion of government paid patients compared to before the pilot; however, the proportion was still well above the threshold established by the practice.

It's clear that both S1 and S2 together either stayed steady or improved their per case NOI in each category. Neither surgeon decreased their average per case NOI in any category. S2 improved his NOI considerably in all categories. S3 also improved his NOI in all categories; however, average NOI for S4 went down in the Commercial and Employee categories. Profitability for Medicare patients increased during the pilot period for all surgeons, suggesting that the efforts to do these surgeries on the best days to avoid uncompensated hospital days were effective for the practice as a whole. It is also likely that the surgeons not participating in the pilot worked harder since they were aware of the pilot. Together with the overall increase in access (cases per day) attributable to the SSSO implementation and other improvement initiatives, the financial sustainability in the orthopedic spine surgery practice has improved and will provide better access for all patients, regardless of reimbursement type, in the future.

In summary, the pilot implementation was deemed successful, but not as comprehensively as desired. As the pilot rolled out, several challenges occurred, including technical issues with the programming of SSSO, lack of desired flexibility in scheduling patients, and some discomfort by users of the tool with its reliability. The following section will discuss some of the lessons we learned and proposed solutions as the system is rolled out more broadly across the surgical practice at Mayo Clinic.

5.2. Lessons Learned from the Pilot

Pilot implementations by their nature are intended as learning experiences. The points below are some of the key lessons we learned from our pilot.

- The SSSO application was generally developed in the classic waterfall approach. The optimization team handed off a completed method to the programming team. There was some integration and communication, but not as much as desired. This resulted in some technical issues with the tool. Some of these issues were the responsibility of the optimization team and some the responsibility of the programming team. For example, as mentioned in §5.1, in the third month of the pilot a slight error was identified with regard to the classification of one particular surgery category; surgeon compliance to the tool reduced during this period and picked up again once the error was fixed. All or most of these issues could have been avoided by earlier involvement and better integration of the teams.
- Some assumptions were built into the optimization method that did not work in practice. In particular, we assumed that case mix could be shaped by how access was controlled at the time of surgery scheduling. However, for spine surgery, it is common for the surgeons to see patients several times before the surgery decision is made. Limiting a patient's surgical access when they had developed a relationship with a surgeon pushed against Mayo Clinic's high-quality service philosophy. Thus, this approach is being adapted for ongoing implementations. Efforts at controlling access before patients come to Mayo Clinic have been implemented and are still under way that will ensure the best use of our capacity while ensuring the needs of the patient come first.
- As identified in the previous section, Surgeon 1 had the most desired performance profile during the pilot. This surgeon and his scheduling team were the most involved during the optimization and tool development process. It is not surprising that the staff in this group had the most confidence in and understanding of what the tool was trying to accomplish. For ongoing implementations of the modified tool we are working to involve more surgeons and staff in the development process.
- Both surgeons participating in the pilot found the ability to see the impact of scheduling a particular case on a day very useful, even if they were overriding what was recommended by the optimization. The visualization shown in the window in Figure 9, was of particular value. As scheduling decisions evolve from being very patient preference oriented to being more system optimized, providing the surgery schedulers with useful information to guide decision making with flexibility is being incorporated into new versions of the tool.

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A great deal was learned from the pilot and specific improvements are being incorporated into new versions that are in development for several surgical practices at Mayo Clinic.

6. Conclusions

In this paper we presented an improved method for scheduling spine surgeries in the orthopedic spine surgery practice at the Mayo Clinic. Unique aspects of our model include the incorporation of both resource utilization and financial objectives. Categorizing surgeries and developing statistical models for predicting surgical lengths using clinical factors is a key contribution. Furthermore, using input from the surgeons to categorize case types that led directly to scheduling decisions assisted in gaining clinical staff engagement.

An implementation using a customized Web-based tool that incorporated our optimization model showed generally positive results. Patient access improved significantly for the surgeons involved in the pilot and operating room utilization improved marginally. For one of the two surgeons participating in the pilot the access benefits were achieved by also reducing the percentage of overtime days. It should be noted that patient access also increased for the surgeons not participating in the pilot, but not by as much.

Our study has limitations. We consider hospital LOS implicitly in considering profitability, but the impact on downstream resource requirements is not investigated. We consider the surgeons as bottlenecks and the impact on inpatient or postanesthesia care unit (PACU) beds is not in the scope of this project. In general, at Mayo Clinic in Rochester, these resources are not constraints. Because of lack of information about cancellations, we did not directly incorporate these into our model. Patient waiting time was not considered in our models. Lastly, since the surgical durations are relatively long, the number of surgical combinations is restricted (20 surgical combinations). As the number of possible surgeries in a combination increases (for specialties with shorter durations) the computational burden will increase as well.

We developed the optimization model using both Excel's Open Solver (Mason 2012) and AMPL. Excel was favored for implementation and the pilot study, and the computational time was around an hour for each stage with the Open Solver. AMPL, which should be favored for research, on the other hand, provides solutions in less than five minutes for each stage. Exploring the general problem (with a greater number of decision variables) will allow us to understand the computational complexity of the optimization model more accurately.

Although this paper highlights a specific case study application, we believe that many of the results and insights will be of interest more broadly. In particular, the emphasis on considering the trade-offs and effects of constraint limits may help other similar surgical operations gain useful insights. At Mayo Clinic the general approach we developed is being considered for other surgical services and would likely benefit other organizations. For this reason, we emphasized the underlying ideas and theory of the application and show results of experiments that develop managerial insight. Other surgical services such as cardiothoracic, neurosurgery, and plastic surgery that have long average and highly variable procedure times may benefit from our research as well. As reported in Abouleish et al. (2003) these services together (with spine surgery) may make up to about 20% of surgical volume in hospitals.

From a literature perspective, we believe our paper is a significant contribution because it does more than just consider the issues of changing case mix and surgical scheduling (which are prevalent in the conceptual operations management literature). We extend the research area by considering the multiple objectives related to utilization (and correspondingly, patient access), overtime, and financial performance. Furthermore, considering the downstream financial issues related to an important class of patients (those with fixed reimbursements) is novel and increasingly important, particularly in the UnitedStates where healthcare reform is a prominent issue. Finally, to the best of our knowledge, such pilots (pre and post; and a test and control group) focused on quantifying an implementation pertaining to operational and scheduling issues do not exist in the healthcare or surgical literature.

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Appendix

We provide more detailed information on the inputs of the problem below.

Spine Surgery Terminology

This section describes the clinical basics of spine surgery. Spine anatomy is divided into 4 major sections, which are defined by the number of vertebrae. Vertebrae are the bones that make up the structure of the back bone. Disc is the tough, elastic structure that is between the bodies of spinal vertebrae. The disc and vertebra above and below the disc comprise one segment of the spine—usually called a spinal level or spinal segment. The spine is divided into 4 main sections: cervical (neck), thoracic (upper back), lumbar (lower back), and sacral region (bottom of the spine).

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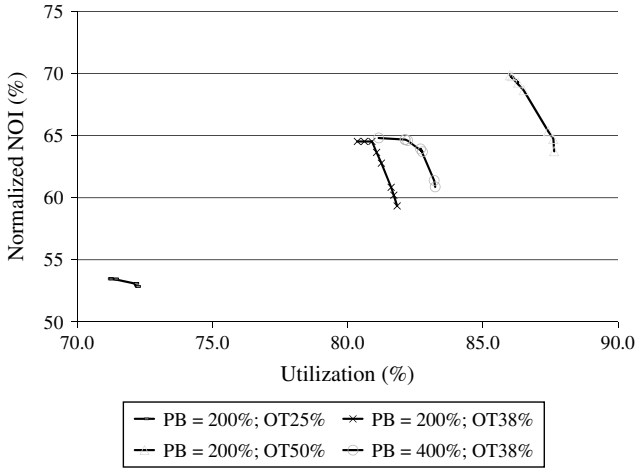
Table A.1 Properties of the 10 Surgical Categories

	Patient categories									
Parameters	1	2	3	4	5	6	7	8	9	10
No. of levels	0	1 or 2	≤1	≥3	≤2	2	≤2	≥3	≥3	≥3
Approach	—	—	Lateral, anterior	—	Posterior, stages	Lateral, anterior	Posterior, stages	—	—	—
Decompression	—	—	—	—	No	—	Yes	—	—	—
Fusion	No	No	Yes	—	Yes	Yes	Yes	—	—	—
Grafting	—	—	—	No	—	—	—		Yes	—
Deformity	—	—	—	No	—	—	—	No	No	Yes
Instruments	—	—	—	—	—	—	—	—	—	—
Age	—	—	—	≥74	—	—	—	<74	—	—
% of cases	3	16	11	3	8	9	13	10	20	6

Table A.2 Most Commonly Observed MDSS Pairs

Combination	Surgery pair	Proportion (%)
1	6_8	9
2	8_9	7
3	4_5	7
4	8_8	5
5	1_2	5
6	7_9	4
7	4_8	4
8	4_9	4
9	2_5	3
10	3_8	3
11	5_9	3
12	1_1	2
13	1_5	2
14	1_8	2
15	2_6	2
16	2_8	2
17	4_6	2
18	7_7	2
19	7_8	2
20	1_6	2

Figure A.1 Trade-Off Between Utilization and NOI



Note. PB, case-mix bound width (i.e., allowed flexibility in changing the case mix); OT, overtime.

Because lumbar section of the spine bears most of the body's weight and allows for the most motion, this is the area associated with most back problems (Patel et al. 2013).

Surgeons can reach the spine by making an incision (cut) in different places on your body. Incision sites are often described as: anterior, posterior and lateral. Anterior fusion is done by making an incision in the abdomen (belly). Posterior fusion refers to surgeon making the incision in the lower back. Lateral is required as surgeons can reach certain parts of the lumbar spine by making an incision in your side.

Spinal deformities are typically called scoliosis. There are many different types of scoliosis and with that different types of procedures to correct these spinal deformities. Spinal fusion is surgery to permanently connect two or more vertebrae in your spine, eliminating motion between them. Bone graft and/or bone graft substitute is needed to create the environment for the solid bridge to form. At the time of the fusion surgery, the use of metal devices, also called implants or instrumentation (e.g., screws and rods) is typically used to provide stability for that section of the spine for the first few months after surgery. In simple terms there are long spinal fusions (across many levels) and short segmental spinal fusions (one or a few levels). Sometimes a fusion is necessary usually in conjunction with a decompression, but sometimes alone. Spinal decompression refers to any surgical technique which aims to free the space for the nerves in the spinal canal (Kuehn 2012).

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