Optimal Allocation of Surgical Services
by
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ABSTRACT Over the past several years Greater Boston has witnessed the consolidation of multiple community hospitals into larger care organizations and a renewed focus on the delivery of affordable care. In order for the Beth Israel Deaconess Medical Center (BIDMC) to respond and adapt to this changing landscape it will be critical to not only understand demand and capacity across the organization's entire network, but also to recognize how the deployment of limited resources can best be improved. From a BIDMC Department of Surgery Perspective, essential business questions include:

1 How to allocate limited existing resources efficiently?
2 Which future growth opportunities should be pursued now?
3 How should a multiple-hospital network be used to meet system demand?

Existing approaches employed for solving these questions often involve heuristic rules-of-thumb that fail to treat sunk costs and opportunity costs appropriately. These approaches often lead to demonstrably sub-optimal operational decisions. We have developed a framework for answering these questions in a more quantitatively rigorous fashion using mathematical programming. Our model captures each surgical case's impact on hospital resources (e.g. OR time, surgeon time, etc.) from when a patient enters the preoperative holding area to when they are released from the post anesthesia care unit. Using knowledge of resource requirements for each procedure, we compute an optimal allocation of cases subject to capacity and demand constraints.

We pilot our framework by studying three surgical service lines within BIDMC: General Surgery, Colorectal Surgery, and Surgical Oncology. We explore three different approaches to more effectively using resources and determine that the most practical approach yields a potential profit increase of more than 5% over 2012 levels.

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1.1 CONTEXT

Over the last decade, the management and delivery of health care has emerged as a critically important issue. Underlying the present renewed focus on health care is the alarming observation that the US trails other developed nations in health and outcome measures despite spending significantly more on care [22] [2].

Another source of concern is that health care costs have consumed an increasing share of GDP over the past fifteen years [11]. Health care spending is unlikely to have an adverse effect on the US economy in the short term, but if present trends continue, the US will be forced to reduce nonhealth GDP per capita by 2040; this has led industry observers to label present health care spending trends as “unsustainable” [20].

The unsettling state of US health care has not gone unnoticed by policymakers; in 2010 the Patient Protection and Affordable Care Act (PPACA) was signed into law, impacting nearly every industry
stakeholder. Representing the largest change to the federal health care system in the past half century, the scope of the PPACA is extensive, but for the remainder of this document we will concern ourselves with one integral component of the PPACA: the establishment of the Accountable Care Organization Model and the emergence of cost as an important factor in health care delivery.

1.1.1 Accountable Care Organizations

An Accountable Care Organization (ACO) is a network of care providers that assume joint responsibility for the quality and cost of delivering care to a population of patients.

A key characteristic that differentiates the ACO model from alternative approaches is that the providers in an ACO are accountable for total cost of meeting a population's health care needs [9]. This is in direct contrast to the traditional fee-for-service payment system in which payors—such as Medicare and insurance companies—are accountable for costs.

However, a frequent criticism of fee-for-service is that separating providers from cost responsibility enables providers to potentially benefit from recommending unneeded care [15]. Advocates of the ACO approach argue that forcing providers to share in cost responsibility eliminates the conflict of interest and that furthermore, providers are better equipped than payors to reconcile the often competing demands of cost and quality.

While some believe that ACOs effectively realign incentives and are capable of containing rising health care costs [12], within the scientific community there is no clear consensus on the efficacy of widespread ACO adoption.

Nevertheless, one consequence of the ACO model is clear: providers can benefit by delivering cost effective care. The PPACA rewards ACOs that implement successful cost reduction measures, allowing them to share in savings, but organizations that fail to meet cost or quality targets are forced to pay penalties.

1.1.2 Health Care in Massachusetts

It has been observed that markets with existing integrated networks of providers are more likely to adopt the ACO model [3]. In Boston, this pattern has held particularly true; east Massachusetts is home to five of the thirty-two organizations nationwide that volunteered to pilot the ACO model [18]:

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Together these organizations constitute the majority of the local care provider market and include several of the country's preeminent medical centers.

The first year of the accountable care transition went well for ACOS in Massachusetts; four out of five organizations outperformed their Medicare cost target [18]. However, as the program matures and further implementation continues, targets will become more aggressive and providers will face increasing cost pressures.

A second important trend occurring in Massachusetts is the rapid consolidation of small community hospitals into larger care organizations. Less than 10 percent of the state's hospitals remain entirely independent and almost a third have been involved in a merger, acquisition or partnership since 2007 [1]. Having a large network provides a care organization two significant advantages:

1. A large network tends to correspond to a sizable patient base, thus organizations with expansive networks have greater leverage when negotiating with insurance companies.
2. Organizations with large networks have opportunities to achieve economies of scale that are unavailable to smaller providers.

While it is unclear whether local organizations have fully realized either benefit, one overarching theme is certain: health care providers in Massachusetts face a highly volatile environment and a confluence of significant changes.

We claim that organizations that utilize their limited resources efficiently and intelligently will be well-equipped to compete and navigate the challenges posed by the evolving health care landscape.

1.2 BETH ISRAEL DEACONESS MEDICAL CENTER

Beth Israel Deaconess Medical Center (BIDMC) was born from the 1996 merger of two historic Boston institutions: the New England Deaconess and Beth Israel hospitals.

New England Deaconess Hospital was founded in 1896 as part of the Methodist Deaconess movement in which religious women
devoted themselves to caring for the underprivileged and ill. Beth Israel Hospital opened in 1916 with the hope of better accommodating the rapidly growing Jewish immigrant population. While both institutions share an origin based in faith, both also started with a similar promise: to care for all sick persons, regardless of creed or nationality.

Today BIDMC is one of the largest hospitals in the Boston region with over 600 licensed beds, 50,000 annual inpatient discharges, and 540,000 outpatient visits. BIDMC is also one of only five adult Level I trauma centers in Boston.

BIDMC spans two campuses in Boston's Longwood Medical Area. Longwood is renowned for housing many distinguished health care institutions including Boston Children's Hospital, Brigham and Women's Hospital, Dana-Farber Cancer Institute, BIDMC, and the Harvard Medical school with which each of the four former organizations is affiliated.

Aligning with the broader Massachusetts trend of hospital consolidation, Beth Israel expanded its network to include community hospitals in Needham (2002) and Milton (2011). While care has not yet been integrated across the entire BID hospital network, the impetus for cooperation has increased with the formation of the BIDCO ACO. We will explore the potential benefits of such collaboration when we apply our methods to the BID network.

1.3 DEPARTMENT OF SURGERY

BIDMC’s mission is, “to provide extraordinary care, where the patient comes first, supported by world-class education and research.” The Roberta and Stephen R. Weiner Department of Surgery serves as an integral component in fulfilling this mission; each year tens of thousands of patients undergo surgery and achieve positive outcomes at BIDMC.

As important as the Department of Surgery is to realizing the hospital’s mission, the department is equally critical to ensuring BIDMC’s financial viability. Perhaps not coincidentally, the department is also one of hospital’s most operationally complex divisions.

Because surgery is both essential and challenging to efficiently execute on a large scale, it is a logical target for operational improvement. Shortly we will visit key issues the department faces and propose a framework for attacking these challenges.
### Organizational Structure

The department's administration is primarily flat, although control remains largely centralized with a few individual leaders; principal departmental leadership includes:

- Surgeon-in-Chief: presides over the entire department as Chairman
- Chief Administrative Officer (CAO): manages and addresses high-level departmental business concerns
- Chief Surgeons: oversee and direct individual service lines

Organizationally the department is divided into the fourteen service lines listed in Table 1.1. Practicing surgeons typically belong to a single service line, although certain service lines have more clinical overlap than others.

Administrative staff constitute the remainder of the employees belonging to the department; anesthesiologists and operating room nurses each are associated with separate departments.

### SUMMARY OF PROBLEM

In this chapter we have outlined a few critical issues that care providers currently face:

- Increasing cost pressure associated with the transition to the Accountable Care Organization model

* OB/GYN and Orthopaedic surgery are managed independently and fall outside the domain of the Department of Surgery*
An uncertain competitive environment driven by rapid consolidation of community hospitals into larger networks.

Growing operational complexity due to the difficulty of providing a large portfolio of services across an entire network.

In light of these conditions, we believe providers must be able to capably answer the following strategic questions in order to remain competitive:

1. How should limited resources best be allocated to meet demand?
2. Which future growth opportunities should be pursued now?
3. How should a multiple-hospital network be used to meet total demand?

These questions are not novel, but the existing approaches many organizations use to answer them may be ad-hoc, heuristic, and suboptimal. The purpose of this research is to develop a more rigorous framework for answering these questions in a longer-term strategic sense—particularly in the context of the BIDMC Department of Surgery. We henceforth refer to these questions as the hospital resource allocation problem.

1.5 SUMMARY OF APPROACH

We develop a linear programming formulation that incorporates relevant operational constraints, ensuring that any proposed mix of surgical cases can actually be realized in practice. Using this model, we determine an allocation of demand and resources that maximizes total benefit. The answers to our previously posed questions are readily extracted from the optimal solution, either from decision variable values or constraint shadow prices.

Our approach overcomes significant limitations of existing ad-hoc alternatives:

- Heuristics often fail to properly capture the opportunity cost of alternative actions; this is particularly true when the space of alternatives is high dimensional
- Resource allocation problems can often be interpreted as packing problems, but packing "by hand" is difficult if many objects are involved or if the box is high dimensional
- Ad-hoc approaches often include sunk costs or arbitrarily assigned overhead costs in determining which items should have priority in resource allocation; this incorrectly favors items which superfi-
cially appear to have low overhead; our approach strictly considers economic marginal costs

1.6 SUMMARY OF FINDINGS

We pilot our model on three service lines within the BIDMC Department of Surgery. Using 2012 operations as a baseline, we observe that operating room time is a critical bottleneck that limits surgical volume. Nevertheless, we identify significant opportunity for improvement over baseline operations; using data on spilled demand, we evaluate the viability of three tactics for recapturing lost demand:

1 Meeting additional capacity needs by taking block time from another service line
2 Holding capacity fixed, but reallocating resources to more efficient case types
3 Using spare community hospital capacity to meet spilled demand

We observe that while all three tactics have the potential to increase profitability, the final approach yields the greatest upside and is also aligned with organizational goals.
In the previous chapter we developed a case for three must-win battles that hospital administrators face:

1. How should limited resources best be allocated to meet demand?
2. Which future growth opportunities should be pursued now?
3. How should a multiple-hospital network be used to meet total demand?

Collectively we refer to these questions as the hospital resource allocation problem. In this chapter we revisit these questions in the context of providing surgery across a network of hospitals; we explore how simple existing approaches to addressing these questions can fall short and then close by reviewing related previous work in this field.
2.1 THE HOSPITAL RESOURCE ALLOCATION PROBLEM

Controlling access to resources is the primary means hospital administrators have for influencing overall business operations. This holds particularly true for surgery where the specific mix of cases performed has considerable impact on profitability.

Naturally, there are substantial challenges in allocating resources on a daily basis; skillful management of daily operations is critical to a hospital's ability to meet highly-variable demand while remaining profitable.

However, perhaps equally important is the long term strategic decisions that a hospital makes. An administrator who does not understand which cases to prioritize is likely to make choices that result in missed profit opportunities. As we will see in later chapters, failing to deliver patients timely access to surgery often results in the case being lost to competitors. Thus failing to ensure valuable cases are easily scheduled means they may be lost in the shuffle; this phenomenon is well-observed in the BID network and is a clear indicator of not only unmet demand, but also the opportunity for better use of existing resources.

Further complicating the decision making process that hospitals face is the fact that many care networks have recently expanded. Now administrators must manage the mix of cases in not only a single hospital, but across an entire network.

The recurring theme we observe is that administrators continually face questions of resource allocation: how should a hospital network strategically use its limited resources to maximize profit while upholding the organization's founding mission?

This question is keenly relevant to surgery where longer-term, strategic resource allocation remains a significant opportunity for operational improvement; our aim is to develop and implement a mathematical framework for addressing this problem.

2.2 HEURISTIC ALLOCATION

Before developing our approach, we feel it is worthwhile to first demonstrate how commonly used allocation strategies can lead to significant lost profit.

We begin by presenting an example that illustrates the risk of using ad-hoc approaches; this example is especially poignant because it involves a common operational mistake many organizations make: giving products access to resources in order of highest
TABLE 2.1: Procedure Assumptions for Heuristic Example

<table>
<thead>
<tr>
<th>Procedure</th>
<th>Hosp. 1 Profit</th>
<th>Hosp. 2 Profit</th>
<th>Duration (min)</th>
<th>Surgeon Type</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complex</td>
<td>4250</td>
<td>4500</td>
<td>120</td>
<td>A</td>
<td>2500</td>
</tr>
<tr>
<td>Moderate</td>
<td>2250</td>
<td>2500</td>
<td>60</td>
<td>B</td>
<td>2500</td>
</tr>
<tr>
<td>Simple</td>
<td>1250</td>
<td>1350</td>
<td>30</td>
<td>B</td>
<td>2500</td>
</tr>
</tbody>
</table>

profit margin.

2.2.1 A Simple Allocation Example

Consider a fictional care network that consists of only two hospitals. Furthermore, suppose the hospitals only perform three types of surgery and the network only employs two types of surgeons (see Table 2.1). Finally, assume we are also given the following capacity data:

- The first hospital has 10 operating rooms and the second hospital has 2.
- The entire network employees 3 type A surgeons and 3 type B surgeons.

Now let's consider the problem of determining which cases to perform over a 13 week period, assuming the hospital is open 40 hours a week.

It should become immediately apparent that even in this greatly simplified example, the best course of action is not obvious. A common-sense approach to attacking this problem is to focus on performing all cases that generate maximum profit followed by all cases that generate the next most profit, et cetera; in fact this logic is similar to the rationale behind the common practice of reserving capacity for elective heart surgery cases.

If we follow this heuristic policy, we obtain the first case mix depicted in Table 2.3. On the other hand, if we use linear programming to find the optimal solution, we obtain the second case mix in the table which is markedly different from the first. Aside from the significant resource allocation differences, the more important
TABLE 2.3: Comparison of Case Mixes, Surgeon Allocation, and Profit by Solution Approach

<table>
<thead>
<tr>
<th>Procedure</th>
<th>Heuristic</th>
<th>Optimal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complex</td>
<td>Hospital 1</td>
<td>260</td>
</tr>
<tr>
<td></td>
<td>Hospital 2</td>
<td>520</td>
</tr>
<tr>
<td>Moderate</td>
<td>Hospital 1</td>
<td>1560</td>
</tr>
<tr>
<td></td>
<td>Hospital 2</td>
<td>0</td>
</tr>
<tr>
<td>Simple</td>
<td>Hospital 1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Hospital 2</td>
<td>0</td>
</tr>
<tr>
<td>Surgeon A</td>
<td></td>
<td>33%</td>
</tr>
<tr>
<td>Surgeon B</td>
<td></td>
<td>67%</td>
</tr>
<tr>
<td>PROFIT</td>
<td></td>
<td>$6.955M</td>
</tr>
</tbody>
</table>

observation is that the heuristic yields over 5% less profit than the optimal solution.

After one sufficiently inspects Tables 2.1 and 2.3, it may become clear what has occurred: Complex procedures generate more profit per case but less profit per OR minute than both Simple and Moderate cases.

Resource-profit efficiency is equally important in real world scenarios, and while we can easily identify the critical resource in this simple example, our ability to do so does not extend well to situations where there are many procedures and resource constraints.

2.2.2 An Accounting Example

The previous example illustrated that manually allocating resources can often be a challenging process. Now we demonstrate a second important observation: directly including accounting costs into business analyses can easily lead to incorrect conclusions.

Many hospitals employ Activity-Based Costing (ABC) systems to help assess the profitability of individual case types. In an ABC system, fixed and indirect costs are allocated to services in a predetermined but subjective fashion*. When providing surgery the fixed and indirect costs often dominate the variable costs, hence the choice of cost allocation approach can have a dramatic effect on

* Subjective in the sense that an alternate allocation of costs could just as readily be justified

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The perceived profitability of any particular service.

In general, it is critical that unavoidable costs be excluded when performing a business analysis; to illustrate this concept we turn to a simple example. Table 2.4 contains assumptions about two hypothetical procedures. In addition, assume that both procedures yield $1000 of revenue per case and require the same amount of OR time.

We observe that labor costs have been allocated according to average patient length of stay; hence Type I procedures incur twice the labor costs as Type II because Type I cases have twice the recovery period. Based on these figures, a rational manager might be indifferent between the two procedure types. However, in actuality the hospital will obtain greatest profits by capturing as many Type I cases as its existing staff can accommodate. This somewhat non-obvious result can be inferred from the following observations:

- The existing staff will likely be retained regardless of this year's case mix. Hence in the intermediate term, labor costs are a sunk cost that will be incurred irrespective of which cases are prioritized.
- If the new case mix does not exceed existing staff capacity, the allocation of labor costs to individual cases may change, but total labor cost will stay the same.
- When the fixed labor costs are removed from consideration, the Type I procedures are 25% more profitable than type II.

Navigating the distinction between incremental and sunk costs is a task that many heuristics fail to satisfactorily address; very often the cost of unused capacity gets allocated to services in a fashion that severely distorts their apparent profitability.

<table>
<thead>
<tr>
<th>Procedure</th>
<th>Average LOS</th>
<th>Variable Cost</th>
<th>Allocated Labor</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type I</td>
<td>2d</td>
<td>$100</td>
<td>$400</td>
<td>$500</td>
</tr>
<tr>
<td>Type II</td>
<td>1d</td>
<td>$300</td>
<td>$200</td>
<td>$500</td>
</tr>
</tbody>
</table>
2.2.3 Limitations

In general there are several shortcomings that common resource allocation heuristics share; the approach we develop in the remainder of this paper will seek to address each of these concerns.

MISSING OPPORTUNITY COSTS Heuristics rarely account for opportunity costs properly. If an OR is used to perform a certain procedure, it means that it cannot be used to perform a different procedure. While this statement may seem obvious, properly accounting for all possible alternatives becomes extremely difficult to manually accomplish for even modestly sized problems.

INABILITY TO HANDLE COMPLEXITY Few heuristics are able to handle the complexity of a large model involving multiple hospitals, dozens of procedures, and hundreds of resources. Many of these approaches are built on computing and comparing individual quantities for each service or product; however, as problem size grows, this becomes an increasingly important oversimplification.

INCORRECT TREATMENT OF INDIRECT AND SUNK COSTS Approaches that directly use profit margin figures from an internal accounting department are likely to yield incorrect results. This is because margin figures often include overhead costs that are assigned in a purely subjective manner; aside from directly distorting the apparent profitability of any procedure, including these costs also has the potential to incorrectly introduce sunk costs into the calculation. By definition, sunk costs will be incurred regardless of future decisions and hence should be omitted from consideration.

2.3 Previous Work

Now that we have explored shortcomings of simple approaches to our problem, we next turn to discussing related work that has been conducted in the fields of health care and operations research.

Jack and Powers [17] and Smith-Daniels et al. [21] each present detailed reviews of the health care capacity and demand management literature. Significant attention has been devoted to studying hospital day-to-day operations, particularly the challenges associated with OR block scheduling, bed allocation, and nurse staffing [5] [13] [14] [25]. However, less focus has been given to bridging the gap between daily operations and longer-term strategy; to the best of our knowledge, the problem of determining an ideal service
mix across a network of hospitals has not been studied.

**YIELD MANAGEMENT** The fundamental business question of how to match capacity to demand has been widely examined in operations research. In service industries this study is often called *yield management*. Talluri and Ryzin [23] present a thorough exploration and analysis of yield management; the authors observe six primary business conditions that are conducive to the application of yield management:

1. Customer Heterogeneity
2. Demand Variability and Uncertainty
3. Production Inflexibility
4. Price as a Signal of Quality
5. Data and Information Systems Infrastructure
6. Receptive Management Culture

These conditions are widely considered to hold in several business environments, most notably the airline and hotel industries. The corresponding analogy to hospitals is strong, but imperfect; in health care the demand for a single service does not exhibit strong heterogeneity in willingness to pay, in contrast, airlines make significant use of the distinction between business and leisure travelers. Nevertheless, there are still clear similarities between the industries such as perishable capacity and a cost structure dominated by high fixed costs and low variable costs.

The approach we develop employs an optimization approach inspired by those utilized yield management, but our model is less real-time focused and oriented more toward longer-term strategy.

**COST ACCOUNTING** As we have seen in Section 2.2.2, the manner in which a hospital chooses to allocate its fixed and period costs can have significant impact on the perceived profitability of surgical services. We now briefly review some of the literature concerning the *ABC* accounting systems that are prevalent at large medical centers.

Cooper [6], and Cooper and Kaplan [8] [7] describe multiple advantages that *ABC* accounting exhibits over traditional standard costing approaches. However, Cooper and Kaplan [8] are careful to emphasize the importance of distinguishing *utilized* capacity from total available capacity when performing cost analyses.
Capettini et al. [4], and Finkler and Ward [10] explore the benefits of applying ABC accounting specifically in a health care setting, and Udpa [24] examines the implementation of ABC in hospitals. Particularly relevant is Lexa et al. [19], which demonstrates certain shortcomings of the ABC approach including issues that arise when using allocated costs to make capital investment decisions.
Our approach to the hospital resource allocation problem utilizes a linear programming optimization model that is derived from four fundamental components: procedure demand, case resource usage, hospital capacity, and profit.

In the remainder of this chapter, we first examine the motivation for each component and then present a formal mathematical description of the model. This chapter is only concerned with illustrating our model's structure; we believe the model is sufficiently general that it can be readily applied to many health care organizations. Implementation details associated with actually deploying our model will be explored in the following chapter.

3.1 Model

The purpose of our model is to compute target volume levels for services across a network of hospitals. From target volume levels, we can infer the associated allocation of resources, calculate utiliza-
tion, and perform a variety of additional informative analyses.

The model chooses target volume levels to maximize total profit over a specified time-horizon, subject to constraints. Constraints often have multiple motivating concerns, whether business, operational, or ethical; in the subsequent sections we describe the constraints included in our model and their respective motivations.

For the remainder of this chapter we describe the model from the perspective of analyzing the delivery of surgery; however, we wish to emphasize that the model can readily be generalized to other services.

### 3.1.1 Demand

The notion of demand is integral to our model because it serves as an upper bound on volume for each studied procedure type. A hospital cannot reasonably expect to fill its operating rooms with only the most profitable cases because there is limited demand for these cases. Conversely, a hospital cannot choose to altogether stop performing an unprofitable procedure because this would be unethical. To address these considerations while providing flexibility, our model includes two types of demand constraints:

1. **Network Demand Constraints** limit the total number of times a procedure can be performed across the entire network of hospitals
2. **Location Demand Constraints** limit the total number of times a procedure can be performed at a single specific hospital

Demand constraints can be used as both upper and lower bounds on case volumes. In addition to preventing overproduction, demand upper bounds can be used to force cases away from specific hospitals. For example, it might not be reasonable to perform a highly-complex pancreatic surgery at a small community hospital.

Demand lower bounds are less intuitive than upper bounds but equally practical; one important use is preventing drastic or unreasonable reallocation of case volumes. A second application is forcing a hospital to meet certain minimum volume criteria, thus sidestepping the previously described ethical dilemma.

### 3.1.2 Resource Usage

The second critical component of our model is resource usage. In order to avoid infeasible solutions that use more resources than are available, our model must understand the resources required
to perform any single case. A reasonable approach to developing this understanding is to think about the entire process a patient undergoes when receiving surgery.

In a general sense, any surgical encounter can be viewed as consisting of multiple distinct phases (see Figure 3.1). For example, before even entering an operating room a patient is brought to the preoperative holding area (PREOP) where various pre-surgery processes are conducted; these might include taking a patient's vitals, inserting an intravenous line, or performing a needle localization.

After completing the preoperative process, a patient is wheeled into the operating room, given anesthesia, and operated on by a surgeon. When the operation is complete the patient is brought to the post-anesthesia care unit (PACU) to recover from anesthesia; after the patient leaves the OR, the room is cleaned and prepared for the subsequent case.

When a patient has sufficiently recovered from anesthesia, they are transferred to a more permanent recovery bed where they may spend multiple days recuperating before being discharged from the hospital.

More generally, we characterize a surgical phase in the following fashion:

- A surgical phase represents a component of a surgical encounter.
- Every phase has a duration; the duration represents the typical am-

FIGURE 3.1: Phases of a Typical Surgical Encounter
ount of time required to complete the phase. Different procedures have different durations for the same phase because certain procedures take longer to complete than others.

- Phases also define the resource requirements for each surgical procedure. Resources associated with a surgical phase include the equipment, staff, and physical facilities (e.g., the room or bed) needed to complete the phase.

For each surgical procedure modeled, we must determine the duration and resource requirements of each phase belonging to the procedure. The total resource usage of the procedure is then simply the sum of the resource needs from each phase of the procedure.

Thinking in terms of phases is advantageous because it makes the model easily extensible while separating physical and temporal resource usage.

3.1.3 Capacity

Hospitals have limited resources for performing surgery—this fact combined with the presence of unmet demand is what makes the hospital resource allocation problem nontrivial. For our model to properly reflect reality, it is essential that we capture any potentially limiting capacity constraints.

A capacity constraint consists of two elements: the total amount of capacity and the amount currently being used. In the previous section, we developed a framework for thinking about usage; we now turn to the question of capacity.

For each resource identified as required in a surgical phase we model:

1. The total number of the resource available at each hospital
2. The typical number of hours per day the resource is available

Combining resource usage data with knowledge of available capacity enables the model to continuously evaluate whether any particular mix of cases is feasible.

Some resources may not be available at certain hospitals; this is not problematic because the model inherently prevents procedures that need a particular resource from being performed at hospitals missing the resource.

* The quantity required versus the time required
SURGEON CAPACITY The capacity constraint for surgeons is handled slightly differently than other resources for the following reasons:

- Not every surgeon can perform every procedure, yet every procedure can be performed by multiple types of surgeons.
- Surgeons, unlike all other resources, are location independent; they are pooled across the entire network.

To address the first issue, we introduce the notion of procedure and surgeon classes. A procedure class can be thought of as a surgical specialty; each procedure is assigned to exactly one class. On the other hand, a surgeon class is precisely a set of multiple procedure classes; this captures the idea that surgeons often have multiple specialties. Using these two definitions, we observe that procedure $p$ belonging to class $k$ can only be performed by a surgeon whose class $s$ includes $k: k \in s$.

The location-independence challenge is handled by allowing the model to decide on the optimal allocation of surgeons’ time. The optimization decides how much time each surgeon class spends on each procedure class at each location.

3.1.4 Profit

The final component of our model is profit. More specifically, we define a modeled procedure’s profit as the expected economic marginal profit from performing the procedure.

$$\text{marginal profit} = \text{revenue} - \text{marginal cost} \quad (3.1)$$

The profit must be taken in expectation because the actual payment a hospital receives for performing the same procedure may vary due to differences in patient insurers, payment delinquency, and total care delivered$^1$.

The use of purely marginal costs is important because hospitals often use cost accounting systems that associate indirect overhead costs to cases in a non-uniquely determined fashion—some costs may be labeled as “variable costs” despite the fact that the total assessed cost doesn’t actually vary with a modest change in the number of cases.

$^1$ Differences in patient length of stay or additional ancillary services that were performed
Costs that do not vary with changes in case volume must be excluded from the model so as to not incorrectly skew results. Including fixed or period costs on a per-procedure basis can make cases that are assessed less indirect costs appear more attractive, despite the fact that these costs will be incurred regardless of the final case mix. Lexa et al. [19] more fully explores the distinctions between fixed, marginal, and variable costs and how use of incorrect costs can lead to poor business decisions in a health care setting. See Section 2.2.2 for a an illustrative example of these concepts.

3.2 VARIABILITY

Throughout the preceding sections, we have suggested that typical or average values be used to approximate various non-deterministic quantities:

- Surgical phase durations
- Procedure equipment and staff requirements
- Hospital resource availability
- Marginal profit

These assumptions are significant and naturally give rise to questions regarding the impact on the model’s results.

FALSE FEASIBILITY In general, using an expected value to approximate a variable quantity in an optimization model can be a risky choice, particularly when attempting to optimize over only a few realizations of a random variable. The main risk is that the optimization will regularly produce a solution that is infeasible in actual practice.

We mitigate this risk by only using our model to study longer time-horizons (e.g. at least half of a year). Our formulation intrinsically models repeated realizations of the same random variables, and by the law of large numbers, we expect our approximations to become increasingly reasonable with larger time-horizons.

OVERUTILIZATION A second variability-related concern involves a widely understood queuing theory result: average wait time increases asymptotically as capacity utilization approaches 100 percent [16]. By default our model considers a solution that completely utilizes a resource to be feasible.

For example, multiple occurrences of the same surgical procedure
On the surface, this appears to be a blatant contradiction of the aforementioned principle, however it is in fact a conscious design choice. Because differing utilization levels are considered acceptable for different resources, we choose not to artificially clamp all resources to a predetermined utilization level.

Instead, we trust that a judicious user of the model will observe if a resource is being overutilized and rerun the model to observe the behavior of the solution near the appropriate limit. This approach is made workable by our observation that in practice, our model rarely produces more than a few active resource constraints in the optimal solution.

3.3 MATHEMATICAL FORMULATION

3.3.1 Sets

<table>
<thead>
<tr>
<th>SET</th>
<th>EXAMPLES</th>
<th>COLLECTION</th>
<th>ELEMENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Procedure Types</td>
<td>Laparoscopic Cholecystectomy, Gastric Bypass</td>
<td>P</td>
<td>p</td>
</tr>
<tr>
<td>Procedure Class</td>
<td>Bariatric, Colorectal, HPB, General</td>
<td>K</td>
<td>k</td>
</tr>
<tr>
<td>Surgeon Class</td>
<td>Breast/Colorectal/General, Colorectal/Endocrine/General</td>
<td>S</td>
<td>s</td>
</tr>
<tr>
<td>Phases</td>
<td>PREOP, OR, PACU</td>
<td>H</td>
<td>h</td>
</tr>
<tr>
<td>Resources</td>
<td>Operating Room, HPB Surgeon, Hydraulic Stirrups</td>
<td>R</td>
<td>r</td>
</tr>
<tr>
<td>Locations</td>
<td>Hospital #1, Hospital #2</td>
<td>L</td>
<td>l</td>
</tr>
</tbody>
</table>
### Constants

<table>
<thead>
<tr>
<th>CONSTANT</th>
<th>DESCRIPTION</th>
<th>UNITS</th>
<th>SYMBOL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marginal Profit</td>
<td>Expected profit from performing procedure $p$ at location $l$</td>
<td>Dollars</td>
<td>$\pi_{pl}$</td>
</tr>
<tr>
<td>Phase Duration</td>
<td>Expected duration of phase $h$ of procedure $p$ at location $l$</td>
<td>Hours</td>
<td>$d_{phl}$</td>
</tr>
<tr>
<td>Resource Usage</td>
<td>Quantity of resource $r$ (or number of surgeons) required by phase $h$ of procedure $p$ at location $l$</td>
<td>—</td>
<td>$u_{rphl}$, $u_{rphl}^{SURG}$</td>
</tr>
<tr>
<td>Simulation Duration</td>
<td>Total length of time being modeled</td>
<td>Days</td>
<td>$d_{total}$</td>
</tr>
<tr>
<td>Capacity Availability</td>
<td>Hours per day each of resource $r$ at location $l$ is available to be used</td>
<td>Hours/Day</td>
<td>$a_{rl}$</td>
</tr>
<tr>
<td>Capacity</td>
<td>Quantity of resource $r$ at location $l$</td>
<td>—</td>
<td>$c_{rl}$</td>
</tr>
<tr>
<td>Surgeon Capability</td>
<td>Indicator variable; 1 if surgeons in surgeon class $s$ can perform procedures in class $k$</td>
<td>—</td>
<td>$\alpha_{sk}$</td>
</tr>
<tr>
<td>Procedure Class Membership</td>
<td>Indicator variable; 1 if procedure $p$ is in procedure class $k$</td>
<td>—</td>
<td>$\beta_{pk}$</td>
</tr>
<tr>
<td>Surgeon Availability</td>
<td>Surgery time available for surgeons belonging to surgeon class $s$</td>
<td>Hours/Day</td>
<td>$a_{SURG}^{s}$</td>
</tr>
<tr>
<td>Network Demand</td>
<td>Upper and lower bounds on demand for procedure $p$ across the entire network of hospitals</td>
<td>Cases</td>
<td>$\Delta_p^+, \Delta_p^-$</td>
</tr>
</tbody>
</table>
3.3.3 Decision Variables

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>DESCRIPTION</th>
<th>UNITS</th>
<th>SYMBOL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Procedure Volume</td>
<td>Number of procedure $p$ performed at location $l$</td>
<td>Cases</td>
<td>$x_{pl}$</td>
</tr>
<tr>
<td>Surgeon Allocation</td>
<td>Surgery hours allocated to performing procedures of class $k$ at location $l$ by surgeons belonging to class $s$</td>
<td>Surgeon Hours</td>
<td>$z_{ski}$</td>
</tr>
</tbody>
</table>

3.3.4 Objective

$$\maximize_{x,z} \sum_{l \in L} \sum_{p \in P} n_{pl} x_{pl} \quad (3.2)$$

3.3.5 Constraints

$$\sum_{p \in P} \sum_{h \in H} d_{phl} x_{phl} \leq d_{total} c_{rl} \quad \forall r \in R, l \in L \quad (3.3)$$

$$\sum_{p \in P} \sum_{h \in H} d_{phl} a_{phl} \leq \sum_{s \in S} a_{ski} z_{ski} \quad \forall k \in K, l \in L \quad (3.4)$$

$$\sum_{k \in K} \sum_{l \in L} a_{ski} z_{ski} \leq d_{total} a_{i}^{SURG} \quad \forall s \in S \quad (3.5)$$

$$\Delta_{p}^{-} \leq \sum_{l \in L} x_{pl} \leq \Delta_{p}^{+} \quad \forall p \in P \quad (3.6)$$

$$\delta_{pl}^{-} \leq x_{pl} \leq \delta_{pl}^{+} \quad \forall p \in P, l \in L \quad (3.7)$$

$x \geq 0$, $z \geq 0$ \quad (3.8)
<table>
<thead>
<tr>
<th>CONSTRAINT</th>
<th>NAME</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.3</td>
<td>Resource Capacity</td>
<td>Usage of resource $r$ at location $l$ cannot exceed capacity</td>
</tr>
<tr>
<td>3.4</td>
<td>Surgeon Allocation</td>
<td>Cannot perform procedures in class $k$ without appropriate surgery hours allocated at location $l$</td>
</tr>
<tr>
<td>3.5</td>
<td>Surgeon Capacity</td>
<td>Cannot allocate more surgery hours of class $s$ than there is total network surgeon capacity</td>
</tr>
<tr>
<td>3.6</td>
<td>Network Demand</td>
<td>Cannot perform too many or too few of procedure $p$</td>
</tr>
<tr>
<td>3.7</td>
<td>Location Demand</td>
<td>Cannot perform too many or too few of procedure $p$ at location $l$</td>
</tr>
<tr>
<td>3.8</td>
<td>Non-negativity</td>
<td>Cannot perform negative procedures or allocate negative surgery hours</td>
</tr>
</tbody>
</table>
In the previous chapter we examined the structure of the model we use to solve the hospital resource allocation problem. We now turn to the challenges and subtleties involved in practically applying the model.

4.1 SCOPE

To pilot our model, we study three service lines in the BIDMC Department of Surgery: General Surgery, Colorectal Surgery, and Surgical Oncology. These categories were selected because they are readily performed in the community, they constitute a significant volume of cases, and they have a demonstrated history of unmet demand. In addition, we model all three hospitals in the BID network: BIDMC, BIDH Milton, and BIDH Needham. Finally, we choose to study a single year of operations because this is a period of time that is easily related to by administrators; however this parameter is easily adjusted.
One of the first questions that arises when implementing our model is which surgical procedures to include in the model. If every procedure ever performed is included, significant complexity is incurred.

Many procedures at an academic medical center are performed infrequently (e.g. less than once a year) and do not have standard resource usage patterns; because we must specify demand, duration, and resource consumption for every procedure, choosing to model nebulously defined cases poses substantial challenges. More importantly, including these procedures is of questionable utility:

- Making multiple assumptions about rare procedures introduces weak input data into the model and potentially skews results.
- The purpose of our model is to provide a hospital administrator insight into how to meet demand and allocate resources. The recommendation that an obscure and unpredictable case be performed on average once every six months is not particularly useful or actionable. Furthermore, multiple similar recommendations may even obfuscate more important macro-trends.

The approach we follow is to only model procedures that have historically been performed at least once a month on average. Us-
ing this down-selection criteria, we obtain 57 procedures that represent 87 percent of 2012 BIDMC case volume within our three service lines; the remaining 13 percent of volume is made up by over 100 different procedures (see Figure 4.1). Appendix A.1 contains a list of all modeled procedures.

4.3 RESOURCE USAGE

Determining the amount of resources used by each studied procedure constitutes the majority of the effort involved in implementing our model. As discussed in Section 3.1.2, we employ the notion of surgical phases to facilitate organizing data on resource usage for each procedure. We elect to model the following phases for every procedure:

1. **PREOP** represents time the patient spends in the preoperative holding area
2. **OR** represents time the patient spends in an operating room
3. **TURNOVER** represents time perioperative staff spends cleaning and preparing the operating room for the next case
4. **PACU** represents time the patient spends in the post-anesthesia care unit
5. **RECOVER** represents time the patient spends in an inpatient bed on the medical floor (pure outpatient cases have a duration of 0 minutes for this phase)

With few exceptions, we assume that a procedure's resource usage is the same at each location in the network. While our model allows us to easily specify different resource usage at each location, in practice we do not expect usage to change as a function of location; case times and resource needs are much more related to clinical aspects inherent to the procedure itself than where it is performed.

This assumption enables us to perform most of our data collection at BIDMC, the only location with IT infrastructure that allows us to readily gather resource usage data in a large-scale automated fashion.

4.3.1 Phase Duration

Phase durations define the length of time that resources are required by a procedure. Duration data is most easily learned by analyzing historical case records. We obtain phase durations for our
pilot study by observing thirteen years of historical case data at BIDMC; we use this data to compute a median duration values for each phase of each procedure.

We choose to use median values for phase durations because the distribution of case times often has a long right tail at academic medical centers (see Figure 4.2); for the purposes of our model, we are interested in modeling typical cases and do not wish to skew our model with outliers. See Section 3.2 for a more extensive discussion of variability considerations.

Turnover time is the only phase for which we use differing durations at each network location. This distinction is made because OR turnover time is more dependent on location scheduling practices than procedure type.

**LENGTH OF STAY** The recovery phase duration must be computed slightly differently than other phases. This is because certain procedures are performed in both inpatient and outpatient settings, hence simply taking the median duration across all cases can mask bimodal tendencies in these procedures. To address this consideration while still avoiding outlier effects, we compute length of stay as a weighted average between inpatient and outpatient cases (which by definition have no overnight stay):

\[
\text{LOS} = \frac{\text{\# of inpatient cases}}{\text{total \# of cases}} \times \text{median inpatient LOS} \quad (4.1)
\]
4.3.2 Equipment and Facilities

Hospitals have a limited supply of equipment and because certain equipment have considerable cost, it is unreasonable to assume a hospital can immediately purchase additional equipment in the event of a bottleneck or shortage. For example, a C-arm is a relatively commonly used imaging tool, but the cost to purchase a new device is over $100K.

While the model we have developed readily allows us to account for equipment constraints, in practice we must determine which equipment to model and how many are required by each procedure.

Usage Normal equipment usage for a procedure can typically be inferred in two ways: through surgeon preference cards, or the historical case audit trail. Almost all hospitals maintain preference cards for each surgeon’s regularly performed procedures; this data is used by perioperative nurses to prepare an operating room for a case. In addition, larger hospitals tend to have IT systems that record exactly which equipment was used in each procedure.

We choose to follow the latter approach for determining resource usage because it more readily allows us to identify average usage. For equipment usage, we choose to use mean values instead of median because averages allows us to better accommodate legitimate clinical variation and differences across surgeons.

In practice, we compute the average usage of a resource by tallying across the entire history of case-specific needs for a procedure and evaluating:

\[
\text{average usage} = \frac{\text{total \# of resource } i \text{ required}}{\# \text{ of cases}}
\]  

We omit equipment that is used in less than 5% of procedure \( p \) cases to avoid including outliers and constraining our solution by equipment that is rarely needed.

Facilities A hospital’s operating rooms, recovery beds and other facilities can be viewed as a special case of equipment. While our model makes no distinction between facilities and other equipment, the IT database we use to infer equipment usage does not include facilities because usage is essentially standard across all case types.

On the other hand, the length of time patients spend in the OR or PACU does vary by procedure, but this variability is already captured in a phase’s duration. Hence we only need to record standard
facility requirements that are missing from the IT database: preop bay, OR, PACU bay, and recovery bed usage.

EQUIPMENT DOWN-SELECTION  In theory choosing to model all equipment might seem like an ideal approach but this strategy has a practical limitation: the model may become constrained by insignificant equipment shortages such as a lack of surgical blankets.

To address this concern, we further reduce our list of modeled equipment to eliminate low-cost items. Down-selection was performed by BIDMC nurses familiar with both equipment requisition and operating room preparation and resulted in a list of 197 types of equipment that we include in our pilot model.

4.3.3 Staffing

For reasons that will be discussed in Section 4.4.2, surgeons are the only staff members we explicitly model as independent resource requirements. Surgeons are more complex than other resources because different surgeons can perform multiple families of procedures. To correctly model this dynamic, we perform two forms of grouping: procedure classification and surgeon classification.

PROCEDURE CLASSIFICATION  Procedure classification is the process of grouping procedures into specialties based on technical similarity. We define two procedures to be technically similar if similarly trained surgeons can perform both procedures. With the assistance of multiple BIDMC surgeons, we group each of the 57 modeled procedures into one of the seven procedure classes listed in Table 4.1.

SURGEON CLASSIFICATION  As previously discussed, most surgeons are capable of performing multiple classes of procedures. To accommodate this flexibility, we develop the concept of a surgeon class. A surgeon class is a set of procedure classes; two surgeons have the same class if they can perform the same classes of procedures.

<table>
<thead>
<tr>
<th>Bariatric</th>
<th>Colorectal</th>
<th>General Surgery</th>
<th>Breast</th>
</tr>
</thead>
<tbody>
<tr>
<td>Esophageal</td>
<td>Endocrine</td>
<td>Hepato-Pancreato-Biliary</td>
<td></td>
</tr>
</tbody>
</table>
We determine each surgeon's class empirically by observing the surgeon's 2012 case history and following a simple procedure:

1. Tally the number of times the surgeon performed each procedure
2. Sum tallies corresponding to the same procedure class
3. For each procedure class, if a surgeon performed more than 5 cases in that class, append the procedure class to the surgeon's class

Using this process we generate the list of surgeon classes that appears in Appendix A.2.

Once we have obtained procedure and surgeon classes, capturing surgeon needs for a procedure is straightforward: a procedure requires a surgeon whose class includes the procedure's class. For example, a Breast surgery case can be performed by a surgeon belonging to any of the following classes: Breast/Endocrine/General, Breast/Colorectal/General, and Breast. The related question of how much time each surgeon should spend on their respective sub-specialties is directly optimized by our model.

4.4 CAPACITY

4.4.1 Equipment and Facilities

In addition to capturing which resources each procedure uses, we must also identify how many of each resource is available at each location. All equipment and facilities previously identified as required by a procedure are included in this process. At BIDMC, equipment capacity data is readily acquired through an IT inventory system. On the other hand, at BIDH Milton and BIDH Needham, we manually perform an inventory of hospital equipment with the assistance of perioperative nurses.

Facility data is also manually collected at all three facilities; we count the number of each facility available at each hospital. Unstaffed facilities do not count toward capacity.

SEGMENTATION Performing a pilot study on a limited subset of procedures introduces a unique challenge in capacity modeling: real resources are shared across all procedures including those that are excluded from our model. To reconcile this discrepancy, we must segment total capacity into the portion that is available for the procedures we are studying.

For operating rooms, we have a natural paradigm to assist us in performing this segmentation: surgeon block time. We first
compute the 2012 block time allocated to surgeons included in our model as percentage of total allocated block time. We then further refine this percentage by taking into account the portion of time these surgeons historically spend working on cases we are studying. This produces a final multiplier we use to scale operating room capacity:

\[
\text{available capacity} = \text{total capacity} \times \text{historical share (\%)} \times \text{in-scope usage (\%)}
\]

We follow a similar procedure for determining available capacity for PACU and preop resources. For recovery beds we were unable to directly estimate the number of beds available to only our three service lines, so we instead approximate the available capacity by computing the number of bed hours used performing our 57 procedures in 2012.

Unfortunately, for equipment resources the appropriate segmentation is less clear; equipment share is not necessarily proportional to case volume or operating room block time. Because of our concern that certain types of equipment maybe highly specialized to specific service lines, we choose not to apply a blanket reduction in capacity for all equipment and instead judiciously monitor utilization levels in our solution output, noting any outliers and manually validating.

### 4.4.2 Staffing

The principal staff required to perform surgery are:

1. Attending Surgeon
2. Attending Anesthesiologist
3. Scrub Nurse
4. Circulating Nurse

Anesthesiologists and nurses are staffed on an aggregate per operating room basis at BIDMC, and although there are some exceptions, both are capable of facilitating most procedures—the PACUs and preoperative holding areas follow a similar staffing model for their nurses.

For these reasons, we associate anesthesia and perioperative nurses with their respective facilities, as opposed to modeling them as independent resources. Any facility that is included in the total modeled capacity is assumed to be staffed; we do not consider an unstaffed operating room to be available capacity.
**SURGEON CAPACITY** Surgeon capacity is computed on a per surgeon class basis. If multiple surgeons share the same class, their capacity is pooled. Capacity is determined empirically for each class using the following procedure:

1. We define a procedure as in-scope if it is one of the 57 modeled procedures.
2. For all surgeons belonging to the same class, we sum the amount of 2012 time spent operating on in-scope cases.
3. For the same set of surgeons, we compute total 2012 block time and scale by the percent of the surgeon's operating time spent on in-scope cases. To this total, we also add time spent on in-scope add-on and waitlist cases (cases not included in the block schedule).
4. Capacity for this surgeon class is then the maximum of the two quantities computed in the previous steps, converted to units of hours per weekday.

This process produces a somewhat conservative estimate of capacity for each surgeon class; a more aggressive (although potentially less accurate) estimate could be obtained by explicitly polling surgeons. Observe that surgeon capacity has different units (surgeon-hours per day) than all other types of capacity; we further discuss this distinction in the subsequent section.

### 4.4.3 Availability

Similar to resource usage, capacity can be divided into two components:

1. The number of a resource available
2. The time the resource is available

Phase duration captures the time component of resource usage; availability is the corresponding concept for capacity. A resource’s availability is the average number of hours per day that resource is available to be used. From this definition, we observe that we can compute the right hand side of capacity constraints as:

\[
\text{capacity} = \text{simulation time (days)} \times \\
\text{availability} \left( \frac{\text{hours}}{\text{day}} \right) \times \# \text{ of resource} \quad (4.4)
\]
The concept of availability naturally applies to a hospital's facilities: operating rooms and PACUS have standard operating hours. Hence we assign availabilities at each location by simply determining the normal operating hours of the respective facility. For equipment, we make the assumption that equipment is available the same hours that the location's ORs are available. Note that we do not need to compute availabilities for surgeons because our approach to computing surgeon capacity directly yields a value in terms of surgeon-hours per day.

4.5 Demand

We collect two types of demand data for our pilot implementation: 2012 existing demand, and 2012 unmet demand. Using only these two types of data we can setup a variety of insightful studies; we will discuss these studies more extensively in the following chapter.

Existing demand is calculated by summing the number of cases performed in 2012 for each of the 57 modeled procedures. Unmet demand is approximated by analyzing claims data containing information on in-network patients who received surgical care from a competitor.

Spilled Demand Approximation BIDMC receives regular claims data on a specific group of patients whose primary care physicians belong to the BID network; this group of patients constitutes a significant portion of BIDMC annual volume. For this population, BIDMC can identify when a patient receives surgery at a competing hospital.

Before we can include the spilled demand data in the model, we must perform a conversion process because the claims data does not use the same system for categorizing procedures as our model. More specifically, our model uses an internal BIDMC coding system called PIMs to identify procedures (this is what allowed us to readily capture resource data for each procedure). In contrast, the claims data uses two forms of diagnosis-related group codes (DRG) to identify procedures: HCFA/CMS-DRG for Medicare cases and AP-DRG for non-Medicare cases.

Converting between coding systems is nontrivial because there exists no one-to-one mapping. We develop an approximate map-

* These reports are anonymized with respect to patient identifiers, but BIDMC is able to quantify the magnitude of spilled cases
ping by observing the empirical distribution of PIMS codes for a
given DRG; this empirical distribution is computed using only the
case history at BIDMC. More specifically, if we let x represent a PIMS
code and y represent a DRG code we can evaluate:

\[ P(x|y) = \frac{P(x, y)}{P(y)} \]  
\[ = \frac{\text{# of BIDMC occurrences of } x \text{ and } y}{\text{# of BIDMC occurrences of } y} \] (4.5)

Repeat applications of this equation allow us to determine an em-
pirical distribution for all DRG codes that occur in the claims data.
We then use these distributions to translate the claims data into an
approximation of spilled demand that our model can use.

4.6 MARGINAL PROFIT

The objective coefficients we use in our model are marginal profits
for each procedure (see Section 3.1.4 for a more detailed discus-
sion). Marginal profit consists of two components: revenue and
marginal cost; we now discuss each component independently.

4.6.1 Cost

We use a strict definition of economic marginal cost in choosing
which costs to include in our model. Any cost that does not truly
vary with the number of procedures performed must be omitted
from our model to avoid skewing results; this includes costs that
are sunk in the intermediate term such as OR nurse salaries. While
it is true that certain indirect costs may change with total output,
these costs do not tend to vary unless their is a drastic change in
overall output, a situation that is outside the intended scope of our
model.

Using the economic definition of marginal cost, we are left with a
only few costs to consider: surgical supplies and miscellaneous neg-
ligible expense (e.g. incremental electricity, etc.). Furthermore, we
can reasonably assume that supplies costs are approximately equal
across the BID network. Hence the only remaining cost data we
need to collect is the average surgical supplies cost at BIDMC for
each of our 57 procedures.

4.6.2 Revenue

Revenue is the most important component of marginal profit for
surgical procedures because it tends to dominate marginal cost. Un-
Fortunately, BID hospitals track payment data using ICD-9 procedure codes, a different means of identifying procedures than the PIMS system our model employs.

To overcome this difficulty, we compute an empirical distribution of ICD-9 codes for each PIMS procedure code, applying the reverse of the technique we used to approximate spilled demand in Section 4.5. Through repeat applications of Equation 4.5, we obtain our desired distributions.

We request 2012 payment data from each of the three BID hospitals and use our empirical distributions to compute PIMS revenue for each of our 57 procedures as a linear combination of ICD-9 payments. Note that this approach correctly accounts for the important phenomena of delinquent payments and the gap between billed charges and actual payments received.

**Sample Size Limitations** For certain ICD-9 codes, there are insufficient community hospital payment samples to obtain a meaningful forecast of PIMS revenue. For these missing or underrepresented codes, we forecast the community ICD-9 payment using the BIDMC payment. For sample sizes $n < 10$, we use the following affine combination to forecast the community payment for ICD-9 $x$:

$$
\hat{p}_{\text{COMMUNITY}}(x) = \frac{n}{10} \bar{p}_{\text{COMMUNITY}}(x) + \frac{10 - n}{10} \gamma \bar{p}_{\text{BIDMC}}(x)
$$

(4.6)

Where $\bar{p}$ is the average observed payment at a particular hospital and $\gamma$ is the observed average payment ratio between BIDMC and the community hospital across all ICD-9 codes with sample size $n \geq 10$. 
In this chapter we present the results of multiple case studies involving the BID network; in each study we have applied our model to the BIDMC network under slightly different assumptions, but we always follow the implementation guidelines detailed in Chapter 4. We close this section by summarizing our findings and suggesting directions for future work.

Please note that all dollar figures presented in this chapter have been uniformly scaled to avoid sharing proprietary business information.

5.1 BASELINE CASE STUDY

The first scenario we explore is simple and not even strictly an optimization: we force our model to recreate 2012 BIDMC operating conditions. We initialize this scenario by clamping demand for each procedure within a tight tolerance ($\pm \varepsilon$) of actual case volume and by forcing community surgical volume to zero.
The purpose of performing this simple exercise is two-fold:

1. Successfully executing this study provides a quick test of our model's assumptions. We know this mix of cases is feasible because it was already performed in actuality, hence if we reach an infeasibility condition we have either made an incorrect assumption or a mistake in inputting data.

2. This baseline scenario provides context that we can use for evaluating other case studies. We can readily compare demand allocation, resource utilization, and objective values across studies to develop a more intuitive understanding of results.

5.1.1 Assumptions

GENERAL ASSUMPTIONS

We now briefly revisit and summarize the framework and assumptions we have developed over the preceding two chapters:

- Our model is a representation of BIDMC, BIDH Milton, and BIDH Needham's ability to perform surgery over a one year time horizon.
- The objective of our model is to maximize total marginal profit subject to capacity and demand constraints.
- 57 procedures are included in the model; these procedures represent all common case types from the General Surgery, Colorectal Surgery, and Surgical Oncology service lines.
- Equipment, facility, and staff requirements for each procedure as well as available capacity are captured by the model.
- Economic contribution margin for each procedure is calculated from historical actual payments and marginal costs.

BASELINE STUDY ASSUMPTIONS

In addition, we make the following assumptions in our baseline case study:

- BIDMC volumes are held to 2012 values.
- Community hospital volumes are forced to zero.
### METRIC | VALUE
--- | ---
Gross Marginal Profit | $100M
BIDMC OR Utilization | 82%
BIDMC PACU Utilization | 35%
BIDMC PREOP Utilization | 62%
BIDMC Bed Utilization | 100%

While the recovery bed utilization we obtain appears unrealistic, this value is in fact reasonable based on the capacity assumption we have made (recall that in Section 4.4.1 we elected to ensure we use no more bed-hours than we used in 2012).

Significantly more interesting is the fact that the OR utilization needed to realize the 2012 case mix is very high; this supports what many BIDMC surgeons have long shared anecdotally: *the OR is likely the bottleneck for surgery at BIDMC and limits the organization's ability to provide timely access to patients.*

Given that there is unmet demand in the BID network (Section 4.5), and unused capacity in BID community hospitals, the natural question that follows is how can the network more efficiently use resources to increase its profitability? We explore this question in the subsequent case studies.

#### 5.2 BORROWED CAPACITY CASE STUDY

Perhaps the simplest way to claim previously spilled demand is to add more capacity. In the case of BIDMC, the limiting constraint is operating room capacity; unfortunately, we can only increase OR capacity by taking away block time from other service lines, hence the term *borrowed capacity*. In this study, we attempt to answer the question, "How much will profits increase if we give the three studied service lines more OR time?"

##### 5.2.1 Assumptions

- BIDMC volumes must be *at least* the 2012 level for each procedure.
- The amount of spilled demand available to be recaptured is gradually increased and we measure the corresponding increase in OR time needed to maintain 82% utilization.
- Community hospital volumes are forced to zero.
• The recovery bed utilization constraint is relaxed; we assume bed capacity can also be borrowed from other service lines.

5.2.2 Results

<table>
<thead>
<tr>
<th>Recaptured Demand (%)</th>
<th>Needed Block Time (HR/WK)</th>
<th>Profit Increase (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>2.39</td>
<td>1.2</td>
</tr>
<tr>
<td>25</td>
<td>5.97</td>
<td>3.0</td>
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<tr>
<td>50</td>
<td>11.93</td>
<td>6.0</td>
</tr>
<tr>
<td>100</td>
<td>23.87</td>
<td>12.0</td>
</tr>
</tbody>
</table>

We note that profits appear to increase linearly as additional spilled demand becomes available for recapture; however this is not surprising when we revisit this case study's capacity assumptions. More interesting, however, are two related observations that we make:

1. The profit increases we have computed are incomplete and overly-optimistic because they ignore the opportunity cost of taking block time from another service line (e.g. the profit the other service line would be generating with the block time we have borrowed).

2. Using the observed linear relationship, we can evaluate the average value of an additional hour of block time to our three service lines: $12M/23.87/52 = $9,667. This number is meaningful because it gives administrator's a benchmark to compare against when evaluating whether to redistribute block time across service lines.

In general, actually implementing this approach to meeting demand is challenging because the allocation of OR block time is a contentious subject in large hospitals. Instead, we now turn towards an alternate means of recapturing spilled demand: making more efficient usage of existing resources.

5.3 Reallocation Case Study

A less controversial approach to better meeting demand is to make more judicious uses of existing resources. In practice this is achieved by performing greater numbers of resource-efficient cases whiles performing fewer that are less-efficient. To prevent too great of a
shift away from any single procedure type (thus violating the hospital's mission), we study multiple thresholds for the maximum allowable decrease in any single procedure's volume.

5.3.1 Assumptions

- BIDMC volumes for any single procedure cannot decrease by more than $x\%$ from 2012 values; we experiment with multiple values of the reallocation threshold $x$.
- Community hospital volumes are forced to zero.
- BIDMC OR utilization cannot exceed 82%.
- The impact of recovery bed utilization is observed by performing studies with recovery bed capacity fixed to 2012 utilization and also with the utilization unconstrained.
- The amount of spilled demand available to be recaptured is varied.

5.3.2 Results

Figures 5.1 and 5.2 graphically depict the results of multiple optimization runs with varying input parameters. We observe that holding recovery bed capacity fixed to 2012 usage levels has a significant damping effect on the additional profit that can be obtained; this is intuitively pleasing because higher profit procedures tend to be more complex and involve a longer length of stay. To better conceptualize the impact of relaxing the recovery bed constraint, we observe that the most extreme unconstrained case requires on average 4 additional recovery beds to be continuously occupied.

The second theme we recognize is that in addition to limiting profit, recovery bed capacity significantly restricts the power of reallocation. When recovery beds are unconstrained, allowing a 25-30% decrease in volume for any procedure enables significant profit gains, but in the bed-constrained case, more drastic reallocation is needed before diminishing returns are reached.

Next we observe that the optimal allocation is not simply obtained by shifting all volume to procedures with the highest marginal profit per OR minute (see Figure 5.3). Practically speaking, this suggests that an administrator must pay significant attention to not only high-margin procedures, but also to specific lower-margin procedures as these procedures may be an even more integral contributor to total earnings. This observation is also a further indictment against heuristic approaches to resource allocation that we examined in Section 2.2.
**FIGURE 5.1:** BIDMC Reallocation Study — Level Curves Depict Increase in Profit (%) under Differing Degrees of Reallocation and Demand Recapture; Recovery Bed Constraint Relaxed

**FIGURE 5.2:** BIDMC Reallocation Study — Level Curves Depict Increase in Profit (%) under Differing Degrees of Reallocation and Demand Recapture; Recovery Bed Utilization Fixed
Lastly and perhaps most importantly, we note that our model has explicitly detailed multiple target case mixes that achieve significant profit increases without committing additional OR capacity. Because the unmet demand we have modeled represents existing BID patients who have chosen to receive surgical care elsewhere, it is plausible that significant inroads can be made in actually realizing this demand through initiatives such as targeted access to the OR.

We now turn to the question of how available capacity in BID community hospitals can be used to meet demand.

5.4 NETWORK OPTIMIZATION CASE STUDY

BIDMC senior management has espoused the view that community hospitals should be better integrated into the network and used to provide more care:

"A strong network of affiliated community hospitals and physician practices is fundamental to fulfilling our belief that care that can be provided in the community should be provided there, and that academic medical centers
should be for sicker patients and more complex cases that require higher levels of specialty care.”

Kevin Tabb, President & CEO, BIDMC

However, thus far minimal integration of surgical services has occurred across the BID network. We now explore the potential benefits of utilizing free capacity in community hospitals to recapture spilled demand.

5.4.1 Assumptions

- Total network volumes for any procedure cannot decrease below BIDMC 2012 values.
- BIDMC volumes for any single procedure cannot decrease by more than x% from 2012 values; we experiment with multiple values of the reallocation threshold x.
- BIDMC OR utilization cannot exceed 82%.
- BIDMC recovery bed utilization cannot exceed the 2012 level.
- The amount of spilled demand available to be recaptured is varied.

5.4.2 Results

Figure 5.4 is a contour plot analogous to the ones obtained in our Reallocation Case Study. We observe that in all scenarios there is sufficient capacity in the BID community hospitals for the network to meet all spilled demand. We further note that additional profit increases can be reached by allowing reduction in BIDMC volumes for certain case types. In this situation, demand remains entirely met but BIDMC tends to retain more complex cases while the community hospitals receive a larger share of simpler cases.

In Figure 5.5 we observe the distribution of cases between BIDMC and the community hospitals. While the community hospitals are predominantly performing simpler, lower-margin cases, the community still receives a significant number of cases that are near or above average marginal profit. This is particularly important because community hospitals are more likely to be willing partners in integration if they expect to receive cases of value.

Finally we observe that the maximum profit attainable by utilizing the BID network exceeds that achieved by adding requisite OR and bed capacity at only BIDMC (when opportunity costs are considered; see Section 5.2).

Of the strategies for recapturing spilled demand that we have
studied, using community hospitals has the greatest potential for increasing profit, but it requires BID to adopt a systems mindset where maximizing network profit is the new goal. Our optimization model outlines an optimal case mix that squeezes additional utility out of existing resources; achieving these mixes is a matter of taking operational actions that improve access and foster growth for case types identified by the model as valuable.

5.5 SUMMARY

We have built the case that successful care organizations must be able to answer a few key strategic questions to remain competitive in the current environment:

- How should limited resources best be allocated to meet demand?
- Which future growth opportunities should be pursued now?
- How should a multiple-hospital network be used to meet total demand?

To address these questions in a long-term strategic sense, we have developed a general optimization framework that can be applied to
a wide spectrum of hospital services. We have used our model to specifically study the delivery of surgery in the BID network and in the process we have identified techniques for overcoming implementation challenges.

Using our model, we have observed that BIDMC operating room time is a bottleneck that limits surgical volume and likely results in spilled demand due to inadequate patient access. In light of the bottleneck, we have performed three case studies that examine different approaches to recovering spilled demand:

1. Meeting additional capacity needs by taking block time from another service line. This approach leads to considerable increases in profit (~6%) but also has a high opportunity because it requires that we take profitable time away from other services.

2. Holding capacity fixed, but reallocating resources to more efficient case types. This tactic yields modest profit (~4%) increases but requires that we substantially decrease existing volume for certain procedures.

3. Using spare community hospital capacity to meet spilled demand. This approach provides significant increases in profit (~6%) but requires better coordination of surgical care across the entire BID network.
While all three approaches have the capability to grow profit without building additional capacity, utilizing available community hospital capacity has the greatest potential upside but requires that BIDMC adopt a system-wide view of both operations and profit-maximization.

5.6 FUTURE WORK

We have developed a framework that can be used to study multiple types of hospital services but have only piloted the model on surgical services. Additional insight could be obtained through a more broad application of the model or by expanding the scope of the model to include an entire surgery department.

A second important avenue for future work is to develop an approach for operationalizing a target annual case mix. In theory, approaches similar to real-time yield management could be employed to assist in the daily scheduling and prioritizing of cases while attempting to track a long-term volume target.


A

Implementation Details

A.1 MODELED PROCEDURES

Anal Condylomata Laserexcision
Anal Fissurectomy
Anal Fistulectomy
Anal Fistulotomy
Appendectomy Laparoscopic
Axillary Dissection
Axillary Sentinel Lymph Nodebiopsy
Cholecystectomy Laparoscopic
Colectomy Left
Colectomy Left Laparoscopic
Colectomy Left Laparoscopically Assisted
Colectomy Right
Colectomy Right Laparoscopic
Colectomy Right Laparoscopically Assisted
Colectomy Sigmoid Laparoscopic
Colectomy Sigmoid Robotic Laparoscopic
Colostomy Takedown
Excision Breast Lesion
Excision Breast Lesion Needlelocalization
Excision Cyst Or Lesion Arm
Excision Cyst Pilonidal
Excision Cyst/lesion Leg
Excision Cyst/lesion Trunk
Excision Tumor Rectal
Exploration Neck
Exploratory Laparotomy
Gastrectomy Subtotal
Gastric Banding Laparoscopic
Gastric Bypass Laparoscopic
Gastric Resection Laparoscopic
Heller Myotomy Laparoscopic
Hemorrhoidectomy
Herniorrhaphy Incisional
Herniorrhaphy Inguinal With Or Without Prosthetic Material
Herniorrhaphy Inguinal Laparoscopic
Herniorrhaphy Umbilical
Herniorrhaphy Ventral
Herniorrhaphy Ventral Laparoscopic
Ileo Anal Pouch
Ileostomy Closure
Incision And Drainageperi-rectal Abscess
Insertion Indwelling Port W/c-arm
Laparoscopy Exploratory
Laparoscopy Staging
Low Anterior Resection Robotic Laparoscopic
Mastectomy Partial Needlelocalization And Axillarydissection
Mastectomy Partial Needlelocalization With Sentinelnode Biopsy
Mastectomy Partial/re-excision
Mastectomy With Sentinelnode Biopsy
Nissen Fundoplication Laparoscopic
Pancreatectomy
Paraesophageal Hernia Repair Laparoscopic
Rectal Examination Under Anesthesia
Removal Indwelling Port
Thyroidectomy
Thyroidectomy Partial
Whipple Procedure

A.2 SURGEON CLASSES

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<tr>
<th>General/HPB</th>
<th>Colorectal/Esophageal/General/HPB</th>
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</thead>
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<td>Breast</td>
<td>Bariatric/Colorectal/General</td>
</tr>
<tr>
<td>Colorectal/General/HPB</td>
<td>Breast/Endocrine/General</td>
</tr>
</tbody>
</table>
To facilitate the process of repeatedly running our model while updating the many parameters described in Section 3.3, we developed a web interface. Our interface allows a user to dynamically change model input parameters and view solution output in a convenient tabular format. Our web framework was built on the following open-source technologies:

- **Database**: SQLite (http://www.sqlite.org), SQLAlchemy (http://www.sqlalchemy.org)
- **Server/URL Routing/Dispatching**: Flask (http://flask.pocoo.org/)
- **Scripting**: Python (http://www.python.org)
- **Javascript Libraries**: jQuery (http://www.jquery.com), SlickGrid (https://github.com/mleibman/SlickGrid)
- **Optimization Engine**: Gurobi (http://www.gurobi.com)

We have included the following screen captures to demonstrate the primary capabilities of our interface:
FIGURE B.1: Home screen of the web interface

Home / Input / Output

Service Resource Utilization
Facility Capacity
Resource Availability
Network Surgeons
Facility Demand
Network Demand
Margin

FIGURE B.2: Menu for changing input parameters
APPENDECTOMY LAPAROSCOPIC
ANAL CONDYLOMATA
ANAL FISTULECTOMY
ANAL FISTULOTOMY
APPENDICETOMY LAPAROSCOPIC
AYLLARY DISSECTION
AYLLARY SENTINEL L'YMPH NODE BIOPSY

<table>
<thead>
<tr>
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<th>BIDMC</th>
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<th>NGHM</th>
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</thead>
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<td>OR</td>
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<td>61m</td>
<td>61m</td>
</tr>
<tr>
<td>PREP</td>
<td>77m</td>
<td>77m</td>
<td>77m</td>
</tr>
<tr>
<td>PACU</td>
<td>96m</td>
<td>96m</td>
<td>96m</td>
</tr>
<tr>
<td>TURNOVER</td>
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<td>25m</td>
<td>30m</td>
</tr>
<tr>
<td>RECOVER</td>
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<td>0m</td>
<td>0m</td>
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</table>

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<th>BIDMC</th>
<th>MLTN</th>
<th>NGHM</th>
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<td>OR</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
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<td>Colorectal Surgeon</td>
<td>STAFF</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
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</table>

**Figure B.3: Resource utilization of the modeled services**

<table>
<thead>
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<th>NDHM</th>
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<td>EQUIP</td>
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<td>C-ARM</td>
<td>EQUIP</td>
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<td>3.00</td>
<td>1.00</td>
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<td>DAO VINCI</td>
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<td>3.00</td>
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<td>EQUIP</td>
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<td>GASTROSCOPE FLEXIBLE</td>
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**Figure B.4: Equipment capacities**
FIGURE B.5: Daily availability of resources categories

<table>
<thead>
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<th>Resource Type</th>
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<td>10.50</td>
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<tr>
<td>PREOP</td>
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<tr>
<td>RECOVER</td>
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</tr>
</tbody>
</table>

FIGURE B.6: Network surgeon capacities
### Figure B.7: Menu for viewing solution output

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<tr>
<th>Variable</th>
<th>Type</th>
<th>Value</th>
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<th>UB</th>
<th>Basis</th>
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</thead>
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<tr>
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<td>Procedure</td>
<td>18.90</td>
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<tr>
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<td>26.10</td>
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### Figure B.8: Decision variable output

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### Home / Output / Constraints

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**FIGURE B.9: Constraint output**