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Determining future capacity for an Ambulatory Surgical Center with discrete event simulation

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ABSTRACT
Background: Ambulatory Surgical Centers (ASC) are providing an increasing number of patients with care for outpatient surgery. They represent a step forward in efficiency and service compared with performing all outpatient surgeries in a hospital setting, allowing that capacity to be reserved for patients requiring hospital stays. When new ASCs are brought online, throughput capacity is either unknown, or estimated from construction schematics.
Methods: A discrete event simulation was created to simulate the operations of the Seattle Children's Bellevue ASC, and identify throughput capacity as the number of operating rooms was increased from three to four, while the Post-anesthesia care unit (PACU) remained constant at 14 beds. The model was queried to determine the number of patients who could receive care while minimizing the duration of crowding (occupancy 13 or greater) in the PACU, limiting mean total crowding time to one hour per week.
Results: The simulation was validated against current practice, and determined that up to 50 patients per day can be scheduled through four operating rooms, and the resulting mean crowded time in the PACU would be limited to approximately 59 min.
Discussion: DES allows hospitals to support strategic decision making through providing predictions of system performance under a variety of loading scenarios. This allows hospital management planners to inform operations with robust analysis and have confidence in the likely outcomes of policy.

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Introduction

Health Care costs as of 2016 account for 17.8% of gross domestic product (GDP) in the United States [1]. As the rate of increase of a hospital's expenses is outpacing the growth of revenues, hospitals are scrambling to move care to lower-cost care centers. Increasing volumes and acuity have also forced institutions to optimize capacity in a resource-constrained environment.

Ambulatory surgery centers (ASCs) are modern health care facilities focused on providing surgical care with patients arriving from and returning to home after their procedures. This practice emerged in the 1970s in the United States, principally in adults, but has rapidly increased in volume and spread into the pediatric population. The rapid growth of ASCs has transformed the outpatient experience for millions of Americans each year by providing them with a more convenient and typically more cost-effective alternative to hospital-based procedures [2]. The National Survey of Ambulatory Surgery reported that 3.2 million children under the age of 15 received care for outpatient surgery in 2006 [3]. Between 1996 and 2006 the number of surgical visits to ASCs increased by almost 300% [4]. Due to continued medical advances and technological innovations, similar increases in ASC utilization were realized over the last decade, as more surgeries can be safely conducted in an ambulatory setting.

A free-standing academic children's hospital system (Seattle Children's Hospital) constructed and opened their ambulatory surgery center in 2010. More than 4000 surgical procedures are completed annually exclusively in children. Using innovative facility design [5] and models of care [6], this team has created a high quality, efficient, safe, and cost-effective clinical perioperative practice. The perioperative process consists of three unique phases: preoperative, intraoperative, and postoperative [7]. Detailed descriptions of all three phases of care at the Bellevue ASC have previously been described [6].

A variety of different methods have been used to enhance operational efficiency, scheduling, and staffing in healthcare settings, such as mixed integer programming [8], neural networks [9, 10], systems modeling [11], and queueing theory [12]. More recently, techniques in predictive analytics have helped us to best understand how to optimize our systems. Discrete event simulation (DES) is a computer

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modeling technique which enables the simulation of processes. DES allows for the creation of a graphical model of a care process or clinic, which can then be used to test hypotheses about the behavior of that system under various alternative scenarios. In healthcare systems, DES is often used to model the flow of patients through clinics and hospitals in order to identify candidate interventions for quality, safety, and performance improvements [13]. Recent examples of DES and clinical capacity include Bal et al., modeling emergency departments [14], and Kritchanchai and Hoeur describing simulation modeling in outpatient settings [15]. DES has been used in the past as well to optimize surgical scheduling [16–18] and reduce postponements of elective procedures [19]

We identified two tactics to create OR capacity in our system and lower the cost of care. The first was to optimize the use of our ambulatory surgery center by mandating that ambulatory cases be done in this setting as opposed to our tertiary care facility. Second, we are opening an additional operating room in our ambulatory facility. Prior to optimizing the system, we wanted to understand the maximum capacity of our ambulatory facility using current model of practice and processes. The objective of this study was to use DES to determine the maximum number of OR cases that could be done in our ambulatory surgery center.

Discrete event simulation

DES as a tool for strategic planning is under-reported in the healthcare literature, but examples exist [20]. DES, which essentially allows for the graphical and mathematical modeling of healthcare processes as a complex queuing system, represents an ideal tool for examining the central question posed in this investigation: how many patients per day can the ambulatory surgical center serve without the post-anesthesia care unit (PACU) becoming overcrowded?

Methods

DES development

Flow mapping

The system flow was mapped through interviews between system stakeholders, and direct observation of the real-world clinical system. The model was simplified to a room-and-resource-occupancy level description of events. That is, rather than attempt to model specific care processes associated with the induction and surgery each patient required, the DES model allowed each patient to proceed through the locations required to complete a surgical visit. Resource consumption was modeled by fitting historical procedure times to distributions, at the surgical-service level. Thus, room occupation was consistent with historical values for surgical services required. Finally, the conceptual model was coded using MedModel 2018 Professional (ProModel Corp., Allentown, PA) according to established best practices [21, 22] (Figure 1).

Because the purpose of the simulation was to model the physical capacity of the ambulatory surgical center, rather than human resources, nursing, and physician scheduling were excluded from the model. However, because physical capacity is heavily influenced by PACU bed turnaround time, bed cleaning between patients (including delay while waiting for available resources) was incorporated into the model. Cleaning times were generated from observational data curve-fitted to a random number generator.

The model was informed with three months of de-identified surgical data, from the time period immediately prior to modeling. This was randomly parsed into a training set, from which the model was built, and a test set, against which the model was validated. Data fields captured from historical patient visits included arrivals per day and time in PACU, stratified by surgical service. Surgical services present in the data includes: 1 – Dermatology, 2 – General Surgery, 3 – Ophthalmology, 4 – Oral Surgery, 5 – Orthopedics, 6 – Otolaryngology, 7 – Plastic, 8 – Urology, and 9 – Unknown. The 'Unknown' represents all those surgeries without a service recorded in the medical record. PACU length of stay was curve-fit for each of these services and then called as a random variable when each simulated patient entered the PACU. The simulation then recorded the entire number of minutes that the PACU census was greater than or equal to 13 patients for the duration of the simulation run. The number of patient arrivals was modeled based on real-world arrivals in the current system, after being fit to a Poisson random variable.

Simulation runs and reporting metrics

The mean number of daily patient arrivals was increased in intervals of 3–6 patients for a total of 12 scenarios, rising from the current practice of approximately 18, up to 60 patients per day. Each 10-week simulation run was repeated with random variation 10 times to capture the natural variation in systemic performance. Thus, each patient volume threshold is represented by 100 weeks of statistically independent data.

Results

Validation

The simulation was presented for face validity to a team of physicians and nurses working within the system. All flow, design, and work was determined to reflect real-world operations. For internal validity, the simulation was subjected to a thorough code review.

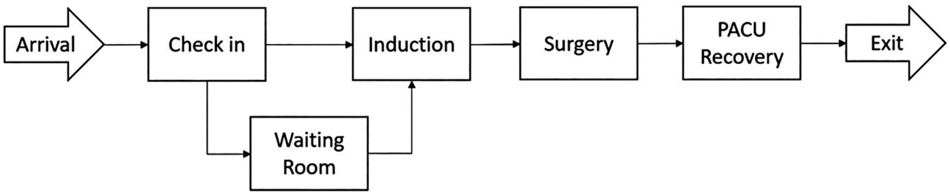

Figure 1. Patient flow through the system.

And finally, for external validation, the simulation was determined to accurately replicate the real-world system with respect to all observable metrics. Patient arrivals fit an appropriate Poisson distributed random variable with $\lambda = 17.8$. The primary outcome metric of interest (crowding time) was difficult to validate against historical real-world performance, as neither the simulation nor the real-world system experienced crowding at current patient loads. Both systems showed zero minutes-per-week of PACU volumes equal to or in excess of 13 patients, based on the current real-world throughput. Thus, for the metric of interest, the simulation was trivially valid; that is, we neither observed nor expected any crowded time in the PACU.

Minutes/week of crowded time

The number of minutes per week of crowded-time in the PACU (defined as 13 or more of 14 PACU rooms filled) followed a typical Malthusian curve. As the number of surgeries performed increased, crowded time rose exponentially, until bounded above by the total time available (there being only 10,080 min in a week). Figure 2 shows the rise in minutes/week of crowded time. The error bars represent one standard deviation around the mean as calculated from the multiple simulation runs. Thus we anticipate that 68% of weeks would have crowding time between the error bars at each patient/week threshold.

Total number of surgeries possible

Based on nursing and physician opinion on the safety and efficiency of operation while crowded, it was determined that a weekly threshold of 60 min of crowding time was the limit that could be tolerated. Beyond this, crowding would represent an unacceptable burden on available nursing resources. Thus, the total number of patients which can be seen in the system is calculated to be 50 per day.

Discussion

The challenge of maximizing throughput given capacity constraints is a classic problem in operations research. Several approaches are appropriate for problems of this sort, especially when they can be simplified into a network of complex queues. Mixed-integer programming for scheduling optimization is a traditional method, but can struggle to support environments such as this one where PACU recovery times are stochastic rather than deterministic. The use of DES in such cases allows us to accurately

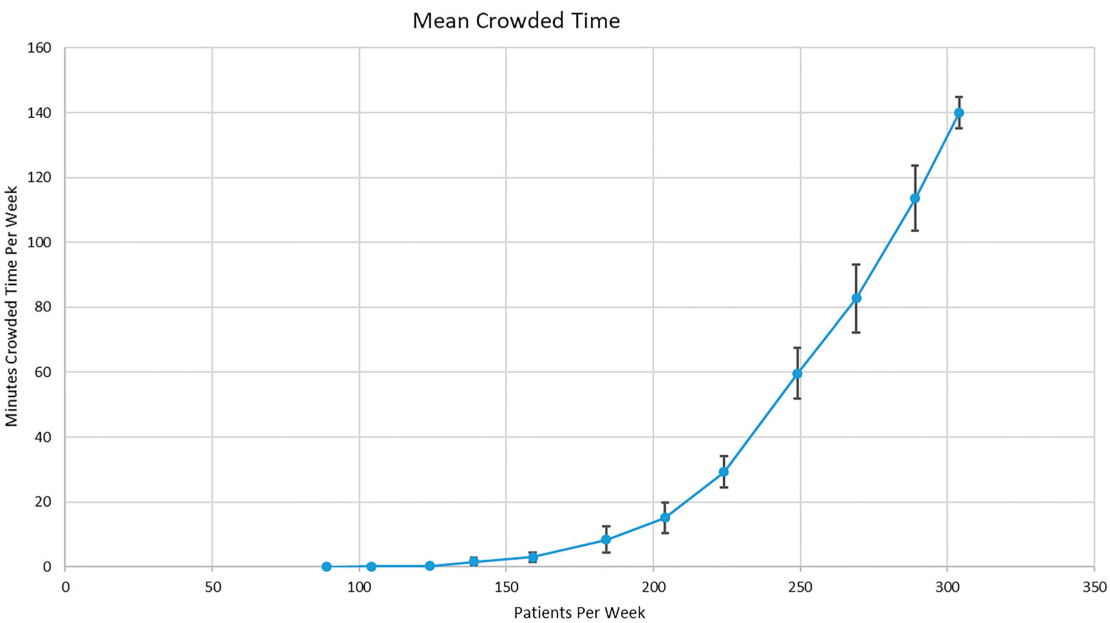

Figure 2. Patients per week vs Mean crowded time (min/wk).

model and simulate the system, taking uncertainty and stochasticity into account. As a result of this analysis, we determined that a maximum of 50 cases could be performed in a fully optimized ambulatory center with four ORs and 14 PACU spaces using current operational processes.

It's important to recognize that systems of this type cannot necessarily be safely assumed to scale linearly; that is, expanding from three operating rooms to four does not necessarily mean that throughput will increase by 33%. Because patients may belong to any one of nine surgical services, each with differing surgical and recovery distributions, the system may respond in any number of unpredictable ways. Thus, facilities duplicating this work should consider their own cycle times and constraints when conducting simulations; a surgical service with high volumes and short recovery times will impact the system differently from a service with lower volume but longer recovery times. The effect of different scheduling decisions may well be to shift a bottleneck from the PACU to the ORs or even the induction rooms.

The modeling described here was predicated on the largest volume of patients occupying the fourth, soon-to-be-opened OR, generally likely to be Otolaryngology patients. This decision reflected both their higher demand for ambulatory surgeries, and shorter surgical durations, resulting in higher demand on the constrained shared-capacity resource of the PACU. Other facilities with similar demand patterns will likely have analogous performance issues, but should be aware that the significant jump in capacity realized in our circumstance is related to heavy planned scheduling of short-duration surgeries.

DES modeling of clinical delivery systems also provides the unique capability to analyze and interpret 'what if' scenarios regarding potential perturbations to current management practice [23]. The model can be tested with various potential patient flow and clinical policy practices in order to determine the likely effect of various decisions. In this way, we can isolate the effect of particular policy decisions, by experimenting on a chosen strategy while holding all other factors constant. We are therefore able to identify those candidate interventions which are likeliest to support effective and efficient care delivery. Our patient flow goal is to cohort cases based on patient flow characteristics (acuity, length of case, length of stay). Ultimately we want to do cases in the area of care that will maximize throughput for that case type at the lowest cost. For instance, our main campus is best structured to handle complex long-duration cases with longer PACU lengths of stay. Given our current case mix, cases done at our ambulatory center may be better performed at our tertiary campus and vice versa. Additional 'what if' scenario testing will help us to best study this and provide objective data to our teams.

Value of testing in computer simulation

Speed

There are a number of clear benefits to analyzing strategic questions using DES. The first is the speed with which the systems can be modeled and decision guidance provided. The model presented here was completed, from conception to recommendation, in a four-week period. It required less than 100 total person-hours of work. The resulting recommendation with reasonably in line with the administration's and medical staff's desires for the unit, but it had been unknown if those desires were realistic. They were reluctant to begin scheduling for 50 patients per day at full capacity without knowing for certain that the system's infrastructure could handle that volume of cases. Ramping slowly up to that many patients, on the other hand, would likely sacrifice a great deal of opportunity in the name of prudential scheduling. Many patients might be delayed in treatment due to necessary institutional caution. The ability to model the system greatly reduced the time needed to analyze the circumstances and begin scheduling at full capacity.

Cost

The cost of the analysis was similarly quite low compared with the potential costs of under-scheduling as the system was brought up to full production. While the exact figures can never be known for certain, the analysis of the system cost less than $10,000 in compensated time, a figure that is dwarfed in revenue from even a few additional surgeries performed as a result of beginning scheduling at full capacity rather than with a slow real-world calibration designed to identify optimal throughput experimentally.

Safety

The sensitivity of crowded time to patient volume becomes significant as throughput exceeds 40 patients per day. The value of modeling systems such as this one *in silico* with respect to safety should be apparent: it could be catastrophic to experiment with the real-world system. The system dynamics support the idea that it is risky to increase patient volumes without proper planning; when patients occupy the entire PACU, the ORs become obstructed and a queue forms. Not only are surgeries delayed, but if PACU beds are occupied for unexpectedly long periods of time, then patients may be ready to leave the operating room with no recovery bed available: a critical operational failure. Thus, it is inadvisable to conduct real-world trial runs without adequate data from modeling.

Implications

Optimizing capacity in ambulatory surgical centers is a growing and critical strategy for providing comprehensive quality of care at the appropriate point of contact for patients. This provides better and more cost-efficient service for patients as well as freeing OR block time at tertiary and quaternary care hospitals for those complex, time-consuming, and inpatient surgeries which cannot be performed in outpaitent settings. Thus, optimal OR block utilization in low-acuity centers robustly supports the provision of care across health systems, not only in their own patient cohort. The result is a better distribution of resources for overall public health.

Limitations

As with any approach, DES analysis in general – and this result in particular – is subject to assumptions and limitations. The model is agnostic to scenarios not modeled; we cannot say that the solution recommended is the best possible solution, only that it represents the likely outcome of a particular desirable management scenario. The model is based on real-world data which is subject to drift as populations and medical practices change.

Conclusion and future recommendations

The ASC at Bellevue can support a capacity of 250 patients/week under the assumptions set forth in this project. This assumes a significant preference for short-duration surgeries, and current distribution of room turnover times. Similarly outfitted ASCs can be reasonably assumed to have similar capacities, but local analysis should be conducted to verify that facility-specific idiosyncracies are not significant enough to limit capacity.

Strategic operational planning for healthcare delivery in a complex environment is challenging using traditional management science and operations research tools. Fluctuations in demand, service time, and resource consumption render deterministic tools useful for only the most basic projections at a highly aggregated scale. For granular analysis, DES provides agile modeling capability in a simulation, which accurately reflects real-world variability, uncertainty, and randomness. This supports robust decision analysis and provides planners, care providers, and schedulers with critical insight into systemic effects of various management strategies.

Our goal of optimizing the surgical system begins with the optimization of our ambulatory surgical center. By enhancing utilization and increasing capacity of our ASC, we have the ability to create space in other operative centers in the system. DES provides a healthcare organization the tools to understand their ultimate OR capacity while accounting for other systemic constrains such as PACU beds. It also allows the flexibility of testing scenarios to empower healthcare leaders to make informed decisions that optimizes an institution's success.

Future work has already begun with respect to modeling and analyzing system-wide surgical resources. The Surgical Care Distribution project will use DES to model the current hospital surgical facilities, the Bellevue ASC, and a new, to-be-constructed surgical suite in a new facility currently in the building phase. Prior work in the use of DES for facility design and process modeling will help inform how new facilities are modeled in our setting [10] This will allow us to identify and separate patients by cohort – the right child in the right OR at the right time. Deploying DES proactively to optimize a large-scale system effort will allow us to bring the new system online rapidly, at capacity, and with prior knowledge of likely systemic effects.

Disclosure statement

Author TED has received consulting fees from ProModel Corp. No other potential conflict of interest was reported by the author(s).

Notes on contributor

Kayla Reece is a nurse director with the Seattle Children's Ambulatory Surgical Center; Jeff Avansino, MD, is VP for Medical Affairs; Maria Brumm is a Lead Data Scientist; Lynn Martin, MD, is an Anaesthesiologist and Principal Investigator; T. Eugene Day, DSc, is a Data Science Manager.

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