

DATA-DRIVEN SIMULATION USE TO DETERMINE BED RESOURCE REQUIREMENTS FOR THE REDESIGN OF PRE- AND POST-OPERATIVE CARE AREAS

Thomas P. Roh
Todd R. Huschka
Michael J. Brown

Yariv N. Marmor

Mayo Clinic
200 First St. SW
Rochester, MN 55905, USA

ORT Braude College
Snunit St
Karmiel 21661, ISRAEL

ABSTRACT

Perioperative services have a high impact on a hospital's financial success. In order to increase patients' privacy and satisfaction, while restraining cost, a redesign of the existing Post-Anesthesia Care Unit (PACU) was suggested at the Mayo Clinic. A simulation model was created to determine the number of beds required in the redesign of the PACU to maintain Operating Room (OR) blocking below 5 %. Since OR time and resources are more costly than the PACU, limiting the resource scarcity of the PACU should minimize delays through the surgical suites. By assuming PACU resourcing as secondary to managing the OR, the underlying complexity of the surgical scheduling did not have to be analyzed. Real data was fed into the simulation model that successfully captured the complexity of the system without the work-intensive requirements of theoretical modeling. The results of the analysis were incorporated into the design plans for remodeling the PACU.

1 INTRODUCTION

Perioperative services infrastructure, which consists of the pre-operative intake and waiting areas, operating rooms (ORs), post anesthesia care units and their associated staffing, is a high cost component of hospital infrastructure (DeRiso et al. 1995, Farnworth et al. 2001). At the same time the services associated with the perioperative practice are often the largest contributors to a hospital's financial success. Perioperative infrastructure, particularly in older facilities, is a factor known to constrain OR productivity. However, to meet the demands of today's procedural practice, an ideally designed perioperative facility needs to ensure patient privacy, provide parallel processing ability, reduce redundant care and staffing processes, promote surgical efficiency and improve patient satisfaction.

In order to address patients' privacy and satisfaction, a redesign of the existing PACU was suggested. Typically, post-operative care occurs in an "open-air" environment. That is, patients are transported to a large room where there are no partitions, apart from hanging curtains, separating them from each other. While this design is cost efficient in terms of construction and allows good visibility for care providers, the design does not ensure patient privacy and is not centered on patient satisfaction. To alleviate these issues, it was decided to implement new redesign rooms that are fully enclosed by walls for each patient. The redesign rooms can also function as multi-purpose in that both pre-operative and post-operative work can be performed there. Three key improvements come from this redesign: (1) The new redesign rooms create better privacy for patients and families with the partitioning; (2) The patient experience should improve since family members are allowed in these rooms; and (3) The multi-purpose rooms will decrease the amount of transportation for the patient.

Taking into account the aforementioned changes, the redesigned facility would plan to support 30,000 surgical cases per year and satisfy the requirements listed above with less than a 5% chance of overcapacity. It was determined that simulation modeling would be the best course of action to determine bed resource requirements given the previous stated constraints. The process was modeled using Arena 14.0 (Kelton et. al 2002).

2 BACKGROUND

Simulation of Health Care systems is not new. The pressures to control costs and improve patient care have made simulation modeling a popular tool for addressing health care problems (Jacobson et al. 2006). It has been shown that simulation modeling can be an effective tool regarding changes to practice during the implementation of the redesign of an existing system (Huschka et al. 2011). Additionally, simulation modeling has been used for the future planning of recovery beds in an ICU (Marmor et al. 2013). The complex nature of these environments works well within the simulation modeling world.

The PACU in question was in the process of remodeling and expansion, providing a relatively blank slate to examine. While the interior room redesign had been determined, there was some flexibility in the arrangement and placement of rooms and additional flexibility in the type of rooms. Previous research using simulation to determine the number of beds in a PACU has been done (Marcon et al. 2003). However, it appears that the majority of PACU simulation focused on the effect that the surgical schedule has on a PACU (Marcon and Dexter 2006, Sokal et al. 2006). Our simulation model largely assumes a complex, yet unchanged scheduling system with some flexibility in order to model future growth.

Because of this approach we used a data- or trace-driven modeling (Balci, 1990) where real PACU information is fed into the simulation creating patients' sequences and times accordingly. The benefits of using this methodology are two-folded. First, we do not limit patients' flow and times by fitting the data into a restricted model and distribution. We are fortunate to have over 90,000 patients' data records spanning 3 years, which strengthens the model validity. The second is that the same model and solution approach can be utilized later in similar complex systems, feeding only the new data (Pidd 1992, Clark and Cash 1993).

3 METHODS

3.1 Process Description

The perioperative process consists of four main components for the patient. First, a patient must be placed in a bed, if they do not already have one, and then prepared for surgery. After the pre-operative process, the patient is transferred to an operating room for surgery. Most patients begin anesthesia in the OR while some patients will begin anesthesia in the pre-op room. Part of the redesign was to help facilitate this process more efficiently. After the surgical procedure has been completed, the patient is moved to a post-anesthesia care unit (PACU) for Phase I care. Phase I care is where a patient is monitored very closely after surgery until the patient has safely recovered from the majority of the effects of anesthesia. After Phase I, some outpatients require less intensive observation after Phase I care, which is called Phase II care. Phase II care occurs in a different location from Phase I because it is less resource intensive.

3.2 Data Description

The simulation used three years of data from 2009-2011. All patient records for those that used the PACU for their first phase of post-anesthesia care were pulled from an internal database that tracks the location of patients on day of surgery. The data used in the simulation was retrieved by individual patient records from the patient tracking system. The timestamps denoted four key patient events occurring in the perioperative process, the patient arriving and leaving for the pre-operative room, the operating room, the Phase I care, and other rooms throughout the hospital for Phase II care. The pathways are shown in Figure

1. Two characteristics paired with the patient location times include: Age and Inpatient, Outpatient, and AM Admit status.

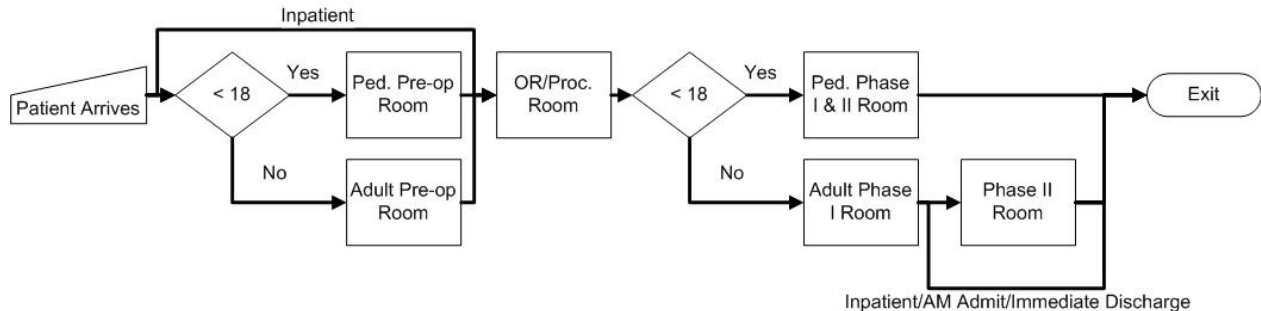


Figure 1: The current state of patient flow through the perioperative process.

3.3 Data Assumptions

Since we decided to model a data-driven simulation, using only empirical data, we did not fit theoretical distributions to the model parameters. As a result the model cannot create new patient events outside those events which have already happened, meaning, the model assumes that the delays that occurred in the past, due to limited resources, remains exactly the same. In order to overcome this issue, and simulate a 5% growth in the system over the next 5 years, 5% of the current records were randomly selected and duplicated. This assumes that growth in the patient population is uniform across the types of surgeries to be performed.

3.4 Data-Driven Simulation Modeling

The data-driven simulation model was built by feeding patient flow timestamps from an Excel file directly into Arena 14.0. Patients advance through the simulation based on their most recent attributes. Patient age and status are used to determine what kind of bed resources they will need to seize. All resources are modeled with unlimited capacity.

In the current design, pediatric patients always seize a pediatric bed, while adult patients seize from the “open-air” beds. In the new design, adult patients can also seize from the new redesign bed pool, if available. On first arrival, adult outpatients and AM Admit patients will seize from the pool of new redesign beds. Adult inpatients will seize “open-air” beds. All patients are then delayed in the system until the simulation clock reaches the timestamp of the patient’s entrance into the operating room. The patients are delayed in the operating room until the simulation clock matches the timestamp of the patient entering Phase I of post-operative care. Pediatric patients are routed back to pediatric beds and seize one bed until the simulation clock matches the appropriate timestamp of the patient. Adult patients can leave the system (e.g. inpatients/AM Admits immediately admitted back to a hospital bed), seize a new redesign bed (e.g. outpatients who will eventually be discharged from the hospital), or seize an “open-air” bed (e.g. inpatients/AM Admits who will stay in the PACU for phase I post-operative care). The patients who seize beds then hold those beds until the simulation clock matches the timestamp of their departure from the system. The initial model only took into account the age attribute for bed type routing. The patient flow was shown previously in Figure 1. The second model routes the patients using both age and outpatient, inpatient, AM admit status. The model shown below in Figure 2 is not an exhaustive list of every possible patient route through the system but does cover the majority of patient pathways.

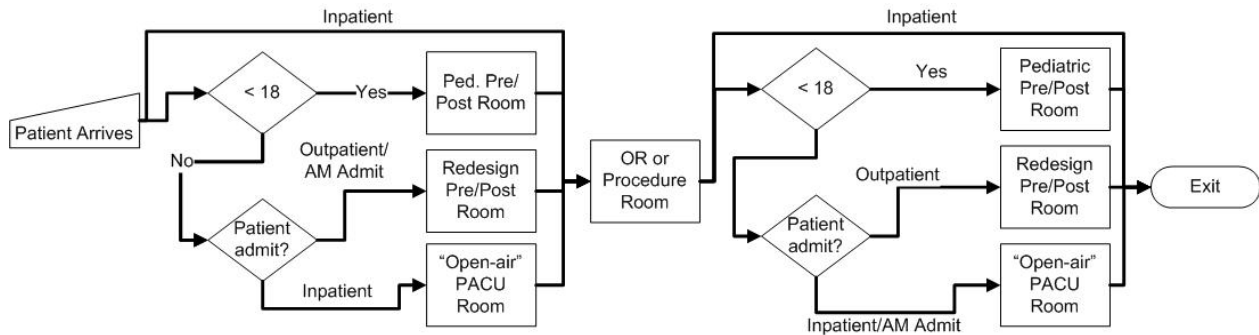


Figure 2: The future state of patient flow through the perioperative process.

The number of patients is tracked in 30 minute intervals over the course of the surgery day. At this interval, the number of simultaneously used beds is summed at each minute interval and then divided by 30 to find the mean number of beds used in the half hour period. The output is captured and then written into an Excel workbook for further analysis.

4 RESULTS

4.1 Initial Assumptions

The first plan to determine bed requirements for the redesign and expansion of the PACU rooms and their functions was developed using the “best guess” approach. Based on the number of beds currently being used and an expectation of slight growth in the next few years, it was decided on completely converting over to the new redesign beds. The initial plans required the construction of 75 new rooms in addition to the 10 redesign rooms that had already been built. The rooms would either be constructed in the new addition to the hospital or the space currently being used. The new areas would designate a pediatric care area with 15 beds and the other areas would total 70 beds for any type of adult patient.

4.2 Initial Model

The initial future modeling results were used as a basis for making the next decision in the iterative process of floor plan design with the architecture firm. The results looked at the total bed use regardless of patient admit status. Patients under 17 could use one of 8 pediatric beds if a bed was available. If a pediatric bed was unavailable, the patients would use an adult type bed. Since the operating room time is deemed as more costly resource, a conservative estimate approach was used to minimize blocking time of the operating rooms. The metric of interest was the maximum of the 95th percentile of bed usage split by half hour intervals for each day of the week. Based on this assumption, a conservative estimate of the total beds needed for each day of the week can be found in Figures 3 & 4. The 8 pediatric beds are excluded from the results shown in the Figure 3.

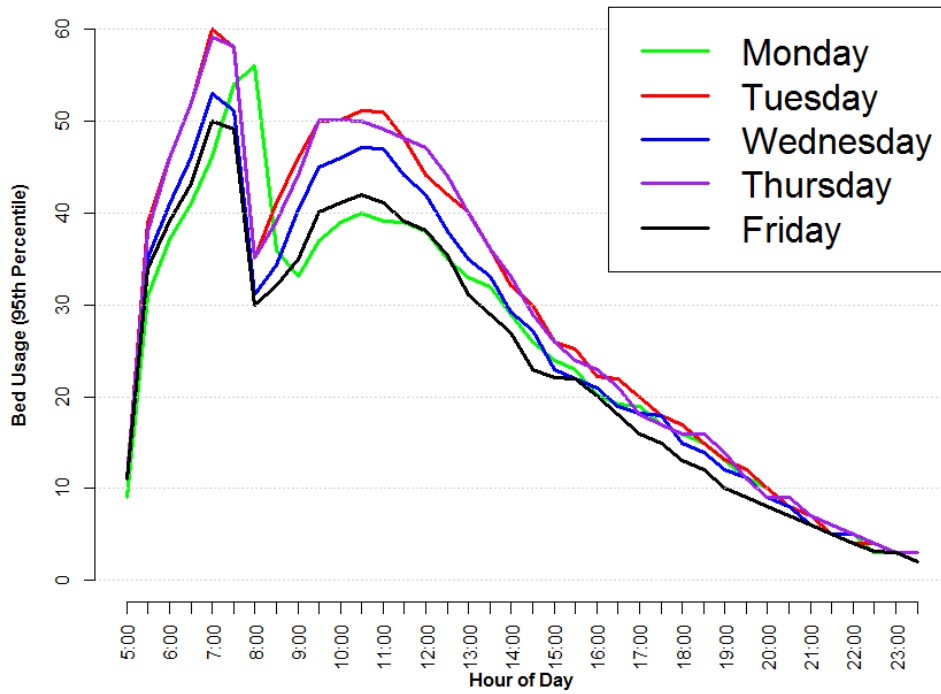


Figure 3: The 95th percentile of total bed usage over the course of a day for adults.

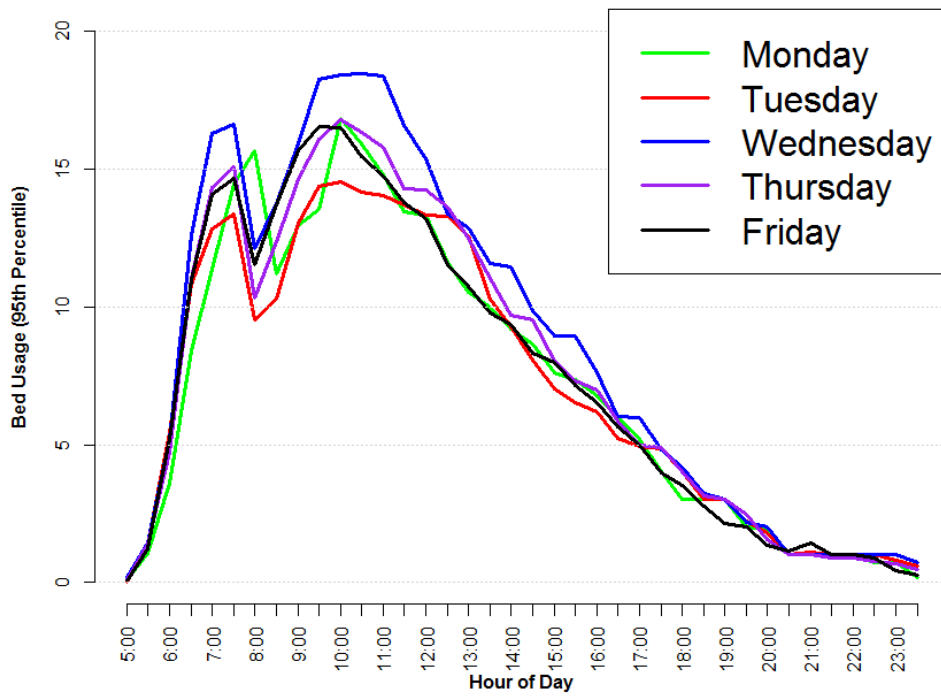


Figure 4: The 95th percentile of total bed usage over the course of a day for pediatric patients.

Based on the results, Tuesday was chosen as the busiest day of the week for adult patients and Wednesday was chosen for pediatric patients. Therefore, the maximum 95th percentile time interval value on that day was used as the benchmark for deciding on the number of beds needed. In Figure 5, the busiest days for pediatric and adult patients were plotted together.

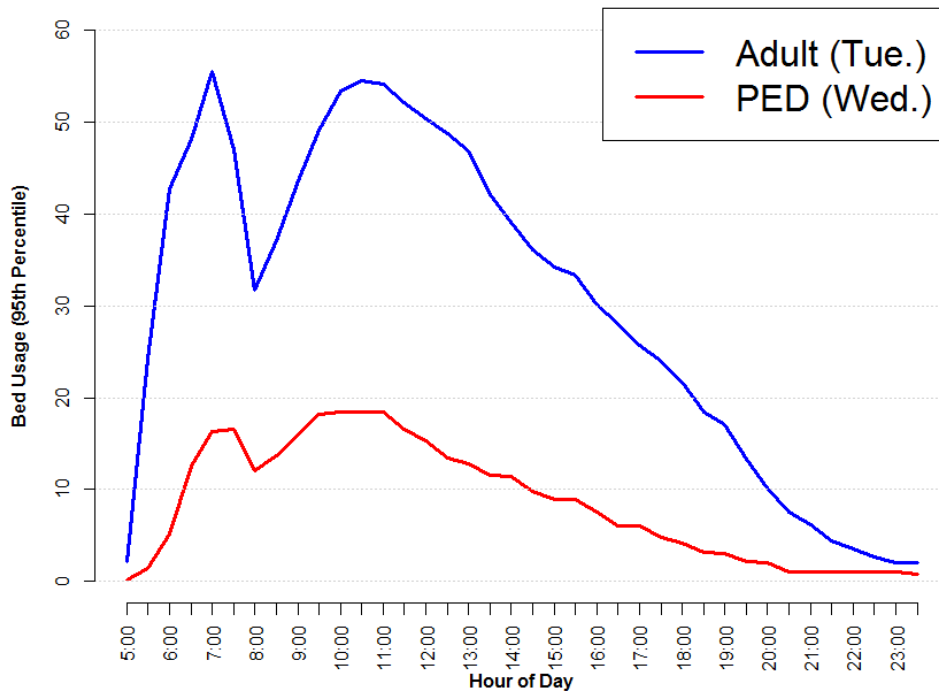


Figure 5: The 95th percentile for adult and pediatric bed use by time of day.

The information was used to decide on the number of pediatric care beds. Pediatric care beds were allotted first because it is possible for pediatric patients to use the adult care beds, but not possible for adult patients to use pediatric care beds. Because of this overflow routing policy, the bed values for Wednesday were not used since adult bed volumes are lower, which allows the unused adult care beds to accommodate the pediatric patient overflow. We chose 15 as the number of pediatric care beds that would be built based on these results, and 55 beds would be built for adult care to total 70 newly constructed redesign beds.

4.3 Final Model

After further detailed work on the floor plans, constructing 55 new beds was found to not be physically possible. The need for beds was re-evaluated based on patient admit status. Outpatients and AM admits would need to be placed into a bed before surgery. Therefore, they would need to be routed to a new redesign bed for pre-operative care. Inpatients were already in a bed so they could use the “open-air” beds to wait for transport to the operating suite. For post-operative care, outpatients would still use the new redesign beds because of privacy, family placement, and ease of discharge. The inpatients and AM admits would use the “open-air” beds for post-operative care since they would not need to be discharged. The routing rules are shown in Figure 2. The results from the final model are shown in Figure 6.

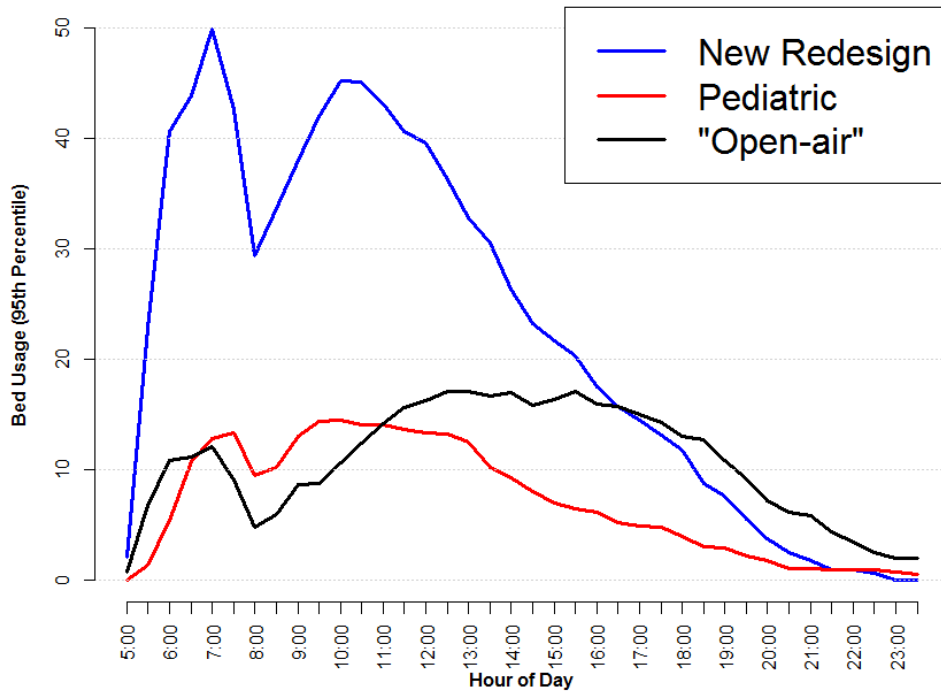


Figure 6: Bed usage in the different care areas by time of day.

With information from construction constraints and the results from Figure 5, the number of beds for each area was determined. Table 1 shows the final number of beds to be constructed as well as the bed allocation for each phase. “Flex” beds were introduced to the final design to address overflow issues. “Flex” beds are new redesign beds with expanded utility in that the beds can accommodate all patient types. None of the bed numbers meet the 95% criteria from Figure 5, but when adding in the “flex” beds the criteria should be met. To test that the number of “flex” beds was sufficient for our goal of less than 5% chance of overcapacity, the bed constraints from the Final Design were put into the simulation model. The percentage of time that the pre/post-operative bed constraints block patients from entering/leaving the operating room is 1.5%.

Table 1: A summary of the number of beds by type for each design phase.

Design Phase	Current State (Post-operative only)	Initial Plan	Design after Initial Model	Final Design	
New Redesign	-	77	55	44	8 "flex"
“Open-air”	34	0	0	14	
Pediatric	8	8	15	8	
Total Newly Constructed	-	77	62	52	
Total	42	85	70	72	

5 CONCLUSION

Perioperative services infrastructure is an expensive component of hospital infrastructure. We describe a data-driven simulation model to effectively plan the redesign of perioperative services infrastructure for a tertiary care hospital that performs in excess of 30,000 surgical procedures per annum. Initial “best guess” estimates would have required the construction of 77 new beds. After performing simulation analysis, the number of newly constructed beds was reduced by 15. Space constraints forced additional analysis to reduce the number of new redesign beds. Inpatients were identified as patients that would not benefit from having private beds, which allowed flexibility in bed allocation to patients. By designating 8 beds as flexible to take in any patient and servicing inpatients in the “open-air” beds, bed resources were utilized more efficiently. This resulted in a final design which required 25 less new redesign beds than the initial plan. Since bed estimates were based on 95th percentiles for each patient group, the constraints were put into the simulation to understand the effect of adding flexibility to patient allocation. The results showed a decrease in OR blocking time to 1.5% which was below the goal of 5%.

One additional interesting observation was the effect of the “flex” beds. While the use of flexible resources is well known to improve overall system process flows; seeing the effect can be surprising to those unfamiliar with systems engineering/operations research techniques. As was the case here, increasing the flexibility of patient allocation to specific care areas reduces the number of bed resource requirements.

In addition to infrastructure planning, further research can be conducted with this method to determine resource scheduling over the course of the day. Different bed groupings can be opened and closed to match demand variability for the perioperative services. We plan to further investigate by pairing auxiliary resources (e.g. nurses) to the bed resource load.

REFERENCES

- Balci, O. 1990. “Guidelines for Successful Simulation Studies.” In *Proceedings of the 1990 Winter Simulation Conference*, O. Balci, R. P. Sadowski, and R. E. Nance, 25-32. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
- Clark, G. M., and C.R. Cash. 1993. “Data-driven Simulation of Networks with Manufacturing Blocking.” In *Proceedings of the 1990 Winter Simulation Conference*, G. W. Evans, M. Mollaghasemi, E. C. Russel, and W. E. Biles, 662-669. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
- DeRiso, B., K. Cantees, and W.D. Watkins. 1995. “The Operating Rooms: Cost Center Management in a Managed Care Environment.” *International Anesthesiology Clinics* 33:133-150.
- Farnworth, L. R., D. E. Lemay, T. Wooldridge, J. D. Mabrey, M. J. Blaschak, T. A. DeCoster, and R. C. Schenck Jr. 2001. “A Comparison of Operative Times in Arthroscopic ACL Reconstruction between Orthopaedic Faculty and Residents: The Financial Impact of Orthopaedic Surgical Training in the Operating Room.” *The Iowa Orthopaedic Journal* 21:31-35.
- Huschka, T. R., T. R. Rohleder, & B.T. Denton. 2011. “Using Simulation to Design and Improve an Outpatient Procedure Center.” In *Management Engineering for Effective Healthcare Delivery: Principles and Applications*, edited by A. Kolker, and P. Story, 216-228. Hershey, PA: IGI Global.
- Jacobson, S. H., S. N. Hall, and J. R. Swisher. 2006. “Discrete-event Simulation of Health Care Systems.” In *Patient flow: Reducing delay in healthcare delivery*, edited by R. W. Hall, 211-252. New York, NY: Springer Science+Business Media, LLC.
- Kelton, W. David, R. P. Sadowski, and D. A. Sadowski. *Simulation with ARENA*. Vol. 3. New York: McGraw-Hill, Inc.

- Marcon, E., S. Kharraja, N. Smolski, B. Luquet, and J. P. Viale. 2003. "Determining the Number of Beds in the Postanesthesia Care Unit: A Computer Simulation Flow Approach." *Anesthesia & Analgesia* 96:1415-1423.
- Marcon, E., and F. Dexter. 2006. "Impact of Surgical Sequencing on Post Anesthesia Care Unit Staffing." *Health Care Management Science* 9:87-98.
- Marmor, Y. N., T. R. Rohleder, D. J. Cook, T. R. Huschka, and E. J. Thompson. 2013. "Recovery bed Planning in Cardiovascular Surgery: A Simulation Case Study." *Health Care Management Science* 16: 314-327.
- Pidd, M. 1992. "Guidelines for the Design of Data Driven Generic Simulators for Specific Domains." *Simulation* 59:237-243.
- Sokal, S. M., D. L. Craft, Y. Chang, W. S. Sandberg, & D. L. Berger. 2006. "Maximizing Operating Room and Recovery Room Capacity in an Era of Constrained Resources." *Archives of Surgery* 141:389-395.

AUTHOR BIOGRAPHIES

THOMAS P. ROH is a Senior Health Services Analyst for the Mayo Clinic Robert D. and Patricia E. Kern Center for Science of Health Care Delivery. Both his prior work at Emory University Hospital and current work at the Mayo Clinic has centered on operations research. He has a M.S. in Health Systems Engineering from the Georgia Institute of Technology and a B.S. from the University of Nebraska. His research has primarily focused on appointment scheduling and resource staffing in healthcare operations. His email address is roh.thomas@mayo.edu.

YARIV N. MARMOR is a lecturer in the Industrial Engineering and Management Department at Braude College. He holds a PhD in Industrial Engineering from the Technion–Israel Institute of Technology. His current research interests are in the area of process analysis and improvement of medical systems. Dr. Marmor has published his research in journals such as *ACM Transactions on Modeling and Computer Simulation (TOMACS)*, *International Journal of Production Research*, *IIE Transactions*, and *Journal of Health Organization and Management*. His email address is myariv@braude.ac.il.

TODD R. HUSCHKA is a Principle Health Systems Analyst for the Mayo Clinic Robert D. and Patricia E. Kern Center for Science of Health Care Delivery. His primary interests are simulation modeling, optimization and statistical analysis relating to improvements in health care systems. He completed his MS in Industrial Engineering Decision Science/Operations Research at the University of Wisconsin in Madison, Wisconsin. His email address is huschka.todd@mayo.edu.

MICHAEL J. BROWN is an Associate Professor of Anesthesiology at Mayo Clinic. He holds the position of Vice Chair, Department of Anesthesiology, Mayo Clinic, and Co-Clinical Practice Chair, Department of Anesthesiology, Mayo Clinic. His research interests include practice management and perioperative patient outcomes. His email address is brown.michael3@mayo.edu.