IISE Transactions on Healthcare Systems Engineering

ISSN: 2472-5579 (Print) 2472-5587 (Online) Journal homepage: http://www.tandfonline.com/loi/uhse21

Evaluating nurse staffing levels in perianesthesia care units using discrete event simulation

Sauleh Siddiqui, Elizabeth Morse & Scott Levin

To cite this article: Sauleh Siddiqui, Elizabeth Morse & Scott Levin (2017) Evaluating nurse staffing levels in perianesthesia care units using discrete event simulation, IISE Transactions on Healthcare Systems Engineering, 7:4, 215-223, DOI: 10.1080/24725579.2017.1346729

To link to this article: https://doi.org/10.1080/24725579.2017.1346729

Accepted author version posted online: 26 Jun 2017.
Published online: 08 Aug 2017.

IISE TRANSACTIONS ON HEALTHCARE SYSTEMS ENGINEERING
2017, VOL. 7, NO. 4, 215–223
https://doi.org/10.1080/24725579.2017.1346729

Taylor & Francis
Taylor & Francis Group

Evaluating nurse staffing levels in perianesthesia care units using discrete event simulation

Sauleh Siddiqui [a], Elizabeth Morse[b], and Scott Levin[c]

[a]Department of Civil Engineering, Whiting School of Engineering, Johns Hopkins University, Baltimore, MD, USA; [b]Johns Hopkins University, Baltimore, MD, USA; [c]Emergency Medicine, Johns Hopkins University School of Medicine, Baltimore, MD, USA

ABSTRACT

High variability in patient flow and changing patient acuity in perianesthesia care units (preparation /postanesthesia recovery [PREP/PACU]) is a challenge to efficient management of nurse staffing. Common approaches to estimate required nurse staffing levels that use PACU patient census over time, multiplied by nurse to patient ratios (NPR), may systematically underestimate nurse staffing needs. The objective of this study is to use discrete event simulation (DES) coupled with a queuing model to project nurse staffing levels and account for the dynamics of assigning nurses to patients. We evaluated the reference timevarying NPR-based method, which takes into account changing patient acuities over time, and showed that the current reference methods underestimate staffing requirements. These data parameterized the DES, which modeled the temporal patterns of weekly perioperative patient flow and mimicked the nurse protocol to manage stochastically simulated patients for a PREP/PACU within an urban 1059-bed medical center. Efficient nurse staffing level estimates over time were the primary outputs computed by the DES. Previously established time-varying (based on acuity) NPR systematically underestimated (up to 20%) nurse staffing needs, given common nurse-to-patient assignment protocols. We show that incorporating a queuing model within a DES will yield a proper estimation of staffing levels.

ARTICLE HISTORY
Received May 2016
Accepted June 2017

KEYWORDS
Discrete event simulation; PACU; staffing

1. Introduction

Perianesthesia care units (Preparation (PREP)/Post-Anesthesia Recovery Unit (PACU)) function in a highly uncertain clinical and operational environment. Workload fluctuates due to daily variability (Ragavan *et al.*, 2013) in surgical cases (often 50% swings on the same day of the week) (Litvak and Long, 2000; McManus *et al.*, 2003; Levin *et al.*, 2011) and patients' diverse and rapidly changing conditions (Ryckman *et al.*, 2009). Variability challenges PREP/PACU managers' ability to predict and optimize nurse staffing to maintain safe and efficient care (AORN, 2008; American Society of PeriAnesthesia Nurses, 2014; AORN, 2005). Understaffed PREP/PACUs may compromise patient safety (Cure *et al.*, 2014), and create operating room holds (delays) or surgical cancellations (Smith *et al.*, 2013) and nurse burn-out (Josten *et al.*, 2003). Numerous larg-scale studies have demonstrated the general association between inadequate nurse staffing levels, decreased quality of care, and even increased patient mortality (Aiken, 2002; Needleman *et al.*, 2002; Kane *et al.*, 2007; Weissman *et al.*, 2007; Tibby *et al.*, 2004; Kuntz *et al.*, 2014). Conversely, an overstaffed unit creates excessive nurse idle time and associated labor costs which are not viable, given tightening economic pressures in health care (Dale Compton *et al.*, 2005). While PREP/PACU nurse staffing has historically been dependent on clinical judgment and intuition of experienced nurse management, statistical methods have been developed to guide planning for perianesthesia nurse staffing (Dexter *et al.*, 2001; Dexter and Rittenmeyer, 1997). The goal of these methods has been to provide an optimal solution for standard nurse scheduling. Moreover, surgical case changes often take place days before the procedure, thus requiring careful planning for PREP/PACU staffing (Dexter *et al.*, 2012; Epstein *et al.*, 2002). Arrival patterns in the PACU also change by time of day, necessitating granularity and time-varying analysis (Ehrenfeld *et al.*, 2013).

Common approaches to determining hourly nurse staffing levels involve using time-varying nurse-to-patient ratios (NPR) (Dexter and Rittenmeyer, 1997), coupled with statistical analyses of historical data (Dexter *et al.*, 2001). These ratios provide an intuitive and quick way to estimate staffing requirements. Different levels of patient acuity (i.e., intensity of nursing care) over time must be accounted for when establishing accurate NPR estimates (Dexter and Rittenmeyer, 1997). Previous studies have shown that length of stay and acuity levels are endogenous to NPR (Lang *et al.*, 2004). However, since our goal is to see what the appropriate staffing levels are, given a particular patient profile, we assume that our patient data came from a unit that was staffed appropriately according to guidelines. As nurse staffing requirements are driven by temporal arrival patterns over the day/week and phases of patients' recovery (Dexter *et al.*, 2006), advanced operations research methods (Ferrand *et al.*, 2014; Carayon *et al.*, 2011; Lovejoy and Li, 2002; Bernes *et al.l*, 2015; Toerper *et al.* 2015), coupled with detailed

CONTACT Sauleh Siddiqui siddiqui@jhu.edu Department of Civil Engineering, Johns Hopkins University, Whiting School of Engineering, 3400 N Charles St., Baltimore, MD 21218, USA.

demand, capacity, and staffing data (Schoenmeyr *et al*., 2009; Turkcan *et al*., 2012; Zhang *et al*., 2012; Denton *et al*., 2010), have been used to quantify patient flow (Hall *et al*., 2006; Das and Boodhoo, 2015; Shi *et al*., 2015) and determine optimal staffing (Dexter 2007; Hamrock *et al*., 2013; Ewen and Mönch, 2014; Mobasher *et al*., 2011; Oh *et al*., 2013; Lin *et al*., 2013; Iskan and Hancock, 1990; Green *et al*., 2013; Abdoo, 1987).

The primary objective of this study was to use discrete event simulation (DES) (Günal and Pidd, 2010; Law *et al*., 1991), coupled with a queuing model (Cassandras and Lafortune, 2009; Connelly and Bair, 2004; Jun *et al*., 1999), to derive and evaluate a new, simple approach to estimate nurse staffing levels in the PACU compared to previous NPR-based methods (i.e., reference standard). We hypothesize that these reference methods may lead to significant understaffing, given nursing requirements that change over patients' phases of recovery. The intuition is that matching patients to nurses in the PACU is better represented by a queuing theory model (Lakshmi and Iyer, 2013; Yankovic and Green, 2011), as opposed to time-varying ratios over time. Using a queuing model coupled with simulation will allow us to properly verify and predict staffing requirements over time. Note that our analysis is meant to provide an accurate level of staffing by projecting patient census under realistic settings. We do this by setting up a DES model that takes historical patient data as inputs, generates empirical distributions for the patient population, and simulates how these patients move through perioperative care. We then couple this DES with a queuing model that accurately estimates staffing levels under realistic operating conditions. Queuing models have been shown to provide accurate estimates of staffing (Ewen and Mönch, 2014), and our article is the first in the literature to couple these in a DES and apply it to PREP/PACU staffing. Our method has shown to be particularly useful in cases where there is limited data and large uncertainty. We apply the method to a PREP/PACU unit which was to be moved to a new location, thus necessitating a DES to predict staffing levels.

In the PACU, there are often limited "hand-offs"—where a patient is assigned to another nurse—resulting in more staff required than estimated through time-varying ratios. Further, changing acuity levels result in exacerbating this underestimation, which may be demonstrated through simulation experiments. While our simulation considers patient flow through the entire perioperative care system, this study focuses on safely and accurately modeling nurse staffing in the PACU (i.e., recovery). This incorporates a simple staffing calculation for PREP which is facility dependent, but easily changeable within the simulation framework. Further, in our analysis we consider the combined PREP/PACU care area, as this is common to hospitals across the United States. Simplifying our analysis to separate PREP and PACU units is trivial, given the simulation structure.

The article proceeds by describing our data set and setting in the methods section. We then set up the simulation and queuing model to replicate staffing in the PREP/PACU. In the results, we discuss the implications of our model. Specifically, we show that NPR can underestimate staffing requirements, even when they account for patient acuity. We present how the simulation can be used to estimate bed capacity and staffing levels under different patient populations and account for the uncertainty in our estimates. We conclude with a discussion of our results and avenues for future work.

2. Methods

The DES was originally developed to determine optimal nurse staffing levels for four individual PREP/PACUs within a large, urban, 1059-bed medical center. As such, nurse staffing projections and further examination of the effects of patients' boarding (e.g., awaiting transfer to a hospital bed for inpatients and discharge documentation for outpatients) on nurse staffing are exhibited within a case study context. This investigation was conducted for operational and quality improvement using time-stamped perioperative patient flow (i.e., aggregate) data collected in retrospect. No IRB approval was required to perform this study.

These patient flow data were collected from the Centricity Operating Room Manager Information System (ORMIS) and supplemented by time-stamped logs embedded with the electronic documentation system and recorded by PREP/PACU staff over four months (10/1/2012–2/3/2013). Data were collected for all patients entering any of four independently operated PREP/PACU located on separate floors of the medical center (i.e., three adult, and one pediatric). For purposes of brevity, detailed analyses for only one adult PREP/PACU (Third Floor) location serving 15 ORs are presented. All results pertaining to staffing were replicated in the other units, so we have not presented the results to reduce repetition. This PREP/PACU is similar to the other two adult PREP/PACUs in layout and is located in the same building. All ambulatory patients were handled similarly in all units and there is no PACU I bypass model (where certain patients skip certain portions of the PACU) in place for any of these units. However, the same approach, analyses, and general interpretation of results were performed for each PREP/PACU separately.

As inputs, the simulation used data pertaining to durations of surgery, patient demographics such as age, gender, and an inpatient or outpatient status from ORMIS. Patient preparatory and recovery phase length were collected from time-stamp logs recorded by nurse staff. Specifically, time stamps for when patients entered the PREP/PACU, the time discharge criteria was met for recovery patients, and when the patient physically exited the unit upon discharge to home or transfer to an inpatient unit. Discharge criteria met were defined as the time the patient was deemed clinically ready to leave the PACU prior to physicalx exit.

For staffing in PREP, a NPR of 1:2 was used per nurse protocol and available evidence. At the start of the day, there is often congestion going from PREP to OR due to common case start times, which we have not explicitly modeled, but are implicitly captured in our time-stamped patient flow data. In this article, we concentrate on determining staffing levels in the PACU (i.e., recovery). This is because staffing levels in the PACU for recovery have shown to be a challenge, given the level of uncertainty and complications due to changing patient acuity, as described in a number of studies in the introduction. The DES probabilistically reconstructs the temporal patterns of patient flow (i.e., arrivals and discharges) over the course of each week within the

DES. The staffing representation in the DES couples a queuing theory model and allows for more complex changes in operations reflected in perioperative care systems (Hamrock *et al.*, 2013). The goal of the DES is to predict the number of nurses required for efficient staffing, given the patient population over time. Hence, the DES mimics the assignment of patients to nurses, and we do not limit the number of nurses *a priori*. Staff assignments to patients in the DES happen for each new patient for the particular day of the year. In the DES, a patient enters the PACU from the OR and is assigned a PACU nurse with no current high-acuity patient and, at most, one other patient in Phase 1. This was the standard nurse-to-patient assignment protocol in the PACU studied. Patients stay with this nurse until they are discharged, avoiding handoffs per observed practice. Institutions have recommended restricting handoffs in PACU, as they cause a risk of degradation, miscommunication, information loss, and misunderstanding, leading to medication errors and poor patient outcomes (Dnap and Dai, 2015). Nurses, on the other hand, cannot take on more than one high-acuity patient at any given time. Once the patient transitions into low acuity, the nurse is available to take on another patient. Note that this implies that the nurse is allowed to have one high-acuity patient and one low-acuity patient at any given time when both patients are in Phase 1 of the PACU. The nurse cannot have more than two patients in Phase 1 of the PACU. Once patients transition into Phase 2, the nurses are allowed to take on an additional patient. Any nurse may not have more than three patients overall. Again, this implies that the nurse can have one patient in Phase 2 and two additional patients in Phase 1. The acuity determines if a nurse can take on a new patient, and is not directly linked to the number of patients a nurse has. This is the exact reason why we believe NPR systematically underestimate staffing requirements.

For this study, the nurse staffing estimates (i.e., output) generated by the DES and queuing theory model are inferred to be the most accurate reflection of the needs of the system, as the queuing accurately reflects nurse-to-patient assignment. This output measure may then be used to evaluate common NPR-based methods of nurse staffing estimation (Dexter and Rittenmeyer, 1997).

The PREP/PACU sees patients at various stages of their care. Figure 1 shows the movement of patients through the system. A majority of patients require preparation in the PREP before surgery and recovery in the PACU after surgery. Patients having

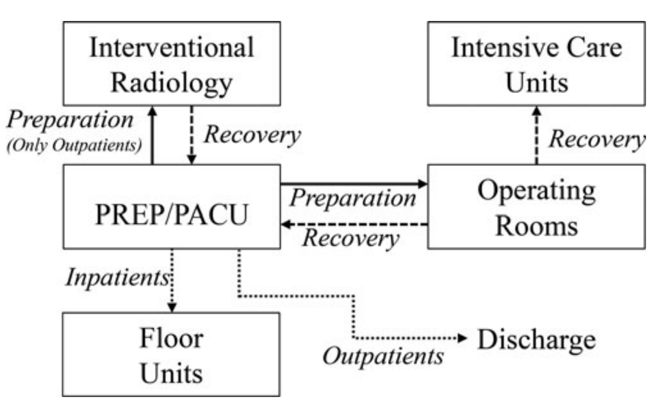

Figure 1. Perioperative patient flow process modeled in the simulation.

interventional radiology (IR) procedures may undergo preparation in the PREP or, if they are already an inpatient, they may go directly to the IR procedural suite and then recover in the PACU. Surgical patients destined for the intensive care unit (ICU) primarily bypass the PACU and are moved directly from the OR to ICU.

The MATLAB SimEvents (Gray, 2007) environment was used to perform these analyses and may be replicable in other discrete event simulation software environments. Data processing and simulation development followed these sequential steps:

2.1. Data processing

1. The start times for patients' arrival and preparation, surgery (i.e., OR time), and recovery phases were designated from the ORMIS and PREP/PACU log data. PACU end times were designated when an inpatient arrived at a destination inpatient unit after the PACU and when an outpatient left the hospital.
2. Patients with incoherent or missing time-stamp data were assumed cancelled or data entry error and removed from the data. This was less than 0.5% of the perioperative visits.
3. Patient arrivals into the perioperative system (i.e., preparation phase or directly to IR) were characterized using available data. The missing preparation and recovery times were imputed using a Poisson random variable fit to the available data; less than 1% of these data were imputed because they were missing.
4. Data were partitioned for each hour over the course of a week on the number of patients present in PREP, OR, and PACU.

2.2. Simulation description

5. Simulation model parameters for each patient were constructed from these processed data. The model simulated patients by generating new patients for each hour of the day over the course of a week, estimating minute-by-minute output measures. Each patient had an associated preparation, OR, and recovery time—as well as a probability dependent acuity level—also generated from empirical distributions of the available data. The probability of patients being at high acuity as they enter the unit is an exogenous parameter in our simulation, as we don't have reliable data for this measure. Hence, initial acuity is assigned using a Bernoulli random variable. Note that, dependent on the situation, appropriate distributions can be used as well (Choi and Wilhelm, 2012). Simulated patients were given a probability of a 1:1 requirement for the first 15 min of Phase 1 PACU (the nurse is allowed to have another patient not in Phase 1, a "high-acuity" patient), then 1:2 until the end of Phase 1, and then 1:3 in Phase 2, where the patient is awaiting discharge from the PACU. The remaining lower-acuity patients did not require any 1:1 assignment. All generated patients, except IR inpatients, queued into the unit for preparation (Figure 1).

6. The patient starts their preparation phase.
7. A panel of perianesthesia nurses estimated a 1:2 NPR for patients in the preparation phase. We note that this estimate is facility dependent, but was applied within the DES, which was focused on more complex estimation of nurse staffing needs for recovery (PACU) patients.
8. Patients transitioned from PREP (preparation) to the OR and then to the PACU (recovery) after their probabilistically assigned service times (from empirical distributions in Step 5) were finished. A subset of patients requiring ICU care bypassed the PACU and were transferred directly to the ICU, reflecting the actual perioperative system modeled (Figure 1).
9. IR patients queued with the recovery patients into the PACU.
10. For PACU (recovery), the staffing estimates required more detailed modeling due to changing patient acuity over time. However, we did incorporate PREP (preparation) staffing in all our results. A new high-acuity (1:1 nurse to patient initial care needs) patient entering the PACU would be assigned only to eligible nurses meeting all of the following criteria:
    a. Eligible nurse must not be managing any other high-acuity patients in their first 15 min of Phase 1 recovery.
    b. Eligible nurse must be currently managing fewer than two total patients in any phase.
11. A new low-acuity patient (not requiring 1:1 nurse to patient initial care needs) would be assigned to eligible nurses meeting all of the following criteria:
    a. Eligible nurse must not be managing any other high-acuity patients in their first 15 min of Phase 1 recovery.
    b. Eligible nurse must be currently managing fewer than three total patients in any phase.
    c. Eligble nurses must currently be managing no more than one patient in Phase 1 recovery.
12. At any given time, the simulation made sure that a minimum of two PACU nurses were always present as per ASPAN guidelines (AORN, n.d.).
13. From PACU, inpatients were transferred to inpatient units and outpatients exited the system, as seen in Figure 1.

2.3. Generating output

14. The DES primary output was nurse-staffing-level estimates minute by minute in the PREP/PACU over a one-year period of simulated time to provide 52 weeks' worth of data to determine staffing levels. It also allows our simulation to be generalizable if we ever wanted to include seasonality (not an issue in the current simulation).

2.4. Validation

15. The simulation was replicated 20 times and an F-test was performed to verify that the mean patient census over the week was the same in each instance. Further, a t-test was done to verify that the expected value of the weekly patient census of the simulation was equal to the expected value of the patient census from the available data. Further sensitivity tests were run with different length-of-stay levels for patients to verify that the model was performing as expected. These are detailed in the results section.

3. Results

The DES was developed using 3926 PREP/PACU patient encounters over the four-month study period. A total of 48% of this cohort required an inpatient stay following surgery. For all encounters, the average preparation time was 1.6 h (95% CI 1.56 to 1.65) and average OR time was 1.3 h (95% CI 1.27 to 1.35). Total recovery time was comprised of 2.2 h (95% CI 2.13 to 2.25) from PREP/PACU arrival to discharge criteria met, followed by a boarding time of 1.49 h (95% CI 1.37 to 1.50) or 0.77 h (95% CI 0.72 to 0.82) for inpatients and outpatients, respectively. The distribution of these perioperative patient flow times for all PREP/PACU patients can be seen in Figure 2. Simulated weekly volumes and patient care hours stratified by stage in PREP/PACU care are shown in Table 1. As mentioned in the methods section, for purposes of brevity, we only present detailed staffing results from one adult PREP/PACU (Third Floor). Our results pertaining to staffing are replicated in the other units as well.

3.1. PREP/PACU patient flow

These data and PREP arrival patterns formed the input parameters to the DES model, which we used to simulate 11 237 PREP/PACU encounters over a one-year time horizon. This was selected after tests to be robust enough for the analysis. Output measures included hourly PREP/PACU patient census levels over the week, demonstrating variability, and the composition of patients in preparatory (dotted line) and recovery (dashed line) stages, as seen in Figure 3. The common pattern of a proportional majority of patients being prepped in the unit between 6 AM and 11 AM, then swapping to recovery thereafter each day, is displayed. These data also show evidence of patients remaining overnight in a PACU, which was consistent with nursing sentiments at our study site.

3.2. Nurse staffing projections

We were able to uniquely model the process of patient-to-nurse assignment following OR exit and entrance into the

Table 1. Weekly components of direct patient care and nursing care hours at baseline.

Measure	Patient Care Hours Average (95th Percentile Range)	Nursing Hours Average (95th Percentile Range)
Weekly Volume	216.1 (193.0–251.0)	—
Total (hours)	875.8 (782.2–1017.2)	544.6 (486.4–632.6)
Preparation (hours)	333.6 (298.0–387.4)	166.8 (149.0–193.7)
Time to discharge criteria met (hours)	384.8 (343.7–446.9)	293.4 (262.0–340.8)
Boarding time (hours)	157.4 (140.6–182.8)	84.4 (75.4–98.0)
Total recovery time (hours)	542.2 (484.2–629.8)	377.8 (337.4–438.8)

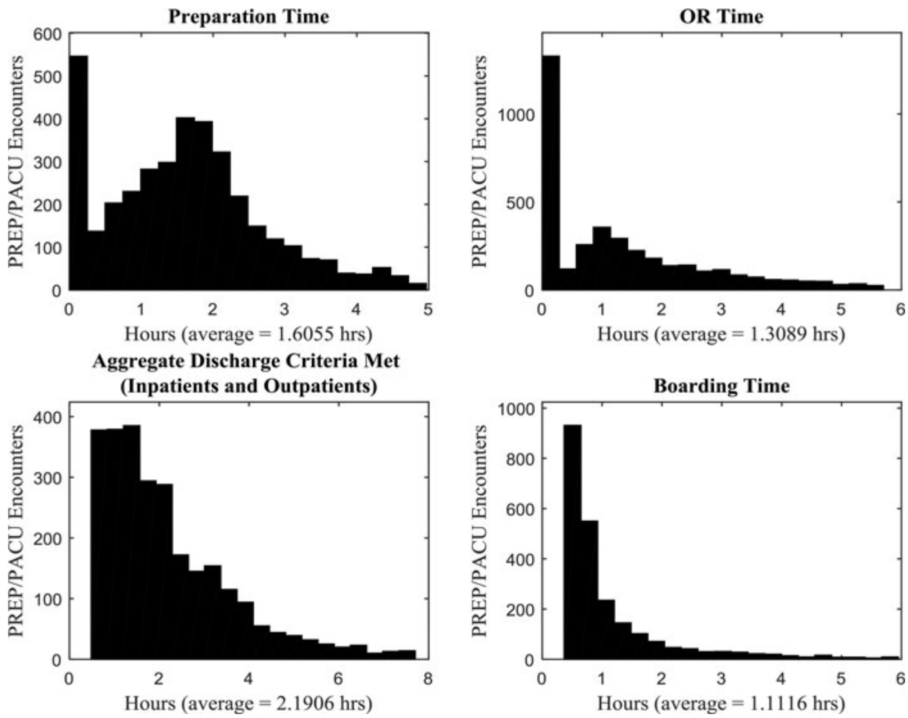

Figure 2. Perioperative patient flow times.

PREP/PACU for recovery by coupling a queuing theory model to the DES. This included immediately assigning the patient to an eligible nurse based on acuity; eligiblity criteria defined in methods (10 and 11). The simulated nursing protocol ensures a limit of 1:1 and 1:2 NPR for high- and low-acuity patients in Phase 1 of recovery, respectively. Figure 4 displays the DES output for nurse staffing levels needed over time, again demonstrating variability, and the composition of nurses required for preparatory (dotted line) and recovery (dashed line) stages. These nurse staffing levels reflect the minimal nurse staffing levels (i.e., most efficient) to provide direct patient care in the PREP/PACU, given patient flow. Simulated weekly nursing hours stratified by stage in PREP/PACU care are shown in Table 1.

Using the hourly patient census levels (Figure 3) and the nurse staffing levels established (Figure 4) in the DES, we may compare several reference approaches to nurse staffing level projections. Previous studies have proposed creating nursing level estimates based on time-varying ratios over time; for example, 1:1 for high-acuity patients in their first 15 min of care and then 1:2 for remaining patients in Phase 1 and 1:3 in Phase 2 recovery time serves as the reference estimate for our scenario (Dexter and Rittenmeyer, 1997). For purposes of comparison to our simulation, we have used this formula to calculate nurses required under time-varying NPR by multiplying the relevant ratio with the number of high- and low-acuity patients at each given minute. This gives us the current method of staffing projections, as shown in Figures 5 and 6. This is evidence that using

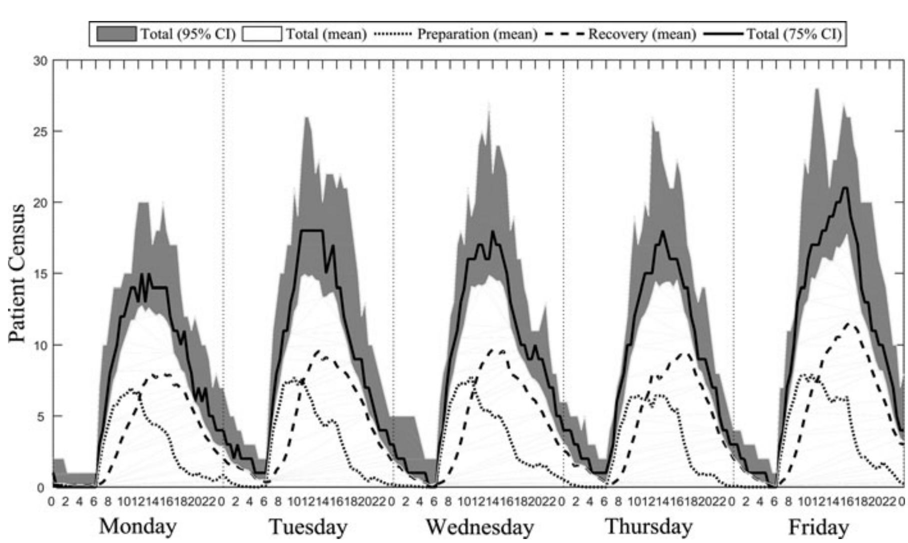

Figure 3. PREP/PACU patient census over the week.

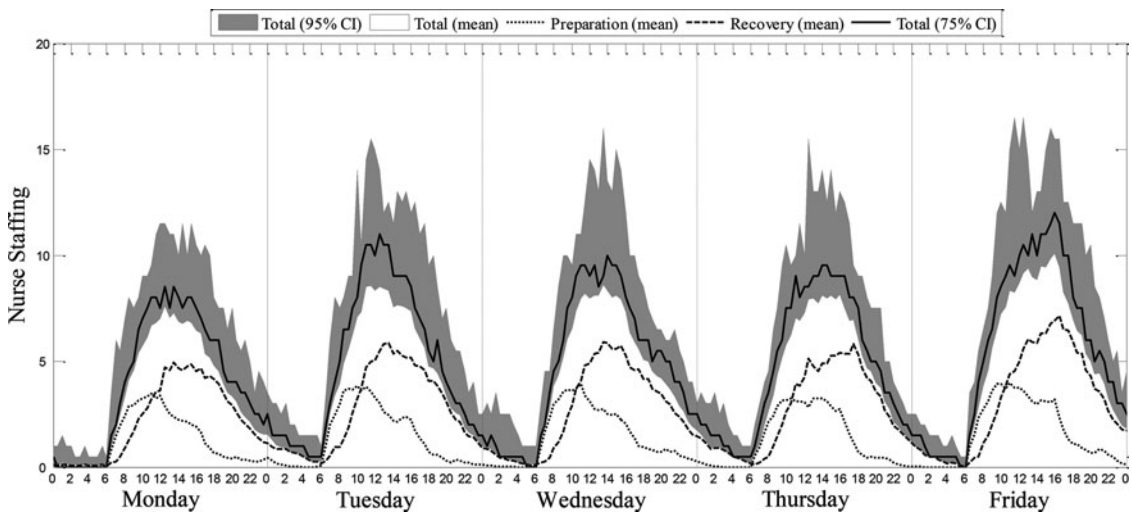

Figure 4. PREP/PACU nurse staffing requirements over the week.

existing methods for NPR, even if accounting for patient acuity and stratified by minutes, still yields an underestimation of staffing requirements.

Figures 5 and 6 display the percentage differences between the simulated estimate of nurse staffing levels (i.e., inferred as most accurate) and estimates obtained using the three relevant approaches. It is important to note that the reference method (time-varying ratio) substantially underestimates up to 20% of nurse staffing levels late in the day (after 4 PM), given common nurse-to-patient assignment protocols. These findings are consistent for PACUs recovering both lower- and higher-acuity patient populations. For example, a low-acuity PACU (Figure 5), where 25% of the patient population requires 1:1 NPR care, and a high-acuity PACU (Figure 6), where 75% of the patient population requires 1:1 NPR care. These figures display relative differences between the time-varying NPR estimation methods and the accurate simulation-based (i.e., queuing theory) result; with zero on the y-axis. We note that actual nursing needs would be further underestimated because of required breaks that must be built in.

3.3. Effects of changes in PACU length of stay on staffing

Initiatives to reduce recovery time in the PACU are underway. Thus, the simulation was used to determine the potential impact on PACU capacity needs (i.e., beds) and nurse staffing levels. We used the simulation to reduce length of stay for each patient from 0–50% in 2% increments (Figure 7). On average, reducing length of stay by one hour (21%) results in a three-patient (17%) decrease in peak census (i.e., bed needs) and one (11%) fewer

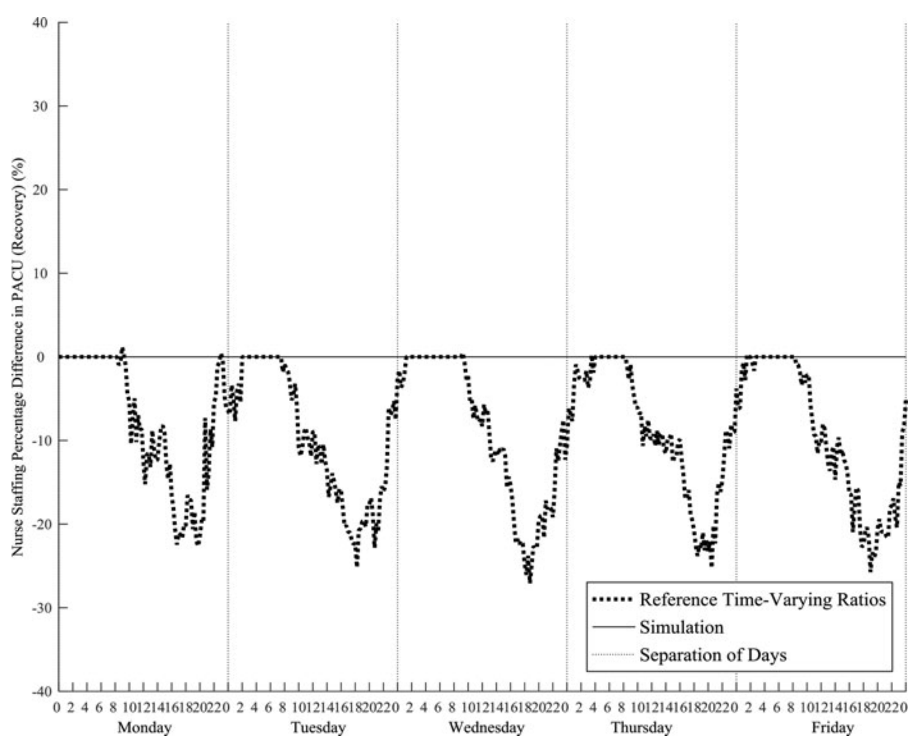

Figure 5. Relative differences in mean staffing levels for a low-acuity PACU; 25% of patients requiring 1:1 nurse to patient ratios at arrival.

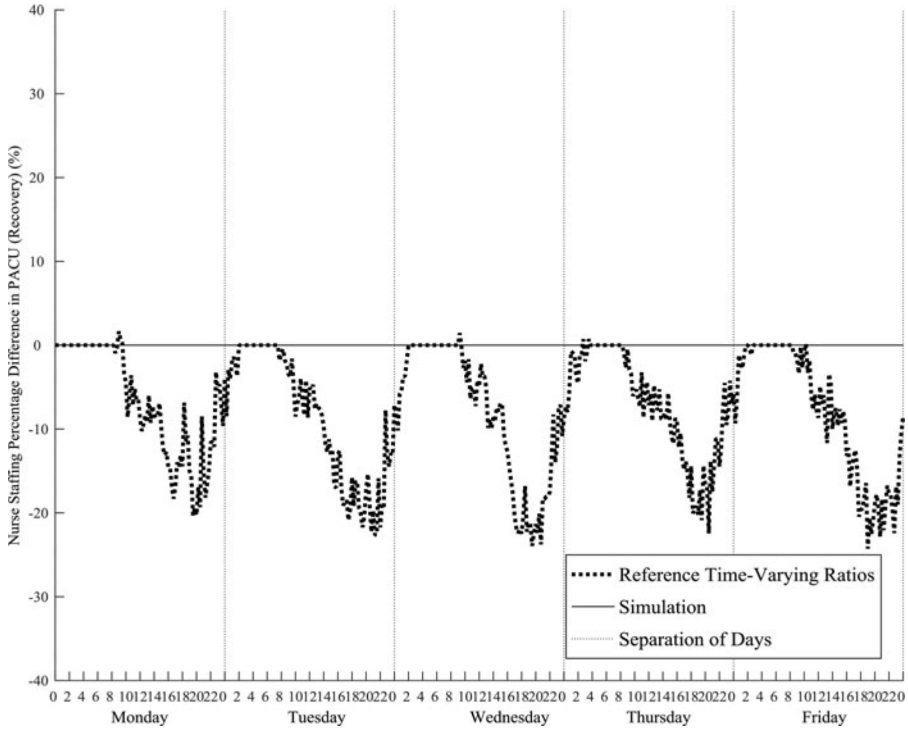

Figure 6. Relative differences in mean staffing levels for a high-acuity PACU; 75% of patients requiring 1:1 nurse-to-patient ratios at arrival.

nurse required. This linear trend is consistent for simulation scenarios at average, seventy-fifth and ninety-fifth percentiles of patient volumes; however, reductions (i.e., the slope) are most significant looking at requirements closer to the ninety-fifth percentile, which is what hospitals often plan for.

4. Discussion

Healthcare expenditures have risen to comprise 17.9% (2012) of the United States gross domestic product (GDP) (WHO, n.d.). A total of 21% of these healthcare costs have been attributed to hospital-based labor; 31.5% of healthcare costs in 2012 were attributed to hospital costs (Centers for Medicare and Medicaid Services, n.d.). Two-thirds of hospital expenditures are attributed to labor (American Hospital Association, n.d.). Reducing non-value-added time and associated costs requires detailed information on patient flow and staffing activity. Often, these data are unavailable to decision makers. Moreover, it is difficult to estimate the effect of proposed patient flow initiatives on staffing needs.

We present a DES model to predict patient flow through perioperative care, specifically related to PREP and PACU. We produce a year of simulation results from four months of data with granularity in minutes for accurate staffing levels for PACU nurses. We show that using NPR for predicting staffing could lead to inaccuracies, depending on the time of day. In particular, we see that using NPR underpredicts the staffing requirements as much as 20% after 4 PM (Figures 5 and 6).

Underpredicting staffing requirements at the end of the day coincides with observations in the PACU about understaffing

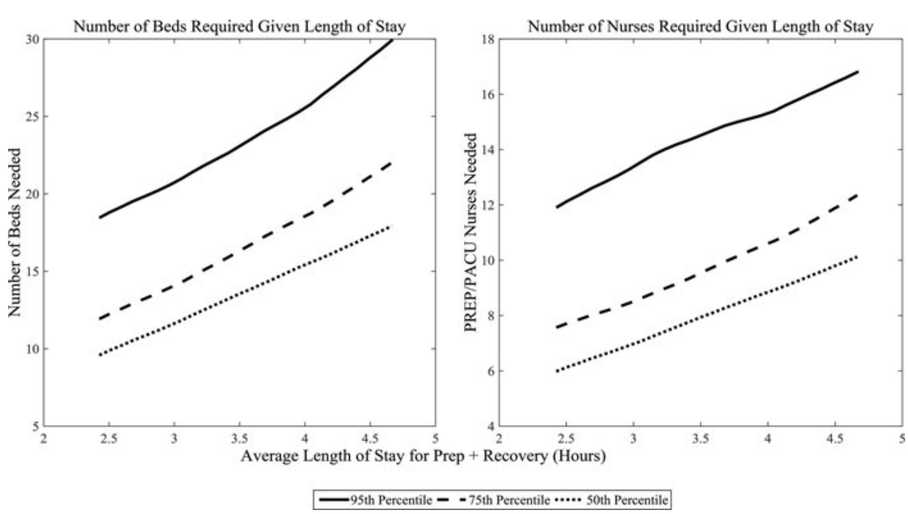

Figure 7. Projections for number of beds and nurses needed in the PREP/PACU, given different average lengths of stay.

towards the end of the day. A NPR of 1:2 implies that fewer nurses would be needed to look after these patients towards the end of the day. The reality, though, is that nurses do not hand off patients, and thus a NPR of 1:2 is not realistic towards the end of the day, especially when total time in recovery can exceed four hours.

An advantage of the simulation model is that it is able to predict patient census and staffing levels over time and assess the impacts of interventions before they take place. Accurately predicting operations through a coupled queuing model enables PACU managers to determine optimal staffing levels and scheduling accordingly. Along with the simulation model, we provide an alternate method to estimate staffing requirements, which proves to be more accurate than NPR. While these estimates are not exact, they provide a better measure of staffing than NPR ratios. Thus, we provide an alternative to using NPR ratios which is as easy to implement for determining staffing.

The DES results provide information that may be generalized to other perioperative systems. Institution-specific input parameters may be included to evaluate patient census and nurse staffing level outcomes. Moreover, our new method of estimating staffing requirements shifts the focus towards acuity of patients, which we have shown is a better indicator of staffing requirements than number of patients. A natural extension is using this data in an optimization problem to produce efficient schedules (Ernst *et al.*, 2004). Given the simulation model output and the ability to capture complex system dynamics under changing acuity of patients, we expect this model to be combined with advanced staffing models to optimize outcomes.

A limitation of this model is that it is not obvious which percentile represents an ideal staffing level (e.g., fiftieth, seventy-fifth, ninety-fifth) and how these percentiles connect to costs associated with OR to PACU holds. Stakeholders in hospitals have different objectives. While staff would prefer to schedule to a worst-case scenario (ninety-fifth percentile), this is inefficient and cost prohibitive. This would overschedule perianesthesia nurses, and result in underutilization of staff and resources. However, fixed scheduling for the average scenario (fiftieth percentile) could lead to a decrease in quality of care for days where staffing levels are outstripped. Hence, the model may be improved by determining how PREP/PACU staffing levels may be flexed daily to optimal levels.

However, implementing this is challenging due to the need to provide nurses with adequate advanced notice for work schedules. Further, we could analyze the perioperative system as a whole to determine staffing levels that would minimize total costs, as labor in the OR often costs more than the PACU. Despite these limitations, this model provides a tool to estimate nurse staffing requirements and the effects of any changes in patient flow preemptively. Engineering tools such as discrete-event simulation provide PREP/PACU managers and administrators with more powerful evaluation and prediction of operations, leading to improved resource (i.e., nurse staffing) management.

ORCID

Sauleh Siddiqui http://orcid.org/0000-0002-2466-8924

References

Abdoo, Y. M. (1987) A model for nurse staffing and the impact of inter-rater reliability of patient classification on nurse staffing requirements. (Doctoral dissertation, University of Michigan, Ann Arbor, MI).

Aiken, L. H. (2002) Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *JAMA*, **288**, 1987–1993.

American Hospital Association (n.d.) The Cost of Caring. http://www.aha.org/content/12/CostofCaring2012.pdf (accessed December 1, 2014).

American Society of PeriAnesthesia Nurses (2014) *ASPAN Standards 2008–2010*. ASPAN, Cherry Hill, NJ.

AORN (2008) AORN position statement on perioperative safe staffing and on-call practices. http://www.aorn.org/Clinical_Practice/Position_Statements/Position_Statements.aspx (accessed October 23, 2014).

AORN (2005) Guidance statement perioperative staffing. *AORN J.*, **81**(5), 1059–1066.

Barnes, S., Hamrock, E., Toerper, M., Siddiqui, S., and Levin, S. (2015). Real-time prediction of inpatient length of stay for discharge prioritization. *Journal of the American Medical Informatics Association*, **23**(e1), e2–e10.

Carayon, P., Bass, E. J., Bellandi, T., Gurses, A. P., Hallbeck, M. S., and Mollo, V. (2011) Sociotechnical systems analysis in health care: A research agenda. *IIE Transactions on Healthcare Systems Engineering*, **1**(3), 145–60.

Cassandras, C. G., and Lafortune, S. (2009) *Introduction to Discrete Event Systems*. Springer Science & Business Media, Berlin, Germany.

Centers for Medicare and Medicaid Services (n.d.) National Health Expenditures 2015 Highlights. http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/downloads/highlights.pdf (accessed December 1, 2014).

Choi, S., and Wilhelm, W. E. (2012) An analysis of sequencing surgeries with durations that follow the lognormal, gamma, or normal distribution. *IIE Transactions on Healthcare Systems Engineering*, **2**(2), 156–71.

Connelly, L. G., and Bair, A. E. (2004) Discrete event simulation of emergency department activity: A platform for system-level operations research. *Academic Emergency Medicine* **11**(11), 1177–85.

Cure, L., Zayas-Castro, J., and Fabri, P. (2014) Challenges and opportunities in the analysis of risk in healthcare. *IIE Transactions on Healthcare Systems Engineering*, **4**(2), 88–104.

Dale Compton, W., Ganjiang, G., Reid, P. P., and Grossman, J. H. (2005) *Building a Better Delivery System: A New Engineering/Health Care Partnership*. National Academies Press, Washington, DC.

Das, S., and Boodhoo, S. (2015) An activity based approach for measuring a hospital's output units of care. *IIE Transactions on Healthcare Systems Engineering*, **5**(2), 89–100.

Denton, B. T., Miller, A. J., Balasubramanian, H. J., and Huschka, T. R. (2010) Optimal allocation of surgery blocks to operating rooms under uncertainty. *Operations Research*, **58**(4–1), 802–16.

Dexter, F. (2007) Why calculating PACU staffing is so hard and why/how operations research specialists can help. *J PeriAn Nurs*, **22**(5), 357–359.

Dexter, F., Epstein, R. H., and Penning, D. H. (2001) Statistical analysis of postanesthesia care unit staffing at a surgical suite with frequent delays in admission from the operating room: A case study. *Anesth Analg*, **92**(4), 947–9.

Dexter, F., and Rittenmeyer, H. (1997) A statistical method for predicting postanesthesia care unit staffing needs. *AORN J*, **65**(5), 947–957.

Dexter, F., Shi, P., and Epstein, R. (2012) Descriptive study of case scheduling and cancellations within 1 week of the day of surgery. *Anesth Analg*, **115**(5), 1188–1195.

Dexter, F., Wachtel, R., and Epstein, R. (2006). Impact of average patient acuity on staffing of the Phase 1 PACU. *J PeriAn Nurs*, **21**(5), 303–310.

Dnap, M., and Dai, F. (2015) Handoffs in the postoperative anesthesia care unit: Use of a checklist for transfer of care. *AANA Journal*, **83**(4), 265.

Ehrenfeld, J. M., Dexter, F., Rothman, B. S., et al. (2013) Lack of utility of a decision support system to mitigate delays in admission from the operating room to the postanesthesia care unit. *Anesth Analg*, **117**(6), 1444–1452. doi:10.1213/ANE.0b013e3182a8b0bd

Epstein, R., Dexter, F., and Traub, R. (2002) Statistical power analysis to estimate how many months of data are required to identify PACU staffing to minimize delays in admissions from ORs. *J PeriAn Nurs*, **17**(2), 84–88.

Ernst, A., Jiang, H., Krishnamoorthy, M., and Sier, D. (2004) Staff scheduling and rostering: A review of applications, methods and models. *European Journal of Operational Research*, **153**(1), 3–27.

Ewen, H., and Mönch, L. (2014) A simulation-based framework to schedule surgeries in an eye hospital. *IIE Transactions on Healthcare Systems Engineering*, **4**(4), 191–208.

Ferrand, Y. B., Magazine, M. J., and Rao, U. S. (2014) Managing operating room efficiency and responsiveness for emergency and elective surgeries: A literature survey. *IIE Transactions on Healthcare Systems Engineering*, **4**(1), 49–64.

Gray, M. A. (2007) Discrete event simulation: A review of SimEvents. *Computing in Science & Engineering*, **9**(6), 62–66.

Green, L. V., Savin, S., and Savva, N. (2013) "Nursevendor problem": Personnel staffing in the presence of endogenous absenteeism. *Management Science*, **59**(10), 2237–56.

Günal, M. M., and Pidd, M. (2010) Discrete event simulation for performance modelling in health care: A review of the literature. *Journal of Simulation*, **4**(1), 42–51.

Hall, R., Belson, D., Murali, P., and Dessouky, M. (2006) Modeling patient flows through the healthcare system. In *Patient Flow: Reducing Delay in Healthcare Delivery* (pp. 1–44). Springer, Berlin, Germany.

Hamrock, E., Paige, K., Parks, J., Scheulen, J., and Levin, S. (2013) Discrete event simulation for healthcare organizations: A tool for decision making. *J Healthc Manag*, **58**, 110–124.

Isken, M. W., and Hancock, W. M. (1990) A heuristic approach to nurse scheduling in hospital units with non-stationary, urgent demand, and a fixed staff size. *Journal of the Society for Health Systems*, **2**(2), 24–41.

Josten, E. J. C., Ng-A-Tham, J. E. E., and Thierry, H. (2003) The effects of extended workdays on fatigue, health, performance and satisfaction in nursing. *J Adv Nurs*, **44**, 643–652.

Jun, J. B., Jacobson, S. H., and Swisher, J. R. (1999) Application of discrete-event simulation in health care clinics: A survey. *Journal of the Operational Research Society*, **50**(2), 109–23.

Kane, R. L., Shamliyan, T. A., Mueller, C., Duval, S., and Wilt, T. J. (2007) The association of registered nurse staffing levels and patient outcomes: Systematic review and meta-analysis. *Med Care*, **45**, 1195–1204.

Kuntz, L., Mennicken, R., and Scholtes, S. (2014) Stress on the ward: Evidence of safety tipping points in hospitals. *Management Science*, **61**(4), 754–71.

Lakshmi, C., and Iyer, S. A. (2013) Application of queueing theory in health care: A literature review. *Operations Research for Health Care*, **2**(1), 25–39.

Lang, T. A., Hodge, M., Olson, V., Romano, P. S., and Kravitz, R. L. (2004) Nurse–patient ratios: A systematic review on the effects of nurse staffing on patient, nurse employee, and hospital outcomes. *Journal of Nursing Administration*, **34**(7–8), 326–37.

Law, A. M., Kelton, W. D., and Kelton, W. D. (1991) *Simulation Modeling and Analysis*. McGraw-Hill, New York, NY.

Levin, S., Dittus, R., Aronsky, D., Weinger, M., and France, D. (2011) Evaluating the effects of increasing surgical volume on emergency department patient access. *BMJ Qual Saf*, **20**, 146–152.

Lin, R. C., Sir, M. Y., Sisikoglu, E., Pasupathy, K., and Steege, L. M. (2013) Optimal nurse scheduling based on quantitative models of work-related fatigue. *IIE Transactions on Healthcare Systems Engineering*, **3**(1), 23–38.

Litvak, E., and Long, M. (2000) Cost and quality under managed care: Irreconcilable differences? *Am J Manag Care*, **6**, 305–12.

Lovejoy, W. S., and Li, Y. (2002) Hospital operating room capacity expansion. *Management Science*, **48**(11), 1369–87.

McManus, M. L., Long, M. C., Cooper, A., et al. (2003) Variability in surgical caseload and access to intensive care services. *Anesthesiology*, **98**, 1491–1496.

Mobasher, A., Lim, G., Bard, J. F., and Jordan, V. (2011) Daily scheduling of nurses in operating suites. *IIE Transactions on Healthcare Systems Engineering*, **1**(4), 232–46.

Needleman, J., Buerhaus, P., Mattke, S., Stewart, M., and Zelevinsky, K. (2002) Nurse-staffing levels and the quality of care in hospitals. *N Engl J Med*, **346**, 1715–1722.

Oh, H. J., Muriel, A., Balasubramanian, H., Atkinson, K., and Ptaszkiewicz, T. (2013) Guidelines for scheduling in primary care under different patient types and stochastic nurse and provider service times. *IIE Transactions on Healthcare Systems Engineering*, **3**(4), 263–79.

Ragavan, M. V., Blinman, T. A., and Fieldston, E. S. (2013) Scheduled surgery admissions and occupancy at a children's hospital: Variation we can control to improve efficiency and value in health care delivery. *Ann Surg*, **257**, 564–70.

Ryckman, F. C., Yelton, P. A., Anneken, A. M., Kiessling, P. E., Schoettker, P. J., and Kotagal, U. R. (2009) Redesigning intensive care unit flow using variability management to improve access and safety. *Jt Comm J Qual Patient Saf*, **35**, 535–543.

Schoenmeyr, T., Dunn, P., Gamarnik, D., Levi, R., Berger, D., Daily, B., Levine, W., and Sandberg, W. (2009) A model for understanding the impacts of demand and capacity on waiting time to enter a congested recovery room. *Anesth*, **110**(6), 1293–1304.

Shi, P., Chou, M. C., Dai, J. G., Ding, D., and Sim, J. (2015) Models and insights for hospital inpatient operations: Time-dependent ED boarding time. *Management Science*, **62**(1), 1–28.

Smith, C. D., Spackman, T., Brommer, K., et al. (2013) Re-engineering the operating room using variability methodology to improve health care value. *J Am Coll Surg*, **216**, 559–570.

Tibby, S. M., Correa-West, J., Durward, A., Ferguson, L., and Murdoch, I. A. (2004) Adverse events in a paediatric intensive care unit: Relationship to workload, skill mix and staff supervision. *Intensive Care Med*, **30**, 1160–1166.

Toerper, M. F., Flanagan, E., Siddiqui, S., Appelbaum, J., Kasper, E. K., and Levin, S. (2015) Cardiac catheterization laboratory inpatient forecast tool: A prospective evaluation. *Journal of the American Medical Informatics Association*, **23**(e1), e49–57.

Turkcan, A., Zeng, B., and Lawley, M. (2012) Chemotheapy operations planning and scheduling. *IIE Transactions on Healthcare Systems Engineering*, **2**(1), 31–49.

Weissman, J. S., Rothschild, J. M., Bendavid, E., et al. (2007) Hospital workload and adverse events. *Med Care*, **45**, 448–455.

World Health Organization (n.d.) National Health Account database. http://apps.who.int/nha/database/DataExplorerRegime.aspx (accessed November 25, 2014).

Yankovic, N., and Green, L. V. (2011) Identifying good nursing levels: A queuing approach. *Operations Research*, **59**(4), 94255.

Zhang, Y., Puterman, M. L., Nelson, M., and Atkins, D. (2012) A simulation optimization approach to long-term care capacity planning. *Operations Research*, **60**(2), 249–61.