Title: Exploratory Study Using Queuing Theory to Improve Nurse Staffing Effectiveness

Principal Investigator
Patricia W. Stone

Team Members:
Linda Green
Haomiao Jia
Pam de Cordova
Sookyung Hyun
Stephanie Goldberg
Patricia Quinlan

Organization
The Trustees of Columbia University in the City of New York
Columbia University School of Nursing
630 W. 168th Street
Mail Code 6
New York, NY 10032
212-305-1738
ps2024@columbia.edu

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Federal Project Officer: Alexis Bakos

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Structured Abstract (200 words)

Purpose: Explore the feasibility and benefit of using queuing models to inform nurse staffing.

Scope: Identification and development of relevant data for an orthopedic unit and comparison of actual vs. queuing-generated nursing levels.

Methods: Focus groups and a Delphi survey were conducted, identifying unit-specific patient demands. Available electronic time-stamped data were collected, analyzed, and used to estimate queuing model parameters to identify nurse staffing levels consistent with various levels of delays. Sensitivity analyses were performed.

Results: Forty-five nurses (83% response rate) agreed that 35 interventions were time sensitive. The most useful electronic time-stamped data were admit/transfer/discharge and call light data. Other electronic data were not extractable. Volume and variability of demands, estimates of nursing times, and call light delays were used to parameterize a queuing model to inform nurse staffing. The model estimates that six to nine nurses are needed, depending on time of the day and day of week, to meet specified target delays. These levels are higher than the average levels currently used. Queuing models are promising; continued development of the electronic data sources is needed to support operational planning.

Key Words: nurse staffing, queuing models

Purpose

A preponderance of evidence indicates a significant positive relationship between nurse staffing levels and patient outcomes. Yet there is no scientifically based approach to determine what level of staffing is required to achieve quality patient outcomes based on the specific characteristics of a clinical unit. Research is needed to identify a method to quantify demands for nursing care in varying settings and translate these into effective staffing levels in an efficient manner given the constraints of human resources. This should be a generalizable methodology that can allow nurse managers, for any given unit and for varying conditions that may exist on different days of the week and/or different times of the day, to identify the required staffing levels to meet appropriate standards.

Queuing theory, which mathematically relates variable demands for service to the response times to meet those demands for a given level of staffing, is a promising methodology to accomplish this goal. A basic queuing system is a service system in which "customers" (e.g., patient demands) arrive to a bank of "servers" (e.g., nurses) and require some level of service. If all servers are busy upon the arrival of a new demand, the customer joins a queue. A queuing model uses the demand and service data from a specific service environment (e.g., a clinical unit) to estimate service delays for any level of staffing. The use of queuing models to guide staffing decisions has been very successful in many service industries and organizations (Green & Kolesar, 1984; Green, Soares, Giglio, & Green, 2006). In healthcare, queuing models have been used to inform personnel decisions in emergency rooms and bed capacity decisions (Green, 2002; Green et al., 2006). However, queuing models have never before been used to inform nurse staffing decisions. A major barrier to the use of queuing models for this purpose is the lack of available electronic data on patient demands for nursing care.

The aims of this exploratory study were to:

Aim 1: Identify unit-specific time-sensitive nursing care interventions (demands) and the average times required to perform them (service times).

Aim 2: Determine unit-specific volume and timing (arrival rates) for nursing care demands.

Aim 3: Develop performance standards for acceptable delays for nursing care.

Aim 4: Develop a registered nurse staffing plan based on queuing models:

Scope

Importance of Adequate Nursing Care: There is a growing realization of the important role nursing care plays in the delivery of quality healthcare. During the past 15 years, evidence has been accumulating to relate higher levels of nurse staffing (both in quantity and level of preparation) to lower rates of adverse patient outcomes. As reported in a systematic review (Lankshear, Sheldon, & Maynard, 2005), the definitions and the quality of data throughout both hospital and unit-level nurse staffing research vary. Despite the variations and limitations of designs, it is now recognized by many, including the Institute of Medicine and the International Council of Nurses, that there is a preponderance of evidence establishing the positive relationship between nursing care and quality patient outcomes (IOM, 2004; ICN, 2006). However, as previously noted by Clarke, the research data lack precision to help determine actual staffing levels (Clarke, 2005). There are still limited data to inform nurse managers and hospital administrators on how to efficiently allocate scarce nurse resources to promote quality patient outcomes within their own setting.

Current Methods Commonly Used To Determine Nurse Staffing and National Guidelines: Minimum nurse-to-patient ratios are sometimes the basis on which staffing is determined. California is the first and only state to mandate a minimum nurse-to-patient ratio. The 1999 law AB 394, which took 5 years to be implemented, went into effect in 2004 and set minimum licensed nurse-to-patient ratios of 1 to 6 on general wards. Similar to nurse-to-patient ratios, many nurse executives and managers budget the number of staff needed by calculating the total direct productive hours of care per patient day (HPPD) for the number of patients expected to require nursing care over a given time period.

The usefulness of the HPPD concept has been questioned by the ANA, because it is a simple quantification of the average patient without considering outlier patients (ANA, 1999). The evidence base supporting mandated minimum staffing ratios has also been questioned (Lang, Hodge, Olson, Romano, & Kravitz, 2004). Arguments against the use of static measures and calls for development of patient-centered staffing policies based on careful analysis of multiple variables, such as differing patient needs, fluctuations in care needs by day and time, expertise and education of the staff, and other setting characteristics, have been proposed (SHS, 2005).

The ANA has established guidelines on what should be incorporated in optimal systems that inform staffing decisions (ANA, 1999). The ANA recommends that staffing decisions be flexible, consider patient characteristics, and be tailored to the needs of the patient by incorporating the intensity of nursing care. Additionally, the staffing plan should consider the expertise of the staff and the context of the unit (e.g., geographic dispersion of patients, size and layout of individual patient rooms, and arrangement of entire patient care unit, and technology). Similar guidelines have also been developed by other organizations (SHS, 2005). Using unit-specific data on demands for care and associated service times to develop queuing models satisfies these requirements.

Use of Queuing Models to Guide Staffing Decisions in Healthcare and Other Industries: Queuing models have been used to guide both professional and non-professional staffing decisions in various industries. Many organizations, such as banks, airlines, and telephone call centers (Brewton, 1989; Stern & Hersh, 1980; Holloran & Byrne, 1986; Brusco, Jacobs, Bongiorno, Lyons, & Tang, 1995; Brigandi, Dargon, Sheehan, & Spencer III, 1994), as well as emergency systems, such as police patrol, fire, and ambulances (Larson, 1972; Chelst & Barlach, 1981; Green et al., 1984; Taylor & Huxley, 1989), routinely use quantitative models based on queuing theory to help determine human resource needs to respond to demands for service in a timely fashion. Queuing models have also been applied in various healthcare settings to guide decisions on bed capacity (McManus, Long, Cooper, & Litvak, 2004; Sonnenberg, 2000; Gorunescu, McClean, & Millard, 2002; Worthington, 1987) and, recently, physician staffing. Green (co-investigator on this grant application) used this methodology successfully in the emergency department of an urban hospital to identify physician staffing levels to better handle the highly variable arrival rate of patients. The result was a reduction in the level of patients who left without being seen by almost 20% without the addition of any personnel (Green et al., 2006). Unlike “static” methodologies, queuing models explicitly incorporate variability in both the timing of demands and the time required to meet them. It is objective, repeatable, and flexible, and it can be tailored to meet the needs of any organization or unit. Although queuing models have the potential to meet the characteristics of an effective process to inform nurse staffing decisions, to our knowledge, this has not been explored.

A queuing model is a mathematical description of a queuing system, which may be defined as a service system in which “customers” (e.g., patient needs) arrive to a bank of “servers” (e.g., nurses) and require some service from one of them. If all servers are busy upon the arrival of a new demand, the customer joins a queue. Queuing models make specific assumptions about the probabilistic nature of the arrival and service processes, the number and type of servers, and the queue discipline, which is the rule that determines the order in which queued customers are served. There are countless variations possible, but some queuing models are more widely used than others because of their “robustness” in being able to provide good estimates of performance for a broad variety of applications and their ease of use with regard to data requirements and fast calculation of various performance measures. The most common queue discipline is the familiar first-come, first-served (FCFS) rule, but others are often used to increase efficiency or reduce the delay for more time-sensitive customers. For example, in a hospital emergency room, the triage system is an example of a priority queue discipline. Priority disciplines may be preemptive or not preemptive, depending on whether a service in progress can be interrupted when a customer with a higher priority arrives. Though many queuing systems have a single line feeding into a single bank of identical servers, other organizational schemes are possible, and they may take into account variable skill mix of personnel.

The effective use of queuing models depends on the ability to obtain good estimates of three parameters: 1) arrival rate of customer demands (e.g., average number of unit-specific demands for nursing care per specified period), 2) average service time per customer (e.g., average duration of nursing time needed to meet a demand), and 3) the performance standard (acceptable delays for patients waiting for care). Because queuing systems (e.g., nursing units) usually have a great deal of variability in both their arrival and service processes, their behavior is nonlinear and nonintuitive; thus, it is impossible to predict without the use of a queuing model.

In this research, the nursing unit constitutes a queuing system; the "customers" are the patients in the unit who generate demands for nursing care (e.g., admissions, discharges, transfers, medication orders, and patient requests for specific nursing interventions). The "servers" are the nurses assigned to the unit. The number of servers (the staffing level) will be identified based on the volume, timing, and time required to deal with the various demands for nursing care and the performance standard (i.e., acceptable delay to respond to a demand).

Nursing Classification Systems: A large body of research systematically classifying nursing care, such as the Nursing Interventions Classification (NIC) (McCloskey & Bulechek, 1995b; McCloskey & Bulechek, 1995a; University of Iowa, 2004; Wakefield, McCloskey, & Bulechek, 1995) and the Omaha System (Martin, 2005), has been conducted. These standardized languages organize nursing interventions into taxonomies and are useful tools to represent nursing care. NIC is organized into seven domains, 30 classes of interventions, 514 interventions, and over 12,000 activities (University of Iowa, 2004). Additionally, for each intervention, the NIC developers had small groups of research teams estimate the average times (15 minutes or less, 16-30 minutes, 31-45 minutes, 46-60 minutes, or more than 1 hour) and educational level (e.g., nursing assistant, registered nurse basic, or registered nurse post basic) needed (2004). Other advantages are the linkages of NIC to SNOMED (the Systematized Nomenclature of Medicine) as well as the “Taxonomy of Nursing Practice,” which provides common structure for nursing diagnoses, interventions, and outcomes. Indeed, researchers, have abstracted data on nursing activities and categorized them using NIC (Henry, Holzemer, Randell, Hsieh, & Miller, 1997; Angermo & Ruland, 2006). Increasingly, NIC is directly being implemented into a number of software products for nursing documentation. We chose NIC as the basis for measuring nursing demands because of 1) its comprehensiveness based on a strong research foundation; 2) the acceptance of NIC within the informatics community and linkages with other initiatives; 3) the ability to compare the results of queuing models using unit-specific service times to those using national estimates of service times; 4) the future possibility of directly accessing electronic patient health records with NIC interventions to assess unit-specific nursing demands; and 5) the future possibility of developing heterogeneous server models informed by the educational levels associated with NIC.

The primary goal of nursing classifications systems has been to describe nursing activities, not to measure the volume or timing of the nursing services needed by patients in a given period of time (although there are general times in 15-minute increments associated with each intervention). The need for some measure of volume of nursing services was highlighted through the inclusion of intensity of nursing care in the seminal work on the Nursing Minimum Data Set (NMDS) (Werely & Lang, 1988; University of Iowa, 2003). In the more than two decades since, intensity of nursing care as a data element attached to patient needs has received little attention in the literature; most work on the NMDS has focused on nursing diagnosis, nursing interventions, and nursing outcomes. Results from our study should not only inform nurse staffing but also inform the future development and use of information technology systems in hospitals.

Methods

A 42-bed orthopedic surgical unit was our test site. On the unit, the staff provided postoperative care primarily for patients who have had spine surgery. In 2006, this unit served a total of 2,942 patients. There are currently 34 registered nurse full-time equivalents (FTEs) employed on the unit. Other personnel include 18 FTE technical partners (unlicensed assistive personnel), 3.5 FTE support partners (housekeepers), and 4.0 FTE administrative partners (clerical). The methods associated with each aim are below.

Aim 1: Identify unit-specific time-sensitive nursing care interventions (demands) and the average times required to perform them (service times): An initial list of nursing care interventions relevant to the test unit was developed by examining the seven domains and 514 NIC interventions. Entire domains not related to care on the unit (e.g., family and community) were eliminated by the research team. Interventions within the other five domains (Physiological Basic, Physiological Complex, Behavioral, Safety, and Health Systems) were reviewed by five RNs with familiarity of the test unit. These nurses included all levels of registered nursing personnel, including the nurse manager and various levels of staff nurses.

Two separate focus groups were conducted, consisting of 1) direct care RNs employed full or part-time for at least 3 months on the unit and 2) nurse managers or administrators familiar with the unit. Eight nurses and eight nurse managers were recruited for the focus groups through hospital email with approval from the nurse manager. Each focus group lasted 1 hour in duration. Participants reviewed the applicable NIC interventions and were asked regarding frequency of occurrence of the intervention. The interventions that participants determined to occur “very often” or “often” were then used in the Delphi questionnaire. The focus groups assisted the research team in adapting the interventions to language more understandable by the staff nurses and concise for the questionnaire.

In Round I of the Delphi process, nurse respondents were asked to consider whether an intervention was time sensitive, how often the intervention occurred, and the average duration of time to complete the intervention. Time sensitivity was defined as “an activity that if not provided within a given time frame, may jeopardize the real or perceived quality of patient care.” To determine the frequency of occurrence of an intervention, the following question was presented: “In general, how often has this unit intervention been needed on your unit considering all days of the week, and both day and night shifts?” Responses were measured using a 5-point Likert scale: (1) never, (2) rarely (less than one time per week), (3) sometimes (more than one time per week, but less than everyday), (4) often (one time everyday), and (5) very often (more than one time everyday). Finally, respondents were asked to estimate “On average, when performing this intervention one time, how long does it take you to perform [the intervention] in minutes?” This question was open ended and allowed for respondents to include comments. In Round II, respondents were asked about the interventions that did not reach consensus (achieving a 75% agreement) as being time sensitive. Only those nurses who participated in Round I were eligible to participate in Round II.

All data were carefully reviewed by two nurses on the research team (PdeC and PWS). Descriptive statistics, including minimum, maximum, mean, and standard deviations for each NIC intervention, were computed using the SPSS Version 16.0 (SPSS Inc., Chicago, IL) database. The amount of time it took to complete an intervention was compared to the previously published NIC times. Additionally, the interventions were categorized as either scheduled or unscheduled events.

Aim 2: Determine unit-specific volume and timing (arrival rates) for nursing care demands: After gaining better understanding of the nursing interventions applicable to the test unit in Aim 1, we carefully examined the feasibility of accessing time=stamped relevant data from the available electronic data sources on the unit. Our primary goal was to determine patterns in the volume and timing of nursing care demands over a retrospective year=long period (5/1/2008 to 4/30/2009) in order to capture variability of patient census and nursing care demands due to time of day, day of week, and month. We also collected time-dependent data on delays in responding to call lights to obtain insights about the level and timing of delays with current staffing levels.

An overview of the electronic data that we reviewed is listed in **Table 1**. We originally had planned to review the HSS patient flow system, the Hill-rom COMLinx Nurse Communication Module, and Computer Physician Order Entry.

However, the latter was not available due to delays in implementation. We therefore explored, using the electronic medical record, which was implemented. All electronic data sources needed to be accurately time stamped to allow us to identify significant differences in arrival rates of nursing demands and delays for nursing care demands by time of day, day of week, and time of year.

Table 1. Overview of Electronic Data Sources

Source	*Data Elements*
HSS Patient Flow	• *Admits* • *Discharges* • *Within unit transfers* • *Within hospital transfers (in and out)*
Hill-rom Nurse Communication Module	• *Call types defined as: code blue, staff emergent, staff call, shower, bathroom* • *Response times for calls.*
Electronic Medical Record	• *Nursing and physician narrative notes* • *Vital signs* • *Care plans* • *Other nursing interventions*

Though the HSS patient flow data were not frequently used by the hospital, programming had been developed to identify patient moves by bed assignment. These data inolved 33 data elements, including patient identification elements (e.g., medical record number, name), admitting diagnosis, admission date and time, admission station, room, transfers (e.g., to another unit, operating room, or radiology), transfer date, time location, and discharge date, time and location. The data regarding transfers to and from radiology were not consistently reliable (e.g., the discharge time from radiology was often recorded as later than the discharge time to home and/or days after admission to radiology) and had to be removed. From the remaining data, we were able to calculate an hourly patient census as well as the workload of nurses due to admissions, transfers, and discharges.

The Hill-rom COMLinx Nurse Communication Module data are part of the current call light system used in the unit. Each staff member's identification badge serves as a locator with infrared signals. Each patient bed is assigned identification. This system captures the time a patient calls, the time the call is answered by the unit clerk and assigned, the time the call is canceled, and the call type. These data were accurately time stamped and did not rely on "batching" by data entry personnel, allowing us to measure the time-dependent rate of call-light demands (Aim 2) as well as delays in providing care (Aim 4). A weakness of these data is that the demand can only be categorized grossly (regular, emergent, and bathroom). Formatting of these data was also very problematic. The dataware in "pre-formatted" reports and took extensive resources to transform into a usable data set. Furthermore, there were time lags in the data due to a lack of synchronization of the Hill-rom software clock. These were identified and corrected.

We explored the use of the patient's electronic medical record. Although relevant data elements are entered into the system, they were not usable for several reasons. The first and foremost reason was that extraction of these data required extensive programming by the vendor, and we had not budgeted for this. Second, the data were not electronically time stamped but were recorded retrospectively. Therefore, the time and date of occurrence of patient-related nursing activities were not reliable.

The last data element that we accessed related to this aim was RN staffing. Using paper forms for actual staffing, we calculated the RN staffing on an hourly basis for the year. These data were based on the actual staffing report and included only the direct care RNs.

Aim 3: Develop performance standards for acceptable delays for nursing care: The premise of using queuing models to guide nurse staffing decisions is that providing high-quality care requires that each clinical unit have enough nurses to meet patients' nursing care needs in a timely manner. In order to determine the number of nurses needed for any given period, performance standards for acceptable delays need to be established. A common form of a performance standard is that X% of the activities are delayed no more than T minutes. For example, the performance standard for high-priority nursing activities may be that 95% of these activities receive a nursing response within 5 minutes.

We initially proposed to obtain expert opinions about what constitutes acceptable delays for various nursing interventions, particularly those that are deemed to require a speedy response. The idea was to categorize nursing demands by priority and use the queuing model to identify nursing levels that would ensure a fast response to the high-priority tasks. However, because electronic data on demands were only available from the call light system and the patient flow records, it wasn't possible to determine the fraction of any specific subset of demands. Therefore, we could only use a general response standard in the queuing model. Thus, we used the existing data on time to canceling the call light as a basis for developing a delay standard in conjunction with the perspectives of the HSS nursing managers.

Aim 4: Develop a registered nurse staffing plan based on queuing models: Based on the data collected in the first three aims, we developed a series of queuing models to inform a registered nurse staffing plan based on model outputs. The demands for nursing care are primarily generated from the current inpatients (e.g., call button requests). However, patient movements, such as admissions, discharges, and transfers, change the census level of the unit and also require nurse involvement. We assumed that the number of nurses is fixed during the shift. In many cases, staffing levels remain constant over a nursing shift (e.g., 8 or 12 hours); in other cases, such as when shifts may overlap, the model would be used for each staffing interval defined as a continuous interval of time during which the nurse staffing level remains constant. We assumed that patients arrived to the unit according to a homogeneous Poisson process. This assumption is very reasonable for units in which most arrivals are unscheduled, such as medical units and obstetrics units (Young, 1965). Even in surgical units like ours, the exact number and timing of patient arrivals into the unit (which typically come from the recovery room) have been found to be very random due to variability, additions, and cancellations in the surgical schedule (Litvak & Long, 2000). We assumed that patient lengths of stay (LOS) in the clinical unit are exponentially distributed. This assumption was well supported by the empirical data on the unit LOS, for which the coefficient of variation was 0.99. At any given time, we assumed that there is a fixed number of patients in the unit, each of which independently generates requests for nursing care according to a Poisson process, and that the amount of time a nurse spends on each patient request is exponentially distributed. Though the assumption of exponentially distributed nursing service times is necessary for analytical tractability, it is also well supported by the only study reported in the literature on the use of nurses' time in a medical-surgical unit (Lundgren & Segesten, 2001). Though patients are usually assigned to a specific nurse for each shift, we assume, as is common in practice, that any available nurse can attend to a patient if the assigned nurse is busy with other patients. We confirmed this practice at HSS. We assume that requests are performed on a first-come, first-served basis. Finally, we assumed that all nurses are equally trained and can perform all requests. This assumption is valid for many hospitals and is also consistent with other nurse staffing methodologies (e.g., nurse to patient ratios). We confirmed the validity of this assumption at HSS.

Results

The results are described below and organized by each aim.

Aim 1: Identify unit-specific, time-sensitive nursing care interventions (demands) and the average times required to perform them (service times).

Overall, 224 nursing interventions were deemed relevant to the orthopedic unit. After the focus groups, nurses indicated that 42 of the interventions were pertinent to the unit. NIC interventions were comprehensive, and no new interventions were needed to represent nursing demand. However, three pairs of interventions were collapsed into single interventions. These include the following: 1) NIC 6486 and 6490 combined Environmental Management: Safety and/or Fall Prevention, 2) NIC 0910 and 0940 combined to Immobilization Care Splinting, and 3) NIC 1450 and 1570 combined to Nausea and/or Vomiting Management. Additionally, descriptions of six of the interventions were modified to be more specific to the nursing unit.

Round I Delphi Survey had a response rate of 87% (n = 45), and Round II was 55% (n = 25). In Round I, consensus was reached on 36 interventions as being time sensitive. In addition, 57% (n=24) of the 42 achieved consensus on the frequency of occurrence. After two Delphi rounds, all 42 interventions achieved consensus as being time sensitive.

Table 2 shows the 31 interventions that nurses reported took more or less time to complete when compared to the NIC published times. These interventions were nearly evenly distributed between scheduled and unscheduled categories. That is, 10 scheduled and 12 unscheduled interventions were estimated by the participants to take less time on average than the times published by NIC researchers, and five scheduled and four unscheduled interventions were estimated by the participants to take more time on average than the times published by NIC researchers.

These results on estimating the time-sensitive nursing demands, using the NIC as the starting point, have been published in two separate publications and venues (de Cordova et al., 2009; Hyun et al., 2009).

The service times needed for the queuing model included “call light,” “admissions,” and “discharges.” For call lights, we calculated the average times estimated for the 16 unscheduled interventions (service time, 20.13 minutes). Direct admission (an NIC intervention) was estimated to have a service time of 38.31, and discharge service time was estimated by summing the average time of “discharge planning” (31.70 minutes) and “transport” (27.97 minutes), for a total of 50.67 minutes.

These data informed the queuing models.

Table 2: Nurse-Reported Average Times to Complete Selected Nursing Interventions and NIC Ranges

Interventions Below NIC	**Mean (SD)**	**Range**	**NIC Range**
Scheduled Interventions†			
0740 Bed rest care	11.96 (6.42)	3-30	16-30
4030 Blood products administration	31.08 (16.99)	5-60	> 60
0140 Body mechanics promotion	15.08 (6.81)	5-30	16-30
7370 Discharge planning	31.70 (22.27)	4-60	46-60
4210 Invasive hemodynamic monitoring	22.71 (19.70)	5-120	46-60
6540 Infection control	14.42 (8.52)	1.5-30	31-45
2620 Neurologic monitoring	11.00 (7.89)	1-30	16-30
2690 Seizure precautions	14.62 (8.05)	2-30	16-30
2690 Surgical preparation	29.35 (17.19)	7.5-75	46-60
3660 Wound care	22.65 (15.54)	4-60	31-45
Unscheduled Interventions††			
4020 Bleeding reduction	17.47 (15.83)	1.5-60	46-60
0450 Constipation management	15.90 (11.70)	5-45	16-30
7910 Consultation	24.96 (19.43)	4-62	46-60
5240 Counseling/Family support*	22.04 (13.08)	5-45	46-60
6460 Dementia/Chronic confusional state management*	35.50 (32.43)	1.5-120	> 60
4110 Embolus precautions	13.47 (7.73)	2-30	16-30
6486/6490 Environmental management: Safety and/or fall prevention	16.74 (11.86)	1-45	31-45
7680 Examination assistance	14.85 (10.87)	2-45	16-30
1450/1570 Nausea and/or Vomiting	14.25 (9.14)	2-45	16-30
management 1400 Pain management	13.39 (10.64)	2-45	> 60
3590 Skin assessment/Surveillance*	11.89 (6.97)	2-30	16-30
5606 Teaching: Individual	21.91 (15.33)	4-60	31-45
Interventions Above NIC	**Mean (SD)**	**Range**	**NIC Range**
Scheduled Interventions			
7310 Direct Admission Care	38.31 (18.28)	5-75	16-30
2080 Fluid/Electrolyte management	19.66 (15.42)	1.5-60	≤ 15
0910/0940 Immobilization/Splinting	15.67 (14.38)	2.5-60	≤ 15
2300 Medication administration	27.11 (27.98)	2-120	≤ 15
0960 Transport	27.97 (20.40)	4-75	≤ 15
Unscheduled Interventions			
6200 Emergency care	40.52 (31.75)	2-120	16-30
7960 Healthcare information exchange	22.34 (16.46)	3-60	≤ 15
1806 Self-care assistance: Transferring	18.98 (10.75)	3.5-45	≤ 15
0580 Urinary catheterization	17.61 (7.48)	3.5-30	≤ 15

Note: NIC: Nursing Interventions Classification. All values are in minutes. The 11 interventions missing were not included in this table, because nurse-reported average completion times fell within the NIC range.
†Scheduled interventions are those that could be anticipated in a given shift.
†† Unscheduled interventions are unpredictable that may or may not occur during a shift.
*Interventions were combined to reflect how these interventions are expressed in nursing practice and during communication.

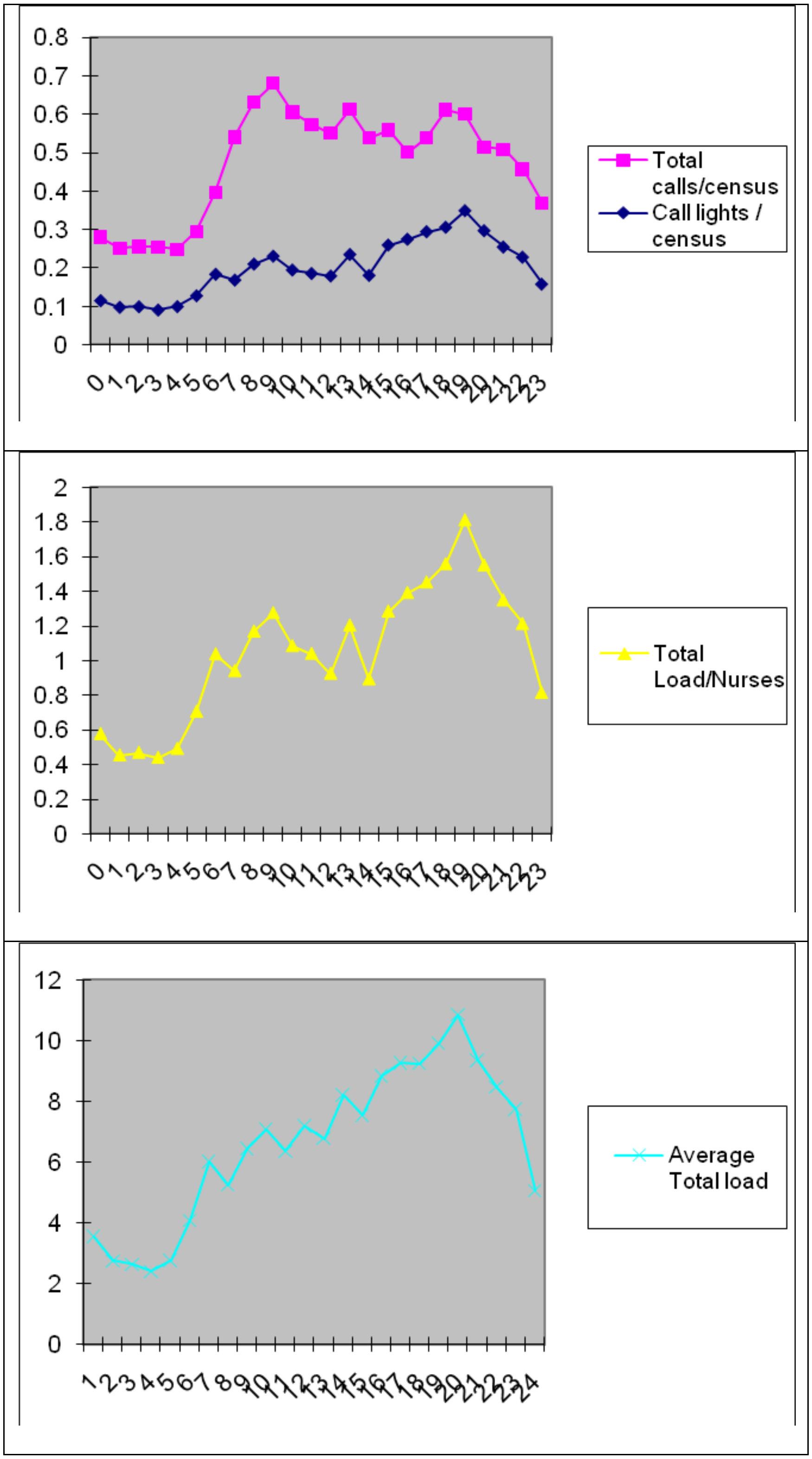


Figure 1: Three Graphs Displaying Demands for Nursing Care per Time of Day

Aim 2: Determine unit-specific volume and timing (arrival rates) for nursing care demands.

First, we examined variability in arrivals of demands for nursing care using the following definitions: Total calls = All the calls registered by the Hill-rom communication system; Call lights = Calls registered by the Hill-rom communication system that were either assigned to nurses (nurse delay >0) or responded to by nurses before being answered at the desk (desk delay = 0 but total delay >0); Total Load = Calls registered by the Hill-rom communication system that were either assigned to the nurses (nurse delay >0) or responded by nurses before being answered at the desk (desk delay = 0 but total delay >0) + admission + discharges + transfers.

The series of three graphs illustrates the variation in demands for nursing by time of day (**Figure 1**). The first graph illustrates the variation in total calls per census (range 0.25 to 0.67) and call lights (assigned) per census (range 0.09 to 0.34). Total calls per census is relatively light between midnight to 4:00 AM and then begins to rise to a peak at 9:00 AM and a second peak at 6:00 PM. The call lights per census follows the same general pattern without the high spike at 9:00 AM, suggesting that many of the calls are handled directly at the desk at that time.

The total load per nurse ranges from a low of 0.44 at 3:00 AM to a high of 1.81 at 7:00 PM. The average total load follows a similar pattern dipping at 2.41 at 3:00 AM and reaching a peak high of 10.85 at 7:00 PM.

We then examined the total load per census per hour by day of the week (**Figure 2).** The vertical axis is the total load per census and the horizontal axis is the hour per day. The graph illustrates similar patterns across the days of week, though the volumes are lowest for Monday and Tuesday and highest for Thursday, Friday, and Saturday. This is likely due to periodicity in the surgical schedule, which is heavier on weekdays than on weekends.

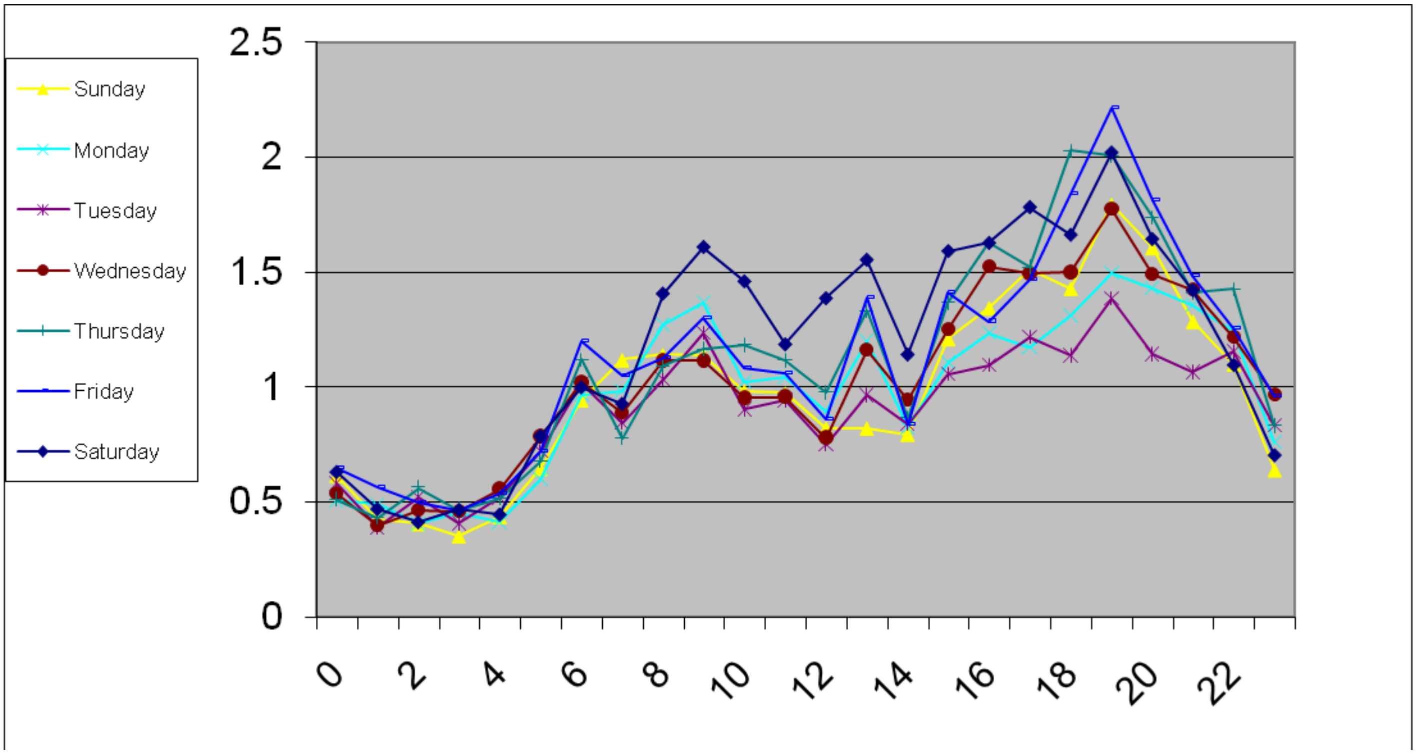


Figure 2: Variation of Demand by Day of Week

Aim 3: Develop performance standards for acceptable delays for nursing care
As discussed in the methods section, because we could not differentiate between the types of demands, we did not develop differentiated performance standards. However, we did examine the actual delays in responding to call lights. We developed two delay measures (both measured in seconds) as described below:

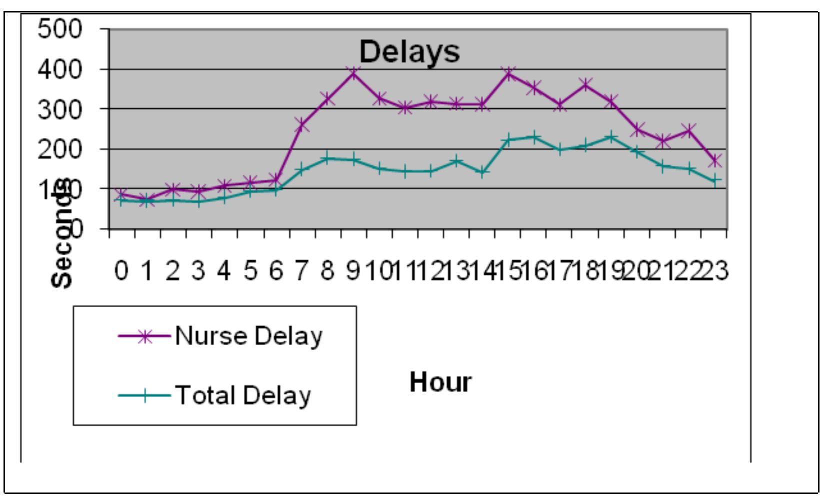


Figure 3: Delays by Hour

Nurse delay = for those calls that were assigned to a nurse; the time from the nurse being assigned the call to the call to cancellation
Total delay = for all calls, the time from the patient initiating the call to cancellation

As can be seen in **Figure 3,** the average nurse delay varied by hour per day ranging from 70 seconds at 3:00 AM to a high of 390 seconds (6.5 minutes) at 9:00 AM. Additionally, because many of the calls are canceled directly at the desk (without any nurse intervention), the overall mean total delay was less than the nurse delay.

After consulting with the nurse managers at HSS, it was determined that we would use an average of 5 minutes as the worst target performance standard and also consider targets of 2 minutes and .5 minutes to represent "moderate" and "best" levels or responsiveness.

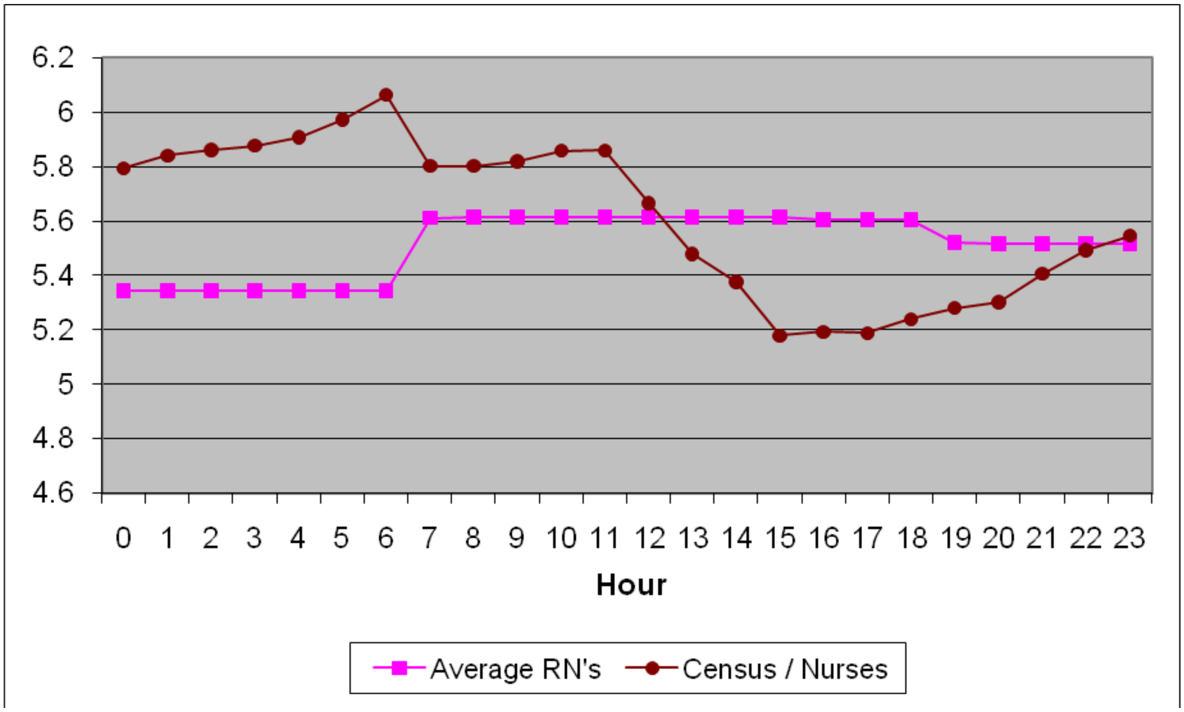
Aim 4: Develop a registered nurse staffing plan based on queuing models:

After analyzing all these data, we developed queuing models for the unit (**Table 3**). In these models, we varied the number of demands for nursing care per patient per hour (.17 to .27), the average nurse service times (21.4 minutes to 26.1 minutes), and the acceptable delay for the patient (<1 min, < 2 min and < 5 min). We defined a "light-load" scenario to correspond to the time period between 8 PM to 10 AM, inclusive, and a "heavy-load" scenario to represent the hours from 10 AM to 7 PM, inclusive. During the latter period, not only is the volume of demands per hour higher but there also is a higher fraction of these demands corresponding to discharges. Because the average time for a nurse to deal with a discharge is more than twice that of other demands, the overall average service time, which is a weighted average of time for call light requests, admissions, and discharges, is higher for this period as well, leading to a need for more nurses for any given delay target.

Table 3: Results from Queuing Models

Combinations of 2 Parameters			**Delay**	**Nurses Needed**	
Nurse Requests	0.27	Requests/patient/hr	< 5 min	8	This is the "heavy-load" scenario
Service Time	26.1	minutes	< 2 min	8	
			< 1 min	9	
Nurse Requests	0.174	Requests/patient/hr	< 5 min	6	This is the "light-load" scenario
Service Time	21.4	minutes	< 2 min	6	
			< 1 min	7	
Nurse Requests	0.21	Requests/patient/hr	< 5 min	6	This is the "average" scenario. Average load and service time including all hours
Service Time	23.2	minutes	< 2 min	7	
			< 1 min	8	
Nurse Requests	0.21	Requests/patient/hr	< 5 min	7	This is average load with "slow" service (because of discharges)
Service Time	26.1	minutes	< 2 min	8	
			< 1 min	8	
Nurse Requests	0.21	Requests/patient/hr	< 5 min	6	This is average load with "fast" service
Service Time	21.4	minutes	< 2 min	7	
			< 1 min	7	
Nominal Bed Utilization	0.7				
LOS	3.79	days			
Number of Beds	42				

The average number of RNs and the average number of patients per RN during our study period is displayed below



Our project has produced several insights of note:

1. Though the information technology software that is currently used by hospitals provides real-time support for nursing personnel in responding to patient needs, it is not very useful for supporting operational planning decisions, such as nurse staffing. This is primarily because there is no one system that collects and stores data on the timing and quantity of nursing care needed. Though demands for nursing care can be partially identified from the call light system and patient medical records, these data exist in different databases and are not easy to merge. Furthermore, we found many errors in the patient records, and the call light system does not allow for easily distinguishing between calls that can be answered by a desk person versus those that need a nursing response. Also, there is no method for identifying the nature of the call. Most importantly, there is no reliable way to determine from electronic sources the amount of time nurses spend on the various patient demands. Therefore, we had to rely on subjective estimates based on focus group discussions. It is clear that the technology exists to regularly collect such data, but this would require the active cooperation of nurses. This would also require vendors to develop data collection systems that could collect the appropriate data with minimal involvement of nurses.

2. Our analyses of the patient census, demands for nursing care, and the resulting delays of call light requests indicate that the most important factor in identifying good nursing levels is not census level but the volume of arrivals, discharges, transfers and call light requests. These data were far more correlated to time of day than to patient census level and indicate that nursing levels should be driven primarily by time of day (and perhaps day of week). This fact is clearly illustrated by the fact that, though the number of patients per nurse decreases in the afternoon, the delay in responding to call lights increases.

3. Queuing models are superior to static nurse-patient ratios in identifying appropriate nurse staffing levels. With the insights gained from this project, we recommend continued development of the electronic data sources to support operational planning.

List of Publications and Products

We have disseminated the project in the following venues:

Publications

1. Hyun S, Bakken S, Douglas K, et al. Evidence-based Staffing: Potential Roles for Informatics. *Nursing Economics.* 2008; 26:151-158.

2. Hyun S, de Cordova P, Green L, et al. Identifying Unit-Specific Nursing Demands Using Nursing Interventions Classifications (NIC). *Stud health Technol Inform*. 2009; 146: 773.

3. deCordova P, Lucero R, Quinlan P, et al. Using the Nursing Interventions Classification System as a Potential Measure of Nurse Workload. *J Nurs Care Qual.*2010; (Epub ahead of print).

4. Yankovic N, Green L. Indentifying Good Nursing Levels: A Queueing Approach, *Operations Research.* (accepted).

Posters

1. Quinlan T, Goldberg S, Green LV, Hyun S, et al. Exploratory Study Using Queueing theory to Improve Nurse Staffing Effectiveness. Poster presentation at the 20th annual scientific session of the Eastern Nursing Research Society, Philadelphia, PA. March 27-29 2008.

Oral Presentations

1. Stone, P.W., & Bakken, S. Staffing Effectiveness and Informatics Solutions. Presented at an invited conference on Staffing Effectiveness, San Diego, CA. (April, 2008).

2. Stone, P.W., & Bakken, S. Staffing Effectiveness and Informatics Solutions. Invited Presentation at the Magnet Conference, Salt Lake City, UT. (October, 2008).

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