An Evidence-Based Approach in Assigning Patients to Nurses

Durai Sundaramoorthi, PhD
Assistant Professor, Steven L. Craig School of Business
4525 Downs Drive, Popplewell Hall 309G
Missouri Western State University, Saint Joseph, Missouri 64507
Email: dsundaramoorthi@missouriwestern.edu
Phone: 816-271-4459
Fax: 816-271-4508

Jay M. Rosenberger, PhD
Associate Professor, Department of Industrial & Manufacturing Engineering
The University of Texas at Arlington, Arlington, TX 76019
Email: jrosenbe@uta.edu

Victoria C. P. Chen, PhD
Associate Professor, Department of Industrial & Manufacturing Engineering
The University of Texas at Arlington, Arlington, TX 76019
Email: vchen@uta.edu

Deborah Buckley-Behan, PhD(c), MS, RN, BC
Clinical Instructor, School of Nursing
The University of Texas at Arlington, Arlington, TX 76019
Email: dbehan@uta.edu

Seoung Bum Kim, PhD
Assistant Professor, Division of Information Management Engineering
Korea University, Seoul, Korea 136-713
Email: sbkim1@korea.ac.kr

COSMOS Technical Report 10-02

An Evidence-Based Approach in Assigning Patients to Nurses

Abstract

Purpose: This article presents a data-integrated simulation based method to evaluate patient-to-nurse assignments ahead of a shift. Unlike patient classification systems, which just estimate the workload, this simulation tool quantifies the workload of nurses by simulating individual nurse's workflow for the entire shift.

Design: To enable building the simulation model, the nurse workflow data was collected from a north Texas hospital for six months. The observational workflow data for six months was continuously collected via locating devices that were embedded with the nurse badges.

Methods: After collecting and processing the data, a data-mining model called classification and regression trees (CART) was fitted to the data. Based on the historical data on nurse workflow, the CART model unearthed patterns in nurse workflow for different patient-to-nurse assignments. A simulation code was written to repeatedly sample from CART to predict the workflow of nurses for the entire shift ahead of time.

Findings/ Conclusion: Generating 1000 scenarios of nurse workflow for the entire shift took only fewer than three minutes. Hence, it is possible to implement the simulation on an actual care unit to quantify workload and evaluate balance in workload among nurses. Introduction of this simulation tool enable charge nurses and hospital management to adapt evidence-based practice in assigning patients to nurses by using performance measures from the simulation.

1. Introduction

Nursing is a vital component of the health care system. It has been on the decrease for the last couple of decades [6]. It has been documented that with increase in number of nurses, mortality and other adverse effects decrease [1, 8, 11]. While on one hand nursing resource is decreasing, on the other hand it is proportionally related to the health of people. Therefore, it is important to optimally utilize the available nursing resource. Traditionally, nursing systems are designed using a top-to-bottom planning approach i.e. nurse budgeting is done before knowing the nurses schedule, and nurse schedule is determined without the knowledge of imbalance in workload among nurses that arise due to patient-to-nurse assignments during a shift. While designing the nursing system, the patient-to-nurse assignment component is not considered adequately. Even in academic research, patient-to-nurse assignment is not researched as much as nurse scheduling and budgeting.

Recently, there has been a debate about patient to nurse ratios [2, 6, 12]. Some states are considering implementing mandatory ratios. For instance, California has implemented mandatory ratios which require hospitals to maintain certain minimum number of nurses for a given set of patients admitted in a care unit [4]. Each nurse's workload depends on combination of factors such as, diagnoses and acuity levels of patients assigned, location of assigned patients, layout of the care unit, and experience and education level of the nurse. Therefore, merely fixing number of patients is not going to resolve the imbalance in workload due to variations occurring from other factors. For this reason, professional organizations like the American Organization of Nurse Executives (AONE), the Society for Health Systems (SHS), and the Healthcare Information and Management Systems Society (HIMSS) called for models that consider hospital-specific factors to address patient-to- nurse assignments

The rest of the paper is organized as follows. In Section 2, design of the simulation model is discussed. Section 3 describes the methods utilized in this research. In Sections 4 and 5, findings and concluding remarks are provided.

2. Design of the Simulation Model

A pictorial summary of the patient-to-nurse assignment simulation model development process is presented in Figure 1. The simulation model development started with data collection on the nurses' workflow and patient data from the repository of north Texas hospital. The resultant data was mined to unearth patterns in workflow for different patient-to-nurse assignments. Based on the patterns learned, a simulation model was developed which quantifies workload of nurses ahead of time to enable evidence-based decision making in assigning patients to nurses. Information about each component of Figure 1 is elaborated below and in Section 3.

At the north Texas hospital nurses wear a tracking device for the purpose of locating the nearest nurse during emergency. All the patient rooms, nursing stations, med-supply room, and hall-ways are equipped with sensors that transmit the nurse location data to the data repository whenever nurses entered that location. The transmitted data holds information on location, date, and time of entry for every location visited by the nurses during their stay in the hospital. By observing successive locations visited by individual nurses, the time of stay at every location was calculated. The data stays in the repository for a month before it gets automatically deleted. To make sure data was collected before it got deleted, we downloaded the data to our research database every weekend. This process of data collection from a medical-surgical unit continued for six months.

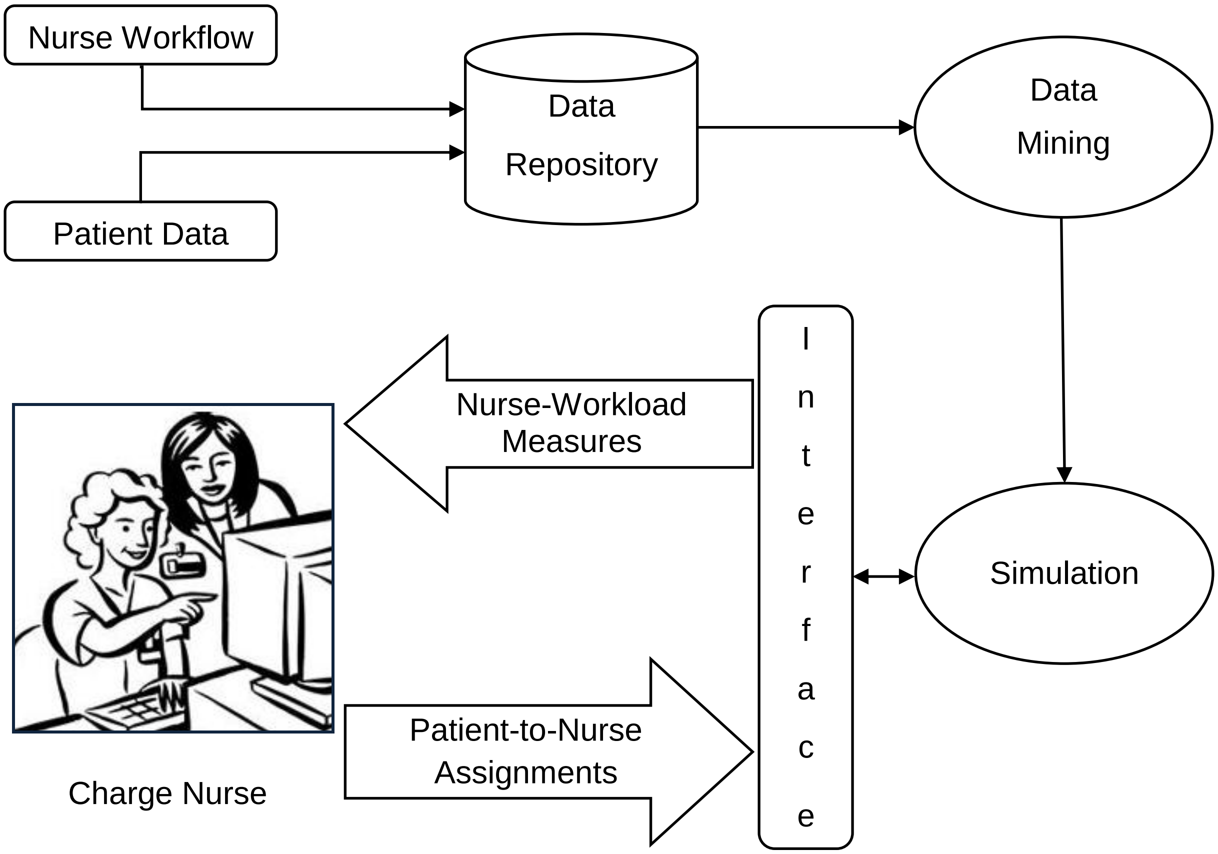

Figure 1: Pictorial representation of the simulation modeling process.

The north Texas hospital, like other hospitals, also tracks patient data. During the same six months period of nurse workflow data collection, admit-date, discharge-date, diagnosis, and patient room information were obtained for the patients admitted to the medical-surgical unit. The north Texas hospital did not use acuity levels to classify patients while assigning patients to nurses. To create artificial acuity levels, patients were divided into four quartiles based on the total amount of time nurses spent with each patient. Four acuity levels were assigned to patients depending upon their quartile i.e. acuity levels of four, indicating the most acute patients, were assigned to the top most quartile and acuity levels of one, indicating the least acute patients, were assigned to the lowest quartile. Acuity levels of three and two were assigned to the other intermediate quartiles. Similarly, the north Texas hospital did not retain the records of patient-to-nurse assignments. To identify patient-to-nurse assignments, among different nurses visiting a patient during a shift, the nurse who spent the most time with the patient was identified as the assigned nurse. The patient data was merged with the nurse workflow data by matching the date and time information. To preserve the confidentiality of the nurses and patients, the entire data set was encrypted using U16807 method [9]. U16807 is utilized for its efficiency in handling cycling issues that arise in large data sets. The resultant data set, after merging and encryption, had 570, 660 observations.

3. Methods

Data mining and Simulation are the two key methods utilized in this research. In particular, Classification and Regression Trees (CART) method was used for data mining [3]. CART is a non-parametric data mining approach which produces easily interpretable tree structures for classification and regression problems. In this research, based on the historical data set from the medical-surgical unit, CART produced tree structures to predict nurse movements and amount of time nurses spend in each location they visit. A simulation code was written in C++ to repeatedly sample from the tree structures to estimate the nurse workflow for different patient-to-nurse assignments ahead of a shift [13]. As indicated in Figure 1 and shown in Figure 2, the charge nurse could interact with the simulation through an interface by entering shift information (Shift Data Tab), nurse data (Nurse Data Tab), and patient data (Patient Data Tab) before the shift begins. After inputting the information for an upcoming shift, simulation could be executed (Simulation Tab) to quantify workloads of nurses in terms of the total direct and indirect care performed by them along with the total amount of time spent in walking for the entire shift. By looking at the results, the charge nurse and in turn the hospital management would know about the balance in workload or lack of it before the shift starts. As a result they would be able to seek additional help before the shift starts and better manage the workload.

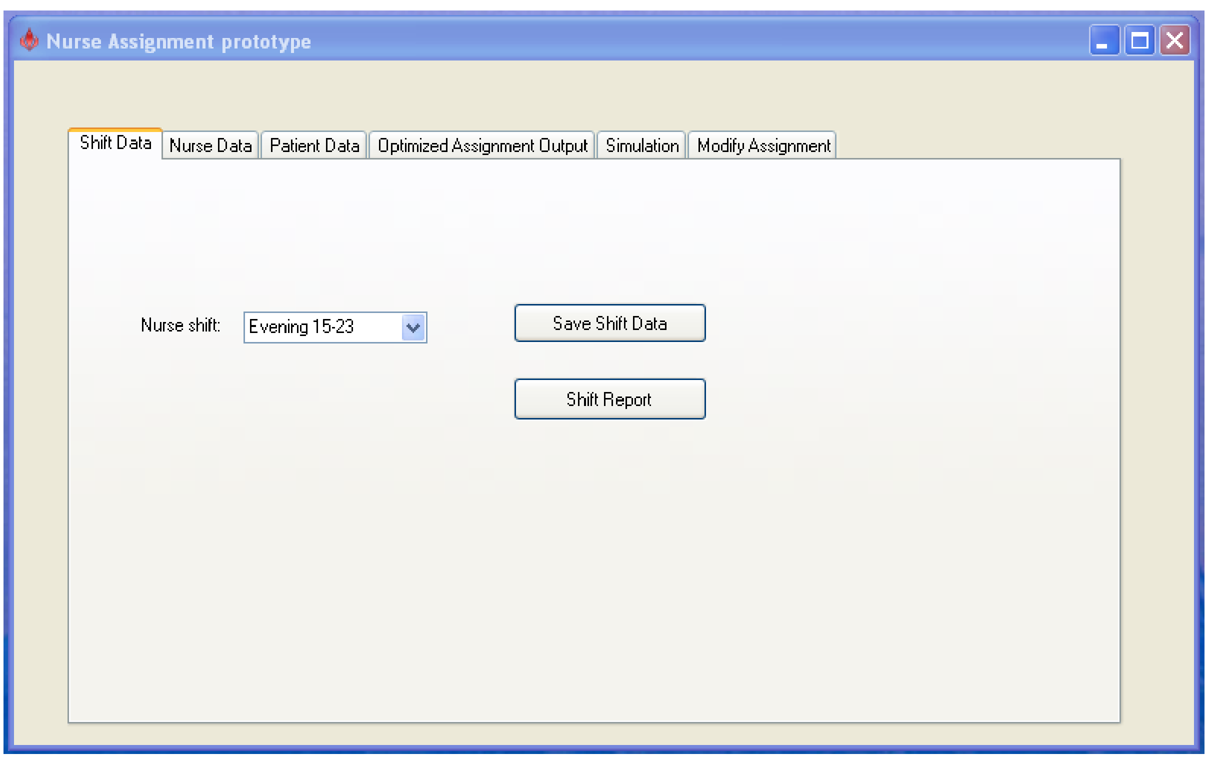

Figure 2: Graphical user interface to the simulation.

Optimized Assignment Output and Modify Assignment tabs use a separate research method, not discussed in this article, to determine optimal patient-to-nurse assignments by penalizing imbalance in nurse load among the nurses working in the same shift. Refer Punnakitikashem et. al. [10] for a comprehensive review of the methodology that generates the optimal patient-to-nurse assignments.

An Information Technology (IT) prototype was created by bundling together the simulation and interface components shown in Figure 1. Unlike patient classification systems, this prototype simulates individual nurse’s workflow for the entire shift and quantifies their walk times, total direct care, and total indirect care. Different hospitals, perhaps even within a hospital, different care units would use different policies to assign patients to nurses. In practice, the hospitals or care units could use the simulation to evaluate assignments from their preferred assignment policy to understand the expected total walk time, total direct care, and total indirect care of individual nurses resulting from patient assignments. It has to be noted that the purpose of the prototype is to help hospital management evaluate patient-to-nurse assignments from any assignment policy ahead of the shift. In the IT prototype, by default, the optimal patient-to-nurse assignments are evaluated by the simulation. The prototype can be easily customized to simulate assignments from a preferred assignment policy depending upon the preferences of the hospitals and care units.

4. Findings

To assess the usability of the prototype, the prototype was introduced to two groups of students. The first group had twenty RN to BSN level students and the second group had thirteen MSN level students. The students were provided with a pre- and post-survey to record their feedbacks. The purpose of the surveys was to understand what the nurses would like and dislike about the prototype. It is also valuable to provide an opportunity for the nurses to have a hands-on experience with the prototype so that they could tell if they would use such a program at their work. Based on the survey, the top five reasons why they would prefer the prototype are:

1. Speed at which patient-to-nurse assignments are determined.
2. Appropriateness of the patient-to-nurse assignments.
3. Unbiased nature of the prototype.
4. Performance of all the computations by the prototype to find the patient-to-nurse assignments.
5. Ease of data entry in the prototype.

The survey also found the drawback of the prototype as follows:

1. Exclusion of subcategories in diagnoses codes.
2. Not considering acuity of patients (This has been addressed in the current version and acuity levels are included as described in Section 2).
3. Multiple steps (This has been addressed and redundant tabs were excluded).

Except for the inclusion of all the diagnoses codes, the drawbacks pointed out by the survey were addressed. The initial version of the simulation model incorporated seventeen ICD-9-CM categories [7]. Based on the feedback, we further included categories to capture 'V codes' of ICD-9-CM. It would be impractical to consider all of the diagnoses codes for a single care unit as it is practically impossible to observe patients with all of the possible diagnoses codes getting admitted in a given care unit. Therefore the current version of the prototype considers only nineteen broader categories of the ICD-9-CM diagnoses codes.

5. Conclusion

The C++ simulation code was written with the ability to read and simulate from any tree structure as long as the same or a subset of variables of this research is used. This way of coding makes it easy to adapt the simulation code to different hospitals as long as nurse workflow and patient data are available. Even for the same hospital, when new data becomes available, tree structures can be updated and in turn simulation could utilize newly learned patterns. The current version of the prototype generates 1000 scenarios of workflow for each shift in less than three minutes. Hence, it is possible to use the simulation on an actual care unit to quantify workload and evaluate the balance in workload or lack of it among nurses. Utilizing the simulation tool will enable charge nurses and hospital management to adapt evidence-based practice in assigning patients to nurses. As a result, the workload of nurses will be managed scientifically to yield a better care for patients.

References

1. L. H. Aiken, S. P. Clarke, D. M. Sloane, J. Sochalski, and J. H. Silber. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. *The journal of the American Medical Association*, 288:1987 – 1993, 2002.
2. AONE. Policy statement on mandated staffing ratios. http://www.aone.org/aone/docs/ps ratios.pdf (accessed September 2007), 2003.
3. L. Breiman, J. H. Friedman, R. A. Oishen, and C. J. Stone. *Classification and Regression Trees*. Wadsworth, Belmont, California, 1984.
4. CDHS. Nurse-to-patient staffing ratio regulations. http://www.dhs.ca.gov/lnc/NTP/default.htm (accessed January 2006), 2005.

5. HIMSS. Himss position statement. http://www.himss.org/content/files/PositionStatements/ AdvancedPositionOnMandatedNurseRatio.pdf (accessed September 2007), 2006.
6. HRSA. Projected supply, demand, and shortages of registered nurses: 2000-2020. ftp://ftp.hrsa.gov/bhpr/nationalcenter/rnproject.pdf (accessed January 2006), 2002.
7. INGENIX. *ICD-9-CM Professional for Hospitals: Volumes 1, 2 & 3*. St. Anthony Publishing/Medicode, Salt Lake City, UT, 2003.
8. T. Lang, M. Hodge, V. Olson, P. S. Romano, and R. L. Kravitz. Nurse-Patient Ratios: A Systematic Review on the Effects of Nurse Staffing on Patient, Nurse Employee, and Hospital Outcomes, *The journal of Nursing Administration*, 34 (7-8): 326-337, 2010.
9. A. M. Law and W. D. Kelton. *Simulation Modeling and Analysis*. McGrawHill, New York, 2001.
10. P. Punnakitikashem, J. M. Rosenberger, D. Buckley Behan. 2008. "Stochastic Programming for Nurse Assignment," *Computational Optimization and Applications*, Vol. 40, 321-349.
11. M. B. Rothberg, I. Abraham, P. K. Lindenauer, and D. N. Rose. Improving Nurse-to-Patient Staffing Ratios as a Cost-Effective Safety Intervention. Medical Care, 43 (8):785 – 791
12. SHS. Nurse-to-patient staffing ratio regulations. http://iienet2.org/uploadedFiles/SHS/Resource Library/Details/ positionPaper.pdf (accessed September 2007), 2005.
13. D. Sundaramoorthi, V. C. P. Chen, J. M. Rosenberger, and B. F. Deborah. A data-integrated simulation model to evaluate nurse-patient assignments. Health Care Management Science, *12*(3), 252 – 268, 2009.