10-2015

Forecasting the Potential for Emergency Department Overcrowding

Jeff Skinner
Spectrum Health, skinneje@mail.gvsu.edu

Raymond J. Higbea
Grand Valley State University, higbeara@gvsu.edu

Forecasting the Potential for Emergency Department Overcrowding

Jeff Skinner BSN, RN, CEN
Corresponding Author
Spectrum Health
100 Michigan Ave NE
Grand Rapids MI, 49503
4674 Egypt Valley Ave NE
Ada MI, 49301
skinneje@mail.gvsu.edu
(810) 820-5862

Raymond J. Higbea, PhD, FACHE
Grand Valley State University
410 Fulton St. W
Grand Rapids, MI 49504-6431
1414 Forrester Street SE
Grand Rapids, MI 49508
higbeara@gvsu.edu
(616) 350-6353

Abstract: This research study used the Dixon Forecasting Model (DFM), a Bed Ratio (BR), and the National Emergency Department Overcrowding Scale (NEDOCS) to establish a reliable two-hour overcrowding forecasting tool within the Emergency Department. The DFM and BR were used together to predict severe overcrowding based on current census data. This two hour prediction was then be validated by the real-time NEDOCS and real-time Bed Ratio scores. Data analysis indicates that the two-hour predicted BR is moderately correlated with a real-time NEDOCS (correlation coefficient 0.508) and real-time BR (correlation coefficient 0.492) at the forecasted time. Further data analysis revealed a strong correlation between the real-time NEDOCS and the real-time BR, as evidenced by a correlation coefficient of 0.949. The results of this study suggest that the DFM can be used with additional data to calculate a two hour forecasted BR and that using either BR or NEDOCS in real-time to determine overcrowding is effective.

***Key words*:** Emergency Department, Overcrowding, NEDOCS, Bed Ratio, Forecasting

INTRODUCTION

Background

In 2001, the Institute of Medicine (IOM) released their publication; *Crossing the Quality Chasm: A New Health System for the 21st Century*. Prepared by the IOM's Committee on the Quality of Health Care in America, this instrumental piece of literature outlined key components lacking within the current health system. Specifically, the report outlined six aims for improvement to impact the quality of care. These aims focus on care that is safe, timely, effective, efficient, equitable, and patient focused (IOM, 2001).

During the release time of the IOM's six aims, electronic health records (EHR) were in place and starting to increase in use. This advancement allowed for improved efficiency, throughput, and quality data metrics (IOM, 2007). According Jones et al (2009) "The IOM recommends that hospitals utilize information technology and use operations research methods to become more efficient". One area of our current healthcare system that could benefit from improved efficiency is the Emergency Department. Failure to improve efficiency and patient throughput are key components contributing to the problem of overcrowding (Hoot, 2006).

Overcrowding

Emergency Departments are open all day, every day and they are an essential access point for patients seeking emergency treatment (Weiss, 2004). According to the IOM's 2007 publication, *Hospital-Based Emergency Care; At the Breaking Point*, overcrowding is an important issue that needs attention within the current health system (IOM, 2007). Annually, Emergency Department visits have been growing at an exponential rate. According to the American Hospital Association (AHA) Trendwatch Chartbook, 2013, from 1993 to 2013 the number of Emergency Department visits increased by forty one million (see figure 1).

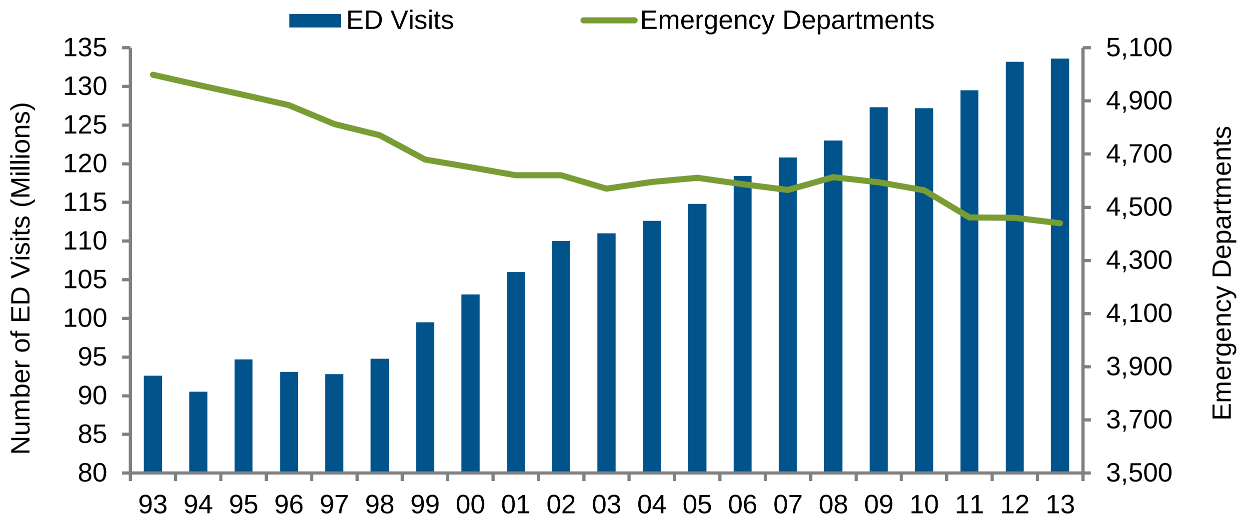

Figure 1 Source: American Hospital Association. Avalere Health for the American Hospital Association. (2013). Trendwatch Chartbook 2013: Trends Affecting Hospitals and Health Systems.

It is important to note that even though patient volumes are increasing, the number of Emergency Departments available to provide treatment is not (Morganti, 2013). As a result, Emergency Departments must maintain efficient throughput in order to meet the demands of incoming patients. Failure to meet this demand results in overcrowding (Hoot, 2006). As this continues to be a problem, Emergency Departments are faced with extreme challenges to eliminate overcrowding. Understanding what overcrowding is and how to predict the likelihood of its occurring is necessary for its prevention (Jones, 2006).

Overcrowding in Emergency Departments put patients at risk for increased length of stay, increased cost of care, and diminished quality of care (IOM, 2007). Through research and data analysis, tools to identify overcrowding in real time have been established. Unfortunately, there is limited research to support forecasting and predicting of overcrowding (Hoot, 2007). As health care leaders, the ability to forecast overcrowding can provide Emergency Departments with early recognition and resource allocation. Keeping in line with the IOM's *A New Health Care System for the 21st Century,* this type of advancement could essentially prevent overcrowding.

METHODS

Design

The following research study was submitted to the Grand Valley State University Internal Review Board for exempt status under Quality Improvement Management. This research study will utilize tools that identify overcrowding in real time, along with department data, to forecast overcrowding two hours into the future. Tools utilized include the Dixon Forecasting Model (DFM), a subset of Real-time Emergency Analysis of Demand Indicators (READI), and the National Emergency Department Overcrowding Scale (NEDOCS). For the purpose of this experiment, the

READI subset that will be utilized is Bed Ratio (BR). The DFM will be utilized to assist in the calculation of a forecasted BR two hours into the future. This two hour prediction will then be validated by a real-time NEDOCS and real-time BR, both of which have been acknowledged in the identification of overcrowding (Jones, 2006).

Research Question

Can as established demand indicator of Bed Ratio be leveraged with the Dixon Forecasting Model to accurately predict Emergency Department overcrowding two hours into the future?

Hypothesis

H1: The Dixon Forecasting Model will forecast Emergency Department overcrowding two hours into the future
H0a: Use of a forecasted BR two hours into the future will predict Emergency Department overcrowding.
H0b: A forecasted BR two hours into the future will be validated with real-time NEDOCS scores.
H0c: A forecasted BR two hours into the future will be validated with real-time BR scores.

Environment

This study will be conducted at Spectrum Health's Butterworth Emergency Department in Grand Rapids, Michigan. The Butterworth Emergency Department has an annual visit volume of 107,000 patients, with an average daily census of 294. This makes the Butterworth Emergency Department one of the highest volume Emergency Departments within the state of Michigan. Additionally, the Butterworth Emergency Department is a designated Level 1 Trauma Center, Certified Chest Pain Center, Certified Stroke Center, and designated Burn Center. In order to handle the large volume of presenting patients, the Butterworth Emergency Department has 68 designated care spaces. This includes 49 general care spaces, 14 Rapid Assessment Zone/Express Care spaces, three trauma bay spaces, and two triage rooms. The Butterworth Emergency Department utilizes an Electronic Health Record, which makes collecting and gathering data manageable for this study.

TOOLS

The following three tools will be used by the Spectrum Health Butterworth Emergency Department Charge Nurse group, consisting of 16 members. Charge Nurses were trained how to use each tool, when to use the tool, and how to record data generated by the tools. The three tools will be used over the course of a two week interval. Data collected during the two week interval will be reviewed and analyzed. To conclude the study, the potential for a reliable two hour forecasted BR to predict Emergency Department overcrowding will be evaluated.

Dixon Forecasting Model

The Dixon Forecasting Model (DFM) is a "home grown" tool developed by the Butterworth Emergency Department Data Analyst, Bill Dixon. The tool was first conceived by Dixon after discussion with management to improve the Butterworth Emergency Department's staffing model. Staffing in the Butterworth Emergency Department is based on 2.55 Hours per Patient Visit (HPPV). In a changing health care climate, fiscal responsibility forced leadership to assess, analyze, and redesign staffing. The forecasted data provided by Dixon allowed leadership to redesign the staffing grid to be more efficient and effective. The ability to assess staffing needs also aided Charge Nurses in resource allocation.

Dixon took historical department census data and built an excel matrix. From these data Dixon created a linear regression model for forecasting future arrivals. This model was then formatted into a data entry tool used by Charge Nurses to enter current department census at pre-determined times in four hour blocks. These four-hour block timeframes were chosen because of the two-hour forecasting ability of the DFM and alignment with Butterworth Emergency Department's staffing model. Department data analysis of the DFM shows that the tool is able to use the current daily census to forecast a daily census two hours into the future. As such, the study design uses the current DFM data with predicted DFM data to calculate predicted arrivals in two hours. This information will be required for calculating Bed Ratio, which can determine overcrowding (Jones, 2006). Currently, this model has only been tested at Butterworth's Emergency Department thus; its findings are not yet generalizable. Future plans include testing the DFM throughout the Spectrum System and, once any refinements are made based on the testing data, move to broader testing and validation of the model.

Bed Ratio

Real-time Emergency Analysis of Demand Indicators (READI) scores have been used as objective measures for predicting Emergency Department demand and overcrowding (Hoot, 2006). Scores evaluate treatment spaces, patient acuity, and physician productivity. Together these scores are used to give an overall demand of the department. Evaluation of treatment spaces is calculated through a Bed Ratio (BR). This ratio assesses the number of patients and available treatment spaces (Reeder, 2003). BR is calculated by taking the total number of ED patients, adding the number of predicted arrivals, subtracting the number of predicted departures, then dividing that by the number of treatment beds. A BR of greater than 1 suggests that there may be inadequate number of treatment spaces available Hoot, 2007). In general, overcrowding occurs when there are not enough care spaces for current and presenting patients. The calculation for BR used in this study is as follows:

BR = (Total ED Patients + Predicted Arrivals – Predicted Departures) / Total Number of Treatment Spaces (Hoot, 2007). (1)

NEDOCS

The National ED Overcrowding Study (NEDOCS) was discussed in 2004 by Weis et al. The NEDOCS is a simple screening tool that can be quickly utilized to determine the degree of ED overcrowding in real-time. The NEDOCS creates a saturation score accounting for a variety of factors including the number of Emergency Department patients, beds, admissions, and Emergency Department throughput. Over the past decade, numerous studies have included the NEDOCS tool in an effort to define overcrowding and assess patient throughput. As a result, the tool has changed since initial implementation in 2004. The calculation and scoring scale used for this study are as follows:

*NEDOCS = -20+85.8 * (Total patients/ED Beds) + 600 * (Admits/Hospital Beds) + 13.4 * (ventilators) + .93 * (longest Admits) + 5.64 *(Last Bed Time).*

Scores 0-50 = Not Busy, 51-100 = Busy, 101-140 = Overcrowded, 141-180 = Dangerous, and above 180 = Disaster (Bhardwaj, 2010). (2)

DATA ANALYSIS

Data was collected from June 17 until June 30, 2015. The necessary data for calculating a forecasted two hour BR was recorded by the Charge Nurse group at four-hour intervals. This included current number of patients in the Emergency Department, DFM two hour predicted arrivals, two hour predicted departures, and the total number of treatment spaces two hours into the future. Criteria for potential discharges used by the Charge Nurse group consisted of the following: patients with discharge written, patients with a current inpatient bed assignment, patients with inpatient admission request placed, patients with observation admission request placed, patients with disposition request placed, and any patients that could potentially leave within the next two hours.

A forecasted two hour BR was calculated using Excel equations. At the forecasted timestamp (0300, 0700, 1100, 1500, 1900, and 2300), the Charge Nurse collected and gathered data needed to run a real-time NEDOCS and real-time BR. This data was entered into an excel spreadsheet and the real-time NEDOCS and real-time BR were calculated using Excel Equations. After the two week time period, data analysis was completed using Excel's Data Analysis Tool Pack. The two hour forecasted BR was analyzed against the Real-time NEDOCS and real-time BR. In addition, the Real-time NEDOCS and real-time BR were analyzed against each other for validation of overcrowding.

Results

A total of 69 observations were recorded during the studies timeframe. Excel's Data Analysis tool pack was utilized to generate descriptive statistics, correlation, and regression analysis for the two hour forecasted BR, real-time NEDOCS, and real-time BR. Descriptive Statistics generated for all three are listed in Table 1. Analysis indicates that the two hour forecasted Bed Ratio is moderately correlated with a real-time NEDOCS score and a real-time Bed Ratio. This is evidenced by a correlation coefficient of 0.508 and .492. Further analysis of the real-time NEDOCS and real-time BR shows a strong correlation evidenced by coefficient of .949 (see table 2). A comparison of data collected was used to create two scatter charts that reflect the aforementioned correlations. See figure 1 for results of the forecasted two hour BR and the real-time NEDOCS. See figure 2 for results from the real-time BR and the real-time NEDOCS.

Table 1

	Bed Ratio	*RT-NEDOCS*	*RT-BR*
Mean	0.946164915	61.69565217	0.860075914
Standard Error	0.035096997	2.641502997	0.027136134
Median	0.930232558	65	0.873015873
Mode	1.253968254	80	0.535714286
Standard Deviation	0.291537554	21.94197183	0.22540966
Sample Variance	0.084994145	481.4501279	0.050809515
Range	1.384920635	100	1.071428571
Minimum	0.107142857	14	0.392857143
Maximum	1.492063492	114	1.464285714
Count	69	69	69
Margin of Error (95.0%)	0.070034967	5.271037164	0.054149313

Table 2

	Bed Ratio	*NEDOCS*	*RT BR*
Bed Ratio	1		
NEDOCS	0.508728	1	
RT BR	0.492642	0.949171	1

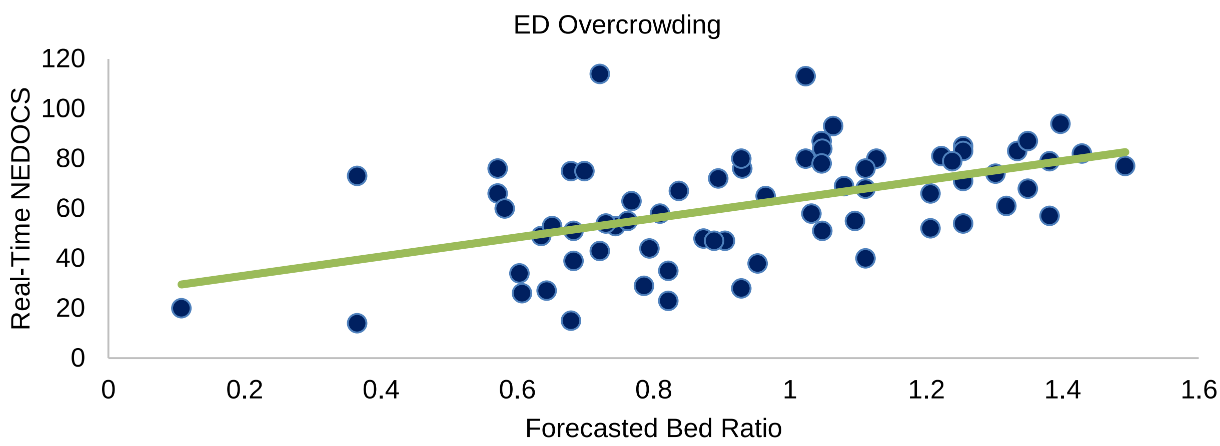

Figure 2

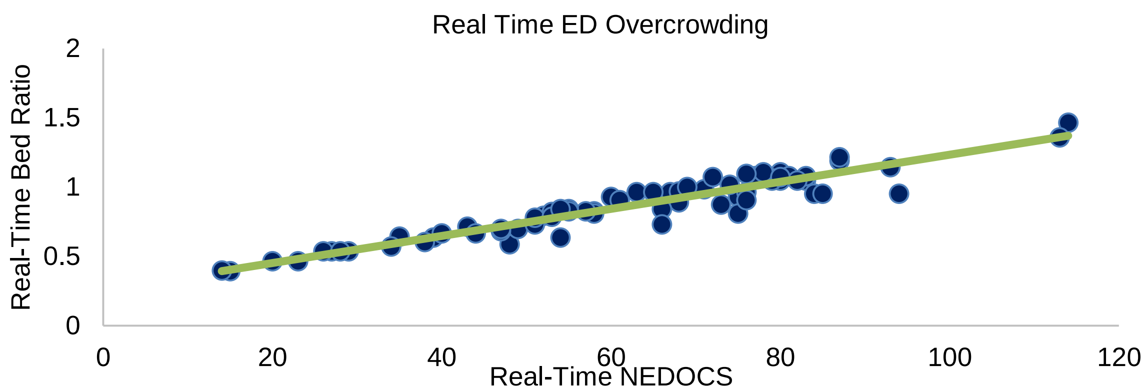

Figure 3

Regression analysis shows that a forecasted two hour BR has statistical significance in predicting future overcrowding. This was validated real-time NEDOCS score and is evidenced by a P-value < .001. Further regression analysis between the two hour forecasted BR and the real-time BR also supports significance in predicting future overcrowding as evidence by a P-value < .001. Results for this analysis are shown below in Table 3.

Table 3

	P-value
BR and Real-Time BR	1.70788E-05
BR and Real-Time NEDOCS	8.07326E-06
Real-Time BR and Real-Time NEDOCS	2.36642E-35

Limitations

Based on the size and volume of the Butterworth Emergency Department, the number of observations recorded in comparison is low. Increasing the number of observations in relation to annual visit volume could improve accuracy of the results. The criteria set forth for predicted departures in two hours are variable and subject to Charge Nurse interpretation. Creating an automated forecasting tool similar to the DFM or in accordance with the DFM could prove beneficial. Automation of these data would require extensive historical data collection, which could not be constructed during the timeframe of this research project. Lastly, during the recording of data by the Charge Nurse group, timestamps to be recorded were missed due to department needs. The complexity of the Charge Nurse role coupled with high volumes and acutely ill patients creates the potential for inaccurate data recording.

CONCLUSION

The results of this study suggest that the DFM can be used with additional data to calculate a two hour forecasted BR. This data would also indicate that using either BR or NEDOCS in real-time to determine overcrowding is effective. When using a forecasted two hour BR, the ability to identify overcrowding is not as strong as real-time identification of overcrowding. Regardless, it is significant in determining the likelihood of overcrowding two hours in the future.

This two hour timeframe for predicting overcrowding has the potential to impact how Emergency Departments deal with resource allocation. One way to ensure appropriate resource allocation is to develop a surge plan. The use of forecasting to assist in development and implementation of surge plans to prevent future overcrowding could prove beneficial (Moseley, 2010). However, with a moderate correlation, forecasting alone will not be sufficient for design and development.

It will be essential to have adequate supplementation when attempting to forecast over long expanses of time. Development of responsive staffing model will be necessary to safeguard staff and patients. The use and implementation of a flexible staffing model could prove beneficial when looking for responsiveness. Also, the development of a staffing algorithm and complimentary standard work could supplement decision making. Solutions and supplementation material like this should be taken into consideration, along with consulting key stakeholders. Further research is needed to determine if these resources coupled with the forecasted two hour BR have the potential to reduce overcrowding.

REFERENCES

American Hospital Association. Avalere Health for the American Hospital Association. (2013). Trendwatch Chartbook 2013: Trends Affecting Hospitals and Health Systems. Retrieved from http://www.aha.org/research/reports/tw/chartbook/ch3.shtml

Bhardwaj, Bharat, (2010). NEDOCS: A Rising Patient Throughput Measure. Retrieved fromwww.spesmedici.it/docs/dal%2520mondo%2520scientifico/27%2520e%252028-10 11/NEDOCS%2520%2520(Bharat%2520Bhardwaj,%2520co founder%2520of%2520NEDOCS.org).pdf+&cd=2&hl=en&ct=clnk&gl=us

Hoot, N., & Aronsky, D. (2006). An early warning system for overcrowding in the emergency department. AMIA. Annual Symposium Proceedings / AMIA Symposium.AMIA Symposium, 339.

Hoot, N. (2007). Measuring and forecasting emergency department crowding in real time. Ann Emerg Med, 49(6), 747-755. doi:10.1016/j.annemergmed.2007.01.017

Institute of Medicine (U.S.). Committee on Quality of Health Care in America. (2001). Crossing the quality chasm: A new health system for the 21st century. Washington, D.C: National Academy Press.

Institute of Medicine (U.S.). Committee on the Future of Emergency Care in the United States Health System. (2007). Hospital-based emergency care: At the breaking point. Washington, D.C: National Academies Press

Institute of Medicine (U.S.). Committee on the Future of Emergency Care in the U.S. Health System. (2006). The future of emergency care in the united states health system. Annals of Emergency Medicine, 48(2), 115-120. doi:10.1016/j.annemergmed.2006.06.015

Jones, S. S., Allen, T. L., Flottemesch, T. J., & Welch, S. J. (2006). An independent evaluation of four quantitative emergency department crowding scales. Academic Emergency Medicine, 13(11), 1204-1211. doi:10.1197/j.aem.2006.05.021

Jones, S. S., Evans, R. S., Allen, T. L., Thomas, A., Haug, P. J., Welch, S. J., & Snow, G. L. (2009). A multivariate time series approach to modeling and forecasting demand in the emergency department. Journal of Biomedical Informatics, 42(1), 123-139. doi:10.1016/j.jbi.2008.05.003

Morganti, K. G., Bauhoff, S., Blanchard, J. C., Abir, M., Iyer, N., & ebrary, I. (2013). The evolving role of emergency departments in the united states. Santa Monica, CA: Rand Corporation.

Moseley, M. G., Moore, T., Vagarali, A., & Rund, D. (2010). Surge: an organizational response to emergency department overcrowding. *JCOM*, *17*(10).

Reeder, T. J., & Garrison, H. G. (2001). When the safety net is unsafe: Real-time assessment of the overcrowded emergency department. Academic Emergency Medicine: Official Journal of the Society for Academic Emergency Medicine, 8(11), 1070-1074. doi:10.1111/j.1553-2712.2001.tb01117.x

Reeder, T. J., Burleson, D. L., & Garrison, H. G. (2003). The overcrowded emergency department: A comparison of staff perceptions. Academic Emergency Medicine, 10(10), 1059-1064. doi:10.1197/S1069-6563(03)00347-6

Weiss, S. J., Derlet, R., Arndahl, J., Ernst, A. A., Richards, J., Fernández-Frackelton, M., Fernández-Frankelton, M. (2004). Estimating the degree of emergency department overcrowding in academic medical centers: Results of the national ED overcrowding study (NEDOCS). Academic Emergency Medicine: Official Journal of the Society for Academic Emergency Medicine, 11(1), 38-50. doi:10.1111/j.1553-2712.2004.tb01369.x