Predicting Patient Volumes in Hospital Medicine: A Comparative Study of Different Time Series Forecasting Methods

Technical Report
January 23, 2014

Kibaek Kim[1]
Changhyeok Lee[1]
Kevin J. O'Leary[2]
Shannon Rosenauer[3]
Sanjay Mehrotra[1]

[1]Industrial Engineering and Management Sciences, Northwestern University, Evanston, Illinois
[2]Division of Hospital Medicine, Feinberg School of Medicine of Northwestern University, Chicago, Illinois
[3]Biomedical Engineering, Northwestern University, Evanston, Illinois

Abstract

Background

Hospital medicine (HM) groups experience fluctuations in patient volume which may be difficult to predict. Patient volume forecast models might allow HM group leaders to prospectively adjust staffing levels.

Objective

To evaluate the predictability of patient volume in HM using a variety of known forecasting techniques.

Design

Observational study comparing univariate and multivariate models. Univariate methods included exponential smoothing, autoregressive integrated moving average (ARIMA), seasonal ARIMA, and generalized autoregressive conditional heteroskedasticity (GARCH) methods. We also used multivariate time-series accounting for HM admissions originating from several potential sources.

Subjects

Non-teaching hospitalist service in a large teaching hospital. Patient volume data were collected from the Northwestern Medicine Enterprise Data Warehouse from January 2009 to June 2012.

Main Measures

Results from univariate and multivariate methods were compared with a benchmark of historical means. The mean absolute percentage error (MAPE) was used to measure the accuracy of forecast. Autocorrelations and cross-correlations of patient volume across the services were also analyzed.

Key Results

The forecasting models outperformed the historical average based approach by reducing MAPE from 17.2% to 6% in one day ahead forecast and to 8.8% MAPE in a month ahead forecast. The ARIMA method outperformed the other methods a day (or beyond) ahead forecast.

Conclusions

Forecasting techniques can be used to accurately predict patient volume HM will experience in the near future. Future research should evaluate adaptive staffing models leveraging these techniques.

Key Words

Patient census forecast, time series methods, hospital medicine

INTRODUCTION

The number of hospitalist physicians and Hospital Medicine (HM) programs have increased dramatically in the United States during the past decade. Over 90% of hospitals with at least 200 beds are now served by hospitalists [1]. Unlike most office practices, where workload may be partially managed by the number and duration of visits, hospitalists experience fluctuations in daily workload which may be difficult to forecast. Hospital medicine groups utilize various methods to adjust staffing levels to workload, but the approach is typically reactionary [2]. Periods of excessive workload may negatively affect patient safety and hospitalist job satisfaction [3]. On the other hand, periods of overstaffing are costly and unsustainable. Better forecasts of patient volume may improve staffing and scheduling decisions to provide a better workload balance.

Patient volume forecasting has been studied extensively for bed occupancy and admissions in the context of emergency medicine (EM) [4-12]. To our knowledge, no prior research has evaluated the use of forecasting models to predict patient volume for an HM practice. The primary objective of the current study was to evaluate the predictability of patient volume in HM using a variety of known forecasting techniques. More specifically, the study compared different known univariate and multivariate time-series forecasting techniques for HM patient volume forecasting. A secondary objective was to estimate the correlation of HM patient volume with those of other services to understand the temporal dynamics in patient volumes across the services. The multivariate forecasting method used accounts for patient admissions to HM from a variety of sources (e.g. emergency medicine, outpatient offices, intensive care services, etc.), while the univariate methods use HM patient volume data only.

METHODS

Setting and Study Design

This observational study involved patients admitted to a non-teaching hospitalist service at Northwestern Memorial Hospital (NMH), an 897-bed tertiary care teaching hospital in Chicago, Illinois. General medical patients were admitted to this service in a quasi-randomized fashion subject to bed availability. This service was staffed by hospitalist physicians who worked independently without the assistance of resident physicians. Hospitalists worked 7 consecutive days, usually followed by 7 days free from clinical duty. Night-time patient care was provided by in-house hospitalists (i.e., nocturnists). During the study period, two hospitalists were scheduled for jeopardy duty each day (i.e., 7AM-7PM) and two were scheduled each night (i.e., 7PM-7AM). Jeopardy hospitalists were called in for clinical duty in cases of sickness, family emergency, or surges in patient volume. No staffing changes were made during periods of low patient volume.

Patient Volume Data and Sources for Hospital Medicine

Electronically recorded encounter data were collected from the Northwestern Medicine Enterprise Data Warehouse (EDW) from January 2009 to June 2012 (1,277 days). The EDW is a single, integrated database of all clinical and research data for patients receiving care and treatment through Northwestern healthcare affiliates (Northwestern Memorial Hospital and the Northwestern Medical Faculty Foundation). In our study, we identified total patient volume in different hospital services for every 4-hour interval. Sources of patient admissions to HM included: emergency medicine, outpatient offices (direct admissions), and transfers from the medical intensive care unit, the cardiac care unit, and other nonmedical services. The study population excluded outpatients except for those under observation in the study hospital.

Forecasting Methods and Measures

Our selection of forecasting methods was based on prior studies of EM patient volume forecasting [8, 11], and hospital admission and discharge volume forecasting [13]. Univariate methods included exponential smoothing [8, 13], exponentially weighted moving average (EWMA) [10], autoregressive integrated moving average (ARIMA) [4, 12-15], seasonal ARIMA [4, 8, 11, 13], and generalized autoregressive conditional heteroskedasticity (GARCH) methods [6]. We also used vector autoregressive (VAR) method in order to incorporate patient demand data as HM admissions may originate from several potential sources (e.g., EM, intensive care services, etc.) [7, 13].

Different forecasting models were trained using patient volume data of 360 days on a rolling horizon basis. For each dataset of 360 days, the forecasted patient volume was calculated for the future periods (from one day to 30 days). The validity of our models was evaluated using the difference between the forecasted patient volume and the actual patient volume beyond the period on which the model was trained. For each model out-of-sample forecast error was assessed by calculating the mean absolute percentage errors (MAPEs). The MAPE is a percentage error that measures the relative difference between the actual and forecast values of a given model [16]. The lower the MAPE, the more accurate the model's forecast.

Adjustment for Systematic Fluctuations

Because patient volume has systematic fluctuations (patterns) in times of a day and days of the week, patient volume snapshots were captured every 4 hours during a week. In this manner, we created 42 snapshots of patient volume per week for our time series. The forecasting models were calibrated on the data adjusted for diurnal and weekly patterns. The systematic (i.e., diurnal and weekly) fluctuation was removed from the original dataset using loess regression [17].

Regression for Mean Patient Volume

Historical mean of patient volume was used as a benchmark for the forecasting methods used in our study. The historical mean was estimated using linear regression with dummy variables that captured the systematic fluctuations of time series data. The loess regression was not used in this case, since the fluctuation was calibrated by dummy variables for each defined period. Moreover, the dummy variables were calibrated only for diurnal fluctuation, since a lower MAPE was observed when using a regression with 6 periods of 4-hours.

Exponential Smoothing

Exponential smoothing [7, 8] was implemented in R software package *forecast*, where a model was considered as a state space model with a single source of error [8, 18, 19]. The software package is fully automated for choosing model parameters, which determines the error type and the trend type of the model [19]. As a simple form of exponential smoothing, EWMA model [10] was also considered by choosing a set of parameters.

Autoregressive Integrated Moving Average (ARIMA)

An ARIMA model was created for auto-correlated and non-stationary time series data. The ARIMA model was represented using parameters (p, d, q), where p was the order of autocorrelation, d was the degree of differencing, and q was the order of moving average process [20]. The model selection was performed using the automated time series algorithm by Hyndman and Khandakar [21] in the R software package *forecast*. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit-root test was used to choose d, and a step-wise selection was performed to choose the other parameters using the Akaike Information Criterion with a correction for finite sample size (AICc).

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

GARCH models allow for adjustment in changes of variances over time in patient volume data. We created a GARCH model, where the residuals of a linear regression model were characterized by autoregressive-moving-average (ARMA) mean process with orders (*p, q*) and GARCH variance process with orders (*m*, *n*). ARMA(*p, q*)-GARCH(*m*, *n*) models were implemented using R software package *rugarch* for parameters p = 1, …, 5, q = 1, …, 5, *m* = 0, 1, and *n* = 0, 1, and the AICc's were compared to choose the best model.

Multivariate Time-Series Model

We categorized the hospital services which admitted patients to HM as follows: EM, outpatient offices (direct admissions), medical intensive care, cardiac care, and other. A multivariate time-series model allowed for use of patient volume data from these other hospital services to predict hospital medicine patient volumes. The multivariate time-series model was estimated using an automated algorithm *bft* in software package *dse* implemented in R software package [22-24]. The algorithm estimated vector autoregressive (VAR) models at different lags up to a given maximum lag, which were converted and reduced to equivalent state-space models. The best estimated model was chosen among several candidates based on AICc.

RESULTS

Aggregate Patient Volume Analysis

Among 83,789 patients considered during the study period 8,148 patients were identified as HM patients. Of the HM patients, 55% were female, 49% were white, and 48% had Medicare or Medicaid as the payer. Details of the patient characteristics for the study population and HM patients are provided in Appendix.

The mean of fraction of patient volumes in HM admitted from the other hospital services is shown in Figure 1. More than 75% of HM patients were admitted from EM.

Figure 2 presents daily and hourly patterns in patient volume for hospital medicine. In addition to the obvious patterns in day of the week and hour of the day, the data exhibits a large variability in patient volumes on a given day.

Univariate Forecasting Models for Patient Volumes for Hospital Medicine

Figure 1. Mean of fraction of patient volume in hospital medicine transferred from the other hospital services

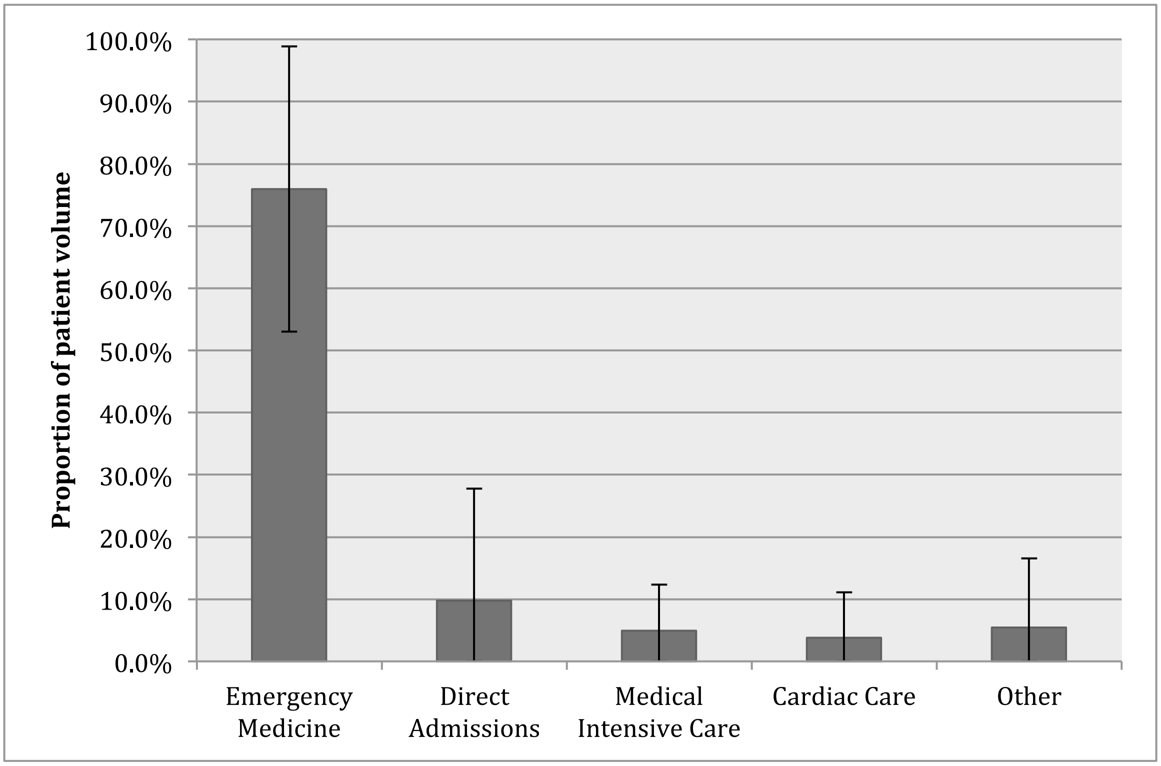
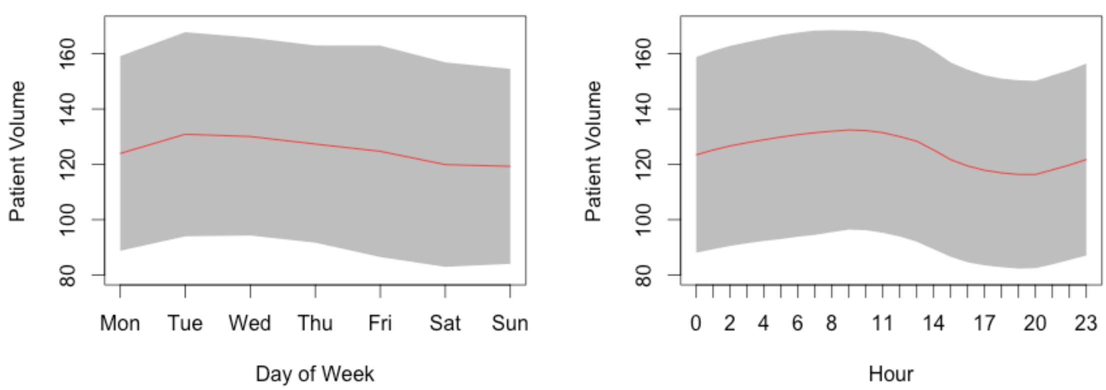
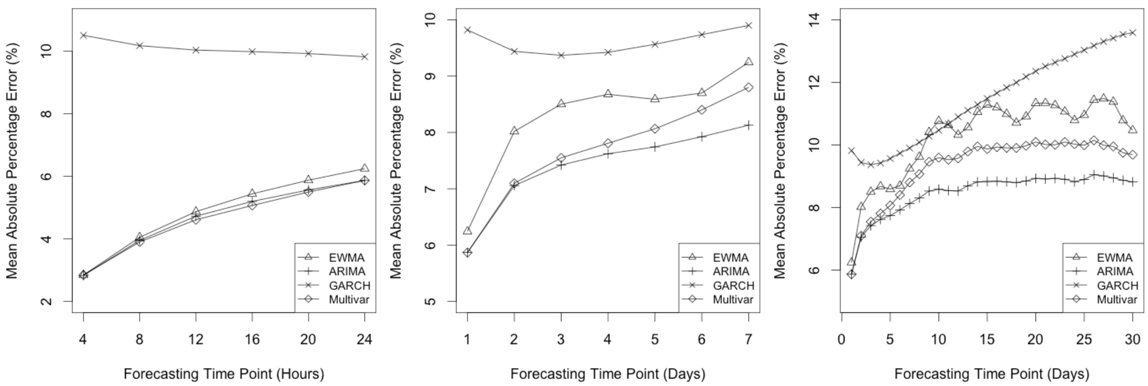


Figure 2. Daily mean patient volumes with 95% confidence band and hourly mean patient volume with 95% confidence band for hospital medicine.



The mean overall patient volume was estimated to 128.3 patients per day. The mean patient volume was the highest (136.8 patients) at 8am and the lowest (121.2 patients) at 8pm. Exponential smoothing method resulted in an EWMA model indicating no trend in the HM patient volume (i.e., no long term progression of HM patient volume).

Figure 3. Mean absolute percentage errors of 4-hourly predictions using the different forecasting methods over 30-day forecast periods.

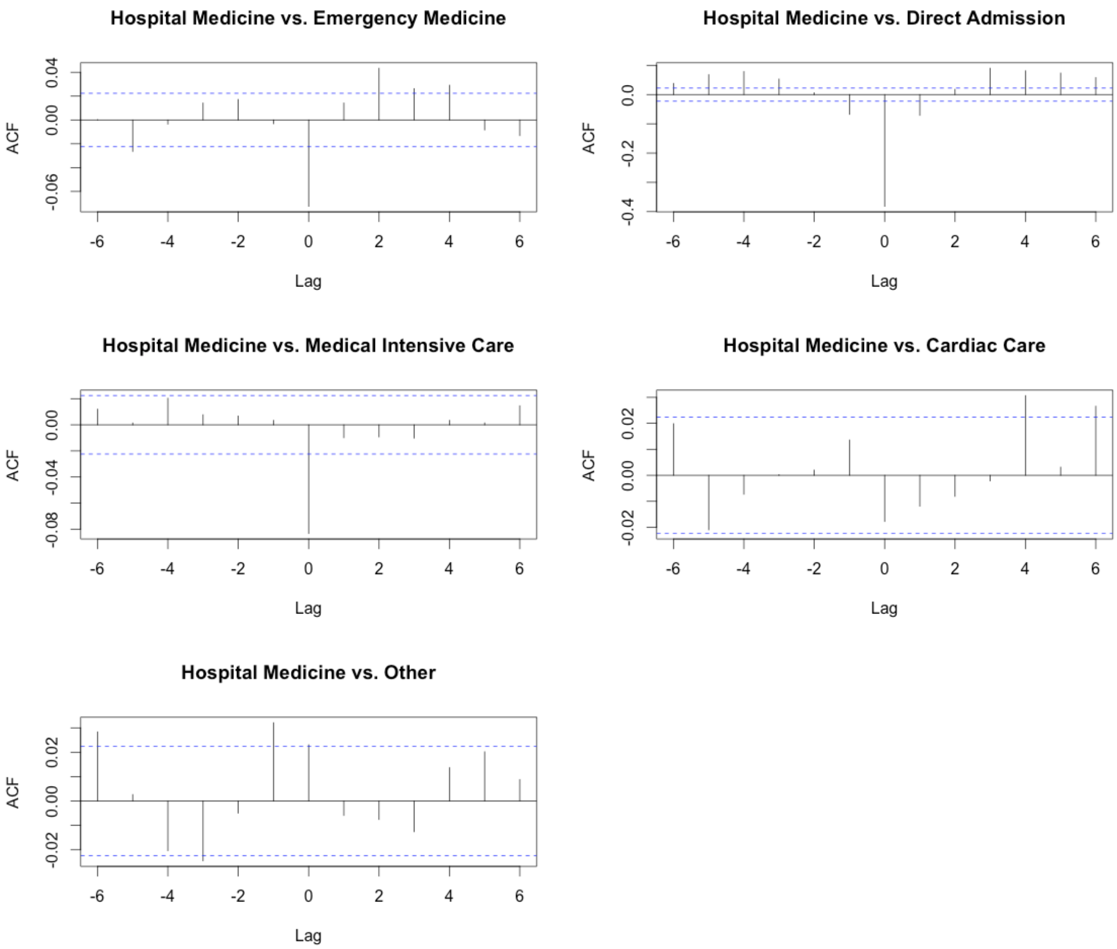


The ARIMA model was fitted with $p = 5$, $d = 1$, and $q = 2$. We found that the HM patient volume was non-stationary, and also found that the best ARIMA model chosen by the stepwise selection algorithm predicts the patient volumes by referring the past 24-hour patient volumes. Among the different model parameters ARMA(5,4)-GARCH(1,1) model was best based on the AICc criterion. The use of regression for mean patient volume for each time period resulted in 17% MAPE. . As shown in Figure 3, the other forecasting models had lower MAPEs. The MAPEs were almost identical for the first 24 hours except for the GARCH model, which performed somewhat worse that then others. The patient volumes for the next 24 hours were predicted with the accuracy of 5.5% MAPE. For one to 30 day forecast horizon, the ARIMA model outperformed the other forecasting models. Moreover, the MAPEs resulting from the ARIMA were significantly lower than those from the VAR model for the forecast horizon of more than five days (p-value < 0.05). The ARIMA model predicted one-week-ahead patient volume within 7.8% MAPE, and the patient volumes in a month horizon were predicted with less than 8.8% MAPEs.

Cross-correlations of HM patient volume with the patient volumes for emergency medicine, direct admissions, medical intensive care, cardiac care, and other services are show in Figure 4. The cross-correlation analysis with emergency medicine suggests that emergency medicine patient volume was likely to lead HM patient volume by about 8 hours. Direct admission volume and hospital medicine patient volumes were likely to affect each other by 12 to 20 hours. However, other hospital service units were not significantly correlated to HM patient volume.

DISCUSSION

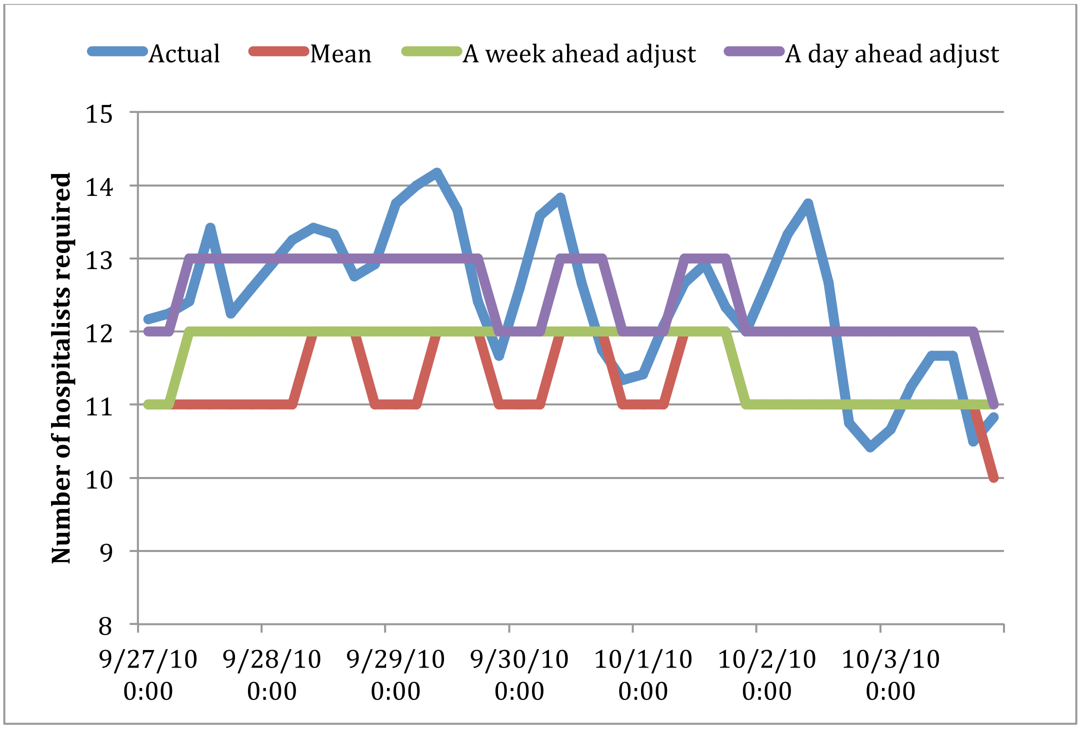
Figure 4. Cross-correlations of patient volumes for hospital medicine to emergency medicine, direct admission, medical intensive care, cardiac care, and Other.



We found that the forecasting models considered in this study outperformed the historical average based approach by reducing MAPE from 17.2% to 6% in one day ahead forecast and to 8.8% MAPE in a month ahead forecast. Our findings support the use of such models by HM groups to forecast workload and make prospective staffing adjustments. Optimized staffing may have a positive impact on patient safety, hospitalist job satisfaction, and cost. In the setting of the hospital used in our study, where the mean patient volume was 128.3, the improvement corresponds to reducing the staffing errors by 14.3 patients per day (from 22 patients to 7.7 patients)

Forecasting models can be used for real-world staffing decisions to provide more sustainable patient care while staying within a limited budget. An adaptive staffing model may be developed where an initial staffing level is determined as a long-term plan and subsequently adjusted to

Figure 5. Hospitalist staffing levels required for actual patient volume, mean patient volume, a-week-ahead forecast, and a-day-ahead forecast during the week of September 27, 2010 at Hospital Medicine at NMH



react to uncertain patient volumes. For the adjustments the adaptive staffing model leverages short-term patient volume predictions using a forecasting model. For example, consider hospitalist staffing decisions at the hospital used in our study during the week of September 27, 2010, where hospitalists experienced unexpected higher workload. Patient volume fluctuated from 125 on Saturday 8pm to 170 on Wednesday 8pm. A long-term staffing level was determined to the mean patient volume with the hospitalist-to-patient ratio of 12. Figure 5 shows the hospitalist staffing levels required for actual patient volume, mean patient volume, a week ahead forecast, and a day ahead forecast during the week of September 27, 2010. The staffing adjustments based on using a week ahead forecast will result in a reduction in shortfall from an average of 1.2 hospitalists to 0.9 hospitalists per day. However, the hospitalist staffing adjustments using a day ahead (i.e. on September 26 for September 27) will reduce the shortfall to 0.3 hospitalists only. Details about operating decisions associated with adjustment and its implications are discussed in [25].

To the best of our knowledge, there are only two studies of multivariate forecasting models for patient volume in EM [7, 26]. Both studies found that the multivariate model provided more accurate forecasts of EM volume, compared to standard univariate models [7, 26]. The multivariate model in our study marginally outperformed the other forecasting models only for the first 24 hours. Surprisingly, the multivariate model did not outperform the univariate ARIMA models, particularly for the forecast periods of more than five days. This is despite the fact that the demand in HM is mostly endogenous. This suggests that, despite patient flow from other services to HM, patient volume information from the other hospital services does not improve the forecasting of HM patient volume. This is further confirmed from the observation that in our study data the correlations of HM patient volume with other hospital services were only marginally significant. The small correlation of HM and EM with 8 hour lagged patient volume is consistent with the observation that the length of stay for high acuity (Emergency Severity Index [ESI] levels 1 and 2) patients in our study was about 6 hours (see Appendix).

The current study is limited to retrospectively using the electronic medical records from only one hospital. The most appropriate forecasting method may be different for hospitals because of the differences in organizational structure. The study was also limited because it ignored clinical factors such as patient acuity, and admission and discharge policies.

In summary, we found that a univariate ARIMA model performed best in forecasting HM patient volume. Importantly, the additional information from patient flow and variances over time did not improve the forecast accuracy. This improved forecasting ability can be used to adjust hospitalist requirements a day ahead to better meet patient needs.

REFERENCES

1. Miller JA AMA report on physician characteristics. Private communication with Joseph A. Miller, Execultive Vice President of the Society of Hospital Medicine, 2012.
2. Michtalik HJ, Yeh HC, Pronovost PJ*, et al.* Impact of attending physician workload on patient care: a survey of hospitalists. JAMA internal medicine 2013; **173**: 375-377. DOI: 10.1001/jamainternmed.2013.1864
3. Sheard S Hospitalist Recruitment and Retention: Building a Hospital Medicine Programme. Occupational Medicine 2010; **60**: 579-580
4. Abraham G, Byrnes GB, Bain CA Short-term forecasting of emergency inpatient flow. Information Technology in Biomedicine, IEEE Transactions on 2009; **13**: 380-388
5. Boutsioli Z Forecasting the stochastic demand for inpatient care: the case of the Greek national health system. Health Services Management Research 2010; **23**: 116-120
6. Jones SA, Joy MP, Pearson J Forecasting demand of emergency care. Health care management science 2002; **5**: 297-305
7. Jones SS, Evans RS, Allen TL*, et al.* A multivariate time series approach to modeling and forecasting demand in the emergency department. Journal of Biomedical Informatics 2009; **42**: 123-139
8. Jones SS, Thomas A, Evans RS*, et al.* Forecasting daily patient volumes in the emergency department. Academic Emergency Medicine 2008; **15**: 159-170
9. Mackay M, Lee M Choice of models for the analysis and forecasting of hospital beds. Health care management science 2005; **8**: 221-230
10. Perry AG, Moore KM, Levesque LE*, et al.* A Comparison of Methods for Forecasting Emergency Department Visits for Respiratory Illness Using Telehealth Ontario Calls. Can J Public Health 2010; **101**: 464-469
11. Schweigler LM, Desmond JS, McCarthy ML*, et al.* Forecasting models of emergency department crowding. Academic Emergency Medicine 2009; **16**: 301-308
12. Sun Y, Heng BH, Seow YT*, et al.* Forecasting daily attendances at an emergency department to aid resource planning. BMC Emergency Medicine 2009; **9**: 1
13. Lin WT Modeling and forecasting hospital patient movements: Univariate and multiple time series approaches. International Journal of Forecasting 1989; **5**: 195-208
14. Earnest A, Chen MI, Ng D*, et al.* Using autoregressive integrated moving average (ARIMA) models to predict and monitor the number of beds occupied during a SARS outbreak in a tertiary hospital in Singapore. BMC Health Services Research 2005; **5**: 36

15. Friede K, Osborne M, Erickson D*, et al.* Predicting trauma admissions: the effect of weather, weekday, and other variables. Minnesota medicine 2009; **92**: 47
16. Bowerman BL, O'Connell RT, Richard T Forecasting and time series: An applied approach. Belmont CA Wadsworth, 1993.
17. Cleveland RB, Cleveland WS, McRae JE*, et al.* STL: A seasonal-trend decomposition procedure based on loess. Journal of Official Statistics 1990; **6**: 3-73
18. Hyndman RJ Forecasting with exponential smoothing. Springer, 2008.
19. Hyndman RJ, Koehler AB, Snyder RD*, et al.* A state space framework for automatic forecasting using exponential smoothing methods. International Journal of Forecasting 2002; **18**: 439-454
20. Cryer JD, Chan K-S Time series analysis: with applications in R. Springerverlag New York, 2008.
21. Hyndman RJ, Khandakar Y Automatic Time Series for Forecasting: The Forecast Package for R. Monash University, Department of Econometrics and Business Statistics, 2007.
22. Gilbert P Brief User's Guide: Dynamic Systems Estimation (DSE). Available in the file doc/dse-guide pdf distributed together with the R bundle dse, to be downloaded from http://cranr-project org 2005
23. Gilbert PD State space and arma models: An overview of the equivalence. Bank of Canada, 1993.
24. Gilbert PD Combining var estimation and state space model reduction for simple good predictions. Journal of Forecasting 1995; **14**: 229-250
25. Kim K, Mehrotra S Valuing Administrative Solutions to Handle Patient Volume Uncertainty in Nurse Staffing and Scheduling. Working paper 2013
26. Kam HJ, Sung JO, Park RW Prediction of Daily Patient Numbers for a Regional Emergency Medical Center using Time Series Analysis. Healthcare informatics research 2010; **16**: 158-165