Forecasting hourly emergency department arrival using time series analysis

Avishek Choudhury[1]
Estefania Urena[2]
Author details can be found at the end of this article
Correspondence to: Avishek Choudhury; achoudh7@stevens.edu

Abstract

Background/Aims The stochastic arrival of patients at hospital emergency departments complicates their management. More than 50% of a hospital's emergency department tends to operate beyond its normal capacity and eventually fails to deliver high-quality care. To address this concern, much research has been carried out using yearly, monthly and weekly time-series forecasting. This article discusses the use of hourly time-series forecasting to help improve emergency department management by predicting the arrival of future patients.

Methods Emergency department admission data from January 2014 to August 2017 was retrieved from a hospital in Iowa. The auto-regressive integrated moving average (ARIMA), Holt–Winters, TBATS, and neural network methods were implemented and compared as forecasters of hourly patient arrivals.

Results The auto-regressive integrated moving average (3,0,0) (2,1,0) was selected as the best fit model, with minimum Akaike information criterion and Schwartz Bayesian criterion. The model was stationary and qualified under the Box–Ljung correlation test and the Jarque–Bera test for normality. The mean error and root mean square error were selected as performance measures. A mean error of 1.001 and a root mean square error of 1.55 were obtained.

Conclusions The auto-regressive integrated moving average can be used to provide hourly forecasts for emergency department arrivals and can be implemented as a decision support system to aid staff when scheduling and adjusting emergency department arrivals.

Key words: Emergency department; Overcrowding; Time series forecasting

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Introduction

Overcrowding in emergency departments is a global concern. Overcrowding can potentially hinder patient care by causing delays and medical errors during the treatment process (Bernstein et al, 2009; Liu et al, 2011; Singer et al, 2011). The detrimental effect of overcrowded emergency departments on quality of care was identified in 1987 (Salway et al, 2017) soon after the first statewide conference addressing issues pertaining to overcrowding was conducted in New York City. This conference involved the American College of Emergency Physicians, the New York Emergency Medical Services, the New York State Department of Health, and state legislators.

This study aimed to address concerns related to overcrowded emergency departments by defining and analysing measures for assessing overcrowding in order to develop a feasible solution.

Defining the problem

Developing a scientific definition for overcrowded emergency departments is a complex problem and the subject of much debate. There is no definition that is based on specific wait times or quantitative permissible delays. In 2006, the American College of Emergency Physicians defined emergency department overcrowding as the situation that 'occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department, hospital, or both' (McKenna et al, 2019: 1). This quote implies

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that overcrowding is a quantifiable relationship between service demand and service delivery (Carter et al, 2014).

In 2003, Asplin et al concluded that emergency department overcrowding is a measure of interdependence between input, throughput and output (Asplin et al, 2003). Pines (2007) added the measure of quality of care within an overcrowded emergency department. It was proposed that 'an emergency department is crowded when inadequate resources to meet patient demands lead to a reduction in the quality of care'. The absence of a scientific definition and measure of overcrowding makes it difficult to develop effective strategies to resolve the ensuing problems. The present study offers the following defintion of emergency department overcrowding: 'when the census (number of patients occupying a bed) goes above floor capacity (number of beds) and hallway beds are used.' This is the same measure of emergency department overcrowding used by many hospitals (Boyle et al, 2016).

Overcrowding at an emergency department can be triggered by various factors, including the patient population, physical capacity, practical capacity, pragmatic capacity, functional capacity and fiscal capacity of the emergency department. Because of the increase in population, emergency department demand in the USA soared from 96.5 million annual visits in 1995 to 115.3 million in 2005 (Institute of Medicine Committee on the Future of Emergency Care in the U.S. Health System, 2006; Moskop et al, 2009). During the same period, 381 emergency departments and 535 hospitals were closed. Superfluous emergency department visits were also found to significantly exacerbate this increasing gap between demand and overall capacity of emergency departments (McCabe, 2001).

Emergency department overcrowding is acknowledged as one of the major causes of staff burnout (Moukarzel et al, 2019), resulting in high turnover rates, clinical errors and poor quality of care. The present study focused on applying time series forecasting methods to address emergency department overcrowding issues. Time series forecasting methods have been used in various fields of healthcare, such as forecasting daily outpatient visits (Luo et al, 2017), inpatient admissions (Zhou et al, 2018), maternal mortality (Sarpong, 2013), emergency department visits (Juang et al, 2017), disease management (Sato, 2013; Song et al, 2016), healthcare waste generation (Chauhan and Singh, 2017) and hospital census data (Capan et al, 2016).

Additionally, time series forecasting methods have been used in various fields, including power and energy (Liu et al, 2012), finance (Qiu and Song, 2016) and traffic-flow (Zhang et al, 2015). Existing studies have adopted several metrics such as the National Emergency Department Overcrowding Score (Hoot and Aronsky, 2006) and ambulance diversion to measure and address emergency department overcrowding. However, these approaches are largely dominated by current or past trends in accident and emergency department conditions and thus perform poorly in predicting upcoming emergency department visits and arrivals. Moreover, such techniques fail to acknowledge the influence of external factors on emergency department arrivals, such as seasonality, and the effects of randomness.

There is a limited number of studies that have used different time series forecasting techniques to overcome the aforementioned limitations and predict annual arrivals (Tandberg and Qualls, 1994), monthly arrivals (Chen et al, 2011; Juang et al, 2017), daily arrivals (Sun et al, 2009), and arrivals at intervals of 4–12 h (Schweigler et al, 2009). However, existing studies have shown complications in predicting hourly patient accident and emergency department arrivals. Furthermore, the practical application of hourly predictions is not well established in the literature. Therefore, this study introduced an hourly forecasting method to forecast emergency department arrivals with an acceptable level of accuracy (usually, over 70% accuracy is considered to be good).

Methodology

Data regarding emergency department arrival patterns were retrospectively extracted from the EPIC database used by a hospital in Iowa. Hourly emergency department arrival data was collected from January 2014–August 2017. Table 1 shows the arrivals by day.

Acuity levels were measured using the Emergency Severity Index for emergency department triage. This is the primary method used in the USA to categorize patients into one of five groups based on the severity of their condition (Table 2). Acuity 1 refers to severely unstable patients who need immediate intervention. Acuity 2 refers to potentially unstable patients who must be seen promptly by a physician. Acuity 3 are the stable patients who must be treated within 30 minutes. Patients classified as acuity 4 are also stable, but do not require urgent care. Acuity 5 patients are the most stable patients and may be treated non-urgently; they typically do not require testing and are discharged the same day.

Table 1. Arrivals by day

Days	Percentage of arrivals
Sunday	15.11%
Monday	13.54%
Tuesday	14.12%
Wednesday	13.96%
Thursday	12.77%
Friday	14.08%
Saturday	13.39%

Table 2. Arrivals by acuity level

Acuity (Emergency Severity Index)	Percentage of patients
1	0.54%
2	19.73%
3	56.59%
4	19.53%
5	1.75%
Unknown (These values were missing from the EPIC database and were not considered in the analysis)	1.85%

Framework explaining the method

The framework used in this study comprises four sections: data pre-processing, exploratory analysis, anomaly detection and forecasting. Every step in the framework encompasses various models and algorithms, each adjustable with various parameters. A typical time-series workflow mandates multiple iteration, implementing different time-series models with different parameters. However, discussing each model and its parameters is outside the scope of this paper. Figure 1 describes the framework of the method used in this study.

The data set was divided into training and actual out-sample patient arrival data sets. The analysis was conducted on the training data set from January 2014 to July 2017, and the forecasted values were matched against actual out-sample patient arrival from January 2014 to August 2017.

During the process, the augmented Dickey–Fuller test (Kwiatkowski et al, 1992) was used to determine whether the time series was stationary around a mean or linear trend, or is non-stationary because of a unit root. White noise was tested using the Box–Ljung test (Seiler and Rom, 1997). The Jarque–Bera test (Jarque, 2011) and the Anderson–Darling test for normality (Djauhari et al, 2014) were also used. The auto-correlation function and partial auto-correlation function were then plotted to determine the autoregressive integrated moving average (p, d, q) where p is the order of auto-regression, d is the lagged difference between the current and previous values, and q denotes the order of the moving average. The largest values of p and q were set as 24, while 4 was set as the maximum number of non-seasonal difference (d).

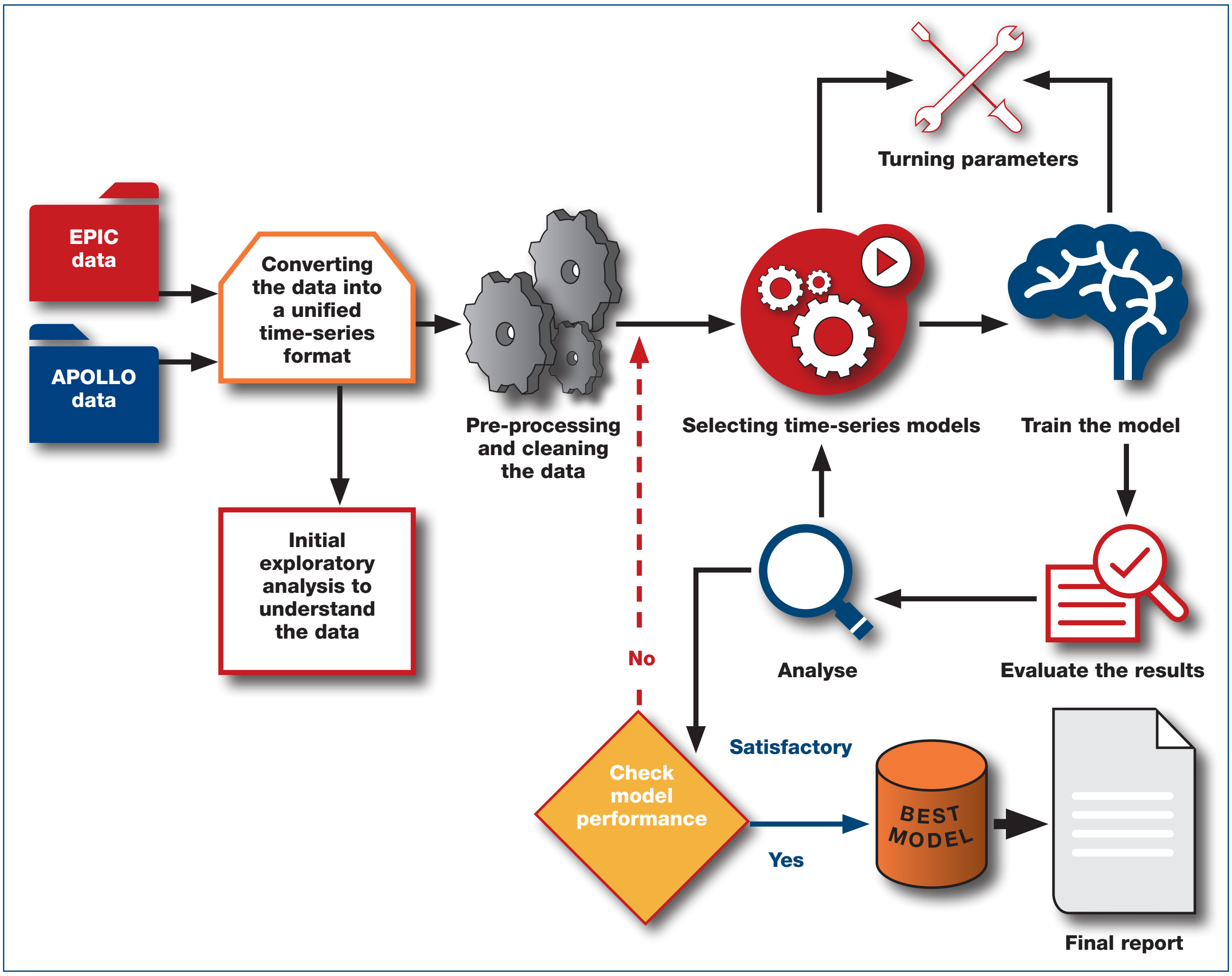

Figure 1. Method

Autoregressive integrated moving average (ARIMA) forecasting models are a commonly used technique for forecasting a stationary time series. A time series is stationary if its statistical properties are all constant over time. A stationary series has no trend; the variations around its mean are consistent and have a constant amplitude. In other words, its short-term, random time patterns always look the same in a statistical sense. The latter condition means that its autocorrelations (correlations with its own prior deviations from the mean) remain constant over time, or equivalently, that its power spectrum remains constant over time. A random variable of this form can be viewed (as usual) as a combination of signal and noise. The signal (if one is apparent) could be a pattern of fast or slow mean reversion, sinusoidal oscillation or rapid alternation in sign. It could also have a seasonal component. An ARIMA model can be viewed as a 'filter' that tries to separate the signal from the noise. The signal is then extrapolated into the future to obtain forecasts.

In the present study, Holt–Winters, TBATS, and neural network methods were also implemented and compared with autoregressive integrated moving average.'TBATS' is an acronym denoting its features: T for trigonometric regressors to model multiple seasonality; B for Box-Cox transformations; A for ARMA errors; T for trend; S for seasonality.

The fitted ARIMA model with minimum Akaike information criterion and Schwartz Bayesian criterion was selected as the optimal forecasting model (Juang et al, 2017). The accuracy of the forecast was then measured based on the root mean square error and mean error.

Results

The best fit model autoregressive integrated moving average (3,0,0) (2,1,0)[24] was selected. Table 3 compares the mean error and root mean squared error of the TBATS, Holt–Winters, neural network and ARIMA models. Table 4 describes the selected ARIMA model.

Although the TBATS and neural network models provide acceptable outcomes, the ARIMA was selected as the best fit model as it exhibited the highest forecasting accuracy. The neural network model is a strong time series forecasting method, but incorrect selection of network parameters might lead to over-fitting (Chatfield, 1996; Faraway and Chatfield, 1998), thus producing good in-sample fit while hindering accurate forecasting.

To ensure a good fit for ARIMA (3,0,0) (2,1,0)[24] the following tests were conducted: Jarque–Bera test, Anderson–Bera test, Anderson–Darling normality test, Box–Ljung test and augmented Dickey–Fuller test (Table 5).

The Jarque–Bera test and Anderson–Darling normality test of residuals yielded a P-value of $2\times2e^{-12}$ ($P<0.05$). Thus, both the tests rejected the null hypothesis of normality implying that the residuals were not normally distributed.

The Box–Ljung test on residuals gave a P-value of 0.17 ($P>0.05$), which implies that there is no significant autocorrelation. In other words, there is a lack of proof of independence. The augmented Dickey–Fuller yielded a P-value of 0.01 ($P<0.05$); thus, the test rejected the null hypothesis of non-stationarity (Figure 2).

The best forecast accuracy was exhibited by ARIMA (3,0,0) (2,1,0)[24] (Figures 3a and b).

Table 3. Comparing time-series models

	Models performance			
Measures	**TBATS**	**Holt–Winters**	**Neural net**	**ARIMA**
Mean error	1.75	1.19	1.40	1.00
Root mean squared error	2.28	27.86	3.26	1.55

Table 4. Autoregressive integrated moving average model

	Performance measures						
	Auto regression1	**Auto regression2**	**Auto regression3**	**Seasonal auto regression1**	**Seasonal auto regression2**	**Mean error**	**Root mean squared error**
Coefficient	0.159	0.100	0.047	–0.584	–0.274	1.001	1.55
Standard error	0.005	0.005	0.005	0.005	0.005		

Table 5. Model evaluation

Test	*P*-value (<0.05)	Inference
Jarque–Bera test	2 ×2e–12	Rejects the null hypothesis of normality
Anderson–Darling normality test	2 ×2e–12	Rejects the null hypothesis of normality
Box–Ljung test	0.17	Indicated no significant autocorrelation
Augmented Dickey–Fuller test	0.01	Rejects the null hypothesis of non-stationarity

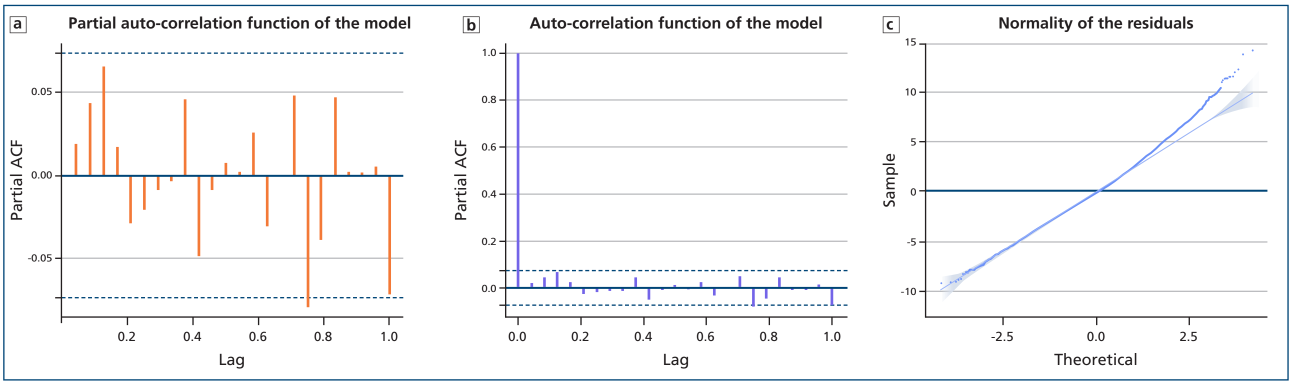

Figure 2. (a) shows the partial auto-correlation function plot with one point exceeding the lower limit at 0.8, (b) shows the auto-correlation function plot, and (c) shows the normality of the residuals (theoretical vs sample).

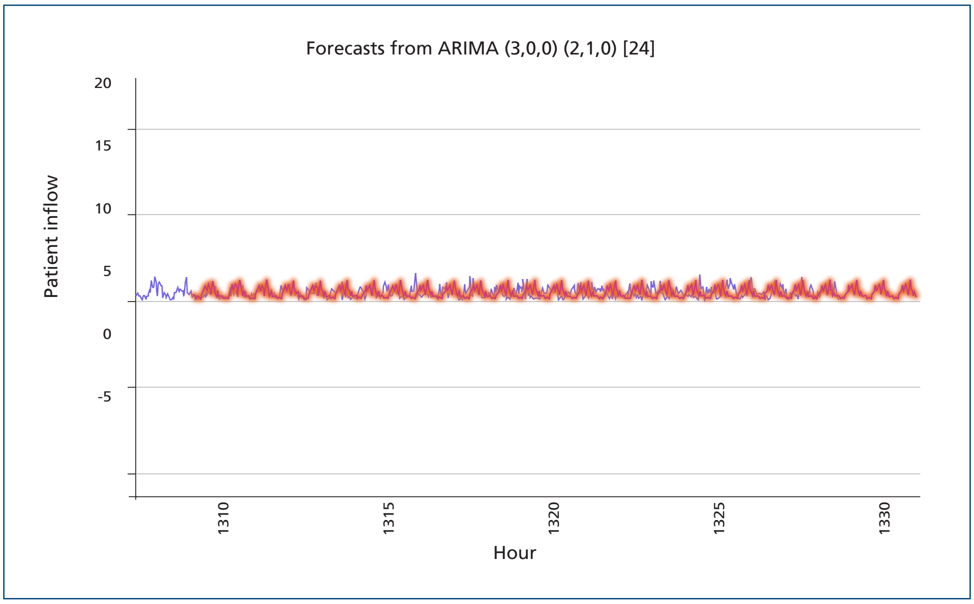

Figure 3a. Actual and forecasted patient arrivals in the emergency department forecasted by ARIMA (3,0,0) (2,1,0) [24]. Time is plotted in the 24-hour format. Forecasted arrivals are plotted in red, while actual arrivals are plotted in blue.

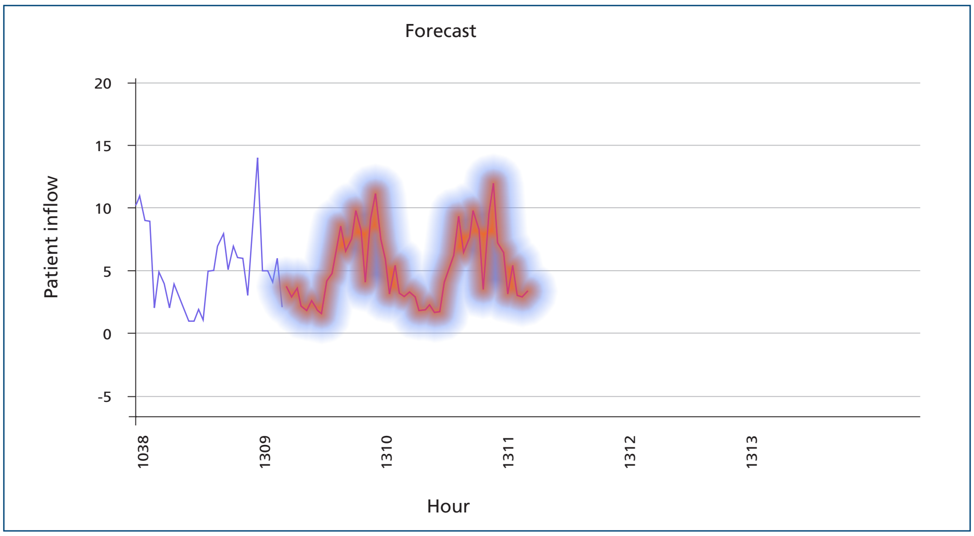

Figure 3b. Close up view of Figure 3a. Different shades of colour represent the range of forecasted values at different confidence intervals, ranging from 99% to 80%.

Discussion

To mitigate the unfavourable consequences of emergency department overcrowding, administrators must make improvements. This may include increasing the physical space available and optimising staffing. To support these improvements, it is useful to forecast the input volume that the emergency department will need to process. The ability to foresee patient visits is imperative to expedite strategic decisions and quality improvements. Numerous methods have been applied to facilitate the forecasting of emergency department arrivals, of which time series analysis has proved relatively simple to implement as such models only use proof regarding the variable being forecasted.

Time series analyses for forecasting emergency department arrivals have been shown to produce acceptable results (Wargon et al, 2009). The ARIMA algorithm proposed in this study was able to accurately predict hourly emergency department visits, with a mean error of 1.001 and an root mean squared error of 1.55. Based on error measures and visual interpretation of the results, it can be inferred that this model's predictions provide a useful hourly forecast of emergency department visits. Moreover, the use of the ARIMA algorithm in an open source platform makes time series analysis applicable to many hospitals, as well as other researchers.

The increase in emergency department arrivals from 2014 to 2017 observed in this study indicates increasing rates of illness, especially in the state of Iowa, USA. For instance, during this period there were several influenza epidemics. The Iowa Influenza Surveillance Network tracks influenza activity, including the age groups affected, outbreaks, the type of virus, its severity and associated risks of seasonal influenza. During 2014, about 300 surveillance sites reported to the Iowa Influenza Surveillance Network, including (but not limited to) health clinics, hospitals, schools, and other public health departments. The 2014–2015 influenza season in Iowa was observed to be more severe than in the recent past. During this season, the Iowa Department of Public Health reported a 59% increase in patients infected with influenza (Iowa Surveillance of Notifiable and Other Diseases Annual Report, 2010).

Given the potential of the ARIMA model proposed in the present study, emergency department administrators could use this method to adjust staffing levels according to the projected clinical activity. With regard to regulating staffing levels, predictions of weekly or hourly emergency department visits would be preferable (Wargon et al, 2009). However, existing literature has demonstrated the complications of predicting daily and hourly patient emergency department visits (Wargon et al, 2009). Meanwhile, there is limited research regarding the development of this staffing modification.

Hertzum (2017) implemented a time series forecasting model using an autoregressive integrated moving average; however, this model did not test for residual normality, stationarity and autocorrelation. The present study, in contrast, not only tested the proposed ARIMA model for normality, stationarity and autocorrelation, but also compared it with neural network, Holt–Winters and TABTS models.

Typically, emergency department staffing is driven by the experience of the scheduling department. In an overcrowded situation, the emergency department is provided with floating nurses from different departments to help perform clinical activities. Moreover, because of limited bed capacity, patients are placed in the hallways. Overcrowding also results in the violation of the prescribed patient:nurse ratio.

The aforementioned issues can occur if the emergency department is unable to accurately forecast patient arrival patterns in advance. At present, the majority of emergency department admissions are only realised a few hours before arrival (including patients presenting directly and those being transferred).

Shifts at an emergency department are usually around 12.5 hours. Therefore, to efficiently manage workforce levels, a minimum notice period of 12.5 hours is necessary. In other words, the member of staff in charge of the staff scheduling pattern must be informed about an expected arrival at least 12.5 hours before. This will enable the scheduler to arrange nurses and other clinicians (such as part time nurses) for the upcoming shifts without affecting the nurse:patient ratio or moving nurses from other departments. Thus, a time series can help to proactively address emergency department staffing issues.

Key points

- A highly accurate, hourly arrival forecasting model and tests for model fitness was developed.
- Unlike monthly or yearly forecasting models, an hourly forecasting model provides a more accurate patient arrival rate and enables the emergency department to schedule their staff.
- Hourly forecasting helps to minimise emergency department overcrowding by enabling staff to take proactive actions, such as preparing beds and initiating fast track triage for patients with high levels of acuity.
- This study considered both appointed and direct emergency department arrivals, as well as both ambulatory and ambulance arrivals.

Future research regarding the forecasting of hourly emergency department arrivals must focus on adopting a systemic approach and incorporate external factors such as climate and traffic into the model. It must also generalise its applicability to other fields of healthcare.

Strengths and limitations of this study

This study proposed an hourly forecasting model with high accuracy to predict patient arrival, which was tested in a hospital in Iowa, USA, forecasting cath lab patient arrivals (Choudhury et al, 2019). Moreover, this method provided information regarding not only ambulatory patient arrivals, but also arrivals in ambulances.

However, the proposed model does not consider any special circumstances (such as bad weather, interrupted transportation and epidemics) that might influence emergency department arrivals.

Conclusions

In this study, ARIMA (3,0,0) (2,1,0)[24] was found to be the best fit model to forecast emergency department arrivals in a hospital in Des Moines city, Iowa. This model can be used by other hospitals with a similar emergency department arrival pattern to predict hourly arrivals. Time series forecasting using ARIMA can therefore be used as a decision support system in the healthcare industry. This model can also be applied to the emergency department census and discharge data for a deeper analysis of overcrowded emergency departments.

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Authors' contribution

A.C and E.U. conceived and designed the study, participated in data collection, analysis, and interpretation, drafted and revised the manuscript, and approved the final version for submission.

Author details

[1]Systems Engineering, School of Systems and Enterprises, Stevens Institute of Technology, Hoboken, NJ, USA

[2]Lincoln Medical and Mental Health Center, The Bronx, NY, USA

Conflict of interest

The authors have no conflict of interest to declare.

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Ethics approval

All anonymised data was collected with the permission of the organisation and patients' medical and personal information was secured.

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