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Forecasting emergency department hourly occupancy using time series analysis

Qian Cheng [a], Nilay Tanik Argon [a], Christopher Scott Evans [b,*], Yufeng Liu [a,c,d,e,f], Timothy F. Platts-Mills [g,h], Serhan Ziya [a]

[a] Department of Statistics and Operations Research, University of North Carolina at Chapel Hill (UNC), NC, USA
[b] Department of Emergency Medicine, Clinical Informatics Fellowship Program, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA
[c] Department of Genetics, University of North Carolina at Chapel Hill (UNC), NC, USA
[d] Department of Biostatistics, University of North Carolina at Chapel Hill (UNC), NC, USA
[e] Carolina Center for Genome Sciences, University of North Carolina at Chapel Hill (UNC), NC, USA
[f] Lineberger Comprehensive Cancer Center, University of North Carolina at Chapel Hill (UNC), NC, USA
[g] Department of Emergency Medicine, UNC School of Medicine, NC, USA
[h] Quantworks, Inc., Carrboro, NC, USA

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Study objective: To develop a novel predictive model for emergency department (ED) hourly occupancy using readily available data at time of prediction with a time series analysis methodology.
Methods: We performed a retrospective analysis of all ED visits from a large academic center during calendar year 2012 to predict ED hourly occupancy. Due to the time-of-day and day-of-week effects, a seasonal autoregressive integrated moving average with external regressor (SARIMAX) model was selected. For each hour of a day, a SARIMAX model was built to predict ED occupancy up to 4-h ahead. We compared the resulting model forecast accuracy and prediction intervals with previously studied time series forecasting methods.
Results: The study population included 65,132 ED visits at a large academic medical center during the year 2012. All adult ED visits during the first 265 days were used as a training dataset, while the remaining ED visits comprised the testing dataset. A SARIMAX model performed best with external regressors of current ED occupancy, average department-wide ESI, and ED boarding total at predicting up to 4-h-ahead ED occupancy (Mean Square Error (MSE) of 16.20, and 64.47 for 1-hr- and 4-h- ahead occupancy, respectively). Our 24-SARIMAX model outperformed other popular time series forecasting techniques, including a 60% improvement in MSE over the commonly used rolling average method, while maintaining similar prediction intervals.
Conclusion: Accounting for current ED occupancy, average department-wide ESI, and boarding total, a 24-SARIMAX model was able to provide up to 4 h ahead predictions of ED occupancy with improved performance characteristics compared to other forecasting methods, including the rolling average. The prediction intervals generated by this method used data readily available in most EDs and suggest a promising new technique to forecast ED occupancy in real time.

1. Introduction

Emergency department (ED) crowding, defined as a state when the "identified need for emergency services exceeds available resources in the ED, hospital or both," is a challenging problem that has been faced by EDs worldwide for over two decades [1,2]. In 2017, there were 139 million ED visits in the US, with only 40.4% of patients being seen within 15 min after arrival [3]. ED crowding has been determined to have negative impact on operational efficiency, patient safety, clinical decision making, and quality of care in the ED [4-10].

Given the complex nature of being prepared to provide emergency care at all times, ED crowding at times is unavoidable. However, EDs can take certain actions to mitigate the severity and duration of ED crowding. Typically, these actions aim either to increase resources by bringing in additional staff, increasing ED bed capacity, and improving hospital bed access [11-15], or to manage patient demand better by closing the ED to non-urgent transfers, moving to ambulance diversion, and performing destination control [16-21]. Precisely which action

* Corresponding author at: Department of Emergency, Medicine University of North Carolina at Chapel Hill, 170 Manning Dr., CB# 7594, Chapel Hill, NC 27514, USA.
E-mail addresses: qcheng@email.unc.edu (Q. Cheng), nilay@email.unc.edu (N.T. Argon), Christopher.Evans2@unchealth.unc.edu (C.S. Evans), yfliu@email.unc.edu (Y. Liu), tim.platts-mills@quantworks.com (T.F. Platts-Mills), ziya@email.unc.edu (S. Ziya).

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should be taken, if any, will depend on a host of factors, but it is important to recognize worsening conditions in an ED as soon as possible and take the appropriate action(s) in a timely manner.

Various ED crowding scores, including the National ED Overcrowding Study (NEDOCS), the Emergency Department Work Index Score (EDWIN), and occupancy rate, have been developed and implemented with the goal of detecting and quantifying crowding [22-25]. However, a limitation of such scores is that they only provide a snapshot of the crowding conditions in the ED at the time they are computed. Continuous monitoring of such scores may aid in recognizing worsening ED crowding, but are not designed to be predictive tools informed by past data.

Time series analysis is a powerful tool to forecast and make predictions based on data indexed by time. In EDs, such methods have been used to model length of stay, daily patient volume, and acuity [26-28]. However, the use of time series analysis of ED hourly occupancy has been more limited. Schweigler et al. [29] compared the performance of seasonal autoregressive integrated moving average (SARIMA) model in forecasting short-term ED hourly occupancy with two other methods and concluded that autoregressive models like SARIMA have better accuracy. Whitt et al. [30] applied SARIMAX to model ED daily visits and then combined it with a previously developed ED patient flow model to generate predictions for future ED hourly occupancy levels. However, neither of these approaches utilized information that is typically available at the time the forecast is made, such as distribution of Emergency Severity Index (ESI) levels and the number of boarding patients in the ED. Jones et al. [31] used a multivariate time series approach to forecast the demands for key resources within the ED, including ED hourly census, and used the current ED census level as well as the patient counts at ED labs and imaging units as external predictors. The findings by Jones et al. suggest benefit in using such external predictors, however, reliable determination of counts related to ED labs and diagnostic imaging studies may be a challenge in some EDs.

The primary objective of this study is to develop a predictive model based on a time series analysis which accounts for key external regressors, and can be used to inform how ED occupancy is likely to change over the course of 1 through 4 h into the future. Additionally, this study aims to compare the performance of this novel predictive model to previously reported methods as well as to determine the accuracy of prediction intervals provided by a time series approach.

2. Materials and methods

2.1. Study design and setting

Following approval from the institutional review board, this study was conducted as a retrospective analysis of the hourly clinical activity of a single ED at a large academic medical center in the southeastern United States. The study ED had a total of 59 beds divided among five adult care areas and one pediatric care area. Two of the adult care areas operated 24 h (A and B), one operated only during peak hours and focused mainly on low acuity patients (D), while the remaining two were primarily dedicated to behavioral health patients (C and Behavioral Health ED). In 2012, the study ED had an annual census of 67,203 ED visits which is similar to the mean ED census of 44 academic EDs across the US surveyed in 2016 [32]. Behavioral health patients were excluded from our analysis due to the variable ED utilization and difference in the clinical considerations in this population compared to medical ED patients. The resulting data set had a total of 65,132 ED visits.

The primary outcome was ED hourly occupancy, defined as the total number of patients in the ED, including patients in the waiting room or those receiving care or boarding in an ED bed. This definition was used because it is easily interpreted and there were no changes in the ED bed capacity during the data collection period. For simplicity, we assumed that all patients arrived at the beginning and left at the end of an hour, and we recorded the occupancy (i.e., counted the total number of patients) at the half-hour mark for each of the 24 h of a day. Hourly occupancy could then be calculated using the arrival and disposition time stamps from patients' data. Additional measures collected for each patient included age, gender, race, ESI score, chief complaint, disposition decision, and additional time stamps including registration and flagged disposition. With these data elements we calculated department-wide controlling variables including average department-wide ESI, and total number of boarding patients.

2.2. Statistical modeling

We utilized 24 separate time series, each dedicated to one specific hour of the day, to model hourly occupancy. In addition to historical ED census for that specific hour, which the time series model directly makes use of, as external regressors, we also considered current ED occupancy, average department-wide ESI, number of boarding patients at the time of prediction, and number of new patient arrivals for up to 5 h prior to the time the prediction is made. Preliminary data analysis had shown that hourly occupancy had strong time-of-day and day-of-week effects. As depicted in Fig. 1, Mondays were the busiest weekday, and afternoons had higher occupancy compared with other time slots. By focusing on a specific hour of the day, as opposed to using a single time series model for all hours, we enable higher modeling flexibility as we allow the variance of the time series to be different. (For example, census at 5 PM may have higher variability compared with census at 7 AM.) Moreover, although having 24 separate models for each hour of the day results in more parameters needing to be estimated, this approach can generate forecasts faster and enable higher prediction accuracy. Furthermore, in a single time series model approach, the day-of-week effect could only be captured by using a time series model with a very high order, making it difficult to fit a model and slowing down the speed with which predictions are made. In contrast, in our approach, by setting the seasonality of the time series to be 7, day-of-week effect was captured since predictions for a specific hour could be dependent on observations made over the same hour in previous weeks.

We chose to model hourly occupancy primarily using time series based on the assumption that ED census in the near future would be strongly dependent on current ED census as well as the census levels in the past, and particularly those that are for the same time period in previous weeks. SARIMA with external regressor (SARIMAX) model was selected as it allows the evolving variable to be dependent on its own lagged value, its past error terms, and related external factors [33]. A typical representation of the SARIMA part of the SARIMAX model is SARIMA $(p,d,q) \times (P,D,Q)_m$. The seasonality m of the time series was set to be 7 to account for the weekly trend and correlations. The parameters d and D respectively describe the number of non-seasonal and seasonal differences used to make the time series stationary. An autoregressive (AR) of order (p) suggests that the model takes hourly occupancy of the same hourly time slot p-days ago into consideration while a moving average (MA) of order (q) considers the error term q-days ago. The seasonal AR (P) term and MA (Q) term follow the same logic but represent weeks instead of days. Moreover, X represents adding one or more external regressors to the forecasting equation. The specifications of all statistical models considered are described further in Supplementary Material S1.

Our occupancy data contained 365 days corresponding to 8760 h. The first 265 days were used only for a training dataset to determine the order of the time series and selection of external regressors. The remaining 100 days were used as a testing dataset. Predictions were made at 2:00 PM each day, with predictions for 3:00 PM (1 h ahead), for 4:00 PM (2 h ahead), for 5:00 PM (3 h ahead), and for 6:00 PM (4 h ahead), and compared the performances of different models. We chose to predict occupancy during the afternoon because this is usually the busiest

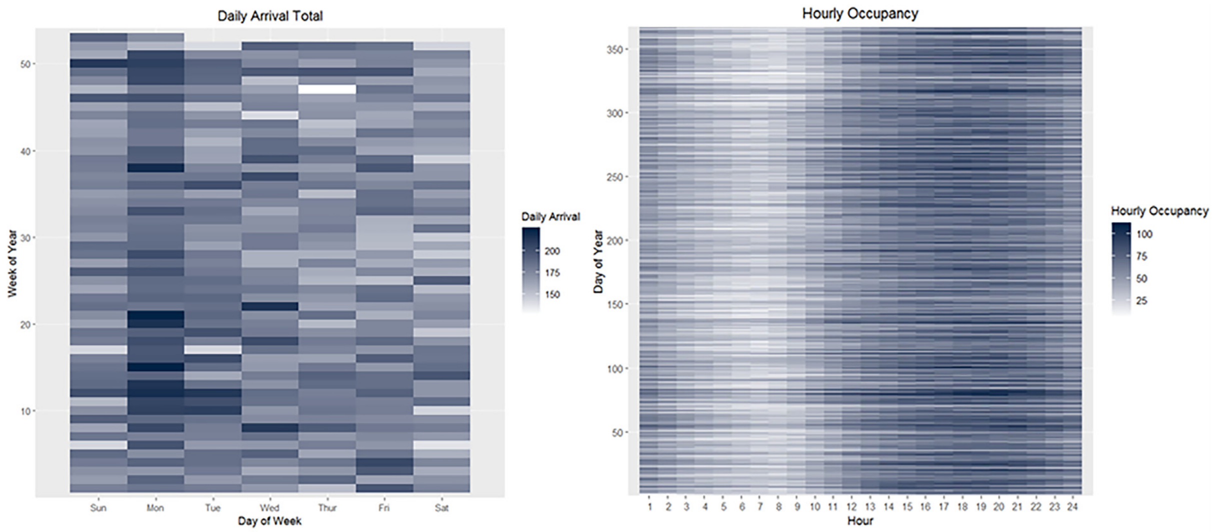

Fig. 1. Heatmap representations of the study period. Notes: Left panel: Day-of-week and week-of-year are shown on horizontal and vertical axes respectively. Daily arrival total is depicted by color with darker color showing more arrivals. Right panel: A similar representation showing hourly occupancy with respect to time-of-day and day-of-year.

time on a given day and likely when future occupancy predictions are most needed.

Each SARIMAX model was fitted repeatedly in a running cross-validation fashion. The training time frame was iteratively expanded in one-day steps. For each SARIMAX model, a search was conducted over models within the order constraints provided by maximum likelihood estimation. Akaike's Information Criteria (AIC) was used to balance the goodness of fit and the complexity of the model [34]. The resulting models were then evaluated by examining whether the residuals of the fitted models follow white-noise distribution using the Ljung–Box test [33]. (The residuals of a model that does not exhibit significant lack of fit should contain no further serial correlation, i.e., act as white noise.)

The following covariates were considered for selection as an external regressor in the model: current ED occupancy, numbers of new arrivals over the last 1, 3, and 5 h, average department-wide ESI, and number of boarding patients. Due to the large number of possible models with each combination of covariates, we utilized a more efficient approach to arrive at the final model with the best predictive power. The performance of our study model was then compared with that of rolling average, Holter-Winters exponential smoothing, and the vector autoregression (VAR) model (See the Supplementary Material S1 for further details of covariate selection and methods of comparison models). We also compare our findings with two alternative methods described by Schweigler et al., and Whitt et al. Comparisons with the method developed by Jones et al. were not possible because our study dataset did not include lab and diagnostic imaging data.

We evaluated different models using their forecasting accuracies as well as prediction intervals. The performances of different models were quantified by comparing the predicted occupancy with actual occupancy during the testing period using measures including mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). MAE provides estimates on how many patients the models' predicted value is off on average, MSE calculates the average squared difference between predicted and actual values, and MAPE provides a normalized unitless measure that is comparable for different hours of the day. When comparing multiple predictive models, those with the smallest MAE, MSE, and MAPE are preferred. We also built prediction intervals in which a future observation will fall with a certain confidence level. For all the methods that provide prediction intervals, we counted how many future observations fell within the specified intervals, so as to compare the methods' performances. (See the Supplementary Material S1 for details of these performance metrics.)

Data were analyzed using R 3.5.3 (Comprehensive R Archive Network, http://cran.r-project.org).

3. Results

Table 1 summarizes the patient characteristics of the study sample. Among the 65,132 total ED visits, patients had a median age of 38 years (with 25% and 75% quantiles being 22 and 55 respectively), 54.6% were female, and 57% had an ESI score of 3. The mean ED

Table 1
Characteristics of study patients.

Characteristic	*n* (%)
Gender	
Female	35,562 (54.6)
Male	29,570 (45.4)
Age	
Below 3 months	521 (0.8)
3 months to 3 years	3387 (5.2)
3 to 8	3061 (4.7)
8 to 18	4885 (7.5)
18 to 40	22,340 (34.3)
40 to 55	14,069 (21.6)
55 to 70	9965 (15.3)
Over 70	6904 (10.6)
Race	
African American	19,540 (30.0)
Asian	716 (1.1)
Caucasian	35,106 (53.9)
Native American	261 (0.4)
Other	7946 (12.2)
Unknown	1563 (2.4)
ESI	
1	586 (0.9)
2	8532 (13.1)
3	37,125 (57.0)
4	16,153 (24.8)
5	2736 (4.2)
Care area	
A	18,107 (27.8)
B	15,241 (23.4)
C	1889 (2.9)
D	17,651 (27.1)
Pediatrics	10,095 (15.5)
Behavioral Health	2149 (3.3)
Disposition	
Admit	19,344 (29.7)
Discharge	45,788 (70.3)

occupancy during the entire study period was 52.99, the standard deviation was 19.13, and the range was 8 to 110. Table 2 reports the comparison of the four SARIMAX models making 4-h-ahead forecasts for 6:00 PM at 2:00 PM of each day. The SARIMAX model had better prediction accuracy when current occupancy information was used instead of arrival information. The inclusion of ESI and boarding information further improves prediction accuracy. Therefore, the model with current occupancy, average department-wide ESI, and boarding total as external regressors was chosen as the "best" SARIMAX model.

Performance characteristics of our final model (now called 24-SARIMAX) with other modeling approaches are shown in Table 3. Our 24-SARIMAX model consistently outperformed other methods as measured by lower MSE, MAE, and MAPE. When making 1-h-ahead predictions, the 24-SARIMAX model had an MSE of 16.20, compared to that of rolling average with an MSE of 123.14. As the prediction time interval moves further into the future (e.g., 4 h ahead instead of 1 h ahead), the predictive power of our model decreases as the current system state will provide less information about the occupancy in a more distant future (24-SARIMAX with MSE 16.19 vs. 64.47 at 1 and 4 h prediction interval, respectively).

For models that provide prediction intervals, we also compared the width and the accuracy of these intervals (Table 4). We found that the two SARIMA-based models (our 24-SARIMAX model and the model by Schweigler et al.) provided narrower and more accurate prediction intervals compared with VAR and Holt-Winters. Moreover, in all cases, the prediction intervals determined by our 24-SARIMAX model perform either similarly or better compared with those by the model of Schweigler et al. Additionally the widths of the prediction intervals are larger when the prediction time interval increased further into the future. Fig. 2 shows an example of the prediction intervals our model provides.

4. Discussion

In this study of ED visits over a 1-year period at a large academic medical center, we developed a novel 24-SARIMAX time series predictive model, which was able to more accurately forecast ED occupancy several hours into the future. Prior studies have shown the benefit of composite scores (such as EDWIN and NEDOCS) of current ED crowding [25], but are unable to make predictions into the future. The availability of reliable hours-ahead predictions of ED occupancy may improve ED operations and department flow by alerting ED managers to impending crowding in the ED and help expedite actions aimed at mitigating its consequences.

Our findings suggest that our modeling approach outperforms other time series forecasting techniques when forecasting occupancy up to 4 h in advance. In comparison to the commonly used rolling average method, using our 24-SARIMAX method we observed an improvement in testing MSE of at least 60% on our dataset. Such an error reduction has important implications, including increased confidence in predictive forecasting models, as well as adding an additional tool to support operational decision-making around ED throughput and efficiency. Unlike some of the crowding scores previously developed, our prediction does not attempt to come up with a complex formula that weighs different factors related to crowding, but rather focuses on a simple measure (ED occupancy). This simpler measure has the advantage of being easier to interpret, and with its explicit focus on the future it might serve as a fitting complement to whichever crowding score is in use.

By building one dedicated time series for each hour of the day and using current occupancy information as one of the external regressors, the 24-SARIMAX model takes both time-of-day and day-of-week effects into consideration and achieves better predictive power. With moderately increased model complexity, our method resulted in lower MA and AR orders, providing not only better accuracy, but also more flexibility as our model is faster and easier to train and generate predictions.

Here we only examined the predictive power of SARIMAX model for up to 4 h, as it was our assumption this would be a sufficient time interval to take actions that would help with imminent increased crowding levels. Beyond that time frame, as the hourly predictive time window

Table 2
Comparison of SARIMAX models using different regressors.

External regressors	MAE	MSE	MAPE
Occupancy	7.13665	74.95466	0.10531
New arrivals over the last 1, 3, and 5 h	8.80926	114.16462	0.13139
Occupancy and ESI	6.58473	67.41719	0.09693
Occupancy, ESI, and boarding total	6.38104	64.47098	0.09443

Table 3
Performance comparison of 24-SARIMAX model with existing models. (Predictions are done at 2:00 PM each day in the test set).

		Performance metrics		
Prediction for	Model	MSE	MAE	MAPE
3:00 PM (1-h-ahead)	Rolling Average	123.136	8.702	0.145
	Holt-Winters	106.704	7.694	0.125
	VAR	100.465	7.712	0.127
	Schweigler et al.	21.600	3.668	0.058
	Whitt et al.	31.057	4.484	0.070
	24-SARIMAX	**16.196**	**3.158**	**0.050**
4:00 PM (2-h-ahead)	Rolling Average	155.597	9.736	0.159
	Holt-Winters	140.814	9.091	0.147
	VAR	127.164	8.490	0.137
	Schweigler et al.	50.554	5.803	0.090
	Whitt et al.	66.471	6.437	0.100
	24-SARIMAX	**36.195**	**4.875**	**0.075**
5:00 PM (3-h-ahead)	Rolling Average	170.959	10.083	0.160
	Holt-Winters	158.715	9.859	0.153
	VAR	142.490	9.369	0.146
	Schweigler et al.	80.894	7.428	0.111
	Whitt et al.	101.496	7.886	0.120
	24-SARIMAX	**58.196**	**6.172**	**0.092**
6:00 PM (4-h-ahead)	Rolling Average	169.254	9.821	0.153
	Holt-Winters	153.722	9.432	0.146
	VAR	140.310	9.187	0.141
	Schweigler et al.	92.178	7.797	0.117
	Whitt et al.	107.997	8.036	0.122
	24-SARIMAX	**64.471**	**6.381**	**0.094**

Note: Current ED occupancy, average department-wide ESI, and number of boarding patients were used as external regressors in the 24-SARIMAX time series model.
Bolded text to highlight performance of 24-SASIMAX model.

Table 4
Width and coverage comparison of prediction intervals for 24-SARIMAX and existing models. (Predictions are done at 2:00 PM each day in the test set).

		80% Prediction interval		95% Prediction interval	
Prediction for	Model	Width	Coverage	Width	Coverage
3:00 PM (1-h-ahead)	Holt-Winters	24.82	79.00	37.96	93.00
	VAR	24.24	79.00	37.07	92.00
	Schweigler et al.	10.58	79.00	16.18	**93.00**
	24-SARIMAX	**10.23**	**83.00**	**15.00**	91.00
4:00 PM (2-h-ahead)	Holt-Winters	25.48	75.00	38.96	92.00
	VAR	24.78	73.00	37.90	91.00
	Schweigler et al.	14.59	67.00	22.31	90.00
	24-SARIMAX	**14.48**	**78.00**	**22.16**	**94.00**
5:00 PM (3-h-ahead)	Holt-Winters	26.01	73.00	39.77	89.00
	VAR	24.98	72.00	38.20	88.00
	Schweigler et al.	**17.27**	64.00	**26.42**	84.00
	24-SARIMAX	17.74	**76.00**	27.13	**91.00**
6:00 PM (4-h-ahead)	Holt-Winters	25.92	76.00	39.64	91.00
	VAR	25.19	76.00	38.52	92.00
	Schweigler et al.	**19.27**	67.00	**29.47**	83.00
	24-SARIMAX	19.58	**78.00**	29.94	**93.00**

Note: Coverage represents the percentage of observations in the test set that fall into the prediction intervals provided by different models.
Bolded text to highlight performance of 24-SASIMAX model.

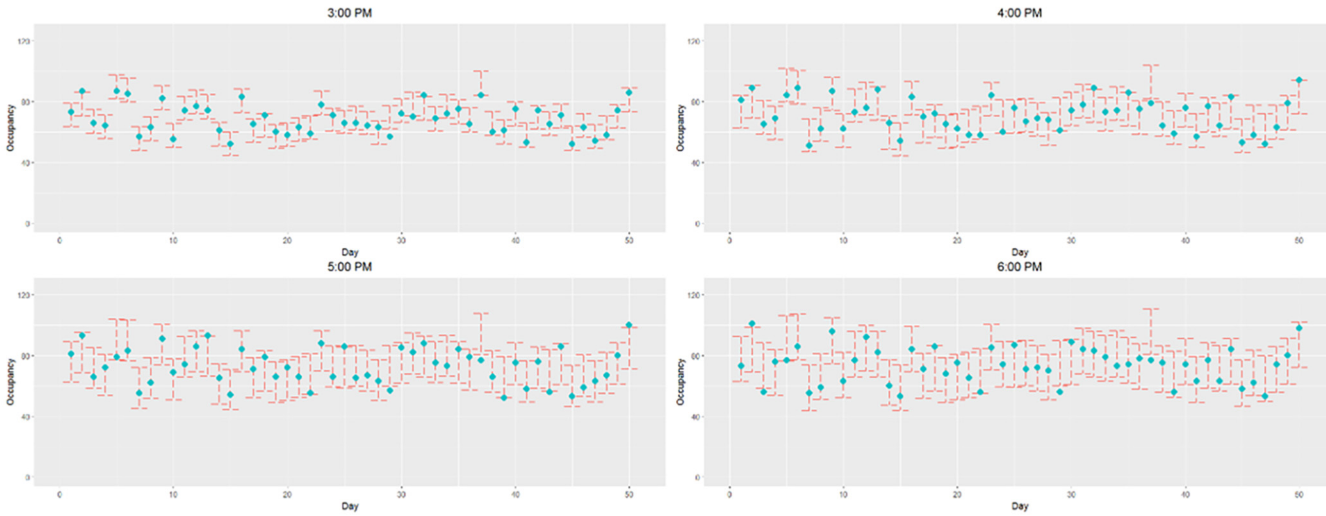

Fig. 2. 95% prediction intervals of the first 50 days in the test set provided by our model 24-SARIMAX. Notes: The red dashed line represents the prediction intervals while the blue points represent the observed occupancy.

moves further into the future, the accuracy of SARIMAX model is expected to keep decreasing since the included regressors will become less informative. Whitt et al. [30] also made a similar observation and suggested that including current system information will not provide much improvement beyond 4 h given the fact that many of the patients present at the time prediction is made would have likely left the ED by that time.

To the best of our knowledge, our study is the first to consider not only prediction accuracy, but also prediction intervals when forecasting ED hourly occupancy. Although the concept of uncertianty in emergency department prediction have been discussed [35,36], previous studies related to forecasting ED hourly occupancy focused only on point accuracy when evaluating their methods. It is our opinion that uncertainty needs to be taken into consideration in ED operational planning in the form of prediction intervals as it gives ED management a sense for the potentially worst- and best-case scenarios.

Lastly, the 24-SARIMAX model was designed to rely on only a few inputs that would be readily available at the time of prediction making the tool more easily generalizable and easy-to-implement in a broad range of EDs. Other commonly utilized approaches to better understand ED operations, such as discrete-event simulation or neural networks, usually rely on proprietary software and take a long time to build and train. Conversely our 24-SARIMAX model requires a small number of inputs and can be easily developed using widely available open-source software R. The simplicity of this method would also make it more accessible for data scientists and application developers to integrate into existing ED information systems for real time prediction in clinical care settings.

4.1. Limitations

This study has several limitations. The analysis was conducted in a single academic medical center, and therefore, our findings on the performance comparisons of different models may or may not be generalizable to EDs of different sizes, demand patterns, and operational routines. A multicenter study consisting of EDs of both academic and community hospitals at different geographical locations will be needed to generalize our results and validate a broader superiority of the model proposed in this paper. Moreover, this study was conducted using data obtained over a relatively short time period of 1 year. Repeating this study using data collected over a longer time period might enable us to estimate the model parameters more accurately and make more reliable comparisons.

Additionally, this study utilizes a fairly small number of inputs. Specifically, the only external regressors included in the model were the current ED occupancy, number of boarding patients, and overall acuity level of the patients. While this approach does have its advantages from a generalizability and computability standpoint, it does not account for patient specific characteristics that can influence ED length of stay and the demand for ED resources including chief complaints, comorbidities, housing stability, and access to outpatient care and home health resources. Similarly, our approach does not account for characteristics outside of the ED, which almost certainly have implications for ED occupancy, including resource and staff intensive services such as trauma or stroke code activations, or even natural disasters or inclement weather. Implementing this approach in other EDs would require time, resources and potentially assistance from a data scientist. To help overcome these challenges in implementing in different ED settings, we provide a step-by-step outline of the procedure used in the Supplementary Material S1.

5. Conclusion

The use of a novel 24-SARIMAX time series model, which accounted for current ED occupancy, average department-wide ESI, and number of boarding patients, was able to more reliably predict ED occupancy up to 4 h into the future compared to prior forecasting methods. This approach outperformed the commonly used method of rolling average, relies on data inputs that are widely available in EDs at the time of prediction, and provides precise prediction intervals to aid decision making about mitigating ED crowding.

Conflict of interest disclosure

All authors (QC, NTA, CSE, YL, TFP, and SZ) report no competing interest or conflicts of interest.

Author contribution

QC - conceived and designed the study; managed the data; analyzed the numerical results; constructed the statistical models; drafted the manuscript.

NTA - conceived and designed the study; analyzed the numerical results; constructed the statistical models; acquisition of funding; revised the manuscript.

CSE – provided clinical interpretations of the results; provided insights into the operational management of emergency department; revised the manuscript.

YL - conceived and designed the study; analyzed the numerical results; constructed the statistical models; revised the manuscript.

TFP - provided clinical interpretations of the results; provided insights into the operational management of emergency department; revised the manuscript.

SZ - conceived and designed the study; analyzed the numerical results; constructed the statistical models; acquisition of funding; revised the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ajem.2021.04.075.

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