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Knowing what to expect, forecasting monthly emergency department visits: A time-series analysis

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ABSTRACT

Objective: To evaluate an automatic forecasting algorithm in order to predict the number of monthly emergency department (ED) visits one year ahead.
Methods: We collected retrospective data of the number of monthly visiting patients for a 6-year period (2005–2011) from 4 Belgian Hospitals. We used an automated exponential smoothing approach to predict monthly visits during the year 2011 based on the first 5 years of the dataset. Several in- and post-sample forecasting accuracy measures were calculated.
Results: The automatic forecasting algorithm was able to predict monthly visits with a mean absolute percentage error ranging from 2.64% to 4.8%, indicating an accurate prediction. The mean absolute scaled error ranged from 0.53 to 0.68 indicating that, on average, the forecast was better compared with in-sample one-step forecast from the naïve method.
Conclusion: The applied automated exponential smoothing approach provided useful predictions of the number of monthly visits a year in advance.

Introduction

Emergency departments (EDs) find themselves in challenging times. The increasing number of emergency department (ED) visits and ED crowding have a negative impact on quality of care. As a result potentially harmful events can occur (Collis, 2010). Threats regarding quality of care and patient safety make ED administrators eager to find solutions (Moskop et al., 2008, 2009). In 2003, Asplin et al. introduced a conceptual model of ED crowding, distinguishing three interdependent components: input, throughput, and output (Asplin et al., 2003). This model provides a framework for researchers and ED administrators in their quest to alleviate ED crowding. Initially, input factors were seen as the root cause of the problem. Recent research, however, strongly suggests that output factors should be seen as the root cause. Especially the inability to transfer ED patients to inpatient beds and the resulting boarding of admitted patients in the ED are the main problem (Moskop et al., 2009). Hence, a first step in finding solutions is to know what to expect. The ability to predict ED visits (input component) is crucial for both medical teams and ED administrators as they could benefit from accurate predictions to optimise planning and supporting strategic decisions.

Several investigators have tried to accomplish this goal, with the most commonly used methods being (linear) regression models and time series analysis (Tandberg and Qualls, 1994; Milner, 1997; Champion et al., 2007; Jones et al., 2008; Schweigler et al., 2009; Sun et al., 2009; Wargon et al., 2009). When forecasting ED visits, a regression model can be very useful. It incorporates information about various predictors, and gives us an insight into the relation between these predictors. However, it can be very difficult to compose an accurate regression model, as the system underlying ED crowding is not fully understood. Moreover, even if it was understood, it might be extremely difficult to measure the relationships assumed to govern its behaviour. In addition, it is necessary to know or forecast the various predictors in order to be able to forecast the number of visiting patients, and this may be too difficult. Also, the main objective is often only to predict what will happen and not to know why it happens.

Time series analysis on the other hand is useful when one is forecasting something that is changing over time (e.g., the number of visiting patients). In essence, these models are used if one wants to estimate how the sequence of observations will continue into the future. Time series models use only information on the variable to be forecasted, and make no attempt to discover the factors

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affecting its behaviour. They will extrapolate trends and seasonal patterns, but ignore all other information such as weather, flu outbreaks, and so on. Considering the barriers as mentioned above, the time series model may give more accurate forecasts than a regression model. Time series models used for forecasting include autoregressive moving average (ARIMA) models, exponential smoothing and structural models.

Although time series models provide an acceptable performance (Wargon et al., 2009), their implementation and practical use can be difficult. For instance, the required statistical software packages may not be available. Moreover, even if software is available, most clinicians and ED managers are no experts at fitting time series models. As a result, EDs often depend on (external) experts to generate predictions. Therefore, the availability of an automatic forecasting algorithm could be an essential tool for clinicians and ED managers. This allows them to immediately make predictions when needed and update the model when new data are available. Additionally, most experts cannot beat the best automatic algorithms. In order to be useful for ED staff and management, algorithms should determine an appropriate time series model, estimate the parameters and compute the forecasts. In addition, they must be robust to unusual patterns, and applicable to large numbers of series without user intervention (Hyndman and Khandakar, 2008). We therefore aimed to study the use of an automatic time series algorithm in order to forecast monthly ED visits one year ahead.

Methods

Design and setting

This was a retrospective study, conducted at the EDs of 4 Belgian hospitals. The participating hospitals included one university hospital and three regional hospitals scattered throughout Belgium's Flemish region. Characteristics of these hospitals are provided in Table 1. Selection of these hospitals was based on informal collaboration meetings and informal contact between the involved study sites.

Data collection

Monthly ED census was extracted from the databases of the study sites, which are registered to the Belgian Data Protection Authority for medical and research purposes. Each site provided a data sheet containing the total number of visiting patients per month for a 6-year period, from 1 January 2005 to 31 December 2011.

Forecast method

We used the exponential smoothing approach proposed by Hyndman et al. to predict the monthly ED visits for the year 2011 (Hyndman et al., 2002). This approach is based on an extended range of exponential smoothing methods and introduced a state space framework that subsumes all the exponential smoothing models. State space models are defined by two equations: an observation equation that defines what is being observed and a state equation that defines the evolution of the process through time. This approach provides exponential smoothing forecasts that are equivalent to forecasts from a state space model and allows the computation of prediction intervals, likelihood and model selection criteria. This method has been demonstrated by applying it to the data from the M3-competition (Makridakis and Hibon, 2000). The method provided forecast accuracy comparable to the best methods in the competitions. It seems to perform especially well for short forecast horizons with seasonal data, particularly monthly data. On the other hand, it seems to perform rather poorly on annual, non-seasonal time series. This method is available in R, a free software programming language and a open source software environment for statistical computing and graphics (R Development Core Team, 2012). More specific, we used the automated exponential smoothing algorithm function "ets()" from the 'forecast' package created by Hyndman et al. (2012). We applied this function using the first 5 years of data for each study site (2005–2010) as a training set for the model in order to predict the following 12 months (2011).

Table 1
Study site characteristics.

Study site	Type	Number of beds	Annual census	Monthly census		
			Mean	Mean	Min	Max
ED 1	University hospital	1472	52546.86	4378.90	3755	5020
ED 2	Regional hospital	270	17896.43	1491.37	1057	1728
ED 3	Regional hospital	266	17688.43	1474.04	1133	1865
ED 4	Regional hospital	355	15889.43	1324.12	1032	1599

Forecast accuracy measures

Forecast accuracy was measured in two ways. First, in-sample model goodness of fit was assessed visually in combination with in-sample diagnostics. The primary outcome of interest was the post-sample forecast accuracy. We compared the predicted number of visits for 2011 and the number of visits actually observed. Several forecast accuracy measures were calculated. These measures serve to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. The *mean absolute error* (*MAE*) is an average of the absolute (without considering their direction) errors/differences between values predicted by a model and the values actually observed. The *mean absolute percentage error* (*MAPE*) is an average percentage of the absolute errors/differences between values predicted by a model and the values actually observed. As the MAPE is being scale-independent, it is frequently used to compare forecast performance between different data sets. A disadvantage is that MAPE puts a heavier penalty on positive errors than on negative errors. In case one of the observed values in the training set is close to zero or negative, the MAPE will have extreme values. The *mean absolute scaled error* (*MASE*) is a scale-free error metric that can be used to compare different forecast methods on a single data set on the one hand and to compare forecast accuracy between data sets with different scales on the other hand. It will never give infinite or undefined values except in the irrelevant case where all historical data are equal. This measure is easily interpretable: values of MASE greater than one indicate on average worse forecasts as compared to in-sample one-step forecasts from the naïve method. Naïve forecasts are the most cost-effective objective forecasting models, and provide a benchmark that more sophisticated models can be compared with. For stationary time series data, this approach claims that the forecast for any period equals the historical average. For time series data that are stationary in terms of first differences, the naïve forecast equals the previous period's actual value.

Ethical considerations

This study only employed the summed numbers of ED visits. Since no personal patient information was used, it was not possible to identify a patient. Therefore, this study was not subject to be reviewed by the Institutional Review Board.

Results

In-sample model goodness of fit

Except for ED 3, the automatic selected models performed well in terms of a visual interpretation. (Fig. 1) The fitted data (dotted line) adequately resembled the actual data (solid black line) in the training set. This visual observation was confirmed with the in-sample error measures, indicating that the automated model provided adequate model fit for monthly ED patient volumes. In contrast, for ED 3, the MAPE was almost two to three times higher as compared to the others study sites. All in-sample error measures are summarised in Table 2.

Post-sample forecast accuracy

The primary outcome of interest for this study was the performance of the forecasting method in terms of post-sample forecast accuracy. Post-sample error measures, reflecting the errors/differences between the numbers of visits predicted by the model and the numbers actually observed for 2011, are summarised in Table 3. A graphical representation of the results is shown in Fig. 1.

The number of actual observed monthly visits in 2011 for ED 1 ranged from 4203 to 4761 with a mean of 4509 visits. Fig. 1 shows a good correlation between the numbers of visits predicted by the model and the numbers actually observed. The mean absolute error (MAE) was 118.96 visits, which on average corresponded to a difference of 2.63% (MAPE) between predicted and actual observed values. For ED 2, the number of actual observed monthly visits ranged from 1500 to 1728 with a mean of 1658 visits. Fig. 1 shows a strong correlation between predicted and observed values during the first 6 months of 2011. The last 6 months of 2011 shows more pronounced differences. All the observed values were in the 95% confidence interval. The mean absolute error (MAE) was 51.33 visits, which on average corresponded to a difference of 3.19% (MAPE) between predicted and actual observed values. For ED 3, the number of actual observed monthly visits ranged from 1432 to 1746 with a mean of 1583 visits. Fig. 1 shows that the selected model

Table 2
In-sample error measures.

Study site	MAE	MAPE	MASE
ED 1	98.56	2.23	0.44
ED 2	42.23	2.92	0.54
ED 3	93.14	6.45	0.74
ED 4	43.25	3.34	0.53

MAE = mean absolute error; MAPE = mean absolute percentage error; MASE = mean absolute scaled error.

Table 3
Post-sample error measures.

Study site	MAE	MAPE	MASE
ED 1	118.96	2.63	0.68
ED 2	51.33	3.19	0.53
ED 3	75.97	4.76	0.58
ED 4	52.85	3.62	0.68

MAE = mean absolute error; MAPE = mean absolute percentage error; MASE = mean absolute scaled error.

did not follow the monthly fluctuations, instead the model showed a general trend. The mean absolute error (MAE) was 75.97 visits, which on average corresponded to a difference of 4.76% (MAPE) between predicted and actual observed values. Finally, for ED 4, the number of actual observed monthly visits ranged from 1320 to 1599 with a mean of 1440 visits. Fig. 1 shows that the predicted visits followed the observed fluctuations, with predictions slightly below actual values. The mean absolute error (MAE) was 52.85 visits, which on average corresponded to a difference of 3.62% (MAPE) between predicted and actual observed values.

The MASE ranged from 0.53 to 0.68 indicating that, on average, the forecast was better compared with in-sample one-step forecast from the naïve method.

Discussion

In their search to reduce the adverse consequences of ED crowding, clinical staff and ED administrators need to make strategic decisions including quality interventions and architectural improvements. To support these decisions, it is useful to know

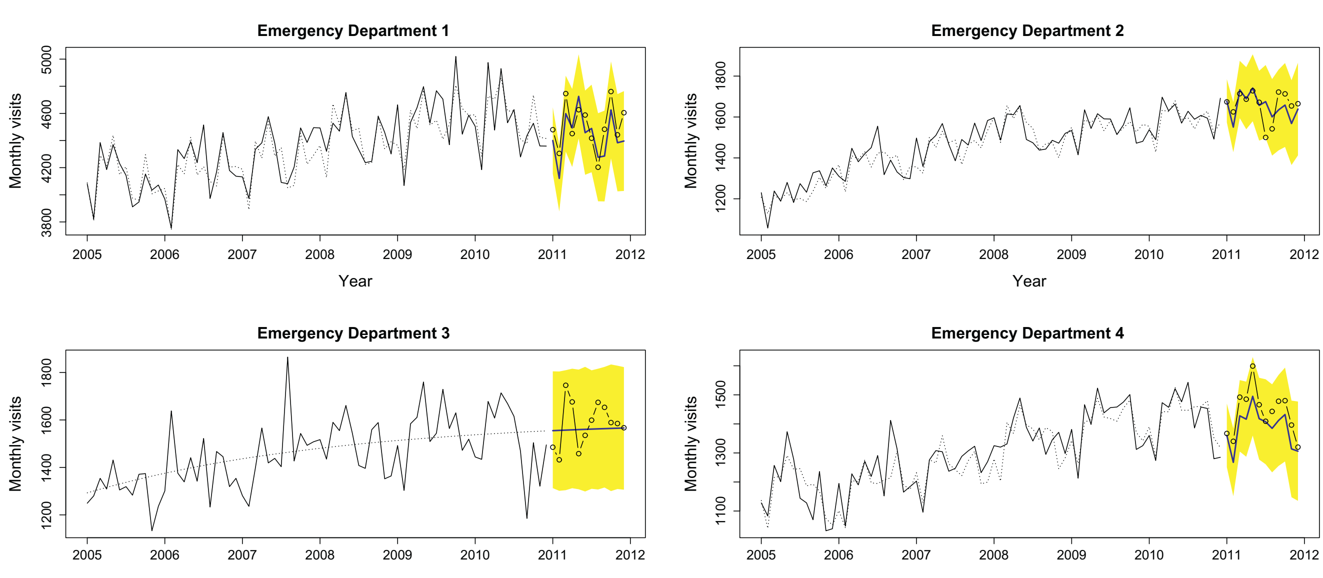

Fig. 1. Graphical representation of the model and its predictions. The solid black line represents the actual observed ED visits included in the training sets. The dotted line indicates model fit. The blue line represents the prediction for 2011 (95% CI = yellow box). The line with dots shows the actual number of ED visits for 2011. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

what to expect in terms of the input demand the ED will be faced with. The ability to predict future patient visits is important to facilitate strategic decisions and supporting quality improvement initiatives. In order to facilitate the prediction of ED input demand several methods have been used. Time series analysis is easier to use compared to linear regression, since time series models use only information on the variable to be forecasted. Time series analysis for forecasting ED visits have been described in previous studies with accurate results (Wargon et al., 2009). In spite of their potential, the widespread use of these techniques is limited. Limiting factors are the skill and knowledge necessary to select and perform an adequate time series model. In an attempt to overcome this hurdle, we investigated the use of an automatic time series algorithm to predict monthly ED visits one year ahead. The automatic algorithm was able to accurately predict monthly visits, with a MAPE ranging from 2.64% to 4.8% and MASE ranging from 0.53 to 0.68. Based on error measures and a visual interpretation of the results, we can state that the obtained prediction provides a useful estimate in order to predict monthly ED visits one year in advance.

This is the first study evaluating the accuracy of an automatic forecasting algorithm within the ED context. The use of an automatic algorithm in an open-source environment makes time series analysis available for many hospitals. Other studies have applied time series models to predict ED visits, but they used specific models that were selected and fitted by a statistician.

We chose to predict monthly visits, as our primary goal was to use these predictions to support strategic decisions on quality improvement initiatives. For example, one of the study sites was engaged in planning and designing a new ED. Another ED site used these predictions leading up to a merger between two hospitals. Theoretically, ED administrators may use predictions of monthly ED visits for adjusting staffing levels to the expected clinical activity. However, there is limited research on the improvement of this staffing adjustment (Wargon et al., 2009). When it comes to adjusting staffing levels, predictions of weekly or daily ED visits would be preferable. However, previous studies have shown difficulties with predicting daily patient ED visits (Wargon et al., 2009). Not only the number of patients affected the required level of staffing, severity of illness and patient dependency play an important role as well. Because of this, alternative methods (e.g. regression) are more appropriate. Future research regarding the application of monthly ED predictions should therefore focus on other arias of application. As the number of visiting ED patients is often related to quality and performance, it could be useful to link this monthly prediction to quality assuring programmes and patient safety interventions.

This study has several important limitations. First, there were only a small number of participating EDs, which were not randomly selected. As a result, findings cannot be generalised to other hospitals or countries. On the other hand, selection of hospitals was such that a variation in EDs was guaranteed, ranging from EDs with a moderate to high number of monthly patient visits. Second, we used a time series model to predict monthly ED visits. This model looks at patterns in monthly visits based on historical data. Variables that may affect the cyclic pattern are not included in these models. As the number of visiting patients is prone to several unpredictable variables, such as the weather or disasters, the obtained predictions could deviate from the real number of ED visits. Finally, since automatic algorithms choose the model which best fits your data based on mathematical decisions, it is possible that the selected model is not the one that would be selected by an experienced statistician. The results of ED 3 are an example in which the predictions from the selected model do not follow the fluctuations of the observed values. This is probably due to the small variation in monthly ED visits, which could have been accounted for by a statistician.

Conclusion

Our findings support the use of the purposed automated exponential smoothing approach. This method provided useful predictions of the number of monthly ED visits a year in advance. Since this method is available in an open source environment, it is accessible to any ED. The resulting prediction may be useful in making strategic decisions and planning interventions to manage ED crowding. However, the monthly forecasts offer little to no benefit in adjusting staffing levels. Future initiatives should therefore have to focus on a more pragmatic application of these predictions.

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