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Short and Long term predictions of Hospital emergency department attendances

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ABSTRACT

Objective: Emergency departments in the United Kingdom (UK) experience significant difficulties in achieving the 95% NHS access standard due to unforeseen variations in patient flow. In order to maximize efficiency and minimize clinical risk, better forecasting of patient demand is necessary. The objective is therefore to create a tool that accurately predicts attendance at emergency departments to support optimal planning of human and physical resources.

Methods: Historical attendance data between Jan-2011 – December-2015 from four hospitals were used as a training set to develop and validate a forecasting model. To handle weekday variations, the data was first segmented into each weekday time series and a separate model for each weekday was performed. Seasonality testing was performed, followed by Box-Cox transformations. A modified heuristics based on a fuzzy time series model was then developed and compared with autoregressive integrated moving average and neural networks models using Harvey, Leybourne and Newbold (HLN) test. The time series models were tested in four emergency department sites to assess forecasting accuracy using the root mean square error and mean absolute percentage error. The models were tested for (i) short term prediction (four weeks ahead), using weekday time series; and (ii) long term predictions (four months ahead) using monthly time series.

Results: Data analysis revealed that presentations to emergency department and subsequent admissions to hospital were not a purely random process and therefore could be predicted with acceptable accuracy. Prediction accuracy improved as the forecast time intervals became wider (from daily to monthly). For each weekday time series modelling using fuzzy time series, for forecasting daily admissions, the mean absolute percentage error ranged from 2.63% to 4.72% while for monthly time series mean absolute percentage error varied from 2.01%–2.81%. For weekday time series, the mean absolute percentage error for autoregressive integrated moving average and neural network forecasting models ranged from 6.25% to 7.47% and 6.04%–7.42% respectively. The proposed fuzzy time series model proved to have statistically significant performance using Harvey, Leybourne and Newbold (HLN) test. This was explained by variations in attendances in different sites and weekdays.

Conclusions: This paper described a heuristic-based fuzzy logic model for predicting emergency department attendances which could help resource allocation and reduce pressure on busy hospitals. Valid and reproducible prediction tools could be generated from these hospital data. The methodology had an acceptable accuracy over a relatively short time period, and could be used to assist better bed management, staffing and elective surgery scheduling. When compared to other prediction models usually applied for emergency department attendances prediction, the proposed heuristic model had better accuracy.

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1. Introduction

Patient flow through emergency departments' (ED), overcrowding and long waiting times are acknowledged as increasing worldwide issues in healthcare [4,15,16]. The implications of poor ED performance are serious and include, for instance, situations in which paramedics have to bypass their closest acute hospital [14,17,29]. This results in increased morbidity and mortality [39,43,44]. Although improving ED performance often requires more staff and infrastructure, accurately predicting the timing and scale of patient attendances allow managers to make better use of their limited resources [28,49].

In 2012-13, there were 5.3 million emergency admissions to NHS hospitals in England of which 71 per cent were admitted through EDs costing £12.5 billion. Further, the number of available beds in NHS-England has decreased between 2000 and 2013 partly due to a growing elderly population who typically spend longer in hospital. [32].

A number of studies have worked on predicting attendances in EDs [2,9,12,21,41]. Several authors have employed time series techniques, such as seasonal autoregressive integrated moving average (SARIMA) and generalised autoregressive conditional heteroscedastic models [1,26,27]. Recent approaches from the statistical machine learning community utilises neural networks [7,11] such as feedforward neural network (FFNN) and Bayesian statistics [20,27,32,33]. Some of the models express accuracy only in terms of the model fitting to historic data, rather than prospective forecast performance, which has limited practical benefit [18].

Hoot et al [19] predicted ED overcrowding and ambulance diversion using logistic regression and neural network models. Their study was conducted at only one site and may involve cost of false alarms. The authors extended their modelling study to forecast ED attendances over 400 days, using a sliding window of the preceding 4 weeks of historical ED data. Forecasts were made at 10 min intervals, which ensures the forecasts reflect current ED status at the cost of relatively high frequency of data integration. McCarthy et al [31] examined the influence of several patient, temporal and climatic factors on hourly ED arrival rates and found the most important predictor to be hour of the day. The authors report an increase in ED arrivals the day after an official holiday compared to a normal day.

Schweigler et al. [3] implemented different forecasting models using historic ED bed occupancy data. Time domain models were limited to 24-h periodicity. Champion et al [10] used the SPSS optimal model selection (Trends package) to forecast monthly ED presentations. Their study raised many additional questions. Can admissions be predicted as distinct from presentations? Can ED presentations be

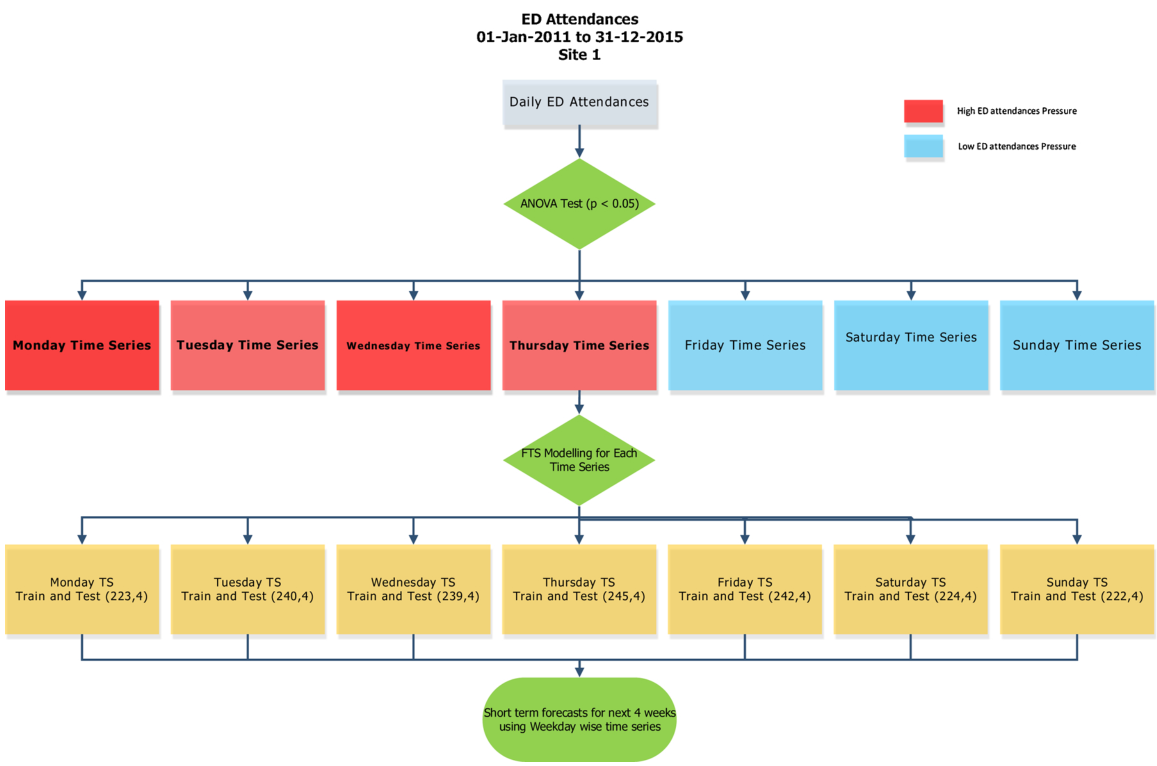

Fig. 1. Emergency Department attendances split into weekday wise time series. Red and blue colours present increased and decreased ED pressure respectively (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 1
Summary Statistics for ED Attendances Time Series for Site-1 from 01-01 – 2011 to 31-12 – 2015.

Weekday	Min	1st Quarter	Median	Mean	3rd Quarter	Max
Monday	134	179	189	190.3	202	244
Tuesday	138	162	172	172.5	181	214
Wednesday	128	155	167	166.4	175	216
Thursday	125	156	166	165.7	176	220
Friday	126	154	163	163.1	173	199
Saturday	138	174	184	184	196	247
Sunday	147	185	194	194	202	252

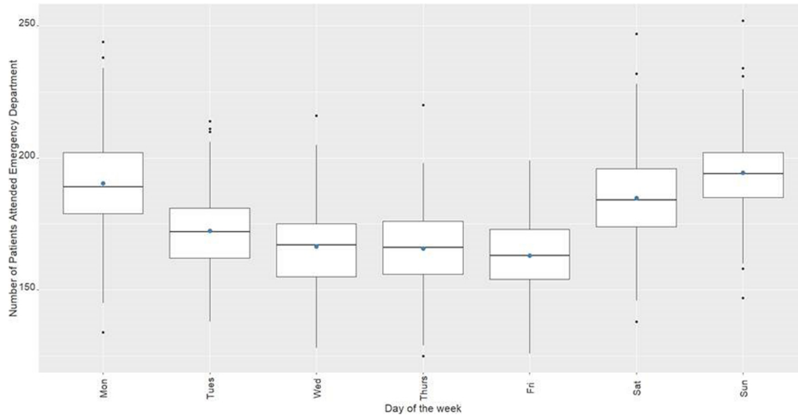

Fig. 2. Emergency Department Patient Attendances in Hospital site-01 in each Week day (from Jan. 2011 to Dec. 2015).

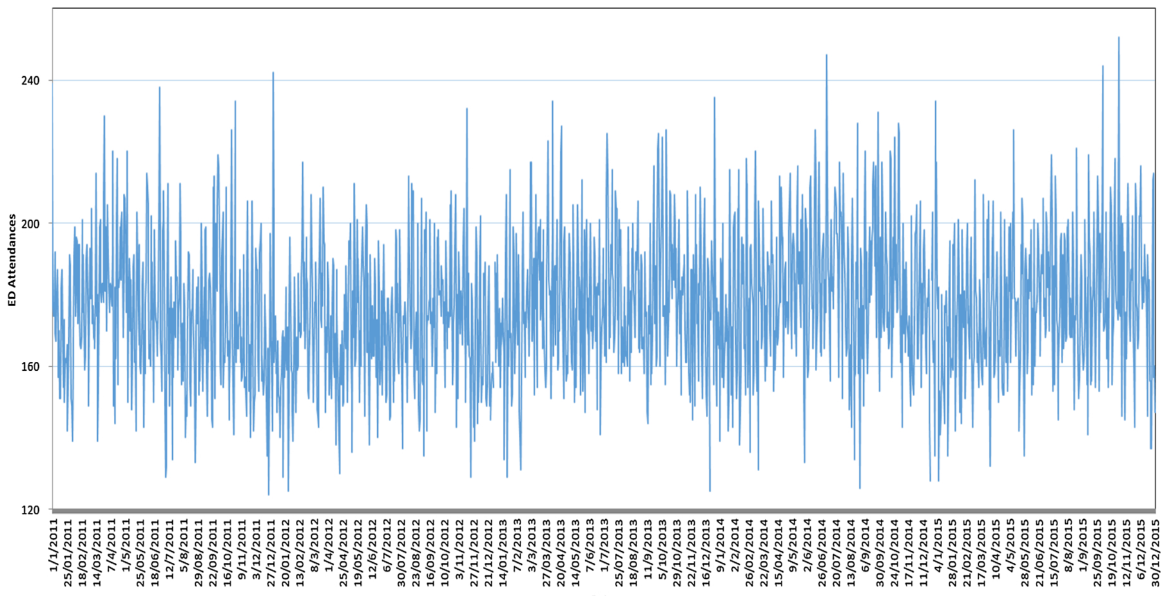

Fig. 3. Patient volume at the emergency department from January'11 to December'15, ED site-1.

examined on a finer scale (daily or hourly)? Would accurate prediction facilitate health service and staff planning? In a study based on daily presentation data.

Jones et al [25] compared regression exponential smoothing, seasonal ARIMA and artificial neural network models to forecast daily presentations at three facilities. The best mean absolute percentage errors (MAPE) figures across 30 days for each facility ranged between 9.0% and 14.0%. Wargon [45] used the SPSS package to determine a regression model, and evaluated its forecast performance across one year using 3 years of training data from four different hospitals. They report MAPEs ranging from 8.1%–17% for each hospital, and 5.3% for the four EDs combined.

Reis and Mandl [38] used the SAS package to fit ARIMA models to nearly a decade of ED presentation data, and report a MAPE of 9.4% when validated against the final two years of the dataset.

On the other side, Fuzzy logic is the study of problems with imprecise and vague knowledge [48]. Fuzzy logic is in practice in medical research and health care services for more than two decades and still growing [33,34,40]. The fuzzy time series, a sub-domain of fuzzy logic, provide simple forecasting approaches that are free from statistical assumptions and mathematical rigour. Fuzzy time series has

Table 2
Performance measures or each weekday time series using ARIMA, NN and FTS forecasting models for Site-1.

Weekday	ARIMA		Neural Networks		Fuzzy Time Series	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
Monday	7.06	16.84	6.87	16.55	3.036	6.873
Tuesday	6.99	16.18	6.99	16.21	3.495	7.100
Wednesday	7.47	15.73	7.42	12.66	3.445	6.641
Thursday	7.28	15.33	6.04	15.66	3.569	7.029
Friday	7.33	14.73	7.28	15.70	3.186	6.166
Saturday	7.15	16.28	6.97	14.67	3.338	7.411
Sunday	6.25	15.68	6.31	15.54	3.330	7.745

Table 3
Comparison between FTS, NN and ARIMA using HLN test for ED site-1.

Weekday	ARIMA vs. NN	FTS vs. ARIMA	FTS vs. NN
Monday	0.032	< 0.001	< 0.001
Tuesday	0.352	< 0.001	< 0.001
Wednesday	0.289	< 0.001	< 0.001
Thursday	0.0217	< 0.001	< 0.01
Friday	0.661	< 0.001	< 0.001
Saturday	0.245	< 0.001	< 0.001
Sunday	0.103	< 0.001	< 0.001

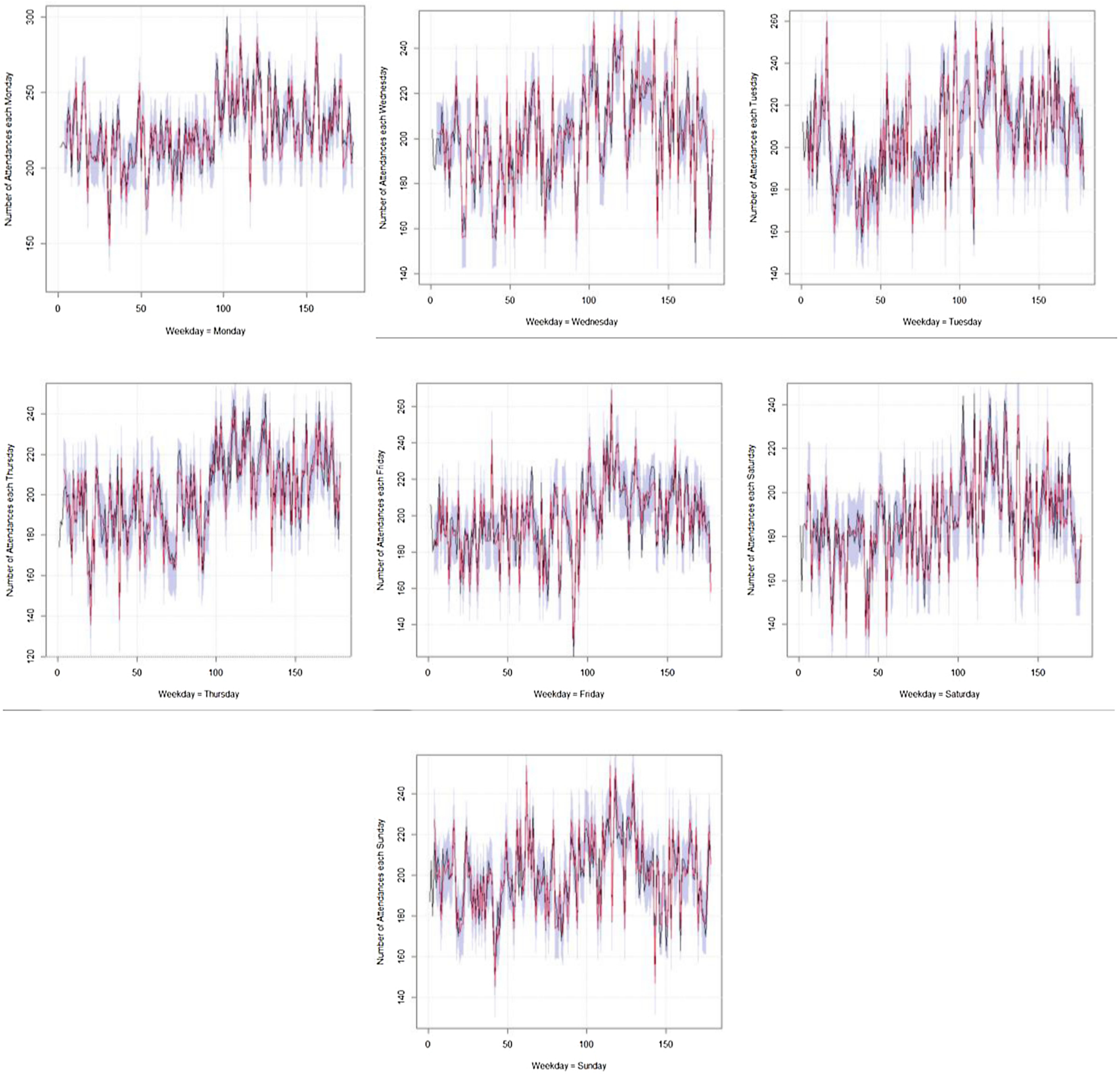

Fig. 4. Weekday wise FTS modelling with 95% confidence Interval for Site-1. For each weekday, separate FTS model was developed due to strong variations in ED attendances.

tremendous applications in various fields [8].

From literature review above, there is a need for a more accurate, robust and reproducible model to predict ED attendances for short and long term time scale. Our proposed model answers all these through prediction results and statistical testing. This is the first research using the fuzzy time series in ED attendances prediction.

The main objectives of this study were to a) develop a heuristic based on Fuzzy Time Series (FTS) forecasting model and compare it with autoregressive integrated moving average (ARIMA) and neural network (NN) forecasting models that are commonly used by other researchers [26,27,37]; and b) to develop and validate a software package that accurately predicts the number of ED attendances on any given day of the month and over a prospective 4 month period.

1.1. Data, methods and models

Data from four hospital ED sites in the UK were used for time series predictive modelling. Historical data on number of ED admissions were available from January-2011 to December- 2015. One way analysis of variance (ANOVA) test was applied to check significantly different patterns for each week day (Fig. 1). Based on the ANOVA test, the data were partitioned into seven time series for short term (four weeks ahead) predictions. The ED pressure on each weekday is visualised using different colours with red for high and blue for low ED attendances load. Each weekday time series was split into train and test for model training and model testing. For long term (4 months ahead) predictions for each ED site, the daily ED attendances were aggregated by month. For daily time series, autoregressive conditional heteroscedasticity (ARCH) test was performed to check for periodicity. The test was insignificant for each daily time series.

As each hospital site had different variations in emergency attendances, a comparison of different time series models was performed in order to choose the best model as per time series complexity. In Table 3, comparison of the proposed heuristic based FTS forecasting model with ARIMA and neural networks (NN) time series models using Harvey, Leybourne and Newbold (HLN) test is presented. A short overview of each of these models and HLN test is presented in the supplementary material. We reported the root mean square errors (RMSE) and mean absolute percentage errors (MAPE) as model fitting performance measure, for each weekday time series. Smaller values of MAPE and RMSE

Table 4
Site-1 ED Attendances short term predictions for the next 4 weeks with 95% prediction intervals using FTS model.

Weekday	Week1		Week2		Week3		Week4	
	Fit	95% PI	Fit	95% PI	Fit	95% PI	Fit	95% PI
Monday	195	182 – 208	190	177 – 203	185	172 – 198	177	164 190
Tuesday	178	164 – 192	182	168 – 196	182	168 – 196	158	144 172
Wednesday	171	158 – 184	162	149 – 175	162	149 – 175	136	123 149
Thursday	170	156 – 184	165	151 – 179	165	151 – 179	159	145 173
Friday	166	154 – 178	170	158 – 182	170	158 – 182	131	119 143
Saturday	191	176 – 206	185	170 – 200	185	170 – 200	176	161 – 191
Sunday	192	177 – 207	189	174 – 204	189	174 – 204	176	161 – 191

are recognised as indicating better prediction model performance [5,30]. For predicted values, 95% prediction intervals were also calculated.

For ARIMA modelling, autocorrelation function (ACF) and partial-autocorrelation (PACF) were first investigated to decide suitable parameters for AR and MA [5,30]. Later, a number of autoregressive (AR) and moving average (MA) orders were tested to reach a parsimonious model with lowest Akaike information criterion (AIC) and RMSE. The residual analyses were performed for the best ARIMA model for each weekday time series. For NN modelling, the number of hidden nodes were decided based on log-likelihood ratio test.

Two R packages FORECAST and AnalyzeTS were used for analyses. Prior to fitting ARIMA(p,d,q) model, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) patterns were first analysed. Only suitable values for AR and MA coefficients were applied to get the ARIMA model. Later, the residual analyses were also performed. Neural network implementation in FORECAST selected the optimal number of hidden neurons using log-likelihood ratio test. The FTS model (fuzzy.ts1) in AnalyzeTS was modified to perform out-of-sample predictions.

2. Results

2.1. Summary data

In the daily ED attendances time series from January-2011 to December-2015 there were 260 data points for each weekday available for training of the time series models. For the month time series, 60 data points were available for each ED site. Holidays were excluded from the analysis due to non-systematic variations in the time series.

Table 1 presented the number of ED attendances for site-1, with median number of attendances per day from 163 to 194. Summary statistics for other sites were presented in Table s1. ANOVA test revealed that there were significant changes in the weekday wise time series for each ED site. The boxplots for daily attendances identified that day of arrival was significantly associated with the number of ED attendances (see Fig. 2). From monthly ED attendances, the ED attendances varied between seasons but the test for seasonality was not significant at 5% level of significance.

2.2. Modelling data

The original Complete time series data for each site were partitioned into weekday wise time series. Replaced with The ED attendances (Jan. 2011 to Dec. 2015) present different patterns and high fluctuations (for example, see Fig. 3 for site-1), therefore, the time series data for each site was partitioned into weekday wise time series. Each weekday time series was split into training and testing set for time series model development and model validation see Fig. 1. Mondays were significantly different from other weekdays, therefore the split of the time series into weekdays was chosen to get better control and improved forecasts. For FTS modelling, the number of fuzzy intervals were adjusted based on the standard deviation of each weekday time series. So, the number of intervals varied from 7 to 15 to get suitable FTS model with low RMSE and MAPE.

For Site 1, the model performance results for three prediction models are reported in Table 2 and 3. The MAPE and RMSE for FTS model are much better than the ARIMA and NN models. The RMSE and MAPE values for FTS models were significantly smaller than those from ARIMA and NN models. Weekday time series with fitted FTS model are presented in Fig. 4. For each weekday, the time series patterns are quite different from each other. Therefore, the results for MAPE and RMSE

Table 5
Monthly ED attendances for four ED sites.

Monthly	MAPE	RMSE	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Site-1	2.01	128.91	4858	5224	5375	5366	5522	5897
Site-2	2.81	87.73	1984	2515	2784	2757	2944	3498
Site-3	2.59	57.30	1600	1824	1906	1910	1993	2246
Site-4	2.19	167.89	5406	6142	6470	6426	6671	7277

Table 6
ED Predicted attendances for the next 4 months with 95% prediction intervals.

Site	Sep-15			Oct-15			Nov-15			Dec-15		
	Actual	Fit	95% PI	Actual	Fit	95% PI	Actual	Fit	95% PI	Actual	Fit	95% PI
Site-1	5374	5231	4978 – 5484	5768	5711	4979 – 5485	5464	5232	4979 – 548l5	5499	5267	5014 – 5520
Site-2	3205	3174	3002 – 3346	3438	3568	3334 – 3678	3712	3506	3334 – 3678	3452	3246	3074 – 3418
Site-3	1922	1970	1858 – 2082	1999	1970	1775 – 1999	1886	1887	1775 – 1999	1870	1871	1759 – 1983
Site-4	6737	6596	6267 – 6925	6839	6732	6366 – 7024	6835	6695	6366 – 7024	6716	6576	6247 – 6905

Table 7
Comparison of forecast performance with related work.

Author group	Target outcome for prediction	Techniques	Target period	Findings	Limitations
this study	Weekly and monthly A&E department predictions	ARIMA, neural networks, Fuzzy time series	4 week and 4 month prior	MAPE: Daily presentations 2.5% to 7%. Monthly presentations 2.09% to 2.81%	One realisation time series, other factors not studied.
Boyle [6]	ED department presentations and subsequent admissions	ARIMA, regression, exponential smoothing	1,2,3,4 years	MAPE: Monthly admissions: 2%, daily admission: 11%, 4-hourly admissions: 38%, Hourly admissions: 50%, daily presentations: 7%.	Simple methods assessed, No outcome, evaluation/intervention based on the tool
Wu [47]	Predicting categorised frequent use of ED care using EHR data	Multivariable Logistic regression	2 years using 1 year	ROC 0.83 to 0.92; sensitivity 0.25, PPV 59.5%, Specificity 99.9%	1 year used to predict 2 years presentations, class imbalanced data not modelled. So the Sensitivity and specificity are not comparable.
Poole [36]	ED department presentations and possible revisits	Random forest	4 years	Receiver Operating Characteristic = 0.96, predicted the visits to ED for 1 ,3 and 6 months in future	one site only, 3 models with different prediction periods,
Hoot et al, [18]	ED overcrowding (ambulance diversion)	Logistic regression, and neural networks; 5 metric of ED crowding	4 months	Good discriminatory power in predicting ambulance diversion; 1 hour into the future ED occupancy level (simple method)	work performance at 1 institution; Cost of false alarms; Forecast error not quantified via MAPE
Hoot et al, [19]	ED operating conditions in next 8 hours	Sliding window of the preceding 4 weeks of historical ED data	1 month	Accuracy (measured by the Pearson's r coefficient) decreased as forecast horizon increased from 2 to 8 hours into the future	Forecasts made at 10-minute intervals (need data integration); No intervention based on tool
McCarthy [30]	Hourly ED presentations	Poisson regression, temporal, climate and patient factors	remaining half of a one–year study period	Hour of the day in the most important predictor in ED arrival rates; Climate factors don't statistically influence patient arrivals to the ED; More visits to the ED on Mondays and weekends; ED arrivals increased the day after an official holiday compared to a normal day	Magnitude of forecast error not measured (only percentage of time observed data was within prediction intervals)
Schweigler [37]	Hourly Ed bed occupancy	seasonal ARIMA, sinusoidal, hourly historical averages	1–2 weeks prior	Best performance from seasonal ARIMA and sinusoidal model	Time domain models limited to 24-hour periodicity (no month of year and holiday effects);
Champion, [9]	Monthly ED presentations	SPSS Trends package to automatically identify optimal models	5 years	optimal forecasting performance from seasonal exponential smoothing model	No assessment of triage categories; Only presentations (not admissions); Only monthly (not daily or hourly)
Jones, [24]	Daily presentations data	Seasonal ARIMA, regression, exponential smoothing and artificial neural network models created with SPSS	2 years	MAPE across 30 days ranged from 9% to 14%	No uncertainty statements in the form of prediction intervals
Wargon [42]	Daily presentations data	Regression model created with SPSS	3 years	MAPE ranged from 8.1% to 17% for 4 individual hospitals or 5.3% when combined	Only presentations data; no prediction intervals
Reis and Mandl [35]	Daily presentations data	ARIMA models using SAS package	10 years	MAPE 9.4%	Longer training data and higher forecast error than current study

varied for different weekdays for all three prediction models. For all four ED sites, the MAPE using FTS modelling ranged from 2.6% to 4.7%, as reported in Table s2.

The ED predicted attendances with 95% prediction intervals (PI) for short term (four week) and long term (four month) are presented in Table 4 and 5 and Table 6. In comparison with ARIMA and NN, the FTS models had lower RMSE and the corresponding 95% PI were compact and closer to the predicted values.

For month wise time series, the summary for the monthly aggregated data are presented in Table 5 along with MAPE and RMSE for FTS model of each site. The MAPE varies from 2.01%–2.81%, which is smaller than weekday time series. Site-1 and Site-4 had the highest median ED monthly attendances but had smaller MAPE when compared with Site-2 and Site-3. For the next four months, the FTS modelling predicted values and corresponding 95% PIs are presented in Table 6.

3. Discussion

NHS-England introduced the four-hour ED target standard in 2000, requiring that 98 percent of the patients attendances be seen, treated and either admitted or discharged in under four hours by January-2004. The standard was relaxed to 95% in 2010 [32]. In 2012–13, there were 5.3 million emergency admissions in NHS England hospitals which was 71% of patients admitted into hospital through EDs. Further, the number of available beds in NHS-England has decreased from 2000 to 2013 due to increase in elderly population [32].

This study had the objective to establish a methodology to assist in providing better estimates of hospital admissions. It therefore assessed the accuracy of three different predictive models using de-identified historic data for four hospital ED sites in the UK. We hope that the model can also be implemented in other facilities. The proposed FTS model is more accurate than the commonly used models tested, is simple to implement and does not require any seasonality, periodicity adjustments.

Compared to Hoot et al [19], our work differed in that we wanted to forecast number of ED patient attendances for the purposes of proactive bed management. In addition we wanted to quantify the forecasting model performance via accepted forecast error metrics, such as MAPE and RMSE. Compared with McCarthy et al [30], we also first performed ANOVA to compare the ED attendances for different weekdays. Forecasts were assessed by the percentage of time the observed data was included within the prediction intervals. Our study included similar prediction intervals, but also distance metric (MAPE and RMSE) to quantify the magnitude of forecast error. Similar to Schweigler et al. [41], our study forecasted accuracy against a separate held-out evaluation set not used in the building of the models. Compared to Champion et al [10], our analysis includes daily, weekly and monthly predictions to answer these questions. Predictions at a daily resolution are expected to be more useful for bed managers than monthly estimates which might be useful for long term policy makers for EDs. Compared to Jones et al [25], we have improved on this forecast performance: the evaluation period in our study was 4 months rather than a 1-month evaluation at the same time of year. Additionally, we provided uncertainty statements in the form of prediction intervals. Compared to Wargon [46], our proposed FTS model have MAPE ranging from 2.2%–8.0% for weekday wise time series modelling. Compare to Reis and Mandle [38], our study achieved lower forecast error for daily presentations (MAPE 2.2%–8.0%) using only less than half of the length of training data. Table 7 compares the study to related work.

The predictive modelling performed in this paper differs from many of these studies. As per our knowledge, this is the first paper using fuzzy logic in ED attendances prediction and also include a heuristic to partition the time series. Compared to other models (GARCH, ANN, SARIMA), the proposed approach of fuzzy time series is best suited for all different sites and can also be used for other sites without any changes.

4. Limitations

The study is for univariate time series and only considers the number of attendances at ED. Other studies also included exogenous variables like meteorological variables (season, daily temperature and precipitation), temporal variables (holidays, local events and international events) and air pollution.

None of the prediction models are able to efficiently predict the busiest days. This makes another challenging study to predict extreme situations, which is a separate class in State Space modelling [5]. That might result in staff shortage in the ED and therefore, decreased quality of care, particularly for chronic patients.

5. Conclusion

Our proposed FTS model is twice more accurate than the most commonly used ARIMA and forecasting models and can handle seasonality, periodicity and imprecisions. The model proved to be suitable in four ED sites and can be easily implemented at other ED sites. This tool has the potential to deliver invaluable insight that can be employed by operational teams to make the best use of their scarce resource; assisting bed management, staffing and elective surgery scheduling. At national level these predictions could support NHS decision makers with strategic planning, in turn delivering safer and more efficient care for patients [35].

As future work, the model performance can improve by applying deep learning, evolutionary computation approaches and type-2 fuzzy logic systems for time series.

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Authors contributions

Tahseen Jilani - manuscript writing and R-programming;
Gemma Housley supported in manuscript,
Grazziela Figueredo supported in R experiments,
Pui-Shan Tang and Jim Hatton data gathering and cleaning,
Dominick Shaw, overall supervision, guidance and corrections

Conflict of interest

No conflict of interest by any author(s).

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijmedinf.2019.05.011.

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