

Forecasting

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Abstract

This is the abstract. An accurate demand forecasting is crucial in Emergency medicine to depict various courses of action that can result in massive savings in terms of patient lives. Inability to match the staff with the demand results in an overcrowding care system which is a serious problem causing challenging situations on patient flow. Also, it is related with increasing length of stay, low patient satisfaction, increasing health care costs, inaccuracy in electronic medical record, and reported waiting times.

Keywords: Forecasting, Ambulance, Hierarchical structure

1. Introduction

An accurate demand forecasting is crucial in Emergency medicine to depict various courses of action that can result in massive savings in terms of patient lives. Inability to match the staff with the demand results in an overcrowding care system which is a serious problem causing challenging situations on patient flow. Also, it is related with increasing length of stay, low patient satisfaction, increasing health care costs, inaccuracy in electronic medical record, and reported waiting times. without incurring last-minute expenses, such as overtime or supplemental staffing [Reference].

An accurate forecasting of the daily demand enables managers to match staff to meet anticipated patients, reconfigure units and redeploy staff and vehicles. This will have many advantages for patients, staff and the quality of healthcare services provided.

The ability to accurately forecast the demand of future health services is critical for planning decisions aimed at improving the quality of service delivery in the health care. Forecasting has been used in various fields of healthcare to inform planning decisions at the strategic, tactical and operational levels. There is at least one or multiple reasons why we need to produce a forecast. Most often reasons determine clearly what to forecast and which level of forecast granularities are required. There are typically some planning process at strategic(long-term) level such as dimensioning resource capacities and budgeting; tactical(medium-term) level such as temporary capacity expansions, staff-shift scheduling, and inventory control; and operational(short-term) level such as planning rosters for staff and allocate resources and medical item distribution. Each planning level will typically have different forecasting needs in terms of granularity and horizon (how far into the future do we forecast). A natural question that arise from these examples is how to generate forecasts to support planning decisions at multiple granularities and horizons.

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In order to answer this question, we first need to understand some fundamental aspects of forecasting in healthcare:

Daily forecasts are required to inform the short-term planning for the current and the upcoming shifts of the day. This involves the decision making related to the execution of the delivery process for various health care services such as Ambulatory ,Emergency. Daily forecasts are important at various levels:

- **Nature of incidents**
- **Category: Red, Amber, Green**
- **Health board**
- **Country level**

Implementing and sustaining improvements in hospital-wide flow requires alignment, cooperation, and co-ordination between hospital units and departments. Without effective executive oversight and collaboration, teams operate in isolation from one another and the aggregated impact of their efforts is limited. In many cases, this isolation leads to duplicative work, rework, or work that runs counter to overall goals to improve hospital-wide patient flow

The combination of demand forecast, incidents being attended, resource availability and delays at hospitals, provide information on the state of the unscheduled care system across the emergency medicine services. Having this full picture enables the delivery managers to focus on the areas that require intervention to enable the most effective delivery of the service to the patients.

Despite a large number of studies dedicated to forecasting in healthcare[ref], this question unanswered in healthcare forecasting. Almost all studies assume that the level of data granularity matches with the level of forecast requirement, e.g. daily series is used to generate daily forecast. Moreover, in the presence of the high data granularity, the recommendation is to first aggregate the data into a requested forecast granularity level and then generate the forecast(Goodwin, 2018). However, there is no empirical evidence to support this claim

2. Research background

Table 1 summarise studies on forecasting in emergency and urgent care.

Focus on the ambulance services!

Gijo and Balakrishna (2016) generated a time series model to forecast the daily and hourly call volume at all centre handling emergency ambulance services. Since historical data showed seasonality, SARIMA models were investigated. Regarding the daily model, the authors generated a SARIMA model, which, however, resulted in the forecast error (MMSE) that significantly increased when the lead time exceeded 8 days. On the other hand, the SARIMA model proposed to forecast the log-calls an hourly basis. This model was found to fit well the model both for shorter and longer lead times.

Forecasting at the daily level of granularity is generally use for roaster planing and deciding when to contact staff on call for instance. Luo et al. (2017) use a combination of seasonal ARIMA (SARIMA) and a single exponential smoothing (SES) model to forecast daily outpatient visits 1 week ahead.They indicate that using combinatorial model can be more effective than each model separately. Whitt and Zhang (2019) examine several alternative models to forecast the total daily arrival for 1-7 days ahead, including a linear regression based on calendar and weather variables, seasonal autoregressive integrated moving average with exogenous regressors (SARIMAX) and the multilayer perceptron (MLP) model. Using a daily ED admission for 3 years, they show that SARIMAX provides the most accurate daily forecast by MSE measure. Marcilio

Table 1: summary of literature review

Author	Year	Forecast variable	Forecast Horizon	Method	Measure
McCarthy 2008	2008	ED arrivals	1 day	Poisson log-linear regression model, including temporal factors, patient characteristics and climatic factors	95% CI
Cote et al.	2013	ED arrivals	1 day	Fourier regression	R^2 , Standard Error
Kim et al.	2014	Hospital demand	1h, 7days, 30days	Linear regression; Exponential smoothing; ARIMA; GARCH; VAR	MAPE
1 day	2007	Ambulance demand	1day	Regression	RMSE
Hertzum	2017	ED arrivals ED occupancy	1day	linear regression; SARIMA; Naïve	MAE, MAPE, MASE
Choudhury and Urena	2020	ED arrivals	1day	ARIMA; Holt-winters; TBATS; ANN	RMSE, ME
Steins et al.	2019	Ambulance call	1day	ZIP and ZINB regression; moving average with seasonality weights	ME, MAE, RMSE
Jones et al.	2009	ED census	1day	VAR; Holt winters	MAE
Morzuch and Allen	2006	ED arrivals	7 days	Regression; ARIMA; Exponential smoothing	RMSE
Taylor	2008	centre volume	14 days	ARMA, Exponential smoothing; Dynamic harmonic regression; Seasonal random walk; Seasonal mean; Random walk; Mean; Median; Simple exponential smoothing	MAE RMSE
Gijo and Balakrishna	2016	call volume	7 days	SARIMA	MMSE

et al. (2013) compare the forecast accuracy of the Generalised Linear Model (GLM), Generalised Estimating Equations (GEE), and Seasonal Autoregressive Integrated Moving Average (SARIMA) methods using total daily patient visits to an ED using MAPE. They conclude that GLM and GEE models provide more accurate forecasts than SARIMA model. Rostami-Tabar and Ziel (2020) propose a model to forecast daily ED attendance with consideration of different types of holidays, weekday effects, auto-regressive effects, long-term trends and date effects. They provide probabilistic forecasts to quantify uncertainties in future ED attendance and they show that the proposed model outperforms three time series techniques including 1) Naive, 2) AutoRegressive, AR(p), 3) exponential smoothing state space model (ETS) and a regression model without considering special events as alternatives. Zhou et al. (2018) SARIMA, NARNN and the hybrid SARIMA-NARNN to forecast the daily number of new admission inpatients. The root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) were used to compare the forecasting performance among the three models. They show that NARNN model outperforms the others. Sun et al. (2009) use SARIMA model to forecast daily patient volume for each patient acuity level. MAPE is used to choose the best-fit model. They fitted separate ARIMA models to the three categories of acuity and overall data. They conclude that the ARIMA model is effective for both short term (weekly) and long term (three months) forecast horizons. Moreover, they observe that the impact of weather is not significant. Zinouri et al. (2018) use SARIMA to develop a statistical prediction model that provides short-term forecasts of daily surgical demand. Our results suggest that the proposed SARIMA model can be useful for estimating surgical case volumes 2–4 weeks prior to the day of surgery, which can support robust and reliable staff schedules. Moustris et al. (2012) use Artificial Neural Network (ANN) models to forecast the total weekly(7 days) number of Childhood Asthma Admission. Three different ANN models were developed and trained to forecast the admission of different age subgroups and for the whole study population. McCoy et al. (2018) compare SARIMA, Prophet and Snaive methods for prediction 365 days of hospital discharge using a daily hospital discharge volumes at 2 large, New England academic medical centers. They show that Prophet model outperforms SARIMA and Snaive.

Khaldi et al. (2019) investigate the combination of the Artificial Neural Networks (ANNs) with a signal decomposition technique named Ensemble Empirical Mode decomposition (EEMD), to make one step ahead weekly forecasting of patients arrivals to ED. using seven years of weekly demand. The results of the proposed model were compared against ANN without signal decomposition, ANN with Discrete wavelet Transform

(DWT). The results show that the combined forecasts outperform the benchmarking models.

Steins et al. (2019) aimed to develop a forecasting model for predicting the number of ambulance services calls per hour and geographical areas, to support managers in decisions-making and to investigate which ones were the factors that affected the number of calls. Data collected consisted of a time and location of historical ambulance call data for three counties in Sweden and a list of explanatory factors of the area, such as socioeconomic and geographic. In order to deal with large number of zeros in the data, authors developed zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) regression models. These were then compared to the currently existing forecasting system, based on moving average with seasonality weights, using ME, MAE and RMSE. Firstly, the factors affecting the number of ambulance calls were found to be the following: population in different age groups, median income, length of road, number of nightlife spots (the number of restaurants), day of the week and hour of the day. Secondly, it was found that the older population (65-100) generated more ambulance calls and that ZIP model performs better than the current model. However, the improvement provided by the more advance model was not much greater than the one provided by the existing model. Authors suggested that it could be because the population, which was used as an independent variable in both models, was so dominant compared to the other factors. Moreover, both models either underestimated or overestimated the number of calls. Authors suggested that the inability to capture a positive trend resulted in underestimation, and the opposite was due to a negative trend. Therefore, authors recommended that further research should add certain temporal variables able to capture the trend.

3. Data

Operations Department and I suppose it's split into three different categories. You've got... you've got Response which is the ambulances. You've got the Control which is the people who take the telephone calls. And then you've got Resilience which are the things that people like have the hazardous response teams so they'll go and save people from water and maybe with fires as well. They've got... they're specially trained in different things so there's the contingency sort of there. So from a Control perspective, they look at... they look at it at least twice a week to see what the... what it... how busy it is. And then they staff... they... they're looking to staff to the worst level, knowing that they will get some people... there will be some abstractions. So they won't manage to... to manage that, because their key area [inaudible]. Excuse me, they try to answer within the... the phone within three seconds 95% of the time. I'm not sure exactly. It's something like that. That's very high up there. That's what they're trying to do. So... and because I got it broken down at the Control level, so we've got North Wales level for calls, and we've also got it broken down by the North, the Mid, and the South Control. It's actually called the North, the South East, and Central and West. Those are the three control areas. So they can see how those break down, knowing that at the moment we've got particularly high demand in the South East, and it's forecast to be just bonkers

4. Experimental set

5. Result and discussion

6. Conclusion

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