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A multi-variate model to forecast Emergency Department arrival rates during a pandemic

Jonathan Harrington

Evelyn Flanagan

Ciara Heavin

Armagan Tarim

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Research in Progress

Jonathan Harrington
University College Cork
120225469@umail.ucc.ie

Evelyn Flanagan
University College Cork

Ciara Heavin
University College Cork

Armagan Tarim
University College Cork

1 Abstract

The COVID-19 pandemic was unprecedented in the modern era. Emergency departments (ED), already under stress, were asked to redraw plans and schedules with little to no data available to aid with resource planning and decision-making. In this paper, we study the arrival rates at three EDs in the South West of Ireland and the impact this unprecedented event had on these patterns. We discuss the predictors commonly used when forecasting ED arrival rates and show the patterns found in other studies also apply to the EDs in this study. We then gather and discuss variables related to the COVID-19 pandemic and determine which can be used to improve forecasting during a pandemic. Finally, we develop a forecasting model to predict the impact of a pandemic on arrival rates that planners and decision-makers can utilise during future exceptional events.

Keywords: *Healthcare, Emergency department, COVID-19, Forecasting, Machine learning, Time-series predictions*

2 Introduction

The first case of COVID-19 in the Republic of Ireland was registered on the 29thFebruary 2020 (RTE 2020) and the WHO declared COVID-19 a pandemic on 11thMarch 2020 (WHO 2020). The period immediately afterwards saw a steady increase in registered COVID-19 cases and a dramatic decrease in the number of ED arrivals across the country. On the 29thMarch 2020, two of the EDs in this study showed decreases of 65% and 83% year on year with the third ED registering its largest decrease of 75% two days later on the 1stApril. These sudden changes highlighted the strain the healthcare system was already under and with no excess capacity it forced planners to re-evaluate schedules, post-phone elective care and shut down hospital departments and services. Given the unprecedented nature of the pandemic, there were little to no decision support tools or data available during this period.

The contribution of a smooth-running ED to overall hospital performance cannot be overstated. It is a key hospital entry point, with on average 1 in 4 arrivals requiring admission to a hospital ward. Due to its importance, it is an area widely studied with key performance indicators (KPI) such as crowding, Length of Stay (LOS) and boarding time covered extensively (Gul et al. 2018). These KPIs are affected by patient arrivals and using predictive analytics to forecast this rate is one of the recommended approaches to facilitate improvements (Rutherford et al. 2020).

The arrival process is widely excepted to be a Non-homogeneous Poisson Process (Kim et al. 2014) and traditionally Auto-regressive Integrated Moving Average models (ARIMA) have been used successfully to forecast the future arrival rate (Milner 1997). More recently machine learning models (Bertsimas et al. 2021) and deep learning models such as Long Short Term Memory (LSTM)(Yousefi et al. 2019) have also been applied successfully.

However, the impact of the COVID-19 pandemic was not foreseen or forecast in previous studies, and the

Medway Foundation Trust in the UK has stated forecasting is of increased importance during exceptional events as these are the periods with the largest unknowns (Duarte et al. 2021).

The pandemic caused national governments to enact rules previously unimaginable, with restrictions on movement and social distancing rules enacted in Ireland on 12 thMarch 2020 (*Coronavirus* 2022). Mobile phone data gathered at the time shows society dramatically changed its behaviour with the number of visitors to retail stores, recreational areas etc. dropping dramatically in the same period[1]. Also, the world is more connected than ever before and the COVID-19 pandemic was the first global pandemic of the internet era (Louis 2021). Free-flowing communications and travel, coupled with social media and 24-hour news channels mean individuals are more up to date on the latest COVID-19 case and fatality numbers than would have been possible at any other time during history. We investigate the effect restrictions and the wide availability of information had on ED arrivals and determine if predictors can be extracted that improve forecasting accuracy.

In this study, we examine both the arrival patterns and the percentage change caused by COVID-19 and assess the performance of machine learning models to forecast it. A percentage change model could be created quickly at a regional or national level based on the current course of the pandemic and easily applied by hospitals at a local level without any knowledge of statistical or machine learning approaches required. A more involved forecasting model can then be created to fully capture patient arrival patterns as the pandemic progresses.

Finally, we use the factors discussed to create a model that predicts the impact of a pandemic on ED arrival numbers. This model can be used to provide decision support to hospital planners during a pandemic enabling them to redeploy resources to areas of most urgent need.

Section 2 gives a brief summary of relevant literature, Section 3 describes the emergency departments and data used in this study. Section 4 outlines how a counterfactual forecasting model for 2020 was built and selected. Section 5 presents the factors used to build the model and the model's performance. Section 6 discusses how the model can be used for decision support and the areas for future study.

3 Related work

Due to the importance of the ED within a hospital, the application of predictive analytics techniques is widely researched. ED service quality, defined by waiting time and length of stay, is heavily impacted by patient demand (Gul et al. 2018), and as such, forecasting patient arrival is seen as a key metric. A systematic review by (Wargon et al. 2009) focuses purely on this metric and found approaches using more traditional methods such as linear regression and time series data were accurate, with Mean Absolute Percent Error (MAPE) rates between 4.2% to 14.4%.

A more recent comprehensive review by (Gul et al. 2018) also discusses patient arrivals but broadens the scope to include all statistical forecasting techniques applied to the other key ED metrics, patient admission (discharge destination), length of stay and crowding, along with the techniques used to forecast and the measures used to assess accuracy. Multiple studies (Milner 1997; Bertsimas et al. 2021) show a model's accuracy can decrease over time, and recommend regular updating to ensure its output remains relevant. This is a key point for anyone wishing to develop a production-ready model. While the majority of historic studies focused on more traditional predictive analytics techniques such as SARIMA and regression, more recent studies have begun to employ techniques such as machine learning and recurrent neural networks. These techniques have been shown to provide accuracy comparable to traditional linear regression and time series approaches (Kutafina et al. 2019), while also being more familiar to hospital IT departments than statistical approaches.

A number of investigations have also been performed focusing on various local explanatory variables and hospital sizes. (Sun et al. 2009) investigated patient acuity and air quality in a tropical environment as potential predictors, while (Whitt et al. 2019) included temperature. More recently the demographic and social predictors that can lead to emergency attendance have been highlighted (Giebel et al. 2019) along with the issues that can be caused by returning patients (Rising et al. 2014). The impact of these exogenous

[1]https://ourworldindata.org/covid-google-mobility-trends

variables is mixed. Due to the complexities involved in gathering the data, we chose not to include them in a model designed for real-world production use.

More recently there have been some efforts to build models which incorporate the change in arrival rates observed during the COVID-19 pandemic. In (Duarte et al. 2021) the authors compared the performance of a number of different models; ARIMA, Facebooks Prophet and General Regression Neural Network (GRNN) across a number of different KPIs, Patients in Department, Patient attendance, unallocated patients with DTA and medically fit for discharge. Root Mean Square Error (RMSE) was calculated for each model and the machine learning GRNN model performed best overall. The authors concluded machine learning models such as GRNN are better able to deal with large changes in underlying data compared to more traditional ARIMA models. (Etu et al. 2022) also compares a number of models on arrivals data. Uni-variate and multi-variate versions of Seasonal Autoregressive Integrated Moving Average with eXogenous factors (SARIMA/SARIMAX), Facebooks Prophet, Holt-Winters and LSTM models were developed and measured. The exogenous variables were climatic (temperature, humidity etc.) and "COVID lockdown", a boolean variable indicating whether the US state of Michigan where the ED is based was under lockdown. Performance was compared over a number of forecasting horizons, 1, 7, 14,21 and 30 days. Of the multivariate models LSTM performed the best across all the horizons, however, the uni-variate models typically outperformed the multivariate versions. The performance of the multi-variate models was more varied with Holt-Winters performing best over the shorter horizons and LSTM over the larger. The authors' results would appear to confirm the findings of (Etu et al. 2022), machine learning models outperform traditional models when large changes occur. A study by (M. A. C. Vollmer et al. 2021) studies the impact, specifically the percentage change in arrival numbers, observed due to the COVID-19 pandemic.

4 Emergency departments overview

Data from 3 hospitals in the South West of Ireland were made available for the study. The hospitals vary in size with one being considered large, while the other two are medium-sized. Geographically they are also quite diverse, one is located in a city centre, one in a suburban location with good road access and one in a regional town. Both have a mix of public and private patients, but the primary focus of all three is the public system. The EDs in all three sites are open 24 hours a day, 7 days a week and all accept walk-in presentations, GP referrals and ambulance services. All three have similar IT systems in place, with a number being shared across the three sites.

None of the sites has a general Electronic Health Record (EHR) system in place, but all three use a Patient Information Management (PIM) system to track patient arrivals and flow. The PIM system has been operational in all three sites since 2013 and data from 2013 to 2020 inclusive was used in this study.

4.1 Data

The data fields made available for this study are RID, a Unique patient identifier along with each patient's arrival and departure time. Each patient is assigned a RID at the regional level, making it possible to track patients across all three sites.

4.2 ED Arrival Process

In the following section, we study the arrival process across all three EDs prior to the pandemic, compare the patterns to previous studies and build an ARIMA model to forecast arrivals for 2020 based on the observations from 2013 to 2019.

Table 1. A summary of daily arrivals over 2,922 days (2013-2020)

Site	Location	Beds	Total arrivals	Mean	std	1st qu.	Median	3rd qu.
ED1	Suburban	800	500992	171	31	147	175	194
ED2	City Centre	300	384834	132	30	109	135	154
ED3	Regional Town	377	261075	89	20	75	90	104

4.2.1 Daily data

The daily dataset was created by counting the number of unique "RID"s in each day based on "Arrival Time" and adding the values together. Table 1 summarises the sites and the daily arrival data. We also create a pooled dataset from the three sites by adding the daily totals together. By combining the three sites, the pooled dataset contains less noise and allows us to identify seasonality in the underlying data, improving forecasting performance.

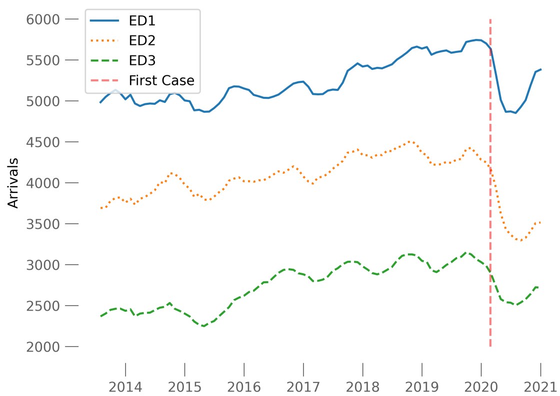

Figure 1. Month on month arrivals

Figure 2. Time series components

Figure 1 shows the monthly totals for the three EDs over the 8-year period available to us, 2013-2020. The mean increase in arrival rate at ED1 was 14% over the 8-year period, while it was 16% at ED2 and 28% at ED3. Daily data typically has a weekly and annual pattern (Rob J Hyndman et al. 2021) which has been shown to be also true for ED data by previous studies (Whitt et al. 2017). All three EDs in this study also show similar patterns of seasonality as visible in figure 2. The overall trend shows a steady rise in the arrival rate from 2013 onwards. All three EDs also have similar weekly and yearly seasonality. Monday, the start of the work week is the busiest day in all three sites, with arrival rates continuing to drop off until Thursday, after this spike they then drop dramatically over the weekend until Monday. Annually we also see common seasonality across the three EDs with May to October being the busiest periods with a decline in arrivals until January, when rates begin to increase again. The consistency of these trends over the seven-year period between 2013 and 2019 would suggest that 2020 would have seen an increase in overall patient arrivals and similar weekly and annually seasonality could also have been expected.

5 Counterfactual forecasting models

To model the impact of COVID-19 on the arrival rates in 2020, we first created a forecasting model to act as a counterfactual to the actual figures for 2020. Differences between this model and the actual arrivals are then assumed to be due to the impact of the COVID-19 pandemic. We built forecasting models using two common approaches and compared their performance. We then selected the forecast arrival numbers created for 2020 by the more accurate model to act as our baseline.

5.1 ARIMA Model

ARIMA models have proved very successful for forecasting arrivals in previous studies (M. A. Vollmer et al. 2021; Gul et al. 2018) so we first built and tested an ARIMA model to forecast 2020 arrivals.

ARIMA models are composed of three components, *AR*, the autoregressive component, which indicates the variable of interest, in our case the number of daily arrivals, has a dependent relationship with a number of previous observations. *I*, the integrated component, indicates differencing is used to make the time series stationary. Finally, *MA*, the moving average component, indicates the model uses past residual errors in a regression-like model.

These three components are specified as model parameters, typically defined as ARIMA(p, d, q) where p, d, q are integer values defined as:

- *p*: The lag order. The number of lagged observations included in the model.
- *d*: The degree of differencing. The number of times the observations have had past values subtracted.
- *q*: The order of the *MA* model. The size of the moving average window.

These model parameters can be discovered using a number of different methods. The traditional Box-Jenkins method (Box et al. 2015) is an iterative three-stage process. Firstly autocorrelation (ACF) and partial autocorrelation (PACF) plots are created to determine stationarity and seasonality. Secondly, parameter estimation techniques are used to calculate the best coefficients for the ARIMA model. Finally, a number of statistical tests are run to test the residuals are independent of each other and have a constant mean and variance over time. More recently, the Hyndman-Khandakar algorithm (Rob J. Hyndman et al. 2008) known as Auto-ARIMA is also widely used. This algorithm performs a number of tests such as Kwiatkowski-Phillips-Schmidt-Shin and Augmented Dickey-Fuller in order to discover the optimum values for *p, d, q*, along with their seasonal components *D, P, Q*. The chosen parameters can be optimised based on chosen criteria, Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (CAIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC) or validation scoring, known as “out-of-bag” (OOB). A third approach, grid-search was used in this study.

5.1.1 Fitting model parameters

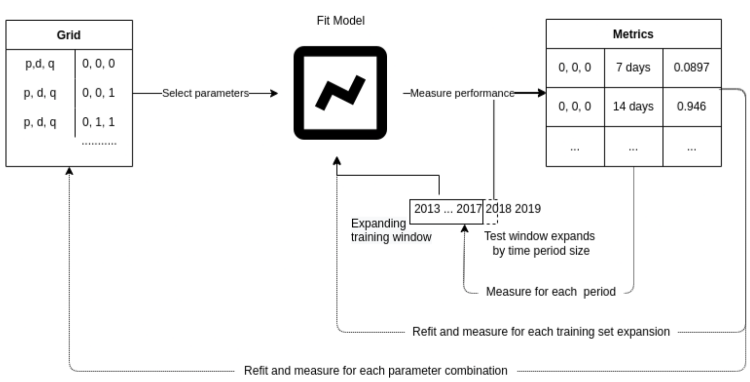

Figure 3. Cross Validation Process Flow

To assess model performance during the grid search, a cross-validation technique was applied with MAPE being used as the key performance metric. MAPE was chosen as it is the most commonly used measurement in studies of ED arrivals (Gul et al. 2018). The process used can be seen in figure 3.

1. A grid of potential combinations for p, d and q is generated,
2. The data is split into two sets, the training window and the testing window with the data from 2013 to 2017 (1,461 days) inclusive used as the initial training window, and data for 2018 and 2019 making up the testing window.

3. Values for p, d and q are selected from the grid and used as parameters to fit the model to the training window.
4. The model is then used to predict various future time horizons: 7, 14, 21, 30, 60, 90 and 180 days ahead. The MAPE is then calculated for the model using the testing data set and stored.
5. The training window is expanded by 90 days (one quarter), the model is refit and the performance metrics are recalculated for all future time horizons.
6. Step 5 is repeated until the testing window is exhausted.
7. New values for p, d and q are selected and the process restarts at step 2

Once the grid search was completed, the performance results were analysed. Initially, the models with the lowest MAPE over each time horizon were extracted. Overall time periods an ARIMA(4, 1, 5) model gave the best results with the mean MAPE of each time horizon being 10%, 9%, 9%, 8%, 9%, 9% and 9%.

5.1.2 Model Diagnostics

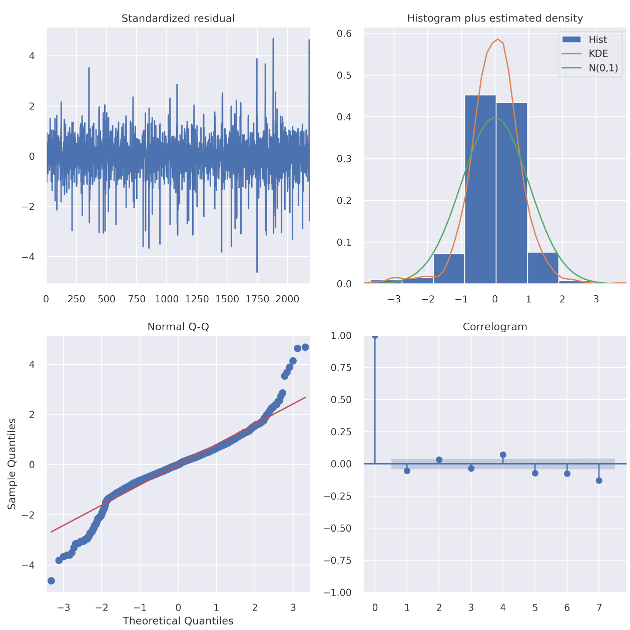

Figure 4. ARIMA Diagnostic Plots

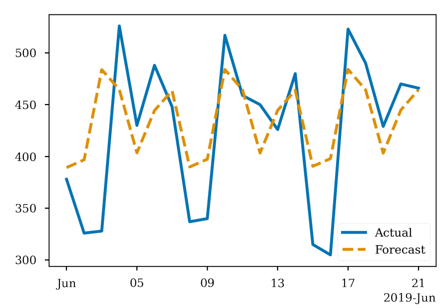

Figure 5. ARIMA Forecast

After selecting an ARIMA(4, 1, 5) we firstly perform a basic visual "goodness-of-fit". If we aim for a model to be adopted by practitioners, a model that does not visually look "accurate" would be rejected out of hand as "obviously inaccurate" or "overly simplistic". Figure 5 shows a sample 3 week period in June 2019. We can see the model captures seasonality and trend and would be acceptable to a practitioner.

Next, we created four diagnostic plots as seen in figure 4. The standardised residual plot shows the majority of our residuals cluster around zero. The Normal Q-Q plot shows a good fit to the line however there is some negative skew towards the end. We also see overdispersion in our histogram indicating positive excess kurtosis. The Correlogram shows auto-correlation indicating we may not be capturing all of the seasonality present in the data.

Finally, we run a number of statistical tests on our model residuals. The Goldfeld-Quandt test for heteroskedasticity has a p-value < 0.05, indicating the residuals are heteroskedastic. The Ljung-Box test also has a p-value of < 0.05, confirming the residuals are not independent and finally, a Jarque-Bera test also has a p-value < 0.05, indicating the residuals have skewness and kurtosis different from that of the normal distribution, with skewness being estimated to be -0.78 and kurtosis to be 6.99.

Despite the MAPE being inline with results from other studies (Gul et al. 2018) these tests show that we are not fully capturing all the components of the time series correctly. There are many components commonly found in standard business forecasts such as outliers, multiple types of seasonality, trend changes and changes caused by public holidays. The authors have had success capturing these changes in the past using a Prophet (Taylor et al. 2017) model, so we next fit our data to a prophet model to determine if it improves our results.

Prophet uses a decomposable time series model (Harvey et al. 1990), with trend, seasonality and holidays into an additive model. Holidays are explicitly accounted for as they can have a large impact on business forecasts but be irregular from year to year. The authors claim this general additive model (GAM) (Hastie et al. 1987) offers a number of advantages over generative ARIMA models by being quick to fit, easily accommodating multi-period seasonality and by working on irregularly spaced data.

Prophet has also been used in other ED studies, and we believe it to be an appropriate option as ED arrival is fundamentally a business time series, with seasonality, public holidays etc. all having a noticeable impact on arrival rates. Prophet also allows hyperparameter tuning. Again, a grid search as described in section 5.1.1 was used to determine the best hyperparameters and a changepoint of 0.1 was found to offer a slightly improved overall MAPE of 6.6%. The other parameters had no impact and were left at the default settings.

Again we assessed a visual ”goodness-of-fit” test and found it to be acceptable. Next, we created four diagnostic plots and again the residual plot shows some heteroskedasticity, confirmed by a Goldfeld-Quandt test. The Q-Q plot also shows some skew, confirmed by the results of a Jarque-Bera test, and the histogram shows some over-dispersion, albeit less than our previous ARIMA model.

While Prophet has improved our forecast, we find we are not capturing all of the time series components and as a next step we will investigate data transformations and decomposition that will further improve model accuracy.

6 Next Steps

A number of steps remain. Firstly, we will include more information regarding the Prophet model and expand on the comparison between the ARIMA and Prophet models. We will endeavour to improve the performance of both 2019 counterfactual models, via appropriate data transforms and model tuning. Once completed we will then use the data and models presented to create forecasting models for 2020 and examine their performance. Firstly, to build a high-level ”impact” model based on nationally available data that can be used at the onset of a pandemic. This model would require no pre-existing forecasting models to be in place, but could still be used by hospital planners as an indication of the impact the pandemic will have on their ED. This model will be applied to each ED and its performance accessed. Based on this performance, a decision on its appropriate use will be documented.

Secondly, a more sophisticated multivariate time series forecasting model will be created and its performance will be accessed using actual arrival data from 2020. Based on its performance, recommendations will be documented and suggestions for future improvements and research will be shared.

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