

# Predicting Demand for Out of Hours Service

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**ABSTRACT:** After performing the initial analysis, we considered the ability of several different forecasting models, namely Singular Spectrum analysis (SSA), Holt's winter (HW) exponential smoothing methods (multiplicative and additive model), seasonal exponential smoothing (SES), Log seasonal exponential smoothing (log SES) and regression to predict daily demand levels for each of the three staffing groups. After constructing the models and used them to generate daily predictions of demand between January and May 2014 we benchmarked their accuracies against the current forecasting method used at the service known as the persistence method. Under this model demand is assumed to be fairly static on a yearly basis, hence the demand observed for the first Monday in 2013 is taken to be the best estimator of demand for the first Monday in 2014, e.t.c. Different prediction models have been tested in this research to predict demand for three categories of staff working at the Gwent OoH. Different prediction models have been tested in this research to predict for three categories of staff working at the Gwent OoH. Whilst all conventional time series model have been shown to offer considerably advanced forecasts than the persistence method; the "best" methods is found to be dependent both upon the forecasting variable of interest and forecasting horizon.

**KEYWORDS:** About four key words or phrases in alphabetical order, separated by commas.

## I. INTRODUCTION

Background of the study This project concerns the Gwent Out of Hours (OoH) Service which provides advice, treatment and information to around 600,000 people living in Aneurin Bevan University Health Board (ABUHB). The service operates for 70% of the 7- day week, 52 weeks a year and can be contacted by patients with urgent healthcare needs from 6:30pm to 8am weekdays, in addition to weekends and bank holidays. Upon calling the service, patients are taken through a series of questions by call handlers, who assign each with a priority label using the adastra call prioritization protocol (ACPP) system. Most patients are subsequently directed to future services to receive appropriate healthcare assistance. Depending on their condition, this can range from advice over the phone, a home visit, a face to face assessment at primary care center (pcc) or an admission to hospital.

Many factors affect the demand for OoH services including the time of day, day of week, month of year, school holidays, and weather and influenza levels. The main aim of this research is to provide insights into the variability in demand levels over time and find statistical models that are capable of generating accurate predictions of future demands. Such models are desired to enable service planners to anticipate peaks and troughs in demand so they can proactively plan to meet future pressures by ensuring the right staff are present at the right times of day in the right locations. In this research, we construct models to predict demand for three staffing different categories of staff:

1. Clinical triage/advice staff;
2. Clinicians at PCCs; and
3. Mobile Clinicians who perform home visits.

The resultant forecasts generated for each staffing group will ultimately be fed into the staffing model constructed in the related OoH staffing project, to aid service planners to optimize resource allocation and improve service delivery.

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## II. LITERATURE

Predicting future demand accurately is critical to allow managers to plan appropriately and to know how many staff to employ at different times of day. This section will provide a brief explanation of demand and prediction and reviewed of research conducted mostly on prediction of demand in healthcare health services. Another study carried out to predict demand for emergency department services, based on patients' arrivals time which served as "temporal, climatic, and patients factors. In this research the accuracy of the predicting models was investigated to ascertain if the assumptions of the models are met (Poisson process) in the process the model accuracy was compared using observed and predicted histograms of patients' arrival data as well as by the number of observed count failures within an interval of 50 and 90 percent prediction. The observed histogram of arrival data was closely to the one predicted by a Poisson process and the demand were appropriately predicted by the models see(Cadigan and Bugarin, 1989).

A study conducted using classification and forecasting daily patients arrivals into an accident and emergency department based on the previous data. The data of patient arrivals were categorised into two the "the walk-in and ambulance" and the two are sum up for the day. The four years data was used to fit "structural time series" (ST) model for each category and the models forecasted the "walk-in and ambulance" for 1-7 days. The walk-in arrivals shows a strong weekly seasonal variation with strong prediction ability ( $r = 0.6205$ ) while as the model shows a weak predictive ability for ambulance ( $r = 0.2951$ ) clearly indicated the two are different and hence requires different model to handle them (Au-Yeung et al., 2009). A study carried out using exponential smoothing and Box-jenkins models has shown that the exponential smoothing exhibited strong prediction ability confirming the time series models plays important role in predicting emergency department demand. Time series models gives better forecast than the regression models in situation where the data under observation has seasonality effects(Champion et al., 2007). A research to investigate the patients daily recorded in the emergency department reveal that, the daily demand for emergency department is best described by seasonal and weekly behaviors and multiple linear regressions is a good model to forecast daily patient admissions in the emergency department. However the regression based model that take into account calendar variables gives more accurate information and better decision approach for forecasting daily admissions (Jones et al., 2008). A good forecast saves huge amount of energy and determine better function of a system, therefore, it is essential to forecast with minimum error as to ensure demand and resources are utilised judiciously. A Box-Jenkins ARIMA Model is an essential forecasting model capable of providing a well-structured explanation on the characteristics of the data under investigation which was why it was often been used in forecasting so many phenomenon (Norizam et al., 2011).

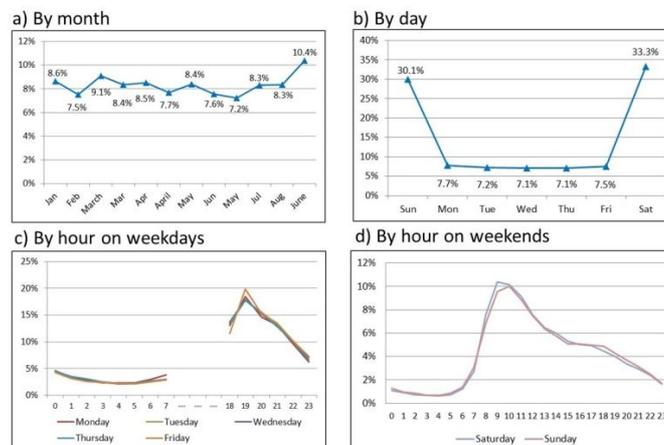
For business and economics small scale time series hourly network traffic data exhibits multiple seasonality behaviour that is hourly-of-day, day-of-week and the month-of-year seasonal characteristics and was not unconnected to the cyclical behaviour of the user vigorous action. The ARIMA time series model has the structure to incorporate double multiple seasonal patterns adequately in addition to Taylor's proposed double seasonal exponential smoothing which has no any requirements to be met. The advantage of double exponential smoothing over ARIMA model is the ability to handle large amount of time series data with minimum delay due to automatic statistical package it has while ARIMA has not so requires more time(Au et al., Vile et al., 2012). conducted to estimate staffing requirement in an emergency unit has highlighted the significant function of Singular Spectrum Analysis. The SSA split the observed time series data into a sum of explanatory components (trend, seasonality and error), no assumption needed to be met as per nonparametric model. The SSA performance was evaluated using mean square error standard this accorded the opportunity to check out the shortage of staffs more accurately than an excessive estimation of staffs, more over the result yielded by the method was considerably accurate hence the authors recommended the method to not only health care modelling but some areas like capacity models and traffic congestion model(Jonathan and Vince, 2012).In a study conducted to forecast hydrological time series revealed the ability of Singular Spectrum Analysis by providing description and clear characteristics of the hydrological univariate time series data as well as good forecast capability. The excellence of the trend adequate was evaluated near riches of bootstrap intervals. The results of the first five forecasts were considerably close to the last five data points of the trend components alongside maximal deviation of 35.0mm and root mean square deviation of 21.3mm and hence a Singular Spectrum Analysis is a reliable model(Marques et al.,

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2006).The Holt’s linear forecasting method has no conditions required to be met by a time series data concerning correlation rules of the time series and hence capable of handling linear and nonlinear behavior present in a given data by simply employing different forecasting techniques and then bring forecasts together with the aim to increase the forecasting performance measure. Employing several forecasting techniques to handle a time series data under observation always yield more reliable result or forecast than just working on a model. This model has been widely used in areas such as business and environmental studies as it is quite simple, for more explanation (Santiago Maia and de Carvalho, 2011). Singular Spectrum Analysis is a simple prediction technique with ability to reveal the actual characteristics and gives clear understanding of the data under investigation such as “trend and seasonality patterns” not only that but has no concern over parametric assumptions. However the selection of components to be included in SSA model need clear understanding as “pure noise” generates a bit decrease in singular values. The SSA, ARIMA and Holt’s winter models’ prediction accuracy was compared using Root Mean Square Error in which SSA came out with the best prediction result (Vile et al., 2012).The Holts’ winter method is typically a time series method which decomposes time series data and has smoothing structure ability to best handle time series data with both trend and seasonality patterns. It is often used and simple as well. When employing Holts’ winter model, the smoothing parameters are kept at a minimum say 0.2 as this will allow proper evaluation of the method and in the long run this parameter may also be optimized for a given series under observation so as to come up with possible minimum value for both MSE and MAPE. The table below compares different forecasting models, using their individual estimate of both mean square error and mean absolute percentage error. Clearly ARIMA multiplicative with intervention has the least value of mean square error mean absolute percentage error and considered to have the most accurate forecast (Al-Sakkaf and Jones, 2014)



### III. METHODOLOGY

#### A. Holt’s winter model

This method split a time series data into many components considered as occurring at different time intervals categorized by four components:

1. Trend present of steady increase or decrease movement over a long period in the time series data.
2. Cycle simply means smooth fluctuation about the trend line
3. Seasonality mean repeated pattern over time say yearly, monthly or weekly. The assumptions of the model are that changes in the time series data can be smoothed by either additive or multiplicative decomposition. A multiplicative decomposition model shows constant variation when there is an increasing or decreasing seasonal behavior in the time series data.

$$Y_t = T + C + S + E \tag{1}$$

In practice the cycle component is negligible. The two techniques for decomposition are explained below:

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Regression-based methods are simply use of simple linear regression model to fit the trend and typically picture out the long term increase or decrease in the data over time.

$$T = \beta_0 + \beta_1 t \tag{2}$$

The trend given by equation above is linear in nature, there are also quadratic and the P<sup>th</sup>-order polynomial as well. The seasonal component can be computed taking into consideration value of each month or periodic function such as sine and cosine.

The least square estimates of the parameters can also be computed by the used of standard regression techniques which assume that, the error is random, independent and identically distributed. If the regression coefficients are significance at  $P < 0.05$ , then that very particular variable will be kept in used. This model is regarded as “global” model since it assumes the trend, seasonal behavior are similar all through time and each data point has equal contribution to the estimate of the “fixed parameters”. The exponential smoothing technique explained in the Holt-winter’s method used to tackle data which is trended or seasonal in nature.

Mathematically equations carry along their sides’ user-choosing smoothing parameters  $\alpha$ ,  $\beta$  and  $\gamma$  as will be seen in the following Holt-winters’ basic equations:

The level component equation

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1 - \alpha)(L_{t-1} + b_{t-1}) \tag{3}$$

The trend component equation

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1} \tag{4}$$

The seasonal component equation

$$S_t = \gamma \frac{Y_t}{L_t} + (1 - \gamma)S_{t-s} \tag{5}$$

The forecasting equation for the period m (Multiplication decomposition)

$$F_{t+m} = (L_t + b_t m)S_{t-s+m} \tag{6}$$

Where  $L_t$  is smooth function of series observation excluding seasonality,  $Y_t$  is the observed or historical data points excluding seasonality and error measurement,  $\gamma$  is the weight function and  $S_t$  is the seasonal function of the data series at hand under observation.

Holt-winter Additive model

The level component equation

$$\text{Level: } L = \alpha(Y_t - S_{t-s}) + (1 - \alpha)(L_{t-1} + b_{t-1}) \tag{7}$$

The trend component equation

$$\text{Trend: } b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1} \tag{8}$$

The seasonal component equation

Seasonality:

$$S_t = \gamma(Y_t - L_t) + (1 - \gamma)S_{t-s} \tag{9}$$

The forecasting equation for the period m (Additive decomposition)

$$F_{t+m} = L_t + b_t m + S_{t-s+m}$$

Where s represents the measure of seasonality,  $L_t$  Stands for level of series of data under investigation,  $b_t$  is given by trend  $S_t$  represent the seasonal component of the data under observation,  $F_{t+m}$  is the forecast function for M period in future. Equation 3 and seven can be compared or considered as a seasonal index resulted from the ratios of the existing values of the data series;  $Y_t$  split by the existing “smoothed” value for the time series observation,  $L_t$  when  $Y_t$  is greater than  $L_t$ , the resulted ratio will be larger than 1 and less than 1 if  $Y_t$  less than  $L_t$ . For a better comprehension of the method it is imperative to accomplish that  $L_t$  is a smoothed value of the data under observation that is deseasonalised (“seasonally adjusted data”).the observed values  $Y_t$ has seasonal effect and random error associated with.

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To get rid of both seasonal and random error factors the equation measures the current calculated seasonality factor with  $\hat{y}_t$  and most freshly seasonal index “corresponding to the season with  $(1-\gamma)$ , this prior seasonal factor was computed in the period  $t-s$ , since  $s$  is the length of the seasonality” (Oblak et al., 2012). This method is easily understood and often so used in practice. It suggested that; the smoothing parameter values should be set up to allow proper evaluation of the performance and accuracy of the model. In some cases the methodology is subjected to smoothing parameter optimization for a given data under observation. This aim at minimizing error (residuals) to the bearing minimum level as it will lead to accurate and reliable forecast for the target future (Al-Sakkaf and Jones, 2014).

### B. Singular spectrum analysis

The singular spectrum analysis is another forecasting technique which is one of the most useful forecasting models for a time series data. Singular spectrum analysis method split time series data into a certain parameter estimate of time series character this could be a “trend component, periodic component, quasi-periodic component or noise”. This technique can be implemented using the following four steps: (Vile et al., 2012) and (Moskvina and Zhiljovsky, 2003).

### C. Multiple linear regressions

In dealing with regression analysis we always try to observe the possible associativity among variables of interest under investigation, this simply refers to as “regression function” the dependent variable denoted by  $Y$ , two or many variables  $x_i$  called “the independent variables”. The regression function takes into account the unknown parameters  $B_i$ . The dependent variables in this research are the clinical triage cases (Home visit, Base visit) and the independent variables are month, year, week days, Bank holiday and school holiday. This specifically allows experimental study of the characteristics of the demand and provide better forecast for the future demand. A linear regression function can be linear in the dependent variables but nonlinear in the independent variables, such can simply be called a “linear regression model”.

Multiple linear models can be represented mathematically as follows:

$$Y = b_0 + b_1x_1 + b_2x_2 + \dots + b_px_p \quad (15) \quad Y = b_0 + \sum_{i=1}^p b_ix_i \quad (16)$$

for  $i = 1, 2, \dots, p$

Polynomial (the model is linear in dependent variables, but nonlinear in independent observations):

Where  $y$  is the dependent variable estimated by the equation (regression model),  $\hat{Y}$  is the future forecasted values which is also term as dependent variable,  $p$  is the number of independent observation (“number of coefficients”),  $x_i$  ( $i=1, 2, \dots, p$ )  $i$ th independent observation that are elements of  $p$  observation,  $b_i$  ( $i=1, 2, \dots, p$ ) the  $i$ th coefficients of  $x_i$ ,  $b_0$  intercept (constant)  $k = p+1$  sum of all observation in addition to intercept (constant),  $n$  represent number of observations in a given data set,  $i = 1, 2, \dots, p$  “independent variables index” and  $j = 1, 2, \dots, n$  dependent variables’ index. Obviously the aim is to achieve “the best set of parameters  $b_i$ , so that the model can predict the future values of the dependent with a minimum error in other words the predicted values should be very closed to the historical or observed values. In the process also have to make sure that, the model will eventually fit the data under consideration and more importantly verify “whether all terms in our model are significant (Michael et al., 1996).

## IV. IMPLEMENTATION OF REGRESSION MODEL

Let explain in detail the mathematical relation and how parameters are computed in order to shade more light to the previous description in section 3.5.

The model (16) can be used to compute least squares parameters and in essence resulted into the values of sum squares with possible minimum errors. The mathematical expression or forecasting equation is given as

$$\hat{y}_i = \hat{b}_0 + \hat{b}_1x_{i,1} + \hat{b}_2x_{i,2} + \dots + \hat{b}_kx_{i,k} \quad (17)$$

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These mathematical symbols maintain the same definition with those in equation (16) except “^” which indicates and estimated parameters.

The mathematical expression which can lead to the estimation of the sum of squares can be itemized below.

$$\begin{aligned}
 SSE &= \sum_{i=1}^n \hat{e}_i^2 && \text{sum of squares, error} \\
 SST &= \sum_{i=1}^n (y_i - \bar{y})^2 && \text{sum of squares, total} \\
 SSR &= \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 && \text{sum of squares, regression}
 \end{aligned}
 \tag{4}$$

n = number of data point in a given sample

“The regression equation is estimated such that the total sum-of-squares can be partitioned into components due to regression and residuals”:

$$SST = SSR + SSE \tag{19}$$

Power function of regression can be pointed out and explain better by “R-squared” estimated by the use of sum-of-squares formulas as below:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{20}$$

“R<sup>2</sup> also called the coefficient of determination” obviously this is known to have provide information or explanation of the amount produce by the regression. “it is important to keep in mind that just as correlation does not imply causation, a higher R<sup>2</sup> in regression does not imply causation”.

The magnitude of the “sum-of-squares terms” determines the capacity or ability of the regression model to fit the data under investigation (“good data fit”). “If the regression is perfect” all the difference between observed and the predicted must turn to zero, hence sum of squared error must also be zero and R<sup>2</sup> is 1 in other hand, a “total failure” of the regression came about when the sum-of-squares of residuals agrees with sum-of-squares total, that is variance and R<sup>2</sup> are all zero.

The whole computation can be summarized in an ANOVA table below:

Table 1: ANOVA

Source	df	SS	MS
Total	n - 1	SST	MST = SST/(n-1)
Regression	K	SSR	MSR = SSR / K
Residual	n - K - 1	SSE	MSE = SSE/(n - K - 1)

“Where source = source of variation, SS = sum-of-squares, df = degree of freedom for the sum- of- squares term, MS = mean squared terms”

The mean squared term is the ratio of the sum-of-squared term to the degree of freedom of term. Mean square error is given by the estimated fraction variance of the regression errors. The mean square error can also be written as  $\delta^2_\epsilon$ , while the sample estimate is given by

$$S^2_\epsilon = \text{MSE} \tag{21}$$

The square root of the mean square error can be taken to obtain root mean square error (RMSE)

$$S_\epsilon = \sqrt{S^2_\epsilon} = \sqrt{\text{MSE}} = \text{RMSE}_c \tag{22}$$

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A subscript “c” was used to differentiate the RMSE computed from “calibration” and the RMSE estimated using “cross-validation”

Now recall the regression function or “power” can be better explained by the regression  $R^2$  and this is estimated from “sum-of-squares terms” the F-ratio is estimated from the mean squared error terms given in the ANOVA table, this will determine “statistical significance of the regression equation”. The F-ratio formula is

$$F = \frac{MSR}{MSE} \quad (23)$$

The benefit of F-ratio compared to  $R^2$  its ability to carry along the number of the sample (population size) and the number of predictor variables in the model. “A model can have  $R^2$  and still not be statistically significant if the sample size is not large compared with the number of predictors in the model”. The F-ratio used both but the sample size and number of “predictors” to evaluate the extent of the relationship if exist.

The significance of F-ratio can be secured by comparing the calculated and the tabulated from an F distribution table, with the help of degrees of freedom (“df1, df2”),” df1 and df2 are degrees of freedom for the regression mean square and residual mean square from the ANOVA table”.

Adjusted  $R^2$  in this case many predictors are incorporated in the regression model to give  $R^2$  high value.  $R^2$  is one of the parameter estimates in statistics that try to enhance the accuracy of a measure. The adjusted  $R^2$  equation is

$$R^2 = 1 - \frac{MSE}{MST} \quad (24)$$

“Where MSE and MST are the mean squared terms previously defined in the ANOVA table”.

Looking back to the ANOVA table will see that the ratio of mean squared terms is connected to the ratio of sum-of-squares in the following mathematical relation.

$$\frac{MSE}{MST} = \frac{(n-1)SSE}{(n-R-1)SST} \quad (25)$$

Where n is the number of data points and k define by number of predictors. In essence  $\frac{(n-1)}{(n-R-1)}$  “must” be larger than zero, hence this proved that the adjusted  $R^2$  always less than  $R^2$ , and also the variation in the two estimators rely on the number of observations and the predictors present in the regression model (Notes\_11, GEOS 585A, Spring 2013).

### 4.1.3.2 Assumptions of Multiple Linear Regressions

The multiple linear regressions some certain assumptions needed to be met. If these conditions are satisfied then the regression predictors are said “optimal, unbiased, efficient and consistent”. Efficient simply refers to have little variation between observed and expected, the predicted value is equal the actual value (unbiased), and consistent simply as the sample size increases the variance tends to zero value. The following are necessary conditions required to attain by a data to fit multiple linear regressions (Notes\_11, GEOS 585A, Spring 2013):

1. There exist linear relationship between dependent and independent variables. This method can only handle linear related data. Should in case the data is not linear the researcher is left with two option (1) transform the data to obtain linearity in relation (2) try an alternative model such as “Neural networks, Binary classification trees”). Scatterplots should also be inspected to verify linearity.
2. There is virtually no relationship what so ever between the errors and the dependent variables (predictors). This can be identified from the scatter plot of residuals. If this condition is not met recommend transformation.
3. The mean of the individual error is zero. This assumption is not identifiable as we can only know the residuals of the regression while as unseen true errors remain “unknown”. “The least square method used to estimate the regression equation guarantees that the mean of the estimated residual is zero”.
4. The mean of square error is always variance (constant). This can be identified in way that the error cannot be larger than forecasted value and can also be checked from the scatterplots with experience in hike over period.
5. The distribution of residual errors follows that of a random and independent or there exist no relationship among residual errors.

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7. The errors obey normal distribution. This is compulsory in other words the condition must be met for a regression model to adequately fit the data at best.

### E. Seasonal exponential smoothing (Multiplicative)

Obvi  $\hat{F}_t = \alpha(Y_t / I_{t-p}) + (1-\alpha)L_{t-1}$  ata demonstrated a seasonality pattern or behaviour with no evidence of trend contain in the data,  $I_t = \gamma(Y_t / L_t) + (1-\gamma)I_{t-p}$  d by the use of seasonal exponential smoothing method as in the case of the out of hours' data  $\hat{F}_t(m) = L_t I_{t-p+m}$  asonal variation with no evidence of trend. This can be express in the following equations.

$$(27)$$

Where  $Y_t$  = data point of time series data at time  $t$ ,  $L_t$  = level,  $I_t$  = seasonal indices,  $\alpha$  = smoothing constant parameter for level,  $\gamma$  = smoothing value for seasonality,  $F_t(m)$  = “smoothed forecast value for  $Y$ ”. Initially for this to work we need to have starting value for the level and the seasonality therefore, “the starting value level (%STARTVL1) is based on the mean of the first seasonal cycle. The starting values for seasonality (%STARTVL3) are based on the ratio between common periods of all seasonal cycles in the in-sample (training) period {William, 2011, Exponential Smoothing Forecasting Using CAB34S and Workbench}.

### D. Log-Seasonal Exponential Smoothing

Log-Seasonal exponential smoothing this often used the same mathematical equation with “seasonal exponential smoothing” as detail in in section 4.1.4 above but unlike seasonal exponential smoothing certain data transformation has to be done (Logarithm transformation) this is done with view to stabilize the variance. The transformation equation is given by

$$W_t = \ln(Y_t) \quad (28)$$

Where  $W_t$  is the transformed data at time  $t$   $\ln$  is the logarithm symbol and  $Y_t$  is the observed data point at time  $t$  (Alexanda, 2003).

## V. PRELIMINARY DATA ANALYSIS

Details of previous calls made to the service between January 2008 and December 2013 were provided directly by Out of Hours Service and analyzed to reveal patterns and trends in the data. Additionally, data concerning activity levels between January 2014 and May 2014 was retained for model evaluation purposes: instead of using the data to construct the models we held back the data to allow us to test how well the daily demand figures generated by the forecasting models compared to the true observed (withheld) quantities for these five months.

Figure 1: Distribution of calls requiring Clinical advice (2008 -2013)

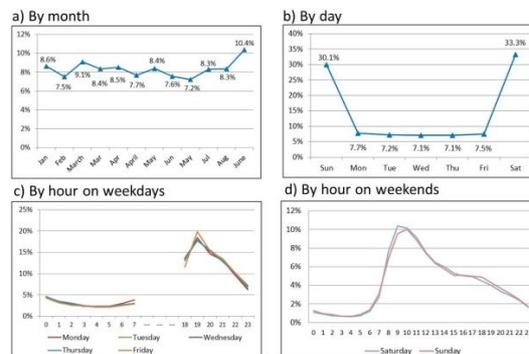


Figure 1 (a): shows the monthly seasonal pattern of calls requiring Clinical advice. Statistical tests constructed to analyze the data presented in the chart find that demand levels in the following months are statistically different from each other:

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- VERY HIGH DEMAND: December
- HIGH DEMAND: January, March, April, May, July, October and & November.
- MEDIUM DEMAND: February, June & August.
- LOW DEMAND: September.

Figure 1 (b) shows the distribution of demand by day of week. It is unsurprising that over 60% of the calls occur on weekends as the service remains open all day on Saturdays Sundays. Figures 1 (c) and (d) finally illustrate the distribution of calls by day of week. Although the service shuts down between 8:00-18:30 on weekdays, a similar pattern is displayed in the distribution of demand throughout the night to weekends.

## VI. FORECASTING MODELS

After performing the initial analysis, we considered the ability of several different forecasting models, namely Singular Spectrum Analysis (SSA), Holt’s Winters (HW) exponential Smoothing, (multiplicative and additive model), Seasonal Exponential Smoothing (SES), Log Seasonal Exponential Smoothing methods (Log SES) and Regression to predict daily demand for each of the three staffing groups.

Table 1: below details the mean Absolute percentage Error (MAPE) for each of the forecasting methods when tested to predict daily call volume for Clinical advice it demonstrates that regression is the best predictor of long-term demands, while the more conventional time series technique SES,HW additive and HW multiplicative models) provide provide generate short-term forecasts. The most significant variable in the regression equation are day of week month of year Bank holidays and School holidays. in all cases , the forecasting models offer considerably advance forecast to the persistence method. A graphical illustration of the five month daily forecast generated by the persistence method and some of the best forecasting models follows in figure 2

MAPE	SES	HW AD D	HW MU LT	LO G S E S	RE GR E S S I O N	SS A	PER SIST ENC E
Mape(Total)	11.52	11.54	9.26	9.02	11.23	12.25	15.02
5 Month forecast	17.91	18.35	8.53	9.22	13.29	18.37	13.50
3 Month forecast	16.98	17.24	7.22	7.37	8.80	16.15	13.28
1 Month forecast	18.56	18.74	8.52	8.89	8.46	12.80	10.22
14-days forecast	14.80	14.86	9.93	10.02	9.66	12.80	10.22
7-days forecast	11.15	11.16	10.53	10.60	9.78	13.32	9.72

Table 5.1: MAPEs for daily Clinical triage cases forecast, (January to May 2014)

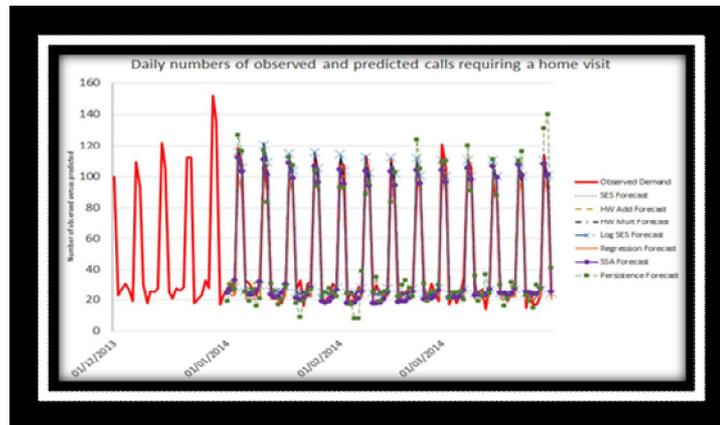


Figure 2: Actual Daily Home Visit Demand versus predicted by seven models

Similar investigations have also been performed to predict daily demands for both mobile clinicians performing home visits and clinicians based at PCCs. They reveal that SSA is the best method to predict long-term demands for mobile clinicians, and Log SES should be used to predict demand for clinicians working at PCCs.

## VII. CONCLUSIONS

Different prediction models have been tested in this research to predict demand for three categories of staff working at the Gwent OoH. Whilst all conventional time series techniques have been shown to offer considerably advanced forecasts than the persistence method; the 'best' method is found to be dependent both upon the forecasting variable of interest and forecasting horizon.

## VIII. FURTHER WORK

In future work it would be beneficial to consider the ability of other more sophisticated statistical models (e.g. Linear mixed models, SSA) to predict demand. It would also be interesting to assess the benefit of including causal time series, such as influenza levels, special events and weather, when estimating future demand levels.

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