Cardiology Admissions from Catheterization Laboratory– Time Series Forecasting

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Abstract

Emergent and unscheduled cardiology admissions from cardiac catheterization laboratory add complexity to the management of Cardiology and in-patient department. In this article, we sought to study the behavior of cardiology admissions from Catheterization laboratory using time series models. Our research involves retrospective cardiology admission data from March 1, 2012, to November 3, 2016, retrieved from a hospital in Iowa. Autoregressive integrated moving average (ARIMA), Holt’s method, mean method, naïve method, seasonal naïve, exponential smoothing, and drift method were implemented to forecast weekly cardiology admissions from Catheterization laboratory. Our study acknowledges ARIMA (2,0,2) (1,1,1) as the best fit model with the minimum sum of error, Akaike information criterion, and Schwartz Bayesian criterion. The model failed to reject the null hypothesis of stationarity, it lacked the evidence of independence and rejected the null hypothesis of normality. The implication of this study will not only improve catheterization laboratory staff schedule, advocate efficient use of imaging equipment and inpatient telemetry beds but also equip management to proactively tackle inpatient overcrowding, and plan for physical capacity expansion.

Keywords: Catheterization laboratory, Cardiology admissions, Telemetry bed, Time Series Forecasting

1. Introduction

Catheterization laboratories are the capital and labor-intensive subdivisions within a hospital. These subdivisions are fiscally crucial for a hospital. Due to the mounting predominance of cardiovascular disorders and burgeoning catheter dealings, the demand for catheterization procedures is at its peak [1]. The number of cardiac catheterizations executed in the United States has escalated significantly over the last 30 years. Catheterization laboratory infrastructure has improved, and during 2007 about 85% of all United States hospitals delivered cardiac catheterization assistance [2]. Although the volume of Catheterization laboratory has dwindled in recent years, the assortment of catheterization procedures has burgeoned to encompass both diagnostic and therapeutic procedures [2]. A diverse amalgam of procedure types and complex patient health condition makes it arduous to predict patients’ post-procedure care needs. Thus, before catheterization, it is unknown whether a patient's post-procedure health situation necessitates an inpatient overnight stay [3]. Uncertainty concerning cardiology admissions from catheterization laboratory defies efficient inpatient bed management and catheterization laboratory resource utilization. Cardiology hospital units contain specialized monitoring equipment (telemetry beds) designed for recovering catheterization patients, in addition to cardiac patients admitted from the emergency department (ED) and external locations (direct admissions). To proficiently manage patient flow, providers must project the number of admissions from each of these sources daily. The Catheterization laboratory is an enormous source of cardiac in-patient admissions, and, due to the high uncertainty of admission numbers from the Catheterization laboratory, daily as well as weekly admission projections often focus on these sources [2]. In several hospitals, providers based on their intuition and experience, envisage the demand for beds (the number of admissions) for a given day or week after assessing the catheterization schedule of the same day or week [4]. Cardiology admission from catheterization laboratory prognostication is a precarious component of hospital resource management that could be supported by time series forecasting.

The objective of this study is to develop and prospectively validate a decision support application to predict cardiology admissions for adults from a catheterization laboratory. The automated ARIMA forecasts admission from catheterization laboratory that can be used to determine cardiology bed requirements. ARIMA is one of the most effective techniques of time series forecasting. This method is standard in various fields such as forecasting energy consumption [5], stock prices [6], population growth [7], and many more. However, the application of time series technique for forecasting cardiology admissions from catheterization laboratory is untapped.
2. Methodology
Our team retrospectively retrieved 244 weeks of cardiology admission data from March 1, 2012, through November 3, 2016, from the databases used by a hospital in Iowa [8] and implemented time series analysis on the first 200 weeks (March 1, 2012, through December 31, 2015). We then compared the forecasted values against the total actual patient admission (March 1, 2012, through November 3, 2016). During the process, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, Phillips-Perron unit root test, and augmented Dickey-Fuller test were performed to determine whether the time series was stationary around a mean or is non-stationary owing to a unit root. White noise was tested using the Box–Ljung test. Moreover, we employed the Shapiro-Wilk test, Cramer-von Mises test, Kolmogorov-Smirnov test, Pearson chi-squared test, Shapiro-Francia test, and the Anderson–Darling test for normality. This was then followed by plotting of the autocorrelation function and partial autocorrelation function to determine $ARIMA\ (p, d, q)$, where $p$ is the order of autoregression (AR), $d$ is the lagged difference between the current and previous values, and $q$ denotes the order of the moving average (MA). The maximum values of $p$ and $q$ were set as 24, and the maximum number of non-seasonal difference ($d$) was established as 4. Additionally, Naïve, seasonal Naïve, mean, exponential smoothing, drift, and Holt's methods were also implemented and compared with ARIMA. The study elects fitted model with minimum Akaike information criterion (AIC) and Schwartz Bayesian criterion (BIC) as the optimal forecasting model [9]. The accuracy of the forecast was then measured based on the sum of errors.

3. Results
3.1. Temporal Analysis
Figure 1 shows the original data decomposed into observed, trend, seasonal, and random data. Figure 2 depicts the seasonal plot for the same. The figure shows the non-polar view of the seasonal plot.

![Decomposed time series plot](image)

**Figure 1:** Decomposed time series plot of weekly cardiology admissions from catheterization laboratory from March 1, 2012, through November 3, 2016. The observation plot shows an increasing trend over the past years and a cyclic seasonal effect.
3.2. Comparative analysis of forecasting methods
To determine the best fit time series model to forecast cardiology admission from catheterization laboratory visits, we implemented the following forecasting methods on the first 200 weeks of data (March 1, 2012 through December 31, 2015): ARIMA, Holt’s method, exponential smoothing, mean, drift, Naïve, and seasonal Naïve. Performance measures such as mean absolute error ($MAE$), mean absolute percentage error ($MAPE$), mean absolute squared error ($MASE$), mean error ($ME$), mean percentage error, and root mean squared error ($RMSE$) for each were measured and compared.

The best fit model $ARIMA (2,0,2) (1,1,1)$ with AIC of 1528 and BIC of 1553 was selected. Table 1 shows the sum of the errors of Naïve, seasonal Naïve (SN), mean, exponential smoothing (SES), drift, and Holt’s method and ARIMA. ARIMA with a minimum error was selected as the best fit model for this study. Table 2 describes the selected ARIMA model.

| Performance Measure | Models | ARIMA | Holt | SES | Mean | Drift | Naive | SN |
|---------------------|--------|-------|------|-----|------|-------|-------|----|
| Sum of error        | 27.9   | 34.0  | 37.7 | 44.6| 45.4 | 45.7  | 60.7  |

Table 2: ARIMA (2,0,2) (1,1,1)

| Coefficients | ar1 | ar2 | Ma1 | Mar2 | sar2 | sma1 | drift |
|--------------|-----|-----|-----|------|------|------|-------|
|              | -0.03 | 0.55 | 0.09 | -0.58 | -0.11 | -0.42 | 0.14  |
| s.e          | 0.87 | 0.65 | 0.87 | 0.69 | 0.21 | 0.23 | 0.01  |

3.3. Model Evaluation
To ensure a proper fit of $ARIMA (2,0,2) (1,1,1)$, we conducted Anderson-Darling normality test, Shapiro-Wilk normality test, Cramer-Von Mises normality test, Kolmogorov-Smirnov normality test, Pearson Chi-Square normality test, Shapiro-Francia normality test, Box-Ljung test, Augmented Dickey-Fuller test, Phillips-Perron unit root test, and Kwiatkowski-Phillips Schmidt Shin test. All the normality test of residuals mentioned earlier yielded a p-value of less than 0.05. Thus, the tests reject the null hypothesis of normality implying the residuals are not normally distributed. The same is shown in figure 4 below. Table 3 lists the values of the normality tests.
The data is likely to be non-normal. Figure 3: Quantile-Quantile plot.

![Quantile-Quantile Plot](image)

**Table 3: Normality tests**

| Test                        | p-value (0.05) | Null Hypothesis of Normality                  |
|-----------------------------|----------------|----------------------------------------------|
| Anderson-Darling            | 1.02 e^{-08}   | Rejects null hypothesis                      |
| Shapiro-Wilk                | 8.38 e^{-05}   | Rejects null hypothesis                      |
| Cramer-Von Mises            | 2.55 e^{-08}   | Rejects null hypothesis                      |
| Kolmogorov-Smirnov          | 7.13 e^{-12}   | Rejects null hypothesis                      |
| Pearson Chi-Square          | 2.20 e^{-16}   | Rejects null hypothesis                      |
| Shapiro-Francia             | 0.0001         | Rejects null hypothesis                      |

The Box–Ljung test on residuals gave a p-value of 0.73 (p-value > 0.05), which implies that there is no significant autocorrelation. In other words, there is a lack of evidence of independence. Figure 5 below shows the autocorrelation and partial autocorrelation plot.

![Autocorrelation and Partial Autocorrelation Plot](image)

**Figure 5:** (a) shows the ACF plot, (b) shows the PACF plot with one point exceeding the lower limit at 0.14

The augmented Dickey-Fuller test, and Phillips-Perron unit root test yielded a p-value of 0.01 each (p-value < 0.05); thus, the test rejects the null hypothesis of non-stationarity. Additionally, Kwiatkowski-Phillips Schmidt Shin test with a p-value of 0.1 fails to reject the null hypothesis of stationarity.

### 3.4. Forecast Accuracy

As discussed above, ARIMA (2,0,2) (1,1,1) exhibits the best weekly forecast accuracy. We forecasted 52 weeks (December 3, 2016, through December 2, 2017) ahead of the actual dataset as shown in figure 6 below. The following
Figure 7 shows a visual comparison of the forecasted and actual cardiology admissions from catheterization laboratory visits.

Figure 6: X-axis represents the years, and Y-axis indicates the number of cardiology admission from the catheterization laboratory. The figure shows the forecasted cardiology admission from catheterization laboratory (December 3, 2016, through December 2, 2017). The color shades in the figure show the different confidence intervals starting from 10% through 99%.

Figure 7: X-axis shows the timeline (January 30, 2016, through December 3, 2016) and Y-axis represents the cardiology admission from catheterization laboratory. The figure compared the actual admission (black line) and forecasted admission (blue line) to cardiology from catheterization laboratory at 80% and 95% upper and lower confidence intervals.

In Figure 7, the solid blue line represents the forecasted admission from January 30, 2016, through December 3, 2016, whereas the dashed black line denotes the actual admissions. The forecasted admission from catheterization laboratory was observed to increase with time, and the forecasted values lie within 80% and 95% upper and lower confidence intervals.

4. Discussion
The analyses performed in this study focus on a time series forecasting method using ARIMA in RStudio. The analysis forecasts weekly cardiology admissions from the catheterization laboratory and proposes the best fit ARIMA model. Based on AIC and BIC, the best fit model was found to be ARIMA (2,0,2) (1,1,1). ARIMA outperformed Holt’s method, exponential smoothing, mean method, drift method, Naïve method, and seasonal Naïve for this dataset. The model proposed in this study tests for normality, stationarity, and autocorrelation.

Several other studies have employed time series forecasting methodology to forecast hourly, weekly, monthly and yearly arrivals of patients, visiting the emergency department with high accuracy. This article is the first study concerning weekly forecasting of cardiology patient admission from the catheterization laboratory. The proposed model can help clinical staffs and management proactively deal with fluctuating patient admission rate. Weekly prediction not only provides a good overall idea of total admission for a month but might also project an acceptable annual telemetry bed demand in cardiology department or floor. All these proactive measures can help minimize overcrowding and advocate apt resource allocation.

5. Conclusion

ARIMA (2,0,2) (1,1,1) was the best fit model to forecast cardiology admission from catheterization laboratory and can serve as a decision support system in the healthcare industry. For future research, time series forecasting method such as neural networks, fuzzy logic, and TABTS shall be implemented and compared against ARIMA. Consecutively, hourly forecasting cardiology admission from catheterization laboratory can be used to manage staff schedules, bed allotment, and optimize in-patient flow.

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Data statement
Anonymized weekly cardiology admission from Catheterization laboratory data (March 1, 2012, through November 3, 2016) is available at DOI:10.17632/wgz36h39wt.2.

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