IOSR Journal of Mathematics (IOSR-JM)
e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 20, Issue 5, Ser. 1 (Sept. – Oct. 2024), PP 35-43
www.iosrjournals.org

Forecasting Outpatient Visits At Marimanti Level 4 Hospital: Time Series Analysis Using Sarima Model

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Abstract
The outpatient department (OPD) is the first point of contact in all hospitals, and patients create opinions about the hospital based on the quality of service they receive at OPD. The purpose of the study is to develop a Statistical model to forecast outpatient attendance at Marimanti Level 4 Hospital using SARIMA modeling. Monthly outpatient visits data obtained from Marimanti level 4 hospital (from January, 2013 to December, 2023) was used in the study. R and R Studio software were used for data analysis. The study employed the Box-Jenkins technique in modelling. The model that minimized the Information criteria was deemed the most plausible among a set of competing models. SARIMA (0,1,2) $(2,1,1)_{12}$ was the best model (AIC = 1139.56, BIC = 1154.52). The forecasting accuracy of the model was evaluated using the MAPE = 1.66% and MASE = 0.47%. Generally, the 2 years ahead forecast showed an increasing trend. Therefore, the hospital Management ought to take into consideration the forecasts to enable them prepare adequately in terms of resource allocation and planning purposes.
Keywords: *SARIMA Model, Forecasting, Information Criteria, Accuracy, Outpatient Visits.*

Date of Submission: 16-10-2024 Date of Acceptance: 26-10-2024

I. Introduction

Outpatient care refers to procedures and treatments which do not require patients to stay in the location of a procedure for additional monitoring or care. Facilities providing outpatient treatment include; primary care offices, community health centers, urgent care facilities, specialty outpatient facilities, pharmacies, and emergency rooms. Outpatient care services account for a number of different procedures, tests, and treatments which a patient can receive. They include; Services for prevention and well-being including psychological support, instruction on nutrition, a weight reduction program and counseling on diets, diagnostic procedures such as (scanning and lab examinations) and rehabilitation services: Physical and occupational therapy.

Time series modeling is crucial for health care administrators to better understand the characteristics and the nature of the variation (Aboagye *et al*., 2015). Because the ARIMA model captures linear patterns in data with least computational effort, most research utilize it to characterize the relationship among variables or as a benchmark to measure the efficacy of combination models. ARIMA models have a wide range of application in projecting hospital daily visits to Outpatient and Emergency Departments due to its efficiency in capturing linear properties of trend (Bergs *et al*., 2014). SARIMA Model is important in modelling and forecasting because of its ability to extract linear pattern from complex data and simplicity in its computations to achieve desired outcome, saving time and effort (Dabral and Murry, 2017).

A great opportunity exists for nations with low or middle-incomes to address the quality while constructing UHC. It is possible to influence, guide, and foster a developing health system in the way that is wanted. As the system expand and changes, quality can be ingrained in its institution, procedures and rules. While delivering excellent medical care to everyone may appear unrealistic, the task is possible across all contexts with effective management, diligent preparation, and proper funding. Indicators have improved across the board in Uganda due to a strategy that involves communities and residents in the design of the healthcare service, including a 33% decrease in child mortality (Citizen Voice and Action, 2012). Low quality of care leads to increase in disease burden, unmet medical need and has enormous cost repercussions for local communities and the global health system. Trillions of dollars are spent each year on patient harm from live-time impairments, disabilities, and productivity loss. The underprivileged groups in society are disproportionately affected by low treatment quality (Slawomirski *et al*., 2017).

For 10-year period data from 2008 to 2017, Borbor *et al*. (2018) modeled hospital attendance in Cape coast teaching Hospital for both Insured and Uninsured patients on a monthly basis. The data used was a secondary source. The preferred models were SARIMA (1,0,0) $(0,1,0)_{12}$ and SARIMA (1,1,1) $(2,0,1)_{12}$ for Insured and Uninsured patients respectively. The research was conducted to ascertain how the Outpatient has impacted on patients' attendance in seeking health care with time using time series analysis.

Kam *et al*. (2010) suggested three models for forecasting daily Emergency Department (ED) patient visits. (a.) Moving Average MA (2); (b.) Univariate SARIMA model: SARIMA (1, 0, 1) (0, 1, 1)$_7$; (c.) Multivariate Seasonal ARIMA model: SARIMA (1,0,2) (0,1,1)$_7$. The MAPE for both SARIMA models were less than 10%, indicating a good level of accuracy. Because the SARIMA models have autoregression and the ability to adjust seasonal components, they are more accurate than the moving average.

Baharsyah and Nurmalasari (2020) used ARIMA and Exponential Smoothing to predict patient visits to the RSUD Kembangan emergency department. Based on the MSE and MAPE, ARIMA (1,1,2) was selected as the most probable model for predicting patient visits to the RSUD Kembangan hospital emergency department outperforming the Exponential Smoothing model.

Luo *et al.* (2017) investigated a prediction method to forecast outpatient visits. In order to estimate short-term daily outpatient visits, they combined a SARIMA model with a Simple Exponential Smoothing (SES) model to evaluate the forecast accuracy for each model, as well as that of a combinatorial model. When predicting daily outpatient visits one week in advance, the combinatorial model outperforms simple models and extracts more precise information with a limited training sample size.

Marimanti level 4 hospital is a public health facility in Kenya. It is a primary care hospital located in Tharaka Nithi County, Tharaka Constituency, Tharaka South Sub-County, and Marimanti ward, along Chiakariga – Marimanti road near Marimanti Market

II. Methodology

Data Collection

The research used secondary data of monthly Outpatients attendance data from Marimanti Level 4 Hospital over a period of 11 years (2013-2023). The data was well documented accurate and authentic to meet the objective of the study. The data had 132 observations.

Data Analysis

The study adopted SARIMA model to model and forecast the outpatient visits at Marimanti Level 4 hospital. The study employed the Box-Jenkins approach in modeling.

Seasonal Autoregressive Moving Average (SARIMA) Process

SARIMA (p, d, q) (P, D, Q) is applied in modeling a time series with both trend and seasonality. Differencing is applied to remove trend in the series (p, d, q), followed by seasonal differencing to remove seasonality (P, D, Q). SARIMA (p, d, q) (P, D, Q)$_s$ model is defined as;

$$\varphi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D X_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \quad (1)$$

Procedure for SARIMA Process

The first step in modeling time series data is to ensure the series is stationary either by transformation of data or differencing. This study employed Augmented Dickey-Fuller (ADF) to test if the series is stationary and to determine the number of trend and seasonal differencing to achieve stationary.

The Hyndman-Khandakar (HK) method was used with the forecast package in R, (Hyndman and Khandakar, 2018). The approach uses an iterative strategy that saves time and make it simple to identify the model with the lowest AIC and BIC without having to compare it to every other model that might be used (Dabral and Tabing, 2020). The flow chart below summarizes SARIMA modeling.

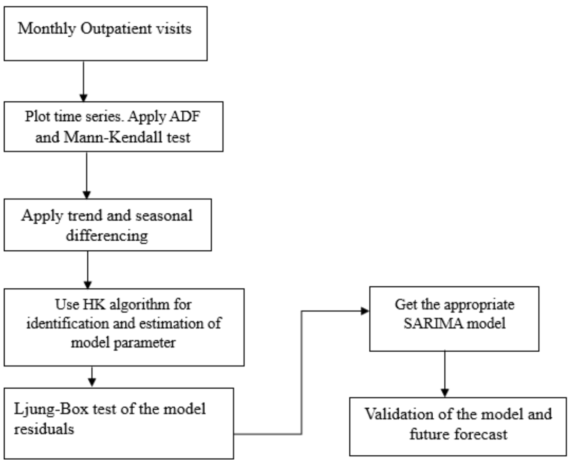

Figure 1. Flow Chart of SARIMA Modeling

Test for trend in Time Series Data

The Mann-Kendall (MK) test was used to determine if the outpatient visits series exhibit a monotonic upward or decreasing trend over time. MK, unlike parametric linear regression analysis, does not require the fitted line's residual be normally distributed. Kendall's test ranks all the data by time order, the difference between consecutive values is calculated and the sum of the signs of difference as the Kendall sum, S statistic, (Kendall, 1948). Mann-Kendall test trend component in time series data and has the following hypothesis.

H_0: There is no trend in the monthly outpatient attendance.

H_1: There is a trend in the monthly outpatient attendance.

The H_0 is rejected if p-value < 5% level of significance (two-tailed), meaning there is a trend in the monthly outpatient attendance

Test for Stationarity for Time Series Data

Test for Stationarity is important in understanding the data and selecting the prediction model. This study will test for stationarity using the Augmented Dickey-Fuller (ADF) test. ADF is a unit root test.

ADF test presence of a unit root and has the following hypothesis.

H_0: The series non stationary.

H_1: The series is stationary.

The H_0 is rejected if p-value < 5% level of significance, meaning the series has no unit root/the series is stationary, (Dickey and Fuller, 1979).

Akaike Information Criteria (AIC)

Akaike information criteria was developed by Hirotugu Akaike in 1974. Assuming X_t is an ARMA process, then, the AIC is defined as;

$$AIC = -2\log\left[L\left(\hat{\varphi},\hat{\theta}\right)\right] + 2k \tag{2}$$

Where $L\left(\hat{\varphi},\hat{\theta}\right)$ is the maximum likelihood function which measures a model fit. k Is the number of parameters; it penalizes overfitting when more terms are added.

Time series model with lowest AIC value is chosen. AIC will favor an over fitted model for small samples (Claeskens and Hjorth 2010). Consequently, AICc was generated to address the overfitting for small sample size. AICc is defined as;

$$AICc = AIC + \frac{2k^2 + 2k}{n - k - 1} \tag{3}$$

where n is the number of observation and k is the number of parameters.

Burnham *et al*. (2002) noted that the extra penalty term converges to zero as the sample size approaches infinity, leading to convergence of AICc to AIC.

Bayesian Information Criteria (BIC)

It was developed by Gideon E. S. (1978). It is defined as;

$$BIC = -2\log\left[L\left(\hat{\varphi},\hat{\theta}\right)\right] + \log(n)\,k \tag{4}$$

Where $\log\ (n)\,k$ is the penalty term.

BIC penalizes model complexity more than AIC. Basing on BIC, the model with the lowest BIC is selected.

Model Diagnostic

The Ljung-Box statistic is a function of the total sample autocorrelation, r_j up to any time lag m. It was developed by Greta Marianne Ljung and George Edward Pelham Box in 1978. The Ljung-Box statistic was used to assess the residuals of the model to see if all autocorrelations for errors are zero. The Ljung-Box statistics is defined as;

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{{r_j}^k}{n-j} \tag{5}$$

where n is the usable number of data points after differencing.

The ideal ACF for residuals is that the autocorrelations are zero. A p-value < 0.05 indicate possibility of non-zero autocorrelation for the first m lags.

Model Accuracy Evaluation

Mean squared error (MSE) and root Mean absolute percentage error (MAPE) values was used to provide insight into the model's performance with the goal of assessing forecasting accuracy and make adjustments as deemed.

III. Results And Discussion

Descriptive Statistics

Table 1 shows the summary statistics of the outpatient series. The large change between the highest and the lowest number of outpatient visits confirms an increasing trend. The negative value of skewness indicates that the data relatively symmetrical about the mean. The negative kurtosis value indicates that the observations are located close to the mean, therefore the series is relatively normally distributed.

Table 1: Descriptive Statistics of the Series

Descriptives:	Mean	Standard deviation	Skewness	Kurtosis	Maximum	Minimum
Statistics:	2563.17	215.47	-0.23	-0.61	3000	2000

The trend of Outpatient Attendance at Marimanti Level 4 Hospital

The first requirement for time series modelling is that the series be stationary. A time series is said to be stationary if its mean (trend) does not change systematically and its variance does not fluctuate (season). The trend in the series is determined via the time plot, series decomposition, unit root test (Augmented Dickey Fuller test), and the ACF and PACF correlograms.

Time Plot

Figure 2 illustrates that the outpatient visit data fluctuates continuously during the study period, with noteworthy peaks and troughs. The low volume of outpatient visits in 2013 can be related to the transition from a national to a devolved system of government. The Hospitalists' strikes in 2016 and 2017 caused a drop in outpatient attendance. Overall, the number of outpatient visits has increased over time, with the lowest number in 2013 at 2000 and the highest in 2023 at 3000.

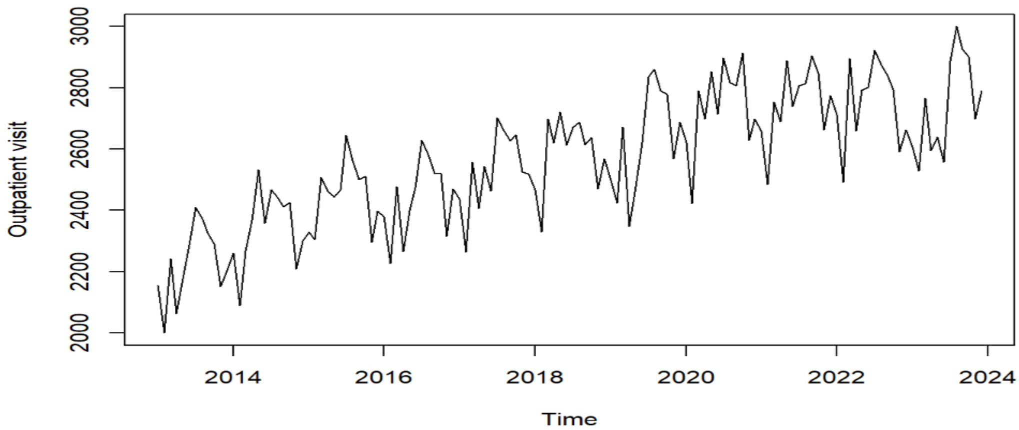

Figure 2. The time plot of the Outpatient visits at Marimanti Level 4 Hospital

ACF and PACF Correlogram

ACF and PACF graphs are crucial for determining whether a data series is stationary. The figure is used to check for randomness; if random, the autocorrelation should be near zero.

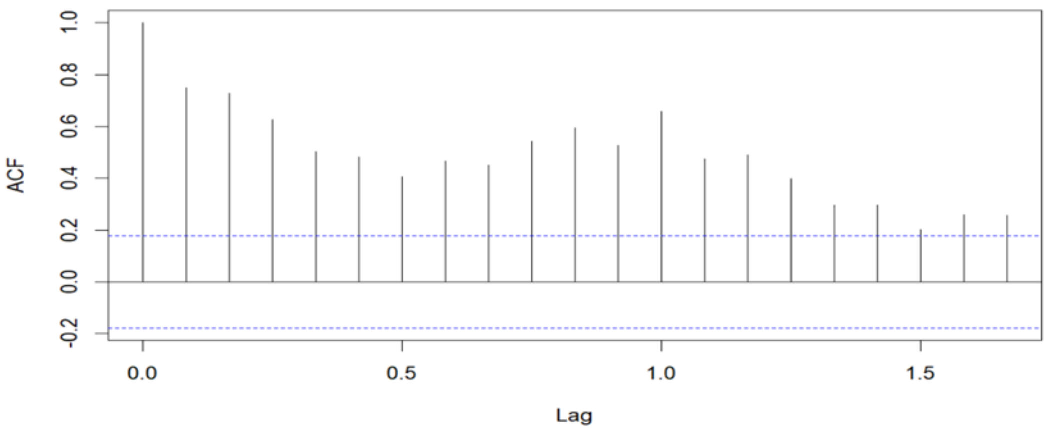

Figure 3. ACF Correlogram

Figure 3 shows that the ACF of the outpatient visit series gradually drops, indicating a link between past and current values. This suggests that the series is not steady. The partial autocorrelation function (PACF) exhibits spikes at the lower latency that surpass the significant bound, as illustrated in Figure 4.

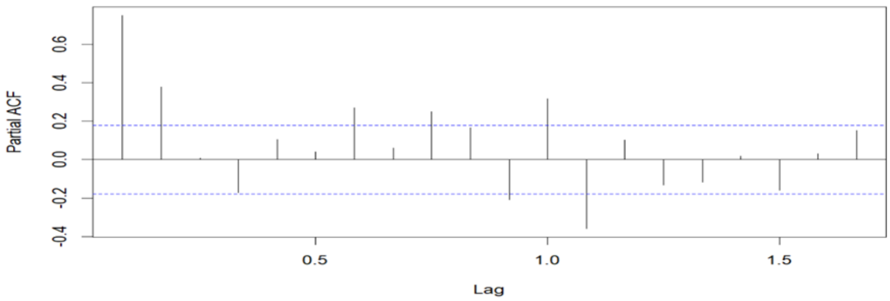

Figure 4. PACF Correlogram

Augmented Dickey Fuller (ADF) Test

The ADF test was used to assess the stationarity of the outpatient visit series. The p value was determined to be 0.4134, which is greater than the level of significance 0.05; thus, the null hypothesis that the outpatient visit series is non-stationary is supported. Furthermore, trend analysis using the Mann Kendal test revealed that outpatient visits at Marimanti Level 4 hospital are growing. The p-value is $2.22e^{-16}$, is less than the 5% level of significance, therefore the series has trend and requires differencing. Unlike the study by Mohamed and Mohamad (2020), which used the ACF and PACF plots to check the stationarity of the series, the current study also used the ADF unit root test and Mann Kendal test to check for stationarity and trend analysis.

Series Decomposition

Series decomposition is a way of breaking down a series in order to extract the individual components. Decomposing the outpatient visits series reveals that the series is made up of trend, periodic, and random components, as illustrated in Figure 5, hence modeling the series with the SARIMA model is appropriate. The seasonal influence is explored for the months of January to December. The highest periodicity is in July, and the lowest in February around, indicating that the number of outpatient visits is anticipated to surge in July and least in February.

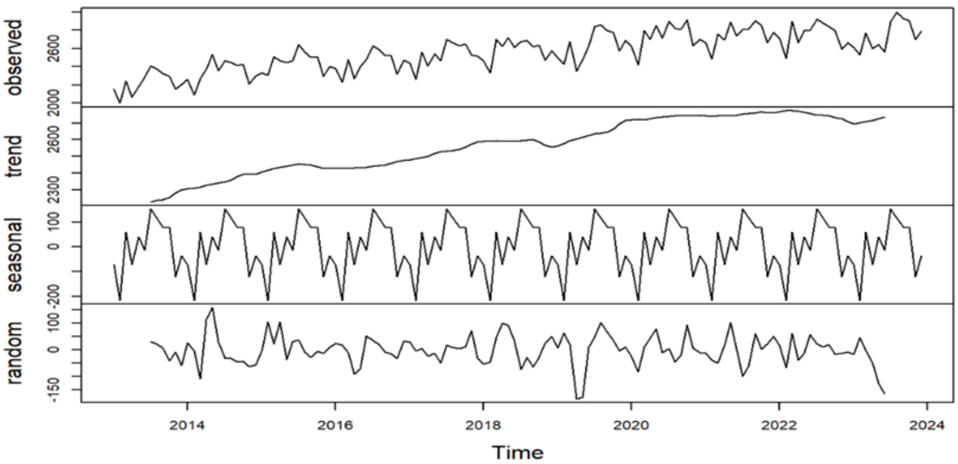

Figure 5. Decomposition of Outpatients' visit

Differencing the Outpatient Visits Series

Figure 6 reveals some noticeable patterns in the series after obtaining the first seasonal difference; thus, to eliminate trends in the series, the first trend difference is used. Figure 7 shows that the outpatient visit series is stationary, as shown by the lack of a distinct pattern across time. The trend analysis was conducted to the first differenced series using the Mann Kendall test. The p-value is 0.85897, which is greater than the 5% level of significance, demonstrating that the series is trend stationary after the initial distinction. Furthermore, the ADF test was done to evaluate the presence of unit roots in the series after the first difference; the test produced a p-value of 0.01, which is less than the 0.05 level of significance; consequently, the null hypothesis of non-stationarity is rejected, and the series is ready for modelling.

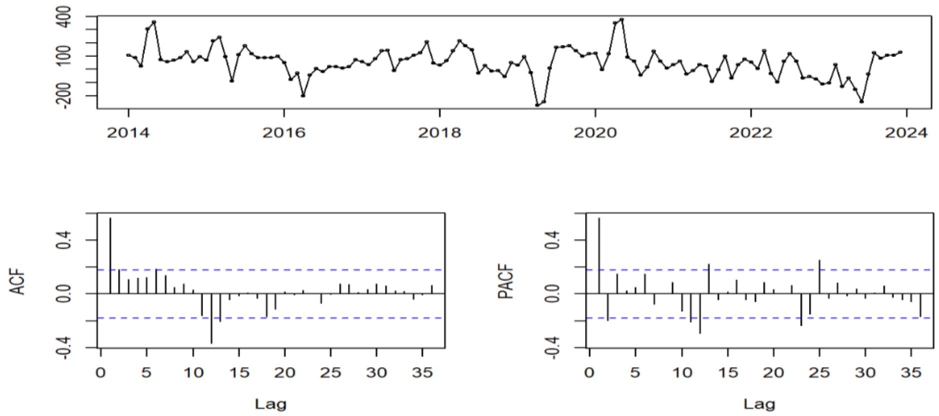

Figure 6. Graph Of First Seasonal Differenced Data

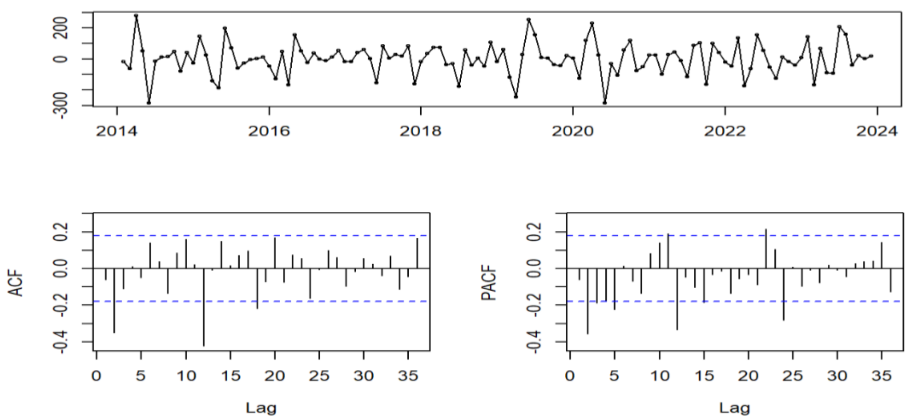

Figure 7. Graph Of Trend Differenced Outpatient Visits

SARIMA Model Development using Outpatient Attendance Data

The SARIMA model was developed using the Box-Jenkins approach, which includes model identification, parameter estimation, and diagnostic checking.

Model Identification

The goal is to generate a suitable SARIMA model from the ACF and PACF of the differenced outpatient series shown in Figure 7. The significant correlation at lag 2 in the ACF suggests a non-seasonal MA (2). The ACF's significant spike at lag 12 suggests a seasonal MA (1). Thus, we begin with the seasonal ARIMA (0,1,2) $(0,1,1)_{12}$ model. Using the PACF plot, we have Seasonal ARIMA (0,1,2) $(2,1,1)_{12}$ model, in which the PACF was used to choose the non-seasonal part and the ACF to pick the seasonal part of the model. The model with the lowest AIC and BIC values is regarded the best among the competing models. Table 2 displays the set of competing SARIMA models, together with their AIC and BIC.

Table 1: Set of Competing SARIMA Models

Model	AIC	BIC
SARIMA (0,1,1) $(1,1,2)_{12}$	1150.63	1163.34
SARIMA (0,1,1) $(2,1,1)_{12}$	1142.71	1155.42
SARIMA (0,1,2) $(1,1,2)_{12}$	1147.44	1162.7
SARIMA (0,1,2) $(1,1,1)_{12}$	1173.52	1188.78
SARIMA (0,1,2) $(2,1,1)_{12}$	**1139.56**	**1154.82**
SARIMA (0,1,2) $(2,1,0)_{12}$	1170.16	1182.87
SARIMA (1,1,1) $(2,1,2)_{12}$	1176.86	1192.12

The SARIMA (0,1,2) $(2,1,1)_{12}$ is the most plausible model for outpatient visits at Marimanti level 4 hospital having the least AIC and BIC values.

Model Parameter Estimation

Maximum likelihood method was used to estimate the model parameters. Equation 1 shows the generic form of the Sarima model. The best model for forecasting outpatient visits at Marimanti Level 4 Hospital is SARIMA (0,1,2) $(2,1,1)_{12}$. The computed coefficients are displayed in Table 3.

Table 2. Table of Coefficients

Variable:	MA (1) [θ_1]	MA (2) [θ_2]	SAR (1) [Φ_1]	SAR (2) [Φ_2]	SMA (1) [Θ_1]
Coefficient:	-0.3965	-0.3456	-0.5925	-0.4579	-0.3407
Standard Error:	0.0926	0.0926	0.1512	0.1148	0.1645

Table 3 reveals negative values for θ_1 and θ_2, indicating that the shock from two periods ago is still felt in the current period. The seasonal AR coefficients Φ_1 and Φ_2 indicate that the value of outpatient visits at time t is significantly influenced by the number of outpatient visits two periods ago, i.e. values of periods 12 and 24. The negative indicates an inverse connection. The seasonal MA coefficient, Θ_1, indicates how the error term from the prior year's season affects the current number of outpatient visits. The negative result indicates that a positive shock from one year ago reduces the current number of outpatient visits by approximately 34.07% of the shock's size.

The SARIMA (0,1,2) $(2,1,1)_{12}$ is given as;

$$(1 + 0.5925B^{12} + 0.4579B^{24})(1 - B)^d(1 - B^s)^D y_t = (1 + 0.3965B + 0.3456B^2 + 0.3407B^{12} + 0.1351B^{13} + 0.1177B^{14})\varepsilon_t \quad (6)$$

where, $(1 - B^s)^D y_t = y_t - y_{t-s}$(Seasonal difference), $(1 - B)^d y_t = y_t - y_{t-1}$ (non-seasonal differencing) and y_t is the number of outpatient visits at time t.

Diagnostic test and Model Accuracy Evaluation

Figure 8 illustrates that the residual autocorrelations for the first 36 lags are all inside the significant bound. As a result, the residues are uncorrelated and exhibit a normal distribution, as demonstrated by the normality plot. This implies that the residues are a sequence of white noise with mean zero and constant variance, which is an ideal condition for the model's residuals. Further diagnostics using the Ljung-Box test revealed that the model's residual autocorrelation is zero, as the test p-value of 0.9409 is greater than the 5% level of significance. MAPE and MASE were used to assess the model's forecasting accuracy. SARIMA (0,1,2) $(2,1,1)_{12}$ has the least MAPE = 1.664% and MASE = 0.46% and is thus considered to accurately estimate the outpatient visit at Marimanti level 4 hospital.

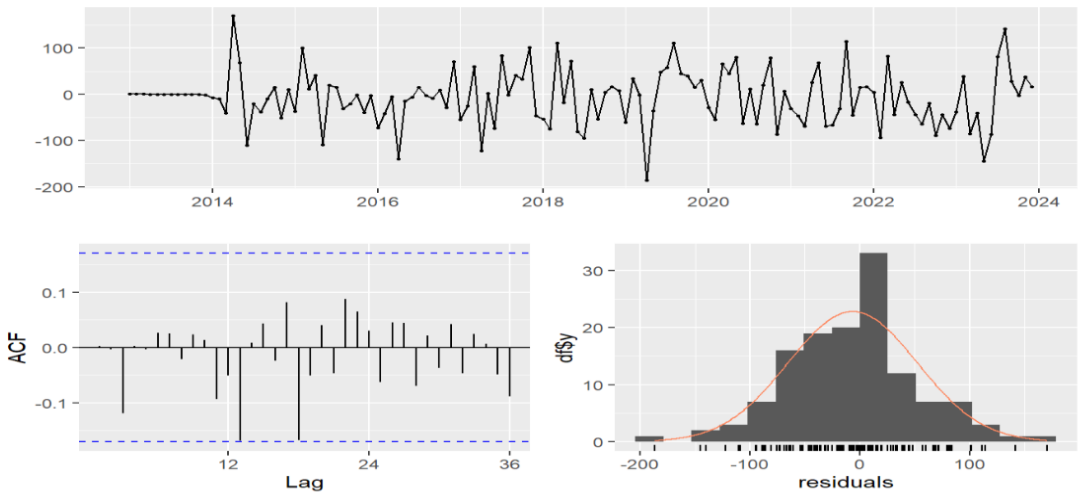

Figure 8. Plot of Residuals from SARIMA (0,1,2) $(2,1,1)_{12}$ model

Forecast the Outpatient Attendance for the next two year

The graph in Figure 10 shows that the number of outpatient visits at Marimanti Level 4 hospital continues to rise in the forecasted period. The forecasts strongly agree with the observed outpatient visits series pattern.

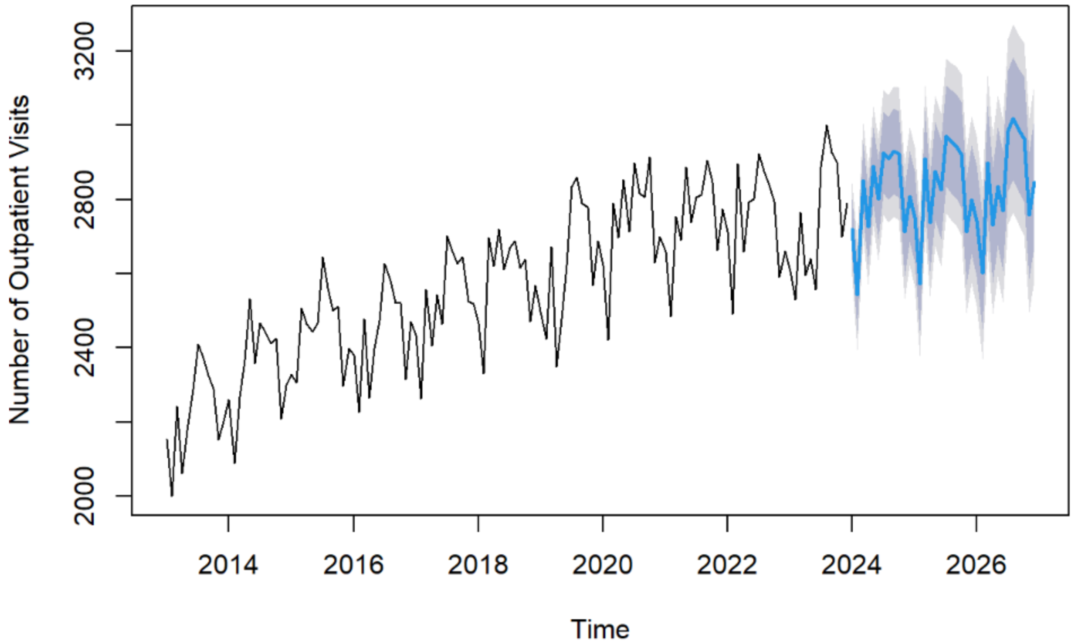

Figure 1. Forecast graph

IV. Conclusions

The study used time series research design in modeling the Outpatient visits series which is a utilize the Box-Jenkins techniques. The study used Monthly outpatient data from Marimanti Level 4 Hospital covering 10 years (January, 2013 - December, 2023). Outpatient visit series is seasonal. The month of February and July had the lowest and highest seasonal effect respective. The outpatient visits series had trend and strong positive correlation from Mann Kendall test which gave tau = 0.617 and a 2-sided P value = $2.22e^{-16}$. First order seasonal and non-seasonal differencing rendered the series stationary. Based on the information criterion, SARIMA (0,1,2)$(2,1,1)_{12}$ emerged as the most plausible model to describe the outpatient visits at Marimanti level 4 hospital having. The model also has the least MAPE and MASE of 1.664% and 0.46% respectively, the model was used to make forecast of the outpatient visits two years ahead. The outpatient visits will increase in the forecasted period and the Management of Marimanti level 4 hospital should put into consideration the forecasts in planning to ensure adequate supplies and human resource. Model update by continuous data collection and analysis to ensure that the model captures any emerging pattern. Machine learning models is recommended to give more insight to the outpatient visits including the disease prevalence and predisposing factors.

V. Acknowledgement

The completion of this endeavour owes much to the Almighty God's Grace and Mercy. Special thanks to my supervisors, Prof. Dennis K. Muriithi and Dr. Daniel Mwangi, for their feedback, critical ideas, and strong sense of direction throughout the study. Special gratitude to the Marimanti level 4 Hospital, led by the Medical Superintendent, for allowing me to do my research on their premises. Special appreciation to the Faculty of Physical Science, Engineering, and Technology, led by Dean Dr. Fidelis Ngugi, for helping me enhance my mathematical skills. God bless you everyone!

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