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Modelling and Predicting Daily Arrival of Patients at the Accident and Emergency Department of the University of Cape Coast Hospital, Ghana

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Abstract

Background: Modelling and forecasting demand for future emergency healthcare services is increasingly gaining wide attention in the emergency healthcare industry worldwide. This aids hospital managers in looking into various options to appropriately plan and allocate available scarce resources for optimal and swift performance. Despite its importance, our knowledge of daily patient flow into the Accident and Emergency Department (AED) of the University of Cape Coast Hospital is incomprehensive, and even the model that best explains its movements remains unknown.

Methods: Using daily periodicity of 517 time-series observations on daily patient arrivals sourced from the AED register over January 2020 through May 2021 the autoregressive integrated moving average (ARIMA) of the classical Box-Jenkins methods of time series analysis was used to analyse the data.

Results: This study revealed twenty-five non-seasonal candidate models for the hospital AED and ARIMA (0, 1, 2) emerged as the best fitting model. The study results showed that the daily patient arrivals at the AED section of the University Hospital witnessed a 50% decline on average within the study period and a further 33% decline in the forecast region. The findings also revealed very high volatility in daily patient arrivals with an average of eight patient arrivals per day.

Conclusion

Non-seasonal ARIMA (0, 1, 2) was identified as the best model. Thus, for policy, intervention, and future research direction, it is recommended that steps are taken to investigate the highly volatile nature of patient arrivals as well as the steady downward trending of the daily patient flow at the Accident and Emergency Department of the University Hospital.

Keywords: Emergency, Hospital, Modelling, ARIMA, Forecasting, University

1. Introduction

The Accident and Emergency Department (AED), plays a critical role in the healthcare delivery system of the Directorate of the University Health Services (DUHS) by providing emergency healthcare services to patients in need. However, the quality of emergency services is significantly affected by patient arrivals to the AED. Research has shown the detrimental effect of overcrowded emergency departments on the quality of carethus putting patients in severe conditions at very high risk (Salway et al., 2017; Xu et al., 2013). The American College of Emergency Physicians defined overcrowding at the emergency as a phenomenon that occurs when required emergency services needed far exceeds available resources for patient care at the emergency department (McKennia et al., 2019). To this end, health facilities equipped with emergency windows are increasingly paying attention to developments at the emergency department to provide better quality services for clients via optimization of human and material resource allocation (Afilal et al., 2016). One key strategy to achieving this goal is demand forecasting.

Time series simply refers to observations on a variable(s) recorded at regular intervals of time. These successive intervals could be hourly, daily, weekly, monthly, and so on. The main focus of time series analysis is to study the past behaviour of a given set of data and to make forecasts for the future for efficient planning. In this regard, time-series techniques are invaluable tools in many fields of research including health and have been greatly exercised. And should be noted that one of the most popular and widely used time series models in the field of forecasting is the autoregressive integrated moving average (ARIMA) model and its variants. There exist a large body of literature on forecasting the arrivals of patients at hospitals' emergency departments (Wargon et al., 2009). However, the extant literature remains silent on forecasting patient demand for emergency services in Sub-Saharan Africa. One study employed auto-regressive integrated moving average (ARIMA), Holt-Winters, and Neural Networks (NN) methods to model and forecast the hourly arrival of patients at an emergency department in a hospital in Des Moines city, Iowa (Choudhury et al., 2020). The study revealed ARIMA (3, 0, 0) $(2, 1, 0)_{24}$ as the best fit model for forecasting the hourly patient arrivals at the hospital's emergency than the other competitive methods. Hence, the study concluded that the ARIMA method can be used as a decision support system in the emergency healthcare industry. Another study modelled the monthly arrival of emergency patients at a medical centre in Southern Taiwan using ARIMA techniques of time series analysis (Juang et al., 2017). The study results revealed six non-seasonal candidate ARIMA models with ARIMA (0, 0, 1) having minimum Akaike information criterion (AIC) value emerging as the best fit model for the hospital. The model was consequently proposed for the decision-making process especially future prediction of emergency patient arrivals at the hospital. Jones et al., (2008) in their study, evaluated time series techniques; seasonal autoregressive integrated moving average (SARIMA), time series regression, exponential smoothing, and artificial neural network (ANN) models to forecast daily arrival of patient volumes at the emergency department of three different health facilities in Utah and southern Idaho in the United States. The results showed that SARIMA models of order (1, 0, 0) (0, 1, 1), (0, 1, 1) (0, 1, 1), and (0, 1, 1) (0, 1, 1) gave adequate model fit for the daily arrival of patients at the emergency department of the three selected different health facilities in Utah and southern Idaho. The study concluded that daily demand for emergency health services is characterized by the seasonal and weekly patterns for the selected health facilities. Another research study (Cheng et al., 2021) also found the seasonal autoregressive integrated moving average with external regressor (SARIMAX) very useful in the forecasting of hourly arrivals of patients visits at an emergency department of a large medical centre. The study results showed the SARIMAX method to be far superior with improved performance compared to other forecasting methods previously used, including the rolling average and were considered for forecasting.

Despite the large body of literature dealing with demand forecasting in the emergency healthcare industry across the globe very little or, no studies have been done in the area in the Ghanaian context from the perspective of university hospitals under Quasi-Government Health Institutions. However, dealing with the challenges of overcrowding and unexpected case spikes at the emergency department of hospitals is a global phenomenon (Asheim et al., 2019). And the unpredictable nature of patients' arrival at the accident and emergency departments of hospitals is of utmost concern to the management of hospitals (Carvalho-Silva et al., 2018). Hence, the demand forecast of daily arrivals of patients at the emergency department of the University of Cape Hospital is not only crucial but also serves as an excellent medium for tactical planning for the management of the hospital. Thus, this study specifically seeks to determine and model adequately the stochastic behaviour of the daily patient arrivals at the Accident and Emergency Department of the University of Cape Coast Hospital for forecasting purposes using one of the most important and widely used time series modelling methods the ARIMA (Juang et al., 2017).

2. Materials and Methods

2.1 Data Set

Daily periodicity data on patients' arrival at the Accident and Emergency Department of the University Hospital were retrospectively collected for a period of over 500 consecutive days ranging from January 2020 to May 2021 from the hospital's emergency ward register. The sample size was thus, made up of 517 daily observations of emergency cases. The ARIMA method which is a subsection of the Box-Jenkins methodology that this study adopted is suitable for application on a sample size of 50 observations and above (Yanovitzky and VanLear, 2008). The data was processed using *Eviews* 12, and *Rstudio* (version 4.0.4) software packages.

2.2 The Theoretical Framework

The publication by Box and Jenkins (1978) of *Time Series Analysis: Forecasting and Control* ushered in a new generation of relatively powerful forecasting tools for which this paper employed. These methods emphasise analysing the probabilistic, or stochastic, properties of the time series on their own under the philosophy *let the data speak for themselves*. The classical Box-Jenkins time series models allow the series Y_t(say daily emergency cases) to be explained by its past, or lagged, values and stochastic error terms. For this reason, ARIMA models are sometimes called *atheor etic*models because they are not based or derived from any theory.

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2.2.1 The Autoregressive (AR) Process

Let Y_t represent daily emergency cases series at time *t*.Y_t can be modelled as

$$(Y_t - \delta) = \alpha_1(Y_{t-1} - \delta) + u_t \qquad (1)$$

Where δ is the mean of *Y* and where u_t is an uncorrelated random error term with zero mean and constant variance $\sigma 2$ (i.e. *white noise*), then $Y_t$follows a first-order autoregressive, or AR (1), stochastic process. Here the value of *Y* at time *t* depends on its value in the previous time period (*t-1*) and a random termu_t . Similarly, an AR (2)can be modelled as

$$(Y_t - \delta) = \alpha_1(Y_{t-1} - \delta) + \alpha_2(Y_{t-2} - \delta) + u_t \qquad (2)$$

Hence, a p^{ath}-order autoregressive process is modelled as

$$(Y_t - \delta) = \alpha_1(Y_{t-1} - \delta) + \alpha_2(Y_{t-2} - \delta) + \cdots + \alpha_p\left(Y_{t-p} - \delta\right) + u_t \qquad (3)$$

In the AR process, only the current and previous *Y* values are involved; there are no other regressors.

2.2.2. The Moving Average (MA) Process

When a series is regressed against its own error term and past or lagged values of the error term then the process is a moving average (MA) process. Hence, an MA (1) process is modelled as

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} \qquad (4)$$

Where μ is a constant and *u*, as mentioned before, is the white noise stochastic error term. Equation (4) means that *Y* follows a first-order moving average, or an MA (1), process. Generally, a q^{th}order MA process or MA (q) can be expressed as

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \cdots + \beta_q u_{t-q} \qquad (5)$$

Simply put, a moving average process is simply a linear combination of white noise error terms.

The Autoregressive and Moving Average (ARMA) Process

Sometimes a series may exhibit characteristics of both AR and MA processes together and is therefore an ARMA process. For instance, an ARMA (1,1) process can be expressed as

$$Y_t = \theta + \alpha_1 Y_{t-1} + \beta_0 u_t + \beta_1 u_{t-1} \qquad (6)$$

where θ represents a constant term together with one autoregressive and one moving average terms. The generalised ARMA (p, q) process can be expressed as

$$Y_t = \gamma + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \beta_0 u_t + \sum_{j=1}^{q} \beta_j u_{t-j} \qquad (7)$$

where model contains p lags of the dependent variable, q lags of the error term with γbeing a constant.

2.2.3 The Autoregressive Integrated Moving Average (ARIMA) Process

The classical Box-Jenkins (1978) methods work on the assumption that the time series involved is (weakly) stationary. However, the empirical literature show that most time series variables are non-stationary, that is, they are not *integrated at level* and has to be differenced at a given order (***d***) to make them stationary. Therefore, if a time series would have to be differenced ***d***times to make it stationary and then apply the ARMA (*p*, *q*) process model to it, then the original time series is an ARIMA (*p*, *d*, *q*), that is, it is an autoregressive integrated moving average time series, where ***p*** denotes the number of autoregressive terms, ***d*** the number of times the series has to be differenced before it becomes stationary, and ***q*** the number of moving average terms in the series. The Box-Jenkins methodology is a four-step process in handling the ARIMA model building: Identification, Estimation, Diagnostic checking, and Forecasting. The identification process in developing the ARIMA model is to first identify the parameters of the model (*p, d, q*)for estimation and evaluation. This is where candidate ARIMA models can be identified and chosen. The main tools for the identification process include the autocorrelation function (ACF), and the partial autocorrelation function (PACF) with their corresponding correlograms. Table 1 gives the theoretical application of ACF and the PACF in the model identification process.

Table 1: Theoretical Application of ACF and PACF

Structure of model	Typical pattern of ACF	Typical pattern of PACF
AR(*p*)	Spikes decays exponentially towards zero	Significant spikes cut off to zero
MA(*q*)	Significant spikes cut off to zero	Spikes decays exponentially towards zero
ARMA(*p, q*)	Exponential decay	Exponential decay

The least squares methods or maximum likelihood estimators or nonlinear (in parameter) estimation methods are used to estimate the parameters after identification of candidate models. Diagnostic checking examines the estimated candidate models for selecting the best model fit under certain criteria such as model with maximum number of significant coefficients, minimum level of volatility, highest R sq. adjusted value, minimum Akaike Information Criteria (AIC) and Bayesian Information Criterion (BIC) value or Hannan-Quinn (HQ)criteria. For this reason, the classical Box-Jenkins methodology is often regarded more of an art than science (Gujarati et al.,2009) and thus considerable skill is required to choose the right ARIMA model. After fitting the appropriate ARIMA model, the goodness of fit is estimated by plotting the ACF of residuals of the fitted model and also conducting the Ljung-Box Test (1978) hypothesis to confirm that the model does not show lack of fit. If most of the sample autocorrelation coefficients of the residuals lie within the limits$(-1.96/\sqrt{N}, +1.96/\sqrt{N})$, where N is the number of observations, and the Ljung-Box test statistic is non-significant then the residuals are *white noise* indicating that the model fit is appropriate for forecasting. Also, the AR roots of the series if any as well as the MA roots must lie inside the unit circle. In other words, the estimated ARMA process must be (covariance) stationary and invertible. Once a model meets all these conditions then it can be safely used for forecasting. This means that there will be no need to look for another model.

3. Results

3.1 Descriptive Analysis

The time plot of AED daily patient visits in UCC Hospital for the period of January 2020 through May 2021 is depicted in figure 1. The results revealed that daily demand for AED services is neither characterised by seasonal nor weekly patterns but highly characterised by irregularities and volatilities for the study period. Hence, patient arrivals at the AED are characterised with large swings denoted as highly volatile and, in common parlance, as highly unpredictable.

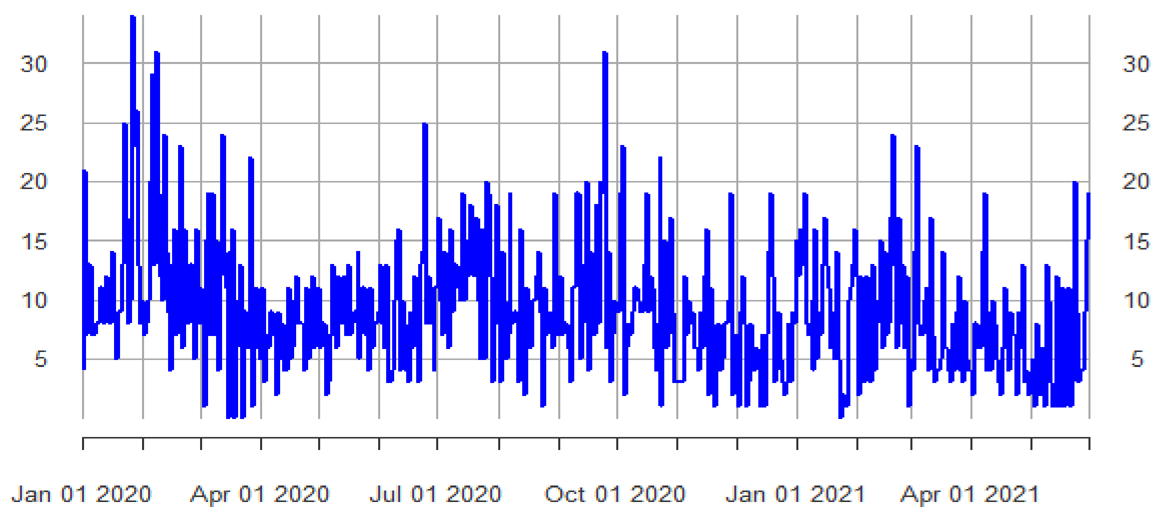

Figure 1: Time plot of AED daily patient arrivalsover January 2020 to May, 2021.

Figure 2 depicts the descriptive statistics as well as the distribution of the daily patient arrivals at the Accident and Emergency Department of the University Hospital. The figure indicates a non-symmetric and highly positively skewed distribution in the AED series with a skewness value of 1.0217. This means that the AED series is highly volatile and subject to surges. Also, the median of the distribution is 8.00 indicating that about 8 patients arrive at the AED of the University Hospital to seek emergency services on daily basis within the study period. Similarly, a bar graph of the quarterly averages for the period of January 2020 through June 2021 is depicted in figure 3. Figure 3 indicates a steady decline in the quarterly averages of daily arrival of patients at the AED of the hospital from 12 patients a day to about 6 for the period.

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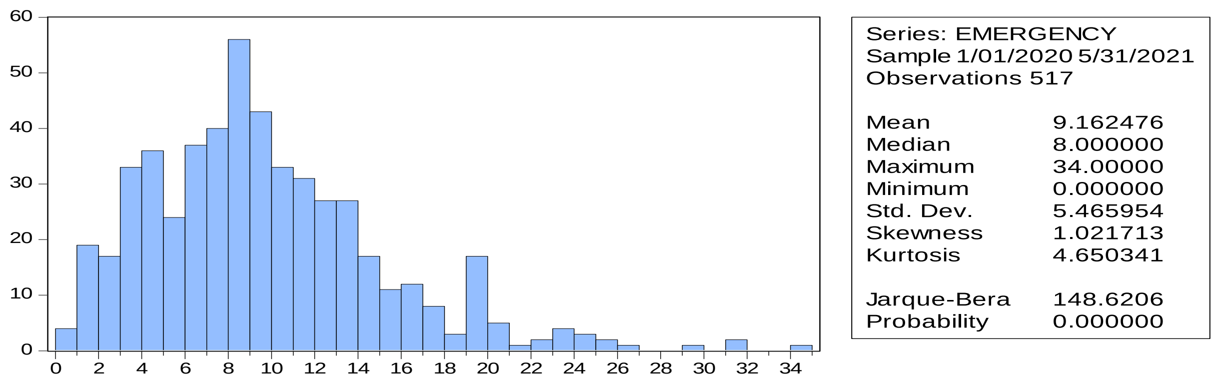

Figure 2: Distribution of the AED series in UCC Hospital over January 2020 to May 2021

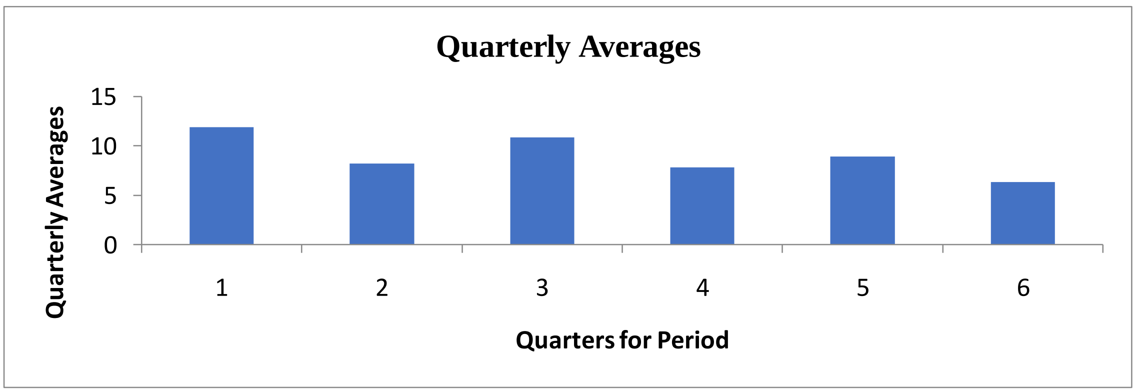

Figure 3: Quarterly averages of daily patient arrivals at AED, January 2020 to June 2021

3.2 Stationarity Test

The classical Box-Jenkins (1978) approach work on the assumption that the time series involved is (weakly) stationary. Hence, the Augmented Dicker-Fuller (ADF), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests were deployed to determine the stationarity or otherwise of the AED daily visit series variable in the hospital. Tables 2, & 3 give the results of the ADF, KPSS, and PP unit root tests of the AED variable respectively. As can be seen from tables 2&3 the unit root tests result revealed that the AED daily patient arrivals series is stationary at first difference.

Table 2: ADF Unit Root Test of AED daily visits in UCC Hospital at 5% significance level

OPD variable	At level		1stDifference	
Eqn Form	*t-statistic*	*p-value*	*t- statistic*	*p-value*
Intercept	-17.97042	0.0000	-12.92998	0.0000
Trend & Intercept	-18.95442	0.0000	-12.91420	0.0000
None	-0.766355	0.3840	-12.94378	0.0000

Null Hypothesis: AED/D(AED) has a unit root

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Table 3: KPSS Unit Root Test of AED daily visits in UCC Hospital at 5% significance level

OPD variable	At level		1st Difference	
Eqn Form	*LM- statistic*	*critical-value*	*LM- statistic*	*critical-value*
Intercept	1.105084	0.463000	0.107865	0.463000
Trend & Intercept	0.117529	0.146000	0.101186	0.146000

Null Hypothesis: AED/D(AED) is stationary

3.3 Identification of Tentative Candidate Models for the AED Daily Series

The study identified and presents twenty-five (25) nonseasonal tentative candidate models for the AED daily patient arrival series. Out of the twenty-five (25) candidate models identified, ARIMA (0, 1, 2) was selected as the best fitting model having the lowest AIC and BIC values of 6.137146 and 6.170012 respectively. Table 4 presents the twenty-five (25) nonseasonal tentative candidate models for the AED series with their corresponding criteria for selection.

Table 4: Model Selection Criteria Table for Tentative Candidate Models for the AED Series

Model	LogL	AIC*	BIC	HQ
(0,2)(0,0)	-1582.452142	6.137146	6.170012	6.150024
(1,1)(0,0)	-1582.502851	6.137342	6.170209	6.150220
(2,4)(0,0)	-1578.743786	6.138274	6.204008	6.164031
(3,3)(0,0)	-1578.778857	6.138410	6.204143	6.164166
(0,1)(0,0)	-1584.134529	6.139785	6.164436	6.149444
(1,2)(0,0)	-1582.367106	6.140685	6.181769	6.156783
(0,3)(0,0)	-1582.409841	6.140850	6.181934	6.156948
(2,1)(0,0)	-1582.445162	6.140987	6.182071	6.157085
(3,4)(0,0)	-1578.742434	6.142137	6.216088	6.171114
(4,3)(0,0)	-1578.747362	6.142156	6.216107	6.171133
(4,2)(0,0)	-1579.893563	6.142722	6.208455	6.168479
(0,4)(0,0)	-1582.233817	6.144038	6.193338	6.163356
(3,1)(0,0)	-1582.285248	6.144237	6.193537	6.163555
(2,2)(0,0)	-1582.350836	6.144491	6.193791	6.163808
(1,3)(0,0)	-1582.354578	6.144505	6.193805	6.163823
(4,4)(0,0)	-1578.363899	6.144541	6.226708	6.176737
(4,1)(0,0)	-1581.933211	6.146744	6.204261	6.169281
(1,4)(0,0)	-1582.221394	6.147858	6.205375	6.170396
(3,2)(0,0)	-1582.229122	6.147888	6.205405	6.170426
(2,3)(0,0)	-1582.332120	6.148287	6.205804	6.170824
(4,0)(0,0)	-1616.678041	6.277284	6.326585	6.296602
(3,0)(0,0)	-1622.369648	6.295434	6.336517	6.311532
(2,0)(0,0)	-1632.844471	6.332087	6.364954	6.344965
(1,0)(0,0)	-1663.062875	6.445118	6.469768	6.454776
(0,0)(0,0)	-1720.489093	6.663401	6.679834	6.669840

The further analysis gave the ARMA criteria graph for the top twenty models identified for the AED series of the University Hospital as well as the forecast comparison graphs and ARIMA (0, 1, 2) as can be seen in figure 4 is the leading model with the lowest AIC value followed by ARIMA (1, 1, 1) and ARIMA (2, 1, 4) respectively. Figure 5 is the forecast comparison graph showing the forecast graphs of the various tentative models identified with the best model depicted in red.

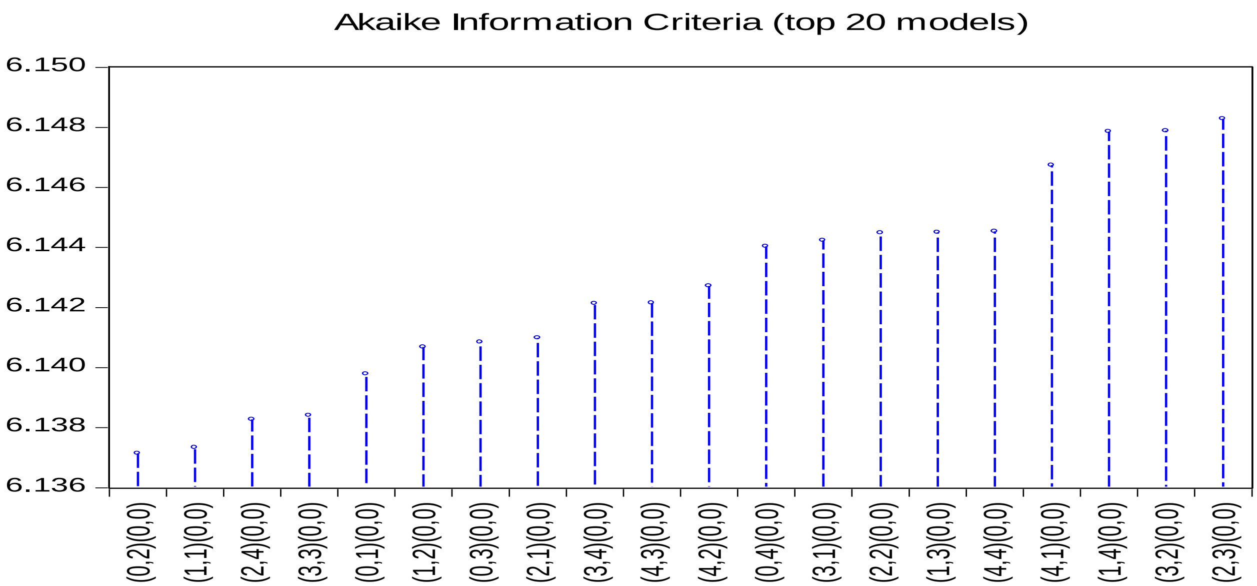

Figure 4: ARMA Criteria Graph showing AIC values of top 20 identified models

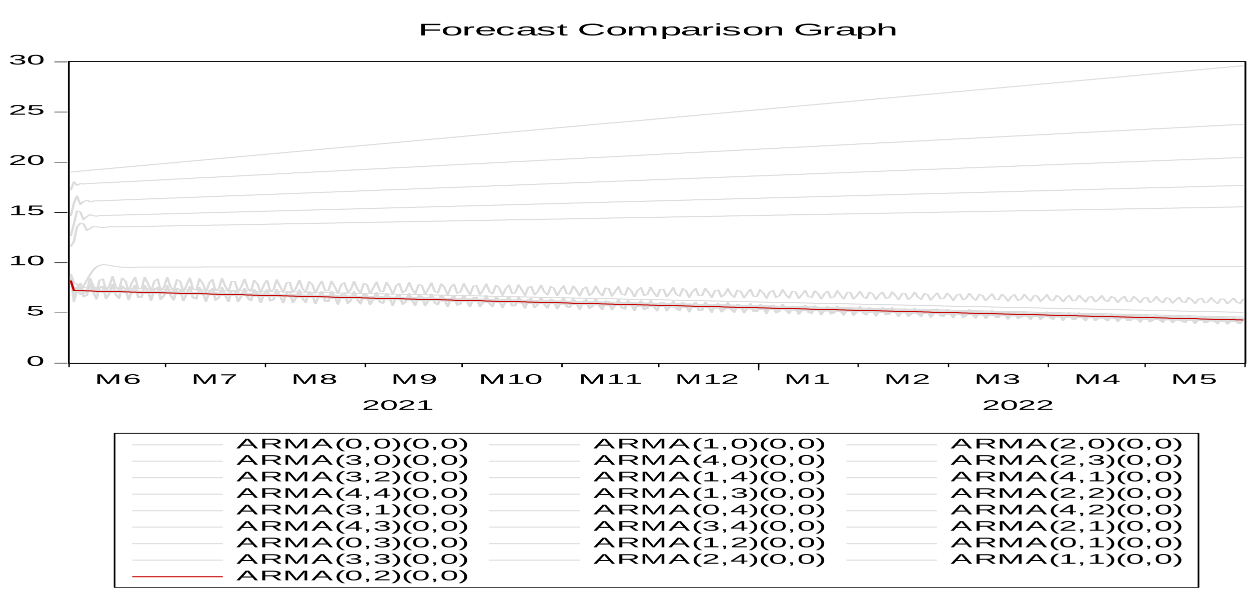

Figure 5: Forecast comparison graphs of candidate models showing the best model in red colour

3.4 Model Estimation, Validation and Forecasting

Attention must be drawn to the fact that ARIMA models are *atheoretic* models, and that they are not based on any theory hence, the estimated parameters of the selected best fit model which has the highest *R squared adjusted* value of 0.413085 are tabulated in Table 5. The estimated variance of the residual noise term is 26.89572, the log-likelihood is -1582.452142 with an AIC value of 6.137146 along a BIC value of 6.170012 are various information criteria for the selected model.

Table 5: Estimated Parameters for best model fit for AED ARIMA (0, 1, 2)

ARIMA(0, 1, 2)	MA(1)	MA(2)	SIGMASQ
Coefficients	*-0.844148**	*-0.083857**	*26.89572**

* (*P-value*< 0.05)

Figures 6&7 display the ACF and PACF plots of the residual of the best fit model. From these figures 6&7 it is clear that almost all of the sample auto-correlation coefficients of the residual lie within the limits $(-1.96/\sqrt{N}, +1.96/\sqrt{N})$otherwise known as the standard error bounds. The Ljung-Box chi-squared formal tests statistics showed non-significance (χ^2 = 3.1667, 4.5375, 37.049 and 40.923; *p-values*> 0.05) at lags 5, 10, 25 and 30 respectively indicating the possibility of zero autocorrelation within the prescribed lags. Therefore, the hypothesis that the residuals of the selected model are independently distributed is not rejected. Finally, the selected model only had two MA roots (0.93 & -0.09 < 1) which indicate that they lie inside the unit circle and this implies that the ARMA process is invertible. Thus, the errors of the selected model are *white noise* and hence model is appropriate for forecasting. The mathematical formula for the fitted model which will be used to produce the forecast plot and estimates is formulated as follows$Visit_t = -0.008066 + \beta_0 u_t - 0.844148u_{t-1} - 0.083857u_{t-2}$. The forecast graph of the daily patient arrival from the best fit model ARIMA (0, 1, 2) over the forecast length period of June 2021 to May 2022 is displayed in figure 8 and the corresponding point estimates are presented in Table 6.

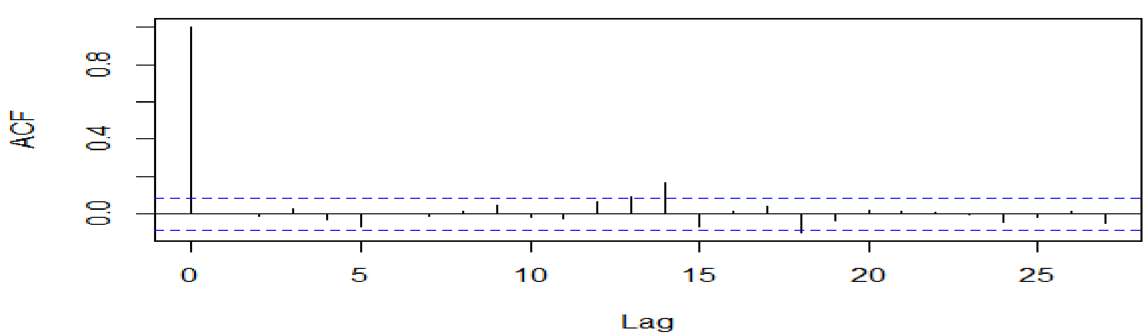

Figure 6: ACF plot of Residuals for selected model ARIMA (0, 1, 2)

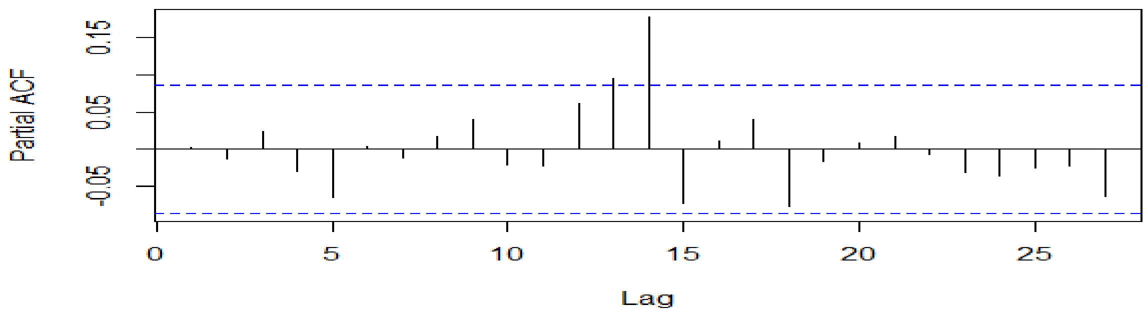

Figure 7: PACF plot of Residuals for selected model ARIMA (0, 1, 2)

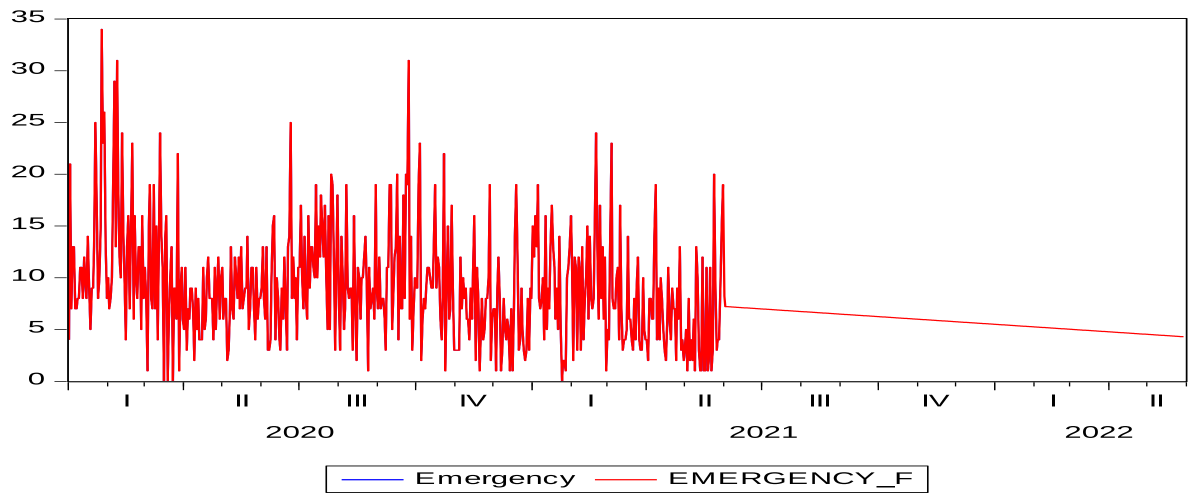

Figure 8: Forecast plot of AED daily patient arrivals over June 2021 to May 2022

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Table 6: Point Forecast estimates of Daily Patient Arrivals at AED over June 2021 to May 2022

Date	Jun-21	Jul-21	Aug-21	Sep-21	Oct-21	Nov-21	Dec-21	Jan-22	Feb-22	Mar-22	Apr-22	May-22
1	8	7	7	6	6	6	6	6	5	5	5	5
2	7	7	7	6	6	6	6	5	5	5	5	5
3	7	7	7	6	6	6	6	5	5	5	5	5
4	7	7	7	6	6	6	6	5	5	5	5	5
5	7	7	7	6	6	6	6	5	5	5	5	5
6	7	7	7	6	6	6	6	5	5	5	5	4
7	7	7	7	6	6	6	6	5	5	5	5	4
8	7	7	7	6	6	6	6	5	5	5	5	4
9	7	7	7	6	6	6	6	5	5	5	5	4
10	7	7	7	6	6	6	6	5	5	5	5	4
11	7	7	7	6	6	6	6	5	5	5	5	4
12	7	7	7	6	6	6	6	5	5	5	5	4
13	7	7	7	6	6	6	6	5	5	5	5	4
14	7	7	7	6	6	6	6	5	5	5	5	4
15	7	7	7	6	6	6	6	5	5	5	5	4
16	7	7	7	6	6	6	6	5	5	5	5	4
17	7	7	7	6	6	6	6	5	5	5	5	4
18	7	7	7	6	6	6	6	5	5	5	5	4
19	7	7	7	6	6	6	6	5	5	5	5	4
20	7	7	7	6	6	6	6	5	5	5	5	4
21	7	7	7	6	6	6	6	5	5	5	5	4
22	7	7	7	6	6	6	6	5	5	5	5	4
23	7	7	7	6	6	6	6	5	5	5	5	4
24	7	7	7	6	6	6	6	5	5	5	5	4
25	7	7	7	6	6	6	6	5	5	5	5	4
26	7	7	7	6	6	6	6	5	5	5	5	4
27	7	7	7	6	6	6	6	5	5	5	5	4
28	7	7	7	6	6	6	6	5	5	5	5	4
29	7	7	7	6	6	6	6	5		5	5	4
30	7	7	7	6	6	6	6	5		5	5	4
31		7	6		6		6	5		5		4

4. Discussion

The study purported to model and predict daily patient arrivals at the Accident and Emergency Department (AED) of the University of Cape Coast Hospital. Data on the daily arrival of patients at the AED section of the University Hospital was collected from the AED register for analysis.

The Jarque-Bera (JB) test of normality of the AED series proved significant (*P-value < 0.05*) as shown in figure 2. The distribution of the series was non-symmetric and extremely positively skewed with a skewness value of 1.0217. This means that the AED series is highly volatile and subject to surges with a median of 8 patients per day within the study period (see figures 1&2). The study results after a rigorous analysis revealed twenty-five (25) nonseasonal candidate ARIMA models. And the best model fit for determining and predicting the daily patient arrivals process of the University of Cape Coast Hospital AED section is ARIMA (0, 1, 2) viz zero-order autoregressive, second-order moving average and first differencing (see Tables 2&3). Among other top competitive models (see figure 4) such as ARIMA (1, 1, 1), ARIMA (2, 1, 4), ARIMA (3, 1, 3), and ARIMA (0, 1, 1) the selected model had maximum significant coefficients, minimum volatility of 26.89572, highest adjusted R-squared value of 0.413085, minimum AIC, BIC, and HQ values of 6.137146, 6.170012, & 6.150024 respectively. Residual analysis of the fitted model which is both formal (Ljung-Box test) and informal (correlogram of residuals) indicated that the model was adequate and stable and was validated for forecasting (see figures 6&7). The finding of a nonseasonal ARIMA model for the AED section of UCC Hospital in this study concurred with the finding of Juang et al., (2017) who found an adequate nonseasonal ARIMA model-ARIMA (0, 0, 1) for the emergency department section of a medical centre in southern Taiwan. Studies have shown that several exogenous factors also play a role and thus influence the arrival of patients at hospital emergencies (Juang et al., 2017; Kunu and Agbede, 2021; Lowen et al., 2007; Al-Reshidi, 2013). This paper, however, did not include in its modelling process exogenous variables such as food poisoning, weather, accidents, epidemics, and even medical or political crisis which may play a crucial role in determining the arrival of patients at hospitals emergencies. It must also be stated clearly that irrespective of how powerful a model could be there are uncertainties abound in the real world to which the model cannot capture into its modelling process and this model is not an exception.

The study did not find any literature on the application of ARIMA modelling in its context domain and boasts that its findings represent the first of its kind in the context under discussion. However, the closest to the purpose of this study in the extant literature is the study by Kunu and Agbede (2021) which discussed modelling patients' waiting time in accessing health care services in Ghana using the University of Cape Coast Hospital as a case study. Kunu and Agbede (2021) established a strong relationship between process factors and unacceptable waiting time at the University of Cape Coast Hospital and pointed out that this can lead to unforeseen health and cost implications on the part of patients. The results of this study have shown an overall declining trend in the AED series for both the study period and as well as the forecast period (see figure 6). It is vividly clear that the average quarterly arrivals of patients to the AED section of the University Hospital for the study period have declined by about half as shown in figure 3. Figure 3 demonstrates the quarterly average decline from 12 patients a day in the first quarter of 2020 to 6 patients a day in the second quarter of 2021. This steady decline continued even into the forecast zone as shown in figure 8. This downtrend phenomenon could probably be linked to the findings of Kunu and Agbede (2021) in which they assert that patients suffer unacceptable waiting times experience when they visit UCC Hospital for medical services. In this sense, dissatisfied clients could probably in subsequent visits choose elsewhere than bring their

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emergency cases to the University Hospital where they know they will suffer unbearable waiting time nor would they likely recommend others to do so. This assertion could probably be investigated in a future study to ascertain its veracity or otherwise. Hence, management of the hospital can investigate the likely causes and implications of this general decline in the trend of the AED series for the period under discussion to ensure that the University Hospital which claims itself as patient-friendly is not losing clients to possible reasonable preventable causes.

The high volatility finding as one of the main results of this study concur with the findings of other studies (Choudhury et al., 2020; Juang et al., 2017; Jones et al., 2008; Cheng et al., 2021) about other facilities. This implies that hourly, daily, weekly or monthly demand for hospital emergency services is characterised by high volatility with seasonal and weekly patterns in some cases. However, unlike other studies (Choudhury et al., 2020; Jones et al., 2008; Cheng et al., 2021), the findings of this study did not show any weekly or seasonal patterns but were highly characterised by irregularities. Hence, the study recommends that the management of the University Hospital logistically positioned the AED section of the hospital for both human and material resources to stand ready for surges in patient arrivals at all times.

5. Conclusions

The study was designed to model and predict daily patient arrivals at the Accident and Emergency Department (AED) of the University of Cape Coast Hospital. The analysis revealed that the distribution of daily patient arrivals at the University Hospital Emergency Department was non-normal and extremely positively skewed. The AED series distribution for the study period was highly volatile with a median of eight (8) patient arrivals per day. The study results showed that among the top twenty-five (25) non-seasonal candidate models rigorously selected for the AED series, ARIMA (0, 1, 2) emerged as the best model fit for the daily patient arrivals at the AED section of the University Hospital. Residual analysis of the fitted model indicated that the model was stable and fit for forecasting.

In addition, there exists a clear declining trend in the daily arrival of patients at the AED section of the University Hospital both within the study period as well as the forecast period. For the study period, the results have shown that the daily patient arrivals series has witnessed a 50% decline on average. This downward trend of the AED series continues even into the forecast period. It is therefore imperative that management of the University hospital investigate possible likely causes and implications of this downward trend. This will at least ensure that the University Hospital is not losing clients at the AED section to possible reasonable preventable causes. Finally, the results did not exhibit any weekly or seasonal patterns in the AED series but were, however, characterized by large irregularities. Hence, the study recommends that management of the University Hospital logistically position and equip the accident and emergency section of the hospital with qualified human resources as well as adequate logistics to stand ready to respond efficiently and effectively to surges in daily patient flow at all times.

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