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Prevalence of Under-Five and Infant Outpatients in the University of Cape Coast Hospital: An Empirical Application of Applied Univariate Statistical Modelling

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Abstract

Background: The healthcare needs of under-fives and infants create major public health and development challenges in Ghana. Though some level of progress has been achieved in the area, there still exist several challenges to be addressed with regard to the survival and development of these vulnerable age groups. One module used in this domain is to monitor, assess, and evaluate the healthcare needs of infants and under-fives in healthcare facilities. Although the literature has dealt greatly with child healthcare in Ghana very little has been done in the area of modelling and forecasting the prevalence of infant and under-five outpatients' healthcare needs across hospitals in the country.

Purpose: This study was conducted to assess, model, and probably predict the outpatient performance variable for infants and under-fives in the University of Cape Coast Hospital.

Methodology: Quantitative methods and a longitudinal research design were used in this study. Monthly data of infant and under-five outpatients covering January 2012 through December 2021 was sourced from the District Health Information Management System (DHIMS II) constituting a total sample size of 120 observations. The classical Box-Jenkins method of applied univariate statistical modelling was used to analyze the data.

Findings: This unbiased study revealed in its findings 100 competitive models for the data. A seasonal autoregressive moving average model SARIMA $(2, 0, 3)(1, 0, 1)_{12}$ emerged as the best fitting model for the data with the lowest AIC value. The Ljung-Box Q-test for serial correlation indicated *p-values* > 0.05 meaning that the model exhibited *white noise* in its residuals. The findings revealed seasonality but no trend with seasonal peaks in March, July, and November every year.

Unique contribution to theory and practice: A seasonal autoregressive moving average model SARIMA $(2, 0, 3)(1, 0, 1)_{12}$ emerged as the best fitting model predicting under-five and infant visits to the outpatient department. This model will logistically guide the management of the hospital to prudently and effectively allocate human and material resources to the paediatric unit of the hospital. Further studies are recommended to investigate why there are seasonal peaks in the months of March, July, and November every year so that appropriate public health interventions can be applied to mitigate the situation.

Keywords: *Under-five and Infant Outpatients, Univariate Modelling, Forecasting, Seasonality*

Introduction

According to the United Nations International Children's Emergency Fund (UNICEF) 2019 annual report, millions of children across the globe die annually and some of these deaths could have been prevented or avoided (UNICEF, 2020) [1]. The report added that among these deaths, infants and under-fives constitute over 5 million. Infections at the childhood stage of human development are a significant cause of infant and under-five morbidity and mortality and most of these infections are curable if presented early for treatment [2]. In sub-Saharan Africa, child morbidity and mortality have become a major public health issue [3] triggering governments to allocate a significant proportion of their budgets to their health sectors to combat the canker. Studies [4,5,6] have shown that Ghana still presents some of the highest indicators in infant and under-five morbidities and mortalities in the sub-region.

One of the key variables used in measuring national development is child mortality [7, 8]. Hence, significant steps have been taken by governments across the globe including Ghana as part of their sustainable development goals to ensure child survival and to end preventable deaths of newborns and children under-5 years of age. In Ghana, the Ministry of Health (MOH) via Ghana Health Services (GHS) through a number of policies brought about increased usage of existing healthcare facilities in the country by infants and under-fives in all public and religious health institutions [9]. This aims to do away with self-medication among caregivers and motivate them to seek early formal healthcare treatment for their infants and under-fives. This phenomenon increases the survival rate of infants and under-fives which goes a long way to enhance national development.

Applied univariate statistical modelling is a branch of statistical modelling that attempts to describe, model, and probably predict data observations that include only a single characteristic or attribute. The classical Box-Jenkins [10] method constituted powerful statistical modelling tools for empirical research. One study [11] employed the autoregressive integrated moving average (ARIMA) models of the Box-Jenkins methods to model annual time series data on the prevalence of anemia in children under 5 years of age in India from 1990 to 2016. The study results revealed an ARIMA (2,0,0) as the optimal model for the series. Diagnostic checks revealed that the model was stable and adequate for forecasting as there was no indication of serial correlation in its residual. A similar study [12] was carried out in Ethiopia using annual time series data on the prevalence of anemia in children under 5 years of age from 1990 to 2016.

The study results revealed an outcome optimal model of ARIMA (5,0,0) for the data. Another study [13] used exponential, logistic, Gompertz growth, and the Box-Jenkins methods to model and forecast the spread of COVID-19 in India. The results of the study revealed superiority in forecast power in favour of the Box-Jenkins method. Biswas *et al* [14] conducted a study using the Box-Jenkins methodology to model the outpatient attendance by under-fives in an urban health training center in West Bengal, India. The study used monthly data for a six-year period spanning from April 2007 to March 2013. The results of the study revealed an optimal model ARIMA (2,0,2) for the data. Residual diagnoses proved the model to be stable and adequate and was consequently used for forecasting the under-five outpatient series of the health training center.

Infants and under-fives have a weak immune system and are thus exposed to various diseases and sicknesses in our communities every day. The ministry of health in collaboration with the Ghana Health Services has instituted a number of programs [15] that focus on preventive measures or early diagnoses and treatment for infants and under-fives. This is purported to monitor and control

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morbidity and mortality among infants and under-fives across the country. One of the key indicants for functional evaluation of a given healthcare facility is the outpatient performance variable for infants and under-fives [16, 17]. Therefore, this study was intended to assess, model, and probably predict the outpatient performance variable for infants and under-fives in the University of Cape Coast Hospital.

Materials and Methods

Study Design

Quantitative methods and a longitudinal research design were used in this study.

Data source

The study used monthly periodicity data of infant and under-five outpatients sourced from the District Health Information Management Systems (DHIMS-2) spanning from January 2012 through December 2021 constituting a total sample size of 120 observations. In this study, an infant outpatient by definition refers to the probability of a visit before the first birthday and an under-five outpatient refers to the probability of a visit between the first birthday and the fifth birthday. These two series are combined as the outcome variable series for ease of analysis. The auto-arima function procedure was implemented for comprehensive model selection of the data. All analyses were performed using *EViews 12* and a *p-value* < 0.05 was considered statistically significant.

Theoretical Framework

The classical Box-Jenkins [10] methods are a class of statistical models that use integrated autoregressive moving average (ARIMA) and its variants seasonal integrated autoregressive moving average (SARIMA), autoregressive fractionally integrated moving average (ARFIMA) to identify, estimate, diagnose, and fit time series models. Successful modelling in Box-Jenkins methodology is preceded by transforming non-stationary series into stationary series.

The ARMA model

The mathematical expression of the autoregressive moving average (ARMA) model is given as:

$$y_t = \emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \qquad (1)$$

Where the $\emptyset$'s (phis) are the autoregressive parameters to be estimated, the θ's (thetas) are the moving average parameters to be estimated in the model. The original series is y_t, and ε_t is the error term series assumed to follow the normal probability distribution.

Seasonal Time Series Models (SARIMA)

Box and Jenkins [10] recommended a general model to incorporate seasonal fluctuations in a series. The model is defined as follows:

$$\emptyset_p(B)\Phi_P(B)(1-B)^d(1-B^s)^D y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \qquad (2)$$

Where ***d*** is the order of non-seasonal differencing, ***s*** is the number of seasons per year, ***D*** is the order of seasonal differencing, and ***B*** is the backshift operator which has the effect of changing time period *t* to time period *t-1*.

The Box–Jenkins (BJ) Methodology

The Box-Jenkins methods use an iterative process in three main stages namely identification, estimation, and diagnostic checking. In the identification stage, the correlogram, the autocorrelation function (ACF), the partial autocorrelation function (PACF) of the data are used to select potential candidate models. This leads up to the second stage which deals with the estimation of the parameters of the candidate models using maximum likelihood techniques. The selection criterion is based on the model with the lowest Akaike Information Criteria (AIC) value. Finally, the best-fitted model is diagnosed for inadequacies by considering the autocorrelations of the model residual series. If stages 1 to 3 are successful, then forecasting of the data can commence.

Results

Descriptive Analysis

The study intended to assess and model outpatient attendance dynamics for under-fives and infants in UCC Hospital for the period of January 2012 through December 2021. Figure 1 depicts the time plot of the prevalence of under-five and infant outpatients in the University of Cape Coast Hospital spanning from January 2012 to December 2021.

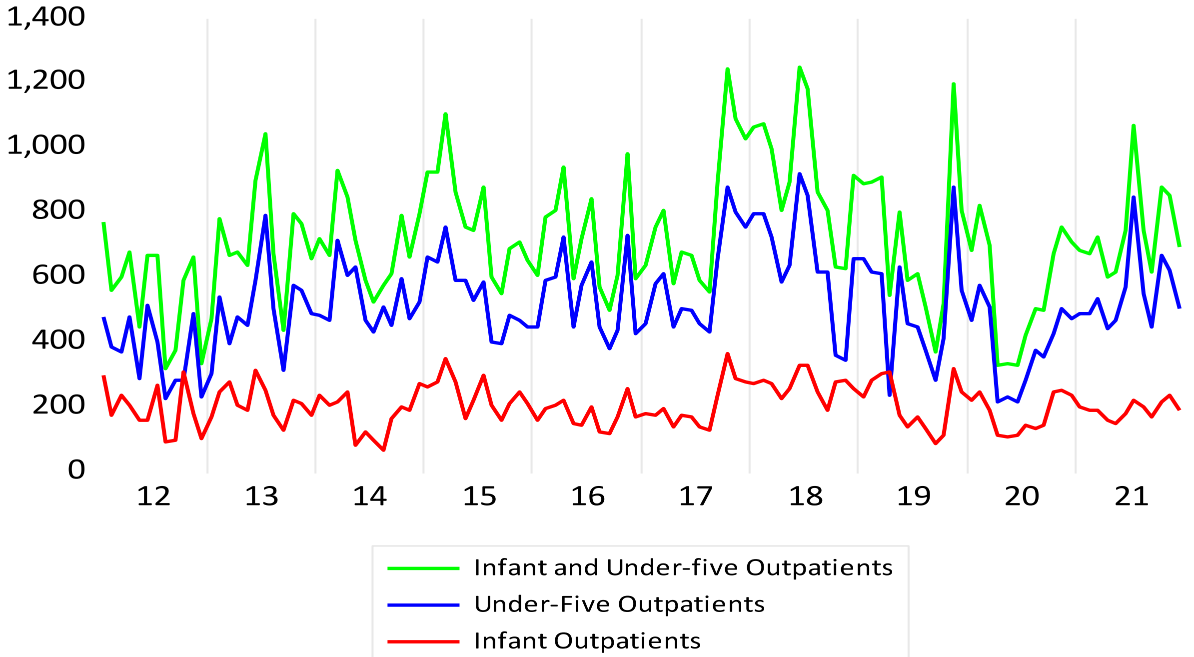

Figure 1: Time plot of Under-five and Infant Outpatients prevalence in UCC Hospital over January 2012 through December 2021

From Figure 1 it is clear that there is no consistent trend (upward or downward) in the monthly Outpatient movement dynamics of the under-fives and infants for the entire study period. Fitting an imaginary line through the mean (720 under-five patients per month) of the series, it can be seen that the series wanders on one side of the mean (below the mean) for a while and then to the other side (above the mean) for another while thereby generating a cyclic pattern. There are no clear outliers in the series and it is quite unclear at this stage to determine whether the variance of the series is constant or otherwise.

Table 1 presents the descriptive statistics of the various outpatient variables included in the study. In Table 1 the Jarque-Bera test of normality has shown that the Infant, Under-five Outpatient variables and their combined series are all normally distributed with *p-values* > 0.05 each. However, the general outpatient variable for the same period is not normally distributed with a *p-value* < 0.05. Table 1 revealed that throughout the entire period of study, a total of 86,341 infant and under-five outpatients were recorded in the hospital with 39.23% constituting infants. The proportion of infant and under-five outpatients to the general outpatients recorded in the facility for the entire period was 12.22% indicating a very significant percentage of all outpatients recorded for the period.

Table 1: Descriptive Statistics for the various time series variables included in the study

Outpatient Variable	Totals	Proportion	Mean	Maximum	Minimum	Std. Dev.	Jarque-Bera	Prob
Infant Outpatients	24326	39.23	203	363	65	64.22	1.9736	0.3728
Under-Five Outpatients	62015	60.77	517	921	216	153.29	2.1388	0.3432
Infant&Under5 Outpatients	86341	100	720	1249	316	198.2	2.9983	0.2233
General OPD	706650	12.22*	5889	10174	1710	1697.88	6.6949	0.0352

Null Hypothesis: Outpatient variable is normally distributed

*Proportion of Infant & Under-Five in General OPD

Figure 2 displays the prevalence of under-five and infant outpatients relative to the general outpatients' movement in the hospital for the entire study period.

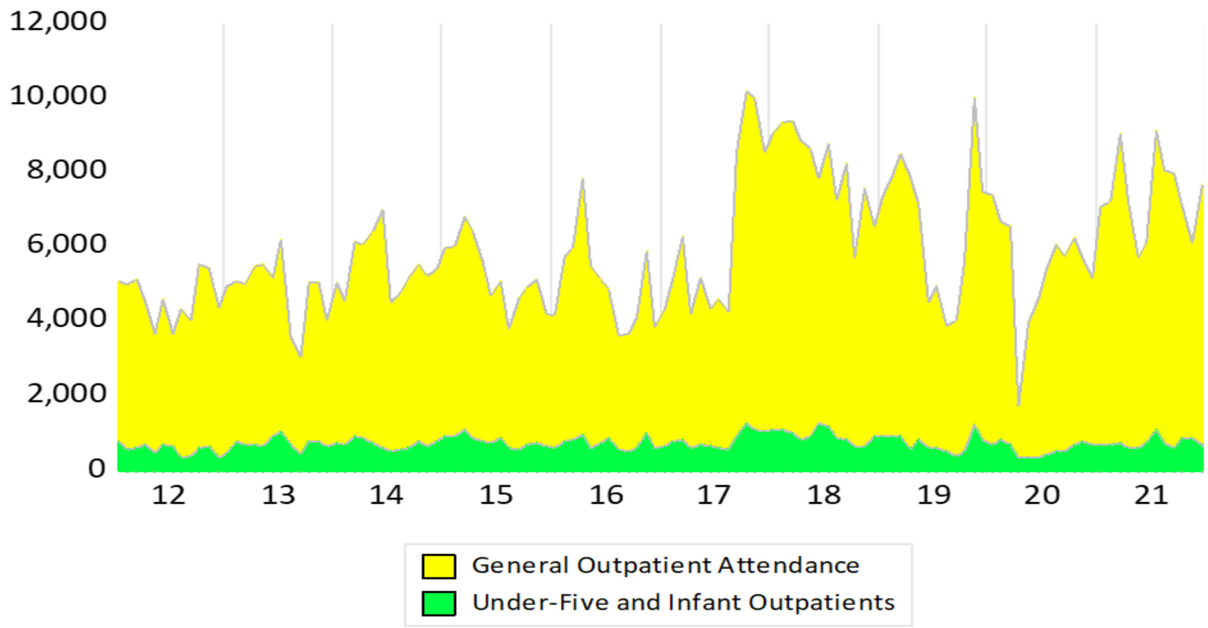

Figure 2: Prevalence of Under-Five and Infant Outpatients in UCC Hospital over January 2012 through December 2021

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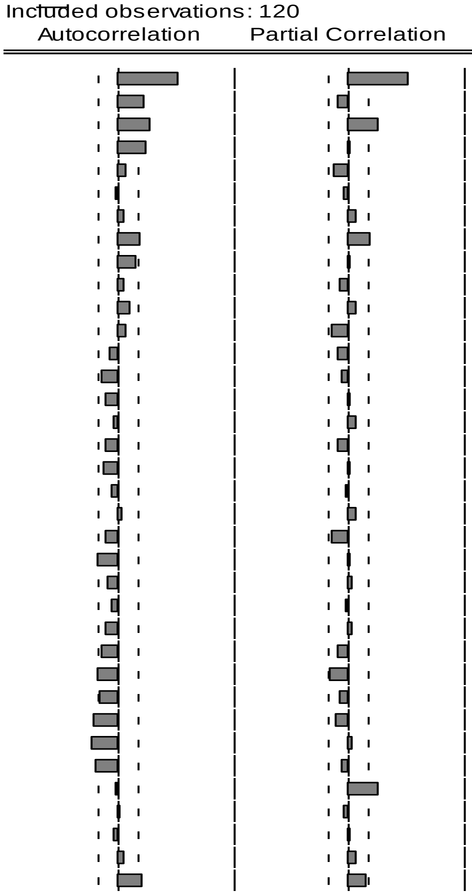
Table 2 also demonstrates seeming seasonality in the data by taking a monthly cross-section of the data for the entire period of study. The results show that under-fives and infant outpatient visits in the hospital peak in November every year with an average attendance of 830 cases. This peaked season of November is closely followed by the months of March, February, and July every year with an average attendance of 823, 793, and 781 respectively throughout the entire study period. The lowest seasonal attendance recorded is in the month of September with an average attendance of 564 cases in the hospital.

Table 2: Seasonal means of infant & under-five outpatients' visit over Jan 2012 through Dec 2021

Season	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average	744	793	823	686	646	746	781	590	564	741	830	717

Figure 3 depicts the correlogram of the under-five and infant outpatient movement series. The series seem to exhibit memory on either side of the mean of the autocorrelation function throughout the 36-lag period. These symptoms probably point to seasonality in the data.

Sample: 2012M01 2021M12
Included observations: 120



	AC	PAC	Q-Stat	Prob
1	0.542	0.542	36.177	0.000
2	0.234	-0.084	42.999	0.000
3	0.280	0.269	52.833	0.000
4	0.260	-0.001	61.339	0.000
5	0.078	-0.116	62.116	0.000
6	-0.014	-0.044	62.142	0.000
7	0.058	0.072	62.584	0.000
8	0.191	0.196	67.366	0.000
9	0.162	0.016	70.820	0.000
10	0.046	-0.076	71.096	0.000
11	0.105	0.068	72.585	0.000
12	0.071	-0.152	73.264	0.000
13	-0.080	-0.089	74.141	0.000
14	-0.151	-0.055	77.289	0.000
15	-0.110	-0.004	78.965	0.000
16	-0.046	0.068	79.259	0.000
17	-0.102	-0.098	80.733	0.000
18	-0.126	-0.006	83.005	0.000
19	-0.051	-0.021	83.379	0.000
20	0.037	0.070	83.581	0.000
21	-0.107	-0.147	85.282	0.000
22	-0.177	-0.005	89.936	0.000
23	-0.088	0.027	91.102	0.000
24	-0.063	-0.019	91.712	0.000
25	-0.105	0.033	93.421	0.000
26	-0.153	-0.094	97.050	0.000
27	-0.178	-0.160	102.01	0.000
28	-0.162	-0.067	106.16	0.000
29	-0.207	-0.108	113.05	0.000
30	-0.236	0.033	122.08	0.000
31	-0.196	-0.063	128.38	0.000
32	-0.014	0.271	128.42	0.000
33	0.004	-0.035	128.42	0.000
34	-0.025	0.002	128.53	0.000
35	0.055	0.073	129.05	0.000
36	0.208	0.159	136.60	0.000

Figure 3: Correlogram of under-fives Outpatient visits series in UCC Hospital exhibits seasonality Formal tests for trend and seasonality in the data

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The least-squares method was deployed to ascertain the existence or otherwise in the data the phenomenon of trend and seasonality. The results show insignificance for the trend component of the series and however indicated the existence of seasonality in the monthly outpatient movements of under-fives in the University of Cape Coast Hospital. Figures 4&5 give further details of the formal tests.

Sample: 2012M01 2021M12
Included observations: 120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	685.1999	35.92776	19.07160	0.0000
@TREND	0.576613	0.521835	1.104971	0.2714

R-squared	0.010241	Mean dependent var	719.5083
Adjusted R-squared	0.001853	S.D. dependent var	198.1994
S.E. of regression	198.0157	Akaike info criterion	13.43110
Sum squared resid	4626804.	Schwarz criterion	13.47755
Log likelihood	-803.8657	Hannan-Quinn criter.	13.44996
F-statistic	1.220962	Durbin-Watson stat	0.924186
Prob(F-statistic)	0.271420		

Figure 4: A formal test for trend in the monthly movements of infants & under-five outpatients' data

Sample (adjusted): 2013M01 2021M12
Included observations: 108 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	301.3609	103.3804	2.915068	0.0044
OPDA_5YRS(-1)	0.612989	0.099071	6.187339	0.0000
OPDA_5YRS(-2)	-0.184692	0.114803	-1.608775	0.1110
OPDA_5YRS(-3)	0.203906	0.115375	1.767329	0.0804
OPDA_5YRS(-4)	0.054320	0.117107	0.463854	0.6438
OPDA_5YRS(-5)	-0.141792	0.115040	-1.232543	0.2208
OPDA_5YRS(-6)	-0.038265	0.117897	-0.324565	0.7462
OPDA_5YRS(-7)	-0.062032	0.117966	-0.525844	0.6002
OPDA_5YRS(-8)	0.185799	0.116437	1.595702	0.1139
OPDA_5YRS(-9)	0.105980	0.117341	0.903179	0.3687
OPDA_5YRS(-10)	-0.185296	0.115121	-1.609575	0.1108
OPDA_5YRS(-11)	0.202740	0.114553	1.769845	0.0800
OPDA_5YRS(-12)	-0.158752	0.097519	-1.627910	0.1069

R-squared	0.413031	Mean dependent var	737.8056
Adjusted R-squared	0.338887	S.D. dependent var	194.7980
S.E. of regression	158.3880	Akaike info criterion	13.08046
Sum squared resid	2383242.	Schwarz criterion	13.40331
Log likelihood	-693.3448	Hannan-Quinn criter.	13.21136
F-statistic	5.570697	Durbin-Watson stat	2.022865
Prob(F-statistic)	0.000000		

Figure 5: Autoregression model of the dependent variable given the seasonality of 12.

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From figure 5, the autoregression model of the dependent variable demonstrates significance in the first lag. This formally indicates that there exists seasonality in the monthly outpatient dynamics of the under-fives in the University of Cape Coast Hospital.

Stationarity Tests

The classical Box-Jenkins approach work on the assumption that the time series involved is (weakly) stationary. Hence, the Augmented Dickey-Fuller (ADF) unit root test was deployed to determine the stationarity or otherwise of the monthly outpatient movements of infants and under-fives in the hospital. Since Figure 4 demonstrated that there is no clear trend in the series, only the constant form of the ADF equation was used. The results show that the series was stationary at level. In other words, the series is already stationary at levels and would need no differencing to commence the modelling process. Figure 6 shows the results of the ADF unit root test of the series.

Null Hypothesis: OPDA_5YRS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.893658	0.0000
Test critical values:	1% level	-3.486064	
	5% level	-2.885863	
	10% level	-2.579818	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OPDA_5YRS)
Method: Least Squares
Date: 03/02/22 Time: 10:55
Sample (adjusted): 2012M02 2021M12
Included observations: 119 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OPDA_5YRS(-1)	-0.457630	0.077648	-5.893658	0.0000
C	328.6976	57.96680	5.670447	0.0000

R-squared	0.228920	Mean dependent var	-0.680672
Adjusted R-squared	0.222329	S.D. dependent var	190.3573
S.E. of regression	167.8678	Akaike info criterion	13.10089
Sum squared resid	3297014.	Schwarz criterion	13.14760
Log likelihood	-777.5032	Hannan-Quinn criter.	13.11986
F-statistic	34.73521	Durbin-Watson stat	1.887392
Prob(F-statistic)	0.000000		

Figure 6: ADF unit root test of outpatient visits of under-fives in UCC Hospital

Model Identification and Estimation

The classical Box-Jenkins approach was deployed on the infants and under-fives outpatient series since it was already stationary at levels. By deploying the alternate auto-Arima function of *EViews 12* the system identified one hundred tentative candidate models for the infants and under-fives

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outpatient series. The top five models identified among other models include the following seasonal autoregressive integrated moving average (SARIMA); SARIMA(2, 0, 3)(1, 0, 1)$_{12}$, SARIMA(2, 0, 3)(0, 0, 1)$_{12}$, SARIMA(3, 0, 0)(1, 0, 0)$_{12}$, and SARIMA(2, 0, 3)(1, 0, 0)$_{12}$. The non-seasonal model among the top five models is ARMA (2, 3)(0, 0). The model SARIMA(2, 0, 3)(1, 0, 1)$_{12}$ with two non-seasonal AR(2) terms, no differencing, three non-seasonal MA(3) terms, one seasonal AR(1) term, no seasonal differencing, a seasonal MA(1) term, a seasonal period of 12 months and having the lowest AIC value was selected as the best-fitting model. The next best fitting model was the non-seasonal model ARMA (2, 3)(0, 0). Presented here in Table 3 are the top 10 models out of the 100 identified candidate models with their corresponding estimated AIC values as a criterion for selection.

Table 3: Model selection criteria table for the under-five and infant outpatient series

Model Structure	LogL	AIC*	BIC	HQ
SARIMA(2, 0, 3)(1, 0, 1)$_{12}$	11.836486	-0.047275	0.161787	0.023613
SARIMA(2, 0, 3)(0, 0, 0)$_{12}$	9.545262	-0.042421	0.120183	0.023613
SARIMA(2, 0, 3)(0, 0, 1)$_{12}$	10.216097	-0.036935	0.148898	0.038533
SARIMA(3, 0, 0)(1, 0, 1)$_{12}$	9.178828	-0.036314	0.126290	0.029720
SARIMA(2, 0, 3)(1, 0, 0)$_{12}$	10.170525	-0.036175	0.149657	0.039292
SARIMA(2, 0, 4)(1, 0, 1)$_{12}$	11.880134	-0.031336	0.200955	0.062999
SARIMA(4, 0, 2)(0, 0, 0)$_{12}$	9.867242	-0.031121	0.154712	0.044347
SARIMA(0, 0, 4)(0, 0, 0)$_{12}$	7.717123	-0.028619	0.110756	0.027982
SARIMA(3, 0, 0)(0, 0, 0)$_{12}$	6.699913	-0.028332	0.087814	0.018835
SARIMA(3, 0, 2)(0, 0, 0)$_{12}$	8.695758	-0.028263	0.134341	0.037771

Table 3 presents the candidate models identified and their corresponding AIC, BIC, and HQ estimates with the objective of selecting the model that best fits the infants and under-fives outpatient visits series using the AIC values. Using a criterion of lowest AIC value, the results show that the seasonal ARIMA model SARIMA (2, 0, 3)(1, 0, 1)$_{12}$ emerged as the most appropriate model fit for the data. This model was subjected to rigorous diagnostics checking for validation or otherwise. Taking notice of the fact that ARIMA models are *atheoretic* models, the following estimated parameters in Table 4 for the selected model are tabulated.

Table 4: Estimated Parameters for selected model SARIMA (2, 0, 3)(1, 0, 1)$_{12}$

Variable	Coefficients	SE	t-Statistic	Prob
C	*6.538915 **	0.067120	97.42131	0.0000
AR(1)	*1.295003**	0.104761	12.36155	0.0000
AR(2)	*-0.769700**	0.107031	-7.191403	0.0000
SAR(12)	*0.999999**	0.000537	1863.786	0.0000
MA(1)	*-0.709791**	0.139004	-5.106266	0.0000
MA(2)	0.198573	0.127204	1.561063	0.1214
MA(3)	*0.523136**	0.094699	5.524213	0.0000
SMA(12)	*-0.999521**	0.001548	-645.8934	0.0000
SIGMASQ	*0.043588**	0.005607	7.773377	0.0000

** Coefficients in italics and asterisked are significant (P-value < 0.05) *Dependent variable: Log(OPDA_5YRS)*

Figure 7 display a comparative graphic representation of the top twenty competitive models with SARIMA (2, 0, 3)(1, 0, 1)$_{12}$ leading with a minimum AIC value of -0.0472747.

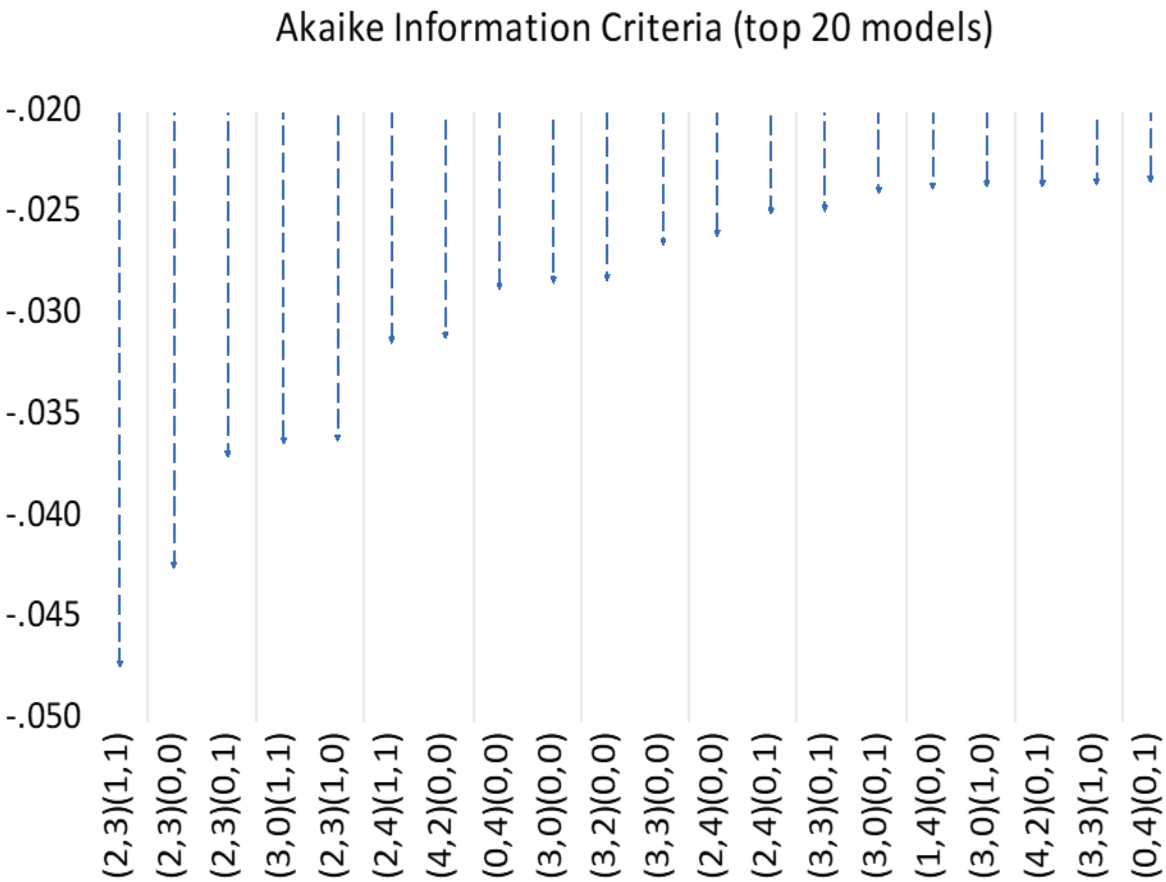

Figure 7: Comparative graphic representation of top twenty competitive models for the series

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Model Diagnostics and Forecasting

After identifying and estimating the best fit model the next step was to diagnose the model for the adequacy or otherwise in forecasting the under-five and infant outpatients' series of the University Hospital. Hence, the Ljung-Box Q-test for serial correlation was deployed to test the null hypothesis that the selected model SARIMA (2, 0, 3)(1, 0, 1)$_{12}$ does not exhibit serial correlation in its residuals for a fixed number of lags. The result of the test is shown in Figure 8. The test results clearly showed that the null hypothesis of no autocorrelation in the residual of the selected model is not rejected. The estimated ACF, PACF, Q-Stats, and the corresponding *p-values* are insignificant even up to lag 36 (*p-values* > *0.05*). Hence, the selected model's sample auto-correlation coefficients lie within the limits $(-1.96/\sqrt{N}, +1.96/\sqrt{N})$ otherwise known as the standard error bounds. This clearly indicates that the errors of the selected model are *white noise* and hence the model is stable and adequate for forecasting the monthly under-five outpatient's movement in the hospital.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.015	0.015	0.0292	
		2	0.018	0.017	0.0680	
		3	0.047	0.046	0.3432	
		4	0.109	0.107	1.8334	
		5	0.021	0.017	1.8913	
		6	0.019	0.014	1.9391	
		7	0.103	0.094	3.3266	
		8	0.079	0.065	4.1432	0.042
		9	0.131	0.126	6.4187	0.040
		10	-0.050	-0.064	6.7451	0.080
		11	0.013	-0.016	6.7663	0.149
		12	0.005	-0.023	6.7695	0.238
		13	-0.065	-0.096	7.3484	0.290
		14	0.001	-0.003	7.3486	0.394
		15	-0.057	-0.076	7.7939	0.454
		16	-0.022	-0.046	7.8622	0.548
		17	-0.092	-0.089	9.0688	0.526
		18	0.012	0.009	9.0889	0.614
		19	-0.027	0.008	9.1978	0.686
		20	0.030	0.064	9.3331	0.747
		21	-0.085	-0.052	10.414	0.731
		22	-0.099	-0.068	11.892	0.687
		23	-0.014	-0.002	11.920	0.749
		24	-0.104	-0.072	13.556	0.698
		25	-0.056	-0.026	14.045	0.726
		26	0.025	0.060	14.144	0.775
		27	-0.084	-0.101	15.250	0.762
		28	-0.063	-0.044	15.884	0.776
		29	-0.108	-0.105	17.755	0.720
		30	-0.005	0.016	17.760	0.770
		31	-0.211	-0.177	25.099	0.400
		32	0.074	0.101	26.002	0.407
		33	-0.015	0.025	26.039	0.461
		34	-0.002	0.010	26.039	0.516
		35	-0.034	0.005	26.240	0.560
		36	0.116	0.176	28.599	0.486

Figure 8: Correlogram of Residuals of selected model SARIMA(2, 0, 3)(1, 0, 1)$_{12}$

The selected model SARIMA $(2,0,3)(1,0,1)_{12}$ has demonstrated superiority over other competitive models mentioned earlier. Hence, the model has proven to be stable and adequate for forecasting the infants and under-fives outpatient visits series of the University Hospital. Figure 10 displays the forecast graph of the series for the next three-year period of January 2022 through December 2024.

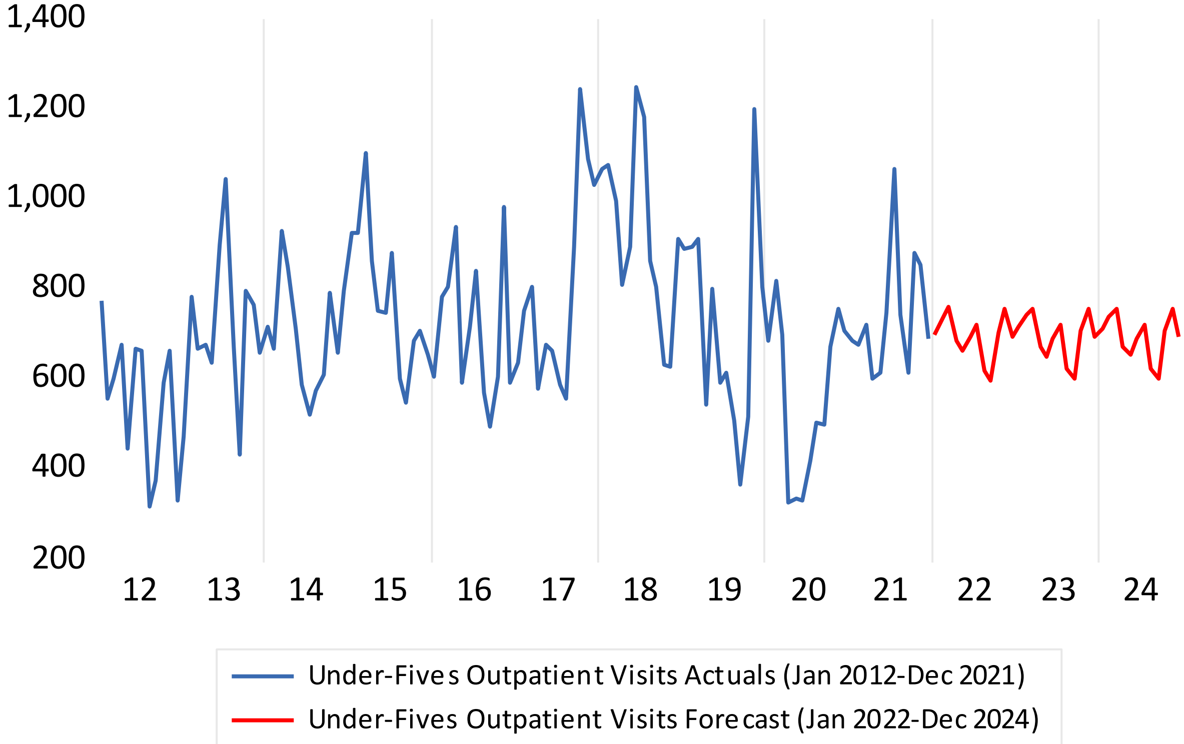

Figure 9: Actuals and Forecast time plot of infant & under-five outpatient visits in UCC Hospital over January 2012 through December 2024

Table 5 presents the point forecast estimates of the series with upper and lower bounds of ± 2 S.E. away from the point estimates of the infants and under-fives outpatients' visits in the University Hospital.

Table 5: A three-year forecast estimates of infants & under-fives outpatient visits in UCC Hospital

Month /Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2022	700	735	766	683	661	693	719	617	596	702	755	696
2023	714	742	757	672	651	687	721	622	602	706	755	693
2024	710	739	756	674	653	689	721	621	601	705	755	693

**Estimates within 2 standard errors*

Discussions

The research study was purported to assess, determine, and model outpatient attendance dynamics for infants and under-fives in UCC Hospital for the period of January 2012 through December 2021 to aid in the effective allocation and utilization of scarce resources. Immurana and Arabi [18] posit that caregivers in Ghana would adopt a healthcare provider as their first choice (instead of resorting to self-medication) to send their infants and under-fives for treatment if their highest expected utility is met by the healthcare provider. To this end, the study intended to assess and model the usage of the University of Cape Coast healthcare facility by caregivers in its environs. The results of the study revealed that for the entire period of January 2012 through December 2021 the facility recorded a total of 86,341 infant and under-five outpatients (constituting a significant 12.22% of general outpatient attendance in the facility) with 39.23% being infants. The under-five and infant outpatients' series did not show any consistent trend (upward/downward) throughout the study period. However, the study results did show some form of seasonality in the data with seasonal peaks in November, March, and July every year. The yearly seasonal averages included 830, 823, and 781 infant and under-five outpatients respectively.

The study results after a rigorous analysis revealed a seasonal autoregressive moving average model SARIMA$(2, 0, 3)(1, 0, 1)_{12}$ as the best fitting model for the under-five and infant outpatients data in the University Hospital. This model emerged with the lowest AIC value followed by its arch-rival SARIMA$(2, 0, 3)(0, 0, 0)_{12}$. Residual analysis of the model indicated that the model was stable and adequate for forecasting the future values of infant and under-five outpatients' series in the hospital. The Ljung-Box Q-test for serial correlation indicated *p-values* >0.05 meaning that the model does not exhibit serial correlation in its residuals for a fixed number of lags. A three-year forecast of the under-five and infant outpatients indicated the seasonal peaks in March, July and November every year. The absence of a trend in the results of this study concurred with the findings of Biswas et al [14] under-five outpatients' series, however, the results are not the same for the seasonal component. This phenomenon could probably be the result of the fact that the morbidity cases reported among the infants and under-five outpatients were not segregated and this is acknowledged as one of the limitations of this study.

The other limitations are the fact that irregularities in time series data are very difficult to predict even using the most sophisticated model and more so exogenous variables were not included in the modelling process. Therefore, the three-year forecast of under-five and infant outpatients from January 2022 through December 2024 is to aid the management of the University Hospital to strategically and prudently allocate available scarce resources both human and material to the paediatrics department of the hospital for optimal performance. This will in the long run motivate and promote mothers/caregivers of infants and under-five outpatients to make the University Hospital their first choice [18]. This will definitely work against archaic practices and self-medication among caregivers; hence, infant and under-five morbidity and mortality will be significantly reduced and national development empowered [15]. By extension, the functional performance of the University Hospital will not only be demonstrated among its peers but will also be significantly improved to greater heights in the field of paediatrics [16, 17].

Conclusion

This study successfully modelled the under-five and infant outpatient visits in the University of Cape Coast Hospital. The Ghana Health Service/Ministry of Health promulgates prevention or early detection and treatment of infections among infants and under-fives by all healthcare institutions in order to avoid most of the child mortalities encountered across all the regions of the country. Also, as part of sustainable development goals, world leaders in 2015, made an objective of reducing infant and under-five deaths to 25 per thousand live births by 2030. Hence, monitoring healthcare demand and provision of infants and under-fives across the country is crucial. In this light, the study assessed, identified, modeled, and successfully forecasted the prevalence of infant and under-five outpatients in UCC Hospital.

Recommendations

The findings of this study can effectively help guide management of the University Hospital to logistically and effectively allocate human and material resources in favour of the expected flow of infant and under-five outpatients in the future and to also help in re-evaluating the hospital's performance in the sector for policy making or review. Further studies are recommended to investigate why there are seasonal peaks in the months of March, July, and November every year. These studies will help to provide needed public health interventions to mitigate the situation.

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