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A Pulse Intervention Modelling of Paediatric Anaemia Prevalence

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ABSTRACT
Anaemia is a severe worldwide health issue that greatly affects children, young girls, and women, especially those who are pregnant. Anaemia burden continues to be a major problem in Akwa Ibom State despite constant efforts by the government, which has made large financial investments in the health sector, especially in the area of making healthcare delivery accessible and affordable. This study aimed at creating an appropriate time series model for the studied series while investigating the government's intervention in the prevalence of paediatric anaemia. The dataset, is the monthly clinical cases of childhood anaemia spanning from January 1997 to 2011, and ARIMA intervention analysis is the statistical technique employed. A total of 9,413 children aged 0 to 14 years were affected, with the highest recorded cases of 147. The ARIMA (1,1,1) model is fitted and adjudged adequate for the dataset in the pre-intervention period. The significant impact parameter with a value of 88.3963 implies that the intervention was not successful in producing the intended result, as indicated by the sign of the impact parameter. It is also evidenced in the number of hospital admission cases, which increased in the post-intervention period, with the highest case number of 145 compared to the period before the intervention. The impact of the intervention was instant, as indicated by the delay parameter, with a growth rate of 0.

KEYWORDS
Intervention analysis, Pulse function, Anaemia prevalence, Time series model

1. Introduction

Anemia is a condition marked by either an abnormally low number of red blood cells or an abnormally low hemoglobin concentration in them [41]. Hemoglobin is necessary for the blood to carry oxygen to the body's tissues; when there is too little hemoglobin or red blood cells, the blood's capacity to perform such would be diminished. Many symptoms result from this, such as fatigue, lightheadedness, dyspnea, and weakness. The optimal level of hemoglobin required to meet physiological demands varies based on age, gender, residence altitude, tobacco use, and childbirth. Anemia is defined by WHO criteria as less than 110 grams per liter of hemoglobin at sea level in children under five and pregnant women, and less than 120 grams per liter in non-pregnant women [31–33]. Thirty percent of women from 15 to 49 years old, thirty-seven percent of pregnant women, and forty percent of infants aged six months to five years of age

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suffered from anemia in 2019. The majority of countries with low and middle incomes experience it. In addition to impairing cognitive function and increasing the risk of infections and mortality, anemia can result in acute exhaustion, poor pregnancy outcomes, lost wages, and stunted growth and development. It is a robust measure of general health [2]. A number of factors can contribute to anemia: the most common cause is thought to be iron deficiency; other causes include infections, both acute and chronic, that cause inflammation and blood loss; deficiencies in other vitamins and minerals, particularly folate, vitamin B12, and vitamin A; and genetically inherited traits, like thalassaemia. Anaemia can also be caused by other illnesses (such as cancer, genetic abnormalities, malaria, and other infections). Anaemia and iron-deficiency anaemia are commonly used as substitutes. Additionally, the prevalence of anemia is frequently used as a stand-in for iron-deficiency anemia, though the extent of intersect varies greatly between populations based on age and gender [2, 32–34, 41–49].

Numerous academics and researchers have looked at forecasting and modeling the frequency of anaemia instances; Wang and Wang (2022) used cross-sectional survey data from 2005 to 2018 to examine trends in the prevalence and treatment rate of anemia in the American population. The findings showed that between 2005 and 2018, the incidence of overall anemia increased significantly, rising from 5.71 percent through 6.8 percent. Then, age categories, genders, socioeconomic status, PIR, and location of birth were found to be substantially correlated with anemia using logistic regression analysis. Ogbuabor et al. (2022) used a cross-sectional analysis of secondary data from the Nigeria Demographic and Health Survey 2018 to examine the factors influencing the incidence of anemia in Nigerian women of reproductive age. According to their investigation, anaemia affects all groups of women in Nigeria who are of age to conceive with a notable frequency. Using a multilevel ordinal logistic regression analysis, Tesema et al. (2021) investigated the incidence and variables influencing the seriousness levels of anemia among children in the sub-Saharan region of Africa between the ages of 6 and 59 months. The findings showed that 64.1 percent of children in sub-Saharan Africa between the ages of 6 and 59 months had anemia generally. 26.2 percent of the sample had light anemia, 34.9 percent had moderate amounts of anemia, and three percent had serious anemia.

In nations with low or medium incomes, Kinyoki et al. (2021) study examined the incidence of anaemia in women who are fertile. Their findings show broad, moderate improvements in the prevalence of anaemia generally, Nevertheless, by 2030, they only find three LMICs that are likely to achieve the WHO GNT at the national level, and none of them are expected to do so in all of their subnational operational divisions. Using yearly time series on the distribution of anaemia among youngsters within five, Nyoni and Nyoni (2020) investigated ARIMA forecasting of the occurrence of anaemia in infants in the Gambia. Employing the technique developed by Box and Jenkins (1976), ARIMA(3,0,0) was fitted to the dataset. Projection from the fitted model revealed an alarming incidence of anaemia prevalence in Gambia. Again, Nyoni and Nyoni (2020) researched ARIMA prediction of young people's rates of anemia in the African nation of Sierra Leone. Fitting an AR of order four to the dataset under study, the study's findings show that anaemia will be common in youngsters in Sierra Leone, with a projected 78.6 percent of the population expected to have the condition by 2025.

Nyoni (2020) studied ARIMA prediction of anaemia incidence in children in Myanmar using statistical techniques due to [4, 5]. ARIMA(4,0,0) was adjudged a better fit. According to the study's findings, the incidence of anemia among young people in Myanmar is projected to climb from about 54.5 percent in 2017 to a whopping 64.8 percent in the year 2025. A study on ”patterns and causes of change in the incidence of anaemia across a million women and children in India, 2006–2016” was conducted by Nguyen et al. (2018). After using the multivariate regression model, the findings showed that expectant mothers and youngsters in India have seen variations in anemia due to a number of well-known factors. Using both classical and bayesian approaches, Kawo et al. (2018) investigated the multifaceted evaluation of the factors influencing the rate of anemia in Ethiopian youngster between six to fifty-nine months old. Their research indicates that anemia hits 42.8 percent of Ethiopian children between the ages of Six and fifty-nine months, which is a significant public health concern.

The building of intervention models, first introduced by Box and Tiao (1975), offers a foundation for evaluating an intervention's impact on a time series. By changing the process's average degree, the modification is assumed to have an impact on it. As a result, it is possible to expect that the pre-change level and the post-change level will vary. Therefore, one is able to probe into these effects by looking at the mean functions of the essential stochastic process. Scholars who have successfully used the Box-Tiao modelling tools, including Deutsch and Alt (1977) looked into how Boston's firearms-related offenses were affected by Massachusetts' weapon restriction legislation. Sharma and Khare (1999) examined the effects of the actions implemented by the Indian government to reduce toxins brought on by vehicle exhaust emissions using an intervention evaluation framework. Girard (2000) examined the the common cold epidemic status in the United Kingdom and Wales from 1940 through 1990 using the ARIMA model with intervention. Nelson (2000) estimates the effect of the Insolvency legislation of 1978 using an ARIMA intervention approach. Lai and Lu (2005) examine how the attacks of the September bomber assault affected the desire for flight travel among passengers in the United States using an intervention strategy.

In order to determine if the 1999 disaster that struck on September 21 and the 2003 epidemic of the extreme acute respiratory syndrome had an effect on the need for tourists coming from Japan, Min (2008) used intervention analysis methodology. To quantify the intervention impacts and the asymptotic shift in the modeling outcomes of the business process redesign which relies upon the task model estimation, Lam et al. (2009) employed a time series intervention with ARIMA model. An analysis of how the worldwide economic meltdown affected the value of Chinese equities was conducted by Jarrett and Kyper (2011). Interrupted time-series evaluation is used by Darkwah et al. (2012) to analyze the origins and effects of local policing's development and implementation in Ghanaian regions. The effect of the Bt-Cotton array on the harvest of cotton in India was evaluated by Mrinmoy et al. (2014). Yang (2014) examined the effect of newly introduced goods on sales using ARIMA intervention model.

Shittu and Inyang (2019) used the Box-Tiao model and lag operator intervention structure to simulate the monthly crude oil prices in Nigeria with the goal of contrasting the results. Moffat and Inyang (2022) looked at how the quantity of crude oil produced was affected by the nation's leniency scheme. The effect of the announcement of alliance on Nigerian crude oil production was examined by Etuk et al. (2022). Following the Box–Tiao method, Inyang et al. (2022) investigated how international energy diplomacy affected the value of Nigerian crude. The December 2016 intervention caused a notable and sudden effect on oil value upon its enactment, as seen by the corresponding 34 percent hike in the price. Inyang et al. (2023) modelled each day's Pakistani/Nigerian currencies using a time series intervention model built on the ESM and ARIMA Models. Inyang et al. (2024) used an intervention model built around the ETS and ARIMA models to study how the Bangladeshi Taka's relative worth responded to the naira as a direct result of year 2016 economic slump. According to the study's findings, there was a 68.50 percent drop in the purchasing power of the naira when it was exchanged, with a decay rate of 0.6. Inyang (2024) employed the intervention model based on exponential smoothing methods and ARIMA models in modelling the Nigerian naira exchange rates in the face of an economic slump. Results revealed that the 2016 economic downturn had a negative impact on the naira, with a percentage change of 47.51. The intervention was considered a step function with a delay of 1 period and a gradual permanent effect with a decay rate of 0.60. Comparatively speaking, nonetheless, the ARIMA-intervention model outperformed the ETS-intervention model. The aim of this study is to propose an appropriate time series model for the studied series in order to investigate how the government's involvement has affected the prevalence of paediatric anaemia.

2. Methodology

2.1. Data Description

The monthly paediatric anaemia cases from January 1997 to December 2011 that make up the study's data set were taken from the medical records of five hospital selected from three senatorial districts in the state. The observations prior to the intervention periods of January 1997–November 2006 and after the intervention periods of December 2006–December 2011 were separated from the dataset. The R language (R-4.1.3-win) statistical software was utilized for the analysis of this work [35].

2.2. ARIMA-Intervention Model

Research indicates that the Box-Jenkins ARIMA model is particularly frequently employed modeling and forecasting technique [3–5]. However, when external events affect the time series, the forecasting power of the ARIMA model could be undermined. As a result, [6] proposed an appropriate technique, the ARIMA-Intervention analysis, given as:

$$\lambda_t = \text{Ģ}\left(\oint\right) + \Game_t \tag{1}$$

Where $\text{Ģ}(\oint)$ is the transfer function part and $\Game_t$ is ARIMA part

ARIMA intervention model is given by

$$\lambda_t = \frac{\eta(\oint)}{\nu(\oint)} \oint^{\text{æ}} \Finv_t + \frac{\hbar(\oint)}{\forall(\oint)} \varepsilon_t \tag{2}$$

since

$$\c{C}\left(\oint\right) = \frac{\eta(\oint)}{\nu(\oint)} \Finv_{t-\text{æ}} \tag{3}$$

$$\Game_t = \frac{\hbar(\oint)}{\forall(\oint)} \varepsilon_t \tag{4}$$

Where:

$$\forall\left(\oint\right) = 1 - \forall_1 \oint - \forall_2 \oint^2 - \cdots - \forall_p \oint^p \tag{5}$$

$$\hbar\left(\oint\right) = 1 + \hbar_1 \oint + \hbar_2 \oint^2 + \cdots + \hbar_q \oint^q \tag{6}$$

$$\nu\left(\oint\right) = 1 - \nu_1 \oint - \nu_2 \oint^2 - \cdots - \nu_r \oint^r \tag{7}$$

$$\eta\left(\oint\right) = \eta_0 - \eta_1 \oint - \eta_2 \oint^2 - \cdots - \eta_s \oint^s \tag{8}$$

λ_t is the childhood Anaemia series at time t, æ=delay parameter, η=impact parameter, ν=the growth rate, $\forall$=regular autoregressive parameter, $\hbar$=regular moving average parameter, ε_t= error term, $\oint$=backward shift operator.

The prior to intervention time frame's benchmark monthly sequence of pediatric anaemia is portrayed by $\Game_t$, a Box – Jenkins ARIMA(p,d,q) model.
$\Finv_t$ is the indicator variable and it is mathematically written as

$$\Finv_t^T = \begin{cases} 1, & t = T \\ 0, & t \neq T \end{cases} \tag{9}$$

$\Finv_t^T$ is called the Pulse function.

2.3. Unit Root Test

Fully diagnosing the properties of the data set employed in the research is relevant and necessary before proceeding with any additional analysis in time series modeling. Based on the regression equation, the Augmented Dickey-Fuller (ADF) test [10] is used.

$$\lambda_t = \forall\lambda_{t-1} + \sum_{j=1}^{p-1} \lambda_j \Delta\lambda_{t-j} + \epsilon_t \tag{10}$$

Where λ_t is the series being tested and p is the number of lagged differenced terms included to capture any autocorrelation.

Hypothesis:
$H_0 : \beta = 1$ (series contains unit root)
Against
$H_1 : \beta \neq 1$

Test statistic:

$$T_p = \frac{\hat{\phi_{-1}}}{SE(\hat{\phi})} \sim t_\alpha(n) \tag{11}$$

If the null hypothesis is rejected, we conclude that the series contains no unit root.

2.4. Akaike Information Criterion (AIC)

The AIC [1], is formulated as

$$AIC = M_T \left[1 + \frac{2p}{T-p} \right] \tag{12}$$

Where:
M_T= Index related to production error (known as residual sum of squares) p= No of parameters in the model, T= No. of data points.

2.5. Bayesian Information Criterion (BIC)

A criterion for selecting a model from a limited number of models is the BIC [7, 36]. The model that comes up with the smallest BIC score among two or more estimated models should be chosen. It is provided by:

$$BIC = n \ln \hat{\sigma}_e^2 + k \ln(n) \tag{13}$$

Where $\hat{\sigma}_e^2$ is the estimated error variance defined by

$$\hat{\sigma}_e^2 = \frac{1}{T} \sum_i^T (\curlywedge_i - \bar{\curlywedge})^2$$

$\curlywedge$= Observed data, T=Number of observations, k= Number of free parameters to be estimated.

2.6. Ljung Box Test

One method to check for the lack of serial autocorrelation up to lag k is the Ljung Box Test [22]. One need to determine the statistic $\mho$ in order to perform the Ljung

Box test. Given a series Q_t of length ς:

$$\mho(m) = \varsigma(\varsigma + 2) \sum_{j=1}^{\aleph} \frac{r_j^2}{\varsigma - j} \tag{14}$$

Where: r_j = accumulated sample autocorrelations, $\aleph$ = the time lag.

Hypothesis:
H_0 :(residuals show no autocorrelation)
Against
H_1 :(H_0 is not true)

3. Results and Discussion

For the investigated periods, Table 1 presents basic summary statistics from the examined dataset in an effort to help better comprehend the series.

Table 1. Descriptive Statistics for Childhood Anaemia Prevalence

Full Series							Pre-Series		Post-Series	
Nobs	Min	Max	Sum	Mean	Var	Stdev	Nobs	Sum	Nobs	Sum
180	5	147	9413	52	694	26	119	5672	61	3741

180 observations in all, made between January 1, 1997, and December 31, 2011. The lowest number of paediatric anaemia cases ever recorded was 5 in January 2011, while the highest number of cases—147—occurred in December 2006. Before the intervention, 5,672 children had anaemia disease, and 3,741 cases were reported as victims who contracted the infection during the post-intervention period. 9,413 children between the ages of 0 and 14 suffered from this illness during the study period; an average prevalence of 52 cases with 26 standard deviation cases were found.

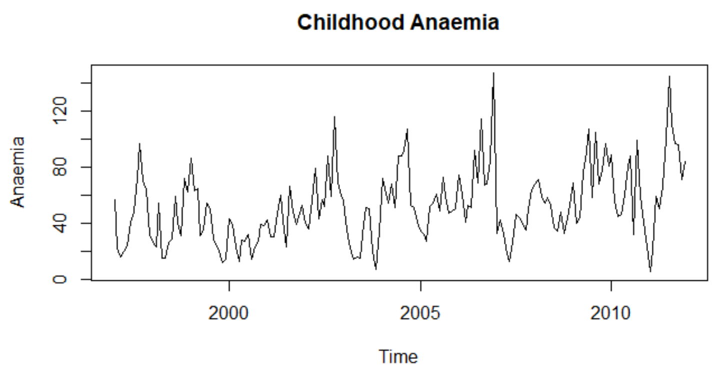

Figure 1. Time Plot of Childhood Anaemia

Figure 1 is the time plot showing the monthly anaemia prevalence rate ranging from January 1997 to December 2011. The series rises and falls at random with no discernible trend pattern, with the highest peak occurring in December 2006, which called for intervention. According to the indicator functions, the suspected location of the intervention is identified as:

$$\daleth_t^T = \begin{cases} 1, & t = December 2006 \\ 0, & t \neq December 2006 \end{cases} \tag{15}$$

Here T= December 2006 and $\daleth_t^T$ is a Pulse function.

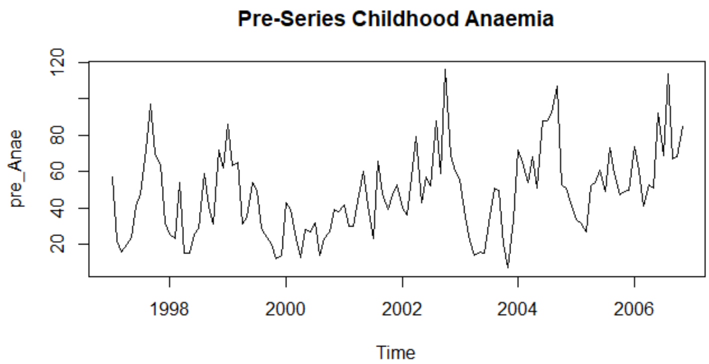

Figure 2. Time Plot of Pre-Series Childhood Anaemia

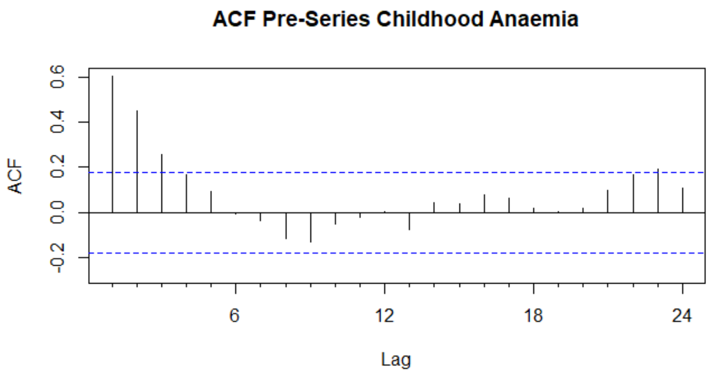

Figure 3. ACF Plot of Pre-Series

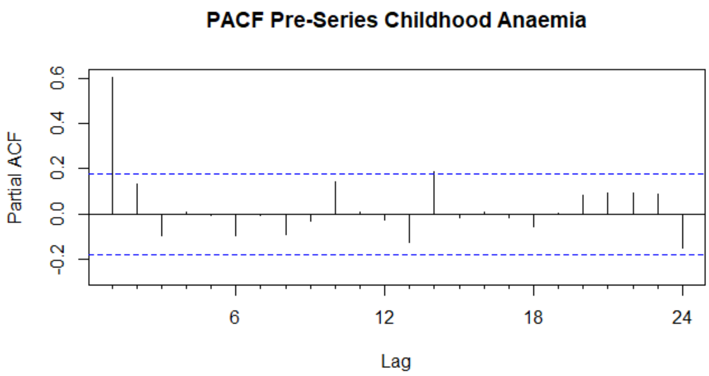

Figure 4. PACF Plot of Pre-Series

The before intervention (pre-series) and after the intervention (post-series) eras of the dataset's values are separated out. Data points from January 1997 to November 2006 are used as the pre-series displayed in Figure 2, and datasets from December 2006 to December 2011 are used as the post-series. For the error component of the intervention model in (2), a set of series prior to the intervention period is utilized

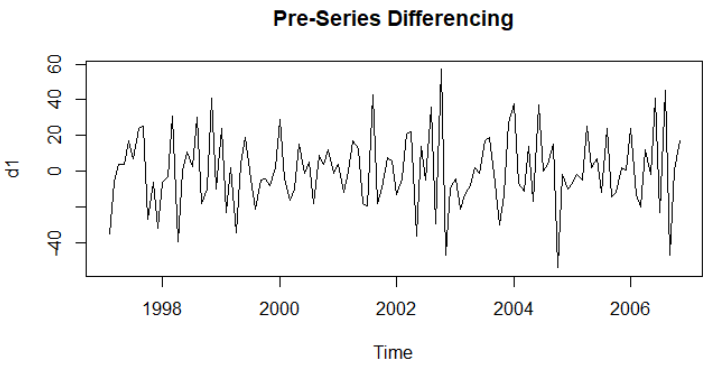

Figure 5. Plot of Pre-Series at First Difference

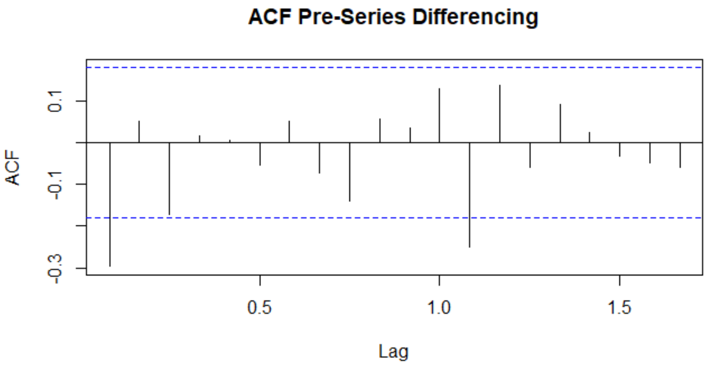

Figure 6. ACF of Pre-Series at First Difference

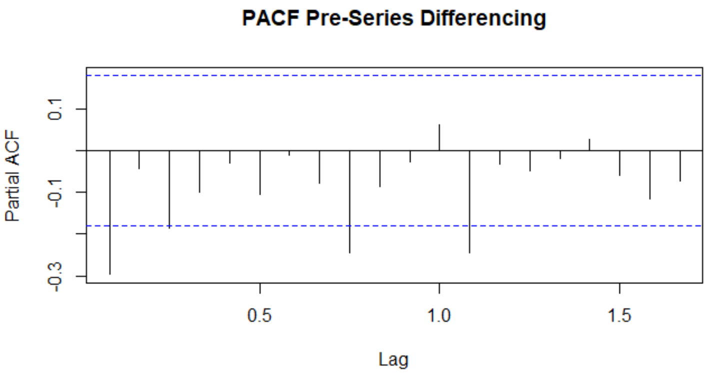

Figure 7. PACF of Pre-Series at First Difference

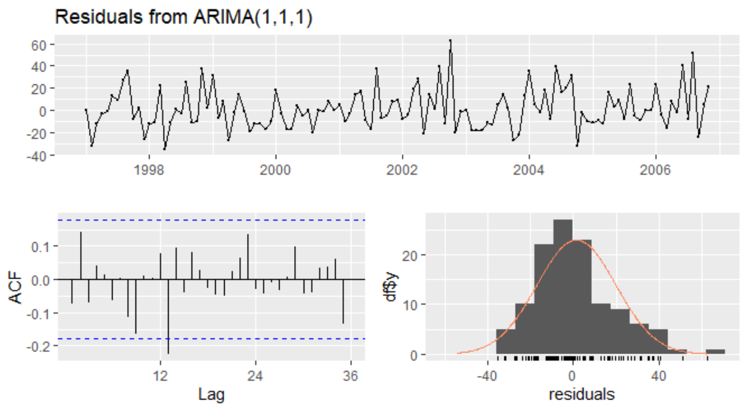

Figure 8. Residuals from ARIMA(1,1,1) Model

for ARIMA model fitting, while dataset in the post-intervention periods is used to compute the transfer function of the intervention component. Figures 2, 3 and 4 shows sign of weakly stationarity, since the autocorrelation function's (ACF) inability to completely die out at high lags points. To eliminate all observable trend, call for series transformation. And the difference method of series transformation is adopted. The series is stationary after first difference in Figures 5, 6 and 7. After initial differencing, Table 2 provides additional evidence for the stationary character of the series with a unit root test, since the p-value of the Augmented Dickey-Fuller Test is smaller than the alpha level.

Table 2. Unit Root Test after Differencing

Test	Augmented Dickey-Fuller
Data	Pre-Series Childhood Anaemia
Dickey-Fuller	-5.9195
Lag Order	4
P-value	0.01
Alternative hypothesis	Stationary

Table 3. Parameter Estimation for ARIMA Models

ARIMA(p,d,q)		Estimate	Std. Error	Z-value	Prob. Value
$(1,1,1)$	$\forall_1$	0.577245	0.085358	6.7627	$1.355e-11***$
	$\hbar_1$	-0.961886	0.031401	-30.6327	$2.2e-16***$
$(0,1,1)$	$\hbar_1$	-0.37533	0.10369	-3.6199	$0.0002947***$
$(1,0,0)$	$\forall_1$	0.610175	0.072912	8.3687	$2.2e-16***$
	$\ltimes$	48.262830	4.264727	11.3167	$2.2e-16***$
$(1,1,0)$	$\forall_1$	-0.303570	0.088716	-3.4218	$0.000622***$
$(1,0,1)$	$\forall_1$	0.714650	0.096577	7.3998	$1.364e-13***$
	$\hbar_1$	-0.166101	0.129740	-1.2803	0.2005
	$\ltimes$	48.371818	4.798721	10.0801	2.2e-16 ***
$(0,0,1)$	$\hbar_1$	0.428148	0.064557	6.632	$3.311e-11***$
	$\ltimes$	47.817936	2.620530	18.247	$2.2e-16***$

Table 4. Model Evaluation for ARIMA Models

Model	BIC	AIC
$ARIMA(1,1,1)$	1039.046	1030.734
$ARIMA(0,1,1)$	1043.732	1038.191
$ARIMA(1,0,0)$	1045.087	1036.749
$ARIMA(1,1,0)$	1045.398	1039.856
$ARIMA(1,0,1)$	1048.272	1037.156
$ARIMA(0,0,1)$	1066.022	1057.685

Table 5. Ljung-Box Test for ARIMA(1,1,1) Model

Residuals from $ARIMA(1,1,1)$
$Q* = 24.386$, $df = 22$, $p-value = 0.3273$
Model df : 2. Total lags used: 24

Table 6. Forecast from $ARIMA(1,1,1)$ Model

Length	Date	Actual Value	Forecast
120	Dec 2006	147	74.24168
121	Jan 2007	33	68.03150
122	Feb 2007	42	64.44669

Table 3 summarizes the statistics used in fitting the ARIMA(1,1,1) model based on the correlograms in Figures 6 and 7. Since nearly all of the residual correlations of the ARIMA(1, 1, 1) model are non-significant, that is, the residuals ACF coefficients fall within significance limits of ±0.1833 (Figure 8) and have the lowest BIC and AIC values of 1039.046 and 1030.734 in Table 4, respectively, the model's suitability is undeniable. Table 5's Ljung-Box test, which yielded a $p - value$ of 0.3273, provided additional evidence that the model is sufficient, appropriate, and statistically significant for the given dataset.

To determine the parameters of the transfer function of the intervention component.

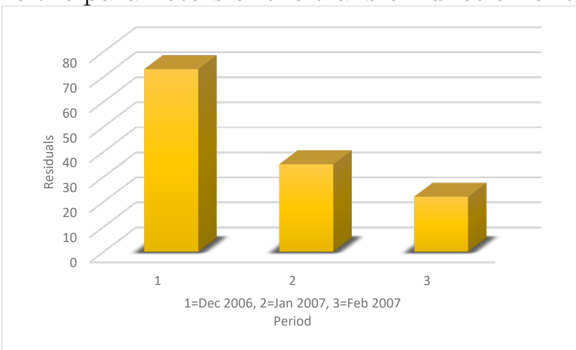

Figure 9. Impulse Response Function

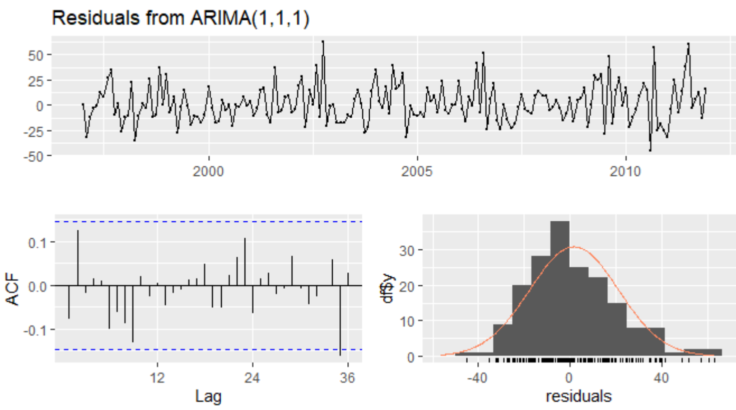

Figure 10. Residual from $ARIMA(1,1,1) - Intervention$ Model

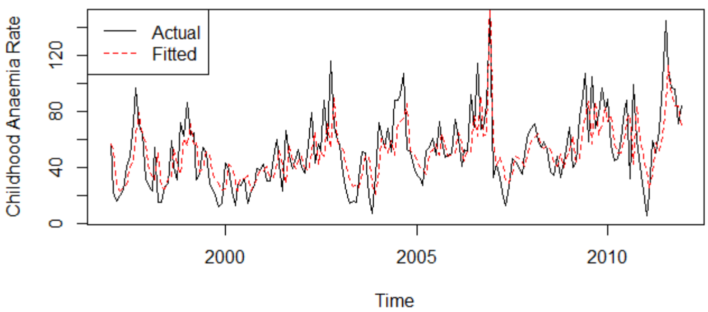

Figure 11. Fitted $ARIMA(1,1,1) - Intervention$ Model with Actual Values

By making use of the fitted ARIMA(1, 1, 1) model to predict the earliest post-series data points, the delay parameter value is calculated. With æ = 0 (Table 7 and Figure 9), suggest that the influence of the intervention was felt at the time of the intervention. The significant p-value for the impact parameter is $7.249e - 08$, with a value of

Table 7. Parameter Estimation for $ARIMA(1,1,1) - Intervention$ Model

Parameter	Estimate	Std. Error	$Z - value$	$Prob.Value$
$\forall_1$	0.602670	0.064770	9.3048	$2.2e - 16 * **$
$\hbar$	-0.971316	0.018387	-52.8255	$2.2e - 16 * **$
η	88.396317	16.415604	5.3849	$7.249e - 08 * **$
æ	0			

Table 8. $Ljung - Box$ Test for $ARIMA(1,1,1) - Intervention$ Model

Residuals from $ARIMA(1,1,1)$
$Q* = 18.187$, $df = 22$, $p - value = 0.6948$
Model df : 2. Total lags used: 24

Table 9. Forecast from $ARIMA(1,1,1) - Intervention$ Model

Length	Date	Forecast	95% Prediction Interval	
			Lower	Upper
175	Jul 2011	77	32	184
176	Aug 2011	65	23	183
177	Sep 2011	59	20	175
178	Oct 2011	56	18	169
179	Nov 2011	54	17	165
180	Dec 2011	52	17	162

88.3963. Hospital admission cases increased in the post-intervention period, with the lowest and highest cases being 5 and 145, respectively, compared to the period before the intervention. This suggests that the intervention was not successful in producing the intended result, as indicated by the significant impact parameter and its sign. The residual of the fitted model in Figure 10 and the Ljung-Box test statistic in Table 8 showed that the model in (16) is statistically significant, sufficient and adequate for the dataset. Plotting the fitted with the actual values further validates the goodness of fit of the model in (16) and established that the fitted values mirror the actual values, as displayed in Figure 11.
Mathematically, the Intervention-ARIMA(1,1,1) model is expressed as

$$\lambda_t = 88.3963 \daleth_{t-0} - \frac{0.9713 \oint}{(1 - 0.6027 \oint)} \varepsilon_t \tag{16}$$

4. Conclusion

The Box-Tiao modeling technique is used to evaluate how the government's action has affected the prevalence of paediatric anaemia. Over the course of the research period, anaemia afflicted 9,413 hospital-admitted youngsters between their years of 0 and 14. With the highest case of anaemia (147 recorded in one month), December 2006 calls for intervention. The intervention function is identified as a pulse point. The ARIMA (1,1,1) model is fitted and adjudged adequate for the data points prior to the intervention period. The impact parameter value is 88.3963 with a p-value of $7.249e-08$. This suggests that the intervention was not successful in producing the intended result, as indicated by the significant impact parameter and its sign. It is also evidenced in the number of hospital admission cases, which increased in the post-intervention period, with the highest case number of 145 compared to the period before the intervention. A delay parameter of value zero (0) implies that the influence of the intervention was felt at the time of the intervention. The intervention effect was immediate and abrupt, with a growth rate of zero. The forecasts generated from the fitted ARIMA(1, 1, 1)-Intervention model were within the 95% prediction interval and were also close to the actual values (Table 9). This suggests that health professionals can use the model to forecast and formulate control mechanisms. Furthermore, since paediatric anaemia has not declined appreciably, there is a need for an intensive anaemia control programme.

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