Journal of the Nigerian Association of Mathematical Physics
Volume 65, (October 2022– August 2023 Issue), pp161 – 172

APPLICATION OF MANN KENDALL AND ARIMA MODEL IN DETECTING AND MODELING THE TRENDS IN UNDER-FIVE DEATHS

Onoghojobi B[1], Tanimu Mohammed[2] and Olewuezi N. P[3]

[1]Department of Statistics, Federal University Lokoja, Kogi State
[2]Department of Statistics, University of Abuja, Abuja
[3]Department of Statistics, Federal University of Technology, Owerri

Abstract

This research work assesses the levels and trends in Under-five mortality in Nigeria. Yearly under-five deaths in Nigeria were sourced from the WHO-World Development Index site and analyzed using Statgraphic software. The data covers a period of 52 years, from 1969 to 2020. The two-sided Mann-Kendall test was used to determine whether a statistically significant monotonic upward or downward trend exists in the data. Since the calculated P-value is less than 0.01, the presence of a trend has been detected at the 1.0% significance level. An autoregressive integrated moving average [ARIMA (0, 2, 2)] model has been selected as the best model for the series. The model assumes that the best forecast for future data is given by a parametric model relating the most recent data value to previous data values and previous noise. The research recommended that even though there is a decline in mortality rate, steps need to be taken to drastically bring the number of deaths to the barest minimum.

Keywords: Under-Five Deaths, ARIMA, Mann-Kendall Test, Time Series.

1. Introduction

The world over, 8.2 million children under age 5 die each year, and more than 40% of these are neonatal deaths, occurring before 30 days of life. In sub-Saharan Africa alone, 1.2 million newborns die every year [1], and the area has the highest risk of neonatal deaths among the 186 countries studied in 2013 [2].Child mortality is largely concentrated in the first year of life, and mortality in this period is known as 'infant death'. Worldwide, 4 million infants die each year in the first 28 days of life (the neonatal period). The child survival Millennium Development Goal cannot be met without a substantial reduction in infant mortality [3].

According to recent estimates, over 4 million babies die each year in the world in the first four weeks of life and 98% of these deaths occur in developing countries; 3 million of these deaths occur in the early neonatal period [4].

Many countries in South Asia and Sub-Saharan Africa including Nigeria still have high under-five mortality unlike some countries in East Asia, Pacific, Latin America, Carribean, and Central/Eastern Europe that have made substantial progress in its reduction [5]. Globally, it appears that attention is focused on childhood survival more than neonates. Reports showed that between 2000 and 2010, the annual rate of reduction for neonatal mortality (2.1%) worldwide is lower than 2.9% recorded for under five mortality with the proportion of under-five deaths in the neonatal period increasing from 37% in 1990 to 44% in 2013 [5]. It goes without saying that overall success in child survival is contingent on a corresponding decline in neonatal mortality. Unfortunately, 39% of neonatal deaths worldwide are in Sub-Saharan Africa [5]. Nigeria provided 6% of the global neonatal deaths in 2005 [6] while the country moved from the third to the second position in terms of the highest number of neonatal deaths in the world between 2000 and 2010 [7].

The Nigeria Demographic and Health Survey (NDHS) 2013 estimated its Neonatal Mortality Rate (NMR) as 37 per 1000 live births which constituted about 54% of infant mortality. The burden of neonatal mortality in Nigeria was higher than

Corresponding Author**:** Onoghojobi B., Email: ngolewe@yahoo.com, Tel: +2348034933133

that of the African region as a whole in 2009 (36 per 1000) [8]. However, there have been some improvement in infant and under-five survival with the former reducing from 100 per 1000 live births in 2003 to 67 per 1000 in 2013 [9]. The rate of reduction recorded for neonatal mortality (53 per 1000 to 37 per 1000) was lower than that for infant and under-five. Several studies have provided useful insights into the determinants of under-five mortality, which were reported to differ in their effects across the age span 0- 5 years [10]. Such age variation in the effect of childhood mortality determinants informed the investigation of factors associated with neonatal mortality. Studies on determinants of neonatal mortality have received attention in Indonesia [11], Bangladesh [12], India and Ethiopia [13].

The decline in the infant mortality rate in Nigeria over the past few years has been inadequate [14]. More specifically, the decrease in infant mortality has been accompanied by an increased concentration of deaths in the first week of life. It is generally argued that two-thirds of all deaths in the first 5 years of life in developing countries are infant deaths, with two-thirds of these deaths being confined to the neonatal period [15]; [16]. In Nigeria, the newborn death rate, especially in the neonatal mortality period, is almost 528 per day. This neonatal mortality is one of the highest in the world. More than a quarter of a million children die under the age of 5 years annually in Nigeria. These deaths occur during the first 28 days of life, especially in the neonatal period. One important thing about this mortality is that about nine out of ten newborn deaths are preventable. In Nigeria, about 5.3 million children are born yearly, which is about 11,000 every day; 1 million of these children die before the age of 5 years [3].

Also, child mortality in Nigeria continues to be a public health challenge despite adopting the various international health agendas aimed at reducing child mortality such as millennium development goals (MDGs), partnerships for maternal, neonatal and child health (PMNCH) and the Countdown Strategy. Despite keying into these programs, neonatal, infant, child and under-5 mortality rates remain high at 37, 69, 64 and 128 per 1000 live births respectively and Nigeria's contribution to the global burden of child mortality is immensely huge at around 13% (or 804,000 child deaths) in 2013 [17]. Nigeria's contribution to global pool of child mortality has marginally decreased from 849,000 in 1990 to 827,000 in 2012 while there is a reversal in the expected decline as neonatal deaths increasing from 207, 000 to 267,000 during the same period [17]

As recommended by different United Nations (UN) organizations, most countries use the reduction in under-five and maternal mortalities as bases for key development [18]. It is also pertinent for countries to estimate their neonatal and infant mortalities so as develop appropriate intervention programs to reduce preventable child deaths. Neonatal mortality remains a significant public health problem worldwide. In the year 2015, 2.7 million deaths occurred in the first 28 days of life; representing a significant reduction to 19 deaths per 1,000 live births from the previously 36 deaths per 1000 live births in 1990 [19]. Though there was a decline in neonatal rates in some sub-Sahara African countries, such as Ghana and Uganda [20], the Nigerian Neonatal Mortality Rate (NMR) reduced by 20.4%, from 49 deaths per 1000 live births in 1990 to 39 in 2011 [5], 37 in 2013 [3] and to 34 deaths per 1000 live births in 2015 [3]. Globally, Nigeria ranks second to India with the highest number of neonatal deaths [5]. Deaths in the first 28 days of life has been linked to the endogenous (genetically-induced malfunctions, premature births) status of a child, quality of antenatal care, whether assistance was given during delivery and post-partum care [21].

With the share of under-five deaths during the neonatal period rising in every region and almost all countries, accelerated change for child survival needs more focus on a healthy start to life. In 2013, 2.8 million newborns died within 28 days of birth, accounting for 44 percent of global under-five deaths. Neonatal health will need to be addressed more effectively to continue the rapid progress on overall child mortality. It is unacceptable that every day 17,000 children still die before their fifth birthday, mostly from preventable causes and treatable diseases, even though the knowledge and technologies for lifesaving interventions are available.

In recent years, the Every Woman Every Child strategy launched by United Nations Secretary- General Ban Ki-moon has boosted global momentum in improving newborn and child survival. The United Nations Children's Fund (UNICEF), the World Health Organization (WHO) and other UN organizations are joining public, private and civil society partners in a global movement to accelerate reduction in preventable maternal, newborn and child deaths. Under the banner of A Promise Renewed, the partners have pledged to redouble efforts to end preventable maternal, newborn and child deaths. In this context, monitoring progress at the global and country levels has become even more critical.

An important determinant of the risk of death in the first 5 years of life repeatedly highlighted in previous studies is the birth interval [22]; [23]. It has been conclusively argued that newborns with a short birth interval (less than 2 years) have a higher probability of dying in the first 5 years of life than those with a birth interval of 3 years or more [24]. The published literature shows that there is high mortality rate in the first years of life in Nigeria, but little is known about trends on Under-five Death, or its determining factors

The aim of this work is to assess the levels and trends in under-five mortality in Nigeria and to examine the importance of the role of health care factors compared with bio-demographic determinants in the persistently high neonatal mortality areas. The aims were achieved with showing the general pattern of under-five death over the period (1969 – 2020), estimating the appropriate models for Under-Five death in Nigeria and forecasting the future under-five death in Nigeria

2. Research Methodology

In this section, the method of data collection and statistical tool for analyzing time series data is discussed. Yearly under-five deaths in Nigeria were soured from the WHO-World Development Index site. The data covers a period of 52 years, from 1969 to 2020.

2.1 The ARIMA Model

ARIMA is an acronym that stands for Auto-Regressive Integrated Moving Average. This is a known time series model and could be defined algebraically by:

$$Y_t=\mu+\alpha_1 y_{t-1}+\ldots+\alpha_p y_{p-1}+e_t-\delta_1 et_{-1}+\delta_q e_{t-1} \quad (1)$$

at time $t=1,\ldots,n$, where e_{t-j} (j=0,1,… ,*q)* are the lagged forecast errors. Usually, the $p+q+1$ unknown parameters $\mu, \alpha_j \ldots,\alpha_p$ *and* $\alpha_i\ldots,\alpha_q$ are determined by minimizing the squared residuals [25].

From the ARIMA technique, the dependent variable Y_t is predicted in the first part of the right hand side of equation (1) above based on its values at earlier time periods. This constitutes the autoregressive (AR) part in equation (1) above. In the second part, the dependent variable Y_t also depends on the values of the residuals at earlier time periods, which may be regarded as prior random alarms. This is the moving average (MA) part of equation (1).

In addition to the AR and MA parameters, ARIMA models may also include a constant. The interpretation of a (statistically significant) constant depends on the model that is fit. Two indicative situations are:

i. The situation of no autoregressive parameters in the series. In such case, the expected value of the constant is the mean of the series;
ii. The situation of autoregressive parameters in the series. In such case, the constant represents the intercept. If the series is differenced, then the constant represents the mean or intercept of the differenced series. For the non-seasonal scenario, the simple ARIMA (p, d,q) model is used with p the number of autoregressive terms, d the number of non-seasonal differences, and q the number of lagged forecast errors in the prediction equation. However, climatic data usually contains the seasonal variations. Thus, it is more apt to incorporate the full Seasonal Auto Regressive Integrated Moving Average (SARIMA) model

2.2 The standard (classic) Mann–Kendall test (MK)

The standard Mann–Kendall tests (MK), also called the classic version of the Mann–Kendall test, has been widely applied to estimate trends in hydro-climatological series. If the sample size is equal to n, the S statistic can be calculated by the following formula:

$$S=\sum_{k=1}^{n-1}\sum_{j=k+1}^{n} sgn(x_j-x_k) \quad (2)$$

where, x_j denotes the jth data, n is the data length and sgn(θ) denotes the sign function that is given as:

$$\text{sign}(x)=\begin{cases}+1\ if\ (x_j-x_k)>0\\ 0\ if\ (x_j-x_k)=0\\ -1\ if\ (x_j-x_k)<0\end{cases} \quad (3)$$

For n >8 the S statistic follows the normal distribution, and its mean and variance can be obtained by the following formulae

$$E(S)=0 \quad (4)$$

$$V(S)=\frac{n-(n-1)(2n+5)-\beta}{18} \quad (5)$$

where, C is a factor for modifying variance. When there are tied data (same consecutive data) in the series, the C is calculated by the formula below and will apply on variance of S.

$C = \sum_{i=1}^{m} t_i(t_i - 1)(2t_i - 5)$ (6)

where, t_i denotes the number of tied data in the i^{th} group. The Z statistic of the MK test can be computed as:

$$Z = \begin{cases} \frac{s-1}{\sqrt{Var(s)}} \; if \; s > 0 \\ 0 \; if \; s = 0 \\ \frac{s+1}{\sqrt{Var(s)}} \; if \; s < 0 \end{cases} \quad (7)$$

In the MK test, the null hypothesis H0, (there is no significant trend in the time series) will be accepted if at the α significance level, $-Z_{1-\alpha/2} \leq Z \leq Z_{1-\alpha/2}$, otherwise the H_0 will be rejected and the alternative hypothesis (existence of significant trend at the significance level of α) will be accepted [26].

2.3 Modified Mann–Kendall test

Modified Mann–Kendall test is the non-parametric statistical tool used for testing monotonic upward or downward trend of the series during positive auto correlation [27]. Here nonparametric block bootstrap technique was included to improve Mann–Kendal test, where it resamples the original series with prefixed block length [28]. The null hypothesis H_0: there has been no trend in given series was tested against there has been a trend in given series. The hypothesis where no trend was rejected when the computed Z transformed test Statistic value was greater in absolute value than the critical value $Z_{1-0.01\alpha}$, at 99% level of significance. The main assumption of the MK test is that the sample data are not significantly correlated.

If a series has significant positive or negative autocorrelation coefficients, then the MK test will show an unrealistically large value of the Z statistic leading to the rejection of the null hypothesis (there is no trend in data series) instead of the acceptance of the null hypothesis, i.e., there is no trend in hydrological data series in reality [29]. The modified version of the Mann–Kendall (MMK) test, suggested by [30], has been used by [26] for analyzing the trends in precipitation over Iran, and [31] for identifying trends in reference evapotranspiration over northeast India. In this method, the effect of all significant autocorrelation coefficients is eliminated from the time series before applying the MK test. In the MMK test, the modified variance V(S)* is calculated as follows:

$V(S)^* = V(S)\frac{n}{n^*}$ (8)

$$\frac{n}{n^*} = 1 + \frac{2}{n(n-1)(n-2)} \sum_{i=1}^{n-1}(n-1)(n-i-1)(n-i-2)r_i \quad (9)$$

where r_i is the i delayed autocorrelation coefficient and V(S) is estimated using Equation (8). For calculating the Z statistic in the MMK test (Equation (12)), V(S) is substituted by V(S)*

3. FORECASTING EVALUATION

Forecasting Evaluation Criteria Numerous error measures are available for forecasts evaluation; thus this study evaluates the forecasting ability of state space and Box-Jenkins type models by means of three different loss functions. These are root mean squared error (RMSE), mean absolute error (MAE) and Theil's U statistic which are defined as follows;

$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2}$ (10)

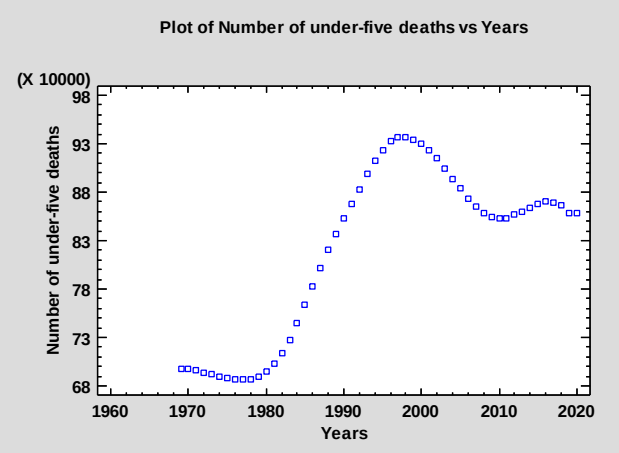
$MAE = \frac{1}{n}\sum_{t=1}^{n}|(A_t - F_t)^2|$ (11)

$$Ut = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - A_{t-1})^2}} \quad (12)$$

where A_t is the actual value in time t, and F_t is the forecast value in time t. Theil's U statistic compares the forecast accuracy of different models. The overall perform of the estimating methods were accessed using the average of the three loss functions, that is $Average = (RMSE + MAE + Ut)/3$, the method with the minimum Average is the best

4. Empirical Results

4.1 Data Presentation



Data Source: WHO- World Development Index

Figure 1: Time Plot of the Number of Under-Five Deaths in Nigeria 1969-2020

Table 1 Summary Statistics for Under-Five deaths in Nigeria

Count	52
Average	820162.
Standard deviation	88818.8
Coeff. of variation	10.8294%
Minimum	686250.
Maximum	936496.
Range	250246.
Stnd. Skewness	-1.31768
Stnd. Kurtosis	-2.00869

Table 1 shows summary statistics for Number of under-five deaths. It includes measures of central tendency, measures of variability, and measures of shape. Of particular interest here are the standardized skewness and standardized kurtosis, which can be used to determine whether the sample comes from a normal distribution. Values of these statistics outside the range of -2 to +2 indicate significant departures from normality, which would tend to invalidate any statistical test regarding the standard deviation. In this case, the standardized skewness value is within the range expected for data from a normal distribution. The standardized kurtosis value is not within the range expected for data from a normal distribution.

Table 2: Run Chart (Individuals) - Number of under-five deaths

Test	*Observed*	*Expected*	*Longest*	*P(>=)*	*P(<=)*
Runs above and below median	4	27.0	22	1.0	1.47107E-10
Runs up and down	6	34.3333	21	1.0	0.0

Data variable: Number of under-five deaths

52 values ranging from 686250. to 936496.
Median = 857288.

Table 2 is used to examine data for trends or other patterns over time. Four types of non-random patterns can sometimes be seen:

i. Mixing - too many runs above or below the median
ii. Clustering - too few runs above or below the median
iii. Oscillation - too many runs up and down
iv. Trending - too few runs up and down

The P-values are used to determine whether any apparent patterns are statistically significant. Since the P(equal or less) value for the runs above and below the median is less than 0.025, there is statistically significant clustering at the 95% confidence level. Since the P(equal or less) value for the runs up and down is less than 0.025, there is statistically significant trending at the 95% confidence level.

Table 3: Mann-Kendall Test
Null hypothesis: No trend
Alternative hypothesis: Upward or downward monotonic trend

Test	*Sum*	*Stnd. Error*	*Statistic*	*P-Value*
Mann-Kendall	580	126.725	4.56893	0.00000490702

The two-sided Mann-Kendall test is used to determine whether a statistically significant monotonic upward or downward trend exists in the data. Since the calculated P-value is less than 0.01, the presence of a trend has been detected at the 1.0% significance level.

Table 4a: ARIMA Model Summary

Parameter	*Estimate*	*Stnd. Error*	*T*	*P-value*
MA(1)	-0.534259	0.0437944	-12.1992	0.000000
MA(2)	-0.898608	0.0377007	-23.8353	0.000000

Table 4b: Forecast Summary

Statistic	*Estimation Period*	*Validation Period*
RMSE	1755.33	
MAE	1065.55	
MAPE	0.127928	
ME	118.069	
MPE	0.0201011	

Backforecasting: Yes
Estimated white noise variance = 3.1158E6 with 48 degrees of freedom
Estimated white noise standard deviation = 1765.16
Number of iterations: 5
Table 4(a,b) shows the forecast future values of number of under-five deaths. The data cover 52 time periods. An autoregressive integrated moving average (ARIMA) model has been selected. This model assumes that the best forecast for future data is given by a parametric model relating the most recent data value to previous data values and previous noise. Table 4a summarizes the statistical significance of the terms in the forecasting model. Terms with P-values less than 0.01 are statistically significantly different from zero at the 99.0% confidence level. The P-value for the MA(2) term is less than 0.01, so it is significantly different from 0. The estimated standard deviation of the input white noise equals 1765.16.
Table 4b summarizes the performance of the currently selected model in fitting the historical data. It displays:

i. the root mean squared error (RMSE)
ii. the mean absolute error (MAE)
iii. the mean absolute percentage error (MAPE)
iv. the mean error (ME)
v. the mean percentage error (MPE)

Each of the statistics is based on the one-ahead forecast errors, which are the differences between the data value at time t and the forecast of that value made at time t-1. The first three statistics measure the magnitude of the errors. A better model will give a smaller value. The last two statistics measure bias. A better model will give a value close to 0.

4.2 Model Comparison
Models
(A) Random walk
(B) Random walk with drift = 3140.33
(C) Constant mean = 820162.
(D) Linear trend = 700666. + 4509.27 t
(E) Quadratic trend = 603204. + 15338.3 t + -204.322 t^2
(F) Exponential trend = exp(13.4587 + 0.00575544 t)
(G) S-curve trend = exp(13.6439 + -0.374024 /t)
(H) Simple moving average of 2 terms
(I) Simple exponential smoothing with alpha = 0.9999
(J) Brown's linear exp. smoothing with alpha = 0.9999
(K) Holt's linear exp. smoothing with alpha = 0.9999 and beta = 0.085

(L) Brown's quadratic exp. smoothing with alpha = 0.9193
(M) ARIMA(0,2,2)
(N) ARIMA(1,1,2)
(O) ARIMA(2,1,2)
(P) ARIMA(2,2,2)
(Q) ARIMA(2,1,0)

Table 5: Estimation Period

Model	*RMSE*	*MAE*	*MAPE*	*ME*	*MPE*	*AIC*	*HQC*	*SBIC*
(A)	9505.25	7340.76	0.886851	3140.33	0.398359	18.3192	18.3192	18.3192
(B)	9060.78	7500.69	0.908608	-3.88051E-11	0.0119898	18.2619	18.2763	18.2994
(C)	88818.8	78651.7	9.99309	6.71627E-12	-1.22786	22.8272	22.8416	22.8647
(D)	57299.4	49095.3	5.89475	-5.59689E-11	-0.478257	21.989	22.0178	22.0641
(E)	39420.1	31968.7	4.02971	0.0	-0.213692	21.2794	21.3226	21.392
(F)	59487.0	50548.9	6.0278	1851.98	-0.235195	22.064	22.0927	22.139
(G)	75616.7	63610.2	8.06155	3655.05	-0.452577	22.5438	22.5726	22.6188
(H)	14449.7	11169.5	1.34425	4818.48	0.604863	19.1953	19.2097	19.2328
(I)	9506.17	7200.27	0.869877	3080.25	0.390737	18.3579	18.3722	18.3954
(J)	2313.14	1725.96	0.208177	-12.3049	0.0109378	15.5312	15.5456	15.5687
(K)	8113.1	6473.86	0.781583	-905.753	-0.0761576	18.0794	18.1082	18.1544
(L)	2001.91	997.967	0.119073	145.347	0.0185162	15.2422	15.2566	15.2797
(M)	1755.33	1065.55	0.127928	118.069	0.0201011	15.0178	15.0465	15.0928
(N)	1734.06	1086.78	0.131034	218.366	0.0324267	15.0318	15.075	15.1444
(O)	1762.13	1149.91	0.139341	239.25	0.0336505	15.1024	15.1599	15.2525
(P)	1804.41	975.522	0.116225	133.546	0.0206964	15.1498	15.2074	15.2999
(Q)	1875.43	1047.33	0.126608	273.817	0.0377302	15.1501	15.1789	15.2252

Table 6: Summary Results of the Tests Run

Model	*RMSE*	*RUNS*	*RUNM*	*AUTO*	*MEAN*	*VAR*
(A)	9505.25	***	***	***	***	OK
(B)	9060.78	***	***	***	***	OK
(C)	88818.8	***	***	***	***	***
(D)	57299.4	***	***	***	OK	OK
(E)	39420.1	***	***	***	OK	OK
(F)	59487.0	***	***	***	OK	OK
(G)	75616.7	***	***	***	***	***
(H)	14449.7	***	***	***	***	OK
(I)	9506.17	***	***	***	***	OK
(J)	2313.14	***	***	***	OK	**
(K)	8113.1	***	***	***	***	OK
(L)	2001.91	OK	*	OK	OK	***
(M)	1755.33	OK	*	OK	OK	***
(N)	1734.06	OK	**	OK	OK	***
(O)	1762.13	OK	OK	OK	OK	***
(P)	1804.41	OK	OK	OK	OK	***
(Q)	1875.43	OK	OK	OK	OK	***

Key:
RMSE = Root Mean Squared Error
RUNS = Test for excessive runs up and down
RUNM = Test for excessive runs above and below median
AUTO = Ljung-Box test for excessive autocorrelation
MEAN = Test for difference in mean 1st half to 2nd half
VAR = Test for difference in variance 1st half to 2nd half
OK = not significant (p >= 0.05), * = marginally significant (0.01 < p <= 0.05), ** = significant (0.001 < p <= 0.01), *** = highly significant (p <= 0.001)

Table 5 compares the results of fitting different models to the data. The model with the lowest value of the Akaike Information Criterion (AIC) is model M, which has been used to generate the forecasts. Table 6 also summarizes the results

of five tests run on the residuals to determine whether each model is adequate for the data. An OK means that the model passes the test. One * means that it fails at the 95% confidence level. Two *'s means that it fails at the 99% confidence level. Three *'s means that it fails at the 99.9% confidence level. Note that the currently selected model, model M, passes 3 tests.

Table 7: Estimated Autocorrelations for residuals

Model: ARIMA(0,2,2)

Lag	*Autocorrelation*	*Stnd. Error*	*Lower 99.0% Prob. Limit*	*Upper 99.0% Prob. Limit*
1	0.0623955	0.141421	-0.277181	0.277181
2	0.097564	0.141971	-0.278258	0.278258
3	-0.0156698	0.143306	-0.280874	0.280874
4	-0.0034454	0.14334	-0.280941	0.280941
5	0.0759744	0.143341	-0.280945	0.280945
6	-0.000175627	0.144145	-0.282519	0.282519
7	-0.129139	0.144145	-0.282519	0.282519
8	0.0714926	0.14644	-0.287018	0.287018
9	-0.0434245	0.147137	-0.288383	0.288383
10	-0.0381586	0.147393	-0.288885	0.288885
11	-0.0416342	0.14759	-0.289272	0.289272
12	0.0386034	0.147825	-0.289732	0.289732
13	-0.0510339	0.148026	-0.290127	0.290127
14	-0.0871764	0.148378	-0.290816	0.290816
15	-0.0430337	0.149399	-0.292817	0.292817
16	-0.0162373	0.149646	-0.293302	0.293302

Table 7 shows the estimated autocorrelations between the residuals at various lags. The lag k autocorrelation coefficient measures the correlation between the residuals at time t and time t-k. Also shown are 99.0% probability limits around 0. If the probability limits at a particular lag do not contain the estimated coefficient, there is a statistically significant correlation at that lag at the 99.0% confidence level. In this case, none of the 24 autocorrelations coefficients are statistically significant, implying that the time series may well be completely random (white noise).

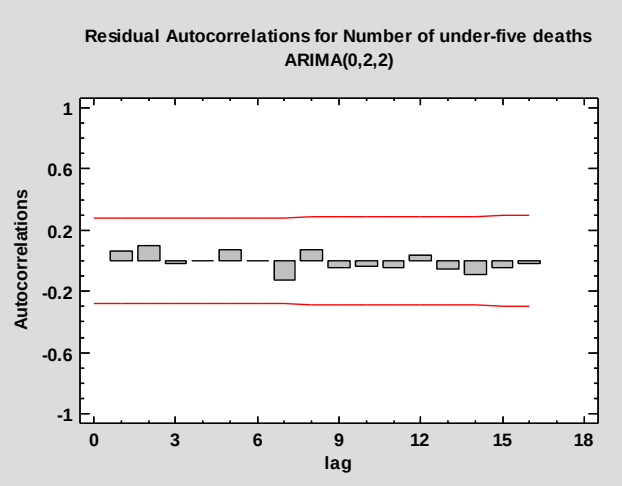


Figure 2: Residual Autocorrelation of Number of Under-Five Deaths

Figure 2 shows the estimated autocorrelations between the residuals at various lags. The lag k autocorrelation coefficient measures the correlation between the residuals at time t and time t-k. Also shown are 95.0% probability limits around 0. If the probability limits at a particular lag do not contain the estimated coefficient, there is a statistically significant correlation at that lag at the 95.0% confidence level. In this case, none of the 24 autocorrelations coefficients are statistically significant, implying that the time series may well be completely random (white noise).

Table 8: Estimated Partial Autocorrelations for residuals
Model: ARIMA(0,2,2)

Lag	*Partial Autocorrelation*	*Stnd. Error*	*Lower 99.0% Prob. Limit*	*Upper 99.0% Prob. Limit*
1	0.0623955	0.141421	-0.277181	0.277181
2	0.0940369	0.141421	-0.277181	0.277181
3	-0.0274004	0.141421	-0.277181	0.277181
4	-0.0102734	0.141421	-0.277181	0.277181
5	0.0820569	0.141421	-0.277181	0.277181
6	-0.00873555	0.141421	-0.277181	0.277181
7	-0.147465	0.141421	-0.277181	0.277181
8	0.0966198	0.141421	-0.277181	0.277181
9	-0.0252126	0.141421	-0.277181	0.277181
10	-0.070192	0.141421	-0.277181	0.277181
11	-0.0247506	0.141421	-0.277181	0.277181
12	0.0834971	0.141421	-0.277181	0.277181
13	-0.0784812	0.141421	-0.277181	0.277181
14	-0.116441	0.141421	-0.277181	0.277181
15	0.026779	0.141421	-0.277181	0.277181
16	-0.00420101	0.141421	-0.277181	0.277181

Table 8 shows the estimated partial autocorrelations between the residuals at various lags. The lag k partial autocorrelation coefficient measures the correlation between the residuals at time t and time t+k having accounted for the correlations at all lower lags. It can be used to judge the order of autoregressive model needed to fit the data. Also shown are 99.0% probability limits around 0. If the probability limits at a particular lag do not contain the estimated coefficient, there is a statistically significant correlation at that lag at the 99.0% confidence level. In this case, none of the 24 partial autocorrelations coefficients is statistically significant at the 99.0% confidence level.

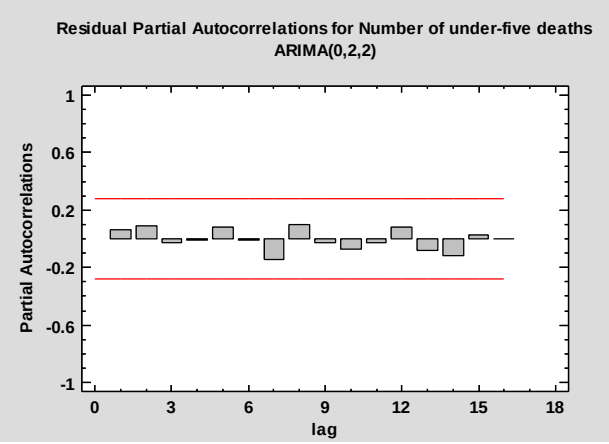


Figure 3: Residual Partial Autocorrelation for Number of Under-Five Deaths

Figure 3 shows the estimated partial autocorrelations between the residuals at various lags. The lag k partial autocorrelation coefficient measures the correlation between the residuals at time t and time t+k having accounted for the correlations at all lower lags. It can be used to judge the order of autoregressive model needed to fit the data. Also shown are 99.0% probability limits around 0. If the probability limits at a particular lag do not contain the estimated coefficient, there is a statistically significant correlation at that lag at the 99.0% confidence level. In this case, none of the 24 partial autocorrelations coefficients is statistically significant at the 99.0% confidence level.

Table 9: Forecast Table for Number of under-five deaths
Model: ARIMA(0,2,2)

Period	*Forecast*	*Lower 99% Limit*	*Upper 99% Limit*
2021.0	861399.	856665.	866134.
2022.0	873146.	860247.	886044.
2023.0	884892.	858070.	911714.
2024.0	896638.	852514.	940762.
2025.0	908385.	844243.	972527.
2026.0	920131.	833606.	1.00666E6
2027.0	931878.	820839.	1.04292E6
2028.0	943624.	806117.	1.08113E6
2029.0	955370.	789575.	1.12117E6
2030.0	967117.	771324.	1.16291E6
2031.0	978863.	751458.	1.20627E6
2032.0	990609.	730055.	1.25116E6

Table 9 shows the forecasted values for Number of under-five deaths. During the period where actual data is available, it also displays the predicted values from the fitted model and the residuals (data-forecast). For time periods beyond the end of the series, it shows 99.0% prediction limits for the forecasts. These limits show where the true data value at a selected future time is likely to be with 99.0% confidence, assuming the fitted model is appropriate for the data.

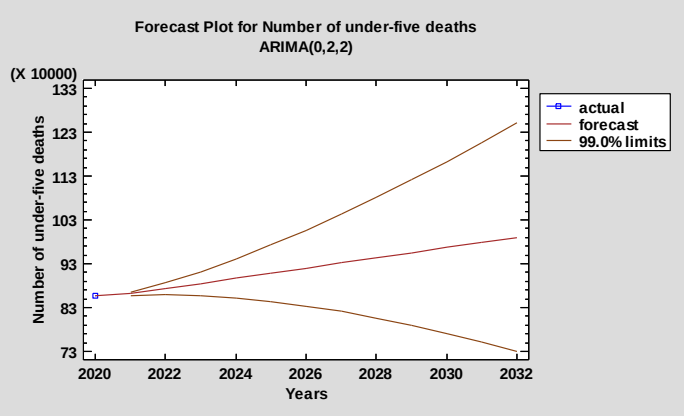


Figure 4: Forecast Plot
Figure 4. shows the forecasted values of Number of under-five deaths. Also included on the plot are 99.0% prediction limits for the forecasts. These limits show where the true value of Number of under-five deaths at any point in the future is likely to be with 99.0% confidence.

5. Conclusion

Mann-Kendall test is used to determine whether a statistically significant monotonic upward or downward trend exists in the data. Since the calculated P-value is less than 0.01, the presence of a trend has been detected at the 1.0% significance level. The P (equal or less) value for the runs above and below the median is less than 0.001, there is statistically significant clustering at the 99% confidence level. Since the P (equal or less) value for the runs up and down is less than 0.001, there is statistically significant trending at the 99% confidence level. ARIMA(0,2,2) was found to be the best fitted model base on the AIC and SIC. The P-value for the MA(2) term is less than 0.05, so it is significantly different from 0. The estimated standard deviation of the input white noise equals 1765.16. Under-Five mortality is declining globally but more slowly than post-neonatal (1-59 months) mortality. The first 28 days of life the neonatal period are the most vulnerable time for a child's survival. Neonatal mortality is becoming increasingly important not only because the proportion of under-five deaths that occur during the neonatal period is increasing as under-five mortality declines, but also because the health interventions needed to address the major causes of neonatal deaths generally differ from those needed to address other under-five deaths and are intimately linked to those that are necessary to protect maternal health.

References

[1]. Kananura, R. M., M. Tetui, P. Waiswa, S. N. Kiwanuka, E. Ekirapa-Kiracho, and F. Makumbi. (2016). "The Neonatal Mortality and its Determinants in Rural Communities of Eastern Uganda." *Reproductive Health* 13: 13. https://doi.org/10.1186/s12978-016-0119-y.

[2]. Oza, S., S. N. Cousens, and J. Lawn. (2014). "Estimation of Daily Risk of Neonatal Death, Including the Day of Birth, in 186 Countries in 2013: A Vital-registration and Modelling-based Study." *The Lancet* 2 (11). https://doi.org/10.1016/S2214-109X(14)70309-2.

[3]. UNICEF (2019) Mother, Newborn and Child Health and Mortality in Nigeria – General Facts. URL: http://www.unicef.org/nigeria/ng_publications_advocacybrochure.pdf (accessed 1st July 2019).

[4]. World Health Organization (2006) *Neonatal and Perinatal Mortality: Country, Regional and Global Estimates.* World Health Organization, Geneva.

[5]. UNICEF, WHO, World Bank, United Nations. Levels and Trends in Child Mortality: Report 2014. In: Levels and Trends in Child Mortality: Report 2014. New York, 10017 USA: United Nations Children's Fund; 2014.

[6]. Lawn JE, Cousens S, Zupan J. (2005). 4 million neonatal deaths: when? where? why? Lancet. 365:891–900.

[7]. Lawn JE, Kinney MV, Black RE, Pitt C, Cousens S, Kerber K, et al. (2012). Newborn survival: a multi-country analysis of a decade of change. Health Policy Plan. 27:iii6–28.

[8]. Oestergaard M, Inoue M, Yoshida S, Mahanani W, Gore F, Cousens S, et al. (2011). Neonatal Mortality Levels for 193 Countries in 2009 with Trends since 1990: A Systematic Analysis of Progress, Projections, and Priorities. PLoS Med. 8:e1001080. https://doi.org/10.1371/journal.pmed.1001080 PMID: 21918640

[9]. National Population Commission. Federal Republic of Nigeria: final report on Nigeria Demographic and Health Survey. (2013) http:// dhsprogram. com/ publications/ publication- fr293- dhs- final- reports. cfm .

[10]. Ahonsi BA. (1995). Age variations in the proximate determinants of child mortality in south-west Nigeria. J BiosocSci.;27:19–30.

[11]. Titaley CT, Dibley MJ, Agho K, Roberts CL, Hall J. (2008) Determinants of neonatal mortality in Indonesia. BMC Public Health. 8. doi:10.1186/1471-2458- 1188-1232.

[12]. Kamal SMM. (2012). Maternal education as a determinant of neonatal mortality in Bangladesh. J Health Manag. 14:269–81.

[13]. Mekonnen Y, Tensou B, Telake DS, Degefie T, Bekele A. (2013). Neonatal mortality in Ethiopia: trends and determinants. BMC Public Health. 13:1–14.

[14]. Aigbe GO and Zannu AE (2012). Differentials in infant and child mortality rates in Nigeria: evidence from the six geopolitical zones. International Journal of Humanities and Social Science 2(16), 206–114.

[15]. Whitworth A and Stephenson R (2002). Birth spacing, sibling rivalry and child mortality in India. Social Science & Medicine 55(12), 2107–2119.

[16]. DaVanzo J, Razzaque A, Rahman M, Hale L, Ahmed K, Khan MA et al. (2004) The Effects of Birth Spacing on Infant and Child Mortality, Pregnancy Outcomes, and Maternal Morbidity and Mortality in Matlab, Bangladesh. Technical Consultation and Review of the Scientific Evidence for Birth Spacing. https://www.rand.org/content/dam/rand/pubs/working_papers/2004/RAND_WR198.pdf

[17]. You D, Hug L, Chen Y (2014). Levels & Trends in Child Mortality. Estimates Developed by the UN Inter-agency Group for Child Mortality Estimation on behalf of the United Nations Inter-agency Group for Child Mortality Estimation (UN IGME), UNICEF.

[18]. Lander T. (2006). Neonatal and Perinatal Mortality: Country, Regional, and Global Estimates. Fourth. Lander T, editor. Geneva WHO Press. Geneva, Switzerland: World Health Organization; 2006.

[19]. UNICEF and WHO. levels and trends in child mortality. 2015. Report 2015 http://www. who. int/ maternal_ child_ adolescent/ documents/ levels_ trends_ child_ mort ality_ 2015. pdf? ua= 1 (accessed Mar 2016).

[20]. Lawn JE, Blencowe H, Oza S, You D, Lee ACC, Waiswa P, et al.(2014). Every newborn: Progress, priorities, and potential beyond survival. Lancet. 384:189–205. https://doi.org/10.1016/S0140-6736(14) 60496-7 PMID: 24853593

[21]. Adebayo SB, Fahrmeir L, Klasen S. (2004). Analyzing infant mortality with geoadditive categorical regression models: A case study for Nigeria. Econ. Hum. Biol. 21:229–44

[22]. Winikoff B (1983) The effects of birth spacing on child and maternal health. Studies in Family Planning 1, 231–245.

[23]. Biradar R, Patel KK and Prasad JB (2019) Effect of birth interval and wealth on under-5 child mortality in Nigeria. Clinical Epidemiology and Global Health 7(2), 234–238.

[24]. Gubhaju BB (1986) Effect of birth spacing on infant and child mortality in rural Nepal. Journal of Biosocial Science 18(4), 435–447.

[25]. Box, G. E. P., & Jenkins, G. (1970). *Time series analysis, forecasting and control*. Holden-Day.

[26]. Dinpashoh, Y., Mirabbasi, R., Jhajharia, D., Abianeh, H. Z. &Mostafaeipour, A. (2014) Effect of short-term and long-term persistence on identification of temporal trends. Journal of Hydrologic Engineering 19 (3), 617–625. https://doi.org/10. 1061/(ASCE)HE.1943-5584.0000819.

[27]. Yue, S., & Wang, C. (2004). The Mann-Kendall test modified by effective sample size to detect trend in serially correlated hydrological series. *Water Resources Management*, *18*(3), 201–218. https://doi.org/10.1023/B:WARM.0000043140.61082.60

[28]. Onoz, B., &Bayazit, M. (2012). Block bootstrap for Mann-Kendall trend test of serially dependent data. *Hydrological Processes*, *26*(23), 3552–3560. https://doi.org/10.1002/hyp.8438

[29]. Ahmadi, F., NazeriTahroudi, M., Mirabbasi, R., Khalili, K. &Jhajharia, D. (2018) Spatiotemporal trend and abrupt change analysis of temperature in Iran. Meteorological Applications 25 (2), 314–321. https://doi.org/10.1002/met.1694.

[30]. Hamed, K. H. & Rao, A. R. (1998) A modified Mann-Kendall trend test for autocorrelated data. Journal of Hydrology 204 (1), 182–196. https://doi.org/10.1016/S0022-1694(97)00125-X

[31]. Jhajharia, D., Dinpashoh, Y., Kahya, E., Singh, V. P. &Fard, A.(2012) Trends in reference evapotranspiration in the humid region of northeast India. Hydrological Processes 26, 421–435. https://doi.org/10.1002/hyp.8140.