Comparative Performance of Simple Exponential Smoothing, Brown’s Linear Trend and ARIMA Model on Forecasting Neonatal Mortality Rate in Nigeria

Christogonus Ifeanyichukwu Ugoh a*, Nneka Chidinma Nwabueze a, Nwabueze Achunam Simeon b, Eze Theophine Chinaza a and Okafor Chinas Ogedi c

a Department of Statistics, Faculty of Physical Sciences, Nnamdi Azikiwe University, Awka, Nigeria.
b Department of Community Medicine, Faculty of Medicine, Nnamdi Azikiwe University, Nnewi, Nigeria.
c Department of Paediatrics, Faculty of Paediatrics Medicine, COOUTH, Nigeria.

Authors’ contributions
This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information
DOI: 10.9734/AJPAS/2022/v16i130391
(1) Dr. Manuel Alberto M. Ferreira, Lisbon University, Portugal.
(1) Iso Precious Oloyede, University of Uyo, Nigeria.
(2) Khder Alakkari, Tishreen University, Syria.
Complete Peer review History, details of the editor(s), Reviewers and additional Reviewers are available here: https://www.sdiarticle5.com/review-history/77244

Received 02 October 2021
Accepted 03 December 2021
Published 07 January 2022

Abstract
Paper proposes an appropriate time series model that is used to forecast the NMR in Nigeria. The data used for the study is sourced from the World Bank for a period of 1980-2019. The ARIMA model and Exponential Smoothing are fitted on the raw data. The Bayesian Information Criterion (BIC) is adopted to assess the adequacy of the ARIMA models. The NMR series is stationary after the second differencing. The ARIMA (0,2,0) with BIC value of -3.358 is considered the appropriate model among other ARIMA models, and it is compared to SES and Brown’s LT using Theil’s U Statistics and MAPE. The results showed that the Brown’s LT model is more ideal and adequate for forecasting NMR in Nigeria based on the Theil’s U forecast accuracy measures of 0.001911, and that by 2030, Nigeria will have a reduced NMR of 31.5 deaths per 1,000 live births, which shows a drop to 21.5%.

Keywords: NMR; exponential smoothing; BIC; ARIMA; SES; Brown’s LT; Theil’s U statistic.

*Corresponding author: Email: christogonusugoh2019@gmail.com;
Introduction

Neonatal Mortality Rate (NMR) is the number of newborns dying before reaching 28 days of age per 1,000 live births in a particular year. Neonatal deaths are an indicator of Healthcare systems in a country [1] and Neonatal death shows the health of children and the economic development of country [2]. The first two days, accounts for more than 50% Neonatal deaths [3], while the first week of life accounts for more than 75% of Neonatal deaths; the major causes of Neonatal deaths are prematurity, birth asphyxia, sepsis and congenital malformation [4,5]. Children face the highest risk of dying in their first month of life at an average global rate of 17 deaths per 1,000 live births in 2019 [6]. Studies conducted by [7] and [8] have shown that so many factors such as prenatal consultation, type of labour, professional responsibility for the childbirth, and maternal socioeconomic conditions are strongly related to total neonatal mortality and early neonatal mortality.

[9] analyzed Neonatal Deaths in Zimbabwe using data from 1966 to 2018, and by applying Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) Model technique, ARIMA (8,2,0) model was selected as the best model for future predictions [10] modeled Neonatal Mortality in Nigeria from 1990 to 2017 using ARIMA (1,1,1), and the result revealed a steady decrease in the incidence of Neonatal Mortality [11] analyzed the Neonatal Mortality in Abia State Nigeria and selected ARIMA (1,0,1) as the best model, using the ARIMA (1,0,1) to forecast, the result shows a steady decrease in the incidence of Neonatal mortality [12] studied the determinants of Neonatal Mortality in Nigeria using the Cox Regression model, and the result showed that a higher birth order of newborn with longer birth interval of more than 2 years and shorter birth interval of less than 2 years all have significant association with Neonatal Mortality [13] analyzed stillbirths and neonatal deaths in Mutare District, using monthly data ranging from January and June 2014. The result of this findings showed that 15.6% of the number of women used experienced stillbirth or neonatal death.

[14] forecasted Indian Infant Mortality Rates (IMR) using ARIMA (2,1,1), which shows that by 2025, the IMR of India will be 15 deaths per 1000 live births [15] analyzed Nigerian Infant Mortality Rate for a period of 1964-2018, and selected ARIMA (1,1,1) as the most appropriate model forecasting. The result of their study shows that IMR will intrinsically reduce by 30% by 2030 [16] forecasted Infant Mortality Rates of Asian countries except Japan and Nepal.

2 Materials and Methods

2.1 Exponential Smoothing

This is a time series forecasting method for univariate data that can be extended to support data with a systematic trend or seasonal component. Forecast produced using exponential smoothing methods are weighted averages of past observation, where the weights decay exponentially as the observations get older. Two types of Exponential Smoothing: Simple Exponential Smoothing (SES) and Double Exponential Smoothing (Brown’s Linear Exponential Smoothing).

2.1.1 Simple Exponential Smoothing (SES)

SES is suitable when there is no trend in the data and the data is non-seasonal. SES is defined as

\[ S_t = \alpha y_t + (1 - \alpha)S_{t-1} \]  

where \(\alpha\) is the smoothing factor and \(0 \leq \alpha \leq 1\); the smoothed statistic \(S_t\) is a simple weighted average of the current observation \(y_t\) and the previous smoothed statistic \(S_{t-1}\). The choice of \(\alpha\) (smoothing factor) is based on the researcher.

Equation (1) can be expanded as

\[ S_t = \alpha y_t + (1 - \alpha)y_{t-1} + (1 - \alpha)^2S_{t-2} \]  
\[ S_t = \alpha[y_t + (1 - \alpha)y_{t-1} + (1 - \alpha)^2y_{t-2} + \cdots + (1 - \alpha)^{t-1}y_1] + (1 - \alpha)^ty_0 \]
where \( y_{t-1}, y_{t-2}, \ldots \) are past observations; \( y_t \) is the current observation

### 2.1.2 Double exponential smoothing (Brown’s linear exponential smoothing)

Double Exponential Smoothing is suitable when there is evidence of trend in the data. It involves a forecasting equation and two smoothing equations (level equation and trend equation). The Forecast equation is defined as

\[
\hat{y}_{t+m} = S_t + mb_t
\]  
(4)

The Level equation is defined as

\[
S_t = \alpha y_t + (1 - \alpha)[S_{t-1} + b_{t-1}]
\]  
(5)

The Trend equation is defined as

\[
b_t = \beta (S_t - S_{t-1}) + (1 - \beta)b_{t-1}
\]  
(6)

where \( \alpha \) is the data smoothing factor and \( 0 \leq \alpha \leq 1 \), and \( \beta \) is the trend smoothing factor and \( 0 \leq \beta \leq 1 \).

When \( \alpha = 1 \), \( m = 1 \) and \( \beta = 1 \), then the forecast equation becomes

\[
\hat{y}_{t+m} = y_t + S_t - S_{t-1}
\]  
(7)

### 2.2 Autoregressive Integrated Moving Average (ARIMA) Model

ARIMA is a statistical model which is used to predict future values based on past values. The ‘AR’ stands for Autoregressive, ‘MA’ stands for Moving Average, and ‘I’ stands for Integrated (which implies that the data values are replaced by difference between the data values and the previous values). ARIMA model is denoted by \( ARIMA(p,d,q) \) and it is written as

\[
y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t
\]  
(8)

where \( \phi_1, \phi_2, \ldots, \phi_p \) are Autoregressive model’s parameters; \( \theta_1, \theta_2, \ldots, \theta_q \) are Moving Average model’s parameters; \( c \) is a constant; \( \varepsilon_t \) is a white noise, and \( y'_t \) is the differenced series which might be differenced more than once.

#### 2.2.1 Autoregressive moving average (ARMA) model

When the time series data is stationary and however does not require differencing, then the resultant model is an Autoregressive Moving Average (ARMA) model. ARMA model is denoted by \( ARMA(p,q) \) and it is written as

\[
y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t
\]  
(9)

#### 2.2.2 Autoregressive (AR) model

AR model is the regression of the current observations against one or more past observations. That is the current observation \( y_t \) are generated by a weighted averages of past time series data going back \( p \) periods, together with a random disturbance in the current period. The AR of order \( p \) denoted by \( AR(p) \) is defined as

\[
y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t
\]  
(10)

Where \( \varepsilon_t \) is a white noise; \( \phi_1, \phi_2, \ldots, \phi_p \) are the parameters of the AR model; \( y_t \) is the current observation, \( y_{t-1}, y_{t-2}, \ldots, y_{t-p} \) are past observations.

#### 2.2.3 Moving Average (MA) Model

MA is a linear combination of error terms occurring at various times in the past. MA model of order \( q \) is denoted as \( MA(q) \) and it is written as
2.3 ARIMA Fitting

ARIMA model is fitted to the data of interest using the Box-Jenkins method. In this stage four steps are applied:

Step one deals with stationarity check of the data of interest. Here, the data is checked if it is stationary (that is the mean and variance are constant over time). If the data of interest is non-stationary, then, it has to be differenced at least once in order to attain stationarity.

2.3.1 Identification of stationary time series

a. If the Autocorrelation Function (ACF) drops to zero relatively quickly, the series is stationary
b. If the Autocorrelation Function (ACF) drops very slowly as lag number increases, the series is non-stationary
c. If there is presence of a unit root in the time series data, then, the time series is non-stationary. In this study, Augmented Dickey-Fuller (ADF) test is used to test the presence of unit root.

2.3.2 Differencing

This is the process of making a non-stationary time series stationary. It stabilizes the mean of time series by removing the changes in the series and eliminating or reducing trend and seasonality.

2.3.3 First order differencing

First Order Differenced series denoted as $y_t'$ is the change between consecutive observations in the original series. It is written as

$$y_t' = y_t - y_{t-1}$$

(12)

If the first differenced series fails to be stationary, there is need to carry out second differencing

2.3.4 Second order differencing

Second Order Differenced series denoted as $y_t''$ is written as

$$y_t'' = y_t' - y_{t-1}'$$

(13)

Where

$$y_{t-1}' = y_{t-1} - y_{t-2}$$

(14)

Again, if the Second Order Differenced series fails to be stationary, third differencing is carried. Using the Backshift Operator B, where the general $d$th order difference can be written as

$$y_t^d = (1 - B)^d y_t$$

(15)

2.3.5 Third order differencing

$$y_t''' = (1 - B)^3 y_t$$

(16)

$$y_t''' = y_t - 3B y_t + 3B^2 y_t - B^3 y_t$$

(17)

where $B y_t = y_{t-1}$

$$y_t''' = y_t - 3y_{t-1} + 3y_{t-2} - y_{t-3}$$

(18)
1. Step Two deals with Estimation of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

2. Step Three deals with model identification, which involves the process of selecting the appropriate orders of AR and/or MA.

3. Step Four deals with diagnostic check for model adequacy. The Akaike Information Criteria (AIC) and/or Bayesian Information Criteria (BIC) is/are used to check for model adequacy. The AIC is written as

$$AIC = n \log(\hat{\sigma}^2) + 2k$$  \hspace{1cm} (19)

$k$ is the number of model parameters; $\hat{\sigma}^2$ is the residual sum of squares, and $n$ is the sample size.

Bayesian Information Criterion (BIC) is written as

$$BIC = n \log(\hat{\sigma}^2) + k \log(n)$$  \hspace{1cm} (20)

The ARIMA model with the lowest AIC and/or BIC are/is considered the best model among others.

### 2.4 Measure of Forecast Accuracy

The measures of forecast accuracy adopted in this study is Theil’s U Forecast Accuracy and Mean Absolute Percentage Error (MAPE).

#### 2.4.1 Theil’s U forecast accuracy

The Theil’s U shows how the forecast conforms to the values of the future periods. It is written as

$$U = \frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{n} y_t^2 + \sum_{t=1}^{n} \hat{y}_t^2}$$  \hspace{1cm} (21)

where $y_t$ is the actual value of a point for a given time period $t$, $\hat{y}_t$ is the forecast value, $n$ is the number of the data points.

If $U$ falls within the range $0 \leq U < 1$, the model obtained is a good fit.
If $U = 0$, the model obtained is a perfect fit.
If $U \geq 1$, the model obtained is not a good fit.

#### 2.5 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is used to measure the error of both methods (ARIMA and WMC). The model with the smallest MAPE is considered the appropriate model. It is defined as

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100\%$$  \hspace{1cm} (22)

### 3 Results and Discussion

Fig. 1 shows the time plot of Neonatal Mortality Rate (NMR) in Nigeria from 1980 to 2019.

Fig. 1 shows the time plot of Neonatal Mortality Rate in Nigeria for the period of 1980-2019. Neonatal Mortality Rate in Nigeria shows a decreasing trend. The Autocorrelation Function (ACF) Plot and the Partial Autocorrelation Function (PACF) Plot of Neonatal Mortality rate are shown in Fig. 2.

In Table 1, the average Neonatal Mortality Rate (NMR) is 44.592 deaths per 1000 live births and the standard deviation is 5.7642 deaths per 1000 live births.
Fig. 1. Time plot of Neonatal Mortality Rate in Nigeria

Table 1. Descriptive statistics for Neonatal Mortality Rates

| Descriptive Statistics | N  | Minimum Statistic | Maximum Statistic | Mean Statistic | Std. Error Statistic | Std. Deviation Statistic |
|------------------------|----|------------------|-------------------|----------------|----------------------|-------------------------|
| Neonatal Mortality Rate| 40 | 35.9             | 53.0              | 44.592         | .9114                | 5.7642                  |

Table 2. Unit root test in Neonatal Mortality Rate (NMR)

Null Hypothesis: NMR has a unit root
Exogenous: Constant
Lag Length: 6 (Automatic - based on SIC, maxlag = 9)

| Augmented Dickey-Fuller test statistic | t-Statistic | Prob.* |
|----------------------------------------|-------------|--------|
| 1% level                               | -3.646342   | 0.9826 |
| 5% level                               | -2.954021   |        |
| 10% level                              | -2.615817   |        |

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

In Table 2, the Augmented Dickey-Fuller (ADF) Test Statistic is 0.460736, with p-value of 0.9826 less than 0.05, implying that there is presence of unit root in the Neonatal Mortality Rate (NMR) and hence need to be differenced at least once.

Fig. 2. (A) ACF plot for Neonatal Mortality Rate  (B) PACF plot for Neonatal Mortality Rate (NMR)
Fig. 2A is the Autocorrelation Function (ACF) Plot of NMR and it shows a slow fall of the lags as the lag number increases, indicating that NMR is not stationary. Since the time series data is not stationary and a model is not fitted on NMR, Fig. 2B which is the PACF plot does not indicate any order, due to the fact no model has been obtained. The ACF Plot and PACF Plot of the first differenced NMR as shown in Fig. 3.

![ACF Plot of NMR](image1)
![PACF Plot of NMR](image2)

**Fig. 3. (C) First Differenced ACF Plot for Neonatal Mortality Rate (D) First Differenced PACF Plot for Neonatal Mortality Rate (NMR)**

The First Differenced ACF Plot for Neonatal Mortality Rate in Fig. 3C shows a slow fall of the lags as the number of the lags increases, thereby indicating non stationarity of the first differenced NMR. Thus in this case, there is still need to obtain the second differenced NMR as shown in Fig. 4.

![ACF Plot for First Differenced NMR](image3)
![PACF Plot for First Differenced NMR](image4)

**Fig. 4. (E) Second Differenced ACF Plot for Neonatal Mortality Rate (F) Second Differenced PACF Plot for Neonatal Mortality Rate (NMR)**

The Second Differenced ACF Plot for NMR in Fig. 4E shows a rapid fall of the lags at lag 1, thereby indicating that the second differenced NMR is now stationary having constant mean and variance. With the sharp fall at lag 1, there is all indication that the required ARIMA is not an Autoregressive (AR). Though in Fig. 4F where lags 2, 3 and 6 are significant cutting through the lower and upper bound, which in the normal sense are the required orders, the expected ARIMA model is not a Moving Average (MA). Therefore, the required ARIMA Model for the Second differenced NMR is ARIMA (0,2,0) which has the smallest BIC of -3.358 as shown in Table 2. The Estimated ACF and PACF for Second Differenced NMR is shown in Table 3.
Table 3. Estimated ACF and PACF for Second Differenced (NMR)

| Lag | Autocorrelation | Partial Autocorrelation | Box-Ljung Statistic |
|-----|-----------------|-------------------------|---------------------|
|     |                 |                         | Value   | df | Sig.   |
| 1   | .031            | -.031                   | .040    | 1  | .841   |
| 2   | .394            | .394                    | 6.606   | 2  | .037   |
| 3   | .311            | .392                    | 10.818  | 3  | .013   |
| 4   | .032            | -.084                   | 10.864  | 4  | .028   |
| 5   | .228            | -.077                   | 13.263  | 5  | .021   |
| 6   | -.178           | -.358                   | 14.768  | 6  | .022   |
| 7   | -.034           | -.266                   | 14.826  | 7  | .038   |
| 8   | -.124           | -.081                   | 15.611  | 8  | .048   |
| 9   | -.287           | -.064                   | 19.928  | 9  | .018   |
| 10  | -.152           | -.022                   | 21.180  | 10 | .020   |
| 11  | -.377           | -.178                   | 29.195  | 11 | .002   |
| 12  | -.096           | .062                    | 29.730  | 12 | .003   |
| 13  | -.282           | .000                    | 34.580  | 13 | .001   |
| 14  | -.317           | -.267                   | 40.938  | 14 | .000   |
| 15  | .063            | .064                    | 41.203  | 15 | .000   |
| 16  | -.280           | -.013                   | 46.635  | 16 | .000   |

a. The underlying process assumed is independence (white noise).
b. Based on the asymptotic chi-square approximation.

Table 4. ARIMA model adequacy

| Model         | ARIMA (0,2,0) | ARIMA (0,2,2) | ARIMA (0,2,3) | ARIMA (0,2,6) |
|---------------|---------------|---------------|---------------|---------------|
| BIC           | -3.358        | -3.330        | -3.325        | -3.113        |

ARIMA (0,2,0) has the lowest BIC value -3.358 implying that it is considered the most appropriate model among other ARIMA models listed.

Table 5. Estimated Parameters of SES and Brown’s Linear Trend (Brown’s LT)

| Model         | Parameters          | Estimate  | t        | Sig.  |
|---------------|---------------------|-----------|----------|-------|
| SES           | Alpha (Trend)       | 1.000     | 6.435    | .000  |
| Brown’s LT    | Alpha (Level and Trend) | 0.996    | 21.755   | .000  |

Table 5 shows the estimated parameters of the Single Exponential Smoothing (SES) and Double Exponential Smoothing (Brown’s LT).

Table 6. Models comparison

| Models       | Theil’s U Statistic | MAPE     |
|--------------|---------------------|----------|
| ARIMA (0,2,0)| 0.054110            | 0.298    |
| SES          | 0.021124            | 1.013    |
| Brown’s LT   | 0.001911            | 0.280    |

Table 6 shows the model adequacy of the ARIMA (0,2,0), SES, and Brown’s LT, where Brown’s LT (Double Exponential Smoothing) has the lowest Theil’s U statistic of 0.001911 and as well the lowest Mean Absolute Percentage Error (MAPE) of 0.280, indicating that Brown’s LT is the best model for forecasting NMR in Nigeria. The Brown’s LT model is given as

\[ S_t = 0.996y_t + 0.004S_{t-1} + 0.004b_{t-1} \]  \hspace{1cm} (23)

\[ b_t = 0.996S_t - 0.996S_{t-1} + 0.004b_{t-1} \]  \hspace{1cm} (24)
Table 7. Out-of-sample Forecast of NMR in Nigeria using Brown’s LT Model

| Year | NMR, $y_t$ | predicted NMR, $\hat{y}_t$ | $(y_t - \hat{y}_t)^2$ | $y_t^2$ | $\hat{y}_t^2$ |
|------|------------|----------------------------|------------------------|----------|----------|
| 1980 | 53         | 53                         | 0                      | 2809     | 2809     |
| 1981 | 52         | 52                         | 0                      | 2704     | 2704     |
| 1982 | 51.2       | 51                         | 0.04                   | 2621.44  | 2601     |
| 1983 | 50.5       | 50.4                       | 0.01                   | 2550.25  | 2540.16  |
| 1984 | 50         | 49.8                       | 0.04                   | 2500     | 2480.04  |
| 1985 | 49.7       | 49.5                       | 0.04                   | 2470.09  | 2450.25  |
| 1986 | 49.5       | 49.4                       | 0.01                   | 2450.25  | 2440.36  |
| 1987 | 49.5       | 49.3                       | 0.04                   | 2450.25  | 2430.49  |
| 1988 | 49.5       | 49.5                       | 0                      | 2450.25  | 2450.25  |
| 1989 | 49.6       | 49.5                       | 0.01                   | 2460.16  | 2450.25  |
| 1990 | 49.7       | 49.7                       | 0                      | 2470.09  | 2470.09  |
| 1991 | 49.7       | 49.8                       | 0.01                   | 2470.09  | 2480.04  |
| 1992 | 49.8       | 49.7                       | 0.01                   | 2480.04  | 2470.09  |
| 1993 | 49.8       | 49.9                       | 0.01                   | 2480.04  | 2490.01  |
| 1994 | 49.8       | 49.8                       | 0                      | 2480.04  | 2480.04  |
| 1995 | 49.6       | 49.8                       | 0.04                   | 2460.16  | 2480.04  |
| 1996 | 49         | 49.4                       | 0.16                   | 2401     | 2440.36  |
| 1997 | 48.8       | 48.4                       | 0.16                   | 2381.44  | 2342.56  |
| 1998 | 48.1       | 48.6                       | 0.25                   | 2313.61  | 2361.96  |
| 1999 | 47.3       | 47.4                       | 0.01                   | 2237.29  | 2246.76  |
| 2000 | 46.3       | 46.5                       | 0.04                   | 2143.69  | 2162.25  |
| 2001 | 45.2       | 45.3                       | 0.01                   | 2043.04  | 2052.09  |
| 2002 | 44         | 44.1                       | 0.01                   | 1936     | 1944.81  |
| 2003 | 42.8       | 42.8                       | 0                      | 1831.84  | 1831.84  |
| 2004 | 41.7       | 41.6                       | 0.01                   | 1738.89  | 1730.56  |
| 2005 | 40.7       | 40.6                       | 0.01                   | 1656.49  | 1648.36  |
| 2006 | 39.9       | 39.7                       | 0.04                   | 1592.01  | 1576.09  |
| 2007 | 39.2       | 39.1                       | 0.01                   | 1536.64  | 1528.81  |
| 2008 | 38.6       | 38.5                       | 0.01                   | 1489.96  | 1482.25  |
| 2009 | 38.3       | 38                         | 0.09                   | 1466.89  | 1444     |
| 2010 | 38         | 38                         | 0                      | 1444     | 1444     |
| 2011 | 37.7       | 37.7                       | 0                      | 1421.29  | 1421.29  |
| 2012 | 37.6       | 37.4                       | 0.04                   | 1413.76  | 1398.76  |
| 2013 | 37.4       | 37.5                       | 0.01                   | 1398.76  | 1406.25  |
| 2014 | 37.3       | 37.2                       | 0.01                   | 1391.29  | 1383.84  |
| 2015 | 37.1       | 37.2                       | 0.01                   | 1376.41  | 1383.84  |
| 2016 | 36.9       | 36.9                       | 0                      | 1361.61  | 1361.61  |
| 2017 | 36.7       | 36.7                       | 0                      | 1346.89  | 1346.89  |
| 2018 | 36.3       | 36.5                       | 0.04                   | 1317.69  | 1332.25  |
| 2019 | 35.9       | 35.9                       | 0                      | 1288.81  | 1288.81  |

Table 8. Actual NMR and predicted NMR and Computation of Theil’s U

Table 7 shows the forecast for NMR in Nigeria for 2020 through 2030 with 95% upper and lower confidence intervals. The out-sample forecast shows a steady decrease in the NMR. By 2030, Nigeria will have a reduced
NMR of 31.5 deaths per 1,000 live births, which shows a drop to 21.5% as compared to the present 53%. This an improvement compared to the previous mortality rates. The actual NMR and out-sample forecast of NMR are shown in Fig. 5. And the Theil’s U statistic is computed for the in-sample as shown in Table 8.

Table 6 gives the actual NMR and predicted NMR, and the result of Theil’s U forecast in equation (26) which is less than one (1) and very close to zero (0) shows that the proposed Brown’s LT model is adequate on forecasting Nigerian NMR.

\[ U = \frac{1}{\sqrt{20 \times 80786.35}} \times 80835.45 + \frac{1}{\sqrt{20 \times 80786.35}} = 0.001911 \]  

(26)

Fig. 5. Time plot of the Actual NMR and Out-Sample Forecast of NMR

4 Conclusion

The purpose of this paper is to model and to identify an adequate model that will be used to forecast NMR in Nigeria. Brown’s LT model predicts NMR adequately compared to SES and ARIMA model. Based on the modeling and forecasting, the NMR is showing an intrinsic decrease from year to year. The findings of this study can help promote health policies in order to address and to reduce NMR in the future, as well as to establish a basis for implementing optimal strategies that can be used to overcome NMR in order to meet up with the target of SDGs.

Competing Interests

Authors have declared that no competing interests exist.

References

[1] Babaei H, Dehghan M, Pirkashani LM. Study of causes of Neonatal mortality and its related factors in the Neonatal intensive care unit of Iman Reza Hospital in Kermanshah during (2014-2016), International Journal of Pediatrics. 2018;6(5):7641-7649.

[2] Chengye J. Child and Adolescent Health, People’s Medical Publishing House, Beijing; 2012.

[3] Nouri A, Barati L, Qhezelsofly F, Niazi S. Causes of infant mortality in Kalaleh City during 2004-2012, Hakim Jorjani Journal. 2013;1(2):2-37.
[4] Carlo WA, Travers CP. Maternal and Neonatal Mortality: Time to act, Journal of Pediatrics, 2016;92(6):543-545.

[5] World Health Organization, Newborns: Reducing mortality; 2019.
Available from https://www.int/news-room/fact-sheet/newborns-reducing-mortality Technical Report.

[6] UNICEF, Neonatal mortality; 2020.
Available https://unicef.org; 2020

[7] Nascimento RMD, Leite AJM, Almeida NMGSD, Almeida PCD, Silva CFD. Determinantes da mortalidade neonatal: Estudo Caso-controle em fortaleza, ceara, Brasil, Caderno de Saude Publica. 2012;28-559-572.

[8] Migoto MT, Oliveira RPD, Silva AMR, Freire MHDS. Early Neonatal mortality and risk factors: A case-control study in Parana state. Revista Brasileira de Enfermagem. 2018;71:2527-2534.

[9] Nyoni SP, Nyoni T. Analyzing neonatal deaths in Zimbabwe using Box-Jenkins ARIMA models, International Journal on Integrated Education. 2020;3, issue vii:39-50.

[10] Usman A, Sulaiman MA, Abubakar I. Trend of neonatal mortality in Nigeria from 1990 to 2017 using Time series analysis, Journal of Applied Sciences and Environment Management. 2019;23(5):865-869.

[11] Chukwudike NC, Offorha CB, Obudu M, Okezie UO, Chisom CO. ARIMA modeling of Neonatal mortality in Abia state of Nigeria, Asian Journal of Probability and Statistics. 2020;6(2):54-62.

[12] Ezeh OK, Agho KE, Dibley MJ, Hall J, Page AN. Determinants of Neonatal mortality in Nigeria: Evidence from the 2008 Demographic and Health Survey, BMC Public Health. 2014;14:521-531.

[13] Chaibva BV, Olomonu S, Nyadundu S, Beke A. Adverse pregnancy outcomes “Stillbirth and Early Neonatal Deaths” in Mutare District, Zimbabwe. A descriptive study, BMC Pregnancy and Childbirth. 2019;19(86):1-7.

[14] Mishra AK, Sahanaa C, Manikandan M. Forecasting Indian Infant mortality rate: An application of autoregressive integrated moving average model, Journal of Family and Community Medicine. 26;123-126.

[15] Ewere F, Eke DO. Time series analysis and forecast of infant mortality rate in Nigeria: An ARIMA modeling approach, Canadian Journal of Pure and Applied Sciences. 2020;14(2):5049-5059.

[16] Khan MS, Fatima S, Zia SS, Hussain E, Faraz TR, Khalid, F., Perpective of GDP (PPP), International Journal of Scientific and Engineering Research. 2019;10(3):18-23.

© 2022 Ugoh et al.; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:
The peer review history for this paper can be accessed here (Please copy paste the total link in your browser address bar)
https://www.sdiarticle5.com/review-history/77244