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

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

1. 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 [4]. The first two days, accounts for more than 50% Neonatal deaths [12], 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 [2,16]. 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 [14]. Studies conducted by [11] and [9] 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.

[13] 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.[15] 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 Mortalit.[5] 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 [6] 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. [3] 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.

[10] 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. [7] 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. [8] forecasted Infant Mortality Rates of Asian countries using ARIMA (1,1,1) for other countries except Japan and Nepal.

2. Materials and Method

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).

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

$$S_t = \alpha y_t + (1-\alpha)S_{t-1} \qquad (1)$$

where α 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 α (smoothing factor) is based on the researcher.

Equation (1) can be expanded as

$$S_t = \alpha y_t + (1-\alpha)y_{t-1} + (1-\alpha)^2 S_{t-2} \qquad (2)$$

$$S_t = \alpha[y_t + (1-\alpha)y_{t-1} + (1-\alpha)^2 y_{t-2} + \cdots + (1-\alpha)^{t-1}y_1] + (1-\alpha)^t y_0 \qquad (3)$$

where $y_{t-1}, y_{t-2}, \cdots$ are past observations; y_t is the current observation

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

$$\hat{y}_{t+m} = S_t + mb_t \qquad (4)$$

The Level equation is defined as

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

The Trend equation is defined as

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

where α is the data smoothing factor and $0 \leq \alpha \leq 1$, and β is the trend smoothing factor and $0 \leq \beta \leq 1$

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

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

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

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (8)$$

where $\phi_1, \phi_2, \cdots, \phi_p$ are Autoregressive model's parameters; $\theta_1, \theta_2, \cdots, \theta_q$ are Moving Average model's parameters; c is a constant; ε_t is a white noise, and y'_t is the differenced series which might been differenced more than once

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

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

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

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

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

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

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \qquad (11)$$

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:

1. 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.

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.

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.

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

$$y_t' = y_t - y_{t-1} \qquad (12)$$

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

Second Order Differencing

Second Order Differenced series denoted as y_t' is written as

$$y_t'' = y_t' - y_{t-1}' \qquad (13)$$

Where

$$y_{t-1}' = y_{t-1} - y_{t-2} \qquad (14)$$

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

$$y_t^d = (1-B)^d y_t \qquad (15)$$

Third Order Differencing

$$y_t''' = (1-B)^3 y_t \qquad (16)$$

$$y_t''' = y_t - 3By_t + 3B^2 y_t - B^3 y_t \qquad (17)$$

where $By_t = y_{t-1}$

$$y_t''' = y_t - 3y_{t-1} + 3y_{t-2} - y_{t-3} \qquad (18)$$

2. Step Two deals with Estimation of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)
3. Step Three deals with model identification, which involves the process of selecting the appropriate orders of AR and/or MA
4. 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

$$AIC = nlog(\hat{\sigma}^2) + 2k \qquad (19)$$

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

$$BIC = nlog(\hat{\sigma}^2) + klog(n) \qquad (20)$$

The ARIMA model with the lowest AIC and/or BICare/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).

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

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

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 mode obtained is a perfect fit
If $U \geq 1$, the model obtained is not a good fit

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

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

3. Result and Discussion

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

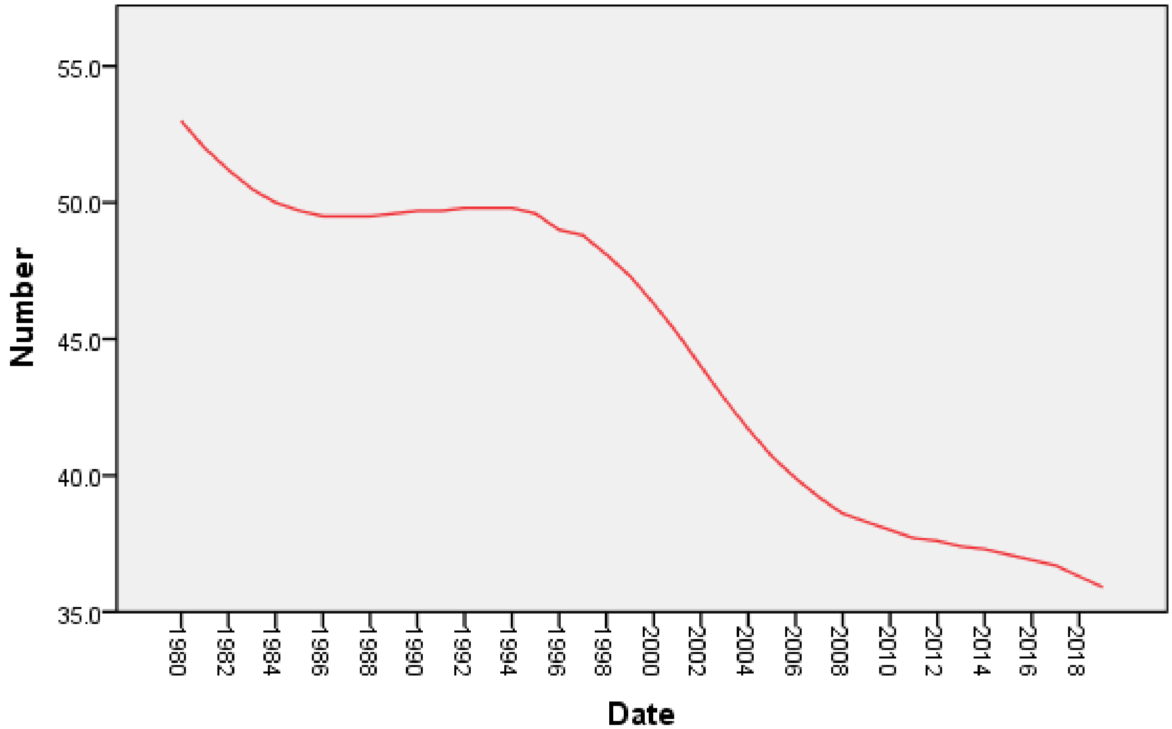


Figure 1: *Time plot of Neonatal Mortality Rate in Nigeria*

Figure 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 Figure 2.

Table 1: Descriptive Statistics for Neonatal Mortality Rates

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

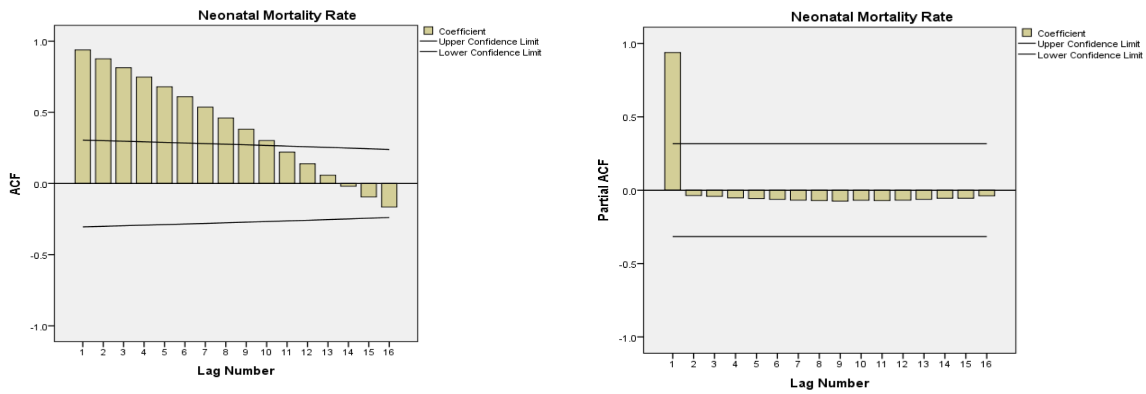
In Table 1, the average Neonatal Mortality Rate (NMR) is 44.592 deaths per 1000 live births and the standard deviation is 5.7642 deaths per 1000 live births.

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)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.460736	0.9826
Test critical values:	1% level	-3.646342	

	5% level	-2.954021
	10% level	-2.615817
*MacKinnon (1996) one-sided p-values.		

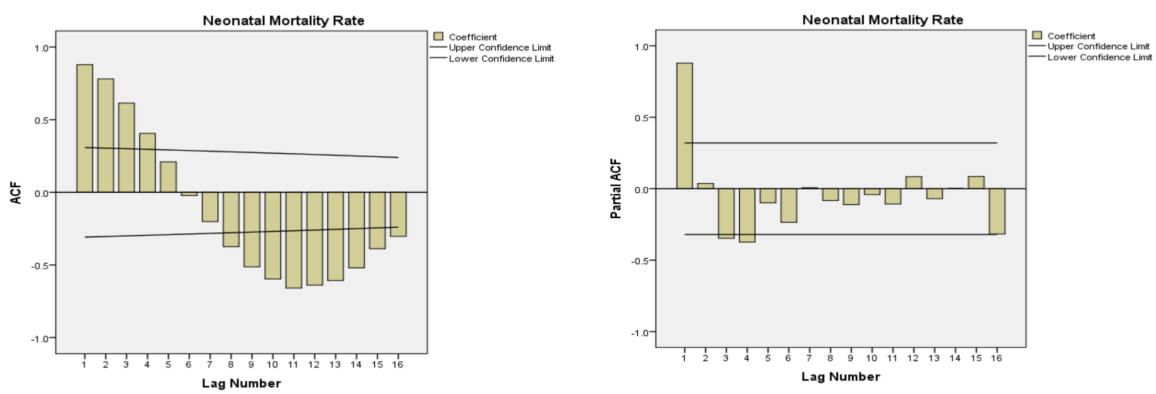
In Table 2, the Augmented Dickey-Fuller (ADF) Test Statistic is 0.460736, with p-value of 0.9826 less than 0.05, implying that there is presence of unit root in the Neonatal Mortality Rate (NMR) and hence need to be differenced at least once.



A **B**

Figure 2: *(**A**) ACF Plot for Neonatal Mortality Rate (**B**) PACF Plot for Neonatal Mortality Rate (NMR)*

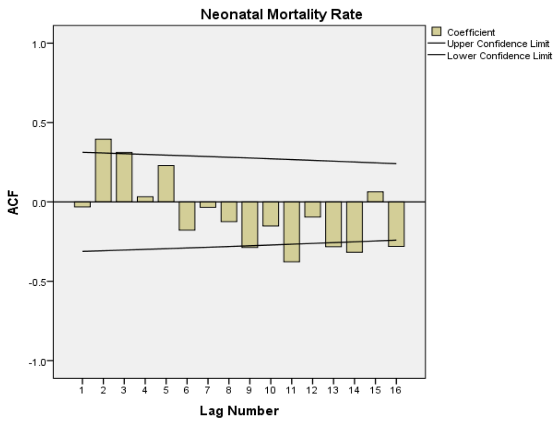
Figure 2A is the Autocorrelation Function (ACF) Plot of NMR and it shows a slow fall of the lags as the lag number increases, indicating that NMR is not stationary. Since the time series data is not stationary and a model is not fitted on NMR, Figure 2B which is the PACF plot does not indicate any order,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



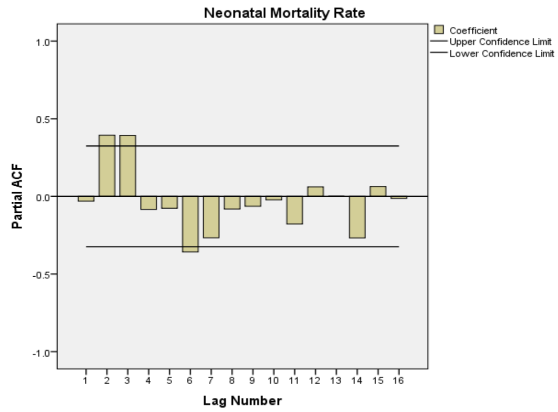
C **D**

Figure 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 Figure 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 Figure 4.



E



F

Figure 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 Figure 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 Figure 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)*

Autocorrelations and Partial Autocorrelations

Series: Neonatal Mortality Rate

Lag	Autocorrelation	Partial Autocorrelation	Box-Ljung Statistic		
			Value	df	Sig.[b]
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	0.000
Brown's LT	Alpha (Level and Trend)	0.996	21.755	0.000

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

$$S_t = 0.996y_t + 0.004S_{t-1} + 0.004b_{t-1} \quad (23)$$

$$b_t = 0.996S_t - 0.996S_{t-1} + 0.004b_{t-1} \quad (24)$$

$$\Rightarrow S_t = 0.499y_t + 0.501S_{t-1} \quad (25)$$

Table 7: *Out-of-Sample Forecast of NMR in Nigeria using Brown's LT*

		Forecast										
Model		2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
NMR	Forecast	35.5	35.1	34.7	34.3	33.9	33.5	33.1	32.7	32.3	31.9	31.5
	UCL	35.9	35.9	36.0	36.2	36.5	36.8	37.2	37.7	38.2	38.8	39.4
	LCL	35.1	34.3	33.4	32.4	31.3	30.2	29.0	27.7	26.4	25.0	23.6

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 Figure 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.

$$U = \frac{\sqrt{\frac{1}{40} \times 1.18}}{\sqrt{\frac{1}{40} \times 80835.45} + \sqrt{\frac{1}{40} \times 80786.35}} = 0.001911 \quad (26)$$

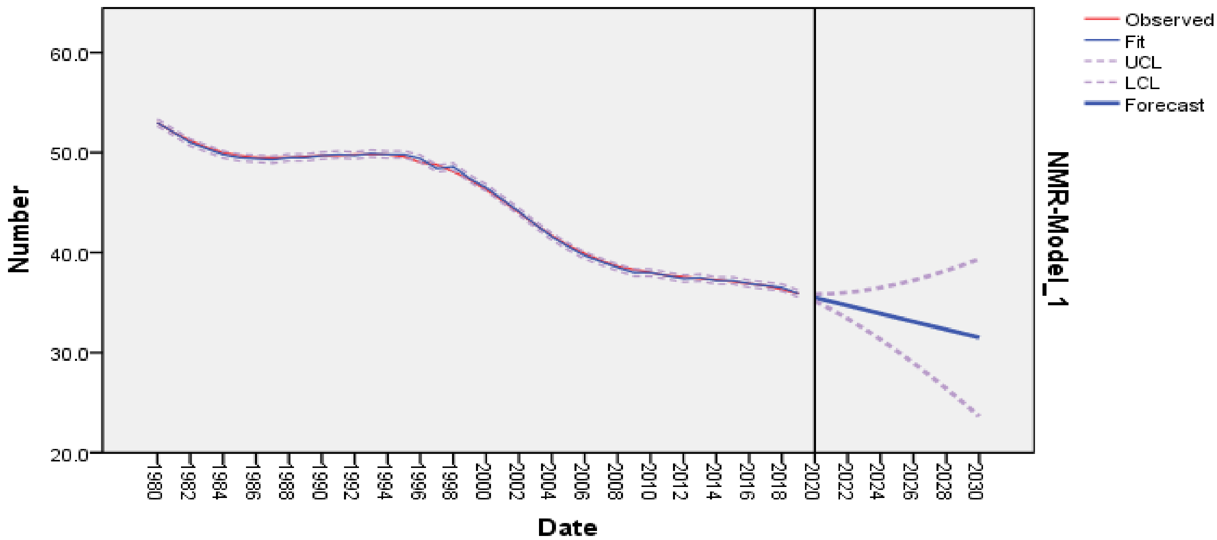


Figure 5: *Time plot of the Actual NMR and Out-Sample Forecast of NMR*

Table 8: *Actual NMR and predicted NMR and Computation of Theil's U*

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
			1.18	80835.45	80786.35

4. Conclusion

The purpose of this paper is to model and to identify an adequate model that will be used to forecast U5MR in Nigeria. Brown's LT model predicts U5MR adequately compared to SES and ARIMA model. Based on the modeling and forecasting, the U5MR is showing an instrinsic decrease from year to year. The findings of this study can help promote health policies in order to address and to reduce U5MR in the future, as well as to establish a basis for implementing optimal strategies that can be used to overcome U5MR in order to meet up with the target of SDGs.

References

[1] Babaei, H., Dehghan, M., and Pirkashani, L. M., 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] Carlo, W. A., and Travers, C. P., Maternal and Neonatal Mortality: Time to act, Journal of Pediatrics, 2016, 92(6), 543-545

[3] Chaibva, B. V., Olorunju, S., Nyadundu, S., and Beke, A., Adverse pregnancy outcomes "Stillbirth and Early Neonatal Deaths" in Mutare District, Zimbabwe (2014): A descriptive study, BMC Pregnancy and Childbirth, 2019, 19(86), 1-7

[4] Chengye, J. (2012). Child and Adolescent Health, People's Medical Publishing House, Beijing

[5] Chukwudike, N. C., Offorha, C., B., Obudu, M., Okezie, U. O., and Chisom, C. O., ARIMA modeling of Neonatal mortality in Abia state of Nigeria, Asian Journal of Probability and Statistics, 2020, 6(2), 54-62

[6] Ezeh, O. K., Agho, K. E., Dibley, M. J., Hall, J., and Page, A. N., Determinants of Neonatal mortality in Nigeria: Evidence from the 2008 Demographic and Health Survey, BMC Public Health, 2014, 14, 521-531

[7] Ewere, F., and Eke, D. O., 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

[8] Khan, M. S., Fatima, S., Zia, S. S., Hussain, E., Faraz, T. R., and Khalid, F., Perpective of GDP (PPP), International Journal of Scientific and Engineering Rearch, 2019, 10(3), 18-23

[9] Migoto, M. T., Oliveira, R. P. D., Silva, A. M. R., Freire, M. H. D. S., Early Neonatal mortality and risk factors: A case-control study in Parana state. Revista Brasileira de Enfermagem, 2018, 71, 2527-2534

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

[11] Nascimento, R. M. D., Leite, A. J. M., Almeida, N. M. G. S. D., Almeida, P. C. D., Silva, C. F. D., Determinantes da mortalidade neonatal: Estudo Caso-controle em fortaleza, ceara, brasil, Caderno de Saude Publica, 2012, 28-559-572

[12] Nouri, A., Barati, L., Qhezelsofly, F., and Niazi, S., Causes of infant mortality in Kalaleh City during 2004-2012, Hakim Jorjani Journal, 2013, 1(2), 2-37

[13] Nyoni, S. P., and Nyoni, T., Analyzing neonatal deaths in Zimbabw using Box-Jenkins ARIMA models, International Journal on Integrated Education, 2020, vol. 3, issue vii, 39-50

[14] UNICEF, Neonatal mortality, retrieved from https://unicef.org, September 2020

[15] Usman, A., Sulaiman, M. A., and 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
[16] World Health Organization, Newborns: Reducing mortality, 2019. Availble from https://www.int/news-room/fact-sheet/newborns-reducing-mortality. Technical Report.