International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 7, Issue 8, pp 329-335, August-2023
https://doi.org/10.47001/IRJIET/2023.708048

Utilizing Predictions Generated by the ARIMA Model to Address High Neonatal Mortality Rates in Lesotho

[1]Dr. Smartson. P. NYONI, [2]Thabani NYONI

[1]ZICHIRe Project, University of Zimbabwe, Harare, Zimbabwe
[2]Independent Researcher & Health Economist, Harare, Zimbabwe

***Abstract* - Lesotho is known for reporting the highest neonatal mortality rates in Sub-Saharan Africa as a result of challenges such as poverty, inadequate medical staff and poor quality healthcare services. Government initiatives have failed to sufficiently reduce neonatal mortality during the past decades. Hence new strategies must address human resource shortages among other measures. This study employs annual time series data on neonatal mortality rate (NMR) for Lesotho from 1960 to 2019 to predict future trends of NMR over the period 2020 to 2030. Unit root tests have shown that the series under consideration is an I (1) variable. The optimal model based on AIC is the ARIMA (3,1,0) model. The findings of this piece of work showed that neonatal mortality will gradually decline from approximately 42 in 2020 to around 32 deaths per 1000 live births by the end of 2030.Therefore, it is necessary for the authorities in Lesotho to direct their efforts towards promotion of institutional deliveries, ensuring availability of adequately trained medical staff and sufficient medical supplies.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

In 2018, Sub-Saharan Africa recorded the highest neonatal mortality rate (NMR) of 28 neonatal deaths per 1000 live births followed by central and southern Asia which reported 25 deaths per 1000 live births (UNICEF, 2019). UNICEF projected that the majority of the countries in Sub-Saharan Africa will miss their 2030 sustainable development goal (SDG) neonatal mortality target of at least 12 deaths per 1000 live births for every country (UNICEF, 2019).The country with the highest predicted neonatal mortality in Sub-Saharan Africa is Lesotho (UN Inter-agency Group for Child Mortality Estimation (UN IGME), 2020b). Among the factors which contribute to neonatal mortality, shortage of skilled birth attendants is an issue which requires urgent attention as 50% of deliveries are conducted by skilled manpower in Sub-Saharan Africa (Baruwa *et al*. 2021). In 2014 Lesotho reported a NMR of 35 deaths per 1000 live births down from 47 per 1000 live births (Lesotho DHS, 2014). The government of Lesotho like other countries in Sub-Saharan Africa adopted several strategies to tackle neonatal mortality such as implementation of ante-natal care, basic knowledge about how to resuscitate the new-born, tetanus-immunization of pregnant women and nutritional support of pregnant women to reduce congenital malformations (Lehtonen *et al*., 2017). However mortality among neonates remains high. The aim of this study is to model and forecast NMR for Lesotho using the popular Box-Jenkins ARIMA model (Nyoni, 2018; Box & Jenkins, 1970). The findings are expected to inform neonatal policies, decision making and assist in the evaluation of intervention strategies.

II. LITERATURE REVIEW

Baruwa *et al*. (2021) applied duration models (Kaplan Mier and Cox proportional hazards) to examine the relationship between type of birth attendant and neonatal mortality while controlling for socio-demographic characteristics of mothers in Lesotho. The findings of the study revealed that the risk of neonatal mortality is two times higher among children delivered by non-skilled birth attendants. A systematic review carried out by Masaba and Phetoe (2020) found out that in 2018, the neonatal mortality rate for Kenya was 19.6 deaths per 1000 live births. The neonatal mortality rate had fallen gradually from 35.4 deaths per 1000 live births in 1975. On the other hand, South Africa had its neonatal mortality rate fall from 27.9 deaths per 1000 live births in 1975 to 10.7 deaths per 1000 live births in 2018. A similar study done by Damian *et al.*(2019) showed that estimates from both global metrics and institutional reporting, although widely divergent, indicate South Africa has not achieved MDG 4a and 5a goals but made a significant progress in reducing maternal and neonatal mortality. Rhoda *et al.* 2018 did a literature review of estimates of NMR, causes of neonatal deaths, and described how the mortality from preventable causes of death could be reduced in South Africa. The study concluded that there was need of high-impact interventions, adequate number of appropriately trained healthcare providers and a more active role played by ward-based community health workers and district clinical specialist teams.

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 329-335, August-2023

https://doi.org/10.47001/IRJIET/2023.708048

III. METHODOLOGY

The Autoregressive (AR) Model

A process L_t (annual NMR at time t) is an autoregressive process of order p, that is, AR (p) if it is a weighted sum of the past p values plus a random shock (Z_t) such that:

$$L_t = \emptyset_1 L_{t-1} + \emptyset_2 L_{t-2} + \emptyset_3 L_{t-3} + \cdots + \emptyset_p L_{t-p} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots [1]$$

Using the backward shift operator, B, such that $BL_t = L_{t-1}$, the AR (p) model can be expressed as in equation [2] below:

$$Z_t = \emptyset(B) L_t \ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where $\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \emptyset_3 B^3 - \cdots - \emptyset_p B^p$

The 1st order AR (p) process, AR (1) may be expressed as shown below:

$$L_t = \emptyset L_{t-1} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots [3]$$

Given $\emptyset = 1$, then equation [3] becomes a random walk model. When $|\emptyset| > 1$, then the series is reffered to as explosive, and thus non-stationary. Generally, most time series are explosive. In the case where $|\emptyset| < 1$, the series is said to be stationary and therefore its ACF (autocorrelation function) decreases exponentially.

The Moving Average (MA) Model

A process is reffered to as a moving average process of order q, MA (q) if it is a weighted sum of the last random shocks, that is:

$$L_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \cdots + \theta_q Z_{t-q} \ldots\ldots\ldots\ldots\ldots\ldots [4]$$

Using the backward shift operator, B, equation [4] can be expressed as follows:

$$L_t = \theta(B) Z_t \ldots\ldots\ldots\ldots\ldots\ldots [5]$$

where $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$

Equation [4] can also be expressed as follows:

$$L_t - \sum_{j \leq 1} \pi_j L_{t-j} = Z_t \ldots\ldots\ldots\ldots\ldots\ldots [6]$$

for some constant π_j such that:

$$\sum_{j \leq 1} |\pi_j| < \infty$$

This implies that it is possible to invert the function taking the Z_t sequence to the L_t sequence and recover Z_t from present and past values of L_t by a convergent sum.

The Autoregressive Moving Average (ARMA) Model

While the above models are good, a more parsimonious model is the ARMA model. The AR, MA and ARMA models are applied on stationary time series only. The ARMA model is just a mixture of AR (p) and MA (q) terms, hence the name ARMA (p, q). This can be expressed as follows:

$$\emptyset(B) L_t = \theta(B) Z_t \ldots\ldots\ldots\ldots\ldots\ldots [7]$$

Thus:

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 329-335, August-2023

https://doi.org/10.47001/IRJIET/2023.708048

$$L_t\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right) = Z_t\left(1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\right) \ldots\ldots\ldots\ldots\ldots.\ldots [8]$$

where $\emptyset(B)$ and $\theta(B)$ are polynomials in B of finite order p, q respectively.

The Autoregressive Integrated Moving Average (ARIMA) Model

The AR, MA and ARMA processes are usually not applied empirically because in most cases many time series data are not stationary; hence the need for differencing until stationarity is achieved.

$$\left.\begin{array}{c} The\ first\ difference\ is\ given\ by: \\ L_t - L_{t-1} = L_t - BL_t \\ The\ second\ difference\ is\ given\ by: \\ L_t(1-B) - L_{t-1}(1-B) = L_t(1-B) - BL_t(1-B) = L_t(1-B)(1-B) = L_t(1-B)^2 \\ The\ third\ difference\ is\ given\ by: \\ L_t(1-B)^2 - L_{t-1}(1-B)^2 = L_t(1-B)^2 - BL_t(1-B)^2 = L_t(1-B)^2(1-B) = L_t(1-B)^3 \\ The\ d^{th}\ difference\ is\ given\ by: \\ L_t(1-B)^d \end{array}\right\} \ldots [9]$$

Given the basic algebraic manipulations above, it can be inferred that when the actual data series is differenced "d" times before fitting an ARMA (p, q) process, then the model for the actual undifferenced series is called an ARIMA (p, d, q) model. Thus equation [7] is now generalized as follows:

$$\emptyset(B)(1-B)^d L_t = \theta(B)Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots\ldots\ldots. [10]$$

Therefore, in the case of modeling and forecasting NMR, equation [10] can be written as follows:

$$\emptyset(B)(1-B)^d L_t = \theta(B)Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. [11]$$

The Box – Jenkins Approach

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018). The Box – Jenkins technique was proposed by Box & Jenkins (1970) and is widely used in many forecasting contexts, including the health sector. In this paper, hinged on this technique; the researcher will use automatic ARIMA modeling for estimating equation [10].

Data Issues

This study is based on annual NMR in Lesotho for the period 1960 to 2019. The out-of-sample forecast covers the period 2020 to 2030. All the data employed in this research paper was gathered from the World Bank online database.

Evaluation of ARIMA Models

Criteria Table

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: DLOG(L)
Date: 01/23/22 Time: 17:22
Sample: 1960 2019
Included observations: 59

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 329-335, August-2023

https://doi.org/10.47001/IRJIET/2023.708048

Model	LogL	AIC*	BIC	HQ
(3,0)(0,0)	268.153825	-8.920469	-8.744406	-8.851741
(4,0)(0,0)	268.400806	-8.894943	-8.683668	-8.812469
(3,1)(0,0)	268.377331	-8.894147	-8.682872	-8.811674
(5,2)(0,0)	271.296536	-8.891408	-8.574496	-8.767698
(3,2)(0,0)	268.438396	-8.862318	-8.615831	-8.766100
(5,0)(0,0)	268.407793	-8.861281	-8.614794	-8.765062
(4,1)(0,0)	268.404131	-8.861157	-8.614669	-8.764938
(2,3)(0,0)	268.153454	-8.852659	-8.606172	-8.756441
(2,2)(0,0)	266.905429	-8.844252	-8.632977	-8.761779
(5,3)(0,0)	270.819976	-8.841355	-8.489230	-8.703900
(3,3)(0,0)	268.534295	-8.831671	-8.549971	-8.721707
(2,4)(0,0)	268.469275	-8.829467	-8.547767	-8.719503
(4,2)(0,0)	268.443213	-8.828584	-8.546884	-8.718619
(5,1)(0,0)	268.412241	-8.827534	-8.545834	-8.717569
(1,5)(0,0)	268.345259	-8.825263	-8.543563	-8.715299
(3,4)(0,0)	268.731765	-8.804467	-8.487554	-8.680757
(2,5)(0,0)	268.602529	-8.800086	-8.483173	-8.676376
(4,3)(0,0)	268.544033	-8.798103	-8.481190	-8.674393
(1,4)(0,0)	266.230823	-8.787486	-8.540998	-8.691267
(2,1)(0,0)	264.159334	-8.785062	-8.609000	-8.716335
(4,4)(0,0)	268.734113	-8.770648	-8.418523	-8.633193
(3,5)(0,0)	268.733545	-8.770629	-8.418504	-8.633173
(1,2)(0,0)	263.301726	-8.755991	-8.579928	-8.687263
(1,3)(0,0)	263.793746	-8.738771	-8.527496	-8.656298
(4,5)(0,0)	268.734114	-8.736750	-8.349412	-8.585549
(5,5)(0,0)	269.585343	-8.731707	-8.309157	-8.566760
(5,4)(0,0)	266.555189	-8.662888	-8.275550	-8.511687
(2,0)(0,0)	258.276952	-8.619558	-8.478708	-8.564576
(1,1)(0,0)	252.101024	-8.410204	-8.269354	-8.355222
(0,5)(0,0)	254.822338	-8.400757	-8.154270	-8.304538
(1,0)(0,0)	247.522629	-8.288903	-8.183265	-8.247666
(0,4)(0,0)	246.543041	-8.154001	-7.942726	-8.071528
(0,3)(0,0)	236.770010	-7.856610	-7.680548	-7.787883
(0,2)(0,0)	216.614505	-7.207271	-7.066421	-7.152289
(0,1)(0,0)	193.477159	-6.456853	-6.351215	-6.415616
(0,0)(0,0)	161.513084	-5.407223	-5.336798	-5.379732

International Research Journal of Innovations in Engineering and Technology (IRJIET)

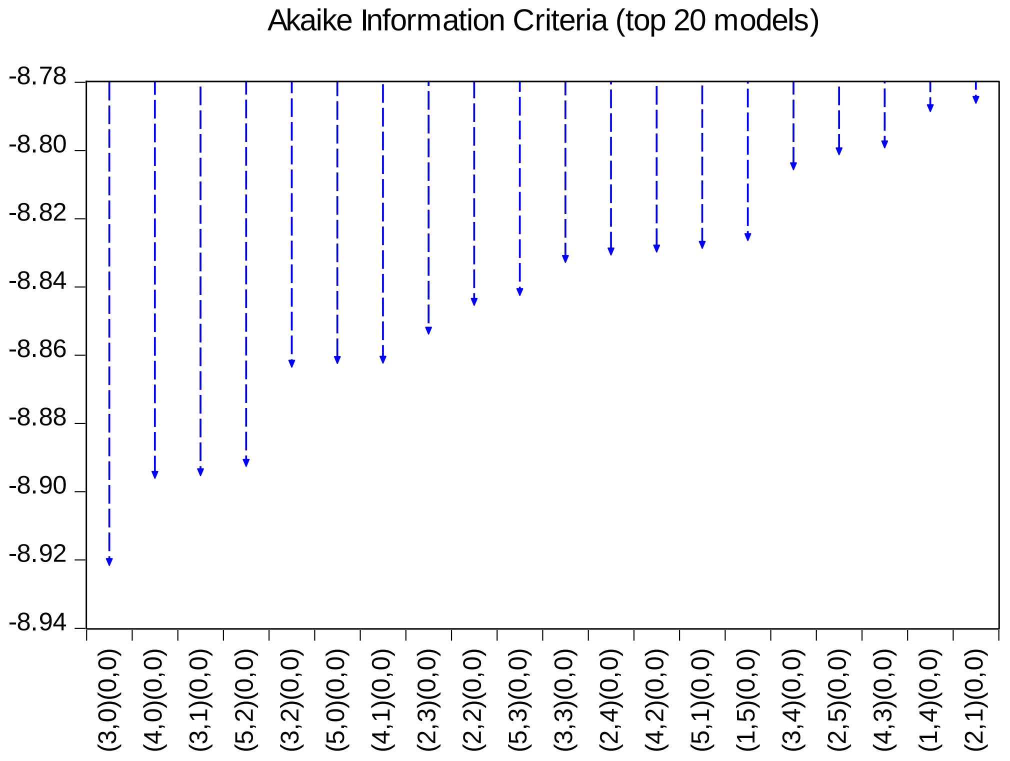
ISSN (online): 2581-3048

Volume 7, Issue 8, pp 329-335, August-2023

https://doi.org/10.47001/IRJIET/2023.708048

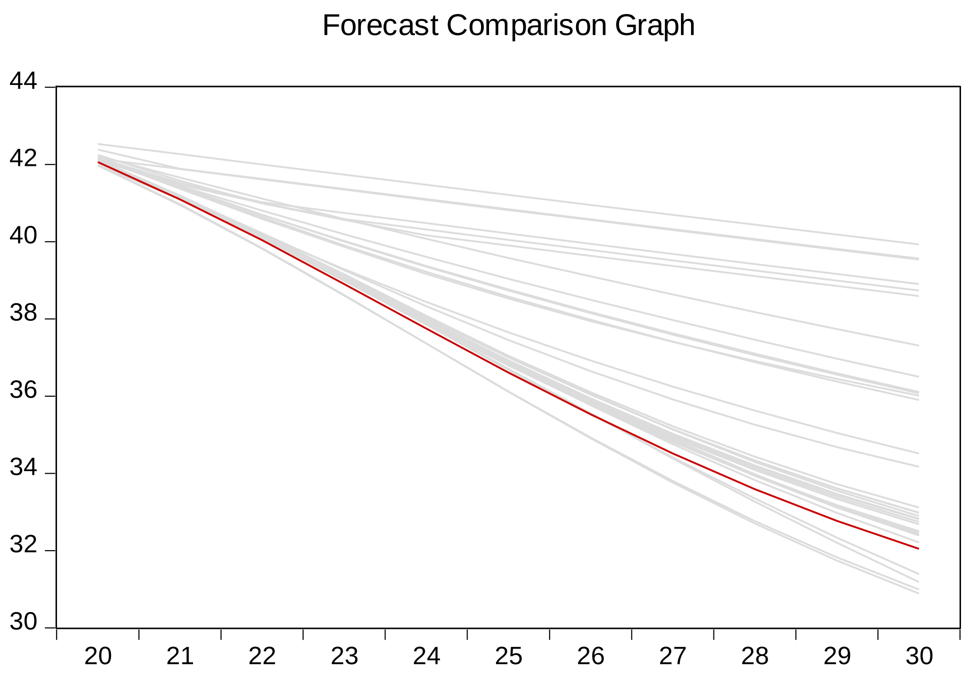
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph



ISSN (online): 2581-3048
Volume 7, Issue 8, pp 329-335, August-2023
https://doi.org/10.47001/IRJIET/2023.708048

Table 2 and Figure 1 indicate that the optimal model is the ARIMA (3,1,0) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (3,1,0) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(L)
Date: 01/23/22 Time: 17:22
Sample: 1960 2019
Included observations: 59
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (3,0)(0,0)
AIC value: -8.92046866097

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(L)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/22 Time: 17:22
Sample: 1961 2019
Included observations: 59
Convergence achieved after 7 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.009503	0.005404	-1.758440	0.0843
AR(1)	1.214264	0.117215	10.35931	0.0000
AR(2)	0.282088	0.216850	1.300843	0.1988
AR(3)	-0.560082	0.127579	-4.390072	0.0001
SIGMASQ	6.08E-06	1.31E-06	4.652127	0.0000

R-squared	0.975237	Mean dependent var	-0.006309
Adjusted R-squared	0.973403	S.D. dependent var	0.015798
S.E. of regression	0.002576	Akaike info criterion	-8.920469
Sum squared resid	0.000358	Schwarz criterion	-8.744406
Log likelihood	268.1538	Hannan-Quinn criter.	-8.851741
F-statistic	531.6664	Durbin-Watson stat	1.843944
Prob(F-statistic)	0.000000		

Inverted AR Roots	.92-.18i	.92+.18i	-.63

ISSN (online): 2581-3048
Volume 7, Issue 8, pp 329-335, August-2023
https://doi.org/10.47001/IRJIET/2023.708048

ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	42.05652133678166
2021	41.09056684928943
2022	40.03733318866905
2023	38.89777283519112
2024	37.74897475170953
2025	36.61099119029579
2026	35.52690971360527
2027	34.51321304433422
2028	33.59075428801126
2029	32.76687851780916
2030	32.04785949574179

Table 5 clearly indicates that neonatal mortality will gradually decline from approximately 42 in 2020 to around 32 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

Neonatal mortality remains a problem in Lesotho and the country's progress towards the substantial reduction of neonatal deaths is unacceptably slow. In this study we proposed the Box-Jenkins ARIMA technique to forecast NMR for Lesotho and the findings revealed that neonatal mortality will gradually decline from approximately 42 in 2020 to around 32 deaths per 1000 live births by the end of 2030. Therefore, it is necessary for the authorities in Lesotho to direct their efforts towards promotion of institutional deliveries, ensuring availability of adequately trained medical staff and sufficient medical supplies.

REFERENCES

[1] Box, D. E., and Jenkins, G. M. (1970). Time Series Analysis, Forecasting and Control, Holden Day, London.
[2] Nyoni, T. (2018). Box-Jenkins ARIMA Approach to Predicting net FDI Inflows in Zimbabwe, *University Library of Munich*, MPRA Paper No. 87737.
[3] UNICEF. Child Mortality 2019. New York: United Nations Children's Fund; 2019.
[4] Baruwa O. J., Amoateng A. Y., and Mkwananzi S (2021). Association between type of birth attendants and neonatal mortality: Evidence from a National survey. Afri Health Sci. 2021, 21,4,1870-6.
[5] UN IGME (2020b) Childmortality.org/data [2021-04-10]
[6] Lehtonen, L., Gimeno, A., Parra-Llorca, A. & Vento, M. (2017). Early neonatal death: A challenge worldwide. Seminars in Fetal and Neonatal Medicine 22(3), p. 153–160. https://doi.org/10.1016/j.siny.2017.02.006
[7] Lesotho DHS, 2014.

Citation of this Article:

Dr. Smartson. P. NYONI, Thabani NYONI, "Utilizing Predictions Generated by the ARIMA Model to Address High Neonatal Mortality Rates in Lesotho" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 8, pp 329-335, August 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.708048

****

