

Implementing Informed Neonatal Healthcare Policies in Botswana through Utilization of the ARIMA Model

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Abstract - Statistical time series forecasting approaches continue to attract the attention of many public health specialists as they have been proven to be useful in guiding policy-making and allocation of resources to maternal and child health programs in any country. This study uses annual time series data on neonatal mortality rate (NMR) for Botswana from 1965 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 (2,1,1) model. The ARIMA model predictions indicate that neonatal mortality is expected to drop to levels below 12 deaths per 1000 live births by the end of 2030. Therefore, the government of Botswana is encouraged to focus on improving the quality of healthcare services during antenatal, delivery and postnatal periods.

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

The launching of global sustainable development goals (SDGs) in 2015 was a clear sign that all UN member states are committed to the substantial reduction of maternal mortality ratio (MMR) to less than 70 maternal deaths per 100 000 live births, under-five mortality to levels as low as 25 deaths per 1000 live births and neonatal mortality to at least 12 per 1000 live births by the end of 2030 especially in low-middle income countries. Worldwide, 2.4 million neonates die each year, with roughly 99 percent of these deaths occurring in low/middle-income countries (WHO, 2020; Burstein *et al.* 2019; Lawn *et al.* 2005). The neonatal period is a vulnerable period in a child's life that carries the highest mortality risk, with over half of deaths occurring in the first 3 days of life (UNICEF, 2020; Sankar *et al.* 2016). It is of great concern that Sub-Saharan Africa has the highest neonatal mortality rate (NMR) (Kayode *et al.* 2017). Causes of neonatal mortality in low and middle income countries are neonatal sepsis, birth asphyxia, severe prematurity and congenital anomalies (Kitt *et al.* 2022). Botswana is a SADC country whose challenges are similar to its regional counterparts. The country has made significant strides in reducing maternal mortality and improving child survival. However, the country has to do more in order to achieve set SDG-3 targets by the end of 2030. Forecasting NMR is very important at this point in time so as to appreciate the likely future trends of NMR for Botswana and assess the feasibility of achieving set SDG target 3.2 by 2030. This study will employ the popular Box-Jenkins ARIMA methodology which has been shown to be a very useful modeling technique for linear data (Nyoni, 2018; Box-Jenkins, 1970).

II. LITERATURE REVIEW

Many researchers investigated the causes and risk factors of neonatal mortality in SSA. Masaba & Phetoe described the trends of neonatal mortality within the two sub-Saharan countries. The study concluded 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. Kayode *et al.* 2017 carried out an ecological study which revealed that there is a wide variation in neonatal mortality in SSA. A substantial part of this variation can be explained by differences in the quality of healthcare governance, prevalence of HIV and socioeconomic deprivation. Rhoda *et al.* 2018 reviewed efforts made by the South African government to reduce neonatal mortality. Indications from the study showed that high-impact interventions, providing an adequate number of appropriately trained healthcare providers and a more active role played by ward-based community health workers and district clinical specialist teams was pivotal to achieve substantial reduction in neonatal deaths. In a descriptive study Indongo, 2014 investigated the common causes and risk factors of neonatal deaths in facilities in five regions in Namibia. The researcher found out that mortality rate was high in low birth weight neonates.

III. METHODOLOGY

The Autoregressive (AR) Model

A process M_t (annual neonatal mortality rate 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:

$$M_t = \phi_1 M_{t-1} + \phi_2 M_{t-2} + \phi_3 M_{t-3} + \dots + \phi_p M_{t-p} + Z_t \dots \dots \dots [1]$$

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

$$Z_t = \phi(B) M_t \dots \dots \dots [2]$$

where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3 - \dots - \phi_p B^p$

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

$$M_t = \phi M_{t-1} + Z_t \dots \dots \dots [3]$$

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

The Moving Average (MA) Model

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

$$M_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \dots + \theta_q Z_{t-q} \dots \dots \dots [4]$$

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

$$M_t = \theta(B) Z_t \dots \dots \dots [5]$$

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

Equation [4] can also be expressed as follows:

$$M_t - \sum_{j \leq 1} \pi_j M_{t-j} = Z_t \dots \dots \dots [6]$$

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 M_t sequence and recover Z_t from present and past values of M_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:

$$\phi(B) M_t = \theta(B) Z_t \dots \dots \dots [7]$$

Thus:

$$M_t(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) = Z_t(1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q) \dots \dots \dots [8]$$

where $\phi(B)$ 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.

$$\left. \begin{aligned} & \text{The first difference is given by:} \\ & M_t - M_{t-1} = M_t - BM_t \\ & \text{The second difference is given by:} \\ & M_t(1 - B) - M_{t-1}(1 - B) = M_t(1 - B) - BM_t(1 - B) = M_t(1 - B)(1 - B) = M_t(1 - B)^2 \\ & \text{The third difference is given by:} \\ & M_t(1 - B)^2 - M_{t-1}(1 - B)^2 = M_t(1 - B)^2 - BM_t(1 - B)^2 = M_t(1 - B)^2(1 - B) = M_t(1 - B)^3 \\ & \text{The } d^{\text{th}} \text{ difference is given by:} \\ & M_t(1 - B)^d \end{aligned} \right\} \dots [9]$$

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:

$$\phi(B)(1 - B)^d M_t = \theta(B)Z_t \dots \dots \dots [10]$$

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

$$\phi(B)(1 - B)^d M_t = \theta(B)Z_t \dots \dots \dots [11]$$

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 public health. 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 Botswana for the period 1965 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

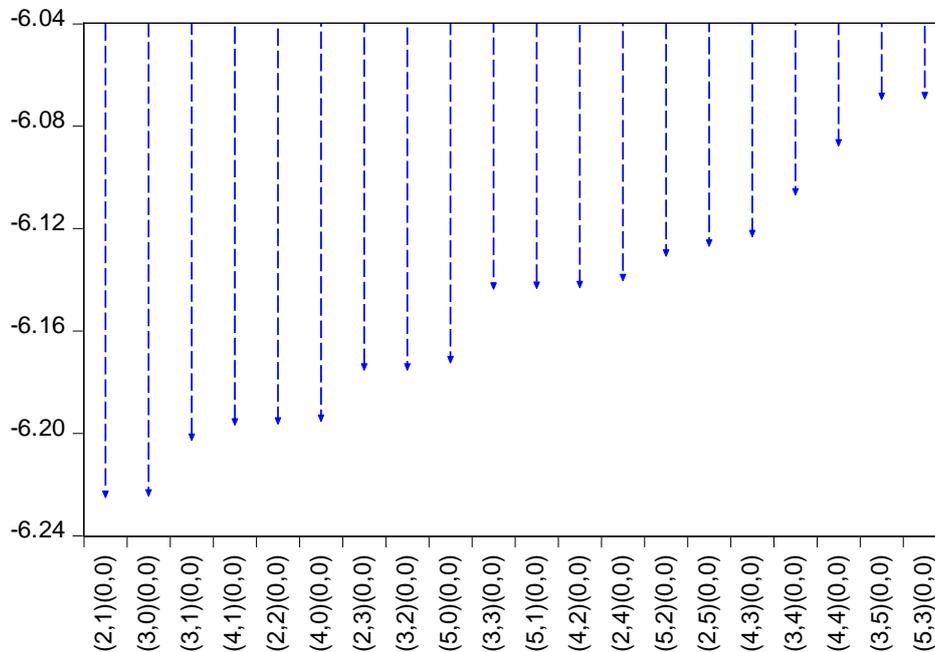
Model Selection Criteria Table
Dependent Variable: DLOG(M)
Date: 01/22/22 Time: 12:46
Sample: 1965 2019
Included observations: 54

Model	LogL	AIC*	BIC	HQ
(2,1)(0,0)	173.038371	-6.223643	-6.039478	-6.152618
(3,0)(0,0)	173.023561	-6.223095	-6.038930	-6.152070
(3,1)(0,0)	173.436074	-6.201336	-5.980338	-6.116106
(4,1)(0,0)	174.273081	-6.195299	-5.937468	-6.095864
(2,2)(0,0)	173.262840	-6.194920	-5.973922	-6.109690
(4,0)(0,0)	173.234318	-6.193864	-5.972865	-6.108633
(2,3)(0,0)	173.693760	-6.173843	-5.916012	-6.074408
(3,2)(0,0)	173.693466	-6.173832	-5.916001	-6.074397
(5,0)(0,0)	173.618351	-6.171050	-5.913219	-6.071615
(3,3)(0,0)	173.840617	-6.142245	-5.847581	-6.028605
(5,1)(0,0)	173.832160	-6.141932	-5.847268	-6.028291
(4,2)(0,0)	173.825955	-6.141702	-5.847038	-6.028062
(2,4)(0,0)	173.751517	-6.138945	-5.844281	-6.025305
(5,2)(0,0)	174.493731	-6.129397	-5.797900	-6.001552
(2,5)(0,0)	174.388038	-6.125483	-5.793986	-5.997637
(4,3)(0,0)	174.286794	-6.121733	-5.790236	-5.993888
(3,4)(0,0)	173.846466	-6.105425	-5.773927	-5.977579
(4,4)(0,0)	174.330313	-6.086308	-5.717978	-5.944257
(3,5)(0,0)	173.840876	-6.068181	-5.699850	-5.926130
(5,3)(0,0)	173.831380	-6.067829	-5.699499	-5.925778
(5,4)(0,0)	174.806766	-6.066917	-5.661754	-5.910662
(1,4)(0,0)	169.978125	-6.036227	-5.778396	-5.936791
(5,5)(0,0)	174.964228	-6.035712	-5.593716	-5.865251
(2,0)(0,0)	166.713430	-6.026423	-5.879091	-5.969603
(1,5)(0,0)	170.600753	-6.022250	-5.727586	-5.908610
(1,3)(0,0)	166.641904	-5.949700	-5.728702	-5.864470
(1,2)(0,0)	165.103519	-5.929760	-5.745595	-5.858735
(4,5)(0,0)	168.483189	-5.832711	-5.427547	-5.676455
(1,1)(0,0)	158.505959	-5.722443	-5.575111	-5.665623
(0,5)(0,0)	155.956000	-5.516889	-5.259058	-5.417453
(1,0)(0,0)	151.360064	-5.494817	-5.384318	-5.452202
(0,4)(0,0)	147.671436	-5.247090	-5.026092	-5.161860
(0,3)(0,0)	137.687125	-4.914338	-4.730173	-4.843313
(0,2)(0,0)	124.041673	-4.445988	-4.298656	-4.389168
(0,1)(0,0)	99.442384	-3.571940	-3.461441	-3.529325
(0,0)(0,0)	68.402775	-2.459362	-2.385696	-2.430952

Criteria Graph

Figure 1: Criteria Graph

Akaike Information Criteria (top 20 models)



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

Forecast Comparison Graph

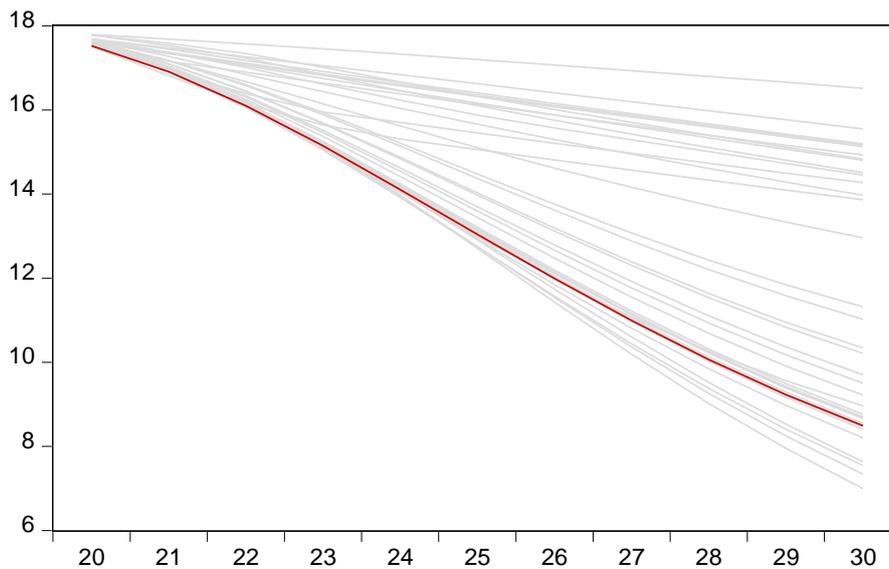


Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,1,1) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (2,1,1)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

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
 Selected dependent variable: DLOG(M)
 Date: 01/22/22 Time: 12:46
 Sample: 1965 2019
 Included observations: 54
 Forecast length: 11

Number of estimated ARMA models: 36
 Number of non-converged estimations: 0
 Selected ARMA model: (2,1)(0,0)
 AIC value: -6.22364335427

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(M)
 Method: ARMA Maximum Likelihood (BFGS)
 Date: 01/22/22 Time: 12:46
 Sample: 1966 2019
 Included observations: 54
 Convergence achieved after 8 iterations
 Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.022772	0.015371	-1.481451	0.1449
AR(1)	1.909556	0.067616	28.24115	0.0000
AR(2)	-0.942081	0.064168	-14.68158	0.0000
MA(1)	-0.632380	0.182595	-3.463303	0.0011
SIGMASQ	8.83E-05	1.73E-05	5.099147	0.0000
R-squared	0.980994	Mean dependent var	-0.015075	
Adjusted R-squared	0.979443	S.D. dependent var	0.068817	
S.E. of regression	0.009867	Akaike info criterion	-6.223643	
Sum squared resid	0.004770	Schwarz criterion	-6.039478	
Log likelihood	173.0384	Hannan-Quinn criter.	-6.152618	
F-statistic	632.2939	Durbin-Watson stat	2.060177	
Prob(F-statistic)	0.000000			
Inverted AR Roots	.95-.17i	.95+.17i		
Inverted MA Roots	.63			

ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	17.52616827187608
2021	16.90992039710029
2022	16.0979371362859
2023	15.14550780615874
2024	14.10972218360548
2025	13.04370326787004
2026	11.99259987432709
2027	10.9915293352814
2028	10.0652377048373
2029	9.229005862889677
2030	8.490271538387394

In line with previous studies such as Waldhor *et al.* (2005) Table 2 clearly indicates that there is likely to be a decline in NMR in Botswana levels below 12 deaths per 1000 live births over the period 2020 to 2030, *ceteris paribus*

V. POLICY IMPLICATION & CONCLUSION

The progress made towards achieving substantial reduction of neonatal mortality by the end of 2030 as agreed during the launch of sustainable development goals in 2015 has met numerous challenges such as lack of adequate resources, brain drain in low-middle income countries, political and civil conflict, economic collapse in various countries and of late the global COVID-19 pandemic. However, health authorities in different countries are expected to adapt to the current situation and to be creative so that they come up with appropriate measures to curb maternal and child mortality. The ARIMA technique was applied in this study to model and predict NMR for Botswana and the results indicate that neonatal mortality is expected to decline to levels below 12 deaths per 1000 live births by the end of 2030. Therefore, the government of Botswana is encouraged to focus on improving the quality of healthcare services during the antenatal, delivery and postnatal periods.

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