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Utilizing ARIMA Model Forecasts to Inform Maternal and Neonatal Health Policies in Namibia

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***Abstract* - Namibia is still struggling to achieve substantial reduction of neonatal mortality with recent evidence suggesting that the nation will miss its target at the end of 2030. Neonatal deaths are mainly due to birth asphyxia, prematurity, congenital anomalies, neonatal sepsis, respiratory distress syndrome and health system related issues. The government has made key achievements in the reduction of neonatal mortality rates, however existing policies and interventions have not managed to end all preventable neonatal deaths. This study uses annual time series data on neonatal mortality rate (NMR) for Namibia from 1969 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 findings of the study indicate that neonatal mortality is expected to gradually decline from around 19 in 2020 to 15 deaths per 1000 live births by the end of 2030. Hence, the government of Namibia is encouraged to implement appropriate neonatal policies to address high neonatal mortality in the country. Control measures should include regular refresher courses on basic & emergency obstetric and newborn care at all levels of healthcare and initiatives to retain medical staff especially in the rural areas.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

A newborn death that occurs within the first 28 days of life after birth is referred to as a neonatal death. Neonatal mortality rate (NMR) is the number of neonatal deaths per 1000 live births during a specified time period. Globally approximately 60 percent of neonatal mortality are as a result of birth asphyxia (Ersdal *et al.* 2012). 1 in 36 newborn babies die within the first month of life in Sub-Saharan Africa whereas 1in 333 die in developed countries (UNICEF, 2017). According to the Namibia Biennial report 2016-2017, in 2015 Namibia reported a maternal mortality ratio of 265 maternal deaths per 100 000 live births and a fertility rate of 3.6 births per woman. The government made key achievements in newborn and child health particularly reduction in infant and neonatal mortality rates. In 2013 the country reported a NMR of 20 neonatal deaths per 1000 livebirths. The country's neonatal deaths are mainly due to birth asphyxia (49.4%), prematurity (12.7%), congenital anomalies (10.8%), neonatal sepsis (10.8%), respiratory distress syndrome (7.2%) and health system related issues (MOH Namibia, 2014).The aim of this paper is to model and forecast neonatal mortality rate for Namibia using the widely applied Box-Jenkins ARIMA model. The model is specified as ARIMA (p, d, q) where p and q are the non-seasonal autoregressive and moving average parts and'd' being the differencing order (Nyoni, 2018; Box & Jenkins, 1970). The findings of this research are expected to help in the assessment of the country's progress towards achieving the SDG goal 3 target 3.2 by 2030.

II. LITERATURE REVIEW

Neonatal mortality is huge concern in Sub-Saharan Africa including Namibia. Several studies in the SADC region have been done in order to understand the nature and the extent of the health problem. Survival modelling was successfully applied by Tiruneh *et al*.(2021)to assess the pooled estimate of infant mortality rate (IMR), time to death, and its associated factors in SSA using the recent demographic and health survey dataset between 2010 and 2018. The study concluded that the most common cause of infant death is a preventable bio-demographic factor. Kayode *et al*.(2017) examined the variation in neonatal mortality and identified underlying causes of variation in neonatal mortality in sub-Saharan Africa (SSA). The ecological study utilized2012 publicly available data from WHO, the US Agency for International Development and the World Bank. Variation in neonatal mortality across 49 SSA countries was examined using control chart and explanatory spatial data analysis. Associations between country-level characteristics and neonatal mortality were examined using linear regression analysis. The findings revealed that there was 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. A descriptive study done by Indongo(2014)

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investigated causes and risk factors of neonatal deaths in facilities in five regions in Namibia.A total of 498 neonatal deaths recorded in each of the facilities during the period under study January 1, 2010–June 30, 2012 were reviewed. These deaths were evaluated for age, gestational age, birth weight, risk factors and cause of death. The findings showed that mortality rate was high in low birth weight neonates.

III. METHODOLOGY

The Autoregressive (AR) Model

A process M_t (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:

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

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

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

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:

$$M_t = \emptyset M_{t-1} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

for some constant π_j such that:

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

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

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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:

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

Thus:

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

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.

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

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:

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

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

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

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 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 Namibia for the period 1969 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.

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Evaluation of ARIMA Models

Criteria Table

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: D(M)
Date: 01/23/22 Time: 18:17
Sample: 1969 2019
Included observations: 50

Model	LogL	AIC*	BIC	HQ
(2,1)(0,0)	43.424546	-1.536982	-1.345780	-1.464171
(3,0)(0,0)	42.092220	-1.483689	-1.292487	-1.410878
(1,3)(0,0)	42.785416	-1.471417	-1.241974	-1.384044
(2,0)(0,0)	40.770964	-1.470839	-1.317877	-1.412590
(1,0)(0,0)	39.706948	-1.468278	-1.353557	-1.424591
(4,5)(0,0)	47.666581	-1.466663	-1.046018	-1.306479
(4,1)(0,0)	43.592578	-1.463703	-1.196020	-1.361768
(4,0)(0,0)	42.536090	-1.461444	-1.232001	-1.374070
(2,2)(0,0)	42.492844	-1.459714	-1.230271	-1.372341
(1,2)(0,0)	41.482398	-1.459296	-1.268094	-1.386485
(1,1)(0,0)	40.429554	-1.457182	-1.304220	-1.398933
(3,1)(0,0)	42.400315	-1.456013	-1.226570	-1.368639
(2,4)(0,0)	44.211636	-1.448465	-1.142542	-1.331968
(5,2)(0,0)	45.023061	-1.440922	-1.096758	-1.309863
(1,4)(0,0)	42.857417	-1.434297	-1.166613	-1.332361
(2,3)(0,0)	42.847422	-1.433897	-1.166214	-1.331962
(3,3)(0,0)	43.705200	-1.428208	-1.122284	-1.311711
(4,2)(0,0)	43.635634	-1.425425	-1.119502	-1.308928
(5,1)(0,0)	43.623545	-1.424942	-1.119018	-1.308444
(5,0)(0,0)	42.571772	-1.422871	-1.155188	-1.320936
(3,5)(0,0)	45.498792	-1.419952	-1.037547	-1.274330
(3,2)(0,0)	42.393040	-1.415722	-1.148038	-1.313786
(4,3)(0,0)	44.218130	-1.408725	-1.064561	-1.277666
(5,4)(0,0)	46.001863	-1.400075	-0.979429	-1.239890
(1,5)(0,0)	42.857723	-1.394309	-1.088385	-1.277811
(3,4)(0,0)	43.743937	-1.389757	-1.045593	-1.258698
(5,5)(0,0)	46.369182	-1.374767	-0.915882	-1.200021
(5,3)(0,0)	44.304196	-1.372168	-0.989763	-1.226546
(4,4)(0,0)	44.273004	-1.370920	-0.988516	-1.225298
(0,5)(0,0)	40.952054	-1.358082	-1.090399	-1.256147
(2,5)(0,0)	42.863041	-1.354522	-1.010358	-1.223462
(0,4)(0,0)	32.792763	-1.071711	-0.842268	-0.984337
(0,3)(0,0)	30.535512	-1.021420	-0.830218	-0.948610
(0,2)(0,0)	22.572809	-0.742912	-0.589951	-0.684664
(0,1)(0,0)	9.851105	-0.274044	-0.159323	-0.230358
(0,0)(0,0)	-15.859421	0.714377	0.790858	0.743501

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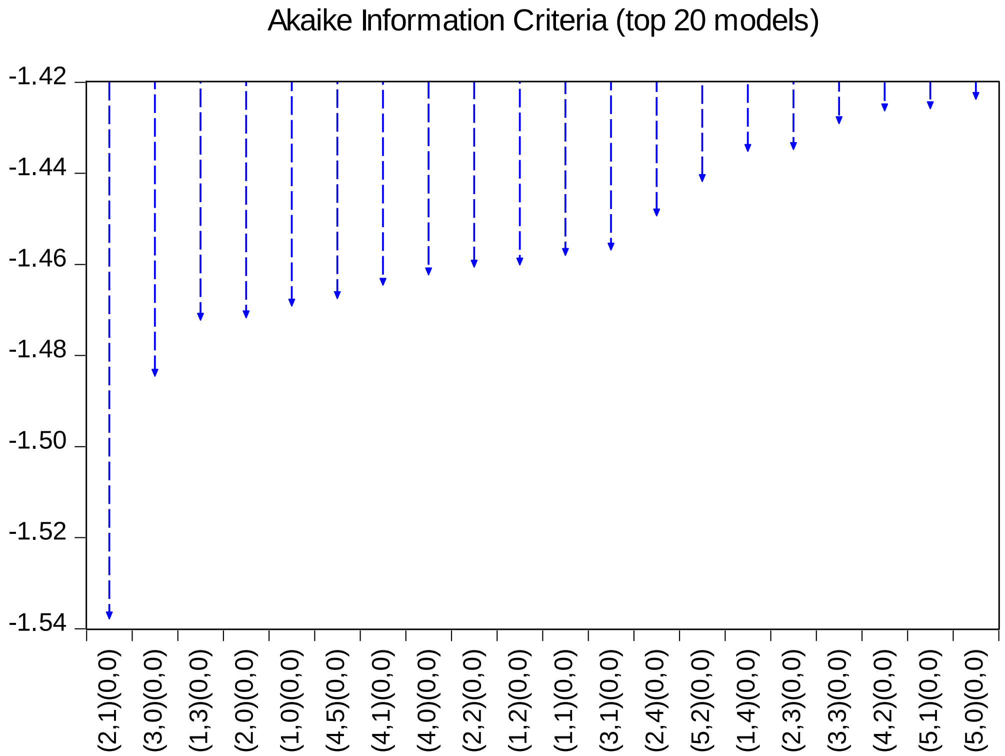
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

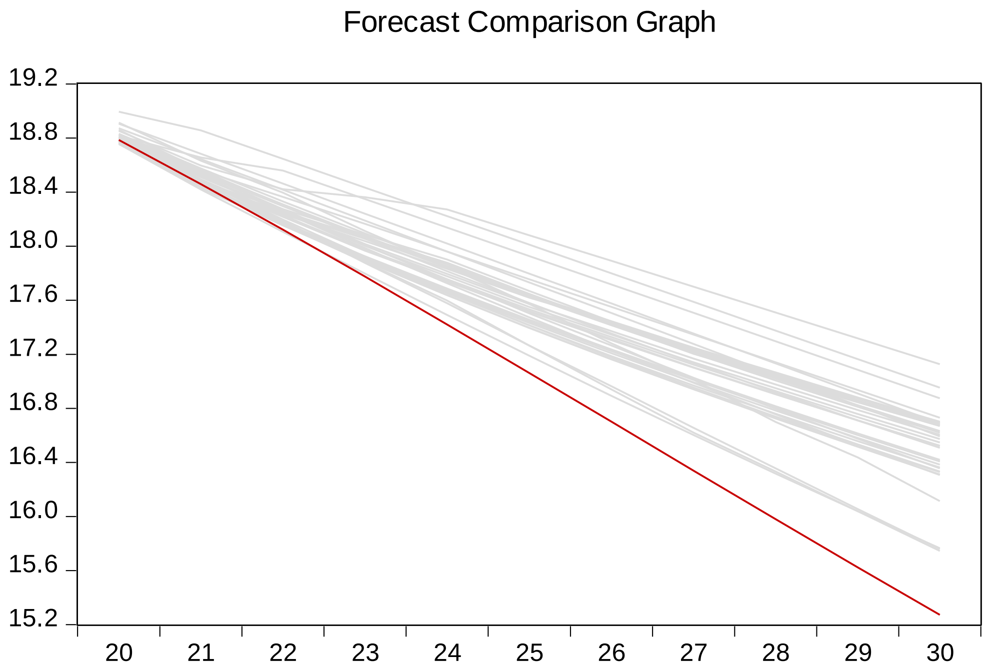


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,1,1) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the 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: D(M)
Date: 01/23/22 Time: 18:17
Sample: 1969 2019
Included observations: 50
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (2,1)(0,0)
AIC value: -1.53698183027

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: D(M)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/23/22 Time: 18:17
Sample: 1970 2019
Included observations: 50
Convergence achieved after 72 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.276473	0.038773	-7.130627	0.0000
AR(1)	1.936529	0.028737	67.38806	0.0000
AR(2)	-0.961320	0.027945	-34.40089	0.0000
MA(1)	-0.999999	1614.255	-0.000619	0.9995
SIGMASQ	0.009252	0.380448	0.024320	0.9807

R-squared	0.916204	Mean dependent var	-0.228000
Adjusted R-squared	0.908756	S.D. dependent var	0.335663
S.E. of regression	0.101393	Akaike info criterion	-1.536982
Sum squared resid	0.462620	Schwarz criterion	-1.345780
Log likelihood	43.42455	Hannan-Quinn criter.	-1.464171
F-statistic	123.0049	Durbin-Watson stat	1.930523
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97-.15i	.97+.15i
Inverted MA Roots	1.00	

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	18.78578193301043
2021	18.45883149096802
2022	18.12089254711045
2023	17.77391393701167
2024	17.41999321692606
2025	17.06131891064843
2026	16.70011273511398
2027	16.33857323784681
2028	15.97882218893089
2029	15.62285494995529
2030	15.27249589650651

Table 2 clearly indicates that neonatal mortality is expected to gradually decline from around 19 in 2020 to 15 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

Sustainable development goals (SDGs) which were launched in 2015 include goal 3 target 3.2 which aims to ensure a substantial reduction of neonatal mortality by the end of 2030. These ambitious goals are achievable, however there is need for low-middle income countries to make use of available resources to improve the quality, accessibility and affordability of healthcare services as a priority. Healthcare and other professionals are continuously leaving for greener pastures where they are offered better remuneration and other incentives. This brain drain has negative consequences on the health delivery system, therefore authorities in low-middle income countries are encouraged to pay better salaries and offer attractive incentives to minimize this problem. This study employed the Box-Jenkins ARIMA model to forecast future trends of NMR for Namibia. The findings of this paper indicate that neonatal mortality is expected to gradually decline from around 19 in 2020 to 15 deaths per 1000 live births by the end of 2030. Hence the government of Namibia is encouraged to implement effective country specific neonatal policies to address high neonatal mortality. Control measures should include regular refresher courses on basic & emergency obstetric and newborn care at all levels of healthcare and initiatives to retain medical staff especially in the rural areas.

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