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Using Empirical Evidence Produced By the ARIMA Model to Improve Neonatal Survival Rates in the Republic of South Africa

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***Abstract* - Neonatal mortality remains a huge heath problem in South Africa with leading causes being prematurity, intrapartum hypoxia and neonatal sepsis. The government has made significant progress towards achieving set SDG3 target 3.2 by the end of 2030. However, there is need to reduce absolute numbers of neonatal deaths. Using time series approaches will assist in designing neonatal health policies, decision making and allocation of resources to the maternal and child health program. This research uses annual time series data on neonatal mortality rate (NMR) for South Africa from 1975 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 (1,1,2) model. The model projections indicate that neonatal mortality will hover around 11 deaths per 1000 live births throughout the forecast period. Therefore, health authorities should craft neonatal policies that will address challenges noted during antenatal, delivery and postnatal periods. There is need to continuously train medical staff on basic and emergency obstetric care & neonatal resuscitation and avail adequate resources at all levels of care especially in primary care health facilities across the country.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

The South African government has made significant progress towards achieving the 3rd sustainable development goal, target 3.2 of reducing neonatal mortality rate to at least 12 neonatal deaths per 1000 live births in every country by 2030. The country has recorded a downward trend in neonatal mortality rate (NMR) over the past decades, however more combined effort is required to reduce the absolute number of neonatal deaths (Rhoda*et al.*2018; Dorrington, 2016; UNAIDS, 2016; WHO, 2015). A myriad of factors have been identified to be the leading causes of neonatal mortality globally namely prematurity, birth asphyxia, infections and congenital abnormalities (Velaphi & Rhoda, 2012).In South Africa, prematurity (36%), intrapartum hypoxia (20%) and infection (14%) are the main causes of neonatal deaths (Masaba & Phetoe, 2020). The United Nations Inter-agency group for child mortality reported that the global neonatal mortality rate (NMR) declined from 36 per 1 000 live births to 19 per 1 000 live births over the period 2005-2015 representing a 47 % reduction in neonatal mortality (Lawn *et al*. 2016). NMR in South Africa remained constant over the period 2005-2015 at around 11-12 neonatal deaths per 1000 live births (Dorrington *et al*. 2016).In a 2018 review paper Rhoda reviewed estimates of the NMR and etiology of neonatal deaths, and outlined how the mortality from preventable causes of death could be reduced. The study concluded 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 necessary to curb neonatal deaths. The aim of this study is to project future trends of NMR for South Africa using the famous Box-Jenkins ARIMA technique (Nyoni, 2018; Box and Jenkins, 1970). The findings of this study are expected to highlight future trends of NMR and help assess the future progress towards achieving the sustainable development goal 3 of reducing of neonatal mortality to at least 12 per 1000 live births in every country by 2030.

II. 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:

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

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:

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

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:

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

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

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

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:

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

Thus:

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

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

The Autoregressive Integrated Moving Average (ARIMA) Model

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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.

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

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 South Africa for the period 1975 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: 01/29/22 Time: 11:27
Sample: 1975 2019
Included observations: 44

Model	LogL	AIC*	BIC	HQ
(1,2)(0,0)	169.334061	-7.469730	-7.266981	-7.394541
(4,0)(0,0)	169.670639	-7.439574	-7.196276	-7.349348

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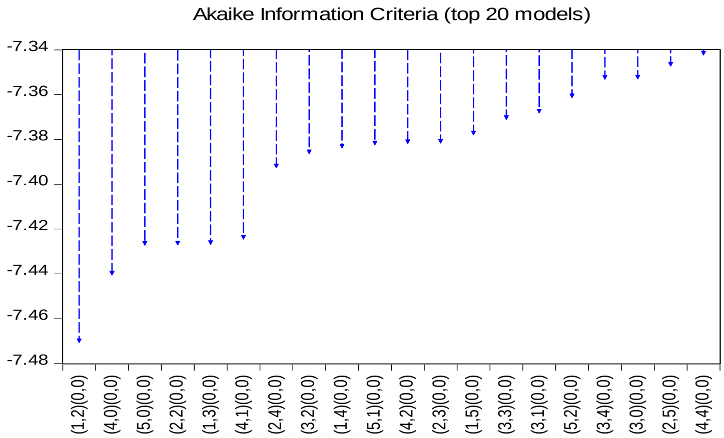
(5,0)(0,0)	170.377497	-7.426250	-7.142402	-7.320985
(2,2)(0,0)	169.374915	-7.426133	-7.182834	-7.335906
(1,3)(0,0)	169.370024	-7.425910	-7.182612	-7.335683
(4,1)(0,0)	170.317888	-7.423540	-7.139692	-7.318276
(2,4)(0,0)	170.617658	-7.391712	-7.067314	-7.271409
(3,2)(0,0)	169.478381	-7.385381	-7.101533	-7.280116
(1,4)(0,0)	169.421056	-7.382775	-7.098927	-7.277511
(5,1)(0,0)	170.392395	-7.381472	-7.057074	-7.261170
(4,2)(0,0)	170.379737	-7.380897	-7.056499	-7.260595
(2,3)(0,0)	169.375052	-7.380684	-7.096836	-7.275420
(1,5)(0,0)	170.294361	-7.377016	-7.052618	-7.256714
(3,3)(0,0)	170.142088	-7.370095	-7.045697	-7.249792
(3,1)(0,0)	168.079403	-7.367246	-7.123947	-7.277019
(5,2)(0,0)	170.928569	-7.360389	-6.995442	-7.225049
(3,4)(0,0)	170.748832	-7.352220	-6.987272	-7.216879
(3,0)(0,0)	166.745583	-7.352072	-7.149323	-7.276883
(2,5)(0,0)	170.619266	-7.346330	-6.981382	-7.210990
(4,4)(0,0)	171.509693	-7.341350	-6.935852	-7.190972
(1,0)(0,0)	164.300318	-7.331833	-7.210183	-7.286719
(2,0)(0,0)	165.065862	-7.321176	-7.158977	-7.261024
(4,5)(0,0)	172.062886	-7.321040	-6.874993	-7.155624
(4,3)(0,0)	169.885141	-7.312961	-6.948013	-7.177621
(1,1)(0,0)	164.780725	-7.308215	-7.146016	-7.248064
(5,3)(0,0)	170.569248	-7.298602	-6.893105	-7.148224
(5,4)(0,0)	171.456543	-7.293479	-6.847432	-7.128063
(2,1)(0,0)	165.401205	-7.290964	-7.088215	-7.215775
(5,5)(0,0)	172.120564	-7.278207	-6.791610	-7.097754
(0,5)(0,0)	167.079570	-7.276344	-6.992496	-7.171079
(0,4)(0,0)	163.914852	-7.177948	-6.934649	-7.087721
(3,5)(0,0)	164.510339	-7.023197	-6.617700	-6.872819
(0,3)(0,0)	159.147435	-7.006702	-6.803953	-6.931513
(0,2)(0,0)	152.163087	-6.734686	-6.572487	-6.674535
(0,1)(0,0)	142.260181	-6.330008	-6.208359	-6.284895
(0,0)(0,0)	125.864326	-5.630197	-5.549097	-5.600121

Criteria Graph

Figure 1: Criteria Graph



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Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

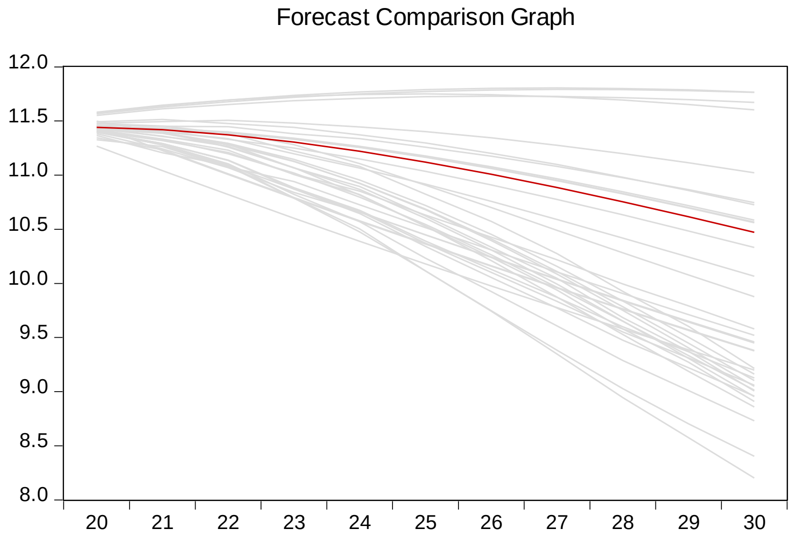

Table 2 and Figure 1 indicate that the optimal model is the ARIMA (1,1,2) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (1,1,2)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

III. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(M)
Date: 01/29/22 Time: 11:27
Sample: 1975 2019
Included observations: 44
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (1,2)(0,0)
AIC value: -7.4697300637

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: 01/29/22 Time: 11:27
Sample: 1976 2019
Included observations: 44
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients

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Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.018253	0.010575	-1.726013	0.0923
AR(1)	0.869291	0.068392	12.71047	0.0000
MA(1)	-0.154552	0.128751	-1.200399	0.2372
MA(2)	0.607082	0.210907	2.878429	0.0065
SIGMASQ	2.49E-05	4.32E-06	5.768376	0.0000

R-squared	0.870206	Mean dependent var	-0.020305
Adjusted R-squared	0.856893	S.D. dependent var	0.014010
S.E. of regression	0.005300	Akaike info criterion	-7.469730
Sum squared resid	0.001095	Schwarz criterion	-7.266981
Log likelihood	169.3341	Hannan-Quinn criter.	-7.394541
F-statistic	65.36883	Durbin-Watson stat	1.941666
Prob(F-statistic)	0.000000		

Inverted AR Roots	.87	
Inverted MA Roots	.08+.78i	.08-.78i

ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	11.44151083240345
2021	11.41910954546283
2022	11.37250639443904
2023	11.30514458718215
2024	11.22011027675666
2025	11.12014775991208
2026	11.00768095481534
2027	10.88483841751491
2028	10.75347990298261
2029	10.61522306552339
2030	10.4714693472526

Table 2 clearly indicates that neonatal mortality will hover around 11 deaths per 1000 live births throughout the forecast period.

IV. POLICY IMPLICATION & CONCLUSION

Despite the fact that current levels of neonatal mortality rate (NMR) are within reach of the Sustainable Development Goal (SDG) 3, target 3.2of at least 12 per 1 000 live births, the absolute number of deaths are of great concern especially for lower-middle-income countries in Sub-Saharan Africa. The decline in Neonatal mortality over the past 10years has been very slow and is not consistent with the level of investment in healthcare. This study utilized the ARIMA technique to model and forecast NMR for South Africa and the findings suggest that neonatal mortality will hover around 11 deaths per 1000 live births throughout the forecast period. This means that health authorities must craft neonatal policies that will address challenges noted during antenatal, delivery and postnatal periods. There is need to continuously train medical staff on basic & emergency obstetric and newborn care and avail adequate resources at all levels of care especially in primary care health facilities across the country.

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