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Drafting and Implementing Appropriate Neonatal Healthcare Solutions in Senegal Using Forecasts Generated By the ARIMA Model

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***Abstract* - This study uses annual time series data on neonatal mortality rate (NMR) for Senegal 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 (2,1,2) model. The study results indicate that neonatal mortality will gradually decline from 21 in 2020 to 18 deaths per 1000 live births by the end of 2030. It is therefore important for the government to address local drivers of mortality among neonates.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Under-five mortality remains a public health problem across the globe and developing countries bear most of the burden. Approximately 4 million neonatal deaths occur globally annually with 75% occurring in the first week of life (WHO, 2020). Previous studies done in clinical settings have identified the major causes of neonatal mortality to be birth asphyxia, neonatal sepsis, and prematurity (Diouf, 2018; Koum *et al*. 2015). The global health community is pushing all countries to implement robust policies aimed at reducing neonatal mortality rate (NMR) to at least 12 per 1000 live births by 2030. This can be achieved by improving the quality of health services during the antenatal, delivery and postnatal periods. Governments are expected to ensure availability of trained birth attendants at all levels of care and make sure supplies of medical drugs and equipment are available, affordable and accessible in primary care settings. Policies to tackle maternal and under-five mortality should be population specific as there are variations in neonatal mortality across regions (Hutchinson *et al*. 2017).In this paper we propose the Box-Jenkins ARIMA modelling technique to project future trends of neonatal mortality rate for Senegal. The statistical technique is an ideal method for modelling linear data (Nyoni, 2018; Box & Jenkins, 1970). The model has been underutilized in public health programming especially in Sub- Saharan Africa and this study being the first of its kind in this country will help policy makers to draft timeous and appropriate neonatal policies to tackle the problem of neonatal deaths in the country. Furthermore, the findings of this piece of work are envisioned to help assess the feasibility of achieving SDG 3 target 3.2 by 2030.

II. LITERATURE REVIEW

Neonatal mortality is a public health problem which requires attention especially in developing countries like the Sub-Saharan Africa. Several research efforts in Africa have been made to investigate the nature and extent of the problem. A multisite retrospective Kenyan cohort study was conducted by Irimu *et al*.(2021)to find out the proportion of all admissions and deaths in the neonatal age group and examine morbidity and mortality patterns, stratified by birth weight, and their variation across hospitals. Intrapartum related complications was the single most common diagnosis among the neonates with birth weight of 2000 g or more who died. A threefold variation in mortality across hospitals was observed for birth weight categories 1000– 1499 g and 1500–1999g. In another Kenyan study, Olack *et al*.(2021)investigated the causes of neonatal LBW and preterm mortality in Migori County, among participants of the PTBI-K (Preterm Birth Initiative-Kenya) study. Verbal and social autopsy (VASA) interviews were conducted with caregivers of deceased LBW and preterm neonates delivered within selected 17 health facilities in Migori County, Kenya. The probable cause of death was assigned using the WHO International Classification of Diseases (ICD-10). The study findings revealed that significant predictors of neonatal mortality were birth asphyxia (45.5%), neonatal sepsis (26.1%), respiratory distress syndrome (12.5%) and hypothermia (11.0%). Sougou & Diouf (2020) conducted a secondary analysis of the 2017 DHS for Senegal to analyze the factors associated with neonatal deaths in Senegal in 2017. The study results indicated that significant predictors of neonatal mortality were newborns with a low birth weight < 2500 g, newborns who are considered "very small" by their mother at birth and birth by caesarean section. Hutchinson*et al*.(2017) examined the most

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common neonatal conditions and outcomes in a community hospital in M'Bour, Senegal.The study employed logistic regression toexamine the relationship between infant death and maternal age, preterm birth, and the most common diagnoses of asphyxia and infection.The study results showed that the most common diagnoses at admission were prematurity (26.4% of cases), neonatal asphyxia (23.3%), infection (17.4%), and neonatal respiratory distress (15.8%).The two significant predictors of death were preterm birth (OR 1.93-2.57, p<0.05) and asphyxia (OR 2.34, p<0.05).

III. METHODOLOGY

The Autoregressive (AR) Model

A process Y_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:

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

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

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

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:

$$Y_t = \emptyset Y_{t-1} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

for some constant π_j such that:

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

This implies that it is possible to invert the function taking the Z_t sequence to the Y_t sequence and recover Z_t from present and past values of Y_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:

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

Thus:

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

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.

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

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:

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

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

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

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 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 Senegal 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

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Criteria Table

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: DLOG(Y)
Date: 01/29/22 Time: 11:18
Sample: 1960 2019
Included observations: 59

Model	LogL	AIC*	BIC	HQ
(2,2)(0,0)	267.693084	-8.870952	-8.659677	-8.788479
(3,2)(0,0)	268.016984	-8.848033	-8.601546	-8.751815
(2,3)(0,0)	268.013148	-8.847903	-8.601416	-8.751685
(4,4)(0,0)	270.437090	-8.828376	-8.476251	-8.690921
(3,3)(0,0)	268.124294	-8.817773	-8.536073	-8.707808
(2,4)(0,0)	268.025295	-8.814417	-8.532717	-8.704453
(4,2)(0,0)	268.021755	-8.814297	-8.532597	-8.704333
(2,5)(0,0)	268.827638	-8.807717	-8.490804	-8.684007
(4,0)(0,0)	265.554372	-8.798453	-8.587178	-8.715980
(5,0)(0,0)	266.542639	-8.798056	-8.551568	-8.701837
(1,5)(0,0)	267.513788	-8.797078	-8.515378	-8.687113
(3,5)(0,0)	269.439999	-8.794576	-8.442451	-8.657121
(4,3)(0,0)	268.127597	-8.783986	-8.467074	-8.660277
(3,4)(0,0)	268.125737	-8.783923	-8.467011	-8.660213
(1,3)(0,0)	265.103767	-8.783179	-8.571904	-8.700705
(5,2)(0,0)	268.084168	-8.782514	-8.465602	-8.658804
(4,1)(0,0)	266.029480	-8.780660	-8.534173	-8.684442
(5,1)(0,0)	267.011249	-8.780042	-8.498342	-8.670078
(1,4)(0,0)	266.011142	-8.780039	-8.533551	-8.683820
(5,4)(0,0)	269.807182	-8.773125	-8.385787	-8.621924
(5,5)(0,0)	270.708144	-8.769768	-8.347218	-8.604821
(4,5)(0,0)	269.682084	-8.768884	-8.381547	-8.617683
(3,1)(0,0)	264.443306	-8.760790	-8.549515	-8.678317
(3,0)(0,0)	263.425621	-8.760191	-8.584128	-8.691463
(5,3)(0,0)	268.246178	-8.754108	-8.401983	-8.616652
(2,1)(0,0)	261.901921	-8.708540	-8.532477	-8.639812
(1,2)(0,0)	260.330121	-8.655258	-8.479196	-8.586531
(2,0)(0,0)	257.251680	-8.584803	-8.443953	-8.529821
(1,1)(0,0)	255.216326	-8.515808	-8.374958	-8.460826
(0,5)(0,0)	257.900955	-8.505117	-8.258630	-8.408898
(1,0)(0,0)	252.861865	-8.469894	-8.364256	-8.428657
(0,4)(0,0)	251.293894	-8.315047	-8.103772	-8.232574
(0,3)(0,0)	244.519086	-8.119291	-7.943229	-8.050563
(0,2)(0,0)	230.440490	-7.675949	-7.535099	-7.620967
(0,1)(0,0)	214.639203	-7.174210	-7.068573	-7.132974
(0,0)(0,0)	184.391163	-6.182751	-6.112326	-6.155260

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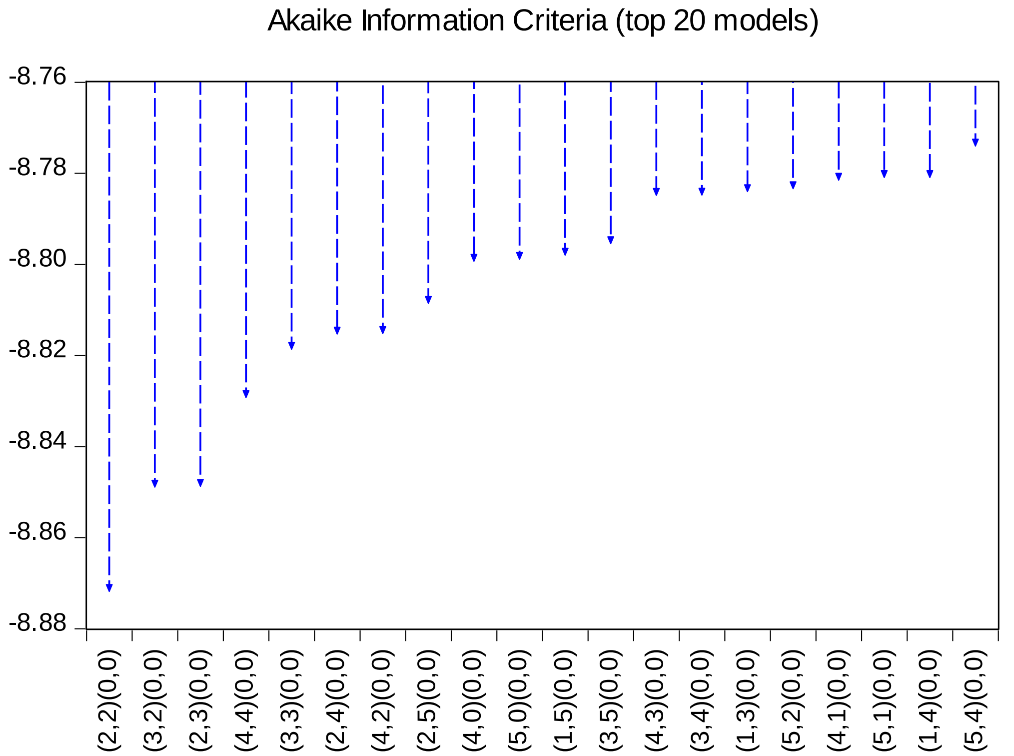
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

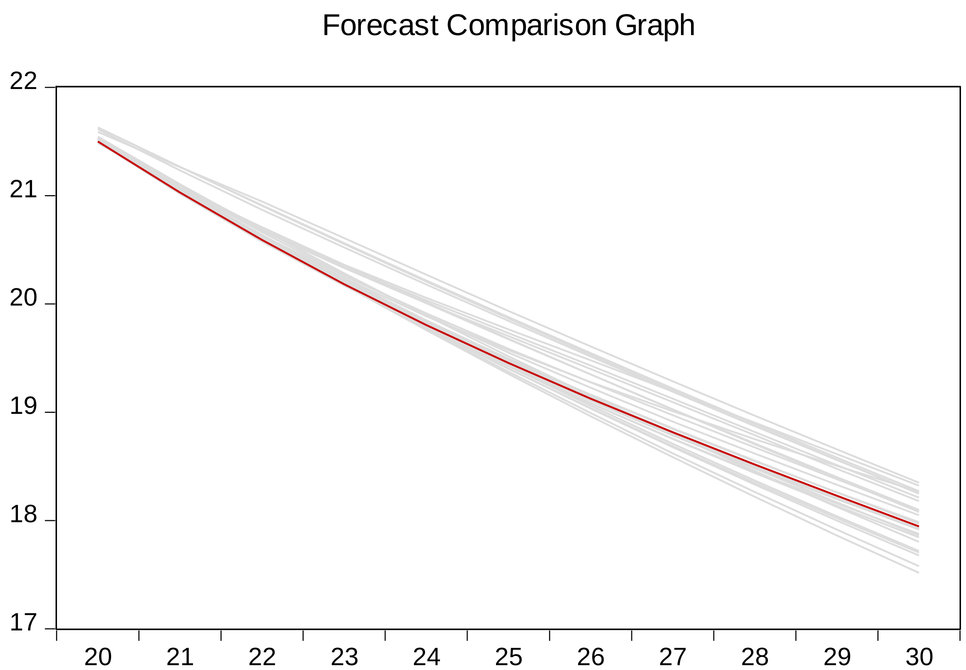


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,1,2) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the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

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(Y)
Date: 01/29/22 Time: 11:18
Sample: 1960 2019
Included observations: 59
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (2,2)(0,0)
AIC value: -8.8709520014

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(Y)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22 Time: 11:18
Sample: 1961 2019
Included observations: 59
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.016730	0.003578	-4.675407	0.0000
AR(1)	1.658692	0.128773	12.88072	0.0000
AR(2)	-0.739213	0.126736	-5.832706	0.0000
MA(1)	-0.704393	0.161925	-4.350131	0.0001
MA(2)	0.580611	0.126391	4.593776	0.0000
SIGMASQ	6.26E-06	1.37E-06	4.562736	0.0000

R-squared	0.944580	Mean dependent var	-0.017005
Adjusted R-squared	0.939352	S.D. dependent var	0.010720
S.E. of regression	0.002640	Akaike info criterion	-8.870952
Sum squared resid	0.000369	Schwarz criterion	-8.659677
Log likelihood	267.6931	Hannan-Quinn criter.	-8.788479
F-statistic	180.6672	Durbin-Watson stat	1.903078
Prob(F-statistic)	0.000000		

Inverted AR Roots	.83+.23i	.83-.23i
Inverted MA Roots	.35+.68i	.35-.68i

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	21.49920488801493
2021	21.02777185697993
2022	20.58869210620294
2023	20.18183321203679
2024	19.8048833743363
2025	19.45418024917947
2026	19.12539524813572
2027	18.81406702596155
2028	18.51599088062206
2029	18.22747790891831
2030	17.94550165790205

Table 5 clearly indicates that neonatal mortality will gradually decline from 21 in 2020 to 18 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

Neonatal mortality will remain a public health challenge in low-middle income countries due to a myriad of challenges such as poverty, war, natural disasters due to climate change and high dependency on donor funding. However, appropriate allocation of available resources will have a positive impact on healthcare service delivery and help in the reduction of both maternal and neonatal mortality. Forecasting of future trends of NMR will detect abnormal trends and facilitate resource mobilization and allocation. This study applies the ARIMA technique to predict NMR for Senegal and model projections reveal that neonatal mortality will gradually decline from 21 in 2020 to 18 deaths per 1000 live births by the end of 2030. It is therefore important for the government to address local drivers of mortality among neonates.

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