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# Determination of Expected Future Trends of Annual Neonatal Mortality Rate for Togo Using the ARIMA Model

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***Abstract* - This study uses annual time series data on neonatal mortality rate (NMR) for Togo 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 (0,1,1) model. The ARIMA model predictions indicate that neonatal mortality is expected to decline from around 24 in 2020 to approximately 18 deaths per 1000 live births by the end of 2030. Therefore, we encourage the health authorities in this country to draft and implement country specific strategies in order to substantially reduce neonatal deaths to at least 12 per 1000 live births by 2030. Neonatal health strategies should include staff retention initiatives, ensuring availability of medical supplies and regular training of healthcare workers on essential newborn care.**

***Keywords:*** ARIMA, Forecasting, NMR.

## I. INTRODUCTION

Maternal and child health is an important component of a healthcare delivery system in every country as it plays a big role in the development of human capital which is necessary for economic growth. The death of a mother or child has serious negative effects on the family and society. Therefore it is prudent for public health specialists to draft maternal and child health policies that are effective and evidence based to tackle maternal and child mortality. Substantial reduction of maternal and neonatal mortality is the focus of sustainable development goal 3 which aims to ensure good health for all at all ages (Newborns, 2015). SDG-3 targets 3.1 & 3.2aim to reduce maternal mortality ratio (MMR) to less than 70 maternal deaths per 100 000 live births and neonatal mortality rate to at least 12 per 1000 live births respectively (UNICEF, 2019). In clinical settings neonatal deaths are due to asphyxia, prematurity, sepsis, respiratory distress syndrome and congenital abnormalities (Diouf, 2018; Koum *et al.* 2015). With proper and timeous allocation ofresources these deaths can be avoided. The aim of this paper is to forecast future trends of NMR for Togo using the popular Box-Jenkins ARIMA approach which is suitable for modeling linear data (Nyoni, 2018; Box &Jenkins, 1970). The findings of this study are envisioned to guide neonatal policy formation and implementation in order to effectively control neonatal mortality in Togo.

## II. LITERATURE REVIEW

Baruwa *et al.*(2021) applied survival models (Kaplan Mier and Cox proportional hazards) to investigate 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 showed 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. Machio(2017)investigated the effects of antenatal and skilled delivery care services on neonatal and under-five mortality in Kenya using pooled Kenya demographic and health survey data for 1998, 2003, 2008/2009 and 2014. Two-stage residual inclusion estimation procedure and the control function approach were used to test and control for potential endogeneity of antenatal and skilled delivery care and for potential unobserved heterogeneity. Findings revealed that adequate use of antenatal care services reduced risk of neonatal and under-five mortality by 2.4 and 4.2 percentage points respectively. Hutchinson*et al.*(2017) examined the most common neonatal conditions and outcomes in a community hospital in M'Bour, Senegal. The study employed logistic regression to examine 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

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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 $X_t$ (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:

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

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

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

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

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

$$X_t = \emptyset X_{t-1} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3]$$

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

for some constant $\pi_j$ 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 $X_t$ sequence and recover $Z_t$ from present and past values of $X_t$ 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:

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

Thus:

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

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.

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

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:

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

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

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

**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.

**Data Issues**

This study is based on annual NMR in Togo 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**

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**Criteria Table**

Table 1: Criteria Table

Model Selection Criteria Table
Dependent Variable: D(X)
Date: 01/29/22 Time: 11:59
Sample: 1965 2019
Included observations: 54

| Model | LogL | AIC* | BIC | HQ |
|---|---|---|---|---|
| (0,1)(0,0) | -54.926954 | 2.145443 | 2.255942 | 2.188058 |
| (0,2)(0,0) | -54.854218 | 2.179786 | 2.327118 | 2.236606 |
| (1,1)(0,0) | -54.865657 | 2.180210 | 2.327542 | 2.237030 |
| (2,0)(0,0) | -55.353424 | 2.198275 | 2.345607 | 2.255095 |
| (0,3)(0,0) | -54.785962 | 2.214295 | 2.398460 | 2.285320 |
| (2,1)(0,0) | -54.798804 | 2.214771 | 2.398936 | 2.285796 |
| (3,0)(0,0) | -54.807877 | 2.215107 | 2.399272 | 2.286132 |
| (1,2)(0,0) | -54.808004 | 2.215111 | 2.399276 | 2.286137 |
| (1,0)(0,0) | -57.356593 | 2.235429 | 2.345928 | 2.278045 |
| (3,1)(0,0) | -54.770920 | 2.250775 | 2.471773 | 2.336005 |
| (4,0)(0,0) | -54.776492 | 2.250981 | 2.471979 | 2.336212 |
| (2,2)(0,0) | -54.779814 | 2.251104 | 2.472102 | 2.336335 |
| (0,4)(0,0) | -54.781034 | 2.251149 | 2.472148 | 2.336380 |
| (1,3)(0,0) | -54.783451 | 2.251239 | 2.472237 | 2.336469 |
| (4,1)(0,0) | -53.972590 | 2.258244 | 2.516075 | 2.357679 |
| (0,5)(0,0) | -54.765963 | 2.287628 | 2.545460 | 2.387064 |
| (5,0)(0,0) | -54.767997 | 2.287704 | 2.545535 | 2.387139 |
| (3,2)(0,0) | -54.769924 | 2.287775 | 2.545606 | 2.387210 |
| (1,4)(0,0) | -54.771379 | 2.287829 | 2.545660 | 2.387264 |
| (2,3)(0,0) | -54.774646 | 2.287950 | 2.545781 | 2.387385 |
| (1,5)(0,0) | -53.837535 | 2.290279 | 2.584943 | 2.403920 |
| (4,2)(0,0) | -53.968969 | 2.295147 | 2.589811 | 2.408787 |
| (4,3)(0,0) | -53.187642 | 2.303246 | 2.634743 | 2.431092 |
| (2,5)(0,0) | -53.301174 | 2.307451 | 2.638948 | 2.435296 |
| (5,1)(0,0) | -54.767702 | 2.324730 | 2.619394 | 2.438370 |
| (2,4)(0,0) | -54.767893 | 2.324737 | 2.619401 | 2.438377 |
| (3,3)(0,0) | -54.768324 | 2.324753 | 2.619417 | 2.438393 |
| (3,5)(0,0) | -53.033984 | 2.334592 | 2.702922 | 2.476643 |
| (3,4)(0,0) | -54.752296 | 2.361196 | 2.692693 | 2.489042 |
| (5,2)(0,0) | -54.763846 | 2.361624 | 2.693121 | 2.489469 |
| (4,4)(0,0) | -54.057085 | 2.372485 | 2.740815 | 2.514535 |
| (5,4)(0,0) | -53.187997 | 2.377333 | 2.782497 | 2.533589 |
| (4,5)(0,0) | -53.359152 | 2.383672 | 2.788836 | 2.539928 |
| (5,3)(0,0) | -54.730413 | 2.397423 | 2.765753 | 2.539473 |
| (5,5)(0,0) | -53.316714 | 2.419138 | 2.861134 | 2.589598 |
| (0,0)(0,0) | -63.747953 | 2.435109 | 2.508775 | 2.463519 |

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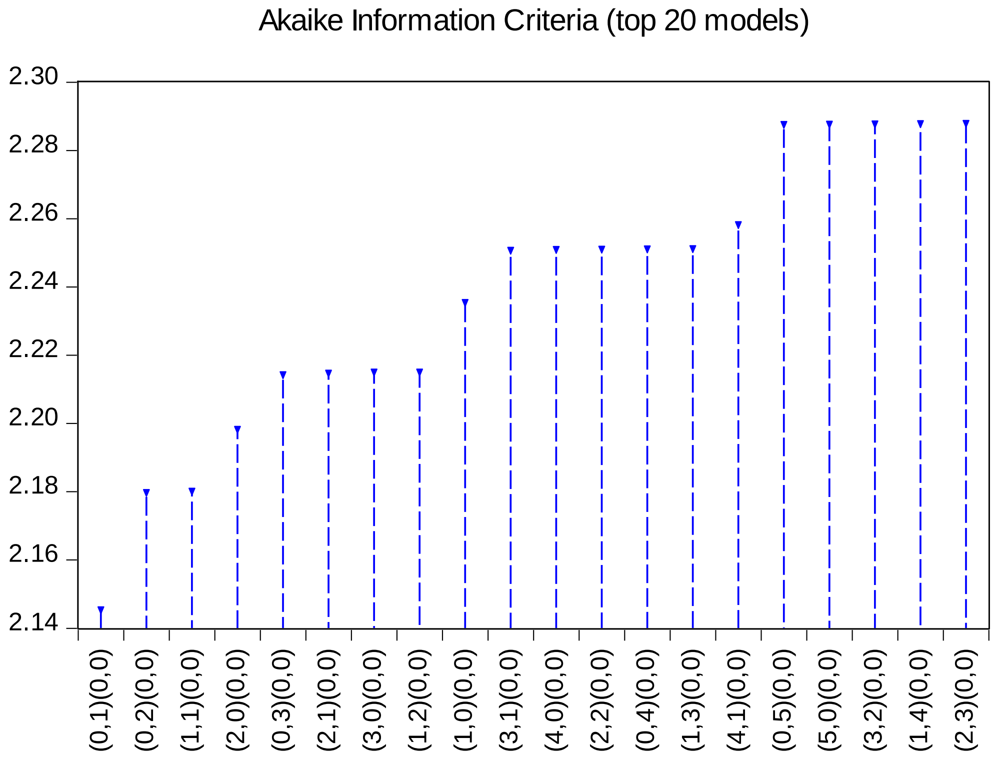
**Criteria Graph**

Figure 1: Criteria Graph




**Forecast Comparison Graph**

Figure 2: Forecast Comparison Graph

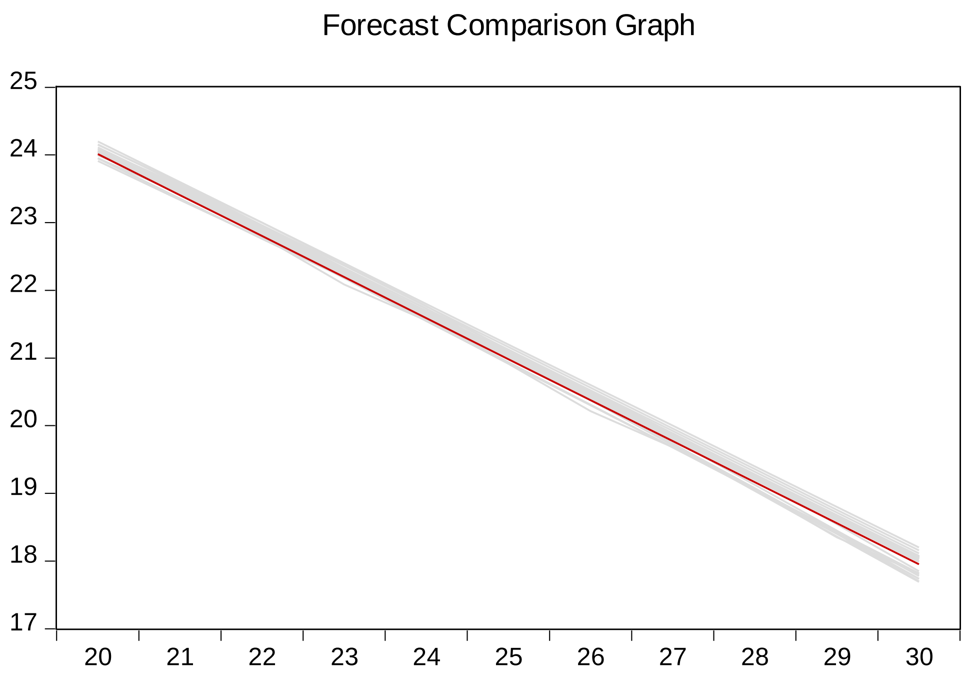



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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (0,1,1) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the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

## IV. RESULTS

### Main Results of the Selected ARIMA () Model

Table 2: Main Results of the Optimal Model

| | | | | |
|---|---|---|---|---|
| Dependent Variable: D(X) | | | | |
| Method: ARMA Maximum Likelihood (BFGS) | | | | |
| Date: 01/29/22 Time: 11:59 | | | | |
| Sample: 1966 2019 | | | | |
| Included observations: 54 | | | | |
| Convergence achieved after 5 iterations | | | | |
| Coefficient covariance computed using outer product of gradients | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | -0.606043 | 0.070705 | -8.571444 | 0.0000 |
| MA(1) | -0.593718 | 0.083420 | -7.117209 | 0.0000 |
| SIGMASQ | 0.444149 | 0.045300 | 9.804708 | 0.0000 |
| R-squared | 0.284485 | Mean dependent var | | -0.600000 |
| Adjusted R-squared | 0.256425 | S.D. dependent var | | 0.795269 |
| S.E. of regression | 0.685767 | Akaike info criterion | | 2.145443 |
| Sum squared resid | 23.98407 | Schwarz criterion | | 2.255942 |
| Log likelihood | -54.92695 | Hannan-Quinn criter. | | 2.188058 |
| F-statistic | 10.13866 | Durbin-Watson stat | | 2.073658 |
| Prob(F-statistic) | 0.000196 | | | |
| Inverted MA Roots | .59 | | | |

### ARIMA () Model Forecast

### Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

| Year | Forecasts |
|---|---|
| 2020 | 24.01353517126426 |
| 2021 | 23.4074916959865 |
| 2022 | 22.80144822070873 |
| 2023 | 22.19540474543097 |
| 2024 | 21.58936127015321 |
| 2025 | 20.98331779487545 |
| 2026 | 20.37727431959769 |
| 2027 | 19.77123084431993 |
| 2028 | 19.16518736904217 |
| 2029 | 18.5591438937644 |
| 2030 | 17.95310041848664 |

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Table 2 clearly indicates that neonatal mortality is expected to decline from around 24 in 2020 to approximately 18 deaths per 1000 live births by the end of 2030.

## V. POLICY IMPLICATION & CONCLUSION

The welfare of women and children is a priority in the economic development of a country. However, it is still worrisome to continuously receive reports of high maternal and neonatal mortality particularly in Africa and Asia. It is crucial to highlight that there has been significant progress made by these governments to address this public health problem. The decline in neonatal mortality has been slower than that of under-five mortality indicating that more resources need to be channeled towards improving the quality of healthcare services during the antenatal, delivery and postnatal periods. Public health specialists should utilize early surveillance tools such as time series forecasting techniques to inform their policies, decisions and resource allocation to effectively deal with this public health problem. This study utilizes the popular Box-Jenkins ARIMA model to predict future trends of neonatal mortality rate for Togo and the results showed thatneonatal mortality is expected to decline from around 24 in 2020 to approximately 18 deaths per 1000 live births by the end of 2030. Therefore, we encourage health authorities to draft and implement country specific strategies in order to substantially reduce neonatal deaths to at least 12 per 1000 live births by 2030.Neonatal health strategies should include staff retention initiatives, ensuring availability of medical supplies and regular training of healthcare workers on essential newborn care.

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