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Demonstrating how to Apply the ARIMA Model to Determine Expected Future Annual Neonatal Mortality Rates for Uganda

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***Abstract* - The general global decline of under-five mortality is a clear testimony that all UN member states are united in their fight against causes of morbidity and mortality among under-fives across all regions. However, neonatal deaths remain a cause for concern as many low-middle income countries are going to miss their set SDG-3 target 3.2 by the end of 2030.New ideas are required to address this issue to end all preventable deaths by the end of 2030.This study uses annual time series data on neonatal mortality rate (NMR) for Uganda 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 (2,1,2) model. The ARIMA model predictions indicate that neonatal mortality will gradually decline from around 19 to approximately 13 deaths per 1000 live births by the end of 2030. We, therefore encourage the Ugandan authorities to craft local maternal and child health policies that will effectively address the deaths of newborns during the first month of life. The authorities should promote institutional deliveries, increase coverage of family planning services and provide incentives for medical staff retention especially those working in rural areas.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Neonatal mortality continues to be a public health problem globally contributing over 60% of neonatal deaths during the first year of life (UNICEF, 2008). The majority of neonatal deaths occur in low and middle income countries with highest mortality rates being reported in Sub-Saharan Africa and South –Central Asian countries (UNICEF, 2018). The main causes of mortality in neonates are birth asphyxia, prematurity, sepsis and congenital anomalies (Ezeh *et al.* 2014). Previous studies have revealed that the global decline in neonatal mortality rates has been slower compared with infant and under-5 years of age mortality rates, especially in sub-Sahara Africa (UNICEF, 2008; Lawn *et al*. 2009). According to Asiimwe et al. 2019, Uganda's neonatal mortality ratio dropped from 33 deaths per 1,000 live births in 2001 to 27 deaths per 1,000 live births in 2006, but no change in the ratio occurred between 2006 and 2016. Significant predictors of neonatal mortality include delayed breastfeeding after birth and multiple maternal risk factors. Kananura *et al.* 2016, established that major causes of Uganda's neonatal deaths include sepsis/pneumonia, tetanus, diarrhea, prematurity, and birth asphyxia. Ewere & Eke (2020) examined the impact of maternal / child care characteristics on neonatal mortality in Nigeria using the logistic regression model. The study concluded that stake holders in the public health sector must improve the quality of existing health care facilities and access to quality services in order to substantially reduce neonatal mortality in the country. A cross sectional study conducted in Nigeria by Ezeh *et al*. (2015) to investigate factors associated with post-neonatal, infant, child and under-5 mortality in Nigeria revealed that no formal education, poor households and living in rural areas increased the risk of post neonatal, infant, child and under-5 mortality among Nigerian children.

The main objective of this study is to project neonatal mortality rate (NMR) for Uganda using the popular econometric model, the Box-Jenkins ARIMA model. The ARIMA model is very useful for modelling linear time series data (Nyoni, 2018; Box-Jenkins, 1970), hence public health practitioners should embrace it. This study being the first of its kind in Uganda is expected to inform policy, decision making and resource mobilization. Furthermore, forecast results are envisioned to help public health authorities to track the country's progress towards achieving set sustainable development goal 3 target 3.2 by 2030 which aims to substantially reduce neonatal mortality rate (NMR) to at 12 deaths per 1000 live births.

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II. 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:

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

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:

$$Z_t = \emptyset(B)Y_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{[2]}$$

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:

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

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:

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

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

$$Y_t = \theta(B)Z_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{[5]}$$

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

Equation [4] can also be expressed as follows:

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

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

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:

$$\emptyset(B)Y_t = \theta(B)Z_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{[7]}$$

Thus:

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

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:

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

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

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

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 Uganda 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(Y)
Date: 01/29/22 Time: 12:10
Sample: 1965 2019
Included observations: 54

Model	LogL	AIC*	BIC	HQ
(2,2)(0,0)	33.151825	-1.005623	-0.784625	-0.920393
(2,4)(0,0)	34.505482	-0.981685	-0.687020	-0.868044
(4,0)(0,0)	32.355307	-0.976122	-0.755124	-0.890892
(2,3)(0,0)	33.228287	-0.971418	-0.713587	-0.871983
(3,2)(0,0)	33.187168	-0.969895	-0.712064	-0.870460
(3,1)(0,0)	31.837901	-0.956959	-0.735961	-0.871729
(4,5)(0,0)	36.830589	-0.956688	-0.551525	-0.800433
(3,0)(0,0)	30.759321	-0.954049	-0.769884	-0.883024
(4,2)(0,0)	33.742351	-0.953420	-0.658756	-0.839780
(2,5)(0,0)	34.701535	-0.951909	-0.620411	-0.824063
(3,3)(0,0)	33.606515	-0.948389	-0.653725	-0.834749
(4,4)(0,0)	35.586396	-0.947644	-0.579314	-0.805594
(5,2)(0,0)	34.492741	-0.944176	-0.612678	-0.816330
(5,5)(0,0)	37.470214	-0.943341	-0.501345	-0.772881
(5,0)(0,0)	32.436484	-0.942092	-0.684261	-0.842657
(4,1)(0,0)	32.388918	-0.940330	-0.682499	-0.840895
(5,4)(0,0)	36.214334	-0.933864	-0.528701	-0.777609
(3,4)(0,0)	33.972226	-0.924897	-0.593400	-0.797052
(5,3)(0,0)	34.825708	-0.919471	-0.551140	-0.777420
(4,3)(0,0)	33.790638	-0.918172	-0.586674	-0.790326
(2,1)(0,0)	29.565118	-0.909819	-0.725654	-0.838794
(5,1)(0,0)	32.357795	-0.902141	-0.607476	-0.788500
(1,4)(0,0)	30.536389	-0.871718	-0.613887	-0.772283
(1,5)(0,0)	30.542567	-0.834910	-0.540246	-0.721269
(1,3)(0,0)	28.494776	-0.833140	-0.612142	-0.747910
(0,5)(0,0)	27.294715	-0.751656	-0.493825	-0.652221
(0,4)(0,0)	25.052082	-0.705633	-0.484634	-0.620402
(2,0)(0,0)	22.513486	-0.685685	-0.538353	-0.628864
(1,2)(0,0)	22.196948	-0.636924	-0.452759	-0.565899
(1,1)(0,0)	17.213916	-0.489404	-0.342072	-0.432584
(1,0)(0,0)	12.557786	-0.353992	-0.243493	-0.311377
(0,3)(0,0)	12.487765	-0.277325	-0.093159	-0.206299
(3,5)(0,0)	8.976807	0.037896	0.406226	0.179947
(0,2)(0,0)	0.859782	0.116304	0.263637	0.173125
(0,1)(0,0)	-11.530563	0.538169	0.648668	0.580784
(0,0)(0,0)	-38.173744	1.487916	1.561583	1.516327

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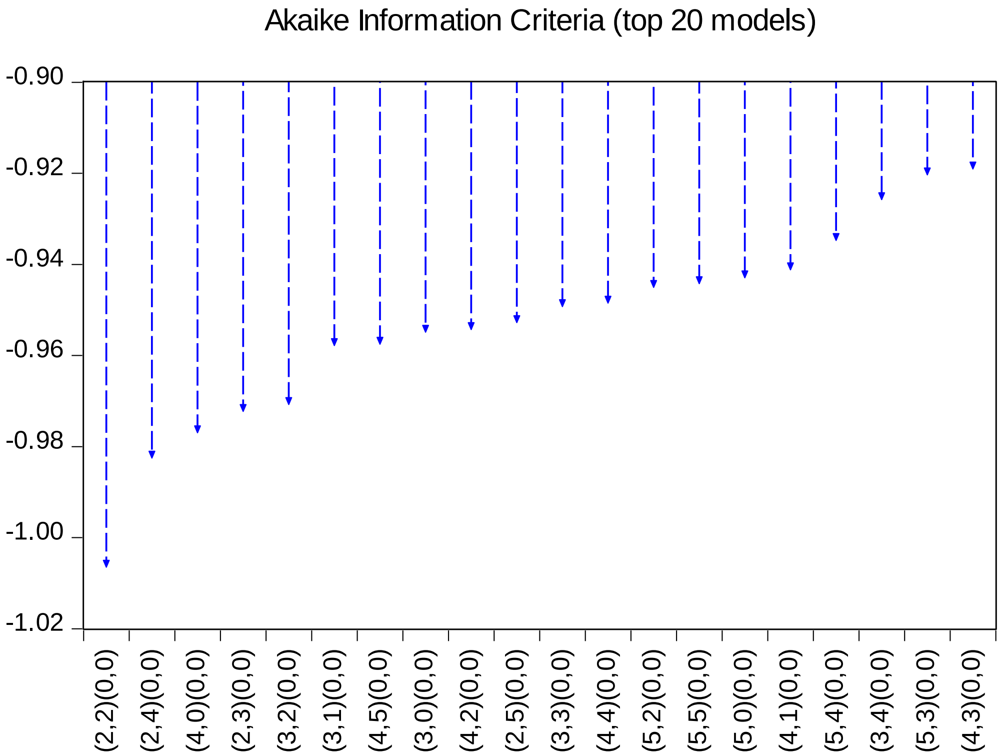
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

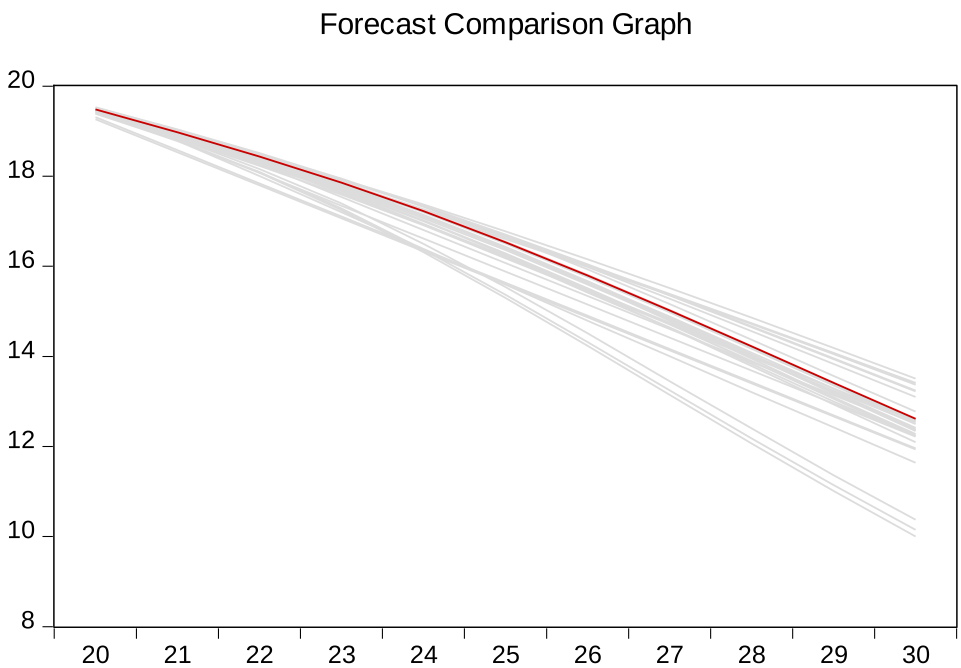


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,1,2) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the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

III. RESULTS

Main Results of the Selected ARIMA () Model

Table 2: Main Results of the Optimal Model

Dependent Variable: D(Y)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22 Time: 12:10
Sample: 1966 2019
Included observations: 54
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.712403	0.114746	-6.208541	0.0000
AR(1)	1.697944	0.092596	18.33704	0.0000
AR(2)	-0.832426	0.091600	-9.087575	0.0000
MA(1)	-0.662049	0.192772	-3.434374	0.0012
MA(2)	0.490534	0.154270	3.179711	0.0026
SIGMASQ	0.015962	0.003520	4.534086	0.0000

R-squared	0.933695	Mean dependent var	-0.733333
Adjusted R-squared	0.926789	S.D. dependent var	0.495261
S.E. of regression	0.134006	Akaike info criterion	-1.005623
Sum squared resid	0.861960	Schwarz criterion	-0.784625
Log likelihood	33.15183	Hannan-Quinn criter.	-0.920393
F-statistic	135.1862	Durbin-Watson stat	1.986132
Prob(F-statistic)	0.000000		

Inverted AR Roots	.85-.33i	.85+.33i
Inverted MA Roots	.33+.62i	.33-.62i

ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 3: Tabulated Out of Sample Forecasts

Year	Forecasts
2020	19.48510688697079
2021	18.9737575209685

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2022	18.43831998095676
2023	17.85903213536488
2024	17.22534052308812
2025	16.53577647553083
2026	15.79663125819285
2027	15.01980965323459
2028	14.22028830831978
2029	13.41358688808351
2030	12.61358996690424

Table 3 clearly indicates that neonatal mortality will gradually decline from around 19 to approximately 13 deaths per 1000 live births by the end of 2030.

IV. POLICY IMPLICATION & CONCLUSION

The problem of neonatal deaths in Uganda is driven by high teenage pregnancies, home deliveries and inaccessibility of primary healthcare facilities in the rural areas among other challenges. This study projected NMR in Uganda using the Box-Jenkins ARIMA technique and the findings indicate that neonatal mortality will gradually decline from around 19 to approximately 13 deaths per 1000 live births by the end of 2030. We therefore encourage the Ugandan authorities to craft local maternal and child health policies that will effectively address the deaths of newborns during the first month of life. The authorities should promote institutional deliveries, increase coverage of family planning services and provide incentives for medical staff retention especially those working in rural areas.

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