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Utilizing ARIMA Model Forecasts to Trigger Identification and Implementation of Evidence Based Neonatal Healthcare Initiatives in Rwanda

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***Abstract* - The 3rd sustainable development goal (SDG-3) is mandated to address all issues regarding the health of different populations across the globe. It focuses on ensuring good health for all at every stage of life. Target 3.2 aims to reduce under five mortality to levels as low as 25 deaths per 1000 live births and neonatal mortality to at least 12 deaths per 1000 live births by the end of 2030. The decline of neonatal mortality has not been satisfactory during the previous two decades in many African countries as a result of poor quality of healthcare services during the antenatal, delivery and postnatal periods. This article employs annual time series data on neonatal mortality rate (NMR) for Rwanda 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 (4,1,1) model. The study findings indicate that neonatal mortality is expected to gradually fall down to levels below 12 neonatal deaths per 1000 live births by the end of 2030. Therefore, Rwandan authorities should continue availing medical staff, sufficient medical supplies and improving health infrastructure in the rural areas amongst other measures.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

According to Worldometer, Rwanda has an estimated population size of 13,872876 as of 17 May 2023. The government has made remarkable progress in reducing child mortality reporting a decline in under-five and neonatal deaths. Over the period 2005-2015 neonatal mortality declined from 37 deaths per 1000 live births to 20 per 1000 live births and under-five mortality declined from 152 to 50 deaths per 1000 live births (Rwanda, 2015). The Rwandan government implemented several strategies such as high vaccination coverage, Vitamin A supplementation, integrated management of childhood illnesses, and an increase in institutional deliveries (Musafili *et al*. 2015; Mugeni *et al*. 2014; Farmer *et al*. 2013). Despite these efforts the decrease in neonatal mortality rate (NMR) has been slower hence more measures must be put into place to effectively control the problem. The aim of this study is to model and project future trends of NMR for Rwanda using the popular Box-Jenkins ARIMA technique. This model is useful in modelling linear data (Nyoni, 2018; Box &Jenkins, 1970). This study being the first of its kind in Rwanda is expected to help public health practitioners to make informed decisions & policies and facilitate allocation of resources towards maternal and child health (MNCH) programs in the country. Furthermore, forecast results will assist to track the country's progress towards achieving the set sustainable development goal 3 target 3.2 by 2030 which aims to substantially reduce neonatal mortality rate to at least 12 per 1000 live births (UNICEF, 2019).

II. LITERATURE REVIEW

A description of household factors associated with under-five mortality in Bankass, a remote region in central Mali was done by Boettiger *et al*. (2021). The authors analyzed baseline household survey data from a trial being conducted in Bankass. The survey was administered to households between December 2016 and January 2017. Under-five deaths in the five years prior to baseline were documented along with detailed information on household factors and women's birth histories. Factors associated with under-five mortality were analyzed using Cox regression. The study concluded that U5 mortality is very high in Bankass and is associated with living a greater distance from healthcare and several other household factors that may be amenable to intervention or facilitate program targeting. A matched case-control study using verbal social autopsy was conducted by Gupta *et al*. (2018) to investigate the causes and predictors of childhood mortality in Rwanda. Authors utilized conditional logistic regression to identify clinical, family, and household risk factors for death. It was found out that there was a large proportion of remaining deaths occur at home, with home deliveries still representing a significant risk factor for neonatal death. The major

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causes of death at a population level remain largely avoidable communicable diseases. Merabet *et al.* (2018) described neonatal deaths and identified their risk factors at the Al Hoceima Provincial Hospital. The findings showed that neonatal mortality in the Al Hoceima hospital remains high and is mainly related to the course of pregnancy and childbirth as well as the characteristics of the newborn at birthKhurmi *et al.* (2017)reviewed evidence-based interventions and coverage levels already implemented in Rwanda and identified key issues and bottlenecks in service delivery and uptake of services by community/beneficiaries. This study utilized mixed method research including qualitative and quantitative analyses of various maternal and newborn health programs implemented in the country. The findings of the study indicated that policies, protocols, various guidelines and tools for monitoring are already in place however, implementation of these remains a challenge.

III. METHODOLOGY

The Autoregressive (AR) Model

A process R_t (Neonatal mortality rate 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:

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

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

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

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:

$$R_t = \emptyset R_{t-1} + Z_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

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:

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

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

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

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

Equation [4] can also be expressed as follows:

$$R_t - \sum_{j \leq 1} \pi_j R_{t-j} = Z_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [6]$$

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 R_t sequence and recover Z_t from present and past values of R_t by a convergent sum.

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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:

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

Thus:

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

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

The Autoregressive Integrated Moving Average (ARIMA) Model

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.

$$\left.\begin{array}{c} The\ first\ difference\ is\ given\ by: \\ R_t - R_{t-1} = R_t - BR_t \\ The\ second\ difference\ is\ given\ by: \\ R_t(1-B) - R_{t-1}(1-B) = R_t(1-B) - BR_t(1-B) = R_t(1-B)(1-B) = R_t(1-B)^2 \\ The\ third\ difference\ is\ given\ by: \\ R_t(1-B)^2 - R_{t-1}(1-B)^2 = R_t(1-B)^2 - BR_t(1-B)^2 = R_t(1-B)^2(1-B) = R(1-B)^3 \\ The\ d^{th}\ difference\ is\ given\ by: \\ R_t(1-B)^d \end{array}\right\} \dots [9]$$

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:

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

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

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

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 Rwanda 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: D(R)
Date: 01/29/22 Time: 11:12
Sample: 1960 2019
Included observations: 59

Model	LogL	AIC*	BIC	HQ
(4,1)(0,0)	-31.527504	1.306017	1.552505	1.402236
(5,0)(0,0)	-32.164571	1.327613	1.574100	1.423831
(5,1)(0,0)	-31.511540	1.339374	1.621074	1.449338
(4,2)(0,0)	-31.517857	1.339588	1.621288	1.449553
(4,0)(0,0)	-33.961755	1.354636	1.565911	1.437109
(2,3)(0,0)	-33.063438	1.358083	1.604570	1.454301
(5,2)(0,0)	-31.152870	1.361114	1.678027	1.484824
(4,3)(0,0)	-31.400561	1.369511	1.686423	1.493220
(1,4)(0,0)	-33.545288	1.374417	1.620904	1.470635
(2,4)(0,0)	-32.651720	1.378024	1.659724	1.487989
(3,5)(0,0)	-30.755809	1.381553	1.733678	1.519008
(2,5)(0,0)	-31.914557	1.386934	1.703847	1.510644
(3,3)(0,0)	-32.916546	1.387002	1.668702	1.496966
(2,1)(0,0)	-35.926049	1.387324	1.563386	1.456051
(3,4)(0,0)	-32.498883	1.406742	1.723654	1.530452
(2,2)(0,0)	-35.594667	1.409989	1.621264	1.492462
(4,5)(0,0)	-30.688914	1.413184	1.800521	1.564384
(4,4)(0,0)	-31.737757	1.414839	1.766964	1.552295
(5,4)(0,0)	-30.776262	1.416144	1.803482	1.567345
(5,3)(0,0)	-31.820045	1.417629	1.769754	1.555084
(3,1)(0,0)	-35.860423	1.418997	1.630272	1.501471
(3,2)(0,0)	-35.454898	1.439149	1.685637	1.535368
(1,3)(0,0)	-36.520631	1.441377	1.652652	1.523851
(1,0)(0,0)	-39.959661	1.456260	1.561897	1.497496
(0,5)(0,0)	-36.003589	1.457749	1.704236	1.553968
(1,1)(0,0)	-39.203181	1.464515	1.605365	1.519497
(2,0)(0,0)	-39.408179	1.471464	1.612314	1.526446
(0,4)(0,0)	-37.686560	1.480900	1.692175	1.563374
(1,2)(0,0)	-38.799454	1.484727	1.660790	1.553455
(3,0)(0,0)	-39.313819	1.502163	1.678226	1.570891
(5,5)(0,0)	-32.431911	1.506166	1.928716	1.671113
(1,5)(0,0)	-37.431705	1.540058	1.821758	1.650022
(0,3)(0,0)	-45.564121	1.714038	1.890100	1.782766
(0,2)(0,0)	-47.325456	1.739846	1.880696	1.794828
(0,1)(0,0)	-56.882184	2.029905	2.135542	2.071141
(0,0)(0,0)	-81.712818	2.837723	2.908148	2.865214

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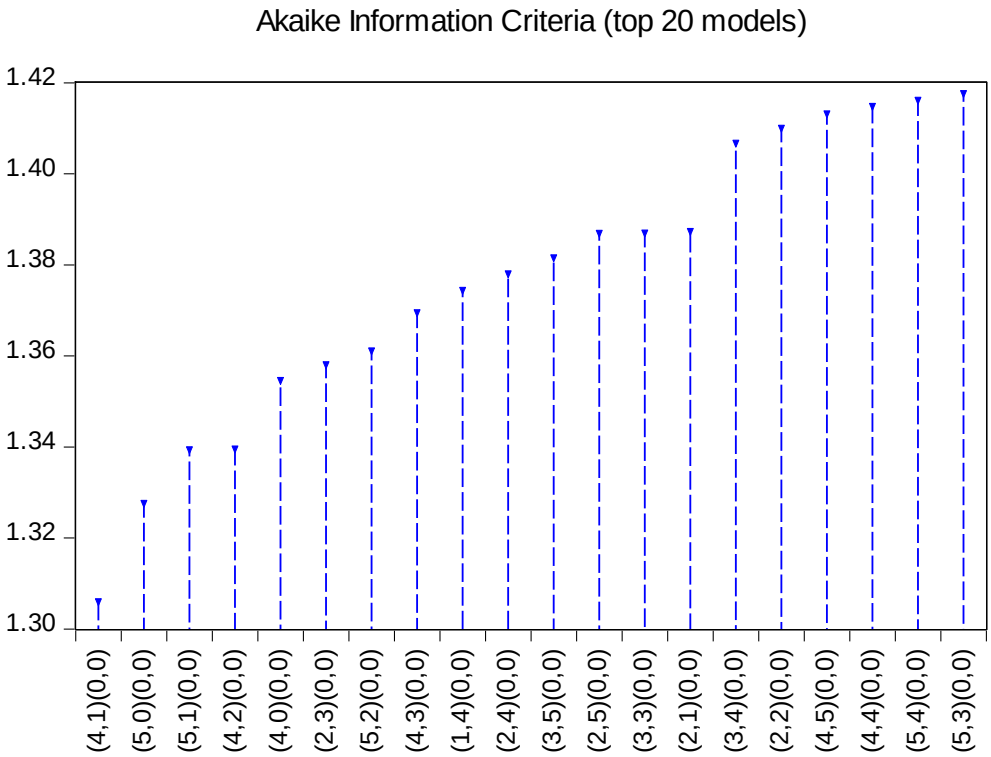
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

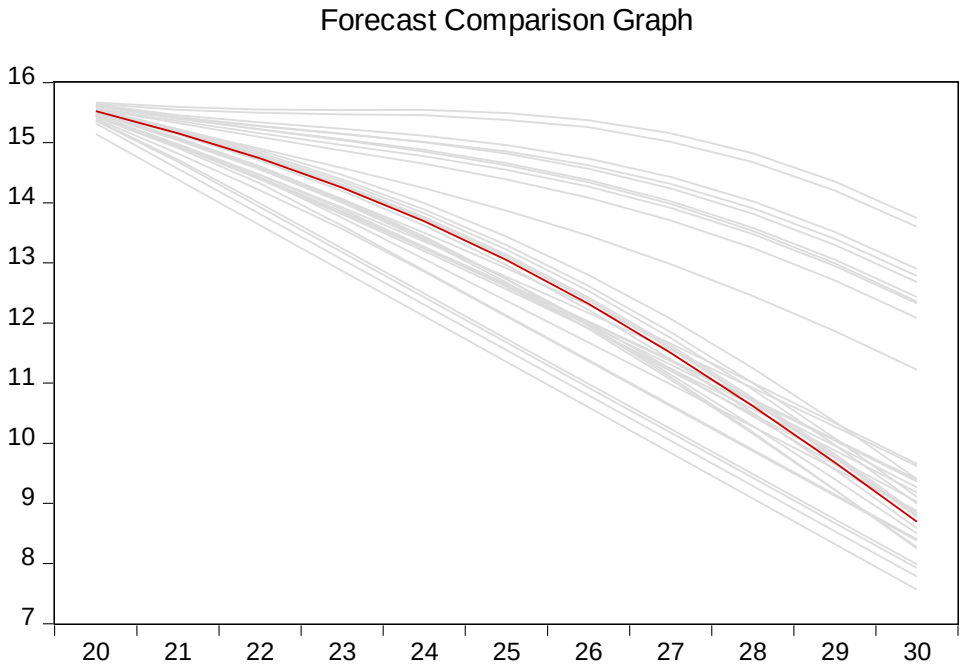


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (4,1,1) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (4,1,1) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: D(R)
Date: 01/29/22 Time: 11:12
Sample: 1960 2019
Included observations: 59
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (4,1)(0,0)
AIC value: 1.3060170846

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: D(R)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22 Time: 11:12
Sample: 1961 2019
Included observations: 59
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.780130	0.283992	-2.747013	0.0082
AR(1)	1.492999	0.214169	6.971120	0.0000
AR(2)	-0.740540	0.284056	-2.607022	0.0119
AR(3)	0.539847	0.239717	2.252019	0.0286
AR(4)	-0.418817	0.134357	-3.117189	0.0030
MA(1)	-0.635124	0.258376	-2.458142	0.0173
SIGMASQ	0.163592	0.024986	6.547268	0.0000

R-squared	0.824906	Mean dependent var	-0.757627
Adjusted R-squared	0.804702	S.D. dependent var	0.974892
S.E. of regression	0.430829	Akaike info criterion	1.306017
Sum squared resid	9.651918	Schwarz criterion	1.552505
Log likelihood	-31.52750	Hannan-Quinn criter.	1.402236
F-statistic	40.83043	Durbin-Watson stat	1.958392
Prob(F-statistic)	0.000000		

Inverted AR Roots	.92+.25i	.92-.25i	-.17+.66i	-.17-.66i
Inverted MA Roots	.64			

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	15.52518639440494
2021	15.15658066476067
2022	14.73671009293195
2023	14.24930074223702
2024	13.69182253308923
2025	13.04947164531535
2026	12.31730471209736
2027	11.50435405486498
2028	10.62083353759974
2029	9.678835082513147
2030	8.695794574568351

Table 5 clearly indicates that neonatal mortality is expected to gradually fall down to levels below 12 neonatal deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

The Rwandan government has made significant progress in reducing neonatal mortality by recording a decline in NMR from 37 per 1000 live births to 20 live births per 1000 live births over the period 2005-2013. This was as a result of several effective public health strategies that have continued to produce positive results even until this day. In this study we apply the ARIMA model to project future trends of NMR for Rwanda and the model projections indicate that neonatal mortality is expected to gradually fall down to levels below 12 neonatal deaths per 1000 live births by the end of 2030. Therefore, Rwandan authorities should continue availing medical staff, sufficient medical supplies and improving health infrastructure in the rural areas amongst other measures.

REFERENCES

[1] Box, D. E., and Jenkins, G. M. (1970). Time Series Analysis, Forecasting and Control, Holden Day, London.

[2] Nyoni, T. (2018). Box-Jenkins ARIMA Approach to Predicting net FDI Inflows in Zimbabwe, *University Library of Munich*, MPRA Paper No. 87737.

[3] National Institute of Statistics of Rwanda. Rwanda Ministry of Health, and ICF international. In: Rwanda demographic and health survey 2014-15. Rockville: Final Report; 2015.

[4] Musafili A., Essen B., Baribwira C., Binagwaho A., Persson L. A., and Selling K. E (2015). Trends and social differentials in child mortality in Rwanda 1990-2010: results from three demographic and health surveys. J Epidemiol Community Health, 69, 9), 834–40

[5] Farmer P. E., Nutt C. T., Wagner C. M., Sekabaraga C., and Nuthulaganti T (2013). Reduced premature mortality in Rwanda: lessons from success. BMJ, 2013, 346, f65.

[6] Mugeni C., Levine A. C., Munyaneza R. M., Mulindahabi E., and Cockrell HC (2014). Nationwide implementation of integrated community case management of childhood illness in Rwanda. Glob Health SciPract, 2, 3, 328–41

[7] UNICEF (2019). Child Mortality 2019. New York: United Nations Children's Fund.

[8] Worldometer (2023). Rwanda demographics: https://wwww.worldometers.info.

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