International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 240-247, August-2023

https://doi.org/10.47001/IRJIET/2023.708033

Utilizing the ARIMA Model to Determine Future Trends of Neonatal Mortality Rate to Inform Neonatal Healthcare Strategies in Cameroon

[1]Dr. Smartson. P. NYONI, [2]Thabani NYONI

[1]ZICHIRe Project, University of Zimbabwe, Harare, Zimbabwe
[2]Independent Researcher & Health Economist, Harare, Zimbabwe

***Abstract* - Review of SDG progress should be part of national plans and budgets. Time series forecasting techniques detect abnormal future trends of health events, hence their use will guide planning, decisions and allocation of resources to maternal and child health programs. This research uses annual time series data on neonatal mortality rate (NMR) for Cameroon 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 (2) variable. The optimal model based on AIC is the ARIMA (2,2,2) model. The ARIMA model predictions indicate that NMR will hover around 25 deaths per 1000 live births throughout the forecast period. Hence, policymakers are encouraged to focus on capacitating primary healthcare and regular training of healthcare workers on essential newborn care and basic& emergency obstetric care.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

The death of a newborn within 28 days of life is referred to as a neonatal death whereas neonatal mortality rate (NMR) is the number of neonatal deaths per 1000 live births. It is also known as the probability of dying during the first month of life (Bitew *et al*. 2020; Yu *et al*. 2003). Neonatal deaths usually occur during the first week of life with the leading causes being birth asphyxia, prematurity, sepsis, respiratory distress syndrome and congenital anomalies (Diouf, 2018; Koum *et al*. 2015). Mortality in neonates can be broadly classified into 2: early (occurring within the first 7days and late (occurring between 7-28 days of life after birth) (Sankar *et al*. 2016; Tran *et al.* 2012). Neonatal mortality contributes approximately 44 percent of under 5 mortality globally and above 99 percent of them occur in low and middle income countries especially in Africa and Asian countries (Sankar *et al.* 2016; PMCH, 2015; Tran *et al.* 2012; Oestergaard *et al*. 2011).The aim of this study is to model and project neonatal mortality rate for Cameroon using the widely applied Box-Jenkins ARIMA model which is suitable for analyzing linear data (Nyoni, 2018; Box & Jenkins, 1970). This study is the first of its kind in this country and expected to help in the assessment of the possibility of achieving set SDG-3 target 3.2 by the end of 2030 and also facilitate drafting of neonatal policies which are effective in controlling neonatal mortality in the country.

II. LITERATURE REVIEW

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 were 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 a similar study, Bitew *et al*. (2020) determined the incidence density rate and predictors of neonatal mortality by utilizing electronic databases. The study findings indicated that the incidence density rate of neonatal mortality in Sub-Saharan Africa is significantly high. Multiple factors (neonatal and maternal) were found to be independent predictors. 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 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, $p<0.05$). 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

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 240-247, August-2023

https://doi.org/10.47001/IRJIET/2023.708033

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 indicated that adequate use of antenatal care services reduced risk of neonatal and under-five mortality by 2.4 and 4.2 percentage points respectively.

III. METHODOLOGY

The Autoregressive (AR) Model

A process C_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:

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

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

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

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:

$$C_t = \emptyset C_{t-1} + Z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

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 C_t sequence and recover Z_t from present and past values of C_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:

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 240-247, August-2023

https://doi.org/10.47001/IRJIET/2023.708033

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

Thus:

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

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.

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

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:

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

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

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

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 Cameroon 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

Criteria Table

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 240-247, August-2023

https://doi.org/10.47001/IRJIET/2023.708033

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: D(C01, 2)
Date: 01/22/22   Time: 13:16
Sample: 1960 2019
Included observations: 58

Model	LogL	AIC*	BIC	HQ
(2,2)(0,0)	53.234003	-1.628759	-1.415609	-1.545733
(3,1)(0,0)	53.155778	-1.626061	-1.412912	-1.543035
(3,2)(0,0)	53.327461	-1.597499	-1.348824	-1.500635
(4,1)(0,0)	53.316578	-1.597123	-1.348449	-1.500260
(2,3)(0,0)	53.284884	-1.596030	-1.347356	-1.499167
(4,4)(0,0)	56.043020	-1.587690	-1.232442	-1.449314
(5,3)(0,0)	55.966057	-1.585036	-1.229788	-1.446660
(4,2)(0,0)	53.816965	-1.579895	-1.295696	-1.469194
(4,3)(0,0)	54.689711	-1.575507	-1.255783	-1.450968
(3,3)(0,0)	53.585577	-1.571916	-1.287717	-1.461215
(2,4)(0,0)	53.566046	-1.571243	-1.287044	-1.460542
(5,1)(0,0)	53.325627	-1.562953	-1.278754	-1.452251
(5,4)(0,0)	56.043088	-1.553210	-1.162436	-1.400996
(5,2)(0,0)	53.825153	-1.545695	-1.225971	-1.421156
(4,5)(0,0)	55.736405	-1.542635	-1.151861	-1.390420
(2,5)(0,0)	53.724345	-1.542219	-1.222495	-1.417680
(3,4)(0,0)	53.701862	-1.541444	-1.221720	-1.416905
(2,1)(0,0)	49.321225	-1.528318	-1.350694	-1.459130
(5,5)(0,0)	55.741461	-1.508326	-1.082028	-1.342274
(4,0)(0,0)	47.186387	-1.420220	-1.207071	-1.337194
(5,0)(0,0)	47.604791	-1.400165	-1.151491	-1.303302
(3,0)(0,0)	43.763779	-1.336682	-1.159058	-1.267494
(1,5)(0,0)	45.918983	-1.307551	-1.023352	-1.196850
(1,4)(0,0)	44.347080	-1.287830	-1.039156	-1.190967
(1,2)(0,0)	41.591738	-1.261784	-1.084160	-1.192596
(0,3)(0,0)	41.562560	-1.260778	-1.083154	-1.191590
(0,4)(0,0)	42.452894	-1.256996	-1.043847	-1.173970
(1,0)(0,0)	39.002523	-1.241466	-1.134892	-1.199953
(2,0)(0,0)	39.300298	-1.217252	-1.075152	-1.161901
(1,1)(0,0)	39.148898	-1.212031	-1.069931	-1.156680
(1,3)(0,0)	41.139057	-1.211692	-0.998542	-1.128666
(0,2)(0,0)	38.942023	-1.204897	-1.062798	-1.149547
(0,5)(0,0)	39.728596	-1.128572	-0.879898	-1.031709
(3,5)(0,0)	40.625150	-1.056040	-0.700791	-0.917663
(0,1)(0,0)	32.143925	-1.004963	-0.898388	-0.963450
(0,0)(0,0)	18.966713	-0.585059	-0.514009	-0.557384

International Research Journal of Innovations in Engineering and Technology (IRJIET)

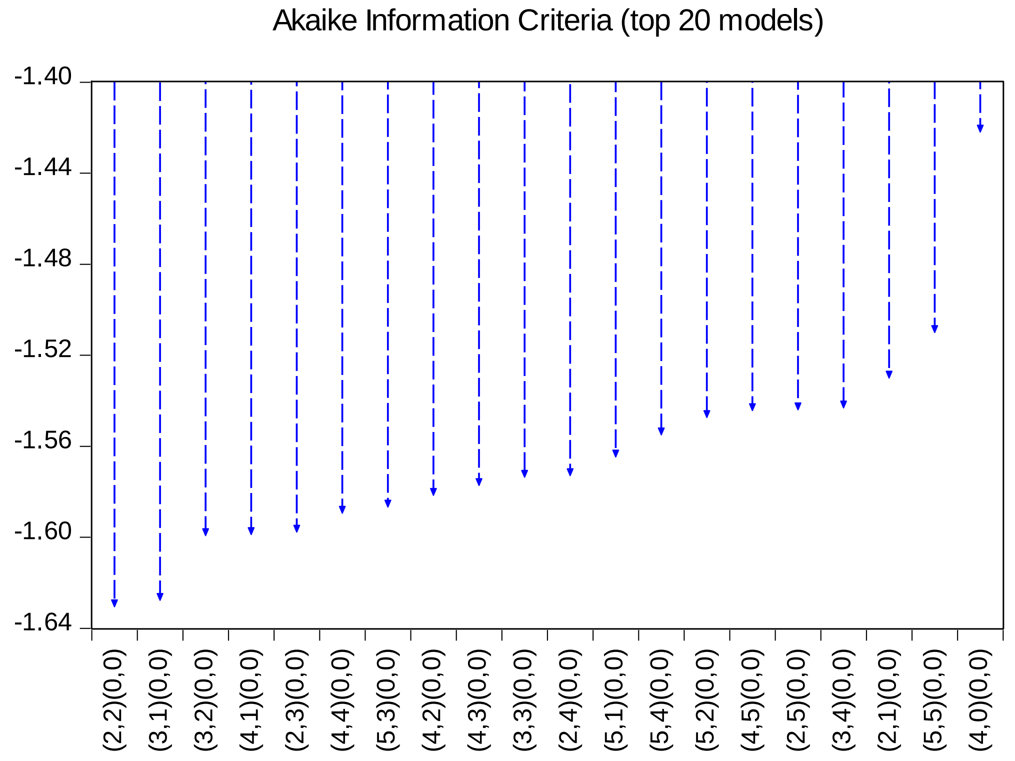
ISSN (online): 2581-3048

Volume 7, Issue 8, pp 240-247, August-2023

https://doi.org/10.47001/IRJIET/2023.708033

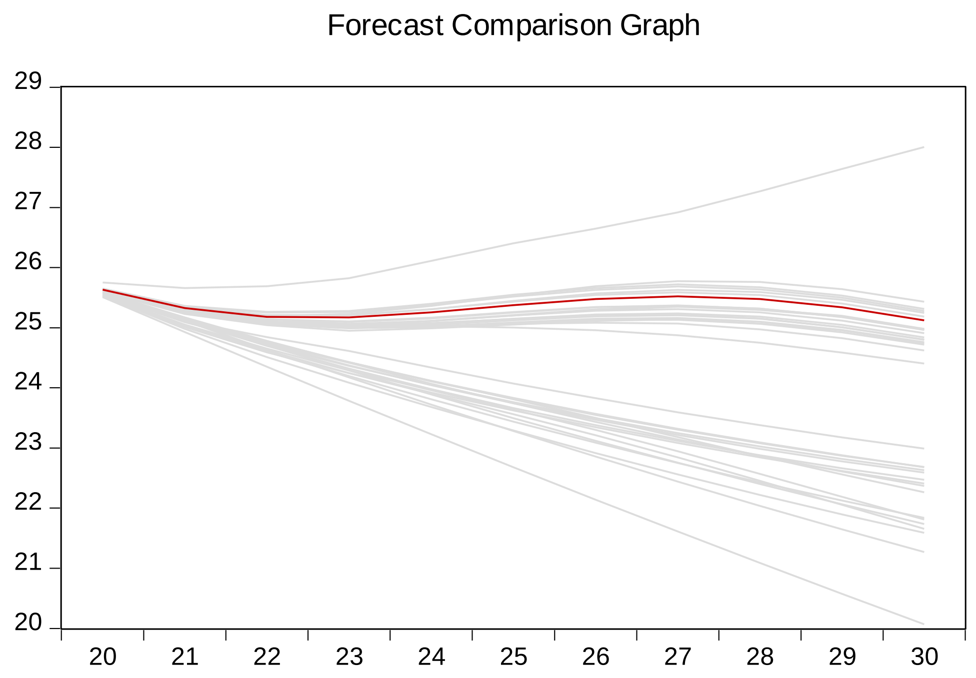
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph



International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 240-247, August-2023

https://doi.org/10.47001/IRJIET/2023.708033

Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,2,2) 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 (2,2,2) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: D(C01, 2)
Date: 01/22/22 Time: 13:16
Sample: 1960 2019
Included observations: 58
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (2,2)(0,0)
AIC value: -1.62875873976

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: D(C01,2)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/22/22 Time: 13:16
Sample: 1962 2019
Included observations: 58
Convergence achieved after 57 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.017855	0.003517	5.075979	0.0000
AR(1)	1.750094	0.048242	36.27743	0.0000
AR(2)	-0.927744	0.047011	-19.73471	0.0000
MA(1)	-1.451227	51.08753	-0.028407	0.9774
MA(2)	0.451227	28.20888	0.015996	0.9873
SIGMASQ	0.008444	0.173716	0.048608	0.9614

R-squared	0.722628	Mean dependent var	0.008621
Adjusted R-squared	0.695958	S.D. dependent var	0.176003
S.E. of regression	0.097048	Akaike info criterion	-1.628759
Sum squared resid	0.489753	Schwarz criterion	-1.415609
Log likelihood	53.23400	Hannan-Quinn criter.	-1.545733
F-statistic	27.09476	Durbin-Watson stat	2.032316
Prob(F-statistic)	0.000000		

International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 8, pp 240-247, August-2023

https://doi.org/10.47001/IRJIET/2023.708033

Inverted AR Roots	.88-.40i	.88+.40i
Inverted MA Roots	1.00	.45

ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	25.63305595735334
2021	25.32684701030919
2022	25.18166961521112
2023	25.1723634570916
2024	25.25462058881156
2025	25.37424026537565
2026	25.47747250924791
2027	25.52053420742509
2028	25.47666699831482
2029	25.33966073845421
2030	25.12347199095693

Table 5 clearly indicates that NMR will hover around 25 deaths per 1000 live births throughout the forecast period.

V. POLICY IMPLICATION & CONCLUSION

Appropriate resource allocation in low and middle income countries is critical to ensure availability, accessibility and affordability of quality health care services especially maternal and child healthcare services. Poor road infrastructure in developing countries has made it difficult to access health care services and led to the occurrence of home deliveries that pose serious health problems to the mother and the newborn baby. Mass exodus of healthcare professionals is being driven by poor remuneration, shortage of accommodation, bad road network and poor internet connectivity in remote areas. Health authorities in various countries must address all these challenges so that patients get quality healthcare. In this study we applied the Box-Jenkins ARIMA approach to predict future trends of NMR for Cameroon and the results indicate that NMR will hover around 25 deaths per 1000 live births throughout the forecast period. Hence policymakers are encouraged tofocus on capacitating primary healthcare and regular training of healthcare workers on essential newborn care and basic& emergency obstetric care.

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] M. J. Sankar., C. K. Natarajan., R. R. Das., R. Agarwal., A. Chandrasekaran., and V. K. Paul (2016), “When do newborns die? A systematic review of timing of overall and causespecific neonatal deaths in developing countries,” Journal of Perinatology, vol. 36, no. S1, pp. S1–S11.

[4] H. T. Tran., L. W. Doyle., K. J. Lee., and S. M. Graham (2012). “A systematic review of the burden of neonatal mortality and morbidity in the ASEAN region,” WHO South-East Asia Journal of Public Health, vol. 1, no. 3, pp. 239–248.

[5] M. Z. Oestergaard., M. Inoue., and S. Yoshida (2011). “Neonatal mortality levels for 193 countries in 2009 with trends since 1990: a systematic analysis of progress, projections, and priorities,” PLoS Medicine, vol. 8, no. 8, article e1001080.

[6] The partnership for maternal and child health: newborn death and illness, 2015, http://www.who.int/pmnch/media/press_materials/fs/fs_newborndealth_illness/en/.

ISSN (online): 2581-3048
Volume 7, Issue 8, pp 240-247, August-2023
https://doi.org/10.47001/IRJIET/2023.708033

[7] V. Y. Yu (2003). “Global, regional and national perinatal and neonatal mortality,” Journal of Perinatal Medicine, vol. 31, no. 5, pp. 376–379.
[8] Bitew Z W., Alemu A., Ayele G E., Jember D A., Haile M T., ands Worku T (2020).
[9] Koum DCK., Essomba NE., Ngaba G., Sintat s., Ndombo PK., and Coppieters Y (2015). Morbidité et facteurs de risque de mortalité néonatale dans un hôpital de référence de Douala. Pan Afr Med J, 20: 258.
[10] Diouf JB (2018). Etude de la mortalité hospitalière au service de pédiatrie de l'hôpital Roi Baudouin de Guédiawaye. Pan African Medical Journal Conference Proceedings, 9, 9, 6.

Citation of this Article:

Dr. Smartson. P. NYONI, Thabani NYONI, “Utilizing the ARIMA Model to Determine Future Trends of Neonatal Mortality Rate to Inform Neonatal Healthcare Strategies in Cameroon” Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 8, pp 240-247, August 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.708033

******