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Addressing Low Neonatal Survival Rates in Cote D'lvoire Using Empirical Evidence from the Box-Jenkins ARIMA Model

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Abstract - **This study uses annual time series data on neonatal mortality rate (NMR) for Cote d'lvoire 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 ARIMA model predictions suggest that NMR will decline from around 32 in 2020 to around 27 deaths per 1000 live births by the end of 2030. We, therefore encourage the authorities in this country to design effective neonatal policies to control neonatal deaths. Special attention should be given to retention of health professionals, capacitating primary health care and strengthening the referral system.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

The majority of maternal and child mortalities which occur in low-middle countries are largely avoidable (Alkema *et al*. 2015; Bhutta *et al*. 2013). Poor quality of care, limited access and shortage of skilled manpower are the main drivers of maternal and neonatal deaths ((WHO, 2012). The global neonatal mortality rates have decreased from 37 deaths per 1000 live births in 1990 to 18 deaths per 1000 live births in 2018 with Sub-Saharan Africa contributing 41% of the global neonatal deaths (UNICEF *et al*. 2019; Hug *et al*. 2019). It is critical for health authorities to prioritize reduction of neonatal mortality to at least 12 per 1000 live births by the end of 2030 through the adoption of country specific neonatal policies which are effective and cost effective by channeling resources towards improving the quality of care during ANC, delivery and postnatal periods. Surveillance tools are important as they help in the detection of abnormal future trends and track progress towards achieving set SDG targets. Therefore, the Box-Jenkins ARIMA model was proposed in this study to model and project future trends of neonatal mortality rate (NMR) for Cote d'lvoire. The statistical model is ideal for modelling linear data (Nyoni, 2018; Box & Jenkins, 1970). This will facilitate planning, decision making and allocation of resources to MNCH programs in the country.

II. LITERATURE REVIEW

There are many previous studies in Africa that have examined causes of neonatal mortality. A multisite retrospective Kenyan cohort study was carried out by Irimu *et al. (*2021) to establish 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.Bitew *et al.*(2020) determined the incidence density rate and predictors of neonatal mortality by utilizing electronic databases. The study findings indicated thatthe 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, $p<0.05$).

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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:

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

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:

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

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

for some constant π_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 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:

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

Thus:

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

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.

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

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:

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

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

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

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 Cote de l'voirethe 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

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: DLOG(C01)
Date: 01/22/22 Time: 13:22
Sample: 1960 2019
Included observations: 59

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Model	LogL	AIC*	BIC	HQ
(2,2)(0,0)	285.859036	-9.486747	-9.275472	-9.404274
(2,4)(0,0)	287.523188	-9.475362	-9.193662	-9.365398
(5,0)(0,0)	286.259521	-9.466424	-9.219937	-9.370206
(4,0)(0,0)	285.000607	-9.457648	-9.246373	-9.375174
(2,3)(0,0)	285.972582	-9.456698	-9.210210	-9.360479
(3,2)(0,0)	285.941291	-9.455637	-9.209149	-9.359418
(4,1)(0,0)	285.682107	-9.446851	-9.200364	-9.350632
(1,3)(0,0)	284.626129	-9.444954	-9.233679	-9.362480
(1,5)(0,0)	286.562375	-9.442792	-9.161092	-9.332828
(3,4)(0,0)	287.533559	-9.441816	-9.124903	-9.318106
(2,5)(0,0)	287.523987	-9.441491	-9.124579	-9.317781
(4,2)(0,0)	286.483349	-9.440114	-9.158414	-9.330149
(5,1)(0,0)	286.446646	-9.438869	-9.157169	-9.328905
(3,3)(0,0)	286.071328	-9.426147	-9.144447	-9.316182
(4,4)(0,0)	287.901655	-9.420395	-9.068270	-9.282940
(1,4)(0,0)	284.820674	-9.417650	-9.171162	-9.321431
(3,5)(0,0)	287.714492	-9.414051	-9.061926	-9.276595
(5,2)(0,0)	286.688249	-9.413161	-9.096248	-9.289451
(3,1)(0,0)	283.658277	-9.412145	-9.200870	-9.329672
(4,3)(0,0)	286.648632	-9.411818	-9.094906	-9.288108
(3,0)(0,0)	282.461575	-9.405477	-9.229415	-9.336749
(1,2)(0,0)	282.246755	-9.398195	-9.222133	-9.329467
(5,4)(0,0)	288.012172	-9.390243	-9.002906	-9.239042
(4,5)(0,0)	287.938006	-9.387729	-9.000392	-9.236528
(5,3)(0,0)	286.710263	-9.380009	-9.027884	-9.242554
(5,5)(0,0)	288.240226	-9.364075	-8.941525	-9.199129
(2,1)(0,0)	280.388418	-9.335201	-9.159138	-9.266473
(0,5)(0,0)	279.420559	-9.234595	-8.988108	-9.138376
(2,0)(0,0)	275.928544	-9.217917	-9.077067	-9.162935
(1,0)(0,0)	274.428842	-9.200978	-9.095340	-9.159741
(1,1)(0,0)	275.211789	-9.193620	-9.052770	-9.138638
(0,4)(0,0)	271.009449	-8.983371	-8.772096	-8.900898
(0,3)(0,0)	267.848430	-8.910116	-8.734054	-8.841389
(0,2)(0,0)	252.825660	-8.434768	-8.293918	-8.379786
(0,1)(0,0)	236.669054	-7.920985	-7.815347	-7.879748
(0,0)(0,0)	207.395280	-6.962552	-6.892127	-6.935061

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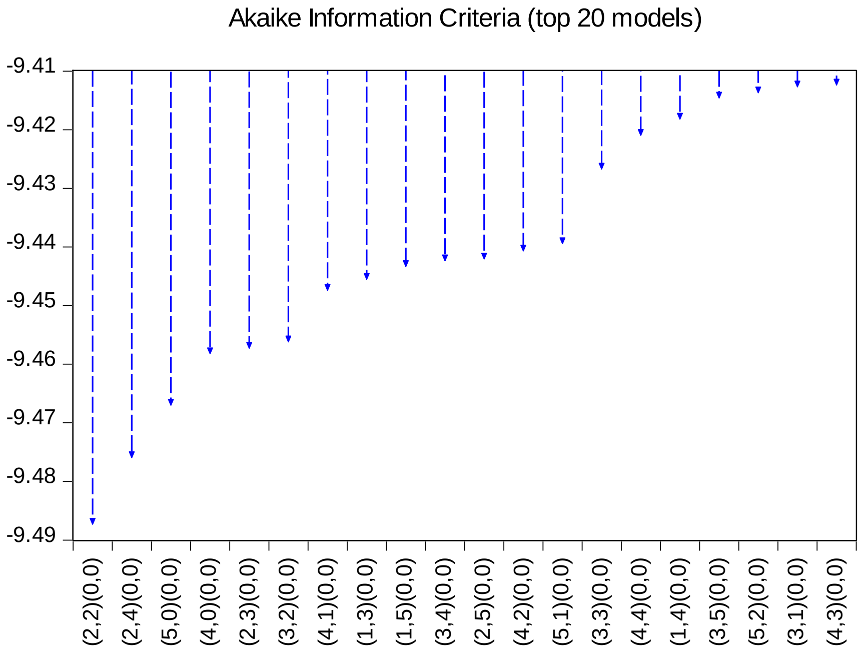
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

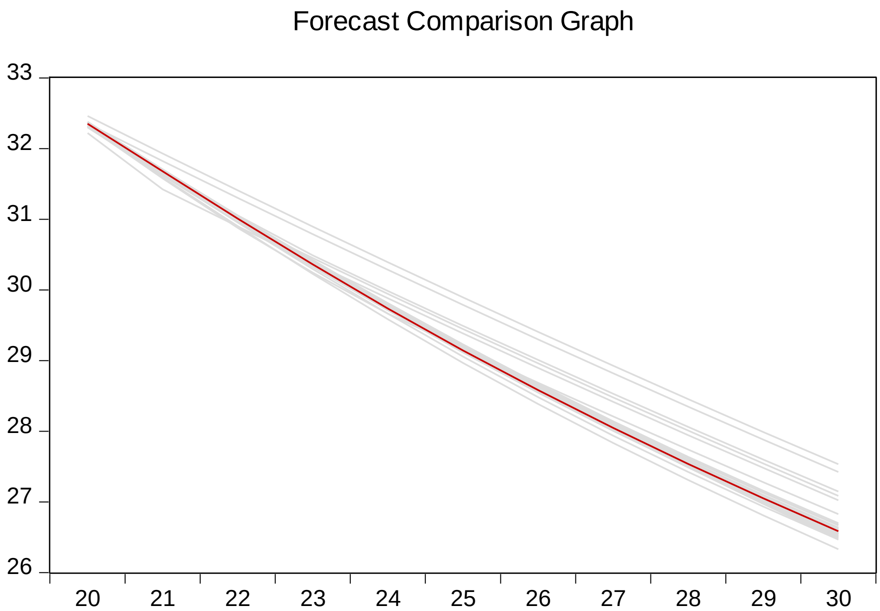


Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,1,2) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (2,1,2)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

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IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(C01)
Date: 01/22/22 Time: 13:22
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: -9.48674697948

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(C01)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/22/22 Time: 13:22
Sample: 1961 2019
Included observations: 59
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.016714	0.003508	-4.763998	0.0000
AR(1)	1.565186	0.202105	7.744416	0.0000
AR(2)	-0.642631	0.207012	-3.104318	0.0031
MA(1)	-0.633728	0.221538	-2.860583	0.0060
MA(2)	0.544746	0.153802	3.541855	0.0008
SIGMASQ	3.41E-06	6.75E-07	5.058018	0.0000

R-squared	0.934129	Mean dependent var	-0.016469
Adjusted R-squared	0.927914	S.D. dependent var	0.007259
S.E. of regression	0.001949	Akaike info criterion	-9.486747
Sum squared resid	0.000201	Schwarz criterion	-9.275472
Log likelihood	285.8590	Hannan-Quinn criter.	-9.404274
F-statistic	150.3195	Durbin-Watson stat	1.931516
Prob(F-statistic)	0.000000		

Inverted AR Roots	.78+.17i	.78-.17i
Inverted MA Roots	.32-.67i	.32+.67i

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	32.34905110134896
2021	31.67769112340534
2022	31.00958245469314
2023	30.3596672434975
2024	29.73624170697329
2025	29.14282579844553
2026	28.57971716204816
2027	28.0452085193857
2028	27.536494823934
2029	27.05031665161648
2030	26.58339114538215

Table 5 clearly indicates that there NMR is expected to decline from around 32 in 2020 to around 27 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

Under 5 mortality is still a public health problem all over the world, however low and middle income countries continue to record the highest numbers of deaths compared to the developed world. The decline in under five deaths globally is commendable and indicates the commitment that governments make towards achieving sustainable development goal targets by the end of 2030. Despite this significant progress, deaths of neonates especially during the first week of life is still a huge problem in Sub-Saharan Africa and Southern Asia. The decline in neonatal mortality is very slow therefore health authorities in different countries must critically look at this problem and design policies that will stimulate a rapid decline in deaths of newborns during the first month of life. Maternal and child health programming should be informed by research, hence in this study we proposed the Box-Jenkins ARIMA technique to project future trends of NMR for Cote de l'voire and the results indicate that NMR is expected to decline from around 32 in 2020 to around 27 deaths per 1000 live births by the end of 2030.We, therefore encourage authorities to design effective neonatal policies to control neonatal mortality. Special attention should be given to retention of health professionals, capacitating primary health care and strengthening the referral system.

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