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Making Use of Forecasts Produced By the ARIMA Model to Attend to Various Neonatal Healthcare Challenges in the Philippines

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

[1]ZICHIRe Project, University of Zimbabwe, Harare, Zimbabwe

[2]Independent Researcher & Health Economist, Harare, Zimbabwe

***Abstract* - Neonatal mortality is an indication of the quality of healthcare services during antenatal, delivery and postnatal periods. Main causes of neonatal mortality in the Philippines are prematurity, asphyxia & birth trauma and congenital malformations. Neonatal healthcare policies should be informed by research evidence, hence this study utilizes the Box-Jenkins ARIMA methodology to detect future trends of neonatal mortality using annual time series data on neonatal mortality rate (NMR) for the Philippines from 1960 to 2019to 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 (3,1,1) model. The study results indicate that neonatal mortality will gradually decline throughout the forecast period to reach levels as low as 8 deaths per 1000 live births by the end of 2030. It is crucial for authorities in the Philippines to address local factors that contribute significantly to adverse maternal and neonatal health outcomes such as lack of medical equipment and inadequate healthcare.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Neonatal and under-five mortality is a global health problem mainly affecting developing countries more than the first world (Lawn *et al.* 2005). Philippines has witnessed a downward trend in neonatal mortality (NMR) from 20 deaths per 1000 live births in 1990 to 12.6 deaths per 1000 live births in 2015 (World Data Atlas, 2018). The major causes of neonatal deaths in this country are prematurity (31%), asphyxia & birth trauma (23%) and congenital malformations (19%) (Vahanian &Vintzelios, 2016). Lack of equipment, and inadequate healthcare are the main contributing factors to adverse maternal and child health outcomes (Filippi*et al.* 2016; Stanton &, Mwanri, 2013). The main of objective of this study is to model and project future trends of NMR for the Philippines using the widely applied ARIMA (p, d, q) model. The model is suitable for analyzing linear time series data (Nyoni, 2018; Box & Jenkins, 1970). Forecast results are expected to guide neonatal policy and inform decision making and resource allocation so that the country can effectively control the problem of mortality in neonates.

II. LITERATURE REVIEW

Li *et al.* (2021) examined the proportion of mothers with history of neonatal deaths using the most recent Demographic and Health Surveys from 56 low- and middle-income countries. Logistic regression models were used to assess the association between maternal history of neonatal death and subsequent neonatal mortality. The adjusted models controlled for socioeconomic, child, and pregnancy-related factors. Country-specific analyses were performed to assess heterogeneity in this association across countries. Study findings suggested that maternal history of neonatal death could be an effective early identifier of high-risk pregnancies in resource-poor countries. In another study by Khader *et al.* (2021) explored the healthcare professionals' perception about the usability of JSANDS.A descriptive qualitative approach, using focus group discussions, was adopted. A total of 5 focus groups including 23 focal points were conducted in five participating hospitals in Jordan. The study findings revealed that JSANDS was perceived positively by the current users. According to them, it provides a formative and comprehensive data on stillbirths and neonatal deaths and their causes. Nath *et al.* (2020) examined the effect of extreme prematurity and early neonatal deaths on infant mortality rates in England. Authors used aggregate data on all live births, stillbirths and linked infant deaths in England in 2006–2016 from the Office for National Statistic. Infant mortality decreased from 4.78 deaths/1000 live births in 2006 to 3.54/1000 in 2014 (annual decrease of 0.15/1000) and increased to 3.67/1000 in 2016 (annual increase of 0.07/1000). This rise was driven by increases in deaths at 0–6 days of life.A descriptive study was carried out by McNamara *et al.* (2018) to reveal intrapartum fetal deaths and unexpected neonatal deaths in Ireland from 2011 to 2014. Anonymised data pertaining to all

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intrapartum fetal deaths and unexpected neonatal deaths for the study time period was obtained from the national perinatal epidemiology centre. The findings of the study indicated that the corrected intrapartum fetal death rate was 0.16 per 1000 births and the overall unexpected neonatal death rate was 0.17 per 1000 live births.Dalmacion *et al.* (2018) examined the benefits of handheld ultrasound (HU) for screening pregnancy related abnormalities in order to avert maternal and neonatal deaths. Using a HU, we trained community healthcare workers (CHWs) to identify 5 obstetrical conditions: fetal viability and number, placental localization, amniotic fluid volume (AFV) and fetal presentation. Women, between 20th and 24th weeks age of gestation from 2 regions of the Philippines, were scanned using the HU and the GE Logic 5 Premium ultrasound machine for validation. Maternal and neonatal deaths averted were estimated as health outcome measures of the study. The study found that there was approximately 95% agreement between the ultrasound readings of the trainees and the trainers, and 99% agreement between the readings made from the HU with the validation machine.

III. METHODOLOGY

The Autoregressive (AR) Model

A process P_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:

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

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

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

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:

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

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

for some constant π_j such that:

$$\sum_{j \leq 1} |\pi_j| < \infty$$

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This implies that it is possible to invert the function taking the Z_t sequence to the P_t sequence and recover Z_t from present and past values of P_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:

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

Thus:

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

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.

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

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:

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

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

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

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 health sector. In this paper, hinged on this technique; the researcher will use automatic ARIMA modeling for estimating equation [10].

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Data Issues

This study is based on annual NMR in Philippines 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

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: D(P)
Date: 01/29/22 Time: 11:00
Sample: 1960 2019
Included observations: 59

Model	LogL	AIC*	BIC	HQ
(3,1)(0,0)	71.619394	-2.224386	-2.013111	-2.141913
(5,3)(0,0)	75.063190	-2.205532	-1.853407	-2.068077
(4,3)(0,0)	73.990188	-2.203057	-1.886145	-2.079347
(2,3)(0,0)	71.713354	-2.193673	-1.947186	-2.097454
(4,4)(0,0)	74.645201	-2.191363	-1.839238	-2.053907
(4,1)(0,0)	71.626436	-2.190727	-1.944239	-2.094508
(3,2)(0,0)	71.623732	-2.190635	-1.944147	-2.094416
(4,2)(0,0)	72.561665	-2.188531	-1.906831	-2.078567
(5,2)(0,0)	73.525551	-2.187307	-1.870394	-2.063597
(2,4)(0,0)	72.195171	-2.176107	-1.894407	-2.066143
(3,3)(0,0)	72.071969	-2.171931	-1.890231	-2.061967
(5,4)(0,0)	75.063692	-2.171651	-1.784313	-2.020450
(5,5)(0,0)	75.233145	-2.143496	-1.720946	-1.978550
(4,0)(0,0)	69.140330	-2.140350	-1.929075	-2.057877
(3,4)(0,0)	71.714097	-2.125902	-1.808989	-2.002192
(3,5)(0,0)	72.607744	-2.122296	-1.770171	-1.984841
(5,0)(0,0)	69.146709	-2.106668	-1.860181	-2.010449
(1,2)(0,0)	66.818977	-2.095559	-1.919496	-2.026831
(4,5)(0,0)	72.666954	-2.090405	-1.703068	-1.939204
(5,1)(0,0)	69.624637	-2.088971	-1.807271	-1.979006
(2,5)(0,0)	70.247347	-2.076181	-1.759269	-1.952471
(2,2)(0,0)	66.967485	-2.066694	-1.855419	-1.984221
(1,3)(0,0)	66.914650	-2.064903	-1.853628	-1.982430
(3,0)(0,0)	65.329259	-2.045060	-1.868997	-1.976332
(1,4)(0,0)	67.096302	-2.037163	-1.790675	-1.940944
(1,5)(0,0)	67.480918	-2.016302	-1.734602	-1.906338
(0,5)(0,0)	65.852575	-1.995003	-1.748515	-1.898784
(2,0)(0,0)	62.555450	-1.984931	-1.844081	-1.929948
(2,1)(0,0)	63.367933	-1.978574	-1.802511	-1.909846
(1,1)(0,0)	61.580780	-1.951891	-1.811041	-1.896909
(1,0)(0,0)	60.398026	-1.945696	-1.840058	-1.904459
(0,4)(0,0)	62.219070	-1.905731	-1.694456	-1.823258
(0,3)(0,0)	56.605039	-1.749323	-1.573261	-1.680596
(0,2)(0,0)	49.148403	-1.530454	-1.389604	-1.475472
(0,1)(0,0)	34.816194	-1.078515	-0.972878	-1.037278

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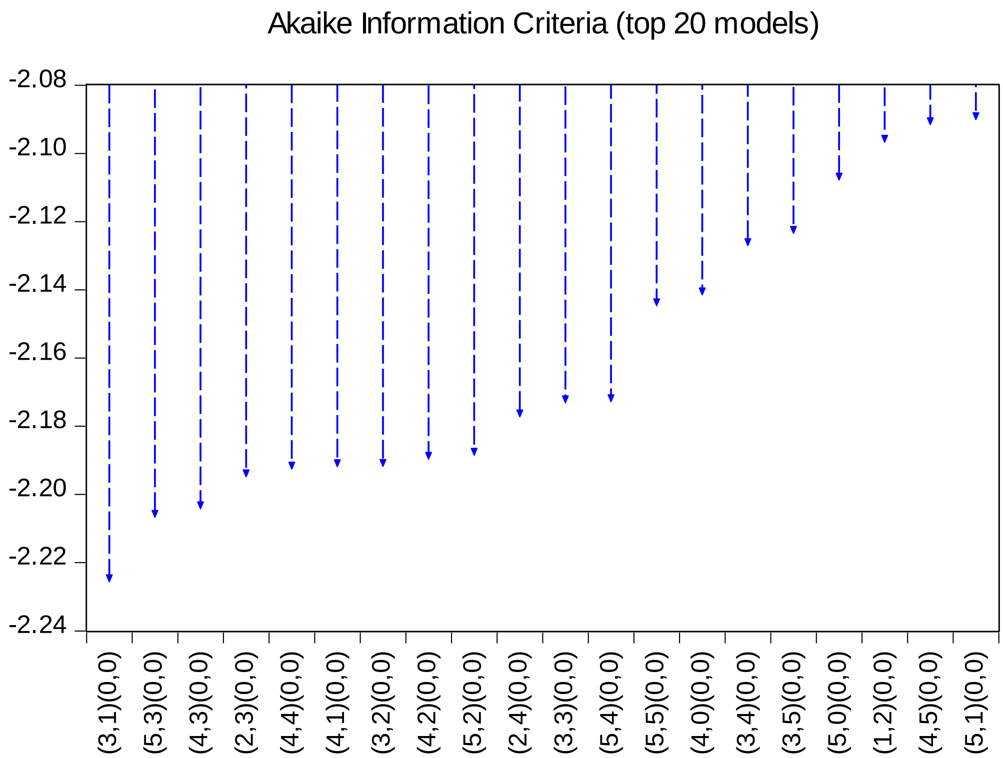
(0,0)(0,0)	15.567388	-0.459911	-0.389486	-0.432420

Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

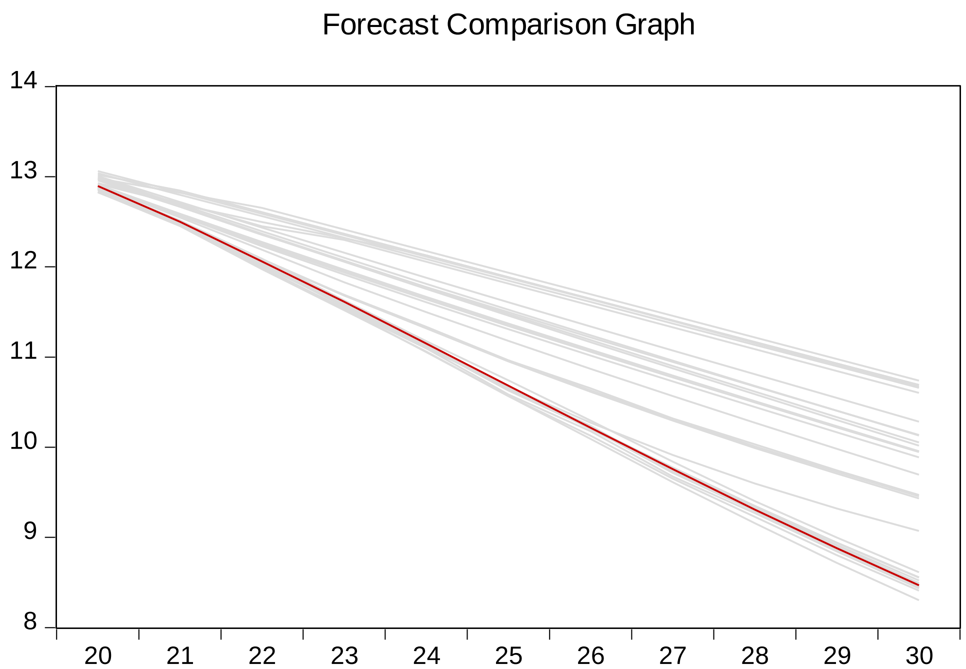


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (3,1,1) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (3,1,1) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: D(P)
Date: 01/29/22   Time: 11:00
Sample: 1960 2019
Included observations: 59
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (3,1)(0,0)
AIC value: -2.22438624619

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: D(P)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22   Time: 11:00
Sample: 1961 2019
Included observations: 59
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.276267	0.013766	-20.06841	0.0000
AR(1)	1.404543	0.144876	9.694761	0.0000
AR(2)	0.058097	0.278583	0.208543	0.8356
AR(3)	-0.510453	0.147120	-3.469637	0.0010
MA(1)	-0.999995	3960.018	-0.000253	0.9998
SIGMASQ	0.004708	0.850208	0.005538	0.9956

R-squared	0.863697	Mean dependent var	-0.237288
Adjusted R-squared	0.850838	S.D. dependent var	0.187450
S.E. of regression	0.072396	Akaike info criterion	-2.224386
Sum squared resid	0.277781	Schwarz criterion	-2.013111
Log likelihood	71.61939	Hannan-Quinn criter.	-2.141913
F-statistic	67.16787	Durbin-Watson stat	1.973795
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97-.17i	.97+.17i	-.53
Inverted MA Roots	1.00		

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	12.89474910472809
2021	12.49909982138101
2022	12.05977637240539
2023	11.61339416497986
2024	11.14965913366983
2025	10.68343484483906
2026	10.21630931143008
2027	9.756631126908886
2028	9.308631351231124
2029	8.877927107872225
2030	8.46839213120777

Table 5 clearly shows that neonatal mortality will gradually decline throughout the forecast period reaching levels as low as 8 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

Substantial reduction of neonatal mortality is the aim of SDG-3 target 3.2and countries all over the world should target to achieve a NMR of at least 12 deaths per 1000 live births by the end of 2030. Philippines has made tremendous progress towards achieving SDG-3 target 3.2 by recording a decline in NMR from 20 per 1000 live births in 1990 to 12.6 in 2015. Utilization of forecasting tools will help to inform neonatal policies, decisions and resource allocation. Hence, in this study we applied the ARIMA model to forecast future trends of NMR and the findings suggest that neonatal mortality will gradually decline throughout the forecast period reaching levels as low as 8 deaths per 1000 live births by the end of 2030. It is crucial for authorities in the Philippines to address local factors that contribute significantly to adverse maternal and neonatal health outcomes such as lack of medical equipment and inadequate healthcare.

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