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Usage of Forecasts Produced By the ARIMA Model to Address Existing Maternal and Neonatal Healthcare Challenges in Panama

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***Abstract* - This study uses annual time series data on neonatal mortality rate (NMR) for Panama 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 (0,2,3) model. The study findings indicate that neonatal mortality will continue to drop throughout the forecast period to reach levels as low as 6 deaths per 1000 live births by the end of 2030. Hence, we encourage authorities in Panama to address local factors which contribute to neonatal mortality such as accessibility, affordability and quality of maternal and neonatal healthcare services especially in marginalized regions of the country.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Quality maternal and child healthcare service provision is essential for the achievement of set targets of the 3rdsustainable development goal (SDG) by the end of 2030. SDG-3 aims to reduce global maternal mortality ratio (MMR) to less than 70 maternal deaths per 100 000 live births, under five mortality to as low as 25 deaths per 1000 live births and neonatal mortality rate (NMR) to at least 12 per 1000 live births (UN, 2020; WHO, 2019; UNICEF, 2019; WHO, 2018;UNICEF, 2018). Panama's MMR decreased from 83.6 per 100 000 live births in 2006 to 24.9 maternal deaths per 100 000 live births in 2010. Infant mortality declined from 14.8 per 1000 live births in 2006 to 11.9 per 1000 live births in 2010 (Panama, 2012). According to Panama Countdown 2030, causes of maternal mortality include obstetric hemorrhage, hypertensive disorders in pregnancy, sepsis and indirect factors. In addition, causes of neonatal mortality are preterm birth, asphyxia, sepsis and congenital anomalies. The objective of this paper is to model and predict future trends of neonatal mortality rate for Panama using the popular Box-Jenkins ARIMA model. The technique is ideal for analyzing linear time series data (Nyoni, 2018; Box & Jenkins, 1970). The results of this study are expected to inform neonatal policies and decision making in order to timeously respond to the problem of neonatal mortality in the country.

II. LITERATURE REVIEW

Acevedo *et al.* (2020) assessed the relationship between distance to a woman's assigned health clinic and obstetric care utilization. The study employed a cross-sectional study design using baseline data from the evaluation of a conditional cash transfer programme to promote greater utilization of maternal and infant health services. Data were collected between December 2016 and January 2017. The findings of the study revealed that Distance is an important barrier to obstetric care utilization, with women in more distant locations suffering significantly lower use of prenatal, childbirth and postpartum care compared with women in closer vicinity to a health establishment. Juarez *et al.* (2020) conducted a quality improvement study to increase the detection of neonatal complications by lay midwives in rural Guatemala, thereby increasing referrals to a higher level of care. A quality improvement team in Guatemala reviewed drivers of neonatal health services provided by lay midwives. Improvement interventions included training on neonatal warning signs, optimized mobile health technology to standardize assessments and financial incentives for providers. The primary quality outcome was the rate of neonatal referral to a higher level of care. It was found that structured improvement interventions, including mobile health decision support and financial incentives, significantly increased the detection of neonatal complications and referral of neonates to higher levels of care by lay midwives operating in rural home-based settings in Guatemala. Raymondville *et al.* (2020) conducted a convergent, mixed methods study to assess barriers and facilitators to facility based childbirth at Hôpital Universitaire de Mirebalais (HUM) in Mirebalais, Haiti. A secondary

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analyses of a prospective cohort of pregnant women seeking antenatal care at HUM was performed and quantitatively assessed predictors of not having a facility-based childbirth at HUM. The study also prospectively enrolled 30 pregnant women and interviewed them about their experiences delivering at home or at HUM. It was found that living further from the hospital, poverty and household hunger were associated with not having a facility-based childbirth. Primigravid women were more likely to have a facility-based childbirth. In 2019, Souza *et al* investigated the determinants of neonatal mortality in Foz do Iguassu in Brazil. The authors analyzed all neonatal deaths that occurred in Foz do Iguassu from 2012 to 2016. Birth and mortality data were extracted from two national governmental databases (SINASC and SIM). It was found that high rate of neonatal death in Foz do Iguassu is strongly associated with newborn characteristics and not associated with maternal socio-demographic characteristics.

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:

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

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:

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

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:

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

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:

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

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 P_t sequence and recover Z_t from present and past values of P_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:

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

Thus:

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

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.

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

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:

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

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

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

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 Panama 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(P, 2)
Date: 01/29/22 Time: 10:42
Sample: 1960 2019
Included observations: 58

Model	LogL	AIC*	BIC	HQ
(0,3)(0,0)	68.086970	-2.175413	-1.997788	-2.106224
(0,2)(0,0)	66.815596	-2.166055	-2.023956	-2.110704
(1,2)(0,0)	67.699439	-2.162050	-1.984425	-2.092861
(2,2)(0,0)	68.371989	-2.150758	-1.937609	-2.067732
(0,4)(0,0)	68.095536	-2.141225	-1.928076	-2.058199
(1,3)(0,0)	68.090023	-2.141035	-1.927886	-2.058009
(2,4)(0,0)	69.997278	-2.137837	-1.853638	-2.027136
(2,5)(0,0)	70.756340	-2.129529	-1.809805	-2.004990
(1,0)(0,0)	64.755713	-2.129507	-2.022933	-2.087994
(3,2)(0,0)	68.722340	-2.128357	-1.879682	-2.031493
(1,4)(0,0)	68.679471	-2.126878	-1.878204	-2.030015
(1,5)(0,0)	69.673832	-2.126684	-1.842485	-2.015983
(0,5)(0,0)	68.560011	-2.122759	-1.874085	-2.025895
(3,5)(0,0)	71.521460	-2.121430	-1.766181	-1.983053
(2,0)(0,0)	65.217834	-2.110960	-1.968860	-2.055609
(3,0)(0,0)	66.191823	-2.110063	-1.932438	-2.040875
(0,1)(0,0)	64.067275	-2.105768	-1.999193	-2.064255
(3,4)(0,0)	69.998999	-2.103414	-1.783690	-1.978875
(1,1)(0,0)	64.969091	-2.102382	-1.960283	-2.047032
(2,3)(0,0)	67.723856	-2.093926	-1.845252	-1.997062
(4,5)(0,0)	71.712699	-2.093541	-1.702768	-1.941327
(2,1)(0,0)	65.702192	-2.093179	-1.915555	-2.023991
(3,3)(0,0)	68.670470	-2.092085	-1.807886	-1.981384
(5,0)(0,0)	67.532918	-2.087342	-1.838668	-1.990478
(4,0)(0,0)	66.453837	-2.084615	-1.871466	-2.001589
(5,2)(0,0)	69.351684	-2.081093	-1.761369	-1.956554
(3,1)(0,0)	66.270409	-2.078290	-1.865141	-1.995264
(0,0)(0,0)	62.227536	-2.076812	-2.005762	-2.049136
(4,1)(0,0)	67.185337	-2.075356	-1.826682	-1.978493
(4,4)(0,0)	70.090735	-2.072094	-1.716846	-1.933718
(5,4)(0,0)	70.913188	-2.065972	-1.675198	-1.913758
(4,3)(0,0)	68.889869	-2.065168	-1.745444	-1.940629
(5,1)(0,0)	67.243552	-2.042881	-1.758682	-1.932180
(4,2)(0,0)	67.219214	-2.042042	-1.757843	-1.931341
(5,3)(0,0)	69.107136	-2.038177	-1.682928	-1.899801
(5,5)(0,0)	71.046186	-2.036075	-1.609777	-1.870023

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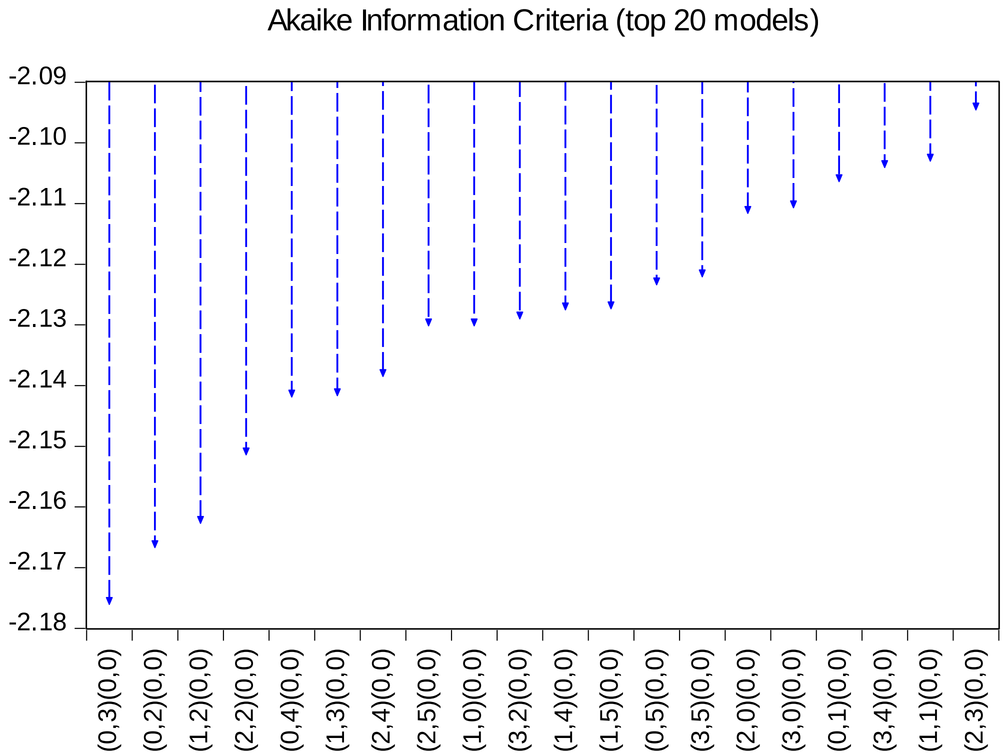
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

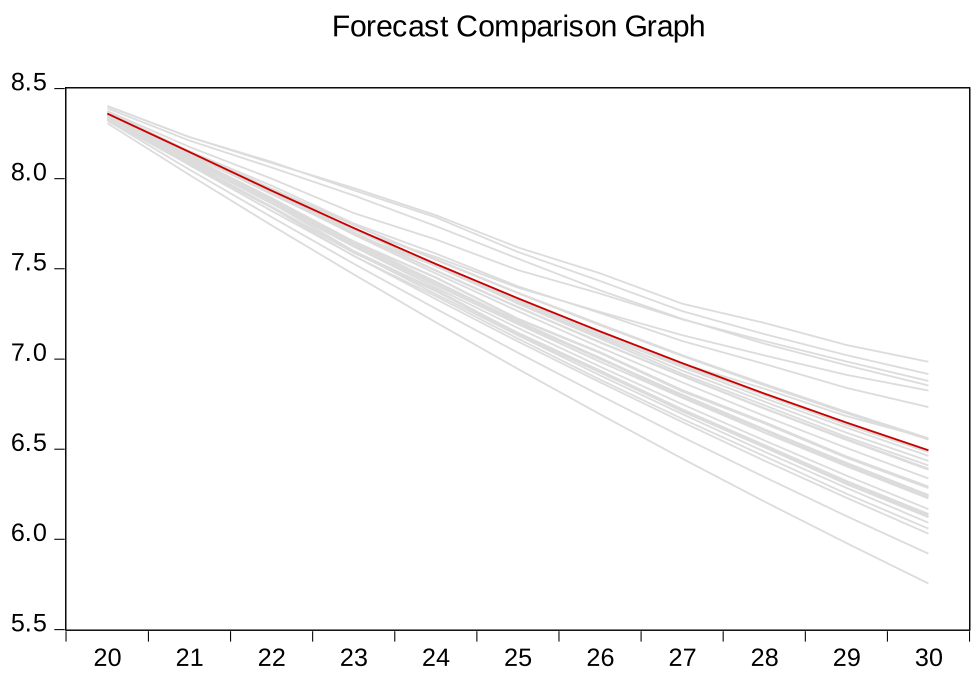


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (0,2,3) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (0,2,3) model.

IV. RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: D(P, 2)
Date: 01/29/22 Time: 10:42
Sample: 1960 2019
Included observations: 58
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (0,3)(0,0)
AIC value: -2.17541274732

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: D(P,2)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22 Time: 10:42
Sample: 1962 2019
Included observations: 58
Convergence achieved after 7 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007635	0.013081	0.583643	0.5619
MA(1)	-0.325184	0.135801	-2.394569	0.0202
MA(2)	0.363421	0.163974	2.216334	0.0310
MA(3)	0.210543	0.138351	1.521795	0.1340
SIGMASQ	0.005531	0.001173	4.713773	0.0000

R-squared	0.192475	Mean dependent var	0.006897
Adjusted R-squared	0.131530	S.D. dependent var	0.083481
S.E. of regression	0.077798	Akaike info criterion	-2.175413
Sum squared resid	0.320782	Schwarz criterion	-1.997788
Log likelihood	68.08697	Hannan-Quinn criter.	-2.106224
F-statistic	3.158160	Durbin-Watson stat	1.969870
Prob(F-statistic)	0.021135		

Inverted MA Roots	.34-.70i	.34+.70i	-.35

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	8.36049920509373
2021	8.146851140223279
2022	7.93270075435928
2023	7.726184870370208
2024	7.527303488256063
2025	7.336056608016845
2026	7.152444229652554
2027	6.97646635316319
2028	6.808122978548753
2029	6.647414105809241
2030	6.494339734944657

Table 5 clearly indicates that neonatal mortality will continue to drop throughout the forecast period to reach levels as low as 6 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

Launching of sustainable development goals in 2015 showed that countries across the globe were committed to addressing numerous social, cultural, economic, climatic, environmental and public health challenges to improve quality of life for both flora and fauna. The set SDG targets are viewed as ambitious particularly by developing countries who are struggling to solve existing challenges. However, it is important to mention that utilization of available resources accompanied by accountability will go a long way towards achieving set SDG targets by the end of 2030. In addition, use of early surveillance tools like time series forecasting techniques will inform policies, decisions and resource allocation. This study applies the ARIMA model to predict future trends of neonatal mortality rate for Panama and the findings indicate that neonatal mortality will continue to drop throughout the forecast period to reach levels as low as 6 deaths per 1000 live births by the end of 2030. Hence, we encourage authorities in Panama to address local factors which contribute to neonatal mortality such as accessibility, affordability and quality of maternal and neonatal healthcare services especially in marginalized regions of the country.

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