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Using Scientific Evidence Generated By the ARIMA Model to Urgently Respond to Numerous Factors Which Significantly Contribute to Neonatal Mortality in Peru

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***Abstract* - This study uses annual time series data on neonatal mortality rate (NMR) for Peru 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 study findings indicate that neonatal mortality will continue to fall to levels below 5 deaths per 1000 live births by the end of 2030. We encourage the Peruvian government to address local factors that influence neonatal mortality such as quality, accessibility and affordability of neonatal healthcare services in poverty stricken regions of the country.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Neonatal mortality is a persistent global health problem with 3 million neonatal deaths being reported each year (Dhaded *et al*. 2015; Lawn *et al*. 2008). At global level neonatal deaths are due to sepsis (36%), prematurity (28%) and birth asphyxia (23%) (Dhaded *et al.* 2015; Gizaw *et al*. 2014). High quality maternal and newborn care interventions have been shown to substantially reduce neonatal mortality (Rayne *et al.* 2015; Bhutta *et al.* 2014; Mason *et al*. 2014; Dickson *et al*. 2014). Lack of adequate resources and home deliveries have been found to be among the causes of mortality in low and middle income countries (Kumar *et al*. 2014; Manasyan *et al.* 2013). The objective of this study is to model and project future trends of neonatal mortality rate for Peru using the widely applied Box-Jenkins ARIMA model. ARIMA models are useful in modelling linear time series data (Nyoni, 2018; Box & Jenkins, 1970). The findings of this paper are expected to inform neonatal policies, decision making and allocation of resources to maternal and child health programs in the country. Furthermore, forecast results will detect abnormal trends of NMR and stimulate an early response to the national public health problem.

II. LITERATURE REVIEW

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 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. Boulos *et al*(2017) investigated the aetiology of severe bacterial infections in neonates. Researchers conducted a secondary retrospective analysis of a de-identified database from the Neonatal Intensive Care Unit (NICU) at Nos Petit Fre`res et Soeurs-St. Damien Hospital (NPFS-SDH). Records from 1292 neonates admitted to the NICU at NPFS-SDH in Port-au-Prince Haiti from 2013 to 2015 were reviewed. Sepsis accounted for 708 of 1292 (54.8%) of all admissions to the NICU. The most common organism cultured was Streptococcus agalactiae, followed by Klebsiella pneumoniae, Pseudomonas aeroginusa, Enterobacter aerogenes,

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Staphylococcus aureus and Proteus mirabillis.A prospective, population-based, observational study was carried out Dhaded *et al.* (2015) to examine risk factors for neonatal mortality in low-middle income countries. The Global Network's Maternal Newborn Health Registry was initiated in the seven sites in 2008. Registry administrators (RAs) attempt to identify and enroll all eligible women by 20 weeks gestation and collect basic health data, and outcomes after delivery and at 6 weeks post-partum. All study data were collected, reviewed, and edited by staff at each study site. The study findings indicated that Low birth weight and prematurity are among the strongest predictors of neonatal mortality. Other risk factors for neonatal deaths included male gender, multiple gestation and major congenital anomalies.

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:

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

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:

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

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:

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

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

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 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:

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

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.

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

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:

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

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

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

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 Peru 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.

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Evaluation of ARIMA Models

Criteria Table

Table 2: Criteria Table

Model Selection Criteria Table
Dependent Variable: DLOG(P, 2)
Date: 01/29/22 Time: 10:48
Sample: 1960 2019
Included observations: 58

Model	LogL	AIC*	BIC	HQ
(2,2)(0,0)	214.332952	-7.183895	-6.970746	-7.100869
(0,4)(0,0)	214.244208	-7.180835	-6.967685	-7.097809
(0,2)(0,0)	211.566632	-7.157470	-7.015371	-7.102119
(3,2)(0,0)	214.364166	-7.150488	-6.901814	-7.053625
(1,4)(0,0)	214.287511	-7.147845	-6.899171	-7.050982
(0,5)(0,0)	214.282592	-7.147676	-6.899001	-7.050812
(1,3)(0,0)	213.124268	-7.142216	-6.929067	-7.059190
(1,0)(0,0)	210.079195	-7.140662	-7.034087	-7.099149
(3,3)(0,0)	214.857900	-7.133031	-6.848832	-7.022330
(3,0)(0,0)	211.819285	-7.131699	-6.954075	-7.062511
(0,3)(0,0)	211.809915	-7.131376	-6.953752	-7.062188
(0,1)(0,0)	209.772912	-7.130100	-7.023526	-7.088587
(1,2)(0,0)	211.650158	-7.125868	-6.948243	-7.056679
(5,0)(0,0)	213.632252	-7.125250	-6.876576	-7.028386
(1,5)(0,0)	214.607789	-7.124407	-6.840207	-7.013705
(0,0)(0,0)	208.521323	-7.121425	-7.050375	-7.093750
(2,3)(0,0)	213.491802	-7.120407	-6.871733	-7.023543
(4,2)(0,0)	214.446104	-7.118831	-6.834632	-7.008130
(2,4)(0,0)	214.354377	-7.115668	-6.831469	-7.004967
(4,0)(0,0)	212.231312	-7.111425	-6.898275	-7.028399
(2,0)(0,0)	210.176866	-7.109547	-6.967448	-7.054196
(1,1)(0,0)	210.111319	-7.107287	-6.965187	-7.051936
(3,1)(0,0)	211.956697	-7.101955	-6.888806	-7.018929
(4,5)(0,0)	216.919628	-7.100677	-6.709903	-6.948463
(4,3)(0,0)	214.881645	-7.099367	-6.779643	-6.974828
(4,1)(0,0)	212.806630	-7.096780	-6.848106	-6.999917
(2,1)(0,0)	210.777636	-7.095781	-6.918156	-7.026592
(5,1)(0,0)	213.667518	-7.091983	-6.807784	-6.981282
(2,5)(0,0)	214.608725	-7.089956	-6.770232	-6.965417
(3,4)(0,0)	214.557584	-7.088193	-6.768469	-6.963654
(4,4)(0,0)	215.519796	-7.086890	-6.731641	-6.948513
(5,5)(0,0)	217.017788	-7.069579	-6.643280	-6.903527
(5,3)(0,0)	214.882413	-7.064911	-6.709662	-6.926534
(3,5)(0,0)	214.577664	-7.054402	-6.699153	-6.916026
(5,4)(0,0)	215.520781	-7.052441	-6.661667	-6.900226
(5,2)(0,0)	172.095636	-5.623987	-5.304264	-5.499449

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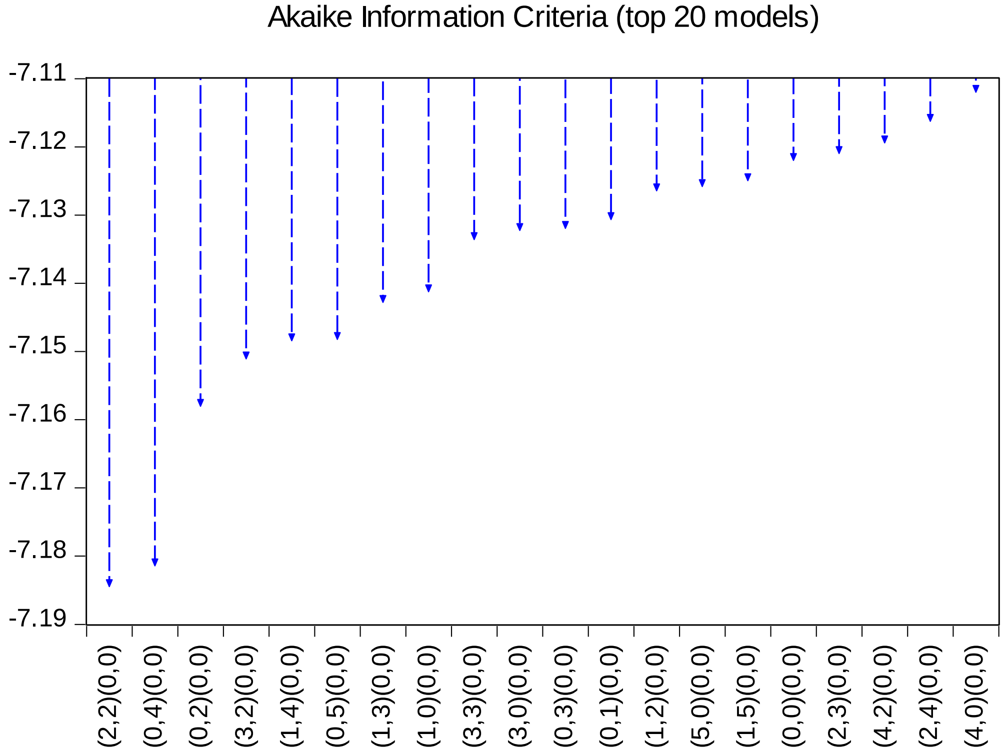
Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

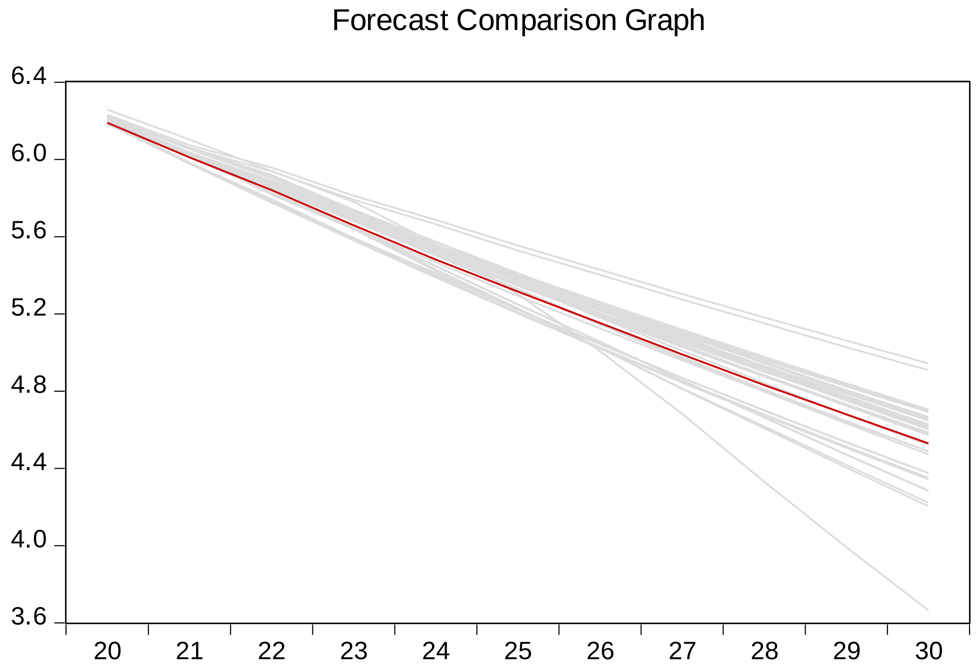


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (2,2,2) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the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

RESULTS

Summary of the Selected ARIMA () Model

Table 3: Summary of the Optimal Model

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(P, 2)
Date: 01/29/22 Time: 10:48
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: -7.18389489281

Main Results of the Selected ARIMA () Model

Table 4: Main Results of the Optimal Model

Dependent Variable: DLOG(P,2)
Method: ARMA Maximum Likelihood (BFGS)
Date: 01/29/22 Time: 10:48
Sample: 1962 2019
Included observations: 58
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000244	0.000945	-0.257729	0.7976
AR(1)	-0.120487	0.140756	-0.855998	0.3959
AR(2)	-0.579410	0.177359	-3.266885	0.0019
MA(1)	-0.126660	0.104746	-1.209209	0.2321
MA(2)	0.878885	0.120155	7.314606	0.0000
SIGMASQ	3.53E-05	5.85E-06	6.044156	0.0000

R-squared	0.199525	Mean dependent var	-0.000247
Adjusted R-squared	0.122556	S.D. dependent var	0.006701
S.E. of regression	0.006277	Akaike info criterion	-7.183895
Sum squared resid	0.002049	Schwarz criterion	-6.970746
Log likelihood	214.3330	Hannan-Quinn criter.	-7.100869
F-statistic	2.592289	Durbin-Watson stat	1.886077
Prob(F-statistic)	0.036232		

Inverted AR Roots	-.06+.76i	-.06-.76i
Inverted MA Roots	.06+.94i	.06-.94i

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	6.189617721122709
2021	6.010558919487586
2022	5.840374303278032
2023	5.658868464894225
2024	5.480604416315548
2025	5.314801071353213
2026	5.152385901018661
2027	4.989328634496229
2028	4.830968506745773
2029	4.678794683914127
2030	4.529654127894776

Table 2 clearly indicates that neonatal mortality will continue to fall to levels below 5 deaths per 1000 live births by the end of 2030.

V. POLICY IMPLICATION & CONCLUSION

The persistence of traditional problems in low and middle income countries is likely to hinder success of maternal and child health programs. Millions of people in various countries are suffering from effects of natural disasters, hunger, poverty and conflict. Policy makers must be innovative and should craft and implement strategies to effectively address local challenges that hinder progress towards achieving set targets of sustainable development goals by the end of 2030. Utilization of surveillance tools will inform policies and resource mobilization. In this study we applied the ARIMA model to forecast NMR and the findings indicate that neonatal mortality will continue to fall to levels below 5 deaths per 1000 live births by the end of 2030. We encourage the Peruvian government to address local factors that influence neonatal mortality such as quality, accessibility and affordability of neonatal healthcare services especially in poverty stricken regions of the country.

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