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

ISSN (online): 2581-3048
Volume 7, Issue 8, pp 390-397, August-2023
https://doi.org/10.47001/IRJIET/2023.708058

Implementing Evidence Based Neonatal Healthcare Strategies to Curb High Neonatal Mortality Rates in Pakistan

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***Abstract* - Pakistan has the third highest neonatal mortality rates in the world and is known for reporting the worst perinatal mortality rates in South Asia. This study uses annual time series data on neonatal mortality rate (NMR) for Pakistan 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 (3,1,0) model. ARIMA model predictions indicate that neonatal mortality will continue to decline but still remain very high throughout the out of sample period. It is therefore crucial for authorities in Pakistan to design neonatal health policies which are country specific and appropriate to tackle worrisome trends of neonatal mortality. In addition, it is very important for authorities to channel adequate resources particularly to primary health care facilities in the rural areas where the problem of neonatal deaths is huge. Special attention should be given to promotion of institutional deliveries, providing adequate medical supplies and availing funds to retain medical staff.**

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Low and middle income countries continue to report high under-five and neonatal mortality rates particularly Sub-Saharan African and South Asian countries. The 3rd sustainable development goal (SDG-3) focuses on ensuring good health for all at all ages. SDG-3 target 3.1 aims to ensure reduction of maternal and neonatal mortality rates to less than 70 maternal deaths per 100 000 live births and target 3.2aims to reduce neonatal mortality rate to at least 12 neonatal deaths per 1000 live births respectively (UNICEF, 2019; UNICEF, 2018). Pakistan is committed to the SDGs 2015-2030 and authorities developed a monitoring and evaluation strategy for the National Health vision 2016-2025 which is line with the sustainable development goals (NIPS & ICF, 2019). In 2015 Pakistan reported a neonatal mortality rate (NMR) of 44 per 1000 live births with rural areas reporting higher neonatal mortality rate (62 per 1000 live births) when compared to urban settings (38 per 1000 live births) (Lawn *et al*. 2016). The country has the third highest NMR in the world with 500 newborns dying on daily basis. In addition, the highest perinatal mortality rates in South Asia are reported by Pakistan (UNICEF, 2018; Basu & Mckeey, 2010). The leading causes of neonatal deaths were found to be birth asphyxia, prematurity, sepsis and congenital anomalies (UNICEF, 2018). The objective of this study is to model and forecast future trends of NMR for Pakistan using the popular Box-Jenkins ARIMA technique. This statistical and econometric model is very useful in modelling linear time series data (Nyoni, 2018; Box & Jenkins, 1970). The model is an important surveillance tool for use in public health programming that can inform policy, decision making and resource mobilization. Forecast results are expected to help in tracking Pakistan's progress towards achieving the set SDG-3 target 3.2 by 2030 and trigger implementation of appropriate neonatal interventions to control the problem of neonatal deaths across the country.

II. LITERATURE REVIEW

Previous studies that were done in Pakistan and Asia at large have examined factors influencing neonatal mortality in the Asian region. Das & Chakraborty (2021) examined the influence of both individual and community level factors on neonatal death in Bangladesh. The study utilized data from Bangladesh Demographic and Health Survey 2014. Bivariate analysis was used to examine the differentials in neonatal mortality by selected background variables of both levels. Multilevel logistic model confirmed that there exists clustering impact on neonatal death. A prospective, population-based observational study was carried out by Aziz *et al*. (2020)to compare pregnancy out- comes in Pakistan to other low-resource countries and explore factors that might help explain these differences. The research included all pregnant women and their pregnancy outcomes in defined

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geographic communities in six low-middle income countries (India, Pakistan, Democratic Republic of Congo, Guatemala, Kenya, and Zambia). Study staff enrolled women in early pregnancy and followed them up soon after delivery and at 42 days to ascertain delivery, neonatal, and maternal outcomes. The Pakistani pregnancy outcomes were found to be much worse than those in the other GN sites. Reasons for these poorer outcomes likely include that the Pakistani sites 'reproductive-aged women are largely poorly educated, under- nourished, anemic, and deliver a high percentage of preterm and low-birth weight babies in settings of often inadequate maternal and newborn care. In another study, Khan *et al.* (2020) assessed the extent to which maternal histories of newborn danger signs independently or combined with birth weight and/or gestational age (GA) can capture and/or predict post second day (age>48 hours) neonatal death. Prognostic multivariable models showed that maternally recalled danger signs, coupled to either birth weight or GA, can predict and capture post-second day neonatal death with high discrimination and sensitivity.A comparison of Pakistan's under-five mortality, neonatal mortality, and postnatal newborn care rates with those of other countries was performed by Ahmed et al. (2017). Neonatal mortality rates and postnatal newborn care rates from the Demographic and Health Surveys (DHSs) of nine low- and middle-income countries (LMIC) from Asia and Africa were analyzed. Pakistan's maternal, newborn, and child health (MNCH) policies and programs, which have been implemented in the country since 1990, were also analyzed. The results highlighted that postnatal newborn care in Pakistan was higher compared with the rest of countries, yet its neonatal mortality remained the worst.

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:

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

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:

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

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:

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

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:

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

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

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

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

Equation [4] can also be expressed as follows:

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

ISSN (online): 2581-3048
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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.

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:

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

Thus:

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

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.

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

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:

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

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

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

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 –

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Volume 7, Issue 8, pp 390-397, August-2023

https://doi.org/10.47001/IRJIET/2023.708058

Jenkins technique was proposed by Box & Jenkins (1970) and is widely used in many forecasting contexts, including the health sector. 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 Pakistan 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: 10:35
Sample: 1960 2019
Included observations: 59

Model	LogL	AIC*	BIC	HQ
(3,0)(0,0)	50.414817	-1.539485	-1.363423	-1.470758
(4,1)(0,0)	51.726769	-1.516162	-1.269674	-1.419943
(2,2)(0,0)	50.690079	-1.514918	-1.303643	-1.432445
(4,0)(0,0)	50.559987	-1.510508	-1.299233	-1.428035
(3,1)(0,0)	50.516154	-1.509022	-1.297747	-1.426549
(1,5)(0,0)	52.156843	-1.496842	-1.215142	-1.386878
(5,0)(0,0)	50.880354	-1.487470	-1.240982	-1.391251
(4,2)(0,0)	51.837304	-1.486010	-1.204310	-1.376046
(5,1)(0,0)	51.825300	-1.485603	-1.203903	-1.375639
(3,2)(0,0)	50.753770	-1.483179	-1.236691	-1.386960
(2,3)(0,0)	50.704013	-1.481492	-1.235004	-1.385273
(2,4)(0,0)	51.438905	-1.472505	-1.190805	-1.362541
(2,5)(0,0)	52.214975	-1.464914	-1.148002	-1.341205
(1,4)(0,0)	50.116944	-1.461591	-1.215104	-1.365373
(4,4)(0,0)	53.087237	-1.460584	-1.108459	-1.323129
(5,2)(0,0)	51.904421	-1.454387	-1.137475	-1.330677
(3,3)(0,0)	50.880355	-1.453571	-1.171871	-1.343607
(3,5)(0,0)	52.720795	-1.448163	-1.096038	-1.310707
(4,3)(0,0)	51.496721	-1.440567	-1.123654	-1.316857
(2,1)(0,0)	47.059453	-1.425744	-1.249682	-1.357017
(4,5)(0,0)	53.006819	-1.423960	-1.036622	-1.272759
(3,4)(0,0)	50.936156	-1.421565	-1.104652	-1.297855
(5,3)(0,0)	51.904605	-1.420495	-1.068370	-1.283040
(1,2)(0,0)	46.405870	-1.403589	-1.227526	-1.334861
(5,4)(0,0)	52.368603	-1.402326	-1.014988	-1.251125
(1,3)(0,0)	47.118888	-1.393861	-1.182586	-1.311387
(0,5)(0,0)	47.598127	-1.376208	-1.129720	-1.279989
(5,5)(0,0)	52.371744	-1.368534	-0.945984	-1.203587
(2,0)(0,0)	42.338663	-1.299616	-1.158766	-1.244634
(1,1)(0,0)	39.627418	-1.207709	-1.066859	-1.152727
(1,0)(0,0)	37.027013	-1.153458	-1.047821	-1.112221
(0,4)(0,0)	36.522677	-1.034667	-0.823392	-0.952194

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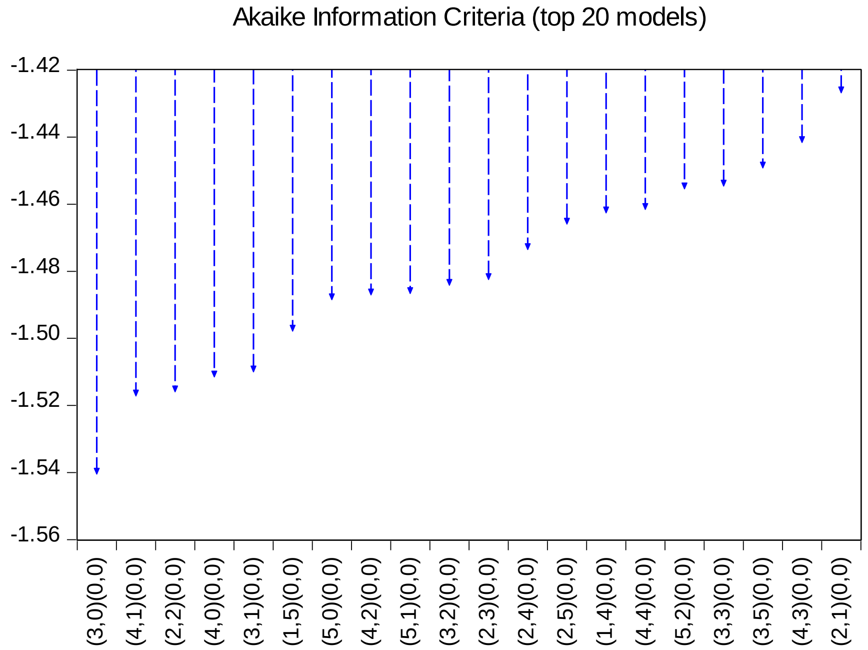
(0,3)(0,0)	31.955171	-0.913735	-0.737672	-0.845007
(0,2)(0,0)	22.858200	-0.639261	-0.498411	-0.584279
(0,1)(0,0)	2.873978	0.004272	0.109909	0.045509
(0,0)(0,0)	-25.100476	0.918660	0.989085	0.946151

Criteria Graph

Figure 1: Criteria Graph



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

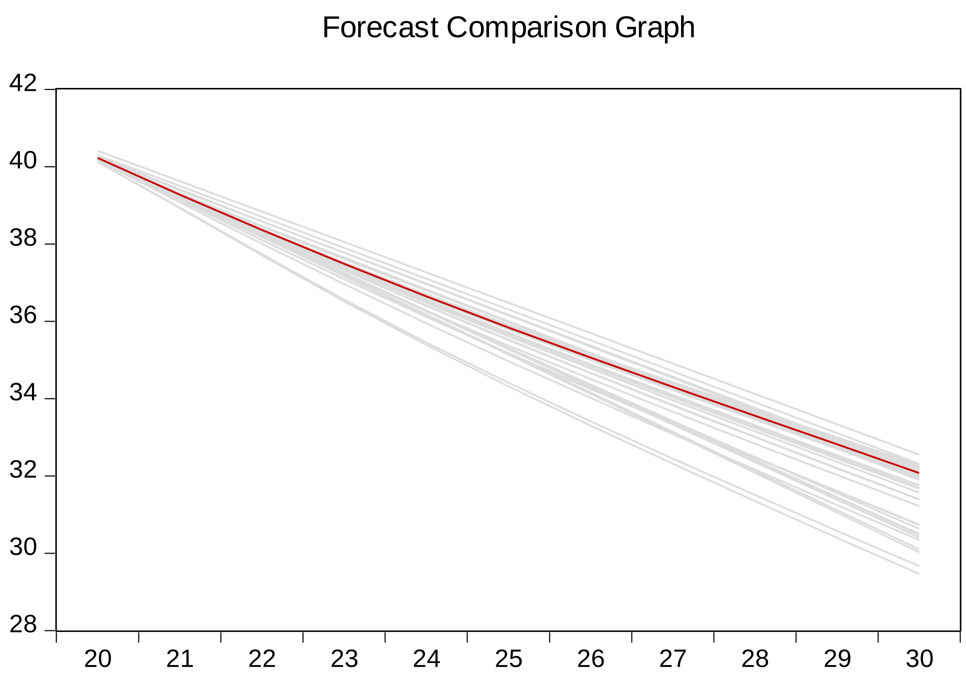


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Table 2 and Figure 1 indicate that the optimal model is the ARIMA (3,1,0) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model, the ARIMA (3,1,0) 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: 10:35
Sample: 1960 2019
Included observations: 59
Forecast length: 11

Number of estimated ARMA models: 36
Number of non-converged estimations: 0
Selected ARMA model: (3,0)(0,0)
AIC value: -1.53948532052

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: 10:35
Sample: 1961 2019
Included observations: 59
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.811139	0.102444	-7.917905	0.0000
AR(1)	1.146239	0.115949	9.885674	0.0000
AR(2)	0.244453	0.203862	1.199113	0.2357
AR(3)	-0.515748	0.105740	-4.877511	0.0000
SIGMASQ	0.009965	0.001941	5.132890	0.0000

R-squared	0.927321	Mean dependent var	-0.786441
Adjusted R-squared	0.921937	S.D. dependent var	0.373454
S.E. of regression	0.104342	Akaike info criterion	-1.539485
Sum squared resid	0.587913	Schwarz criterion	-1.363423
Log likelihood	50.41482	Hannan-Quinn criter.	-1.470758
F-statistic	172.2478	Durbin-Watson stat	2.126440
Prob(F-statistic)	0.000000		

Inverted AR Roots	.88-.25i	.88+.25i	-.61

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ARIMA () Model Forecast

Tabulated Out of Sample Forecasts

Table 5: Tabulated Out of Sample Forecasts

2020	40.22361814282766
2021	39.27430832498227
2022	38.36180302356778
2023	37.48592133073789
2024	36.64705366615583
2025	35.84058383453825
2026	35.06140931334999
2027	34.30235159928737
2028	33.55631587711646
2029	32.81604660328622
2030	32.07519513765532

Table 5 clearly indicates that neonatal mortality will continue to decline but still remain very high throughout the out of sample period.

V. POLICY IMPLICATION & CONCLUSION

Pakistan, a country in South Asia remains surrounded by numerous public health challenges which include a rise in new HIV infections, high numbers of maternal deaths and under five mortality. The country has the highest perinatal and neonatal mortality rates in South Asia. It is important for the policy-makers in Pakistan to utilize early surveillance tools such as time series forecasting techniques to predict likely future trends of neonatal mortality to inform neonatal policies, decisions and allocation of resources to the maternal and child health (MNCH) programs in the country. Hence in this study we apply the Box-Jenkins ARIMA approach to model and forecast NMR for Pakistan. The findings suggest that neonatal mortality will continue to decline but still remain very high throughout the out of sample period. It is therefore crucial for the authorities in Pakistan to design neonatal policies which are country specific and appropriate to tackle worrisome trends of neonatal mortality. It is very important for the authorities to channel adequate resources particularly to primary health care facilities in the rural areas where the problem of neonatal deaths is huge. Special attention should be given to promotion of institutional deliveries, providing adequate medical supplies and availing funds to retain medical staff.

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ISSN (online): 2581-3048
Volume 7, Issue 8, pp 390-397, August-2023
https://doi.org/10.47001/IRJIET/2023.708058

Citation of this Article:

Dr. Smartson. P. NYONI, Thabani NYONI, "Implementing Evidence Based Neonatal Healthcare Strategies to Curb High Neonatal Mortality Rates in Pakistan" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 8, pp 390-397, August 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.708058

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