

Identification of Neonatal Healthcare Solutions in Austria Using Empirical Evidence Generated By the ARIMA Model

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

¹ZICHIRE Project, University of Zimbabwe, Harare, Zimbabwe

²Independent Researcher & Health Economist, Harare, Zimbabwe

Abstract - Time series forecasting techniques continue to attract the attention of researchers globally. Their relevance in public health is well recognized as many researchers are using statistical, econometric and machine learning approaches to analyze linear and nonlinear data. This research paper uses annual time series data on neonatal mortality rate (NMR) for Austria 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 (5,1,4) model. The ARIMA model predictions indicate that NMR is likely to decline over the out-of-sample period. Therefore, the Austrian government must craft and implement neonatal policies to address causes of neonatal deaths so as to keep neonatal mortality under control.

Keywords: ARIMA, Forecasting, NMR.

I. INTRODUCTION

Neonatal mortality is defined as the death of a newborn within the first 28 days of life (Rajaratnam, 2010). It reflects the quality of healthcare services during the antenatal, delivery and postnatal periods (Fawole *et al.* 2011). The death of a child during the first year of life is referred to as an infant death. Austria's infant mortality has continued to decline over the past 3 decades. Infant mortality rate (IMR) declined from 11.2 per 1000 live births in 1985 to 4.7 per 1000 live births in 1997 (Waldhor *et al.* 2005). Several factors have been found to be associated with neonatal deaths and can be classified as maternal, newborn and health system related factors. In this paper we proposed the popular Box-Jenkins ARIMA technique to model and forecast future trends of neonatal mortality rate for Austria. This econometric and statistical model is suitable for analyzing linear time series data (Nyoni, 2018; Box & Jenkins, 1970). The results of the study are expected to detect abnormal future trends of NMR and help to keep neonatal mortality under control following implementation of timeous evidence based neonatal strategies.

II. LITERATURE REVIEW

Muin *et al.* (2021) conducted a population-based study on epidemiological characteristics of singleton antepartum stillbirth in Austria between January 2008 and December 2020. Data were derived from the validated Austrian Birth Registry. The study found that from January 2008 through December 2020, the antepartum stillbirth rate $\geq 20+0/40$ was 3.10, $\geq 22+0/40$ 3.14, and $\geq 24+0/40$ 2.83 per 1000 births in Austria. The highest incidence was recorded in the federal states of Vienna, Styria, and Lower and Upper Austria, contributing to 71.9% of all stillbirths in the country. Harpur *et al.* (2021) investigated trends in infant mortality rates (IMR) and stillbirth rates by socio-economic position (SEP) in Scotland, between 2000 and 2018, inclusive. Data for live births, infant deaths, and stillbirths between 2000 and 2018 were obtained from National Records of Scotland. Annual IMR and stillbirth rates were calculated and visualized for all of Scotland and when stratified by SEP. Negative binomial regression models were used to estimate the association between SEP and infant mortality and stillbirth events, and to assess for break points in trends over time. The study revealed that IMR fell from 5.7 to 3.2 deaths per 1000 live births between 2000 and 2018, with no change in trend identified. Stillbirth rates were relatively static between 2000 and 2008 but experienced accelerated reduction from 2009 onwards. When stratified by SEP, inequalities in IMR and stillbirth rates persisted throughout the study and were greatest amongst the sub-group of post-neonates. 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 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. Waldhör *et al.* (2005) outlined the trends in infant mortality, based on 1,654,519 individual birth records, in Austria since 1984. The infant mortality rate dropped rapidly from about 12 per 1000 live births in 1985 to 4.6 per 1000 live births during the last two years of our study (2001/02). Infant mortality rates stratified by cause of death showed somewhat differing trends. In particular, the number of deaths due to peripart problems decreased as the result of improvements in obstetrics and neonatology, but in 1995 a change in the definition of live birth led to a rise of about 20% in the stillbirth rate.

III. METHODOLOGY

The Autoregressive (AR) Model

A process A_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:

$$A_t = \phi_1 A_{t-1} + \phi_2 A_{t-2} + \phi_3 A_{t-3} + \dots + \phi_p A_{t-p} + Z_t \dots \dots \dots [1]$$

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

$$Z_t = \phi(B)A_t \dots \dots \dots [2]$$

Where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3 - \dots - \phi_p B^p$

The 1st order AR (p) process, AR (1) may be expressed as shown below:

$$A_t = \phi A_{t-1} + Z_t \dots \dots \dots [3]$$

Given $\phi = 1$, then equation [3] becomes a random walk model. When $|\phi| > 1$, then the series is referred to as explosive, and thus non-stationary. Generally, most time series are explosive. In the case where $|\phi| < 1$, the series is said to be stationary and therefore its ACF (autocorrelation function) decreases exponentially.

The Moving Average (MA) Model

A process is referred to as a moving average process of order q , MA (q) if it is a weighted sum of the last random shocks, that is:

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

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

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

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

Equation [4] can also be expressed as follows:

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

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 A_t sequence and recover Z_t from present and past values of A_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:

$$\phi(B)A_t = \theta(B)Z_t \dots \dots \dots [7]$$

Thus:

$$A_t(1 - \phi_1B - \phi_2B^2 - \dots - \phi_pB^p) = Z_t(1 + \theta_1B + \theta_2B^2 + \dots + \theta_qB^q) \dots \dots \dots [8]$$

where $\phi(B)$ 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. 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:

$$\phi(B)(1 - B)^d A_t = \theta(B)Z_t \dots \dots \dots [9]$$

Therefore, in the case of modeling and forecasting NMR, equation [9] can be written as follows:

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

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. In this paper, hinged on this technique; the researcher will use automatic ARIMA modeling for estimating equation [9].

Data Issues

This study is based on annual NMR in Austria 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 1: Criteria Table

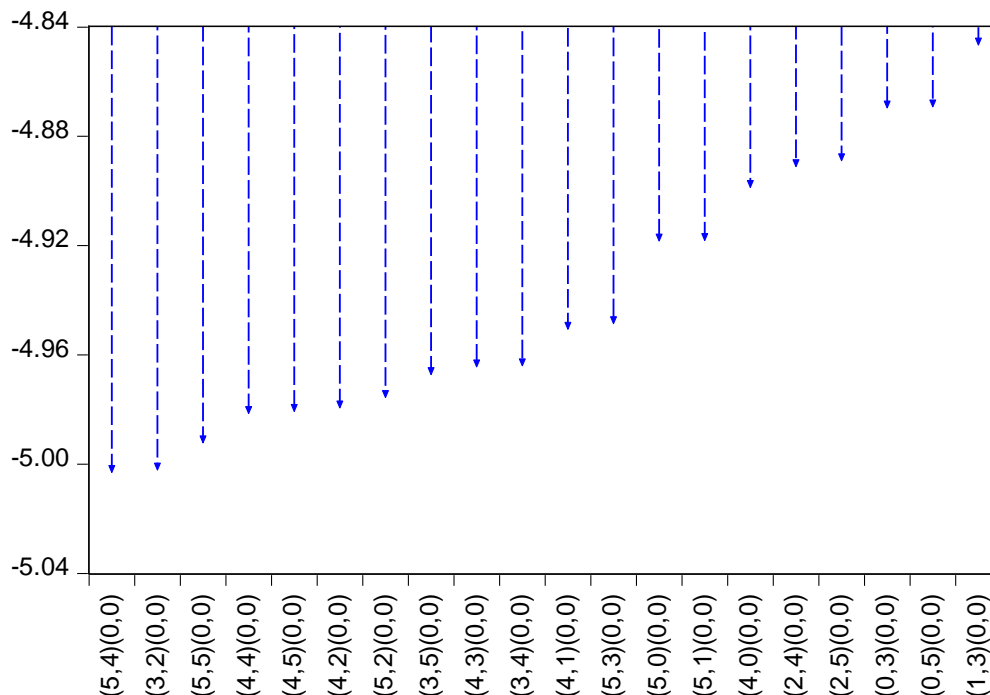
Model Selection Criteria Table		
Dependent Variable: DLOG(A)		
Date: 01/22/22 Time: 12:04		

Sample: 1960 2019				
Included observations: 59				
Model	LogL	AIC*	BIC	HQ
(5,4)(0,0)	158.545639	-5.001547	-4.614210	-4.850346
(3,2)(0,0)	154.521406	-5.000726	-4.754238	-4.904507
(5,5)(0,0)	159.228015	-4.990780	-4.568230	-4.825834
(4,4)(0,0)	156.910247	-4.980008	-4.627883	-4.842553
(4,5)(0,0)	157.886402	-4.979200	-4.591863	-4.827999
(4,2)(0,0)	154.848731	-4.977923	-4.696223	-4.867959
(5,2)(0,0)	155.737492	-4.974152	-4.657240	-4.850442
(3,5)(0,0)	156.489676	-4.965752	-4.613627	-4.828296
(4,3)(0,0)	155.405472	-4.962897	-4.645985	-4.839188
(3,4)(0,0)	155.396010	-4.962577	-4.645664	-4.838867
(4,1)(0,0)	153.001648	-4.949208	-4.702721	-4.852990
(5,3)(0,0)	155.938910	-4.947082	-4.594957	-4.809626
(5,0)(0,0)	152.047985	-4.916881	-4.670393	-4.820662
(5,1)(0,0)	153.042632	-4.916699	-4.634999	-4.806735
(4,0)(0,0)	150.467874	-4.897216	-4.685941	-4.814743
(2,4)(0,0)	152.244762	-4.889653	-4.607953	-4.779689
(2,5)(0,0)	153.179972	-4.887457	-4.570544	-4.763747
(0,3)(0,0)	148.610886	-4.868166	-4.692103	-4.799438
(0,5)(0,0)	150.599846	-4.867791	-4.621304	-4.771573
(1,3)(0,0)	148.931408	-4.845132	-4.633857	-4.762659

Criteria Graph

Figure 1: Criteria Graph

Akaike Information Criteria (top 20 models)



Forecast Comparison Graph

Figure 2: Forecast Comparison Graph

Forecast Comparison Graph

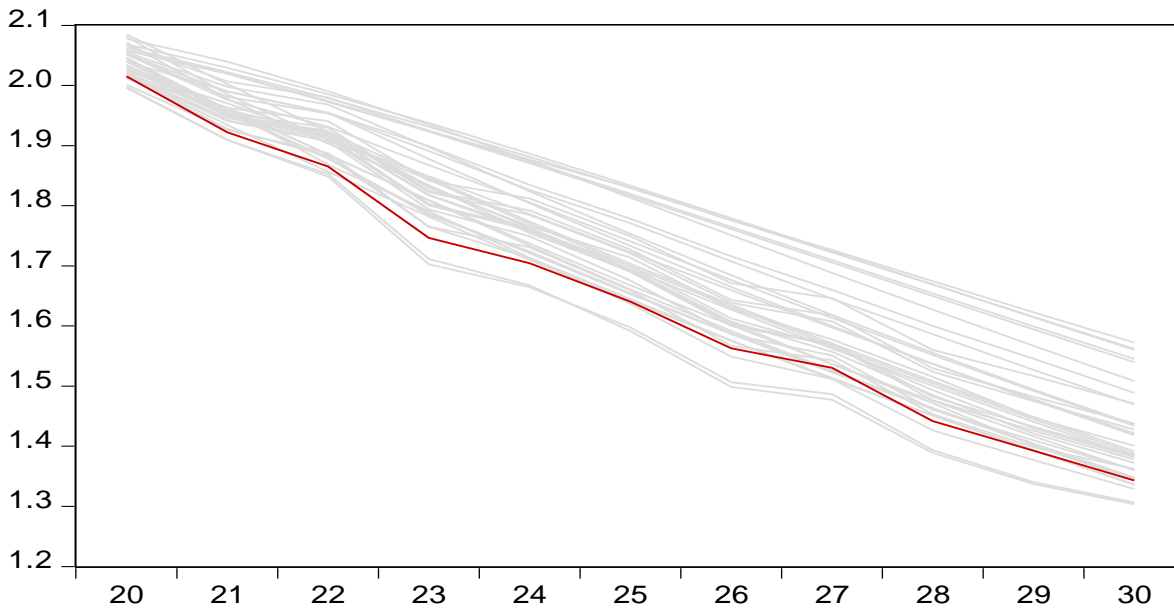


Table 1 and Figure 1 indicate that the optimal model is the ARIMA (5, 1, 4) model. Figure 2 is a combined forecast comparison graph showing the out-of-sample forecasts of the top 25 models evaluated based on the AIC criterion. The red line shows the forecast line graph of the optimal model.

IV. RESULTS

ARIMA (5,1,4) Model Forecast

Tabulated Out of Sample Forecasts

Table 2: Tabulated Out of Sample Forecasts

Year	Forecasts
2020	2.014897
2021	1.922196
2022	1.865324
2023	1.746325
2024	1.704429
2025	1.640429
2026	1.562942
2027	1.530415
2028	1.441869
2029	1.392539
2030	1.343148

In line with previous studies such as Waldhor *et al.* (2005) Table 2 clearly indicates that there is likely to be a decline in NMR in Austria over the period 2020 to 2030, *ceteris paribus*.

V. POLICY IMPLICATION & CONCLUSION

According to the global estimates developing countries bear the largest burden of under-five and neonatal mortality rates with Sub-Saharan Africa and South Asian nations reporting the highest numbers. There has been tremendous progress made by first world countries in controlling under-five and neonatal mortality, however neonatal mortality still remains a public health problem. This paper applies the ARIMA model to predict future trends of NMR for Austria and we established a downward trajectory over the next decade. Therefore, the Austrian government must craft and implement neonatal policies to address causes of neonatal deaths so as to keep neonatal mortality under control.

REFERENCES

- [1] Box, D. E., and Jenkins, G. M. (1970). *Time Series Analysis, Forecasting and Control*, Holden Day, London.
- [2] Nyoni, T. (2018). *Box-Jenkins ARIMA Approach to Predicting net FDI Inflows in Zimbabwe*, University Library of Munich, MPRA Paper No. 87737.
- [3] Rajaratnam J. K., Marcus J. R., and Flaxman A. D (2010). Neonatal, post neonatal, childhood, and under-5 mortality for 187 countries, 1970–2010: a systematic analysis of progress towards millennium development goal 4. *Lancet*, 375: 1988–2008.
- [4] Fawole A. O., Shah A., Tongo O., Dara K., El-Ladan A. M, Umezulike A. C, Alu F. E (2011). Determinants of perinatal mortality in Nigeria. *Int J Gynaecol Obstet*, 114 (1):37–42
- [5] Waldhör T., Vutuc C., Haidinger G., Martina Mittlböck M., Kirchner L., and Wald M (2005). Trends in infant mortality in Austria between 1984 and 2002, *Wien Klin Wochenschr Publishers* 117/15–16: 548–553.

Citation of this Article:

Dr. Smartson. P. NYONI, Thabani NYONI, “Identification of Neonatal Healthcare Solutions in Austria Using Empirical Evidence Generated By the ARIMA Model” Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 8, pp 196-201, August 2023. Article DOI <https://doi.org/10.47001/IRJIET/2023.708025>
