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

ISSN (online): 2581-3048

Volume 5, Issue 3, pp 662-666, March-2021

https://doi.org/10.47001/IRJIET/2021.503115

Forecasting Infant Mortality Rate in Burundi Using Artificial Neural Networks

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***Abstract* - In this study, the ANN approach was applied to analyze infant mortality rate (IMR) in Burundi. The employed annual data covers the period 1964-2020 and the out-of-sample period ranges over the period 2021-2030. The residuals and forecast evaluation criteria (Error, MSE and MAE) of the applied model indicate that the model is stable in forecasting IMR in Burundi. The applied ANN (12,12,1) model predicted that over the next 10 years infant mortality rate will be around 38/1000 live births per year. Therefore the government should prioritize retention of skilled health labor force and capacitating primary health facilities and district hospitals with medical supplies, reliable ambulance services and neonatal & maternity equipment. This ought to be done in line with the suggested policy directions.**

Keywords: ANN, Forecasting, infant mortality rate.

I. INTRODUCTION

Time series forecasting techniques have been adopted in various fields such as public health, finance, economics, environment and hydrology (Song et al, 2017; Song et al, 2016; Zhou et al, 2016; Sirigasatien et al, 2016;Omar et al, 2016; Qiu & Song, 2015;Zhang et al, 2015;Wu et al, 2015; Liu et al, 2012; Araujo et al, 2011;). These approaches are classified into statistical and machine learning methods (Zhao et al, 2020; Nyoni et al, 2020; Panch et al, 2018). The widely used statistical model is the Autoregressive Integrated Moving average (ARIMA) model which is used for forecasting linear time series (Nyoni & Nyoni, 2020; Zhou et al, 2018). The ARIMA model was proposed by Box and Jenkins in the 1970s. If the model is assigned to capture seasonality it becomes the SARIMA model. In the ARIMA (p, d, q) model, p & q represents the nonseasonal autoregressive and moving average components and d represents the degree of regular differencing. For the SARIMA (p,d,q) (P, D, Q)s, P & Q represents the seasonal autoregressive and moving average parts, D represents the degree of seasonal differencing and S is the length of the seasonal periods (Nyoni & Nyoni, 2019 a & b). The procedure of ARIMA model building involves model identification, parameter estimation and diagnostic checking. Machine learning methods are a component of artificial intelligence and are very useful for modeling nonlinear time series (Zhou et al, 2018). The artificial neural network (ANN) model is the widely used ML algorithm in time series forecasting problems (Zhang, 2003; Kishan, 1997; Patterson, 1995). Nowadays some researchers are applying the hybrid models such as ANN-SARIMA model (Yolcu et al, 2013; Khashei & Bijari, 2012; Zhou et al, 2014). In this paper we aim to model and predict infant mortality rate in Burundi. The results of the study are envisioned to reveal future trends of infant mortality rate and help in the evaluation of maternal and child health intervention programs in the country.

II. LITERATURE REVIEW

Nyoni & Nyoni (2020) modelled and forecasted infant deaths in Zimbabwe using ARIMA model. The study utilized annual time series data on total infant deaths in Zimbabwe from 1960 to 2018. The best model based on AIC was the ARIMA (1, 2, 5) model. The study findings indicated that the number of infant deaths per year, over the out-of-sample period, would follow a downward trajectory. In a related study, Nyoni & Nyoni (2020) used monthly time series data on neonatal deaths cases at Chitungwiza Central Hospital (CCH) from January 2013 to December 2018; to forecast neonatal deaths over the period January 2019 to December 2020 using the Box-Jenkins SARIMA approach. The parsimonious model was found to be the SARIMA (0, 0, 3) (2, 0, 0)12 model and its predictions indicate slow but steady decrease in neonatal deaths at CCH. Khan et al (2019) modelled and forecasted infant mortality rates of Asian countries in the perspective of GDP. Secondary data of IMR and GDP (PPP) from 1980 to 2015 was analyzed and forecast was done from 2016 to 2025. AR (1) was found to be suitable for all the countries except Japan and Nepal for which ARIMA (1, 1, 1) model was appropriate based on FMSE and FRMSE.

Akinwande et al (2016) Analyzed Infant and Child (Under-five) Mortality in Zaria using a regression Analysis Approach. The study was carried out using secondary data from Ahmadu Bello University Teaching Hospital, Zaria, on infant and child (under-five) mortality and delivery rates. Findings from the study showed that both infant and child mortality rates have a

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direct relationship with delivery rates. The correlation analysis result showed that there is a very strong and positive relationship between mortality and delivery rates. The study revealed that infant and child mortality rates will continue to decrease if there can be improvement in the factors under study.

III. METHODOLOGY

The Artificial Neural Network (ANN), which we intend to apply in this study; is a data processing system consisting of a huge number of simple and highly interconnected processing elements resembling a biological neural system. It has the capability of learning from any data-set to describe the nonlinear and interaction effects with great accuracy. No strict rules exist for the determination of the ANN structure hence the study applies the popular ANN (12, 12, 1) model based on the hyperbolic tangent activation function. This paper applies the Artificial Neural Network (ANN) approach in predicting infant mortality rates in Burundi.

Data Issues

This study is based on annual infant mortality rates in Burundi for the period 1964 – 2020. The out-of-sample forecast covers the period 2021 to 2030. Infact mortality rate, which is simply a proxy for infant deaths; for the purposes of this study, is defined as the number of infants dying before reaching one year of age, per 1000 live births in a given year. All the data employed in this paper was gathered from the World Bank.

IV. FINDINGS OF THE STUDY

ANN Model Summary

Table 1: ANN model summary

Variable	V
Observations	45 (After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	12
Hidden Layer Neurons	12
Output Layer Neurons	1
Activation Function	Hyperbolic Tangent Function
Back Propagation Learning:	
Learning Rate	0.005
Momentum	0.05
Criteria:	
Error	0.021558
MSE	1.673099
MAE	1.036509

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Residual Analysis for the Applied Model

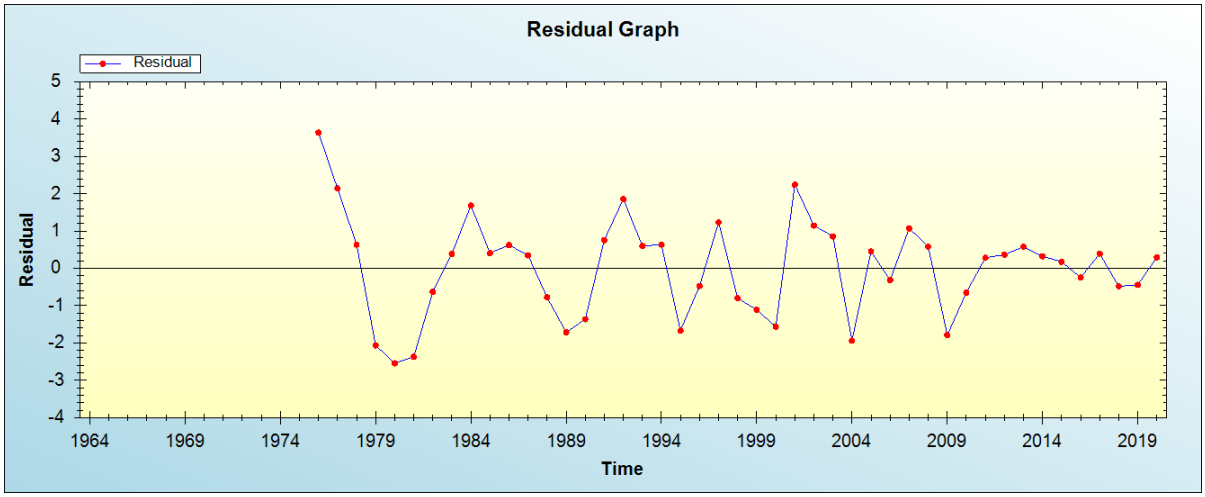

Figure 1: Residual analysis

In-sample Forecast for V

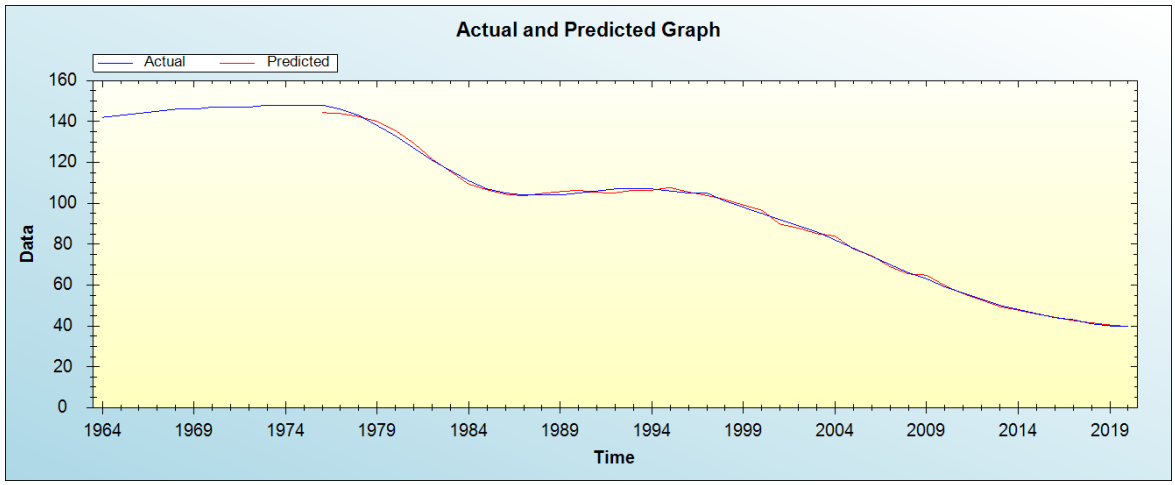

Figure 2: In-sample forecast for the V series

Out-of-Sample Forecast for V: Actual and Forecasted Graph

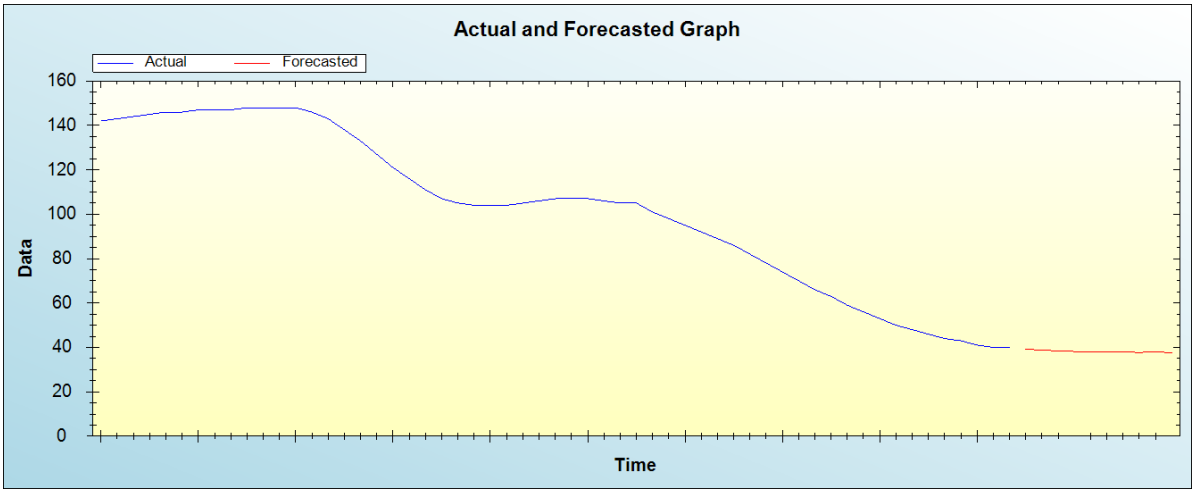

Figure 3: Out-of-sample forecast for V: actual and forecasted graph

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Out-of-Sample Forecast for V: Forecasts only

Table 3: Tabulated out-of-sample forecasts

Year	Forecasts
2021	39.2121
2022	38.7791
2023	38.4532
2024	38.1697
2025	37.9010
2026	37.9455
2027	37.9013
2028	37.7351
2029	37.8978
2030	37.6992

The main results of the study are shown in table 1. It is clear that the model is stable as confirmed by evaluation criterion as well as the residual plot of the model shown in figure 1. It is projected that infant mortality in Burundi is likely to remain around 38/1000 live births per year over the next decade.

V. CONCLUSION AND POLICY RECOMMENDATIONS

Preventing infant mortality remains one of the main objectives of the health ministry in Burundi. The government remains committed to ending preventable deaths infants in the country. The study used annual data to analyze the trends of infant mortality in Burundi. The applied model is the ANN model. In order to make sure that infant mortality in the country significantly declines, the government of Burundi ought to consider the following policy suggestions:

i. The government should continue to encourage mothers to breast-feed their babies adequately.

ii. There is need for all child-bearing women to be vaccinated against common illnesses.

iii. There is need to prevent birth defects in Burundi.

iv. The government of Burundi should address preterm birth, low birth-weight and their outcomes.

v. The government of Burundi should also ensure adequate access to pre-pregnancy and prenatal care.

vi. There is need to educate, especially, mothers on the importance of creating a safe infant sleep environment in the country.

vii. Healthcare providers in Burundi need to use newborn screening activities in order to detect hidden conditions.

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Citation of this Article:

Dr. Smartson. P. NYONI, Thabani NYONI, "Forecasting Infant Mortality Rate in Burundi Using Artificial Neural Networks" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 5, Issue 3, pp 662-666, March 2021. Article DOI https://doi.org/10.47001/IRJIET/2021.503115

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