

Prediction of Infant Mortality Rate in Namibia Using Artificial Neural Networks

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Abstract - In this research article, the ANN approach was applied to analyze infant mortality rate in Namibia. The employed annual data covers the period 1967-2020 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 infant mortality rate in Namibia. The results of the study indicate that infant mortality will slightly decline over the next 10 years. The government of Namibia is encouraged to allocate more resources to the health sector in order to reduce infant mortality in the country. We specifically advise the government to put into consider the suggested 7-fold policy directions.

Keywords: ANN, Forecasting, Infant mortality rate.

I. INTRODUCTION

Public health surveillance is a vital way to continuously collect, analyze, interpret and disseminate health information for prevention and control of conditions or health related problems (Weng et al, 2017; Zhang et al, 2014). The purpose of surveillance is identify abnormal patterns of diseases or health events so as to implement control measures. Time series forecasting techniques have been applied in medicine as a surveillance tool. Time series methods project or predict epidemiological behaviors by modeling historical surveillance data (Zhao et al, 2020; Nyoni et al, 2020; Zhang et al, 2014). Different forecasting models have been utilized to predict epidemic incidence in previous studies (Gonzalez-Parra et al, 2009; Chadwick et al, 2006; Farrington et al, 2003; Spaeder & Fackler, 2012). The use of time series analysis in public health is an under-utilized tool that can assist in effective health programs, planning, delivery of health services and improved emergency preparedness action (Camilla et al, 2018). Accurate and reliable forecasts are key in order prevent and control epidemic incidences (Balasubramanian & Ravindran, 1979). Time series forecasting techniques can be classified into two categories (1) statistical and (2) machine learning methods. Statistical methods include Autoregressive integrated moving average (ARIMA) and exponential smoothing models whereas machine learning methods constituted by artificial neural networks, Bayesian networks, decision trees, K nearest neighbors and the support vector machine (Zhao et al, 2020; Nyoni et al, 2020; Weng et al, 2017; Zhang et al, 2014). ARIMA models are the widely used statistical models in time series forecasting problems (Pai & Lin, 2005; Zhang, 2003). The ARIMA model was proposed by Box and Jenkins in the 1970s. The model is derived from three basic time series models: Autoregressive (AR) process, moving average (MA) process and the Autoregressive moving average process (ARMA) (Nyoni & Nyoni, 2019 a & b; Zhang et al, 2014). The ARIMA model is a combination of the AR and MA processes.

Stationarity of time series is the prerequisite for ARIMA model building. The ARIMA model is represented in the form ARIMA (p, d, q) where p and q represent the non-seasonal autoregressive and moving average components, d represents the degree of non-seasonal differencing. Nowadays machine learning based time series models are being successfully applied in the prediction of epidemic incidences (Chang & Li, 2011). Artificial neural networks especially the multilayer perceptron have general popularity in forecasting infectious disease incidence and prevalence. The support vector machine (SVM) was proposed by Vapnik in 1990. The algorithm is based on the statistical learning theory (Thissen et al, 2003). The main objective of this technique is to construct an optimal hyper plane or linear decision boundary through non-linear mapping of input data X to a higher dimensional feature space H. The training process is equivalent to solving a linearly constrained quadratic optimization problem. In this paper, the objective is to predict infant mortality in Namibia using the Multilayer Perceptron (MLP), the ANN (12, 12, 1) model. The results of this study are expected to highlight future trends of infant mortality in Namibia. Therefore this will facilitate planning and health service delivery with the aim of reducing infant mortality in the country.

II. 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 Namibia.

Data Issues

This study is based on annual infant mortality rates in Namibia for the period 1967 – 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.

III. FINDINGS OF THE STUDY

ANN Model Summary

Table 1: ANN model summary

Variable	G
Observations	42 (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	0.032681
MSE	0.403809
MAE	0.480108

Residual Analysis for the Applied Model

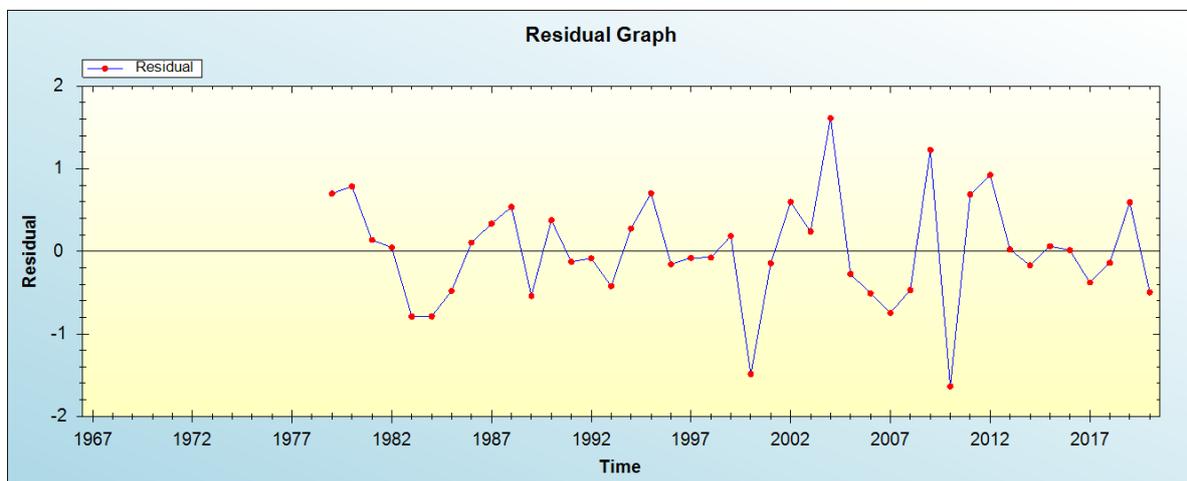


Figure 1: Residual analysis

In-sample Forecast for G

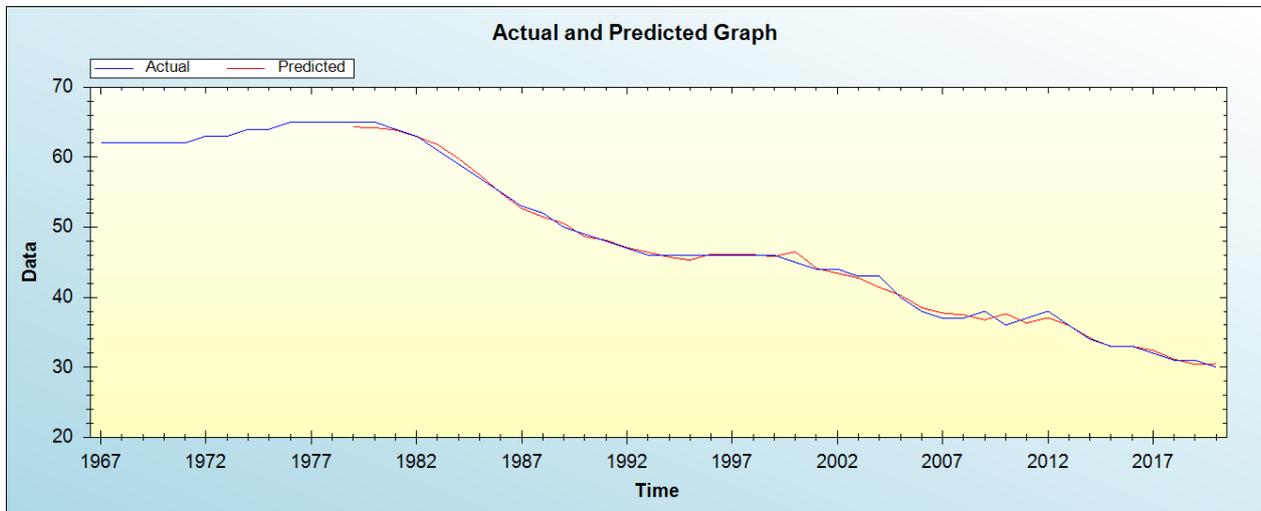


Figure 2: In-sample forecast for the G series

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

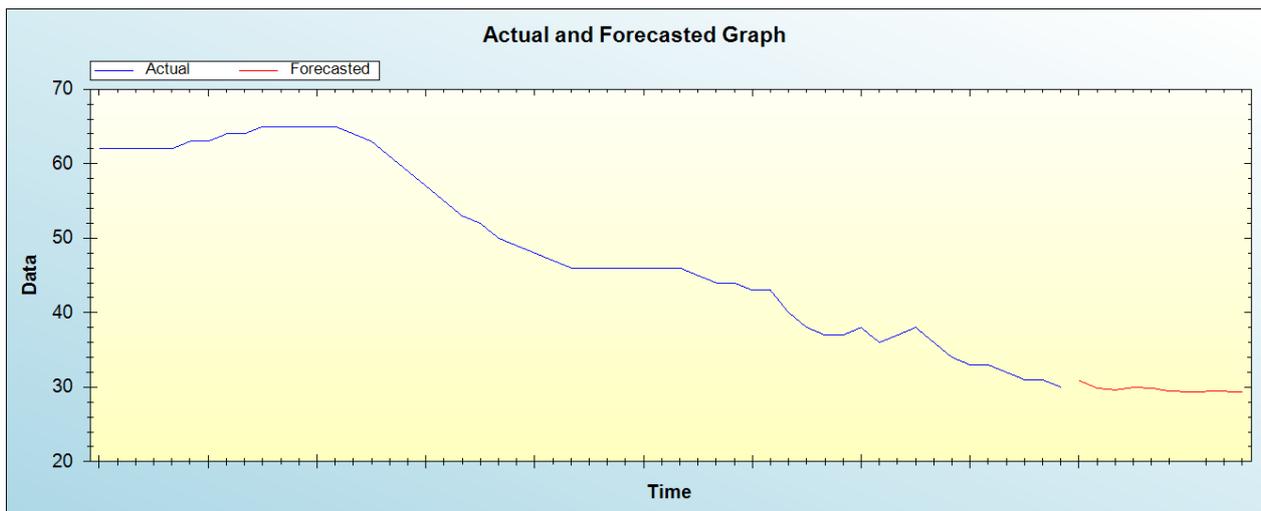


Figure 3: Out-of-sample forecast for G: actual and forecasted graph

Out-of-Sample Forecast for G: Forecasts only

Table 3: Tabulated out-of-sample forecasts

Year	Forecasts
2021	30.9177
2022	29.8604
2023	29.6263
2024	29.9519
2025	29.8832
2026	29.4595
2027	29.3861
2028	29.4113
2029	29.4387
2030	29.3217

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 Namibia is likely to slightly decline as shown in table 3 above.

V. CONCLUSION AND POLICY RECOMMENDATIONS

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

- i. The Namibian government should continue to encourage mothers to breast-feed their babies adequately.
- ii. There is need for all Namibian child-bearing women to be vaccinated against common illnesses.
- iii. There is need to prevent birth defects in Namibia.
- iv. The government of Namibia should address preterm birth, low birth-weight and their outcomes.
- v. The government of Namibia 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 Namibia need to use newborn screening activities in order to detect hidden conditions.

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