

Forecasting Infant Mortality Rate in Sudan Using the Multilayer Perceptron Neural Network

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Abstract - In this research article, the ANN approach was applied to analyze infant mortality rate in Sudan. The employed annual data covers the period 1960-2020 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 Sudan. The ANN (12, 12, 1) model projections suggest that infant mortality will be around 40/1000 live births per annum over the next 10 years in Sudan. The government is encouraged to intensify maternal and child health surveillance and control programs amongst other measures in order to curb infant mortality in Sudan. This can be done by adopting the suggested 7-fold policy recommendations.

Keywords: ANN, Forecasting, Infant mortality rate.

I. INTRODUCTION

Artificial intelligence (AI) has become popular over the last decade and is being driven by a variety of high profile applications in autonomous vehicles, intelligent robots, image and speech recognition, automatic translations, and in the field of medicine (Makridakis, 2017). Machine learning is part of AI and can be utilized to improve predictive accuracy in time series forecasting (Robson et al 2017; Salaken et al, 2017; Voyant et al, 2017; Zhang & Suganthan, 2016; Deng, 2014, Hamzacebi et al, 2009; Zhang et al, 1998). There are several machine learning (ML) techniques which are used in time series forecasting problems namely artificial neural networks (ANNs), K nearest neighbors (KNN), support vector machine, decision trees and Bayesian networks (Ahmed et al, 2010; Hastie et al, 2009; Alpaydin, 2004). The objective of machine learning methods is the same as that of statistical techniques (Makadris et al, 2018). The idea behind both techniques is to improve forecasting accuracy by minimizing a loss function typically the sum of squared errors. The technique of minimizing the loss function defines the type of method used for forecasting. ML methods utilize nonlinear algorithms whereas statistical ones use linear processes (Zhao et al, 2020, Makadris et al, 2018). ML methods have gained popularity over time. They are used in forecasting financial time series, macroeconomic variables, accounting balance sheet information and health indicators in the field of public health (Wang & Wang, 2017; Hamid & Habib, 2014; Kock & Terasvirta, 2016; Gabor & Dorgo, 2017; Marr, 2016). Artificial neural networks (ANNs) are widely used in time series forecasting. There are different types of neural networks namely the multilayer perceptron (MLP), Radial basis function (RBF), Generalized regression neural network (GRNN) and recurrent neural network (RNN). The multilayer perceptron is composed of 3 layers neurons are input, hidden and output nodes. The layers are connected by connection weights (Zhao et al, 2020, Makridakis, 2018; Kawushik & Sahi, 2018; Yan et al, 2018; Fojnica et al, 2016; Zhang, 2003). The neural network framework is feed forward neural network type. K nearest neighbor regression is a non-parametric regression method basing its forecasts on a similarity measure, the Euclidean distance between the points used for training and testing the method. Given N points, the method picks the closest K training data points and sets the prediction as the average of the target output values for these points (Makridakis et al, 2018; Weng et al, 2017). The support vector machine (SVM) was proposed by Vapnik and his co-workers in 1990. The support vector regression process (SVR) identifies an optimal hyperplane or linear decision boundary which is closest to all the data points (Weng et al, 2017) whereas the support vector classifier constructs an optimal hyperplane that separates the two classes with a maximum margin after nonlinear mapping of input data into a higher dimension feature space. In this paper we aim to model and forecast infant mortality rate in Sudan using the MLP ie ANN (12, 12, 1) model. The results of the study are envisioned to reveal future trends of IMR and help in the decision process in order to reduce infant mortality in Sudan.

II. METHODOLOGY

The Artificial Neural Network (ANN) is merely 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 dataset 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 Sudan.

Data Issues

This study is based on annual infant mortality rates in Sudan for the period 1960 – 2020. The out-of-sample forecast covers the period 2021 to 2030. In fact 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 | A |
| Observations | 49 (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 | 0.014795 |
| MSE | 0.294307 |
| MAE | 0.4283131 |

Residual Analysis for the Applied Model

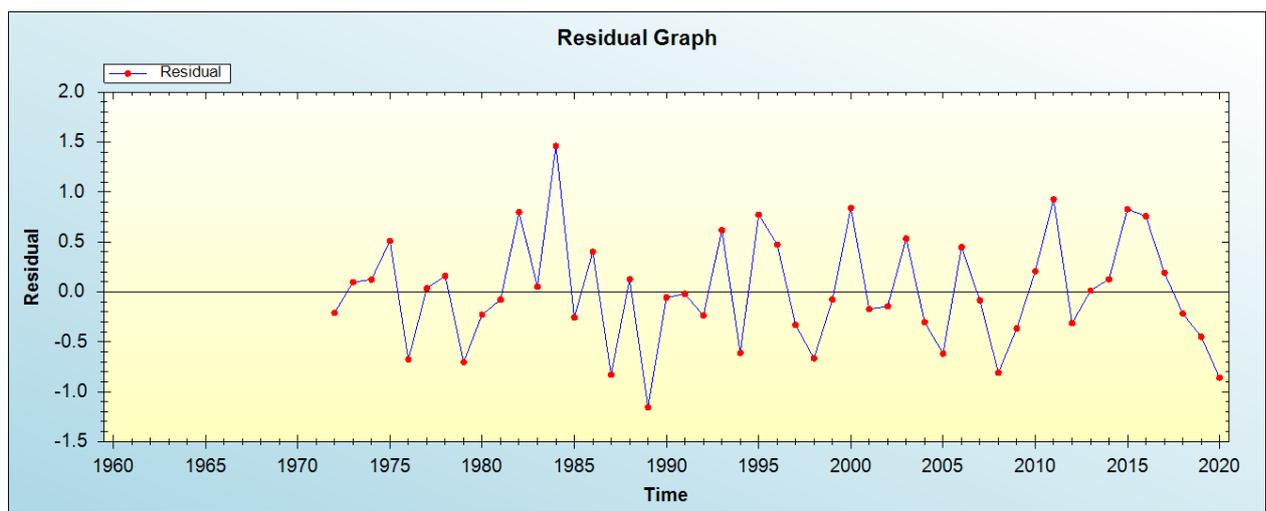


Figure 1: Residual analysis

In-sample Forecast for A

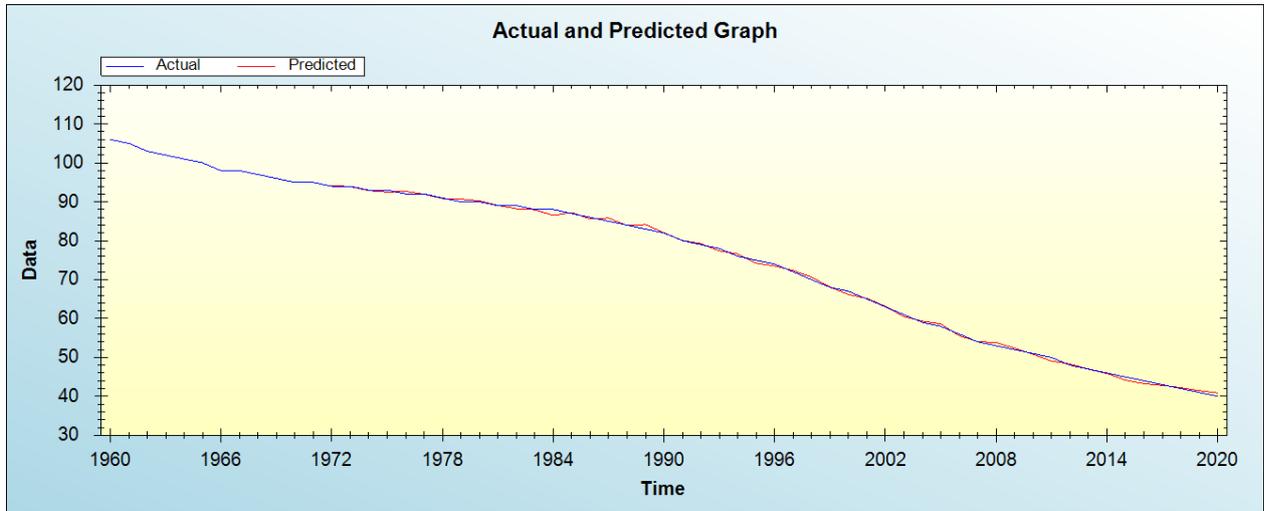


Figure 2: In-sample forecast for the A series

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

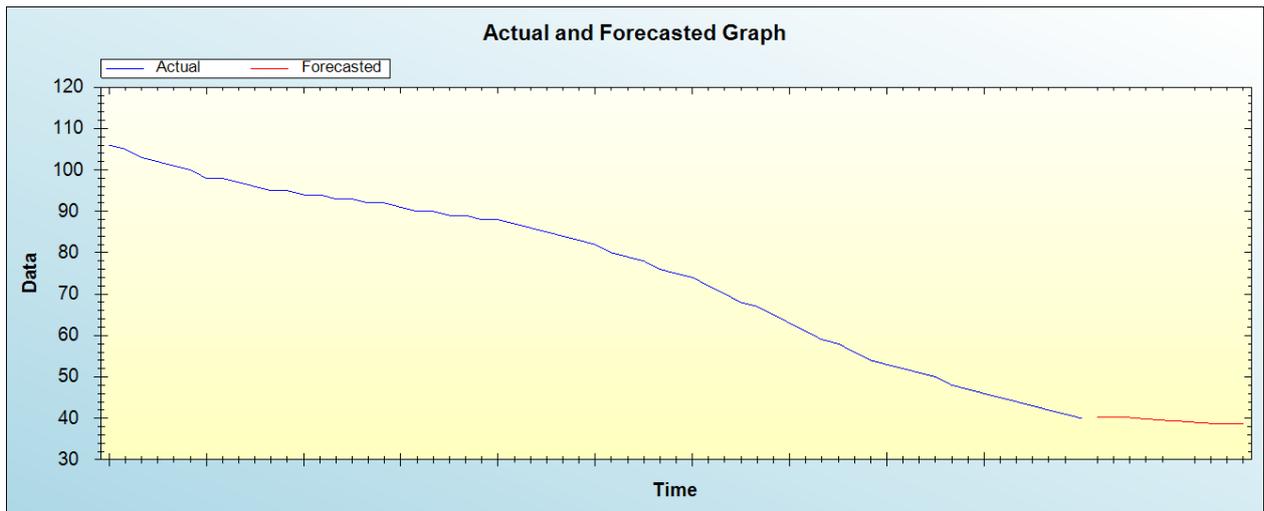


Figure 3: Out-of-sample forecast for A: actual and forecasted graph

Out-of-Sample Forecast for A: Forecasts only

Table 3: Tabulated out-of-sample forecasts

| Year | Forecasts |
|------|-----------|
| 2021 | 40.3686 |
| 2022 | 40.3291 |
| 2023 | 40.1703 |
| 2024 | 39.8307 |
| 2025 | 39.5135 |
| 2026 | 39.3197 |
| 2027 | 39.0256 |
| 2028 | 38.7640 |
| 2029 | 38.6631 |
| 2030 | 38.6177 |

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 Sudan is likely to remain around 40/1000 live births per year over the next decade.

IV. CONCLUSION AND POLICY RECOMMENDATIONS

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

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

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