TB Program Success Story in Togo: Evidence from the Multilayer Peceptron Neural Network

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Abstract - **Modeling and forecasting TB incidence is necessary in order to inform policy and stimulate an appropriate national response to the epidemic. In this research article, the ANN approach was applied to analyze TB incidence in Togo. The employed annual data covers the period 2000-2018 and the out-of-sample period 2019-2023. The residuals and forecast evaluation criteria (Error, MSE and MAE) of the applied model indicate that the model is stable in forecasting TB incidence in Togo. The model predicts that the incidence of TB will low, close to 30 cases per 100 000/year over the period 2019-2023.The government is encouraged to continue on this desirable path by strengthening TB/HIV collaboration.**

Keywords: ANN, Forecasting, TB incidence.

I. INTRODUCTION

Tuberculosis (TB) is an important public health problem internationally with approximately 33% of the World's population being infected with TB (WHO, 2019; Singh, 2019; Nyoni & Nyoni 2019a & b). According to WHO, in 2015 10.4 million people got infected with TB and more than 1.5 million people died from TB. More than 95% of TB deaths occur in low and middle income countries (Kabunga et al, 2020) TB disease is caused by mycobacterium Tuberculosis (MTB) and it affects mainly the lungs. Other organs that may be affected include liver, kidney, spleen, meninges, pericardium, brain and the bones. Togo's National TB program aims to detect and treat all sputum positive cases early in order to stop the transmission of the infectious disease among communities. The government is committed to the global strategy to ''End TB'' by 2035 (WHO, 2014) by improving access to high quality TB services, high political commitment and the engagement of the private sector in the provision of quality TB services. The program also aims to ensure screening of all TB contacts using the symptom screening tool. Early identification of cases will not only reduce community spread but will also reduce morbidity and mortality from TB. TB diagnosis in the program plays a critical role in the identification of positive cases. History of exposure, presence of TB symptoms, physical examination and confirmatory laboratory tests are key in the diagnosis of the disease. Sputum samples are sent to the laboratory for microscopy, Gene-X-pert machine analysis, culture and drug sensitivity testing. The chest x-ray is very important in the radiological diagnosis of pulmonary TB. The presence of cavitary lesions, lung infiltrates and pleural effusion constitute some of the radiological features of pulmonary TB. Tests which are used in the diagnosis of extra pulmonary TB include tissue biopsy for histological examination, ultrasonography and CT scan, and microbiological and chemistry analysis of abdominal fluid and cerebrospinal fluid.

In this paper the researchers apply the artificial neural network model, ANN (9,12,1) model, to model and forecast annual TB incidence in Togo. The findings from this piece of work will reveal the future trends of TB incidence thereby facilitating early planning and an appropriate response to the TB epidemic.

II. LITERATURE REVIEW

Internationally there are several empirical studies on TB incidence. Vinh et al (2018) modelled TB dynamics with presence of hyper susceptible individuals for Ho Chi Minh City (HCMC), China from 1996 to 2015. The study applied a simple mathematical model using known prevalence of hyper susceptible individuals in the population. The results showed that TB transmission in HCMC has been declining among people without HIV. For hyper susceptible individuals the model suggested that the risk of a new active TB infection occurring is significantly higher than the risk of relapsed active TB, while this is not the case for people without hyper susceptibility.

Patowary et al (2015) developed a SARIMA model to forecast TB detection rate in the Dibrugarh District of Assam, India. The study analyzed data covering the period 2001 -2011.The study found out that the SARIMA $(0,0,0) (1,1,0)_4$ model was suitable

for the given data. Wang et al (2017) applied the SARIMA and SARIMA-NAR hybrid model to model and forecast monthly TB incidence in China using data covering the period January 2007 to March 2016. The study revealed that the hybrid model was an effective method to fit the linear and nonlinear patterns of time series data and it is helpful in the prevention and control of TB. Mao Q et al (2018) developed a forecasting model for the incidence of TB in China. The study focused on monthly TB incidence from January 2004 to December 2015. The best model was the SARIMA $(1,0,1)$ $(0,1,1)_{12}$. The study concludes that there is a seasonal pattern of TB incidence in China and the SARIMA model was a useful tool for monitoring epidemics. Nyoni & Nyoni (2019a) developed a SARIMA model to predict the monthly TB incidence at Zengeza clinic in Chitungwiza, Zimbabwe. The study utilized data covering the period January 2013 to December 2018. The best model SARIMA $(2,0,2)$ $(1,0,1)_{12}$ predicted that TB notifications would decline over the out of sample period. In another study Nyoni &Nyoni (2019b) developed a SARIMA model to project TB notifications at Silobela District Hospital in Zimbabwe. The best model SARIMA $(1,0,1)$ $(0,1,1)_{12}$ projected that monthly TB notifications would decline over the out of sample period.

III. METHOD

The Artificial Neural Network (ANN) is a data processing system consisting of a large number of simple and highly interconnected processing elements resembling a biological neural system. It has the unique capability of learning from an experimental or real data set to describe the nonlinear and interaction effects with great accuracy. ANN-based curve fitting technique is one of the most employed artificial intelligence methods that are used for forecasting and prediction purpose. It consists of basically 3 layers i.e., input layer, hidden layer, and output layer, the present work includes the number of years as input layer and the annual TB incidence in Togo as output data for the network. In this paper, our ANN is based on the hyperbolic tangent function.

Data Issues

This study is based on TB incidences (referred to as G series in this study) in Togo. The annual data covers the period 2000-2018 while the out-of-sample forecast covers the period 2019-2023. All the data employed in this research paper was gathered from the World Bank online database.

IV. FINDINGS OF THE STUDY

DESCRIPTIVE STATISTICS

Table 1: Descriptive statistics

Mean	Median	Minimum	Maximum
62.053	64.000	36.000	78.000
Std. Dev.	C.V.	Skewness	Ex. Kurtosis
12.968	0.20898	-0.43540	-0.92966
5% Perc.	95% Perc.	IQ range	Missing obs.
Undefined	78.000	22.000	0

ANN MODEL SUMMARY FOR TB INCIDENCE (new cases per 100 000 population/year) IN TOGO

Table 2: ANN model summary

Variable	G
Observations	10(After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	9
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	0.013498
MSE	0.099196
MAE	0.279136

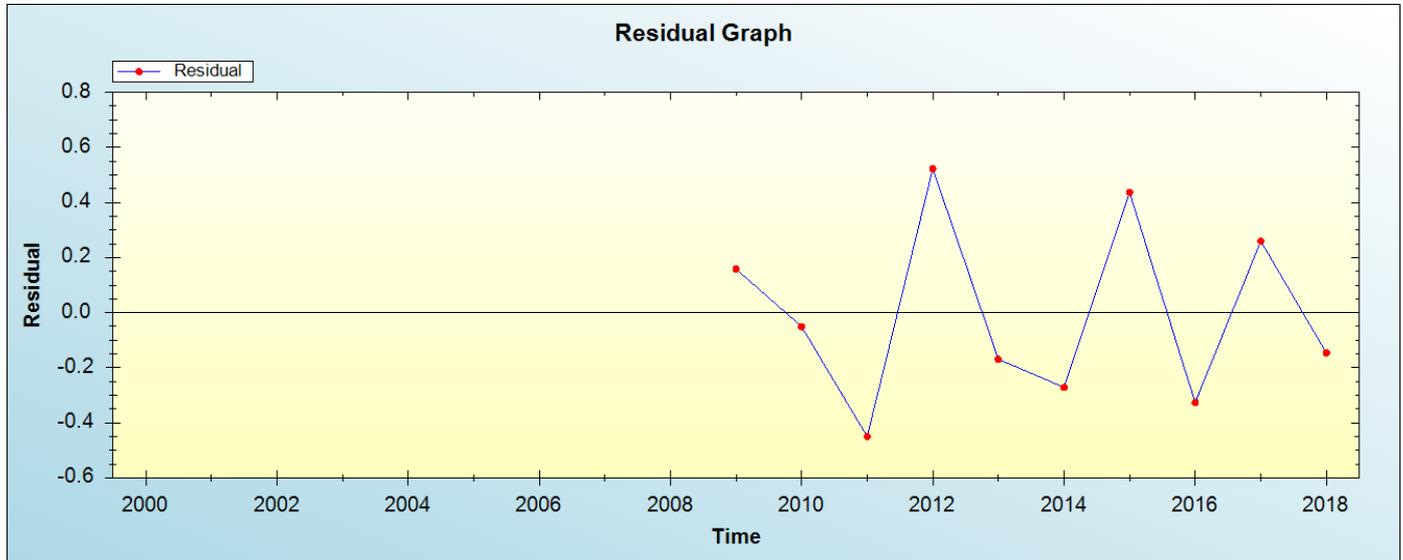*Residual Analysis for the ANN model*

Figure 1: Residual analysis

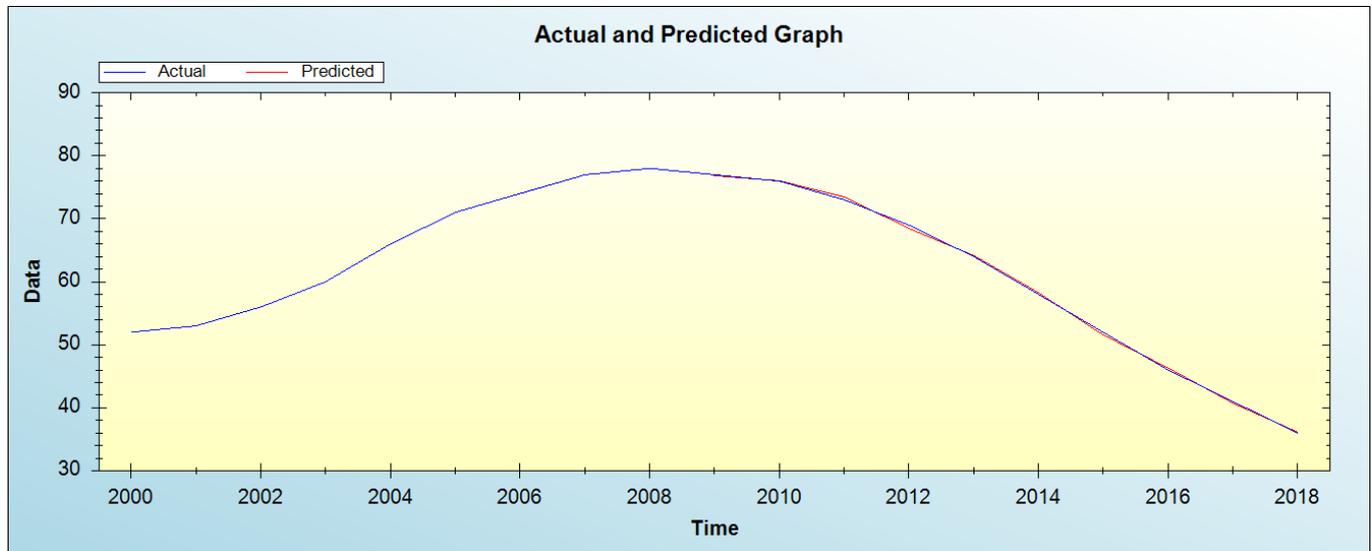*In-sample Forecast for G*

Figure 2: In-sample forecast for the G series

Figure 2 shows the in-sample forecast for G series.

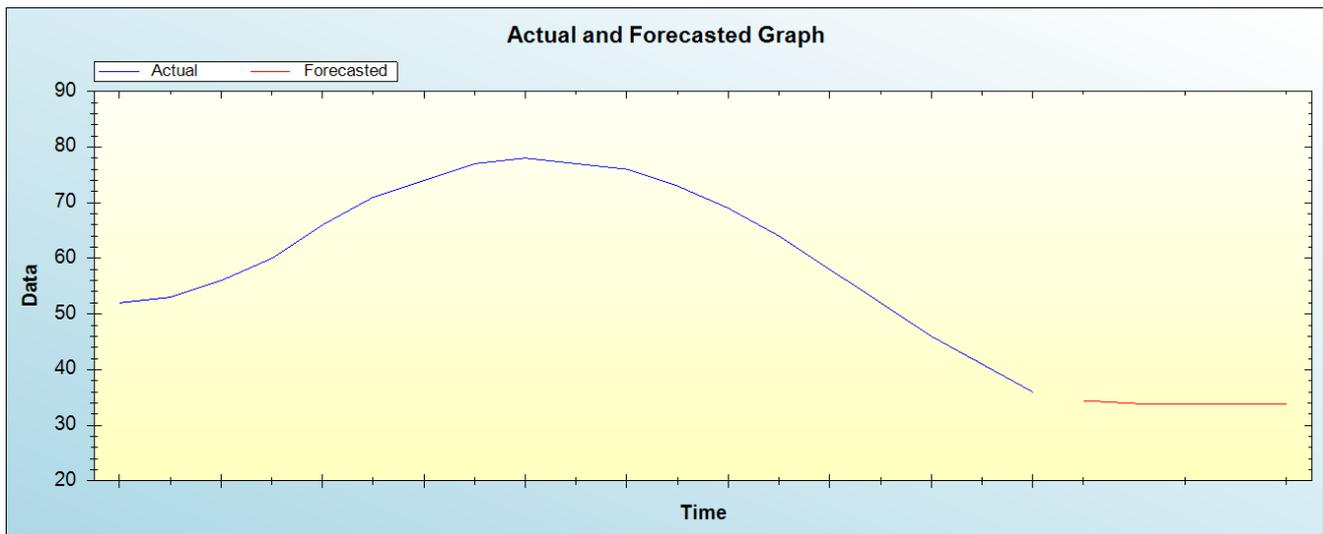*Out-of-Sample Forecast for G: Actual and Forecasted Graph*

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
2019	34.4385
2020	33.9227
2021	33.7506
2022	33.7585
2023	33.8012

Table 1 shows that over the study period 2000-2018 the minimum and maximum TB incidence was 36 and 78 cases per 100 000 population/year respectively. The applied data is negatively skewed   and with an excess kurtosis value of -0. 92966. The residual graph and model evaluation criteria indicate that the model is stable and suitable for forecasting TB incidence in Togo. Figure 2 shows that the applied ANN (9,12,1) model for TB incidence in Togo simulates the observed data very well. The model predicts that the incidence of TB will be low at a constant level of around 34 cases per 100 000 population/year throughout the period 2019-2023.

V. CONCLUSION & RECOMMENDATIONS

Togo has performed very well in its fight against the TB epidemic. The government implemented robust measures and desirable outputs were seen over the period 2008-2018 where the country recorded a downward trend in the incidence of TB. The model predictions clearly indicate that the incidence of TB will be close to 30 cases per 100 000 population/year signifying the government's success in curbing new TB infections. The authorities in Togo should continue strengthening TB/HIV collaboration in order to maintain this desired outcome.

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