Forecasting Art Coverage in Kenya Using the Multilayer Perceptron Neural Network

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Abstract - **In this research article, the ANN approach was applied to analyze ART coverage in Kenya. The employed annual data covers the period 2000-2018 and the out-of-sample period ranges over the 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 ART coverage in Kenya. The ANN (9,12,1) model projections suggests that the country is likely record a decline in ART coverage over the period 2019-2023. Therefore the government is encouraged to intensify demand creation for HIV testing and ART services and allocate more resources to TB/HIV program collaboration amongst other strategies.**

Keywords: ANN, ART coverage, Forecasting.

I. INTRODUCTION

According to Ministry of Health (MOH) Kenya, 2014, the HIV prevalence in Kenya was at 6% with 1.6million people living with HIV. The 2014 Kenya HIV estimates showed that a total of 101,560 new infections were reported. 15.2% of new adult HIV infections occurred among men who have sex with men (MSM) and prisoners and 14.1% among sex-workers. In 2013 about 58,465 people died of AIDS related diseases compared to 167,000 in 2003 (MOH Kenya, 2015). Cumulative 1.1million children children have been orphaned by HIV and AIDS (MOH Kenya, 2014). The Kenyan government is committed to the provision of ART to all people living with HIV. The country has made significant progress in increasing access to HIV care and treatment through collaboration with implementing and development partners. By end of 2014 the country had achieved an ART coverage of about 55% among adults above 15 years and 53% for children 0-14 years. The ART program aims to identify and treat HIV and TB cases early in all age groups including pregnant and breastfeeding mothers (NASCOP, 2014). There is evident TB/HIV collaboration in the country. The programmatic reports reveal that there is over 95% TB screening among all people living with HIV although reporting on the use of Ionized preventive therapy is poor (MOH Kenya, 2015). Access to ART has been found to be higher in females than males, lower among young compared with the elderly people and among those living in poverty (Cleary et al, 2010; Tromp et al, 2014; Loubiere, 2009; Makwiza et al, 2009). Stigma and discrimination as well as incomplete or incorrect information about HIV and treatment are associated with lower ART use. In addition to that, development of drug resistant HIV and TB as a result of poor adherence complicates HIV treatment and leads to undesirable treatment outcomes (Mooney, 2017; WHO, 2015).

In this study we choose to apply the artificial neural network, ANN model to predict ART coverage in Kenya. The model consists of 3 layers; input, hidden and output layers connected by acyclic links called connection weights. It is biologically inspired and mimics the function of the human brain. The model is self-adaptive in nature and is able to analyze complex data (Fojnica et al, 2016; Zhang, 2003; Yan et al, 2019). The results of the study will reveal the ART coverage trends over the period 2019-2023 and acts as useful tool to assess the impact of HIV care and treatment programs in the country.

II. LITERATURE REVIEW

Young et al (2017) investigated HIV associated mortality in the era of ART scale up in Nairobi, Kenya. HIV seropositivity in cadavers measured at the two largest mortuaries in Nairobi was used to estimate HIV prevalence in adult deaths .Model based estimates of the HIV infected and uninfected population for Nairobi were used to calculate a standardized mortality ratio and population attributable fraction for mortality among the infected versus uninfected population. Monte Carlo simulation was used to assess sensitivity to epidemiological assumptions. The study results indicated that 73.6% of adult people living with HIV receive antiretroviral drugs in Nairobi .Their risk of death is four fold greater than the uninfected while 16.1% of all adult deaths in the country can be attributable to HIV infection. Another study was done by Wakibi et al (2011).The study assessed adherence to ART and identified factors responsible for non-adherence in Nairobi. A multiple family based cross sectional study where 416

patients aged over 18 years were systematically selected and interviewed using a structured questionnaire about their experience taking ART. Additional data was extracted from hospital records. Multivariate regression model was used to determine predictors of non-adherence. The study concluded that there was better adherence to HAART in Nairobi compared to previous studies in Kenya. Moyo et al (2017) examined changes and equity in ART use in Kenya and South Africa. The study analyzed national population based household surveys conducted in Kenya and South Africa between 2007 and 2012 for factors associated with lack of ART use among people living with HIV aged 15-64 years. The findings from the study revealed that ART use among PLHIV increased from 29.3% to 42.5% from 2007to 2012 in Kenya and 17.4% to 30.3% from 2008 to 2012 in South Africa. Areas needing improvement include rural Kenyans, students in South Africa and among young people and drug users in both countries.

III. METHOD

The Artificial Neural Network (ANN), which we intend to use for this study; 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 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 extensively applied artificial intelligence methods that are used for forecasting and prediction purpose. It consists of basically three 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 Kenya as output data for the network. In this research article, our ANN is based on the hyperbolic tangent function.

Data Issues

This study is based on annual ART coverages (referred to as K series in this study) in all age groups in Kenya. 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
28.105	23.000	0.00000	73.000
Std. Dev.	C.V.	Skewness	Ex. kurtosis
26.004	0.92524	0.39600	-1.2802
5% Perc.	95% Perc.	IQ range	Missing obs.
Undefined	73.000	48.000	0

ANN MODEL SUMMARY FOR ART COVERAGE IN KENYA

Table 2: ANN model summary

Variable	K
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	0.037951

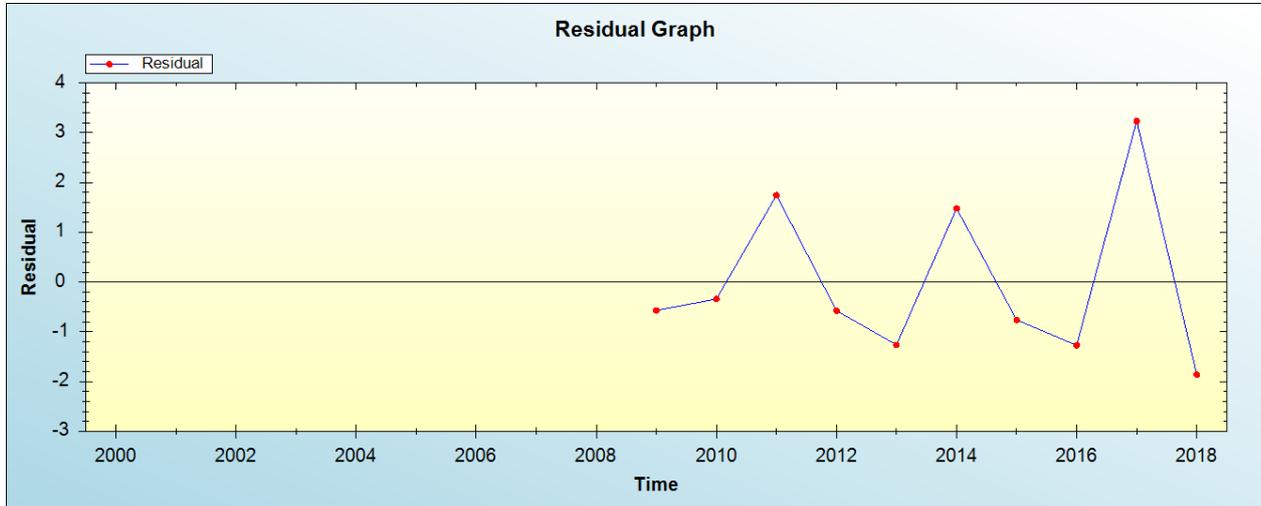| MSE	2.368898
MAE	1.309520

Residual Analysis for the ANN model

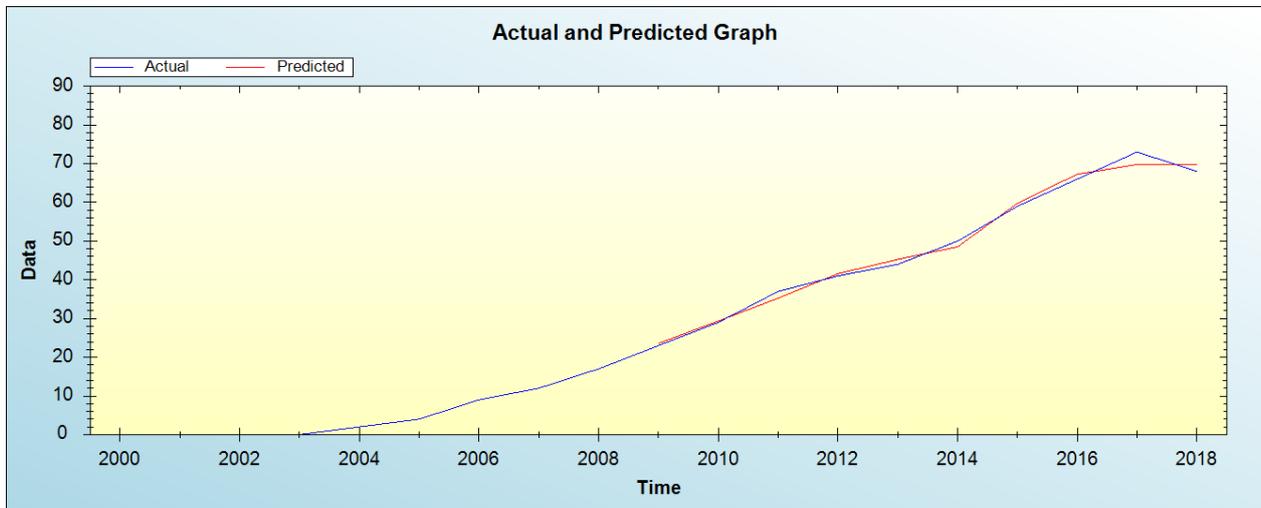**Figure 1: Residual analysis**

In-sample Forecast for K

Figure 2: In-sample forecast for the K series

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

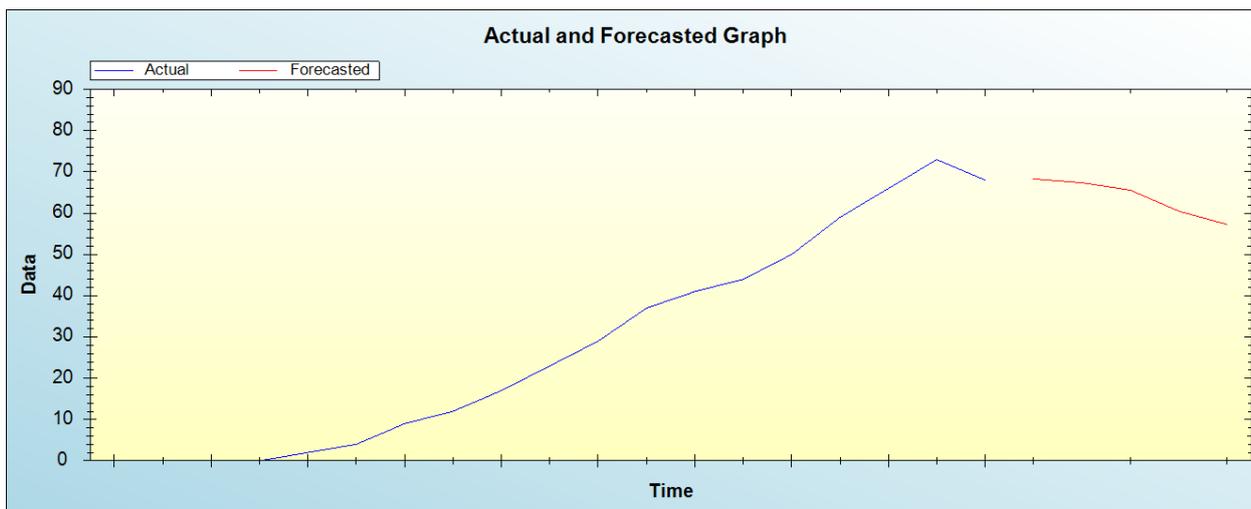*Out-of-Sample Forecast for K: Actual and Forecasted Graph*

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

Out-of-Sample Forecast for K: Forecasts only

Table 3: Tabulated out-of-sample forecasts

Year	Forecasted ART coverage
2019	68.2956
2020	67.3724
2021	65.5772
2022	60.4930
2023	57.2708

Over the study period 2000-2018, the minimum and maximum ART coverage was 0 and 73 % respectively. The average ART coverage was 28 %.The data utilized in this study is not normally distributed. The model evaluation criteria (Error, MSE, MAE) and residual graph indicate that the applied ANN (9,12,1) model is stable and suitable for forecasting ART coverage in Kenya . The ANN model simulated the observed data very well as shown in Figure 2. The model predicted that ART coverage is likely to decline from 68 % in 2019 to 57 % in 2023.

V. CONCLUSION & RECOMMENDATIONS

Kenya has numerous challenges in the National ART program however the country has shown commitment to achieve the 90-90-90 global goal to control the HIV epidemic .The country recorded an upward trend in ART coverage over the period 2000-2018. Unfortunately the model predictions suggest that this commendable effort is likely to be reversed over the period 2019-2023. Therefore we implore the government to intensify demand creation for HIV testing and ART services through mass-media and strengthen HIV/TB collaboration amongst other measures.

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