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Forecasting Art Coverage in Gabon Using the Artificial Neural Network Model

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***Abstract* - In this paper, the ANN approach was applied to analyze annual ART coverage in Gabon. The employed 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 Gabon. The ANN (9,12,1) model predictions suggest that ART coverage will be around 70% throughout the period 2019-2023. The government is strongly encouraged to intensify demand creation for HIV testing and ART services, strengthen the system of tracking loss to follow up ART clients and allocating more resources for TB/HIV collaboration.**

Keywords: ANN, ART coverage, Forecasting.

I. INTRODUCTION

Time series forecasting is increasingly becoming vital as an early surveillance tool in the prevention and control of infectious diseases (Wang, 2017; Nyoni et al, 2020). Many developing countries need to strengthen their surveillance systems in order to effectively control epidemics such as TB and HIV among their citizens. Reliable forecasting models must be chosen so that accurate and reliable predictions are produced to guide decision makers in their health response to the epidemics. Various models have been proposed or applied by researchers around the world and examples of such techniques are machine learning methods, exponential smoothing and Autoregressive Integrated Moving Average (ARIMA) models (Nyoni et al, 2020; Li et al, 2015; Li et al, 2012; Zhang et al, 2014; Yan et al, 2014). Machine learning is a field of study which enables computers to perform certain tasks without being explicitly programmed (Wang et al, 2017). A machine learning algorithm learns a predictor function from the given data and uses it for generalization. When the input and output values are provided the learning process is called supervised learning meaning learning from examples. When the algorithm finds the inherent or hidden structures or patterns in the input data provided the learning process is then referred as unsupervised learning(Nyoni et al, 2020; Weng et al, 2017). There are many machine learning algorithms namely artificial neural networks (ANNs) ,support vector machine (SVM) ,decision trees ,ensembles and Bayesian Networks. All of them apply optimization techniques during the learning process. The support vector machine was proposed by Vapnik and his co-workers in 1990 (Vapnik, 1998; Cao &Francis, 2003; Farooq et al, 2007). The SVM is based on the structural minimization principle. The objective of the SVM is to construct an optimal hyper plane after nonlinear mapping of input data to a higher dimensional feature space. The learning process is equivalent to solving a linearly constrained quadratic optimization problem (Cao &Francis, 2003; Vapnik, 1998). The SVM is widely used in time series forecasting in many fields such as engineering, agriculture and in Human medicine. Time series SVM algorithms are support vector for regression (SVR), least square SVM (LS-SVM) and the dynamic least square SVM (DL-SVM). Artificial neural network (ANNs) are also widely used in time series forecasting and the commonly applied ANN is the multilayer perceptron (MLP). The model is made up of 3 layers namely the input, hidden and output layers which are connected by weights (Fojnica et al, 2016; Zhang, 2003; Yan et al, 2018). The ARIMA (p,d,q) model was proposed by Box and Jenkins in 1970.p and q are the non-seasonal autoregressive (AR) and moving (MA) parts and d is the non-seasonal differencing order (Nyoni & Nyoni, 2019 a & b; Kaushiki & Sahi, 2018). Box and Jenkins proposed a 3 stage iterative process of ARIMA model building which must be followed in order to obtain a parsimonious model. The steps are model identification, parameter estimation and diagnostic checking.

In this study we applied the ANN (9, 12, 1) model to predict ART coverage in Gabon. The study findings are expected to provide likely future trend of ART coverage and progress towards achieving the 95-95-95 targets by 2030. This will trigger an early response to the HIV epidemic in terms of resource allocation and program areas to focus on in the HIV care and treatment program.

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II. LITERATURE REVIEW

Desmonde et al (2018) analyzed the time from enrollment into HIV care to ART initiation in HIV-infected children within the International Epidemiology Databases to Evaluate AIDS (IeDEA) Global Cohort Consortium. included 135,479 HIV-1-infected children, aged 0–19 years and ART-naïve at enrollment, between 1 January 2004 and 31 December 2015, in IeDEA cohorts from Central Africa (3 countries; n = 4,948), East Africa (3 countries; n = 22,827), West Africa (7 countries; n = 7,372), Southern Africa (6 countries; n = 93,799), Asia-Pacific (6 countries; n = 4,045), and Latin America (7 countries; n = 2,488). Follow-up in these cohorts is typically every 3–6 months. We described time to ART initiation and missed opportunities (death or loss to follow-up [LTFU]: last clinical visit>6 months) since baseline (the date of HIV diagnosis or, if unavailable, date of enrollment). Cumulative incidence functions (CIFs) for and determinants of ART initiation were computed, with death and LTFU as competing risks. The study findings revealed that 68% of HIV-infected children initiated ART by 24 months. However, there was a substantial risk of LTFU before ART initiation, which may also represent undocumented mortality. In 2015, many obstacles to ART initiation remained, with substantial inequities. More effective and targeted interventions to improve access are needed to reach the target of treating 90% of HIV-infected children with ART. Bigelow & Verguet (2020) sought to characterize the changes over time in antiretroviral therapy (ART) coverage in sub- Saharan Africa using growth curve models. This was a retrospective observational study. The study used publicly available data on ART coverage levels from 2000 to 2017 in 42 sub-Saharan African countries. They developed two ordinary differential equations models, the Gompertz and logistic growth models, that allowed for the estimation of summary parameters related to scale- up and rates of change in ART coverage. We fitted non-linear regressions for the two models, assessed goodness of fit using the Bayesian information criterion (BIC), and ranked countries based on their estimated performance drawn from the fitted model parameters. The findings of the study showed that growth curve models can provide benchmarks to assess country performance in ART coverage evolution. They could be a useful approach that yields summary metrics for synthesizing country performance in scaling up key health services. . In another study, Johnson et al (2017) assessed South Africa's progress towards the 2020 targets and variations in performance by province .A mathematical model was fitted to the HIV data for each of South Africa's provinces and for the country as a whole .The study results revealed that ART coverage varied between 43% in Gauteng and 63 % in Northern Cape and most provinces face challenges in reaching the remaining two 90% targets. A mathematical modelling approach was also applied by Hontelez et al (2013).In the study nine mathematical models were developed for South Africa's HIV epidemic elimination. All models confirmed previous predictions that the HIV epidemic in South Africa can be eliminated through universal testing and immediate treatment at 90 % coverage. Adam &Johnson (2009) estimated adult antiretroviral treatment coverage in South Africa using the Markov model .The findings of the study showed that ART coverage in 2008 varied between Provinces from 25.8% in the Free State to 71.7%.

III. METHOD

The Artificial Neural Network (ANN), which we going to apply; 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 Gabon as output data for the network. In this article, our ANN is based on the hyperbolic tangent function.

Data Issues

This study is based on annual ART coverage (referred to W series in this study) in all age groups in Gabon. The 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.

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IV. FINDINGS OF THE STUDY

DESCRIPTIVE STATISTICS

Table 1: Descriptive statistics

Mean	Median	Minimum	Maximum
27.000	24.000	0.00000	67.000
Std. Dev.	C.V.	Skewness	Ex. Kurtosis
22.093	0.81827	0.41742	-1.0476
5% Perc.	95% Perc.	IQ range	Missing obs.
undefined	67.000	38.000	0

ANN MODEL SUMMARY FOR ART COVERAGE IN GABON

Table 2: ANN model summary

Variable	W
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	0.033320
MSE	1.538189
MAE	0.954508

Residual Analysis for the ANN model

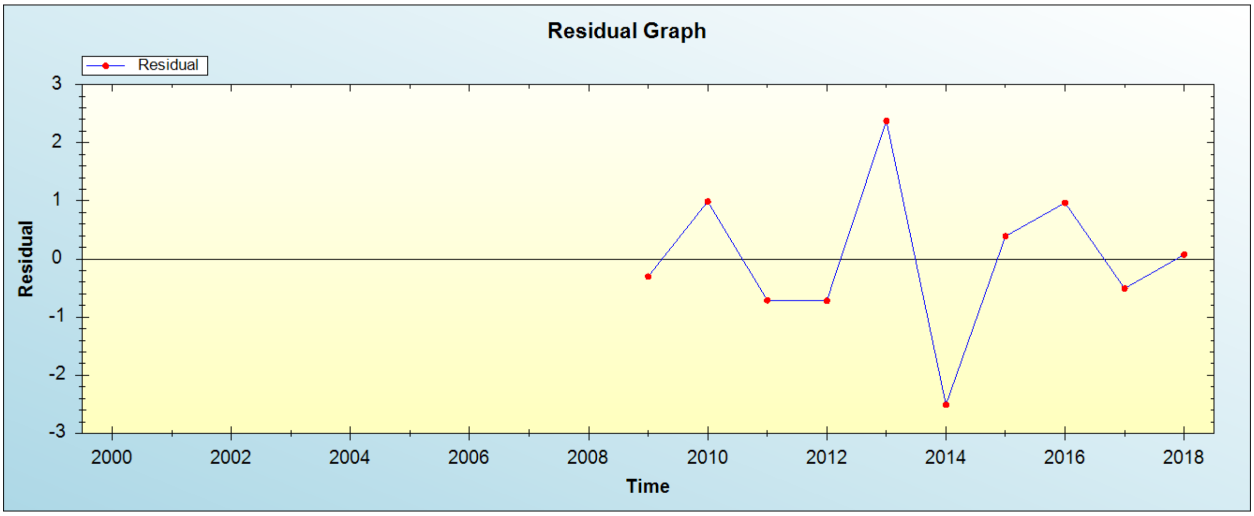

Figure 1: Residual analysis

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In-sample Forecast for W

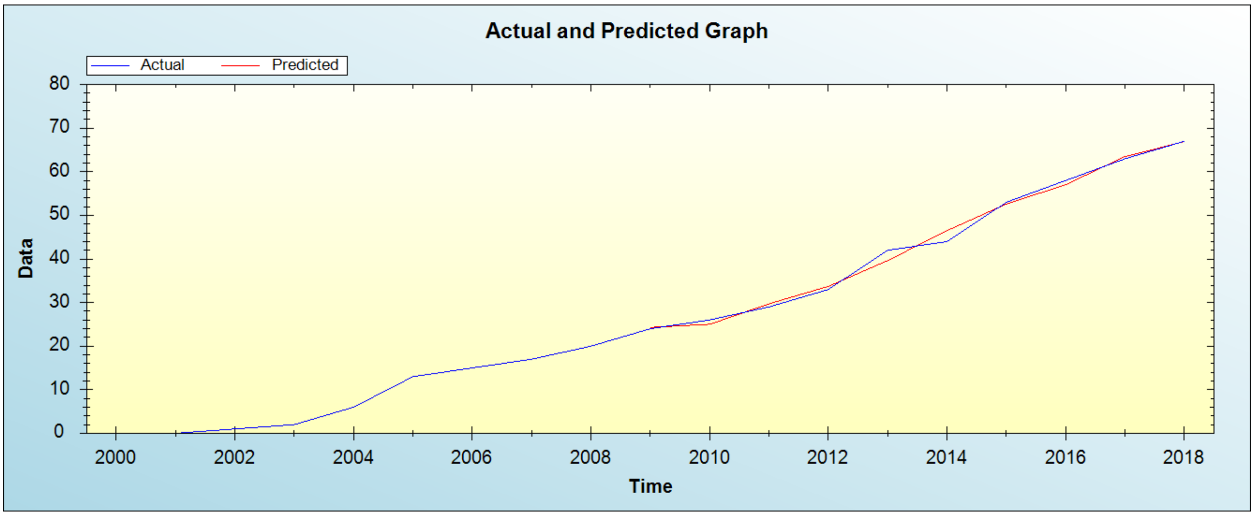

Figure 2: In-sample forecast for the W series

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

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

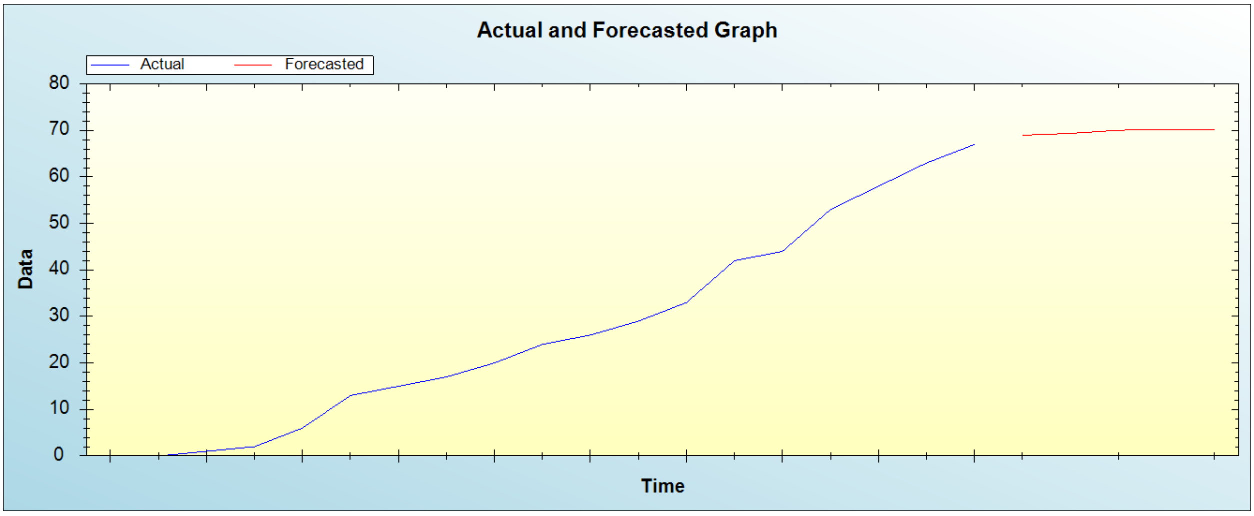

Figure 3: Out-of-sample forecast for W: actual and forecasted graph

Out-of-Sample Forecast for W: Forecasts only

Table 3: Tabulated out-of-sample forecasts

Year	Forecasted ART coverage
2019	68.9720
2020	69.3652
2021	70.0389
2022	70.2447
2023	70.2382

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Over the study period the minimum and maximum ART coverage was 0 and 67 % respectively. Gabon started national ART roll out in 2002 hence the country recorded zeros in 2000 and 2001. The average ART coverage over the study period was 27 %. The data is positively skewed with excess kurtosis of -1.0476 meaning that the data applied in this study is not normally distributed. The model evaluation criteria and residual graph indicate that the model is stable and suitable for forecasting ART coverage in Gabon. In-sample forecasts revealed that the ANN (9,12,1) model simulates the observed data very well. Table 2 shows the model projections which indicate that ART coverage will be around 70% over the period 2019-2023.

V. CONCLUSION & RECOMMENDATIONS

Gabon has made significant strides in the provision of ART services as the country recorded an upward trend in ART coverage over the period 2000-2018. The model predicted that ART coverage will be around 70% throughout the period 2019-2023.Although the country is doing its best to control the HIV epidemic; it is far away from achieving the global HIV goal of 90-90-90 target. Therefore the authorities need to intensify demand creation for HIV and testing services, allocate more resources for TB/HIV collaborative programs and strengthen the system of tracking loss to follow up ART patients.

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