

# Forecasting Art Coverage in Thailand 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 Thailand. 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 Thailand. The results of the study indicate that ART coverage is likely to decline slightly from 75% in 2019 to 69% in 2023. Therefore the government is encouraged to intensify the test and treat approach, strengthen TB/HIV collaboration and create more demand for ART services through mass media sensitization amongst other measures.

**Keywords:** ANN, ART coverage, Forecasting.

## I. INTRODUCTION

At the of 2014 Thailand reported 445,504 people living with HIV with an estimated number of new HIV infections of about 7,816 and 20,492 AIDS related deaths (Annual report, 2015). The estimated number of AIDS related deaths sharply decreased by 63 % between 2000 and 2010 (Annual report, 2015). The government is committed to ending the HIV epidemic as a public health threat by 2030. The HIV epidemic in this country is concentrated among the key populations such as sex workers, transgender women, and men who have sex with men. Evidence from observational and synthetic cohort studies found that HIV prevalence among Male sex workers (MS) > 25years in Bangkok exceeds 40 % (Annual progress report, 2015).

The national ART (antiretroviral treatment) program has managed to reinforce the implementation of the test and treat approach and community based HIV testing services. Both community and clinic based HIV testing and ART services are envisioned to increase ART coverage in the country and all HIV prevention efforts target the key population. In this study we aim to forecast ART coverage in Thailand. In public health there are many time series modeling techniques and these include Autoregressive Integrated Moving Average (ARIMA), exponential smoothing and machine learning methods (Nyonni et al, 2020; Zhao et al, 2020). Machine learning include decision trees, K nearest neighbors, support vector machine (SVM), artificial neural networks (ANNs) and Bayesian networks (Gambhir et al, 2018; Laurean-Rosario et al; 2018; Scavuzzo et al, 2018; Weng et al, 2017; Guo et al, 2017; Althouse et al, 2011).

ARIMA models were proposed by Box and Jenkins in 1970 and these models have been widely used in many disciplines. In the ARIMA (p, d, q) model, p and q represent the non-seasonal autoregressive and moving average parts and d represents the non-seasonal differencing order (Nyonni & Nyonni 2019a & b; Kaushik & Sahi, 2018; Yan et al, 2018, Fojnica et al, 2016; Zhang, 2003). Box and Jenkins also proposed a 3 stage iterative method of ARIMA model building which involves model identification, parameter estimation and diagnostic checking. The optimal model chosen based on information criteria such as Akaike information criterion (AIC) and Bayesian Information Criterion (BIC).

The Multilayer Perceptron is the artificial neural network which is commonly applied in time series forecasting. The model is made up of 3 layers of neurons which are the input, hidden and output layers and the framework is a feed forward neural network. The layers are connected by acyclic links called weights. Other ANN frameworks that have been applied in literature are the Radius Basis Function, Generalized regression network and recurrent neural network. In this study we used the ANN (9, 12, 1) model where 9,12,1 represent the number of input, hidden and output respectively. The results are expected provide likely future trends of ART coverage in Thailand and help in the assessment of the progress towards achieving the global targets by 2030.

## II. LITERATURE REVIEW

Jose et al (2020) did a study aimed to determine the prevalence and risk factors for HIV infection among young Thai men. A total survey was conducted of Royal Thai Army new conscripts, participating in the national HIV surveillance in November 2010

and May 2011. Behavioral risk factors for HIV infection were determined using a standardized survey questionnaire in the total study population and men who have sex with men (MSM) subgroup. The study showed that the prevalence of HIV infection among young Thai men has continued to be below 0.5% in 2010 and 2011. High risk sexual activity, including MSM, played a major role in the HIV epidemic among this population. Phanuphak et al (2020) studied linkages to HIV confirmatory test and antiretroviral therapy (ART) initiation among Thai MSM and TGW who chose online and/or offline platforms for HIV testing and factors associated with unsuccessful linkages. MSM and TGW were enrolled from Bangkok Metropolitan Region and Pattaya during December 2015 to June 2017 and followed for 12 months. Participants could choose between: 1) offline HIV counselling and testing (Offline group), 2) online pre-test counselling and offline HIV testing (Mixed group) and 3) online counselling and online, supervised, HIV self-testing (Online group). Sociodemographic data, risk behavior and social network use characteristics were collected by self-administered questionnaires. Linkages to HIV confirmatory testing and/or ART initiation were collected from participants who tested reactive/positive at baseline and during study follow-up. Modified Poisson regression models identified covariates for poor retention and unsuccessful ART initiation. The authors concluded that online, supervised, HIV self-testing allowed more MSM and TGW to know their HIV status. However, linkages to confirmatory test and ART initiation once tested HIV-reactive are key challenges. Alternative options to bring HIV test confirmation, prevention and ART services to these individuals after HIV self-testing are needed. Sabin et al (2019) in 2007–2008 conducted a nationwide evaluation of PEPFAR-supported outreach programs in Vietnam. The evaluation focused on assessing program effect on HIV knowledge, high-risk behaviors, and HIV testing among high-risk populations—results relevant to Vietnam’s push to meet global HIV goals. The researchers used a mixed-methods cross-sectional evaluation design. Data collection encompassed a quantitative survey of 2199 individuals, supplemented by 125 in-depth interviews.

Participants were members of high-risk populations who reported recent contact with an outreach worker (intervention group) or no recent contact (comparison group). They assessed differences in HIV knowledge, risky behaviors, and HIV testing between groups, and between high-risk populations. The findings from the study indicated that outreach programs appear to have reduced risky sexual behaviors and increased use of HIV testing services among high-risk populations in Vietnam. These programs could play a key role in reducing gaps in the HIV care cascade, achieving the global 90–90–90 goals, and creating an AIDS-free generation. . Ronquillo et al (2017) measured the level of understanding of the community on HIV/AIDS as part of measuring the impact of decentralized initiative against HIV/AIDS. The study applied the Systems’ Theory of Policy Process developed by David Easton. The study showed that: age, gender, civil status and religion have nothing to do with the level of understanding of the HIV/AIDS. The study revealed that respondents’ of the issue of HIV/AIDS as measured in terms of knowledge, attitudes and beliefs fall within the median range of scores: 2.89 for knowledge, 2.59 for beliefs and 2.93 for attitudes. The study further concluded that there is no significant relationship between the personal profile of the respondents and their level of understanding. The study found that heightened understanding of HIV/AIDS among Rural Health Unit 4 respondents was due to decentralized mass information and dissemination campaign of the Local Government Unit.

### III. METHOD

The Artificial Neural Network (ANN) is a data processing system consisting of a large number of 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 ART coverage in Thailand as output data for the network. In this research, our ANN is based on the hyperbolic tangent function.

#### Data Issues

This study is based on annual ART coverages (referred to as N series in this study) in all age groups in Thailand. 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.

#### IV. FINDINGS OF THE STUDY

##### DESCRIPTIVE STATISTICS

Table 1: Descriptive statistics

Mean	Median	Minimum	Maximum
32.316	32.000	0.00000	75.000
Std. Dev.	C.V.	Skewness	Ex. Kurtosis
23.596	0.73018	0.16538	-1.0895
5% Perc.	95% Perc.	IQ range	Missing obs.
Undefined	75.000	42.000	0

##### ANN MODEL SUMMARY FOR ART COVERAGE IN THAILAND

Table 2: ANN model summary

Variable	N
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	0.031904
MSE	1.767161
MAE	1.101961

##### Residual Analysis for the ANN model

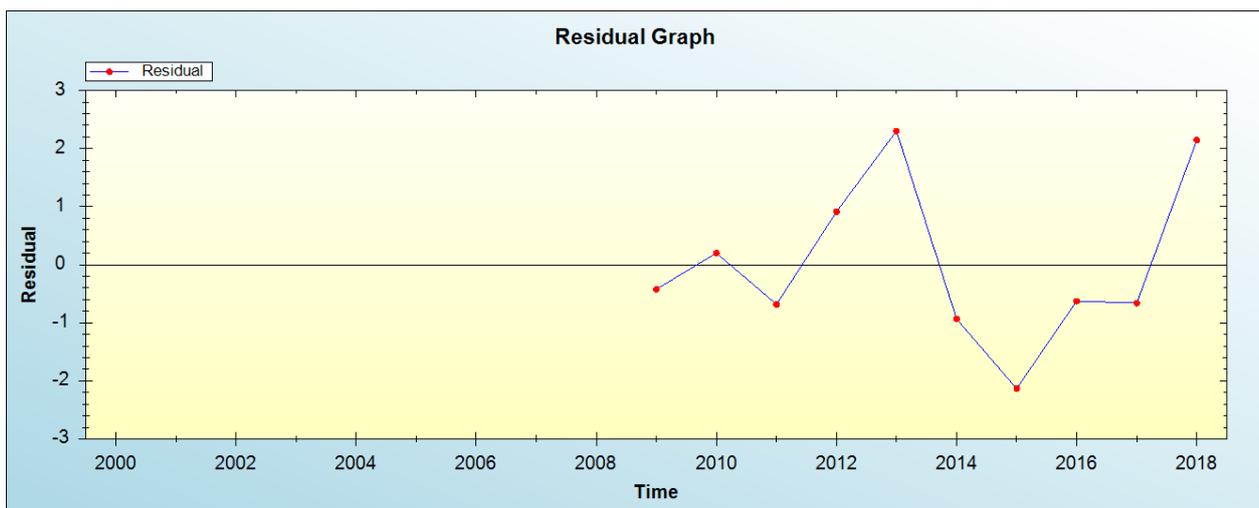


Figure 1: Residual analysis

*In-sample Forecast for N*

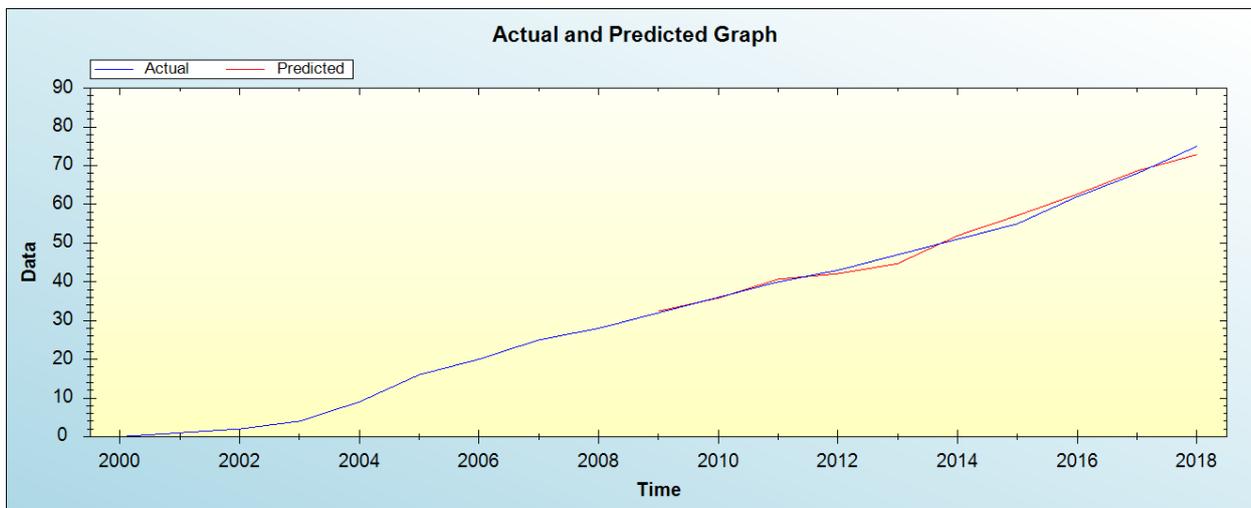


Figure 2: In-sample forecast for the N series

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

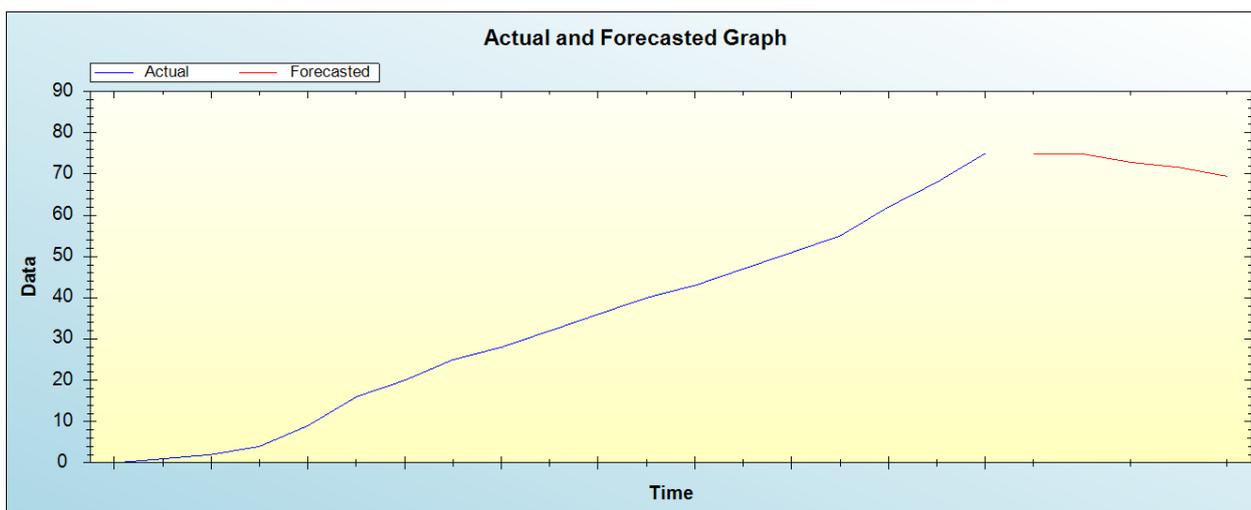


Figure 3: Out-of-sample forecast for N: actual and forecasted graph

*Out-of-Sample Forecast for N: Forecasts only*

Table 3: Tabulated out-of-sample forecasts

Year	Forecasted ART coverage
2019	74.9455
2020	74.8850
2021	72.8428
2022	71.6278
2023	69.4517

Over the study period, the minimum and maximum ART coverage was 0 and 75 % respectively with an average of 32 %. The country started rolling out the ART program in 2001, hence zero reporting was noted for 2000. The data employed in this paper is positively skewed with excess kurtosis value of -1.0895 meaning that the data is not normally distributed. The residual graph and model evaluation criteria (Error, MSE, MAE) have shown that the applied model is stable and suitable for forecasting ART coverage in Thailand. Figure 2 implies that the model simulates the observed data very well. Predictions from the model suggest that ART will decline slightly over the period 2019-2023, from around 75 % in 2019 to 69 % in 2023.

## V. CONCLUSION & RECOMMENDATIONS

Thailand has demonstrated its commitment to the global goal of controlling the HIV epidemic by offering antiretroviral therapy to people living with HIV. Over the period 2000-2018, the country recorded an upward trend in ART coverage indicating that more people are accessing antiretrovirals when they test HIV positive. However, these gains are likely to be reversed in the out of sample period 2019-2023 as suggested by the model projections. Therefore, the government has to intensify the test and treat approach, strengthen TB/HIV collaboration, create more demand for ART services through mass media communication and improve access to antiretroviral treatment for key populations in the country.

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