

## **PREDICTION OF MALARIA CASES IN CHILDREN AGED 15 YEARS AND BELOW AT GWERU PROVINCIAL HOSPITAL USING ARTIFICIAL NEURAL NETWORKS**

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### **ABSTRACT:**

**In this study, ANN models are applied to analyze malaria cases in children under the age of 15 confirmed at Gweru Provincial Hospital (GPH). The used data covers the period January 2010 to December 2019 while the out-of-sample period ranges over the period January 2020 to December 2021. The residuals as well as the evaluation criteria (Error, MSE, MAE) of the applied model show that the model is stable and suitable for forecasting the series under consideration. The results basically indicated that over the out-of-sample period malaria cases will range between 1 and 4 cases. These are relatively low figures and quite manageable for a referral hospital such as GPH. The study recommends the following: through its community-based programs, GPH should create public awareness on malaria and engage in indoor residual spraying amongst other initiatives; GPH should make sure there are adequate malaria commodities in stock, especially essential malaria medicines.**

**KEYWORD: ANN, Forecasting, Malaria.**

### **INTRODUCTION:**

Nowadays disease attack is very common but among all malaria, a vector-borne disease, caused by Plasmodium parasites (Parveen et al., 2017) that infect the red blood cells (Rajaraman et al., 2019); is one of the major causes of death (Parveen et al., 2017) and affects about two-thirds of the world population, with estimated resultant deaths

close to a million annually (Modu et al., 2017). In Zimbabwe, approximately 1.5 million malaria episodes occur, with an average of 1000 people dying from this disease. In fact Malaria accounts for 30% of outpatients at clinics and 40% of hospital admissions in Zimbabwe (Guidelines for Management of Malaria in Zimbabwe, 2009).

The most common infection in Zimbabwe is with the parasite species Plasmodium falciparum (Guidelines for Management of Malaria in Zimbabwe, 2015). When a person is infected with malaria, they suffer from fever and flu-like symptoms such as chills, headache, muscle aches, tiredness, nausea, vomiting and diarrhoea (Dan et al., 2014). Malaria is a very preventable and treatable disease (Hassan & Bin, 2018; Awaab et al., 2019). However, when malaria is not treated, it can lead to coma and hence death (Dan et al., 2014). The best way to deal with malaria is to actually prevent mosquito bites, vector control and personal protection strategies (Guidelines for Management of Malaria in Zimbabwe, 2015). The effects of malaria are much more profound in third world countries, which have very limited medical resources. When an intense outbreak occurs, most of these countries cannot cope with the high number of patients due to the lack of medicine, equipment and hospital facilities (Modu et al., 2017).

Timely prediction of malaria cases is key in the control of malaria morbidity, mortality as well as reducing the risk of transmission of malaria in the community and

can help policy makers, health providers, medical officers, ministry of health and other health organizations to better target medical resources to areas of greatest need (Sharma et al., 2015). Children are the most vulnerable; accounting for at least 61% of the estimated death counts worldwide (Rajaraman et al., 2019). Therefore, it has become unavoidable to model and forecast malaria cases in children aged below 15 years of at Gweru Provincial Hospital (GPH).

#### LITERATURE REVIEW:

In Mozambique, Zacarias & Bostrom (2013) predicted the incidence of malaria cases using regression trees and forests and found out that indoor residual spray, month of January, minimal temperature and rainfall variables were the most important factors when predicting the number of malaria cases in Mozambique. In an Indonesian study, Arifianto et al. (2014) examined malaria incidence using the Polynomial Neural Network and found out that the GMDH PNN was able to reduce the earning time by 72% and improve the accuracy up to 88.02%. Sharma et al. (2015) used machine learning techniques to predict malaria outbreak in India and found out that the performance of the model developed using SVM is more accurate than ANN. Parveen et al. (2017) predicted malaria in Pakistan using ANN models. The authors developed an application which is useful for those areas where there is no any laboratory facility or where there is no doctor, in such situations, people who are able to operate the application by giving only verbal history and their physical appearance can be diagnosed. Modu et al. (2017) forecasted malaria outbreak in the United Kingdom based on a predictive analytics-based intelligent warning system and concluded that their developed smart healthcare application was able to identify hidden ecological factors of malaria.

Twumasi-Ankrah et al. (2019) forecasted malaria cases in Ghana, using the data covering the period January 2008 – December 2017 and applied SARIMA, ETS and ANN models and found out that the SARIMA technique is the appropriate one for predicting malaria cases in Ghana. In United States of America, Rajaraman et al. (2019) evaluated the performance of deep neural ensembles toward malaria parasite detection in thin-blood smear images using convolutional neural networks and found out that the ensemble model constructed with VGG-19 and SqueezeNet outperformed the state-of-the-art in several performance metrics towards classifying the parasitized and uninfected cells to aid in improved disease screening. In a recent Zimbabwean study, Nyoni & Nyoni (2020) forecasted malaria cases in Chitungwiza urban district in Zimbabwe using data covering the period January 2012 to December 2018 and applied the Box-Jenkins technique and out that malaria cases will generally decline over the period January 2019 – December 2020 in Chitungwiza urban district. This study is inspired by Nyoni & Nyoni (2020) but, however, applies the ANN approach, since it performs better than Box-Jenkins models (Sharma et al., 2015; Rajaraman et al., 2019; Datilo et al., 2019).

#### METHODOLOGY:

Forecasting problems arise in all spheres of life (Datilo et al., 2019) and malaria incidence prediction is not an exception (Zacarias & Bostrom, 2013; Arifianto et al., 2014; Sharma et al., 2015; Parveen et al., 2017; Modu et al., 2017; Rajaraman et al., 2019). ANN model is a mathematical evolutionary problem-solving approach that makes decisions based on the organization concept of signals transmission in the human nervous system (Eftekha et al., 2005). An ANN model learns what to do directly from the problem data, and

then renders the output (Datilo et al., 2019). This study applied the ANN (12, 12, 1) model to predict malaria cases in children under the age of 15 at GPH, Gweru, Zimbabwe.

**Data Issues:**

This study is based on newly diagnosed monthly Malaria cases (referred to as CM series in this study) in children aged 15 years and below under at GPH. The data ranges over the period January 2010 to December 2019 whereas the out-of-sample forecast covers the period January 2020 to December 2021. All the data employed in this paper was gathered from GPH Health Information Department.

**FINDINGS OF THE STUDY:  
DESCRIPTIVE STATISTICS:**

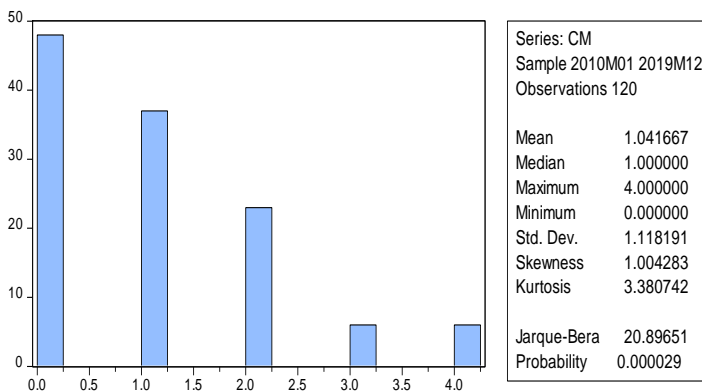


Figure 1: Descriptive statistics

The average number of malaria cases recorded at GPH is 1 per month while the minimum number of malaria cases at GPH is 0 over the study period. The maximum is 4 cases. These are relatively small numbers and we would expect GPH to have the capacity to effectively manage all the cases.

**ANN MODEL SUMMARY FOR MALARIA CASES AT GPH**

Table 1: ANN model summary

Variable	CM
Observations	108 (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	0.141537
MSE	0.098927
MAE	0.247986

Residual Analysis for the ANN model

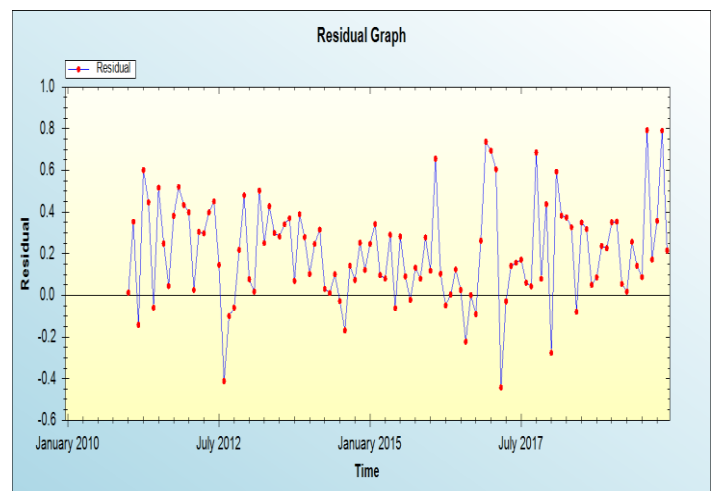


Figure 2: Residual analysis

Table 1 is the estimated model while figure is the residual analysis of the model. From table 1, the applied model architecture is ANN (12, 12, 1) model. From figure 2, the residuals of the model are close to 0 and this points to the possible stability of the model.

**In-sample Forecast for CM**

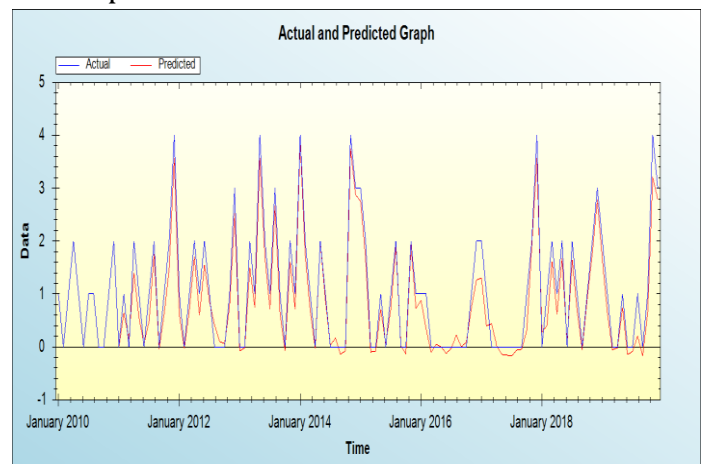


Figure 3: In-sample forecast for the CM series

Figure 3 shows the in-sample forecast of malaria cases in children under 15 years of age at GPH.

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

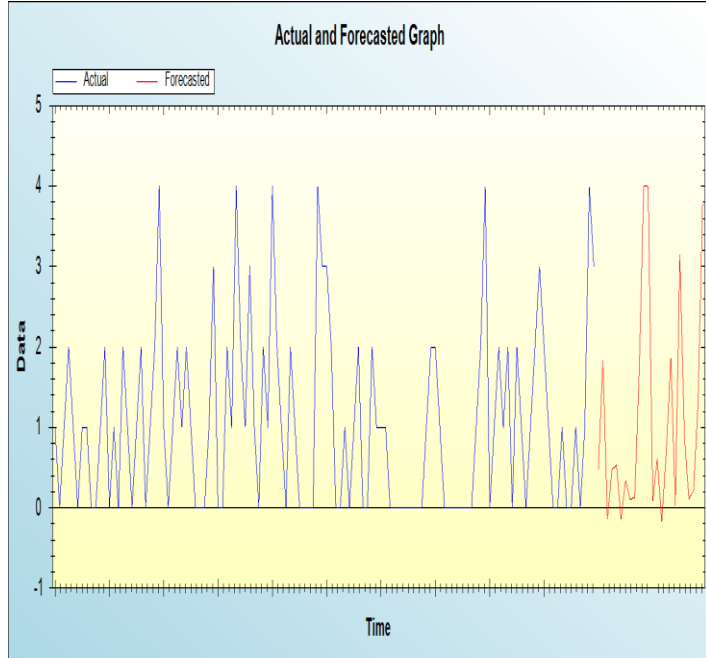


Figure 4: Out-of-sample forecast for CM: actual and forecasted graph

Out-of-Sample Forecast for CM: Forecasts only

Table 2: Tabulated out-of-sample forecasts

Month/Year	Predicted CM
January 2020	0.4772
February 2020	1.8316
March 2020	-0.1374
April 2020	0.4758
May 2020	0.5304
June 2020	-0.1475
July 2020	0.3393
August 2020	0.1062
September 2020	0.1263
October 2020	1.6696
November 2020	3.9957
December 2020	3.9924
January 2021	0.0823
February 2021	0.6042
March 2021	-0.1753
April 2021	0.6986
May 2021	1.8595
June 2021	0.0264
July 2021	3.1490
August 2021	0.8971
September 2021	0.1093
October 2021	0.2163
November 2021	1.2907
December 2021	3.7830

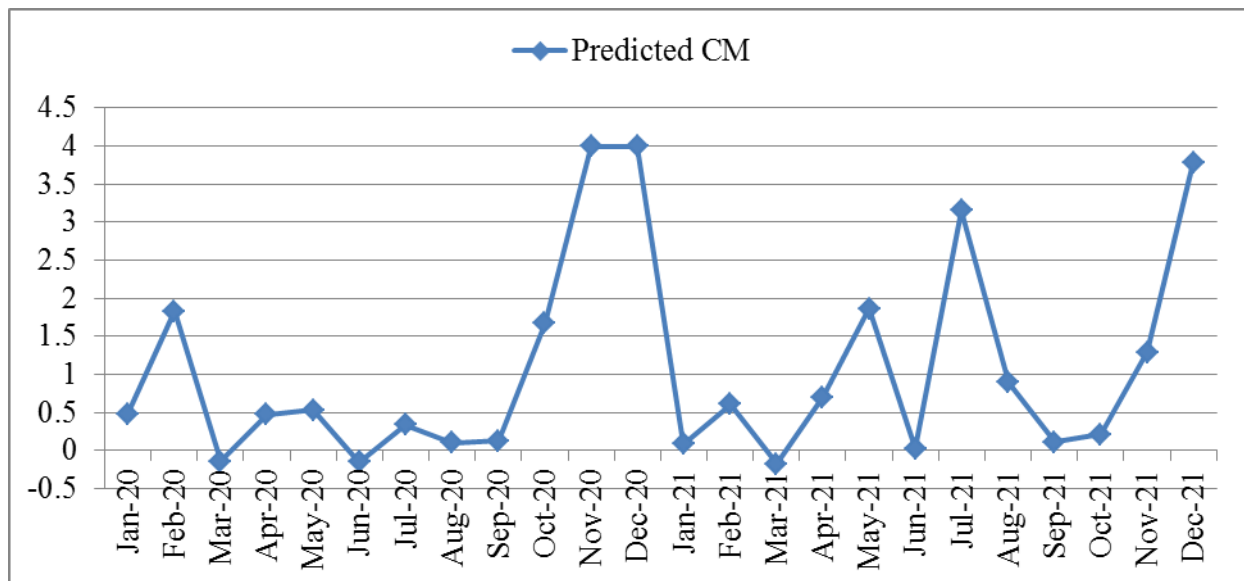


Figure 5: Graphical presentation of out-of-sample forecasts

Table 2, and figures 4 and 5 show out-of-sample forecasts of the series under

consideration. The maximum number of malaria cases is expected to be recorded in the

months of November and December 2020, with maximum number of cases of 4 cases per month. It is clear that these month are to experience more numbers of cases, precisely due to high temperatures and rainfall over the same period. This is reasonable because malaria cases are also linked to climatic factors such rainfall and temperature as already argued by Zacarias & Bostrom (2013). The few figures generally predicted point to the fact that GPH is a referral hospital; therefore, most of the malaria cases could have been managed at district hospitals and less complicated and yet unconfirmed cases are referred to GPH.

#### CONCLUSION & RECOMMENDATIONS:

The burden of malaria in Zimbabwe cannot be undermined. Hence, the need for continued preventive and control measures to be implemented effectively. This study forecasted malaria cases for children aged below 15 because children are highly vulnerable to this disease. The study relied on a univariate series covering the period January 2010 to December 2019. The results of the study are expected enhance future planning at GPH. The following recommendations are put forward:

- i. Through its community-based programs, GPH should create public awareness on malaria and engage in indoor residual spraying amongst other initiatives.
- ii. GPH should make sure there are adequate malaria commodities in stock, especially essential malaria medicines.

#### REFERENCES:

- 1) Arifianto, A., et al. (2014). Malaria Incidence Forecasting From Incidence Record and Weather Pattern Using Polynomial Neural Network, *International Journal of Future Computer and Communication*, 3 (1): 60 – 65.
- 2) Awaab, J. A., et al. (2019). Using ARIMA Models to Forecast Malaria Cases in

Bolgatanga Municipality, *East African Scholars Multidisciplinary Bulletin*, 2 (3): 90 – 99.

- 3) Datilo, P. M., et al. (2019). A Review of Epidemic Forecasting Using Artificial Networks, *International Journal of Epidemiologic Research*, 6 (3): 132 – 143.
- 4) Eftekha, B., et al. (2005). Comparison of Neural Network and Logistic Regression Models for Prediction of Mortality in Head Trauma Based on Initial Clinical Data, *BMC Medical Informatics and Decision Making*, 5 (1): 1 – 17.
- 5) Guidelines for Management of Malaria in Zimbabwe (2009). *Diagnosis, Management of Uncomplicated and Severe Malaria*, Government of Zimbabwe, Harare.
- 6) Guidelines for Management of Malaria in Zimbabwe (2015). *Diagnosis and Management of Uncomplicated and Severe Malaria*, Government of Zimbabwe, Harare.
- 7) Hasan, H. E., & Bin, Y. (2018). Time Series Analysis and Forecasting Model for Monthly Malaria Infection By Box-Jenkins Techniques in Kass Zone, South Darfur State, Sudan, *Journal of Scientific and Engineering Research*, 5 (9): 35 – 42.
- 8) Modu B., et al. (2017). Towards a Predictive Analytics-based Intelligent Malaria Outbreak Warning System, *Applied Sciences*, 7 (836): 1 – 20.
- 9) Nyoni, S. P., & Nyoni, T. (2020). Does the Box-Jenkins “Catch All” Model Explain Malaria Epidemiology in Chitungwiza Urban District? *International Journal of Multidisciplinary Research*, 6 (1): 64 – 74.
- 10) Parveen, R., et al. (2017). Prediction of Malaria Using Artificial Neural Network, *International Journal Computer Science and Network Security*, 17 (12): 79 – 86.
- 11) Rajaraman, S., Jaeger, S., & Antani, S. S. (2019). Performance Evaluation of Deep Neural Ensembles toward Malaria Parasite

Detection in Thin-blood Smear Images, PeerJ, 7 (6977): 1 – 16.

- 12) Sharma, V., et al. (2015). Malaria Outbreak Prediction Model Using Machine Learning, International Journal of Advanced Research in Computer Engineering and Technology, 4 (12): 4415 – 4419.
- 13) Twumasi-Ankrah, S., et al. (2019). Comparison of Statistical Techniques for Forecasting Malaria Cases in Ghana, Journal of Biostatistics and Biometric Applications, 4 (1): 1 – 9.
- 14) Zacarias, O. P., & Bostrom, H. (2013). Predicting the Incidence of Malaria Cases in Mozambique Using Regression Trees and Forests, International Journal of Computer Science and Electronics Engineering, 1 (1): 50 – 54.