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USING ARTIFICIAL NEURAL NETWORKS FOR PREDICTING MONTHLY SURGICAL CASE VOLUMES AT GWERU PROVINCIAL HOSPITAL IN ZIMBABWE

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Abstract:

Modeling and forecasting surgical case volumes can potentially support robust and reliable staff schedules, especially in health facilities such as the Gweru Provincial Hospital (GPH) where patient volumes vary on a monthly basis. This piece of work uses monthly time series data on surgical caseloads at Gweru Provincial Hospital (GPH) from Janaury 2010 to December 2019, to predict surgical cases over the period January 2020 to December 2021. The study applied the ANN (12, 12, 1) model. Residual analysis of this model indicates that the model is stable and therefore suitable for predicting monthly surgical cases at GPH over the out-of-sample period. The results of the study reveal that surgical caseloads for GPH will gradually increase over the out-of-sample period. The study calls for the need for proper monthly staff schedules, especially with regards to improving healthcare service delivery while at the same reducing stress levels among both staff and patients.

Keywords: Modeling and forecasting, health facilities, reliable staff, surgical case, improving healthcare, ANN Model.

1.0 INTRODUCTION

How can we plan our nursing schedule weeks in advance, not knowing how many and when patients will require surgery? (Zinouri *et al*., 2018). This is increasingly becoming the most important question for health facilities around the globe, especially given that demand for surgery is largely driven by patient needs, physician constraints, and weeks or seasonal fluctuations. Poorly planned weekly or monthly nurse schedules can lead to costly day-of-surgery adjustments and can eventually lead to increased stress levels among staff and patients. This can also negatively affect patient safety, as well as increase health costs (Jalalpour *et al*., 2015). In order to properly utilize this scarce and costly nursing resource more effectively and efficiently (Abdel-Aal & Mangoud, 1998; Jones & Joy, 2002; Tiwari *et al*., 2014), reliable predictions of monthly surgical case volumes are needed.

1.1 OBJECTIVES OF THE STUDY

i. To assess new surgical case volumes at GPH over the period January 2010 to December 2019.
ii. To predict surgical case volumes for GPH over the period January 2020 to December 2021.
iii. To determine whether surgical case volumes are increasing or decreasing for GPH over the out of sample period.

2.0 RELATED STUDIES

Studies on modelling and forecasting surgical case volumes are scanty, especially in Zimbabwe. Very few studies have been done for other countries such as the United States, where Tiwari *et al*. (2014) applied ARIMA models to forecast monthly surgical case volumes. The study concluded that ARIMA models are not sufficient for short-term prediction of surgical case volumes in the country. In another United States based study, Zinouri *et al*. (2018) modeled and forecasted daily surgical case volumes using SARIMA models. The results of the study showed that the proposed model was potentially useful for estimating surgical case volumes 2 – 4 weeks prior to the day of surgery. The current study will apply Artificial Neural Networks (ANNs) to model and forecast monthly surgical case volumes for GPH.

3.0 METHOD

The study applies the Artificial Neural Network (ANN) approach in modeling and forecasting monthly surgical case volume at GPH. Following Fischer & Gopal (1994), who argue that no strict rules exist for the determination of the ANN structure; the study applies the popular ANN (12, 12, 1) model based on the hyperbolic tangent activation function.

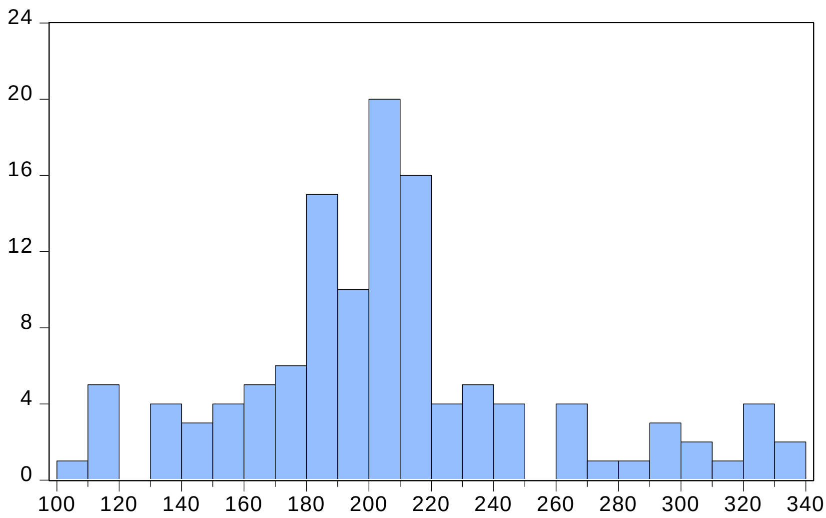
3.1 Data Issues

This study is based on newly diagnosed monthly surgical case volumes (reffered to as S series in this study) at GPH. The data covers the period January 2010 to December 2019 while the out-of-sample forecast covers the period January 2020 to December 2021. All the data employed in this study was gathered from GPH Health Information Department.

4.0 FINDINGS OF THE STUDY

4.1 DESCRIPTIVE STATISTICS

Figure 1: Descriptive statistics



Series: S
Sample 2010M01 2019M12
Observations 120

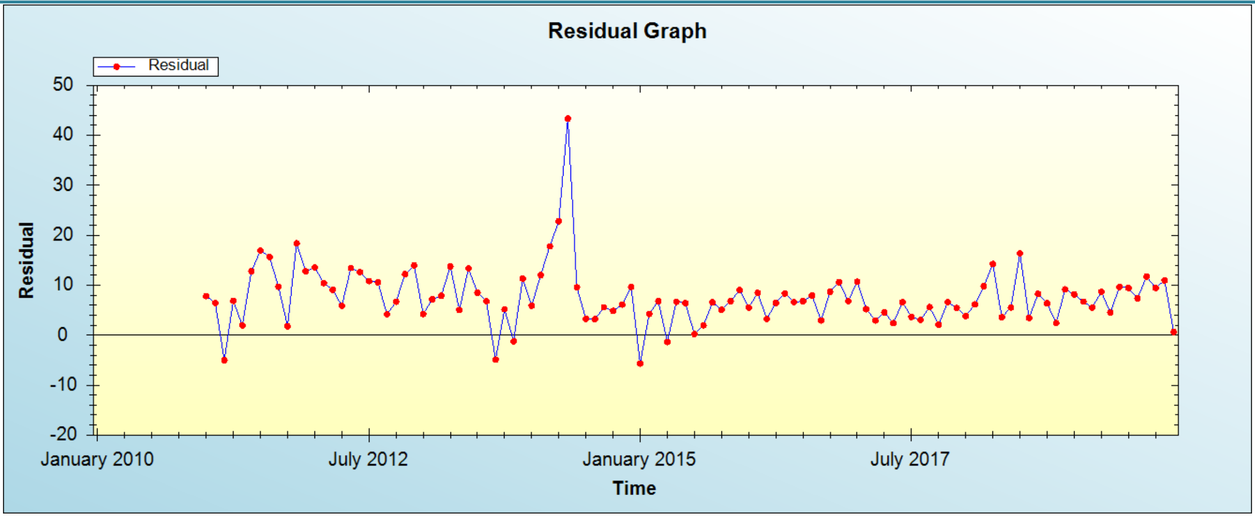
Mean	207.0750
Median	201.0000
Maximum	334.0000
Minimum	108.0000
Std. Dev.	49.49903
Skewness	0.637554
Kurtosis	3.530621
Jarque-Bera	9.537305
Probability	0.008492

4.2 ANN Model Summary for Surgical Case Volumes at GPH

Table 1: ANN model summary

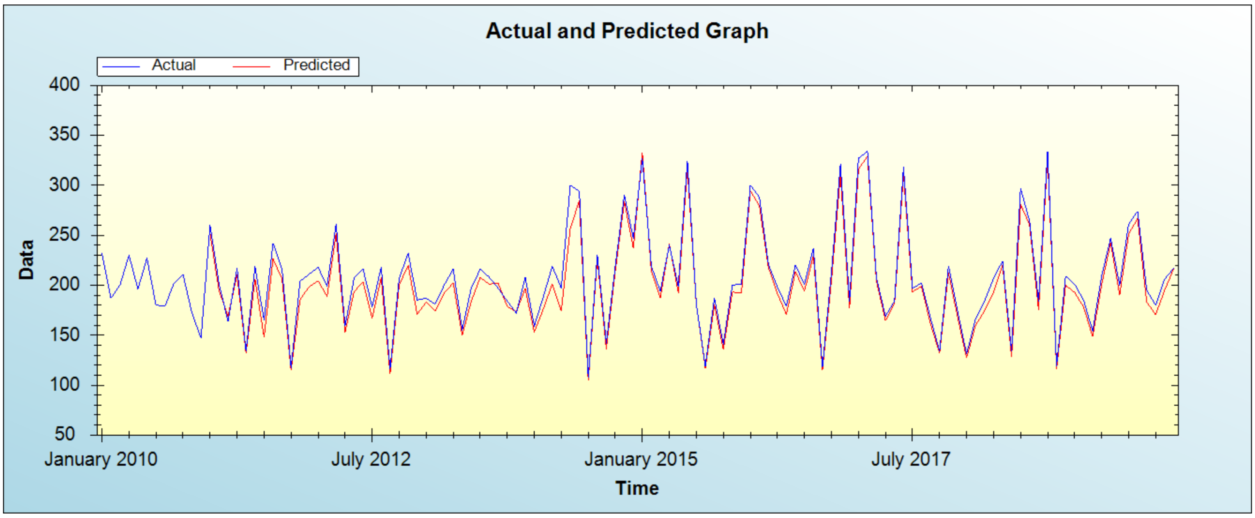
Variable	S
Observations	108 (After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	12
Hidden Layer Neurons	12
Output Layer Neurons	1
Activation Function	Hyperbolic Tangent Function
Back Propagation Learning:	
Learning Rate	0.005
Momentum	0.05
Criteria:	
Error	0.076337
MSE	91.862809
MAE	7.934626

Residual Analysis for GPH Surgical Case Volumes
Figure 2: Residual analysis for S



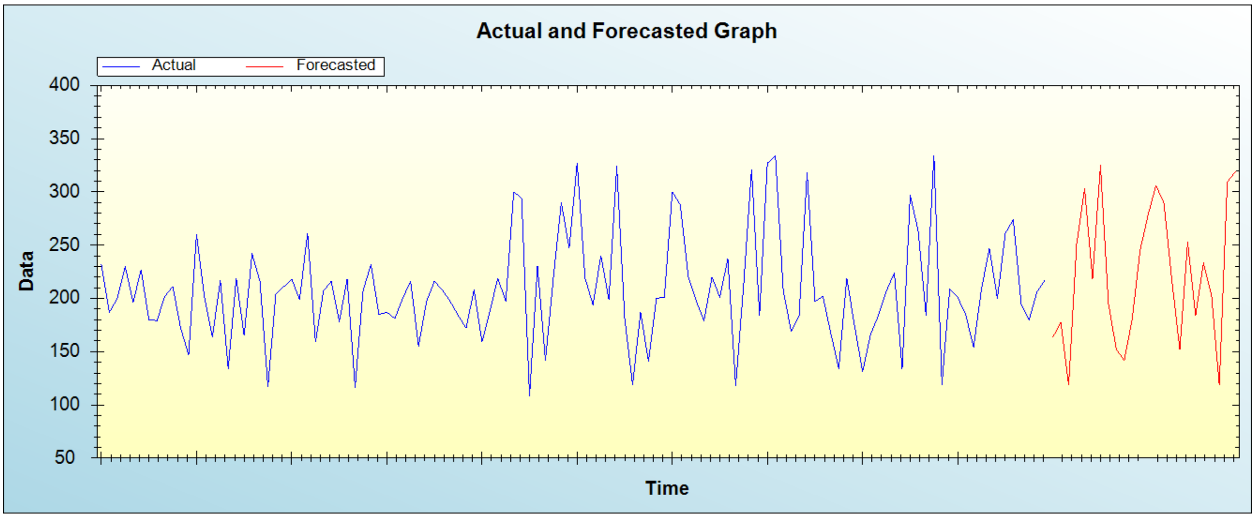
In-sample Forecast for S

Figure 3: In-sample forecast for the S series



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

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

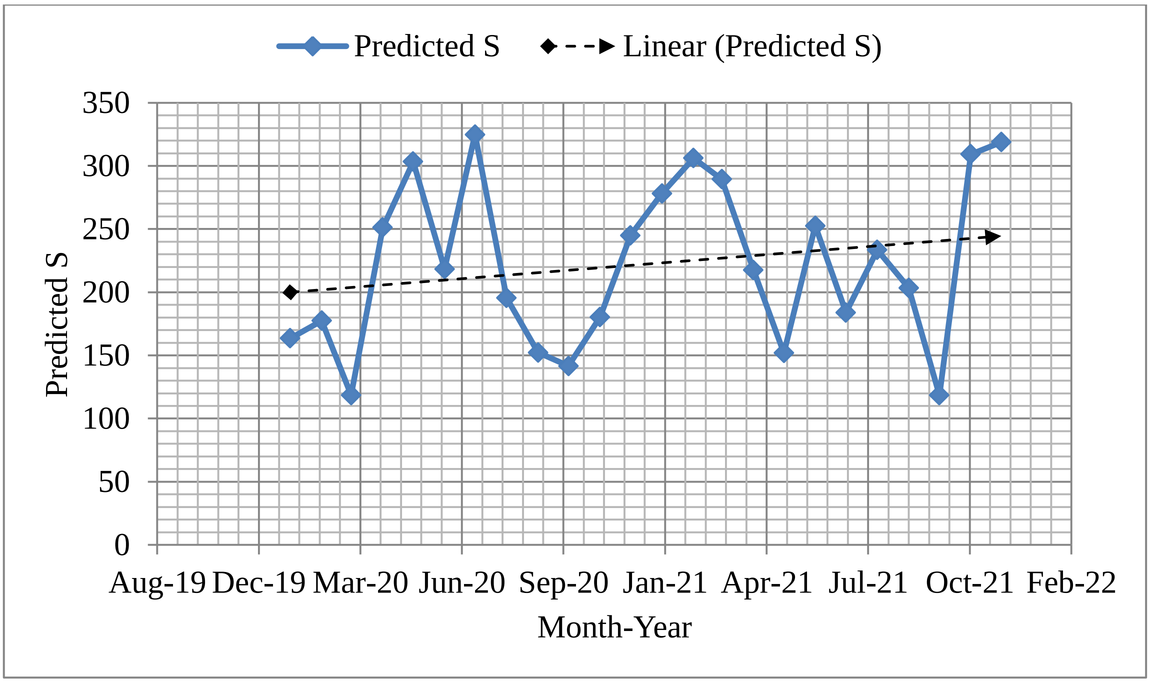


Out-of-Sample Forecast for S: Forecasts only

Table 2: Tabulated out-of-sample forecasts

Month/Year	Predicted S
January 2020	163.5009
February 2020	177.4643
March 2020	118.5681
April 2020	251.2268
May 2020	303.3699
June 2020	218.3712
July 2020	324.8030
August 2020	195.4664
September 2020	152.2406
October 2020	141.6480
November 2020	180.3343
December 2020	245.0210
January 2021	278.1180
February 2021	306.2003
March 2021	289.4786
April 2021	217.5914
May 2021	151.8564
June 2021	252.5745
July 2021	183.9703
August 2021	233.4096
September 2021	203.4228
October 2021	118.4473
November 2021	309.2480
December 2021	318.8027

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



4.3 DISCUSSION OF THE RESULTS

Table 1 is the ANN model summary and basically shows the ANN (12, 12, 1) neural network model, which is based on the hyperbolic tangent function as its activation function. The "criteria" are the evaluation statistics and they all show that the model is adequate. Figure 1 shows the descriptive statistics of the series under consideration: over the period under study, there has been a monthly average surgical case volume of approximately 207 cases. Figure 2 shows the residuals of the model and since the residuals are as close to zero as possible, the model is deemed stable and acceptable for generating forecasts for GPH monthly surgical case volumes, over the period under study. Figure 3 shows the in-sample forecast of the model and it can be deduced that the model fits well with the data. Figure 4, table 2 and figure 5 are out of sample forecasts for S. A striking feature of our forecast is that the surgical case volumes will generally be increasing over the out-of-sample period. This implies that future surgical demand is likely to rise gradually over the out-of-sample period.

5.0 CONCLUSION & RECOMMENDATIONS

This piece of work basically illustrated the importance of applying an ANN model to estimate monthly surgical demand as well as forecasting future demand. Using monthly data over the period Janaury 2010 to December 2019, the study accurately predicted monthly surgical case volumes over the out-of-sample period. This study supports the idea that, indeed, ANNs are beneficial when it comes to estimating and forecasting surgical caseloads. Given the projected gradual increase in the monthly surgical caseloads for GPH over the out-of-sample period, the hospital management team ought to plan in advance in terms of gradually increasing staffing levels as well as acquiring other necessary material resources for use.

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