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FORECASTING THE NUMBER OF OUTPATIENT VISITS AT SILOBELA DISTRICT HOSPITAL IN ZIMBABWE USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This paper employs monthly time series data on outpatient visits at Silobela District Hospital (SDH) from January 2012 to December 2019, to predict healthcare demand (outpatient visits) using Artificial Neural Networks (ANNs). Residual analysis of the ANN model indicates that the employed model is adequate. This paper is the first of its kind in Zimbabwe and its primary contribution is finding that there is need for more prudent resource planning and allocation at SDH as warned by high numbers of projected outpatient visits over the period January 2020 to December 2021. The study managed to come up with a 3-fold policy recommendation envisaged to improve healthcare management at SDH.

1. INTRODUCTION

Forecasting the number of patient visits to hospitals has aroused an increasingly large interest from both theoretic and application perspectives (Yu *et al.* 2017). This can be attributed to the fact that forecasting the number of patient visits to hospitals is paramount in allocating human and material resources of hospitals (Hadavandi *et al.* 2012). The Outpatient Department (OPD) is the window of the hospital external service from the hospital actual operation, and can experience increasing stress from year to year due to increasing patient volumes (Luo *et al.* 2017). Therefore, the ability to predict outpatient visits is essential for resource planning and allocation as well as efficient appointment scheduling in OPD aimed at avoiding overcrowding and providing high quality patient care service (Hadavandi *et al.* 2012). Precise and reliable predictions of outpatient amount can contribute to allocate the main healthcare resources effectively. Hence, it is important to make an accurate forecast of outpatient visits in advance, in order to help hospital managers to make the right decisions to meet the anticipated healthcare demand effectively and timely (Luo *et al.* 2017; Huang & Wu, 2017).

Hence, these days, forecasting the number of patient visits to hospitals has achieved an overwhelmingly significant status in hospital management (Huang & Wu, 2017). Thus, more accurate hospital visits prediction can contribute to higher efficiency of hospital management without any doubt (Yu *et al.* 2017). In fact, the importance of this paper to SDH is basically three fold:

i. To offer adequate and safe patient care supported by appropriate resource planning.
ii. Understanding outpatient visits dynamics at SDH has implications for administrative and clinical decisions, for example; nurse-to-patient ratios and bed management decisions.
iii. This paper will also facilitate optimal allocation of limited personnel and resources in order to avoid problems such as poor nurse and doctor staffing levels.
iv. This study will also go a long way in minimizing patient wait time (which is economically inefficient) at SDH, while not having more on-duty nurses and doctors than necessary.

Motivated by overcrowding and resource scheduling problems prevalent in Zimbabwe, we select a typical district hospital – Silobela District Hospital (SDH) and consider a time series forecasting problem of monthly outpatient visits. SDH is a government run district hospital in the Midlands province of Zimbabwe, and just like many public hospitals in Zimbabwe, has large-scale outpatients. This paper will go a long way in helping the SDH health executive team in making the necessary policy decisions in order to meet the expected healthcare demand in Silobela.

1.1 OBJECTIVES

i. To analyze SDH outpatient visits over the period January 2012 to December 2019.
ii. To forecast SDH outpatient visits over the period January 2020 to December 2021.
iii. To determine whether the outpatient visits at SDH are increasing or decreasing over the out of sample period.
iv.

1.2 RELEVANCE OF THE STUDY

Overcrowding of hospital waiting rooms by patients characterizes the OPDs of healthcare centres of developing countries (Bahadori *et al.* 2017; Yarmohammadian *et al.* 2017). Patients wait for so long and such medical wait times are economically inefficient as they represent lost productivity for patients (Oostrom *et al.* 2017). After all, time spent waiting to see a doctor influences a patient's healthcare experience and can lead to dissatisfaction with the hospital or medical establishment. Lengthy clinical wait times are a signal of sub-optimal processes within the healthcare system and are caused by overcrowding and under-staffing of medical facilities that exceed peak volumes in times of high demand. But the problems of overcrowding and understaffing can be ameliorated (Guan & Engelhardt, 2019), especially through modeling and forecasting outpatient visits. In this paper, an Artificial Neural Network (ANN) model is proposed to predict outpatient visits at SDH. The model is envisioned to aid in overcoming the effects of overcrowding in hospital waiting rooms and places, which results from a mismatch between hospital staffing ratios and the demand for healthcare services.

2. LITERATURE REVIEW

Table 1: Summary of Reviewed Previous Studies

Author/Year	Country	Period	Method	Main Findings
Wang *et al*. (2015)	Taiwan	January 2009 – December 2011	Google Trends	Google Trends are a powerful prediction tool
Sukmak *et al*. (2015)	Thailand	January 2007 – December 2010	ANNs (RBF & MLP)	The RBF was selected as the final model
Capan *et al*. (2016)	USA	January 2008 – December 2012	ARIMA; SARIMA	Best fitting models included the ARIMA (1,0,0), SARIMA $(1,0,0)(1,1,2)_{12}$, SARIMA $(2,1,4)(1,1,2)_{14}$ as well as the Seasonal Linear Regression (SLR) model
Yu *et al*. (2017)	China	January 2011 – December 2015	WD; ANN	ANN models are powerful prediction tools
Luo *et al*. (2017)	China	2016	SARIMA; SES; CFM	CFM performs better
Huang & Wu (2017)	China	Janauary 2005 – December 2013	EMD; ANN; PSO	EMD-BPANN is a powerful predictive hybrid tool
Tamatta (2018)	UK	January 2014 – June 2016	ARIMA; TBATS; ANN	ARIMA model is the best
Zhou *et al*. (2018)	China	January 2010 – June 2016	SARIMA; NARNN; SARIMA-NARNN	The hybrid SARIMA-NARNN was the best model
Rochman *et al*. (2018)	Indonesia	2016	ELM	ELM is a powerful predictive tool
Mtonga *et al.* (2019)	Rwanda	2018	Machine Learning; Transfer Systems	Machine learning-based patient load prediction model performs better

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Guan & Englehardt (2019)	USA	January 2010 – September 2018	ANNs, Linear Regression; SARIMA	RNN models are the best and are also able to capture seasonality
Elgohari *et al*. (2019)	Egypt	January 2011 – December 2017	ARIMA; ES	The ARIMA (3,1,3) model was found to be the best model
Choudhury & Urena (2020)	USA	January 2014 – August 2017	ARIMA; HW; TBATS; ANN; SARIMA	The SARIMA $(3,0,0)(2,1,0)_{12}$ model was the best fit model

There is no doubt; this paper is new in Zimbabwe. To the best of our knowledge, there is no similar study done in Zimbabwe so far. Although, we are inspired by Elgohari *et al.* (2019), we adopt the ANN approach due to its efficiency and novelty as already proven by Sukmak *et al.* (2015), Huang & Wu (2017), Yu *et al.* (2017), Guan & Englehardt (2019), Mtonga *et al.* (2019).

3. METHODOLOGY

The number of outpatient visits is a non-linear and non-stationary series (Huang & Wu, 2017). Hence, the suitability of the ANN approach in this study since it can properly handle noisy non-linear and non-stationary processes. This paper uses the ANN approach based on the Multi Layer Perceptron Neural Network (MLPNN) which belongs to a general class structure of ANNs called Feedforward Neural Networks (FNNs). All the data used in this study was collected from the OPD at SDH. The data is for all age-groups and covers the period January 2012 to December 2019.

4. FINDINGS OF THE STUDY

4.1 DESCRIPTIVE STATISTICS

Figure 1: Descriptive Statistics

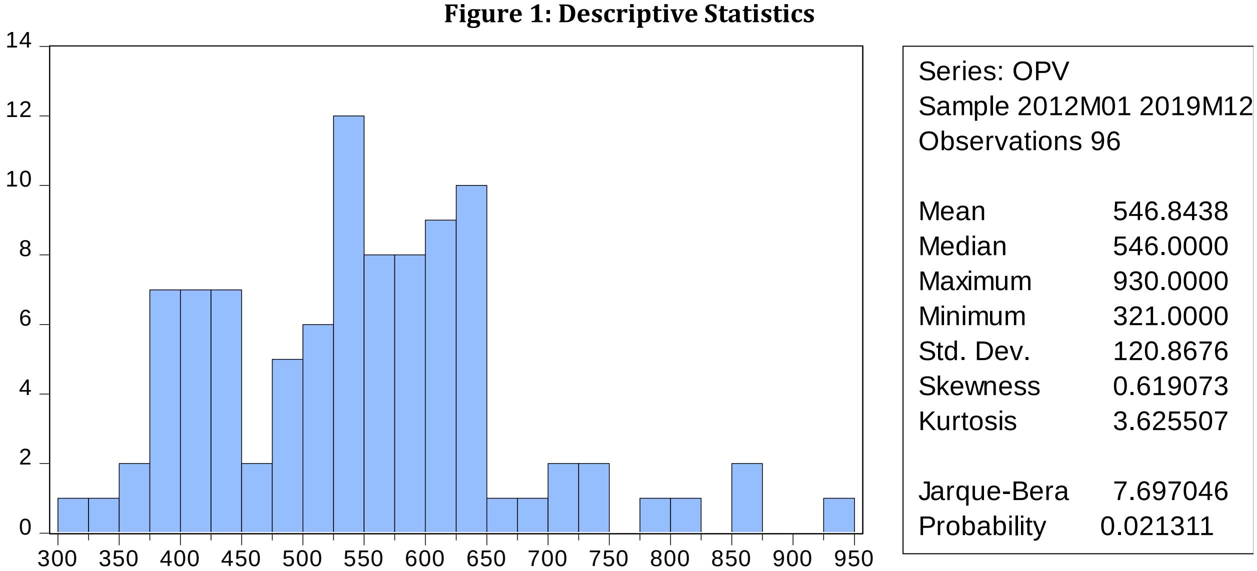

Figure 1 indicates, as expected, a positive a high average outpatient visits figure of approximately 547 visits per month over the study period. For a district hospital like SDH, this figure is already too much right away. This is a warning sign to policy makers and relevant authorities; doctor and nurse staffing levels need to be re-checked if healthcare demand is to be adequately met at SDH, otherwise long wait times and patient dissatisfaction may continue haunting the hospital's reputation. The minimum is 321 visits while the maximum is a high as 930 visits. The series under consideration is positively skewed as shown by the skewness statistic of o.619073 and is not normally distributed as indicated by the kurtosis of 3.625507.

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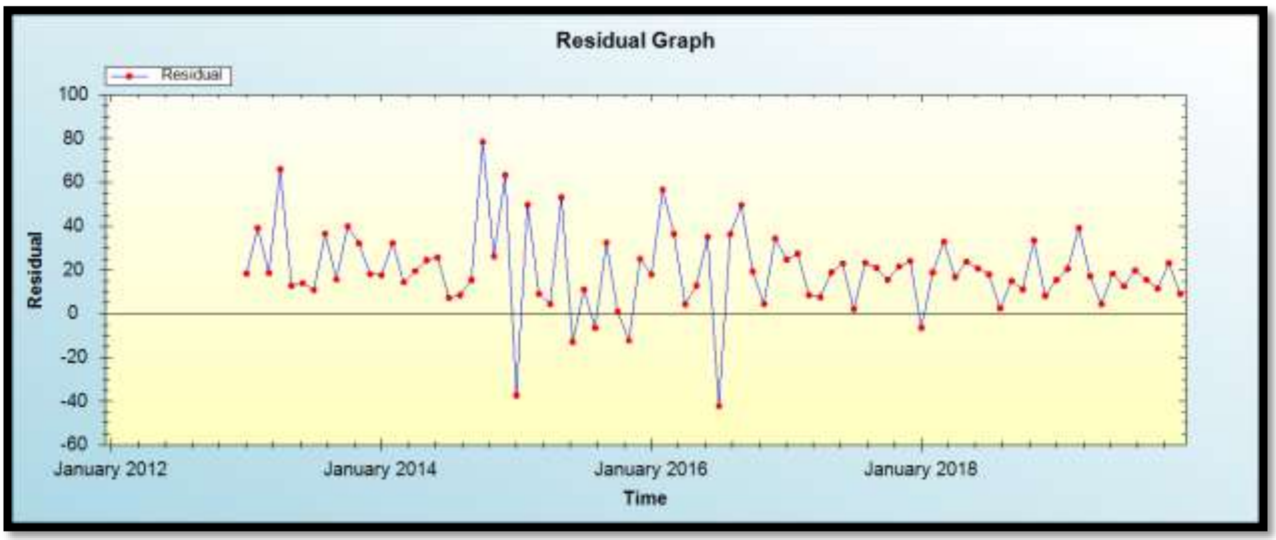
4.2 ANN MODEL SUMMARY FOR SDH OUTPATIENT VISITS

Table 2: ANN model summary for SDH outpatient visits

Variable	SDH Outpatient Visits
Observations	84 (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	0.080314
MSE	738.372941
MAE	22.508823

Residual Analysis for SDH Outpatient Visits

Figure 2: Residual Analysis for SDH Outpatient Visits



In-sample Forecast for SDH outpatient visits

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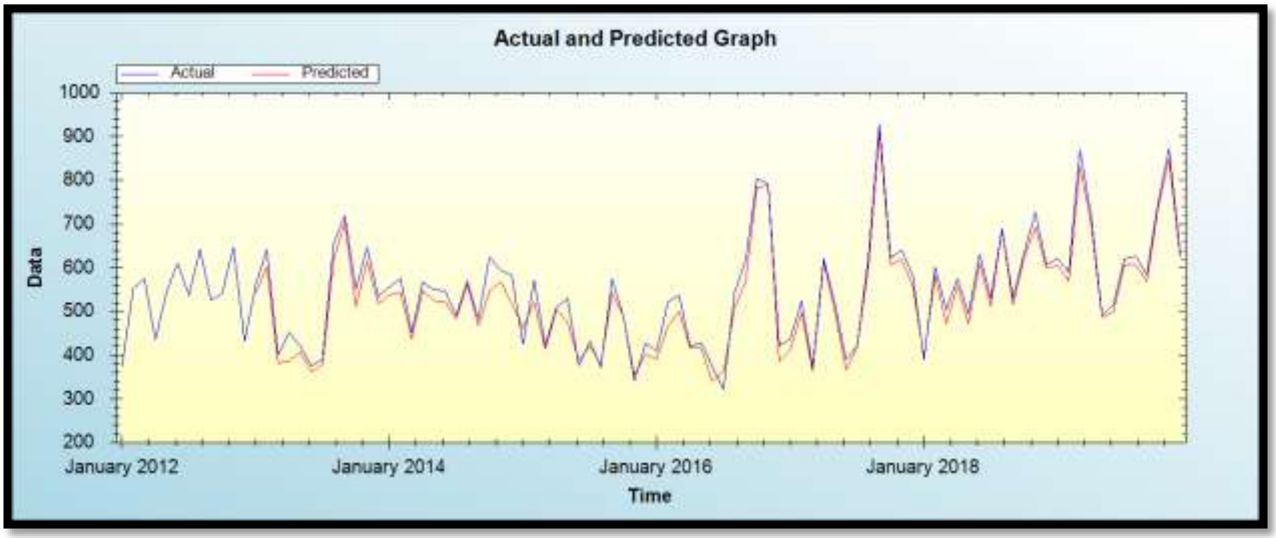
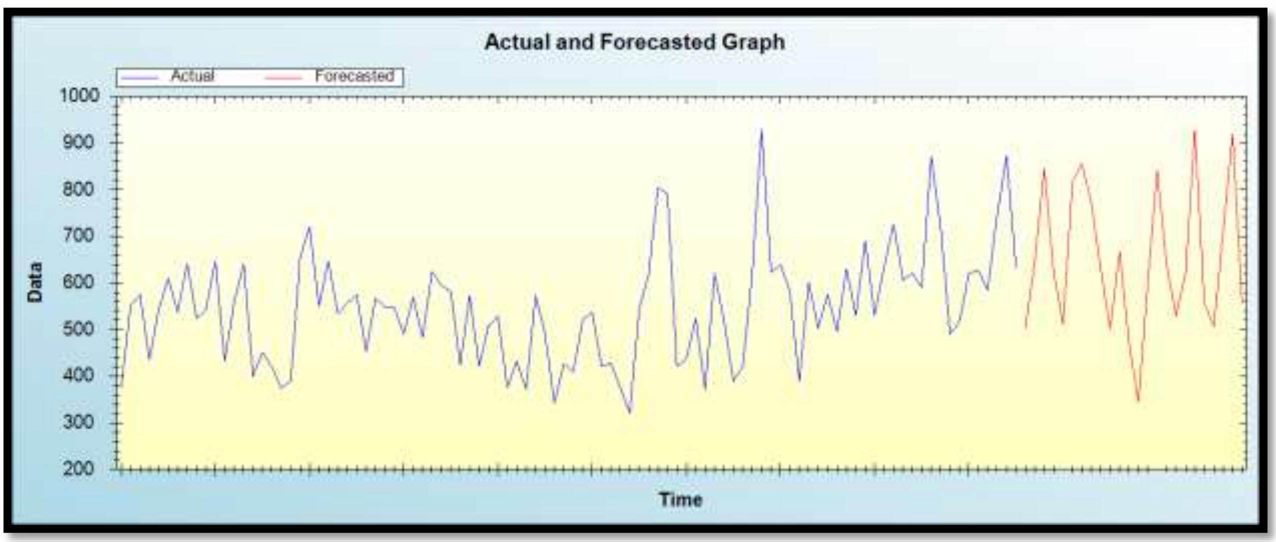
Figure 3: In-sample Forecast for SDH outpatient visits



Out-of-Sample Forecast for SDH outpatient visits: Actual and Forecasted Graph

Figure 4: Actual and Forecasted Graph



Out-of-Sample Forecast for SDH outpatient visits: Forecasts only

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Figure 5: Forecasts only

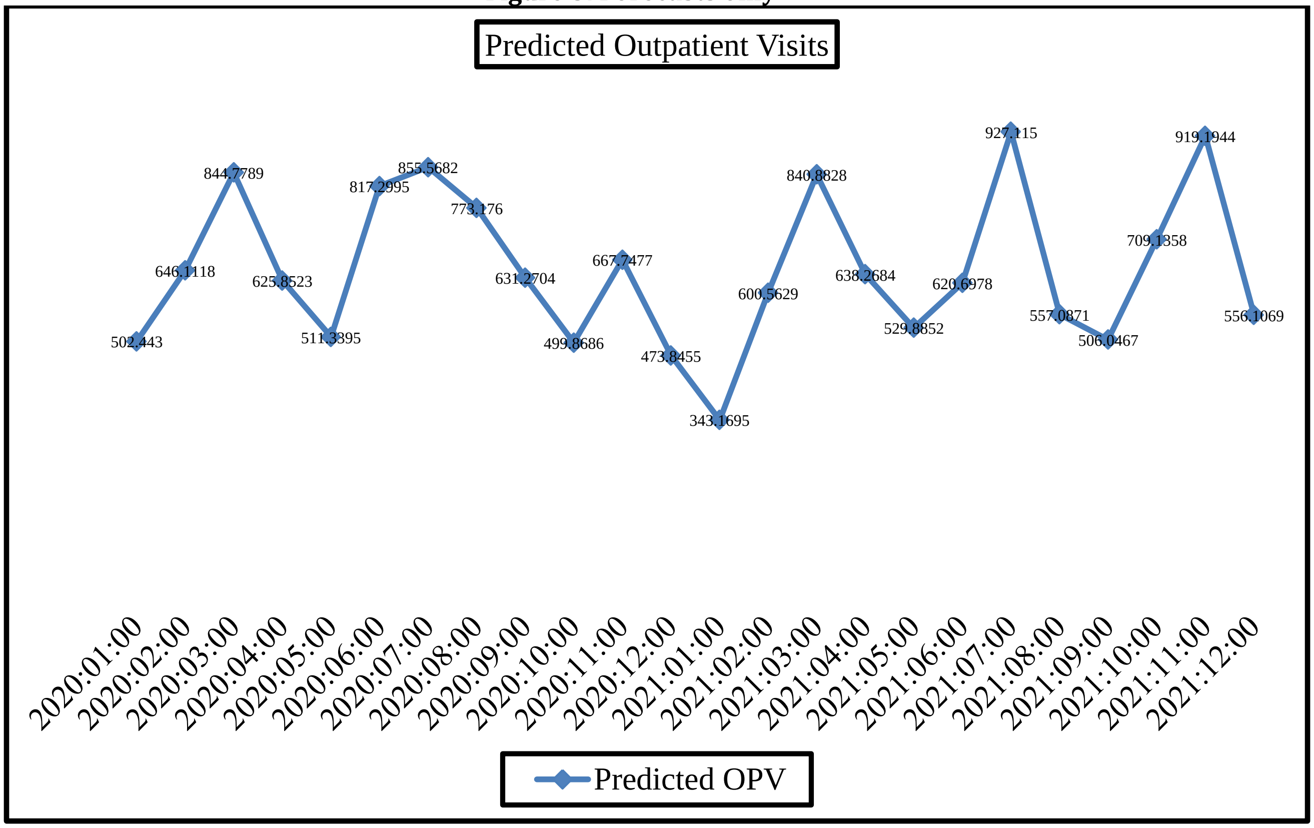

Table 2 is the summary of the ANN model used in this study. The residual analysis of the model in figure 2 shows that the model fits the data well. Figure 3 are in-sample forecasts while figure 4 & 5 and out-of-sample forecasts. Policy makers are very much interested in figures 4 and 5 which present the forecasts of the anticipated healthcare demand at SDH. From figure 5, we can see that over the out-of-sample period, SDH will likely experience at least 343 visits per month and this least number of outpatient is projected to be realized in January 2021. The highest number of outpatient visits (i.e. 927) is projected to be realized in July 2021. All the forecasts show that there will be relatively high healthcare demand at SDH over the period January 2020 – December 2021 and hence there is need for careful human and material resource planning in order to enhance efficiency at SDH.

4.3 RECOMMENDATIONS

The study basically recommends the following:

i. There is need to increase doctor staffing levels at SDH. At the moment, there are only two doctors (Nyoni & Nyoni, 2019); two more doctors could help meet the current and projected demand more efficiently.
ii. There is need to increase nurse staffing levels at SDH.
iii. There is need for the government to capacitate clinics in the SDH catchment area so that patients are well taken care of in the primary levels of care and only reffered to the secondary level (district hospital) when necessary.

5. CONCLUSION

Modeling and forecasting outpatient visits is now becoming very crucial in public health policy discourse, particulary in light of overcrowding and persistent patient dissatisfaction in many hospitals and clinics around the globe, especially in developing countries. Zimbabwe, just like any other developing country, also faces problems of overcrowding, long wait times and patient dissatisfaction. Almost, every health facility in Zimbabwe is characterized by these issues, especially in district rural hospitals such as SDH. These problems can be solved if reliable forecasting models could be constructed to make sound projections of outpatient visits. This could help in terms of planning ahead with regards to human and material resources. This paper used 96 observations of outpatient visits in order to project healthcare demand for SDH

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over the next 24 months. Our forecasts are an early warning sign to the district health executive at SDH and are envisioned to enhance resource planning and allocation.

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