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Modeling and Forecasting New HIV Infections at Silobela District Hospital, Zimbabwe: Empirical Evidence From a Box-Jenkins "Catch All" Model

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Abstract: This study uses monthly time series data on new HIV infections at Silobela District Hospital from January 2014 to December 2018; to forecast new HIV infections based on the Box-Jenkins technique of analyzing univariate time series data. Diagnostic tests indicate N is an I (1) variable. Based on the AIC, and for all age-groups, the study presents the SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model, the diagnostic tests further show that this model is generally stable and therefore acceptable for forecasting new HIV infections at Silobela District Hospital. The selected optimal "catch-all" model shows that new HIV infections in the community of Silobela will decline over the out-of-sample period, which implies that SDH has a brighter future with regards to its response to the HIV epidemic in the community of Silobela. The study encourages continued intensification of the HIV/AIDS surveillance system at SDH in order to control the spread of the pandemic in line with the government's "zero new infections" mantra.

Keywords: Forecasting, HIV/AIDS, New HIV Infections, SDH.

1. Introduction

Since the first reported case of AIDS in 1981, the United Nations Programme on HIV/AIDS (UNAIDS) estimated the global people living with HIV/AIDS to be 35.3 million in 2012 (UNAIDS, 2013). Young people are disproportionately affected by HIV globally of which 25% of infected persons are aged between 10 and 24 years. Those aged between 15 – 24 years have imminently 35% probability for new infections, resulting in 900 000 new infections occuring annually (UNAIDS, 2010). The first cases of AIDS in Zimbabwe were identified in the mid 1980s (WHO, 2005). Current evidence indicates that Zimbabwe has a mature generalized epidemic which is tracked by a comprehensive monitoring and evaluation system (Ministry of Health & Child Care, 2018). The HIV epidemic in Zimbabwe is generalized and is largely driven by unprotected heterosexual sex. Women are disproportionately affected, particulary adolescent girls and young women. However, there are growing epidemics among key populations such as sex workers and men who have sex with men who are at higher risk of HIV. National data on these populations is sparse as only a minimal amount of data is collected and reported in national documents. In 2018, new infections dropped to 38000 from 79000 in 2010, with behaviour change communication, high treatment coverage and prevention of mother-to-child transmission (PMTCT) services thought to be responsible for this decline. Deaths from AIDS-related illnesses continue to fall – from 61000 in 2013 to 22000 in 2018 (UNAIDS, 2018).

The HIV programme at Silobela District Hospital (SDH) is run in collaboration with the TB program. The District Medical Officer (DMO) is the program manager and the responsible officer for the program at district level. The HIV programme at the hospital has the following components which constitute the HIV prevention strategy: consistent and correct use of condoms, Voluntary Medical Male Circumcision (VMMC), Prevention of Mother To Child Transmission (PMTCT), post exposure prophylaxis, as well as testing & treating all new HIV positive clients using the Test and Treat Approach (TTA). Besides being aimed at controlling the HIV/AIDS pandemic in the Silobela community, the other goal of the HIV program at SDH is to do TB screening in all HIV positive patients. The program also emphasizes on screening for cervical cancer in women and screening for other HIV related malignancies. All HIV positive pregnant mothers are initiated on Antiretroviral Therapy (ART) to reduce the risk of HIV transmission to the fetus. ART is monitored after 6 months of ART initiation using Viral Load Testing (VLT) as the gold standard. Those who fail on treatment are switched on to second line therapy after they are assessed by the medical officers or senior nurses who have experience in HIV treatment and care.Furthermore, it is important to note that all departments at SDH, namely; outpatient, inpatient, labour & maternity, family & child health, VMMC, and Opportunistic (OI) or ART departments are HIV testing points and all HIV positive patients or clients are promptly initiated on ART in these departments. Clients who test positive in the VMMC program are reffered to OI/ART clinic for ART

initiation and follow up. Treatment of sexually transmitted infections (STIs) is also done in every department of the hospital. It is also imperative to highlight the fact that pediatric ART is also an important component of the HIV programme at SDH. All babies who are positive using DNA PCR are promptly initiated on ART and given INH prophylaxis.

Modeling and forecasting new HIV infections is crucial for planning and monitoring of trends at national, regional and worldwide level. The results of this study are particularly envisioned to support health policy makers in Zimbabwe; especially at district level (i.e secondary level healthcare management and administration) in order to understand the magnitude of the HIV/AIDS problem and stimulate efforts to improve prevention and healthcare programs in Silobela. The DMO of SDH, as a manager of the HIV program at district level, will also benefit from this endeavor because this paper will act as a guide in taking precautionary measures as well as making appropriate interventions on how to control and minimize the repercussion effect of HIV/AIDS. The forecasts of this paper will also go a long way in improving the general scholarly public health policy discourse in Zimbabwe.

Objectives

i. To analyze the trend of new HIV infection at SDH over the period January 2014 – December 2018.
ii. To predict new HIV infections in Silobela over the period January 2019 – December 2021.

Problem Statement

Despite the fact that there is a global consensus that the HIV/AIDS epidemic could be halted by 2030 (Rubaihayo *et al*, 2016), we cannot rule out the reality that HIV/AIDS prevention is never easy (He *et al*, 2018). In fact, HIV/AIDS remains one of the lethal diseases which cause millions of deaths every year around the world (Gould, 2009; Girum *et al*, 2018). More than 40 million people have been infected with HIV worldwide since the beginning of the epidemic and an estimated 70% of those infected people live in Africa (Rauner *et al*, 2005). Actually, Zimbabwe has one of the highest HIV prevalences in Sub-Saharan Africa (SSA) at 12%, with 1.3 million people living with HIV in 2018 (UNAIDS, 2019). This is consistent with table 1 below:

Table 1: Estimated Number of People Living with HIV & AIDS in Zimbabwe

Description	2014	2015	2016	2017
HIV Population Adults + Children	1,285,205	1,302,105	1,315,883	1,325,823
Adult Population Adults 15+	1,194,760	1,216,615	1,234,982	1,249,172
HIV population (10-19 years)	85,099	81,552	77,943	74,460
HIV Population (15-49)	1,005,850	1,014,440	1,016,238	1,014,395
HIV Population Female 15+	703,467	717,172	728,927	738,399
HIV+ pregnant women (15-24 years)	16,160	15,800	15,320	14,816
HIV Population (0-14)	90,445	85,489	80,902	76,650

Source: Ministry of Health & Child Care (2018)

Estimated HIV population (adults + children) increased from 2014 to 2017. Therefore, HIV/AIDS is still a major public health problem in Zimbabwe despite the use of Antiretroviral Therapy (ART) medicine. This

study seeks to model and forecast new HIV infections at SDH, and is envisaged to contribute a lot, especially at district level, in terms of health policy and healthcare management.

2. Literature Review

In Asia, Yu *et al* (2013) forecasted the number of new HIV infections in the Korean population using the ARIMA model over the period 2013 to 2017, using an annual data set covering the period 1985 to 2012. The authors relied on the Akaike's Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC) statistics in order to evaluate the constructed models. Their estimation was via the Maximum Likelihood (ML) method. The study also made use of the Mean Absolute Percentage Error (MAPE) between the number of observed and fitted HIV infections over their study period. The study basically found out that the optimal model to forecast new HIV infections in Korea was the ARIMA (2, 2, 1) model. Based on Yu *et al* (2013)'s forecast of the number of newly diagnosed HIV infections and cumulative number of HIV infections, the cumulative number of HIV infected Koreans was approximated to reach 15 000. In another Asian study, He *et al* (2018); unlike Yu *et al* (2013); used the Baidu Search Index (BSI) to predict the incidence of HIV/AIDS in China, with a panel data set of 30 provinces and a time-frame from January 2009 to December 2013. In their study, He *et al* (2018) found out that the Pooled Mean Group (PMG) model showed that the BSI positively predicts the increase in HIV/AIDS incidence, with a 1% increase in HIV/AIDS incidence on average.

In an African study, Aboagye-Sarfo *et al* (2013), forecasted new HIV cases in the Ashanti region of Ghana using the Box-Jenkins ARIMA model of time series analysis, using a monthly data set covering the period January 1998 to December 2007. The study also applied the Holt's Double Exponential Smoothing (HDES) approach. Their constructed models were diagnostically tested using Mean Squared Error (MSE), Mean Absolute Error (MAE) and MAPE. The HDES predicted 2580 new HIV cases per year in Ashanti region whereas the Box-Jenkins ARIMA model predicted a constant number of 2556 new HIV cases per year, implying that the epidemic in the Ashanti region will relatively be in stable equilibrium for the years 2014, 2015 and 2016. In another African study, Demissew (2015) formulated a model to determine the trend and project HIV/AIDS epidemics in Ethiopia, using an annual data set covering the period 1990 to 2013. The data was analyzed using the ARIMA time series analysis model. In order to evaluate the constructed models, the study employed the AIC and the Bayesian Information Criterion (BIC). All the models were estimated using the ML estimation method. The ARIMA (2, 3, 2) model was found to be the optimal model. The trend showed that the HIV/AIDS prevalence in Ethiopia was increasing very fast from around mid 1990s and reached its peak in the years 2002 to 2004 and decreased onward. Demissew (2015)'s prediction indicates that the prevalence of HIV/AIDS would subside in Ethiopia from 2015 to around 2020. The trend and the prevalence indicated that th status of HIV/AIDS in Ethiopia is likely to be controllable.

3. Methodology

Mathematical modeling is deemed as the only likely way of measuring the efficacy of HIV intervention in order to predict, assess the past and future events and explaining the impact of the disease (Demissew, 2015). In forecasting infectious diseases, the Box-Jenkins ARIMA model (generalized or seasonal) is the most widely used mathematical model (Earnest *et al*, 2005; Gomez-Elipe *et al*, 2007; Wu *et al*, 2008; Luz *et al*, 2008; Aboagye-Sarfo *et al*, 2010; Liu *et al*, 2011; Siriwan *et al*, 2012; Nsoesie *et al*, 2014; Zheng *et al*, 2015; Imai & Hashizume, 2015; Xie, 2018; Coelho *et al*, 2019). In fact, ARIMA models have been used successfully to monitor and forecast different infectious diseases including new annual HIV infections in Korea (Yu *et al*, 2013) and the Ashanti region of Ghana (Aboagye-Sarfo *et al*, 2013). Even though He *et al* (2018) maintain that the effective method in the prediction of HIV epidemic is almost nil; this paper prioritizes the Box-Jenkins approach and thus follows the leads of previous researchers such as Yu *et al* (2013) and Aboagye-Sarfo *et al* (2013).

The SARIMA Model

The Box – Jenkins technique is accredited to Box & Jenkins (1970) and in this paper; it will be used for analyzing monthly new HIV infections for SDH. A generalized Box-Jenkins SARIMA model may, thus, be specified as shown in equation [1] below:

$$\phi_p(B)\emptyset_p(B^s)N_t = \theta_q(B)\Theta_q(B^s)\varepsilon_t \quad \ldots [1]$$

Where B is the backshift operator, $\phi_p, \emptyset_p, \theta_q \; and \; \Theta_q$ are polynomials of order p, P, q and Q respectively. $\varepsilon_t$is a white noise process and $N_t = \nabla_d \Delta_s^D Y_t$ is the differenced N series.

Data

This study is based on monthly observations of new HIV infections (adults and children-all age groups) at SDH, from January 2014 to December 2018. The out-of-sample forecast ranges over the period January 2019 to December 2021. All the data employed in this research was gathered from SDH.

Diagnostic Tests and Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1: Graphical Analysis

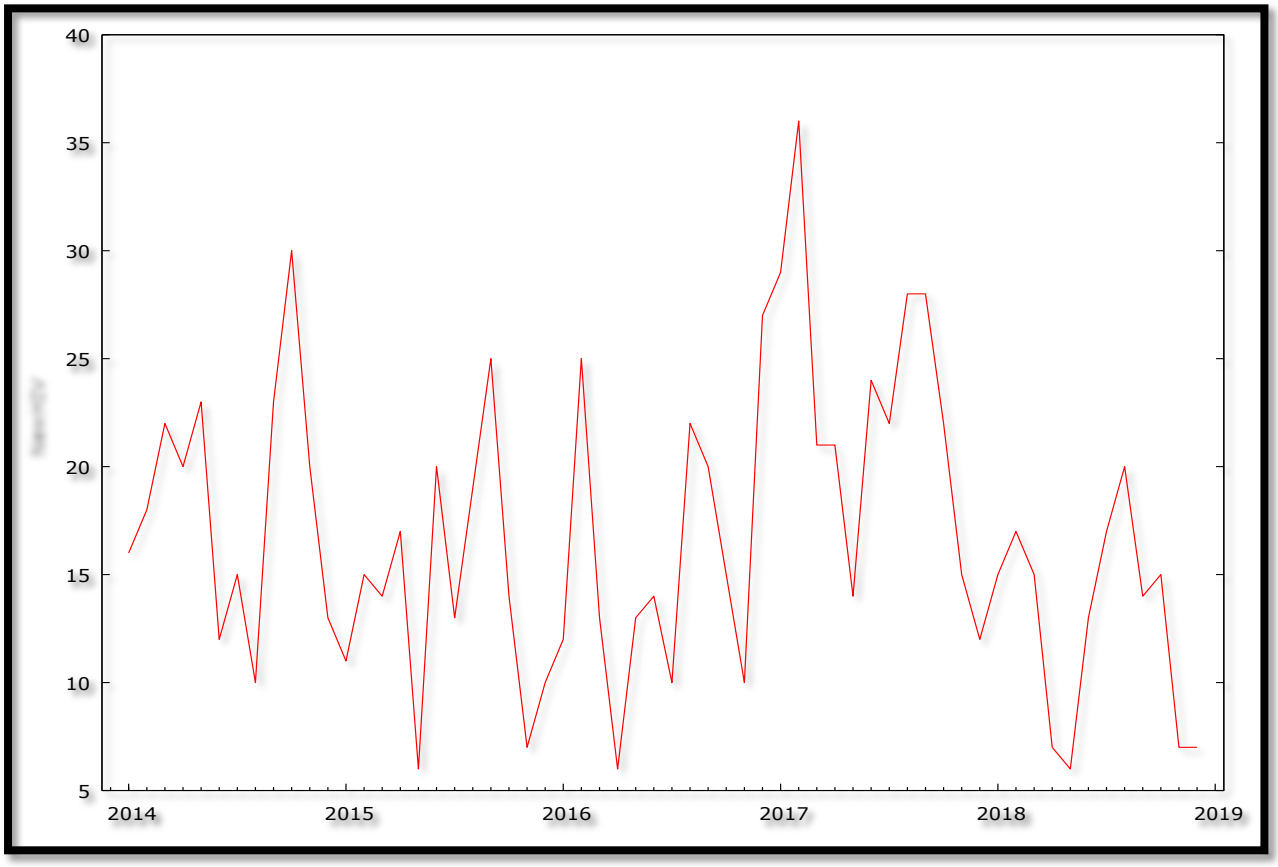

Figure 1 above indicates that the N series doesn't follow any particular trend. However, in as much as it is reasonable to suspect stationarity, it is quite imperative to formally test the series for stationarity.

The ADF Test

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
N_t	-4.560216	0.0005	-3.546099	@1%	Stationary
			-2.911730	@5%	Stationary
			-2.593551	@10%	Stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
N_t	-4.553455	0.0029	-4.121303	@1%	Stationary
			-3.487845	@5%	Stationary
			-3.172314	@10%	Stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
N_t	-0.983953	0.2875	-2.606911	@1%	Not stationary
			-1.946764	@5%	Not stationary
			-1.613062	@10%	Not stationary

Table 5: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(N_t)$	-7.624996	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 6: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values	Conclusion

$D(N_t)$	-7.568220	0.0000	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

Table 7: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
$D(N_t)$	-7.677420	0.0000	-2.606911	@1%	Stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

Figure 2 and tables 2 to 6 indicate that the N series is an I (1) variable.

Evaluation of SARIMA Models (without a constant)

Table 8: Evaluation of SARIMA models

Model	AIC	ME	MAE	RMSE	MAPE
SARIMA (0, 1, 1)(0, 1, 1)	**327.8593**	0.005697	5.8768	7.6112	42.425
SARIMA (1, 1, 1)(1, 0, 0)	389.3749	-0.33755	4.993	6.1115	37.589
SARIMA (1, 1, 1)(2, 1, 0)	330.6909	0.077206	5.977	7.5338	42.638
SARIMA (0, 1, 1)(1, 1, 1)	329.7451	0.0080967	5.8725	7.6068	42.377

The SARIMA $(0, 1, 1)(0, 1, 1)_{12}$model is the best model in terms of the AIC, thus it is chosen.

Analysis of the Residuals of the SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ Model

Residual Correlogram of the SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ Model

Figure 2: Residual Correlogram

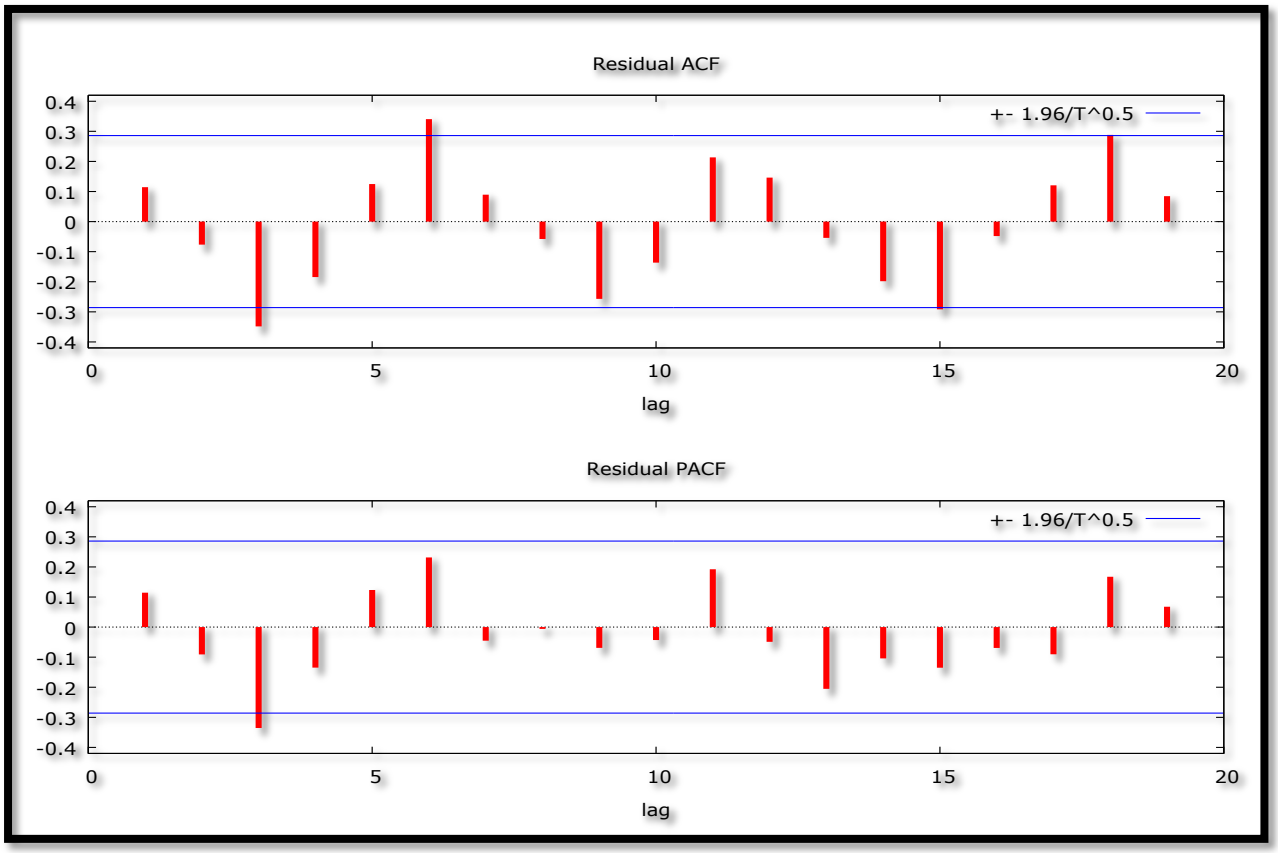

Figure 2 above shows that the residuals of the selected Box-Jenkins ARIMA "catch-all" model are stationary since the ACFs at various lags, generally, lie within the bands. This also implies that the chosen model is stable and acceptable for forecasting monthly SDH new HIV infections.

Results of the Study

Descriptive Statistics

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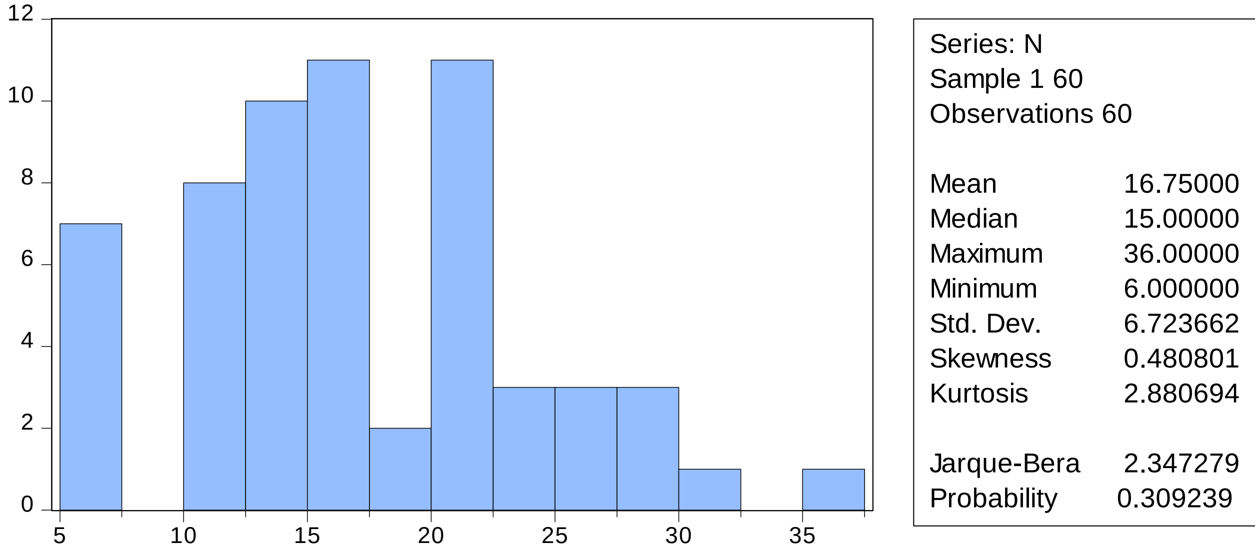
Figure 3: Descriptive Statistics



As shown in the figure above, the mean is positive, i.e 16.75. This implies that on average, 17 people per month have been infected by HIV in Silobela District over the study period. The median is 15. The maximum is 36. This means that at most 36 people when infected with HIV over the study period and this occurred in the month of February in 2017. The minimum is 6. This means that the least number of new HIV infections in Silobela District was 6 people over the study period and this was observed in the month of April 2016. Since skewness is 0.480801, it implies that the series is positively skewed. Kurtosis is 2.880694, which is approximately equal to 3: according to Nyoni & Bonga (2017), the rule of thumb for kurtosis is that it should be around 3 for normally distributed variables. Therefore, based on the kurtosis statistic, the N series can be described as normally distributed. The insignificant p-value also confirms that it is reasonable to refer to the N series as normally distributed.

Results Presentation[1]

Table 9: Main Results of the SARIMA (0, 1, 1)(0, 1, 1)$_{12}$ Model

The SARIMA (0, 1, 1)(0, 1, 1)$_{12}$ model can be presented as follows:

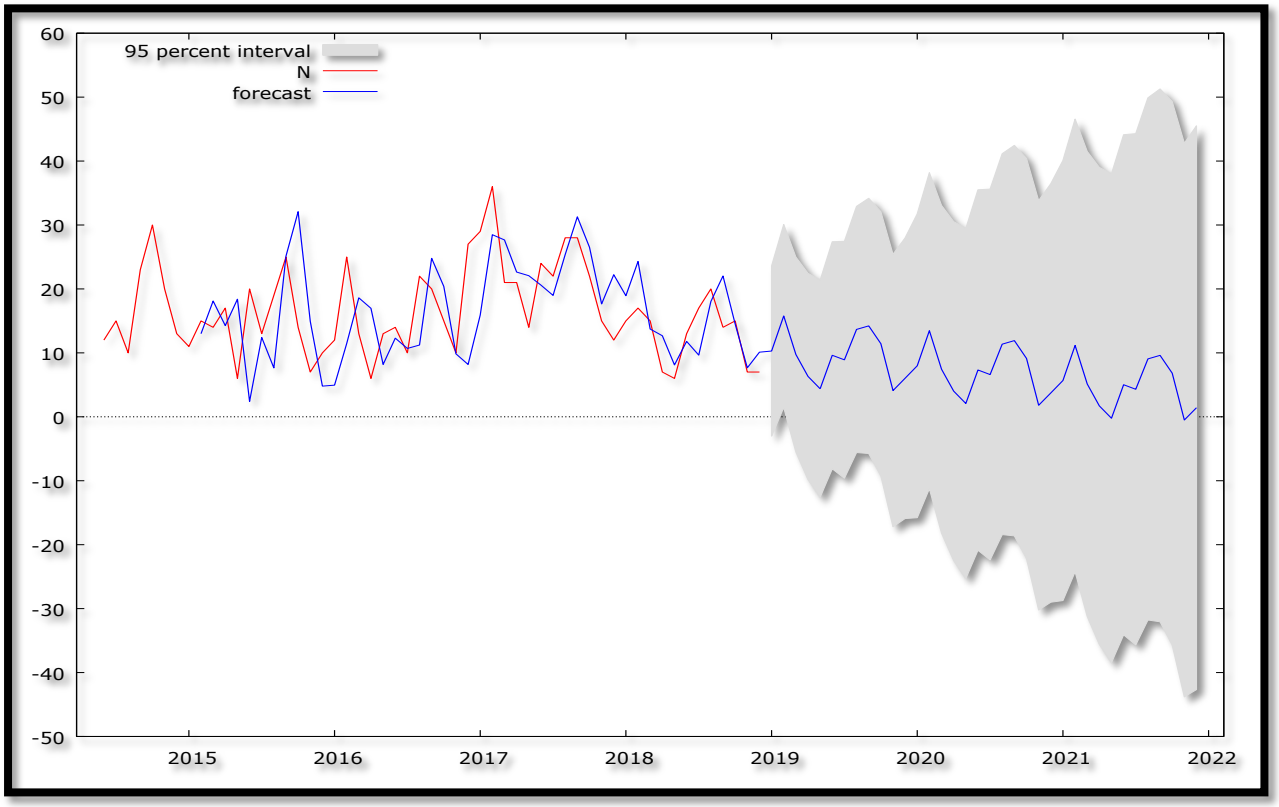
$$(1 - B)(1 - B^{12})N_t = (1 + \theta B)(1 + \Theta B^{12})\varepsilon_t \dots \dots \dots \dots [2]$$

Variable	Coefficient	Standard Error	z	p-value
θ_q	-0.604475	0.110907	-5.45	0.00000503***
Θ_q	-0.710434	0.283098	-2.509	0.0121**

Forecast Graph

Figure 4: Forecast Graph

[1] ****, ** and * means significant at 1%, 5% and 10% level of significance, respectively.*



Out of Sample Forecasts

Table 10: Out-of-sample forecasts

Year: Month	Prediction	Standard Error	95% Confidence Interval
2019:01	10.2830	6.78789	(-3.02100, 23.5870)
2019:02	15.7760	7.29955	(1.46916, 30.0829)
2019:03	9.74299	7.77762	(-5.50087, 24.9869)
2019:04	6.31881	8.22797	(-9.80771, 22.4453)
2019:05	4.38336	8.65491	(-12.5800, 21.3467)
2019:06	9.62311	9.06176	(-8.13761, 27.3838)
2019:07	8.91181	9.45111	(-9.61202, 27.4357)
2019:08	13.6666	9.82505	(-5.59015, 32.9233)
2019:09	14.2191	10.1853	(-5.74360, 34.1819)
2019:10	11.4304	10.5332	(-9.21420, 32.0750)
2019:11	4.10523	10.8699	(-17.1995, 25.4099)
2019:12	6.03083	11.1966	(-15.9141, 27.9757)
2020:01	7.97863	12.1239	(-15.7838, 31.7410)
2020:02	13.4716	12.6086	(-11.2407, 38.1840)
2020:03	7.43861	13.0753	(-18.1884, 33.0657)
2020:04	4.01443	13.5259	(-22.4958, 30.5247)
2020:05	2.07898	13.9620	(-25.2859, 29.4439)
2020:06	7.31874	14.3848	(-20.8750, 35.5125)
2020:07	6.60744	14.7956	(-22.3914, 35.6063)
2020:08	11.3622	15.1953	(-18.4200, 41.1444)
2020:09	11.9148	15.5847	(-18.6307, 42.4603)
2020:10	9.12604	15.9647	(-22.1641, 40.4162)
2020:11	1.80086	16.3358	(-30.2166, 33.8184)

2020:12	3.72646	16.6986	(-29.0022, 36.4551)
2021:01	5.67425	17.5586	(-28.7400, 40.0885)
2021:02	11.1673	18.0632	(-24.2359, 46.5704)
2021:03	5.13424	18.5541	(-31.2310, 41.4995)
2021:04	1.71005	19.0323	(-35.5925, 39.0126)
2021:05	-0.225393	19.4988	(-38.4423, 37.9915)
2021:06	5.01436	19.9543	(-34.0954, 44.1242)
2021:07	4.30306	20.3998	(-35.6797, 44.2859)
2021:08	9.05783	20.8357	(-31.7793, 49.8950)
2021:09	9.61039	21.2626	(-32.0636, 51.2844)
2021:10	6.82167	21.6812	(-35.6727, 49.3160)
2021:11	-0.503517	22.0918	(-43.8026, 42.7956)
2021:12	1.42208	22.4949	(-42.6672, 45.5113)

Graphical Presentation of the Predicted Monthly SDH New HIV Infections (Out-of-Sample)

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

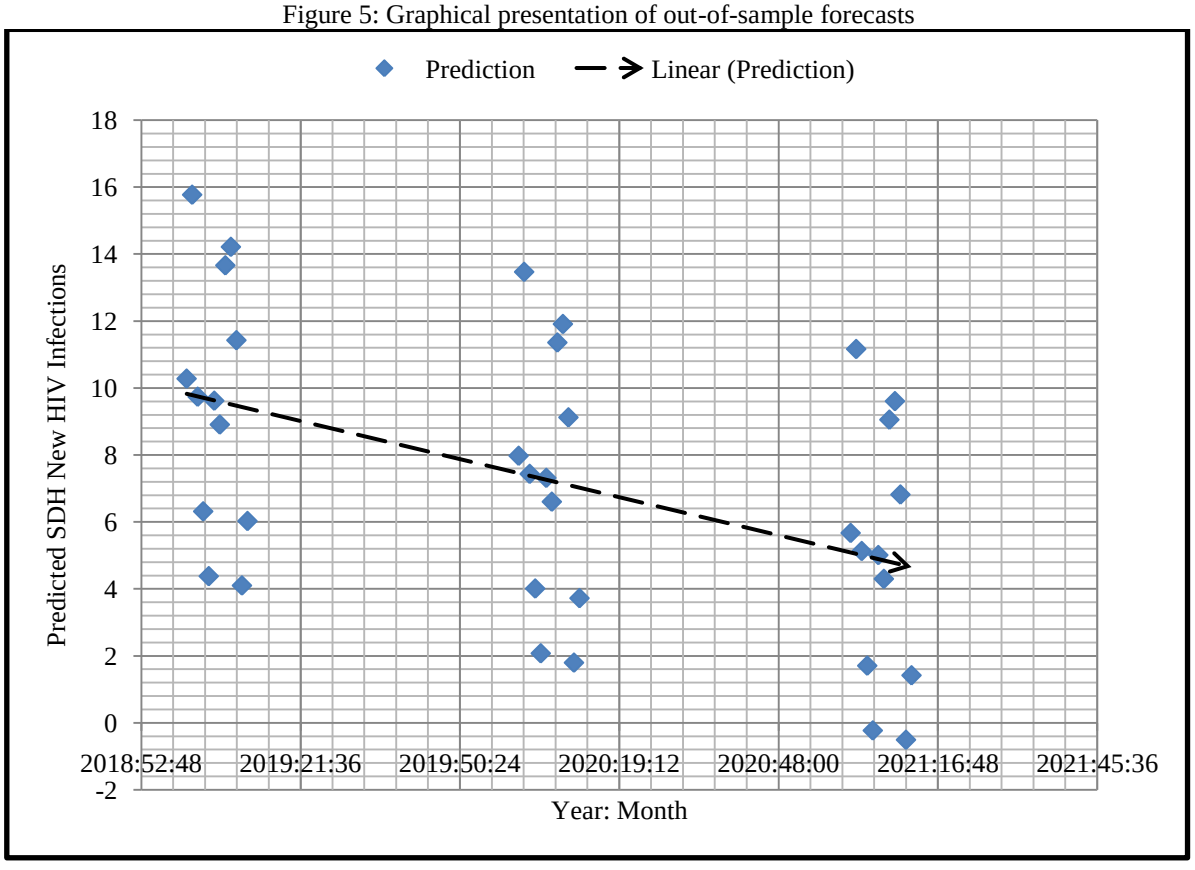


Table 9 shows the main results of the optimal model. Figure 4 is the forecast graph of both in-sample and out-of-sample forecasts. Table 10 and figure 5 show the actual out-of-sample forecasts derived from the selected optimal model. These results apparently show a downward trend in new HIV infections at SDH over the out-of-sample period. The results of this study are in line with the Ministry of Health & Child Care (2018) which reported that new HIV infections are generally on downwards spiral. These results are not surprising given the following reasons:

i. PMTCT programme: all HIV positive pregnant and breastfeeding mothers are promptly initiated on highly effective Antiretroviral Therapy (ART) and are closely followed up for adherence to treatment.
ii. HIV programme linkages – all clients seen in other departments are offered HIV testing and counseling services; this includes TB/HIV program linkages.
iii. HIV self testing offers another opportunity to find more HIV positive clients and start on treatment.

iv. There is a good uptake of male circumcision program [through the Voluntary Medical Male Circumcision (VMMC)] and other preventive strategies for example, correct and consistent use of condoms.
v. Community awareness on TB/HIV both at local level through local leadership and at national level through mass media communication.

Further Research

The current study only focused on SDH; therefore, further studies should be done for the whole country in order to comprehensively appreciate the dynamics of HIV/AIDS in the country. There is also the need to construct various different ARIMA models for all age groups separately.

Recommendations and Conclusion

There is need for continued intensification of HIV/AIDS surveillance at SDH in order to sufficiently control HIV/AIDS. In this regard, the SDH management team, with the help from relevant government and non-governmental authorities; should among other things:

i. Intensify evaluation of HIV/AIDS prevention programmes at Silobela.
ii. Engage in district-level policy formulation and resource allocation for HIV/AIDS prevention programmes.
iii. Make a comprehensive plan for care and support for those infected with HIV.
iv. Continue to assess the magnitude of the epidemic and the distribution of infection at Silobela.
v. Engage in more HIV/AIDS awareness programmes
vi. Initiate behavioral surveillance, i.e regular monitoring of sexual behaviour could also become part of an HIV prevention strategy at SDH and could be implemented even at national level through the "national surveillance programmes".

The current study relied on 60 monthly observations of new HIV infections at SDH, from January 2014 – December 2018; to model and forecast 36 out-of-sample new HIV infections, that is, from January 2019 to December 2021. We employed the Box-Jenkins SARIMA time series analysis approach. The study showed that new HIV infections are expected to decline over the out-of-sample period.

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