FORECASTING TB NOTIFICATIONS AT SILOBELA DISTRICT HOSPITAL, ZIMBABWE

Dr. Smartson. P. NYONI[1], Thabani NYONI[2]

[1] *Medical Doctor, ZICHIRe Project, University of Zimbabwe, Harare, Zimbabwe*
[2] *MSc Economics Scholar, Department of Economics, University of Zimbabwe, Harare, Zimbabwe*

ABSTRACT

This research employs monthly time series data on TB notifications at Silobela District Hospital (SDH) from January 2014 to December 2018; to forecast TB notifications using SARIMA models. Diagnostic tests indicate that the TB notifications series is I (0). Based on the AIC, the study presents the special SARIMA model, the SARMA (1, 0, 1)(0, 1, 1)$_{12}$ model. Diagnostic tests further reveal that this model is stable and hence suitable for forecasting the TB notifications at SDH. The chosen parsimonious model shows that TB notifications will generally decline over the out-of-sample period, but it remains worrisome to note that this anticipated decline in TB notifications will not be as fast as it should be. The main policy direction emanating from this study is that there should be serious intensification of TB surveillance and control programmes in Silobela district in to order to reduce TB incidences not only in the Silobela community but also in Zimbabwe at large.

Keywords: - *Forecasting, TB, TB Notifications*

I. Introduction

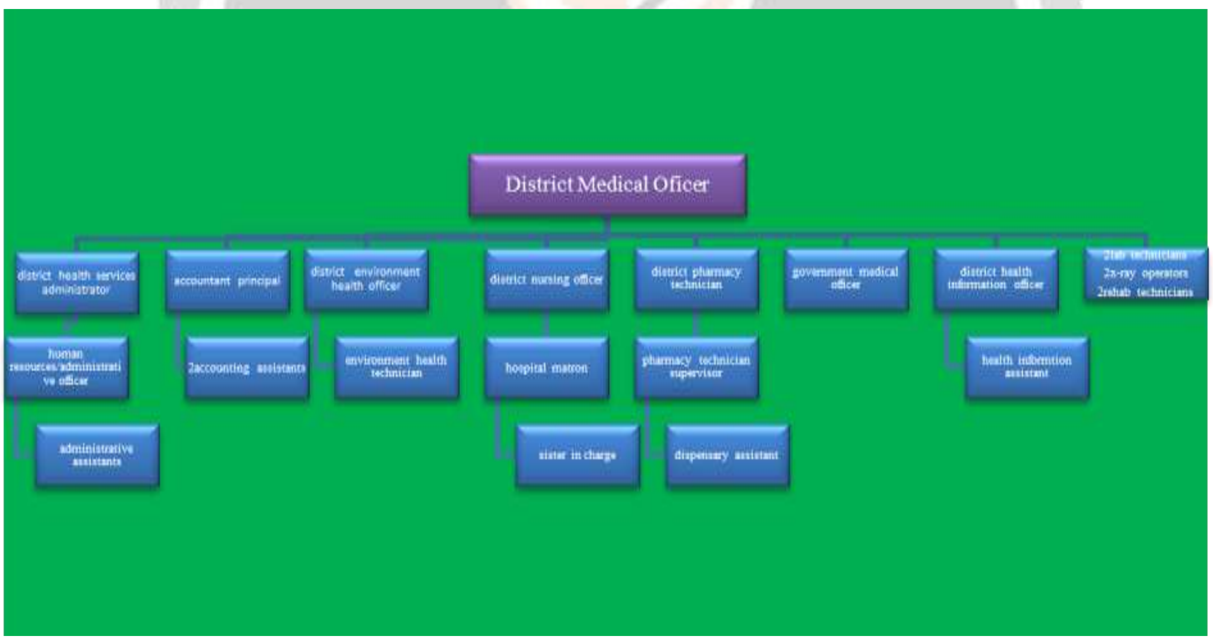
Tuberculosis (TB) is a respiratory infectious disease caused by “Mycobacterium Tuberculosis” (Sharma *et al*, 2016) and generally spreads through air droplets by sneezing and coughing of the infected person (Ricks *et al*, 2011) and is also capable of emanating from reactivation of a past latent TB infection (Nasehi *et al*, 2012). Despite the fact that global TB incidence has declined by 1-2% per year (Raviglione *et al*, 2012), TB is still a major public health problem in many developing countries (Sgaragli & Frosini, 2016) and Zimbabwe is not an exception. This study focuses on TB notifications at Silobela District Hospital (SDH), which is also known as Kwekwe District Hospital (KDH).

SDH is a rural district hospital located in the Midlands Province of Zimbabwe. It was originally a clinic which was run by Roman Catholic nuns. It belonged to the nearby school Loreto High School to provide medical services to the students at the institution. In 1997 construction and upgrading as a district hospital began. Some of the hospital wards were previously used as administration offices. There was no doctor at the hospital, back then; the doctor used to visit on specific days and ambulance services were requested all the way from Kwekwe General Hospital (KGH). In the year 2001 on the 14th of September, SDH was commissioned as a district hospital for Kwekwe district by the then Minister of Health & Child Welfare, the late Dr. Timothy Stamps. Previously Kwekwe district had no district hospital, so SDH was ideal as it is centrally located in the district. It is situated 63km northwest of Kwekwe town and it is a referral center for 35 clinics in the district; with a population of over 300 000 people in the district. With the status of district hospital, SDH became a referral hospital with all clinics reporting to the hospital and in some instances some collecting drugs from the institution. All the clinics send presumptive TB case sputum samples to SDH for smear microscopy and gene expert testing; samples are tested and results sent back on the same day to ensure that TB positive patients are commenced on treatment promptly. The hospital now consists of several departments namely, health information, physiotherapy, pharmacy, laboratory, x-ray, environmental health, the OI (opportunistic infection) and the family child health department. The institution is now in a position to provide vital medical procedures like circumcision procedures, perform x-ray operations, CD4 counts and various other tests especially with the current availability of 2 doctors and a clinical officer at the institution.

The TB program at SDH is funded by the government of Zimbabwe with the support of its partners like USAID, Challenge TB and The UNION. There is collaboration of HIV and TB programs at the hospital, each department has screening tool for TB and sends sputum samples for presumptive TB cases to the hospital laboratory for testing and results are reported within a day and patients are commenced immediately on treatment when they test positive for TB. At the same time, all TB positive cases are tested for HIV and commenced on Antiretroviral Treatment (ART) immediately when HIV positive under the “Test and Treat” approach. All HIV positive patients are screened for TB if sputum positive, started on anti-TB treatment in line with WHO guidelines. All HIV positive patients with no contraindications and under 5 children who are in contact with sputum positive TB patients are given isoniazid (INH) prophylaxis. The TB focal person coordinates TB programs at the hospital and attends to TB patients on a daily basis including client follow ups. He or she reports to the hospital matron. The District Medical Officer is the program manager at district level and ensures that there is TB/HIV collaboration and attends to program challenges. The TB awareness program is done by village health workers, clinic nurses and environmental health workers. The use of local political administrative structures during community gatherings plays a pivotal role in disseminating information on TB and promoting community participation in TB case identification, treatment and follow up. All the data is registered in the appropriate registers (Presumptive TB register, Attendance register, Notification register etc for monthly reports). Quarterly reports are recorded in the District Health Information System (DHIS2). As a rural hospital, SDH faces a number of challenges with regards to TB and these include TB patients missing their scheduled visits due to financial constraints, drug-resistant TB cases coming from South Africa during the festive season, patients defaulting treatment because of religious beliefs as well as poor adherence.

The mission of SDH is to “have the highest possible level of health and quality of life for all citizens of Silobela” and as such, to attain this mission; an administrative structure is in place at the hospital which outlines the reporting structure at the institution as shown in the diagram below:

Figure 1: SDH organizational structure



Previously the hospital was run by the KGH with all the administration being done there. There just used to be clerks who did the administration whilst reporting to the KGH administration. However with the upgrading of the hospital’ status into being the district hospital, all departments became functional. The hospital is a non-profit making organization. Its existence is to solely provide medical care to patients and not to make profit. Thus it gets most of its funding from fees charged as well as government funds. These monies are then used in the day to day running of the institution from administration costs to purchasing provisions used in assisting patients.

Objectives of the Study

i. To analyze the trend of TB notifications at SDH over the period January 2014 to December 2018.
ii. To determine the forecasted number of TB notifications over the period January 2019 to December 2021.

Relevance of the Study

TB remains a serious threat to public health in the world (Ade *et al*, 2016) with a vast health burden due to the high incidence, medical expenses, drug resistance and co-infections (WHO, 2016) and is the second major cause of mortality, especially in poor and low economic countries (WHO, 2001). 95% of TB cases and 98% of TB deaths occur in low and middle income families (WHO, 2000). TB is a major public health problem in Zimbabwe (Dube, 2015) and regrettably; continues to be a serious cause of morbidity and mortality in Zimbabwe (National TB Guidelines, 2010).

Despite full implementation of national TB programs, TB still continues to be a leading cause of mortality and economic burden, not only in Silobela but also in Zimbabwe at large. In Silobela district, just like in any other district in Zimbabwe, TB has not spared communities. The results of this study are envisioned to go a long way in assisting health policy makers in reducing the TB burden not only in Silobela but also in Zimbabwe at large.

This research is in line with the "End TB Strategy" of the WHO hatched and implemented in 2014 whose targets are that of reducing by 2035 the incidence and mortality of TB by 90% and 95% respectively. The study is also not only consistent with the Zimbabwe National TB Control Strategy's vision of "A TB-free Zimbabwe" but also in line with the mission statement of SDH which is "to have the highest possible level of health and quality of life for all citizens of Silobela". In order to attain the 2020 milestones of the "End TB Strategy" and the Zimbabwe National TB Control Strategy and to fulfill the mission of SDH, there is need for additional and relevant TB modeling and forecasting techniques at all levels. From a district-level (secondary level) analysis, this study is poised to deepen the understanding of epidemiological dynamics of TB in Zimbabwe.

II. Literature Review

A number of papers can be found on issues to do with forecasting TB incidences using Box-Jenkins type of models, for example; Moosazadeh *et al* (2014), Azeez *et al* (2016), Frah & Alkhalifa (2016), Patowary & Barman (2017), Mao *et al* (2018), Mbau (2018), Mohammed *et al* (2018), Liu *et al* (2019) and Nyoni & Nyoni (2019). Most of these previous studies (Moosazadeh *et al*, 2014 for Iran; Frah & Alkhalifa (2016) for Sudan, Patowary & Barman, 2017 for India; Mao *et al*, 2018 for China, Mbau (2018) for Indonesia and Nyoni & Nyoni (2019) for Zimbabwe) generally agree that these Box-Jenkins models are suitable for modeling and forecasting TB notifications.

Other previous studies have used alternative analysis techniques such as generalized ARIMA, ARCH and HW (Imran *et al*, 2014; Dube, 2015 for Zimbabwe; Aryee *et al*, 2018 for Ghana) and ARIMAX (Anggraeni *et al*, 2017 for Indonesia) while some researchers have also attempted using hybrid models such as BPNN (Wei *et al*, 2017 and Liu *et al*, 2019 for China) and SARIMA-NNAR, SARIMA-ETS as well as SARIMA-ANFIS (Azeez *et al*, 2016 for South Africa; Mohammed *et al*, 2018 for Iran). In the case of neighboring South Africa, Azeez *et al* (2016) concluded that their hybrid model, the SARIMA-NNAR model out-performed the generalized SARIMA models. Similarly, in China; Wei *et al* (2017) found out that the new ARIMA-GRNN model may be more suitable for forecasting TB incidence in Heng County than traditional models. In line with Wei *et al* (2017), Liu *et al* (2019) discovered that their hybrid model, the BPNN model performs better than SARIMA models.

However, Nyoni & Nyoni (2019), by finding that the SARIMA model, in its special form, the SARMA model, is optimal for forecasting TB notifications at Zengeza clinic in Chitungwiza; generally confirmed the findings of many previous studies such as Moosazadeh *et al* (2014), Patowary & Barman (2017) and Mao *et al* (2018). Despite the fact that this paper follows the intuition already presented in previous papers such as Moosazadeh *et al* (2014), Patowary & Barman (2017), Mao *et al* (2018) and Nyoni & Nyoni (2019); it is quite imperative to note that its contribution to literature is different in the sense that we focus on a district hospital, SDH, which has never been explored before and it is almost unnecessary to aver that this paper will provide new insights on how to deal with the TB scourge not only in the community of Silobela but also in Zimbabwe at large. Interestingly, our results will help us compare and contrast SDH TB notification dynamics with both local and international empirical evidence and hence consolidate our policy direction.

III. Methodology

The SARIMA Model

The basic SARIMA model can be specified as shown in equation [1] below:

$$\Phi_p(B)\emptyset_p(B^s)TBN_t = \theta_q(B)\Theta_q(B^s)\varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

Where B is the backshift operator, $\Phi_p, \emptyset_p, \theta_q$ *and* Θ_q are polynomials of order p, P, q and Q respectively. ε_t is a white noise process and $TBN_t = \nabla_d \Delta_s^D Y_t$ is the differenced TBN series. If the series are stationary in levels, equation [1] becomes a SARMA [Seasonal ARMA] model or technically a special SARIMA model. SARIMA models are Box-Jenkins type models and were coined by Box & Jenkins (1970).

Data

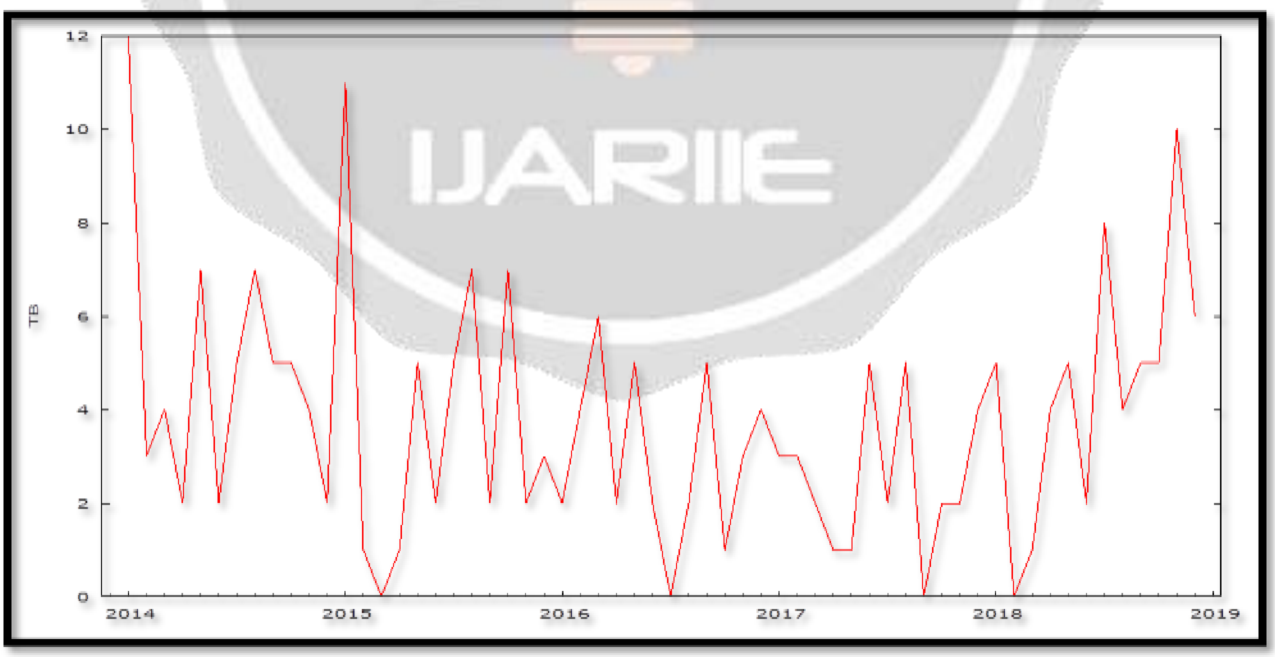
This study is based on monthly observations of TB notifications (TBN) at Silobela District Hospital (SDH), Kwekwe District, Zimbabwe, from January 2014 to December 2018. Our out-of-sample forecast ranges over the period January 2019 to December 2021. All the data employed in this research was collected from SDH TB unit; the source document was the TB notification register.

Diagnostic Tests and Model Evaluation for SDH TB notifications

Stationarity Tests: Graphical Analysis

Before one pursues formal stationarity tests, it is always advisable to plot the time series under study. Such plots give an initial clue about the likely nature of the time series. Such an intuitive feel is the starting point of more formal tests of stationarity (Gujarati & Porter, 2008). Below is a time series plot of SDH TB notifications:

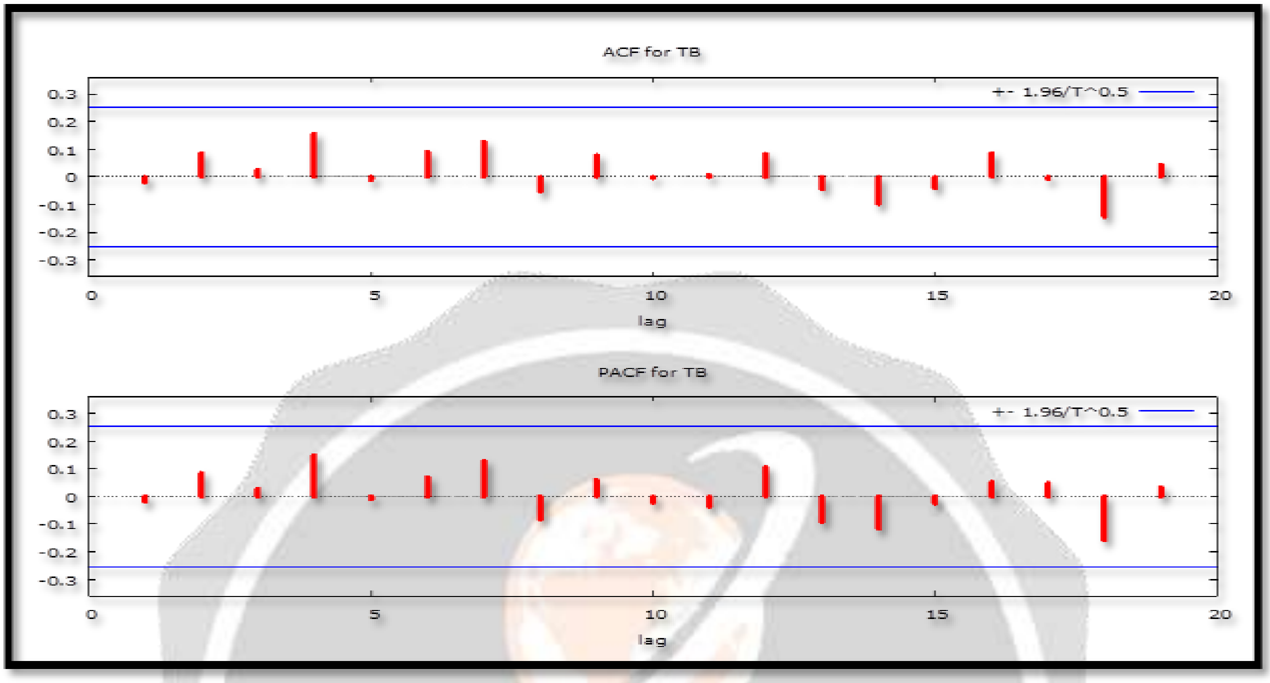
Figure 2: Graphical Analysis



The series under consideration doesn't follow any trend and for that reason alone, we now suspect that it could be stationary in levels. Below is correlogram test for stationary, to try and verify our suspicion:

The Correlogram in Levels

Figure 3: Correlogram in Levels



As expected, the autocorrelation coefficients at various lags are very low and within the bands. Hence figure 3 is the typical correlogram of a stationary time series. Therefore, in this regard, there is no need for further tests of stationary because the correlogram has already confirmed that the series under consideration is stationary at levels.

Evaluation of SARIMA Models (without a constant)

Table 1: Evaluation of SARIMA Models (without a constant)

Model	AIC	ME	RMSE	MAE
SARIMA (1, 0, 1)(0, 1, 1)$_{12}$	**249.0616**	-0.088313	2.9311	2.2185
SARIMA (1, 0, 1)(1, 0, 1)$_{12}$	297.0399	0.045972	2.9758	2.2553
SARIMA (2, 0, 2)(0, 1, 1)$_{12}$	251.7256	-0.051568	2.8896	2.145
SARIMA (1, 0, 1)(2, 1, 0)$_{12}$	252.012	0.034348	2.9728	2.2596
SARIMA (0, 0, 0)(1, 1, 1)$_{12}$	249.2906	-0.53969	3.012	2.268
SARIMA (2, 0, 2)(0, 0, 0)$_{12}$	297.0787	0.083209	2.9939	2.2368
SARIMA (2, 0, 2)(1, 0, 0)$_{12}$	298.1186	0.12076	2.9858	2.2588
SARIMA (2, 0, 2)(0, 0, 1)$_{12}$	297.86	0.1246	2.9824	2.2673

This paper uses the AIC as the goodness of fit criterion. A model with the lowest AIC value is regarded as the parsimonious model. Thus, the SARMA (1, 0, 1)(0, 1, 1)$_{12}$ model is selected as the optimal model.

Residual Test of the Selected Model

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

Figure 4: Residual Correlogram of the SARMA (1, 0, 1)(0, 1, 1)$_{12}$ Model

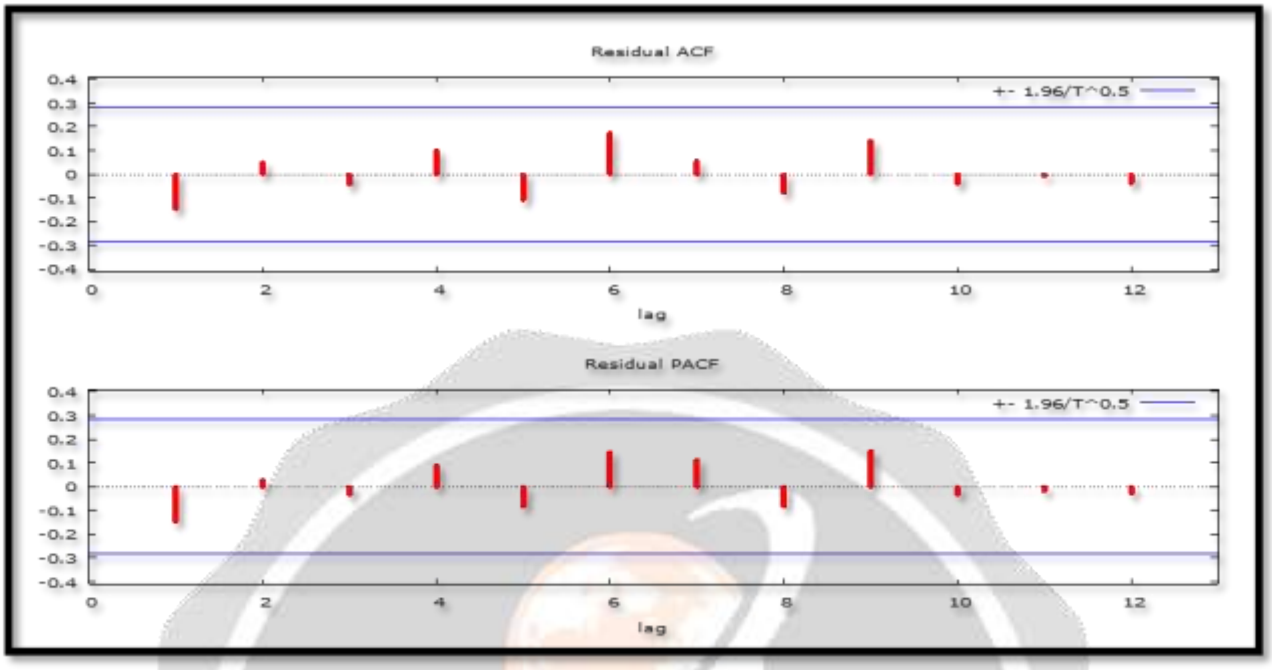


Figure 4 indicates that the residuals of the SARMA (1, 0, 1)(0, 1, 1)$_{12}$ model are stable and stationary. Hence, this model is suitable for forecasting TB notifications at SDH.

IV. Results

Descriptive Statistics

Table 2: Descriptive Statistics

Description	Statistic (SDH TBN)
Mean	3.75
Median	3.5
Minimum	0
Maximum	12
Standard deviation	2.6078
Skewness	0.99348
Excess kurtosis	1.1192

As shown in table xx above, the mean is positive, that is, 3.75. The median is 3.5. The minimum is 0 while the maximum is 12. The skewness is 0.99348 and is positive, implying that the variable under consideration is positively skewed and non-symmetric. Excess kurtosis is 1.1192 and this shows that the variable under consideration is normally distributed.

Results Presentation[1]

Table 3: Results Presentation – the SARIMA (1, 0, 1)(0, 1, 1)$_{12}$

Variable	Coefficient	Std. Error	z	p-value
Non-seasonal AR	0.954934	0.109601	8.713	0.00000000000000000296***
Non-seasonal MA	−0.828140	0.161193	−5.138	0.0000278***

[1] *** and ** imply statistical significance at 1% and 5% levels of significance, respectively.

Seasonal MA	−0.708714	0.288452	−2.457	0.0140**

Applying equation 1, table 3 results can be mathematically presented as follows:

$$\Phi_1(B)(B^{12})TBN_t = \theta_1(B)\Theta_1(B^{12})\varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots [2]$$

Figure 5: Graph showing both in-sample and out-of-sample forecasts

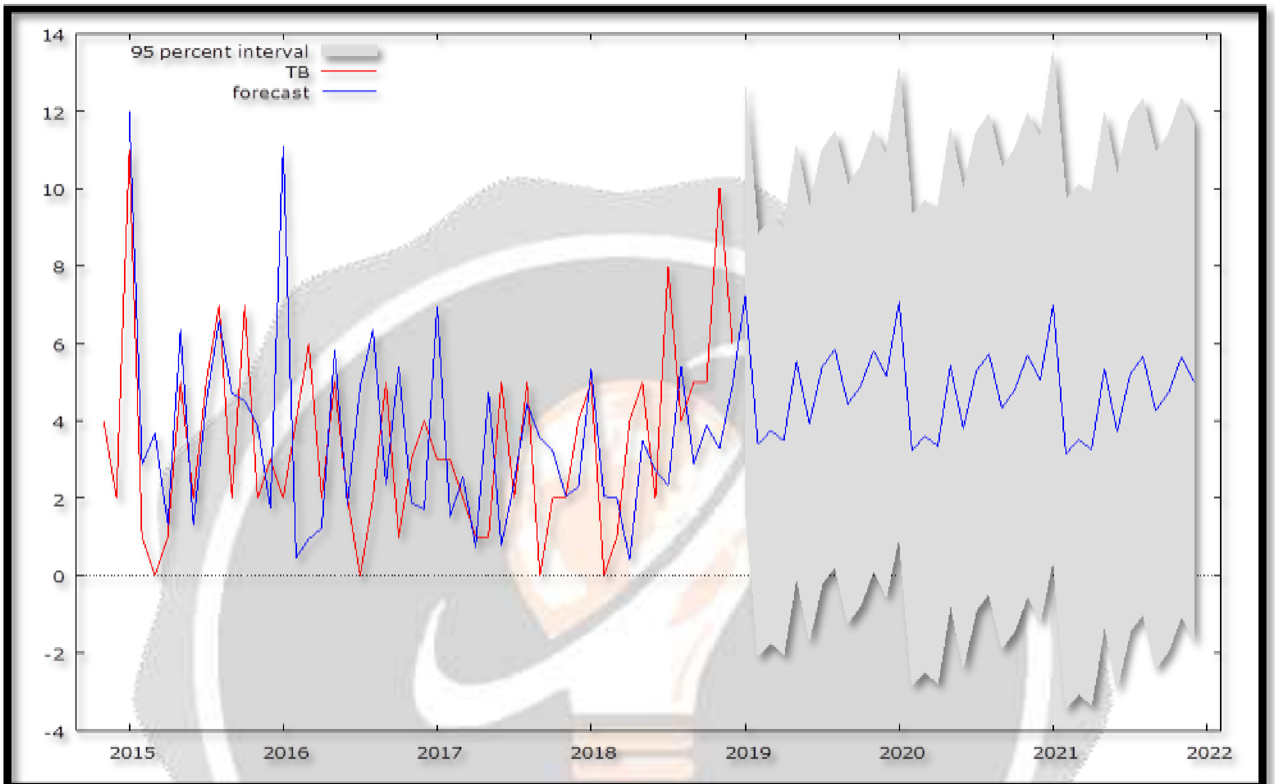


Table 4: Forecasted TB Notifications for SDH (January 2019 – December 2021)

Year: Month	Prediction	Standard Error	95% Confidence Interval
2019:01	7.23	2.755	1.83-12.63
2019:02	3.39	2.777	2.06-8.63
2019:03	3.74	2.797	1.74-9.23
2019:04	3.48	2.815	2.04-9
2019:05	5.55	2.831	0-11.1
2019:06	3.92	2.846	1.66 -9.5
2019:07	5.40	2.859	0.21-11
2019:08	5.85	2.872	0.22-11.47
2019:09	4.44	2.883	1.21-10.09
2019:10	4.90	2.893	0.77-10.57
2019:11	5.81	2.902	0.12-11.50
2019:12	5.15	2.910	0.55-10.85
2020:01	7.07	3.082	1.03-13.11
2020:02	3.23	3.096	2.84-9.3
2020:03	3.60	3.110	2.50-9.69
2020:04	3.34	3.122	2.78-9.46
2020:05	5.42	3.133	0.73-11.56
2020:06	3.79	3.143	2.37 -9.95

2020:07	5.27	3.152	0.90-11.45
2020:08	5.73	3.161	0.47-11.92
2020:09	4.33	3.168	1.88-10.54
2020:10	4.79	3.175	1.43-11.02
2020:11	5.71	3.182	0.53-11.94
2020:12	5.05	3.187	1.19-11.3
2021:01	6.98	3.336	0.44-13.52
2021:02	3.15	3.347	3.42-9.71
2021:03	3.51	3.358	3.07-10.09
2021:04	3.26	3.367	3.34-9.86
2021:05	5.34	3.375	1.28-11.95
2021:06	3.72	3.383	2.91-10.35
2021:07	5.20	3.390	1.44-11.85
2021:08	5.66	3.397	1.00-12.32
2021:09	4.26	3.403	2.41-10.93
2021:10	4.73	3.408	1.95-11.41
2021:11	5.65	3.413	1.04-12.34
2021:12	5.00	3.417	1.70-11.7

Figure 6: Graph showing out-of-sample forecasts only

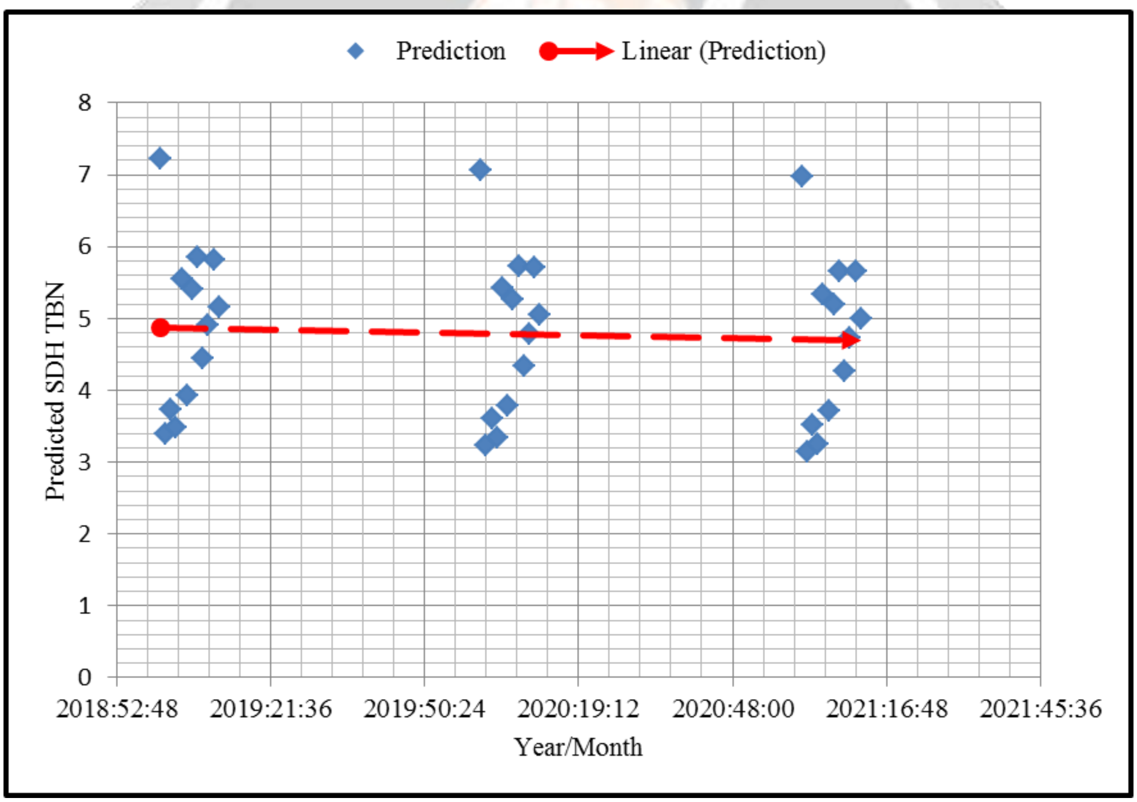


Table 3 shows the main results of the SARIMA (1, 0, 1)(0, 1, 1)$_{12}$ model for SDH TB notifications. Equation [2] is a mathematical representation of the model tabulated in table 3. Figure 5 and 6 as well as table 4 show the forecasted TB notifications over the period January 2019 – December 2021. SDH TB notifications are generally likely to fall over the out-of-sample forecast as shown in figures 4 and 5 and table 7, although not as fast as it should be, given the fact that TB programmes continue to be implemented in Silobela since the opening of the hospital. The fitted trend line figure 6 should typically be a very steep downwards sloping curve. Nonetheless, the results of this study are consistent with WHO (2018i) which highlighted that the disease burden caused by TB is falling globally, in all WHO regions, and in most countries, but not fast enough to reach the first (2020) milestones of the End TB

Strategy; neither is it enough to achieve the vision of the Zimbabwe National TB Control Strategy. These results are also in line with previous studies such as Frah & Alkhalifa (2016) and Nyoni & Nyoni (2019). In both of these previous studies, researchers attributed the predicted decrease in TB notifications to intensive national TB programmes in both Sudan and Zimbabwe, respectively. The predicted trend of SDH TB notifications could be attributed to the following reasons and issues that arise thereof:

i. Early case detection. However, due to financial constraints faced by both SDH and members of the community, treatment of all detected TB cases continues to be compromised and this fuels the spread of TB infection in the community.
ii. TB awareness in the community. As in (i) above, TB awareness programmes in Silobela are currently limited due to lack of adequate funding.
iii. Isoniazid (INH) prophylaxis for children under 5 years who are in contact with sputum positive TB patients as well as INH prophylaxis for all HIV positive patients who have no contraindications and have been screened for TB. This initiative is also affected by the availability of funding highlighted in (i) above.

V. Recommendations

i. The research recommends increased intensification of TB surveillance and control programmes in order to reduce TB incidences in Silobela.
ii. HIV/TB collaboration initiatives should be intensified at SDH in order to reduce TB-related morbidity and mortality in Silobela.
iii. For (i) and (ii) to materialize, the government of Zimbabwe and its partners (especially, those in the non-governmental sector), should provide adequate funding for TB surveillance and control programmes. Without such funding, the community of Silobela will continue to suffer from the TB scourge and yet there is room for reducing it significantly if adequate funds are availed.

VI. Conclusion

TB continues to be a serious threat to public health in Zimbabwe. There is need for continued monitoring of this scourge in order to reduce morbidity and mortality it causes. In order to reduce TB incidences in Silobela, the study offered a two-fold policy prescription. The current study relied on 60 monthly observations of TB notifications at SDH (January 2014 – December 2018) to model and forecast 36 out-of-sample TBNs, that is, from January 2019 to December 2021. We employed the Box-Jenkins SARIMA technique. The study showed that TB notifications are generally expected to decline over the out-of-sample period, but not as fast enough to achieve the vision of the Zimbabwe National TB Control Strategy; neither is it enough to reach WHO's first (2020) milestones of the End TB Strategy.

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