Forecasting TB notifications at Zengeza clinic in Chitungwiza, Zimbabwe

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Abstract

This study uses monthly time series data on TB notifications at Zengeza clinic in Chitungwiza from January 2013 to December 2018; to forecast TB notifications using the Box & Jenkins (1970) approach to univariate time series analysis. Diagnostic tests indicate that TBN is an I (0) variable. Based on the AIC, the study presents the SARMA (2, 0, 2)(1, 0, 1)$_{12}$ model, the diagnostic tests further show that this model is quite stable and hence acceptable for forecasting the TB notifications at Zengeza clinic. The selected optimal model shows that the TB notifications will decline over the out-of-sample period. The main policy recommendation emanating from this study is that there should be continued intensification of TB surveillance and control programmes in order to reduce TB incidences not only at Zengeza clinic but also in Zimbabwe at large.

Key Words: Forecasting, TB, TB Notifications

JEL Codes: I18

I. Introduction & Background

Tuberculosis (TB), discovered by Robert Koch (1882), is an ancient scourge (Daniel, 2006); it has been known for centuries (Daniel & Daniel, 1999). In fact, the earliest detection of TB is associated with evidence of the disease in the remains of bison dated to nearly 17000 years ago. Scientists discovered tubercular decay in the spines of Egyptian mummies dating from 3000-2400 BC (Crubezy, 2009). Mummies from the Egyptian pre-dynastic era and the Peruvian pre-Columbian era show typical vertebral lesions (Cave, 1939; Morse *et al*, 1964). The first weak

evidence for TB in humans relies on lesions compatible with bone TB in a 500000 year-old skull in Turkey (Kappelman *et al*, 2008). The first undisputed evidence of "Mycobacterium Tuberculosis" was obtained by PCR sequencing and detection of mycobacteria lipids in bone lesions of a 17000 year-old bison found in Wyoming, USA (Rothchild *et al*, 2001; Lee *et al*, 2012). The oldest evidence for human TB was found in Neolithic infant and woman in a 9000 year-old settlement in the Eastern Mediterranean (Hershkovitz *et al*, 2008).

TB is a respiratory infectious disease caused by "Mycobacterium Tuberculosis" (Ignatova *et al*, 2006; Nasehi & Mirhaghghani, 2010; Ricks *et al*, 2011; Moosazadeh *et al*, 2013; Fogel, 2015; Dheda *et al*, 2016; Sharma *et al*, 2016) and spreads through air droplets by sneezing and coughing of the infected person (Ricks *et al*, 2011). TB can also result from reactivation of a past latent TB infection. Reactivation of TB is more common in countries that have controlled transmission properly, but recent transmission is more common in endemic countries (Dye *et al*, 2002; Corbett *et al*, 2007; Nasehi *et al*, 2012). Persons with TB bacteria have a 5-15% lifetime risk of falling ill with TB; but people with compromised immune systems such as people living with HIV, malnutrition or diabetes, and those with tobacco use have much higher risk of falling ill (WHO, 2018). After, suffering from TB, if the patients are not given timely, thorough treatment, they can be faced with a serious threat to their health, even making them completely lose ability to work, but also possibly infecting others (Zheng *et al*, 2015). Although the global TB incidence has declined by 1-2% per year (Raviglione *et al*, 2012), it is still a major public health problem in many developing countries (Bele *et al*, 2014; Sgaragli & Frosini, 2016).

Zengeza clinic is located in Chitungwiza, a high density dormitory town in Zimbabwe, which is affectionately known as "Chi Town". The clinic is quite accessible by foot for those staying within the clinic's vicinity and by public and private transport to those further afield. It is imperative to note that Zengeza clinic serves as the first medical point of entry for children and adults living in these suburbs. Zengeza clinic utilizes its proximity to the Chitungwiza Central Hospital, located only 3km away; and refers in-and out-patient cases for specialized care in emergency medicine, surgery as well as pediatrics. The clinic offers preventive, curative and diagnostic services which include immunizations (Zimbabwe expanded programme on immunization), voluntary medical male circumcision, maternity services, family planning services, treatment of chronic medical conditions, and treatment of infectious diseases such as TB, HTS (HIV Testing Services) as well as screening and testing for TB.

The TB program at the city of Chitungwiza is funded by the government of Zimbabwe with the support of its partners, namely; The UNION, Challenge TB and USAID. Zengeza clinic has two main cadres who are responsible for coordinating and implementing the TB program, namely the TB focal person for the district and the TB focal nurse for the clinic. These focal persons report to the Sister-in-Charge for the clinic who then reports to the City Matron, who finally reports to the City Health Director. The clinic has nurses in each department who are capacitated to screen for TB and refer patients to Outpatient department where a presumptive diagnosis of TB is made and sputum samples are collected and sent to the clinic laboratory, where a confirmatory test is done. The clinic uses the Gene X-pert machine to detect MTB (Mycobacterium Tuberculosis). The machine is able to detect both drug sensitive TB and Rifampicin Resistant TB, thereby making it easy to start the patients on appropriate anti TB treatment promptly.

Moreso, Directly Observed Treatment Support (DOTS) is also practised; this means that health workers and treatment supporters directly observe patients as they take their daily medications.

Treatment follow up is done by clinic nurses with the help of the focal person and TB coordinator. Treatment cure is done by doing sputum microscopy, culture and sensitivity testing at the end of the treatment course, for example, 6 months for Drug Sensitive TB. A sputum negative sample means no MTB is detected and thus the patient is cured. A sputum positive sample means that the patient is still suffering from TB and drug resistance has developed, therefore a different class of anti-TB drugs is required since the resistance to rifampicin and isoniazid has developed. Hence, in this regard, injectable anti TB drugs are required.

The district uses a mobile X-ray machine to detect sputum negative pulmonary TB and the radiological features are cavitary lesions, lung consolidation and pleural effusion. Complicated presumptive TB cases are reffered to Chitungwiza Central Hospital where further tests are done which include ultrasonography, CT scanning and biochemistry tests. Additionally, there is an observable HIV/TB collaboration where all HIV positive clients are screened for TB and all TB patients are tested for HIV and commenced on treatment promptly when they test positive. The clinic's Health Education and Promotion department is seized with awareness programs in the community in order to help reduce the burden of TB. This research focuses on Zengeza clinic TB notifications and seeks to achieve the following objectives:

Objectives of the Study

i. To analyze the trend of TB notifications under the study period.
ii. To determine the forecasted number of TB notifications over the period January 2019 to December 2030.

Statement of the Problem

Despite the discovery of the causative agent more than a century ago, a vaccine, highly effective medications, and recent improvement in biological molecular field and genetic engineering, TB remains a major public health concern in the world (Dye, 2006; Zheng *et al*, 2015; Ade *et al*, 2016) with a vast health burden due to the high incidence, medical expenses, drug resistance and co-infections (WHO, 2016; Marais & Sintchenko, 2017). TB is one of the biggest health challenges which the world is facing and is the second major cause of mortality, especially in poor and low economic countries (WHO, 2001; Glaziou *et al*, 2009; Liu *et al*, 2010; Lin & Liao, 2013; Glaziou *et al*, 2014). 95% of TB cases and 98% of TB deaths occur in low and middle income families (WHO, 2000). Globally, in 2014 alone, there was an estimated 9.6 million incident cases, of which 1.5 million were estimated to have died. The burden of TB is particulary immense in Africa from where the case rate is approximately 281 per 100000 people (WHO, 2015). TB is a significant public health problem in Zimbabwe (Dube, 2015) and continues to be a significant cause of morbidity and mortality in Zimbabwe (National TB Guidelines, 2010). Zimbabwe is among the 22 countries in the world, reffered to as "the TB high burden countries" and has an estimated TB incidence per capita of 603 per 100000 population (WHO, 2014). In Zimbabwe, besides full implementation of national TB programs, TB still continues to be a leading cause of mortality and economic burden. The major causes for vulnerable situation of TB in Zimbabwe include but are not limited to poverty, malnutrition, high prevalence of HIV/AIDS and lack of awareness and education. In Chitungwiza district, just like in any other district in Zimbabwe, TB is a major health problem. The results of this paper are envisioned to go a long way in assisting health policy makers in reducing the TB burden not only at Zengeza clinic but also in Zimbabwe at large.

Significance of the Study

This paper is, in line with the "End TB Strategy" of the WHO launched in 2014 whose targets are that of reducing by 2035 the incidence and mortality of TB by 90% and 95% respectively. The paper is also consistent with the Zimbabwe National TB Control Strategy's vision of "A TB-free Zimbabwe". It is almost unnecessary to reiterate the fact that in order to attain the 2020 milestones of the "End TB Strategy" and the Zimbabwe National TB Control Strategy, there is need for additional and relevant TB modeling and forecasting techniques at all levels. From a micro-level analysis, this study is envisioned to enhance the understanding of the past and current epidemiology of TB in Zimbabwe.

II. Literature Review

Table 1: Previous Studies Reviewed

Author(s)/Year	Country	Period	Methodology	Key Findings
Imran *et al* (2014)	Pakistan	2001 – 2011	ARIMA	ARIMA (3, 1, 0) model was the best model.
Moosazadeh *et al* (2014)	Iran	January 2005 – December 2011	SARIMA	SARIMA $(0, 1, 1)(0, 1, 1)_{12}$ model was the optimal model.
Dube (2015)	Zimbabwe	1990 – 2013	ARIMA, ARCH, HW	Best models were found to be the ARIMA (2, 2, 1) and ARIMA (2, 2, 1)-ARCH (1) models.
Azeez *et al* (2016)	South Africa	January 2010 – December 2015	SARIMA, SARIMA-NNAR	The SARIMA-NNAR model was the best model.
Patowary & Barman (2017)	India	2001 – 2011	SARIMA	The optimal model was the SARIMA $(0, 0, 0)(1, 1, 0)_4$.
Anggraeni *et al* (2017)	Indonesia	January 2007 – September 2016	ARIMAX	The best model is the ARIMAX (3, 1, 0).
Mao *et al* (2018)	China	January 2004 – December 2015	SARIMA	The best fit model was the SARIMA $(1, 0, 0)(0, 1, 1)_{12}$.
Mohammed *et al* (2018)	Iraq	January 2010 – December 2016	SARIMA, SARIMA-NNAR, SARIMA-ETS, SARIMA-ANFIS	The optimal model was the SARIMA-ANFIS model.
Aryee *et al* (2018)	Ghana	January 2008 – December 2017	ARIMA	ARIMA (1, 0, 1) or ARMA (1, 1) model was the best model.
Liu *et al* (2019)	China	January 2005 – December 2015	SARIMA, BPNN	BPNN model performs better than the SARIMA model.

As shown in table 1 above, 60% of the reviewed previous studies, that is; Moosazadeh *et al* (2014), Azeez *et al* (2016), Patowary & Barman (2017), Mao *et al* (2018), Mohammed *et al* (2018) and Liu *et al* (2019); have used the SARIMA technique in modeling and forecasting TB, and this clearly confirms the increasing popularity of SARIMA models in analyzing TB trends. Half of these studies (Moosazadeh *et al*, 2014; Patowary & Barman, 2017; Mao *et al*, 2018) have concluded that the SARIMA model is suitable for modeling and forecasting TB. Only 40% of the reviewed previous studies have used other analysis techniques such as generalized ARIMA, ARCH and HW (Imran *et al*, 2014; Dube, 2015; Aryee *et al*, 2018) and ARIMAX (Anggraeni *et al*, 2017). Other researchers have also attempted using hybrid models such as BPNN (Liu *et al*, 2019) and SARIMA-NNAR, SARIMA-ETS as well as SARIMA-ANFIS (Azeez *et al*, 2016; Mohammed *et al*, 2018). However, Azeez *et al* (2016) concluded that their hybrid model, the

SARIMA-NNAR model performed better than generalized SARIMA models. Similarly, Liu *et al* (2019); finally noted that their hybrid model, the BPNN model was superior to SARIMA models. In line with previous studies such as Moosazadeh *et al* (2014), Patowary & Barman (2017) and Mao *et al* (2018); this research employs the SARIMA technique to model and forecast TB notifications at Zengeza clinic in Chitungwiza.

III. Methodology

The SARIMA Model

A general SARIMA model may, thus, be specified as shown in equation [1] below:

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

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. 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.

The Box – Jenkins Technique

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018). The Box – Jenkins technique is accredited to Box & Jenkins (1970) and in this research; it will be used for analyzing monthly TB Notifications for Zengeza clinic in Chitungwiza, Harare, Zimbabwe.

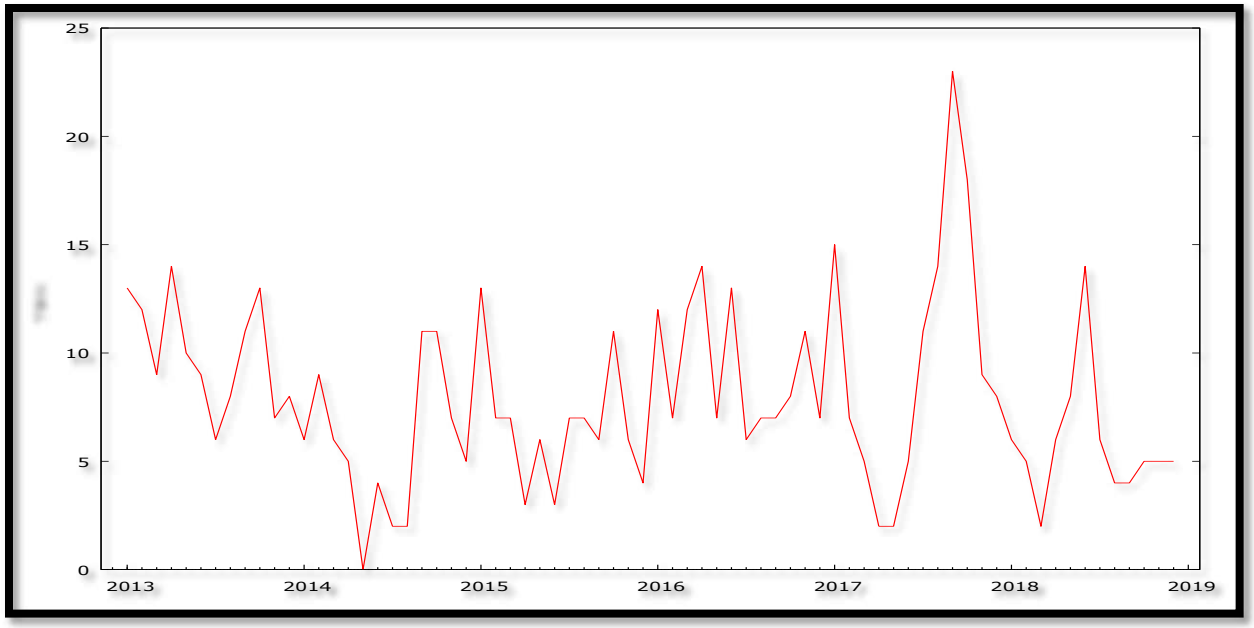
Data

This study is based on monthly observations of TB notifications (TBN) at Zengeza clinic, Chitungwiza, Zimbabwe, from January 2013 to December 2018. Our out-of-sample forecast ranges over the period January 2019 to December 2030. All the data employed in this research was gathered from Zengeza clinic.

Diagnostic Tests and Model Evaluation for TB notifications

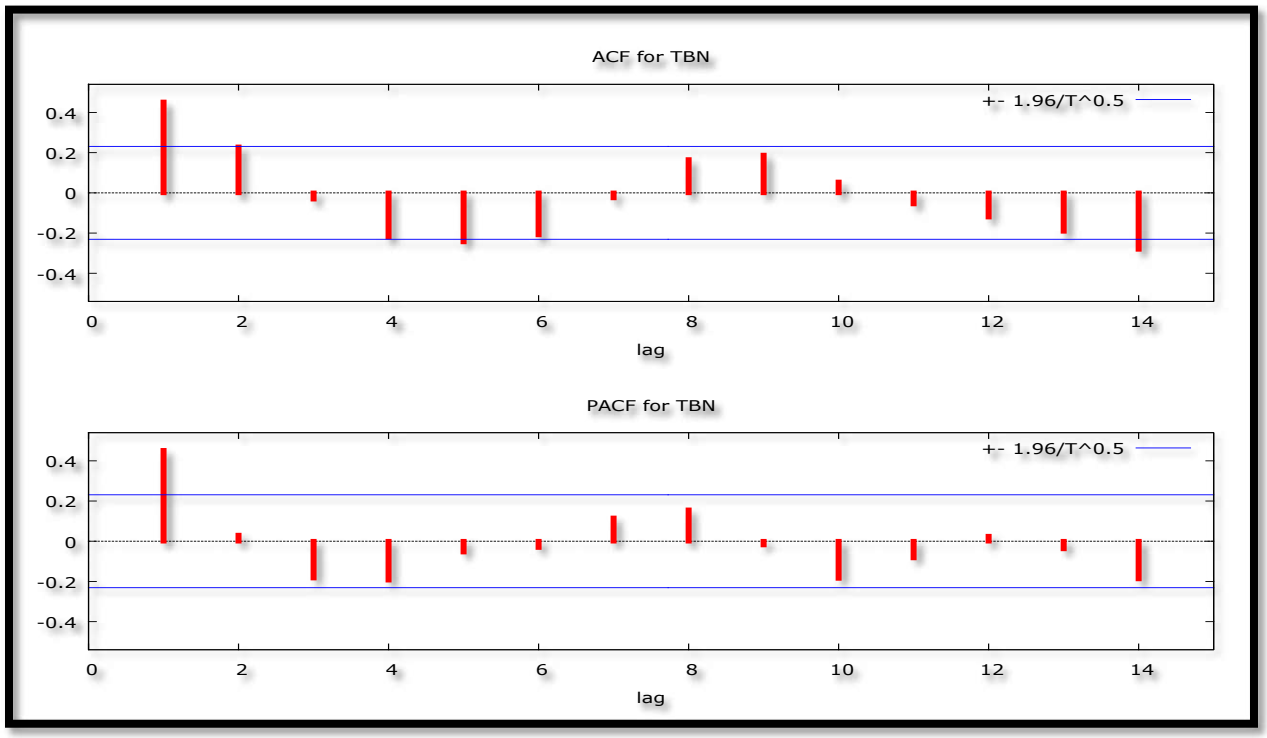
Stationarity Tests: Graphical Analysis

Figure 1: Graphical Analysis



The Correlogram in Levels

Figure 2: Correlogram in Levels



The ADF Test

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TBN	-5.128440	0.0001	-3.525618	@1%	Stationary
			-2.902953	@5%	Stationary
			-2.588902	@10%	Stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TBN	-5.092354	0.0004	-4.092547	@1%	Stationary
			-3.474363	@5%	Stationary
			-3.164499	@10%	Stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
TBN	-2.301511	0.0216	-2.597939	@1%	Not stationary
			-1.945456	@5%	Stationary
			-1.613799	@10%	Stationary

Figures 1 and 2 as well as tables 2 – 4 show that the series under consideration is I(0).

Evaluation of SARMA Models (without a constant)

Table 5: Evaluation of SARMA Models (with a constant)

Model	AIC	ME	RMSE	MAE
SARMA (1, 0, 1)(0, 0, 0)$_{12}$	398.5972	-0.035141	3.6501	2.9732
SARMA (1, 0, 1)(0, 0, 1)$_{12}$	400.5226	-0.027931	3.648	2.9605
SARMA (1, 0, 1)(1, 0, 1)$_{12}$	401.9278	-0.017039	3.6314	2.9512
SARMA (1, 0, 1)(1, 0, 0)$_{12}$	400.5007	-0.025775	3.6474	2.9574
SARMA (2, 0, 2)(0, 0, 0)$_{12}$	393.8185	0.026317	3.4311	2.8932
SARMA (2, 0, 2)(0, 0, 1)$_{12}$	395.1647	-0.00011013	3.4154	2.8775
SARMA (2, 0, 2)(1, 0, 1)$_{12}$	**389.1094**	0.056132	3.2588	2.7139
SARMA (2, 0, 2)(1, 0, 0)$_{12}$	395.002	-0.0056874	3.4115	2.8754
SARMA (0, 0, 0)(1, 0, 1)$_{12}$	414.2855	0.045798	4.0632	3.1871
SARMA (0, 0, 1)(1, 0, 1)$_{12}$	403.8767	0.015386	3.7292	2.9694
SARMA (1, 0, 0)(1, 0, 1)$_{12}$	399.9407	-0.014318	3.6316	2.9446

The study uses the AIC as the goodness of fit criterion. A model with the lowest AIC value is the optimal model. Thus, the SARMA (2, 0, 2)(1, 0, 1)$_{12}$ model is selected as the optimal model. It is imperative to note that the selected optimal model also satisfies the law of parsimony or the rule of thumb represented by the following equality:

$$p + d + q + P + D + Q \leq 6 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

Residual Test of the Selected Model

Residual Correlogram of the selected SARIMA (2, 0, 2)(1, 0, 1)$_{12}$ Model

Figure 3: Residual Correlogram of the SARMA (2, 0, 2)(1, 0, 1)$_{12}$ Model

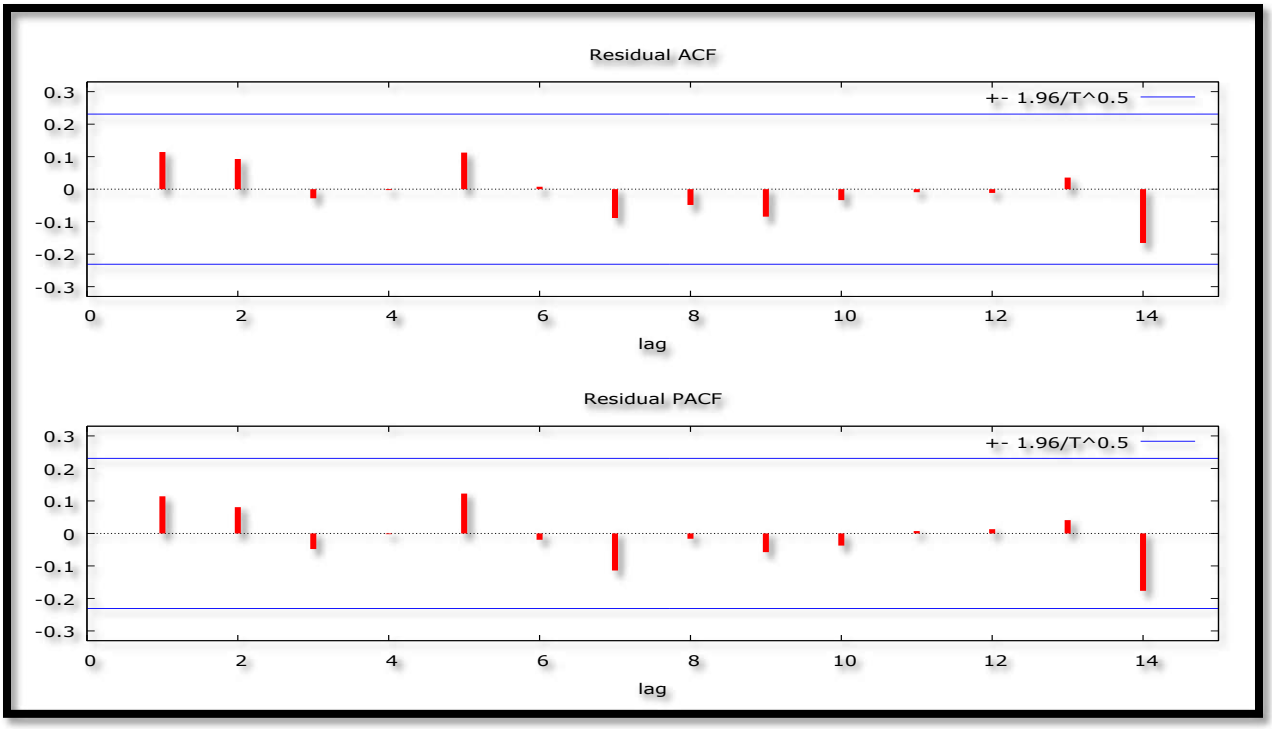


Figure 6 shows that the residuals of the SARIMA (2, 0, 2)(1, 0, 1)$_{12}$ model are stable and stationary.

IV. Findings of the Study

Descriptive Statistics

Table 6: Descriptive Statistics

Description	Statistic (TBN)
Mean	7.8889
Median	7
Minimum	0
Maximum	23
Standard deviation	4.1267
Skewness	0.89712
Excess kurtosis	1.3113

As shown in table 6 above, the mean is positive, that is, 7.8889. The median is 7. The minimum is 0 while the maximum is 23. The skewness is 0.89712 and is positive, implying that the variable TBN is positively skewed and non-symmetric. Excess kurtosis is 1.3113 and this shows that TBN is normally distributed.

Results Presentation[1]

Table 7: Results Presentation – the SARMA (2, 0, 2)(1, 0, 1)$_{12}$

[1] *** means significant at 1% level of significance

Variable	Coefficient	Std. Error	z	p-value
const	7.90221	0.908032	8.703	0.0001***
phi_1	1.42490	0.0870945	16.36	0.0001***
phi_2	−0.929864	0.0841586	−11.05	0.0001***
Phi_1	1.34338	0.372536	3.606	0.0003***
theta_1	−1.17446	0.139200	−8.437	0.0001***
theta_2	0.842463	0.124570	6.763	0.0001***
Theta_1	−0.910665	0.991293	−0.9187	0.3583

Equation 1 can be used to mathematically present the results in table 7 as shown below:

$$\phi_1(B)\emptyset_2(B^{12})TBN_t = \theta_1(B)\Theta_2(B^{12})\varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots\ldots\ldots..\ldots\ldots\ldots\ldots.[3]$$

Figure 4: Graph showing both in-sample and out-of-sample forecasts

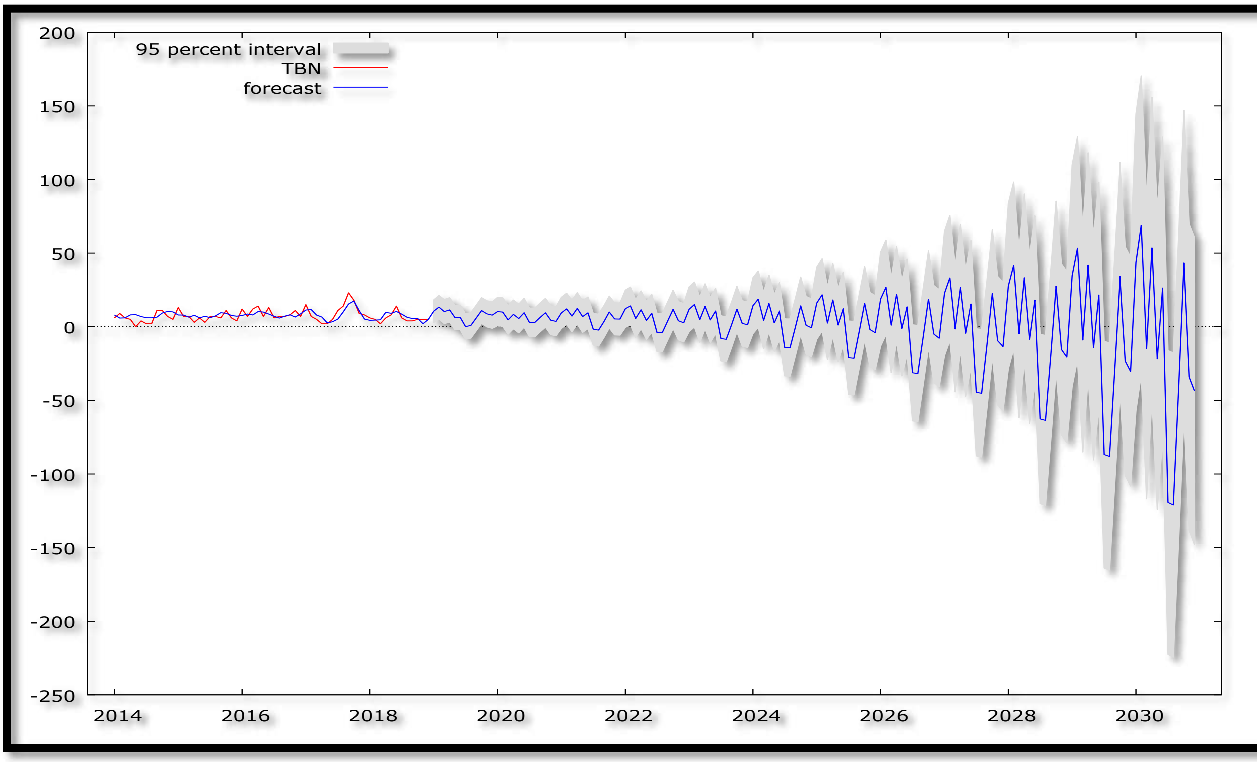


Table 8: Predicted TB Notifications for Zengeza Clinic (2019 – 2030)

Year: Month	Prediction	Standard Error	95% Confidence Interval
2019:01	10.4997	3.91998	(2.81666, 18.1827)
2019:02	13.3397	4.04104	(5.41940, 21.2600)
2019:03	10.2638	4.17680	(2.07737, 18.4501)
2019:04	11.4514	4.21857	(3.18317, 19.7197)
2019:05	6.25743	4.22084	(-2.01527, 14.5301)
2019:06	6.26821	4.28657	(-2.13332, 14.6697)
2019:07	0.0656059	4.38776	(-8.53425, 8.66547)
2019:08	0.952782	4.43414	(-7.73797, 9.64353)

2019:09	5.94480	4.43432	(-2.74631, 14.6359)
2019:10	10.9821	4.46677	(2.22740, 19.7368)
2019:11	8.75315	4.53841	(-0.141976, 17.6483)
2019:12	7.86276	4.58398	(-1.12168, 16.8472)
2020:01	10.2565	4.95000	(0.554648, 19.9583)
2020:02	9.95614	4.95049	(0.253353, 19.6589)
2020:03	4.64849	4.95487	(-5.06287, 14.3598)
2020:04	8.39586	4.96805	(-1.34135, 18.1331)
2020:05	5.57768	4.97847	(-4.17995, 15.3353)
2020:06	9.51780	4.97998	(-0.242780, 19.2784)
2020:07	2.91145	4.98155	(-6.85220, 12.6751)
2020:08	2.91244	4.99009	(-6.86796, 12.6928)
2020:09	6.31678	4.99908	(-3.48125, 16.1148)
2020:10	9.48631	5.00150	(-0.316455, 19.2891)
2020:11	4.43617	5.00183	(-5.36723, 14.2396)
2020:12	3.65586	5.00693	(-6.15753, 13.4693)
2021:01	9.37564	5.39524	(-1.19884, 19.9501)
2021:02	12.1537	5.40987	(1.55053, 22.7568)
2021:03	7.22832	5.44499	(-3.44365, 17.9003)
2021:04	12.4457	5.46882	(1.72707, 23.1644)
2021:05	6.87088	5.47094	(-3.85198, 17.5937)
2021:06	9.44434	5.47697	(-1.29032, 20.1790)
2021:07	-1.64208	5.50045	(-12.4228, 9.13861)
2021:08	-2.26326	5.52178	(-13.0857, 8.55922)
2021:09	3.47953	5.52610	(-7.35143, 14.3105)
2021:10	9.98268	5.52786	(-0.851722, 20.8171)
2021:11	5.31026	5.54244	(-5.55272, 16.1732)
2021:12	5.18335	5.56011	(-5.71425, 16.0810)
2022:01	12.2163	6.47519	(-0.474856, 24.9074)
2022:02	14.1641	6.51529	(1.39434, 26.9338)
2022:03	5.61044	6.53612	(-7.20012, 18.4210)
2022:04	11.5183	6.53652	(-1.29298, 24.3297)
2022:05	4.26148	6.54770	(-8.57177, 17.0947)
2022:06	9.07341	6.57622	(-3.81574, 21.9626)
2022:07	-4.10534	6.59644	(-17.0341, 8.82344)
2022:08	-3.75663	6.59854	(-16.6895, 9.17626)
2022:09	4.04979	6.60300	(-8.89185, 16.9914)
2022:10	11.8164	6.62195	(-1.16237, 24.7952)
2022:11	4.07282	6.63988	(-8.94110, 17.0867)
2022:12	2.71388	6.64384	(-10.3078, 15.7356)
2023:01	11.8322	7.74760	(-3.35281, 27.0172)
2023:02	15.0844	7.77367	(-0.151757, 30.3205)
2023:03	4.80562	7.80204	(-10.4861, 20.0973)
2023:04	13.8782	7.81015	(-1.42942, 29.1858)
2023:05	4.62123	7.81094	(-10.6879, 19.9304)
2023:06	10.7298	7.82626	(-4.60940, 26.0690)
2023:07	-7.93829	7.84875	(-23.3216, 7.44498)

2023:08	-8.51280	7.85849	(-23.9151, 6.88956)
2023:09	1.38448	7.85849	(-14.0179, 16.7868)
2023:10	11.9475	7.86657	(-3.47064, 27.3657)
2023:11	2.27797	7.88325	(-13.1729, 17.7288)
2023:12	1.37630	7.89334	(-14.0944, 16.8470)
2024:01	14.2605	9.68736	(-4.72634, 33.2474)
2024:02	18.6750	9.75461	(-0.443682, 37.7937)
2024:03	4.34138	9.81214	(-14.8901, 23.5728)
2024:04	15.7382	9.82239	(-3.51335, 34.9897)
2024:05	2.66399	9.82853	(-16.5996, 21.9276)
2024:06	10.6957	9.87076	(-8.65068, 30.0420)
2024:07	-14.0372	9.91896	(-33.4780, 5.40359)
2024:08	-14.1548	9.93384	(-33.6247, 5.31520)
2024:09	-0.247898	9.93474	(-19.7196, 19.2238)
2024:10	14.2047	9.95908	(-5.31476, 33.7241)
2024:11	1.02048	9.99677	(-18.5728, 20.6138)
2024:12	-0.711704	10.0141	(-20.3390, 18.9156)
2025:01	16.0351	12.4834	(-8.43196, 40.5022)
2025:02	21.6496	12.5570	(-2.96166, 46.2609)
2025:03	2.46640	12.6196	(-22.2675, 27.2003)
2025:04	18.1731	12.6306	(-6.58236, 42.9285)
2025:05	1.10741	12.6374	(-23.6615, 25.8764)
2025:06	12.2376	12.6838	(-12.6222, 37.0975)
2025:07	-20.9654	12.7364	(-45.9283, 3.99760)
2025:08	-21.4080	12.7525	(-46.4025, 3.58649)
2025:09	-3.15249	12.7536	(-28.1490, 21.8440)
2025:10	15.9196	12.7804	(-9.12955, 40.9687)
2025:11	-1.88400	12.8217	(-27.0140, 23.2460)
2025:12	-4.02334	12.8405	(-29.1902, 21.1435)
2026:01	18.8271	16.2773	(-13.0758, 50.7299)
2026:02	26.6982	16.3877	(-5.42119, 58.8175)
2026:03	1.06794	16.4867	(-31.2453, 33.3812)
2026:04	22.0618	16.5062	(-10.2898, 54.4134)
2026:05	-1.14529	16.5148	(-33.5137, 31.2231)
2026:06	13.5044	16.5833	(-18.9981, 46.0070)
2026:07	-31.2688	16.6651	(-63.9318, 1.39434)
2026:08	-31.8232	16.6923	(-64.5395, 0.893110)
2026:09	-7.08468	16.6932	(-39.8028, 25.6335)
2026:10	18.8045	16.7321	(-13.9897, 51.5988)
2026:11	-4.92953	16.7954	(-37.8479, 27.9889)
2026:12	-7.79246	16.8262	(-40.7712, 25.1862)
2027:01	22.7499	21.5641	(-19.5150, 65.0149)
2027:02	33.0937	21.7135	(-9.46404, 75.6514)
2027:03	-1.52171	21.8419	(-44.3311, 41.2876)
2027:04	26.6321	21.8650	(-16.2226, 69.4868)
2027:05	-4.44175	21.8785	(-47.3227, 38.4392)
2027:06	15.4290	21.9721	(-27.6357, 58.4936)

2027:07	-44.5414	22.0796	(-87.8166, -1.26626)
2027:08	-45.2115	22.1130	(-88.5522, -1.87087)
2027:09	-12.0364	22.1149	(-55.3808, 31.3080)
2027:10	22.5905	22.1688	(-20.8596, 66.0405)
2027:11	-9.45608	22.2527	(-53.0706, 34.1585)
2027:12	-13.3926	22.2915	(-57.0832, 30.2979)
2028:01	27.6596	28.6947	(-28.5809, 83.9001)
2028:02	41.6712	28.8947	(-14.9613, 98.3037)
2028:03	-4.68569	29.0704	(-61.6626, 52.2912)
2028:04	33.2335	29.1037	(-23.8087, 90.2757)
2028:05	-8.50498	29.1203	(-65.5798, 48.5698)
2028:06	18.1052	29.2450	(-39.2138, 75.4243)
2028:07	-62.5816	29.3911	(-120.187, -4.97599)
2028:08	-63.5808	29.4382	(-121.279, -5.88304)
2028:09	-19.0400	29.4403	(-76.7419, 38.6619)
2028:10	27.5323	29.5114	(-30.3091, 85.3736)
2028:11	-15.4154	29.6250	(-73.4793, 42.6485)
2028:12	-20.6085	29.6789	(-78.7780, 37.5611)
2029:01	34.5799	38.3622	(-40.6087, 109.769)
2029:02	53.3710	38.6355	(-22.3531, 129.095)
2029:03	-8.98581	38.8735	(-85.1765, 67.2049)
2029:04	41.8663	38.9178	(-34.4112, 118.144)
2029:05	-14.2527	38.9412	(-90.5760, 62.0707)
2029:06	21.5073	39.1119	(-55.1506, 98.1651)
2029:07	-86.8226	39.3102	(-163.869, -9.77593)
2029:08	-88.0871	39.3733	(-165.257, -10.9169)
2029:09	-28.1994	39.3764	(-105.376, 48.9768)
2029:10	34.3671	39.4741	(-43.0006, 111.735)
2029:11	-23.3730	39.6285	(-101.043, 54.2975)
2029:12	-30.4162	39.7010	(-108.229, 47.3964)
2030:01	43.6693	51.3936	(-57.0603, 144.399)
2030:02	68.8992	51.7591	(-32.5468, 170.345)
2030:03	-14.8393	52.0781	(-116.911, 87.2320)
2030:04	53.5296	52.1377	(-48.6583, 155.718)
2030:05	-21.8080	52.1688	(-124.057, 80.4410)
2030:06	26.2523	52.3970	(-76.4439, 128.948)
2030:07	-119.293	52.6627	(-222.510, -16.0756)
2030:08	-121.036	52.7474	(-224.419, -17.6527)
2030:09	-40.6313	52.7515	(-144.022, 62.7597)
2030:10	43.3931	52.8820	(-60.2538, 147.040)
2030:11	-34.1666	53.0888	(-138.219, 69.8855)
2030:12	-43.5943	53.1861	(-147.837, 60.6485)

Figure 5: Graph showing out-of-sample forecasts only

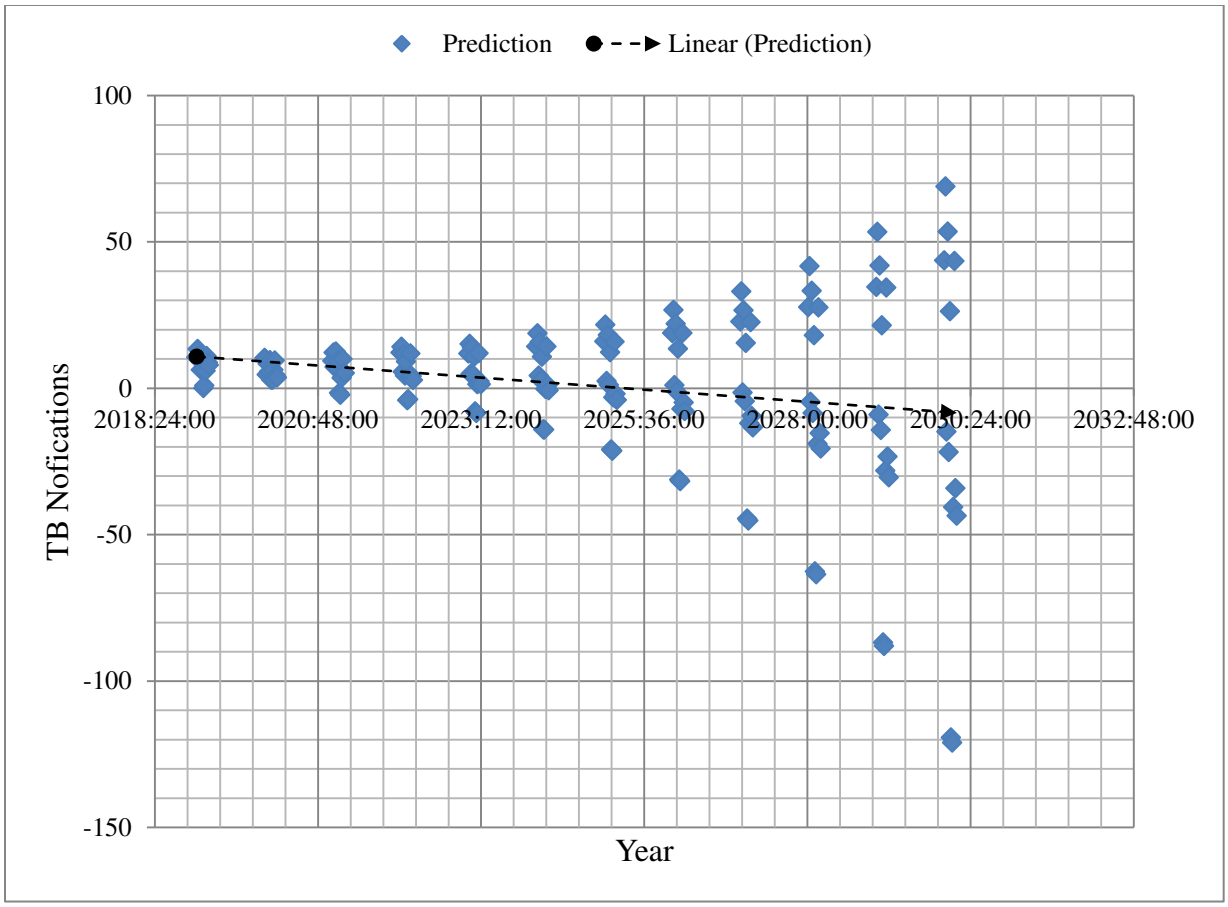


Table 6 shows the main results of the SARMA $(2, 0, 2)(1, 0, 1)_{12}$ model for Zengeza clinic TB notifications. Equation [3] is a mathematical representation of the model tabulated in table 6. Figure 4 and 5 as well as table 7 show the predicted TB notifications over the period 2019 – 2030. It is imperative to note that TB notifications are generally likely to fall over the out-of-sample forecast as shown in figures 4 and 5 and table 7. Our results 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. The following reasons account for the anticipated fall in TB notifications at Zengeza clinic:

i. Early case detection and early treatment of all TB cases, thereby reducing the spread of TB infection in the community.
ii. Follow up of treatment defaulters and ensuring that they take their treatment thereby reducing the risk of developing drug resistance which may make it difficult to treat and control the spread of the disease.
iii. TB awareness in the community and increased community participation in identification and treatment of sputum positive TB patients.
iv. Isoniazid (INH) prophylaxis for children under 5 years who are in contact with sputum positive TB patients and also INH prophylaxis for all HIV positive patients who have no contraindications and have been screened for TB.
v. HIV/TB collaboration in the clinic.

V. Recommendations & Conclusion

TB remains a threat to public health in Zimbabwe and continuous monitoring of this epidemic is not unimportant for its control and intervention, in order to reduce morbidity and mortality caused by this disease. The study recommends the intensification of TB surveillance and control programmes in order to reduce TB incidences not only at Zengeza clinic but also in Zimbabwe at large. The current study relied on 72 monthly observations of TB notifications at Zengeza clinic (January 2013 – December 2018) to model and forecast 144 out-of-sample TBNs, that is, from January 2019 to December 2030. We employed the Box-Jenkins SARMA approach. The study showed that TB notifications are expected to decline over the out-of-sample period. It is important to note that the data employed is generally limited: further research should make use of a wide data set on the basis that univariate time series models perform better when applied over longer time series data. While it is a fact that Box-Jenkins models are increasingly becoming popular in modeling and forecasting communicable diseases such as TB, it would be good as well for researchers to explore other forecasting techniques such as the use of Artificial Neural Networks (ANNs) and ARIMAX models.

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