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MODELING AND FORECASTING INFANT DEATHS IN ZIMBABWE USING ARIMA MODELS

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ABSTRACT:

Employing annual time series data on total infant deaths in Zimbabwe from 1960 to 2018, the study models and forecasts total infant deaths over the next decade using ARIMA models. Diagnostic tests indicate that the Zimbabwe annual infant deaths series is an I (2) variable. Guided by Mishra et al. (2019), the study uses the "minimum AIC criteria" to select the optimal model, the ARIMA (1, 2, 5) model. The ADF test of the residuals, the correlogram of the residuals as well as the inverse roots of the AR/MA polynomials; all indicate that the presented model is stable and suitable for forecasting annual infant deaths in Zimbabwe. The study, whose results are not surprising, indicates that the number of infant deaths per year, over the out-of-sample period, will follow a downward trend. A five-fold policy implication has been put forward in order to reduce infant deaths in the country.

INTRODUCTION:

Infant death (mortality) is the probability of dying between birth and age one (Zimstats, 2015). It is regarded as a socioeconomic development indicator of a nation (Mishra et al., 2019). It is no longer uncommon to assert that, worldwide, infant mortality has generally declined by approximately 23/1000 live births and mortality of older infants by nearly 25/1000 live births (Popline, 2018). The reason is that economies around the world have generally improved over time and mobilized resources for use in their respective health sectors. Infant mortality rate of Zimbabwe fell gradually from 74.1 deaths per 1000 live births in 1969 to 33.9 deaths per 1000 live births in 2018 (Knoema, 2018). Developing countries such as Zimbabwe, still need to work harder towards improving health service delivery in order to significantly reduce or possibly eradicate infant deaths. The figure below shows the trends of infant deaths in Zimbabwe over the period 1960 – 2018:

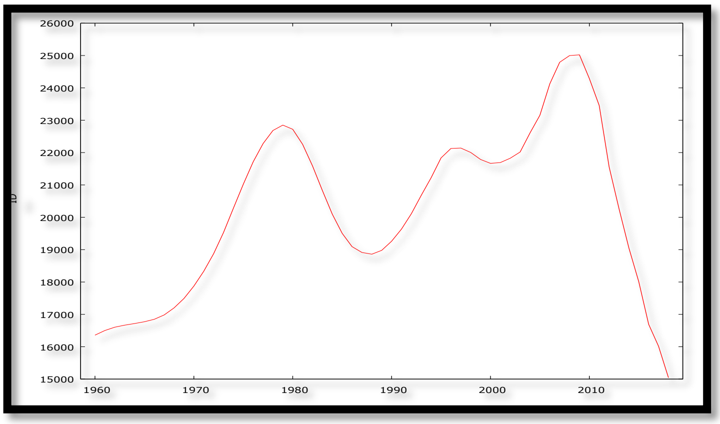


Figure 1

Infant mortality fluctuates according to health status of the country, which is a dynamic process (Mishra et al., 2019). Figure 1 shows that generally over the period 1960 to 2009, annual infant deaths were on the rise in Zimbabwe. This could be attributed to recurrent phrases of economic stagnation that crippled the health sector in Zimbabwe. The introduction of the multicurrency era in 2009 is argued to have stabilized the economy and hence the health sector also improved in terms of its performance. This is the reason why we observe a sharp decline in annual infant deaths over the period 2010 – 2018.

1. OBJECTIVES OF THE STUDY:

i. To investigate the years during which infant deaths peaked in Zimbabwe.
ii. To forecast the number of infant deaths for the out-of sample period.
iii. To examine the pattern of infant deaths for the out-of-sample period.

2. RELEVANCE OF THE STUDY:

Infant mortality accounts for over 80% of under-5 mortality rate (WNTA, 2017) and at the same time there is a tendency of infant mortality to fluctuate according to health status of the country, which is a dynamic process (Mishra et al., 2019). Therefore, the availability of predicted number of infant deaths would facilitate healthcare intervention programmes in a more effective manner. To the best of our knowledge, no similar study has been done in Zimbabwe. The paper is envisioned to steer-up a scholarly debate in public health discourse, particularly in Zimbabwe.

LITERATURE REVIEW:

Chakrabarty (2013) forecasted infant mortality in South Asia using the random walk model over the period 1970 – 2010 and found out that when demographic processes contain a stochastic trend component, the random walk model may not be suitable and when such is the case, the ARIMA (1, 1, 0) model can be applied. In the United States of America (USA), Saravanou et al. (2016) carried out a study on infant mortality prediction using features extracted from birth certificates. The authors trained classification models to decide whether an infant will survive or not. Their results show that their methodology outperforms standard classification methods used by epidemiology researchers.

Khan et al. (2019) compared infant mortality rate with GDP (PPP(Purchasing Power Parity)) of developed, underdeveloped and lower developing countries of Asia such as Bangladesh, China, India, Japan, Sri Lanka, Nepal, Oman, Pakistan, Philippines, Saudi Arabia, Singapore, Thailand and Turkey. The results of the study revealed that there is a strong negative correlation between infant mortality rate and GDP (PPP). The study also found out that the AR (1) model is suitable for analyzing infant mortality rates for all the countries except Japan and Nepal for which ARIMA (1, 1, 1) model is appropriate. Mishra et al. (2019) gave a detailed presentation of how they used the ARIMA model to forecast infant mortality rates (2017 – 2025). The forecast of the sample period (1971 – 2016) showed accuracy by the selected ARIMA (2, 1, 1) model. The post-sample forecast with ARIMA (2, 1, 1) model showed a decreasing trend of infant mortality (2017 – 2025). The forecast infant mortality rate for 2025 in India is 15/1000 live births. Nyoni & Nyoni (2020) used monthly time series data on neonatal deaths cases at Chitungwiza Central Hospital (CCH) from January 2013 to December 2018; to forecast neonatal deaths over the period January 2019 to December 2020 using the Box-Jenkins SARIMA approach. The parsimonious model was found to be the SARIMA $(0, 0, 3)(2, 0, 0)_{12}$ model and its predictions indicate slow but steady decrease in neonatal deaths at CCH.

MATERIALS & METHODS:

ARIMA Models:

Due to its simplicity, the Autoregressive Integrated Moving Average (ARIMA) model is one of the most common methods of forecasting, widely used in the field of health (Mishra et al., 2019; Khan et al., 2019; Nyoni, 2019). This paper will employ the ARIMA models in order to analyze annual infant deaths in Zimbabwe. ARIMA models were postulated by Box & Jenkins (1970), hence the term "Box-Jenkins ARIMA models". The basic ARIMA (p, d, q) model can be represented by a backward shift operator as follows:

$$\emptyset(B)(1-B)^{d}ID_{t} = \theta(B)\mu_{t} \ldots [1]$$

Where the autoregressive (AR) and moving average (MA) characteristic operators are:

$$\emptyset(B) = (1-\emptyset_{1}B-\emptyset_{2}B^{2}-\cdots-\emptyset_{p}B^{p}) \ldots [2]$$

$$\theta(B) = (1-\theta_{1}B-\theta_{2}B^{2}-\cdots-\theta_{q}B^{q}) \ldots [3]$$

and

$$(1-B)^{d}ID_{t} = \Delta^{d}ID_{t} \ldots [4]$$

Where $\emptyset$the parameter estimate of the autoregressive component is, θ is the parameter estimate of the moving average component, Δ is the difference operator, d is the difference, B is the backshift operator and μ_t is the disturbance term.

The Box – Jenkins Methodology:

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, 2018c).

Data Collection:

This study is based on 59 observations of annual total Infant Deaths (ID) in Zimbabwe. All the data was gathered from the World Bank online database.

Diagnostic Tests & Model Evaluation:

Stationarity Tests:

The Correlogram in Levels:

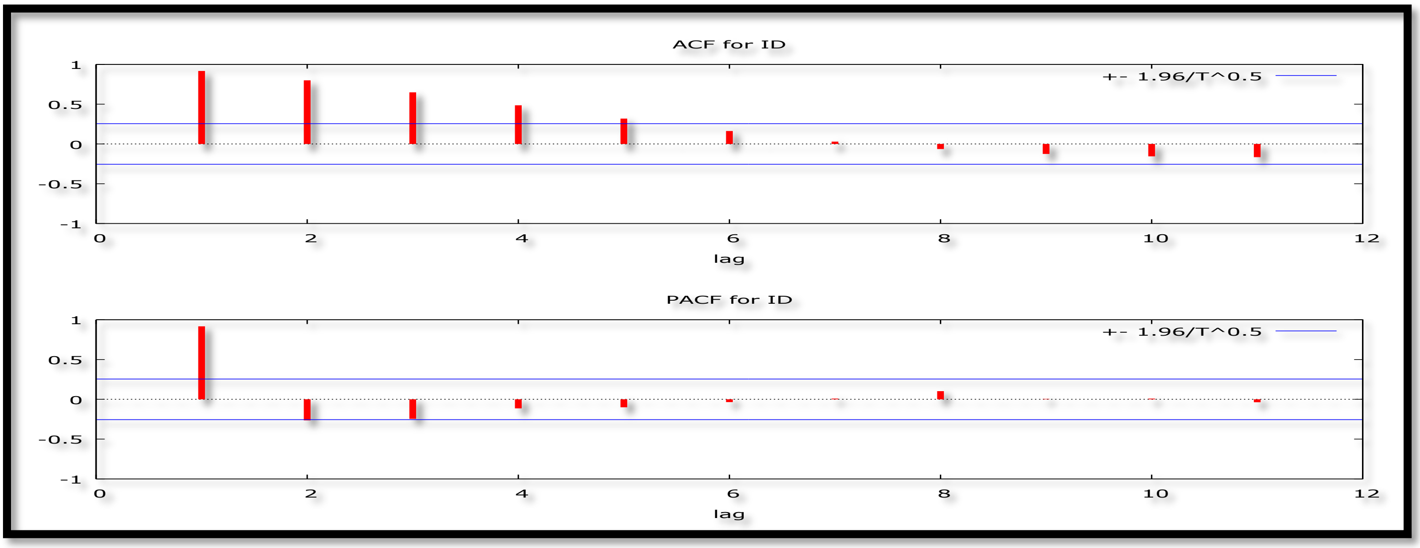


Figure 2

The ADF Test:

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ID	-2.178865	0.2161	-3.555023	@1%	Not stationary
			-2.915522	@5%	Not stationary
			-2.595565	@10%	Not stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ID	-1.174842	0.9057	-4.133838	@1%	Not stationary
			-3.493692	@5%	Not stationary
			-3.175693	@10%	Not stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ID	-0.279866	0.5806	-2.607686	@1%	Not stationary
			-1.946878	@5%	Not stationary
			-1.612999	@10%	Not stationary

The Correlogram (at 1st Differences)

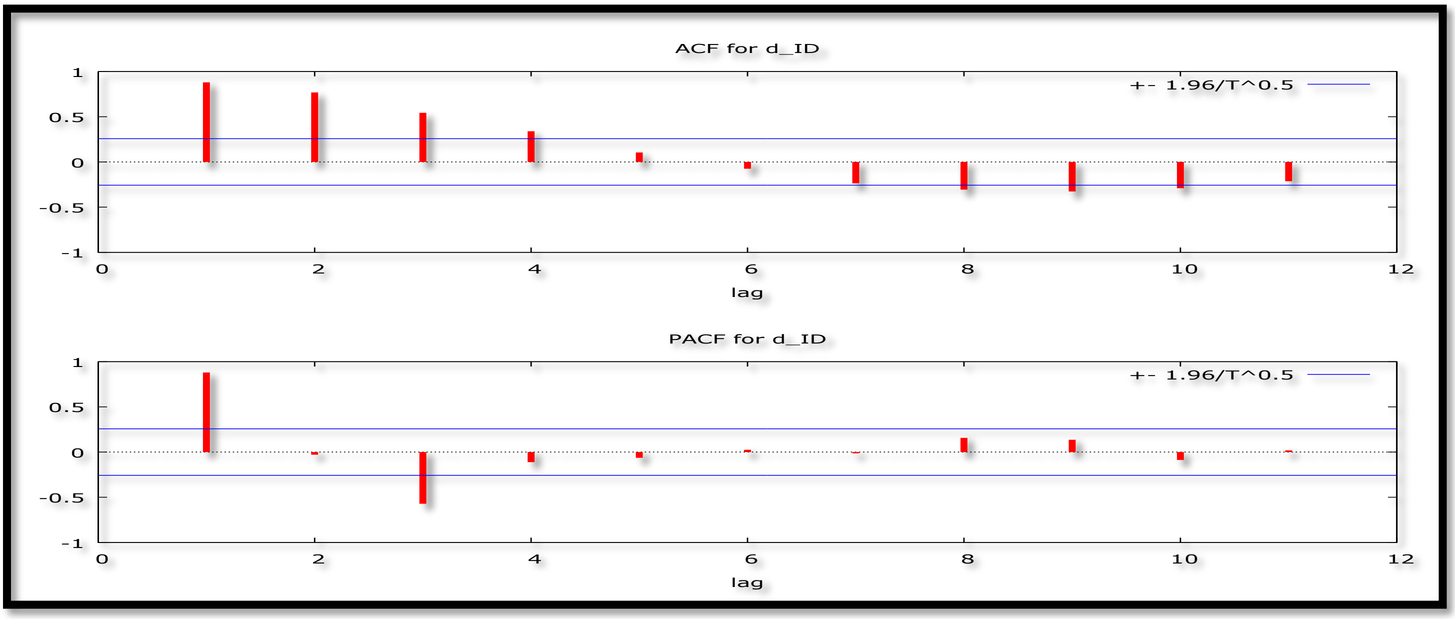


Figure 3

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(ID)	-3.277544	0.0208	-3.555023	@1%	Not stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(ID)	-3.809340	0.0234	-4.133838	@1%	Not stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

Table 6: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(ID)	-3.313348	0.0013	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Figures above, that is; 2 and 3 and tables above, that is; 1 to 6 show that the ID series is not stationary in levels and even after taking first differences.

The Correlogram in (2nd Differences):

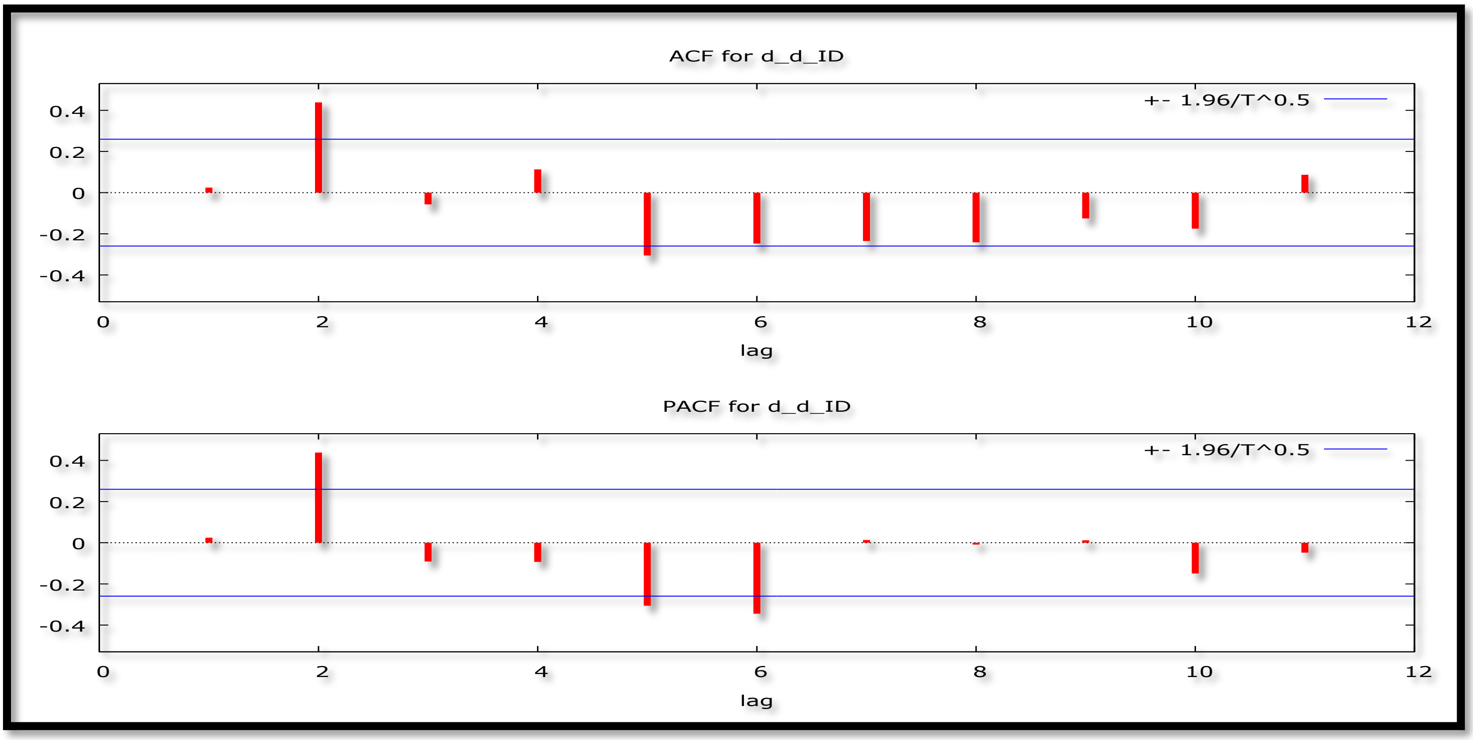


Figure 4

Table 7: 2nd Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(D(ID))	-2.938281	0.0475	-3.555023	@1%	Not stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 8: 2nd Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(D(ID))	-2.917804	0.1651	-4.133838	@1%	Not stationary
			-3.493692	@5%	Not stationary
			-3.175693	@10%	Not stationary

Table 9: 2nd Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
D(D(ID))	-2.964236	0.0037	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Figure 4 and tables 7 – 9 illustrate that the ID series is essentially an I (2) variable.

Evaluation of ARIMA Models (without a constant):

Table 10: Evaluation of ARIMA Models

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 2, 1)	805.4103	0.41933	-14.567	177.9	268.57	0.86467
ARIMA (1, 2, 0)	805.0406	0.42143	-19.176	186.73	272.52	0.90368
ARIMA (0, 2, 1)	805.0615	0.42107	-19.371	187.56	272.58	0.90721
ARIMA (0, 2, 4)	789.6988	0.34769	-9.0029	153.93	221.86	0.74806
ARIMA (0, 2, 5)	790.0062	0.32744	-9.6117	143.16	214.81	0.6914
ARIMA (1, 2, 4)	790.8645	0.33516	-8.8255	144.18	216.81	0.69965
ARIMA (1, 2, 5)	**786.8755**	0.31273	-23.854	135.66	204.35	0.65643
ARIMA (2, 2, 5)	788.8212	0.31344	-24.058	135.69	204.28	0.65723
ARIMA (4, 2, 4)	794.7500	0.33538	-27.411	142.33	217.18	0.69095
ARIMA (4, 2, 1)	790.6860	0.34658	-28.066	142.64	220.86	0.69859
ARIMA (5, 2, 1)	790.6725	0.33251	-24.808	145.6	217.33	0.70269
ARIMA (2, 2, 2)	796.4435	0.37111	-8.687	158.87	238.52	0.77163
ARIMA (2, 2, 1)	794.4643	0.37019	-8.5955	158.68	238.56	0.76987
ARIMA (3, 2, 1)	789.0877	0.34693	-27.824	143.55	221.59	0.70217
ARIMA (1, 2, 3)	796.800	0.36862	-9.9668	163.29	238.52	0.78546
ARIMA (3, 2, 3)	794.4893	0.34155	-11.3	157.42	224.29	0.75312
ARIMA (0, 2, 3)	796.8366	0.37731	-11.494	165.13	243.6	0.79719
ARIMA (3, 2, 0)	794.2667	0.37135	-9.1981	158.78	238.12	0.77181
ARIMA (2, 2, 0)	793.3381	0.37441	-7.3522	160.25	240.57	0.77778
ARIMA (0, 2, 2)	795.9508	0.38732	-11.607	164.19	246.55	0.79782
ARIMA (4, 2, 0)	795.7856	0.3741	-10.282	158.02	237.08	0.77181
ARIMA (8, 2, 0)	792.6631	0.32831	-24.088	149.16	212.46	0.722
ARIMA (7, 2, 0)	791.3509	0.33255	-25.27	148.98	214.57	0.72205
ARIMA (6, 2, 0)	789.3534	0.33251	-25.192	149.06	214.56	0.72232
ARIMA (5, 20)	793.0115	0.34412	-15.334	149.69	226.53	0.71668
ARIMA (8, 2, 1)	794.6025	0.32788	-24.113	148.92	212.24	0.72066
ARIMA (7, 2, 1)	793.2374	0.33208	-25.511	148.53	214.28	0.72022
ARIMA (6, 2, 1)	791.3522	0.33253	-25.23	149.02	214.56	0.72219
ARIMA (6, 2, 2)	792.5209	0.32772	-23.767	148.94	212.05	0.72035
ARIMA (5, 2, 1)	790.6725	0.33251	-24.808	145.6	217.33	0.70269
ARIMA (5, 2, 2)	792.3038	0.33178	-23.791	148.75	216.6	0.71745

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018b) Similarly, the U statistic can be used to find a better model in the sense that it must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018a). In this piece of work, following Mishra et al. (2019), only the AIC is used to select the optimal model. Therefore, the ARIMA (1, 2, 5) model is selected.

Residual & Stability Tests:

ADF Tests of the Residuals of the ARIMA (1, 2, 5) Model:

Table 11: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R	-6.921333	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 12: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R	-7.112756	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R	-6.974242	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Table 13: without intercept and trend & intercept

Tables 11 – 13 indicate that the residuals of the chosen optimal model, the ARIMA (1, 2, 5) model; are stationary.

Correlogram of the Residuals of the ARIMA (1, 2, 5) Model:

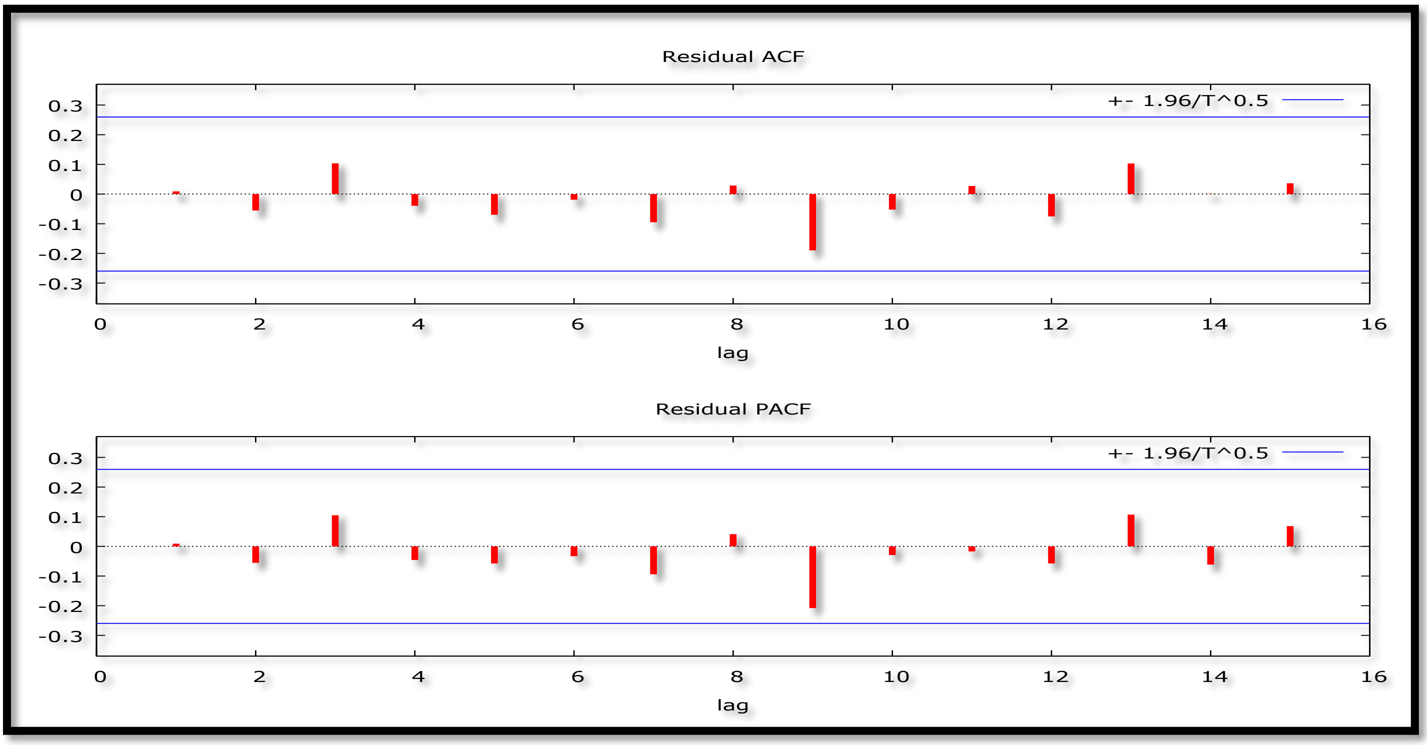


Figure 5: Correlogram of the Residuals

Figure 5 indicates that the estimated ARIMA (1, 2, 5) model is adequate since ACF and PACF lags are quite short and within the bands. This implies that the "no autocorrelation" assumption is not violated in this paper.

Stability Test of the ARIMA (1, 2, 5) Model:

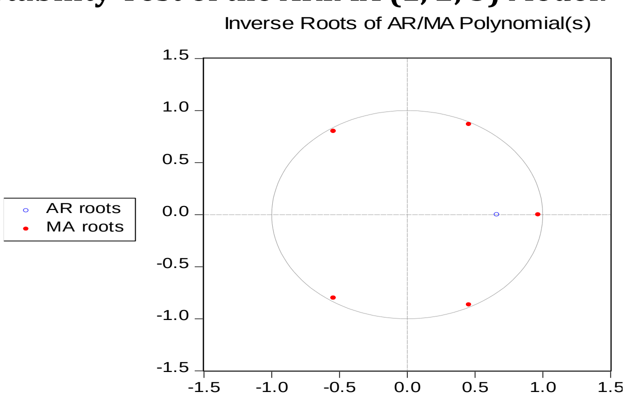


Figure 6: Inverse Roots

Since all the AR and MA roots lie inside the unit circle, it means that the estimated ARIMA process is (covariance) stationary; hence confirming that the ARIMA (1, 2, 5) model is quite stable and suitable for forecasting annual infant deaths in Zimbabwe.

FINDINGS:

Descriptive Statistics:

Table 14: Descriptive Statistics

Description	Statistic
Mean	20229
Median	20280
Minimum	15043
Maximum	25021
Standard deviation	2574.8
Skewness	-0.083445
Excess kurtosis	-0.94608

As anticipated, the mean is positive, i.e. 20229. This means that the average number of infant deaths over the study period is 20229 deaths per annum. The minimum number of infant deaths over the study period is 15043 deaths and this was recorded recently in 2018 while the maximum number of infant deaths is 25021 deaths and this was recorded in 2009. The skewness is -0.083445 and the most important characteristic is that it is negative, meaning that the ID series is negatively skewed and non-symmetric. Excess kurtosis is -0.94608; showing that the ID series is not normally distributed.

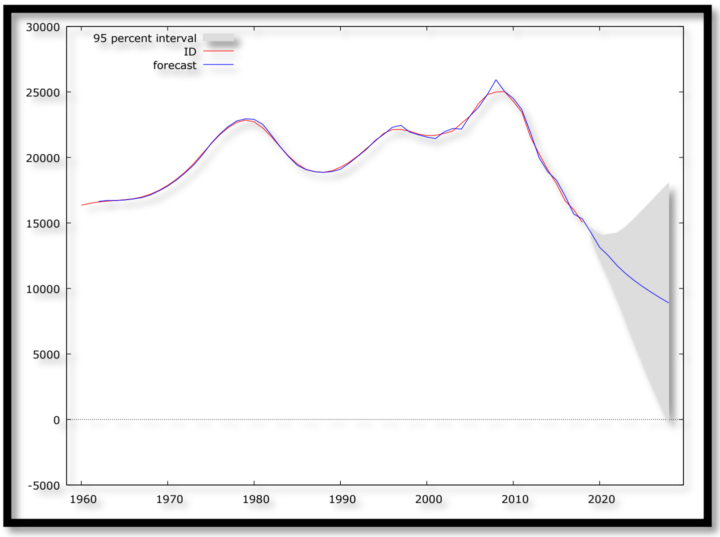
Results Presentation:

Table 15: Main Results

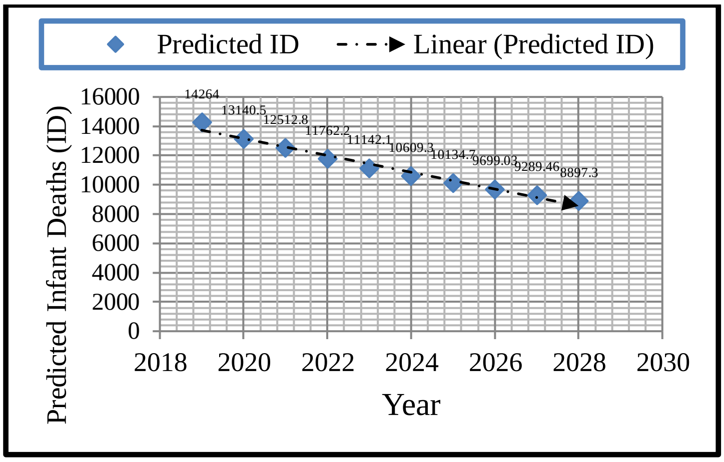
ARIMA (1, 2, 5) Model:

$$\Delta^2 ID_t = 0.668535\Delta^2 ID_{t-1} - 0.752241\mu_{t-1} + 0.680767\mu_{t-2} - 0.711983\mu_{t-3} + 0.710472\mu_{t-4} - 0.798584\mu_{t-5} \ldots\ldots [5]$$

Variable	Coefficient	Standard Error	z	p-value
ϕ_1	0.668535	0.189329	3.531	0.0004***
θ_1	-0.752241	0.184750	-4.072	0.0000***
θ_2	0.680767	0.112742	6.038	0.0000***
θ_3	-0.711983	0.156343	-4.554	0.0000***
θ_4	0.710472	0.133863	5.307	0.0000***
θ_5	-0.798584	0.155319	-5.142	0.0000***



Forecast Graph Figure 7: Forecast Graph – In & Out-of-Sample Forecasts



Predicted ID Figure 8: Graphical Analysis of Out-of-Sample Forecasts

Table 15 shows the main results of the ARIMA (1, 2, 5) model. Figure 7 and 8 show out-of-sample forecasts of the ARIMA (1, 2, 5) model. As clearly shown in figure 8, the number of infant deaths per year, over the out-of-sample period, show a sharply downwards trend. In order to maintain such a trend, the policy implications below ought to be taken seriously. The results of this study confirm the assertion made by Popline (2018) that infant deaths are generally declining worldwide. The results are similar to Mishra et al. (2019). Most importantly, the results of this endeavor are consistent with Nyoni & Nyoni (2020).

Policy Implications:

i. There is need for the government of Zimbabwe to improve sanitation and access to safe water in order to curb infectious diarrhoeal diseases in the country.
ii. There is need for continued immunization of infants against infectious diseases. In this regard, the government of Zimbabwe should also reach out to religious sects which traditionally refuse immunization.
iii. The government of Zimbabwe should also improve pre-pregnancy and pre-natal care. In this regard, there is need for the government of Zimbabwe to strengthen HIV prevention programs such as the PMTCT program in order to reduce pediatric HIV infections and infant deaths related to HIV.
iv. The government of Zimbabwe should also improve coverage and quality of obstetric and essential newborn care.
v. The government of Zimbabwe should strengthen the referral system so that patients who need specialist care are reffered early.

Further Research

Further studies may analyze infant deaths by province and examine variations across different provinces in Zimbabwe. Further research should also be done in terms of analyzing infant deaths by sex and examine the hypothesis whether or not the female infant deaths are higher than the male infant deaths.

CONCLUSION:

The economy of Zimbabwe is riddle with poverty, inequality, informality, chronic and recurrent phases of economic stagnation, poor institutional climate, cash crisis, rampant corruption, political volatility, low savings and investment, high interest rates, high costs of production, lack of competitiveness, low aggregate demand, poor infrastructure as well as high rates of unemployment (Nyoni & Bonga, 2017). These are the main hindrances that can potentially reverse the predictions of the optimal model, the ARIMA (1, 2, 5) model. However, if the government mobilizes enough resources to implement the recommendations of this study, infant deaths are likely to decline even further.

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