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Modelling Infant Mortality Rate using Time Series Models

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ABSTRACT

The world's main indicator of children's health and general development is the infant mortality rate for infant under the age of five. Infant mortality is the term used to describe the death of a child before their first birthday. The infant mortality rate (IMR), which is the number of deaths of infants under one year of age per 1,000 live births, can be used to describe the prevalence of infant mortality in a population. Comparing the death rate of children under the age of five is the child mortality rate, commonly referred to as the under-five mortality rate. Nigeria, one of the nations with a high under-five mortality rate of 117 per 1,000 live births in 2019, is among those nations. The nation is among the top five nations with the highest mortality rate for children under five in 2019. This study aims to model infant mortality(Live birth and Still birth) rate using time series models and to predict the mortality rate using these models. Adeoyo Maternity Hospital Yemetu in Ibadan provided the data for this study. The data set is a monthly data and also a secondary data span for a period of 12 years (2009 to 2020). The time plot showed visual inspection and non-stationarity. Differencing was done and the unit root test performed for the purpose of comparison thereafter. Augmented-Dickey Fuller test and Phillip Perron unit root test was further tested for the establishment of stationarity in order to the main objectives. Three time series methods are the Autoregressive Integrated Moving Average Model(ARIMA), Exponential Smoothing and the Holt-Winters Method were used to model and predict the infant mortality rate data. The result shows that ARIMA order=c(0,0,1) with zero (0) mean for stillbirth and ARIMA order=c(1,0, 2) for live birth with the smallest AIC = (9.102 and 13.991). Akaike Information Criterion(AIC) values of (9.289, 14.139) and (9.102, 13.991) for live birth and still birth, respectively, were derived by exponential smoothing and Holtwinters technique. This means that Holtwinters' technique, which yielded the lowest AIC when compared to ARIMA and exponential smoothing, is the most accurate predictor of both stillbirth and live birth data. Given the high mortality rate for children under the age of five, it is crucial for the government to place more of an emphasis on health issues and to solve the problems plaguing Nigeria's child health care system.

1. Introduction

Infant mortality refers to the death of infants under the age of one year in a generation; the infant mortality rate (IMR) is defined as the proportion of that generation's children who die before reaching their first birthday. Apart from socioeconomic change, which causes newborn mortality, the social environmental pattern is given for the key causes of infant mortality. Mortality can be defined as the total or permanent loss of all signs of life at any moment after birth. That is, the inability of a whole body component to function after birth. As a result, death can occur only after birth has occurred. Mortality is the risk of dying in a particular year, as measured by the death rate, which is the number of deaths per 100,000 individuals in a population throughout the universe(Adepoju et al, 2022).

The infant mortality rate compares the number of newborn deaths under one-year-old in a particular year to the number of live births in the same year. This rate is frequently cited as an indicator of a country's state of health. The current global infant mortality rate in 2023 is 26.052 deaths per 1000 live births, a 2.4% decrease from 2022. In 2022, the global infant mortality rate was 26.693 deaths per 1000 live births, a 2.35% decrease from 2021. In 2021, the global infant mortality rate was 27.334 deaths per 1000 live births, a 2.29% decrease from 2020. The global infant mortality rate in 2020 was 27.974 deaths per 1000 live births, a 2.24% decrease from 2019. Africa's mortality rate in 2022 was 42.760 deaths per 1000 live births, a 2.67% decrease from 2021. Africa's infant mortality rate in 2021 was 43.934 deaths per 1000 live births, a 2.6% decrease from 2020. Africa's infant mortality rate in 2020 was 45.107 deaths per 1000 live births, a 2.54% decrease from 2019.

According to a Commonwealth Fund report, Nigeria is ranked fifteenth in the world in terms of infant mortality rates, with the current infant mortality rate in 2023 being 54.740 deaths per 1000live births, a 2.63% decrease from 2022, and the infant mortality rate in 2022 being 56.220 deaths per 1000 live births, a 2.57% decrease from 2021. Nigeria's infant mortality rate in 2021 was 57.701 deaths per 1000 live births, a 2.5% decrease from 2020, and the infant mortality rate in 2020 was 59.181 deaths per 1000 live births, a 2.44% decrease from 2019, while Africa's current infant mortality rate in 2023 is 41.586 deaths per 1000 live births. Infant mortality is classified into two classes namely; Prenatal infant mortality and Neonatal infant mortality. Prenatal infant mortality simply refers to the death of child in the first week while Neonatal mortality is the death of the child less than four weeks, which from all indications tells us that prenatal, is the subset of neonatal mortality. Infant mortality, defined as a child dying within the first year of life, is still a major global concern(Graffam et al, 2023). It not only represents a population's overall health and well-being, but it also acts as a measure of the effectiveness of healthcare systems and social support structures. Numerous studies have been done to examine the causes, risk factors, and potential solutions in an attempt to solve this essential issue(Ogundunmade and Adepoju, 2021; Ogundunmade et al, 2022).

Premature delivery is one of the leading causes of infant death. Preterm delivery problems are responsible for nearly 35% of all neonatal fatalities worldwide, according to a study by Ayansola et al, (2022). The necessity of good antenatal care, including access to experienced birth attendants and early diagnosis of at-risk pregnancies, is emphasized by the researchers. Furthermore, their data imply that boosting the quality of neonatal care, such as kangaroo mother care and basic infant care, can cut mortality rates dramatically. Socioeconomic factors have been established as important predictors of infant mortality (Zilidis and Hadjichristodoulou, 2020). According to Singh and Stella (2019), low socioeconomic level, including poverty, restricted access to healthcare, and inadequate education, strongly contributes to newborn death rates. To improve infant survival rates, the researchers emphasize the importance of tailored interventions that address underlying social and economic inequities.

Maternal variables are important in infant mortality. Reed and Rijhsinghani (2023) addressed the influence of maternal obesity on infant mortality, stating that obese mothers are more likely to have preterm or stillborn babies. Early treatments supporting healthy lifestyles and weight control for women of childbearing age, according to the study, could help minimize infant mortality. Medical research advances in recent years have provided insight on the genetic and epigenetic variables influencing infant mortality. Holm et al, (2022) illustrated the significance of genetic screening and counseling in identifying probable inherited diseases that may raise newborn mortality risk. Furthermore, research into epigenetic pathways sheds light on how prenatal environmental variables influence baby health outcomes.

Infectious diseases have a significant influence. The global burden of infectious causes of infant mortality, such as streptococcus, pneumonia, sepsis, and diarrhea illnesses, was highlighted in a research by Gonçalves et al, (2022). The researchers underline the importance of preventive methods such as vaccines, improved sanitation, and access to safe drinking water, which can considerably lower infectious disease-related infant death rates.

Finally, the multidimensional character of infant mortality and the complicated interaction between its different factors are discussed. Addressing this issue clearly necessitates a comprehensive approach that includes healthcare interventions, targeted socioeconomic strategies, maternal health programs, genetic screening, and infectious disease prevention measures. Only by understanding the underlying causes and risk factors can effective measures to improve infant mortality rates be applied globally. Advances in medical research have provided light on the genetic and epigenetic variables impacting newborn mortality in recent years(Wojcik et al, 2019).

Finally, infectious diseases have a significant impact, premature birth is one of the leading causes of infant death (Muhe et al, 2019). Kulkarni et al, (2021) aimed to determine the trend of infant mortality and to forecast the future mortality rate. The remainder of this paper is structured as follows; Section 2 describes the studies, materials and methodology; Section 3 presents the findings and discussions while Section 4 shows the conclusion of this paper. The last section shows the conclusion of the study.

2. Methods and Materials

In this section, we discussed the data used for the study. We also discussed the time series models used to model the infant mortality(live birth and still birth) data. These methods are the Autoregressive Integrated Moving Average Model(ARIMA), Exponential Smoothing and the Holt-Winters Method. These methods are used to model univariate time series data.

2.1 Data for the Study

The data for this study were gathered from Adeoyo Maternity Hospital Yemetu Ibadan. It is monthly data; thus, the data set employed is secondary data. Adeoyo Maternity Hospital Yemetu Ibadan, founded in 1928, acts as a reference health center for numerous primary health centers and private clinics throughout the LGAs. The hospital has an obstetrics and gynecology department with four consultants and medicals, as well as senior medical and main medical officials. One of the primary goals of creating this hospital is to improve maternal healthcare, which is one of the Millennium Development Goals.

2.2 Autoregressive Integrated Moving Average Model(ARIMA)

The ARIMA methodology is carried out in three stages, viz. identification, estimation and diagnostic checking. Parameters of the tentatively selected ARIMA model at the identification stages are estimated at the estimation stage and adequacy of tentatively selected model is tested at the diagnostic checking stage. If the model is found to be inadequate, three stages are repeated until satisfactory ARIMA models is selected for the time series under consideration.

2.3 Exponential Smoothing

A time series strategy for predicting univariate time series data is exponential smoothing. The underlying idea behind time series approaches is that a prediction is simply the weighted linear sum of previous observations, or lags. By giving previous observations exponentially decreasing weights, the exponential smoothing time series approach functions. It gets its name from the exponentially decreasing weight that is given to each demand observation.

The model makes the supposition that the near future will mostly resemble the recent past. The level, or the average value around which the demand fluctuates over time, is the only pattern that Exponential Smoothing learns from demand history. In most cases, exponential smoothing is used to forecast time-series data based on the user's prior assumptions, such as seasonality or systematic trends.

The time series forecasting technique known as simple or single exponential smoothing (SES) is employed with univariate data that lacks a seasonal pattern or trend. The smoothing factor, often known as alpha (a), is the only parameter required. The exponential decay of the influence of prior observations is governed by alpha. A common setting for the parameter is a number between 0 and 1. Here is the straightforward exponential smoothing formula:

$$s_t = \propto x_t + (1-\propto) \tag{1}$$

$$x_t = s_{t-1} - 1 + s_{t-1} \tag{2}$$

here,

s_t = Simple weighted average of the most recent observation,

x_t = Prior smoothed statistic:

s_{t-1} = Data smoothing factor; 0; 1; and t stands for time.

2.4 Holt-Winters Method

This is a time series behavior model. Forecasting usually necessitates the use of a model, and Holt-Winters is one method for modeling three components of a time series: a typical value (average), a slope (trend) through time, and a cyclical repeating pattern (seasonality). Hence the Holt winter's method takes into account average along with trend and seasonality while making the time series prediction.

Forecast equation:

$$y_{t+h|t} = \ell_t + hb_t \tag{3}$$

Level equation:

$$\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{4}$$

Trend equation:

$$b_t = \beta * (\ell_t - \ell_{t-1}) + (1 - \beta *) b_{t-1} \tag{5}$$

Where ℓ_t is an estimate of the level of the series at time t, b_t is an estimate of the trend of the series at time t, α is the smoothing coefficient.

2.5 Comparison criteria

2.5.1 Alkaike Information Criterion (AIC)

The Alkaike Information Criterion (AIC) is a Bayesian statistics indicator that is used to choose between two or more alternative models. The analysis of the collected data was done with the aid of SPSS software and E-Views.

3. Results and Discussion

In this session, we present the results of the analysis of the data. The descriptive statistics of the data is presented in the Table 1.

Table 1. Descriptive Statistics of the Data

Still Birth	Live Birth

Min	52.00	Min	1494.00
Median	97.50	Median	2568.00
Mean	146.17	Mean	2905.33
Range	248.00	Range	3271.00
Variance	10322.52	Variance	1173103.152
Std. Deviation	101.60	Std. Deviation	1083.099
Max	300.00	Max	4765.00

Table 1 above shows the descriptive statistics of the variables used in the analysis. The mean value of still birth and live birth at Adeoyo Maternity Hospital, Yemetu Ibadan is 146.17 and 2905.33. The minimum and maximum of still birth is (52.00,300.00) and the minimum and maximum for live birth is (1494.00, 4765.00). Time plot was used to visualize the data, time series was the tools used for the analysis in which ARIMA, Exponential Smoothing and Holt-Winters models was used to fit the trend line and forecast for the next 5years.

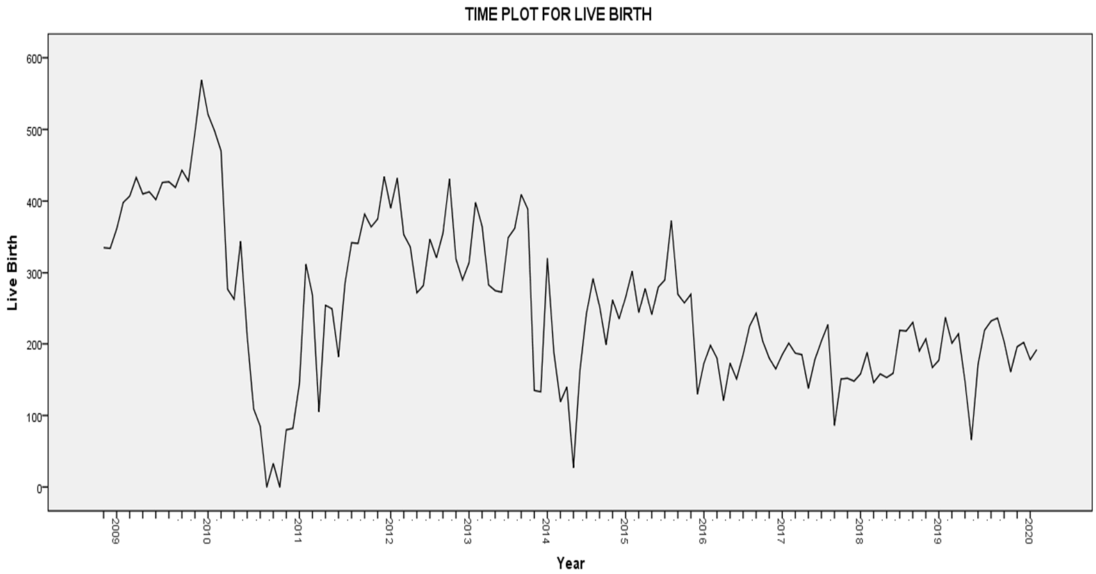

Figure 1. Time Plot of Still Birth

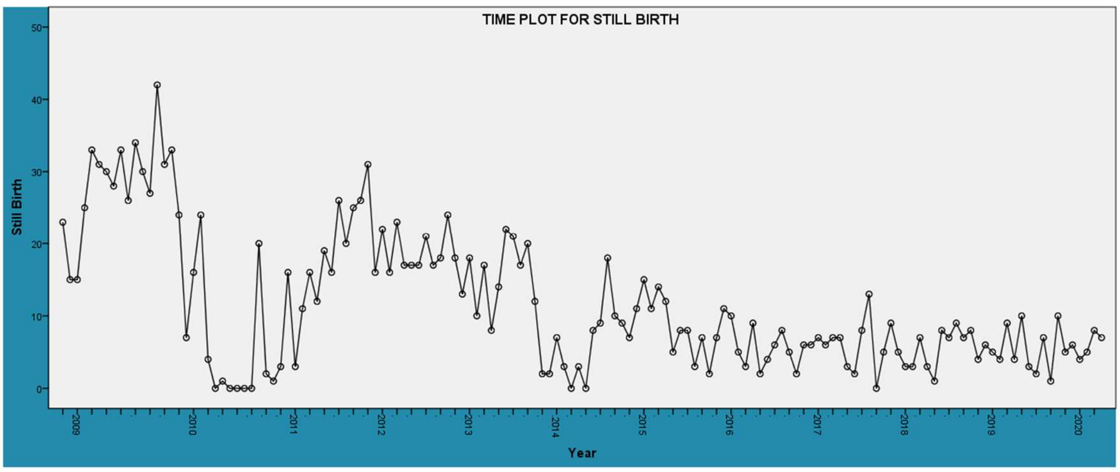

Figure 2. Time Plot of Still Birth

Represented in figure 1 and figure 2 above are the time plot of all the variables used in this analysis (still birth and live birth). A critical look at the plots show that the series exhibited and seasonal effect. Since the plots cannot provide sufficient evidence to render the series not stationary, it is essential to use standard tests of stationarity.

Table 2. Stationary Tests for Live Births

ADF Level		
	t-statistic	**P-value**
ADF Test Statistic	-0.393080	0.8713
Test critical values: 1% level	-4.420595	
5% level	-3.259808	
10% level	-2.771129	
ADF Level at First Difference		
	t-statistic	**P-value**
ADF Test Statistic	-6.155682	0.0008
Test critical values: 1% level	-4.297073	
5% level	-3.212696	
10% level	-2.747676	
PP at Level		
	Adj.t-statistic	**P-value**
Phillips-Perron test statistic	-3.252124	0.0443
Test critical values: 1% level	-4.200056	
5% level	-3.212696	
10% level	-2.728985	
PP Level at First Difference		
	Adj. t-statistic	**P-value**
Phillips-Perron test statistic	-9.167532	0.0000
Test critical values: 1% level	-4.297073	
5% level	-3.212696	
10% level	-2.747676	

Table 2 above shows the result for the stationarity tests of live births using Augumented dickey fuller (ADF)tests and the Philip Perron(PP) tests. The adf test shows and insignificant result p-value(0.8713) result for the data but a significant p-value(0.0008) result after the first difference. Philip Perron test shows a significant p-value(0.0443) for the data and even after its first difference(0.000).

Table 3. Stationary Tests for Still Births

ADF Level		
	t-statistic	**P-value**
ADF Test Statistic	-0.256303	0.8965
Test critical values: 1% level	-4.420595	
5% level	-3.259808	
10% level	-2.771129	
ADF Level at First Difference		
	t-statistic	**P-value**
ADF Test Statistic	-5.763437	0.0019
Test critical values: 1% level	-4.420595	
5% level	-3.259808	
10% level	-2.771129	
PP at Level		
	Adj.t-statistic	**P-value**
Phillips-Perron test statistic	-2.273116	0.1951
Test critical values: 1% level	-4.200056	
5% level	-3.175352	
10% level	-2.728985	

PP Level at First Difference		
	Adj. t-statistic	**P-value**
Phillips-Perron test statistic	-6.939515	0.0003
Test critical values: 1% level	-4.297073	
5% level	-3.212696	
10% level	-2.747676	

Table 3 shows the result for the stationarity tests of still births using Augumented dickey fuller (ADF)tests and the Philip Perron(PP) tests. The adf test shows and insignificant result p-value(0.8965) result for the data but a significant p-value(0.0019) result after the first difference. Philip Perron test shows a insignificant p-value(0.1951) for the data but a significant p-value after its first difference(0.0003).

Table 4. Model Parameters for Live Birth using ARIMA

	Estimate	**SE**	**t**	**Sig.**
Constant	146.167	29.329	4.984	.000
MA1	3.12	0.231	1.223	0.023

Table 5. Model Parameters for Still Birth using ARIMA

	Estimate	**SE**	**t**	**Sig.**
Constant	2905.333	312.664	9.292	.000
AR2	4.87	0.415	-2,83	0.023
MA1	-1.43	0.651	2.11	0.213
MA2	2.01	0.321	3.65	0.033

Table 4 and Table 5 show the ARIMA results for the live birth and still birth respectively. Table 4 shows the result of ARIMA(0,1,1) for live birth and ARIMA(1,0,2) for the still birth respectively.

Table 6. Comparison of The Three Models for Still Births and Live Births

	AIC	
	Still Births	**Live Births**
ARIMA	9.449	14.182
Exponential Smoothing	9.289	14.139
Holt-Winter Method	9.102	13.991

Table 6 displays the AIC model performance for the time series models taken into consideration. For stillbirths and live births, ARIMA shows values of 9.449 and 14.182, respectively. Both Holt-Winter Method and Exponential Smoothing generated 9.289 and 14.139 for stillbirth and live birth, respectively, as well as 9.102 and 13.991 for live birth. The outcome demonstrates that Holt-Winter provided the best model for the study's data.

3.1 Forecast

Using ARIMA, Exponential Smoothing and Holt-Winter method, we obtained 5years forecast (2021 to 2025) for Still Birth and Live Birth at Adeoyo Maternity Health Centre, Yemetu, Ibadan.

Table 7. Forecast Table for Still Birth

Year	ARIMA	Exponential Smoothing	Holt-Winters Method
2021	146	73	17
2022	146	73	-3
2023	146	73	-24
2024	146	73	-45
2025	146	73	-65

Table 8. Forecast Table for Live Birth

Year	ARIMA	Exponential Smoothing	Holt-Winters Method
2021	2905	2310	1649
2022	2905	2310	1446
2023	2905	2310	1243
2024	2905	2310	1040
2025	2905	2310	837

Tables 7 and 8 above show the 5years forecast for Live Birth and Still birth data for Adeoyo Maternity Health Centre.

3.2 Discussion of the Study

This study applied Alkaike Information Criterion (AIC) using ARIMA, Exponential Smoothing and Holt-Winter method, the order with minimum value is the best. Therefore, ARIMA order=c(0,0,1) with zero (0) mean for stillbirth and ARIMA order=c(1,0,2) for live birth with the smallest AIC = (9.449 and 14.182). Exponential smoothing and Holtwinters method produced AIC values of (9.289, 14.139) and (9.102, 13.991) for live birth and still birth respectively. This therefore implies that Holtwinters method best predict both the still birth and live birth data as it produced lowest AIC, compared to ARIMA and Exponential smoothing. Table 1 shows the descriptive statistics of the data which contains the minimum, maximum, median, range, standard deviation, variance for still births and live birth. Table 2 and 3 show the test of stationarity for still births and live births using Augmented Dickey Fuller test, Phillip-Perron test and P-value. Table 4 and 5 contains the model parameters for the study using ARIMA. Table 6 contains the comparison of the three models used in this study. Table 7 and 8 contains the forecast table for still births and live births for 5 years. Figure 1 and 2 contains the time plot for still births and live births.

4. Conclusion

The goal of conducting any type of research is to gather the data that will enable an adequate investigation and act as a tool for decision-making. There is no doubt that the primary goal of this paper has been fully achieved as a result of the employment of essential and appropriate methodology consistent with the goals and objectives of this study. This paper investigated the Child mortality rate in Nigeria using Adeoyo Maternity Health Centre, Yemetu, Ibadan as a case study for a period of 12 years (2009 to 2020). In view of this high rate of mortality rate for children under 5 years, it is important for government to focus more on the health factor and by readdressing the ailing points of the child health care sector in Nigeria.

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Conflict of Interest

The authors have no conflict of interest.

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Authors Contribution

Ogundunmade TP. performed conceptualization, review and edited the article, while Daniel AO and Abdulazeez AM did data curation and wrote the article.

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