ANALYZING NEWBORNS WITH LOW AND NORMAL BIRTH WEIGHT IN CHITUNGWIZA URBAN DISTRICT IN ZIMBABWE USING ARTIFICIAL NEURAL NETWORKS

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

In this study, ANN models were applied in analyzing birth weights, that is, Low Birth Weight (LBW) and Normal Birth Weight (NBW) in Chitungwiza urban district. The employed data covers the period January 2012 to December 2019 and the out-of-sample period ranges over the period January 2020 to December 2021. The residuals and forecast evaluation criteria of the applied models indicate that the models are adequate in predicting LBW and NBW incidence in Chitungwiza urban district over the out-of-sample period. The results of the study basically indicate that NBWs are always more than LBWs and this has been forecasted to persist into the out-of-sample period. In order to reduce LBW and increase the numbers of NBW, there is need to implement the suggested 4-fold policy recommendations.

Keyword: - *ANN, Forecasting, LBW, NBW, Newborn*

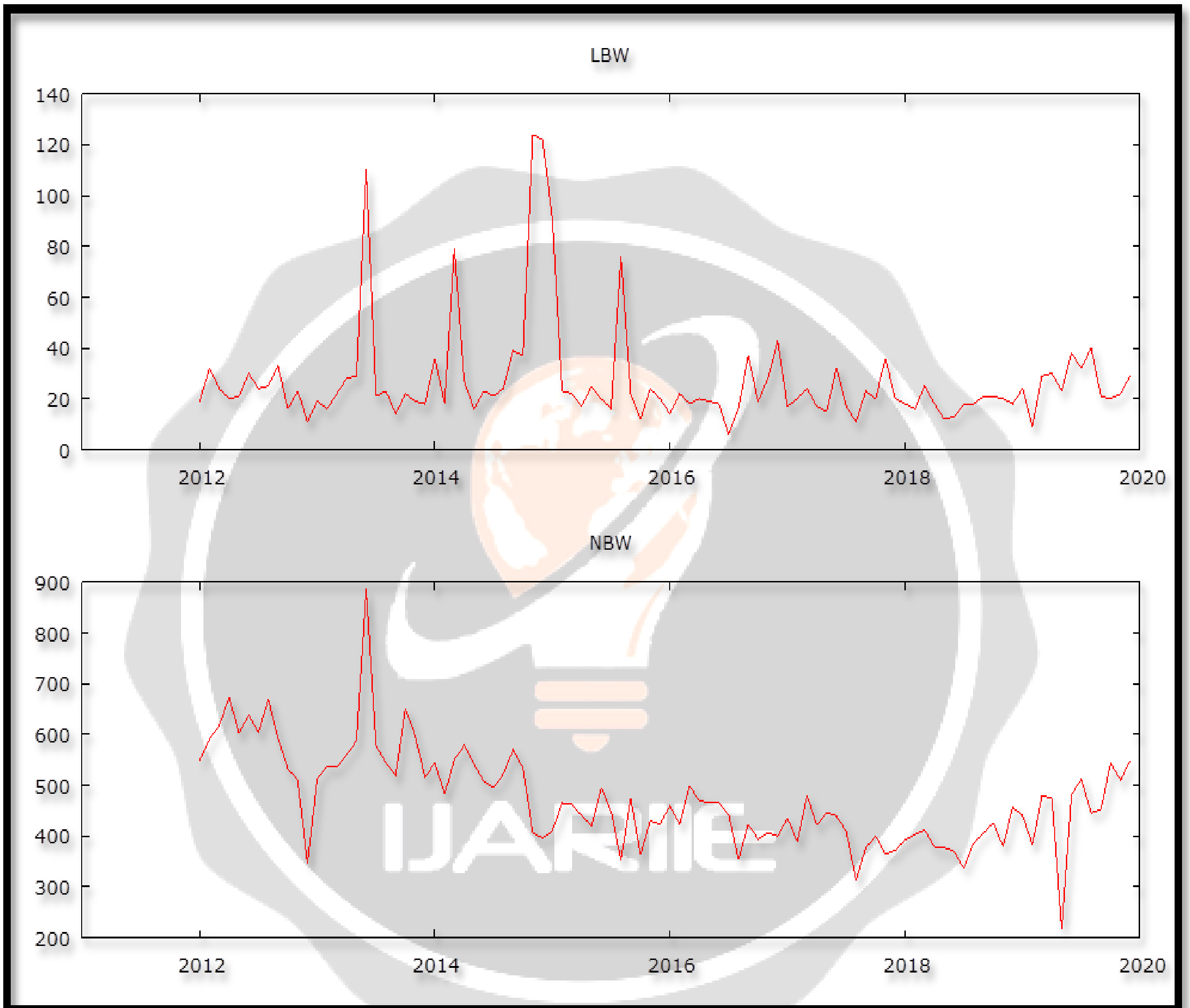
1.0 INTRODUCTION

Birth weight is a measure of an infant's maturity and is used as a measure of an infant's relative chance of survival (Hale, 1990). Birth weight is an important indication of health status of the infant and the main factor that determines the infant's survival and physical and mental growth in the future. (Soheili, 2004). It also indicates the past and present health status of the mothers (Edmond & Bahl, 2006; Viengsakhone *et al*., 2010; Dekieviet *et al*., 2011; Tshotetsi *et al*., 2019; WHO, 2019). Infants with birth weight less than 2.5kg are Low Birth Weight (LBW) (Behrman & Kliegman, 2002; Tshotetsi *et al*., 2019; WHO, 2019). An infant whose birth weight is less than 2.5kg is a high-risk infant. LBW is one of the most important factors in infant mortality (Behrman & Alderman, 2004) since the mortality of LBW babies is 40 times more than the normal-weight babies (Soheili, 2004). In developing countries 17% of all births have low birth weight (Ewbank & Gribble, 1993).

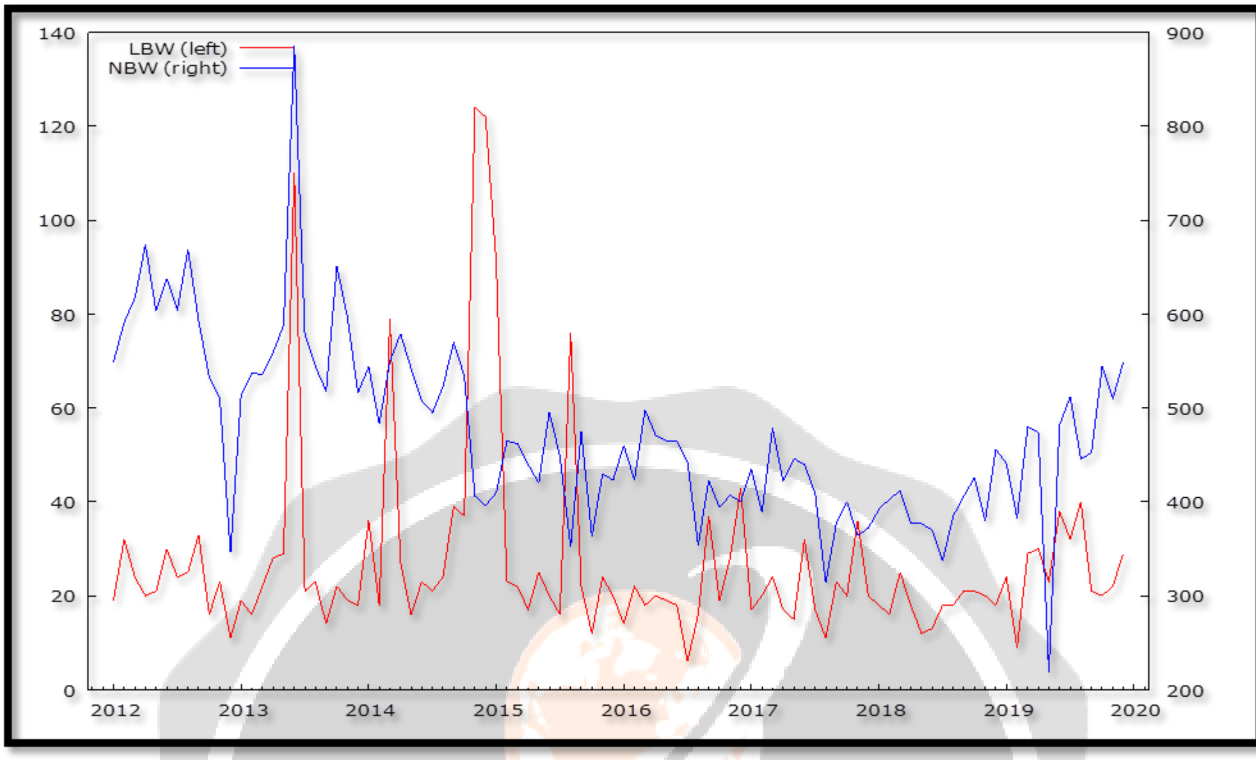
LBW is a serious public health concern low- and middle-income countries (Mahumud *et al*., 2017; Sema *et al*., 2019) and one of the strongest risk factors for early neonatal mortality and morbidity (Assefa *et al*., 2012; Rezende *et al*., 2016). There are approximately 23 million LBW infants from 121 million births in a year, a high proportion of which are in developing countries (Soheili, 2004). Many of these LBW babies die during their first month of life (WHO, 2004; Reyes & Manalich, 2005; Jornayvaz *et al*., 2016; Gu *et al*., 2017; Aryastami *et al*., 2017; Rosy *et al*., 2018), contributing significantly to neonatal mortality, which now makes up the largest proportion of infant mortality in many developing countries (Ramakhrisnan, 2004).

Most of the LBW children who survive infancy suffer cognitive and neurological impairment (WHO, 2004; Barbara *et al*., 2010; Campbell, 2013; Lee *et al*., 2013) and are stunted as adolescents and adults (Behrman & Alderman, 2004). In the perinatal period, LBW infants are in a critical state with regard to survival and approximately half of all neonatal deaths are directly or indirectly linked to LBW (Lau *et al.*, 2013). LBW may also be an intergenerational problem because LBW girls who survive tend to be undernourished when pregnant, with relatively high incidence of LBW children (Behrman & Alderman, 2004). Figure 1 and 2 below show LBW and NBW series in Chitungwiza urban district:

Figure 1: Low and normal birth weight cases in Chitungwiza urban district



From figure 1 above, it is clear that the NBW series is basically downwards trending. The LBW series is generally trending between 20 and 40 cases per month over the study period. Peaks are observable in the months of June 2013 (110 cases), November 2014 (124 cases) as well as December 2014 (122 cases). It is quite clear that NBW babies are always more than LBW babies at Chitungwiza urban district, even though NBW series generally declining. This is clearly illustrated in figure 2 below. Ideally, the numbers of NBW babies must be increasing; we would also expect to see a downwards trajectory in the numbers of LBW babies.



Predicting birth weight before the birth of the baby is the best way to help the baby get specialized care as early as possible. This also helps us to arrange for doctors and specialized facilities before the baby is born (Karthiga *et al.*, 2019). This paper analyzes the trends of LBW and NBW babies in Chitungwiza urban district using Artificial Neural Networks (ANNs).

1.1 OBJECTIVES OF THE STUDY

i. To analyze low and normal birth weight cases in Chitungwiza urban district over the period January 2012 to December 2019.
ii. To forecast low and normal birth weight cases in Chitungwiza urban district over the period January 2020 to December 2021.
iii. To determine whether low and normal birth weight cases in Chitungwiza urban district are increasing or decreasing over the period January 2020 to December 2021.

2.0 RELATED STUDIES

Madebwe & Madebwe (1997) examined relationships between maternal risk factors and incidence of low birth weight using maternity registers for two hospitals in the Midlands Province in Zimbabwe over a four-year period. Only full term births were included in the analysis. A low birth weight incidence rate of 9.8% was found among the 7251 index births included in the study. Logistic regression analysis showed that extremes in maternal age (too young or too old), high parity and rural residence were positively associated with low birth weight. LBW incidence rate varied only marginally over the four-year period. Roudbari *et al.* (2007) investigated the prevalence and risk factors of LBW in 1109 hospital births in Zahedan city, in Iran. The overall prevalence of LBW was 11.8%. LBW was significantly associated with mother's ethnic origin, birth interval less than 3 years, twin birth, no use of supplements during pregnancy, less than 4 prenatal care visits, no education, younger age and presence of maternal disease. There was no effect of mother's parity, occupation and smoking status. After logistic regression analysis, the only significant risk factors were: birth interval less than 3 years, twin birth, no use of ferrous sulfate and maternal disease.

Khatun & Rahman (2008) analyzed the determinants of LBW. 108 LBW babies were compared with 357 normal birth weight babies. Out of 20 possible risk variables analyzed, 9 were found significant when studied separately. Mother's age, education, occupation, yearly income, gravid status, gestational stage at first visit, number of antenatal care visit attended, quality of antenatal care received and pre-delivery body mass index had significantly associated with the incidence of LBW. Using the stepwise logistic regression, mother's age, education, number of antenatal care visit attended and yearly income created the best model, which predicted 86.1% and 94.4% of the LBW babies and normal birth weight babies respectively. Mahumud *et al.* (2017) investigated the determinants that influence the prevalence of LBW in selected developing countries. Secondary data analysis was conducted using 10 recent Demography and Health Surveys from developing countries based on the availability of the required information for the years 2010 to 2013. Associations of demographic, socioeconomic, community-based, and individual factors of the mother with LBW infants were evaluated using the multivariate logistic regression analysis. The study concluded that delayed conception, advanced maternal age, and inadequate ANC visits had independent effects on the prevalence of LBW. Ghafarokhi *et al.* (2018) used data mining techniques to identify accurate predictors of LBW in Iran. The authors relied on secondary data from 450 medical records of newborns in the educational hospitals affiliated to Ilam University of Medical Sciences. The birth records were reviewed from April 2015 to April 2016. Their findings show that LBW is a multifactorial condition requiring a systematic and accurate program to reduce LBW.

Sema *et al*. (2019) examined the prevalence and the associated factors of LBW in Dire Dawa city in Ethiopia. A cross-sectional study design was conducted, and using a systematic sampling technique, 431 mothers who gave birth in the public hospitals in Dire Dawa city from July 1 to August 30 2018 were selected. Stillbirth and infants with birth defects were excluded from the study. The multivariate logistic regression model was applied. The results of their study show that the prevalence of LBW was 21%. Not received nutritional counseling during antenatal care, preterm birth, maternal smoking and height of the mother less than 150cm were significantly associated with LBW. Al-Shawwa & Abu-Naser (2019) predicted birth weight in Palestine using Artificial Neural Networks (ANNs). A model based on multi-layer concept topology was developed and trained using the data from some birth cases in hospitals. The authors finally note that the ANN model is capable of correctly predicting the birth weight with 100% accuracy. Kirisci & Yilmaz (2019) used ANNs for analysis of factors affecting birth weight in Turkey. Factors such as gender of the baby, maternal age, body mass index, nutrition habits, mother's education, gestational age, maternal pre-pregnancy weight, maternal weight gain in pregnancy, mother's alcohol use and mother's cigarette use were found to have a significant effect on birth weight. Karthiga *et al*. (2019) focused on developing a web application that predicts baby weight taking baby's gender, plurality, gestation weeks and mother's age as inputs. Wide and deep neural network model was developed using TensorFlow library in Google cloud environment. The study indicates that the developed predictive application is scalable and provides high performance.

Most studies (Madebwe & Madebwe, 1997; Roudbari *et al*., 2007; Khatun & Rahman, 2008; Mahumud *et al*., 2017; Ghafarokhi *et al*., 2018; Sema *et al*., 2019) analyze the prevalence and the associated determinants of LBW. Few papers (Al-Shawwa & Abu-Naser, 2019; Kirisci & Yilmaz, 2019; Karthiga *et al*., 2019) attempt to predict LBW using ANN models. This study follows the leads of these few papers but also includes normal birth weight in its forecasts. In the case of Zimbabwe, it is imperative to note that, not even a single paper has attempted to present forecasts of LBW and NBW babies and yet such forecasts are quite essential for planning especially with regards to arranging for doctors and nurses and putting in place adequate specialized facilities before LBW babies are born.

3.0 METHODOLOGY

Literature review is plenary with a multivariate logistic regression approach to analyzing LBW (Madebwe & Madebwe, 1997; Roudbari *et al*., 2007; Khatun & Rahman, 2008; Mahumud *et al*., 2017; Sema *et al*., 2019) and yet logistic regression models are not suitable for predictive purposes although we cannot rule out their importance in analyzing the prevalence and risk-factors of LBW. However, latest studies now make use of the ANNs in forecasting LBW (Al-Shawwa & Abu-Naser, 2019; Kirisci & Yilmaz, 2019; Karthiga *et al*., 2019). An ANN is an application of Artificial Intelligence (AI) (Kashf *et al*., 2018; Al-Massri *et al*., 2018; Alghoul *et al*., 2018; Metwally *et al*., 2018; Heriz *et al*., 2018; El-Jerjawi & Abu-Naser, 2018; Almurshidi & Abu-Naser, 2018; Nassr & Abu-Naser, 2018; Elqassas & Abu-Naser, 2018; Musleh & Abu-Naser, 2018; Dahouk & Abu-Naser, 2018; Abu-Naser & Abu-Naser, 2018). An ANN is an arithmetical model that is motivated by the functional feature of biological neural networks and contains an interrelated set of artificial neurons. ANNs are often used to model intricate relationships among inputs and outputs or to uncover patterns in data (Kashf *et al*., 2018; Al-Massri *et al*., 2018). This study will apply the ANN model hinged on the multi-layer perceptron neural network, in order to analyze LBW and NBW for Chitungwiza Urban District in Zimbabwe.

3.1 DATA ISSUES

The data used in this study, that is, low birth weight (LBW) and normal birth weight (NBW) covers the period January 2012 to December 2019 and was recorded for newborn babies in Chitungwiza urban district. All the data was taken from the DHIS2 system for Chitungwiza urban district.

4. FINDINGS OF THE STUDY

4.1 DESCRIPTIVE STATISTICS

Table 1: Descriptive statistics

Variable	Mean	Median	S.D.	Min	Max
LBW	27.1	21	20.8	6	124
NBW	474	464	95.6	219	885

The average numbers of LBW and NBW babies over the study period are 27 and 474 respectively. The minimum numbers of LBW and NBW babies over the study period are 6 and 219 respectively while the maximum numbers are 124 and 885 respectively.

4.2 ANN MODEL SUMMARY-LBW

Table 2: ANN model summary – LBW

Variable	LBW
Observations	84 (After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	12
Hidden Layer Neurons	12
Output Layer Neurons	1
Activation Function	Hyperbolic Tangent Function
Back Propagation Learning:	
Learning Rate	0.005
Momentum	0.05
Criteria:	
Error	0.161055
MSE	111.471829
MAE	7.639174

Table 2 shows the main results of the ANN model describing LBW.

In-sample Forecast – GUD in LBW

Figure 2: In-sample forecast – LBW

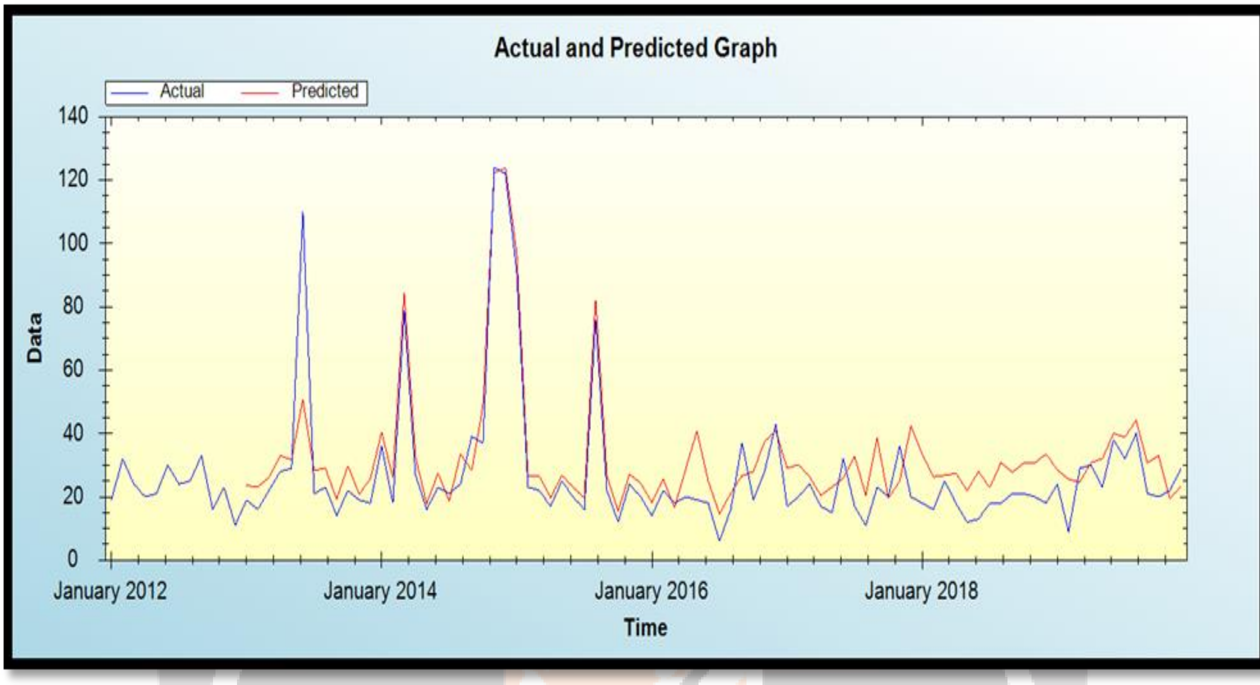


Figure 2 shows the in-sample forecast of the ANN model for LBW.

Out-of-Sample Forecast – LBW: Actual and Forecasted Graph

Figure 3: Out-of-sample forecast – LBW: actual and forecasted graph

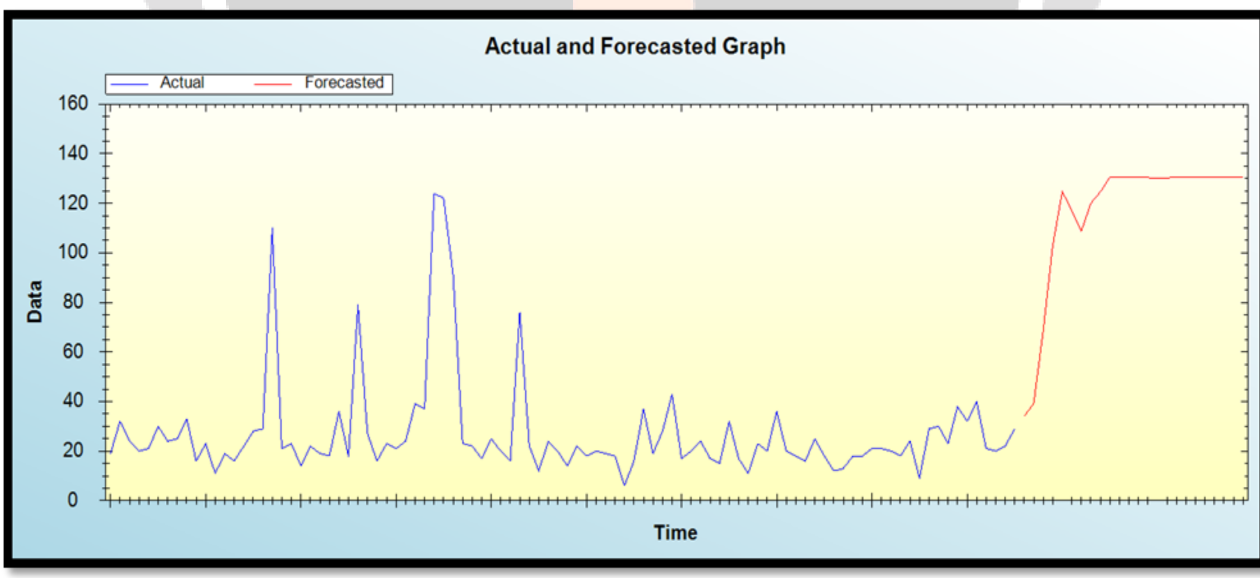


Figure 3 shows the out-of-sample forecasts for the LBW series; the same is also tabulated below.

Out-of-Sample Forecast – LBW: Forecasts only

Table 3: Out-of-sample forecast – LBW: forecasts only

Month/Year	Predicted LBW
January 2020	34.1014
February 2020	39.2336
March 2020	68.7495
April 2020	102.8665
May 2020	124.7155
June 2020	117.0809
July 2020	108.6762
August 2020	119.9730
September 2020	124.6062
October 2020	130.4956
November 2020	130.3512
December 2020	130.3421
January 2021	130.3757
February 2021	130.3316
March 2021	130.2737
April 2021	130.2621
May 2021	130.4735
June 2021	130.4094
July 2021	130.3895
August 2021	130.3601
September 2021	130.3541
October 2021	130.3741
November 2021	130.3737
December 2021	130.3762

Figure 4: Graphical presentation – LBW: out-of-sample forecasts only

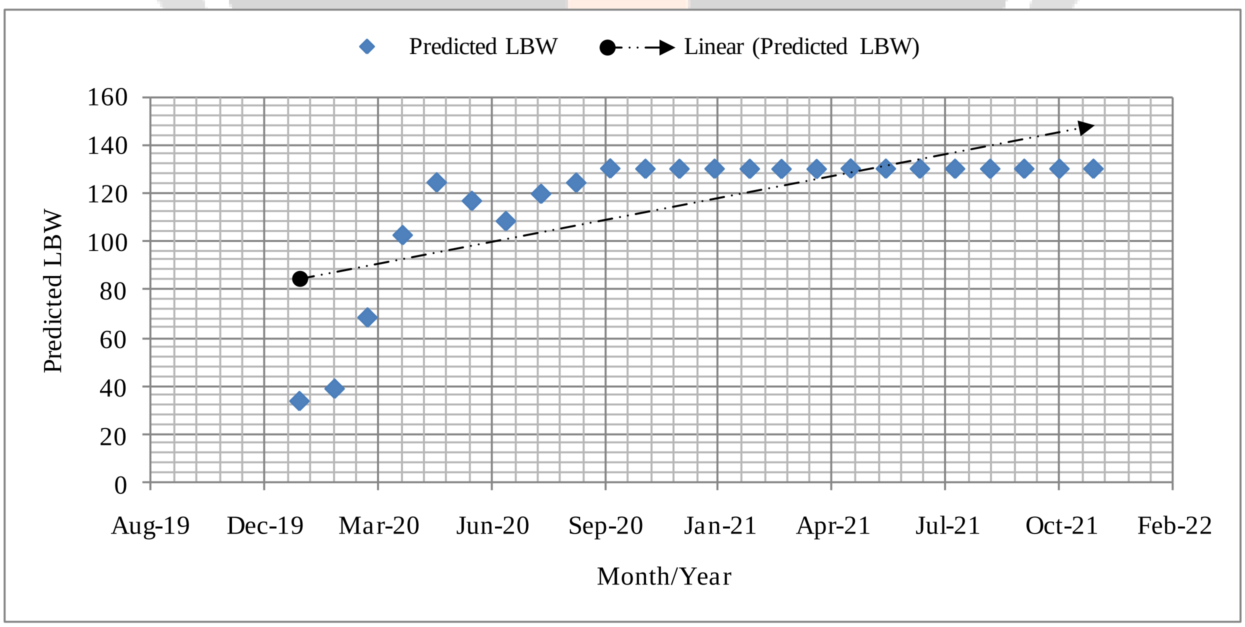


Figure 4 is the graphical presentation of the predictions of LBW babies in the out-of-sample period. LBW babies are expected to be on the increase until August 2020, after which the numbers of LBW babies will reach the state of equilibrium between September 2020 and December 2021.

Table 4: ANN model summary – NBW

Variable	NBW
Observations	84 (After Adjusting Endpoints)
Neural Network Architecture:	
Input Layer Neurons	12
Hidden Layer Neurons	12
Output Layer Neurons	1
Activation Function	Hyperbolic Tangent Function
Back Propagation Learning:	
Learning Rate	0.005
Momentum	0.05
Criteria:	
Error	0.095356
MSE	1244.975381
MAE	25.649924

Table 4 shows the main results of the ANN model describing NBW.

In-sample Forecast – NBW

Figure 5: In-sample forecast – NBW

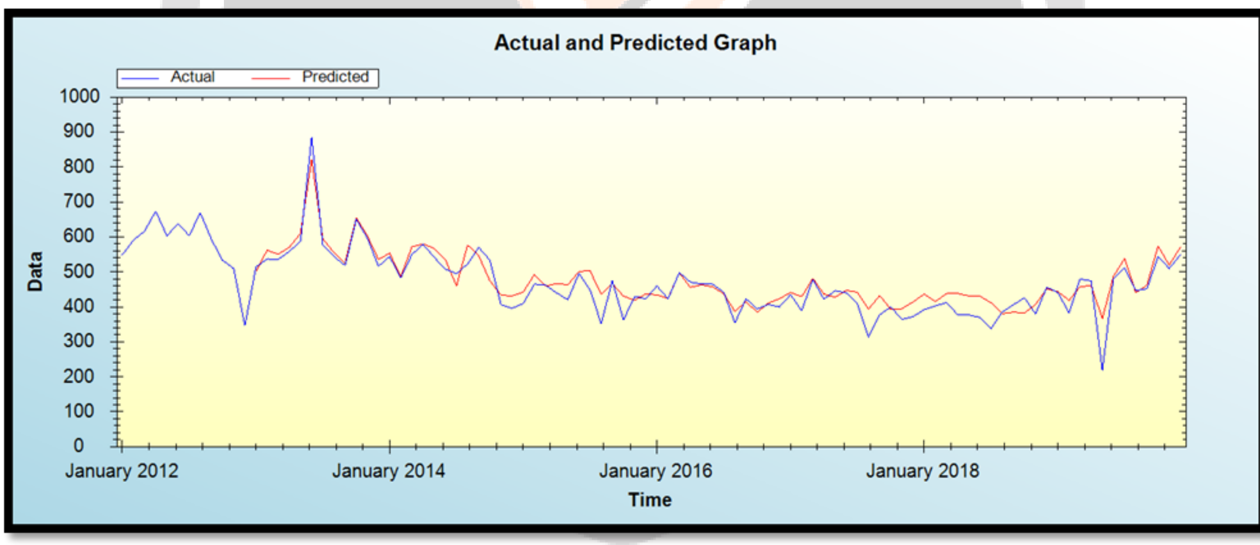


Figure 5 shows the in-sample forecast of the ANN model for NBW.

Out-of-Sample Forecast – NBW: Actual and Forecasted Graph

Figure 6: Out-of-sample forecast – NBW: actual and forecasted graph

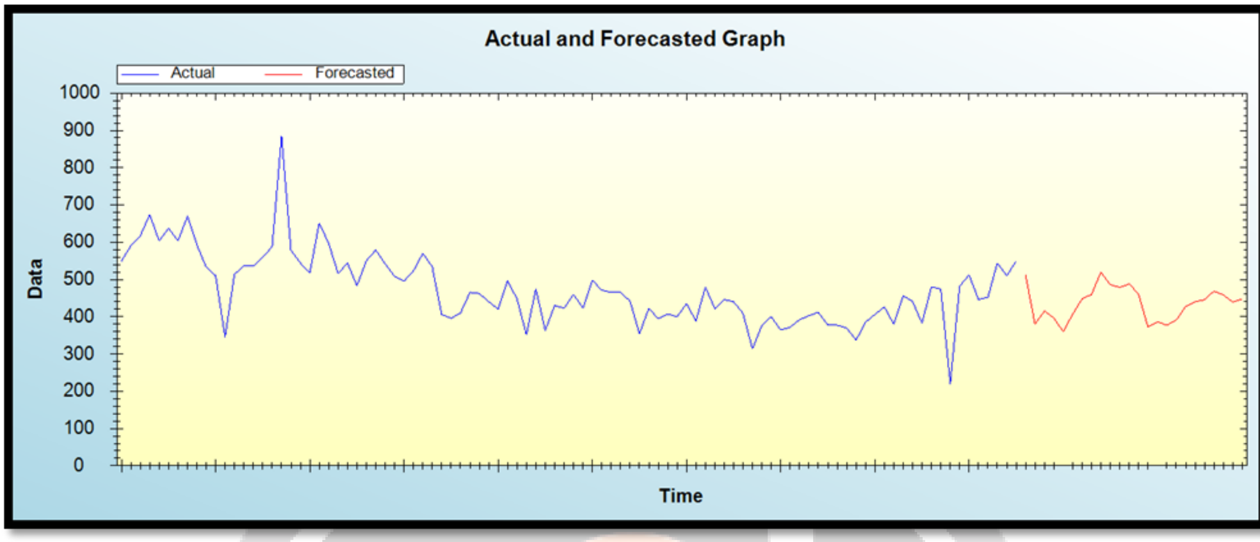


Figure 6 shows the out-of-sample forecasts for the NBW series; the same is also tabulated below.

Out-of-Sample Forecast – NBW: Forecasts only

Table 5: Out-of-sample forecast – NBW: forecasts only

Month/Year	Predicted NBW
January 2020	511.4943
February 2020	380.1925
March 2020	415.0540
April 2020	396.5577
May 2020	360.0783
June 2020	406.6098
July 2020	448.1263
August 2020	459.8407
September 2020	519.4742
October 2020	486.0655
November 2020	478.6906
December 2020	488.1901
January 2021	460.3380
February 2021	372.5204
March 2021	386.2439
April 2021	377.1849
May 2021	391.0899
June 2021	427.6266
July 2021	440.5062
August 2021	445.2261
September 2021	468.8771
October 2021	458.4428
November 2021	439.4299
December 2021	447.5867

Figure 7: Graphical presentation – NBW: out-of-sample forecasts only

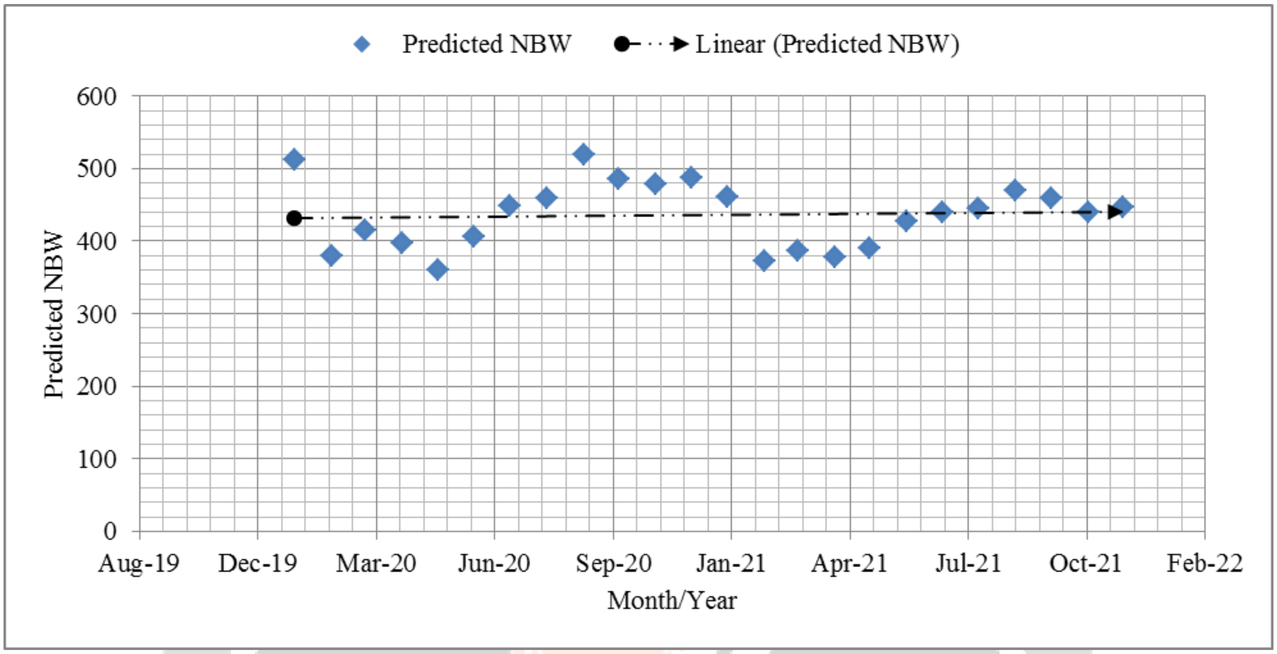


Figure 7 is the graphical presentation of the predictions of NBW babies in the out-of-sample period. NBW babies are expected to be on the increase, but quite slowly, over the period January 2020 – December 2021.

Predicted LBW and NBW on a Single Graph

Figure 8: Predicted LBW and NBW on a single graph

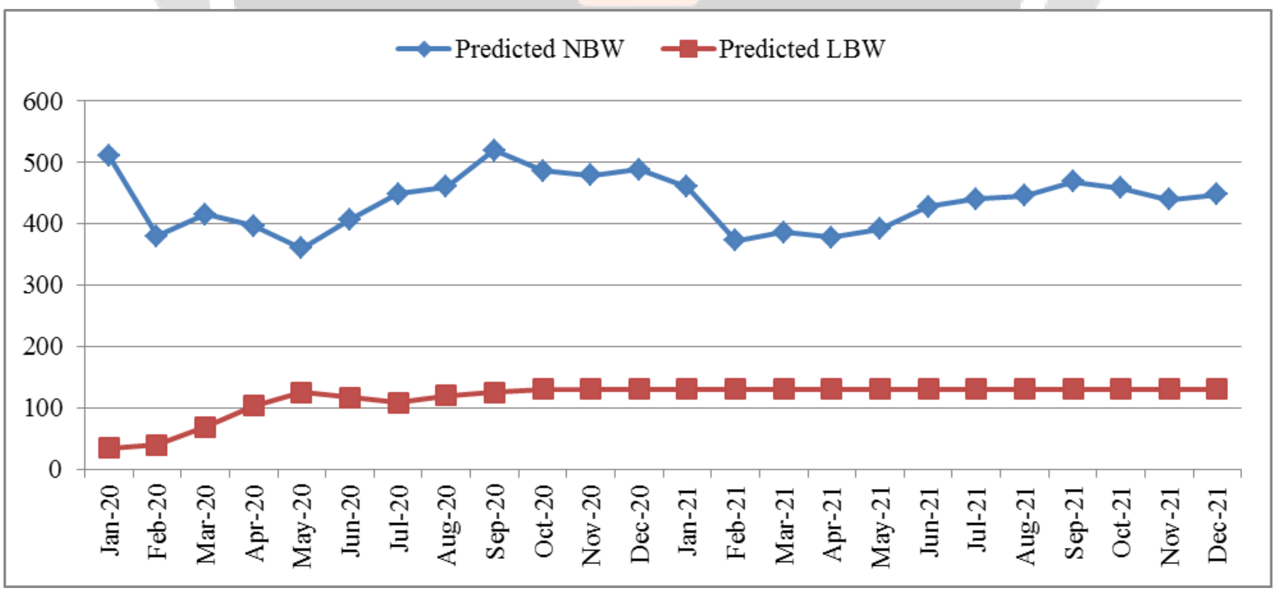
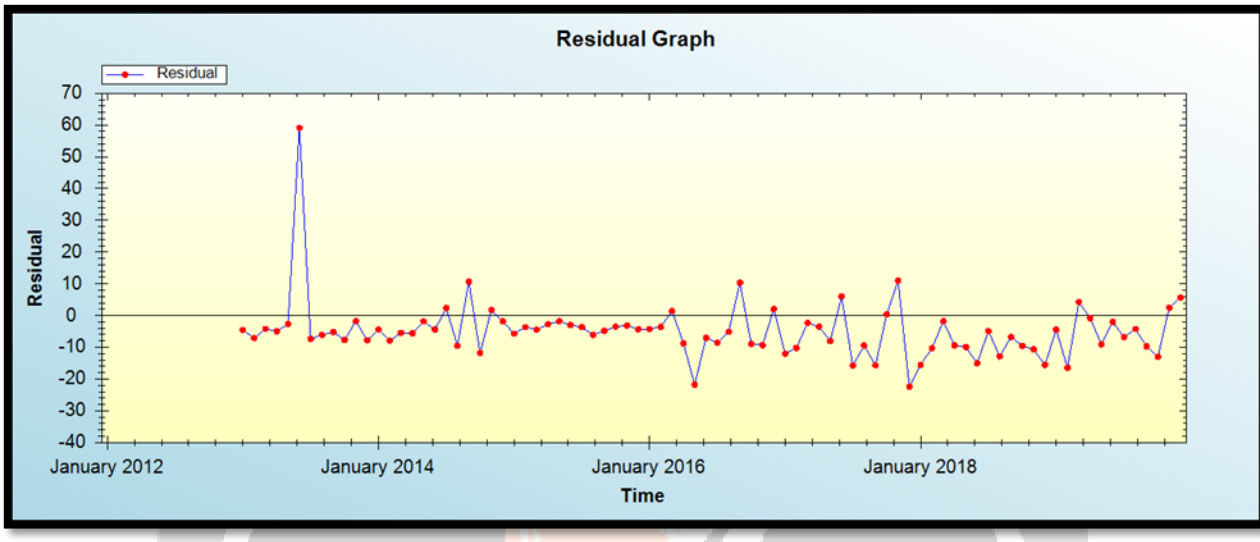


Figure 8 shows the predictions of LBW and NBW series plotted on the same graph. Ideally, the NBW series should be upwards trending while the LBW series should be downwards trending if child and maternal health programmes are achieving the desired health outcomes in Chitungwiza urban district. Figure 8 indicates that the NBW forecasted series, as expected, is largely above the LBW forecasted series.

Residual Analysis and Forecast Evaluation for the ANNs

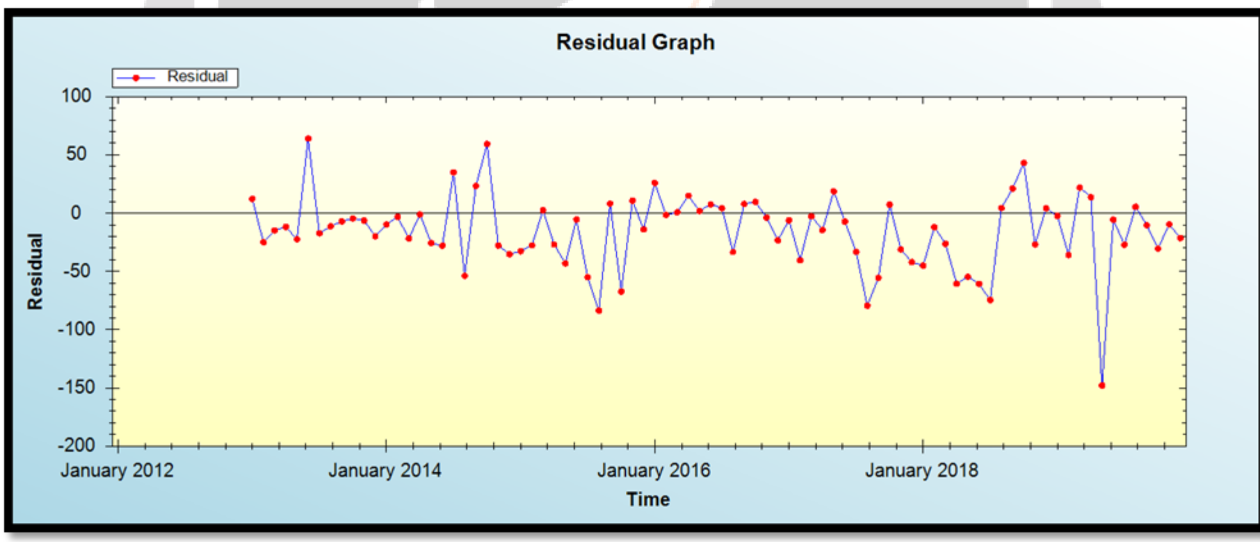
Residual Analysis for LBW

Figure 9: Residual analysis for LBW



Residual Analysis for NBW

Figure 10: Residual analysis for NBW



Forecast Evaluation Statistics for Both LBW and NBW ANNs

Table 6: Forecast evaluation statistics

Evaluation Statistic	LBW ANN	NBW ANN
Error	0.161055	0.095356
MSE	111.471829	1244.975381
MAE	7.639174	25.649924

Figure 9 and 10 show the residual of the models applied in this paper. In both scenarios, the residuals are reasonably as close to zero as possible. Table 6 shows the model criteria. These statistics should typically be as minimum as possible. As shown in table 6, the evaluation statistics are quite very low and thus the models are relatively more accurate.

4.3 RECOMMENDATIONS

i. Commence prenatal care early.
ii. Maintenance of a healthy weight gain and proper nutrition.
iii. Pre-existing medical conditions should be under control in order to minimize complications.
iv. Relevant healthcare authorities in Chitungwiza ought to encourage people to stick to healthy life styles. Furthermore, there is need for health education to pregnant mothers on the risk factors of LBW such as smoking and maternal hypertension and the need to book early when they become pregnant.

5.0 CONCLUSION

Modeling and forecasting LBW and NBW is very important in public health policy discourse, especially in light of neonatal mortality and morbidity in developing countries such as Zimbabwe. Early neonatal mortality and morbidity can be avoided if the volume of LBW babies can be projected and prepared for, well before the babies are born. This research article used 108 observations of LBW and NBW babies in order to come up with reliable forecasts of LBW and NBW babies over the out-of-sample period. These forecasts are envisioned to enhance planning and resource allocation by health facilities in Chitungwiza urban district.

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