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ARIMA FORECASTING OF THE PREVALENCE OF ANEMIA IN CHILDREN IN YEMEN

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ABSTRACT:

Using annual time series data on the prevalence of anemia in children under 5 years of age in Yemen from 1990 – 2016, the study makes predictions for the period 2017 – 2025. The study applies the Box-Jenkins ARIMA methodology. The diagnostic ADF tests show that, AY, the series under consideration is an I (2) variable. Based on the AIC, the study presents the ARIMA (1, 2, 0) model as the optimal model. The diagnostic tests further prove beyond any reasonable doubt, that the presented model is stable and its residuals are not serially correlated and are also normally distributed. The results of the study indicate that the prevalence of anemia in children in Yemen will decrease by 0.8% over the period 2017 – 2025. This implies that by 2025, the prevalence of anemia in children in Yemen would have declined to approximately 82.6% from the estimated 83.4% in 2017. However, this is still very high and unacceptable. The study basically recommends that the government of Yemen, with the help from its development partners; ought to intensify nutritional supplementation and food fortification programmers, especially in rural areas.

INTRODUCTION:

Anemia, especially in children, is one of the most common and prevalent health concerns in the world (WHO, 2002). In fact, anemia affects one-quarter of the world's population with a significant impact on pre-schooled aged children (6-59 months) as well as pregnant women (McLean et al., 2009). As estimated the global prevalence of anemia is 24.8%, and its prevalence in pre-school aged children and women are 47.4% and 41.8%, respectively (Khan et al., 2019). Anemia is a condition which decreases hemoglobin (Hb) concentration in blood, consequently impeding its capacity to export oxygen. If it occurs among children, it can result in adverse effects on their cognitive developments and immunization abilities against diseases (WHO, 2001; Brabin et al., 2001; McCann & Ames, 2007). These negative impacts may also continue into adulthood and cause low work productivity with effects on the economic productivity which trap the communities at risk of infections in a cycle of poverty, underdevelopment and diseases (Haas & Brownlie, 2001; bleakly, 2007). Anemia is a multi-factorial health problem in which the health factors could be nutritional (iron, folate, and vitamin B12 deficiencies), clinical (infectious diseases such as malaria, helminth infections, TB, HIV/AIDS, and general inflammatory disorders), socioeconomic factors (education levels of parents and low household income), and demographic factors (age, gender and family size) (Hashizume et al., 2003; WHO, 2008; Al-Mekhlafi et al., 2008).

In the Middle East region, the prevalence of anemia is high with approximately 63% of preschool children suffering from iron deficiency anemia (INACG, 2014). The prevalence of anemia in this region varies from 17% to more than 70% among preschool children; from 14% to 42% among adolescents, and from 11% to more than 40% among pregnant women (Bagchi, 2004). Amongst the Middle East countries, Yemen has the highest percentage of people living in poverty (Al-alimi et al., 2018); in fact, more than half of the country's population: more than 25 million people live below the poverty datum line (World Bank, 2010, World Bank, 2014). This situation has contributed to the high prevalence of many nutritional disorders, especially anemia among children (Albiti et al., 2010). Indeed, anemia in children is a serious public health problem in Yemen (Al-alimi et al., 2018). The main goal of this study is to forecast the prevalence of anemia in children under the age of 5 in Yemen over the period 2017 – 2025.

LITERATURE REVIEW:

Al-Zabedi et al. (2014) carried out a cross-sectional study in order to investigate the prevalence and risk factors of iron deficiency anemia among 187 children aged below 15 years from rural areas in Yemen. Clinical data was collected by measuring hemoglobin (Hb) level, serum iron (SI), serum ferritin (SF), and total iron binding capacity (TIBC). Furthermore, fecal samples were collected and examined for the presence of intestinal parasites. Demographic and socioeconomic data was collected by a pretested questionnaire. The study established that the overall prevalence of anemia and iron deficiency anemia was 48.7% and 34.2%, respectively with iron deficiency anemia representing approximately 70.2% of all anemia cases. Consistently and more recently, Al-alimi et al. (2018) conducted a cross-sectional study in order to determine the prevalence and risk factor of iron deficiency anemia among Yemeni medical students at Hodeida University. Participants were subjected to different tests including complete blood counts (CBC), serum ferritin (SF), serum iron (SI), and total iron binding capacity (TIBC). Moreover, q questionnaire was designed to collect demographics, food and drink habits, and socioeconomic status. The results of the study showed that overall prevalence of anemia among Yemini medical students was 30.4%. Both studies did not forecast the prevalence of anemia in Yemen. It is this information gap that this paper seeks to fill in literature, in Yemen. No study has predicted the prevalence of anemia in the country. This research will be the first of its kind and will go a long way in analyzing and understanding trends of childhood anemia in Yemen.

METHODODOLOGY:

3.1 The Box – Jenkins (1970) Methodology:

The first step towards model selection is to difference the series in order to achieve stationary. 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). This approach will be used to analyze, AY, the series under consideration.

3.2 The Applied Box – Jenkins ARIMA Model Specification:

If the sequence $\Delta^d AY_t$ satisfies an ARMA (p, q) process; then the sequence of AY_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d AY_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i AY_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots \ldots [1]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

3.3 Data Collection:

This study is based on annual observations (that is, from 1990 – 2016) on the prevalence of anemia in children under the age of 5 in Yemen [denoted as AY]. Prevalence of anemia in children under 5 years of age in Yemen, refers, to the percentage of children under the age of 5 whose hemoglobin level is less than 110 grams per liter at sea level. Out-of-sample forecasts will cover the period 2016 – 2025. All the data was gathered from the World Bank online database.

3.4 Diagnostic Tests & Model Evaluation:

3.4.1 The ADF Test in Levels:

Table 1: with intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
AY	-1.852024	0.3482	-3.724070	@1%	Non-stationary
			-2.986225	@5%	Non-stationary
			-2.632604	@10%	Non-stationary

Table 1 shows that AY is not stationary in levels.

3.4.2 The ADF Test (at First Differences):

Table 2: with intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
ΔAY	-2.173176	0.2202	-3.724070	@1%	Non-stationary
			-2.986225	@5%	Non-stationary
			-2.632604	@10%	Non-stationary

Table 2 indicates that AY is not an I (1) variable.

3.4.3 The ADF Test (at Second Differences):

Table 3: with intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Δ^2AY	-7.536430	0.0000	-737853	@1%	Stationary
			-2.991878	@5%	Stationary
			-2.635542	@10%	Stationary

Table 3 indicates that the series under consideration is an I (2) variable.

3.4.4 Evaluation of ARIMA models (without a constant):

Table 4: Evaluation of ARIMA Models (without a constant)

Model	AIC	U	ME	RMSE	MAPE
ARIMA (1, 2, 1)	-52.75106	0.56593	-0.0056838	0.07491	0.074016
ARIMA (1, 2, 0)	**-54.58679**	0.56793	-0.005679	0.07515	0.073365
ARIMA (1, 2, 2)	-52.0299	0.54996	-0.0056495	0.072993	0.070086
ARIMA (0, 2, 1)	-53.22439	0.58414	-0.0050422	0.077125	0.074976
ARIMA (0, 2, 2)	-54.028	0.55	-0.005664	0.072999	0.070204
ARIMA (2, 2, 0)	-52.84648	0.56474	-0.0056908	0.074769	0.073946
ARIMA (0, 2, 3)	-52.03089	0.54993	-0.0056406	0.072989	0.070021

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 research paper, only the AIC is used to select the optimal model. Therefore, the ARIMA (1, 2, 0) model is finally chosen.

3.5 Residual & Stability Tests:

3.5.1 Correlogram of the Residuals of the ARIMA (1, 2, 0) Model:

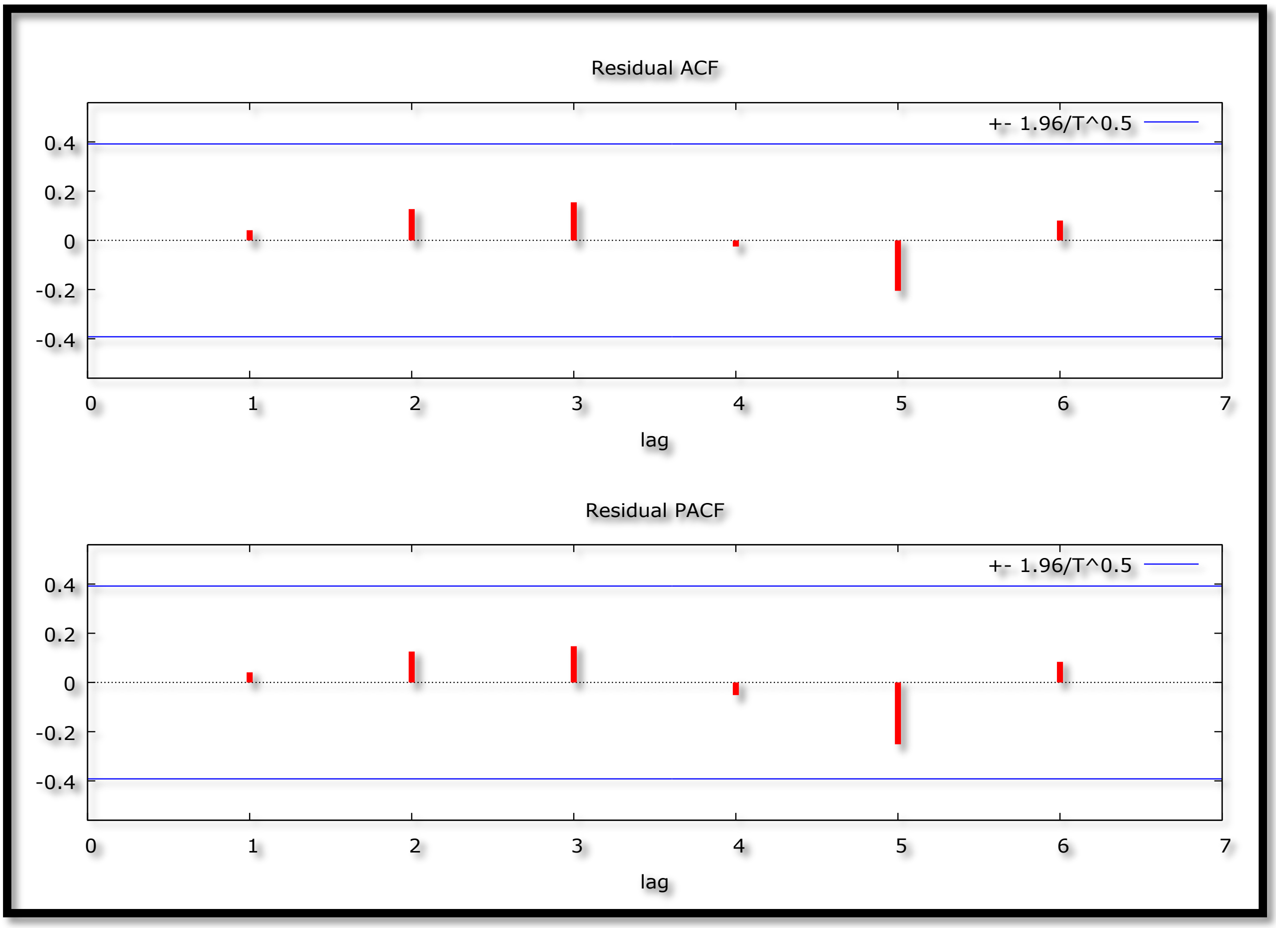

Figure 1: Correlogram of the Residuals

Figure 1 indicates that the estimated optimal ARIMA (1, 2, 0) model is adequate since ACF and PACF lags are quite short and within the bands.

3.5.2 Stability Test of the ARIMA (1, 2, 0) Model:

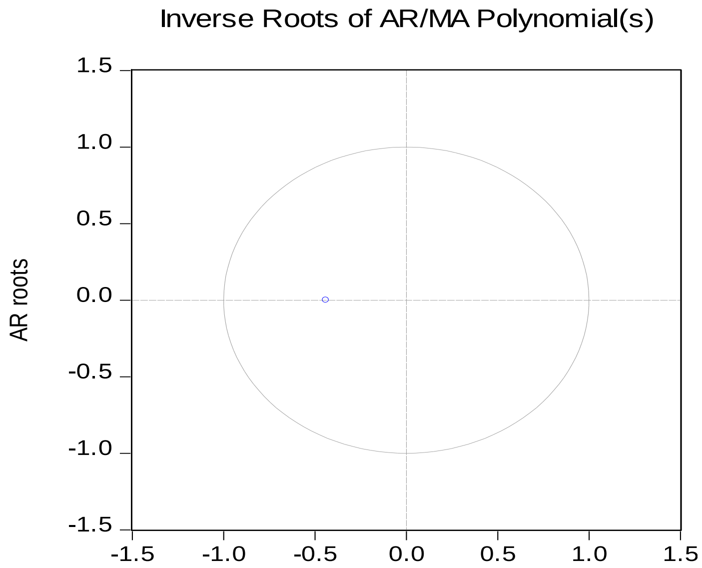

Figure 2: Inverse Roots

Since the AR root lies inside the unit circle, it implies that the estimated ARIMA process is (covariance) stationary; thus confirming that the ARIMA (1, 2, 0) model is really stable and suitable for forecasting the prevalence of anemia in children in Yemen.

3.5.3 Normality Test of the Residuals of the ARIMA (1, 2, 0) Model:

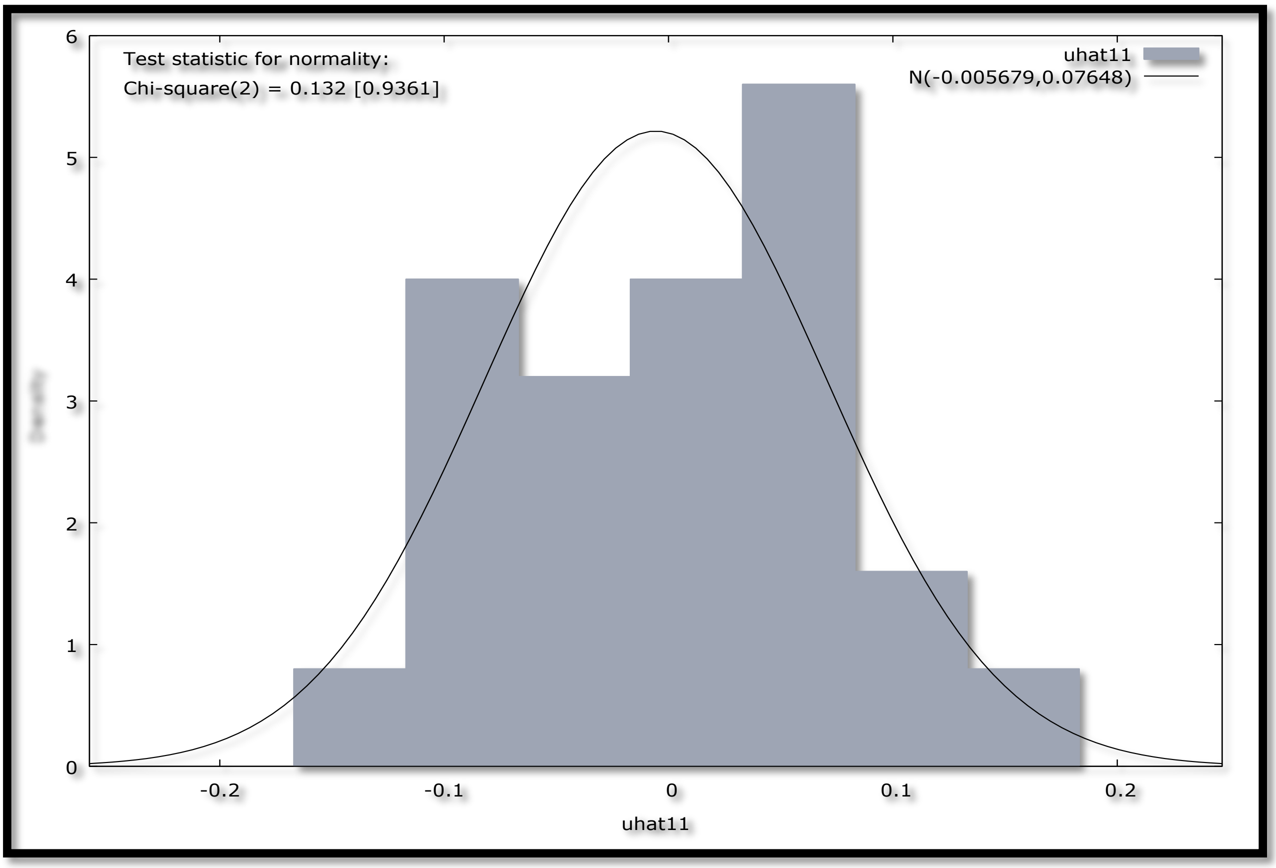

Figure 3: Normality Test

Since the probability value of the chi-square statistic is insignificant, we reject the null hypothesis and conclude that the residuals of the ARIMA (1, 2, 0) model are normally distributed.

FINDINGS OF THE STUDY:

4.1 Results Presentation:

Table 5: Main Results

ARIMA (1, 2, 0) Model:

The chosen optimal model, the ARIMA (1, 2, 0) model can be expressed as follows:

$$\Delta^2 AY_t = -0.41974\Delta^2 AY_{t-1} \quad \ldots\ldots [2]$$

Variable	Coefficient	Standard Error	z	p-value
β_1	-0.41974	0.181124	-2.317	0.0205**

Table 5 shows the main results of the ARIMA (1, 2, 0) model.

Forecast Graph

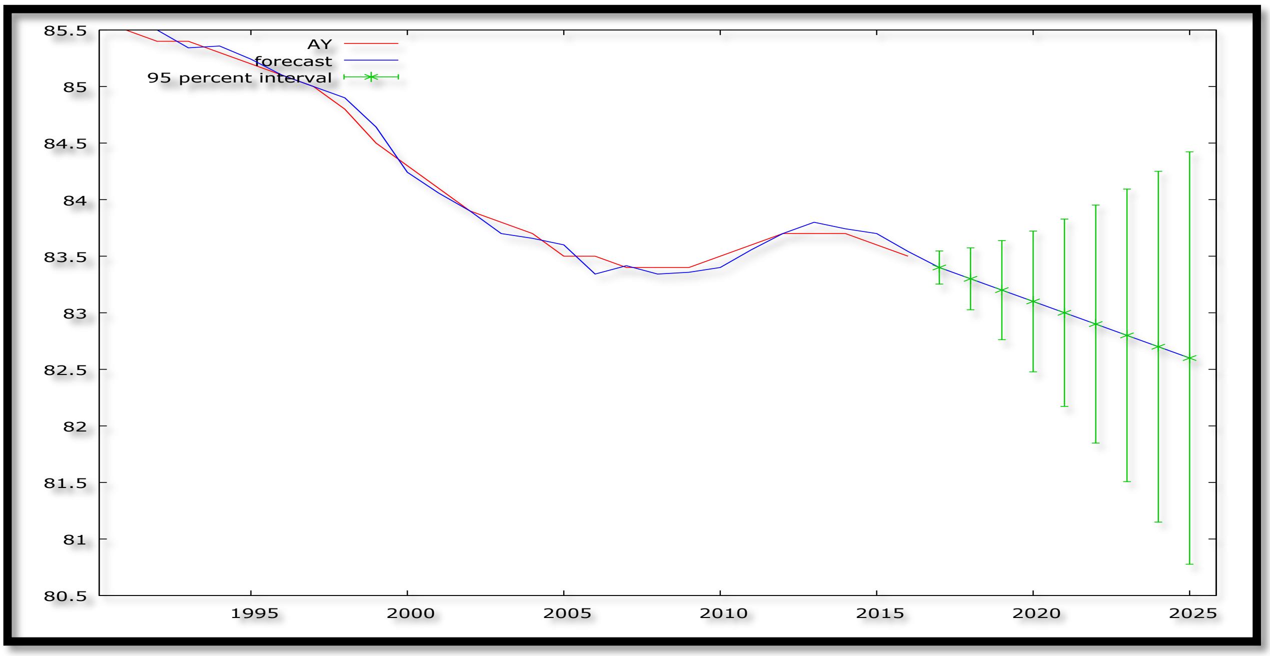

Figure 4: Forecast Graph – In & Out-of-Sample Forecasts

Figure 4 shows the in-and-out-of-sample forecasts of the AY series. The out-of-sample forecasts cover the period 2017 – 2025.

Predicted AY– Out-of-Sample Forecasts Only

Table 6: Forecasts of AY

Year	Forecasts	Standard Error	95% Confidence Interval
2017	83.4000	0.0746794	(83.2536, 83.5464)
2018	83.3000	0.139657	(83.0263, 83.5737)
2019	83.2000	0.223507	(82.7619, 83.6381)
2020	83.1000	0.317479	(82.4778, 83.7222)
2021	83.0000	0.422491	(82.1719, 83.8281)
2022	82.9000	0.536756	(81.8480, 83.9520)
2023	82.8000	0.659851	(81.5067, 84.0933)
2024	82.7000	0.791074	(81.1495, 84.2505)
2025	82.6000	0.929991	(80.7773, 84.4227)

Table 6 shows the out-of-sample forecasts only. The prevalence of anemia in children in Yemen is predicted to decline slightly from the estimated 83.4% in 2017 to almost 82.6% in around 2025. Anemia is still highly prevalent and considered as a serious health problem among children in Yemen, especially those who live in rural areas (Al-Zabedi et al., 2014).

CONCLUSION:

The study shows that the ARIMA (1, 2, 0) model is not only stable but also the most suitable model to forecast the prevalence of anemia in children in Yemen over the period 2017 – 2025. The model predicts a decrease in the prevalence of anemia in children in Yemen. Unfortunately the projected decline in anemia prevalence is still unacceptably slow and far lagging behind what is expected. This points to the longstanding argument that anemia in children in Yemen is far from being eradicated in the country. The study, however; recommends that the government of Yemen, with the help from its development partners; ought to intensify nutritional supplementation and food fortification programmes, especially in rural areas. In this regard, the government and its supporting non-governmental organizations should provide financial resources and technical support for the rural populace so that people can have income generating projects to sustain their families. There is also, the need for health education programs, especially on healthy diets; throughout the country as this will also help in the fight against anemia. The government of Yemen should also engage on early detection and treatment of TB and HIV in children through TB/HIV collaborative programmes.

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