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# ARIMA FORECASTING OF THE PREVALENCE OF ANEMIA IN CHILDREN IN INDIA

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**Abstract:**

Using annual time series data on the prevalence of anemia in children under 5 years of age in India 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 the ODL series under consideration is an I (0) variable. Based on the AIC, the study presents an AR (2) process or the ARIMA (2, 0, 0) model as the optimal model. The diagnostic tests further reveal that the presented model is indeed stable and its residuals are not serially correlated. The results of the study show that the prevalence of anemia in children in India is set to decrease from almost 57% in 2017 to nearly 54.7% by 2025. This is good but that is not a desirable public health outcome, anywhere. For the government of India to accelerate the eradication of anemia in children in the country, nutritional supplementation and food fortification programmes ought to be intensified.

**Keywords:** Box-Jenkins ARIMA methodology, nutritional supplementation, prevalence of anemia in children.

## 1.0 INTRODUCTION

Anemia, especially in children (Dey et al., 2013; Goswami & Das, 2014; Alvarez-Uria et al., 2014; Singh & Patra, 2014; Ritu et al., 2017; Unnikrishnan, 2018; Nguyen et al., 2018; Onyeneho et al., 2019), is a major public health problem in India (Alvarez-Uria et al., 2014). In fact, India is the highest contributor to childhood anemia (Benoist et al., 2008; Pasricha et al., 2010). Statistics show that at least 89 million children in India are anemic (Singh & Patra, 2014). Childhood anemia is one of the main deficiency diseases in the world and is associated with functional abnormalities and lymphocytes and neutrophils, including increased mortality (Ayoya et al., 2013; Saraiva et al., 2014). The condition leads to the lack of oxygen in organs and tissues, and people with anemia often feel tired, weak, cold, and short of breath (McLean et al., 2009; Jain & Jain, 2012). At least 2 billion people in the world have anemia, half of this anemia is due to iron deficiency (WHO, 2001). In fact, anemia is a late indicator of iron deficiency (Pasricha et al., 2010; Dey et al., 2013). Actually, the prevalence of iron deficiency is 2.5 times that of anemia (WHO, 2001; Zimmermann & Hurrell, 2007).

In children, iron deficiency affects cognitive and motor development and increases susceptibility to infections (Baker, 2010). Young children, especially the under-fives, are more vulnerable to anemia because of their rapid growth and high need for iron. Risk factors of anemia include but are not limited to low family income, low maternal level of education, lack of access to healthcare services, inadequate sanitary conditions and a diet with poor quantities of iron (Osorio *et al*., 2004; Oliveira *et al*., 2007). Iron deficiency, linked to low nutritional iron consumption is of the critical causes of childhood anemia in India (Thankachan *et al*., 2008). Other critical factors, equally associated with anemia in Indian children are vitamin deficiencies, especially folate, vitamin B12 and A, infections with malaria parasite, hookworm and hemogloblinopathies (Schneider, 2005; Thankachan *et al*., 2008; Calis *et al*., 2008). Given the magnitude and severe consequences of anemia in India (Goswami & Das, 2014; Unnikrishnan, 2018; Nguyen *et al*., 2018; Onyeneho *et al*. 2019), in order to better plan preventive and control measures, this study models and forecasts the prevalence of the disease in the country amongst children aged below five. Our study is also important in the sense that it will generate empirical evidence needed to facilitate the acceleration of reductions in anemia in Indian under-fives.

## 2.0 LITERATURE REVIEW

There is currently a dearth of published literature on issues of modeling and forecasting anemia in children in India or elsewhere. However, the subject of childhood anemia has been widely studied in the country. In fact, the available literature can be categorised into two: the one focusing on determinants of childhood anemia (Goswami & Das, 2014; Onyeneho *et al.*, 2019) and the other focusing on the prevalence of anemia in children (Alvarez-Uria *et al.*, 2014; Singh & Patra, 2014; Ritu *et al.*, 2017; Unnikrishnan, 2018; Nguyen *et al.*, 2018). Goswami & Das (2014) showed that childhood anemia was more common in rural than urban areas in India while Onyeneho basically found out that children with anemia were more prone to be being iron deficient. The reviewed studies on prevalence of anemia in children in India agree on the fact that the prevalence of anemia in the country is still unacceptably high. No study has attempted to model and forecast the prevalence of anemia in children in the country. This paper will be the first of its kind in India.

## 3.0 METHODODOLOGY

### 3.1 The Box – Jenkins (1970) 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). This approach will be used to analyze, AI, the series under consideration.

### 3.2 The Applied Box – Jenkins ARIMA Model Specification

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

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

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 India [denoted as A1]. Prevalence of anemia in children under 5 years of age in India, is 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 |
|---|---|---|---|---|---|
| AI | -3.236410 | 0.0327 | -3.808546 | @1% | Non-stationary |
| | | | -3.020686 | @5% | Stationary |
| | | | -2.650413 | @10% | Stationary |

Table 1 shows that the series under consideration is stationary in levels.

#### 3.4.2 Evaluation of ARIMA models (without a constant)

Table 2: Evaluation of ARIMA Models (without a constant)

| Model | AIC | U | ME | RMSE | MAPE |
|---|---|---|---|---|---|
| ARIMA (1, 0, 0) | 76.37032 | 0.99441 | 2.1265 | 14.858 | 4.8031 |
| ARIMA (2, 0, 0) | **-14.66863** | 0.21796 | 2.8329 | 14.839 | 3.8873 |
| ARIMA (3, 0, 0) | -14.79895 | 0.21387 | 2.8387 | 14.839 | 3.8826 |
| ARIMA (0, 0, 1) | 274.469 | 44.559 | 36.198 | 37.409 | 53.993 |

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 (2, 0, 0) model is finally chosen. This model is indeed an AR (2) process.

### 3.5 Residual Tests

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

Figure 1: Correlogram of the Residuals

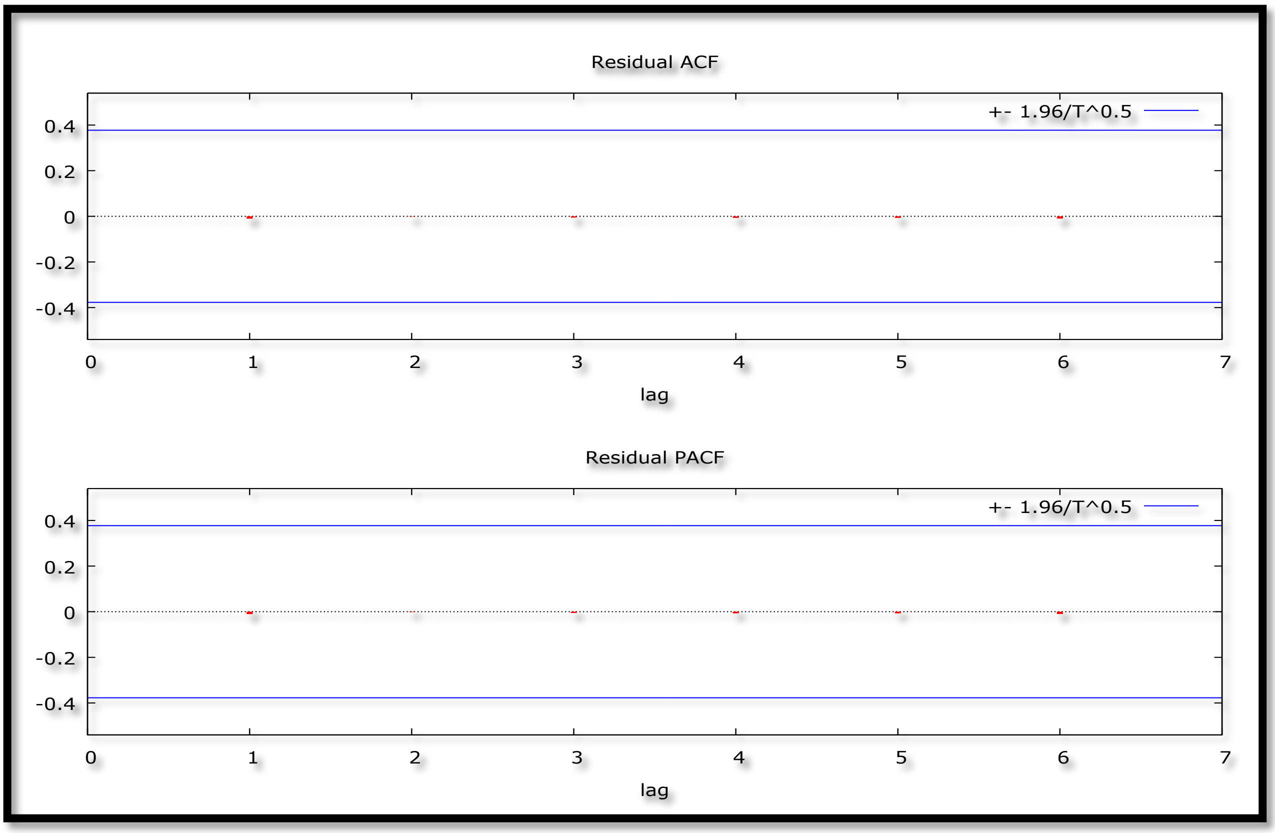


Figure 1 indicates that the estimated optimal model is adequate since ACF and PACF lags are quite short and within the bands.

## 4.0 FINDINGS OF THE STUDY

### 4.1 Results Presentation[1]

Table 3: Main Results

**ARIMA (2, , 0) Model:**

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

$$AI_t = 1.97867AI_{t-1} - 0.978726AI_{t-2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

| Variable | Coefficient | Standard Error | z | p-value |
|---|---|---|---|---|
| $\beta_1$ | 1.97867 | 0.140655 | 14.07 | 0.0000*** |
| $\beta_2$ | -0.978726 | 0.139047 | -7.039 | 0.0000*** |

Table 3 shows the main results of the ARIMA (2, 0, 0) model.

[1] *The *, ** and *** imply statistical significance at 10%, 5% and 1% levels of significance; respectively.*

### 4.2 FORECAST GRAPH

Figure 2: Forecast Graph – In & Out-of-Sample Forecasts

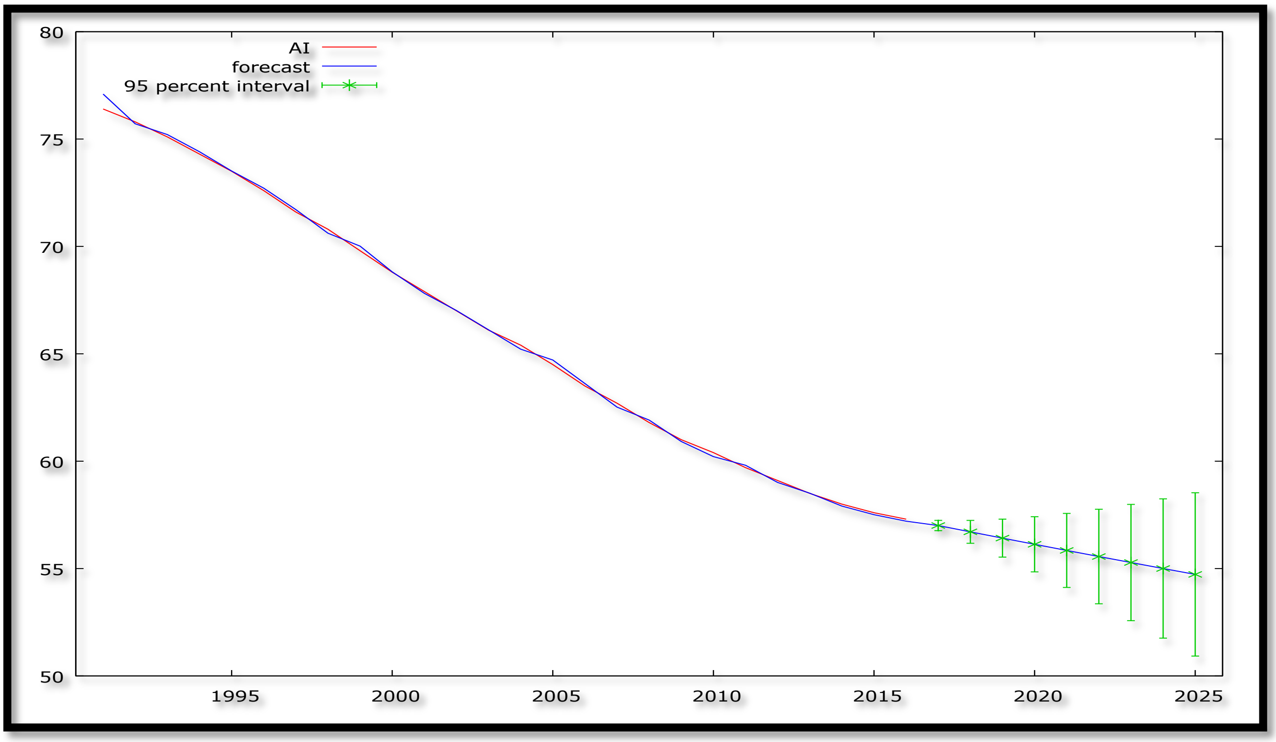


Figure 2 shows the in-and-out-of-sample forecasts of the AI series. The out-of-sample forecasts cover the period 2017 – 2025.

### 4.3 Predicted AI– Out-of-Sample Forecasts Only

Table 4: Predicted AI

| Year | Predicted AI | Standard Error | 95% Confidence Interval |
|---|---|---|---|
| 2017 | 57.0029 | 0.122602 | (56.7626, 57.2432) |
| 2018 | 56.7088 | 0.271810 | (56.1760, 57.2415) |
| 2019 | 56.4175 | 0.451094 | (55.5333, 57.3016) |
| 2020 | 56.1289 | 0.654999 | (54.8452, 57.4127) |
| 2021 | 55.8432 | 0.879764 | (54.1189, 57.5675) |
| 2022 | 55.5602 | 1.12261 | (53.3599, 57.7605) |
| 2023 | 55.2798 | 1.38138 | (52.5724, 57.9873) |
| 2024 | 55.0021 | 1.65431 | (51.7598, 58.2445) |
| 2025 | 54.7270 | 1.93993 | (50.9248, 58.5292) |

Figure 3: Graphical Analysis of Out-of-Sample Forecasts

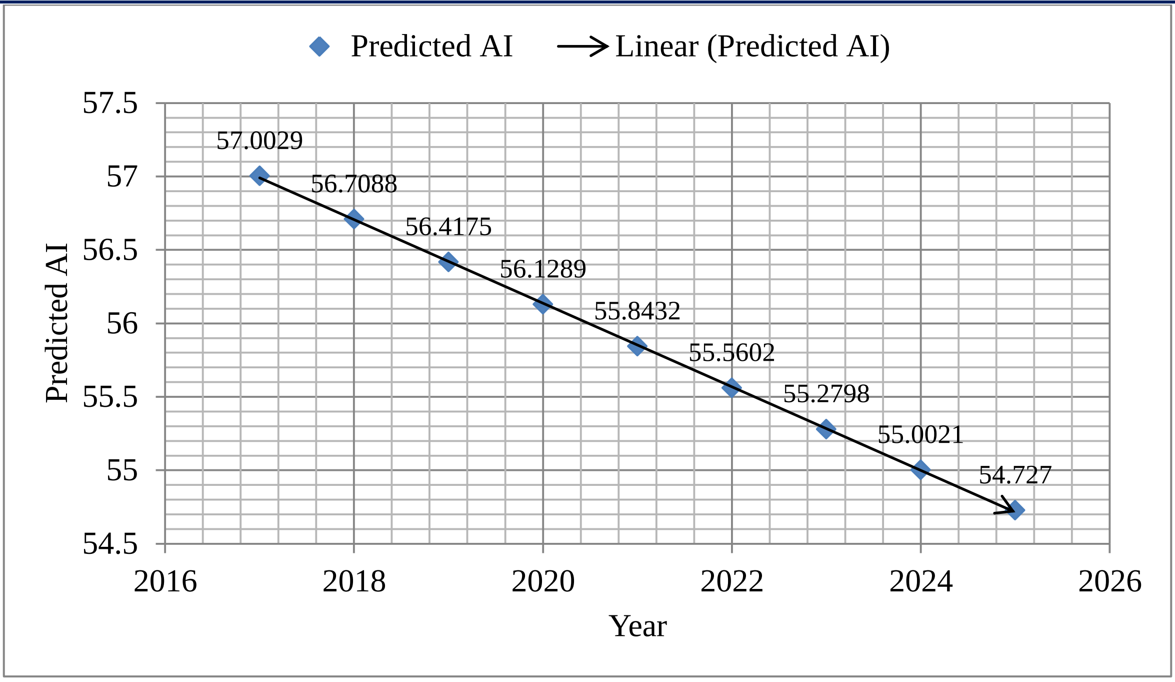


Table 4 and figure 3 show the out-of-sample forecasts only. The prevalence of anemia in Indian children is projected to continue declining from the estimated 57% in 2017 to almost 54.7% by 2025. The lack of significant anemia reduction is surprising given India's rapid economic growth (World Bank, 2018) during the period 1990 – 2016, as anemia rates are expected to decline approximately as quarter as fast as income increases (Alderman & Linnemayr, 2009).

## 5.0 CONCLUSION

The study shows that the ARIMA (2, 0, 0) model is not only stable but also the most suitable model to forecast the prevalence of anemia in children in India over the period 2019 – 2030. The model predicts a decrease in the prevalence of anemia in children in the country. Unfortunately the projected decrease is still slow and far lagging behind what is expected. This points to the argument that anemia in Indian children is far from being eradicated in the country. The study recommends the government of India to intensify nutritional supplementation and food fortification programmes, especially in rural areas where significant groups of households are economically under-privileged. Additionally, there is need for continued early diagnosis and treatment of HIV and TB in order to reduce the incidence of HIV-related anemia in children.

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