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ARIMA FORECASTING OF THE PREVALENCE OF ANEMIA AMONG PREGNANT WOMEN IN NEPAL

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ABSTRACT:

Anemia is a common public health threat, especially in developing countries such as Nepal. Pregnant women in developing countries are even more vulnerable. Using annual time series data on the prevalence of anemia among pregnant women in Nepal from 1990 – 2018, the study seeks to make forecasts for the period 2017 – 2025. The study applies the Box-Jenkins ARIMA methodology. The diagnostic ADF tests show that the AN series under consideration is an I (2) variable. Based on the AIC, the study presents the ARIMA (4, 0, 0) model [or the AR (4) model] as the optimal model. The residual correlogram indicates that the model stable. The results of the study show that there is likely to be a sharp rise in the prevalence of anemia in Nepal in pregnant women over the period 2017 to 2025, from the estimated 39.8% to about 42.3% by 2025. The study basically encourages the government of Nepal to intensify its support to pregnant women through the routine supplementations with iron and folate.

INTRODUCTION:

Anemia is the most common nutritional disorder in the world (Singh et al., 2013). The prevalence of anemia in pregnant women in developed and developing countries is 14% and 51%, respectively (Mayer & Tegman, 1998). Anemia in pregnancy is considered as one of the major risk factors for contributing to maternal deaths in developing countries such as Nepal (Abou & Royston, 1991). In fact, pregnant women are vulnerable to deficiencies in iron, folate, cobalamin and vitamin A, all of which can cause anemia (Mayet, 1985; Surharno et al., 1992; Underwood & Arthur, 1996; Msolla & Kinabo, 1997). Anemia during pregnancy increases the risk of fetal growth retardation and low birth weight, premature delivery, increased perinatal mortality, reduced resistance to infection of both mother and baby (Kozuma, 2009). The main goal of this study is to predict the prevalence of anemia among pregnant women in Nepal over the period 2017 – 2025. Despite the fact that there are many studies on anemia in pregnancy in Nepal (Prakash & Yadav, 2015), no research has been done with regards to modeling and forecasting the prevalence of anemia among pregnant women in the country.

LITERATURE REVIEW:

In a case-control study, Bondevik et al. (2000) examined the importance of nutritional deficiencies and infections in the development of anemia in pregnant Nepali women of Kathmandu, who were receiving healthcare services at Patan Hospital. The study found out that there was high prevalences of nutritional deficiencies and intestinal infections. Singh et al. (2013) evaluated the prevalence of anemia among pregnant women in the western part of Nepal over the period January 2012 to December 2012. A total of 512 pregnant women (15 – 45 years old) were included in the study. Cyanmethaemoglobin technique was used to determine the hemoglobin level. The prevalence of anemia was higher in the pregnant women at the second trimester (51.1%) and also at the 20-35 years age group (62.79%). Consistently, Prakash & Yadav (2015), in a review article, analyzed martenal anemia in pregnancy in Nepal and argued that women of low socioeconomic groups and teenagers were more susceptible to anemia during pregnancy. This paper, rather studying the risk factors of anemia, like previous studies, will simply forecast the prevalence of the disease in the country among pregnant women.

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, AN, the series under consideration.

3.2 The Applied Box – Jenkins ARIMA Model Specification:

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

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

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 – 2018) on the prevalence of anemia among pregnant women, that is, the percentage of pregnant women whose hemoglobin level is less than 110 grams per liter at sea level [denoted as AN] in Nepal. Out-of-sample forecasts will cover the period 2017 – 2025. All the data was collected 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
AN	-5.376349	0.0002	-3.724070	@1%	Stationary
			-2.986225	@5%	Stationary
			-2.632604	@10%	Stationary

Table 1 shows that AN 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 (2, 0, 2)	-26.03634	0.10233	2.2452	11.74	3.8516
ARIMA (1, 0, 0)	82.65528	0.99246	1.489	11.772	5.2678
ARIMA (2, 0, 0)	-21.69802	0.12153	2.2476	11.74	3.864
ARIMA (3, 0, 0)	-27.16371	0.10182	2.2433	11.74	3.8533
ARIMA (4, 0, 0)	**-33.78488**	0.087833	2.2458	11.74	3.8307
ARIMA (5, 0, 0)	-33.23685	0.085141	2.245	11.74	3.8241

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 (4, 0, 0) model [or the AR (4) process] is finally chosen.

3.5 Residual Tests:

3.5.1 Correlogram of the Residuals of the ARIMA (4, 0, 0) Model:

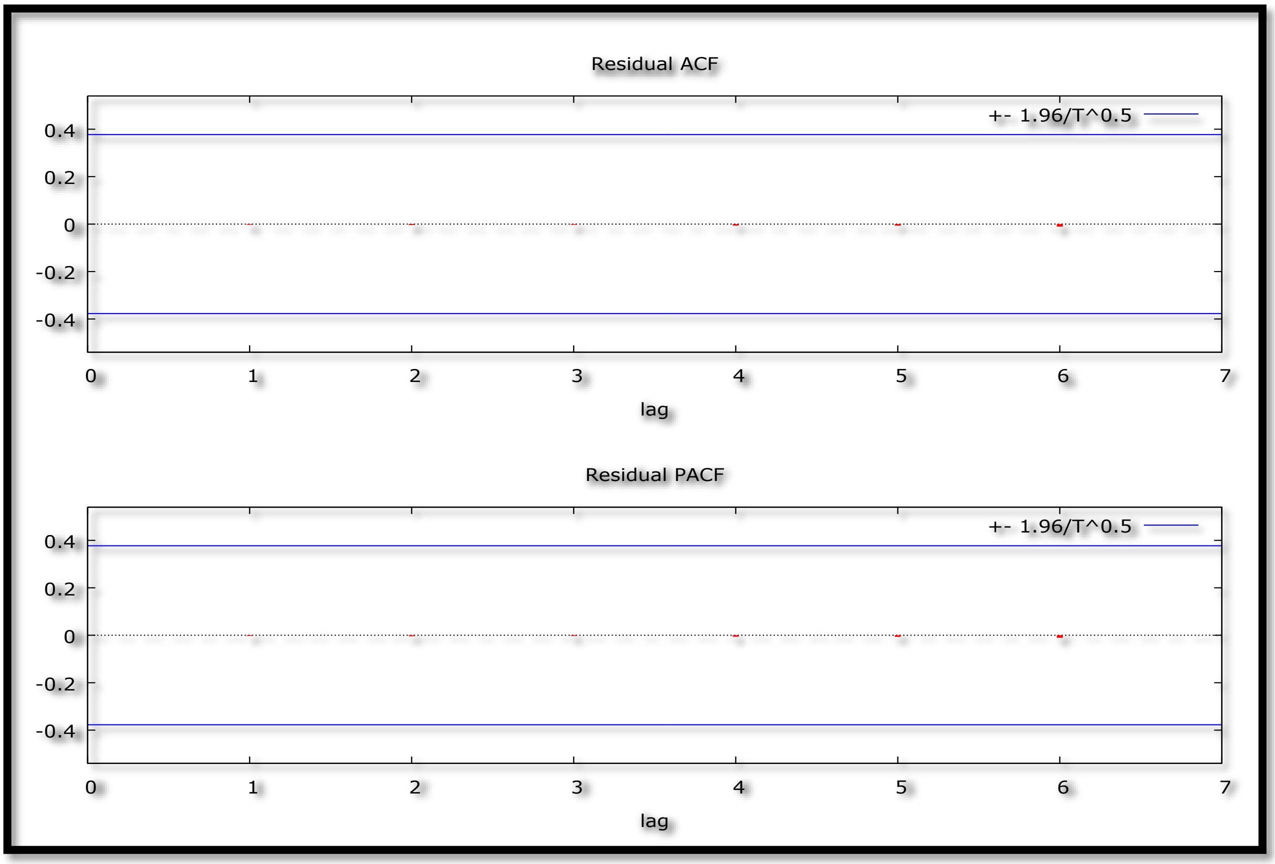

Figure 1: Correlogram of the Residuals

Figure 1 indicates that the estimated best 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.

FINDINGS OF THE STUDY:

4.1 Results Presentation:

Table 3: Main Results

ARIMA (4, 0, 0) Model:

The chosen optimal model, the ARIMA (4, 0, 0) model can be expressed as follows:

$$AN_t = 2.23207AN_{t-1} - 0.926702AN_{t-2} - 0.871568AN_{t-3} + 0.566169AN_{t-4} \ldots \ldots \ldots . . \ldots . [2]$$

Variable	Coefficient	Standard Error	z	p-value
β_1	2.23207	0.163949	13.61	0.0000***
β_2	-0.926702	0.43863	-2.113	0.0346**
β_3	-0.871568	0.461275	-1.889	0.0588*
β_4	0.566169	0.182895	3.096	0.002***

Table 3 shows the main results of the ARIMA (4, 0, 0) model.

Forecast Graph

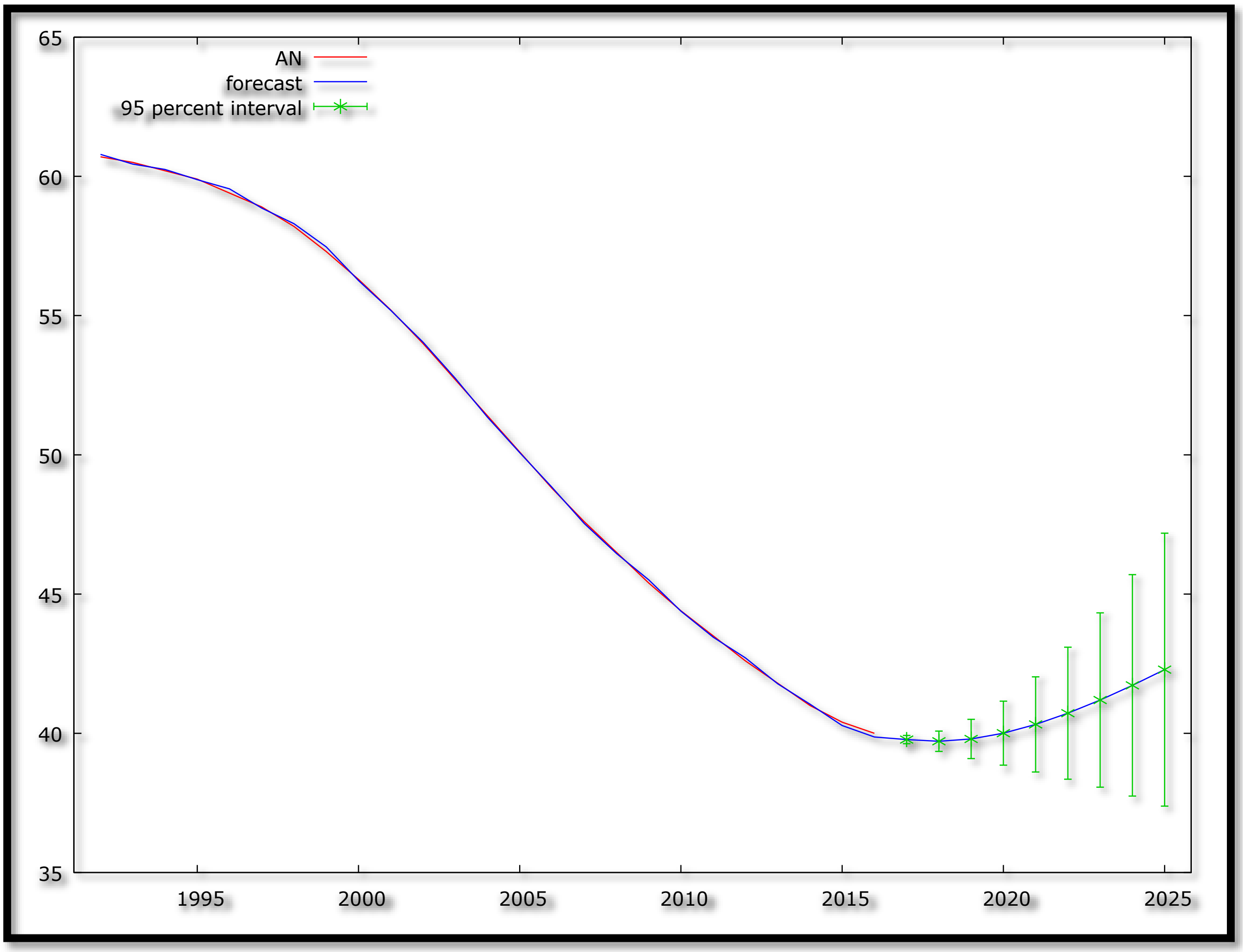

Figure 2: Forecast Graph – In & Out-of-Sample Forecasts

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

Predicted AN– Out-of-Sample Forecasts Only

Table 4: Predicted AN

Year	Predicted AN	Standard Error	95% Confidence Interval
2017	39.7754	0.0758428	(39.6268, 39.9241)
2018	39.7149	0.185499	(39.3513, 40.0785)
2019	39.7968	0.359182	(39.0928, 40.5007)
2020	40.0049	0.586418	(38.8555, 41.1542)
2021	40.3191	0.871751	(38.6105, 42.0277)
2022	40.7221	1.20918	(38.3522, 43.0921)
2023	41.1954	1.59669	(38.0659, 44.3249)
2024	41.7222	2.02853	(37.7463, 45.6980)
2025	42.2861	2.50007	(37.3860, 47.1861)

Table 4 shows the out-of-sample forecasts only. The prevalence of anemia in Nepal among pregnant women is projected to rise from approximately 39.8% to an estimated 42.3% by 2025.

CONCLUSION:

The study shows that the ARIMA (4, 0, 0) model is not only stable but also the most suitable model to forecast the prevalence of anemia in Nepal among pregnant women over the period 2017 to 2025. The presented model hints of a possible sharp resurgence in the prevalence of anemia in the country's pregnant women. The study encourages the government of Nepal to intensify its support to pregnant women through the routine supplementations with iron and folate. This could potentially reverse the predicted trend. Additionally, there ought to be regular screening of women when they visit a health facility: emphasis should be directed towards screening for anemia, HIV, TB, breast cancer as well as cervical cancer. Furthermore, there should also be increased anemia awareness programs targeting women within the reproductive age group.

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