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Analysis of Under Five Mortality Rate for Gabon Using Holt's Linear Method

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***Abstract* - This study uses annual time series data on under five mortality rate (U5MR) for Gabon from 1960 to 2020 to predict future trends of U5MR over the period 2021 to 2030. Residuals and forecast evaluation criteria indicate that the applied model is stable in forecasting U5MR. This study utilizes Holt's linear exponential smoothing model to forecast future trends of U5MR in Gabon. The optimal values of smoothing constants α and β are 0.9 and 0.1 respectively based on minimum MSE. The results of the study indicate that annual U5MR will decline over the out of sample period. Therefore, we implore the government of Gabon to channel more resources to maternal and child health (MNCH) program activities to ensure availability of adequate medical supplies and staff at all levels of healthcare. In addition, there is need to aggressively implement health related SDGs that will positively impact on population health such as poverty reduction, infrastructure development, and sustainable production and consumption.**

Keywords: Exponential smoothing, Forecasting, U5MR.

I. INTRODUCTION

Time series forecasting techniques are essential early surveillance tools that can be utilized in tracking sustainable development goal (SDG) progress. Various methods are currently being used to forecast future trends of diseases and other health related events (Panch *et al.* 2018). Statistical and machine learning (ML) approaches are dominating in time series prediction problems (Zhao*et al.* 2020; Panch *et al.* 2018; Zhou *et al.* 2018). Traditional statistical approaches such as the Box-Jenkins ARIMA methodology and exponential smoothing models have been widely applied in public health and other fields, and proved to produce accurate and reliable forecasts (Nyoni & Nyoni, 2019 a & b;Coghlan, 2018). The ARIMA model is a regression model where the dependent variable is regressed on the current error term, lags of the error terms and its own lags (Box& Jenkins, 1970). The model is specified as ARIMA (p, d, q) where p and q represent the non-seasonal autoregressive and moving average terms, and d represents the non-seasonal differencing order. Construction of the ARIMA models is a 3 stage iterative process that involves model identification, parameter estimation, and diagnostic checking (Nyoni, 2018; Box & Jenkins, 1970). In exponential smoothing weighted past values of a variable are used to generate forecasts with more recent observations being allocated more weights than the observations in the more distant past (Ostertagová & Oskar Ostertag, 2011). In this study we apply the Holt's linear exponential smoothing method to forecast future trends of under-five mortality rate for Gabon with the expectation that the findings will inform child health policies, planning and allocation of resources to child health programs with the aim of ending all preventable under five deaths in the country.

II. LITERATURE REVIEW

Bariki *et al.* (2020) examined factors affecting infant mortality among the general population of Ethiopia, 2016. A Community-based cross-sectional study was conducted in all regions of Ethiopia from January 18 to June 27, 2016. A total of 10,641 live births were included in the analysis. Data were analyzed and reported with both descriptive and analytic statistics. Bivariable and multivariable multilevel logistic regression models were fitted by accounting correlation of individuals within a cluster. Adjusted odds ratio (AOR) with 95% confidence interval was reported to show the strength of the association and its significance. The study findings indicated that sex of the child, multiple births, prematurity, and residence were notably associated with infant mortality. The risk of infant mortality has also shown differences across different regions. Masaba & Phetoe (2020) described the trends of neonatal mortality within the two sub-Saharan countries. The study concluded that in 2018, the neonatal mortality rate for Kenya was 19.6 deaths per 1000 live births. The neonatal mortality rate had fallen gradually from 35.4 deaths per 1000 live births in 1975. On the other hand, South Africa had its neonatal mortality rate fall from 27.9 deaths per 1000 live births in 1975 to 10.7 deaths per 1000 live births in 2018.A case control study was conducted by Elida *et al.* (2019) to investigate the influence of maternal age, parity, and education on infant mortality in West Aceh Regency. A case group was 45 mothers whose babies died when they were under one years old and a control group was 45 mothers whose babies were alive when they were under one year old. The matching was done on the babies based on their age and sex. The findings of this study showed that maternal age and parity significantly influence of infant mortality. In the other hand, maternal education did not significantly influence infant mortality. The most significant variable which influences infant mortality was maternal age (OR=4.745). Weddhi

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et al. (2019) conducted a cross-sectional study to examine factors associated with neonatal mortality at the Referral Hospital in Nouakchott, Mauritania. The study was conducted between January 2013 and December 2013 and included neonatal patients hospitalized at the National Referral Hospital (NRH). Data were collected by reviewing the medical charts and through questionnaires administered to the parents. The authors concluded that neonatal mortality remains a significant burden in Mauritania.

III. METHODOLOGY

This study utilizes an exponential smoothing technique to model and forecast future trends of under-five mortality rate in Gabon. In exponential smoothing forecasts are generated from the smoothed original series with the most recent historical values having more influence than those in the more distant past as more recent values are allocated more weights than those in the distant past. This study uses the Holt's linear method (Double exponential smoothing) because it is an appropriate technique for modeling linear data.

$G_t = \mu_t + b_t t + \varepsilon_t$

Smoothing equation

$L_t = \alpha G_t + (1-\alpha)(L_{t-1} + b_{t-1})$

Trend estimation equation

$T_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1}$

Forecasting equation

$f_{t+h} = L_t + h b_t$

G_t is the actual value of time series at time t

L_t is the exponentially smoothed value of time series at time t

α is the exponential smoothing constant for the data

β is the smoothing constant for trend

f_{t+h} is the h step ahead forecast

T_t is the trend estimate

Data Issues

This study is based on annual under five mortality rate in Gabon for the period 1960 – 2020. The out-of-sample forecast covers the period 2021 – 2030. All the data employed in this research paper was gathered from the World Bank online database.

IV. FINDINGS OF THE STUDY

Exponential smoothing Model Summary

Table 1: ES model summary

Variable	G
Included Observations	61 (After Adjusting Endpoints)
Smoothing constants	
Alpha (α) for data	0.900
Beta (β) for trend	0.100
Forecast performance measures	
Mean Absolute Error (MAE)	1.965296
Sum Square Error (SSE)	1440.642345

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Mean Square Error (MSE)	23.617088
Mean Percentage Error (MPE)	0.234168
Mean Absolute Percentage Error (MAPE)	1.441249

Residual Analysis for the Applied Model

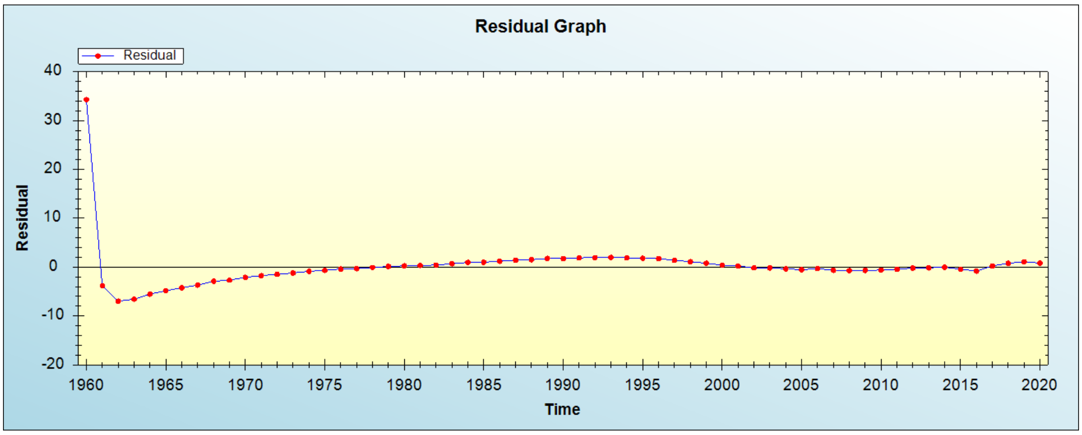

Figure 1: Residual analysis

In-sample Forecast for G

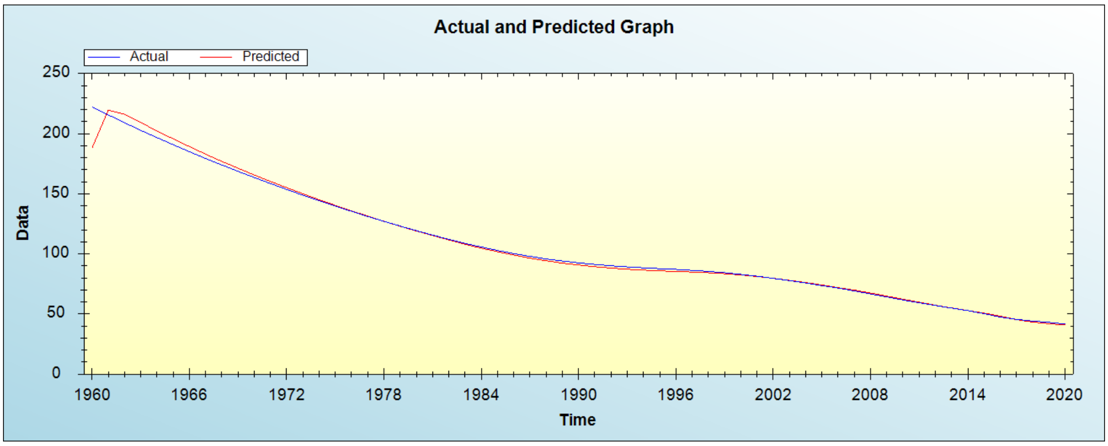

Figure 2: In-sample forecast for the G series

Actual and Smoothed graph for G series

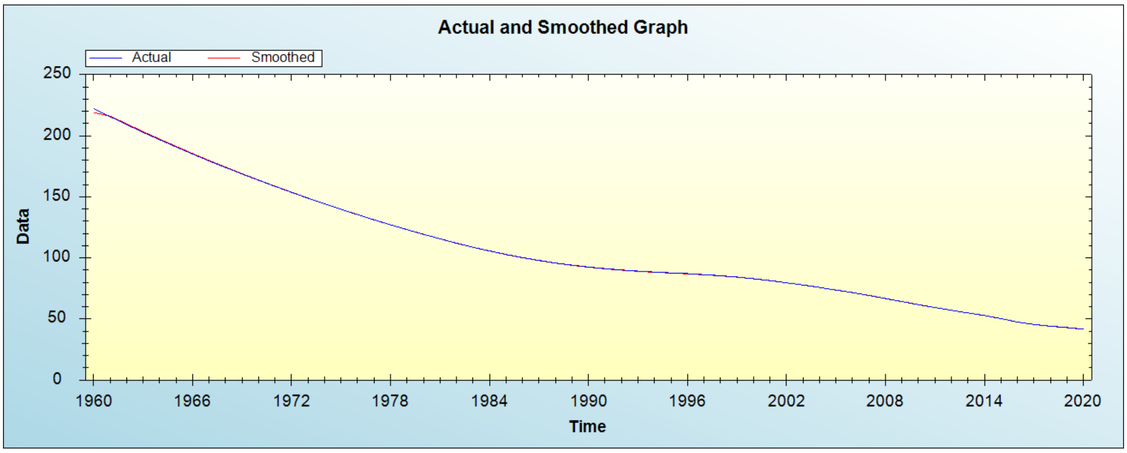

Figure 3: actual and smoothed G series

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Out-of-Sample Forecast for G: Actual and Forecasted Graph

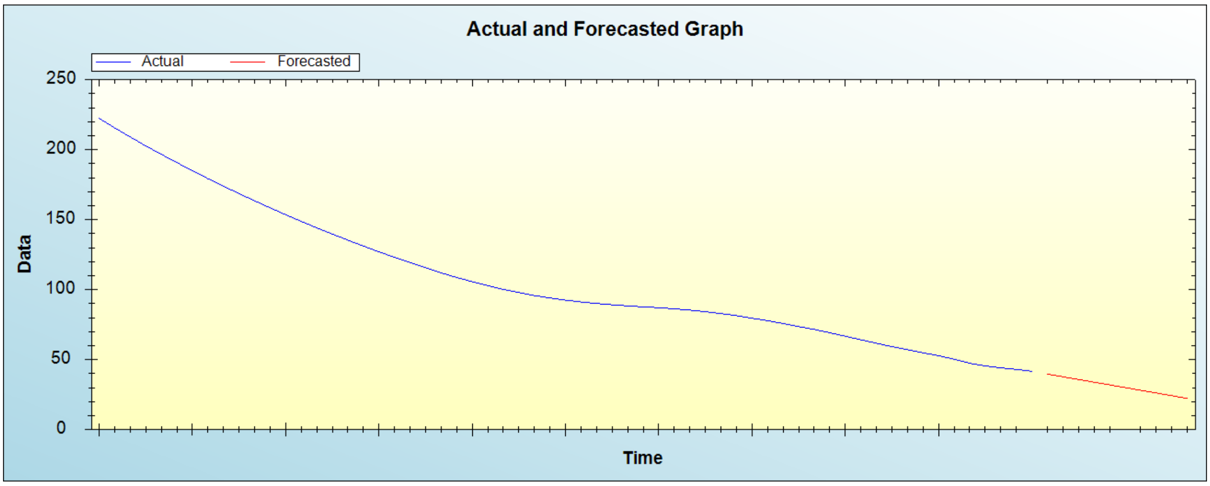

Figure 4: Out-of-sample forecast for G: actual and forecasted graph

Out-of-Sample Forecast for G: Forecasts only

Table 2: Tabulated out-of-sample forecasts

2021	39.6802
2022	37.7425
2023	35.8048
2024	33.8671
2025	31.9294
2026	29.9917
2027	28.0540
2028	26.1163
2029	24.1786
2030	22.2409

The main results of the study are shown in table 1. It is clear that the model is stable as confirmed by evaluation criterion as well as the residual plot of the model shown in figure 1. It is projected that annual U5MR will decline over the out of sample period.

V. POLICY IMPLICATION & CONCLUSION

The government of Gabon has made significant progress in the reduction of under-five mortality. Over the past decades under five and neonatal mortality have been on a downward path. This trend must be accelerated in order to achieve the set target of 25 under five deaths per 1000 live births by 2030. This study applied the Holt's linear exponential smoothing model and forecast future trends of under-five mortality rate in Gabon. The model projections suggested that annual U5MR will decline over the out of sample period. Hence, authorities in Gabon must allocate more resources to the maternal and child health (MNCH) program to ensure availability of adequate medical supplies and staff at all levels of healthcare. Health related SDGs must be implemented aggressively as they positively impact on population health.

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