

Estimating Future Trends of Under Five Mortality Rate for the DRC Using Double Exponential Smoothing

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Abstract - This study uses annual time series data on under five mortality rate (U5MR) for the DRC from 1969 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 in the DRC. Holt's linear method was applied in this study to predict U5MR. The optimal values of smoothing constants α and β are 0.9 and 0.9 respectively based on minimum MSE. The double exponential smoothing model projections indicated that annual U5MR will continue to fall but still remain high over the out of sample period. Therefore, we implore the DRC government to address all the challenges faced by under five children especially in the rural areas where socio-demographic factors significantly contribute to mortality among under five children and allocate more resources to child health program activities.

Keywords: Exponential smoothing, Forecasting, U5MR.

I. INTRODUCTION

It is important for public health policies to be formulated based on research evidence so that appropriate and effective strategies are implemented to address existing problems. Time series forecasting approaches have been found to be useful tools that provide policy guidance to enable adequate resource mobilization and allocation (Zhao *et al.* 2020; Panch *et al.* 2018; Zhou *et al.* 2018). Statistical and machine learning approaches are widely applied in time series prediction problems and the results are accurate and reliable (Nyoni & Nyoni, 2019; Nyoni, 2018; Box & Jenkins, 1970). The Cape Town Global Action Plan (2017) encourages all UN member countries to embrace efficient and effective statistical approaches that bring out the desired results. It also expects countries to capture detailed information of SDG indicators that will help in policy making and planning. During the Launch of sustainable development goals (SDGs) in September 2015, all UN member states agreed to strengthen statistical systems to ensure all the activities are documented and used in decision making (UN, 2016; UN, 2015). Tracking of SDG progress should be an ongoing process and all countries should strive to have effective monitoring and evaluation mechanisms. For example, SDG3 focuses on healthy lives and promotion of well-being for all at all stages of life. Under this goal, every country is expected to end all preventable maternal, newborn and under five deaths by 2030. Neonatal and under five deaths should reach levels as low as 12 neonatal deaths per 1000 live births and 25 under five deaths per 1000 live births (UN, 2020; UNICEF, 2019; WHO, 2019; UNICEF, 2019). Therefore, in this study we propose Holt's linear exponential smoothing technique to model and forecast future trends of under-five mortality rate in the DRC. We expect study findings to guide child health policies and allocation of resources in order to end all avoidable under five deaths in the country.

II. LITERATURE REVIEW

A multisite retrospective Kenyan cohort study was conducted by Irimu *et al.* (2021) to find out the proportion of all admissions and deaths in the neonatal age group and examine morbidity and mortality patterns, stratified by birth weight, and their variation across hospitals. Intrapartum related complications were the single most common diagnosis among the neonates with birth weight of 2000 g or more who died. A threefold variation in mortality across hospitals was observed for birth weight categories 1000–1499 g and 1500–1999g. 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. In China Cao *et al.* (2017) analyzed trends in mortality and causes of death among children aged under 5 years in Beijing, China between 1992 and 2015 and forecasted under-5 mortality rates (U5MRs) for the period 2016–2020. An entire population-based epidemiological study was conducted. Data collection was based on the Child Death Reporting Card of the Beijing Under-5 Mortality Rate Surveillance Network. Trends in mortality and leading causes of death were analyzed using the χ^2 test and SPSS 19.0 software. An autoregressive integrated moving average (ARIMA) model was fitted to forecast U5MRs between 2016 and 2020 using the E Views 8.0 software. The study revealed that Beijing has made considerable progress in reducing U5MRs from 1992 to 2015. However, U5MRs could show a slight upward trend from 2016 to 2020. Akinwande *et al.* (2016) Analyzed Infant and Child (Under-five) Mortality in Zaria using a regression Analysis Approach. The study was carried out using secondary data

from Ahmadu Bello University Teaching Hospital, Zaria, on infant and child (under-five) mortality and delivery rates. Findings from the study showed that both infant and child mortality rates have a direct relationship with delivery rates. The correlation analysis result showed that there is a very strong and positive relationship between mortality and delivery rates. The study revealed that infant and child mortality rates will continue to decrease if there can be improvement in the factors under study.

III. METHODOLOGY

This study utilizes an exponential smoothing technique to model and forecast future trends of under-five mortality rate in DRC. 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.

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

Smoothing equation

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

Trend estimation equation

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

Forecasting equation

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

D_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 DRC for the period 1969 – 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	D
Included Observations	52 (After Adjusting Endpoints)
Smoothing constants	
Alpha (α) for data	0.900
Beta (β) for trend	0.900
Forecast performance measures	
Mean Absolute Error (MAE)	0.245632
Sum Square Error (SSE)	7.548281
Mean Square Error (MSE)	0.145159

Mean Percentage Error (MPE)	0.026256
Mean Absolute Percentage Error (MAPE)	0.150387

Residual Analysis for the Applied Model

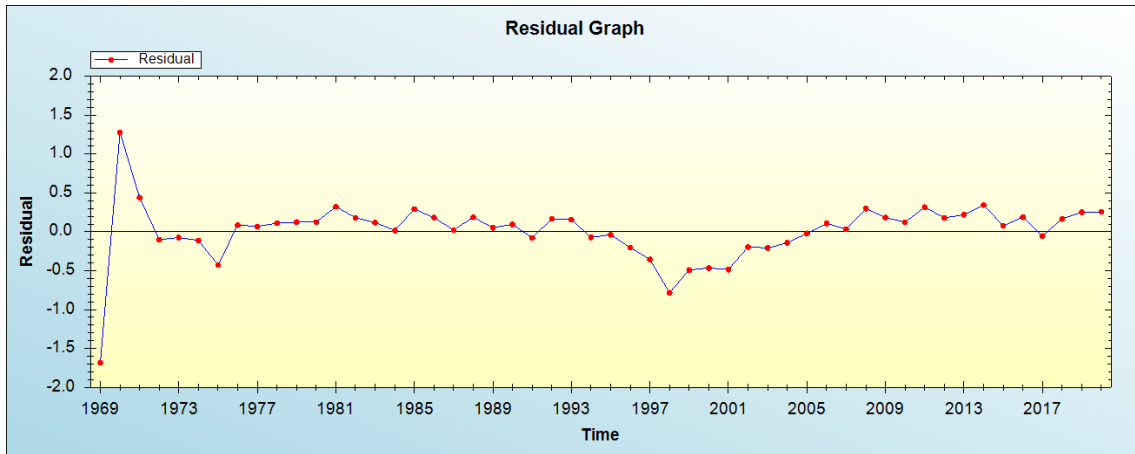


Figure 1: Residual analysis

In-sample Forecast for D

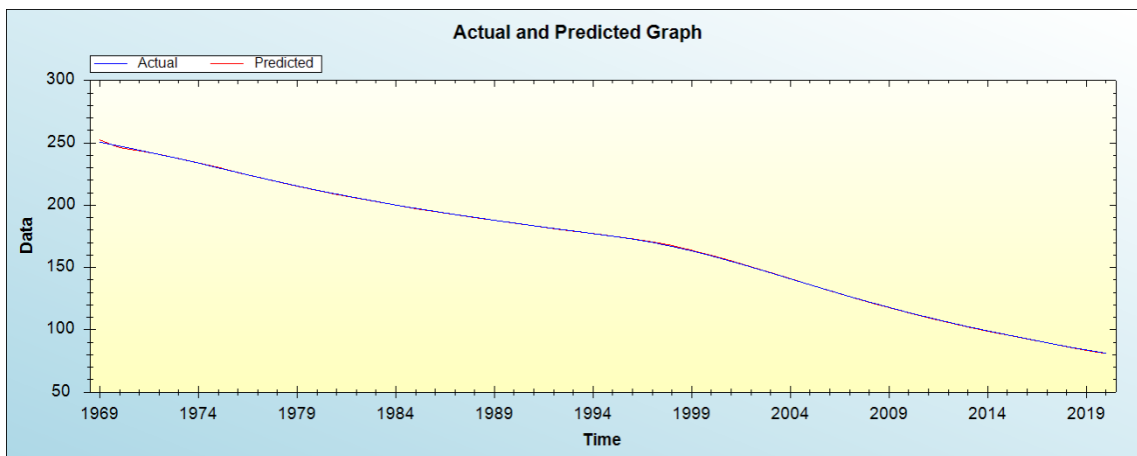


Figure 2: In-sample forecast for the D series

Actual and Smoothed graph for D series

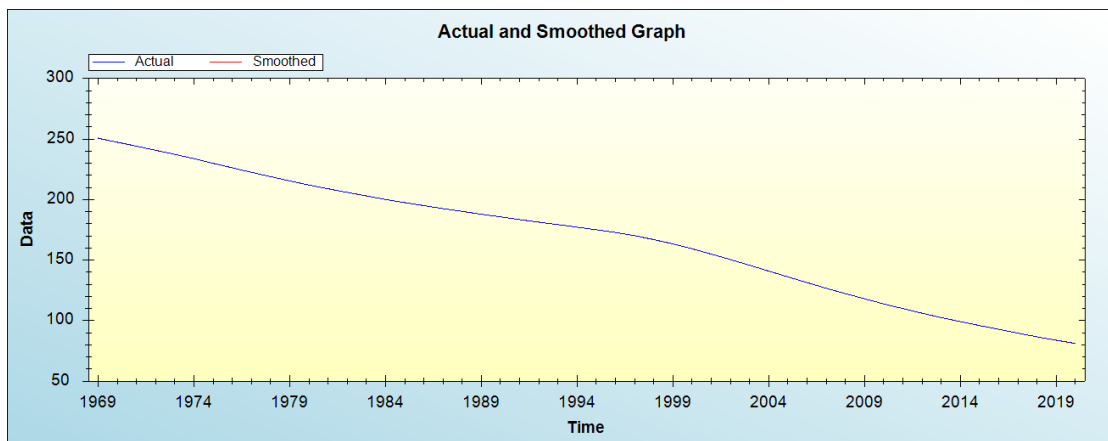


Figure 3: smoothed D series

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

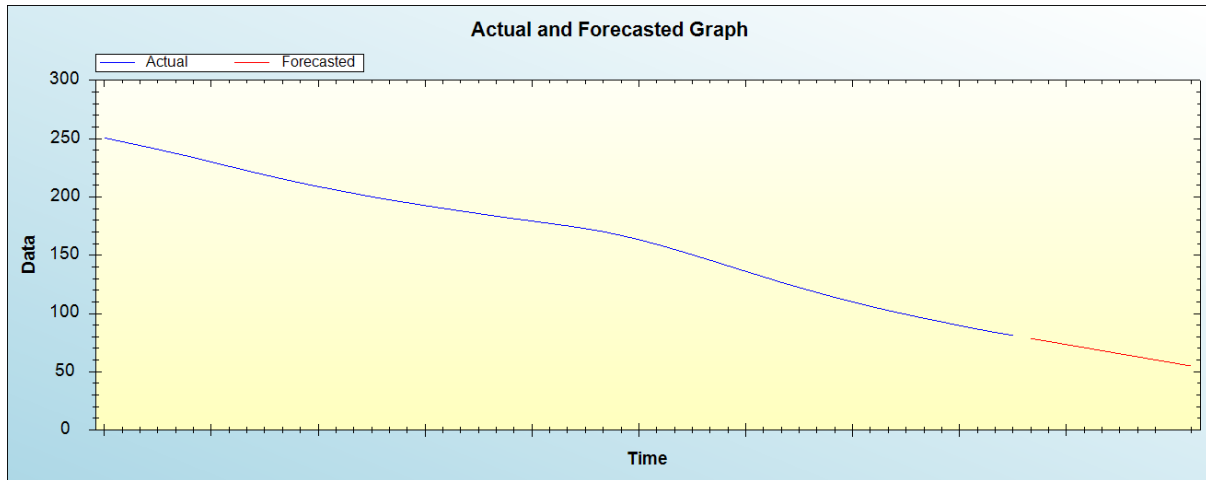


Figure 4: Out-of-sample forecast for D: actual and forecasted graph

Out-of-Sample Forecast for D: Forecasts only

Table 2: Tabulated out-of-sample forecasts

2021	78.5508
2022	75.9274
2023	73.3039
2024	70.6804
2025	68.0569
2026	65.4335
2027	62.8100
2028	60.1865
2029	57.5630
2030	54.9396

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 continue to fall but still remain high over the out of sample period.

V. POLICY IMPLICATION & CONCLUSION

DRC has made tremendous progress over the past decades in the reduction of under-five mortality. However, absolute numbers of under-five and neonatal deaths remain high requiring urgent attention. Several factors have been found to contribute to mortality in under five children such as socio-cultural, demographic and proximate factors. Informed decisions will facilitate in the reduction of these avoidable deaths. In this study we apply the Holt’s linear exponential smoothing model to forecast future trends of under-five mortality rate in this country. The findings of this paper suggest that annual U5MR will continue to fall but still remain high over the out of sample period. Therefore, we encourage the DRC government to address all the various challenges affecting under five children particularly in the rural areas where socio-demographic factors significantly contribute to under five mortality and allocate more resources to child health program activities.

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