STATISTICS IN TRANSITION new series, December 2024
Vol. 25, No. 4, pp. 119–136, https://doi.org/10.59139/stattrans-2024-006
Received – 28.08.2023; accepted – 09.10.2024

Forecasting under-five child mortality in Bangladesh: progress towards the SDGs target by 2030

Sacchidanand Majumder[1]**, Soma Chowdhury Biswas**[2]

Abstract

In order to facilitate progress towards achieving the SDGs target regarding under-five child mortality in Bangladesh, the study explores the relevant mortality trends and makes a projection of the situation by 2030. The yearly dataset regarding mortality among children aged five and under (per 1,000 live births) in Bangladesh employed in this study was collected from the World Bank Databank (https://data.worldbank.org/indicator) for the 1972-2022 period. The selection of the best-fitted model for the purpose of forecasting was between the ARIMA model and the Double Exponential Smoothing Holt's Method. Compared with the ARIMA (1,2,1) model, the Double Exponential Smoothing Holt's method proved the best-fitted model for forecasting the under-five child mortality in the future. The results show that under-five child mortality in Bangladesh is an annually declining trend. The average under-five child mortality is forecasted to drop by one during the 2023-2035 period. Thus, the predicted value of under-five child mortality would be 26 in 2025 and 22 in 2030, which contributes to the achievement of the national target of 27 (per 1,000 live births) in 2025 and the SDGs target (25 deaths per 1,000 live births) regarding the under-five mortality rate. Bangladesh will then achieve the SDGs target regarding the under-five child mortality by 2026 if the existing strategy and plan of reducing under-five child mortality is successful.

Key words: under-five child mortality, forecasting, SDGs, Bangladesh.

1. Introduction

Under-five child mortality is a significant metric that serves as a measurement of child health and the overall progress of a nation. It provides insights into the socio-economic conditions in which children live, encompassing their access to healthcare (McGuire, 2006). The reduction of child mortality is a crucial target

[1] Department of Statistics, University of Chittagong, Bangladesh. E-mail: mithu.m2011@gmail.com. ORCID: https://orcid.org/0000-0002-9197-0381

[2] Department of Statistics, University of Chittagong, Bangladesh. E-mail: soma.c.biswas@gmail.com. ORCID: https://orcid.org/0009-0005-1034-1735.

within the framework of the Sustainable Development Goals (SDGs). The SDG 3 mentioned ensuring healthy lives and promoting well-being for all ages. The achievement of SDG 3 is contingent upon advancements made in many other SDGs, including No Poverty, Zero Hunger, Quality Education, Gender Equality, Clean Water and Sanitation, Affordable and Clean Energy, and Sustainable Cities and Communities. In order to attain these health goals, a series of targets have been established. Several of the targets outlined in the SDGs pertain to the domains of maternity, neonatal, and child health (Nino, 2015; WHO, 2016). The SDGs frameworks are referenced in target 3.2 within SDG 3, which aims to drop new-born and under-five mortality rates to 12 and 25 deaths per 1,000 live births correspondingly by 2030 (UN, 2015; Chao F., et al., 2018).

The advancements made in dropping child mortality globally have been noteworthy. Globally, the child mortality under five experienced a significant drop to 38 deaths per 1,000 live births in 2019, compared to 93 in 1990 and 76 in 2000, representing a decline of 59% and 50%, respectively, and the neonatal mortality fell to 17 deaths in 2019 from 37 deaths in 1990 and 30 in 2000, representing a decline of 52% and 42%, respectively (UNIGME, 2020). Globally, there was a substantial drop in the figure of deaths every day among under-five children, with a decline to 14,000 in 2019 from 27,000 in 2000 and 34,000 in 1990 (UNIGME, 2020).

Children persistently encounter significant regional inequalities in their prospects for survival. In the region of Sub-Saharan Africa, the under-five child mortality continues to be the highest (average 76 deaths per 1,000 live births in 2019) among all regions globally. This statistic indicates that the under-five child mortality is 1 in 13, 20 times higher than the Australia and New Zealand region (1 in 264) and equal to the world average in 1999 (UNIGME, 2020).

However, it is worth noting that by 2019, 122 nations had successfully attained an under-five mortality rate that fell below the specified target set by the SDGs, which aims to achieve 25 or less deaths per 1,000 live births. Those nations must strive towards sustaining advancements and actively mitigating inequalities within their people. To meet the SDGs target by 2030, 53 of the 73 remaining countries would need to step up their efforts. More nations are expected to fail to achieve the new-born mortality objective by 2030. Specifically, over 60 countries will be required to expedite their efforts to meet SDGs neonatal mortality target within the designated timeframe (UNIGME, 2020).

Bangladesh, situated in Asia, is categorized as a developing nation with a notable prevalence of under-five child mortality. However, it has substantially reduced this mortality rate, witnessing a decline from 133 deaths per 1000 live births in 1990 to 30.2 in 2018 (UN, 2015; Khan and Awan, 2017). This achievement can be attributed to the effective execution of the MDGs. In Bangladesh, the mortality rate among children under five decreased significantly to 28 deaths per 1,000 live births in 2019 from 125 deaths in 1995, 84 deaths in 2000, and 46 deaths in 2014 (GoB, 2020a;

MICS, 2019; BDHS 2014). Nevertheless, the prevalence remains elevated within South Asian nations, with Bangladesh ranking third after Pakistan (69.3) and India (36.6) (UNICEF, 2018; WHO, 2018). It is indisputable that a substantial amount of work and ongoing endeavors are crucial in order to secure additional declines in neonatal mortality and mortality rates among children under five, with the ultimate aim of attaining the corresponding SDG targets. Bangladesh has made notable progress in effectively decreasing child mortality over the past few decades (Ahmed et al., 2012). This achievement has played a crucial role in attaining the MDG 4 target. To make strides towards attaining the SDGs target, it is imperative to decrease the death rate among children under five. It is imperative to examine the trend of under-five child mortality to mitigate the susceptibility of child survival. This study aims to examine the patterns of mortality among under-five children and estimate projections for the year 2030 to advance the attainment of the SDGs target pertaining to under-five child mortality in Bangladesh.

2. Methodologies

2.1. Source of Data

The present study mainly employs secondary data sources. The annual dataset about the mortality rate of children under five (per 1,000 live births) in Bangladesh, utilized in this study, is collected from the World Bank Databank. The dataset covers the period from 1972 to 2022 and is categorized under the indicator "Mortality rate, under-5 (per 1,000 live births)." The dataset can be found at the following URL: https://data.worldbank.org/indicator. The dataset utilized in this study is displayed in Table 1 below:

Table 1: The yearly under-five child mortality rate (per 1,000 live births) in Bangladesh

Year	Number	Year	Number	Year	Number	Year	Number
1972	228	1985	178	1998	97	2011	47
1973	227	1986	171	1999	91	2012	45
1974	226	1987	165	2000	86	2013	42
1975	224	1988	159	2001	81	2014	40
1976	222	1989	152	2002	76	2015	39
1977	218	1990	146	2003	72	2016	37
1978	215	1991	140	2004	68	2017	35
1979	210	1992	133	2005	65	2018	34
1980	206	1993	127	2006	61	2019	32
1981	201	1994	121	2007	58	2020	31
1982	195	1995	115	2008	55	2021	30
1983	190	1996	109	2009	52	2022	29
1984	184	1997	103	2010	49		

Source: World Bank (Access on 2nd July 2024).

2.2. Methods of Analysis

Various statistical approaches are available for analyzing trends, ranging from basic linear regression to advanced parametric and non-parametric approaches (Hesel and Hirsch, 1992; Chen et al., 2007). Nevertheless, it is imperative to select a suitable methodology that guarantees the precise identification of all events pertaining to variability and change, as well as their subsequent influence on future predictions (Machiwal and Jha, 2008). The Mann-Kendall test, first proposed by Mann in 1945 (Mann, 1945) and further developed by Kendall in 1975 (Kendall 1975), was employed in this study to conduct trend analysis and ascertain the slope of the trend line. The time series modeling and forecasting task involved the utilization of the Non-seasonal Auto-Regressive Integrated Moving Average (ARIMA) model, as suggested by Box and Jenkins in 1976 (Box and Jenkins, 1976).

Double exponential smoothing Holt's method, often called Holt's method, was developed by Holt in 1957 to make predictions closer to actual values while displaying a trend in the data series (Holt, 1957). The selection of the most suitable forecasting model was based on evaluating error measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The chosen model would be utilized to forecast the under-five child mortality (per 1,000 live births) in Bangladesh for 2023–2035.

2.2.1. Mann-Kendall Test

The Mann-Kendall test is a statistical procedure commonly applied to analyses trends in time series data. It is a non-parametric method, meaning that it does not rely on any specific assumptions about the underlying distribution of the data (Kendall, 1975). One significant benefit of the Mann-Kendall test is its independence from the statistical distributions necessary for parametric methods. The null hypothesis (H_0) in the context of the Mann-Kendall test posits an absence of trend or serial correlation within the population under analysis. Conversely, the alternative hypothesis (H_1) implies the presence of a monotonic trend, either growing or decreasing.

2.2.2. Auto-Regressive Integrated Moving Average (ARIMA) Model

The Box-Jenkins procedure is often regarded as the most effective approach for model selection, as it leverages real-world datasets to determine the most suitable model. This methodology has several advantages, including calculating a reduced number of parameters and assessing the presence of seasonality in the data. The model construction process primarily comprises of four key steps: identification, estimation, diagnostic verification, and forecasting (Box and Pierce, 1970). The ARIMA model is a widely used time series. The parameters (p, d, q) are commonly used in time series analysis. In this context, "p" represents the autoregressive coefficient, "d" denotes the order of differencing required to achieve stationarity in the time series, and "q" signifies the number of moving average components involved in the analysis. Conduct an initial stationarity test on the time series, and if it fails to meet the stationarity assumption, employ techniques such as differencing and logarithmic transformations to induce stationarity. The autocorrelation function (ACF) exhibits a decay for several lags, indicating the absence of significant correlation. Conversely, spikes in the plot suggest the presence of q parameters. On the other hand, the partial autocorrelation function (PACF) diminishes for numerous lags, indicating the lack of substantial correlation. However, spikes in the plot suggest the presence of p parameters.

In the event that multiple models are constructed, the Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) are employed to select the most suitable model, as determined by the model with the lowest value of AIC and BIC. In addition to diagnostic checks, a test is employed to assess the model's appropriateness in relation to random errors by utilizing the Ljung-Box Q Statistics. The Q statistic is employed to assess the degree of randomness exhibited by the error term and to determine the statistical significance of the estimated parameters. In the event that the parameters lack significance or exhibit non-random errors, it is advisable to explore other p and q ordering until statistically significant p and q values are obtained. In this study, many models were employed to analyze the train dataset and determine the optimal model based on multiple criteria for predicting the yearly under-five child mortality rates in Bangladesh. The non-seasonal ARIMA model is

$$y_t = \mu + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots .. + \emptyset_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_q \varepsilon_{t-q} - \epsilon_t;\ \epsilon_t \sim iid$$

where $\emptyset$, θ are unknown parameters.

2.2.3. Double Exponential Smoothing Holt's Method

Double exponential smoothing, often called Holt's method, was developed by Holt in 1957 to make predictions closer to actual values while displaying a trend in the data series (Holt, 1957). Holt's method is used when predicting data with a linear trend. Due to the data trend, the simple smoothing model will frequently make significant errors that swing from positive to negative or vice versa. The model includes a forecast equation as well as two smoothing equations (Wilson and Keating 2007). Holt's method smooths the slope and trend of the time series using two separate smoothing constants (α for the level and γ for the trend).

The equation for forecast, $$y_{t+h} = l_t + hb_t$$

The equation for the level, $$l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})$$

The equation for a trend, $b_t = \gamma(l_t - l_{t-1}) + (1-\gamma)b_{t-1}$
where y_{t+h} is the prediction for h periods into the future, l_t is an estimate of the level at the time t, b_t is an estimate of trend (slope) at the time t, h are future forecasting periods, periods to be forecast into the future, α is the level's smoothing constant ($0 \leq \alpha \leq 1$), and γ is the trend's smoothing constant ($0 \leq \gamma \leq 1$).

2.2.4. Measures of Forecasting Accuracy

When faced with the task of choosing among several types of forecasting methodologies, it is of utmost importance to consider the accuracy of the forecasts. In this context, the term "accuracy" pertains to the differentiation between the observed and projected value of a specific timeframe, also known as the forecasting error. The three forecasting error factors applied in this study are Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The measure commonly used to quantify the average discrepancy between the observed and predicted values for a given time frame is denoted as MAE. At the same time, the RMSE represents the root of the average of the squared differences between the observed and predicted values. On the other hand, the MAPE is used to represent the average of absolute percentage mistakes. The equations utilized for calculating the aforementioned errors are as follows:

$$\mathrm{MAE} = \frac{\sum|\mathrm{D_t} - \mathrm{F_t}|}{\mathrm{n}}$$

$$MAPE = \frac{\sum|e_t/D_t|}{n} \times 100$$

$$RMSE = \sqrt{\frac{\sum(D_t - F_t)^2}{n-1}}$$

where D_t refers to the observed demand during period t, while F_t represents the estimated demand during the same period. The variable n represents the designated number of periods, and e_t denotes the discrepancy between the observed demand (D_t) and the estimated demand (F_t), which is calculated as the difference between the two (D_t -F_t).

3. Results and Discussion

All the analysis is done by SPSS (V23.0). The analysis of continuous data on the under-five child mortality rate (per 1,000 live births) is of significant importance in examining the patterns of variation in under-five child mortality. The Mann-Kendall test is utilized to determine the trends in time series data of under-five child mortality rate. The utilization of ARIMA model and Double Exponential Smoothing Holt's Method for time series data analysis yields results that are subsequently employed for selecting the best-fitted model for the purpose of forecasting. The chosen model would then be utilized to forecast the under-five child mortality rate (per 1,000 live births) in Bangladesh for the period 2023–2035.

3.1. Mann-Kendall Test

In order to identify the seasonal trend in time series data pertaining to the under-five child mortality rate, the Mann-Kendall statistics (Zc statistics) is performed. The hypotheses to be examined under Kendall's Tau test for trend were as follows:
H_0: There is no trend in the under-five child mortality rate (per 1,000 live births).
H_1: There is a trend in the under-five mortality rate (per 1,000 live births).

Table 2: The Results of Mann-Kendall trend test (two-tailed test).

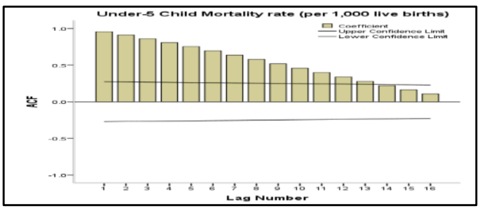
Statistic	Estimate
Kendall's Tau Coefficient	-.1.000**
p-value (two-tailed)	.000
N	51

The calculated p-value is found to be below the predetermined significance level of α=0.05. As a result, the null hypothesis H_0, which states that there is no observed trend in the mortality rate of children under five in Bangladesh, is rejected. Conversely, the alternative hypothesis H_1, which suggests the presence of a trend in the aforementioned mortality rate, is accepted.

3.2. Model Selection and Forecasting of Under-Five Child Mortality Rate

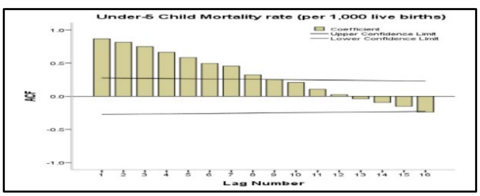
3.2.1. ARIMA Model

Figure 1 displays the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots regarding the under-five mortality rate in Bangladesh. The plots visually represent the confidence limits by the continuous line positioned above and below the X-axis. Figure 1(a) presents the ACF plot without applying differencing. It is observed that first thirteen spikes at lag 1-13 are above the confidence limit and the last three spikes at lag 14-16 are within the confidence limit. Figure 1(a) demonstrates that the ACF steadily decreases to zero as time delays t rise, suggesting a geometric decay representative of an AR process. Once more, Figure 1(b) illustrates the PACF plot without differencing. It indicates a single spike over the confidence limit at lag 1, and all other lags are within the significant level. Additionally, Figure 1(c) illustrates the autocorrelation function (ACF) plot after applying differencing. It is observed that first eight spikes at lag 1–8 are above the confidence limit and the last one spike at lag 16 which falls below the confidence level. Moreover, Figure 1(d) illustrates the plot of the partial autocorrelation function (PACF) after applying differencing. The plot indicates two spikes, with the first one above the confidence limit at lag 1 and the second one below the confidence limit at lag 8. All other lags are within significant level.

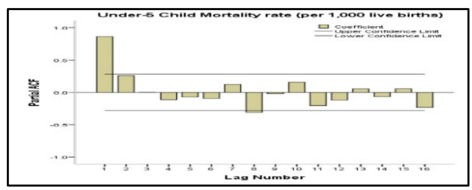


(a). Without differencing

(b). Without differencing



(c). With differencing

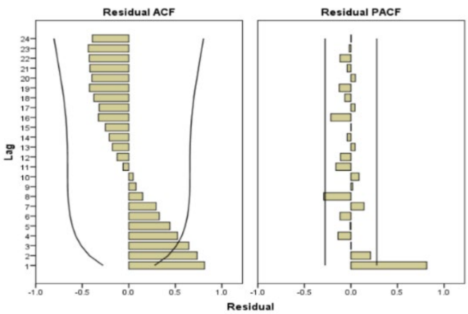


(d). With differencing

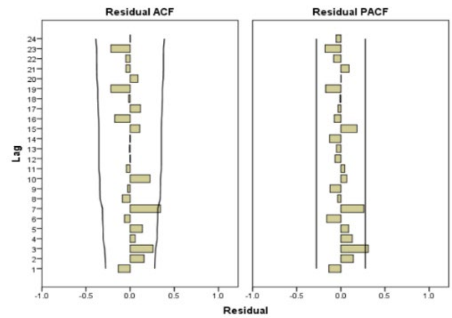
Figure 1: Autocorrelation and partial autocorrelation of under-five child mortality rate in Bangladesh

After detecting the theoretical attributes of the ACF and PACF as an AR process, it is evident that the ACF of the differenced series exhibits a progressive decline towards zero due to the AR component's influence. This decline in the ACF effectively mitigates the impact of the moving average (MA) component, hence reducing the presence of any underlying trend. The ARIMA model can be specified as ARIMA (0, 1, 0), ARIMA (1, 1, 1), ARIMA (0, 2, 0), or ARIMA (1, 2, 1), depending on whether the decision is made to incorporate a lagged error term.

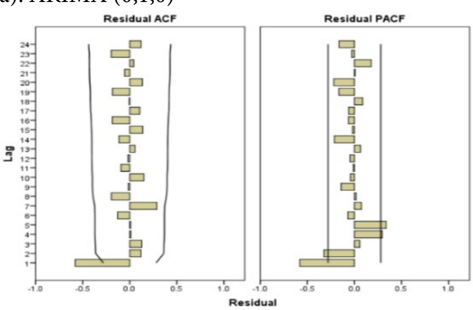
In order to investigate whether the four selected models present any apparent systematic patterns that may be eliminated to enhance the predictability of these models, we conducted a further analysis of the ACF and partial ACF of the residuals. Figure 2 displays the ACF and Partial ACF of the residuals obtained from the models used to analyze the under-five mortality rate. Figure 2 demonstrates that ACF and partial ACF of the residuals fall within the confidence interval and do not exhibit substantial deviation from zero. This finding suggests that the models have been chosen properly.



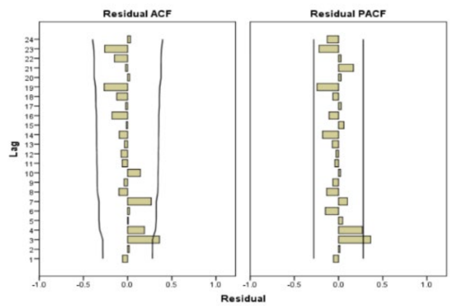
(a). ARIMA (0,1,0)



(b). ARIMA (1,1,1)



(c). ARIMA (0,2,0)



(d). ARIMA (1,2,1)

Figure 2: Autocorrelation (ACF) and partial autocorrelation (PACF) of residuals for four selected models for the under-five child mortality rate

Table 3 displays the proposed models determined by applying the principle of parsimony and the recognizable pattern of the ACF and PACF. The optimal estimate to the data within the ARIMA family is determined by evaluating the Akaike's Information Criterion (AIC), Schwarz's Bayesian Criterion (BIC) values and Ljung-Box Q Statistics.

Table 3: ARIMA models selection for diagnostic analysis for the under-five child mortality rate in Bangladesh

Model	AIC	BIC	Ljung-Box Q		
			Statistics	DF	Sig.
ARIMA (0,1,0)	210.911	212.823	166.651	18	.000
ARIMA (1,1,1)	121.732	127.468	23.006	16	.114
ARIMA (0,2,0)	123.159	125.051	35.454	18	.008
ARIMA (1,2,1)	115.141	120.816	20.632	16	.193

Compared to the values of AIC, the BIC and Ljung-Box Q Statistics for the possible models displays that ARIMA (1,2,1) has the lowest values of AIC, BIC and Ljung-Box Q Statistics. Hence, ARIMA (1,2,1) is selected as the best-fitted ARIMA model for the data. Figure 3 displays the result of the fitted model of the under-five child mortality rate in Bangladesh using the ARIMA (1,2,1) model.

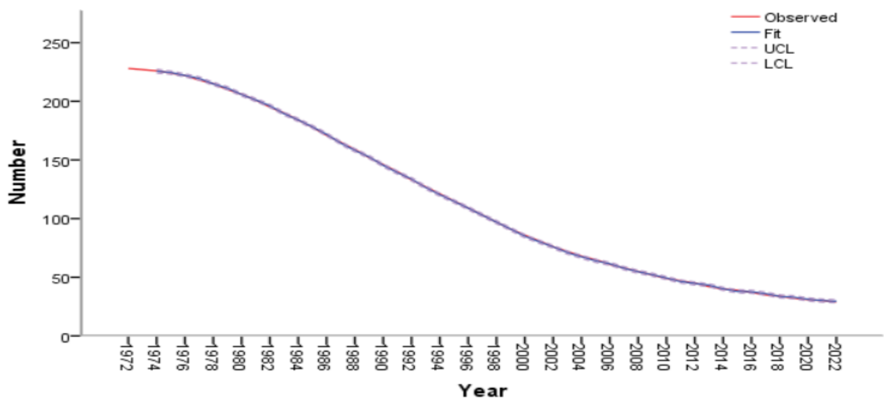


Figure 3: The Fitted Model of the Under-five Child Mortality Rate in Bangladesh using ARIMA (1,2,1) Model

3.2.2. Double Exponential Smoothing Holt's method

The yearly data for the period 1972-2022 are displayed in Table 1 and it is observed that this data pattern is a linearly decreasing trend. So, the Double Exponential Smoothing method is applied in this study. The step in using Double Exponential Smoothing Holt's method for forecasting is to plot the data to determine the data pattern. The goal of this step is to find out whether there is a trend, cycle, seasonal, random, or stationary component. Figure 4 shows the plotted results of the data series pattern from the actual data.

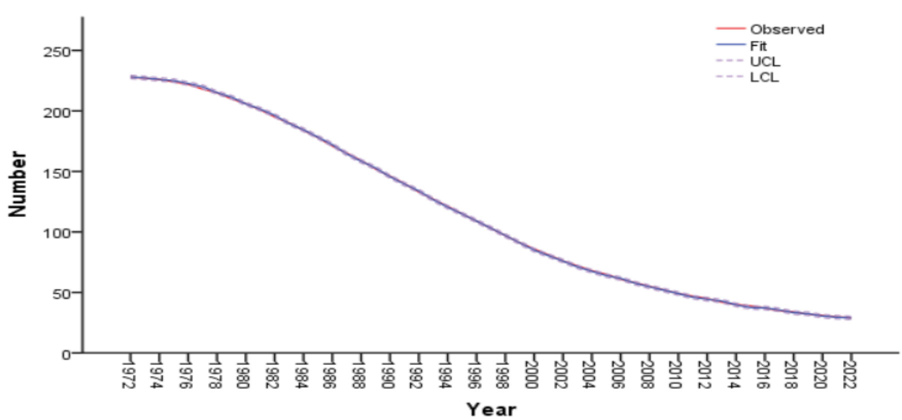


Figure 4: Time Series Data Plot of Number of under-five child deaths (per 1,000 live births) using Double Exponential Smoothing Holt's method

Figure 4 illustrates that the data pattern of under-five child mortality (per 1,000 live births) is a linear trend, thus Double Exponential Smoothing Holt's approach is the best and appropriate way to apply. In smoothing out linear trend data, this method employs two smoothing parameters: alpha (α) and gamma (γ).

Determination of Smoothing Parameters

The alpha parameter (α) is used to smooth the actual data while smoothing the trend on a regular basis. Parameter values ranging from 0 to 1 (Mega, 2003). The value of these factors can be determined through trial and error. This parameter determines the difference between the forecasted value and the actual data. When the alpha value approaches one, the weight given to the most recent data increases, resulting in the minor smoothing effect. When the alpha value approaches 0, it will have a minimal response to the most recent data, resulting in the substantial smoothing effect.

Although theoretically, alpha (α) and gamma (γ) can be assumed to be worth 0 and 1, in practice, alpha (α) and gamma (γ) parameters can only be determined using a limited range of values. This was narrowed due to the choice of alpha (α) and gamma (γ); the Double Exponential Smoothing method is typically seen as a more simply implemented method (Nurkse, 1953). The gamma parameter (γ) is used to remove some flexibility from the forecasted data. The result of the estimation of exponential smoothing model parameters is displayed in Table 4.

Table 4: Exponential Smoothing Model Parameters

Specification	Estimate
Alpha (Level)	.700
Gamma (Trend)	1.000

Table 4 displays the parameter estimates for the double exponential smoothing Holt's model. The result mentions that the model gave the estimated values of alpha and gamma of 0.700 and 1.000 respectively. The value of alpha (0.700) is relatively high, indicating that the estimate of the level at the current time point is based upon more recent observations. Again, the value of gamma (1.000) is high; indicating that the estimate of the trend at the current time point is based upon more recent observations.

3.2.3. Forecast Evaluation

The complete data are from 1972 to 2022, but to calibrate the model the study used data from 1972 to 2014. Then, the study used the data from 2015 to 2022 with the assumption that they have not been observed to conduct an out-of-sample forecast.

The values of the out-of-sample forecast as compared to the actual (observed) values are presented in Table 5.

Table 5: The Number of the under-five child mortality (per 1,000 live births) testing and forecast data in Bangladesh using both ARIMA (1,2,1) and Holt's Method

Year	Actual Value	ARIMA (1,2,1) Model		Holt's Method	
		Predicted Value	Difference	Predicted Value	Difference
2015	39	38	1	38	1
2016	37	37	0	37	0
2017	35	37	2	36	1
2018	34	37	3	33	1
2019	32	37	5	32	0
2020	31	38	7	30	1
2021	30	39	9	30	0
2022	29	41	12	29	0

Table 5 displays the values of the out-of-sample forecasts compared to the actual values for both methods. In comparison with ARIMA (1,2,1) model, the out-sample forecasting values of Double Exponential Smoothing Holt's method are closer to actual values. So, the Double Exponential Smoothing Holt's method gives a probable good forecast result.

3.2.4. Forecast Methods Comparison

In-sample forecast is the process of formally evaluating the predictive capabilities of the models developed using observed data to see how effective the algorithms are in reproducing data. It is kind of similar to a training set in a machine learning algorithm and the out-of-sample is similar to the test set. In this study, the total dataset period is from 1972 to 2022. The study considered the in-sample forecasting data period of 1972-2014 and out-sample forecasting data period of 2015–2022. To compare the performance of the best fitting models from the two methods, the ARIMA (1,2,1) model and Holt's Method, the study used three forecast error statistics: RMSE, MAPE, and MAE for this comparison. Hyndman (2006) mentioned that the out-of-sample period has smaller errors than the in-sample period because the in-sample period includes some relatively large observations. This error statistics are applied on the forecasts of the testing and training set (in-sample & out-of-sample forecasts) and are presented in Table 6.

Table 6: Forecast error statistics of the two forecast methods for the under-five child mortality (per 1,000 live births)

Model	In-Sample Forecasting Error			Out- Sample Forecasting Error		
	RMSE	MAPE	MAE	RMSE	MAPE	MAE
ARIMA (0,2,0)	0.632	0.504	0.469	0.567	0.444	0.276
Holt's Method	0.697	0.517	0.521	0.484	0.470	0.314

From Table 6, it could be seen that for both methods, in-sample forecasting errors are higher than out-sample forecasting errors.

3.2.5. Forecast Accuracy

The appropriate forecasting method is selected based on the accuracy of the measure set of values, whereby the method that has the smallest forecasting error is the best forecasting method. The general rule of thumb is the method with the lowest forecast error statistic is the best. The calculation of accuracy measure values of RMSE, MAE, and MAPE for those two selected methods is illustrated in Table 7.

Table 7: Result of comparison of forecast accuracy for forecasting of the under-five child mortality (per 1,000 live births)

Model	RMSE	MAPE	MAE
ARIMA (1,2,1)	0.661	0.713	0.513
Holt's Method	0.643	0.688	0.506

From Table 7, it is observed that compared to the ARIMA (1,2,1) model, the Double Exponential Smoothing Holt's method has the lowest values of RMSE, MAPE and MAE, which are 0.643%, 0.688% and 0.506%, respectively, whereas RMSE, MAPE and MAE for the ARIMA (1,2,1) model are 0.661%, 0.713% and 0.513% respectively. Hence, based on the findings, it is decided that the Double Exponential Smoothing Holt's method is the best and most appropriate forecasting method due to its high accuracy in forecasting the under-five child mortality (per 1,000 live births) in Bangladesh. Zainun and dan-Majid (2003) mentioned that if the MAPE value is less than 10%, the model performs extremely well; if the MAPE value is between 10% and 20%, the model performs well. The result displays in Table 7 that the MAPE value indicates the proportion of forecasting errors of 0.688% for the Double Exponential Smoothing Holt's method; this forecasting model performs very well with MAPE values below 10%.

3.2.6. Forecasting of Under-Five Child Mortality

The result of the forecasting plot of the under-five child mortality rate (per 1,000 live births) in Bangladesh is shown in Figure 5.

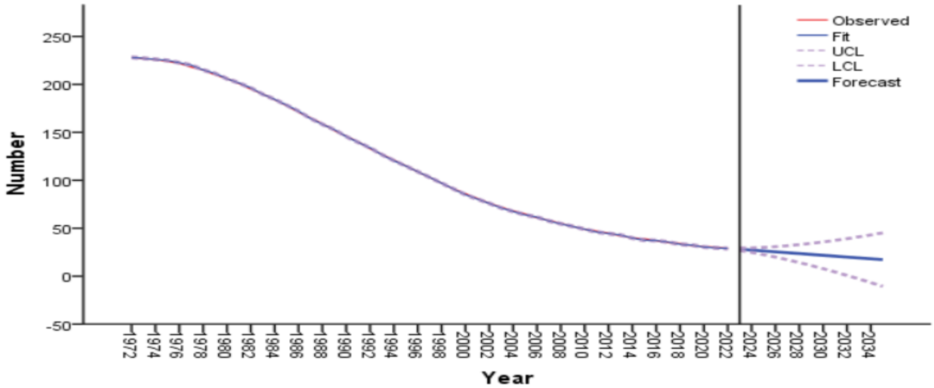


Figure 5: Predicted levels of the under-five mortality rate in Bangladesh

In Figure 5, the actual variables, fits, forecast, and 95% of confidence interval are shown. Alpha (α) of 0.700 and Gamma (γ) of 1.000 are the smoothing constants in this graph. The analysis of predicting models of the under-five child mortality (per 1,000 live births) is a data pattern with a linear trend; as a result, Holt's method is very appropriate for use. The forecasting values of the under-five child mortality (per 1,000 live births) using the Double Exponential Smoothing Holt's method for the period 2023–2035 are displayed in Table 8.

Table 8: The Result of forecasting of under-five child mortality (per 1,000 live births) for the period 2023–2035 using the Double Exponential Smoothing Holt's method

Years	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
Forecasted value	28	27	26	25	24	24	23	22	21	20	19	18	17
GoB Targets			27										

From Table 8, it is observed that in Bangladesh, the value of under-five child mortality (per 1,000 live births) for the period 2023–2035 continues to decline year after year, with a trend linear data pattern. The result also shows that the average value of the under-five child mortality (per 1,000 live births) declined by 1 (per 1000 live births) during the period 2023–2035. Further, the value of the under-five child mortality (per 1,000 live births) will reach 26 (per 1000 live births) in 2025 and 22 (per 1000 live births) in 2030 whereas the government of Bangladesh set a target of 27 for the under-five child mortality rate (per 1,000 live births) by 2025 in the 8th five-year plan (GoB, 2020b). From the findings of this study, it is clearly understood that Bangladesh will achieve the SDGs target of the under-five child mortality by 2026 if the current declining trend is continued.

4. Conclusion and Recommendation

Child mortality is a crucial indicator of a nation's socio-economic advancement and the well-being of mothers, reflecting the overall quality of life within a society. Bangladesh, as one of the developing nations in Asia, has committed to pursuing the SDGs. The objective of achieving a reduction in under-five mortality to a level no higher than 25 per 1,000 live births by the year 2030 is commonly known as the third Sustainable Development Goal (SDG) (UN, 2015). The study explores the under-five child mortality trends and estimates projection by 2030 to make progress towards achieving the SDGs target regarding the under-five child mortality in Bangladesh. The yearly dataset regarding the under-five child mortality in Bangladesh utilized in this study is collected from the World Bank Databank (https://data.worldbank.org/indicator) for the period 1972–2022 by the indicator "Mortality rate, under-5 (per 1,000 live births)". For selecting the best-fitted model for the purpose of forecasting, the ARIMA model and the Double Exponential Smoothing Holt's Method are employed. As compared to the ARIMA (1, 2, 1) model, the Double Exponential Smoothing Holt's method is the best-fitted model for forecasting the estimate of future projections. The result depicts that the under-five child mortality rate in Bangladesh is a continuously declining trend in each and every year. The result also shows that the under-five child mortality rate will drop by 1 (per 1,000 live births) during 2023-2035. The under-five child mortality rate is expected to fall to 26 in 2025 and to 22 in 2030, whereas Bangladesh's national target is to reduce the under-five child mortality to 27 (per 1,000 live births) by 2025 in the 8th five-year plan. From the result of this study, it is clearly understood that Bangladesh will achieve the SDGs target regarding the under-five child mortality by 2026 if the current declining trend is continued. The factors that influence the under-five child mortality rate are education, awareness and health campaigning, access to health care, maternal health care, access to antennal care and prenatal care, vaccination, housing condition, earning patterns of household and various health and various strategies and initiatives of government and NGOs.

Abbreviations

Abbreviation	Details
ACF	Autocorrelation Function
AR	Autoregressive (AR)
ARIMA	Auto-Regressive Integrated Moving Average
BDHS	Bangladesh Demographic and Health Survey
BIC	Bayesian Information Criterion
GoB	Government of Bangladesh

(cont.)

Abbreviation	Details
LCL	Lower Confidence Limits
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MaxAE	Maximum Absolute Error
MaxAPE	Maximum Absolute Percentage Error
MDGs	Millennium Development Goals
MICS	Multiple Indicator Cluster Survey
PACF	Partial Autocorrelation Function
RMSE	Root Mean Squared Error
SDGs	Sustainable Development Goals
UCL	Upper Confidence Limits
UN	United Nations
UNICEF	United Nations International Children's Emergency Fund
UNIGM	United Nations Inter-agency Group for Child Mortality Estimation
WHO	World Health Organization

References

Ahmed, T., Mahfuz, M., Ireen, S., Ahmed, A. S., Rahman, S., Islam, M. M., et al., (2012). Nutrition of children and womenin Bangladesh: trends and directions for the future. *Journal of Health, Population, and Nutrition,* Vol. 30, No. 1, pp. 1-11.

BDHS, (2014). Bangladesh Demographic and Health Survey (BDHS), 2014. NIPORT, Dhaka, Bangladesh; Mitra andAssociates, Dhaka/ Bangladesh.

Box, G. E. P., Jenkins, G. M., (1976). Time series analysis, forecasting and control. Holden Day: San Francisco, California, USA, p. 625.

Box, G. E. P., Pierce, D., (1970). Distribution of Residual Autocorrelations in Autoregressive Integrated Moving Average Time Series Models. *Journal of the American Statistical Association,* Vol. 65, pp. 1509–1526.

Chao, F., et al., (2018). National and regional under-5 mortality rate by economic status for low-income and middle income countries: a systematic assessment. *The Lancet Global Health*, Vol. 6, No. 5, pp. 535–547. https://doi.org/10.1016/S2214-109X(18)30059-7.

Chen, H. U., Guoa, S., Chong-Yu X. U., Singh, V. P., (2007). Historical temporal trends of hydro-climatic variables and runoff response to climate variability and their relevance in water resource management in the Hanjiang basin. *Jour. Hydrol.,* Vol. 344, pp. 171–184.

GoB, (2020a). Sustainable Development Goals: Bangladesh Progress Report 2020, SDGs Publication No. # 23 by Bangladesh Planning Commission, Ministry of Planning, Government of the People's Republic of Bangladesh (GoB), Dhaka.

GoB, (2020b). *8th Five Year Plan (July 2020-June 2025),* General Economics Division (GED), Bangladesh Planning Commission, Government of the People's Republic of Bangladesh (GoB), Dhaka.

Hesel, D. R., Hirsch, R. M., (1992). *Statistical Methods in Water Resources*, Elsevier, Amsterdam.

Holt, C. E., (1957). *Forecasting seasonals and trends by exponentially weighted averages* (O.N.R. Memorandum No. 52). Carnegie Institute of Technology, Pittsburgh USA. https://doi.org/10.1016/j.ijforecast.2003.09.015

Hyndman, R. J., (2006). Another Look At Forecast-Accuracy Metrics For Intermittent Demand. *Foresight, 4,* pp. 43–46.

Khan, J. R., Awan N., (2017). A comprehensive analysis on child mortality and its determinants in Bangladesh using frailty models. *Archives of Public Health,* Vol. 75, No. 1, p. 58. https://doi.org/10.1186/s13690-017-0224-6.

Kendall, M. G. (1975). Rank Correlation Methods. Charles Griffin: London.

Machiwal, D., Jha, M. K., (2008). Comparative evaluation of statistical tests for time series analysis: Application to hydrological time series. *Hydrological Sciences, Journal-des Sciences Hydrologiques,* Vol. 53, No. 3, pp. 353–366.

Mann, H. B., (1945). Nonparametric tests against trend. *Econometrica,* Vol. 13, pp. 245–259.

McGuire, J. W., (2006). Basic health care provision and under-5 mortality: a cross-national study of developing countries. *World Development*, Vol. 34, NO. 3, pp. 405–425.

Mega, F., (2003). *Strategi Bersama Masyarakat Sipil Indonesia: Empat Pilar Demokratisasi untuk Melawan Kemiskinan dan Pemiskinan.* Jakarta: Gerakan Anti Pemiskinan (GAPRI).

MICS, (2019). Progotir Pathey, *Bangladesh Multiple Indicator Cluster Survey*, Survey Findings Report. Dhaka, Bangladesh: Bangladesh Bureau of Statistics (BBS) and UNICEF Bangladesh.

Nino, F. S., (2015). *Sustainable Development Goals*. United Nations.

Nurkse, R., (1953). *Problems of Capital Formation in Underdeveloped Countries*.

UN, (2015). *The Millennium Development Goals Report*. The United Nations, New York, USA.

UNICEF, (2018). *2018–2021 Progress Report - Save Newborns*, UNICEF South Asia.

UNIGME, (2020). *'Levels & Trends in Child Mortality: Report 2020*. The United Nations Inter-agency Group for Child Mortality Estimation (UNIGME), United Nations International Children's Emergency Fund, New York.

WHO, (2018). *WHO | Under-five mortality*, World Health Organization (WHO).

WHO, (2016). *World health statistics 2016: monitoring health for the SDGs sustainable development goals*, World Health Organization (WHO).

Wilson, J. H., Keating, B., (2007). *Business Forecasting with Accompanying Excel-Based ForecastX Software*, 5th ed., Boston, Mass: McGraw-Hill.

Zainun, N. Y., dan Majid, Z. A., (2003). *Low Cost Demand Predictor*, Malaysia. Universitas Teknologi Malaysia.