Mid-Term Forecasting of Fatalities Due to COVID-19 Pandemic: A Case Study in Nine Most Affected Countries

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Abstract The outbreak of COVID-19 pandemic has presented the entire world with an unrivalled challenge of public health leaving a remarkable impact on the social, economic, and financial lives of humanity. Though a major portion of the globe is under lockdown due to this deadly virus, the number of causalities is still growing rapidly. Therefore, it is very important to predict the number of infected and fatality cases for the future to overcome the consequences, save the lives of people, and plan accordingly. This paper proposes a data-driven analysis based on univariate Holt’s double exponential smoothing method with parameter optimization and polynomial curve fitting technique for one month ahead forecasting of the death cases in nine profoundly affected countries across the world namely India, USA, Italy, UK, China, France, Iran, Spain, and Germany. In contrast to the complex deep learning-based predictors, the proposed Holt’s model is simple yet efficient enough to give outstanding prediction performance for all the countries under this study and can be further used for the prediction of infections and causalities for the rest of the countries in future. The future estimation of the number of death cases will act as a beneficial tool for the successful allocation of the medical resources and as an early warning to the policymakers and health officials as well as to the residents of the country to boost their self-awareness.

Keywords Coronavirus · Fatality rate · Mid-term forecasting · Optimized Holt’s model · Polynomial curve fitting method

1 Introduction

Coronavirus disease (COVID-19) which was first identified in December 2019 in Wuhan, China is declared as a global pandemic by WHO on March 11. COVID-19 pandemic is the highest global crisis faced by the entire world since World War-II.
This pandemic is moving like a wave all around the globe and as of May 21, 2020, the outbreak has resulted in 5,105,902 infected cases with 330,004 reported deaths and 2,035,445 recovered cases worldwide [1–3]. 215 countries or territories around the world have been affected so far by this deadly virus. Apart from the health crisis, COVID-19 has taken away the peace of the people by devastating the social, economic, and political crisis in every country under its effect [4]. The whole world is competing to reduce the havoc created with the spread of the virus by slowing down the contamination rate through increased testing and treatment of the patients, promoting self prevention and social distancing, quarantining people, contact tracing, stopping gatherings, etc. [5]. Social media platforms such as Facebook, Instagram, YouTube, and Twitter allow the spread of an enormous amount of fake information and rumors which manipulate the human mind [6]. A self-report instrument is developed in [7] to test the different psychological problems such as fear, panic, or phobia experienced by the people during this pandemic situation. The epicenter of the new crisis and death toll for COVID-19 has shifted in several months from China initially to Europe and then to USA [8–10]. The rapid increase in the contagion and deaths caused by COVID-19 is putting a significant load on the health care system of every highly affected country in the world [11]. Thus, it has become cutting edge research to develop the future trends of the novel COVID-19 causalities at this moment.

The present study is therefore motivated to develop a prediction model which can accurately predict the daily death toll in nine most affected countries like India, USA, Italy, UK, China, France, Iran, Spain, and Germany and could be used to predict the number of infections and causalities that will occur in future around the world. This prediction is extremely required by the government to develop a proper health care structure that is highly effected regions to minimize the damage of mankind due to this deadly virus by utilising the available resources in the best possible way. For building the prediction model, many conventional and modern forecasting techniques are available whose prediction accuracy mainly depends on the data availability and the reliability of the selection of different attributes used for forecasting [1, 12–15]. Depending upon the length of the forecast interval, forecasting may be classified as (i) short-term (ii) mid-term, and (iii) long-term. In this study, a univariate time series method has been proposed to generate forecasts of death cases in multiple countries for a few weeks to a month ahead which comes under midterm forecasting. Since the variation of the COVID-19 cases is highly non-linear in nature, therefore the decisions based on the linear time series forecasting methods like ARIMA [16, 17] and regression techniques [18–20] would be highly crucial. In many studies, the wavelet-based prediction model [21, 22] has shown good prediction accuracy for non-stationary data but fine analysis, it becomes computationally intensive and it becomes a tedious job to select the proper wavelet for the specific purpose and implement it correctly. A population model developed in [23] for healthy and infected people using fractional-order derivatives identify free immigration as an important factor to increase the infection of the current outbreak. In [24], it has been demonstrated that the predictions using more
complex models (like SEIR) may not be more dependable as compared to the simpler models.

This work proposes a Holt’s double exponential smoothening model which is a univariate time series method and is independent of the other attributes affecting the forecasts and performs direct prediction of the data by considering the historical data as model input [25–27]. The added advantage of Holt’s model is that the smoothening coefficients representing the level, trend, and seasonal component of the data can be optimized to get the high prediction accuracy of the model. Unlike the advanced deep learning-based methods such as long short-term memory (LSTM) and convolution neural network (CNN) [15], the Holt’s method with optimized parameters gives accurate and consistent prediction results for all the countries under this study with very less computational time and memory space requirement. For establishing the superiority of the proposed model, the results obtained by Holt’s model are compared with the prediction results of the polynomial curve fitting model which is a basic mathematical technique to find a mathematical function that can be used to model a data [28]. In [29], the polynomial curve fitting model has been used to forecast energy production by the renewable sources and it has been found better than the linear regression model in terms of accuracy and model fit. It is a simple and basic method of forecasting but has one limitation that the prediction does not take into account the significant fluctuations in the historical data (like trend and seasonality factors) [30], and hence it is more accurate for short-term forecasts and may not yield good prediction performance for long-term forecasts. The suitability of the proposed Holt’s model for nine profoundly affected countries signifies that the model will be applicable to any country for short-term, mid-term, and long term predictions of the cases related to infections and deaths due to COVID-19 pandemic.

The rest of the paper is organised as follows: Sect. 2 introduces the proposed prediction methods for one month ahead (mid-term) prediction of COVID-19 death cases for India, USA, Italy, UK, France, China, Iran, Spain, and Germany. The country-wise dataset description and their temporal variation are given in Sect. 3. Section 4 presents the results and discussion along with the comparison of the two prediction models discussed in Sect. 2. Finally, Sect. 5 concludes the paper.

2 Methodology

This work proposes the Holt’s Double Exponential Smoothening method with optimized coefficients and Polynomial fitting method to predict the total number of deaths due to COVID-19 across the nine most affected countries across the world. The complete forecasting procedure is shown in Fig. 1. The data for daily death cases is collected for nine most affected countries namely India, USA, Italy, UK, France, China, Spain, Iran, and Germany. Now, as the rise in the daily death cases in all the affected countries is extremely high, therefore a suitable prediction model is required to predict the causalities (deaths, infections, etc.) which can occur in the
future at a faster rate and higher accuracy. Due to this reason, the univariate time series prediction method is used here which requires only the past input data of the variable to be predicted and takes very less processing time to provide precise results. The entire dataset is divided into two parts: training and testing dataset.

The models are trained by the past data and the prediction results obtained are compared to select the best prediction model for all the countries. Finally, the selected model is used for one month ahead prediction of death cases in all the nine countries as mentioned above.

2.1 Holt’s Exponential Smoothening Method

Holt’s double exponential method is a univariate time series forecasting method used to predict the data having a trend. This method depends upon two smoothening coefficients, one for the level component and the other for the trend component. The mathematical equations describing the level and trend component are given below:

Level: \[ A_t = \alpha \times y_t + (1 - \alpha) \times (A_{t-1} + T_{t-1}) \]  \hspace{1cm} (1)

Trend: \[ T_t = \beta \times (A_t - A_{t-1}) + (1 - \beta) \times T_{t-1} \]  \hspace{1cm} (2)

Fig. 1 The stages of forecasting
The final forecast is the sum of the level and trend component of the predicted data. The final forecast equation can be written as:

\[ \text{Forecast} : F_{t+m} = A_t + T_t \times m \]  

The initial value of the level and trend component can be calculated using the following equations:

\[ A_1 = y_1, \quad T_1 = \frac{(y_2 - y_1) + (y_4 - y_3)}{2} \]

where; \( \alpha \) and \( \beta \) are the level and trend smoothening coefficients, \( A_t \) is the level component, \( T_t \) is the trend component, \( y_t \) is actual load, \( t \) is time period, \( F_{t+m} \) is the forecasted load for \( m \) periods ahead.

### 2.2 Polynomial Curve Fitting

The polynomial curve fitting method is a simple mathematical technique to model a data having a non-linear trend by assigning the best fit curve along with the entire range of the data spread. The polynomial function which fits the data more accurately is decided using the least square method that minimizes the sum of residuals of the actual and the plotted points. Initially, polynomial interpolation is performed to find the lowest degree polynomial which passes through the maximum given data points, and the obtained polynomial is extrapolated to estimate the data beyond the actual range of the observed data. The polynomial with the \( n^{th} \) degree can be described by the given mathematical equation:

\[ p = p_1x^n + p_2x^{n-1} + p_3x^{n-2} + \cdots + p_n + p_{n+1} \]  

where; \( p(x) \) is the polynomial of degree \( n \), \( p_1, p_2, \ldots, p_{n+1} \) are the polynomial coefficients and the length of polynomial \( p \) is \( n + 1 \). The prediction performance of the model is determined by the different performance parameters discussed below.

### 2.3 Performance Parameters

The prediction accuracy of the developed model is determined using the mean absolute percentage error (MAPE), root mean square error (RMSE), and the Pearson correlation coefficient \( (r) \). The mathematical formulas for the calculation of all the three metrics are given below:
MAPE = \frac{1}{N} \left| \sum_{i=1}^{N} \frac{(y_i - \tilde{y}_i)}{y_i} \right| \times 100 \quad (6)

where; \( N \) is the number of testing data samples, \( y_i \) is actual data and \( \tilde{y}_i \) is predicted data.

The RMSE between the actual and the predicted data is calculated as:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \tilde{y}_i)^2}{N}} \quad (7)
\]

Pearson correlation coefficient (\( r \)) is used to determine the relationship between the actual and predicted variable. It is calculated as:

\[
r_{xy} = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n \sum x_i^2 - (\sum x_i)^2} \sqrt{n \sum y_i^2 - (\sum y_i)^2}} \quad (8)
\]

where \( r_{xy} \) is the Pearson correlation coefficient between \( x \) and \( y \), \( n \) is the number of observations used for testing, \( x_i \) and \( y_i \) are the values of \( x \) and \( y \) for the \( i \)th observation.

### 3 Case Study

This section describes the datasets used for testing and validating the proposed prediction models. This paper deals with the daily death cases due to COVID-19 in the nine most affected countries across the world namely India, USA, Italy, China, UK, Spain, France, Iran, and Germany. The proposed Holt’s model is trained by the daily death cases used as input and the prediction results are compared with the polynomial model to obtain the best-suited prediction model for the given test system. The dataset consists of 218 daily observations ranging from 31/12/19 to 04/08/20. Here, 85% (188 data points) of the total data is used for training, and the remaining 15% (30 data points) is used for testing and validation of the model. The temporal variation of death cases of ten countries is shown in Fig. 2. From Fig. 2 it can be seen that the number of deaths has increased exponentially from around March 2020 for all the shown countries except China, as it has entered the recovery phase.
4 Results and Discussion

The Holt’s double exponential smoothing method with optimized parameters is used to predict the future death cases due to COVID-19 in nine most affected countries of the world. The performance of the optimized Holt’s model is compared with the fundamental statistical polynomial extrapolation method to determine the most accurate prediction with the least errors.

Optimized Holt’s method

Holt’s method is a univariate method for the prediction of the temporal data. It comprises three components: level, trend, and seasonality. In this paper, Holt’s double exponential smoothing method is used to predict the data having a level and trend components. Two smoothing coefficients $\alpha$ and $\beta$ (0–1) and the three Eqs. (1), (2) and (3) mentioned in Sect. 2.1 are used to develop the prediction model. Initially, the value of level and trend coefficients $\alpha$ and $\beta$ are taken as 0.5 each and the corresponding MAPE and RMSE values are computed for all the testing scenarios. To improve the prediction accuracy of the model, the coefficients $\alpha$ and $\beta$ are optimized to give the minimum MAPE value. The objective function is mentioned below:

$$\text{Minimize } \text{MAPE}(\alpha, \beta) = \sum_{i=1}^{N} \left| \frac{y_i - \tilde{y}_i}{y_i} \right| \times 100$$  \hspace{1cm} (9)

where $y_i$ is the actual data, $\tilde{y}_i$ is the predicted data and $N$ is the number of testing samples used. In this work, Generalized Reduced Gradient (GRG) nonlinear solver is used for parameter optimization. Initially, the solver calculates the objective...
function value which is MAPE by taking the parameters $\alpha$ and $\beta$ as 0.5. Now, as the input value changes, the GRG nonlinear solver calculates the slope of the objective function and finds the optimum solution when the partial derivatives become 0. Finally, it calculates the optimum value of the smoothening coefficients which yields the minimum MAPE and RMSE for all the given inputs. The optimized values of $\alpha$ and $\beta$ and the corresponding MAPE and RMSE values before and after are given in Table 1.

It can be observed that the performance of Holt’s model in terms of MAPE and RMSE is improved many times after the optimization of the smoothening parameters ($\alpha$ and $\beta$) for each country under study. The comparison of the prediction performance by Holt’s model and polynomial curve fitting method is given in Table 2. The degree of the polynomial ($n$) is the minimum degree which gives the least computed error or there is no significant decrease in the error as the degree is increased. The results show that the prediction performance of Holt’s method with optimized parameters is far better than the statistical polynomial curve fitting method in all the cases. This proves the accuracy of the optimized Holt’s model over the polynomial model for the non-linear temporal testing data. The MAPE for all the nine mentioned countries is reduced by 80% by using Holt’s model as observed from Table 2. The minimum and maximum MAPE obtained by Holt’s model is between 0-3% whereas the polynomial fitting model is around 5–25% in all the cases which again signifies that the predicted values are very close to the actual data resulting in greater prediction accuracy and high goodness of fit.

The real-time prediction plots showing the comparison of the model forecasts for all the countries under study are shown in Fig. 3. The plots indicate that the predicted data is much closer to the observed data points in the case of Holt’s model in all the nine countries used for this study. The red line for Holt’s model in the plots indicates the least deviation of the predicted data from the actual data for all the nine countries as visualized from (i) to (viii) of Fig. 3. It can be seen from the comparison plot of China in Fig. 3(iv), that the prediction curve is plotted for the

| Table 1 | Forecasting using Holt’s model |
|---------|-------------------------------|
| S. No.  | Country | Before optimization | After optimization |
|         |        | $\alpha$ | $\beta$ | MAPE | RMSE | $\alpha$ | $\beta$ | MAPE | RMSE |
| 1       | India  | 0.5     | 0.5     | 7.87 | 3326.80 | 0.15 | 1.0     | 2.21 | 767.43 |
| 2       | Italy  | 0.5     | 0.5     | 0.46 | 194.64  | 0.14 | 0.23    | 0.34 | 148.22 |
| 3       | USA    | 0.5     | 0.5     | 0.99 | 2189.82 | 0.36 | 1.0     | 0.71 | 1261.93 |
| 4       | UK     | 0.5     | 0.5     | 1.73 | 924.58  | 0.08 | 0.22    | 0.91 | 100.21 |
| 5       | China  | 0.5     | 0.5     | 0.18 | 12.88   | 1.0 | 0.06    | 0.082 | 5.32 |
| 6       | France | 0.5     | 0.5     | 0.30 | 112.13  | 0.67 | 1.0     | 0.75 | 286.83 |
| 7       | Iran   | 0.5     | 0.5     | 3.74 | 734.06  | 0.18 | 1.0     | 1.89 | 408.55 |
| 8       | Spain  | 0.5     | 0.5     | 0.54 | 178.08  | 0.99 | 0.85    | 0.11 | 51.73 |
| 9       | Germany| 0.5     | 0.5     | 0.67 | 73.76   | 0.14 | 1.0     | 0.382 | 42.88 |
entire range of data including the training and testing dataset i.e. total 136 data points, unlike other countries where the prediction plot is shown for the testing dataset only. This is because of the entire different trend in the variation of death cases in China as it has entered into the recovery phase when all other countries are facing the exponential rise in the death cases, this can also be proved from Fig. 2 which shows the time-series variation of death cases for different countries. The comparative MAPE values obtained by both the prediction models for the nine most affected countries can also be visualized by the box plot shown in Fig. 4. The two boxes in the plot show the range of MAPE values obtained for all the nine countries using Holt’s and Polynomial prediction models. The red line in each box represents the median of the MAPE values. From the two boxes of the box plot, it can be observed that the MAPE values are lower and in a comparable range in the case of Holt’s model as compared to the polynomial model of prediction. For Holt’s model, the MAPE is in the range of 0–3% whereas, for the polynomial model, the range of MAPE is between 5 and 25% which concludes that the Holt’s model with optimized parameters gives the high prediction accuracy for all the nine countries tested under this study and hence can be used further for prediction of various causalities across the whole world due to this pandemic.

The one month ahead prediction of death cases in all the nine most affected countries mentioned above using Optimized Holt’s double exponential smoothing method is shown in Fig. 5.

As a case study, the actual and predicted death counts in all the nine countries for two days (15/07/20 and 08/08/20) are given in Table 3. The data of 15/07/20 is used for testing the proposed model and 08/08/20 is the independent out of sample data for which the prediction has been done. It has been found that the death count predicted by the proposed method is very close to that of the actual death count irrespective of the country under observation. On an average, the accuracy for the

| S. No | Country | Optimized Holt’s model MAPE | RMSE | r | Polynomial fitting model MAPE | RMSE | r | n |
|-------|---------|-----------------------------|------|---|-------------------------------|------|---|---|
| 1.    | India   | 2.21                        | 767.43 | 0.990 | 2.45                        | 1095.72 | 0.986 | 3 |
| 2.    | Italy   | 0.34                        | 148.22 | 0.989 | 24.61                       | 8.84E + 03 | 0.982 | 1 |
| 3.    | USA     | 0.71                        | 1261.93 | 0.997 | 7.37                        | 1.04E + 04 | 0.988 | 3 |
| 4.    | UK      | 0.91                        | 100.21 | 0.992 | 6.82                        | 3.72E + 03 | 0.977 | 3 |
| 5.    | China   | 0.082                       | 5.32   | 0.989 | 14.81                       | 805.32 | 0.974 | 4 |
| 6.    | France  | 0.75                        | 286.83 | 0.980 | 22.26                       | 7.92E + 03 | 0.968 | 2 |
| 7.    | Iran    | 1.89                        | 408.55 | 0.995 | 4.90                        | 9.95E + 03 | 0.991 | 2 |
| 8.    | Spain   | 0.11                        | 51.73  | 0.985 | 10.15                       | 2.62E + 03 | 0.977 | 2 |
| 9.    | Germany | 0.382                       | 42.88  | 0.988 | 13.78                       | 1.11E + 03 | 0.970 | 3 |

$n$ = degree of the polynomial
Fig. 3 Real-time forecasts (for 30 days) of Holt’s and Polynomial curve fitting model for 9 countries namely (i) Italy, (ii) USA, (iii) UK, (iv) China, (v) France, (vi) Iran, (vii) Spain, (viii) Germany, and (ix) India
two mentioned dates as per Table 3 is 99.57% and 97.85% respectively. This confirms that the proposed model gives remarkably good prediction results for the in sample (testing) as well as for out of sample future data for various countries under this study.

Fig. 4 Box plot showing MAPE values using two prediction models

Fig. 5 One month ahead forecasts of death cases using Holt’s model
5 Conclusion

This paper proposes a new prediction technique for forecasting of fatalities caused due to the outbreak of COVID-19 pandemic using optimized Holt’s double exponential smoothening method. The model is developed using the datasets collected from the nine most affected countries around the world namely India, USA, UK, Italy, China, France, Spain, Iran, and Germany. The accuracy of the proposed method is evaluated by training the model using the past 188 daily death cases data and tested for 30 days ahead prediction within the sample which was further used to forecast one month ahead out of sample death cases in nine countries mentioned above. The suitability of the proposed method is validated through the comparison of forecasts obtained by the polynomial curve fitting method. The average MAPE for all the given countries calculated by Holt’s method is around 1% and by Polynomial fitting model is around 12%, which concludes that the Holt’s model gives the best forecasting performance for all different scenarios of input datasets. The proposed method has been used to estimate the total death counts for a future date (08/08/20) with an average accuracy close to 98%. As the model performs well in the mid-term, the same work can be extended for forecasting the number of infections and death cases in all the countries for a mid-term, short-term, and long-term period too. The prediction of fatalities can help in the social, economical, and financial planning of the governments in advance so that the least possible devastation of lives can occur.

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