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Prediction of Infectious Disease to Reduce the Computation Stress on Medical and Health Care Facilitators

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Abstract

Prediction of the infectious disease is a potential research area from the decades. With the progress in medical science, early anticipation of the disease spread becomes more meaningful when the resources are limited. Also spread prediction with limited data pose a deadly challenge to the practitioners. Hence, the paper presents a case study of the Corona virus (COVID-19). COVID-19 has hit the major parts of the world and implications of this virus, is life threatening. Research community has contributed significantly to understand the spread of virus with time, along with meteorological conditions and other parameters. Several forecasting techniques have already been deployed for this. Considering the fact, the paper presents a proposal of two Rolling horizon based Cubic Grey Models (RCGMs). First, the mathematical details of Cubic Polynomial based simple grey model is presented than two models based on time series rolling are proposed. The models are developed with the time series data of different locations, considering diverse overlap period and rolling values. It is observed that the proposed models yield satisfactory results as compared with the conventional and advanced grey models. The comparison of the performance has been carried out with calculation of standard error indices. At the end, some recommendations are also framed for the authorities, that can be helpful for decision making in tough time.

Keywords: grey system theory (/search?q=grey+system+theory); **Mean Absolute Percentage Error (/search?q=Mean+Absolute+Percentage+Error)**; **forecasting (/search?q=forecasting)**; **grey forecasting (/search?q=grey+forecasting)**

MSC: 60G25; 68U01

1. Introduction

COVID-19 or coronavirus is rapidly spreading all over the world since its first case in December 2019 at Wuhan city, China. The initial symptoms are similar to viral pneumonia, which can be further converted into severe respiratory disease or even lungs failure. The virus named as SAES-CoV-2 is very infectious and easily transmissible [**1**] and thus became a threat to society. Due to its exponential infectious rate, it is challenging task to treat infected persons [**2**] and stop the spread further. Despite all types of safety measures like social distancing, washing hands regularly, proper sanitization, and use of mask to cover nose and mouth, a large number of cases are reported worldwide creating panic among people. Under these severe conditions, it has been declared a global pandemic by world Health Organization [**3**].

In India, the first infection of coronavirus has came in light on 30 January 2020 and after that, it spread in almost every city although rural areas remain safe. Later-on, the spread became hazardous as till 28 May 2021, there are 2,343,152 active cases recorded out of which 318,895 have lost their lives. This create a lot of stress and pressure on health officials and administration as they are doing multitasking works. To treat the infected, proper vaccination, arrangement of various safety measures at work places and common places and prepare policies for future are among top priorities. Scientist community did not left behind this crucial time and many researcher use forecasting techniques as a powerful boon to predict the future conditions [**4**,**5**].

Forecasting, became a new research tool in recent years and widely used in almost all areas of social sciences like economics, energy prediction and energy demand, engineering, air pollution, recommendation systems, control systems, retail fashion etc. Refs. [**6**,**7**,**8**,**9**,**10**,**11**,**12**,**13**,**14**] are some fine examples of application of different methods in forecasting. There exists traditional forecasting methods like LR (Linear Regression), ARIMA (Auto Regressive Integrated Moving Average), ANN (Artificial Neural Network), SVR (Support Vector Machine) etc., which need ample amount of data. In case of disease, it is not easy to collect the data of large sample size following a, specific distribution model at early stages. It has became more difficult, when facing the pandemic like COVID-19. A time series based prediction has been conducted for Canada. The research employed Long short-term memory (LSTM) network for carrying out the prediction [**15**]. Auto Regressive Integrated Moving Average (ARIMA) based models are employed for prediction of the COVID-19 in five countries namely US, Brazil, India, Russia and Spain [**16**]. A rich review of forecasting model pertaining to COVID-19 has been presented in paper [**17**]. A comparative analysis of strength and weakness of different forecasting models has been presented in the paper. The analysis conducted in the paper inherent problems pertaining to limited data availability (Deep learning algorithms), stability of the ARIMA models and black box characteristics of Artificial Neural Networks.

Grey prediction theory proposed by Prof. J. Deng [**18**], is the best tool to approach problems having limited data with uncertainty. It can be said that grey model employs local information and act as a local predictor. Grey theory works as a transform model as it transform the unknown data into consistent data. This transformation has done through Accumulation Generation Operator known as AGO. The main objective of Grey theory is to provide a real time based non-functional model which can replace the regression and stochastic models while dealing with poor and hidden data. Recently some authors approached Grey models for forecasting due to their accurate prediction and practical approach. Halis Bilgil [**19**] proposed an exponential Grey model to forecast the prediction no of new cases, recovered cases and no. of deaths from COVID-19 in Turkey. In [**20**] authors developed a grey forecasting model enabled with quadratic terms to predict about the COVID-19 impact at early stages in China. A. Saxena [**21**] used optimized Grey prediction model for forecasting about the pandemic using the data of four different states of India. Similarly Particle Swarm Optimization is used in [**22**] to optimized the results provided by GM(1,1) and others.

GM(1,1) [**23**] model has considered as the classical grey model due to its accuracy and practical approach. Cui and others [**24**] proposed NGM having a linear function of time in the whitening equation. This model is further improved as NGM(1,1,k,c) [**25**] by adding a constant term in RHS component of whitening equation. A kernel based model is introduced in [**26**] to increase the accuracy and application areas of NGM. A novel discrete Grey forecasting model known as DGM has been developed for further improvisation in existing grey models in [**27**,**28**]. Some multivariable grey models are also proposed as an extensions of earlier grey models in [**29**,**30**,**31**]. However, GM(1,1) model provide very good results with homogeneous data set only. Some models which can deal with non-homogeneous terms also provide large amount of errors with some specific sequences. Some very useful experimentation for the prediction of market clearing price is showcased in references [**32**,**33**]. Further the rich review of forecasting methods has been presented in reference [**34**]. Also come of the approaches used grey model in financial transactions [**35**].

The parameter of grey action term is also an important factor which fluctuate the accuracy of prediction using grey models. Some recent approaches also employed, advance meta heuristic approaches for tuning the parameters of grey model. In [**36**] cuckoo search algorithm is used to select the optimal value of grey parameter. Similarly Whale Optimization Algorithm has been applied in [**37**] to find the best suitable value of nonlinear parameter.

Hence, to overcome these weaknesses, we proposed a grey model (RCGM), which has a negative term in its whitening equation and act as a corrector while dealing with specific data sequence. This literature review clearly indicates that scope of improvement is always available.

Hence, the research directions of developing the new grey models can be identified as follows:

- Change in accumulation operator
- Change in back ground value information
- Transformation of the series into a new one in order to deal with negative data.

Hence, It is pragmatic to state that a new model that possess better matching quality (or mechanisms discussed above) of limited data availability can be potential area of investigation. On the basis of the critical review, we framed the following research objectives for this work

1. To develop a rolling horizon based grey model for identification of Novel Corona virus cases in a span of week.
2. To establish mathematical framework of Cubic polynomial driven grey model by analysing the response and mathematical induction.
3. To present a comparative analysis of developed models with some known grey models and evaluate the performance with the calculation of various error indices.
4. To frame the recommendations on the basis of forecasting results for authorities to take preventive steps for combating Corona effectively.

Paper Structure

Remaining part of this paper is organized as follows: in **Section 2**, development of grey models is explained. In **Section 3**, results of the proposed models are exhibited and last but not the least some future directions along with conclusions of the study are presented in conclusion section. **Figure 1**, shows the basic philosophy adopted in this research work.

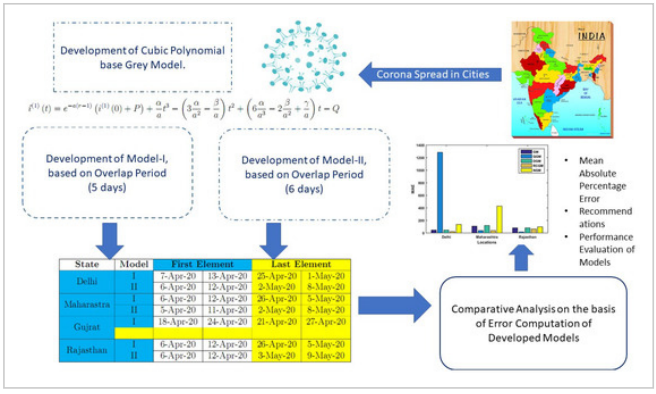


Figure 1. Paper structure.

2. Development of Rolling Horizon Grey Model Comprises with Cubic Polynomial (RCGM)

2.1. Details of Conventional Grey Models

This subsection provides a general outlook of some well known Grey models and their mathematical equations, which will be used further in this paper

1. GM(1,1) model: The classical GM(1,1) model is also known as the basic foundation model of grey theory and widely used in the forecasting of data with uncertainty. This model comprises of differential equation varying with time for variance of parameters. The basic equation of this model is

$$\frac{dy^{(1)}(t)}{dt} + ay^{(1)}(t) = b \quad (1)$$

The sequence based on time series is given by

$$\widehat{y}^{(1)}(k+1) = e^{-a(k)}\left(y^{(1)}(0) - \frac{b}{a}\right) + \frac{b}{a} \tag{2}$$

$$\widehat{y}^{(0)}(k) = e^{-a(k-2)}\left(y^{(1)}(0) - \frac{b}{a}\right)(e^{a} - 1) \tag{3}$$

2. DGM(1,1) model: The mathematical terms of discrete grey model (DGM) proposed in [**27**,**38**] are given by

$$y^{(1)}(k+1) = ay^{(1)}(k) + b \tag{4}$$

$$\widehat{y}^{(1)}(k+1) = a^{k}y^{(0)}(1) + \left(\frac{1-a^{k}}{1-a}\right)b \tag{5}$$

3. NGM(1,1) model: The grey differential equation of NGM [**25**] is

$$y^{(0)}(k) + az^{(1)}(k) = kb + c \tag{6}$$

The time response equation is given by

$$\widehat{y}^{(1)}(k) = \left(y^{(1)}(1) - \frac{b}{a} + \frac{b}{a^{2}} - \frac{c}{a}\right)e^{-ak} + \frac{b}{a}k - \frac{b}{a^{2}} + \frac{c}{a} \tag{7}$$

and the restored value is given mathematically as

$$\widehat{y}^{(0)}(k) = \left(y^{(1)}(1) - \frac{b}{a} + \frac{b}{a^{2}} - \frac{c}{a}\right)(1-e^{a})e^{-ak} + \frac{b}{a} \tag{8}$$

4. QGM model: This nonlinear grey model was first proposed by [**20**] and provide higher prediction accuracy than previously proposed model. The whitenization differential equation of QGM model is represented by

$$\frac{dy^{(1)}(t)}{dt} + ay^{(1)}(t) = bt^{2} + ct + d \tag{9}$$

The time response term and restored values can be given as

$$\begin{aligned}\widehat{y}^{(1)}(k+1) = \left(y^{(1)}(0) - \frac{b}{a} + 2\frac{b}{a^{2}} - 2\frac{b}{a^{3}} - \frac{c}{a} + \frac{c}{a^{2}} - \frac{d}{a}\right)e^{-ak} + \frac{b}{a}(k+1)^{2} \\ -\left(2\frac{b}{a^{2}} - \frac{c}{a}\right)(k+1) + 2\frac{b}{a^{3}} - \frac{c}{a^{2}} + \frac{d}{a}\end{aligned} \tag{10}$$

$$\begin{aligned}\widehat{y}^{(0)}(k+1) = \left(y^{(1)}(0) - \frac{b}{a} + 2\frac{b}{a^{2}} - 2\frac{b}{a^{3}} - \frac{c}{a} + \frac{c}{a^{2}} - \frac{d}{a}\right)e^{-a(k-1)}(e^{a} - 1) \\ +2\frac{b}{a}(k+1) - \frac{b}{a} - 2\frac{b}{a^{2}} + \frac{c}{a}\end{aligned} \tag{11}$$

In recent years, grey models have been developed on several theories such as change in accumulation operators, transformation of the series to some other hyper space and incorporation of different background value modification techniques. In this work, we first explain some terms.

Definition 1. *Let us assume initial sequence as*

$$I_{(W,\mu)}^{(0)} = i^{(0)}(1), i^{(0)}(2), \cdots i^{(0)}(r) \tag{12}$$

where all terms of the sequence are taken non-negative.

The one time accumulated generating term is given by

$$I_{(W,\mu)}^{(1)} = i^{(1)}(1), i^{(1)}(2), \cdots i^{(1)}(r) \tag{13}$$

$$i_{(W,\mu)}^{(1)} = \sum_{j=1}^{r} i^{(0)}(j), r = 1, \cdots n \tag{14}$$

Definition 2. *The inverse process of finding the accumulated generation sequence can be given as*

The sequence mean of $I_{W,\mu}^{(0)}$ can be given as

$$Z^{(1)} = z^{(1)}(1), z^{(1)}(2), \cdots z^{(1)}(r) \tag{15}$$

where

$$Z^{(1)}(k) = \frac{i^{(1)}(k) + i^{(1)}(k-1)}{2} \text{for} k = 2, \cdots r \tag{16}$$

2.2. Rolling Horizon Based Cubic Grey Model (RCGM)

The first order linear differential equation known as whitening equation of proposed model GMCP is given by

$$\frac{di^{(1)}(t)}{dt} + ai^{(1)}(t) = \alpha t^3 + \beta t^2 + \gamma t + \delta \tag{17}$$

where *a* is the development coefficients and right hand side term is known as grey action quantity of grey model.

It can be easily observed that when $\alpha = 0$, the GMCP model reduced to QGM model. When $\alpha = 0, \beta = 0$, it reduced to NGM(1,1,k,c) model. On putting $\alpha = 0, \beta = 0, \gamma = 0$, one can find the classical GM(1,1) model.

Theorem 1. *If $y^{(0)}(r)$ is a term of the non-negative sequence and $z^{(1)}(r)$ is the rth term of mean sequence $Z^{(1)}(r)$ defined by (16) then*

$$i^{(0)}(r) + az^{(1)}(r) = \alpha\left(r^3 - \frac{3}{2}r^2 + r - \frac{1}{4}\right) + \beta\left(r^2 + r - \frac{1}{3}\right) + \gamma\left(r - \frac{1}{2}\right) + \delta \tag{18}$$

Proof. Integrating the whitening equation defined in (17) both sides w. r. to t between the interval $[r-1, r]$

$$\int_{r-1}^{r}\left[\frac{di^{(1)}(t)}{dt} + ay^{(1)}(t)\right]dt = \alpha\int_{r-1}^{r} t^3 dt + \beta\int_{r-1}^{r} t^2 dt + \gamma\int_{r-1}^{r} t dt + \delta\int_{r-1}^{r} dt \tag{19}$$

which gives us

$$i^{(0)}(r) + a\int_{r-1}^{r} + i^{(1)}(t)\,dt =$$

$$\alpha\frac{\left(r^4 - (r-1)^4\right)}{4} + \beta\frac{\left(r^3 - (r-1)^3\right)}{3} + \gamma\frac{\left(r^2 - (r-1)^2\right)}{3} + \delta \tag{20}$$

using Trapezoidal formula $\int_{r-1}^{r} i^{(1)}(t)\,dt = \frac{i^{(1)}(r)+i^{(1)}(r-1)}{2} = z^{(1)}(r)$ and after some simplification, we have the RHS of Theorem 1. □

Theorem 2. *If the initial sequence and its inverse accumulated sequence is given by Definitions 1 and 2 and the mean sequence is represented by (16) then the values of parameters a, α, β, γ and δ in terms of matrix A and X are given by*

$$(a,\alpha,\beta,\gamma,\delta)^T = \left(A^TA\right)^{-1}A^TX \tag{21}$$

where

$$A = \begin{bmatrix} -z^1(2) & \frac{15}{4} & \frac{7}{3} & \frac{3}{2} & 1 \\ -z^13 & \frac{77}{4} & \frac{19}{3} & \frac{5}{2} & 1 \\ \vdots & \vdots & \vdots & \vdots & \\ -z^1(r) & \left(r^3-\frac{3}{2}r^2+r-\frac{1}{4}\right) & \left(r^2-r+\frac{1}{3}\right) & \left(r-\frac{1}{2}\right) & 1 \end{bmatrix} \tag{22}$$

and

$$X = \begin{bmatrix} i^0(2) \\ i^0(3) \\ \vdots \\ i^0(r) \end{bmatrix} \tag{23}$$

Proof. Using the concept of mathematical induction on taking $r = 2, 3, \cdots n$ in Theorem 1, we find

$$\begin{cases} i^0(2) = -az^{(2)} + \frac{15}{4}\alpha + \frac{7}{3}\beta + \frac{3}{2}\gamma t + \delta \\ i^0(3) = -az^{(3)} + \frac{77}{4}\alpha + \frac{19}{3}\beta + \frac{5}{2}\gamma t + \delta \\ \vdots \\ i^0(n) = -az^{(n)} + \left(n^3-\frac{3}{2}n^2+n-\frac{1}{4}\right)\alpha + \left(n^2-n+\frac{1}{3}\right)\beta + \left(n-\frac{1}{2}\right)\gamma t + \delta \end{cases} \tag{24}$$

On expressing the above system of linear equations in matrix form we obtain

$$\begin{bmatrix} -z^1(2) & \frac{15}{4} & \frac{7}{3} & \frac{3}{2} & 1 \\ -z^13 & \frac{77}{4} & \frac{19}{3} & \frac{5}{2} & 1 \\ \vdots & \vdots & \vdots & \vdots & \\ -z^1(r) & \left(r^3-\frac{3}{2}r^2+r-\frac{1}{4}\right) & \left(r^2-r+\frac{1}{3}\right) & \left(r-\frac{1}{2}\right) & 1 \end{bmatrix} \begin{bmatrix} a \\ \alpha \\ \beta \\ \gamma \\ \delta \end{bmatrix} = \begin{bmatrix} i^0(2) \\ i^0(3) \\ \vdots \\ i^0(n) \end{bmatrix} \tag{25}$$

□

Theorem 3. *The time response sequence of proposed model GMCP is given by*

$$\hat{i}^{(1)}(r) = e^{-a(r-1)}\left(i^{(1)}(0)+P\right) + \frac{\alpha}{a}r^3 - \left(3\frac{\alpha}{a^2}-\frac{\beta}{a}\right)r^2 + \left(6\frac{\alpha}{a^3}-2\frac{\beta}{a^2}+\frac{\gamma}{a}\right)r - Q \tag{26}$$

and its restored value is

$$\hat{i}^{(0)}(r) = e^{-a(r-2)}\left(i^{(1)}(0)+P\right) + \frac{\alpha}{a}\left(3r^2-3r-1\right) - \left(\frac{3\alpha}{a}-\frac{\beta}{a}\right)(2r-1) + Q \tag{27}$$

where

$$P = -\frac{\alpha}{a} + \frac{3\alpha}{a^2} - \frac{6\alpha}{a^3} + \frac{6\alpha}{a^4} + \frac{\beta}{a} - \frac{2\beta}{a^2} + \frac{2\beta}{a^3} + \frac{\gamma}{a} - \frac{\gamma}{a^2} + \frac{\delta}{a} \tag{28}$$

$$Q = \frac{6\alpha}{a^3} - \frac{2\beta}{a^2} + \frac{\gamma}{a} - \frac{\delta}{a} \tag{29}$$

Proof. The general solution of whitening equation can be obtained easily from the theory of first order ordinary differential equation and given by

$$i^{(1)}(t) = i^{(1)}(0)e^{-a(t-1)} + \int_1^t (\alpha s^3 + \beta s^2 + \gamma s + \delta)e^{\int_t^s a du} ds \tag{30}$$

Now using the formula of simple integration, we can easily get

$$\widehat{i}^{(1)} = e^{-a(r-1)}\left(i^{(1)}(0) + P\right) + \frac{\alpha}{a}t^3 - \left(3\frac{\alpha}{a^2} - \frac{\beta}{a}\right)t^2 + \left(6\frac{\alpha}{a^3} - 2\frac{\beta}{a^2} + \frac{\gamma}{a}\right)t - Q \tag{31}$$

we can easily obtained its restore value by using the relation $i^{(0)}(r) = i^{10)}(r) - i^{(1)}(r-1)$.

To examine our proposed model we have used Mean Absolute Percentage Error (MAPE), Absolute Percentage error (APE) and Mean Absolute Error (MAE) defined as

- Mean Absolute Percentage Error

$$\text{MAPE} = \frac{1}{n}\sum_{r=1}^{n}\left|\frac{\widehat{y}^{(0)}(r) - y^{(0)}(r)}{y^{(0)}(r)}\right| \times 100$$

- Absolute Percentage Error

$$\text{APE} = \left|\frac{y^{(0)}(r) - \widehat{y}^{(0)}(r)}{y^{(0)}(r)}\right| \times 100 \quad r = 2, 3 \cdots n$$

- Mean Absolute Error

$$\text{MAE} = \frac{1}{n-l+1}\sum_{r=l}^{n}\left|\widehat{y}^{(0)}(r) - y^{(0)}(r)\right|$$

- Mean Square Error

$$\text{MSE} = \frac{1}{n}\sum_{r=l}^{n}\left(y^{(0)}(r) - \widehat{y}^{(0)}(r)\right)^2$$

Here n = total no of data points, $y^{(0)}(r)$ = actual value and $\widehat{y}^{(0)}(r)$ = predicted value.

□

2.3. Development of Rolling Cubic Grey Model (RCGM)

In this section, we explain the development of the rolling horizon based cubic grey model for prediction of covid cases at different locations of India. For constructing these models infected case values of a week are chosen and the mean values of the infected cases of this duration are considered as the element of time series. For obtaining second element of the time series, the values of infected cases are rolled to two places for model-I

and one place for Model-II as shown in **Figure 2**. In the figure, the yellow boxes show the rolled values of infected cases. Further, the construction of the time series data can be understood by reading the values from **Table 1**. The data presented in this work has been taken from reference [**21**]. The time series constructed on the basis of rolling horizon of a week data of infected cases at different locations of India [**39**,**40**].

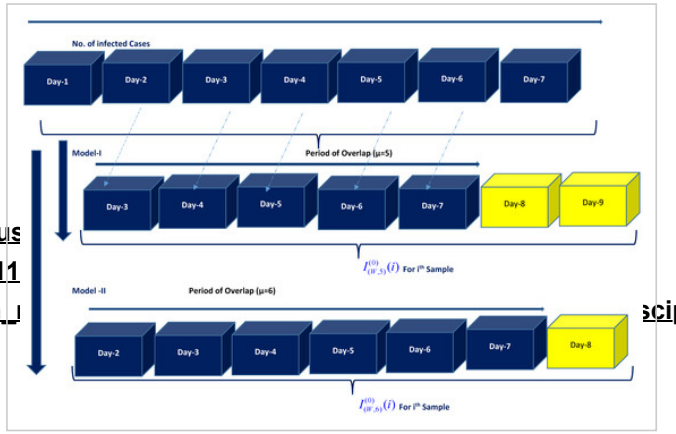


Figure 2. Proposed Rolling horizon based Grey Forecasting Models.

Table 1. Construction of Rolling Grey Models-I and II [**21**].

This table shows the relevant statistics for construction of the time series data for three different states and Capital. The column entries under first element shows the mean values of infected cases during the mentioned time period for different states. Like wise, last entry of the time series is shown under last element. For example, for state of Maharashtra the first element of the time series of the model-I mean values of 6 April 2020 to 12 April 2020 and the mean values of infected cases between 26 the April-2020 to 5 May 2020 will be the last value for time series. The data presented in this work has been taken from reference [**21**]. The time series constructed on the basis of rolling horizon of a week data of infected cases at different locations of India [**39**,**40**].

2.4. Discussion

Normally grey models are employed for the forecasting of the variable that contains exponential component. Corona spread between the duration mentioned in **Table 1**, observed an exponential increment during the period of time. Hence, application of rolling models on this particular duration for dealing with non-linearity is very helpful in prediction on the other hand exponential trend makes the model more compatible for prediction the spread. From the reference [**21**], it has been observed that the presence of monotonically increasing exponential component in the data pattern , the grey models are applicable on these data sets. Hence, the mechanisms that can improve the internal prediction capability of grey structure can substantially enhance the prediction.

Motivation of the two models has been taken from the reference paper of COVID-19, where the article showcases the impact of different windowing and overlap period. Further, we directly implement our algorithm from the results and discussions from the paper. We also argue whether the same results are obtained with the philosophy. Hence, the two models by considering the same overlap period are proposed in the work with optimized cubic grey model.

3. Results

On the basis of framework developed in previous section, in this section we present a comparative analysis of the proposed model with some contemporary models such as GM(1,1) and NGM model. Following are the salient features of this analysis: a. Establishment of the efficient architecture on the basis of calculation of error indices. Calculation of the mean values of infected cases in the state of Rajasthan, Gujarat and Maharashtra and Capital of India (Delhi).

3.1. Model I

Results of model-I are shown in **Table 2**, **Table 3** and **Table 4**. From the results shown in tables following points can be concluded:

Table 2. Predicted values from Delhi data Model I.

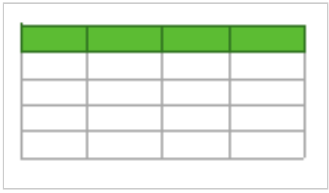


Table 3. Predicted values from Maharashtra data Model I.

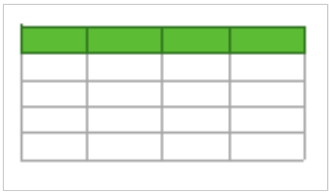
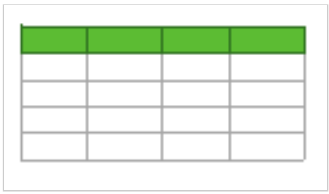


Table 4. Predicted values from Rajasthan data Model I.



1. For obtaining the results of Model-I, the time series is constructed with overlap period of five days and a rolling model is developed by rolling the mean values of a week by two days. The prediction of this series is evaluated with proposed RCGM and four other models such as (GM [**23**], NGM [**24**], DGM [**38**] and QGM [**20**]).
2. The prediction results of the states of Maharashtra, Rajasthan and Delhi are shown in tables. These prediction results show that pandemic spread is exponentially increasing in these locations and an acute requirement or advisory is necessary along with the medical help.
3. Inspecting the results of Delhi, we observed that the values of infected cases in the Capital is accurately predicted by RCGM as the value of MAPE is optimal as compared to others. Also, it is observed that the values of MAPE are optimal for state of Maharashtra and Rajasthan. The analysis of the MAPE values are depicted in **Figure 3**. Addition to that analysis MAE is for these places are also depicted in **Figure 4**.

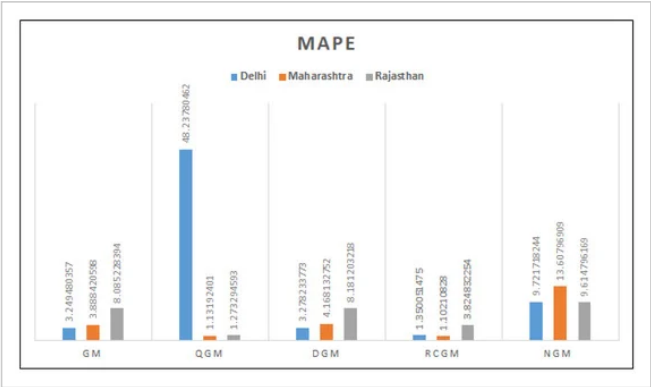


Figure 3. Forecasting Results-MAPE for Model-I.

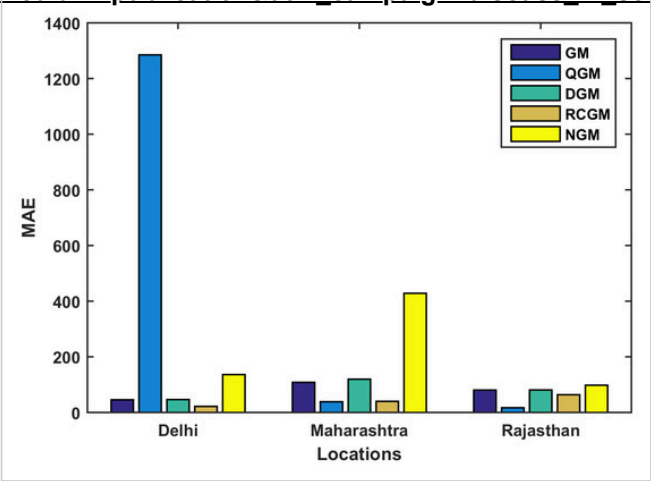


Figure 4. Forecasting Results-MAE.

3.2. Model II

Table 5, **Table 6**, **Table 7** and **Table 8** showcase the results of model II. After inspecting the results the following points can be framed:

Table 5. Predicted values from Delhi data Model II.

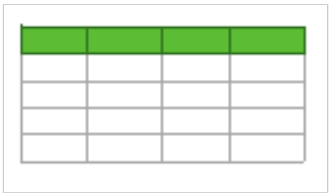


Table 6. Predicted values from Maharashtra data Model II.

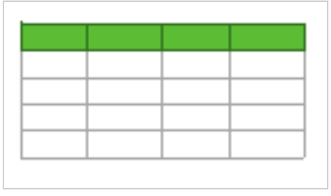


Table 7. Predicted values from Gujarat data Model II.

Table 8. Predicted values from Rajasthan data Model II.

1. For obtaining the results of Model-II, the time series is constructed with overlap period of six days and a rolling model is developed again. The prediction of this series is evaluated with proposed RCGM and four other grey models.
2. The prediction results in terms of MAPE are depicted through **Figure 5**, from the figure, it is empirical to state that the MAPE values are optimal for proposed model. This fact affirms the applicability of of this RCGM model.

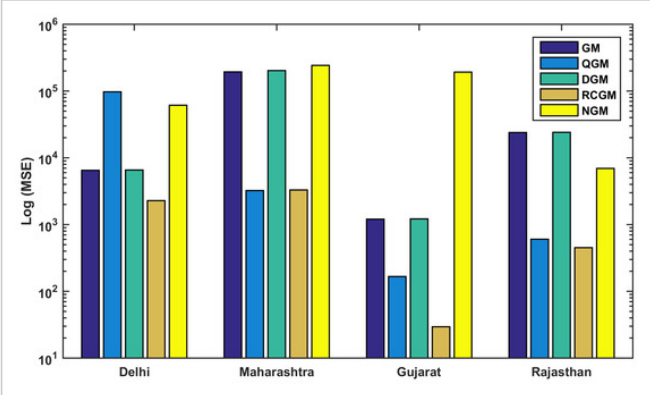


Figure 5. Forecasting Results-MSE for Model-II.

3. In case of all states along with Delhi, the values of MAPE are optimal. Addition to that, Mean absolute errors are also calculated for this model. Inspecting these values, it is concluded that these values are also quite optimal for RCGM. The analysis of MAE and MSE are shown in **Figure 4** and **Figure 5**.

3.3. Discussion

Further, with the help of error indices, we can conclude that developed forecast is meaningful as the MAPE calculated for different models are meaningful. In reference [**33**] criterion has been employed to judge the quality of forecast. We conclude that the forecasting performance of the Model-I and II falls in the range of good and excellent as MAPE values are less than 10%.

3.4. Recommendations

On the basis of forecasting performance of the RCGM, it is concluded that proposed model yields satisfactory performance for obtaining the infected cases at the major hot spots of India. Based on the forecasts following recommendations can be given to the authorities:

- It is empirical to state that the no. of infected cases can be increased in due course of time, hence an acute arrangement of medical facilities and health care related facilities can be appended.
- An awareness program can be initiated for imparting the education to the rural areas about the disease and its implications. Addition to that, an online alert can be issued to major spots and guidelines for travel and other social gatherings can be changed according to the situation.

- Adequate arrangements can be done for converting the unused buildings/schools and colleges for conversion in major relief centres of the corona. Also, the awareness programs can be arranged by the people who have successfully defeated this disease. This can be broadcast on social media and local channels of televisions and radio.

4. Conclusions

Forecasting of a pandemic is a challenging task due to various reasons such as unavailability of the data, effect of unexpected influence of policy decisions, public fear and scant facility of the medical resources. During last two years, the world is fighting hand in hand with corona virus. The work presented in the paper describes development of Rolling horizon forecast model based on Cubic polynomial realization. First the mathematical aspects of the cubic model are explained and then the development of the optimized models is carried out for identifying the corona infected cases at different location of India.

- Two time series models based on diverse overlapping periods and rolling horizon are presented. Mathematical representation of these models is presented. Further, the analysis of these models is conducted with the help of COVID-19 case studies at different states of India.
- It has been observed that proposed models produce accurate results as compared to previous reported approaches on the same data. Comparison of the performance of the models has been done on the basis of different error indices evaluation. Further, we argue that due to lack of abundant data, we employ grey model with rolling horizon and also analyses are conducted with the calculation of many indices.
- It is concluded that the proposed approach is effective and yields accurate results and further can be implemented for improving medical facilities and other life supporting resources.

It would be interesting to observe the performance of RCGM on forecasting of energy price and market clearing price for the energy markets along with other existing problems that suffers from limited data availability.

Author Contributions

Formal analysis and Funding acquisition, R.A.Z. and A.W.M. ; Investigation and Methodology, S.S. and A.S.; Project administration, A.S.; Software, A.S. ; Supervision, A.S. and A.W.M.; Validation, A.W.M. and R.A.Z.; Visualization, A.S.; Writing—original draft, S.S. and A.S.; Writing, review & editing, S.S. and A.S. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Not applicable.

Acknowledgments

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Conflicts of Interest

The authors declare no conflict of interest.

References

1. Huang, C.; Wang, Y.; Li, X.; Ren, L.; Zhao, J.; Hu, Y.; Zhang, L.; Fan, G.; Xu, J.; Gu, X.; et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet* **2020**, *395*, 497–506. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Clinical+features+of+patients+infected+with+2019+novel+coronavirus+in+Wuhan,+China&author=Huang,+C.&author=Wang,+Y.&author=Li,+X.&author=Ren,+L.&author=Zhao,+J.&author=Hu,+Y.&author=Zhang,+L.&author=Fan,+G.&author=Xu,+J.&author=Gu,+X.&publication_year=2020&journal=Lancet&volume=395&pages=497%E2%80%93506&doi=10.1016/S0140-6736(20)30183-5&pmid=31986264)**] [**CrossRef (https://doi.org/10.1016/S0140-6736(20)30183-5)**] [**PubMed (http://www.ncbi.nlm.nih.gov/pubmed/31986264)**] [**Green Version (http://www.thelancet.com/article/S0140673620301835/pdf)**]

2. Vellingiri, B.; Jayaramayya, K.; Iyer, M.; Narayanasamy, A.; Govindasamy, V.; Giridharan, B.; Ganesan, S.; Venugopal, A.; Venkatesan, D.; Ganesan, H.; et al. COVID-19: A promising cure for the global panic. *Sci. Total. Environ.* **2020**, *725*, 138277. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=COVID-19:+A+promising+cure+for+the+global+panic&author=Vellingiri,+B.&author=Jayaramayya,+K.&author=Iyer,+M.&author=Narayanasamy,+A.&author=Govindasamy,+V.&author=Giridharan,+B.&author=Ganesan,+S.&author=Venugopal,+A.&author=Venkatesan,+D.&author=Ganesan,+H.&publication_year=2020&journal=Sci.+Total.+Environ.&volume=725&pages=138277&doi=10.1016/j.scitotenv.2020.138277&pmid=32278175)**] [**CrossRef (https://doi.org/10.1016/j.scitotenv.2020.138277)**] [**PubMed (http://www.ncbi.nlm.nih.gov/pubmed/32278175)**]

3. Cucinotta, D.; Vanelli, M. WHO declares COVID-19 a pandemic. *Acta Bio Medica Atenei Parm.* **2020**, *91*, 157. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=WHO+declares+COVID-19+a+pandemic&author=Cucinotta,+D.&author=Vanelli,+M.&publication_year=2020&journal=Acta+Bio+Medica+Atenei+Parm.&volume=91&pages=157)**]

4. Tobías, A. Evaluation of the lockdowns for the SARS-CoV-2 epidemic in Italy and Spain after one month follow up. *Sci. Total. Environ.* **2020**, *725*, 138539. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Evaluation+of+the+lockdowns+for+the+SARS-CoV-2+epidemic+in+Italy+and+Spain+after+one+month+follow+up&author=Tob%C3%ADas,+A.&publication_year=2020&journal=Sci.+Total.+Environ.&volume=725&pages=138539&doi=10.1016/j.scitotenv.2020.138539&pmid=32304973)**] [**CrossRef (https://doi.org/10.1016/j.scitotenv.2020.138539)**] [**PubMed (http://www.ncbi.nlm.nih.gov/pubmed/32304973)**]

5. Wang, L.; Li, J.; Guo, S.; Xie, N.; Yao, L.; Cao, Y.; Day, S.W.; Howard, S.C.; Graff, J.C.; Gu, T.; et al. Real-time estimation and prediction of mortality caused by COVID-19 with patient information based algorithm. *Sci. Total. Environ.* **2020**, *727*, 138394. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Real-time+estimation+and+prediction+of+mortality+caused+by+COVID-19+with+patient+information+based+algorithm&author=Wang,+L.&author=Li,+J.&author=Guo,+S.&author=Xie,+N.&author=Yao,+L.&author=Cao,+Y.&author=Day,+S.W.&author=Howard,+S.C.&author=Graff,+J.C.&author=Gu,+T.&publication_year=2020&journal=Sci.+Total.+Environ.&volume=727&pages=138394&doi=10.1016/j.scitotenv.2020.138394)**] [**CrossRef (https://doi.org/10.1016/j.scitotenv.2020.138394)**]

6. Bräuning, F.; Koopman, S.J. Forecasting macroeconomic variables using collapsed dynamic factor analysis. *Int. J. Forecast.* **2014**, *30*, 572–584. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Forecasting+macroeconomic+variables+using+collapsed+dynamic+factor+analysis&author=Br%C3%A4uning,+F.&author=Koopman,+S.J.&publication_year=2014&journal=Int.+J.+Forecast.&volume=30&pages=572%E2%80%93584&doi=10.1016/j.ijforecast.2013.03.004)**] [**CrossRef (https://doi.org/10.1016/j.ijforecast.2013.03.004)**] [**Green Version (http://papers.tinbergen.nl/12042.pdf)**]

7. Wu, L.; Liu, S.; Chen, D.; Yao, L.; Cui, W. Using gray model with fractional order accumulation to predict gas emission. *Nat. Hazards* **2014**, *71*, 2231–2236. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Using+gray+model+with+fractional+order+accumulation+to+predict+gas+emission&author=Wu,+L.&author=Liu,+S.&author=Chen,+D.&author=Yao,+L.&author=Cui,+W.&publication_year=2014&journal=Nat.+Hazards&volume=71&pages=2231%E2%80%932236&doi=10.1007/s11069-013-0960-z)**] [**CrossRef (https://doi.org/10.1007/s11069-013-0960-z)**]

8. Zhou, W.; He, J.M. Generalized GM (1, 1) model and its application in forecasting of fuel production. *Appl. Math. Model.* **2013**, *37*, 6234–6243. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Generalized+GM+(1,+1)+model+and+its+application+in+forecasting+of+fuel+production&author=Zhou,+W.&author=He,+J.M.&publication_year=2013&journal=Appl.+Math.+Model.&volume=37&pages=6234%E2%80%936243&doi=10.1016/j.apm.2013.01.002)**] [**CrossRef (https://doi.org/10.1016/j.apm.2013.01.002)**]

9. Zeng, B.; Tan, Y.; Xu, H.; Quan, J.; Wang, L.; Zhou, X. Forecasting the Electricity Consumption of Commercial Sector in Hong Kong Using a Novel Grey Dynamic Prediction Model. *J. Grey Syst.* **2018**, *30*, 159–174. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Forecasting+the+Electricity+Consumption+of+Commercial+Sector+in+Hong+Kong+Using+a+Novel+Grey+Dynamic+Prediction+Model&author=Zeng,+B.&author=Tan,+Y.&author=Xu,+H.&author=Quan,+J.&author=Wang,+L.&author=Zhou,+X.&publication_year=2018&journal=J.+Grey+Syst.&volume=30&pages=159%E2%80%93174)**]

10. Zhang, Y.; Xu, Y.; Wang, Z. GM (1, 1) grey prediction of Lorenz chaotic system. *Chaos Solitons Fractals* **2009**, *42*, 1003–1009. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=GM+(1,+1)+grey+prediction+of+Lorenz+chaotic+system&author=Zhang,+Y.&author=Xu,+Y.&author=Wang,+Z.&publication_year=2009&journal=Chaos+Solitons+Fractals&volume=42&pages=1003%E2%80%931009&doi=10.1016/j.chaos.2009.02.031)**] [**CrossRef (https://doi.org/10.1016/j.chaos.2009.02.031)**]

11. Ou, S.L. Forecasting agricultural output with an improved grey forecasting model based on the genetic algorithm. *Comput. Electron. Agric.* **2012**, *85*, 33–39. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Forecasting+agricultural+output+with+an+improved+grey+forecasting+model+based+on+the+genetic+algorithm&author=Ou,+S.L.&publication_year=2012&journal=Comput.+Electron.+Agric.&volume=85&pages=33%E2%80%9339&doi=10.1016/j.compag.2012.03.007)**] [**CrossRef (https://doi.org/10.1016/j.compag.2012.03.007)**]

12. Javed, S.A.; Liu, S. Predicting the research output/growth of selected countries: Application of Even GM (1, 1) and NDGM models. *Scientometrics* **2018**, *115*, 395–413. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Predicting+the+research+output/growth+of+selected+countries:+Application+of+Even+GM+(1,+1)+and+NDGM+models&author=Javed,+S.A.&author=Liu,+S.&publication_year=2018&journal=Scientometrics&volume=115&pages=395%E2%80%93413&doi=10.1007/s11192-017-2586-5)**] [**CrossRef (https://doi.org/10.1007/s11192-017-2586-5)**]

13. Lin, W.M.; Hong, C.M.; Huang, C.H.; Ou, T.C. Hybrid control of a wind induction generator based on Grey–Elman neural network. *IEEE Trans. Control Syst. Technol.* **2013**, *21*, 2367–2373. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Hybrid+control+of+a+wind+induction+generator+based+on+Grey%E2%80%93Elman+neural+network&author=Lin,+W.M.&author=Hong,+C.M.&author=Huang,+C.H.&author=Ou,+T.C.&publication_year=2013&journal=IEEE+Trans.+Control+Syst.+Technol.&volume=21&pages=2367%E2%80%932373&doi=10.1109/TCST.2012.2231865)**] [**CrossRef (https://doi.org/10.1109/TCST.2012.2231865)**]

14. Xia, M.; Wong, W.K. A seasonal discrete grey forecasting model for fashion retailing. *Knowl. Based Syst.* **2014**, *57*, 119–126. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=A+seasonal+discrete+grey+forecasting+model+for+fashion+retailing&author=Xia,+M.&author=Wong,+W.K.&publication_year=2014&journal=Knowl.+Based+Syst.&volume=57&pages=119%E2%80%93126&doi=10.1016/j.knosys.2013.12.014)**] [**CrossRef (https://doi.org/10.1016/j.knosys.2013.12.014)**]

15. Chimmula, V.K.R.; Zhang, L. Time series forecasting of COVID-19 transmission in Canada using LSTM networks. *Chaos Solitons Fractals* **2020**, *135*, 109864. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Time+series+forecasting+of+COVID-19+transmission+in+Canada+using+LSTM+networks&author=Chimmula,+V.K.R.&author=Zhang,+L.&publication_year=2020&journal=Chaos+Solitons+Fractals&volume=135&pages=109864&doi=10.1016/j.chaos.2020.109864)**] [**CrossRef (https://doi.org/10.1016/j.chaos.2020.109864)**]

16. Sahai, A.K.; Rath, N.; Sood, V.; Singh, M.P. ARIMA modelling & forecasting of COVID-19 in top five affected countries. *Diabetes Metab. Syndr. Clin. Res. Rev.* **2020**, *14*, 1419–1427. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=ARIMA+modelling+%2526+forecasting+of+COVID-19+in+top+five+affected+countries&author=Sahai,+A.K.&author=Rath,+N.&author=Sood,+V.&author=Singh,+M.P.&publication_year=2020&journal=Diabetes+Metab.+Syndr.+Clin.+Res.+Rev.&volume=14&pages=1419%E2%80%931427)**]

17. Rahimi, I.; Chen, F.; Gandomi, A.H. A review on COVID-19 forecasting models. *Neural Comput. Appl.* **2021**, 1–11. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=A+review+on+COVID-19+forecasting+models&author=Rahimi,+I.&author=Chen,+F.&author=Gandomi,+A.H.&publication_year=2021&journal=Neural+Comput.+Appl.&pages=1%E2%80%9311&doi=10.1007/s00521-020-05626-8)**] [**CrossRef (https://doi.org/10.1007/s00521-020-05626-8)**]

18. Ju-Long, D. Control problems of grey systems. *Syst. Control Lett.* **1982**, *1*, 288–294. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Control+problems+of+grey+systems&author=Ju-Long,+D.&publication_year=1982&journal=Syst.+Control+Lett.&volume=1&pages=288%E2%80%93294&doi=10.1016/S0167-6911(82)80025-X)**] [**CrossRef (https://doi.org/10.1016/S0167-6911(82)80025-X)**]

19. Bilgil, H. New grey forecasting model with its application and computer code. *AIMS Math.* **2021**, *6*, 1497–1514. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=New+grey+forecasting+model+with+its+application+and+computer+code&author=Bilgil,+H.&publication_year=2021&journal=AIMS+Math.&volume=6&pages=1497%E2%80%931514&doi=10.3934/math.2021091)**] [**CrossRef (https://doi.org/10.3934/math.2021091)**]

20. Zhang, J.; Jiang, Z. A new grey quadratic polynomial model and its application in the COVID-19 in China. *Sci. Rep.* **2021**, *11*, 12588. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=A+new+grey+quadratic+polynomial+model+and+its+application+in+the+COVID-19+in+China&author=Zhang,+J.&author=Jiang,+Z.&publication_year=2021&journal=Sci.+Rep.&volume=11&pages=12588&doi=10.1038/s41598-021-91970-1)**] [**CrossRef (https://doi.org/10.1038/s41598-021-91970-1)**]

21. Saxena, A. Grey forecasting models based on internal optimization for Novel Corona virus (COVID-19). *Appl. Soft Comput.* **2021**, *111*, 107735. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Grey+forecasting+models+based+on+internal+optimization+for+Novel+Corona+virus+(COVID-19)&author=Saxena,+A.&publication_year=2021&journal=Appl.+Soft+Comput.&volume=111&pages=107735&doi=10.1016/j.asoc.2021.107735&pmid=34335122)**] [**CrossRef (https://doi.org/10.1016/j.asoc.2021.107735)**] [**PubMed (http://www.ncbi.nlm.nih.gov/pubmed/34335122)**]

22. Ceylan, Z. Short-term prediction of COVID-19 spread using grey rolling model optimized by particle swarm optimization. *Appl. Soft Comput.* **2021**, *109*, 107592. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Short-term+prediction+of+COVID-19+spread+using+grey+rolling+model+optimized+by+particle+swarm+optimization&author=Ceylan,+Z.&publication_year=2021&journal=Appl.+Soft+Comput.&volume=109&pages=107592&doi=10.1016/j.asoc.2021.107592&pmid=34121965)**] [**CrossRef (https://doi.org/10.1016/j.asoc.2021.107592)**] [**PubMed (http://www.ncbi.nlm.nih.gov/pubmed/34121965)**]

23. Akay, D.; Atak, M. Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. *Energy* **2007**, *32*, 1670–1675. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Grey+prediction+with+rolling+mechanism+for+electricity+demand+forecasting+of+Turkey&author=Akay,+D.&author=Atak,+M.&publication_year=2007&journal=Energy&volume=32&pages=1670%E2%80%931675&doi=10.1016/j.energy.2006.11.014)**] [**CrossRef (https://doi.org/10.1016/j.energy.2006.11.014)**]

24. Cui, J.; Liu, S.f.; Zeng, B.; Xie, N.M. A novel grey forecasting model and its optimization. *Appl. Math. Model.* **2013**, *37*, 4399–4406. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=A+novel+grey+forecasting+model+and+its+optimization&author=Cui,+J.&author=Liu,+S.f.&author=Zeng,+B.&author=Xie,+N.M.&publication_year=2013&journal=Appl.+Math.+Model.&volume=37&pages=4399%E2%80%934406&doi=10.1016/j.apm.2012.09.052)**] [**CrossRef (https://doi.org/10.1016/j.apm.2012.09.052)**]

25. Chen, P.Y.; Yu, H.M. Foundation settlement prediction based on a novel NGM model. *Math. Probl. Eng.* **2014**, *2014*, 242809. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Foundation+settlement+prediction+based+on+a+novel+NGM+model&author=Chen,+P.Y.&author=Yu,+H.M.&publication_year=2014&journal=Math.+Probl.+Eng.&volume=2014&pages=242809&doi=10.1155/2014/242809)**] [**CrossRef (https://doi.org/10.1155/2014/242809)**] [**Green Version (http://downloads.hindawi.com/journals/mpe/2014/242809.pdf)**]

26. Ma, X.; Hu, Y.s.; Liu, Z.b. A novel kernel regularized nonhomogeneous grey model and its applications. *Commun. Nonlinear Sci. Numer. Simul.* **2017**, *48*, 51–62. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=A+novel+kernel+regularized+nonhomogeneous+grey+model+and+its+applications&author=Ma,+X.&author=Hu,+Y.s.&author=Liu,+Z.b.&publication_year=2017&journal=Commun.+Nonlinear+Sci.+Numer.+Simul.&volume=48&pages=51%E2%80%9362&doi=10.1016/j.cnsns.2016.12.017)**] [**CrossRef (https://doi.org/10.1016/j.cnsns.2016.12.017)**]

27. Xie, N.m.; Liu, S.f. Discrete grey forecasting model and its optimization. *Appl. Math. Model.* **2009**, *33*, 1173–1186. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Discrete+grey+forecasting+model+and+its+optimization&author=Xie,+N.m.&author=Liu,+S.f.&publication_year=2009&journal=Appl.+Math.+Model.&volume=33&pages=1173%E2%80%931186&doi=10.1016/j.apm.2008.01.011)**] [**CrossRef (https://doi.org/10.1016/j.apm.2008.01.011)**]

28. Xie, N.M.; Liu, S.F.; Yang, Y.J.; Yuan, C.Q. On novel grey forecasting model based on non-homogeneous index sequence. *Appl. Math. Model.* **2013**, *37*, 5059–5068. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=On+novel+grey+forecasting+model+based+on+non-homogeneous+index+sequence&author=Xie,+N.M.&author=Liu,+S.F.&author=Yang,+Y.J.&author=Yuan,+C.Q.&publication_year=2013&journal=Appl.+Math.+Model.&volume=37&pages=5059%E2%80%935068&doi=10.1016/j.apm.2012.10.037)**] [**CrossRef (https://doi.org/10.1016/j.apm.2012.10.037)**]

29. Zeng, B.; Luo, C.; Liu, S.; Li, C. A novel multi-variable grey forecasting model and its application in forecasting the amount of motor vehicles in Beijing. *Comput. Ind. Eng.* **2016**, *101*, 479–489. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=A+novel+multi-variable+grey+forecasting+model+and+its+application+in+forecasting+the+amount+of+motor+vehicles+in+Beijing&author=Zeng,+B.&author=Luo,+C.&author=Liu,+S.&author=Li,+C.&publication_year=2016&journal=Comput.+Ind.+Eng.&volume=101&pages=479%E2%80%93489&doi=10.1016/j.cie.2016.10.009)**] [**CrossRef (https://doi.org/10.1016/j.cie.2016.10.009)**]

30. Ma, X.; Liu, Z.B. The kernel-based nonlinear multivariate grey model. *Appl. Math. Model.* **2018**, *56*, 217–238. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=The+kernel-based+nonlinear+multivariate+grey+model&author=Ma,+X.&author=Liu,+Z.B.&publication_year=2018&journal=Appl.+Math.+Model.&volume=56&pages=217%E2%80%93238&doi=10.1016/j.apm.2017.12.010)**] [**CrossRef (https://doi.org/10.1016/j.apm.2017.12.010)**]

31. Zeng, B.; Li, C. Improved multi-variable grey forecasting model with a dynamic background-value coefficient and its application. *Comput. Ind. Eng.* **2018**, *118*, 278–290. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Improved+multi-variable+grey+forecasting+model+with+a+dynamic+background-value+coefficient+and+its+application&author=Zeng,+B.&author=Li,+C.&publication_year=2018&journal=Comput.+Ind.+Eng.&volume=118&pages=278%E2%80%93290&doi=10.1016/j.cie.2018.02.042)**] [**CrossRef (https://doi.org/10.1016/j.cie.2018.02.042)**]

32. Saxena, A.; Alrasheedi, A.F.; Alnowibet, K.A.; Alshamrani, A.M.; Shekhawat, S.; Mohamed, A.W. Local Grey Predictor Based on Cubic Polynomial Realization for Market Clearing Price Prediction. *Axioms* **2022**, *11*, 627. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Local+Grey+Predictor+Based+on+Cubic+Polynomial+Realization+for+Market+Clearing+Price+Prediction&author=Saxena,+A.&author=Alrasheedi,+A.F.&author=Alnowibet,+K.A.&author=Alshamrani,+A.M.&author=Shekhawat,+S.&author=Mohamed,+A.W.&publication_year=2022&journal=Axioms&volume=11&pages=627&doi=10.3390/axioms11110627)**] [**CrossRef (https://doi.org/10.3390/axioms11110627)**]

33. Saxena, A. Optimized Fractional Overhead Power Term Polynomial Grey Model (OFOPGM) for market clearing price prediction. *Electr. Power Syst. Res.* **2023**, *214*, 108800. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Optimized+Fractional+Overhead+Power+Term+Polynomial+Grey+Model+(OFOPGM)+for+market+clearing+price+prediction&author=Saxena,+A.&publication_year=2023&journal=Electr.+Power+Syst.+Res.&volume=214&pages=108800&doi=10.1016/j.epsr.2022.108800)**] [**CrossRef (https://doi.org/10.1016/j.epsr.2022.108800)**]

34. Saini, V.K.; Kumar, R.; Mathur, A.; Saxena, A. Short term forecasting based on hourly wind speed data using deep learning algorithms. In Proceedings of the 2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE), Jaipur, India, 7–8 February 2020; pp. 1–6. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Short+term+forecasting+based+on+hourly+wind+speed+data+using+deep+learning+algorithms&conference=Proceedings+of+the+2020+3rd+International+Conference+on+Emerging+Technologies+in+Computer+Engineering:+Machine+Learning+and+Internet+of+Things+(ICETCE)&author=Saini,+V.K.&author=Kumar,+R.&author=Mathur,+A.&author=Saxena,+A.&publication_year=2020&pages=1%E2%80%936)**]

35. Faghih Mohammadi Jalali, M.; Heidari, H. Predicting changes in Bitcoin price using grey system theory. *Financ. Innov.* **2020**, *6*, 13. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Predicting+changes+in+Bitcoin+price+using+grey+system+theory&author=Faghih+Mohammadi+Jalali,+M.&author=Heidari,+H.&publication_year=2020&journal=Financ.+Innov.&volume=6&pages=13&doi=10.1186/s40854-020-0174-9)**] [**CrossRef (https://doi.org/10.1186/s40854-020-0174-9)**] [**Green Version (https://jfin-swufe.springeropen.com/track/pdf/10.1186/s40854-020-0174-9)**]

36. Jiang, P.; Zhou, Q.; Jiang, H.; Dong, Y. An optimized forecasting approach based on grey theory and Cuckoo search algorithm: A case study for electricity consumption in New South Wales. In *Abstract and Applied Analysis*; Hindawi: London, UK, 2014; Volume 2014, p. 183095. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=An+optimized+forecasting+approach+based+on+grey+theory+and+Cuckoo+search+algorithm:+A+case+study+for+electricity+consumption+in+New+South+Wales&author=Jiang,+P.&author=Zhou,+Q.&author=Jiang,+H.&author=Dong,+Y.&publication_year=2014&pages=183095)**]

37. Zhang, P.; Ma, X.; She, K. A novel power-driven grey model with whale optimization algorithm and its application in forecasting the residential energy consumption in China. *Complexity* **2019**, *2019*, 1510257. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=A+novel+power-driven+grey+model+with+whale+optimization+algorithm+and+its+application+in+forecasting+the+residential+energy+consumption+in+China&author=Zhang,+P.&author=Ma,+X.&author=She,+K.&publication_year=2019&journal=Complexity&volume=2019&pages=1510257&doi=10.1155/2019/1510257)**] [**CrossRef (https://doi.org/10.1155/2019/1510257)**]

38. Xie, N.; Liu, S. Discrete GM (1, 1) and mechanism of grey forecasting model. *Syst. Eng. Theory Pract.* **2005**, *1*, 93–99. [**Google Scholar (https://scholar.google.com/scholar_lookup?title=Discrete+GM+(1,+1)+and+mechanism+of+grey+forecasting+model&author=Xie,+N.&author=Liu,+S.&publication_year=2005&journal=Syst.+Eng.+Theory+Pract.&volume=1&pages=93%E2%80%9399)**]

39. Ministry of Health and Family Welfare MHFQ COVID-19 India Dataset. 2020. Available online: **https://www.mohfw.gov.in/ (https://www.mohfw.gov.in/)** (accessed on 25 July 2021).

40. Kaggle Data. COVID-19 Corona Virus India Dataset. 2020. Available online: **https://www.kaggle.com/imdevskp/covid19-corona-virus-india-dataset (https://www.kaggle.com/imdevskp/covid19-corona-virus-india-dataset)** (accessed on 25 July 2021).

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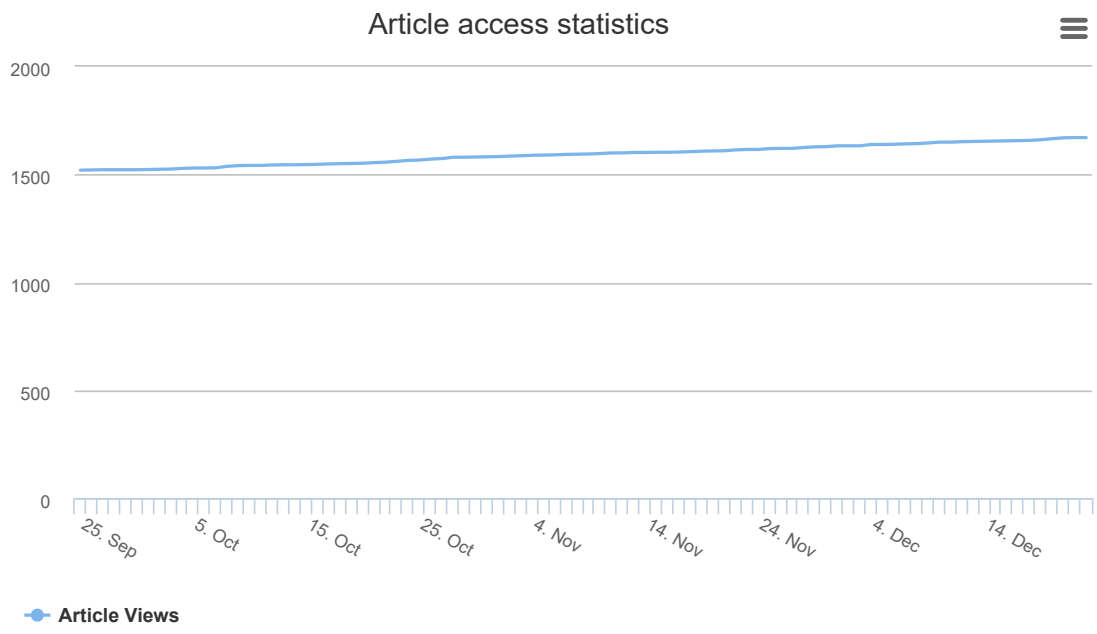

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