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The data used to support the findings of this study are available from the corresponding author upon request

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All authors contributed equally to this work. Each author participated in the conceptualization, methodology, data analysis, and manuscript preparation.

ORIGINAL STUDY

Enhancing COVID-19 Forecasting in Dagestan with Quasi-linear Recurrence Equations by Using GLDM Algorithm

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Abstract

This research delineates the advancement of a refined predictive algorithm centered on the Generalized Least Deviation Method (GLDM) specifically configured for analyzing COVID-19 infection trends in Dagestan using univariate time series data. Our methodology is characterized by its enhancement of forecast precision through diligent minimization of a bespoke loss function. The algorithm's innovation lies in its formulation, incorporating second-order relationships within the time series data:

$x_t = \sum_{j=1}^{v(\mathrm{W})} \eta_j g_j(\{x_{t-k}\}_{k=1}^{w}) + \varepsilon_t,$

where η_j are the computed weights ascribed to historical data, and ε_t denotes the error component. Our empirical analysis substantiates that by strategically accentuating pertinent coefficients and optimizing the loss function, there is a significant elevation in the model's forecasting accuracy. Consequently, the refined second-order GLDM model emerges as an advanced and applicable instrument for the prognostication of COVID-19 infection cases in Dagestan.

Keywords: COVID-19 forecasting, Generalized Least Deviation Method, Univariate time series analysis, Epidemiological modeling, Predictive analytics, Dagestan COVID-19 trends, Loss function optimization

1. Introduction

The emergence of the COVID-19 pandemic has spurred a pressing demand for sophisticated analytical instruments capable of forecasting its propagation and appraising prospective public health strategies. Mathematical modeling, and in particular, univariate time series analysis, stands as a cornerstone for generating such projections, shedding light on potential epidemic trajectories. This study introduces a state-of-the-art algorithm, based on the Generalized Least Deviation Method (GLDM), specifically designed for analyzing epidemic datasets. The algorithm focuses on optimizing a clearly defined loss function, which leads to enhanced accuracy in forecasting [27,28]. The predictive ability of our approach is summarized in the equation [27,28].

$$x_t = \sum_{j=1}^{v(\mathrm{W})} \eta_j g_j\left(\{x_{t-k}\}_{k=1}^{w}\right) + \varepsilon_t, t = 1, 2, \ldots, T, \tag{1}$$

This idea is supported by evidence from sources [17,18]. Having a thorough understanding of a machine's dynamics is often crucial when it comes to troubleshooting. Choosing a suitable mathematical model that links a machine's state with its diagnostic indicators streamlines this procedure. Possible models can encompass discrete equations, empirical representations, structural frameworks, or regression analyses. The most suitable model depends on

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the specific characteristics and actions of the process being examined. Throughout history, statistical approaches, neural networks, and mathematical modeling have played a crucial role in several fields for identification purposes [1–16]. Currently, these methodologies are being used in areas beyond industrial applications, including efforts to track the progress of the COVID-19 pandemic, as demonstrated by Ref. [19]. This study examines the prediction abilities of different well-known models, creates software implementations for these methods, and conducts computational tests using COVID-19 datasets. The investigators confirm that their forecasting system is adaptable and can be used to a wide range of time series. When making predictions, especially for large datasets, the most commonly used approach is to utilize a wide range of neural network models. As an illustration [20], describes a study that focuses on a specialized neural network model designed for predicting short-term changes in ferrosilicon pricing in Russia's domestic market. This model stands out due to its exceptional predictive accuracy and has the ability to enhance strategic decision-making in research institutions and metallurgical companies. Although these models are useful, they are sometimes criticized for their lack of transparency, as they often provide findings without clear explanations of their underlying processes. In order to improve the accuracy of these predictions, certain researchers are investigating the combination of cognitive modeling with neural networks [21,22].

2. Method

Before discussing the specific details of our analytical technique, it is important to emphasize the mathematical and computational framework that underlies the Generalized Least Deviation Method (GLDM). The core principle of GLDM is to reduce disparities between real observations and model forecasts. This is contained within the optimization challenge: minimize $L(\eta) = \sum_{i=1}^{n}|x_i - \mathrm{x}_i(\eta)|$, where x_i represents the recorded infection counts, $\widehat{x}_i(\eta)$ denotes the forecasted values furnished by the model, and $\eta = \{\eta_1, \eta_2, ..., \eta_k\}$ encompasses the model's coefficients. The appeal of this strategy rests in its ability to withstand data abnormalities and its effectiveness in producing reliable forecasts in the face of non-linear dynamics. Our objective is to determine the optimal model configuration that effectively balances complexity and forecast accuracy by applying GLDM to several model orders and datasets specific to Dagestan. This undertaking establishes a strong foundation for future discussions on the effectiveness of the model and its significance in predicting the course of COVID-19 infections [17–26].

The coefficients $\eta_1, \eta_2, \eta_3, \ldots, \eta_w \in \mathbb{R}$ are meticulously determined to dissect and forecast the evolution of COVID-19 infections in Dagestan, leveraging observational data spanning several months. The discourse extends to evaluating the model's capability in accurately projecting the future incidence of infections, thereby underscoring its utility in public health planning and intervention strategies.

The initial stage of the forecasting procedure involves a *Time Series* dataset, denoted as $\{x_t\} \in \mathbb{R}^{T}_{t=1-w}$, where each x_t signifies a datum at time t, encapsulated within a period from 1 to T, with the initiation at an earlier point indexed by w.

After gathering a series of time data, the method utilizes a GLDM Estimator algorithm. The GLDM, which stands for Generalized Least Deviation Method, is used to calibrate the data by deducing a collection of critical factors $\{\eta_1, \eta_2, \ldots, \eta_w\} \in \mathbb{R}$. These factors, which are inherent real values, represent the estimated parameters derived from the time series data.

The collected elements are utilized by a Predictor mechanism to forecast future values. This predictor is specifically built to produce outputs that include the Forecasting Horizon (FH) and anticipated future values, which represent the time frame and predicted data points for this horizon, respectively.

3. Error metrics for COVID-19 infection cases estimations

Estimating the number of COVID-19 infection cases using univariate time series analysis entails predicting future patterns by examining past data. Forecast accuracy and reliability are crucial for Dagestan's public health response and policy-making. Our prediction models are evaluated using various error measures to determine model accuracy and biases. In this part, metrics like RMSE, R-Squared R^2, MAPE, MSE, and ME are discussed. This extensive review of our models helps us identify strengths and weaknesses in our COVID-19 infection prediction methods. Understanding these metrics will improve our models to make more accurate and trustworthy predictions for Dagestan's health condition.

3.1. Root Mean Square Error (RMSE)

By measuring standard deviation, the RMSE measures prediction error variability. The quadratic mean of the disparities between expected and actual values is the square root of the second sample moment.

The equation for Root Mean Square Error (RMSE) is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{2}$$

where x_i are the observed values, x_i are the predicted values, and n is the number of observations.

3.2. R-squared (R^2)

The R^2 metric provides an indication of the goodness of fit of a set of predictions to the actual values. It represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model. The formula for R^2 is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{x})^2} \tag{3}$$

where $\overline{x}$ is the mean of the observed data.

3.3. Mean Absolute Percentage Error (MAPE)

MAPE measures the size of the error in percentage terms. It is calculated as the average of the absolute percentage errors of the predictions. The formula for MAPE is:

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \tag{4}$$

3.4. Mean Absolute Error (MAE)

The MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It's calculated as the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight. The formula for MAE is:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i| \tag{5}$$

3.5. Mean Squared Error (MSE)

The Mean Squared Error (MSE) is a measure of the quality of an estimator—it is always non-negative, and values closer to zero are better. It represents the average of the squares of the errors—the average squared difference between the estimated values and the actual value. The formula for MSE is:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{6}$$

where x_i are the true values and x_i are the predicted values by the model, with n being the total number of observations.

3.6. Mean Error (ME)

The Mean Error (ME) provides a measure of the central tendency of the predictive errors. Unlike the MSE, the ME considers the direction of the errors and can indicate if a model's predictions are systematically high or low. The ME is calculated as the average of the prediction errors. The formula for ME is:

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i) \tag{7}$$

A positive value of ME indicates a tendency of the model to overestimate, while a negative ME indicates a tendency to underestimate the observed values.

4. Results

As detailed in Table 1, the dataset encompasses a total of 1005 days of daily COVID-19 infection cases for the region of Dagestan. This extensive dataset allows for a comprehensive analysis of the pandemic's progression within the region, providing valuable insights into infection trends over an extended period.

Table 2 lists the coefficients from a first-order GLDM model applied to COVID-19 infection cases in Dagestan. The coefficient η_1, with a value of exactly 1.0000, suggests a one-to-one impact of previous case numbers on subsequent predictions.

Table 1. Total number of days with COVID-19 data in Dagestan.

No	Region	Length (Days)
1	Dagestan	1005

Table 2. First order GLDM model coefficients for COVID-19 infection cases in Dagestan.

Coefficient	Value
η_1	1.0000
η_2	0.0000

The η_2 coefficient is zero, indicating no additional effect from the second term in this model's context. These values imply that the first-order model closely mirrors the actual data without the need for further adjustments from the secondary term.

In Table 3, the coefficients for the second-order GLDM model used to analyze COVID-19 infection trends in Dagestan are presented. The table lists coefficients η_1 through η_5 with their respective values, indicating the model's estimation of the factors influencing infection rates. The coefficient η_1 is less than one, η_2 is slightly positive, and η_3 and η_4 are minimal, suggesting a nuanced influence on the infection trend, whereas η_5 is a small negative value, implying a slight decrease in the trend.

The analysis of COVID-19 infection trends in Dagestan is presented in Table 4. This table showcases an error matrix that compares the predictive accuracy of two Generalized Least Deviation Method (GLDM) models — a first-order model and a second-order model — through various statistical metrics.

The evaluation metrics for the models consist of the Root Mean Square Error (RMSE), which quantifies the standard deviation of prediction errors, and the R-squared R^2 value, which indicates the proportion of the dependent variable's variance that is accounted for by the independent variable(s) in the model. In addition, the Mean Absolute Percentage Error (MAPE) calculates the average size of the errors in terms of percentages, whereas the Mean Absolute Error (MAE) measures the average size of the errors in a linear manner. The Mean Squared Error (MSE) measures the average of the squared errors, whereas the Mean Error (ME) evaluates the average error, showing any potential bias in the model.

Table 3. The second order GLDM model coefficients for COVID-19 infection cases in Dagestan.

Coefficient	Value
η_1	0.9388
η_2	0.0801
η_3	0.0036
η_4	0.0028
η_5	−0.0066

Table 4. Error matrix for COVID-19 infection in Dagestan.

Order	RMSE	R-squared	MAPE	MAE	MSE	ME
First	16.31	0.9786	12.67	6.35	265.91	0.002
Second	15.10	0.9816	12.91	6.40	227.94	−0.44

The first-order model has an RMSE of 16.31 and a high R^2 value of 0.9786, indicating a strong fit to the observed data. The Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) exhibit relatively low values of 12.67% and 6.35, respectively. This indicates a high level of prediction accuracy with little average error. The Mean Squared Error (MSE) is currently 265.91, but the Margin of Error (ME) is almost zero at 0.002, suggesting an unbiased model.

The second-order model exhibits a slightly enhanced root mean square error (RMSE) of 15.10 and an R-squared R^2 value of 0.9816, indicating a slightly superior fit in comparison to the first-order model. The Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) exhibit slightly higher values, specifically 12.91% and 6.40, respectively. The Mean Squared Error (MSE) has been decreased to 227.94, while the Mean Error (ME) of −0.44 suggests a small negative deviation in the accuracy of forecasts.

The data demonstrate the efficacy and subtle distinctions between the first and second-order GLDM models in predicting COVID-19 infection rates in Dagestan. The second-order model has superior performance compared to the first model in terms of RMSE and R^2. However, it does introduce a tiny negative bias, as evidenced by the ME value.

The graphical representations in Figs. 1 and 2 contrast the original reported COVID-19 infection cases with the projections of the first and second order GLDM models for the Dagestan region. Both figures illustrate the temporal progression of infections and the corresponding model's performance in capturing the epidemiological trend. The models' outputs, delineated by dotted lines, closely track the empirical data, represented by the solid lines, underscoring the robustness of the GLDM approach in encapsulating the inherent variability of the infection rates over time.

The radar chart in Fig. 3 provides a visual comparison of the goodness of fit for two GLDM models used to forecast COVID-19 infection cases in Dagestan. The chart plots multiple statistical measures around a circle, allowing for an at-a-glance assessment of model performance across different criteria. The axes represent various error metrics including Root Mean Square Error (RMSE), R-squared (R^2), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Error (ME).

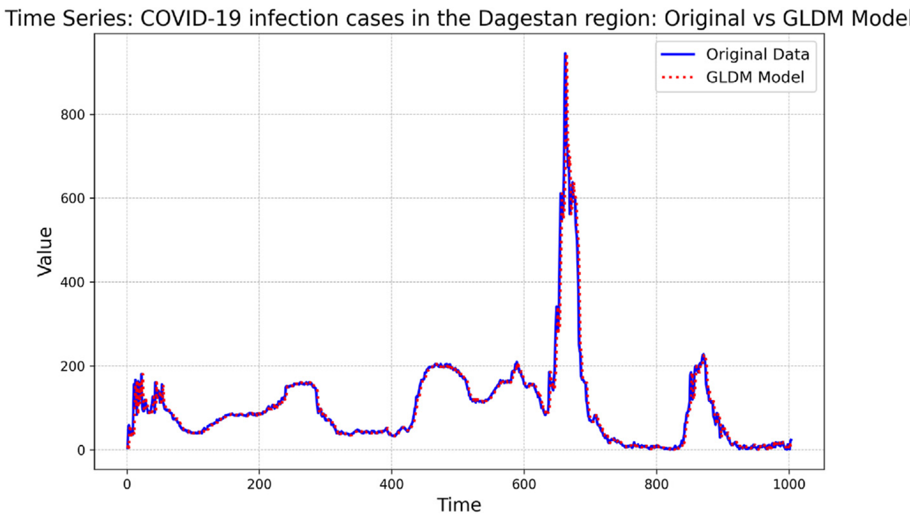

Fig. 1. Time series: COVID-19 infection cases in the Dagestan region: original vs GLDM Model first order.

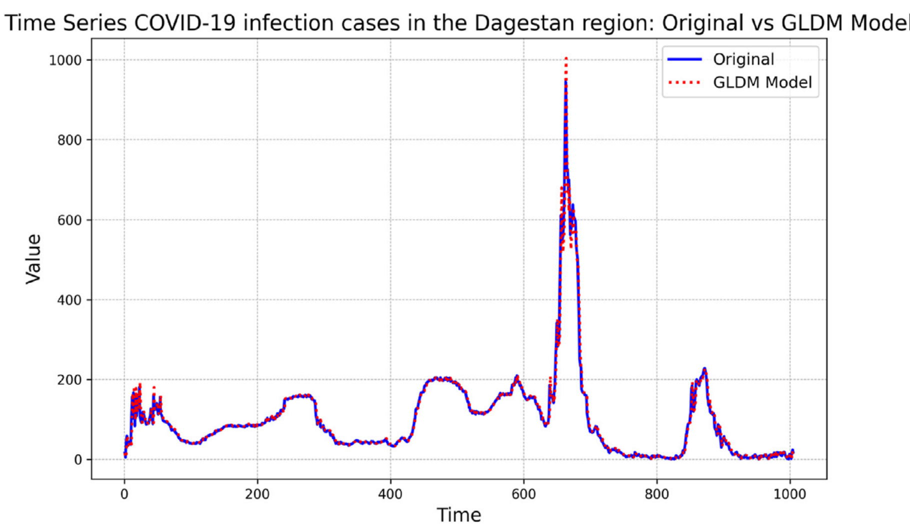

Fig. 2. Time series: COVID-19 infection cases in the Dagestan region: original vs GLDM Model second order.

Model Order 1, depicted by the blue line, shows performance metrics for the first-order GLDM model, while Model Order 2, depicted by the orange line, shows those for the second-order model. The distance from the center of the radar chart to a point on a line indicates the magnitude of that metric for the respective model. For instance, a point closer to the outer edge of the circle indicates a higher value for that metric.

In general, a model with lower values for RMSE, MAPE, MAE, MSE, and ME and a higher value for R-squared is considered to have a better fit. As seen in the radar chart, Model Order 2 appears to perform better on several metrics compared to Model Order 1, suggesting it may provide a more accurate forecast for COVID-19 cases in the region.

5. Quasilinear recurrence equations for COVID 19 for Dagestan

The second-order GLDM equation for forecasting COVID-19 infection cases in Dagestan is represented as follows:

$$\widehat{x}_t = (0.9388 \times x_{t-1}) + (0.0801 \times x_{t-2}) + \left(0.0036 \times x_{t-1}^2\right) + (0.0028 \times x_{t-1} \cdot x_{t-2}) + \left(-0.0066 \times x_{t-2}^2\right), \quad (8)$$

where:

- $\widehat{x}_t$ is the forecasted number of COVID-19 infection cases for day t.
- x_{t-1} and x_{t-2} represent the observed number of COVID-19 infection cases for the days

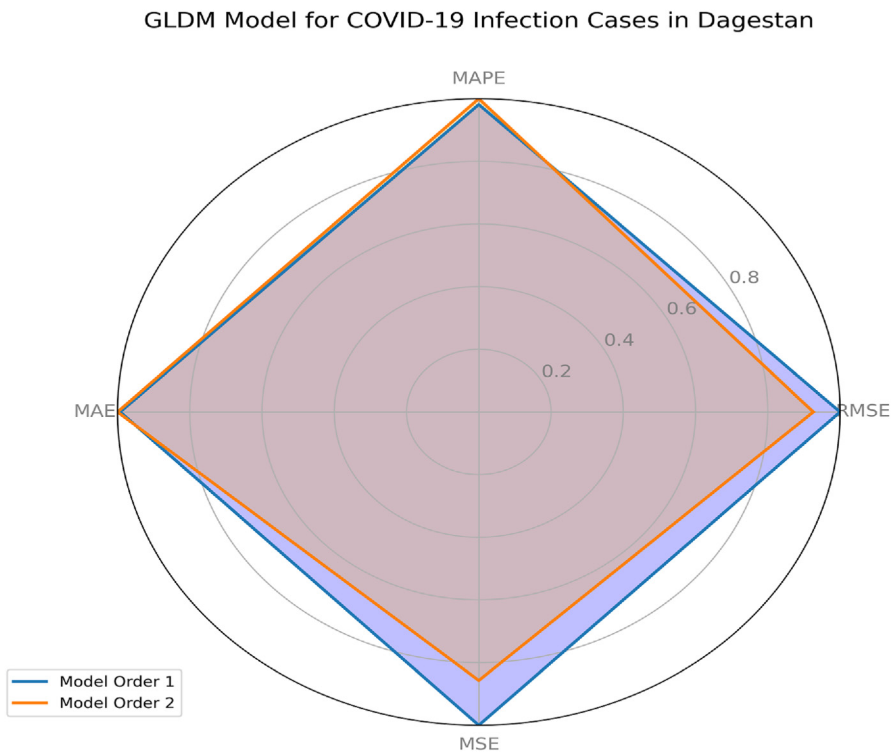

Fig. 3. Radar diagrams for goodness of fit of GLDM models for COVID-19 cases in Dagestan.

immediately preceding day t and two days before day t, respectively.
- 0.9388, 0.0801, 0.0036, 0.0028, and −0.0066 are coefficients derived from the GLDM analysis, quantifying the relationship between past infection rates and the forecast for day t.

The coefficients in this equation play distinct roles:

- 0.9388 and 0.0801 adjust the linear influence of the past one day and two days' infection rates on the forecast, respectively, emphasizing the immediate past as a strong predictor for the future.
- 0.0036 modifies the forecast based on the square of the previous day's infection rate, introducing a nonlinear component that accounts for exponential growth or decline in infection rates.
- 0.0028 represents the interaction between the infection rates of the past two days, capturing complex dynamics between these two time points.
- −0.0066 applies a negative adjustment based on the square of the infection rate two days prior, potentially reflecting a corrective mechanism for overestimation by the model under certain conditions.

This model effectively incorporates both the recent trend (through linear terms) and the rate of change in trend (through quadratic terms and interaction term), allowing for a nuanced forecast of COVID-19 infection cases.

6. Discussion

The application of the Generalized Least Deviation Method (GLDM) to COVID-19 infection data in Dagestan has revealed significant insights into the epidemic's trajectory. The comparison of first and second-order models within this framework has elucidated their respective abilities to forecast the infection trend based on historical data.

Figure 3 presents a radar chart summarizing the performance of these models across various statistical metrics: RMSE, R-squared (R^2), MAPE, MAE, MSE, and ME. A model's efficacy is inversely proportional to the values of RMSE, MAPE, MAE, MSE, and ME, while a higher R^2 value is indicative of a superior fit to the observed data. In our case, the second-order GLDM model exhibits a larger proximity to the chart's periphery along most axes, signifying an overall improved prediction capability over the first-order model.

$$\begin{aligned} &\mathrm{RMSE}_{\text{second-order}} &&< \mathrm{RMSE}_{\text{first-order}}, \\ &R^2_{\text{second-order}} &&> R^2_{\text{first-order}}, \\ &\mathrm{MAE}_{\text{second-order}} &&\leq \mathrm{MAE}_{\text{first-order}}. \end{aligned} \tag{10}$$

However, a closer examination of the coefficients—particularly η_1 and η_2 in the second-order model—provides a nuanced perspective. The coefficient η_1 at 0.9388 underscores the previous day's infection rate as a significant predictor, corroborated by an almost perfect R^2 value. Meanwhile, η_2 reflects a smaller, albeit impactful, influence from the infection data two days prior.

7. Conclusion

The extensive analysis conducted utilizing the Generalized Least Deviation Method (GLDM) has yielded a robust model for forecasting COVID-19 infection cases in Dagestan. The models, particularly the second-order iteration, have demonstrated their predictive prowess, as evidenced by statistical measures such as RMSE, R^2, MAPE, MAE, MSE, and ME. The success of these models can be encapsulated by the equation:

$$\widehat{x}_t = \sum_{i=1}^{w} \eta_i f_i(x_{t-1}, x_{t-2}, \ldots, x_{t-n}), \tag{11}$$

where $\widehat{x}_t$ forecasts future infection cases, and the function f_i represents the derived factors from the historical data points used in the GLDM.

The application of these models has not only provided a pathway to predict future trends but has also offered valuable insights into the dynamics of infectious disease spread. The ability to quantify and interpret these dynamics is crucial for strategic decision-making and public health planning.

Data availability

The data used to support the findings of this study are available from the corresponding author upon request.

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