ORIGINAL RESEARCH ARTICLE | UHD JOURNAL OF SCIENCE AND TECHNOLOGY

Forecasting of the Infant Mortality Rate in Iraq

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ABSTRACT

This study investigates applying the GM(1,1) model to forecast the infant mortality rate (IMR) in Iraq from 2025 to 2034, utilizing historical data spanning 2015–2024. The findings indicate a consistent decline in IMRs during the analyzed period, reflecting effective public health interventions. The model's parameters were estimated using the Ordinary Least Squares method, revealing an intercept of 0.0278 and a slope of 26.7693. The forecasting accuracy of the GM(1,1) model was exceptional, demonstrated by a Mean Absolute Percentage Error of only 0.2869% and a precision rate of 99.7131%, categorizing the forecasts as highly accurate. Projected IMRs show a continued decline, decreasing from 20.55 deaths per 1000 live births in 2025 to approximately 16.00 by 2034. These results underscore the utility of the GM(1,1) model in providing reliable forecasts to inform health policy and intervention strategies aimed at improving maternal and child health in Iraq.

Index Terms: Forecasting, Infant, Mortality Rate, Iraq

1. INTRODUCTION

The infant mortality rate (IMR) is a crucial indicator of a nation's health status and reflects the effectiveness of health systems and social conditions. In Iraq, the IMR has experienced fluctuations due to various factors, including healthcare access, conflict, and socioeconomic conditions. Historically, Iraq has faced significant challenges in improving health outcomes, particularly following decades of war and instability. World Bank [1] reported that while there have been improvements in healthcare services, disparities remain between urban and rural areas, impacting the overall IMR. Understanding and forecasting IMR is essential for effective health policy planning and intervention strategies.

Access this article online

DOI:10.21928/uhdjst.v9n2y2025.pp357-362

E-ISSN: 2521-4217

P-ISSN: 2521-4209

Advancements in statistical methods and data analytics have provided new opportunities for forecasting IMR in Iraq. Time series analysis has become popular, allowing researchers to examine historical trends and predict future rates. A study done in 2022 utilized time series data spanning several decades to demonstrate how statistical models can effectively forecast IMR trends in Iraq. This analysis highlighted that while there has been a general decline in IMR, periods of instability have caused significant fluctuations, indicating the need for adaptive health policies that respond to changing circumstances [2].

Integrating machine learning techniques offers an even more refined approach to forecasting IMR. Recent research has shown that artificial intelligence and machine learning models, such as back propagation neural networks, can enhance predictive accuracy beyond traditional statistical methods [3]. Also investigated the use of machine learning to predict IMR in the Kurdistan Region of Iraq, finding promising results that could aid policymakers in anticipating healthcare needs and resource allocation effectively. These advanced forecasting methods provide valuable insights influencing public health strategies to reduce infant mortality [2].

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Received: 24-03-2025 Accepted: 14-08-2025 Published: 01-12-2025

Furthermore, addressing the factors contributing to IMR is vital for improving overall child health in Iraq. Critical determinants include maternal education, access to healthcare, and nutritional status. Therefore, efforts to reduce IMR should encompass multidimensional strategies that address these underlying factors. Wang *et al*. [2] emphasize the importance of comprehensive maternal and child healthcare programs prioritizing education and access to services. By forecasting IMR based on these determinants, stakeholders can develop targeted interventions that facilitate improved health outcomes for mothers and infants.

Enhancing forecasting models has significant implications for public health planning in Iraq. Accurate forecasts of IMR can guide resource allocation, inform interventions, and ultimately contribute to achieving global health targets, such as the Sustainable Development Goals. Addressing IMR contributes to individual health outcomes and plays an essential role in national development, emphasizing health as a critical component of socio-economic growth [4]. Therefore, continuous efforts to refine forecasting techniques and implement evidence-based policies are crucial for advancing maternal and child health in Iraq.

2. MATERIALS AND SUBJECTS

2.1. Study Design

This study employed a quantitative descriptive forecasting design using secondary data to predict future trends in Iraq's IMR. The study design was selected to enable the application of time-series forecasting models, specifically the GM(1,1) model from Grey System Theory, to evaluate and project patterns based on historical data.

2.2. Sample of the Study

This study investigates applying the GM(1,1) model to forecast the infant mortality rate in Iraq from 2025 to 2034, utilizing historical data spanning 2015 to 2024 by using secondary data to predict future trends in Iraq's infant mortality rate (IMR) (appendix).

2.3. Setting of the Study

The setting of this study is virtual and data-driven, relying on publicly accessible online databases. The IMR data for Iraq from 2015 to 2024 was sourced from Macrotrends.net, a reputable database compiling global health and development indicators. Forecasting was conducted in a simulated environment using statistical software capable of applying Grey System models.

2.4. Method of Data Collection

Grey System Theory, introduced by Deng in 1989, addresses systems lacking complete information, such as structure, operation mechanisms, and behaviour documentation, termed Grey Systems. Examples include the human body, agriculture, and the economy. Grey System Theory aims to bridge the social and natural sciences gap, fostering interdisciplinary collaboration across various fields. It has demonstrated enduring relevance since its inception, particularly in China, where it is widely known and applied across sectors such as agriculture, ecology, economics, meteorology, medicine, geography, and industry [15].

In Grey System Theory, the GM (m, n) model, where m represents the order of the difference formula and n indicates the number of factors, is employed to predict future system outputs with relatively high accuracy, even without a complete mathematical model of the actual system. The GM (1, 1) model is particularly prominent due to its computational efficiency, with researchers often focusing on it for predictions. This model utilises first-order differential equations to match data generated by the accumulation generating operation (AGO).

Grey System Theory encompasses five main groups: gray generating, gray relational analysis, gray forecasting, gray decision-making, and gray control. Among these, gray forecasting plays a significant role in addressing uncertainty and information insufficiency within systems. The general form of the gray forecasting model is GM (n, m), where n and m denote the order of ordinary differential equations and the number of gray variables. Various forecasting models are proposed based on different ordinary differential equations and the number of gray variables utilized. The advantage of the GM(1,1) model lies in its computational efficiency, offering accurate predictions despite minimal data requirements (Li *et al*., 2015). This study presents the concepts of the GM(1,1) model. More specifics are given as follows:

2.5. Gray Model GM(1,1)

The commonly used gray prediction model is often the GM(1,1), indicating the utilization of a single variable within the model (Liu *et al*., 2015). The calculation process of GM(1,1) involves six steps (Ahmed *et al*., 2023).

2.6. Evaluate Precision of Forecasting Models

2.6.1.Mean absolute percentage error (MAPE)

Several statistical tests and measurements assess the accuracy and performance of the proposed model, among them MAPE. To evaluate the reliability and performance of the

TABLE 1: Categorizing the grade of predicting accuracy.

Grade level	Highly accurate	Good	Reasonable	Inaccurate
MAPE (%)	<10	10–20	20–50	>50

forecasting technique in this study (Ahmed *et al*., 2023), the forecasting accuracy level can be classified into four grades based on the MAPE of each model, as indicated in Table 1:

A lower MAPE indicates higher precision in the forecasting model. Typically, an MAPE below 10% signifies an accurate model, while an MAPE between 10% and 20% denotes a good model with acceptable accuracy.

2.6.2. Precision rate (p)

Precision Rate, which measures the level of the closeness of the statement of forecast quantity and the actual value, p is defined as follows:

Table 2 shows a higher precision rate, which indicates greater precision in the forecasting model. Typically, a precision rate >99% signifies an accurate model, while a precision rate between 98.0% and 95.0% suggests a good model with acceptable accuracy.

2.7. Ethical Considerations

This study used secondary data that are publicly available and are not contain any personal or identifiable information. Therefore, ethical approval was not required. However, appropriate attribution to the data source (Macrotrends.net) has been made to ensure transparency and integrity. All data were handled in accordance with ethical research standards concerning the use of open-access information.

3. RESULT OF THE STUDY

In this study, time series data regarding the IMR in Iraq, spanning the years 2015 to 2024, were analyzed. This study evaluates the GM(1,1) model for forecasting Iraq's Infant Mortality from 2025 to 2034 using data spanning from 2015 to 2024.

The IMR from 2015 to 2024 is displayed in Table 3, which demonstrates a steady decrease over time. In 2015, the rate was 26.737 fatalities per 1000 live births; by 2024, it had dropped to 20.661. This pattern shows that within the past 10 years, maternity care, healthcare services, and child survival circumstances have improved.

TABLE 2: Categorizing the grade of predicting accuracy.

Precision rank	Highly accurate	Good	Reasonable	Inaccurate
Precision rate (p) (%)	p≥99.0	p≥95.0	p≥90.0	p≤90.0

TABLE 3: The infant mortality rate

Years	Infant mortality rate	Years	Infant mortality rate
2015	26.737	2020	22.918
2016	25.86	2021	22.324
2017	24.982	2022	21.731
2018	24.105	2023	21.137
2019	23.511	2024	20.661

Deaths per 1000 live births

3.1. Estimated Model Forecasting of GM(1,1)

Using the Ordinary Least Squares (OLS) method, the parameters of the GM(1,1) model have been estimated as follows: the intercept (*a*) is 0.027813794, and the slope (*b*) is 26.7692722.

Table 4 represents the actual value, forecasted value, and percentage error (PE%) of the GM(1,1) model. It is seen that the MAPE value for the GM(1,1) is (0.2869%), and it can be said that the efficiency and accuracy values obtained are ($P = 100 - \text{MAPE}(\%) = 100 - 0.2869\% = 99.7131\%$). This means that the forecasting value is considered a highly accurate prediction because the value of the precision rate in $P \geq 99.0\%$. The forecasted values for 2025–2035 are presented in Table 5.

The projected IMR s using the GM(1,1) model for 2025–2034 are shown in Table 5. According to the data, the number of deaths per 1000 live births decreased steadily from 20.55 in 2025 to 15.99 in 2034. If present trends continue, this prediction points to further advancements in newborn health outcomes.

4. DISCUSSION

The analysis of the IMR in Iraq from 2015 to 2024 presents significant insights into the utility of the GM(1,1) model in forecasting future trends. The data indicate a consistent decline in IMRs over the observed period, highlighting effective public health interventions and evolving healthcare access in Iraq. This trend is crucial, as it reflects improvements in maternal and infant health services and aligns with global objectives to reduce mortality rates among vulnerable populations [5]. The application of the GM(1,1) model,

TABLE 4: Predicted value and rate error value of the GM (1,1) model

Year	No. k	Real value	Forecasted value	Percentage error (PE%)
2015	k=0	26.737	26.737	0.0000
2016	k=1	25.86	25.66701172	0.7463
2017	k=2	24.982	24.96295143	0.0762
2018	k=3	24.105	24.2782039	0.7185
2019	k=4	23.511	23.61223937	0.4306
2020	k=5	22.918	22.96454261	0.2031
2021	k=6	22.324	22.33461254	0.0475
2022	k=7	21.731	21.7219618	0.0416
2023	k=8	21.137	21.1261164	0.0515
2024	k=9	20.661	20.54661537	0.5536
Results		MAPE (%)		0.2869%
	Precision Rate (p)		99.7131%	

TABLE 5: The forecasted value by GM (1,1) model

Years	Infant mortality rate	Years	Infant mortality rate
2025	20.54661537	2030	17.87900743
2026	19.98301037	2031	17.38857639
2027	19.43486537	2032	16.91159815
2028	18.90175629	2033	16.44770368
2029	18.38327069	2034	15.99653409

Deaths per 1000 live births

noted for its computational efficiency, has proven effective in predicting future values despite the inherent complexities and uncertainties associated with health data [6].

The estimated parameters from the GM(1,1) model–an intercept (a) of 0.0278 and a slope (b) of 26.7693–afford a robust framework for understanding the dynamics influencing infant mortality in Iraq. Such parameters reinforce the model's capability to accurately reflect historical data patterns, ensuring that forecasting for 2025–2034 captures expected trends for continued decline. This is mirrored in similar studies, which have demonstrated that time series models, particularly those grounded in Grey System Theory, can provide significant predictive power even in fields characterized by limited data [7].

The results demonstrate a highly accurate forecasting performance with a MAPE of 0.2869%, suggesting exceptional precision in the GM(1,1) model's predictions. This performance aligns with established thresholds for model accuracy, indicating that forecasts developed through this approach are reliable and strategically beneficial for policy formulation. A precision rate of 99.7131% indicates a model that can significantly guide health policy decisions, targeting interventions effectively to reduce the IMR further [11], [12].

Moreover, the forecasted values for 2025–2034 reveal a trend toward a continual reduction in IMRs, with estimates showing values consistently declining from 20.55 deaths/1000 live births in 2025 to approximately 16.00 by 2034. This outlook is aligned with the global health agenda, which emphasizes the importance of sustained efforts to improve healthcare systems and children's outcomes [13]. The substantial decrease projected by the GM(1,1) model underscores the potential impacts of ongoing health initiatives and resource allocation strategies to improve maternal and child health, particularly in developing regions [14].

Applying the GM(1,1) model provides valuable insights into predicting infant mortality trends in Iraq, backed by a strong statistical foundation and high forecasting accuracy. Continued research in this area could explore further enhancements to the model by incorporating additional variables, such as socioeconomic factors and environmental influences, to enrich the predictive capabilities and policy implications [15]. The findings of this study reinforce the significance of effective health prediction models as tools for enhancing public health strategies and advancing the broader objectives of global health initiatives.

5. CONCLUSION

This study demonstrated the effectiveness of the GM(1,1) model from Grey System Theory in forecasting Iraq's IMR using data from 2015 to 2024. The model showed high accuracy, with an MAPE of 0.2869% and a precision rate of 99.7131%, projecting a continued decline in IMR from 2025 to 2034. These results highlight the model's value in supporting health policy and planning. The findings underscore the need for continued investment in maternal and child health, and future research could improve the model by integrating socioeconomic and environmental factors.

6. DISCLOSURE

The authors report no conflicts of interest in this work.

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APPENDIX

1. GREY MODEL GM(1,1)

The GM(1,1), which uses a single variable in the model, is frequently the most widely used gray prediction model (Liu *et al*., 2015). There are six steps in the GM(1,1) computation procedure (Ahmed *et al*., 2023), which are as follows:

Step 1: The non-negative original sequence data is given by $X^{(0)}$

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}, n \geq 4 \quad (1)$$

Step 2: Using the non-negative original sequence data $X^{(0)}$, $X^{(1)}$ is constructed by a one-time accumulated generating operation (1-AGO), represented as

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\} \quad (2)$$

Where:

$$x^{(1)}(1) = x^{(0)} \quad (1)$$

$$X^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(k = 1, 2, \ldots, n)$$

Step 3: Determine the background value z through mean generating operation (MGO).

$$z^{(1)}(k) = 0.5\, x^{(1)}(k+1) + 0.5 x^{(1)}(k)\ k = 23 \quad (3)$$

Step 4: The result of 1-AGO produces a continuously rising sequence, resembling the solution curve of a first-order linear differential equation. Thus, the solution curve of the following differential equation approximates the 1-AGO data:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (4)$$

The parameters a and b are called the development coefficient and gray input, respectively. $x^{(1)}(1) = x^{(0)}(1)$ represents the corresponding initial condition

Step 5: The parameters a and b can be calculated using the OLS method

$$\begin{pmatrix} a \\ b \end{pmatrix} = (\beta^T \beta)^{-1} \beta^T Y_n \quad (5)$$

Where β and Y_n are defined as follows:

$$\beta = \begin{bmatrix} x^{(1)}(2) & 1 \\ x^{(1)}(3) & 1 \\ \vdots & \cdots \\ x^{(1)}(n) & 1 \end{bmatrix} \text{ and } Y_n = [x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)]^T,$$

Solving Eq. (5) along with the initial condition yields the solution.

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}\ k = 1, 2, 3\ldots. \quad (6)$$

Step 6: Utilizing the inverse accumulated generating operation (I-AGO) on $\hat{x}^{(1)}(k)$, the predicted data of $\hat{x}^{(0)}(k)$ Can be estimated as follows:

$$\hat{x}^{(0)}(k+1) = (1 - e^{-a}) \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} \quad (7) \text{ or}$$

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad (8)$$

2. EVALUATE PRECISION OF FORECASTING MODELS

2. 1. MAPE

The correctness and performance of the suggested model are evaluated using a number of statistical tests and metrics, including Mean Absolute Percentage Error (MAPE). The MAPE index was used to assess the forecasting technique's performance and dependability in this study (Ahmed *et al*., 2023). It has the following definition.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} |PE_k| * 100\% = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| * 100\% \quad (9)$$

2. 2. Precision Rate (p)

Precision Rate, which measures the level of the closeness of the statement of forecast quantity and the actual value, p is defined as follows:

$$P = 100 - MAPE(\%) \quad (10)$$