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Optimizing the Grey model (1,1) through neural networks model for Forecasting the Contributions of Agriculture per GDP of Iraq

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Abstract: This study compares the performance of the Grey Model (GM (1,1)) and Grey Model Neural Network (GMNN(1,1)) models in forecasting the proportion percent of agriculture per GDP of Iraq. This study aims to improve the accuracy of the Grey (1,1) model through the integration of a neural network model. While previous studies have focused on optimizing similar models in various sectors, to the best of the researchers' knowledge, this is the first time such an optimized model has been applied in this field internationally. This study aims to estimate a more reliable forecasting model to forecast the aforementioned series. The findings of this research are especially significant for Iraq's GDP planning, providing valuable insights for enhancing economic forecasting within the country. The GMNN (1,1) model provides more accurate forecasts with lower error magnitude. However, a downward trend in the forecasted Agriculture per GDP values over the five years suggests a potential decline in the agricultural sector's contribution to the overall GDP ratio. This raises concerns about the sector's relative importance within the economy and its ability to sustain growth. The forecasted values and confidence intervals highlight potential challenges facing the agricultural sector, including fluctuations in productivity, market conditions, and external factors like climate change and global trade dynamics. Addressing these challenges requires targeted policies and interventions to enhance the sector's resilience and competitiveness.

Keywords: Grey system theory, Ordinary least squares, Backpropagation Neural Networks.

تحسين نموذج (١,١) GM من خلال نموذج الشبكات العصبية لتوقع مساهمات الزراعة في الناتج المحلي الإجمالي للعراق

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المستخلص: تقارن هذه الدراسة أداء نموذج (GM (1,1)) مع نموذج الشبكات العصبية جراي (GMNN (1,1)) في توقع نسبة مساهمة الزراعة في الناتج المحلي الإجمالي للعراق. تهدف الدراسة إلى تحسين دقة نموذج GM (١،١) من خلال دمج نموذج الشبكة العصبية. بينما ركزت الدراسات السابقة على تحسين نماذج مشابهة في قطاعات مختلفة، وفقًا لمعرفة الباحثين، هذه هي المرة الأولى التي يتم فيها تطبيق نموذج محسن كهذا في هذا المجال دوليًا. تسعى الدراسة إلى تقدير نموذج توقع أكثر موثوقية للتنبؤ بالسلسلة الزمنية المذكورة. تمثل نتائج هذه الدراسة أهمية خاصة في التخطيط للناتج المحلي الإجمالي للعراق، حيث توفر رؤى قيمة لتعزيز دقة التنبؤات الاقتصادية داخل البلاد. أظهر نموذج GMNN (١،١) دقة توقع أعلى من نموذج GM (١،١)، مع حجم خطأ أقل. ومع ذلك، أظهر الاتجاه التنازلي للقيم المتوقعة لمساهمة الزراعة في الناتج المحلي الإجمالي على مدى خمس سنوات احتمالية انخفاض مساهمة القطاع الزراعي في إجمالي الناتج المحلي. يثير هذا القلق بشأن الأهمية النسبية للقطاع الزراعي في الاقتصاد وقدرته على تحقيق الاستدامة والنمو. كما تسلط القيم المتوقعة وفواصل الثقة الضوء على التحديات المحتملة التي تواجه القطاع الزراعي، مثل تقلبات الإنتاجية، ظروف السوق، العوامل الخارجية مثل تغير المناخ والديناميكيات التجارية العالمية. يتطلب التصدي لهذه التحديات سياسات وتدخلات مستهدفة لتعزيز مرونة وتنافسية القطاع الزراعي

الكلمات المفتاحية: نظرية الأنظمة الرمادية، المربعات الصغرى العادية، الشبكات العصبية بالتغذية العكسية.

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Introduction

An overview of how agriculture contributes to Iraq's GDP sheds light on its economic importance within the nation's broader financial landscape. Historically, agriculture has been a cornerstone of Iraq's economy, offering employment to a significant portion of its populace and bolstering national food security (World Bank, 2022). Despite the diversification of Iraq's economy over time, particularly with the rise of sectors like oil and gas, agriculture remains a fundamental pillar, particularly in rural regions (World Bank, 2019). This study is incredibly useful due to its new revolutionary methods. It uses the integrated strengths of a Grey (1,1) models and neural networks to solve forecasting challenges - and it works. (Hu & Jiang 2017). This altered method makes an impact in economic forecasting. As such, this study uses Zeng and Wu (2007) which serves a critical gap in existing literature and provides a unique contribution towards global understanding. Additionally, this study places importance to Iraq where appropriate forecasting is essential for optimal economic preparation and resource allocation. Accurate forecasting can be proving bolstering results and is going to aid Iraq in ensuring their development strategies align better with its economic goals (World Bank 2025). The use of advanced techniques should promote innovative measures in other nations and sectors and similar importance is placed within the realm of economic and financial forecasting. Recent data provided by the World Bank suggests that agriculture makes up approximately 4.4 percent of Iraq's GDP reaffirming its enduring significance which suffers a myriad of problems such as political, environmental, and infrastructure issues (World Bank, 2023).

1. Literature Review

Ruijing Gan and et al. (2015). In this study they explore the use of a hybrid algorithm combining grey model (GM) and back propagation artificial neural networks (BP-ANN) to forecast hepatitis B in China based on yearly hepatitis B numbers. The results show that the proposed method has advantages over GM (1, 1) and GM (2, 1) in all evaluation indexes. The study also compares predictions from two GM models and the proposed method, showing that the two GM models have greater dispersion than the proposed method. Accurate incidence forecasting of infectious diseases is crucial for early prevention and health services management.

And, Sham Azad Rahim and et al. (2020). In this study they used a combined grey regression model to predict Iraq's GDP from 2000 to 2018. This statistical technique is known for its high accuracy, and it provides less MSE than grey or regression models alone. The model's estimated parameters are 2.9 and 0.205, respectively, and its intercept is 1.8569. The results show that the new model can achieve preferable predicting results compared to different methods, demonstrating its potential in shaping policy and determining public spending affordability.

Furthermore, Azhy A. Aziz and et al. (2023). In the study, they used neural recurrent neural networks (RNN) and Back-propagation algorithm to forecast the daily price of the dollar against Iraqi dinars for the next 30 days. Despite government efforts to control prices, the exchange rate has risen again, indicating an economic problem in Iraq. The best architecture for the RNN model was [1,10,1,1] using the soft plus activation function, with 85% performance for the training dataset and 92% and 90% performance for the testing and validation datasets, respectively. The forecasted values for the periods from 15 May 2023 to 13 June 2023 suggest that the dollar price will be between 1390 and 1435. The dollar crisis in Iraq continues to persist despite adjusting the exchange rate.

2. Methodology

A. Grey system theory

Deng Julong (1982) developed the grey system theory to analyze a system's uncertainty.

As far as fisher information is concerned, the systems that lack information, such as structure behavior documents, operation machinery, and messages are referred to as grey systems. The grey system theory consists of five major parts which are grey prediction, relation, decision, programming, and control. The grey model is the core of grey system theory, which features available information to obtain internal regularity without assumptions. The intention is to make forecasting useful for decision-makers and policymakers who need future predictions.

B. Advantage of Grey models

The most important advantages of Grey Prediction Model have been shown below:

(1) Grey models can be used even if you have four observations.
(2) To characterize an unknown system a few discrete data are sufficient.
(3) The researchers can depend on the results of the grey system theory in case having a suspected large sample.

C. Time series Data and use of Grey Model

Time series data is observing data at equal periods respectively, to forecast phenomena depending on a time series model a large full information sample is needed, sometimes it is the common problem that the researchers face at the beginning of their study, which is why advise to use grey models instead of time series models in case lack of information (Ahmed, S. T., & Tahir, H. A. 2021).

D. Grey Theory Steps

The lack of information is named by grey, the Grey system provides adequate results despite uncompleted information or small samples under study that is because of the cumulative generate operator which gives more weights for each observation of the sample (Ahmed, S. T., & Tahir, H. A. 2021).

E. Grey Model

In grey systems theory, GM (m,n) definition of the lack information model, where m is the order of the difference formula and n is the number of factors. Grey models can predict the future outputs of systems with relatively high accuracy without a mathematical model of the actual system. The majority of the incisive researchers have fastened their awareness on the GM (1, 1) model in their predictions because of its computational efficiency (Javed, Saad Ahmed et al. 2018).

F. The GM (1, 1) Model

The GM (1, 1) is most type model that is used among the other type models of the Grey System model, which determines that there is one input variable in the model. The accumulation generating operation (AGO) is the first-order differential equation that is adapted to match the data. For the algorithm of GM (1, 1), the raw data sequences are presented as follows:
First of all, to ensure the feasibility of the modeling method, it is necessary to make the necessary known data column inspection treatment (Huo, H. et al. 2012).

$X^{(0)} = (x^{(0)}(1), x^{(0)}(2) \ldots x^{(0)}(n))$, calculation sequence stage than

$$\sigma(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)} \quad , k = 2,3,\ldots.n \qquad (1)$$

Wher $X^{(0)}$ is the original series and k is number of lag.
If all the levels than $\sigma(k)$ have fallen on can let cover $\left(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}}\right)$ inside, series $x^{(0)}$ can be used as a model GM (1, 1) of grey prediction data. Otherwise, need to series $x^{(0)}$ make the necessary transformation processing, make its fall into can let cover inside. Namely take appropriate constant c, for translational transformation

$$y^{(0)} = x^{(0)}(k) + c \, , k = 1,2,\ldots,n$$

$$y^{(0)} = \left(y^{(0)}(1), y^{(0)}(2), y^{(0)}(n)\right)$$

A level that $\sigma_y(k)$ falls into can let coverage area.

In grey system theory, the GM (1, 1) model is one of the most widely used models (Ahmed, S. T., & Tahir, H. A. 2021). In general, GM (1, 1) requires a few numbers of observations to build a prediction model. Assume that is the original sequence as follows (Guo, Z. et al. 2005):

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$$

Where n is the total number of modeling data. The accumulated generating operation (AGO) formation of $x^{(1)}$ is defined as:

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

Where $x^{(1)}(1) = x^{(0)}(1)$, and

$$x^{(1)}(t) = \sum_{i=1}^{t} x^{(0)}(i) \quad , \qquad t = 1, 2 \ldots m \qquad (2)$$

The GM (1, 1) model can be built by establishing a first-order differential equation for $x^{(1)}(t)$ as:

$$\frac{dx^{(1)}(t)}{dt} + \alpha\, x^{(1)}(t) = b \qquad (3)$$

Then the discrete form of the GM (1, 1) differential equation model is expressed as:

$$x^{(0)}(t) + \alpha z^{(1)}(t) = b \qquad (4)$$

Where $z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n))$ are called background values of $\frac{dx^{(1)}(t)}{dt}$ and calculated by:

$$z^{(1)}(t) = 0.5\left(x^{(1)}(t-1) + x^{(1)}(t)\right) \quad , t = 2,3,\ldots n \qquad (5)$$

Coefficients **α** and **b** are called the updating coefficient and grey input, respectively. In practice, coefficients **α** and **b** are not calculated directly from Eq. (3). Therefore, the solution of Eq. (5) can be obtained by using the least square method that is (Deng, L. R. et al. 2012):

$$\acute{\alpha} = [\alpha, \mathrm{b}]^T = (B^T B)^{-1} B^T Y \qquad (6)$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \qquad (7)$$

$Y = \left[x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)\right]^T$ (8)

Then, the modeling values of Eq. (3) are obtained as:

$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}$ (9)

Applying the inverse accumulated generation operation (IAGO)

$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k),\ k = 1,2, \ldots, n$ (10)

The prediction sequence can be obtained as:

$\hat{x}^{(0)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)(1 - e^{a})e^{-ak}\ ,\ k = 1,2, \ldots, m.$ (11)

Where $\hat{x}^{(0)}(1) = x^{(0)}(1), \{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n)\}$ are called the GM (1, 1) fitted values, while $\{\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \ldots, \hat{x}^{(0)}(n+j)\}$ are called the GM (1, 1) predicted values.

G. Backpropagation Artificial Neural Model and Computational Schemes

An artificial neural network comprises numerous elementary information processors, termed neurons or nodes. The prevalent and well-developed model, featuring multi-layered nodes and employing error backpropagation, serves as a widely utilized computational method within artificial neural network systems (Taher, H. A., & Ahmed, N. M. 2023). This model effectively transforms the input-output problem from a given sample into a nonlinear optimization challenge. It proves to be a potent tool for uncovering hidden laws and patterns within extensive datasets. Utilizing artificial neural networks to simulate data sequences offers several inherent advantages. Firstly, it can adeptly model various types of functions, including nonlinear and piecewise-defined functions. Secondly, unlike conventional methods that necessitate pre-assumed functional relationships between data sequences, artificial neural networks can establish these relationships based on the inherent attributes and intentions within the provided data variables, without presupposing the distributions of parameters (Nader, R. A. et al. 2018). Thirdly, this approach efficiently utilizes available information while mitigating the risk of losing the true meanings and insights of the data.

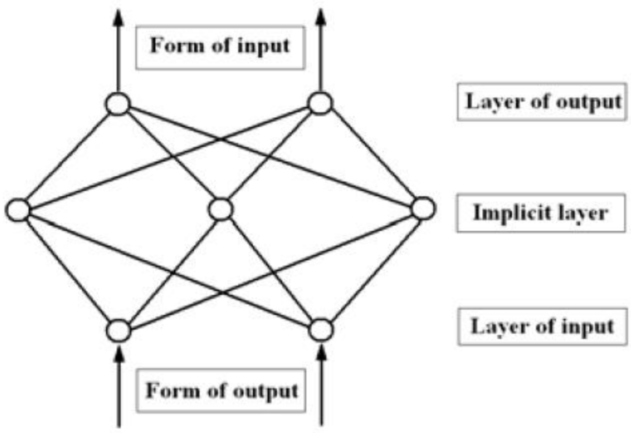

Figure (1) A backpropagation neural network

Different combinations of data mining methods, including the incorporation of positive and negative values, can enhance the effectiveness of the GM(1,1) model. Specifically, the artificial neural network method proves to be particularly beneficial in this regard. Illustrated in Figure (1) is a three-layer backpropagation network comprising an input layer, a hidden (or latent) layer, and an output layer. The learning process involves both forward and backward propagation. The specific learning scheme is outlined below (Aziz, A. A. et al. 2023):

- Putting initial weights (W_i) which is between (± 0.6) and threshold α_j for node j.
- Inputting the training datasets of X_{hs} and Y_{hq}.
- Calculating the product of each node of each layer;
  $Q_{hj} = f\sum_i(W_{ij}\ I_{hi} - \alpha_j)$ for the h^th sample point, where I_{hi} stands for the output of node i and the input of node j.

- Compute the information error of each layer.,
  $\delta_{hq} = Q_{hq} (Y_{hq} - Q_{hq}) (1 - Q_{hq})$ For the input layer.
  $Q_{hi} = Q_{hi} (1 - Q_{hi}) \sum_i W_{ij} \delta_{hq}$ For the latent layer.
- For the backward propagation, the modifiers of the weights are

$$W_{ij} (t+1) = \alpha\delta_{hi} Q_{hi} + W_{ij} (t) \tag{12}$$

And the modifiers of the thresholds;

$$\alpha_j (t+1) = \alpha_j (t) + Đ\delta_{hi} \tag{13}$$

Where α stands for the learning factor and Đ the momentum factor for accelerated convergence.

- Then compute the error as follows:

$$E_h = \frac{1}{2} (\sum_h \sum_q) (Q_{hq} - Y_{hq})^2 \tag{14}$$

H. Test of Residuals

Augmented Dickey-Fuller tests the hypothesis which states that the residuals are distributed normally or not (Rahim, S. A. et al. 2020), the test can be performed up to the below equation:

$$\Delta x^{(0)}(\mathrm{k}) = \beta_0 + \mathrm{a}_k + \beta_1 x^{(0)}(k-1) + \sum_{k=1}^{p} \lambda_k \Delta x^{(0)}(k-i) + \varepsilon_k \tag{15}$$

Where a random walk, $\mathrm{a}_k = \mathrm{a}_{k-1} + \mathrm{a}\varepsilon_k$ is allowed.

I. Model Selection Criteria

(1) Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is used to test the accuracy of the forecasting model, there is an index used to evaluate the performance and reliability of the forecasting technique (Ahmed, B. K. et al. 2020). It is defined as follows:

$$MAPE = \frac{1}{n} \sum_{k=2}^{n} \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \times 100\% \tag{16}$$

Where $x^{(0)}(k)$: the actual value in time period k

$\hat{x}^{(0)}(k)$: the forecast value in time period k

(2) Root Mean Square Error (RMSE)

The RMSE is expressed by:

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=2}^{n} (x^{(0)}(k) - \hat{x}^{(0)}(k))^2} \tag{17}$$

Where: $x^{(0)}(k)$ = actual value.

$\hat{x}^{(0)}(k)$ = forecasteed value.

(3) Mean Square Error (MSE)

The MSE is expressed by:

$$MSE = \frac{1}{n} \sum_{k=2}^{n} \frac{(x^{(0)}(k) - \hat{x}^{(0)}(k))^2}{n-2} \tag{18}$$

3. Applications

A. Introduction

Making decisions based on forecasting methods requires careful consideration, as these methods are highly sensitive. Researchers must exercise caution when utilizing forecasting techniques, as their accuracy depends on factors such as the quantity of observations and the duration of the forecasting period. Additionally, the choice of estimation method is crucial for determining the parameters of the model being used, The R-Language and Matlab have been used for Implementation.

B. Data Description

The dataset employed for analysis in this study is the yearly income of agriculture per GDP, taken from the Central Bank of Iraq from the years (1991 to 2023).

$$B^T B = \begin{pmatrix} 1100876.898 & 5592.73151 \\ -5592.73151 & 32 \end{pmatrix}, \quad B^T Y = \begin{pmatrix} -32418.2 \\ 239.4925 \end{pmatrix}$$

$$(B^T B)^{-1} = \begin{pmatrix} 0.0000081025 & 0.001416091 \\ 0.001416091 & 0.278744 \end{pmatrix}, \quad a = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y = \begin{pmatrix} 0.076476108 \\ 20.85009019 \end{pmatrix}$$

Table (1) shows the actual, GM (1,1) and GMNN (1,1) values.

Years	Actual values	GM(1,1) values	GM(1,1) Error	GMNN(1,1) values	GMNN(1,1) Error
1991	15.61566584	18.92307398	-3.307408138	16.27714747	-0.661481628
1992	19.87057417	17.23966268	2.630911497	19.34439187	0.526182299
1993	15.50271431	16.24636826	-0.743653945	15.6514451	-0.148730789
1994	20.11210342	14.78044014	5.331663288	19.04577077	1.066332658
1995	20.58513659	13.66658381	6.918552778	19.20142603	1.383710556
1996	18.59708233	12.76024257	5.836839759	17.42971438	1.167367952
1997	8.456601885	12.292622	-3.836020119	9.223805909	-0.767204024
1998	10.9097071	11.28183718	-0.372130088	10.98413311	-0.074426018
1999	7.203503924	10.59920919	-3.395705264	7.882644977	-0.679141053
2000	4.634745507	9.913867194	-5.279121687	5.690569844	-1.055824337
2001	6.930957055	9.105272762	-2.174315708	7.365820196	-0.434863142
2002	8.562671712	8.383099021	0.179572692	8.526757174	0.035914538
2003	8.405608293	7.770513527	0.635094766	8.278589339	0.127018953
2004	6.938561306	7.238377294	-0.299815987	6.998524504	-0.059963197
2005	6.886862735	6.706757556	0.180105179	6.8508417	0.036021036
2006	5.826032905	6.237774768	-0.411741863	5.908381278	-0.082348373
2007	4.929498276	5.797936505	-0.868438229	5.103185922	-0.173687646
2008	3.847780195	5.392767081	-1.544986886	4.156777573	-0.308997377
2009	5.229933191	4.970036547	0.259896644	5.177953863	0.051979329
2010	5.162283547	4.605283109	0.557000438	5.050883459	0.111400088
2011	4.563773437	4.27576609	0.288007348	4.506171968	0.05760147
2012	4.124271438	3.967457407	0.15681403	4.092908632	0.031362806
2013	4.768439716	3.666536642	1.101903074	4.548059101	0.220380615
2014	4.929407772	3.394547328	1.534860444	4.622435683	0.306972089
2015	4.191868175	3.153287818	1.038580357	3.984152104	0.207716071
2016	3.977189811	2.923463532	1.05372628	3.766444556	0.210745256
2017	2.923230267	2.718848439	0.204381828	2.882353901	0.040876366
2018	2.815817643	2.51967668	0.296140963	2.756589451	0.059228193
2019	3.334400514	2.329679685	1.004720828	3.133456348	0.200944166
2020	6.06997004	2.136234756	3.933735284	5.283222983	0.786747057
2021	3.310780564	1.999438694	1.31134187	3.04851219	0.262268374
2022	2.851425262	1.85538944	0.996035822	2.652218098	0.199207164
2023	3.039615287	1.717587714	1.322027574	2.775209773	0.264405515

Table (2) Dickey-Fuller test of residuals for both models

Models	Test	t-Statistic	P-value
GM(1,1)	ADF	-6.592854	0.000
GMNN(1,1)		-8.046703	0.000

Table (2) explains that the p-value of the Dickey-Fuller test equals 0.000 and it is less than 0.05. This result indicates that the residuals both models are normally distributed, then the goodness of fit assumption is achieved.

Table (3) demonstrates the evaluation measurements of both models

Metrics	**GM (1,1)**	**GMNN (1,1)**
MSE	0.45433	0.09087
MAPE	0.3057	0.04963
RMSE	0.67404	0.30144

These metrics in the above table are commonly used to evaluate the performance of forecasting models the three of them in GMNN (1,1) recorded lower values than GM (1,1) indicating that the GMNN (1,1) model provides more accurate forecasts with lower error magnitude.

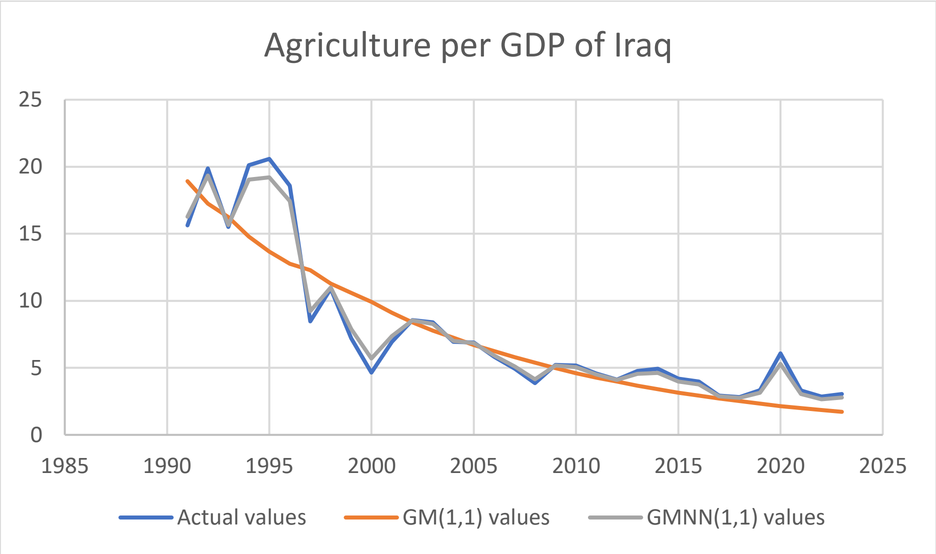

Figure (1) represents the curve of the actual, GM (1,1) and GMNN (1,1) values.

Table (4) represents the forecasted values of the GMNN (1,1) model

Years	Forecasted Agriculture per GDP	%95 Confidence Interval	
		Lower	Upper
2024	1.6090701	0.84677008	2.37137008
2025	1.4906025	0.72830253	2.25290253
2026	1.3808571	0.61855714	2.14315714
2027	1.2791917	0.51689174	2.04149174
2028	1.1850114	0.42271143	1.94731143

Table (4) shows the forecasted values of the GMNN(1,1) model for the periods (2024 to 2028), according to these forecasts agriculture`s contribution to the GDP of Iraq will decrease exponentially to 1.185% in 2028.

4. Conclusions and Recommendations

A. Conclusions

Based on the forecasted Agriculture per GDP values and their associated 95% confidence intervals for the years 2024 to 2028, the following conclusions can be drawn:
There is a downward trend in the forecasted Agriculture per GDP values over the five-year period, indicating a potential decline in the agricultural sector's contribution to the overall GDP ratio. This trend may raise concerns about the sector's relative importance within the economy and its ability to sustain growth. The forecasted values and confidence intervals highlight potential challenges facing the agricultural sector, including fluctuations in agricultural productivity, market conditions, and external factors such as climate change and global trade dynamics. Addressing these challenges will require targeted policies and interventions to enhance the sector's resilience and competitiveness. Policymakers should carefully assess the implications of the forecasted trends for agricultural development, food security, and economic growth. Strategies may include promoting diversification, increasing productivity, improving market access, and enhancing sustainability practices within the agricultural sector. Additionally, investments in infrastructure, research and development, and capacity-building initiatives may be needed to support the sector's long-term growth and resilience. Continuous monitoring of key indicators and timely adaptation of policies and strategies will be essential to address emerging challenges and capitalize on opportunities within the agricultural sector. Flexibility and agility in policymaking will help ensure that the sector remains responsive to changing economic, social, and environmental conditions. Overall, while the forecasted Agriculture per GDP values provide valuable insights into the sector's expected performance in the coming years, careful consideration of uncertainties, challenges, and policy implications is necessary to formulate effective strategies for sustainable agricultural development and economic growth.

B. Recommendations

Given the forecasted values for Agriculture per GDP and their associated 95% confidence intervals for the years 2024 to 2028, here are some recommendations:

(1)**Enhance Agricultural Resilience and Sustainability:** Promote diversification, sustainable practices, and climate adaptation strategies to reduce risks associated with price fluctuations, climate variability, and resource depletion. This includes encouraging crop diversification, conservation agriculture, and the adoption of climate-resilient technologies.

(2)**Invest in Infrastructure and Innovation**: Allocate resources to improve agricultural infrastructure (irrigation, storage, and transportation) and foster research and development for technological advancements. Enhanced infrastructure and innovation can boost productivity, reduce losses, and support sustainable growth.

(3)**Empower Farmers and Value Chains:** Support smallholder farmers by providing access to credit, markets, and technical assistance. Additionally, promote value addition and agro-processing to increase incomes, reduce post-harvest losses, and enhance competitiveness in local and global markets.

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