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35. Fatima Saidu and Lawal Adamu(2023). Prediction of Annual Rainfall of Minna and Its Environs Using Grey-Artificial Neural Network. A paper presented at 32nd Annual Colloquium and Congress of the Nigerian Association of Mathematical Physics. University of Benin, Nigeria. 31st January – 3rd February, 2023.

THE NIGERIAN ASSOCIATION OF MATHEMATICAL PHYSICS (NAMP)

32nd ANNUAL COLLOQUIUM AND CONGRESS

of the Nigerian Association of Mathematical Physics

BOOK OF ABSTRACTS

31ST JANUARY – 3RD FEBRUARY 2023.

Banquet Hall, University Of Benin, Benin City, Nigeria

41. A CLASS OF IMPLICIT SIX STEP HYBRID BACKWARD DIFFERENTIAL FORMULAE (HBDF) FOR THE SOLUTION OF SECOND ORDER DIFFERENTIAL EQUATIONS.

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ABSTRACT
In this research work, the Block Hybrid Backward Differentiation Formulae (BHBDF) for the step number K= 6 were developed for the solution of general second order ordinary differential equations ODE. The Continuous formulations of the shemes were obtained through interpolation and collocation approaches with power series polynomial as basis function at some selected grids and off-grids points. The continuous schemes were further evaluated at those points to produce discrete schemes which are combined to form block method. Analysis of the basic properties of the method investigated showed consistency, zero stability and convergence of the proposed block method. Numerical examples were solved to examine the efficiency and accuracy of the proposed method. The results showed that the proposed methods with relatively small errors performed favorably in comparison with the existing methods.
Keywords: Backward Differentiation Formula (BDF), Block Methods Hybrid, Implicit, Multistep Collocation, Interpolation, Ordinary Differential Equation, Approximate Solution, Convergent, Second Order.

42. PREDICTION OF ANNUAL RAINFALL OF MINNA AND ITS EMVIRONS USING GREY-ARTIFICIAL NEURAL NETWORK

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Minna, Niger State

ABSTRACT
Providing farmers and governments with reliable and dependable information, about rainfall variability and quantity ahead of time is the focus of this paper. In this study a Grey-Artificial Neural Network Model (GANNM) has been used to predict annual rainfall pattern of Minna and its environs using the annual rainfall data of ten years (2011 to 2020). The annual rainfall was collected from the archive of National Oceanic and Atmospheric Administration (NOAA). The fitted model showed 95% accuracy, this indicates that the model is reliable and dependable. Therefore, information from this study could be beneficial to the farmers, governments, water resources management scientists and other relevant stakeholders in agricultural sector in decision making for optimal use of the rainfall.

PREDICTION OF ANNUAL RAINFALL IN MJNNA AND ITS ENVIRONS USING GREY ARTIFICIAL NEURAL NETWORK

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Keywords: Rainfall, Grey System, Artificial Neural Network, Minna, Niger State.

INTRODUCTION

The earth and its inhabitants and sustenance of all creatures revolve around the rainfall. The rainfall effect is immense in human civilization, and the continue human existence on the planet earth is dependent on this natural resource. Accurate information on rainfall variability and quantity is essential for planning and management of water resources, for reservoirs operation and flood prevention. Precipitation is one of the metereological variables that plays an important roles in conversing the natural cycle and water supply sources (Schmidt, Mattos, 2013; Silva et al, 2021; Neto et al, 2022; Maud 2022).S Grey Artificial Neural Network (GANN) is used to predict the annual rainfall of Minna and its environs for the fact of its ability to detect all possible interactions between predictive variables, and for its ability to detect complex nonlinear relationships between dependant and independent variables implicitly. Also, they are more fault tolerant because they are always able to respond and small changes in input do not cause change in output.

MATERIALS AND METHODS

We begin this section by introducing Grey system GM(1,1) model and its properties, after which the Grey-Artificial Neural Network model will be presented.

Grey System GM (1,1) Model

The Grey Model GM(1,1) model make use of discrete data series to establish an equation of grey continuous differential equation by adding these data from the first in Accumulating Generation Operator (AGO), and the equation can then be solved to perform forecast (Li Q et al, 2007).

Let the raw data series be represented by $x^{(0)}(k)$, $k = 1,2,3 \ldots, n$, $x^{(0)}(k) \geq 0$ which can also be represented as:

$$X^{(0)}(k) = (x^{(0)}(1), x^{(0)}(2, x^{(0)}(3), \ldots, x(^{0}(n) \quad (1)$$

Let the accumulated generating sequence be represented as:

$X^{(1)}(k) = (x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n))$ (2)

Where $X^{(1)}(k) = \sum_{i=0}^{k} x^{(0)}(i),\ k = 1,2,\ldots,n$ (3)

$X^{(1)}(k)$ is called accumulated generating operation (AGO)

$X^{(0)}(k)$ denoted as 1- AGO

By differentiating $X^{(1)}(k)$, a whitened differential equation is obtained;

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

Where a and b are parameters to be identified. a is called the developing coefficient and b is the grey input.

The difference form is given as:

$X^{(0)}(k) + ax^{(1)}(k) = b$ (5)

Equation (5) represents the original form of GM (1,1) model. The symbol GM (1,1) stands for first order Grey Model in one variable.

Equation (6) is the solution of equation (4)

$\hat{X}^{(1)}(k+1) = \left(\hat{x}^{(1)}(0) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a}$ (6)

Equation (6) is the time response function while parameters a and b are estimated using Least Square Method as follows

$\begin{bmatrix} a \\ b \end{bmatrix} = [B^T B]^{-1} \times B^T Y$ (7)

Where B= $\begin{bmatrix} -z^1_{(2)} & 1 \\ -z^1_{(3)} & 1 \\ -z^1{}_{(4)} & 1 \\ \vdots & \vdots \\ -z(_{n)} & 1 \end{bmatrix}$ (8)

$Z^{(1)}(k) = \frac{(X(1)(k) + X(1)(k-1))}{2}, (k = 2,3,4 \ldots\ldots. n)$ (9)

$Y = [\hat{x}^{(0)}(2), \hat{x}^{(0)}(3), \hat{x}^{(0)}(4), \ldots\ldots.\hat{x}^{(0)}(n)]^T$ (10)

The reduction value equation (6) is given in equation (11) below

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

Prediction Accuracy Test

To determine the accuracy of our forecast, we shall adopt Mean Absolute Percentage Error (MAPE). This tool is often used for determining prediction accuracy showing the same characteristics i.e the smaller the value, the higher the prediction accuracy.

MAPE

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\% \quad (12)$$

Where

$\hat{x}$ is the Grey-Model predicted value.

x is the Grey-Model actual value.

n is the number of prediction samples (Xin Z et al., 2018)

Lewis (1982) divided the prediction accuracy of models into four grades and the division of prediction accuracy grades is shown in the table below:

Table 1

MAPE	Prediction Accuracy
<10%	High
10% - 20%	Good
20% - 50%	Feasible
> 50%	Low

GREY ARTIFICIAL NEURAL NETWORKS

The Grey-Artificial Neural Network model is an hybrid model made up of Grey system GM(1,1) and a Neural Network model. The neural network model is used to improve the performance of the grey system model GM(1,1) model. We begin this section by presenting Steps in the development of Grey Back Propagation neural network Model.

Steps in Grey BP Neural Network Modelling

The steps to establish a grey BP neural network model are as follows:

Step 1: Assume that a time series $\{x^{(0)}(i)\}$, $i = 1,2,,\dots,n$, using is given. We then obtain the restored values $\hat{x}^{(0)}(i)$, $i = 1,2,,\dots,n$, using the outputs of the GM (1, 1) model.

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If the order of prediction is S, it means that we use the information of $e^{(0)}(i-1), e^{(0)}(i-2), \dots, e^{(0)}(i-S)$ to predict the value at the ith moment; we will treat $e^{(0)}(i-1), e^{(0)}(i-2), \dots, e^{(0)}(i-S)$ as the input sample points of the back propagation network training, while using the value of $e^{(0)}(i)$ as the expected prediction of the back propagation network training. By using the back propagation computational scheme outlined earlier,

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Step 3: Determine the simulation values of $\{e^{(0)}(k) = x^0(k) - \hat{x}^0(k)\}$, $k = 1, 2, \ldots, n$. Assume that the simulation sequence $\{\hat{e}^{(0)}(k)\}$, $k = 1, 2, \ldots, n$, which is obtained by the BP neural network.

Step 4: Based on $\{\hat{x}^{(0)}(i)\}$ and $\{\hat{e}^{(0)}(k)\}$, $i, k = 1, 2, \ldots, n$, we have the following result.

$$\hat{x}^{(0)}(i,k) = \hat{x}^{(0)}(i) + \hat{e}^{(0)}(k) \tag{13}$$

Which is the predicted sequence of the grey artificial neural network model.

RESULTS AND DISCUSSION

Application of Grey GM (1,1) Model for forecasting Annual Rainfall of Minna, Niger State

Table2: Annual rainfall of Minna and Environs for 10 years from 2010 to 2020.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Amount of rainfall	1055.6	1543.2	1140.3	1264.9	1056.0	965.4	873.5	787.6	1135.0	1200.7

Source : National Oceanic and Atmospheric Administration (NOAA)

We begin by substituting the raw data in Table 2 into eqtn (1) to get eqtn (14) below

$X^{(0)}(k) = X^{*}_1, X^{*}_2, X^{*}_3 \ldots\ldots\ldots\ldots\ldots, X^{*}_n.\ k = 1, 2, 3 \ldots\ldots\ldots\ldots, n.$

$$X^{(0)}(k) = (1055.6, 1543.2, 1140.3, 1264.9, 1056.0, 965.4, 873.5, 787.6, 1135.0, 1200.7) \quad (14)$$

Eqtn (2) is used to obtain eqtn (15), the Accumulated generating operating (AGO), that is the successive addition of the original data sequence

$$X^1_{(k)} = (1055.6, 2598.8, 3739.1, 5004.0, 6060, 7025.4, 7898.9, 8686.5, 9821.5, 11022.2) \quad (15)$$

Using eqtn (9), eqtn (16) is obtained shown below; $Z^1_{k+1} = (X^1_{(k)} + X^1_{(k+1)})/2,\ k = 1, 2, 3, \ldots\ldots\ldots n$

$$Z^1_K = (1827.2, 3168.95, 4371.55, 5532.00, 6542.70, 7462.15, 8292.7, 9254.00, 10421.85) \quad (16)$$

Using eqtn (10) we obtain eqn (17)

$$Y = \begin{bmatrix} 1543.20 \\ 1140.30 \\ 1264.90 \\ 1056.00 \\ 965.40 \\ 873.50 \\ 787.60 \\ 1135.00 \\ 1200.70 \end{bmatrix} \quad (17)$$

From eqtn (8), we obtained eqtn (18)

$$B = \begin{bmatrix} 1827.20 & 1 \\ 3168.95 & 1 \\ 4371.55 & 1 \\ 5532.00 & 1 \\ 6542.70 & 1 \\ 7462.70 & 1 \\ 8292.70 & 1 \\ 9254.00 & 1 \\ 10421.85 & 1 \end{bmatrix} \quad (18)$$

Equation (19) is obtained using equqtion (7) by the help of Maple 17 software

$$\hat{a} = \begin{bmatrix} 0.0428 \\ 1378.1419 \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix} \quad (19)$$

Where a=0.0428

b=1378.1419

Substituting for a and b in eqtn (6), eqtn (20) below:

$$\hat{x}(k+1) = 32199.5771 - 31143.9771e^{-0.0428*k} \quad (20)$$

Evaluating for (20) for k=0,1,2,3,...,9, we obtained eqtn (21) below;

$\hat{X}^{(1)}$ =(1055.60, 2360.44, 3606.94, 4804.88, 5952.64,7052.31,8105.90,9115.36, 10082.52, 11009.15) (21)

We compute the simulated value for our model using equation (22) below; Simulated values were computed using eqtn (28) below

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) = 1,2,3\ldots\ldots 10 \quad (22)$$

The simulated values are presented in equation (23) below

$\hat{X}^{(0)}$=(1055.60,1304.84,1246.50,1197.94,1147.76, 1099.67,1053.59,1009.46,967.16,926.63) (23)

These are the simulated gray values of annual rainfall in Minna

Table 3: Comparison of Actual and Grey simulated values for Annual Rainfall in Minna from 2011 to 2020

S/N	Year of Rainfall	Actual Annual Rainfall (mm)	Grey Stimulated Values of Rainfall (mm)	Residual Error	Relative error (%)
1	2011	1055.60	1055.60	0	0
2	2012	1543.20	1304.84	239.36	15.51
3	2013	1140.30	1246.50	-106.20	-9.31
4	2014	1264.90	1197.94	66.96	5.29
5	2015	1056.00	1147.76	-91.76	8.69
6	2016	965.40	1099.64	-134.24	-13.91
7	2017	873.50	1053.59	-180.09	-20.62
8	2018	787.60	1009.46	-221.86	-28.17
9	2019	1135.00	967.16	167.84	14.79
10	2020	1200.7	926.63	274.06	22.83
					139.12

Using eqtn (12), we observed from Table 3 that

MAPE = 13.9% as calculated below, which is the error of the forecast, described as high accuracy (Lewis, 1982)

Hence the accuracy s calculated as:

ACCURACY=100%-13.9%=86.1%=86% this shows that the simulated is high.

A GRAPH OF ACTUAL AND GREY SIMULATED VALUES OF RAINFALL

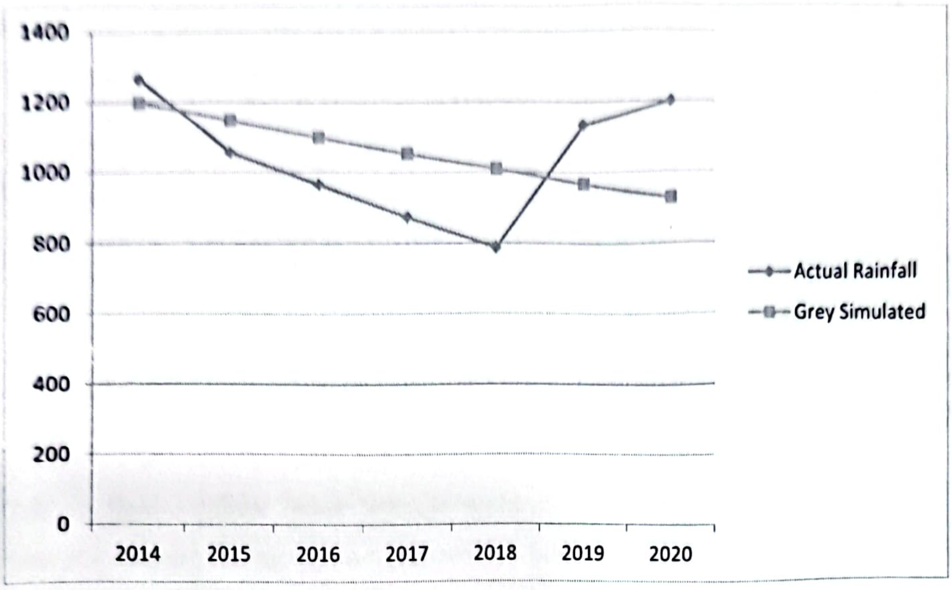


Fig 1

GREY ARTIFICIAL NEURAL NETWORK ON RAINFALL

Artificial neural network is also another model of prediction. It is also used here for the prediction of rainfall. But before the prediction is made, it is used to stimulate values and values are compared to the original value to know how efficient or accurate it is, before it is used for prediction.

Since ANN is used to enhance/correct the flaws of the Grey Model, the residual errors gotten from comparison of original and Grey Stimulated Values are fed into the Matlab using three (3) different train, Validity and Test ratio. The table below is for the year and residual error.

A well trained neural network model to simulate error sequence is developed. Several back neural networks model were developed based on trial and error method to simulate error sequence . All the developed network models were tested for performance criteria of root mean square error, coefficient of determination and coefficient of correlation . The model with highest value of correlation coefficient and lowest value of root mean square error is then considered as the best fit model. The back propagation neural network simulated error sequence using matlab software is presented in the table below

Table 4: Comparison of Actual residual error and back eural network simulated residual error

The Neural network errors generated from Matlab after feeding it with Grey residual error in the table 4

S/N	Year Of Rainfall	Actual annual Rainfall	Grey Model Simulated Values	Residual Error	Neural Network Simulated Residual error
1	2011	1055.60	1055.60	0	-
2	2012	1543.20	1304.84	239.36	-
3	2013	1140.30	1246.50	-106.20	-
4	2014	1264.90	1197.94	66.96	66.9600
5	2015	1056.00	1147.76	-91.76	-91.7600
6	2016	965.40	1099.64	-134.24	-123.2400
7	2017	873.50	1053.59	-180.09	-180.0900
8	2018	787.60	1009.46	-221.86	-192.2621
9	2019	1135.00	967.16	167.84	-163.8306
10	2020	1200.7	926.63	274.06	274.060

Table 5: Grey-Artificial Neural Network Model Simulated Values

This is obtained by using equation (13) and data from Table 4

S/N	Year of Rainfall	Grey-Artificial Neural Network Model Simulated Values
1	2014	1264.9000
2	2015	1056.0000
3	2016	976.4000
4	2017	873.5000
5	2018	817.1979
6	2019	803.3294
7	2020	1200.6900

Table 6: Comparison of Actual and Simulated Grey-Artificial Neural Network Model values for the Rainfall of Minna

S/No.	Year	Actual Annual Rainfall	Grey-Artificial Neural Network Model Simulated Values	Residual Error	Relative Error(%)
1	2014	1264.900	1264.9000	0	0
2	2015	1056.000	1056.0000	0	0
3	2016	965.400	976.4000	-11.000	-1.1394
4	2017	873.500	873.5000	0	0
5	2018	787.600	817.1979	-29.5978	-3.7580
6	2019	1135.000	803.3294	331.6706	29.2221
7	2020	1200.700	1200.6900	0.01	0.0008328

Using equation (12), we observed from table (5) that:

$MAPE = 4.8743\%$

$ACCURACY = 100\% - 4.8743\% = 95.1257\% = 95\%$

Fig 2: the graph of Actual values and GANN simulated values of Rainfall

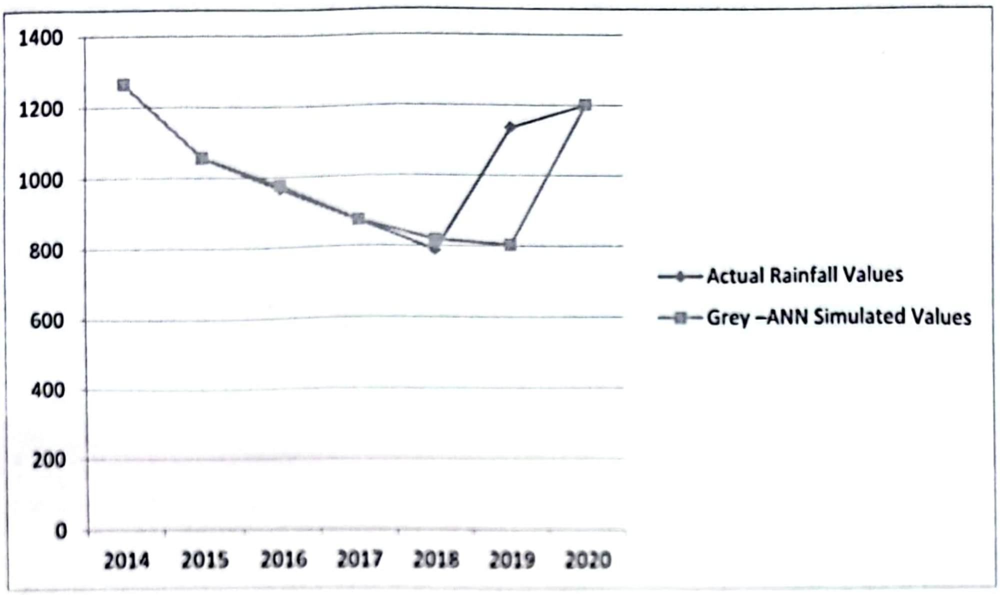
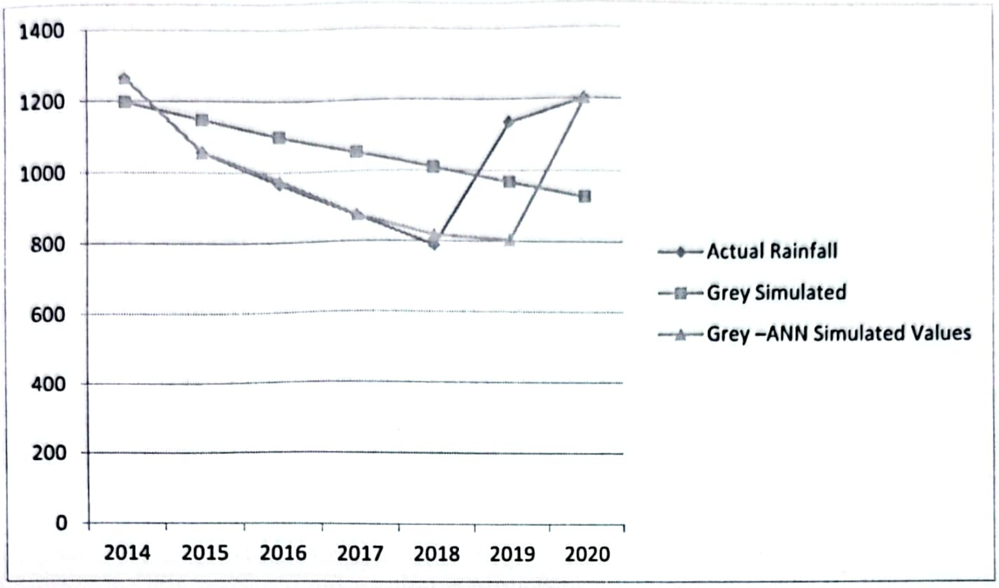


Table 7: Comparison of the actual values, GM(1,1) simulated values and grey-artificial neural network model simulated values of Rainfall of minna

S/N	Year Of Rainfall	Actual Annual Rainfall	Grey Model Simulated Values	Grey-Artificial Neural Network Model Simulated Values
1	2014	1264.9	1197.94	1264.9000
2	2015	1056	1147.76	1056.0000
3	2016	965.4	1099.64	976.4000
4	2017	873.5	1053.59	873.5000
5	2018	787.6	1009.46	817.1979
6	2019	1135	967.16	803.3294
7	2020	1200.7	926.63	1200.7000



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Grey Prediction from 2021 to 2030

Evaluating equation (15) for $k = 10,11,12.,...,19$, we obtained the following values below:

$\hat{R}^{(1)} = (11399.58,12750.09,135564.96,114345.70,115093.72,15810.41,16497.06,17154.95,17785.25,18389.19)$ (19)

We compute the predicted value using equation (17) below:

$\hat{r}^{(0)}(k) = \hat{r}^{(1)}(k) - \hat{r}^{(1)}(k-1)$

$\hat{R}^{(0)} = (890.43,850.51,814.87,780.74,748.0,716.69,686.65,657.89,630.30,603.94)$ (20)

Equation (20) is the grey predicted values from 2021-2030

Table 7: GM(1,1) model prediction of Rainfall from 2021 to 2030

Year	Grey GM(1,1) prediction for Rainfall
2021	890.43
2022	880.51
2023	814.87
2024	780.74
2025	748.02
2026	716.69
2027	686.65
2028	657.89
2029	630.30
2030	603.94

To obtain the grey-artificial neural network prediction from 2021 to 2030, we add the ANN predicted error sequence to Grey predicted values, that is using back propagation neural network and then use equation (11) to obtain the prediction in the table 8 below

Table 8: the predicted error sequence from 2021 -2030 using back propagation network

Year	ANN Predicted error sequence
2021	302.8597
2022	492.5909
2023	472.6565
2024	523.1112
2025	520.8892
2026	524.5278
2027	524.3099
2028	524.4630
2029	524.4457
2030	524.4523

Using the Grey GM(1,1) prediction in table 7, the back propagation neural network error sequence prediction in table 8 and equation (11), we obtain the Grey-Artificial Neural Network prediction in table 9 below

Table 9 : Grey-Artificial Neural Network model prediction for Rainfall 2021 to 2030

Year	GANN model predicted values
2021	1193.2897
2022	1373.1009
2023	1287.5265
2024	1303.8512
2025	1268.9092
2026	1241.2178
2027	1210.9599
2028	1182.3530
2029	1154.7457
2030	1128.3923

CONCLUSION

Grey-Artificial Neural Network has been used in this research to predict rainfall of Minna and its environs using data obtained from the archive of National Oceanic and Atmospheric Administration (NOAA). This was achieved as a result of its error back propagation and its ability to uncover patterns hidden in large amount of data and to establish the needed functional relationship by using the attributes in the data variables without presuming the kind of distributions the parameters satisfy. The result indicates that the model is reliable and dependable. Therefore, information from this study could be useful to the farmers, government and other relevant stakeholders in agriculture sector in decision making for optimal use of the rainfall.

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