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PREDICTION OF THE NUMBER OF ROAD TRAFFIC ACCIDENTS OCCURRENCE ON THE LOKOJA-ABUJA-KADUNA EXPRESSWAY USING GREY-ARTIFICIAL NEURAL NETWORK MODEL

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ABSTRACT

Road traffic accidents (RTAs) are one of the leading causes of death worldwide, especially in developing countries where road transportation is the primary means of mobility. In recent years, the demand for reliable road accident prediction models has increased dramatically globally, with the aim of reducing loss of life and property. Although the grey GM (1,1) prediction model has been employed in many fields and has demonstrated promising results, its predictions sometimes suffer from over- or under-estimation of real-world values, reducing reliability. To optimize the predictive performance of the grey GM (1,1) model and enhance its capability, an hybrid model called the Grey-Artificial Neural Network (GANNM) model is proposed in this paper. This model improves predictive accuracy for RTAs on Nigeria's Lokoja-Abuja-Kaduna expressway from 85.97% to 96.02%. Additionally, the results demonstrate that the GANNM resolves the estimation inaccuracies of the grey GM (1,1) approach, yielding critical data to support Nigerian policymakers in crafting effective road management strategies to enhance safety on this highway

Keywords: Road Traffic Accidents, Vehicular Crashes, Grey System Model, Artificial Neural Network Model, Lokoja-Abuja-Kaduna Expressway

INTRODUCTION

Road Traffic Accidents (RTAs) represent a significant public health and economic burden in Nigeria, with its extensive road networks, is particularly vulnerable. Accurate prediction of road traffic accidents (RTAs) is essential for effective road safety policy. The data generated by these predictive models directly informs strategies aimed at minimizing injuries, fatalities, and economic losses (Saeed *et al.*, 2021).

In Nigeria, road transport serves as the prevailing mode of transit. This reliance stems from an underdeveloped rail network, minimal use of inland waterways, and the high cost of air travel, making roads the most economical choice for the majority (Enwerem and Ali, 2016). The country boasts an extensive surfaced road network of approximately 195,000 km, the most extensive in West Africa and the second largest in sub-Saharan Africa, comprised of about 32,000 km of federal and 31,000 km of state roads.

Globally, Road Traffic Accidents (RTAs) cause around 1.3 million fatalities and 20-50 million non-fatal injuries each year, with over half of these casualties being vulnerable users like pedestrians, cyclists, and motorcyclists (WHO, 2023). RTAs are a primary cause of death for those aged 5-29, with young males under 25 representing 73% of fatalities. The economic impact is severe, costing nations up to 3% of GDP. The WHO projects RTAs could become the world's seventh leading cause of death by 2030, prompting a UN goal to halve related deaths and injuries by that year. Developing nations bear a disproportionate burden, accounting for 93% of fatalities despite owning only 60% of global vehicles. In Nigeria, RTAs present a critical public health issue, with an injury rate of 41 per 1000 and a mortality rate of 1.6 per 1000. The fact that most incidents are preventable renders this trend especially alarming (Enwerem and Ali, 2016).

To reduce RTAs, previous studies have employed various techniques for RTA prediction, including regression analysis, time-series models (ARIMA), and standalone machine learning models. While these methods have shown promising results; they often require large datasets or make strict assumptions about data distribution. For example, Nyothiri *et al.*, (2018) presented an accident prediction system based on a Hidden Markov Model for Vehicular Ad-hoc Networks in urban environments. XiaoXia *et al.*, (2018) used a System Cloud Grey Model (SCGM(1,1))-Markov model for road accident prediction, demonstrating strong engineering practicability. Traffic accident risk prediction based on deep learning and spatiotemporal features of vehicle trajectories (Li H Chen L , 2025), road accident prediction for smart cities(Thanikachaam *et al*, 2025), enhancing road crash prediction using machine learning algorithms(bayode *et al*., 2025). Saeed *et al*., (2021) used a grey-system GM(1,1) model to study accident occurrences on the Lokoja-Abuja-Kaduna expressway. Despite high accuracy of their model, it could not eliminate the problems of overestimation and underestimation inherent to GM(1,1), reducing its reliability. This constant underestimation and overestimation, along with a steady decline in simulated values, are major limitations of the GM (1,1) forecasting model.

This paper aims to improve the predictive accuracy on the work of Saeed *et al.* (2021) and also to eliminate underestimation and overestimation that characterized their study. This result of this paper will assist the government of Nigeria with reliable information to help reduce loss of life and property on the Lokoja-Abuja-Kaduna expressway. The Lokoja-Abuja-Kaduna expressway is among the busiest expressways in Nigeria because it connects the southern and northern parts of the country. Because of the high volume of vehicular movements on this expressway, frequent RTAs are usually experienced, resulting in significant loss of life and property.

The chosen Grey-Artificial Neural Network Model (GANNM) integrates a GM(1,1) grey system model with an artificial neural network to achieve superior predictive performance (Sifeng *et al.*, 2016). This approach is grounded in grey system theory, developed by Deng Julong in the 1980s, which is specifically designed for uncertain systems characterised by limited data and incomplete information, thereby offering a robust framework for forecasting (Deng, 2002; Chen *et al*., 2024; Xu *et al*., 2024; D'Amico *et al*., 2025). The GANNM has been successfully applied in network security evaluation (Zhao and Yue, 2015), prediction of transportation disruptions (Chunxia *et al.*, 2016), bridge alignment prediction (Li Q, 2024), near miss prediction in commercial aviation (Zhou, 2024), design of sustainable construction cost estimation system (Wei, 2024) and prediction of the number of employees in the cultural and sports industry of Yunnan province (Xiaoyan, 2025).

MATERIALS AND METHODS

We begin with the single-variable grey system model GM(1,1).

$$R^{(0)} = (r^{(0)}_{(1)}, r^{(0)}_{(2)}, r^{(0)}_{(3)}, \ldots, r^{(0)}_{(n)}) \quad (1)$$

The accumulated generated sequence (AGO) of the grey GM (1, 1) model is given as

$$R^{(1)} = (r^{(1)}_{(1)}, r^{(1)}_{(2)}, \ldots, r^{(1)}_{(n)}) \quad (2)$$

where

$$R^{(1)} = \sum_{i=1}^{n} r^{(0)}_{(i)}, i = 1,2,\ldots,n$$

$R^{(1)}$is called the Accumulated Generating Operation $R^{(0)}$denoted by 1-AGO. By differentiating $R^{(1)}$, a whitened differential equation is obtained as

$$\frac{dr^{(1)}}{dt} + ar^{(1)} = b \quad (3)$$

(Deng, 1990)

Equation (3) can be represented by

$$r^{(0)}_{(k)} + az^{(1)}_{(k)} = b \quad (4)$$

and is called the differential equation of the GM (1,1) model.

Where $Z^{(1)}_{(k)} = \frac{1}{2}(r^{(1)}_{k} + r^{(1)}_{(k-1)})$ (5)

$r^{(0)}_{(k)}$ is the grey derivative that optimizes the information density inherent in the data series. Here, a denotes the developing coefficient, while b represents the grey input. The resolution of equation (3) leads to the solution shown in Equation (6). The parameters a and b in this solution are then determined through an application of the least squares estimation technique.

$$\hat{r}^{(1)}_{(k+1)} = (r^{(1)}_{(0)} - \frac{b}{a})e^{-ak} + \frac{b}{a} \quad (6)$$

Parameter a and b in Equation (6) are estimated using the least square method as follows

Assume a time series is given as: $\{r^{(0)}(k)\}k = ,1,2,\ldots,n$

It can also be represented by

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} B^T & B \end{bmatrix}^{-1} B^T Y \quad (7)$$

Where,

$$B = \begin{bmatrix} -Z^{(1)}_{(1)} & 1 \\ -Z^{(1)}_{(2)} & 1 \\ -Z^{(1)}_{(3)} & 1 \\ . & \\ . & \\ . & \\ -Z^{(1)}_{(n)} & 1 \end{bmatrix} \quad (8)$$

$$Y = \begin{bmatrix} r^{(0)}_{(2)}, r^{(0)}_{(3)}, r^{(0)}_{(4)}, \ldots, r^{(0)}_{(n)} \end{bmatrix}^T \quad (9)$$

Now, using the output of the GM(1,1) model

That is

$$\hat{r}^{(1)}_{(k+1)} = (r^{(1)}_{(0)} - \frac{b}{a})e^{-ak} + \frac{b}{a}$$

denoted by,$e^{(0)}(L)$, is the error of the moment L, is obtained as follows

$$e^{(0)}(L) = r^{(0)}(L) - \hat{r}^{(0)}(L) \quad (10)$$

The back propagation network model is then established for the error sequence $\{e^{(0)}(L)\}$

To determine new prediction values of$\{e^{(0)}(L)\}$. We assume that out of a well-trained back propagation network, the predicted error sequence of $\{e^{(0)}(L)\}$ is$\{\hat{e}^{(0)}(L)\}$. We now build a new predicted sequence $\hat{R}^{(0)}(i,l)$ on the foundation of the previous prediction as follows:

$$\hat{R}^{(0)}(i,l) = \hat{R}^{(0)}(i) + \hat{e}^{(0)}(l) \quad (11)$$

Grey-Artificial Neural Network Architectural Diagram

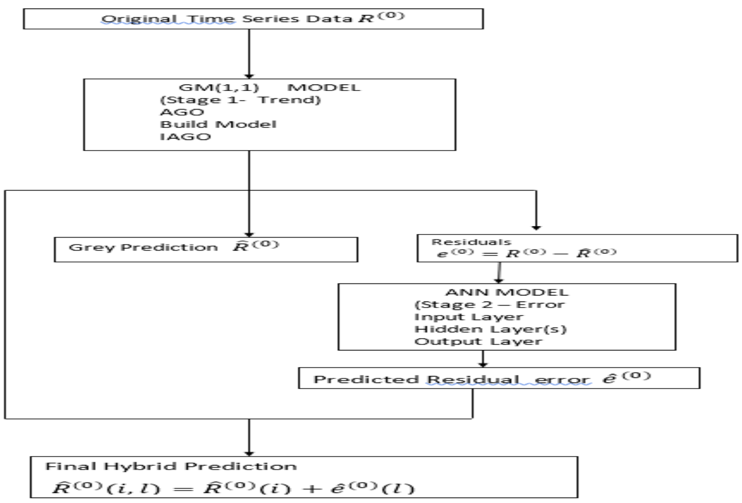

Figure 1: Grey-Artificial Neural Network Architectural Diagram

To assess prediction accuracy, we adopt the Mean Absolute Percentage Error (MAPE) metric from (Zou *et al*., 2018). It is defined as

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

Where;
$\hat{y}_i$is the predicted value.
$y_i$is the actual value.
$n$is the number of the data points

RESULTS AND DISCUSSION

Application of GM(1,1) for the Prediction of RTAs Along Lokoja-Abuja-Kaduna Expressway, Nigeria

This study utilizes a ten-year dataset (2010–2019) obtained from the Federal Road Safety Corps of Nigeria (Saeed *et al*., 2021).

Table 1: RTAs Dataset for Ten Years

S/N	Year of RTAs	Number of RTAs Within the Year
1	2010	877
2	2011	806
3	2012	560
4	2013	1170
5	2014	929
6	2015	672
7	2016	654
8	2017	655
9	2018	780
10	2019	701

Source: Federal Road Safety of Nigeria (Saeed *et al*..(2021)

Following the computation of (Saeed *et al*., 2021)
We have that

$$R^{(0)} = (877,806,560,1170,929,672,654,655,780,701) \qquad (13)$$

Utilizing equation (2), the accumulated generating sequence is obtained in Equation (13), as given below:

$$R^{(1)} = (877,\ 1683,\ 2243,\ 3413,\ 4342,\ 5014,\ 5668,\ 6323,\ 7103,\ 7804) \qquad (14)$$

$$\hat{a} = \begin{bmatrix}0.02241\\869.607\end{bmatrix} = \begin{bmatrix}a\\b\end{bmatrix} \qquad (15)$$

From Equation(14), The value of $a = 0.02241$ and the value of $b = 869.607$

Replacing a and$b$in Equation (6), we have Equation (15)

$$r^{(1)}_{(k+1)} = 38804.42 - 37927.42e^{-0.02241k} \qquad (16)$$

Evaluating equation (15) for k = 0, 1, 2, 3, 4, 5, 6, 7, 8, 9. We have equation (16)

$$\hat{R}^{(1)} = (877,1718,2539,3343,4129,4897,5649,6383,7102,7805) \qquad (17)$$

We utilize Equation (17) to obtain the simulated values as presented in Equation (18)

$$\hat{r}^{(0)}(k) = \hat{r}^{(1)}(k) - \hat{r}^{(1)}(k-1) \qquad (18)$$

$$\hat{R}^{(0)} = (877,841,\ 821,804,786,768,752,734,719,703) \qquad (19)$$

Table 2: Comparison of Actual and Grey Simulated Values for RTAs along Lokoja-Abuja-Kaduna Express Way Nigeria from 2010-2019

S/N	Year of Accidents	Actual Number of RTAs	Grey Model Simulated Values for RTAs	Residual Error	Relative Error (%)
1	2010	877	877	0.00	0.00
2	2011	806	841	-35.00	-7.60
3	2012	560	821	-261.00	-46.46
4	2013	1170	804	366.00	31.10
5	2014	929	786	143.00	17.00
6	2015	672	768	-96.00	-5.90
7	2016	654	752	-98.00	-5.50
8	2017	655	734	-79.00	1.60
9	2018	780	719	61.00	-31.10
10	2019	701	703	-2.00	7.90

Utilizing Equation (12) and information in Table 2 , we obtained the MAPE as shown below
That is:

$$\text{MAPE} \quad \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|\times 100\% \qquad (20)$$

Where;
$\hat{y}_i$is the Grey model simulated values for RTAs
$y_i$is the actual number of RTAs
n is the number of the data points
thus
$MAPE = 14.62\%$
$That\ is,\quad accuracy = 100\% - 14.62\% = 85.97\%$

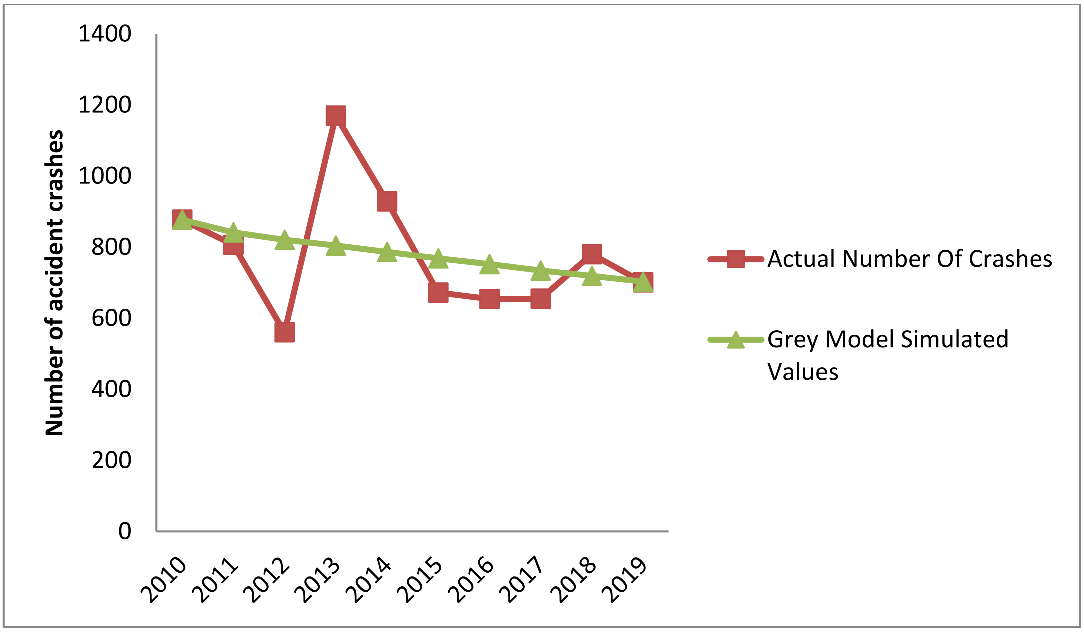

Figure 2: Comparison of Actual and Grey Simulated Values for RTAs along Lokoja-Abuja-Kaduna Expressway Nigeria from 2010-2019 (Saeed *et al.*, 2021)

Figure 2 shows that the simulated values constantly decline and lack the randomness and fluctuation observed in the actual data. This misrepresentation is a major setback of the exponential GM(1,1) model and the work of (Saeed *et al.*, 2021). The GANNM is applied to correct this setback. A backpropagation neural network was trained to simulate the error sequence using Matlab 2018 software. Various architectures were tested via trial and error. The best model was selected based on the highest correlation coefficient (R), highest coefficient of determination (R^2), and lowest root mean square error (RMSE). The simulated residual errors using MatLab 2018 are shown in Table 3.

Table 3: Comparison of Actual Residual Errors and Back Propagation Neural Network Simulated Residual Errors

S/N	Year of Accidents	Actual Number RTAs	Grey Model Simulated Values	Residual Error	The back Propagation Neural Network Simulated Residual error
1	2010	877	877	0	0.00
2	2011	806	841	-35	-10.00
3	2012	560	821	-261	-200.00
4	2013	1170	804	366	250.00
5	2014	929	786	143	120.00
6	2015	672	768	-96	-70.00
7	2016	654	752	-98	-130.00
8	2017	655	734	-79	-90.00
9	2018	780	719	61	80.00
10	2019	701	703	-2	-15.00

Using Equation (11), the Grey simulated values and the back propagation simulated errors sequence, we obtained the simulated GANNM values of the RTAs on the expressway from 2010 to 2019. It is presented in the Table 4 below

Table 4: GANNM Simulated Values

S/N	Year of Accidents	GANNM Simulated Values
1	2010	877
2	2011	831
3	2012	621
4	2013	1054
5	2014	906
6	2015	698
7	2016	622
8	2017	644
9	2018	799
10	2019	688

Table 5: Comparison of Actual and Simulated GANNM Values for the RTAs on the Expressway

S/N	Year	Actual Number of RTAs	GANNM Simulated Values	Residual Error	Relative Error(%)
1	2010	877	877	0	0
2	2011	806	831	-25	-3.10
3	2012	560	621	-61	-10
4	2013	1170	1054	116	9.91
5	2014	929	906	23	2.48
6	2015	672	698	-26	-3.87
7	2016	654	622	32	4.90
8	2017	655	644	11	1.68
9	2018	780	799	-19	-2.44
10	2019	701	688	13	1.86

Utilizing Equation (12) and information in Table 5 , we obtained the MAPE as shown below

$$\text{MAPE} \quad \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|\times 100\% \qquad (21)$$

Where;

$\hat{y}_i$is the GANNM simulated values for RTAs

$y_i$is the actual number of RTAs

n is the number of the data points

thus

$MAPE = 14.62\%$

$That\ is, \quad accuracy = 100\% - 14.62\% = 85.97\%$

$MAPE = 3.98\%$

$ACCURACY = 100\% - 3.98\% = 96.02\% \approx 96\%$

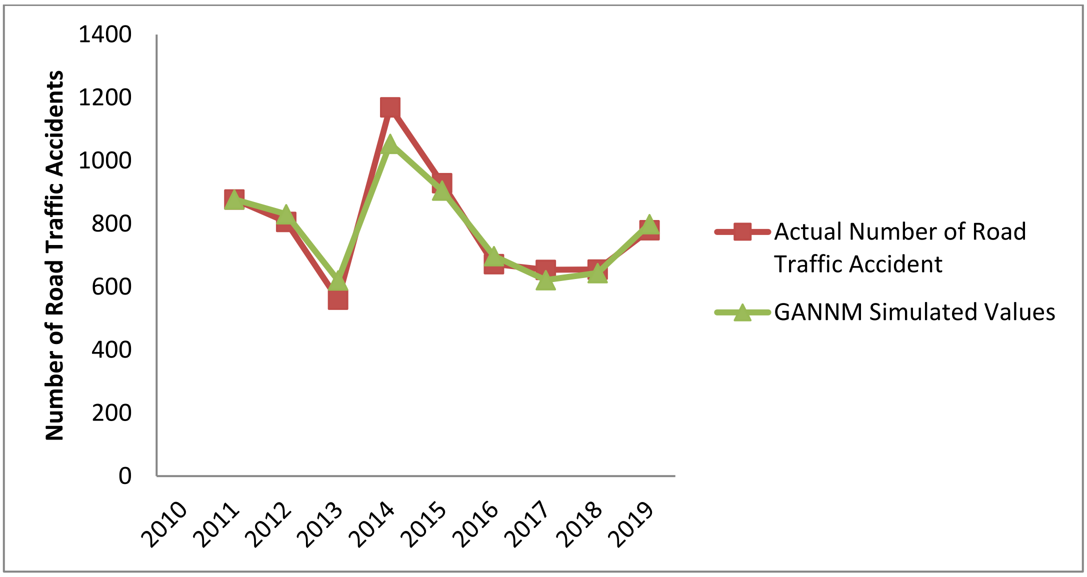

Figure 3: THE graph of Actual Values and GANNM Simulated Values of Vehicular Accidents Crashes

Table 6: Comparison of the Actual Values, GM(1,1) Simulated Values, and GANNM Simulated Values of RTAs on the Expressway

S/N	Year Of Crash	Actual Number of Road Traffic Accidents	Grey Model Simulated Values	GANNM Simulated Values
1	2010	877	877	877
2	2011	806	841	831
3	2012	560	821	621
4	2013	1170	804	1054
5	2014	929	786	906
6	2015	672	768	698
7	2016	654	752	622
8	2017	655	734	644
9	2018	780	719	799
10	2019	701	703	688

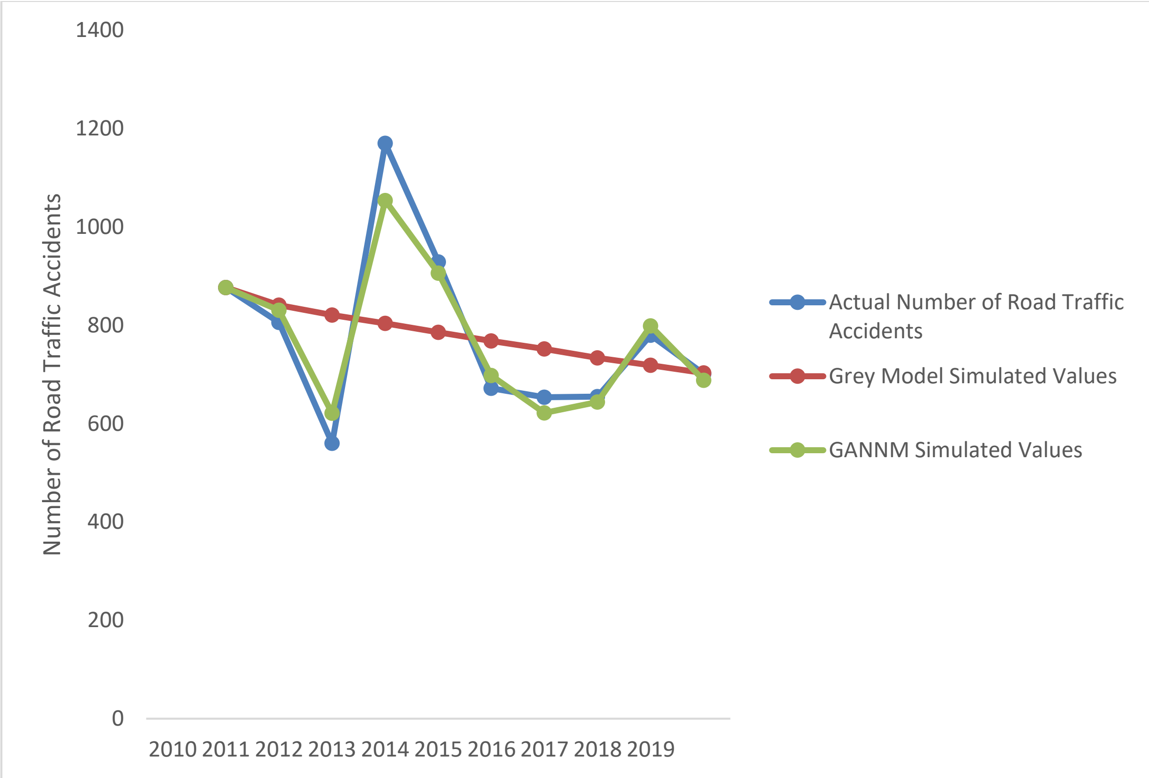

Figure 4: Graph of Actual Values, GM(1,1) Simulated Values, and GANNM Simulated Values of RTAs on the Expressway

Grey Prediction from 2020 to 2028

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

$$\hat{R}^{(1)} = (8491,9163,9820,10462,11091,11705,12305,12892,13467,14028) \quad (22)$$

Utilizing Equation (17), we obtained the predicted values in Equation (22)

$$\hat{R}^{(0)} = (672,657,\ 642,629,614,600,587,575,561) \quad (23)$$

Equation (22) is the grey predicted values from 2010-2028

Table 7: GM(1,1) Model Prediction of Number of RTAs on the Expressway from 2020 to 2028

Year	Grey GM(1,1) prediction for RTAs
2020	672
2021	657
2022	642
2023	629
2024	614
2025	600
2026	587
2027	572
2028	561

To generate GANNM predictions for 2020–2028, we first predict the error sequence using a backpropagation neural network, then apply Equation (11) to compute the final result. The predicted error sequence is shown below.

Table 8: the Predicted Error Sequence from 2020 -2028 using Back Propagation Network

Year	Predicted error sequence
2020	-126.78
2021	-24.27
2022	110.69
2023	-0.0025
2024	-83.22
2025	9.88
2026	70.78
2027	0.22
2028	-34.91

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 GANNM prediction in table 9 below

Table 9: GANNM Prediction for the Number of RTAs from 2020 to 2028

Year	GANNM prediction for RTAs
2020	545
2021	633
2022	753
2023	629
2024	531
2025	610
2026	658
2027	572
2028	562

Table 9 is the GANNM prediction of road traffic accident occurrence on the Lokoja-Abuja-Kaduna Expressway from 2020 to 2028

CONCLUSION

Although the GM(1,1) model achieves a high percentage accuracy, its predictions in Table 2 and Figure 1 reveal a persistent pattern of underestimation and overestimation, following an unrealistic downward trend. In contrast, the GANNM model, leveraging its mathematical sophistication and machine learning efficiency, significantly improves upon the earlier work of Saeed *et al.*, (2021), correcting its limitations (see Figure 2 and Table 5). With its minimal data requirements and capacity for accurate long-term prediction, the GANNM proves more reliable. Consequently, these findings offer valuable evidence to inform Nigerian road safety policy, potentially reducing the loss of life and property on expressways.

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