Analysis and Prediction of Road Accidents in Nepal by Grey System Theory

Smriti Khatiwada
College of Transportation,
Shandong University of Science and Technology
Qingdao 266590, China
smritee500@gmail.com

Zhaohui Liu *
College of Transportation,
Shandong University of Science and Technology
Qingdao 266590, China
zhaohuiliu@sdust.edu.cn
(* *Corresponding author*)

***Abstract*—Although the road safety status of Nepal has improved in recent years, it still falls among the countries with high fatality rates in traffic accidents. Statistics from the traffic police division of Nepal shows that an average of 2,500 people are killed and thousands are injured annually. Despite road traffic accidents being a major public health issue, there are limited studies that focus on probabilistic and statistical analysis of accident data. The application of statistical, probabilistic, and machine learning methodologies plays a pivotal role in forecasting time series, with their effectiveness contingent upon the precision, volume, and accuracy of the employed datasets. Realizing that part of the solution is to find an appropriate methodology to understand the actual trends in the collected data, the grey theory is hereby used to estimate the accident risks in Nepal. Grey theory has proven to be effective because of its quick, brief, and accurate predictions even for vague, incomplete, or imprecise data sets. Therefore, the grey one-order one variable model GM (1,1) is used in this paper as a precise technique to analyze the accident rate for the past decade and predict the next five years. For the available data sets, the efficiency of the constructed GM (1,1) model is compared with the exponential smoothing approach, which is one of the most popular and well-known forecasting techniques. The grey forecasting model is found to perform better with a mean relative simulation accuracy of 92.59%. The reasonable accuracy of the obtained model shows that the grey theory is an effective and efficient approach for predicting road traffic accidents in Nepal using limited available data.**

***Keywords*—exponential smoothing, grey theory, GM (1,1), road traffic accidents, traffic safety**

I. Introduction

Safety is the concept of preserving and protecting life, health, and property, and thus is an integral part of all planning processes. Road traffic safety is a significant factor to be considered in road transportation planning. Road traffic accidents not only cause considerable losses to individuals and their families, but also significant economic losses to entire nations [1]. On a daily basis, roughly 3,700 individuals lose their lives in accidents involving various modes of transport such as cars, buses, motorcycles, bicycles, trucks, or pedestrians around the globe. Pedestrians, motorcyclists, and cyclists account for over half of these fatalities [2]. The World Health Organization reports that 93% of fatalities due to road accidents occur in countries with low to medium income, despite these nations owning only around 60% of the globe's vehicles. Accident-related mortality rates are over threefold higher in low-income nations compared to high-income ones [3].

Road safety is one of the most common and critical issues at national and global levels. Nepal, the landlocked Asian country located on the southern slopes of the Himalayan Mountains, is no exception. Road transport is the most popular and developed mode of transportation in Nepal, for both goods and passengers. The number of deaths and injuries from road accidents has been rising steadily since the early 2000s. Statistics from the traffic police division of Nepal show that about 2,500 people are killed in traffic accidents each year, while thousands are injured and in some cases suffer permanent disabilities. The 58th Annual Report of the Office of the Auditor General (OAG) for fiscal year 2019/20 showed that road accidents increased by an annual average of 7 percent in fiscal year 2017/18, 22 percent in 2018/19, and 17 percent in 2019-20 [8]. The fiscal year runs from July 16 to July 15 of the next year. Nepal recorded 54,010 tragic road accidents in the past five years. In the 2017/18 fiscal year, 2,541 traffic fatalities were officially reported in Nepal, which is equivalent to a fatality rate of 8.59 per 100,000 population [10]. During the same period, 4,144 serious injuries and several minor injuries were also officially reported. In fiscal year 2018/19, 2,789 fatalities were reported with 4,376 serious injuries. For the 2019/20 fiscal year, 2251 fatalities and 4,617 serious injuries were reported. However, the slight decrease in the number of fatalities could be due to the low traffic on the roads due to the lockdown. 2500 fatalities were reported in fiscal year 2020/21, which increased to 2883 in fiscal year 2021/22. According to the traffic police, an average of seven to eight people are killed in traffic accidents every day in Nepal. The data shows that the number of male road fatalities is significantly higher than female fatalities and that motorcycles are more likely to be involved in accidents than other vehicles in Nepal. Ten years of data shows that road safety is still a major problem in Nepal.

Research data indicates an increasing trend in road traffic accidents in Nepal, despite the country's road network being the least extensive among its South Asian counterparts. The complete road system spans 12,493 kilometers, with approximately 51 percent being paved with asphalt, 36 percent remaining as earthen roads, and the residual 13 percent made up of gravel surfaces[8]. The World Bank has estimated that Nepal needs to invest an additional US$879 million in road safety over the next decade to reduce road deaths by half [9]. Road traffic accidents in Nepal seem to be mainly related to driver behavior. Traffic congestion, mixed traffic, traffic pressure, poor visibility, lack of traffic signs and signals at sharp junctions, inadequate safety precautions, haphazard roadside parking, poor road construction, etc. also contribute to accidents. The number of public transport accidents in Nepal is very high and is usually caused by driving errors such as speeding, overtaking, overloading and alcohol consumption. In addition, factors such as poor road conditions, slippery and narrow mountain roads, landslides, overcrowded vehicles, negligence, and stray livestock also contribute. The analysis of the causes of accidents for the fiscal year 2013/14 to 2021/22 based on the national statistics collected by traffic police division of Nepal is shown in Fig. 1.

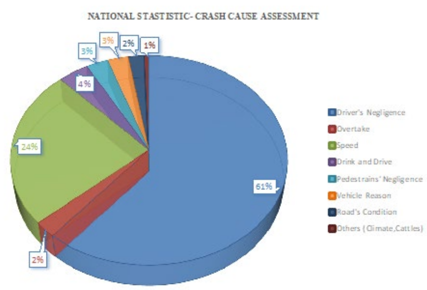

Fig. 1. Crash cause assessment based on national statistics from 2013/14 to 2021/22) (Statistics available from Traffic Police Division of Nepal)

II. Related Work

Various methods and techniques are used in the analysis and prediction of road traffic crashes to identify patterns, trends, and contributing factors and to develop effective strategies to reduce the frequency and severity of crashes. Traditional statistical approaches have their limitations in dealing with multidimensional data sets, whereas machine learning based approaches are more effective. Machine learning techniques, such as clustering and classification algorithms, convolutional neural networks, and long-term memory networks, have been used for accident prediction [25][26]. The hybrid K-Means and random forest algorithm has been shown to perform better than individual classifiers and deep neural networks in predicting the target-specific severity of traffic accidents [24]. Traditional statistical methods have also been used to analyze and predict the duration of traffic accidents [26]. Oyegoke, O. J., & Oladepo, A. A. used statistical methods to investigate the relationship between road safety and traffic accidents in Nigeria, using statistical models such as Poisson regression and negative binomial regression [27]. Assiamah, E. K., & Nyame, F. K. investigated the factors contributing to road traffic accidents in Ghana using statistical methods such as logistic regression and chi-square tests [28]. Al-Ghamdi, A., & Al-Khalifa, S. used statistical methods such as multiple regression and factor analysis to identify the factors contributing to road accidents in Saudi Arabia [29]. Wijesinghe, K. D. R. N., & Wanigasooriya, W. A. D. P. analyze traffic accidents in Sri Lanka using statistical methods such as regression analysis and time series analysis [30]. Garg, V. K., & Jain, S. K. studied the relationship between road safety and road accidents in Delhi, India using statistical methods such as regression analysis and correlation analysis [31].

Machine learning techniques are increasingly used to analyze and predict road traffic accidents. Common algorithms include decision trees, neural networks, support vector machines, and random forests. These algorithms can be trained on historical accident data to develop models to predict the probability of future accidents. Nadarajan, P., Botsch, M., & Sardina, S. introduced a novel approach in machine learning architecture, aiming to effectively estimate the probabilistic representation of space-time in intricate traffic situations [13]. Mishra, A., & Mathew, A. G. present a machine-learning approach for traffic safety analysis that uses decision trees and random forests to identify the factors that contribute to accidents [14].

Grey systems theory is being actively used in transportation research, and its applications in traffic safety are being further explored by researchers. Wang, J.-W. and Fan, Z.-P. proposed a grey theory-based road safety evaluation model that takes into account multiple factors such as road conditions, weather, and driver behavior [16]. Wang, Z., & Zhang, J. used a grey system theory-based road accident prediction model that uses historical accident data and other relevant factors for prediction [35]. Zhang, X., & Zhang, W. proposed a grey model for predicting traffic accidents based on traffic flow parameters such as traffic volume, speed, and occupancy obtained from traffic sensors [12]. Other scholars used GM (1,1) a grey theory based model to analyze and predict traffic accident risk [32][33][34].

Researchers in Nepal have conducted some studies on road traffic accidents and are continuously working to improve road safety. Singh, S. K., & Singh, R. and Adhikari, S. P., Shrestha, R. M., & Shrestha, P. analyzed data on road accidents in Nepal and identified the factors contributing to accidents [22][23]. Yadav, B. K., & Singh, S. K. compared the data on road accidents in Nepal and India and identified the similarities and differences between the two countries [15]. Shakya, S. M., & Nahar, A. M. A. studied the policy and institutional framework for road safety in Nepal and identified the gaps and challenges in the current system [4]. Khanal, D. R., & Singh, S. K., Singh used statistical and geospatial techniques to analyze road traffic accidents in Nepal and identify high-risk areas [5][6]. Shakya, S. M., & Bhatta, S. R. used time series models to analyze road traffic accidents in Kathmandu Valley in Nepal and identify patterns and trends in accident rates [7].

Road safety has become one of the most common and important issues in Nepal nowadays. However, the studies conducted by experts in Nepal focus mostly on evaluating the past and present situation of road safety. The data presented show that limited progress has been made in addressing these issues and Nepal still faces major road safety challenges. The main purpose of this study is to provide a clear insight into the road safety situation in Nepal and to predict future risks using the grey system theory.

III. Research Methodology

A. *Grey Prediction Method*

Grey System Theory (GST), introduced by the Chinese mathematician Deng Julong in 1982 [11], provides a comprehensive approach for managing imprecise, incomplete, and vague datasets. Its utility spans system analysis, data processing, modeling, forecasting, decision-making, and control. Systems are categorized as black when all information is unknown, white when all information is known, and grey when information is partially known and partially unknown. The grey prediction model finds its applications in multiple categories including time-series prediction, disaster forecasting, seasonal disaster prediction, topological prediction, and systematic forecasting [16][17][18].

The one-order one-variable grey model, GM (1,1), is the most prevalently used grey prediction model, exhibiting its effectiveness even when the time series data available is as sparse as four points[17]. The goal of grey system theory is to offer theory, methods, concepts, and ideas for solving latent and complex systems. The grey system creates a non-function model rather than using a regressive analysis. This technique is used to transform the chaotic raw data into a more regular series for modeling purposes rather than modeling using the original data.

B. Steps for Construction of GM(1,1) Model

The grey prediction model's details are derived as follows[17][18][19]:

1. Establishment of the Original Data Sequence

The observed data is used to establish the data sequence as per equation (1):

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

2. Generation of First Order Accumulated Generator Operator (1-AGO)

The first-order accumulated generating operation sequences x(1) are based on original data sequences x(0)(k) as shown in equation (2):

$$x^{(1)}\left(\sum_{k=1}^{1} x^{(0)}(k), \sum_{k=1}^{2} x^{(0)}(k), .., \sum_{k=1}^{n} x^{(0)}(k)\right) \quad (2)$$

3. Calculation of background value

The background value z(1) (k) is calculated through operation on x(1), generating the sequence z(1) (k) as shown in equations (3) and (4):

$$z^{(1)}(k) = \left(z^{(1)}(1), z^{(1)}(2), z^{(1)}(3), .. z^{(1)}(n)\right) \quad (3)$$

Where,

$$z^{(1)}(k) = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k-1) \quad (4)$$

and the generating coefficient α is determined as:

When -α≤0.3, the model can be used for medium and long-term forecasts; when 0.3<-α≤0.5, the model can be used for short-term forecasts; when 0.5<-α≤0.8, the model is inapplicable to short-term forecasts.

4. Construction of First-order Differential Equation

The first-order differential equation of GM (1,1) and its whitening equation are calculated per equation (5) and (6):

$$x^{(0)}(k) + az^{(1)}(k) = b \quad (5)$$

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (6)$$

5. Solving the differential equation

The development coefficient 'a' and grey input 'b' are calculated using the least square method as per equation (7) (8).

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

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ x^{(0)}(4) \\ . \\ . \\ . \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ -z^{(1)}(4) & 1 \\ . & \\ . & \\ . & \\ -z^{(1)}(n) & 1 \end{bmatrix} \quad (8)$$

6. Solution of the whitening equation

The solution is shown in equation (9):

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

Where,

$$x(1)\,(1)= x(0)\,(1) \quad (10)$$

7. Generation of prediction sequences

The recovered data can be retrieved by inverse accumulated generating operation as shown in equation (11):

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \quad (11)$$

Finally, the predictive sequence is obtained as equation (12):

$$\hat{x}^{(0)} = \left(\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \hat{x}^{(0)}(3), .., \hat{x}^{(0)}(n),\right) \quad (12)$$

C. Exponential Smoothing Prediction Method

A time series prediction model called exponential smoothing uses information from the past to predict the future. It is a relatively simple model, but its performance in prediction is better compared to more complex approaches[20][21]. The weight given to past data sets is determined by the smoothing constant (α). α has a value between 0 and 1. The prediction is done using equation(13).

$$F=\alpha A_{t-1}+ (1+\alpha)F_{t-1} \quad (13)$$

Where,

α − Exponential smoothing constant

$At-1$ − Demand at time period t-1

F$t-1$ – Forecast for time period t-1

The forecasting accuracy of this model is influenced by the selection of the smoothing constant (α), and a sensitivity analysis is performed to ascertain the α value that minimizes error. The following steps were done to get the obtained results:

1. The first value is considered the initial forecast.
2. The remaining forecasts were made by choosing an arbitrary value of α.
3. Using SOLVER in Excel, a sensitivity analysis was conducted to find the value of (α), with the aim of minimizing the Mean absolute value.

IV. Prediction and Comparison

A. Prediction and analysis based on GM(1,1) Model

The construction of the GM (1,1) model for the prediction of values, as presented below, tables are discussed in the following steps:

1. The recorded data for road traffic accidents in Nepal is presented in Table I to establish the model and inputted for the x(0), and the cumulative sequence (x(1)) is then

established. The data exhibits a monotonously increasing sequence, which aligns with first-order linear ordinary differential sequences.

2. The quasi-index pattern of x(1) and the quasi-smoothness of x(0)(k) is tested next. Background values are subsequently calculated, serving as inputs for matrix B, while elements of the original sequence form matrix Y.

3. After the formation of the matrix, the differential equation is solved to obtain *a* and *b*. *a* is the developing coefficient and *b* is the grey input. The solution was obtained by the least square method and the following values of *a* and *b* were obtained.

   a=-0.1635369199, b=5405.019325

4. Those obtained values are fed into the whitening equation to obtain the solution, i.e., $\hat{x}(1)(k)$.

5. The prediction series is then obtained by application of inverse accumulated generating operation.

Table I shows the number of accidents recorded by the Nepal Traffic Police from fiscal year 2013/14 to 2021/22 and the values predicted by the GM (1,1) model after constructing and solving the model using MATLAB.

TABLE I. RECORDED AND FORECASTED NO. OF ACCIDENTS ON NATIONAL STATISTICS

S.N	Year	Recorded Accidents	Forecasted Value
1	2013/14	8406	8406
2	2014/15	9145	7365.57
3	2015/16	10013	8674.21
4	2016/17	10178	10215.34
5	2017/18	10965	12030.29
6	2018/19	13366	14167.70
7	2019/20	15559	16684.86
8	2020/21	20640	19649.24
9	2021/22	24537	23140.29

The calculation of the relative error of recorded and forecasted accidents is presented in Table II.

TABLE II. CALCULATION OF ERROR

S.N	Error	Relative Error(Δ)	Q
1	0	0	
2	1779.425977	0.194579112	
3	1338.79303	0.133705486	
4	37.3432065	0.003669012	
5	1065.291321	0.097153791	
6	801.6991507	0.059980484	0.07404144
7	1125.857737	0.072360546	
8	990.7630465	0.048002086	
9	1396.706031	0.056922445	

After calculating the relative error, the model is used to predict the number of accidents for the fiscal years 2022/23 through 2026/27 as shown in Table III.

TABLE III. PREDICATED NO. OF ACCIDENTS

S.N	Year	Predicated Values
1	2022/23	27,251.60
2	2023/24	32,093.36
3	2024/25	37,795.35
4	2025/26	44,510.41
5	2026/27	52,418.52

The projection of accidents done by the prediction model constructed by GM(1,1) using MATLAB is presented in Fig. 2.

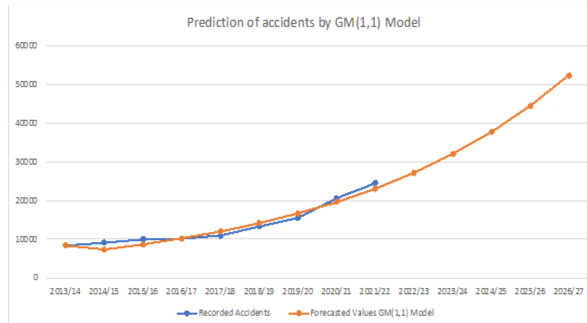

Fig. 2. Prediction model constructed by GM(1,1) model

(Recorded data from Traffic Police Division of Nepal)

The mean relative error is calculated to be 0.07404144. The mean relative simulation accuracy for the model is obtained to be 92.595%. The comprehensive data on road traffic accidents in Nepal is expected to increase, seeing the previous trends. The number of accidents can be expected to double within the next five years.

B. *Prediction and analysis based on Exponential smoothing technique*

Calculation Steps: Table IV shows the number of recorded traffic accidents by the traffic police division of Nepal for fiscal year 2013/14 to 2021/22 and the forecasted values using an exponential smoothing technique. The smoothing constant (α) was calculated using SOLVER in Excel by performing sensitivity analysis.

TABLE IV. RECORDED AND FORECASTED NO. OF ACCIDENTS BY THE EXPONENTIAL SMOOTHING TECHNIQUE

S.N	Year	Recorded Accidents	Smoothing Constant	Forecasted Values
1	2013/14	8406		
2	2014/15	9145		8406.00
3	2015/16	10013		8892.90
4	2016/17	10178		9630.89
5	2017/18	10965		9991.36
6	2018/19	13366	0.658864072	10632.86
7	2019/20	15559		12433.63
8	2020/21	20640		14492.82
9	2021/22	24537		18542.98

The relative error is then calculated to check the accuracy of the constructed model and presented in Table-V.

TABLE V. CALCULATION OF ERROR

S.N	Error	Relative Error	Mean Relative Error
1	0	0	
2	739	0.080809185	
3	1120.099451	0.111864521	

4	547.1061661	0.053753799	
5	973.6375699	0.088795036	
6	2733.142756	0.204484719	0.142521451
7	3125.373191	0.200872369	
8	6147.177085	0.297828347	
9	5994.022962	0.244285078	

The illustration of the recorded and forecasted values obtained by the exponential smoothing technique is shown in Fig. 3.

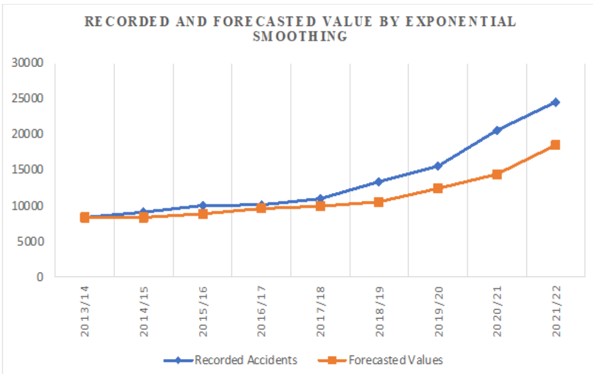

Fig. 3. Recorded and forecasted value by an exponential smoothing technique

(Recorded data from Traffic Police Division of Nepal)

The mean relative error of the model is 0.142521451. Thus, the mean relative simulation accuracy of the model is obtained to be 85.747%.

C. Comparison of GM(1,1) Model and Exponential smoothing technique

The number of accidents forecasted by the GM(1,1) model and by the exponential smoothing technique model is presented in Table VI to compare with the recorded number of accidents.

TABLE VI. FORECASTED NO. OF ACCIDENTS BY GM(1,1) MODEL AND EXPONENTIAL SMOOTHING TECHNIQUE

S.N	**Year**	**Recorded Accidents**	**Forecasted Values Exponential Smoothing Method**	**Forecasted Values GM(1,1) Model**
1	2013/14	8406	8406	8406
2	2014/15	9145	8406	7365.57
3	2015/16	10013	8892.90	8674.21
4	2016/17	10178	9630.89	10215.34
5	2017/18	10965	9991.36	12030.29
6	2018/19	13366	10632.86	14167.70
7	2019/20	15559	12433.63	16684.86
8	2020/21	20640	14492.82	19649.24
9	2021/22	24537	18542.98	23140.29

A comparison diagram between two prediction methodologies against recorded values is shown in Fig. 4. The grey line represents the value predicted with the GM (1,1) model, while the orange line shows the value predicted with the exponential smoothing method. The blue line shows the recorded values.

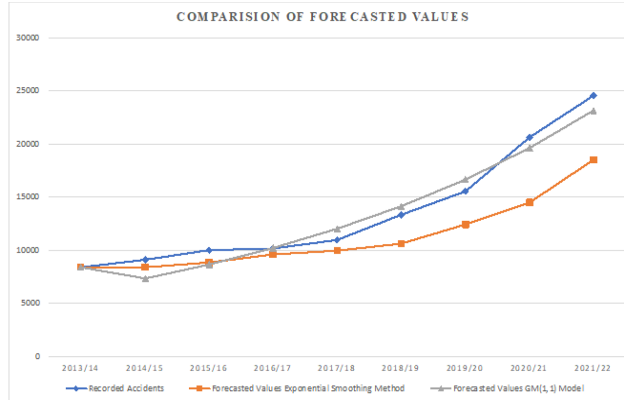

Fig. 4. Comparison of forecasted values by GM(1,1) and exponential smoothing technique

The grey model's prediction has been established to be more accurate on the basis of simulation results. A mean relative error of 0.07404144 was obtained for the case of GM (1,1) as opposed to 0.142521451 for exponential smoothing. Similarly, mean relative prediction accuracy was calculated at 92.59% for GM(1,1) model compared to 85.74% for the exponential smoothing method.

V. DISCUSSION

Based on the simulated results of the grey prediction model, it has been found that the comprehensive data of Nepal is expected to increase in the coming years, considering past trends. Limited progress has been made in addressing road safety problems, and Nepal still faces major challenges. The current level of road safety is still unacceptable. The trends in the growth of the accident rates in Nepal can only be expected to drop down if the national framework for a more interconnected, safe, sustainable, and efficient traffic management system that takes into account potential human errors and damage tolerances can be developed and effectively implemented.

Comparing Nepal with other countries, some exemplary measures and regulations can be implemented to improve road traffic accident rates. Similar to the countries where these countermeasures are successfully implemented, Nepal also has the potential to improve. We can see that analysis and research to build capacity for effective and sustainable management of accident databases are still pending. Research aimed at increasing the robustness of existing processes and exploring new strategies may be a topic for further analysis.

VI. CONCLUSION

Analyzing the recorded data from previous years and predicting the accident rate for the future is one of the most crucial components of accident analysis. The results obtained highlight that despite the existence of many models and techniques, the grey model capably handles the uncertainty of source data, delivering satisfactory accuracy even with limited datasets. The model engages directly with the input data, seeking inherent regularities, and producing results without any assumptions. In the grey prediction model, the original data series undergoes aggregation over time. This aggregated data is utilized to formulate a differential equation, which is then solved using the least square method. The prediction is achieved after performing an inverse accumulated generation operation. The stability of the source data is ascertained by observing the changes in the data points. The quasi-smoothness of the source data and the quasi-index pattern of the accumulated data are verified, thus meeting the conditions for the application of the GM (1,1) model. The prediction model, in the context of national statistics analysis, reveals a mean relative error of 0.07404144 for GM (1,1) compared to 0.142521451 for exponential smoothing. The mean relative prediction accuracy for GM (1,1) stands at 92.59% as opposed to 85.74% for exponential smoothing. These results indicate that the grey model serves as a proficient and efficient tool for forecasting future time series with a minimal amount of historical data, thus making it a suitable model for predicting road traffic accidents in this study

REFERENCES

[1] World Health Organization, "Road traffic injuries," Fact Sheet, 20 June 2022. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries.

[2] World Health Organization, "Global status report on road safety 2018," Geneva, Switzerland, 2018.

[3] M. Peden et al., Eds., "World report on road traffic injury prevention: summary," World Health Organization, Geneva, Switzerland, 2004.

[4] S. M. Shakya and A. M. A. Nahar, "Road safety status in Nepal: A review of policy and institutional frameworks," J. Nepal Health Res. Counc., vol. 17, no. 2, pp. 162-168, 2019.

[5] D. R. Khanal and S. K. Singh, "Analysis of Road Traffic Accidents in Nepal Using Geospatial Techniques," J. Nepal Geogr. Assoc., vol. 16, pp. 81-95, 2018.

[6] S. K. Singh and D. R. Khanal, "Identification of High Risk Areas for Road Traffic Accidents in Nepal," J. Nepal Geogr. Assoc., vol. 17, pp. 49-62, 2019.

[7] S. M. Shakya and S. R. Bhatta, "Analysis of Traffic Accidents in Kathmandu Valley Using Time Series Models," J. Nepal Health Res. Counc., vol. 16, no. 3, pp. 343-355, 2018.

[8] Office of the Auditor General, "58th annual report for fiscal 2019/20," Nepal, 2020.

[9] H. Schafer, "Renewing Our Commitment to Road Safety in Nepal," World Bank, Washington, DC, 2021. [Online]. Available: https://www.worldbank.org/en/news/speech/2021/09/30/renewing-our-commitment-to-road-safety-in-nepal.

[10] World Bank, "Delivering Road Safety in Nepal: Leadership Priorities and Initiatives to 2030," Washington, DC, 2020. [Online]. Available: https://openknowledge.worldbank.org/entities/publication/41c101e5-a91e-5cc3-a35b-c2d6322030cc.

[11] J.-L. Deng, "Control problems of grey systems." Sys. Contr. Lett., vol. 1, no. 5, pp. 288-294, 1982.

[12] X. Zhang and W. Zhang, "Grey Model for Predicting Traffic Accidents Based on Traffic Flow Parameters," IEEE Access, vol. 8, pp. 197829-197838, Sep. 2020

[13] P. Nadarajan, M. Botsch, and S. Sardina, "Machine Learning Architectures for the Estimation of Predicted Occupancy Grids in Road Traffic," in Journal of Artificial Intelligence and Technology, vol. 9, no. 1, pp. 1-9, Feb. 2018, doi: 10.12720/jait.9.1.1-9.

[14] A. Mishra and A. G. Mathew, "A machine learning approach to road safety analysis," IEEE Trans. Intell. Transp. Syst., vol. 17, no. 9, pp. 2498-2507, 2016.

[15] B. K. Yadav and S. K. Singh, "A comparative study of road traffic accidents in Nepal and India," J. Nepal Health Res. Counc., vol. 12, no. 28, pp. 220-225, 2014.

[16] J.-W. Wang and Z.-P. Fan, "A Gray Theory-Based Road Safety Evaluation Model," IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 3, pp. 846-855, Mar. 2016.

[17] A. Ur Rahman and M. T. Zahura, "A Grey Approach for Predicting Supply Chain Demand." American Journal of Industrial Engineering, vol. 5, no. 1, pp. 25-30, 2018.

[18] L.-C. Hsu, "Using improved grey forecasting models to forecast the output of opto-electronics industry," Expert Syst. Appl., vol. 38, no. 11, pp. 13879-13885, Oct. 2011

[19] Liu, T. Shu, S. Chen, S. Wang, K. K. Lai, and L. Gan, "An improved grey neural network model for predicting transportation disruptions," Expert Syst. Appl., vol. 45, pp. 331-340, 2016.

[20] B. Billah, M. L. King, R. D. Snyder, and A. B. Koehler, "Exponential smoothing model selection for forecasting," Int. J. Forecast., vol. 22, no.2, pp. 239-247, 2006.

[21] S. Makridakis et al., "The accuracy of extrapolation (time series) methods: Results of a forecasting competition," J. Forecast., vol. 1, no. 2, pp. 111-153, 1982.

[22] S. K. Singh and R. Singh, "A study on road traffic accidents in Nepal," J. Inst. Med., vol. 32, no. 2, pp. 52-56, 2010.

[23] S. P. Adhikari, R. M. Shrestha, and P. Shrestha, "Road safety in Nepal: A review," J. Nepal Health Res. Counc., vol. 14, no. 33, pp. 272-277, 2016.

[24] S.S. Yassin and P. Pooja, "Road accident prediction and model interpretation using a hybrid K-means and random forest algorithm approach," SN Appl. Sci., vol. 2, no. 9, pp. 1576, 2020.

[25] C. Gutierrez-Osorio and C. Pedraza, "Modern data sources and techniques for analysis and forecast of road accidents: A review," J. Traffic Transp. Eng., vol. 7, no. 4, pp. 432-446, 2020.

[26] R. Li, F. Pereira, and M. E. Ben-Akiva, "Overview of traffic incident duration analysis and prediction," Eur. Transp. Res. Rev., vol. 10, no. 1, pp. 22, 2018.

[27] O. J. Oyegoke and A. A. Oladepo, "Analysis of traffic accidents in Nigeria using statistical models," J. Transp. Saf. Secur., vol. 5, no. 1, pp. 1-17, 2013.

[28] E. K. Assiamah and F. K. Nyame, "A statistical analysis of road traffic accidents in Ghana," J. Data Sci., vol. 10, pp. 325-337, 2012.

[29] A. Al-Ghamdi and S. Al-Khalifa, "Statistical analysis of road accidents in Saudi Arabia," Int. J. Eng. Res. Appl., vol. 4, no. 10, pp. 18-23, 2014.

[30] K. D. R. N. Wijesinghe and W. A. D. P. Wanigasooriya, "Statistical analysis of road accidents in Sri Lanka," J. Traffic Transp. Eng., vol. 2, no. 2, pp. 107-115, 2015.

[31] V. K. Garg and S. K. Jain, "Road safety analysis using statistical methods: A case study of Delhi," J. Transp. Eng., vol. 140, no. 10, pp. 04014046, 2014.

[32] L. Wang and Z. Shen, "Risk Analysis of Traffic Accidents Based on GM(1,1) Grey Theory," in 2017 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), Nov. 2017, pp. 69-74.

[33] Z. Deng and L. Wang, "A Grey Theory-Based Approach for Traffic Accident Risk Analysis," IEEE Access, vol. 7, pp. 104209-104219, Jul. 2019.

[34] C. Xie and J. Zhang, "Prediction of Traffic Accident Risk Based on GM(1,1) Grey Model," IEEE Access, vol. 8, pp. 49953-49961, Mar. 2020

[35] Z. Wang and J. Zhang, "Grey System Theory-Based Road Accident Prediction Model," IEEE Access, vol. 6, pp. 11087-11095, Feb. 2018