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ANALYSIS AND FORECAST OF ROAD TRAFFIC ACCIDENTS IN VIETNAM BASED ON GREY BP NEURAL NETWORK

Vuong Xuan Can[1,2], Mou Rui Fang[1], Vu Trong Thuat[2]

[1]School of Transportation and Logistics, Southwest Jiaotong University, Chengdu, 630031, China
[2] University of Transport and Communications, Hanoi, Vietnam

vuongcan@gmail.com, 472909402@qq.com, vutrongthuattvt@gmail.com

ABSTRACT: *With development of economy and society, developing countries like Vietnam have to deal with transportation issues, such as traffic accidents, traffic congestion, environmental pollution and so on. Especially road traffic accidents (RTAs) have a great impact on sustainable development. Forecast of RTAs is an important step in the traffic safety management, it not only helps us to know the rules of RTAs, but also plays an important role to reduce the likelihood of RTAs and to improve the management levels of road traffic safety. The Grey BP Neural Network forecasting model (GM-BP model) of RTAs in short-term was proposed. This model combines the GM(1,1) model and BP Neural Network model with the aim of identifying its suitability for forecast of RTAs under Vietnam condition. An example is given with the number of fatalities by RTAs in Vietnam from 2002 to 2013. The results showed that, the proposed model is better than single GM(1,1) model and BP Neural Network model. This proves the applicability of GM-BP model to the short-term forecast of RTAs in Vietnam.*

Keywords: *Analysis, Forecast, Grey BP Neural Network, Road Traffic Accidents (RTAs).*

I. INTRODUCTION

With the rapid development of urbanization and motorization across Vietnam, traffic problems have become the most important feature in modern transportation systems. It induces traffic congestion, air pollution, traffic accidents and so on. Among which RTAs in Vietnam still remain high in recent years. According to the National Traffic Safety Committee of Vietnam (NTSC) [1], in 2016, there were 21,094 traffic accidents, 8,417 fatalities and 19,035 injured people, and the economic losses by RTAs were estimated at 2-3% of GDP per year. In order to reduce traffic accidents, a number of comprehensive solutions, including road safety management solutions and technical solutions and so on, are needed. Road traffic accident analyses and forecast are the most important issues in road safety management. Hence, effective accident forecast would greatly contribute to reasonable road networks planning and the improvement management of road safety [2].

There are many models of RTAs prediction that have been announced recently such as Regression models and time series analysis techniques [3, 4], Grey models [5, 6], Artificial Neural Network (ANN) [7, 8], Hybrid models [2, 9], and so forth. In the forecast models mentioned above, due to a shortage in comprehensive statistics regarding RTAs, Grey models have been commonly used in practice to predict RTAs. Besides, ANN has been proposed and employed successfully by many scientists as an alternative to the conventional regression approach in forecasting time series pertaining to complex atmospheric and environmental phenomena [8]. Therefore, a model that combines Grey model and ANN will be able to promote the advantages of each model to improve the forecasting accuracy of RTAs.

In Vietnam, traffic accidents prediction in both short and long term have not been respected, so there are few studies related to traffic accident prediction. In addition, the statistics of traffic accidents are still difficult and exist many inadequacies, such as lack of systematization, underreporting, incompleteness, incorrectness and inaccessibility [10]. Although there are many sources but the data is not sufficient, it is difficult to apply traditional statistical analysis methods that require data and information large enough. On the basis of analysis above, a model that combined the Grey model GM (1,1) and the BP Neural Network was constructed to improve the forecasting accuracy of RTAs in short-term in Vietnam.

II. GREY BP NEURAL NETWORK MODEL PRODICTING ROAD TRAFFIC ACCIDENTS

The grey model GM(1,1) and BP neural network are combined, which can improve the prediction accuracy of the RTAs in Vietnam. The combined model can weaken the randomness of the raw data.

A. The GM (1,1) model

In 1982, Prof. Deng [11] came up with the grey system theory and applied this theory in analyzing forecasts for the behavior of an uncertain system to achieve high efficiency with only a limited amount of data. Grey prediction models are a time series predicting models and have many forms, generally n of grey difference equation and m of variables, denoted by G(n, m). In that GM (1,1) model is the basic model of grey prediction with simple structure and high accuracy [12]. The principle of the GM (1, 1) model is as follows: The Accumulating Generation Operator (AGO) is used to form the accumulation sequence of original data and then establish the first order differential equation of

GM(1,1) in order to obtain predicted value of the accumulated time response sequence of GM(1,1). Finally, the Inverse AGO (IAGO) is applied to find the predicted values of original data. It is obtained as the following steps:

- Step 1: Assume that $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3),..., x^{(0)}(n))$ with $n \geq 4$ denotes the non-negative original time series data and $x^{(1)} =$ $(x^{(1)}(1)$, $(x^{(1)}(2)$, $(x^{(1)}(3),...,$. $(x^{(1)}(n))$ is an accumulation sequence of $x^{(0)}$ computed as in Eq.(1).

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

- Step 2: The grey difference equation of GM(1,1) is

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{2}$$

where, a is development coefficient, b is grey action coefficient and $z^{(1)}(k)$ is the mean value of adjacent data, i.e.

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1), k \geq 2 \tag{3}$$

- Step 3: The first-order differential equation of GM(1,1), i.e., the whitening equation of the GM(1,1) is described as follows:

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

where, the coefficients $[a,b]^T$ can be obtained by the Ordinary Least Squares (OLS) method:

$$[a,b]^T = (B^T.B)^{-1}.B^T.Y \tag{5}$$

In that:

$$Y = \begin{bmatrix} \mathrm{x}^{(0)}(2) \\ \mathrm{x}^{(0)}(3) \\ ... \\ \mathrm{x}^{(0)}(\mathrm{n}) \end{bmatrix}, \; B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ ... & ... \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{6}$$

where, Y is called data series, B is called data matrix

- Step 4: The accumulated time response sequence of GM(1,1) at time (k+1) can be obtained by solving Eq. (4):

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} \tag{7}$$

- Step 5: To obtain the fitted value of the original data at time (k + 1), the Inverse AGO is used to establish the following grey model:

$$\hat{x}^{(0)}(k+1) = (1 - e^{a}) \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} \tag{8}$$

and the forecasted value of the original data at time (k + H) with $k > n$

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

B. The BP neural network model

The BP neural network is one of the most widely used artificial neural networks (ANNs) which was brought up by Rumelhart et al. in 1986. BP neural network is a multi-layer feed forward neural network conducting error back-propagation (BP) training algorithm and uses gradient descent algorithm to reduce errors, achieving the arbitrary nonlinear mapping from input to output. A typical BP network consists of an input layer, an output layer and one hidden layer, as shown in Figure 1. Each node in a layer can connect to all the neurons of the next layer behind it and the neurons of the same layer are not interconnected. In order to speed up the convergence rate of network exercises, the input data can be standardized and all connecting values are given initial values. One-hidden-layered BP neural network's computational steps as follows [13, 14, 15].

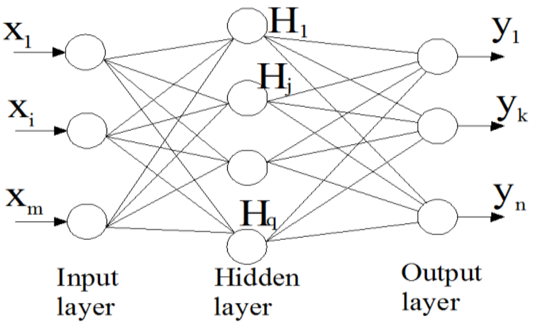

Figure 1. The three-layer BP Neural Network Model

- Step 1: Initialize weight and threshold.

- Step 2: Input sample: x_i $(i=1\sim m)$ is the input vector , and t_k $(k=1\sim n)$ is the excepted output vector of the BP neural network.

- Step 3: Calculate the output of j-th neuron of hidden layer, as in Eq. (10), and the output of k-th neuron of output layer, as in Eq. (11). H_j $(j=1\sim q)$ is the output vector of hidden layer, y_k is the output vector of output layer, w_{ij} is the weight of the j-th neuron in the hidden layer, w_{jk} is the weight of the k-th neuron in the output layer, θ_j is the threshold of the j-th neuron in the hidden layer, θ_k is the threshold of the k-th neuron in the output layer. The $f(\cdot)$ is output node's transfer function.

$$H_j = f(\sum_{i=1}^{m} w_{ij}x_i + \theta_j) \quad (j=1, 2, 3,\ldots,q) \tag{10}$$

$$y_k = f(\sum_{j=1}^{q} w_{jk}H_j + \theta_k) \quad (k=1, 2, 3,\ldots,n) \tag{11}$$

- Step 4: Calculate the error, as in Eq. (12), T is sample number.

$$E = \frac{1}{2}\sum_{t=1}^{T}\sum_{k=1}^{n}(t_{k,t} - y_{k,t})^2 \tag{12}$$

The error E is the function of the weights w_{ij} and w_{jk} and can be reduced by adjusting the weights, as in Eq.(13). The η is learning rate, ranges (0, 1) reflecting the learning speed of the model

$$\Delta w_{ij} = -\eta.\frac{\partial E}{\partial w_{ij}}, \quad \Delta w_{jk} = -\eta.\frac{\partial E}{\partial w_{jk}} \tag{13}$$

- Step 5: Repeat the above from step 3 to step 4 until all sample data are inputted. If E is larger than the specified error value $e_{\min}$, then return to step until $E < e_{\min}$.

C. The GM-BP model

BP neural network has possessing learning and memory capability and easy adaptability, but the initial weight values and threshold values are selected randomly and inappropriate selection will lead to slow convergence rate and local optimum. The GM (1,1) can weaken the randomness of data variation to discover the potential rules of system operation, bearing the characteristics of easy calculation [14], but error accuracy cannot be controlled [15]. In order to give full play to the advantages of GM (1,1) model and BP neural network model, two models are integrated to construct a GM-BP model. The structure of GM-BP model with three-layer BP Neural Network is shown in Figure 2. The forecasted values of the GM (1,1) reflect the changing trend of the actual data in a certain precision, and have a great correlation with the actual data. Thus, it and other related indexes can be used as the input of the BP neural network and the actual data as output of the BP neural network model to achieve more accurate forecasting results. The established GM-BP model is as follows:

(1) From the original data set up GM (1,1) models, then the GM (1,1) model with the smallest error will be selected.

(2) The forecasted values of GM (1,1) model as input data for the BP neural network and the actual values as output of BP neural network to establish Grey BP neural network forecasting model.

(3) Operational forecasting models and given the forecast results.

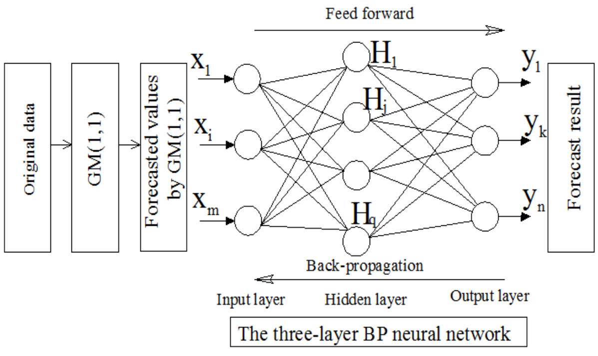

Figure 2. The structure of GM-BP Model

In order to eliminate the impact on the prediction results from fluctuations of initial data and to speed up the training speed of GM-BP/BP model, we normalize it into the range between [0, 1]. The normalization method is shown in following equation:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{14}$$

in (14), x_i and x_i' are fatalities of RTAs before and after processing, $x_{\max}$ is the maximum value of fatalities of RTAs, $x_{\min}$ is the minimum value of fatalities of RTAs. Then, in order to calculate real forecasted value ($\hat{x}$), the prediction results of the GM-BP/BP model ($\hat{x}'$) needs to be anti-normalized, as in Eq.(15)

$$\hat{x} = \hat{x}'(x_{\max} - x_{\min}) + x_{\min} \tag{15}$$

D. Model Evaluation Indicator

In order to predict the accuracy of forecasting model in this study, errors are used for comparison: absolute percentage error and mean average percentage error (MAPE) [16], [17] are calculated as shown in (16):

$$\begin{cases} e_i = \dfrac{|x_i(k) - \hat{x}_i(k)|}{x_i(k)} \\ MAPE = \dfrac{1}{n}\sum_{k=1}^{n} e_i \end{cases} \tag{16}$$

where: $\hat{x}_i(k)$ is the forecast value at time k, $x_i(k)$ is the actual value at time k and e_i is the absolute percentage error (APE) with respect to $x_i(k)$. Wang and Phan [18] interpret the MAPE results as a method to judge the accuracy of forecasts, where more than 10% is an inaccurate forecast, 5%-10% is a reasonable forecast, 1%-5% is a good forecast, and less than 1% is an excellent forecast.

III. EXPERIMENT

A. Data Sources

Experimental data set is the fatalities of RTAs data of Vietnam from 2002 to 2016, collected from NTSC [1]. Fatalities data from 2002 to 2013 is used as samples, i.e., the initial data of forecast and the data from 2014 to 2016 is used as test sample data.

Table 1. Fatalities of RTAs data of Vietnam from 2002 to 2016

Year	No. of fatalities	Year	No. of fatalities	Year	No. of fatalities
2002	13186	2007	13150	2012	8949
2003	11864	2008	11594	2013	9369
2004	12230	2009	11516	2014	8996
2005	11534	2010	11406	2015	8671
2006	12757	2011	11395	2016	8417

B. Experimental Procedure

Firstly, the processing of the sample data is conducted to facilitate the GM (1,1) forecasting. As the number of samples affects the forecasted results, hence, a number of forecasting models, including GM-12, GM-10, GM-08 and

GM-06 should be established corresponding to 12, 10, 8 and 6 of samples to select more reasonable model. The results are shown in Table 2 and Figure 3.

Table 2. Predicted results of GM (1,1) and errors

Year	No. of fatalities	GM-12		GM-10		GM-08		GM-06	
		Forecasted	APE (%)	Forecasted	APE (%)	Forecasted	APE (%)	Forecasted	APE (%)
2014	8996	9936	10.45	9512	5.74	8865	1.46	8674	3.58
2015	8671	9710	11.98	9197	6.07	8401	3.11	8143	6.09
2016	8417	9490	12.74	8893	5.65	7962	5.41	7645	9.18
MAPE (%)			11.73		5.82		3.33		6.28

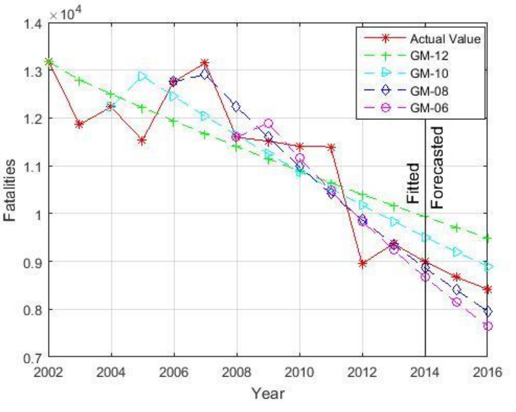

Figure 3. Predicted results of GM (1,1)

Table 2 and Figure 3 show, when the observed data reaches 8 of samples, the prediction error is smaller, so 8 of samples can be taken as the GM (1,1) model. All the forecasted values of the GM-08 model are shown in Table 3.

Table 3. Forecasted results of GM-08 and normalized values

Year	Forecasted	Normalized	Year	Forecasted	Normalized	Year	Forecasted	Normalized
2006	12757	0.969	2010	10989	0.612	2014	8865	0.182
2007	12911	1.000	2011	10415	0.496	2015	8401	0.089
2008	12236	0.864	2012	9870	0.386	2016	7962	0.000
2009	11596	0.734	2013	9354	0.281	-	-	-

From data in Table 3, conduct forecasting of fatalities of RTAs based on the steps of BP neural network. In that, the predicted values of fatalities of RTAs are taken as the input of GM(1,1) model and the actual values are taken as the output of GM-BP model. The training samples include eight samples, the predicted data of the GM(1,1) for 2006 ~ 2013. To increase the accuracy of the forecast results, 5-year data are used to conduct a one-time forecast, i.e., the data of five years from 2006 to 2010 of GM(1,1) are selected as a set of sample and the fatalities of RTAs of the 6-th year (2011) is taken as output data. Then, the data during 2007~2011 of GM(1,1) to predict the fatalities of RTAs of 2012, and the data during 2008~2012 of GM(1,1) to predict the fatalities of RTAs of 2013. We take actual values of 2011~2013 as excepted output values of the GM- BP neural network. The data for 2014~2016 are taken as the test sample to test the accuracy of GM-BP model. The obtained data during 2009~2013, 2010~2014 and 2011~2015 from GM(1,1) model are taken as input of GM-BP model. Afterwards, the output values of GM-BP model are compared with actual values of 2014~2016 in order to analyze the accuracy of forecasting. The selection of training samples is shown in Table 4.

Table 4. Training samples

No. of sample	Input	Output
1	The fatalities of GM(1,1) for 2006~2010	The fatalities of 2011
2	The fatalities of GM(1,1) for 2007~2011	The fatalities of 2012
3	The fatalities of GM(1,1) for 2008~2012	The fatalities of 2013
Test sample		
1	The fatalities of GM(1,1) for 2009~2013	The fatalities of 2014
2	The fatalities of GM(1,1) for 2010~2014	The fatalities of 2015
3	The fatalities of GM(1,1) for 2011~2015	The fatalities of 2016

Acording to Table 4, a BP network of 5×5×1 is established in this paper with structure parameters as: the function of hidden layer is sigmoid function and the function in output layer is linear function, and the Levenberg-Marquardt algorithm is used to the training; the maximum training frequency is 1000 times, the training accuracy is

0.0001, the training display interval is 50 times and the rate of the learning is 0.05. MATLAB software is adopted to training network through network training simulation platform with network structures as in Figure 4. The training process converges to given error range after 2 trainings, as is shown in Figure 5. Similarly, it is easy to get forecasted values by the single BP neural network. The forecasted values and error of fatalities of RTAs of these three methods are shown in Table 5 and Figure 6.

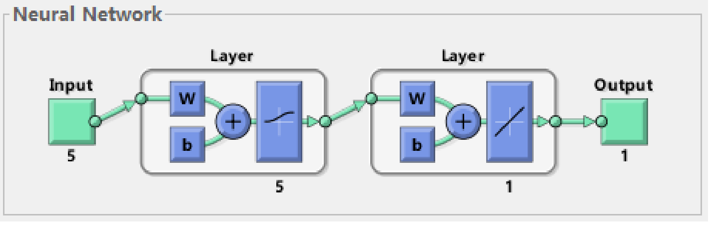

Figure 4. Training Structure of GM-BP Neural Network model

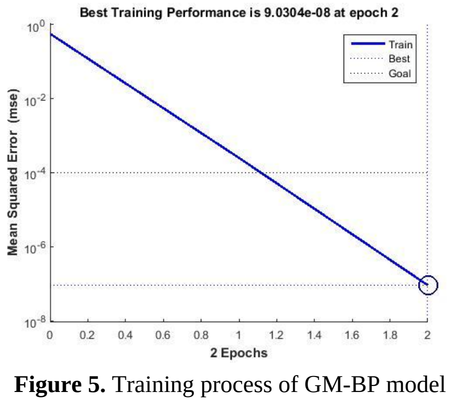

Figure 5. Training process of GM-BP model

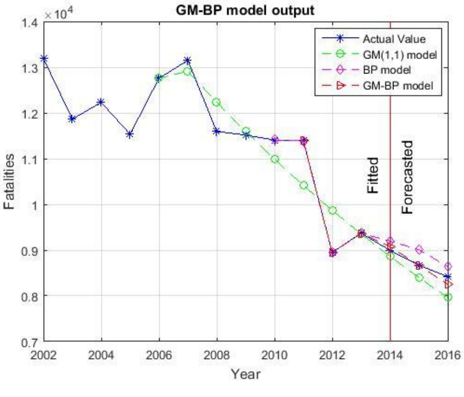

Figure 6. Predicted fatalities of RTAs

Table 5. Forecasted fatalities of RTAs and error

Year	Actual Value	GM(1,1) model		BP model		GM-BP model	
		Forecasted	APE (%)	Forecasted	APE (%)	Forecasted	APE (%)
2014	8996	8865	1.46	9197	2.23	9076	0.89
2015	8671	8401	3.11	9010	3.91	8669	0.02
2016	8417	7962	5.41	8640	2.65	8249	2.00
MAPE (%)			3.33		2.93		0.97
Acuracy			Good		Good		Excellent

From Table 5 and Figure 6, we can see the forecast accuracy of the GM-BP model, which shows better features, providing higher accuracies than that of both the GM(1,1) model and BP neural network. The MAPE of forecast results is 3.33%, 2.93%, 0.97% for the GM(1,1) model, the BP neural network and the GM-BP model, respectively. The MAPE is obviously reduced and the accuracy is obviously enhanced. Hence, using the GM-BP model to forecast is feasible and the forecasted result is realistic. Therefore, the trend of fatalities of RTAs in Vietnam is on the decrease, but the situation is still grim. To reduce the number of RTAs as well as the number of fatalities, measures of traffic safety should be adopted, road traffic safety management should be enhanced and the number of fatalities should be effectively reduced.

IV. CONCLUSION

In this paper, the main purpose of the proposed model is to identify its suitability for forecast of RTAs in short-term under Vietnam condition. The forecasting results show that proposed model (i.e., the GM-BP model) with the combination of both the GM (1,1) model and BP neural network has better forecasting results by GM(1,1) and BP neural network. GM(1,1) model is employed to understand the general trend of fatalities of RTAs over time series while BP neural network is used to reflect the effects of random volatility in predictions and to determine the transfer discipline of status. Hence, the GM-BP model not only explores data from the time series but also considers the possibility of a strong random feedback of the data to improve efficiency in RTAs prediction. As such, the proposed model may continue to be developed for use in other short-term forecasts related to traffic accidents in Vietnam. In addition, the study results of the paper not only supplement the gap in the study of traffic safety in Vietnam, but also useful information for people who work in ensuring traffic safety.

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PHÂN TÍCH VÀ DỰ BÁO TAI NẠN GIAO THÔNG ĐƯỜNG BỘ Ở VIỆT NAM DỰA TRÊN GREY BP NEURAL NETWORK

Vương Xuân Cần, Mou Rui Fang, Vũ Trọng Thuật

TÓM TẮT: *Cùng với sự phát triển của nền kinh tế và xã hội, các nước đang phát triển như Việt Nam đang phải đối phó với các vấn đề giao thông, như tai nạn giao thông, ùn tắc giao thông, ô nhiễm môi trường,... Đặc biệt tai nạn giao thông đường bộ (RTA) ảnh hưởng lớn đến sự phát triển bền vững. Dự báo tai nạn giao thông đường bộ là một bước quan trọng trong công tác quản lý an toàn giao thông, nó không chỉ giúp chúng ta hiểu rõ quy luật của tai nạn giao thông, mà còn đóng vai trò quan trọng để giảm khả năng tai nạn và cải thiện trình độ quản lý an toàn giao thông. Mô hình dự báo Grey BP Neural Network (mô hình GM-BP) về tai nạn giao thông đường bộ trong ngắn hạn đã được đề xuất. Mô hình này được kết hợp giữa mô hình GM (1,1) và BP Neural Network với mục đích xác định sự phù hợp cho dự báo tai nạn trong điều kiện Việt Nam. Một ví dụ với số người chết do tai nạn giao thông ở Việt Nam từ 2002-2013 đã được thực hiện. Kết quả cho thấy, mô hình đề xuất tốt hơn so với mô hình GM (1,1) và BP Neural Network đơn thuần. Điều này chứng tỏ khả năng ứng dụng mô hình GM-BP vào dự báo ngắn hạn về tai nạn giao thông đường bộ ở Việt Nam.*

Từ khóa: *Phân tích, Dự báo, Grey BP Neural Network, Tai nạn giao thông đường bộ (RTAs).*