



Forecasting Road Traffic Accidents: Grey System Theory GM(1,1) and Grey Entropy Based Approach (GMEPA)

Liyanah Alfred^{1*} and Sabri Ahmad¹

¹*School of Informatics and Applied Mathematics, Universiti Malaysia Terengganu, Malaysia.*

Authors' contributions

This work was carried out in collaboration between both authors. Author LA designed the study, performed the statistical analysis, wrote the protocol, managed the literature searches and wrote the first draft of the manuscript. Author SA edited and checked the document. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/ACRI/2018/39403

Editor(s):

- (1) Marco Caniato, Engineering and Architecture Department University of Trieste, Italy.
(2) Tatyana A. Komleva, Department of Mathematics, Odessa State Academy of Civil Engineering and Architecture, Ukraine.
(3) Sivakumar Manickam, Professor, Chemical and Nanopharmaceutical Process Engineering, Associate Dean, Research and Knowledge Exchange, Nanotechnology and Advanced Materials (NATAM), The University of Nottingham Malaysia Campus, Malaysia.

Reviewers:

- (1) Lingtao Wu, Texas A&M Transportation Institute, USA.
(2) Syuji Yoshiki, Fukuoka University, Japan.
(3) N. S. S. R. Murty, Mumtaz College of Engineering, Jawaharlal Nehru Technological University, India.
(4) Ahmet Shala, University of Prishtina, Kosovo.

Complete Peer review History: <http://www.sciencedomain.org/review-history/23690>

Received 25th December 2017

Accepted 6th March 2018

Published 17th March 2018

Case Study

ABSTRACT

Road collision is one of the worst case scenarios involving massive damages and casualties. It has become a major concern for everyday road users as well as the government. Traffic accidents in terms of forecasting can be considered as a grey system considering the complexity and unknown influencing factors causing these accidents. Therefore, it can be analyzed using GM(1,1) since grey model has the criteria of handling limited amount of data to estimate the behavior of an unknown system. However, conventional method of GM(1,1) has several drawbacks that requires improvements in order to provide a more reliable references allowing responsible authorities to come out with strategies to prevent road accidents. In this study, we compare the results of propose method which is the hybrid Grey model with Minimize Entropy Principle Approach (GMEPA) and original grey model GM(1,1) based on the minimization of forecasting error. The

*Corresponding author: Email: liyanahalfred@gmail.com;

data used are road traffic accidents in Malaysia from 2003 to 2016 and road traffic accidents in India from year 2002 to 2015. Mean average percentage error(MAPE) and Mean Squared Error(MSE) were calculated for both models to examine which method gives the best prediction accuracy. The results conclude that GMEPA can improve the measurement of forecasting accuracy for road accident data in India but vice versa in road accident data Malaysia where it was much preferable for the application of GM(1,1).

Keywords: Road traffic accident; grey system theory; forecasting; minimize entropy principle Approach (MEPA); GM(1,1).

1. INTRODUCTION

The growth rate of vehicles usage is the backbone of economic development. In a rapidly developing country, road transportation is essential to enable more trade and a greater spread of people. It provides easy access to markets, employment and additional investment. Unfortunately, with the increment of registered vehicles on the road, more accidents happen unexpectedly. Road accidents shows a rising tendency as a result of increasing motor vehicles users. Various factors that cause these car crashes, for instant, self-negligence of road users, vehicles breakdown, weather condition and the imperfection of road infrastructure. Due to the complexity and uncertainty of influencing factors on road traffic accidents, grey system theory is suitable to apply as it fulfills the criteria of overcoming insufficient information when dealing with raw data.

Grey system theory was first introduced by Deng Julong in 1982 [1]. Articles that has been published and accepted widely based on grey system theory are “The control problem of Grey system” and “The Grey Control System” [2]. Grey model forecasting has the specialty of dealing and solving problems under uncertainty [3]. It has the ability of applying only a few set of data with the minimum of 4 [4,5]. The theoretical derivation can be easily understood and the method is simple [6]. It can be applied to various field for example in tourism demand [7], financial and economic [8,9,10] and energy [11].

One of the main challenges is how to forecast trends under the limitation of lack of information while still being able to produce forecast with least prediction errors. Countless approaches have been done by researchers to improve the performance of original GM(1,1). It is important to discover new approach which helps researchers to obtain a much better result compared to conventional GM(1,1) method for forecasting purposes and future planning. It can also provide reliable references to other

authorities in solving problems. To address the issue, a new approach was introduced, which is by combining grey model GM(1,1) with Minimize Entropy Principle Approach(MEPA) where MEPA is a method that function to partition the universe of discourse and build up membership functions(MFs) [12].

The propose method focuses on estimating the parameters of the model to improve the forecasting accuracy. Originally, GM(1,1) uses least square method(OLS) to determine the parameters of “a” and “b” with different α values [13]. While in GMEPA, the values of α is determine in MEPA and will be used to estimate the parameters in GM(1,1). The aim is to reduce the coefficient of “a” because according to Liu and Deng [14], the larger the coefficient “a” will result a larger prediction error.

Firstly, basic concept of GM(1,1) is explained. Then, combined MEPA with GM(1,1) is shown in detailed. Where MEPA is use starting after step 2 in the method of GM(1,1). This study covers the accidents data from year 2003 to 2016 data in Malaysia [15] and traffic collision data in India from year 2002 to 2014 [16].

2. METHODOLOGY

2.1 Grey System Theory GM(1,1)

This model stands for “single variable first order grey model” to forecast quantitative data [17]. Grey model uses a understandable formula which includes 3 main operator [18].

1. Accumulating Generation Operator (AGO)
2. Grey model
3. Inverse Accumulating Generation Operator (IAGO)

Step 1: $x^{(0)}$ represent original data

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

$x^{(0)}(i)$ time series on time i , n must be equal or more than 4

Step 2: Accumulating Generation Operator(AGO)

A new set $x^{(1)}$ is obtained by using AGO

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

$$x^{(1)}(t) = \sum_{i=1}^t x^{(0)}(i), t=1,2,\dots, n.$$

Step 3: from step 1 and 2, obtained the parameter

Parameter is calculated by traditional least square method

$$A = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_n$$

$$Y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \quad B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \quad A = \begin{bmatrix} a \\ b \end{bmatrix}$$

$Z^{(1)}$ defined as

$$Z^{(1)} = \{Z^{(1)}(1), Z^{(1)}(2), \dots, Z^{(1)}(i), \dots, Z^{(1)}(n)\}$$

$$Z^{(1)}(k) = \alpha x^{(1)}(k) + (1 - \alpha)x^{(1)}(k + 1), \\ t = 1, 2, \dots, n - 1$$

α symbolized horizontal coefficient and $0.1 < \alpha < 1.0$. The value of α is chosen to obtained the smallest forecast error.

Step 4: theoretically through difference equation, to solve GM(1,1) is as follow:

$$\hat{x}^{(1)}(t + 1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-at} + \frac{b}{a}$$

Step 5: IAGO is to forecast the value of data at $t + 1$

$$\hat{x}^{(0)}(t + 1) = [\hat{x}^{(1)}(t + 1) - \hat{x}^{(1)}(t)]$$

Where $t = 1, 2, \dots, n$, sequence stated as below:

$$\hat{x}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \dots, \hat{x}^{(0)}(t + 1))$$

The calculation will be repeated for GM(1,1) using different level of significant which for this paper $\alpha = 0.4, 0.5, 0.6, 0.7$ and 0.8 has been

used. Previous research had stated that $\alpha=0.5$ is the best alpha value for prediction [19]. Additionally, Huang [20] also mentioned in his research that $\alpha=0.4$ gives a high accuracy towards GM(1,1). Plus, Ho [21] has proved that alpha value that is more than 0.5 can provide the lowest MAPE.

FORECAST:

To obtained forecast values from original data set, the steps in GM(1,1) is repeated.

IAGO calculation is to predict the accidents data at $t+1$ using:

$$\hat{x}^{(0)}(t + 1) = [\hat{x}^{(1)}(t + 1) - \hat{x}^{(1)}(t)]$$

Where $t = 1, 2, \dots, n$, sequence stated as below:

$$\hat{x}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \dots, \hat{x}^{(0)}(t + 1))$$

n is the future forecast value.

2.2 Minimize Entropy Principle Approach (MEPA)

MEPA is a method that is combined starting after step 2 in Grey model.

Step 1: determining the class of each data entry

Each data has to be assigned a class initially. There is no specific rule to determine the classes of each data and it is due to the character of entropy [12]. But in this paper, a method of Fuzzy C- Mean Clustering [22] is introduced to determine the classes that will be assigned to each data entry from year 1975 to 1995. Previous research by Cheng et al. (2006), 3 classes has been assigned to the sample data. So, in this research also assigned 3 classes towards each data entry.

Step 4: The data set must be sorted (ascending order) based on the value of each year. The threshold value is sought for a sample in the range between x_1 and x_2 . An entropy equation with each value of x is written for the regions $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$ and denote the first part as region p and the second as region q .

Step 5: calculate the threshold value (PRI, SEC1, SEC2, TER1, TER2, TER3, TER4). An entropy with each value of x in the region x_1 and x_2 is expressed as [23].

$$S(x) = p(x) s_p(x) + q(x) s_q(x)$$

Where

$$s_p(x) = - [p_1(x) \ln p_1(x) + p_2(x) \ln p_2(x)]$$

$$s_q(x) = - [q_1(x) \ln q_1(x) + q_2(x) \ln q_2(x)]$$

$p_k(x)$ and $q_k(x)$ = conditional probabilities that the class k sample is in the region $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$ respectively.

$p(x)$ and $q(x)$ = probabilities that all sample are in the region $[x_1, x_1 + x]$ and $[x_1 + x, x_2]$ respectively.

$$p(x) + q(x) = 1$$

Minimum entropy of x is the optimum threshold value. The value estimates of $p_k(x)$, $q_k(x)$, $p(x)$ and $q(x)$ are calculated as follow:

$$p_k(x) = \frac{n_k(x)+1}{n(x)+1}$$

$$q_k(x) = \frac{N_k(x)+1}{N(x)+1}$$

$$p(x) = n(x)/n$$

$$q(x) = 1 - p(x)$$

Where

$n_k(x)$ = number of class k samples located in $[x_1, x_1 + x]$

$n(x)$ = the total number of samples located in $[x_1, x_1 + x]$

$N_k(x)$ = number of class k samples located in $[x_1 + x, x_2]$

$N(x)$ = the total number of samples located in $[x_1 + x, x_2]$

n = total number of samples in $[x_1, x_2]$

While moving x in the region $[x_1, x_2]$, entropy values is calculated for each position of x , as in

Table 1. The value of x in the region that holds the minimum entropy is called the primary threshold (PRI) value. By repeating the process, we can determine the second threshold value denoted by SEC1 and SEC2. Finally, we need to find tertiary threshold values, denoted by TER1, TER2, TER3 and TER4 which complete the seven partitions. Above Table 2 is the calculation of entropy value and the entropy that holds the minimum value $S(x)$ will be the threshold value which is 405876.

Step 6: determine the length of intervals. Calculating standard deviation and let universe of discourse, $U = [D_{min} - \sigma, D_{max} - \sigma]$ Where D_{min} and D_{max} are the minimum and maximum of accidents data in Malaysia.

$$\text{Standard deviation, } \sigma = \sqrt{\frac{\sum(x - \text{mean } x)^2}{N}}$$

Universe of discourse,

$$U = [D_{min} - \sigma, D_{max} - \sigma]$$

$$= [298653 - 68842, 521466 + 68842]$$

$$= [229811, 590308]$$

Step 7: calculate each data membership function

$$\mu_{\tilde{A}}(a) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x < b \\ \frac{c-x}{c-b}, & b \leq x < c \\ 0, & x \geq c \end{cases} \quad (7.1)$$

Where

x represent the accidents data $x^{(0)}(n)$

Table 1. Class assigned to data each year

Year	T	Data	Classes	Year	T	Data	Classes
2003	1	298653	1	2010	8	414421	2
2004	2	326815	1	2011	9	449040	3
2005	3	328264	1	2012	10	462423	3
2006	4	341252	1	2013	11	477204	3
2007	5	363319	2	2014	12	476196	3
2008	6	373071	2	2015	13	489606	3
2009	7	397330	2	2016	14	521466	3

Table 2. Example of entropy value calculation

x	$\frac{328264 + 341252}{2} = 334758$	$\frac{397330 + 414421}{2} = 405876$	$\frac{462423 + 476196}{2} = 469310$
$p_1(x)$	$\frac{1+1}{3+1} = 0.500$	$\frac{2+1}{7+1} = 0.375$	$\frac{6+1}{10+1} = 0.6363$
$p_2(x)$	$\frac{3+1}{1+1} = 0.500$	$\frac{7+1}{3+1} = 0.5$	$\frac{10+1}{1+1} = 0.1818$
$p_3(x)$	$\frac{3+1}{1+1} = 0.500$	$\frac{7+1}{2+1} = 0.375$	$\frac{10+1}{3+1} = 0.3636$
$q_1(x)$	$\frac{3+1}{1+1} = 0.167$	$\frac{7+1}{0+1} = 0.125$	$\frac{10+1}{1+1} = 0.400$
$q_2(x)$	$\frac{11+1}{4+1} = 0.417$	$\frac{7+1}{1+1} = 0.250$	$\frac{4+1}{1+1} = 0.400$
$q_3(x)$	$\frac{11+1}{6+1} = 0.583$	$\frac{7+1}{6+1} = 0.875$	$\frac{4+1}{2+1} = 0.600$
$p(x)$	$\frac{11+1}{3} = 0.2143$	$\frac{7+1}{7} = 0.500$	$\frac{4+1}{10} = 0.7143$
$q(x)$	$\frac{14}{11} = 0.7857$	$\frac{14}{7} = 0.500$	$\frac{14}{4} = 0.2857$
$S_p(x)$	1.0397	1.0822	0.9654
$S_q(x)$	0.9778	0.7233	1.0395
$S(x)$	0.9911	0.9027	0.9866

Table 3. Thresholds of MEPA for Road Accident data in Malaysia

TER1	SEC1	TER2	PRI	TER3	SEC2	TER4
312734	352286	385201	405876	455732	476700	505536

Table 4. Length of intervals of road accident data for Malaysia

Lower bound	Midpoint	Upper bound	Length of Interval
229811	312734	352286	122475
312734	352286	385201	72467
352286	385201	405876	53590
385201	405876	455732	70531
405876	455732	476700	70824
455732	476700	505536	49804
476700	505536	590308	113608

The value of a is calculated using equation in (7.1) to obtained a new value of B in Grey model Membership function is calculated using above formula that is later use in step 3 of GM(1,1) to estimate the coefficient of “a” and “b” and followed by the corresponding step to find the prediction value.

3. CASE STUDY

In this section, both GM(1,1) and combined MEPA & GM(1,1) forecasted values are used for comparison. The road traffic accidents data in Malaysia and India is tested to show and detect the accuracy between GM(1,1) and GMEPA(1,1). It is important to evaluate the applicability of the

model by identifying the best model that is suited to the data [24]. The process of data division, according to common opinion $\frac{1}{4}$ of the series will be served as the evaluation(out sample) purposes and the remaining $\frac{3}{4}$ will be consider as the estimation part(in sample).The data is separated into two section where 2003 to 2012 is the in sample and 2013 to 2016 is the out sample. Whereas for road accident data in India use the data from 2002 to 2011 as in sample and 2012 to 2015 as out sample. The evaluation of accuracy of each method are measured using mean average percentage error(MAPE) and Mean Square Error(MSE).The formulas of MAPE and MSE are shown below:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|\hat{y}_t - y_t|}{y_t} \times 100$$

\hat{y}_t = the value predicted by the model for time point t

y_t = the value observed at time point t

n = size of the sample

Mean Squared Error, MSE

$$MSE = \frac{\sum_{t=1}^n e_t^2}{n}, \quad e_t = y_t - \hat{y}_t$$

e^2 = error squared

y_t = the value observed at time t (original data)

\hat{y}_t = the value predicted by the model at time t

Original and forecasted values are shown in Table 5 and Table 6 to compare both methods accuracy and its mean average percentage error.

The values of parameter “a” and “b” for the road accident data in India is as shown in Table 6. Since the value of parameter $a \leq 0.3$, every α can be used for long term forecasting

purposes [25,26]. Each parameter has increasing pattern with every addition of α values. MAPE and MSE that has the lowest result is $\alpha=0.8$ which is 9% and 2059587405. However, GMEPA is able to improve the measurement of accuracy with MAPE of 8% and MSE of 1840954265. GMEPA also has the capability to estimate the lowest coefficient of “a” and “b” for accident data in India as shown in Table 7.

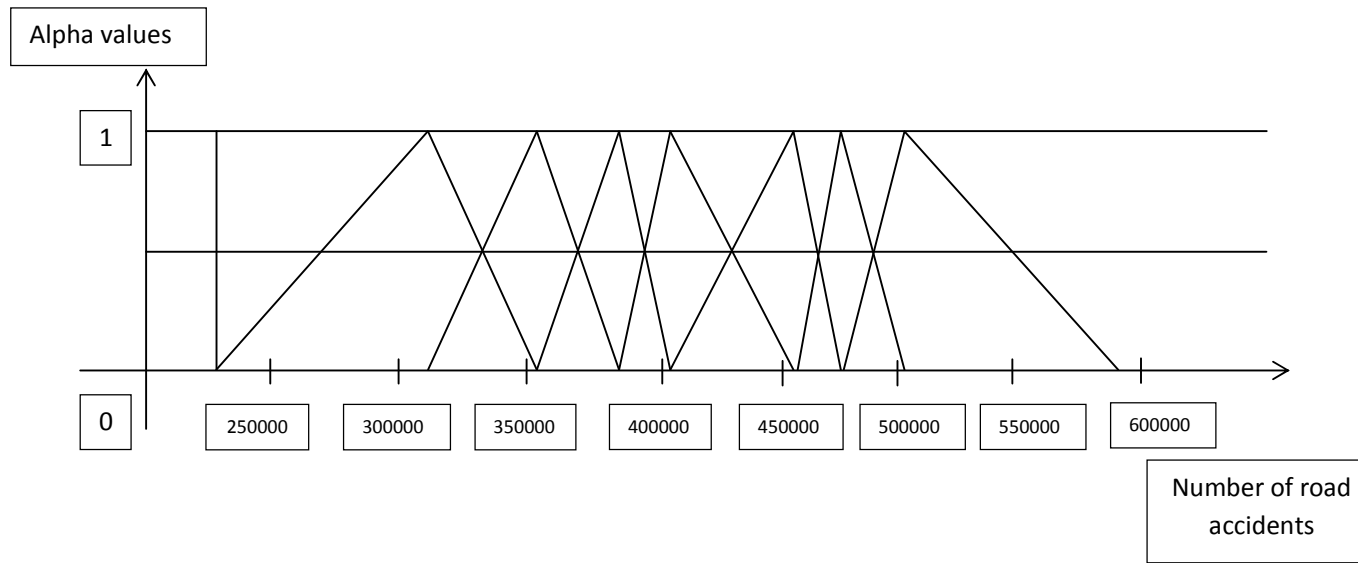
The values of parameter “a” and “b” for the road accident data in Malaysia is as shown in Table 9. Since the value of parameter $a \leq 0.3$, every α also can be used for long term forecasting purposes. The parameters shows an increasing pattern with the addition of α values. MAPE and MSE that has the lowest result is $\alpha=0.4$ which is 5% and 820916287 which gives a very highly accurate forecasting based on the interpretation of MAPE values. However, GMEPA is not able to minimize the measurement percentage of MAPE with a result of 8% and MSE of 1804128863. Road Accident in Malaysia shows a positive result towards original GM(1,1).

Table 5. Forecast values and prediction error of the accidents data in India for GM(1,1) with different α values

Year	Original data	Estimation Sample Forecast Values				
		$\alpha=0.4$	$\alpha=0.5$	$\alpha=0.6$	$\alpha=0.7$	$\alpha=0.8$
2002	407497	407497	407497	407497	407497	407497
2003	406726	419844	420891	421944	423001	413934
2004	429910	430187	431283	432385	433492	424223
2005	439255	440785	441932	443084	444242	434767
2006	460920	451644	452843	454049	455260	445574
2007	479216	462770	464024	465284	466550	456649
2008	484704	474171	475481	476798	478121	467999
2009	486384	485852	487221	488596	489978	479632
2010	499628	497821	499250	500686	502130	491553
2011	497686	510085	511577	513076	514583	503771
MAPE%		1	1	1	2	2
MSE		79925462	78460445	79906440	84306527	127610085

Evaluation Sample

2012	490383	522651	524208	525772	527345	516293
2013	486476	535527	537150	538782	540423	529125
2014	489400	548720	550413	552115	553826	542277
2015	501423	562238	564003	565777	567561	555756
MAPE%		10	11	11	11	9
MSE		2666154203	2837690804	3015720613	3200340834	2059587405



Graph 1. Membership function of MEPA for road traffic accidents in Malaysia

Table 6. Parameters values for different alpha(α) used in Road Traffic Accident in India

		$\alpha=0.4$	$\alpha=0.5$	$\alpha=0.6$	$\alpha=0.7$	$\alpha=0.8$
GM	Parameter "a"	-0.02434	-0.02439	-0.02444	-0.02449	-0.02455
	Parameter "b"	404838	405841	406847	407858	408874

Table 7. Estimation sample and evaluation sample in Road Traffic Accident in India by using concept of MEPA

Year	Estimation Sample		
	Original Data	Alpha(α)	Forecasted values
2002	407497		407497
2003	406726	1	414643
2004	429910	0.8	424695
2005	439255	0.7	434991
2006	460920	0.7	445536
2007	479216	0.9	456337
2008	484704	0.5	467399
2009	486384	0.7	478730
2010	499628	0.9	490336
2011	497686	0.6	502222
Parameter values	a = -0.02395 b = 409697		
MAPE(%)	2		
MSE	133317516		

Evaluation sample

Year	Original data	Forecasted values
2012	490383	514397
2013	486476	526868
2014	489400	539640
2015	501423	552722
MAPE(%)	8	
MSE	1840954265	

Table 8. Forecast values and prediction error of the accidents data in Malaysia for GM(1,1) with different α values

Year	Original data	Estimation Sample Forecast Values				
		$\alpha=0.4$	$\alpha=0.5$	$\alpha=0.6$	$\alpha=0.7$	$\alpha=0.8$
2003	298653	298653	298653	298653	298653	298653
2004	326815	313216	314752	316304	317870	319452
2005	328264	328449	330133	331835	333554	335290
2006	341252	344422	346266	348129	350011	351914
2007	363319	361172	363186	365222	367281	369362
2008	373071	378737	380934	383156	385402	387675
2009	397330	397156	399549	401969	404418	406896
2010	414421	416471	419074	421707	424372	427070
2011	449040	436726	439552	442414	445311	448244
2012	462423	457965	461032	464137	467282	470468
MAPE%		1	1	1	2	2
MSE		40748129	35450803	39730663	53926433	78388651

Evaluation Sample

2013	477204	480237	483561	486927	490338	493793
2014	476196	503593	507191	510836	514531	518276
2015	489606	528084	531975	535919	539918	543972
2016	521466	553766	557971	562234	566557	570942
MAPE%		5	6	7	7	8
MSE		820916287	1032204703	1275367630	1551652992	1862357661

Table 9. Parameters values for different alpha(α) used in Road Traffic Accident in Malaysia

		$\alpha=0.4$	$\alpha=0.5$	$\alpha=0.6$	$\alpha=0.7$	$\alpha=0.8$
GM	Parameter "a"	-0.04749	-0.04771	-0.04793	-0.04816	-0.04839
	Parameter "b"	291656	293054	294468	295894	297333

Table 10. Estimation sample and evaluation sample in Road Traffic Accident in Malaysia by using concept of MEPA

Estimation Sample			
Year	Original Data	Alpha(α)	Forecasted values
2003	298653		298653
2004	326815	0.6	316751
2005	328264	0.6	332674
2006	341252	0.8	349397
2007	363319	0.7	366961
2008	373071	0.6	385408
2009	397330	0.6	404782
2010	414421	0.8	425130
2011	449040	0.9	446501
2012	462423	0.7	468946
Parameter values	a = -0.04905 b =294399		
MAPE(%)	2		
MSE	57172223		

Evaluation sample

Year	Original data	Forecasted values
2013	477204	492519
2014	476196	517278
2015	489606	543281
2016	521466	570591
MAPE(%)	8	
MSE	1804128863	

Table 11. Interpretation of typical MAPE value

MAPE	interpretation
<10	Highly accurate forecasting
11-20	Good forecasting
21-50	Reasonable forecasting
>50	Inaccurate forecasting

Lewis (1982, p.40) [27]

4. CONCLUSIONS AND FUTURE RESEARCH

In this paper, we compare the accuracy of Grey model and the combining Grey model with Minimize Entropy Principle Approach(MEPA) to forecast road accident data. MEPA is able to

estimate a better parameter in GM for road accidents data in India. But Malaysia road accident data performs better in original grey model. This means that only some sample data can used GMEPA(1,1) to improve the measurement of accuracy depending on the estimated coefficient of "a" and "b". For future

studies, researcher can perform GMEPA in other road accident data for other countries or anything that is related to the issue such as road fatalities and road injuries to identify the efficiency of the method.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Julong D. Introduction to grey system theory. *Journal of Grey System*. 1989;1-24.
2. Sifeng L, Forrest J, Yingjie Y. A brief introduction to grey system theory. *IEEE Grey Systems and Intelligent Services (GSIS)*; 2011.
3. Jia Y, He P, Liu S, Cao L. A combined forecasting model for passenger flow based on GM and ARMA. *International Journal of Hybrid Information Technology*. 2016;9(2):215-226.
4. Tseng P, Lin F, Ch. Feng. The analysis of human and vehicle factors for Taiwan freeway traffic accidents. *Journal of the Eastern Asia Society for Transportation Studies*. 2003;5.
5. Zhou P, Ang BW, Poh KL. A trigonometric grey prediction approach to forecasting electricity demand. *Energy Conversion & Management*. 2006;31:2839-2847.
6. Shurong H, Fang Y, Zhenzhen L, Qiang L, Jianguo D. Application of grey system theory to forecast the growth of larch. *International Journal of Information and Systems Sciences*. 2009;5(3-4):522-527.
7. Ying HF, Thanh NL, Ming SH. Forecasting inbound tourism demand in Thailand with grey model. *Applied Economics and Management*; 2013.
8. Kayacan E, Ulutas B, Kaynak O. Grey system theory based models in time series prediction. *Expert Systems with Applications*; 2010.
9. Askari M, Askari H. Time series grey system prediction-based models: Gold price forecasting. *Trends in Applied Sciences Research*; 2011.
10. Tsai LC, Yu YS. Forecast of the output value of Taiwan's IC industry using the Grey forecasting model. *International Journal of Computer Applications in Technology*; 2004.
11. Kang J, Zhao H. Application of improved grey model in long-term load forecasting of power engineering. *Systems Engineering Procedia*; 2012.
12. Ching HC, Jing RC, Che AY. Entropy-based trapezoid fuzzification-based fuzzy time series approaches for forecasting IT project cost. *Technological Forecasting and Social Change*. 2005;73:524-542.
13. Hsu CC, Chen Chia YC. A modified grey forecasting model for long-term prediction. *Journal of the Chinese Institute of Engineers*. 2003;26(3):31-308.
14. Liu SF, Deng JL. The range suitable for GM(1,1). *System Engineering Theory and Application*. 2000;5(2):111-124.
15. Statistical Report Road Accident, Road Traffic Branch, Royal Malaysian Police; 2007.
16. States/UTs, Police Departments of India.
17. Jiang X, Zhang L, Chen XM. Short-term forecasting of high-speed rail demand: A hybrid approach combining ensemble empirical mode decomposition and gray support vector machine with real-world applications in China. *Transportation Research Part C*. 2004;44:110-127.
18. Tseng FM, Yu HC, Tzeng GH. Applied hybrid grey model to forecast seasonal time series. *Technological Forecasting and Social Change*. 2001;67:291-320.
19. Deng JL. Control problems of grey system theory. *The Journal of Grey System*. 1989;1:1-24.
20. Huang YL. Forecasting the demand for health tourism in Asian countries using a GM(1,1)- alpha model. *Tourism and Hospitality Management*. 2012;18(2):171-181.
21. Ho PHK. Comparison of the Grey Model and the Box Jenkins Model in Forecasting Manpower in the UK Construction Industry. Smith, S.D (Ed) *Procs 28th Annual ARCOM Conference*, 3-5 September 2012, Edinburgh, UK, Association of Researchers in Construction Management. 2012;369-379.
22. Dunn JC. A fuzzy relative of the ISODATA process and its use in detecting compact, well separated clusters. *J. Cybernet*. 1974; 3:32-57.
23. Christensen R. *Entropy Minimax Sourcebook*, Entropy Ltd., Lincoln, MA. 1980;1-4.
24. Alias Lazim. *Introductory Business Forecasting – a practical approach (3rd edition)*. UiTM Press; 2011.
25. Yu X, Le Y, Meijuan Yang, Zhenyan L. The Application of grey system in futures price

- forecasting. International Journal of Science and Technology. 2012;2(12):860-869.
26. Huang YF, Wang CN, Dang HS, Lai ST. Predicting the Trend of Taiwan's Electronic Paper Industry by an Effective Combine Grey Model Sustainability. 2015;10664-10683.
27. Lewis CD. Industrial and business forecasting methods. London: Butterworths. 1982;40.

© 2018 Alfred and Ahmad; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Peer-review history:
The peer review history for this paper can be accessed here:
<http://www.sciencedomain.org/review-history/23690>