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Original Research Article

MFFNN and GRNN Models for Prediction of Energy Equivalent Speed Values of Involvements in Traffic Accidents

Ali Can Yilmaz[1], Cigdem Inan Aci[2], Kadir Aydin[1]

[1] Department of Automotive Engineering, Cukurova University, Adana, Turkey
[2] Department of Computer Engineering, Cukurova University, Adana, Turkey

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Abstract

Accident reconstruction is a scientific study field that depends on analysis, research and drawing. Scientific reconstruction of related traffic accident on computer eliminates making decisions depending on initiative or experience of the expert and yields impartial decisions and evidences especially on events like matter for the courts or forensic investigations. In this study, data collected from accident scene (police reports, skid marks, deformation situation of involvements, crush depth etc.) were inserted properly into the software called “vCrash” which is able to simulate the accident scene in 2D and 3D. Then, 784 parameters, related to calculating Energy Equivalent Speed (EES) with a prediction error, were prepared according to several accidents. These parameters were also used as teaching data for the Multi-layer Feed Forward Neural Network (MFFNN) and Generalized Regression Neural Network (GRNN) models in order to predict EES values of involvements, which give idea about severity and dissipation of deformation energy corresponding to the observed vehicle residual crush, without requirement of performing simulation for probable accidents in future. Using 10-fold cross validation on the dataset, standard error of estimates (*SEE*) and multiple correlation coefficients (*R*) of both models are calculated. The GRNN-based model yields lower *SEE* whereas the MFFNN-based model yields higher *R*.

Keywords: Accident reconstruction, EES, artificial neural network, MFFNN, GRNN.

* Corresponding Author:

E-mail: acyilmaz@cu.edu.tr

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1. Introduction

Safety and efficiency are the two primary goals of transportation engineering. The effort that public agencies put into reducing traffic accidents is highly justifiable. Traffic accidents place a huge financial burden on society. Two major factors usually play an important role in traffic accident occurrence. The first is related to the driver, and the second is related to the roadway design. Many of the important road user factors in traffic safety depend strongly on the gender and the age of the driver [1]. As countries develop death rates usually fall, especially for diseases that affect the young and result in substantial life-years lost. Deaths due to traffic accidents are a notable exception: the growth in motor vehicles that accompanies economic growth usually brings an increase in road traffic accidents. Traffic injuries come first in rank among all injury-related deaths all around the world. In 2004, World Health Organization (WHO) devoted the World Health Day (April 7) to prevention of traffic injuries. Indeed, the WHO has predicted that traffic fatalities will be the sixth leading cause of death worldwide and the second leading cause of disability-adjusted life-years lost in developing countries by the year 2020 [2].

According to 2002 annual reports, traffic accidents are the 11th reason for fatalities in Turkey. Traffic accidents have the 2nd priority for fatalities at the age interval of 5-29 and the 3rd for the age interval of 30-44. In 1999, while the number of registered traffic accidents was 466000, it was 501000 in year 2000. General Directorate of Highway reports indicate 2954 fatalities and 94497 injuries involving 409407 accidents in year 2001 and 570419 accidents in year 2005 [3].

2. Examinations and analysis

Most frequent PDO and injury accidents were observed and data relevant to these were loaded into vCrash [4] software to simulate it. In the first step, some scenarios were carried out in order to reconstruct accident occurrence moment as real as possible. According to the result data of the accident which had been got before, scenarios were assessed to get the most accurate one. Related impulse-momentum and energy transfer analysis of the software, occurrence type of the accident, vehicles' locations and situations after the crash and damages comprised on the involvements were tried to be examined and interpreted. These simulation results yield precautions those are to be taken to minimize causes to these type of accidents. 840 data parameters, according to several accidents related to calculating EES, were prepared and used as teaching parameters for the MFFNN and GRNN models in order to predict EES values of involvements without requirement of performing simulation for probable accidents in future.

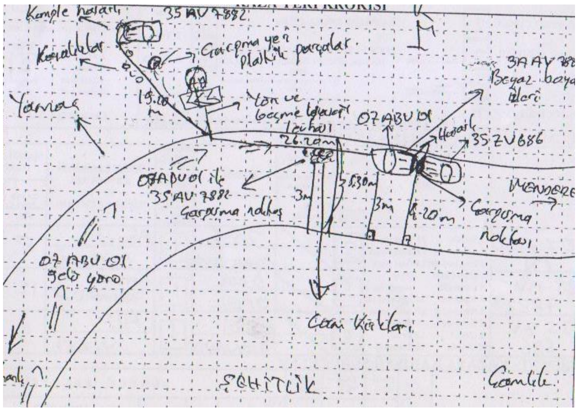

Figure 1. Accident scene simple plan

A. Analysis of a sample accident

<u>Occurrence Type of Accident:</u> According to claims stated in police report, Chrysler had a little touch on Opel while cornering and Opel did a tip over onto the cliff at the side of the road. Then, Chrysler crashed into Renault coming from opposite direction and they stopped.

Available Data:

- Traffic police report
- Photographs of involvements

A scale drawing of the accident scene finding report on computer and similar scene created on the software are demonstrated in Fig. 1 and 2, respectively.

Vehicles should have crashed to each other as shown above according to claims made by involvements. Main road lane width was chosen as 6 m and due to dry surface conditions, surface coefficient of friction was accepted as 0.7. Sizes of vehicles according to their technical specifications and measures entered into the software were depicted on appropriate scale basis.

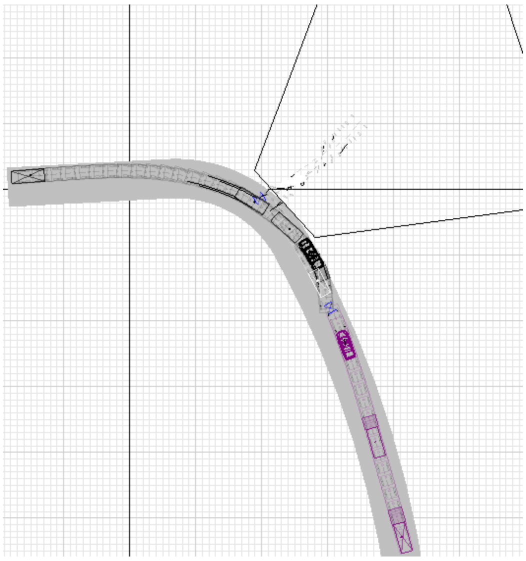

Figure 2. Generation of the accident scene on the software

Data Collection from Involvements: Crush regions on Chrysler and Renault are shown in Fig. 3 and 4, respectively.

Figure 3. Region on the front bumper where the first collision occurred on Chrysler

Figure 4. Perpendicular crash force exerted on the left front headlight of Renault

Figure 5. Damage formed on the top of the vehicle

Figure 6. View of in-question side of Opel

It was concluded that a 30 km/h change in speed should have occurred in order to obtain a similar damage on the first collision point of Chrysler with Renault. Front impact strength coefficient of Chrysler was considered 2 times of Renault. According to observations on damaged area of Renault, a 30-cm crush was made in the moment of accident which could have been occurred in an opposite direction collision of vehicles with speed of 20 km/h for both of them. These speeds are too small to have an impact and the accident should have been avoided by the involvements in the speed of 20 km/h. The speed of Opel just before tip over was determined as 70 km/h and this tip over could stop after 4-5 flips.

Damage formed on the top of Opel and view of in-question side of the vehicle are depicted in Fig. 5 and 6, respectively.

Approximately 30 cm crush was observed on the roof of Opel which could cause neck damage, scratches on face or arms of driver and/or passenger(s). A big contact force should have been exerted on Opel in order to cause a tip over. However, there is no sign of contact on the left side of the car. Therefore, there was no possibility for Opel to tip over because of contact with Chrysler.

1) Pre-impact velocity (v_1): Velocity of vehicle(s) at the time of contact to each other, in km/h.

2) Post-impact velocity (v_2): Velocity of vehicle(s) at the time of separation from each other, in km/h.

3) Deformation (ε): Average crush depth of damaged region, in meters (m)

4) Pre-omega and post-omega (ω_1, ω_2): Angular velocities of vehicles at the time of contact to each other and at the time of separation from each other, respectively, in rad/s.

5) Impulse (Imp): The result of impact force, over a specific time period "t", in N.s.

6) Time (t): Time elapsed during the collision in seconds (s).

7) X, y, z: Location of involvements just before the collision in Cartesian coordinates in meters (m).

8) Delta-v (Δv): The change in velocity of a vehicle's occupant compartment during the collision phase of a motor vehicle crash (i.e. from the moment of initial contact between vehicles until the moment of their separation) in km/h [5].

Energy Equivalent Speed (EES):EES has been defined by Burg, Martin and Zeidler in the year 1980 and was suggested for a common use. EES is a speed measure which will be transformed into deformation energy during the collision or in international standard definition, "The equivalent speed at which a particular vehicle would need to contact any fixed rigid object in order to dissipate the deformation energy corresponding to the observed vehicle residual crush." For accident reconstruction and for accident research, there are tools necessary for a realistic assumption of the accident circumstances. But in most of the cases there are not enough data for a reliable statement of the crash, especially the crash severity and the relationship between the crash severity and the occupant load which represents difficult and controversial problem. The plastic deformation energy of the damaged car is expressed as a kinetic energy of the car with the virtual velocity value "EES". For an authentic EES estimation various crash tests with different conditions are necessary, because the energy absorption depends on various parameters. If the EES of one vehicle that was involved in a vehicle to vehicle collision is known, then it is possible to determine the unknown EES based on the principle of action equals reaction by approximating the other crush. EES may be calculated as shown in Eq. (1).

$$\frac{EES_1}{EES_2} = \sqrt{\frac{m_2}{m_1}\frac{s_{Def1}}{s_{Def2}}} \text{ and } EES_2 = \sqrt{\frac{2.E_D}{m_2\left(\frac{s_{Def1}}{s_{Def2}}+1\right)}} \text{ (km/h)} \quad (1)$$

Where;

m_1, m_2: mass of each vehicle (kg)

s_{Def1}, s_{Def2}: crush depth of each vehicle, outer surface to impact point in line with impact force (m)

E_D: energy lost by both vehicles in the collision due to damage (J).

Two phases can be distinguished during the crash of a vehicle: there is a compression phase and a restitution phase. The compression phase lasts from the contact of the vehicle with an obstacle (another vehicle or anything else) to the point of maximum compression. During this phase, the energy is stocked until the maximum deformation. The restitution phase begins when deformation is maximum and ends when the vehicle separates from the obstacle. During this phase, the deformation energy is released [5]. EES values of involvements just before collision (pre-impact) and after collision (post-impact) are circled in red on the collision chart.

9) Deformation Energy (E): The plastic deformation energy of the damaged car is expressed as a kinetic energy of the car with the virtual velocity value EES, in Joule (J).

10) Generalized extreme value (GEV): Possible limit distribution of properly normalized maxima of a sequence of independent and identically distributed random variables [6].

A. Accident Scenarios

1) Scenario 1: In Fig. 7 and 8, Chrysler (55 km/h) contacts Opel (25 km/h) and Opel tips over on to the right side of the road. Then, Chrysler (25 km/h) crashes into Renault (16 km/h).

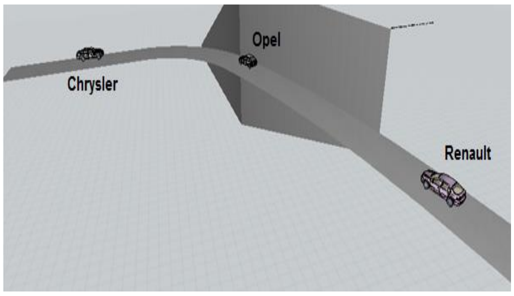

Figure 7. Direction of vehicles before the accident

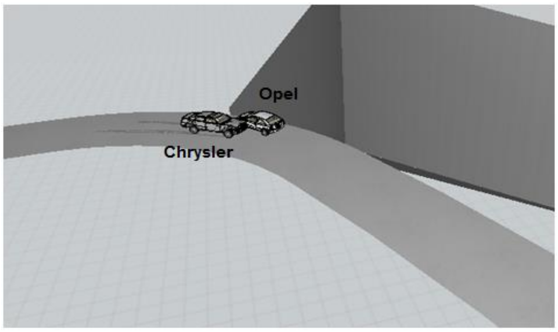

Figure 8 Contact moment of Chrysler and tip over of Opel

2) Scenario 2: In Fig. 9 and 10, Chrysler (53 km/h) contacts Opel (23 km/h) and Opel does not tip over on to the right side of the road. Then, Chrysler (43 km/h) crashes into Renault (19 km/h).

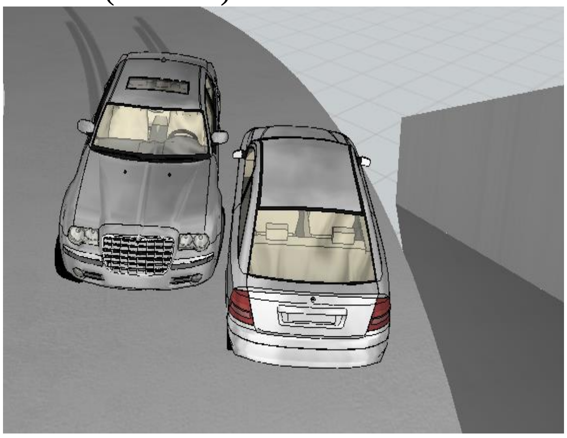

Figure 9. Positions of Chrysler and Opel in 3D simulation

EES values almost match with damages formed on the vehicles.

B. Results and Interpretation of Accident Scene

- Opel could not tip over with a smooth contact with Chrysler because of low speed of Chrysler. It is impossible that Chrysler encroached other lane again due to its low speed. Any impact marks due to these claims were not seen on the in-question regions.
- Serious injuries should have been formed on the driver in Opel if it tipped over as claimed. However, little scratches and wounds were stated in doctor report.
- This accident with Opel occurred with a different driver in a different time.
- Statements of drivers did not match with drawings made by police in the report.

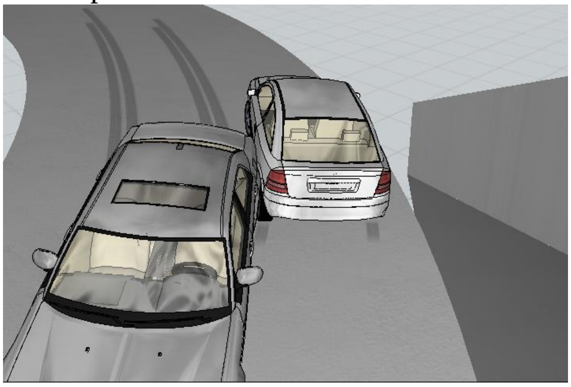

Figure 10. Smooth contact on the left rear fender of Opel

3. Overview of methods

A. Multi-layer Feed-Forward Neural Network (MFFNN)

An MFNN consists of at least three layers: input, output, and hidden layer. The schematic diagram of a MFNN is shown in Fig. 11. Each neuron in a layer receives weighted inputs from a previous layer and transmits its output to neurons in the next layer. The summations of weighted input signals are calculated and this summation is transferred by a nonlinear activation function. The results of the network are compared with the actual observation results and the network error is trained until the error reaches an acceptable value [7].

In Fig. 11, X_i is the neuron input, W_{ij} and W_{kj} are the weights, M is the number of neurons in the hidden layer, and Y is the output value [8].

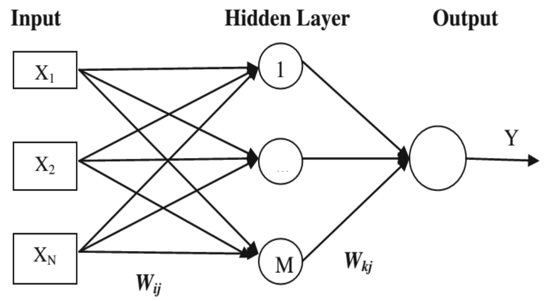

Figure 11. A typical multi-layer feed-forward neural network architecture

B. Generalized Regression Neural Networks (GRNN)

The GRNN is a generalization of both radial basis function networks and probabilistic neural networks that can perform linear and nonlinear regression [9]. These feed-forward networks use basis function architectures which can approximate any arbitrary function between input and output vectors directly from training samples, and they can be used for multidimensional interpolation [7, 12]. The main function of a GRNN is to estimate a linear or nonlinear regression surface on independent variables (input vectors) U, given the dependent variables (desired output vectors) X. That is, the network computes the most probable value of an output, O_X, given only training vectors U. Specifically, the network computes the joint probability density function of U and X. The expected value of X given U is expressed as [9]:

$$E[X/U]=\frac{\int_{-\infty}^{\infty} X f(U,X)\,dx}{\int_{-\infty}^{\infty} f(U,X)\,dx} \tag{2}$$

$$R = \sqrt{1-\frac{\sum (Y-Y')^2}{\sum (Y-\bar{Y})^2}} \tag{3}$$

$$SEE = \sqrt{\frac{\sum (Y-Y')^2}{N}} \tag{4}$$

4. Results and discussion

The dataset used in this study contains 14 predictor variables (t, x-y-z, phi, Δv, Imp, E, ε, ν_1, ν_2, ω_1, ω_2, GEV). Descriptive statistics for the dataset is given in Table 1. The performance of both models are evaluated by using 10-fold cross validation and calculating the *SEE* and *R*, whose formulas are given in Eq. (3) and (4), respectively.

Table 1. Descriptive statistics of the dataset

	Statistics Name			
Data	**Mean**	**Maximum**	**Minimum**	**Std. Deviation**
t	1,656	4,625	0,06	1,174
x	8,525	111,657	-78,109	30,132
y	-1,436	8,756	-82,966	16,494
z	0,431	0,642	0,005	0,114
phi	85,983	171,962	0,073	45,649
Δv_1	8,771	75,095	0,237	14,759
Imp	10895,695	100191,035	532,244	19254,068
E	74881,498	1112047,522	781,718	203453,981
ε	0,200	0,705	0,025	0,142
ν_1	28,290	94,471	0	25,613
ω_1	0,053	1,724	-0,467	0,270
ν_2	25,953	69,304	0,055	19,391
ω_2	0,245	8,016	-3,708	1,597
Δv_2	14,804	48,092	0	12,620
GEV	0,930	1,614	0	0,356
EES	14,671	44,22	0,001	10,938

Table 2. R and see values of the MFFNN and GRNN models by means of 10-fold cross-validation

	MFFNN-based model		GRNN-based model	
Folds	***R***	***SEE***	***R***	***SEE***
Fold 1	0,86	3,44	0,95	3,66
Fold 2	0,89	3,65	0,90	4,52
Fold 3	0,90	3,57	0,89	3,68
Fold 4	0,87	4,41	0,91	4,38
Fold 5	0,95	2,21	0,93	4,72
Fold 6	0,90	3,15	0,91	3,98
Fold 7	0,88	4,01	0,94	3,00
Fold 8	0,89	4,56	0,88	4,03
Fold 9	0,91	3,66	0,94	4,44
Fold 10	0,87	5,55	0,96	3,95
Average	0,89	3,82	0,92	4,04

In (3) and (4), Y corresponds to measured EES value, Y' corresponds to predicted EES value, $\bar{Y}$ is the mean of the measured values of EES and N is the number of samples in a test subset. Descriptive statistics of the dataset are demonstrated in Table 1.

The inputs have been pre-processed by using the Principal Component Analysis method to orthogonalize the components of the input vectors (so that they are uncorrelated with each other) and to order the resulting orthogonal components (principal components) so that those with the largest variation come first [10]. The other important parameters of models are the number of epochs (selected as 100), the learning rate and momentum default values are used [11].

For both MFFNN-based and GRNN-based EES prediction models, the individual *SEE* and *R* values for each fold as well as their average are shown in Table 2. The averages are simply the arithmetic averages of the *SEE* and *R* values of each fold. As is clearly seen from Table 2, the GRNN-based model yields higher averaged *R* values whereas the MFFNN-based model yields lower averaged *SEE* values.

5. Conclusions

At this term, a sample traffic accident was examined with the aid of data collection from the accident scene. Simulation and analysis relevant to these data were conducted on traffic accident reconstruction tool (software) called vCrash which showed the occurrence type of the accident and damage levels comprised on involvements in 3D. As a result, these examinations were interpreted to comprehend the general reasons causing these accidents and precautions to minimize them. MFFNN and GRNN models were used to develop new models for EES prediction by using vCrash variables. The results suggest that MFFNN-based and GRNN-based prediction models can be valid predictors of EES for traffic accidents without requirement of performing simulation for probable accidents in future.

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