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Prediction of accident severity using artificial neural networks

F. Rezaie Moghaddam[1], **Sh. Afandizadeh**[2,*], **M. Ziyadi**[1]

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Abstract

In spite of significant advances in highways safety, a lot of crashes in high severities still occur in highways. Investigation of influential factors on crashes enables engineers to carry out calculations in order to reduce crash severity. Therefore, this paper deals with the models to illustrate the simultaneous influence of human factors, road, vehicle, weather conditions and traffic features including traffic volume and flow speed on the crash severity in urban highways.

This study uses a series of artificial neural networks to model and estimate crash severity and to identify significant crash-related factors in urban highways. Applying artificial neural networks in engineering science has been proved in recent years. It is capable to predict and present desired results in spite of limited data sets, which is the remarkable feature of the artificial neural networks models.

Obtained results illustrate that the variables such as highway width, head-on collision, type of vehicle at fault, ignoring lateral clearance, following distance, inability to control the vehicle, violating the permissible velocity and deviation to left by drivers are most significant factors that increase crash severity in urban highways.

Keywords: Crash Severity, Human Factors, Highway, Traffic Volume, Artificial Neural Networks.

1. Introduction

Although considerable efforts have been made to investigate the crash severity, relationship between risk factors and crash severity hasn't been properly identified. Here, one of the reasons may be that the factors associated with levels of crash severity are complicated due to a number of factors including personal characteristics such as "age, gender", vehicle such as "type of vehicle", environment such as "weather condition" and road such as "Geometrical Design"[1]. Therefore, current study uses a series of artificial neural networks to model the simultaneous crash-related factors. So different neural models were trained and finally models illustrating crash-related factors in crash severity "fatal, injury or damage" are presented. To achieve this goal, data collected from organizations was set into unit data bank and crash severity categorized into two levels; "fatality-injury" crashes and the "property loss" ones. Because every crash with specific factors in some cases were fatality-injury and in some other cases were property loss (but with some priority to one of them) the percent of crash severity calculated showing that which percent of each crash is fatality- injury and which percent is property loss. For example to say fatality-injury percent of a crash is 11%, means that 11% of that kind of crash with its specific crash-related factors caused to fatality or injury of driver. Then neural models were adjusted and trained and finally tested to show how able neural networks are to predict the severity level of crashes.

The crash severity models are of great importance because in these models, the crash-related factors, particularly fatalities are identified and effective preventive measures are prioritized.

Artificial neural networks (ANN) a massively parallel distributed information processing system, based on nature of human brains, are capable of approximating any finite non-linear models to determine the relation between dependent and independent variables. In fact the function is based on error-back propagation so that the error between out put of the network and desired output (target) is required low. Neural networks are parts of Artificial Intelligence which have been applied in different areas successfully [2].

Considering this high capability researchers are researching on new generations of ANN with more power and precision [3].

* *Corresponding Author: zargari@iust.ac.ir*
1 *Department of Engineering, University of Mohaghegh Ardebili, Ardebil, Iran*
2 *School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran*

2. Background

Chen and Jovanis, obtained a relationship between crash severity and its associated factors using Loglinear Model. In the study, 408 observations considering bus crashes in a freeway in Taiwan for the period of 1985 to 1993 were used and since the number of crashes, fatalities were low, they have been combined with crash injuries. They emphasized on the importance of proper categorization of a number of data such as the time of crash. Frontal impact collisions, driving in late hours of night or early morning, driver fault and etc. are among factors affecting higher crash severity [4]. Kockelman investigated models of crashes including two-vehicle, single-vehicle and all other types of crashes, separately. Because of the different nature of crashes and their cause, it is suggested to separate them in order to get the best results in the model. Finally, he identified the head-on impact collision, high speed, rollover, alcohol use, older age, overtaking maneuver, night crashes and etc. as high severity crashes and rear or lateral impact collisions and day crashes as low severity ones[5]. Saccomanno used the Binary Logit Models in his investigations and considered factors including driver fault, bad conditions of the driver (being tired or sick), poor vision, wet road, night crashes, vehicle breakdown, alcohol use and etc. as increasing factors of crash severity and factors such as belt seat usage as decreasing one. In representing models, he showed that if in a category (for example, fatality crashes), the number of observations were less compared with total crashes, its combination with injury crashes and considering both as one category will lead to more meaningful variables and better model results[6]. Also, Voget and Bareed obtained a relationship between rural two-lane road crash severity and its contributing factors [7].

In prior studies using artificial neural networks as the modeling approach for crash severity and it's relating factors such as human factors, roadway condition, weather condition and etc, has been scarce. Abdelwahab and Abdel-Aty in 2001, classified crash severity into three injury severity levels, that is related to two-vehicle accident that occurred at signalized intersections. They used MLP for classifying data and get correctly classifying 65.6% and 60.4% of cases for the training and testing data, respectively [8].

Also Abdelwahab and Abdel-Aty in 2004 applied multilayer perceptron and fuzzy adaptive resonance theory and neural networks to analyze driver injury severity in traffic accident. The results indicated that gender, vehicle speed, seatbelt use, vehicle type, point of impact and area type of accident location can affect injury severity likelihood [9]. Dursun Delen, et al in 2005, developed eight binary neural models to classify accidents by level of injury severity from no-injury to fatality and conducted sensitivity analysis to identify the prioritized importance of crash-related factors [10]. Mussone et al. in 1999 employed ANN modeling approach to analyze vehicular accidents that occurred in intersections in Milan, Italy. Results showed that most of accidents occur in non-signalized intersections at night-time [11].

Literature review shows different results for crash-related factors affecting crash severity. In fact these studies show ascending or descending factors' effects, due to kind of data available.

But what differentiates our study from those is that, we tried to predict crash severity by percent. While prior studies classify crash into 2,3,5,8 etc. severity levels. Besides we developed and used sensitivity analysis on best models to identify the prioritized importance of crash-related factors. And after ignoring independent variables with less importance, among 92 variables, we trained networks with 25 significant independent variables.

3. Artificial neural network

It's been used different learning rules for training networks. One of the best known rules is multilayer perceptron (MLP) learning rule. MLP is a feed forward network in which information flow from input side and pass through the hidden layers to the output layer to produce outputs. Detailed information is found in literature. Many studies have shown that MLP is a universal approximator. A MLP with one hidden layer is capable of approximating any finite nonlinear function with very high accuracy [12].

Each layer consists of neurons that are processing elements (PEs) of network.

A three layer network represented in fig.1.Each neural cell (neuron) in any layer related with the entire next layer neurons through lines contained with coefficients called "weight coefficients". Any change in coefficients alters the function of the network. In fact, the main goal of the network training would be determining the best weight coefficients to obtain the desired output. The change in weight coefficients results from learning patterns and methods and as already mentioned, MLP and GFF- generalized type MLP- are two learning methods applied in the current study. In training, MLP the inputs of the first layer multiplied in weight coefficients that would be any randomly selected number and then enter into the neurons in second layer. Any neuron functions, in two ways: 1-calculating the sum of the inputs, defined as neti 2- inserting the sum in a function called" activation function". Fig2 represents the function of a neuron in a network.

$$net_i=\sum w_{ij}.x_i \quad (1)$$

$$out_i=F(net_i) \quad (2)$$

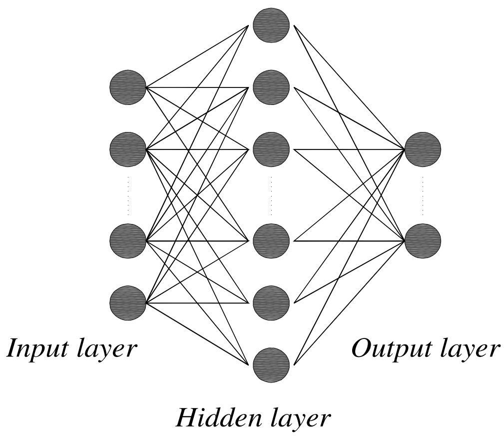


Fig. 1. three-layer neural network

Where:

out_i : Neuron output

w_{ij} : Weight coefficient from i-th neuron of the first layer to j-th neuron of the second layer

x_i : i-th neuron input

Various activation functions can be used in the current study, we used two known type called" hyperbolic tangent and sigmoid factions" [fig.3]. This process continues in the rest neurons of the middle layer and finally the outputs generated in the last layer.

It should be mentioned that the network's output could be multi-valued, but in the current study, the output is only crash severity by fatality-injury percent. During learning, the error between network output and target output calculated and again sent from the last layer to the previous one and thus the weight coefficients corrected using equations 3,4. this process is called" error-back-propagation". Once again the network generates output, using the new weight coefficients and also calculates the reducing error and back propagates it into the network until the error reaches to its least value that is the desired value, after many epochs.

$$w_{ij}(t+1)=w_{ij}(t)+\eta\delta_{pi}o_{pj} \tag{3}$$

$$\delta_{pi}w_{ij}(t+1)=w_{ij}(t)+\eta\delta_{pi}o_{pj}+\alpha\left[w_{ij}(t)-w_{ij}(t-1)\right] \tag{4}$$

Where:

$W_{ij}(t+1)$: Weight coefficient in step t+1, from neuroni to neuron^j .

$W_{ij}(t)$: Weight coefficient in step t, from neuron i to neuron j .

η: learning coefficient

δpi: Difference between desired output and network output in neuron p of layer j

o_{pi}: Output of neuron p of layer j

δ_{pi}: Output of neuron p of layer i

α: Momentum coefficient

$W_{ij}(t-1)$: Weight coefficient in step $t-1$, from neuron i to neuron j .

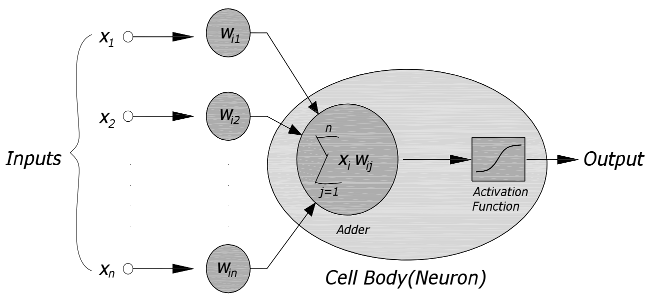


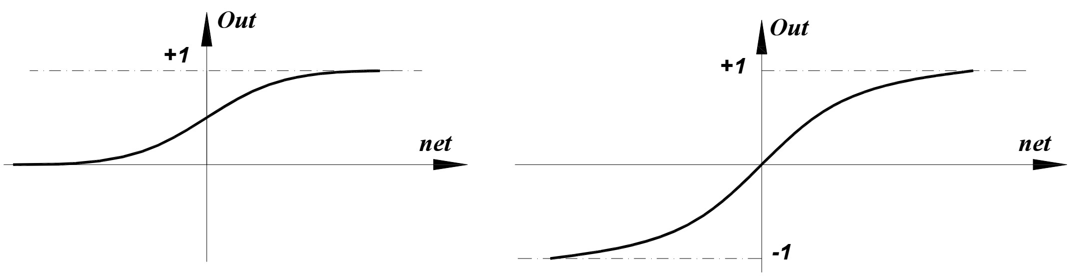
Fig. 2. structure of a neural cell

4. Data collection

Developing a model requires some data and information, so in the current study, highways of Tehran (capital city of Iran) has been considered as a case study and the required information were collected in the following steps:

1. Gathering Data related to traffic volume and speed in different sections of urban highways.
2. Collecting information related to geometrical characteristics such as shoulder width, lane number and width in different sections of urban highways.
3. Selecting data related to urban highway crashes in recent years.

In order to investigate the influence rate of various factors such as environment, traffic, human, geometrical feature, vehicle and etc on crash severity in highways, data associated with traffic characteristics such as volume and flow speed and highways geometrical characteristics collected from Tehran Traffic and Transportation organization and Tehran Comprehensive Traffic and Transportation studies Co., respectively. Information related to crash, obtained from Tehran's police department databank, prepared from gathering completed forms by police at the site of the crash (Form "k113"). Form "k113" is an accident data collection record sheet filled by police in accident place. The form includes accident data such as: day and hour of the accident, highway width, driver age, gender, light condition, weather condition, reason of crash, vehicle in fault, road condition in accident place, type of crash, manner of crash, driver education, human factor, traffic volume and traffic flow speed, etc. Regarding the qualitative nature of the information inserted in the form, data should be defined quantitatively, in which the best method identified was binary method (0 and 1). For data analyzing and usage, obtained information, were delivered into Access software. It must be mentioned that for using information in modeling they should be placed in a databank in which the information collected from separate organizations and companies, could



$Out=f(net)=Sig(net)=\dfrac{1}{1+e^{-net}}$ $\quad$ $Out=\tanh(net)$

Fig. 3. Activation functions

be investigated and those information that over lap with one another and also those with probable error, could be identified and excluded from the databank in Access software. At first the databank included 66 variables that variables with high correlation were omitted with a correlation analysis and finally with 25 remaining variables as listed below network training carried out.

Final variables are: Traffic volume(v1), traffic flow speed(S3), highway width(Lw3(15-18 m) or L4(18-22m)) gender(M), driver age(age1), crash type (A2(multi-vehicle), A6(other types)), manner of accident (B1(frontal) or B3(head-to-side)), vehicle type (Veh2(Passenger car), veh6(truck), veh8(motorcycle and bicycle)), light condition(light2), reason of crash (C1(ignoring frontal space), C2(ignoring lateral space), C6(inability to control the vehicle), C7(violating the permissible velocity), C8(Deviation to left), C10(backward movements), C11(vehicle technical defects), C14(other reasons)), accident place (E7(square or roundabout), E8(bridge), E10(others)).

The number of data collected from crashes (regarding a number of problems associated with preparing this type of information through competent sources), traffic and geometrical characteristics for a 4 year period during 2003-2007(regarding limitations in information resources) includes 52447 crash cases in which 134, 3314 and 48999 cases are related to fatalities, injuries and property loss crashes, respectively. These statistics include crashes occurred in urban highways of Tehran. Considering that in data collection for samples with the same variables, there were injury and property damage crashes, so, in the current study, similar crashes omitted and percent of fatality damage occurrence considered as output, using MATLAB software and finally, modeling performed with 2889 non-iterated data.

5. Defining dependent and independent variables in developing a model

In order to investigate and model crash statistics some changes in databank structure via Access software were made and another databank was prepared in which available data were in the form of nominal or categorical variables that indicates the presence or absence of assumed state. The assumed independent variables in these models include 11 types of variables and actually show the crash type of vehicle.

The dependent variable in these models is crash severity and since the fatality crashes were low in number, so the crash severity categorized into two levels of fatality-injury crashes and the property loss ones in the current study. In these models, Z1 and Z2 represent fatality-injury and property damage crashes, respectively.

Table 1: Crash severity variables

Variable symbol	Variable and its description
Z1	Fatality and injury 1, herwise 0
Z2	Property damage 1, herwise 0

6. Network Results

Total 2889 data divided into 3 categories. Data of year 2006 considered as network test data and among data of 2002 to 2005, 15% were cross-validating data and the rest, randomly categorized as network training data. Actually cross-validating data is a criterion witch indicates that what would be the result of network in meeting non-experienced data (network test data).

For training network, Neurosolutions5 software used and for comparing different network models, MSE, NMSE and correlation coefficient(r) tests-equations 5,6,7 relatively-used.

$$MSE = \frac{\sum_{i=0}^{N}(d_i - y_i)^2}{N} \tag{5}$$

$$NMSE = \frac{N^2.MSE}{N\sum_{i=0}^{N} d_i^{\,2} - \left(\sum_{i=0}^{N} d_i\right)^2} \tag{6}$$

$$r = \frac{\frac{\sum(y_i - \bar{y})(d_i - \bar{d})}{N}}{\sqrt{\frac{\sum_i(d_i - \bar{d})^2}{N}}\sqrt{\frac{\sum_i(y_i - \bar{y})^2}{N}}} \tag{7}$$

Where:
di : Desired output of i-th data
yi : Network output of i-th data
N : Number of data set
$\bar{d}$: mean of desired outputs
$\bar{y}$: Mean of network outputs
MSE : Mean Square Error
NMSE: Normalized Mean Square Error
r : Correlation coefficient

It should be mentioned that a model which meets all the three criteria would be a desired model. For example the MSE error changes with multiplying the output values in a fixed number. The least, MSE and NMSE errors (approaching zero) and r approaching 1, the most acceptable the results of the network. In the current study different models of neural networks investigated and the summary of the models and results represented in table 2 and 3.

In these models:

1. All models have one hidden layer; expect ANN-4 and ANN-13 that have two hidden layers.
2. For different models, number of neurons in each layer is different.
3. Activation function for models ANN-10, 11 and 12, is Tanh function and for the others is sigmoid function.
4. For models ANN-7, 8 and 9, learning rule is Levenberg and for the others is Momentum learning rule.
5. For models ANN-17 and 18, GFF algorithm and for the others MLP algorithm is used.

Table 2 and 3 indicate that at the first step, learning models of MLP with tanh activation function and momentum pattern presented acceptable results. Although sigmoid functions show the least MSE error in training and cross-validating data

Table 2. Training results and evaluation of the results

model	Algorthm	hidden layer	nodes	function (F)	learning rule	training			C.V.		
						MSE	NMSE	r	MSE	NMSE	r
ANN-1	MLP	1	4	tanh	momentum	4.1E-06	0.226	0.88	3.9E-06	0.241	0.874
ANN-2	MLP	1	8	tanh	momentum	3.8E-06	0.204	0.892	4.3E-06	0.262	0.86
ANN-3	MLP	1	9	tanh	momentum	3.5E-06	0.191	0.9	4.3E-06	0.269	0.856
ANN-4	MLP	1	12	tanh	momentum	3.5E-06	0.192	0.899	4.4E-06	0.264	0.859
ANN-5	MLP	1	13	tanh	momentum	3.6E-06	0.194	0.898	4.9E-06	0.295	0.54
ANN-6	MLP	1	14	tanh	momentum	3.4E-06	0.189	0.901	4.4E-06	0.269	0.855
ANN-7	MLP	1	7	tanh	Levenberg	3E-06	0.164	0.916	4.2E-06	0.339	0.837
ANN-8	MLP	1	11	tanh	Levenberg	2.3E-06	0.223	0.932	4.6E-06	0.401	0.805
ANN-9	MLP	1	14	tanh	Levenberg	3.1E-06	0.207	0.895	4.4E-06	0.312	0.826
ANN-10	MLP	1	6	sigm	momentum	1.2E-06	0.259	0.861	1E-06	0.256	0.863
ANN-11	MLP	1	9	sigm	momentum	1.2E-06	0.258	0.842	1E-06	0.257	0.862
ANN-12	MLP	1	14	sigm	momentum	1.2E-06	0.266	0.857	1.1E-06	0.262	0.859
ANN-13	MLP	2	9_5	tanh	momentum	4.1E-06	0.227	0.88	4.4E-06	0.272	0.854
ANN-14	MLP	2	17_7	tanh	momentum	3.2E-06	0.173	0.91	4.3E-06	0.266	0.857
ANN-15	MLP	1	17_9_4	tanh	momentum	3.7E-06	0.199	0.899	4.3E-06	0.259	0.863
ANN-16	GFF	1	6	tanh	momentum	3.3E-06	0.179	0.906	4.2E-06	0.26	0.867
ANN-17	GFF	1	11	tanh	momentum	4.1E-06	0.222	0.882	4.7E-06	0.293	0.842
ANN-18	GFF	1	23	tanh	momentum	3.6E-06	0.197	0.896	4.9E-06	0.303	0.837

Table 3. Testing results of the models

model	Algorthm	hidden layer	nodes	funcn (F)	learning rule	testing		
						MSE	NMSE	MSE
ANN-1	MLP	1	4	tanh	momentum	0.0318	0.2689	0.855
ANN-2	MLP	1	8	tanh	momentum	0.031	0.2628	0.859
ANN-3	MLP	1	9	tanh	momentum	0.0292	0.247	0.868
ANN-4	MLP	1	12	tanh	momentum	0.0305	0.2581	0.862
ANN-5	MLP	1	13	tanh	momentum	0.0326	0.2762	0.851
ANN-6	MLP	1	14	tanh	momentum	0.0322	0.2724	0.853
ANN-7	MLP	1	7	tanh	Levenberg	0.0398	0.3377	0.823
ANN-8	MLP	1	11	tanh	Levenberg	0.0346	0.2938	0.841
ANN-9	MLP	1	14	tanh	Levenberg	0.0341	0.2895	0.843
ANN-10	MLP	1	6	sigm	momentum	0.0315	0.2665	0.858
ANN-11	MLP	1	9	sigm	momentum	0.0315	0.2662	0.857
ANN-12	MLP	1	14	sigm	momentum	0.0322	0.2722	0.854
ANN-13	MLP	2	9_5	tanh	momentum	0.0308	0.2606	0.862
ANN-14	MLP	2	17_7	tanh	momentum	0.0293	0.2479	0.868
ANN-15	MLP	1	17_9_4	tanh	momentum	0.0315	0.2677	0.859
ANN-16	GFF	1	6	tanh	momentum	0.0312	0.2633	0.86
ANN-17	GFF	1	11	tanh	momentum	0.033	0.2791	0.85
ANN-18	GFF	1	23	tanh	momentum	0.0309	0.2615	0.86

but exclusive goodness of a criteria doesn't mean that the whole network would be a desired one.

Figures 5, 6, 7, and 8 illustrate correlations between desired output (fatality-injury crash percent) and networks predicted output for models ANN-3, 5, 8 and 9 respectively. And figures 9 and 10 illustrate coincidence between desired output and predicted output for models ANN-3 and 13 respectively that are magnified and selected from 722 testing data.

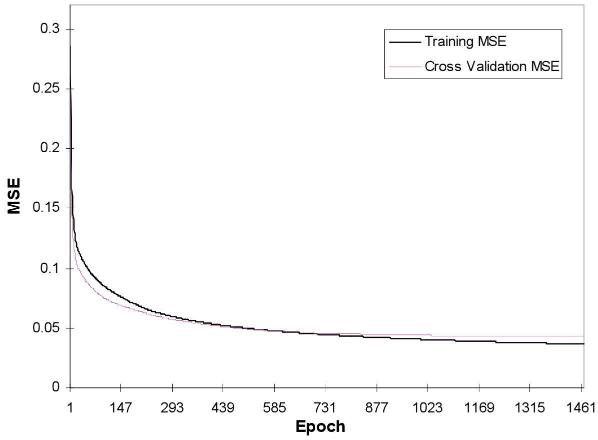


Fig. 4. Error graph versus learning epochs

Sensitivity analysis performed between fatality-injury percent as output and the network inputs which are 25 independent inputs in order to obtain their effect on network output and to omit the least effective input variables. According to fig.11 because the effect of the total 25 independent variables on the network output is so high that can't be omitted to reduce network complexity, therefore the selection of these 25 variables have been a desired selection.

Comparing the network results for test data, it's observed that MSE errors have been in an acceptable range (3%-4%). and for models ANN-3 and ANN-14 data correlation coefficient (86%-87%) is observed for the best network.

7. Conclusion

In this study ANN approach has been utilized for crash severity prediction in urban highways and identifying significant crash-related factors. For this purpose after omitting less important variables, 25 independent variables that have highest effect in network output (crash severity by fatality-injury crash percent) were selected. Studies showed that feed forward back propagation (FFBP) networks like

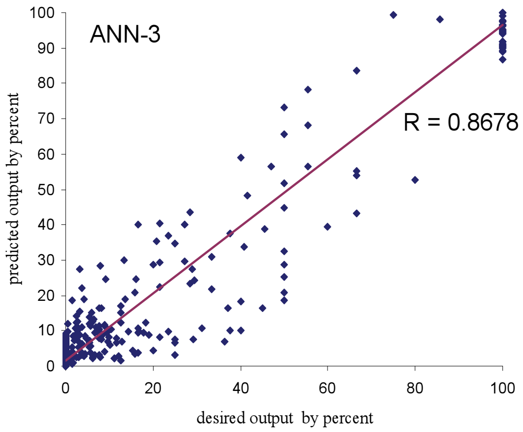


Fig. 5. Fitness curve of ANN-3 model

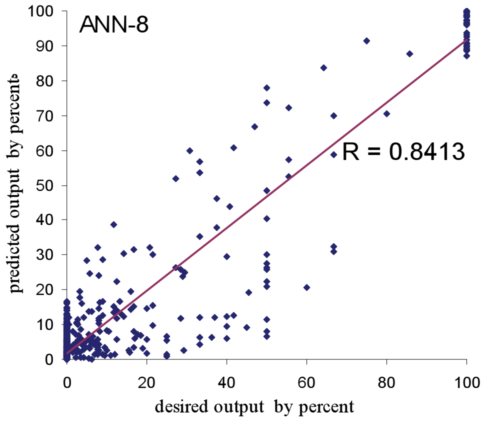


Fig. 7. Fitness curve of ANN-8 model

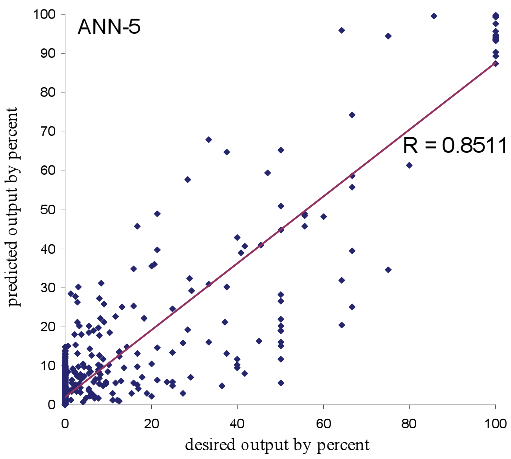


Fig. 6. Fitness curve of ANN-5 model

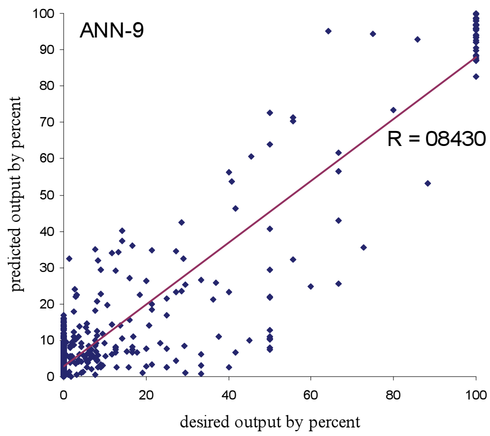


Fig. 8. Fitness curve of ANN-9 model

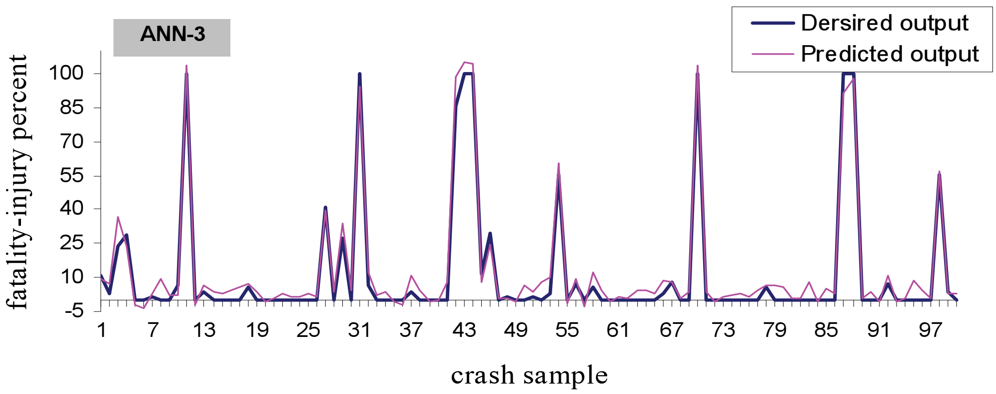


Fig. 9. Convergence and coincidence of test data for ANN-3 model

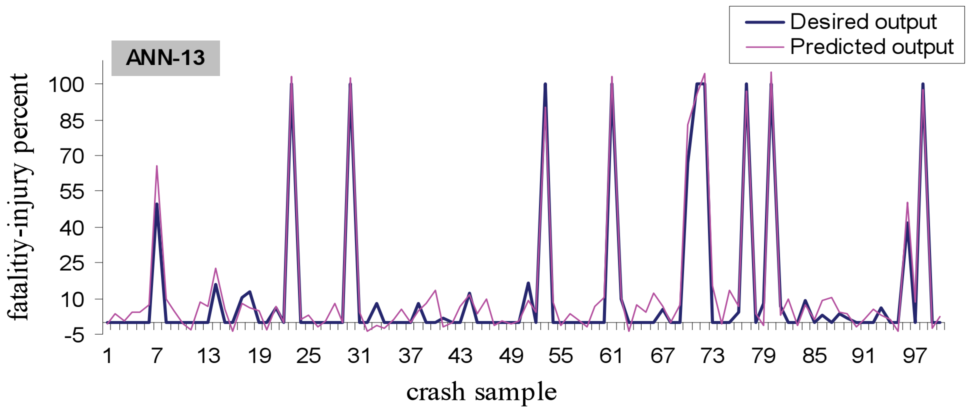


Fig. 10. Convergence and coincidence of test data for ANN-13 model

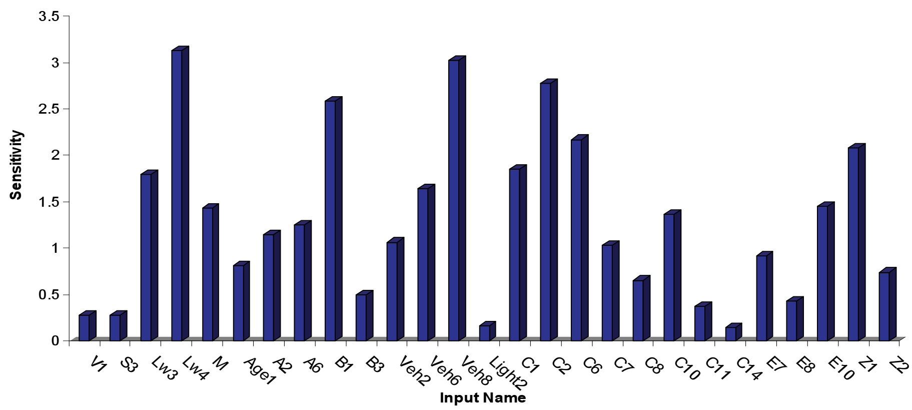


Fig. 11. sensitivity analysis result for independent variables

MLP models yield the best results.

There has been no model developed in previous researches encompassing the simultaneous effects of all variables on crash severity of urban highways. Therefore, models presented in the present study reflect the relationship between crash severity in urban highways, and traffic variables such as traffic volume, flow speed, human factors, road, vehicle and weather conditions. These models can be suitable in identifying the influential factors in crash severity. In addition, these models suggest that changes in crash severity doesn't occur necessarily by any single dependent parameter, but occur as a simultaneous result of changes of these parameters.

Obtained results illustrate that the frontal crashes, 18-22 meter wide highways, type of vehicle at fault (motorcycle, bicycle), ignoring length space, ignoring width space, inability to control the vehicle, violating the confidence speed and leftward deviation, are the most significant factors that increase crash severity in urban highways

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