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Modeling of Road Accidents Using the Model of Interactive Highway Safety Design (Case Study: Roads of Qazvin, Zanjan and Hamadan)

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ABSTRACT

Although the increasing expansion of traffic in cities has increased economic and welfare benefits, it has, on the contrary, increased the number and severity of traffic accidents. Reducing the number of victims and injuries caused by road accidents in any common moral-value system is urgent and inevitable. In this way, finding effective factors on the severity of road injuries can be considered as a practical step towards achieving the values. Finding effective factors on severity of injuries, with emphasis on statistical efficacy of effective policy-making factors, will be used as an appropriate tool in the middle level of road safety management. Accident prediction results using MATLAB software in selected roads showed that although this model, by choosing the appropriate calibration factor and using the appropriate parameters and high precision, can produce good outputs, but the results are less accurate than the MLP. The statistical analysis of the observed values and the predicted crash values showed that their differences were not statistically significant at the 5% confidence level, and their results could be used to predict crashes and determine future conditions.

Keywords: MATLAB software, crash prediction, two-lane roads, Interactive Highway Safety Design

1. INTRODUCTION

The design of accidents, especially accident prediction, is one of the major research areas in traffic engineering [1,2]. In the study of accidents in the rural roads of the country, the relationship between geometric factors and accident occurrence has not been paid much attention [3-5]. Simon Huskying and colleagues in 2009 examined the effects of sending short messages to young drivers. According to their studies, the amount of time the driver does not pay attention to and does not pay attention to the driver while sending an SMS is more than 400% of the driver who does not send a message while driving. Also, according to their research, the safety clearance of these drivers decreased by 150% [6]. In 2018, Hou

Reviewed the role of road geometric design parameters in safety and reduction of road accidents. In his opinion, an accident and safety appear against each other. The accident is due to the lack of understanding the design principles as well as the lack of attention to traffic rules and regulations. But safety increases with respect to design rules and engineering principles. In this study, the effects of vehicle-road and driver have been investigated as three factors affecting traffic. Also, the parameters of the geometric design, which have an effective role in increasing road safety and reducing accidents, have been studied in detail [7]. Li studied the effective parameters on the reduction of accidents at the accident points. His research results show that crashes caused by human factors, based on distance from the source, are very high. The results also show that human immunization, road optimization and vehicle immunization, seat belts, helmets, and regulations, precise control and supervision of the police, raising the level and quality of road safety education and training of interspace traffic in Different levels have a significant effect on improving the passage and correction of accidental points [8]. Russo (2016) identified and ranked the factors affecting road accidents in Bushehr Province using a hierarchical analysis technique. The statistical population of his research included data on accidents occurring in 2010. He used Analytical Hierarchy Process Analysis (AHP) technique to rank each of the effective factors in road accidents. The research findings showed that the share of human factor in road accidents in Bushehr province was 75% in the first place. While the role of the road operator with 17% and the vehicle with 8% were ranked next. Also, under the criteria of "hurry and unwanted acceleration" in the human factor, "defect in vertical marks" on the road operator, and finally, "other defects (defects in safety belts, defects or lack of mirrors, defective glass windows, defective warning signs, motor vehicle defects Automotive) have been the most involved in road vehicle accidents in Bushehr province [9].

Several statistical methods are used to develop prediction models of accidents [10,11]. For example, an artificial neural network is a new method for predicting the number of accidents. Other models, such as IHSDM, are also methods that are used for stated purposes [12-14]. Abdelatti et al. (2006) used a potential accidental neural network in Orlando Intercity Corridor and found that at least 70% of accidents could be predicted correctly with the probabilistic neural network model [15]. In 2011, Abdul Aziz surveyed the frequency of traffic accidents in Riyadh. The main purpose of this study was to investigate the frequency of factors affecting accidents using statistical methods and GIS. The results of his investigations include determining the spatial distribution of accidents and determining the range of factors affecting crashes with the help of the negative binomial model [16]. Aachenger and Yildiz (2007) examined the sensitivity of variables in the prediction model of accidents. In this study, the sensitivity of the average variables of daily accidents, daily traffic volume, road width, shoulder width and mid-range, individually, and their interactions were examined together. Their studies showed that the most important parameter in the incidence of accidents is average daily crash rates, then the width of the road, the width of the shoulder of the road and the mid-range, with the three parameters mentioned secondary importance [17].

In 2004, Castela and Peres also found the relationship between different behavioral patterns and offenses committed by the psychoanalysis test and drivers' reaction to the penalties imposed, in such a way that drivers who, when committing an offense with Fewer punishments and punishments, tend to be more likely to violate traffic laws, and this is more evident in women than men [18]. Yasin Çodur In 2015, the mathematical model designated the parameters of the road geometric road design on the road ***safety*** of bronchoscopes (a case study of the interconnections of Qom province) in which they attempted to use a collection of databases to present a model in The effect of the effective parameters of the geometric design on the safety of rural roads is investigated. For this purpose, effective variables were chosen for modeling. Then, based on field surveys and field studies, the calibrated and presented model was provided in the study fields and the necessary information was completed. Using the proposed model is possible to identify incident sections along the roads and to address the deficiencies and related problems and thus improve the safety level of the roads [19]. Park et al., in 2017, studied the factors affecting the severity of intra-city crashes using Probit, Logit and Artificial Neural Network models. In their research, they investigated the factors affecting the prevalence of inner-city traffic accidents using Probit models, logit and artificial neural networks. In this study, it was concluded that the three models of Probit, Logite and Artificial Neural Network have almost the same predictive accuracy, but if the accuracy of prediction of models is evaluated based on the classification accuracy, then the weakest was Probit model and the strongest was an artificial neural network model [20].

Similar to the pattern of the MLP neural networks, there are other types of neural networks in which CPU units are focused on a particular location in terms of processing. This focus is modeled through Radial Basis Functions (RBF) (Figure 1). In terms of overall structure, RBF neural networks do not differ much from MLP networks, and they differ only in the type of processing that neurons perform on their cores. However, RBF networks often have faster learning and preparation processes. In fact, due to the concentration of neurons on a specific functional range, it will be easier to adjust them.

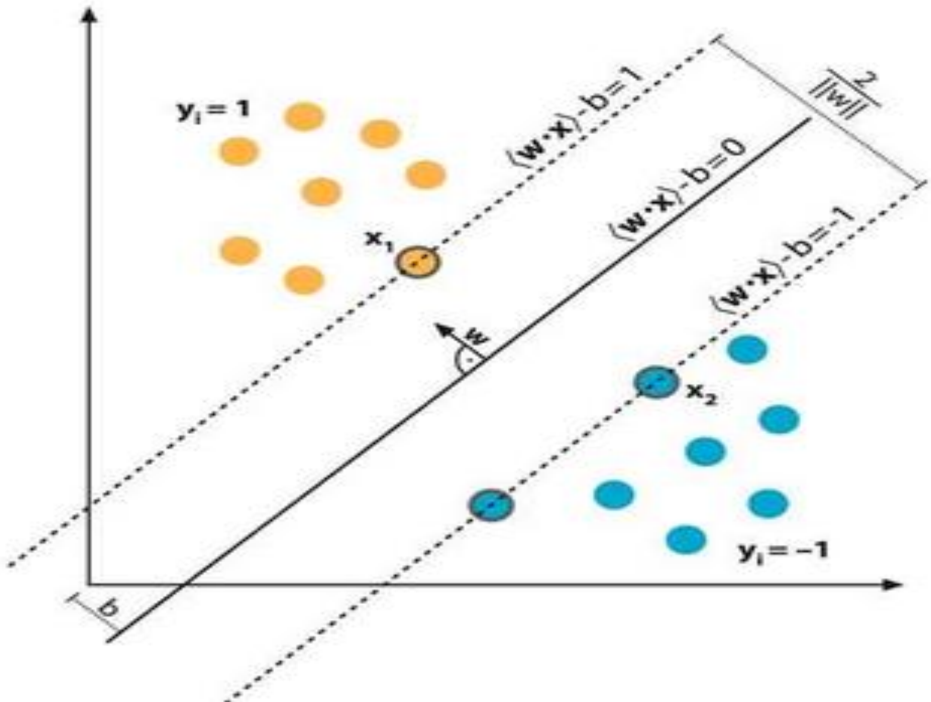

Figure 1. RBF network

In recent years, road accident prediction models have been developed using various analytical techniques, but the use of these models is not easy when a large number of variables are used in the modeling level. By selecting the studied paths as a case study, the variables used in this study were road width, average speed, number of heavy vehicles per 10 km, vertical arch radius, the number of lighting per 10 km and the traffic volume as independent variables and the number of accidents in a three-year study period are defined as the dependent variable and the output of the examined models.

2. METHODOLOGY

In the following section, the results of this paper are to examine the output values resulting from the implementation of the interoperable highway safety design model in MATLAB software. First, for each path, as in the neural network, the actual values of collisions, along with the values predicted by the model for the selected sections, will be presented. The Explanatory factor, as well as the distribution diagram and column graph of observed and modeled values, will be plotted for each path. Finally, the MLP results and the software mentioned for the selected sections in the testing phase will be examined and the best model for prediction. Accidents will be reported based on correlation coefficients and MSE statistics. Initially, the results for the selected axis of Hamedan region are presented and then two axis of Qazvin and Zanjan regions will be investigated.

2.1 Case study

The set of studied roads includes Hamadan to Avaj, Hamadan to Ghorveh, Hamadan to Malayer and Hamadan to Bijar in the field of protection of Hamadan province, as well as Abhar to Keidar in the field of protection of Zanjan province and the old road to Abyek to Qazvin in Qazvin province. Figure (2) shows the selected roads in Hamadan province and Figure (3) shows selected routes in Zanjan and Qazvin provinces. These roads are considered as one of the most troubling roads of the country.

Figure2. Hamadan position and selected routes

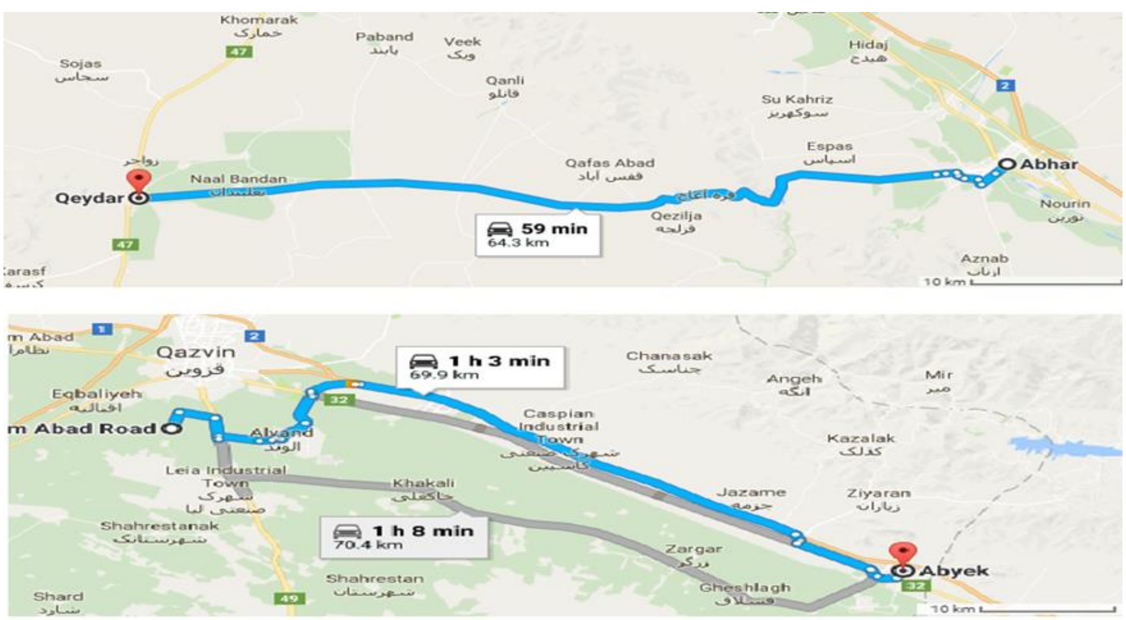

Figure 3. The position of Abhar's direction towards Qeydar and Qazvin toward Abyek

This section includes a statistical survey of crashes in selected roads. Data were analyzed in two sections. The first part of the data is based on Hamadan's four main points and the second part, including crash statistics and two-axis selected data in Qazvin. In the modeling section, the time series of the crashes will be used. Table (1) shows the selected roads and the number of corresponding pieces and encounters

Table1. Selected roads and number of accidents of selected segments

Province	Road Name	Number of sections studied	Number of accidents
Hamadan	Qorveh	40	185
	Avaj	37	102
	Bijar	35	56
	Malayer	40	210
Qazvin	Abyek	35	31
Qeydar	Abhar	32	91

According to Table (1), it can be concluded that the number of crashes in Qorveh and Hamedan roads is high among the selected roads. In order to model the crashes in selected sections and also predict the future conditions of these paths, we first examined the roads Using the main components analysis method, whose main objective was to reduce input variables to prediction systems of crashes and time series modeling.

2.2 MODELING DATA

In this section, data collected from different roads are presented in Tables (2) and (3). It should be noted that in the tables of this part, the variables used are defined as follows.

Table 2. Variables used in model

Variable abbreviation	Variable name
NA	Number of accidents
ADT	Average Daily Traffic Volume
W	Road width
NB	The number of lights per 10 km
ACR	Average radius of the vertical arch
AS	Average speed
NV	Number of heavy vehicles per 10 km

In Table (3), which is presented below, the parameters used for modeling in the studied roads and their measured values, the number of sectors that are indexed, along with statistical characteristics such as the mean and the range of changes are visible.

Table 3. Parameters used for modeling in the studied roads

Variables								
NV	AS	ACR	NB	W	Number of accidents		Segment	Road
20	40	10.36	0.7	90/2	0.00	Minimum	37	Hamadan-Bijar
45	89	14.6	1.65	45/3	10.00	Maximum		
32	75	12.3	1.32	30/3	2.11	Average		
5.68	12.25	2.45	0.21	12/0	8.58	Standard deviation		
15	35	9.5	0.78	55/3	0.00	Minimum	45	Hamadan-Qorveh
29	78	18.41	3.25	55/3	14.00	Maximum		
21	65	14.62	1.40	55/3	3.95	Average		
4.26	14.65	3.5	0.17	00/0	11.48	Standard deviation		
18	55	2.65	0.28	20/2	0.00	Minimum	31	Hamadan-Avaj
38	100	8.24	2.26	55/3	7.00	Maximum		
30	86	7.10	1.49	60/2	2.21	Average		
2.58	11.64	3.24	1.24	12/0	2.04	Standard deviation		
30	56	1.56	12	40/3	0	Minimum	30	Hamadan-Malayer
60	91	3.57	18	70/3	13.00	Maximum		
44	80	3.01	15	40/3	5.26	Average		
2.87	10.8	1.28	4.26	65/0	7.15	Standard deviation		
14	44	4.5	19	65/2	0	Minimum	35	Qeydar-Abhar
33	75	5.2	21.6	40/3	6	Maximum		
25	58	3.6	20.08	20/3	2.8	Average		
2.05	16.58	1.27	2.15	0.04	2.36	Standard deviation		
10	35	0	4.2	68/2	0	Minimum	46	Qazvin-Abyek
28	95	3.27	8.6	59/3	8	Maximum		
19	84	1.29	7.2	30/3	2.98	Average		
2.52	16.28	2.14	3.26	12/0	1.99	Standard deviation		

3. RESULTS AND DISCUSSION

Hamadan-Bijar road

Figure (4) shows the results of the output of MATLAB software based on the inputs stated in the previous part. Given that this software requires a lot of data input as well as the need for calibration models, it generally provides good results for paths that are similar to the data on which software was developed. The software calibration coefficient for the Bijar road of Hamadan was 1.9. In the above path, the 12 end sections were used as a test phase, with the results as follows:

The software predicted for all accident levels, and in section 24 with the highest number of collisions recorded, the number of accidents is higher than other levels. The correlation coefficient between observed and modeled data was 61%, which is much lower than the correlation coefficient obtained with MLP (96%). Also, unlike the MLP, which predicts only one incident at the end of the selected section at the end of the 37th, the software estimates collisions for these sections

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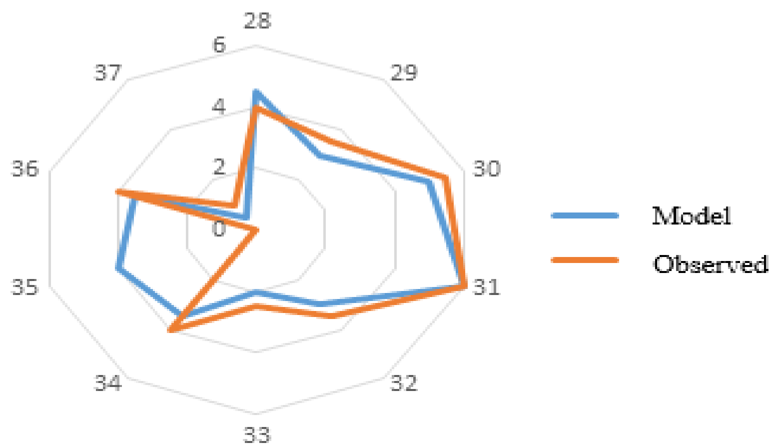

Figure 4. Estimated values by software and crashes observed at the Hamadan-Bijar axis

To better understand the model outcomes, the distribution chart was mapped and the correlation coefficient between the observation time series and the predicted model was 61%.

Analysis of RMSE statistics for software outputs showed that the value of this statistic is 1.91, which is much lower than the model of the neural network with a statistic of 0.59, and the lower the description, the Less it is, The modeling results will be more accurate and close to real conditions. To perform the F-test, the results were that the variances were not equal (the value of the calculated F-statistic was larger than the value of table, and therefore, the T-test was assumed to be based on the assumption of inequality of variances.

HAMEDAN-QORVEH ROAD

The diagram depicted in Figure (5) shows the results of the output of the MATLAB software for the Hamadan road towards Qorveh. The calibration coefficient for the Hamedan road of Qorveh was 1.75. In the above path, the number of accidents was predicted for the 12th end of the year and the results were as follows:

The software predicts the number of collisions for the desired sections, and at section number 36, which has more crashes, the software also had a good estimate of the crashes. The correlation coefficient between observational and model data was 57%, which was less than the correlation coefficient obtained with MLP (85% for MLP).

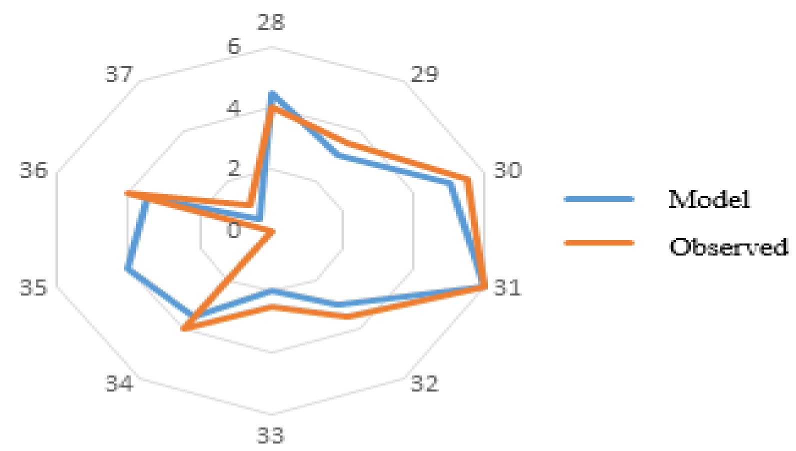

Figure 5. Estimated values by software and accidents observed at Hamedan-Qorveh axis

In order to better understand the model outputs, the distribution chart was drawn and the coefficient of data analysis between the observation time series and the predicted model was 57%, much lower than the MLP (85%) results for the same sections. In order to further examine the results, the RMSE statistic for the observed and predicted values was calculated to be 1.24 for software output and 0.61 for MLP output, which indicates the greater accuracy of the neural network in predicting crashes of the road.

By performing the F-test, the results were that the variances were not equal (the value of the calculated f statistic was larger than the value of table f), and therefore, the T-test was assumed to be based on the assumption of inequality of variances. According to output, the calculated statistic was 1.44, which is smaller than the table statistics (at 5% level and 10 degrees of freedom) (the statistic is 21.2). Therefore, we can say that the meanings do not differ significantly

THE HAMADAN-MALAYER ROAD

Figure (6) shows the results of the output of MATLAB software for the Hamedan road towards Malayer. The calibration coefficient for the Hamadan Malayer road was 3.5. In the above path, the software anticipates collisions for the last eight. Except for the number 36, where the highest number of collision cases was registered, in other sections, the number of accidents was estimated to be almost appropriate.

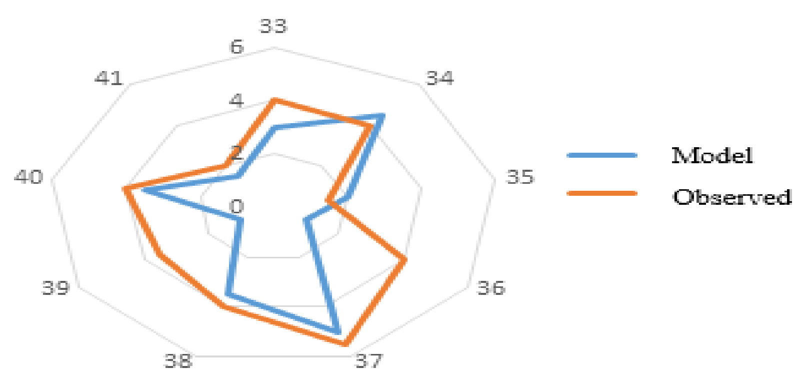

Figure 6. Software-predicted values and observed crashes at Hamedan-Malayer axis

The correlation coefficient between observational and model data was 86%, which was 5% less than the correlation coefficient obtained with MLP. To better understand the model outcomes, the distribution chart was also drawn and the coefficient of data extinction between the observation time series and the predicted model was 86%, which was 10% lower than the MLP results for the same sections.

The RMSE statistics for modeling results for MLP and software were calculated for this road. The results showed that although the correlation coefficient between the output data of the software and the observational values is appropriate, but the calculation of RMSE states that the results of MLP (RMSE = 0.87) have a higher accuracy and compared to the software with an RMSE value of 1.41, for this road is a better model. By performing the F-test, the results were that the variances were not equal (the value of the calculated f statistic was larger than the value of table f), and therefore, the T-test was assumed to be based on the assumption of inequality of variances. The calculated statistic was 1.08, which is smaller than the table statistics (at 5% level and no degree of freedom) (the statistic is 2.25). Therefore, we can say that meanings do not differ significantly.

HAMADAN-AVAJ ROAD

The diagram depicted in Figure (7) shows the output of the MATLAB software for the Hamadan axis toward Avaj. The calibration coefficient was obtained for the road between Avaj 2. In the above path, the number of accidents was predicted for the 12th end of the year and the results were as follows:

The software predicted conflicts for two non-randomized sections (Sections 35 and 41), and generally predicted crashes more than real values for this road. The correlation coefficient between observational and model data was 48%, which was much lower than the correlation coefficient obtained with MLP (91%). It is also possible to find that the software for this road and in selected segments where more encounters are observed, predicts the number of accidents to some extent close to reality, which can be attributed to the similarity of this route to the United States route that the software based on its data.

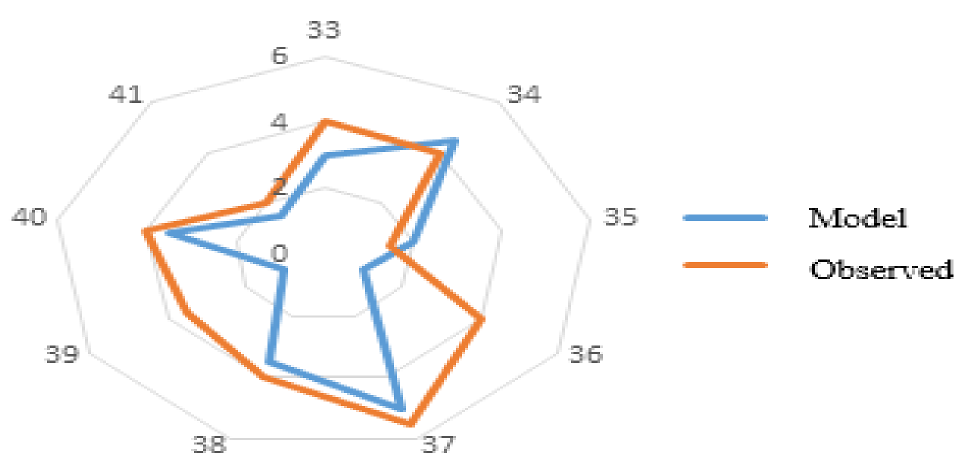

Figure 7. Estimated values by software and crashes observed in Hamadan-Avaj

To better understand the outputs of the model, the distribution chart was drawn and the correlation coefficient between the observation time series and the predicted model was 48%, which is lower than the MLP results (83%) for the same level. Examining RMSE values suggests that although there is a low correlation between software outputs and actual values, this statistic (R2) cannot be the only suitable benchmark for comparison. The RMSE value for the software output was 0.58, which is slightly higher than the value for the neural network (RMSE was 0.42 in the network).

By performing the F-test, the results were that the variances were not equal (the value of the calculated f statistic was larger than the value of table f), and therefore, the T-test was assumed to be based on the assumption of inequality of variances. The calculated statistic is equal to -0.08, which is smaller than the table t (at 5% and freedom grade 13) (the value of the T-statistic is equal to 19.2). Therefore, we can say the meanings do not differ significantly.

QAZVIN-ABYEK ROAD

The diagram depicted in Figure (8) shows the output of the MATLAB software for the Abyek to Qazvin. The Calibration coefficient for Qazvin-Abyek road was 0.54. In the above path, for the last eight sections, the number of accidents was predicted and the results were as follows:

The software is well anticipated the collision at section number 35, where the number of hits was recorded, but for other sections, it also predicts the possibility of an accident. The correlation coefficient between the observational and model data was 58%, which is lower than the correlation coefficient obtained with artificial neural network (98%), which is due to the difference in environmental conditions and other parameters affecting the occurrence of accidents in the same road, the model has expanded in the US and based on it.

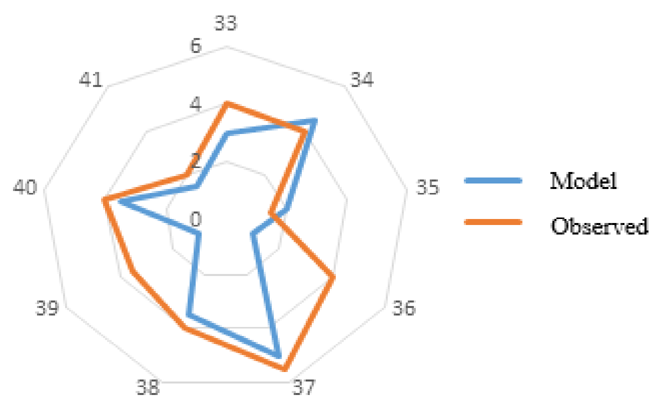

Figure 8. Estimated values by software and crashes observed in Qazvin-Abyek axis

To better understand the model outcomes, the distribution diagram was also drawn and the coefficient of correlation between the observation time series and the predicted model was 58%, which is lower than the results of the neural network (98%) for the same reasons, due to the number of collisions it is predicted in the other part. As previously stated, by calculating RMSE, a better comparison between observed values and modeling values can be made.For this axis, the RMSE software output and MLP were respectively 0.59 and 0.1, respectively. The MLP model is a better tool for predicting Qazvin-Abyek axis accidents. The result of the f test was that the variances were not equal (the value of the calculated f was higher than the value of table f), and therefore, the T-test was assumed to be based on the assumption of inequality of variances. The calculated statistic was -3/51, which is smaller than the table F-table (at 5% and the degree of freedom 11) (the value of the statistic is -2/23). Therefore, we can say that the difference in meanings is significant.

THE QEYDAR-ABHAR ROAD

As the last chosen route in the modeling stage, Qeydar's road was selected to Abhar. Figure (9) shows the results of the output of the MATLAB software for this axis. The Qeydar to Abhar road had a calibration coefficient of 1.2. In the above path, for the last eight, the number of accidents was predicted and the results were as follows: The software has estimated the occurrence of the collision for the sections in which the hit was recorded, and only for the section number 37, in which there was no accident, predicts the number of collisions. The correlation coefficient between the observational and model data was 69%, which is slightly lower than the correlation coefficient obtained with MLP (82%), which is due to the similarity of environmental conditions and other parameters affecting the accident in the same axis as the model In the United States and based on it. It is also possible to find that the software for the most part of this road, with a calibration coefficient of 1.2, predicts the number of collisions slightly lower, which can be attributed to the lower safety of the route compared to the same route in the United States.

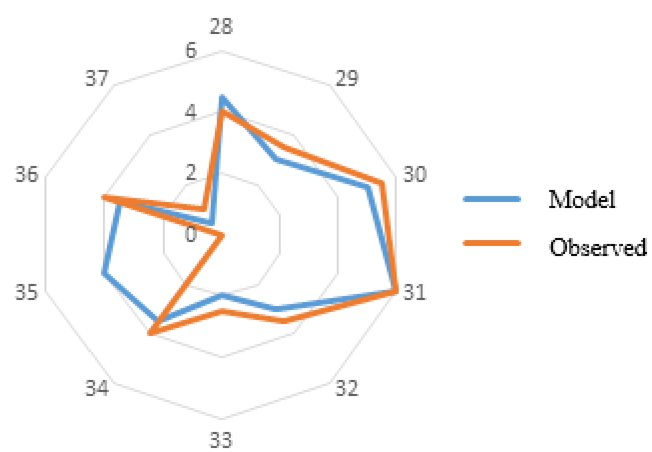

Figure 9. Estimated values by software and accidents observed in the Qeydar-Abhar axis

To better understand the model outcomes, the distribution chart was also depicted and the correlation coefficient between the observation time series and the predicted model was 69%, which was less than the MLP (82%) for the same range and the stated values show the ability of the neural network model to predict the conditions of this route in the event of accidents. Of course, as stated, the correlation coefficient alone is not a valid statistic for measuring the accuracy of the model. Therefore, the RMSE values of software output and neural network were also calculated. These values were respectively 0.95 and 0.79, respectively. Accordingly, the proposed neural network model in this road is a more appropriate model for predicting crashes. To perform the F-test, the results were that the variances were not equal (the value of the calculated F-statistic was larger than the value of table f), and therefore, the T-test was assumed to be based on the assumption of inequality of variances. The calculated statistic was -0.91, which is larger than the table f statistics (at 5% and the degree of freedom 9) (the statistic is -2.32). Therefore, we can say that meanings do not differ significantly.

4. CONCLUSION

Although the increasing expansion of traffic in cities has increased economic and welfare benefits, it has, on the contrary, increased the number and severity of traffic accidents. Reducing the number of victims and injuries caused by road accidents in any common moral-value system is urgent and inevitable. In this way, finding effective factors on the severity of road injuries can be considered as an effective step towards achieving the values. Finding effective factors on severity of injuries, with emphasis on statistical efficacy of effective policy-making factors, will be used as an appropriate tool in the middle level of road safety management. Accident prediction results using MATLAB software in selected axes showed that although this model, by choosing the appropriate calibration factor and using the appropriate parameters and high precision. And can produce good outputs, but the results are less accurate than the MLP. The statistical analysis of the observed values and the predicted crash values showed that their differences were not statistically significant at the 5% confidence level, and their results could be used to predict crashes and determine future conditions.

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AUTHORS CONTRIBUTION

This work was carried out in collaboration among all authors.

CONFLICT OF INTEREST

The author (s) declared no potential conflicts of interests with respect to the authorship and/or publication of this paper.

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