Development of Safety Improvement Method in City Zones Based on Road Network Characteristics

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Abstract

Background and Objective: Extensive studies have so far been carried out on developing safety models. Despite the extensive efforts made in identifying independent variables and methods for developing models, little research has been carried out in providing amendatory solutions for enhancing the level of safety. Thus, the present study first developed separate accident frequency prediction models by transportation modes, and then in the second phase, a development of safety improvement method (DSIM) was proposed. **Materials and Methods:** To this end, the data related to 14,903 accidents in 96 traffic analysis zones in Tehran, Iran, were collected. To evaluate the effect of intra-zone correlation, a multilevel model and a negative binomial (NB) model were developed based on both micro- and macro-level independent variables. Next, the DSIM was provided, aiming at causing the least change in the area under study and with attention to the defined constraints and ideal gas molecular movement algorithm. **Results:** Based on a comparison of the goodness-of-fit measures for the multilevel model with those of the NB model, the multilevel models showed a better performance in explaining the factors affecting accidents. This is due to considering the multilevel structure of the data in such models. The final results were obtained after 200 iterations of the optimization algorithm. Thus, to decrease accidents by 30% and cause the least change in the area under study, the independent variable of "vehicle kilometer traveled per road segment" underwent a considerable change, while little change was observed for the other variables. **Conclusions:** The final results of the DSIM showed that the ultimate solutions derived from this method can be different from the final solutions derived from the analysis of the results from the safety models. Hence, it is necessary to develop new methods to propose solutions for increasing safety.

Keywords: Micro/macro variable, multilevel model, optimization algorithm, traffic analysis zone

Introduction

Extensive studies have been carried out so far on identifying the factors which affect accidents at both micro- and macro-levels and also on developing models for predicting the number and severity of accidents.[1-5] The main focus of these studies had been identifying and analyzing the effect size of different factors on accidents, and based on the obtained results, some solutions were proposed, which involved the decrease or increase of some factors depending on their roles in accidents. For instance, if speeding was considered an effective factor that increasing the number of accidents at an intersection, some solutions were presented for slowing down the traffic in that area. Due to the interaction among the factors affecting accidents, focusing on a single factor in providing a solution can result in deficiencies such as a decrease of accidents in one mode of transport and an increase of the same in another mode. Therefore, reaching a practical and appropriate amendatory

Access this article online	
Quick Response Code:	**Website:** www.archtrauma.com
	DOI: 10.4103/atr.atr_44_19

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How to cite this article: Soltani N, Saffarzadeh M, Naderan A, Abolhasani M. Development of safety improvement method in city zones based on road network characteristics. Arch Trauma Res 2020;9:16-23.

Received: 08-06-2019, **Accepted:** 27-11-2019, **Published:** 27-03-2020.

solution necessitates the inclusion of all influential factors across all modes of transport at the same time. On the other hand, any change in the road network entails a variation in traffic parameters and imposes new costs. Calculating the amount of change in traffic parameters, such as the delay and speed of vehicles, requires spending a lot of time and money, and thus, to come up with an effective scheme, it is of high significance to develop a solution that not only increases safety but also causes the least amount of change in the road network as well. Considering the above-mentioned points as well as the few studies carried out on developing a solution, the present work of research aims at providing a development of safety improvement method (DSIM) so that the level of safety can improve in the area under study. To this end, the following steps were considered:

1. Developing separate accident frequency prediction models for different modes of transport (vehicle, motorcycle, and pedestrian)
2. Achieving the DSIM aiming at improving safety in the area under study.

Therefore, the next section reviewed the related studies in this regard. Then, Section 3 addressed the methods and materials of the study. Next, the results obtained from the study were presented, and in the end, the conclusion of the study was given.

Literature review

The studies on safety have mainly focused on identifying and investigating the effect size of diverse factors on accidents in different modes of transport. Cai *et al*. investigated the influence of macro-level variables at the level of traffic analysis zones (TAZs) on pedestrians and cyclists' accidents using dual-state models. They were also trying to measure the influence of the neighboring zones on the accidents of one zone. According to their results, some factors such as population density, employment rate, and the number of public transport users in one TAZ increase the number of accidents. Moreover, the influence of adjacent zones on the accidents of one zone turned out to be significant, and dual-state models, especially the zero-inflated negative binomial (NB) model, showed a better performance in comparison to single-state models.[6]

Since in the DSIM, the accident frequency prediction models are taken as input data, it is of high importance to employ proper models that show high precision. In this process, finding a suitable method of analysis and selecting influential independent variables are two factors that affect the development of safety models. In the past years, researchers have proposed numerous methods such as NB,[7] Poisson log-normal,[8] zero-inflation,[9] multivariate,[10] finite mixture/latent class,[11] and multilevel[12,13] to develop accident prediction models using different variables. The details and assessments of crash frequency models are presented in review papers.[14,15]

In this study, the independent variables used in the modeling procedure come from both micro- and macro-levels. The models developed based on the variable at each level have their own distinctive performance and applications. The accident prediction models are mostly developed using micro-level variables.[16-18] These studies have helped determine solutions for decreasing the number of accidents in different transport facilities such as intersections or road segments. On the other hand, prediction models using macro-level variables have been developed in recent years. These variables include traffic data such as road length with different functional classification in a zone[19,20] and trip generation and trip distribution of TAZ,[21] environmental conditions such as land use specifications,[22] and socioeconomic factors such as household income.[23] The results of these researches have led to the consideration of safety indices in road network planning.

To reach an accurate and comprehensive safety model, it seems necessary to consider suitable variables at both micro- and macro-levels simultaneously and develops appropriate models. Therefore, in the present study, a separate accident frequency prediction model was developed for each mode of transport using variables at both micro- and macro-levels. The structure of data in this study is multilevel because the macro variables are extracted at the TAZ level, and they are the same for accidents that have occurred in one TAZ. The data which lowerlevel data are nested in the higher level is regarded as multilevel data. When accident data are multilevel, using multilevel models, which consider the intra-group correlation of accident data, is useful.[24] Detailed explanation on multilevel data and the adoption of multilevel models in studies related to safety may be found in.[25]

Shi *et al*. investigated the number of highway accidents using multilevel and NB models. In their research, the highway was divided into 196 segments based on its geometrical specifications. The traffic data used in their study were obtained through automatic vehicle identification (AVI) systems installed on the highway. Since the output data of AVI systems divided the highway into 43 segments, each AVI system represented the data related to some segments. Due to the dual-level structure of the data, a multilevel model was used for investigating traffic accidents. Based on the obtained results, the multilevel model had a better performance than the NB model. Moreover, based on the results, increasing some factors such as the speed or the horizontal degree of curvature, decrease the number of accidents.[26]

The DSIM is developed using the ideal gas molecular movement (IGMM) algorithm, the objective function, and the constraints only after coming up with separate accident frequency prediction models for each mode of transport. Some of the novel metaheuristic algorithms are the artificial bee colony Algorithm,[27] cuckoo optimization algorithm,[28] ant lion optimizer,[29] krill herd algorithm,[30,31] earthworm optimization algorithm,[32] gravitational search algorithm,[33] monarch butterfly optimization algorithm,[34] elephant herding optimization algorithm,[35,36] and the grey wolf optimizer algorithm.[37] Many successful applications of metaheuristic algorithms in engineering optimization problems have been reviewed by researchers.[38,39]

There are a lot of applications for the use of optimization algorithms in different sections of transportation.[40-44] Peñabaena-Niebles *et al*. have investigated the use of the ant colony algorithm on optimizing the timing of traffic signals throughout the day based on the fluctuating volume of traffic flow.[45]

Materials and Methods

As stated earlier, the changes in urban road network for enhancing the level of safety had mostly been related to a limited area and were based on considering factors in isolation, disregarding the existing significant interactions among them. In this study, all the independent variables were simultaneously taken into account in recommending any change.

The DSIM refers to a scheme that not only observes sufficient safety criteria but also rates the lowest in criteria such as change in traffic parameters or the cost. Accordingly, the present study was carried out in two phases. In the first phase, separate accident frequency prediction models were developed for different modes of transport (vehicle, motorcycle, and pedestrian). In the second phase, using the obtained models, an applied method was proposed to improve the safety of urban areas.

For developing accident prediction models using micro and macro variables, the data related to all accidents over the years 2014 and 2015 were collected from the west and the southwest main areas of Tehran, Iran. Therefore, in general, the data related to 14,903 accidents (9807 vehicle accidents, 2838 motorcycle accidents, and 2258 pedestrian accidents), which had occurred in 96 TAZs, were collected. Tehran, as the capital of Iran, has five main areas, which in total comprise 22 regions. The west and the southwest main areas are composed of the regions 9, 10, 17, 18, and 19.

The accident data were obtained through the database available in the Tehran Traffic Police Center. Moreover, the traffic data were collected through the Tehran Transportation and Traffic Organization and based on the results obtained from running Tehran traffic model.

After collecting the required data, all information was imported to GIS. Then, the objected variables related to each accident were obtained after doing the required calculations. The macro variables used in this study have been collected at the level of TAZs. The use of TAZs is more common than other geographical levels (such as census tract and country) because zone divisions are more in line with the studies related to transport planning models, and their pertinent traffic variables (such as trip generation and trip distribution) are more readily accessible. The independent variables used in this study are shown in Figure 1, and Table 1 lists their descriptive statistics in road segments.

Since in regression models, there is usually a logarithmic relation between independent variables and the response variable, using the logarithm of independent variables in the modeling process makes the interpretation of the results much easier. This is also very common in previous studies.[46,47] Moreover, this method also decreases the variance among variables.[19,48] Due to the mentioned reasons, the present study used logarithmic conversion of the variables related to the road segment and vehicle kilometer traveled of each road segment.

Macro variables were extracted at the level of TAZs. These variables are the same for the accidents which have occurred at the road segments available in one zone. Hence, the data were categorized into two levels. The first level accommodated the micro variables related to each segment, and the second level included the macro variables related to TAZs. The hierarchical structure of the data using in this study is shown in Figure 2. Therefore, the present study adopted a multilevel model.

Table 1: Descriptive statistics of variables

Variable	Definition	Vehicle				Motorcycle				Pedestrian			
		Minimum	Maximum	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum	Mean	SD
Count	Count of accident at road segment	1.00	277.00	69.14	69.29	1.00	33.00	11.14	8.44	1.00	35.00	9.81	8.70
Pro_Highway	Proportion of length of highway roads in TAZ	0.00	0.51	0.19	0.13	0.00	0.51	0.14	0.13	0.00	0.51	0.13	0.12
Pro_Arterial1	Proportion of length of principal arterial roads in TAZ	0.00	0.33	0.05	0.08	0.00	0.33	0.06	0.09	0.00	0.33	0.05	0.08
Pro_Arterial2	Proportion of length of minor arterial roads in TAZ	0.00	1.00	0.29	0.22	0.00	1.00	0.32	0.24	0.00	1.00	0.34	0.25
Pro_Collector	Proportion of length of collector roads in TAZ	0.00	1.00	0.45	0.18	0.00	1.00	0.45	0.20	0.00	1.00	0.43	0.21
Pro_Local	Proportion of length of local roads in TAZ	0.00	0.36	0.03	0.05	0.00	0.36	0.04	0.07	0.00	0.36	0.04	0.07
Log (S-L)	Logarithm of road segment	1.26	3.33	2.59	0.32	1.26	3.33	2.51	0.30	1.26	3.33	2.49	0.28
Log (V-K)	Logarithm of vehicle kilometer traveled per road segment	2.25	7.66	6.32	0.75	2.43	7.61	5.96	0.70	2.41	7.61	5.91	0.71
Int_density	(Number of intersection in a TAZ/area of TAZ)*10,000	0.01	0.58	0.17	0.14	0.01	0.58	0.22	0.14	0.01	0.58	0.22	0.14

SD: Standard deviation, TAZ: Traffic analysis zone

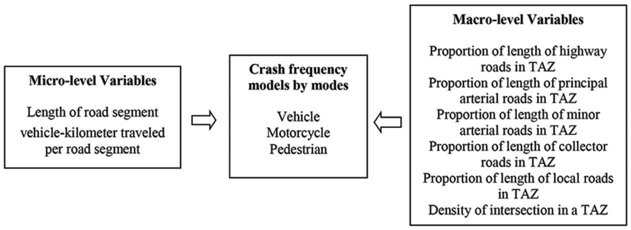

Figure 1: Micro and macro variables connected with crash frequency models

Furthermore, a NB model was also used for making comparisons and investigating the performance of multilevel model.

The general equation for the single-level model or the frequently used simple regression model is as follows:

$$y_i = \beta_0 + \beta_1 X_{i1} + e_i \quad (1)$$

In the above equation, the subscript I represents an individual respondent and y and x stand for the dependent and independent variables, respectively. There are also two fixed parameters (β_0 and β_1) that show the intercept and the slope and a random part (e) that makes it possible to have fluctuations around the fixed part. The word "random" here means "allowed to vary."

The micro-level of the individual is the sole place where this equation is specified. For developing a multilevel model, this micromodel needs to be respecified through differentiating TAZ with the subscript j.

$$y_{ij} = \beta_0 + u_{0j} + (\beta_1 + u_{1j})\, X_{1ij} + e_{ij} \quad (2)$$

The fixed parameters ($\beta_0 + u_{0j}$) show the intercept and allow for differential TAZ intercept to change from one TAZ to another around the overall intercept (β_0) through the addition of random component u_{0j}. The second fixed parameters ($\beta_1 + u_{1j}$) allow for differential slope to change around the overall slope (β_1) through the addition of random component u_{1j}.[49]

The best accident model for road segments in each mode of transport was chosen based on three criteria, namely log-likelihood, Akaike's information criterion corrected (AICC), and Bayesian information criterion (BIC). What follows are the formula for this measure:

$$\text{AICC} = 2k - 2\text{LL(full)} + \frac{2k(k+1)}{n-k-1} \quad (3)$$

$$\text{BIC} = k\ln(n) - 2\text{LL(full)} \quad (4)$$

In the above formula, k represents the number of parameters, n indicates the number of observations, and LL (full) shows the log-likelihood for the entire model.

Having finalized an accident frequency prediction model for each mode of transport (vehicle, motorcycle, and pedestrian), in the second phase of the study, the DSIM was developed in MATLAB environment according to Figure 3 and through using the objective function, the constraints in question, the IGMM optimization algorithm, and the accident frequency prediction models.

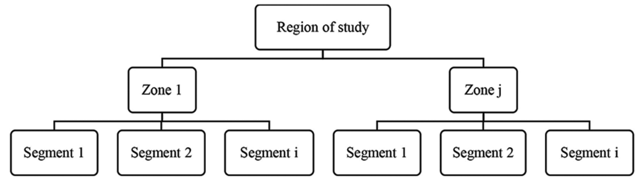

Figure 2: Multilevel structure of the data

The procedure for reaching characteristics of road network regarding safety at the level in question is an iterative procedure in which the different options available in predefined restrictions are assessed in each step until the response is finally reached by the optimization algorithm.

This study was proposed that, besides increasing safety, factors such as traffic parameters and cost should also receive due attention. Because estimating the cost of a change depends on the time and location, and also, it is too complicated to come up with all the traffic parameters resulted from a change, the least amount of change in the area under study was considered the objective function in the present study. Needless to say, when considering this objective, changes in factors such as traffic parameters and cost resulted from any other change are also considered at a minimum level. The objective function is illustrated in Relation 5.

$$Z = \left(\frac{\text{pro - Highway(new)}}{\text{pro - Highway}} - 1\right) + \left(\frac{\text{pro - Arterial1(new)}}{\text{pro - Arterial1}} - 1\right) + \left(\frac{\text{pro - Collector(new)}}{\text{pro - Collector}} - 1\right) + \left(\frac{\text{pro - Local(new)}}{\text{pro - Local}} - 1\right) + \left(\frac{\text{Log}(\text{S - L})(\text{new})}{\text{Log}(\text{S - L})} - 1\right) + \left(\frac{\text{Log}(\text{V - K})(\text{new})}{\text{Log}(\text{V - K})} - 1\right) + \left(\frac{\text{int - density(new)}}{\text{int - density}} - 1\right) \quad (5)$$

In this study, three constraints were considered:

The first constraint

The purpose of this study was to provide a method for decreasing the number of accidents by a certain amount. Hence, during the coding stages, the coefficient α was taken as the reduction factor for adjusting the number of accidents. Therefore, if Y stands for the total number of accidents in the existing situation and Y_{new} shows the total number of accidents after the improvements are made, according to Relation 6, the first constraint is as follows:

$$Y_{new} = \alpha * Y \quad (6)$$

The second constraint

Since factors place different effects on accidents at different modes of transport, in this study, for each mode of transport, a separate accident frequency prediction model was developed;[50] therefore, each independent variable needs to have the same amount of change in all accident frequency prediction models. For instance, the changes in the "length of segment" for vehicle accidents should be the same as the one for the accidents in the pedestrian mode of transport.

The third constraint

Using this constraint, the minimum and maximum amounts of change for each independent variable were determined based on three criteria:

1. The decreasing or increasing effect of an independent variable on the number of accidents in different modes of transport
2. The minimum and maximum values of that independent variable
3. The physical and geometrical restrictions applied to the amount of change in an independent variable.

The acceptable range of each index was formulated using independent variable as shown in Table 2.

Table 2: Considered range of indexes

Index	Minimum	Maximum
$\frac{\text{Pro} - \text{Highway(new)}}{\text{Pro} - \text{Highway}} - 1$	-1	0
$\frac{\text{Pro} - \text{Arteriall(new)}}{\text{Pro} - \text{Arteriall}} - 1$	-1	0
$\frac{\text{Pro} - \text{Collector(new)}}{\text{Pro} - \text{Collector}} - 1$	-1	1
$\frac{\text{Pro} - \text{Local(new)}}{\text{Pro} - \text{Local}} - 1$	0	1
$\frac{\text{Log}(\text{S} - \text{L})(\text{new})}{\text{Log}(\text{S} - \text{L})} - 1$	-1	0
$\frac{\text{Log}(\text{V} - \text{K})(\text{new})}{\text{Log}(\text{V} - \text{K})} - 1$	-1	0
$\frac{\text{Int} - \text{density(new)}}{\text{Int} - \text{density}} - 1$	-1	0

Varaee and Ghasemi introduce a new met heuristic optimization method based on the IGMM to solve mathematical and engineering optimization problems. Ideal gas molecules scatter throughout the confined environment quickly.[51] This is embedded in the high speed of molecules, collisions between them, and the surrounding barriers. In the IGMM algorithm, the initial population of gas molecules is randomly generated, and the governing equations related to the velocity of gas molecules and collisions between those are utilized to accomplish the optimal solutions. A comparison of results obtained by IGMM with other optimization algorithms shows that the proposed method has a challenging capacity in finding the optimal solutions and exhibits significance both in terms of the accuracy and reduction on the number of function evaluations vital in reaching the global optimum.

Results

As already mentioned, in the first step, NB models and multilevel models were used for the accidents occurring in road segments within each mode of transport (vehicle, motorcycle, pedestrian), and the roles of both micro and macro variables were investigated. As it has been shown in Table 3, Based on the criteria of model goodness-of-fit (log-Likelihood, AICC, and BIC), multilevel models show a better performance for the data with multilevel structures because they consider within-zone correlation. Table 4 lists the significant variables ($P < 0.05$) along with the coefficient of each across different modes of transport.

Having come up with a separate accident frequency prediction model for each mode of transport, the researchers focused, in the second phase of the study, on developing the DSIM in MATLAB environment using the IGMM algorithm. To come up with numerical results for employing this method, the accident reduction factor (α) was considered 0.7 in this study. In other words, the numerical results are obtained through employing solutions for decreasing the number of accidents by 30% in the area under study.

Since the optimization process is an iterative one until the optimized scheme is reached, the total number of accidents

Table 3: Goodness-of-fit measures for different models

Type of model	Multilevel			NB		
Mode of transportation	Vehicle	Motorcycle	Pedestrian	Vehicle	Motorcycle	Pedestrian
Count of accident	9807	2838	2258	9807	2838	2258
AICC	95,123.22	18,409.66	14,495.73	97,078.74	19,279.62	14,859.76
BIC	95,187.92	18,463.16	14,547.15	97,136.25	19,327.17	14,905.5
Log likelihood	47,561.61	9204.83	7247.865	48,539.37	9639.81	7429.88

AICC: Akaike's information criterion corrected, BIC: Bayesian information criterion, NB: Negative binomial

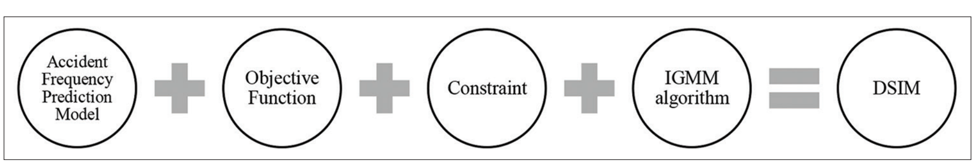

Figure 3: The process of development of the safety improvement method

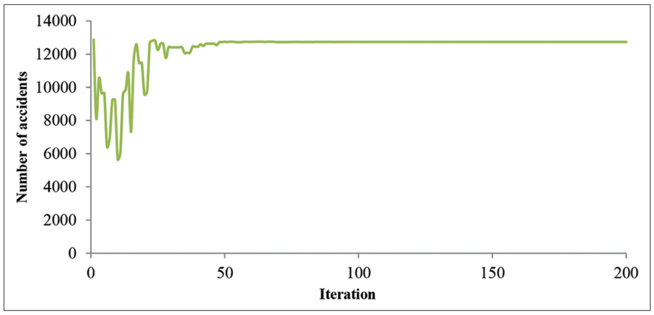

Figure 4: The total number of accidents in each iteration of the ideal gas molecular movement algorithm

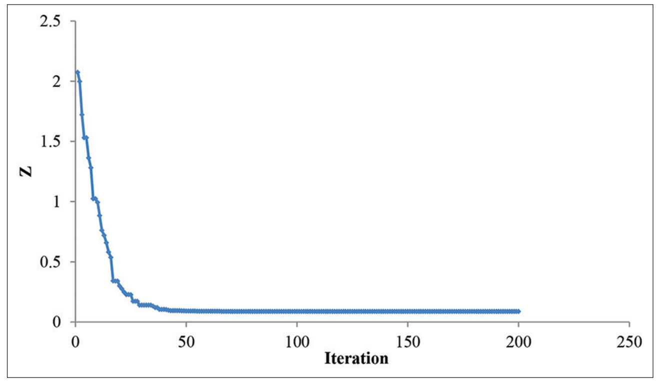

Figure 5: The values of the objective function in the iterations of the ideal gas molecular movement algorithm

Table 4: Results of final models for road segments by mode of transportation

Variable	Vehicle		Motorcycle		Pedestrian	
	Coefficient	*P*	Coefficient	*P*	Coefficient	*P*
Intercept	-2.404	0.00	-1.504	0.00	-0.914	0.01
Pro-highway	1.511	0.00	0.317	0.02	-	-
Pro-arterial1	0.578	0.00	1.686	0.00	0.541	0.02
Pro-collector	-0.228	0.01	0.383	0.00	-	-
Pro-local	-2.091	0.00	-	-	-1.954	0.02
Log (S-L)	0.269	0.00	0.496	0.00	0.483	0.00
Log (V-K)	0.859	0.01	0.356	0.01	0.325	0.00
Int-density	0.366	0.02	0.747	0.00	0.73	0.00

Table 5: The final results of the ideal gas molecular movement algorithm

Index	Value
$\frac{\mathrm{Log}(\mathrm{V-K})\mathrm{new}}{\mathrm{Log}(\mathrm{V-K})}-1$	-0.0879
Objective function (Z)	0.08825
Number of accidents in current situation base on safety model	18,179
Number of accidents after corrections base on safety model	12,738

in each iteration of the IGMM algorithm is given in Figure 4. The values of independent variables differ in each iteration until the final results are reached. Thus, in the initial iterations, the number of accidents changes considerably. This shows the effort made by the IGMM algorithm for finding the response range in the problem's search space. At the end, the number of accidents based on the first constraint displays a 30% reduction.

Figure 5 shows the values of the objective function for each iteration of the IGMM algorithm. These values started from about 2.1 in the initial iterations of the algorithm and after a decreasing trend reached the final value of 0.09. Since the objective function is causing the least change in the area under study, the solution for increasing safety is reached through causing the least change in independent variables.

With the observance of the objective function and the pertinent constraints, the final response was reached after 200 iterations of the IGMM algorithm. The final results are observable in Table 5, according to which the variable of "vehicle kilometer traveled per road segment" shows the greatest change, while the changes observable in other variables are so little that they equal 0 by 4 decimals. The final value of the objective function is 0.08825, and the number of accidents shows a 30% reduction.

Conclusions

The results of safety studies are limited to considering engineering solutions aiming at decreasing or increasing the factors affecting safety. In these studies, solutions are determined through considering a single factor influencing accidents in isolation without investigating its effect size on other related factors. For example, narrowing the road aiming at increasing pedestrians' safety might lead to increasing front-to-back accidents through causing abrupt vehicle brakes. This has limited the effectiveness of such solutions or in some cases, which has even rendered then ineffective. Therefore, presenting a practical solution necessarily entails simultaneous consideration of all factors across different modes of transport. On the other hand, each change in the road network for increasing safety not only results in changes in traffic parameters in the area under study but also entails costs. Thus, to come up with a scheme which is considered both the economic and the traffic points of view, it is of utmost importance to cause the least change in the area under study.

Since, in past studies, little attention was paid to offering effective solutions, the present study first developed separate accident frequency prediction models for each mode of transport (vehicle, motorcycle, and pedestrian). Then, in the second step, the DSIM was provided through using the IGMM optimization algorithm, the objective functions, and the determined constraints. In this method, the objective function is taken as causing the least change in the road network of the area under study. Moreover, all the factors affecting safety in different modes of transport were simultaneously taken into account. Next, to come up with numerical results of DSIM, the values obtained for a 30% reduction in accidents were presented.

The data used in this study came from the information available from 14,903 accidents that occurred in 2014 and 2015 in 96 TAZs in Tehran, Iran. The independent variables used in this study were collected at both micro- and macro-levels. The length of the road segment and the vehicle kilometer traveled in each segment were taken as the independent variables at the micro-level. At the macro-level, the ratio of road length, while considering their functional classification (highway, principal arterial, minor arterial, collector, and local), to the total length of all roads of one zone and the density of intersections in one TAZ were taken as the independent variables. The multilevel model was used for modeling, and the NB model was also used for making comparisons and investigating the performance of the multilevel model. The final models were selected based on the criteria of model fit, including log-likelihood, AICC, and BIC. Based on the obtained results, the multilevel model has a better performance than the NB model because the former considers the within-zone correlation resulted from the same macro variables for the accidents occurring in one TAZ.

Based on the results of DSIM, the amount of change in the independent variables under study in this work of research was little except for the variable of "vehicle kilometer traveled per road segment," which showed a significant change. The difference in the final results of DSIM with the results of the analysis of the final accident models reveals the necessity of creating such methods.

For further research, one can address the use of other independent variables affecting safety and also different optimization algorithms. Moreover, if possible, one can consider new constraints and include traffic parameters in the optimization process to directly investigate the effect size of safety measures on traffic parameters in the area under study.

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

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