Neural Computing and Applications (2022) 34:5367–5381
https://doi.org/10.1007/s00521-022-06952-9

ORIGINAL ARTICLE

Highway accident number estimation in Turkey with Jaya algorithm

Mehmet Fatih Tefek[1] · Muhammed Arslan[2]

Received: 13 July 2021 / Accepted: 11 January 2022 / Published online: 31 January 2022

Abstract

In the transportation sector in Turkey, approximately 90% of cargo and passenger transportation is carried out on highways. In recent years, increasing population and welfare levels have brought along an increase in demand for and intensity of highway use. Accidents experienced along with the increased intensity in the use of highways result in fatalities and loss of property. In order to minimize such losses on the highways and determine plans and programs for the future by benefiting from historical data, it is necessary to conduct accurate, consistent, effective, and reliable accident estimations. In the study, highway accident number estimation (HANE) in Turkey was made by using the meta-heuristic Jaya optimization algorithm. For HANE, Jaya linear (Jaya-L) and Jaya Quadratic (Jaya-Q) models were proposed. Indicators such as the number of accidents that occurred between 2002 and 2018, population, gross domestic product (GDP), total divided road length (TDRL), and the number of vehicles were taken for HANE. Indicators were analyzed for four different conditions. HANE was made by using Population–GDP–TDRL–Number of Vehicle indicators together. A total of 75% of the total 17-year data between 2002 and 2018 were used for training purposes, and 25% of the data were used for testing. The results of the proposed Jaya-L and Jaya-Q models were analyzed by comparing them with the Andreassen estimation model (AEM) and multiple linear regression (MLR) methods. Following the successful training and testing results, low, expected, and high scenarios were proposed, and the number of accidents between 2019 and 2030 was estimated.

Keywords Highway accident estimation models · The number of accidents · Meta-heuristic Jaya algorithm · Scenarios

1 Introduction

Highway traffic accidents are an important public health problem that necessitates coherent efforts for effective and sustainable prevention [1]. The World Health Organization (WHO) reports that each year more than 50 million injuries and 1 million and 350 thousand deaths resulting from traffic accidents occur worldwide [2]. In terms of public health, it is important to convince policymakers and decision-making authorities of countries to determine essential problems related to accident numbers and associated losses [1]. WHO initiated the road safety project in ten countries, including Turkey, which account for 48 percent of traffic accident-related fatalities worldwide [3].

More than 90% of transportation in Turkey is realized through land transportation. As a result of the rising welfare level and population of the country, the number of vehicles in Turkey' climbed by 165% between 2002 and 2018 [4, 5]. Moreover, there has been a 72% rise in traffic accidents occurring as a result of the increased number of vehicles compared to the ten-year average [4]. Smeed (1949) reported that there was an increase in the number of accidents in parallel with the increase in population in his study [6]. When accident statistics from recent years in Turkey are analyzed, it is observed that over one million accidents occur annually that in these accidents, about four thousand people lose their lives at the accident scene, and that around four thousand individuals lose their lives at the hospital within 30 days following the accident. In addition, around three hundred thousand injury cases are

✉ Mehmet Fatih Tefek
mehmetfatihtefek@osmaniye.edu.tr

Muhammed Arslan
marslan@ahievran.edu.tr

1 Department of Computer Engineering, Osmaniye Korkut Ata University, Osmaniye, Turkey

2 Department of Computer Technology, Ahi Evran University, Kırşehir, Turkey

encountered [4]. The accurate determination of traffic accidents and situation analysis is very important in terms of re-regulating the traffic flow and reducing severe injuries and deaths [7]. Accidents bring along economic losses as well as loss of lives and injuries [8–10]. Given that one in every two cars purchased in Turkey is imported, the economic losses due to traffic accidents are a significant factor, also having a growing effect on Turkey's current account deficit [11].

In order to minimize the number of accidents that may occur on highways, to reduce material and spiritual losses, and to be able to make future plans, it is necessary to make accurate, consistent, effective, and reliable estimations. For this purpose, there are studies conducted on accident estimation in the literature. Some of the examples of the studies conducted on accident estimations are as follows: Smeed [6] proposed an accident estimation model through simple statistical methods based on the relationship between deaths, the number of vehicles, and population. Chakraborty and Roy [12] examined the deaths resulting from the number of motor vehicles in Kolkata (India) over 15-year data. Valli [13] developed an Indian highway accident estimation model based on the 25-year population, number of accidents, and number of motor vehicles. Partyka [14] proposed simple models in order to understand various factors that affected the increase in the number of accidents in the country by using employment and population data. Mekky [15] used time series data for analysis and examined the effect of the rapid increase in the number of motor vehicles in some developing countries on death rates. Andreassen [16] examined the relations between the number of deaths and the number of vehicles in accidents and proposed an accident estimation model. Miaou and Lum [17] analyzed vehicle accidents and highway geometrical design relationships in terms of modeling capabilities by using the standard linear regression model and Poisson regression model. Okamoto and Koshi [18] developed the method of overcoming mistakes of accident rates which occur randomly depending on the number of accidents by using linear multiple regression analysis. Akgüngör and Yıldız [19] employed partial factorial design method and revealed that annual average daily traffic was the most effective parameter in the model. Akgüngör and Doğan [20] applied Smeed and Andreassen's accident estimation models with different scenarios for Turkey's accident estimation by using data on population and the number of vehicles, accidents, injuries, and deaths. Özgan, et al. [21] performed regression analysis using the data of the accidents that occurred on D200/20 highway between 1999 and 2002, proposed a mathematical model equation for the number of accidents, and estimated traffic accidents on a monthly basis. Akinyemi [22] investigated the relationship between Nigeria's economic development and highway traffic accidents, and loss of lives. He demonstrated that gross domestic product (GDP) had a significant effect on accidents, deaths, and injuries in the long term with an econometric model. Kumar and Jain [23] analyzed accident data of Yamuna highway in India and developed a negative binomial model for the estimation of accidents on the highway.

The studies mentioned above were carried out with classical statistical analysis calculation methods. There are also studies related to artificial neural networks (ANN) for accident estimation. Some of these studies are as follows: Mussone et al. [24] proposed an alternative model based on artificial neural networks (ANNs) for a model study related to the analysis of vehicle accidents in Milan. Abdelwahab and Abdel-Aty [25] developed ANN models in order to estimate forecasting driver injuries in traffic accidents at intersection points. Xie, et al. [26] performed an empirical analysis using regression and Bayesian network-based artificial neural networks to estimate motor vehicle crashes. Çinicioglu et al. [27] analyzed the factors causing traffic accidents in the Silivri district of Istanbul province through Bayesian Networks and exemplified the results they obtained over Turkey population. Çodur and Tortum [28] proposed an artificial neural networks model for highway accident estimation and applied it with Turkey/Erzurum sample. Ture Kibar et al. [29] performed data analysis for truck accidents on the intercity highway between Ankara-Aksaray-Ereğli by comparing the performances of negative binomial regression and ANN models. Kıyıldı [30] proposed a traffic accident estimation model for Turkey by using ANN according to the 15-year data on the number of vehicles, population, and the number of deaths in accidents. Cansız, et al. [31] made estimations on the number of accidents and number of injuries by using the 2002–2017 data on population, driver fault, vehicle fault, passenger fault, and road fault through ANN and multiple regression methods. Rahim and Hassan [32] made a deep learning-based estimation of the severity of accidents. Thus, they sought to estimate the damage that accidents would produce and to prevent the scale of the accident and the damage from becoming too severe.

When the studies conducted on highway accident number estimation (HANE) are examined, it is seen that initially, classical analysis techniques were used, but later ANN and regression techniques were also employed. In recent years, accident estimation studies utilizing meta-heuristic optimization algorithms have been presented in the literature, albeit in limited numbers. When studies conducted with meta-heuristic optimization algorithm techniques are examined, some of them can be listed as follows: Akgüngör and Doğan [33] estimated the number of traffic accidents by using different methods such as regression analysis, ANN, and genetic algorithm (GA), and they proposed an exponential estimation model based on Smeed and Andreassen's accident model. Akgüngör and Korkmaz [34] estimated the number of accidents in Turkey by using the differential evolution (DE) algorithm. For estimation, they used two indicators related to population and the number of vehicles and proposed linear, semi-quadratic, and exponential models with these indicators [34]. When the literature [35] was examined, no HANE studies using meta-heuristic algorithms were found except for the studies of [33, 34].

In the present study, a different perspective based on a meta-heuristic optimization algorithm for accident estimation in the literature was aimed to be proposed. Accordingly, linear and quadratic models were proposed, and in addition to the indicators of population and gross domestic product (GDP) available in the literature, total divided road length (TDRL) and the number of vehicles were included, totaling four different indicators. In the study, the Jaya algorithm, which is one of the current meta-heuristic optimization algorithms, was employed for HANE in Turkey. Jaya algorithm was preferred because it did not involve any algorithm-specific parameters, was simple to understand and was easily applicable to optimization problems [36]. For HANE, Jaya linear (Jaya-L) and Jaya Quadratic (Jaya-Q) models were proposed. The data on population, GDP, TDRL, and the number of vehicles between 2002 and 2018 were taken as entry indicators of Jaya-L and Jaya-Q models. A total of 75% of the data between 2002 and 2014 were used for training purposes, and 25% of the data, which covered the period between 2015 and 2018, were used for testing. Most of the traffic accident estimation models in the literature are based on multiple linear regression model (MLR) methods [17, 18]. Therefore, the success of Jaya-L and Jaya-Q models in terms of training and testing results was compared with MLR method and Andreassen estimation model (AEM). It was determined that the success of Jaya-Q model was better than Jaya-L, MLR method, and AEM. In terms of testing results, it was determined that Jaya-L and Jaya-Q models yielded more accurate, effective, and reliable accident estimations compared to MLR. Following the successful training and testing results, low, expected, and high scenarios were created, and the number of accidents by 2030 was estimated.

2 Variable selection and data set used

Highway traffic accident statistics constitute a basis for monitoring the progress of efforts shown to prevent national and global traffic accidents and evaluate the effectiveness of these efforts [37]. The official data on highway traffic accidents reported by governments worldwide are usually accepted to be reliable and valid [37]. The indicators used in the study for estimating the number of accidents were obtained from the Turkish Statistical Institute (TSI), which is an organization with high reliability and validity [4]. For HANE study, four different indicators taken from TSI for the period between 2002 and 2018, which are population, gross domestic product (GDP), total divided road length (TDRL), and the number of vehicles, were used. The number of accidents between 2002 and 2018 and four different indicators used for HANE is given in Table 1 [4].

Population indicator [6, 13, 14, 20, 30] and the number of vehicles indicator [6, 12, 13, 15, 16, 20] were used in many studies in combination. In addition to these indicators, GDP and TDRL were used for the first time in models created with the Jaya algorithm. R^2 correlation coefficients between population, GDP, TDRL, and the number of vehicles based on the number of accidents for the 2002–2018 period and their graphs are shown in Fig. 1. In Fig. 1, it is seen that GDP and TDRL indicators used for HANE have a strong correlation with the number of accidents with their respective values of 0.9069 and 0.9312 correlation coefficients (R^2).

3 Materials and methods

Jaya algorithm, which is a meta-heuristic optimization algorithm, was used for HANE. Through the Jaya algorithm, two different estimation models were proposed as linear and quadratic models. The multiple linear regression (MLR) method, which is frequently used in the literature, was also included in the study.

3.1 Jaya algorithm

Jaya is a population-based meta-heuristic optimization algorithm proposed by Venkata Rao [36] to solve restricted and unrestricted continuous optimization problems. Jaya algorithm easily adapts to problems, and it does not involve any parameters specific to the algorithm. The main principle of the Jaya algorithm is to ensure that a given problem progresses toward the best solution and to avoid the worst solution [36].

Consider f(x) as the objective function to be minimized or maximized. Assume any ith iteration, m is the number of design variables (i.e., $j = 1, 2, \ldots, m$), with n being the number of candidate solutions (i.e.,$k = 1, 2, \ldots, n$). Jaya algorithm uses both the best and the worst solutions in order to upgrade candidate solutions. In the candidate solutions, the best candidate gets the best $f(x)$ (i.e., $f(x)_{best}$) and the worst candidate gets the worst $f(x)$ value (i.e.,

Table 1 Number of accidents between 2002 and 2018 and the values of the indicators of population, GDP, TDRL, and the number of vehicles used for HANE [4]

Years	Number of accidents that occurred (10^5)	Population (10^6)	GDP (10^{10} \$)	TDRL (10^3 km)	Number of vehicles (10^6)
2002	4.39777	66.4	23.8428	6.04	8.65517
2003	4.55637	67.1	31.1823	7.2	8.903843
2004	5.37352	68.01	40.4787	8.972	10.23636
2005	6.20789	68.86	50.1416	10.178	11.14583
2006	7.28755	69.72	55.2487	11.685	12.22739
2007	8.25561	70.5	67.577	12.973	13.02295
2008	9.5012	71.5	76.4336	14.458	13.7654
2009	10.53346	72.5	64.464	16.494	14.3167
2010	11.06201	73.7	77.1902	18.863	15.0956
2011	12.28928	74.7	83.2524	20.273	16.08953
2012	12.96634	75.6	87.3982	21.193	17.03341
2013	12.07354	76.6	95.0579	22.079	17.93945
2014	11.9901	77.7	93.4186	22.583	18.82872
2015	13.13359	78.7	85.9797	23.107	19.99447
2016	11.82491	79.8	86.3722	23.831	21.09042
2017	12.02716	80.8	85.2677	24.507	22.21895
2018	12.29364	82.03	77.135	25.113	22.86592

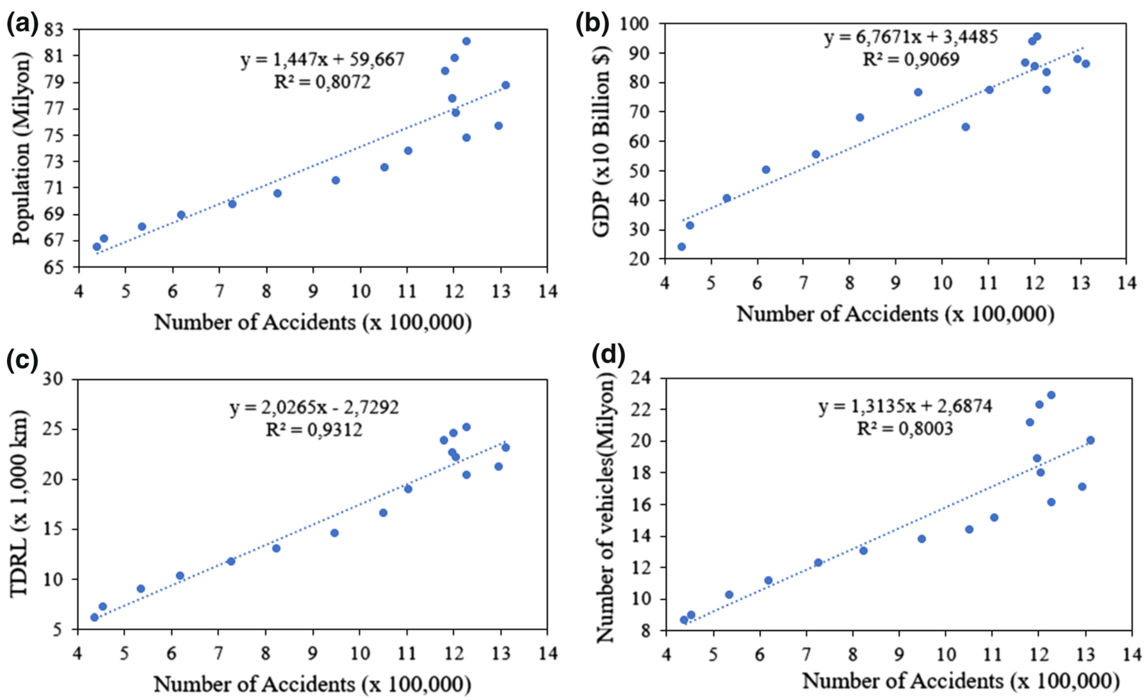

Fig. 1 Regarding the indicators used for HANE, R^2 correlation between **a** Number of accidents–Population, **b** Number of accidents–GDP, **c** Number of accidents–TDRL, **d** Number of accidents–Number of vehicles

$f(x)_{worst}$). If $X_{j,k,i}$ is the value of jth variable for kth candidates in ith iteration, this value is updated as shown in Eq. 1. [36].

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i} * \left(X_{j,best,i} - \left|X_{j,k,i}\right|\right) - r_{2,j,i} * \left(X_{j,worst,i} - \left|X_{j,k,i}\right|\right) \quad (1)$$

where $X_{j,best,i}$ is the value of j variable for the best candidate. $X_{j,worst,i}$ is the value of the j variable for the worst candidate. $X'_{j,k,i}$ is, for J. variable at i. iteration, the updated value of $X_{j,k,i}$. $r_{1,j,i}$ and $r_{2,j,i}$ are two different random numbers varying in the [0,1] interval for j. variable at i. iteration. Jaya basically functions as follows: if at i. iteration, the solution found by updated $X'_{j,k,i}$ value in fitness function is better than (f_{new}) the solution found by $X_{j,k,i}$ value (f), then take the new solution as the current solution $(f = f_{new})$. Otherwise, take the current solution (f) and update the new population produced as in Eq. (1). Pseudo-codes of Jaya are presented in Algorithm 1.

number of accidents was estimated using the Population–Number of Vehicle, Population–GDP–Number of Vehicle, Population–TDRL–Number of Vehicle and the indicators we suggested hereby Population–GDP–TDRL–Number of Vehicle. The equations of the models created based on these indicators are given below.

Equations based on Population (X_1)–Number of Vehicles (X_4) indicators: (T = 2)

$$Jaya - L = w_1X_1 + w_2X_4 + w_0 \quad (2)$$

$$Jaya - Q = w_1X_1 + w_2X_4 + w_1X_1 + w_3X_1X_4 + w_4X_1^2 + w_5X_2^2 + w_0 \quad (3)$$

$$MLR = \beta_1X_1 + \beta_2X_4 + \beta_0 \quad (4)$$

Algorithm 1. Jaya Pseudo Codes

Input
- Set the dimension of the problem (D)
- Determine the number of population (N)
- Enter purpose function evaluation number (FEs)
- Set the ending criterion (MaxFEs)

Output
- Minimized or maximized function value (min. or max. func.)
- Values that minimize or maximize fitness function

Begin

1. Produce initial population
2. Produce N numbered at D-dimension random candidate solutions in the search space in problem definition: $X(N,D)$;
3. **WHILE** FEs<=MaxFEs
4. $F_{best} = F_{obj}(X(N,D))$; *// Apply candidate solutions to fitness function*
5.   **FOR** each candidate solution $(X(N,D))$
6.   Create the new population by using Eq. (1) $(X(N,D)^{\iota})$
7.   Calculate fitness function value for $(X(N,D)^{\iota})$ $(F_{new,best})$
8.   **IF fitness value of** F_{best} is better than $F_{new,best}$
9. $X(N,D) = X(N,D)^{\iota}$
10. $F_{best} = F_{new,best}$
11.   **END IF**
12.   FEs=FEs+1;
13.   **END FOR**
14. Take the candidate solution with the best fitness function value $(X(N,D))$.
15.   **IF** ending criterion is not provided
16.   Go to step 3
17.   **ELSE**
18.   Take the best solution found (F_{best}).
19. **END WHILE**

End

3.2 HANE models

In this study, Jaya-linear (Jaya-L) and Jaya-quadratic (Jaya-Q) models are proposed. Moreover, MLR and AEM were utilized. The AEM is used in the literature to estimate the number of accidents with the population and number of vehicles indicators [16, 38]. Furthermore, the population and number of vehicle indicators, which are frequently utilized for HANE in the literature, GDP, and TDRL indicators, are also used in this study. In this context, the

$$AEM = const V^{B_1} P^{B_2} \quad (5)$$

Equations based on Population (X_1)–GDP (X_2)–Number of Vehicle (X_4) indicators: (T = 3)

$$Jaya - L = w_1X_1 + w_2X_2 + w_3X_4 + w_0 \quad (6)$$

$$Jaya - Q = w_1X_1 + w_2X_2 + w_3X_4 + w_4X_1X_2 + w_5X_1X_4 + w_6X_2X_4 + w_7X_1^2 + w_8X_2^2 + w_9X_4^2 + w_0 \quad (7)$$

$$MLR = \beta_1X_1 + \beta_2X_2 + \beta_3X_4 + \beta_0 \quad (8)$$

Equations based on Population (X_1)–TDRL (X_3)–Number of Vehicle (X_4) indicators: (T = 3)

$$Jaya - L = w_1X_1 + w_2X_3 + w_3X_4 + w_0 \quad (9)$$

$$Jaya - Q = w_1X_1 + w_2X_3 + w_3X_4 + w_4X_1X_3 + w_5X_1X_4 + w_6X_3X_4 + w_7X_1^2 + w_8X_3^2 + w_9X_4^2 + w_0 \quad (10)$$

$$MLR = \beta_1X_1 + \beta_2X_3 + \beta_3X_4 + \beta_0 \quad (11)$$

Equations based on Population (X_1)–GDP (X_2)–TDRL (X_3)–Number of Vehicle (X_4) indicators: (T = 4)

$$Jaya - L = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_0 \quad (12)$$

$$Jaya - Q = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4 + w_5X_1X_2 + w_6X_1X_3 + w_7X_1X_4 + w_8X_2X_3 + w_9X_2X_4 + w_{10}X_3X_4 + w_{11}X_1^2 + w_{12}X_2^2 + w_{13}X_3^2 + w_{14}X_4^2 + w_0 \quad (13)$$

$$MLR = \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_0 \quad (14)$$

The w values in the Jaya-L and Jaya-Q models between Eqs. (2–14) are the weight values to be calculated. Weight coefficient values are taken between [−100, 100]. In the MLR method, on the other hand, β values are the regression coefficients that must be calculated. In Eq. (5), the number of const represents the constant value in AEM. V-value indicates the number of vehicles, P-value indicates population indicators, B_1 and B_2 values indicate the exponential values of vehicle numbers and population. The T value represents the number of indicators. T values between Eqs. (2–14) take $T = 2$, $T = 3$ and $T = 4$ values depending on the number of indicators. Among the indicators used in the equations, X_1 indicates the population number, X_2 indicates GDP, X_3 TDRL, and X_4 the number of vehicles.

Jaya-L and Jaya-Q models were proposed, and the MLR method was applied in order to minimize root-mean-square error (RMSE), which is the purpose function in Eq. (15). The low value of RMSE is an indicator of good estimation results. As the RMSE value approaches zero (0), the error value decreases.

In the study, the first 75% of the total 17-year data between 2002 and 2018 were used for training purposes, and the remaining 25% were used for testing. For the training data set, 13 years covering the years 2002 and 2014 were taken. The min RMSE for the experiment was calculated according to Eq. (15). Weight values $(w_1, w_2, w_3, \ldots, w_i, w_0)$ are determined depending on Eq. 15. The i value in w_i is the final weight value calculated based on the gauge number and the Jaya-L and Jaya-Q models. w_0 is the last weight value. For the testing, the proposed Jaya-L and Jaya-Q models and MLR methods according to 2015 and 2018 were employed. The reason why the first 13 years of data were chosen for training and the last 4 years of data for testing is that generally the first years of training are preferred for training and the last years are preferred for testing. For many years, training and testing data have been determined to establish a relationship between the past and the future for the estimation of the number of accidents. The years close to the present have been used for testing purposes. Kankal et. al. (2011) used the years between 1980 and 2000 as training and between 2001 and 2007 as testing in their estimation study for Turkey [39]. Tefek et. al. (2019) used the years 1980 to 2010 for training and the years 2011 to 2014 for testing in estimation study [40].

$$\min RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(y_g - y_t\right)^2\right]^{1/2} \quad (15)$$

where n refers to the total 13-year data number estimated between 2002 and 2014 (n = 13); y_g is the number of accidents that occurred for each year; and y_t shows the number of estimated accidents calculated with Jaya-L, Jaya-Q, MLR, and AEM in Eqs. (2–14).

4 Estimation results

Jaya-L and Jaya-Q models, proposed for accident number estimation, were applied in order to minimize RMSE value, which constitutes purpose function for training data set between 2002 and 2014. Jaya-L and Jaya-Q models were run on a laptop computer with Windows 10 operating system and i7-6700Hq CPU 2.60 GHz, 16 GB RAM in MATLAB R2016a program 30 times at 1,000 iterations and 50 population number. The minimum RMSE (min RMSE) values obtained as a result of running the models were determined as given in Table 2.

When the Population–Number of Vehicle indicators are used in Table 2, the proposed Jaya-Q model achieved better results than the others in both training and testing. The AEM method achieved good results in training; however, the min RMSE value was high in testing. Table 2 shows that the Jaya-Q model gives better results in both testing and training when the Population–GDP–Number of Vehicle indicators are used. Although the MLR method in training gives better results than Jaya-L, the min RMSE value was calculated high in testing. In Table 2, the min

Table 2 Accident estimation study results of Jaya-L and Jaya-Q models, MLR and AEM method according to min RMSE value for HANE

Indicators	Number of indicators (T)	Models	Training (%75) (2002–2014) min RMSE	Testing (%25) (2015–2018) min RMSE
Population–Number of Vehicle	2	Jaya-L	1,252,923	1,495,826
		Jaya-Q	**0,829,973**	**1,040,239**
		MLR	1,25,671	1,47,672
		AEM	0,877,663	5,19,985
Population–GDP–Number of Vehicle	3	Jaya-L	0,759,223	0,60,993
		Jaya-Q	**0,6,718,860**	**0,5,801,110**
		MLR	0,72,449	1,38,501
Population–TDRL–Number of Vehicle	3	Jaya-L	0,440,139	0,783,877
		Jaya-Q	**0,356,254**	**0,644,291**
		MLR	0,35,885	1,02,003
Population–GDP–TDRL–number of vehicle	4	Jaya-L	0,432,561	0,560,291
		Jaya-Q	**0,334,694**	**0,531,074**
		MLR	0,35,753	0,84,528

RMSE values calculated for training in population, TDRL, and number of vehicle data where indicator number is 3 ($T = 3$) are very close to each other in Jaya-Q and MLR. However, the min RMSE value of the MLR method in testing is higher than both Jaya-L and Jaya-Q models.

Population–GDP–TDRL–Number of Vehicle indicators are used in Table 2, the min RMSE value of the Jaya-Q model is lower in training data compared to MLR. In testing data, the min RMSE value of MLR is higher than the proposed Jaya-L and Jaya-Q. When the indicators used in Table 2 are analyzed, it is seen that the MLR value in training produces close values compared to Jaya-Q. However, when MLR is compared with the proposed Jaya-L and Jaya-Q in the testing data, it is determined in Table 2 that MLR calculated the min RMSE value as high. In the results in Table 2, lower min RMSE values are obtained in the case where the number of indicators is high ($T = 4$) compared to the other cases. Table 2 proves that the Population–GDP–TDRL–Number of Vehicle indicators used in this study and the Jaya-L and Jaya-Q models are appropriate and compatible according to the min RMSE results.

The coefficient values calculated according to the models in the Population–Number of Vehicle indicators ($T = 2$) are given in Table 3. The coefficient values calculated according to the models in the Population–GDP–Number of Vehicle indicators ($T = 3$) are given in Table 4. The coefficient values calculated according to the models in the Population–TDRL–Number of Vehicle indicators ($T = 3$) are given in Table 5. The calculated coefficient values for the Population–GDP–TDRL–Number of Vehicles indicators ($T = 4$) are given in Table 6.

When the coefficient values in Tables 3, 4 and 5 are replaced in Eqs. (2–11), Population–Number of Vehicle, Population–GDP–Number of Vehicle, and Population–TDRL–Number of Vehicle values in Table 7 are obtained, respectively. The years between 2002 and 2014 are calculated as training and between 2015 and 2018 as testing.

In this study, it is given in Table 2 that the Population–GDP–TDRL–Number of Vehicle ($T = 4$) indicators and the accident number estimation of the proposed Jaya-L and Jaya-Q models were also successful. Therefore, the Population–GDP–TDRL–Number of Vehicle indicators and models proposed for accident number estimation studies are compared and analyzed in more detail. The weight values (in Table 6), calculated according to the Population–GDP–TDRL–Number of Vehicle ($T = 4$) indicators, are substituted in Eqs. (12–14). The calculated accident number estimation results of Jaya-L, Jaya-Q, and MLR methods are given in Table 8, and the differences between the estimate and occurred, and the relative error rate percentages of these differences are given.

The number of accidents that occurred and the change graph of Jaya-L, Jaya-Q models, and MLR method between 2002 and 2018 are shown in Fig. 2. The period between 2002 and 2014 was used for training and between 2015 and 2018 for testing.

Figure 2 shows the values of the number of accidents that occurred and estimation results of the proposed Jaya-Q model overlap in 2005, 2006, 2007, 2011, and 2018, the estimation results of the Jaya-L model overlap in 2010 and 2018, and the results of MLR method overlap in 2007, 2011, 2014, and 2016. There is a small difference between the number of accidents that occurred and the estimation

Table 3 Population–Number of Vehicle calculated coefficient values

Population–number of vehicle (T = 2)							
Jaya-L		Jaya-Q		MLR		AEM	
w_1	0,6,382,603	w_1	−0,014,521	β_1	0,89,957,303	B_1	1.6278
w_2	−0,0,881,054	w_2	−0,002,249	β_2	−0,3,756,082	B_2	−0.6278
w_0	−35,972,703	w_3	0,038,066	β_0	−50,79,659	*const*	0.183
		w_4	−0,002,653				
		w_5	−0,074,618				
		w_0	0,210,764				

Table 4 Population–GDP–Number of Vehicle calculated coefficient values

Population–GDP–number of vehicle (T = 3)					
Jaya-L		Jaya-Q		MLR	
w_1	0,43,381	w_1	−0,00,062	β_1	0,77,165
w_2	0,09,576	w_2	−0,02,912	β_2	0,06,916
w_3	−0,26,261	w_3	0,00,119	β_3	−0,4257
w_0	−24,8344	w_4	−0,00,028	β_0	−45,107
		w_5	0,03,538		
		w_6	−0,02,022		
		w_7	−0,00,126		
		w_8	0,002,978		
		w_9	−0,03,756		
		w_0	−3,66,449		

Table 5 Population–TDRL–Number of Vehicle calculated coefficient values

Population–TDRL–number of vehicle (T = 3)					
Jaya-L		Jaya-Q		MLR	
w_1	−0,52,064	w_1	−0,17,836	β_1	−1,44,317
w_2	1,02,777	w_2	4,88,604	β_2	1,127,616
w_3	−0,30,169	w_3	0,08,141	β_3	0,554,821
w_0	35,18,502	w_4	−0,06,818	β_0	88,2187
		w_5	−0,00,898		
		w_6	0,06,728		
		w_7	0,00,178		
		w_8	−0,00,129		
		w_9	0,00,560		
		w_0	6,18,123		

Table 6 Population–GDP–TDRL–Number of Vehicle calculated coefficient values

Population–GDP–TDRL–number of vehicle (T = 4)					
Jaya-L		Jaya-Q		MLR	
w_1	−0,8,147,237	w_1	0,010,762	β_1	−1,5,487,194
w_2	−0,0,161,332	w_2	0,056,638	β_2	−0,0,084,574
w_3	0,9,611,234	w_3	1,411,393	β_3	1,15,275,699
w_4	0,227,884	w_4	0,011,253	β_4	0,68,657,524
w_0	51,177,946	w_5	−0,002,439	β_0	94,1,736,498
		w_6	−0,001,617		
		w_7	0,0096		
		w_8	−0,003,401		
		w_9	−0,004,469		
		w_{10}	0,005,006		
		w_{11}	−0,008,143		
		w_{12}	0,001,643		
		w_{13}	−0,003,618		
		w_{14}	0,005,529		
		w_0	28,19,708		

results of the Jaya-L, Jaya-Q models, and the MLR method. Estimation numbers of the Jaya-L model dropped in 2013 and 2014. Between 2013 and 2016, drops can be observed in the estimations of the Jaya-Q model. It is seen that there is a continuous decrease in the estimation results of the MLR method between 2013 and 2018. Jaya-L model estimation results increased a little between 2015 and 2017 but decreased in 2018. Similarly, the results of the Jaya-Q model increased a little in 2017, and they were very close to the realized value in 2018.

In Fig. 2, it is seen that the number of accidents that occurred reached a peak in 2015. This situation can be explained by the price changes in a barrel of oil between 2014 and 2015 [41]. While the average price of a barrel of oil in 2014 was 98.97 $, it dropped to 52.37 $ in 2015 [41]. This means that there was a decrease in the price of a barrel of oil by approximately 47%. Similarly, as given in Table 1, while the total number of vehicles sold was around 888 thousand on average in previous years, it climbed to

Table 7 For different indicators, HANE results calculated according to years with MLR method, AEM, the proposed Jaya-L and Jaya-Q models

Years		Number of accidents that occurred (10^5)	Population–number of vehicle (T = 2) (10^5)				Population–GDP–number of vehicle (T = 3) (10^5)			Population–TDRL–number of vehicle (T = 3) (10^5)		
			Jaya-L	Jaya-Q	MLR	AEM	Jaya-L	Jaya-Q	MLR	Jaya-L	Jaya-Q	MLR
Training	2002	4.39777	5.6452	3.8162	5.6841	4.4075	3.9812	4.6619	4.0944	4.2111	3.8265	4.0053
	2003	4.55637	6.0701	4.0975	6.2204	4.5852	4.9224	4.5925	5.0363	4.9639	4.5581	4.4411
	2004	5.37352	6.5335	5.6102	6.5385	5.7053	5.8575	5.7412	5.8142	5.9093	5.8041	5.8652
	2005	6.20789	6.9959	6.5512	6.9615	6.5023	6.9128	6.6004	6.7513	6.4319	6.5372	6.5030
	2006	7.28755	7.4495	7.5690	7.3289	7.5016	7.4909	7.4941	7.3077	7.2067	7.6042	7.5613
	2007	8.25561	7.8773	8.2648	7.7318	8.2543	8.8009	8.6890	8.4236	7.8843	8.4425	8.3294
	2008	9.5012	8.4501	8.9043	8.3525	8.9544	9.8879	9.9708	9.4917	8.6659	9.1993	8.9727
	2009	10.53346	9.0398	9.3967	9.0450	9.4626	9.0307	9.2656	9.2008	10.0715	10.2420	10.1312
	2010	11.06201	9.7371	10.0418	9.8319	10.2091	10.5654	10.6427	10.6754	11.6465	11.3478	11.5029
	2011	12.28928	10.2878	10.7194	10.3582	11.2303	11.3187	11.5043	11.4432	12.2752	12.0258	12.2011
	2012	12.96634	10.7790	11.2799	10.8132	12.2300	11.8583	12.0601	12.0226	12.4674	12.3901	12.4633
	2013	12.07354	11.3375	11.7854	11.3725	13.1972	12.7877	13.1114	12.9383	12.5840	12.5278	12.5219
	2014	11.9901	11.9612	12.2587	12.0280	14.1514	12.8744	12.8616	13.2951	12.2611	12.1602	11.9962
Testing	2015	13.13359	12.4968	12.6586	12.4897	15.4803	12.2897	12.0606	13.0560	11.9273	12.2713	11.7906
	2016	11.82491	13.1023	12.9841	13.0676	16.7386	12.5167	12.1058	13.4654	11.7680	12.2983	11.6276
	2017	12.02716	13.6411	13.1678	13.5433	18.0790	12.5483	12.0348	13.6802	11.6017	12.4966	11.5728
	2018	12.29364	14.3692	13.5011	14.4068	18.7649	12.1332	12.6341	13.7914	11.3890	11.6063	10.8400

Table 8 HANE results from 2002 to 2018 according to Population–GDP–TDRL–Number of Vehicle (T = 4) indicators

Years		Number of accidents that occurred (10^5)	Estimated number of accidents (10^5)			Difference (10^5) (occurred–estimated)			Relative error (difference/occurred) (%)		
			Jaya-L	Jaya-Q	MLR	Jaya-L	Jaya-Q	MLR	Jaya-L	Jaya-Q	MLR
Training	2002	4.39777	4.4732	4.0545	4.0421	0.07543	−0.34327	0.3557	1.7152	−7.8055	8.0882
	2003	4.55637	4.956	4.2995	4.4039	0.39963	−0.25687	0.1525	8.7708	−5.6376	3.347
	2004	5.37352	6.0714	5.6699	5.8735	0.69788	0.29638	−0.4999	12.9874	5.5156	−9.303
	2005	6.20789	6.5894	6.2472	6.49	0.38151	0.03931	−0.2821	6.1456	0.6332	−4.5442
	2006	7.28755	7.5012	7.4436	7.5947	0.21365	0.15605	−0.3071	2.9317	2.1413	−4.214
	2007	8.25561	8.0861	8.2449	8.3134	−0.16951	−0.01071	−0.0577	−2.0533	−0.1297	−0.6989
	2008	9.5012	8.7249	9.101	8.9113	−0.7763	−0.4002	0.5899	−8.1705	−4.2121	6.2087
	2009	10.53346	10.1858	10.3168	10.1894	−0.34766	−0.21666	0.3441	−3.3005	−2.0569	3.2667
	2010	11.06201	11.4572	11.5102	11.4889	0.39519	0.44819	−0.4269	3.5725	4.0516	−3.8592
	2011	12.28928	12.1264	12.2317	12.1967	−0.16288	−0.05758	0.0925	−1.3254	−0.4685	0.7527
	2012	12.96634	12.4256	12.5643	12.4764	−0.54074	−0.40204	0.4899	−4.1703	−3.1006	3.7782
	2013	12.07354	12.5453	12.7739	12.5063	0.47176	0.70036	−0.4328	3.9074	5.8008	−3.5847
	2014	11.9901	12.3626	12.2985	12.0081	0.3725	0.3084	−0.018	3.1067	2.5721	−0.1501
Testing	2015	13.13359	12.4372	12.2764	11.9267	−0.69639	−0.85719	1.2069	−5.3024	−6.5267	9.1894
	2016	11.82491	12.4802	12.2728	11.8069	0.65529	0.44789	0.018	5.5416	3.7877	0.1522
	2017	12.02716	12.5902	12.4559	11.8216	0.56304	0.42874	0.2056	4.6814	3.5648	1.7095
	2018	12.29364	12.4492	12.3885	11.1282	0.15556	0.09486	1.1654	1.2654	0.7716	9.4797

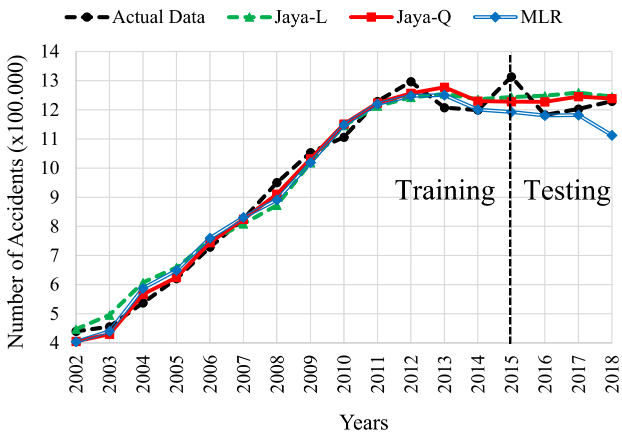

Fig. 2 Curve of the number of accidents that occurred between 2002 and 2018 for the proposed Jaya-L and Jaya-Q models and MLR method according to Population–GDP–TDRL–Number of Vehicle (T = 4) indicators

about 1 million 165 thousand in 2015. In Table 1, it is seen that 2015 was the year in the second place in terms of the increase in the number of vehicles in traffic compared to previous years. Parallel to the growth in the number of vehicles as a result of the significant decline in the price of oil in 2015, vehicle mobility on highways increased, resulting in an extraordinary increase in the number of accidents, as shown in Fig. 2.

Regarding the test data set between 2015 and 2018, it is seen that while the estimation values of Jaya-L and Jaya-Q models were close the each other, the proposed models yielded closer estimation values to the number of accidents that occurred in 2018. There were serious deviations in the MLR method in the test data sets according to the number of accidents occurring in 2015 and 2018. In this context, it is seen that according to the test data sets, both RMSE values in Table 2 and estimation results of the MLR method in Fig. 2 are not good.

The increases and decreases in the number of accidents that occurred between 2012 and 2018 in Fig. 2 and the increases and decreases observed in the estimations of the proposed Jaya-L and Jaya-Q models show that the models proposed by the Jaya algorithm did not memorize and that the estimation results were consistent. The continuous increases until 2012 and continuous decreases after 2012 in the MLR method indicate that it memorized to make estimations and that it did not make consistent estimations. Also, Fig. 2 shows that the Jaya-Q model proposed for training and test data set made better estimations of the number of accidents that occurred than the Jaya-L model and MLR method. In Table 9, the estimation results of study with DE algorithm and comparative test results of MLR method, AEM, the proposed Jaya-L and Jaya-Q models are given.

In Table 9, RMSE values in the estimation results of Jaya-L and Jaya-Q models were calculated to be lower than DE-Linear [34] model. In DE-Linear [34] model, population and the number of vehicles were used as entry parameters. Although the AEM method gives good results in training, it is seen in Table 9 that the min RMSE value is quite high in testing. It is seen that the four indicators used in the proposed Jaya-L and Jaya-Q models and MLR method yielded both better training results and better test results. This situation shows that as the number of indicators increases, the training of the proposed models and, therefore, their estimation results are better.

5 Scenarios and hane

5.1 Creating scenarios

In the study, after the trial and test work obtained from Jaya-L and Jaya-Q models, scenarios were created. In this respect, with low, expected, and high scenarios, accident number estimation was made for the period between 2019 and 2030. In the expected scenario, for the population indicator, the main population scenario of TSI for the period of 2019–2030, and for GDP, 4.3%, which is the growth rate determined by the Republic of Turkey Presidential Strategy and Budget Directorate in the 11th Development Plan (2019–2023), was taken, and the changes in the period between 2015 and 2018 were taken as [42] TDRL and number of vehicles test data values. For the expected scenario, the increase rates in TDRL and the number of vehicles were taken as 2.7% and 5%, respectively. In the low scenario, for population, the low population scenario of TSI (2020) between 2019 and 2030 was taken, while for GDP, TDRL, and the number of vehicles, one basis point lower than the expected scenario was taken. In the high scenario, for population, the high population scenario of TSI (2020) for 2019–2030, GDP, TDRL, and the number of vehicles, one basis point higher than the expected scenario was taken. The scenarios proposed are given in Table 10.

5.2 HANE between 2019 and 2030

Calculated with low, expected, and high scenarios in Table 10, w_{Jaya-L} weight values were applied to the Jaya-L model proposed in Eq. 12, w_{Jaya-Q} weight values to Jaya-Q model proposed in Eq. 13, and β_{MLR} weight values to MLR method in Eq. 14. Estimation values for the period between 2019 and 2030 were calculated as in Table 11. Estimation graphs formed according to the proposed Jaya-L and Jaya-Q models and MLR method in the low scenario in Fig. 3,

Table 9 Comparison of the proposed Jaya-L and Jaya-Q models with the results of MLR, AEM, and DE [34]

Years	Number of accidents that occurred (10^5)	DE-Linear [34] (10^5)	Jaya-L (10^5)	Jaya-Q (10^5)	MLR (10^5)	AEM (10^5)
2015	13.13359	14.15052	12.4372	12.2764	11.9267	15,4803
2016	11.82491	15.16466	12.4802	12.2728	11.8069	16,7386
2017	12.02716	15.90167	12.5902	12.4559	11.8216	18,0790
2018	12.29364	16.91915	12.4492	12.3885	11.1282	18,7649
	RMSE	3.485514567	0.560291	**0.531074**	0.84528	5,19,985

Table 10 Low, expected, and high scenarios proposed for HANE

Scenarios	Population	GDP (%)	TDRL (%)	Number of Vehicles (%)
Low	Obtained from TSI data (TSI, 2020)	3.3	1.7	4
Expected		4.3*	2.7	5
High		5.3	3.7	6

*Obtained from TEDP [42]

Table 11 HANE results for the period between 2019 and 2030

Years	Accident number estimation								
	Low (10^5)			Expected (10^5)			High (10^5)		
	Jaya-L	Jaya-Q	MLR	Jaya-L	Jaya-Q	MLR	Jaya-L	Jaya-Q	MLR
2019	12.52985	12.54442	11.28195	12.61017	12.58252	11.34038	12.69028	12.61900	11.39842
2020	12.39724	12.35566	11.03656	12.67112	12.61422	11.36774	12.95015	12.87611	11.70683
2021	12.28456	12.20533	10.83564	12.76603	12.70564	11.46549	13.26406	13.22134	12.12111
2022	12.19240	12.09630	10.68068	12.89618	12.86183	11.63662	13.63451	13.66304	12.64669
2023	12.12128	12.03143	10.57306	13.06278	13.08806	11.88403	14.06400	14.21008	13.28913
2024	12.08142	12.03041	10.53259	13.27684	13.40691	12.22927	14.56494	14.88931	14.07284
2025	12.07380	12.09753	10.56156	13.54013	13.82568	12.67641	15.14061	15.71268	15.00493
2026	12.09954	12.23746	10.66252	13.85463	14.35236	13.22988	15.79451	16.69332	16.09307
2027	12.15980	12.45511	10.83813	14.22238	14.99545	13.89434	16.53035	17.84548	17.34535
2028	12.25573	12.75548	11.09105	14.64545	15.76389	14.67452	17.35193	19.18444	18.77011
2029	12.38844	13.14367	11.42390	15.12590	16.66704	15.57519	18.26313	20.72662	20.37599
2030	12.55895	13.62474	11.83911	15.66574	17.71458	16.60106	19.26785	22.48951	22.17174

in the expected scenario in Fig. 4, and in the high scenario in Fig. 5 are presented.

In the low scenario, the number of accidents estimated with the Jaya-L model decreased in the period between 2019 and 2025, while it increased between 2026 and 2030. While the number of accidents estimated with the Jaya-Q and MLR method decreased between 2019 and 2024, it had an increasing tendency between 2026 and 2030. The decreases and increases in the MLR method are at a lower level compared to the proposed Jaya-L and Jaya-Q models, as shown in Fig. 3. In 2030, accident number estimations of Jaya-L and Jaya-Q models were about 1.26 million and 1.36 million, respectively.

It is seen in Fig. 4 that in the expected scenario, the increase in the number of accidents continued in Jaya-L and Jaya-Q models and MLR method proposed according to the expected scenario for the data on GDP, TDRL, and the number of accidents belonging to the scenario proposed for HANE in Table 10. It is seen that accident number estimation constantly increases in Jaya-L and Jaya-Q models and that the number of accidents estimated is between 1.56 million and 1.77 million by the end of 2030.

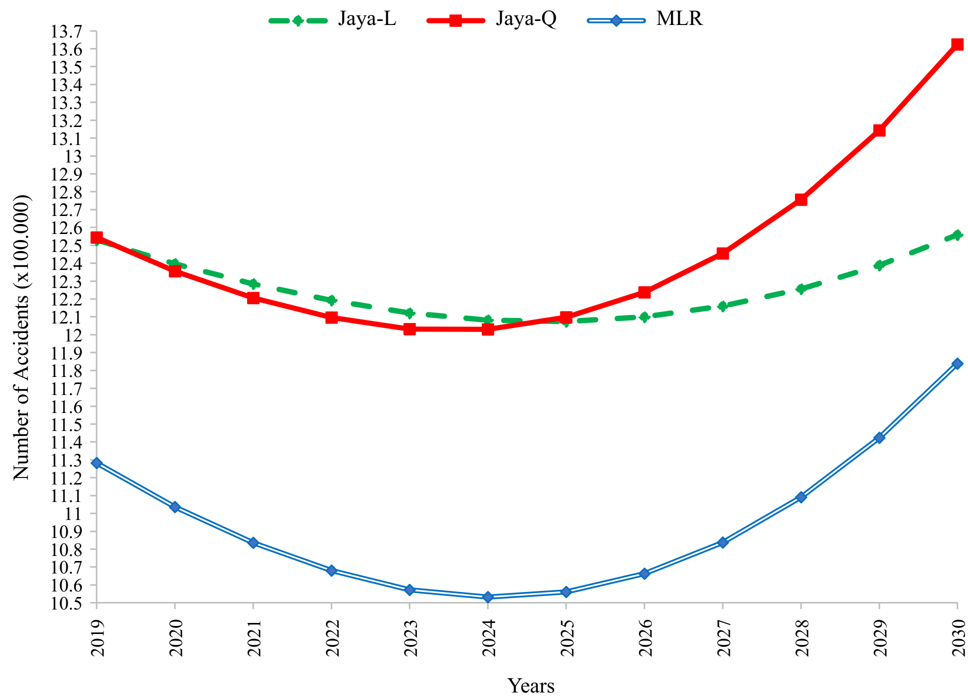

Fig. 3 Accident number estimation graph in Jaya-L and Jaya-Q models and MLR method according to the low scenario

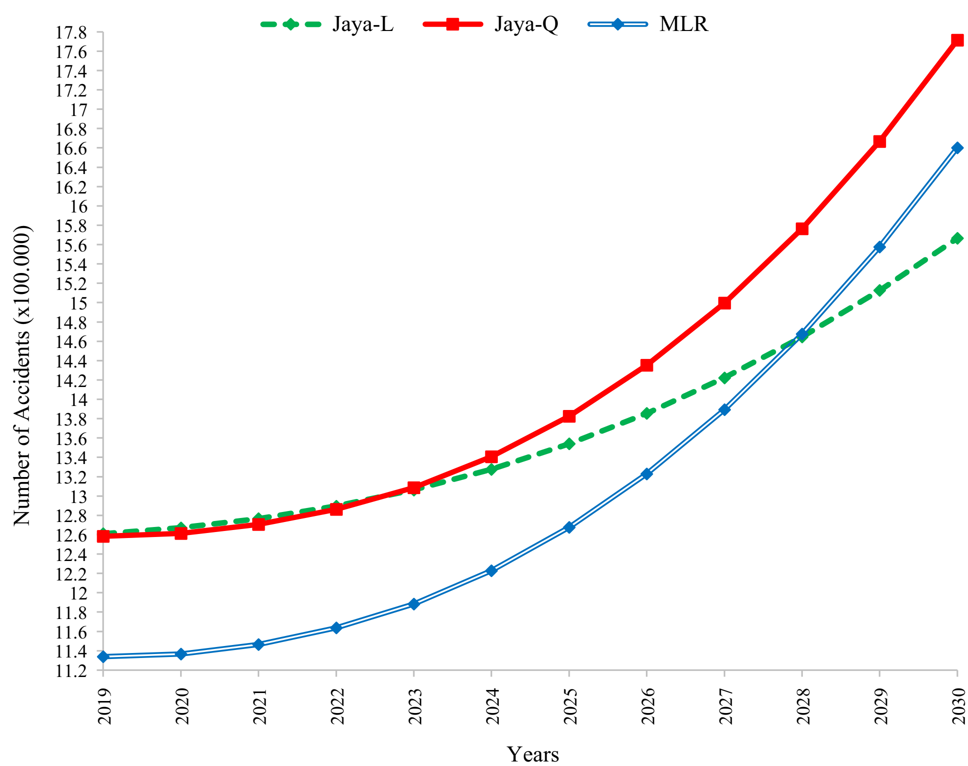

Fig. 4 Accident number estimation graph in Jaya-L and Jaya-Q models and MLR method according to the expected scenario

In Fig. 5, it is seen that in the high scenario, the number of accidents continues to increase by 300–400 thousand on average annually according to Jaya-L and Jaya-Q models proposed according to the high scenario in the case that GDP, TDRL, and the number of accidents, which are among the data belonging to the scenario proposed for HANE in Table 10, increase by 1% of the expected increase. Figure 5 shows that according to the high scenario, accident number estimation values for 2030 are between 1.92 million and 2.24 million in Jaya-L and Jaya-Q models.

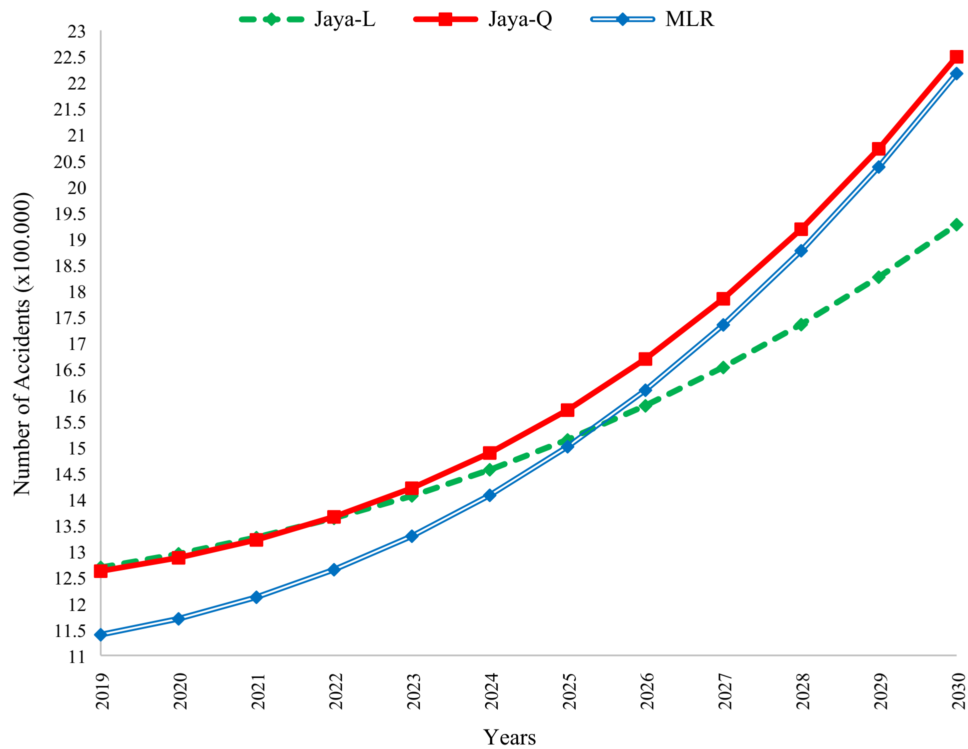

Fig. 5 Accident number estimation graph in Jaya-L and Jaya-Q models and MLR method according to the high scenario

6 Conclusion

A great increase in the number of accidents occurring on the highways in Turkey has been observed in recent years. Most of the accidents occurring on highways cause deaths and injuries as well as material damage. In order to minimize the number of accidents that may occur on highways, it is necessary to make accurate, consistent, effective, and reliable accident number estimations by using previous data to be able to determine future plans and programs. Highway accident number estimation plays an important role in terms of policymakers and decision-making authorities of countries to forecast the number of accidents and take precautions accordingly.

In the study, for highway accident number estimation (HANE), a meta-heuristic Jaya optimization algorithm, which does not contain any parameters specific to the algorithm and can be easily adapted to problems, was used. For estimation, Jaya-linear (Jaya-L) and Jaya-quadratic (Jaya-Q) models were proposed. In order to compare the results of the proposed Jaya-L and Jaya-Q models, the multiple linear regression (MLR) method, which is frequently used in accident number estimation in the literature, was employed. For HANE, the indicators of population, gross domestic product (GDP), total divided road length (TDRL), and the number of vehicles between 2002 and 2018 were used. The proposed Jaya-L and Jaya-Q models and MLR methods were trained with the data between 2002 and 2014 and were tested with the data between 2015 and 2018. A purpose function that minimizes the root-mean-square of errors (RMSE) was used for training and testing. Each model was run 30 times for training, and the min RMSE value was taken as the result. Indicators used for accident estimation were calculated in four different cases, respectively, Population–Number of Vehicle, Population–GDP–Number of Vehicle, Population–TDRL–Number of Vehicle, and Population–GDP–TDRL–Number of Vehicle. It has been determined that the min RMSE values of the Population–GDP–TDRL–Number of Vehicle indicators are suitable and usable for these four different cases.

In the training results, the min RMSE value was calculated as 0.432561 for the Jaya-L model, and the min RMSE value of the Jaya-Q model was calculated to be 0.334694. Min RMSE value in the training results of the MLR method was calculated as 0.35753. In this context, it is seen that the success of the Jaya-Q model was better than those of the Jaya-L model and MLR method. Based on the successful training results, weight values for Jaya-L and Jaya-Q models and the MLR method were determined. Weight values determined in each model at the training stage were placed in their positions, and testing results were obtained. In the testing results, the min RMSE value of the Jaya-L model was calculated as 0.560291, the min RMSE value of the Jaya-Q model as 0.531074, and the min RMSE value of the MLR method as 0.84528. According to the testing results, it was determined that the min RMSE value of the Jaya-Q model was better than that of the Jaya-L model and that the Jaya-L model was better than the MLR method in this respect. Thus, it is seen that the estimations made with the proposed Jaya-L and Jaya-Q models were more consistent, accurate, and reliable compared to estimations made with the MLR method. From the successful training and testing results, scenarios were created for accident number estimation.

By designing low, expected, and high scenarios for HANE, the number of accidents was estimated for the period between 2019 and 2030. In the low scenario, it is seen that the number of accidents first decreases and then increases again that there is a certain amount of increase in the number of accidents per year in the expected scenario, and that the number of accidents significantly increases in the high scenario. The years in which HANE has a tendency to decrease in the low scenario, Jaya-L, and Jaya-Q models and MLR the method show that the number of accidents can be reduced. According to the expected and high scenario estimation results, although TDRL increased, the number of accidents continued to increase due to the increase in GDP and the number of vehicles. In this case, the prices and figures paid in the current accidents today will continue to increase every passing year.

In this study, Population–GDP–TDRL–Number of Vehicles indicators were used for the first time for accident estimation using the Jaya algorithm. Unlike the accident estimation models developed by Andreassen, linear and quadratic models were proposed for HANE. In this context, these indicators can be used in future studies, and also by adding different indicators and adapting them to linear and quadratic models, accident number estimation can be made. For example, different indicators can be created for HANE, and the results can be analyzed for indicators such as seasonal conditions, gender, age groups, accidents occurring according to vehicle classes, and time zones during the day and road conditions. In addition, by using different meta-heuristic algorithms related to these indicators and the proposed linear and quadratic models, estimation results can be improved.

Author contribution Mehmet Fatih Tefek involved in conceptualization, methodology, investigation, validation, and writing–original draft. Muhammed Arslan involved in conceptualization, methodology, data curation, supervision, writing–review and editing.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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