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AN ARTIFICIAL INTELLIGENT APPROACH TO TRAFFIC ACCIDENT ESTIMATION: MODEL DEVELOPMENT AND APPLICATION

Ali Payıdar Akgüngör[1], **Erdem Doğan**[2]

Dept of Civil Engineering, Kirikkale University, 71451 Kirikkale, Turkey
E-mails: [1]aakgungor@yahoo.com; [2]erdemdogan71@gmail.com

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Abstract. This study proposes an Artificial Neural Network (*ANN*) model and a Genetic Algorithm (*GA*) model to estimate the number of accidents (*A*), fatalities (*F*) and injuries (*I*) in Ankara, Turkey, utilizing the data obtained between 1986 and 2005. For model development, the number of vehicles (*N*), fatalities, injuries, accidents and population (*P*) were selected as model parameters. In the ANN model, the sigmoid and linear functions were used as activation functions with the feed forward-back propagation algorithm. In the GA approach, two forms of genetic algorithm models including a linear and an exponential form of mathematical expressions were developed. The results of the GA model showed that the exponential model form was suitable to estimate the number of accidents and fatalities while the linear form was the most appropriate for predicting the number of injuries. The best fit model with the lowest mean absolute errors (*MAE*) between the observed and estimated values is selected for future estimations. The comparison of the model results indicated that the performance of the ANN model was better than that of the GA model. To investigate the performance of the ANN model for future estimations, a fifteen year period from 2006 to 2020 with two possible scenarios was employed. In the first scenario, the annual average growth rates of population and the number of vehicles are assumed to be 2.0 % and 7.5%, respectively. In the second scenario, the average number of vehicles per capita is assumed to reach 0.60, which represents approximately two and a half-fold increase in fifteen years. The results obtained from both scenarios reveal the suitability of the current methods for road safety applications.

Keywords: accident prediction model, artificial neural network (ANN), genetic algorithm, injury, Ankara.

1. Introduction

Growing population, economic development and the rise of living standards have caused an increase in the number of vehicles and traffic accidents. Today, due to traffic accidents, injuries and fatalities have become a major public health and socio-economic problem in Turkey. Unfortunately, about four thousand people lose their lives every year in traffic accidents and as many as one hundred and thirty five thousand people are injured countrywide. These figures are much higher than those of European countries. This is due to the fact that freight and passenger traffic is not shared proportionally among transportation systems and mostly concentrates on highway transportation. More specifically, 95% of freight and passengers are transported on highways while only 4% of them use railways and the remaining demands are shared by airways and maritime. Another reason behind traffic accidents is an unpredictably rapid increase in the number of motorized vehicles. Considering the general situation of the country during the period of 1986–2005, the population has grown in approximately by 38% and has increased from 52 to 72 million. During the same period, the number of vehicles has increased in about 294% reaching 10.5 million.

Reviewing the above introduced situation at city level for the same period, the highest increase in the number of vehicles occurred in Ankara, the capital city of Turkey. While an increase in the population of the city has been 47%, the number of vehicles has increased by 304% during the same period. The number of vehicles per one thousand persons in Ankara sharply increased from 88 in 1986 to 242 in 2005. Today, the highest vehicle ownership ratio in Ankara makes 0.24 in Turkey. For this reason, this paper refers to the city of Ankara which is selected to develop accident prediction models.

The number of traffic accidents in any country depends on various factors such as population, the number of vehicles, road geometry, driver's behavior and vehicle characteristics. Therefore, traffic accident prediction models are developed including certain parameters to represent the effect of these factors. Thus, the

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existing conditions are investigated and received results are evaluated by accident prediction models. The outputs are utilized to improve the existing conditions and to determine new traffic safety strategies for the future. Literature points to different analytical accident prediction models that have been presented using various assumptions and techniques. Recently, in addition to analytical methods in modelling engineering, artificial intelligent (neural network and genetic algorithm) approaches have been used to provide rich, powerful and robust modelling in transportation engineering and road safety applications. Using the Artificial Neural Network (ANN) approach, Kalyoncuoglu and Tigdemir (2004) investigated the relationship between driver characteristics (i.e. age, gender, education, driving experience and driving time per day) and the number of drivers involved in traffic accidents. Using ANN, Miao and Xi (2008) studied the quantitative forecasting method of agile forecasting logistics demand for a dynamic supply chain environment. Basu and Maitra (2006) applied their models to modelling stream speed in the heterogeneous traffic environment using ANN-lessons learnt. Manik *et al.* (2008) applied their ANN models to simulating payment risk in pavement construction. Blinova (2007) analysed the possibility of using the neural network to forecast passenger traffic flows in air transport in Russia. Faghri and Hua (1995) used the ANN model to estimate the average annual daily traffic including seasonal factors and comparing its performance with clustering and regression methods. They pointed out that the neural network model yielded better results than the other two approaches. Murat and Ceylan (2006) developed an ANN transport energy demand model for Turkey using relevant data collected between 1970 and 2001 to estimate transportation energy demand for the country with different scenarios until 2020. Wang (1998) developed ANN and regression models to estimate the traffic emission rates of CO, HC and NO_x. The author showed that the ANN model produced lower average relative variances. Ivan and Sethi (1998) used ANN with the back-propagation (BP) algorithm for traffic incident detection. Similarly, the ANN approach with BP was employed by Sayed and Abdulwahab (1998) to classify road accidents in order to improve the situation on the roads.

Besides ANN, GAs has also been adapted for a large number of applications in road safety engineering. The GA approach was employed to analyze driver's behavior in collision avoidance (Nagai *et al.* 1997), optimal transport safety planning with accident estimation process (Akiyama *et al.* 2000), highway design (Jong *et al.* 2000), the optimization of passenger car design for mitigating pedestrian head injury (Carter *et al.* 2005) and developing driver fatigue detection system (Jin *et al.* 2007).

The main objective of this study is to develop models for the future estimates of the number of accidents, fatalities and injuries in Ankara, Turkey applying ANN and GA approaches. Two different scenarios are proposed to provide a guideline for decision makers for new road safety strategies. The utility of ANN and GA approaches are also investigated.

2. Artificial Intelligent Approach

2.1. Artificial Neural Network

An artificial neural network is a computational model based on biological neural networks to overcome the limitations of conventional approaches to solve complex problems. In the late 1940s, Donald Hebb introduced Hebbian learning rule which is one of the fundamental learning rules for ANNs. Some other researchers such as Hopfield (1982), Kohonen (1988) and Rumelhart and McClelland (1986) developed various learning rules and network architectures. The ANN consists of an interconnected group of artificial neurons and processes information using the connectionist approach to computation. An artificial neuron is a computational model inspired in the natural neurons receiving signals through synapses located on dendrites. When the received signals are strong enough, the neuron is activated and emits a signal through the axon. This signal may be sent to another synapse and may activate other neurons. The complex structure of biological neurons is simplified with artificial neurons. An artificial neuron incorporates weights, summing function, bias and activation function. The structure of an artificial neuron is illustrated in Fig. 1. An artificial neuron is a basic operating unit to constitute the ANN. It basically consists of three layers, namely input, the hidden layer and output. The input layer consists of all input factors. Information from the input layer is then processed with one or more hidden layers acting as intermediate layers between the input and output layers. The neurons are joined together by weighted connections, then, the output vector is computed in the output layer.

In a neural network, the first important stage is training step input in which is introduced to the network together with desired outputs. The purpose of training is to minimize the global error level such as mean square error (MSE), mean absolute percent error (MAPE) and root mean square error (RMSE). Artificial neural networks typically start with randomized weights for all their neurons. This means that they do not know anything and must be trained to solve a particular problem for which they are intended. When a satisfactory level of performance is reached, training is ended and the network uses these weights to decide. The model of multi-layer perception (MLP) networks is usually preferred in engineering applications because many learning algorithms might be used in MLP. One of the commonly used learning algo-

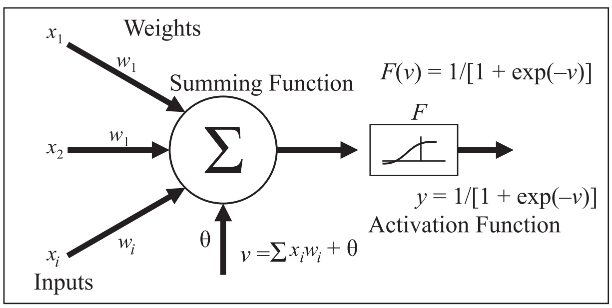

Fig. 1. An artificial neuron

rithms in ANN applications is the back propagation algorithm (BP) which is also applied in this research. The idea of the back propagation algorithm is to reduce errors which are the difference between observed and expected results until the ANN learns data on training. An activation function is a mathematical function used to transform the activation level of a neuron into an output signal and to obtain increased computational power from multiple neurons. This function must be differentiable and continuous. Linear, sigmoid and hyperbolic tangent functions are the most common activation functions used in literature. An activation function is used as a boundary of output. These boundary levels usually change from zero to one [0, 1] or from minus one to plus one [–1, +1] according to the type of the activation function used.

2.2. Genetic Algorithm

Genetic Algorithms are adaptive methods that may be used to solve the problems of search and optimization. They are based on the genetic process of biological organisms that are explained by the principles of natural selection and survival of the fittest ones. If suitably encoded, GAs can be used to solve real world problems by mimicking this process. GAs substantially differ from traditional optimization methods searching for the population of points in parallel rather than a single point to obtain the best solution. Therefore, they provide several potential solutions to a given problem and the choice of the final solution is left to the user. Holland (1992) was first to introduce the main principles of Gas. Some authors, including Goldberg (1989), Mitchell (1998), Gen and Cheng (1997) and Coley (1997) clarified the further concepts of GAs that later have been widely used as an alternative method in working towards a solution to the problems of engineering.

The genetic algorithm initiates the search for finding the optimum in a discrete space by randomly selecting some individuals at the first stage and collecting together to constitute the initial population at the second. Each individual in a population is called an artificial chromosome which can be encoded as a binary string with constant length. Each chromosome signifies a point in a discrete space and is subject to random change mutation. The next generation is produced by selecting individuals from the current one based on their fitness which is a measure of how individuals perform in the problem domain. The individuals having very high fitness are more frequently selected, and therefore following some generations, the population consists of the individuals of very high fitness representing a feasible solution to the problem of optimization. The genetic algorithm applies three operators including reproduction, crossover and mutation to the initial population to generate a new population. A detailed explanation of these operators is given by (Beasley *et al.* 1993; Ceylan and Bell 2004; Kameshki and Saka 2007).

During the reproduction stage of the GA, most fit individuals are selected from the population according to some individual selection operators such as roulette wheel and tournament selection, recombined and produced offspring. The selection operator chooses the individuals from the initial population for mating according to their fitness value. In case the value of an individual in the population is great enough, the individual most probably participates in the operation, i.e. the fitness value corresponds to the number of offsprings that an individual can expect to produce in the next generation. More fit individuals of the population can participate more than once, while less fit individuals may be suppressed which leads to an increase in average fitness. In this study, the roulette wheel selection method is used as a selection operator due to probabilistically selected individuals based on some measure of their performance.

Crossover is the exchange of chromosomes between two individuals. This operation consists of some steps that select two mating parents randomly choosing two sites on each of the chromosomal strings and swapping the strings between the sites among the pair. Thus, parents create offsprings having different genetic structures that include some mix of their chromosomes set. An illustration of the crossover operation is as follows:

	Crossover Point ⇓	Crossover Point ⇓
Parents	10101110 1010101	<u>10001011 1101010</u>
Offspring	10101110 <u>1101010</u>	<u>10001011</u> 1010101

The crossover process is repeated from one generation to another until one individual dominates the population or until the predetermined numbers of generations are reached. On the other hand, crossover is not usually applied to all pairs of individuals selected for mating. A random choice is made where the probability of crossover being applied typically varies from 0.4 to 0.95. The mutation is a random process where one allele of a gene is replaced by another to produce a new genetic structure. Mutation operator serves a crucial role in GAs either by replacing the genes lost from the population during the selection process or providing the genes that are not in the initial population. In GAs, mutation is randomly applied with a small probability which is typically in the range between 0.001 and 0.01 and modifies genes in the chromosomes. The effect of mutation on a binary string is illustrated as follows:

Offspring	10101110 1101010
Mutated Offspring	10101110 0101010

3. Artificial Intelligent Models

3.1. The Neural Network Models

In this study, population (P) and the number of vehicles (N) are taken as input parameters due to Smeed's law and practical considerations. More specifically, they are easy to obtain from the official database but other parameters such as driver, road and environmental factors need to be obtained from observations and/or measurements which are generally costly. Also note that this specific model is constructed for the whole city not for a road segment or a region. To develop the models, the historical input data (i.e., P and N) has been collected from Turkish Statistical Institute (Road Traffic Accident Statistics 2005) while the recorded output parameters (i.e., F, I, and A) are gathered from the General Directorate of Public Security (2005).

Three different ANN models were developed to estimate the output variables for Ankara. The Sigmoid and linear function respectively were employed in the hidden and output layers of the networks. Various network architectures were tested to develop the models. The network architecture with 2–5–1 was determined to be the most suitable for this study as shown in Fig. 2. The back-propagation algorithm has been applied to determine errors and modification for the weight of the hidden layer neurons. To avoid undesirably long training time or network being trapped in local error minima, various learning rates have been tried. All data has been normalized between 0.1 and 0.9. In the ANN model, the data between 1986 and 2000 was used for training while the data between 2001 and 2005 was used for testing.

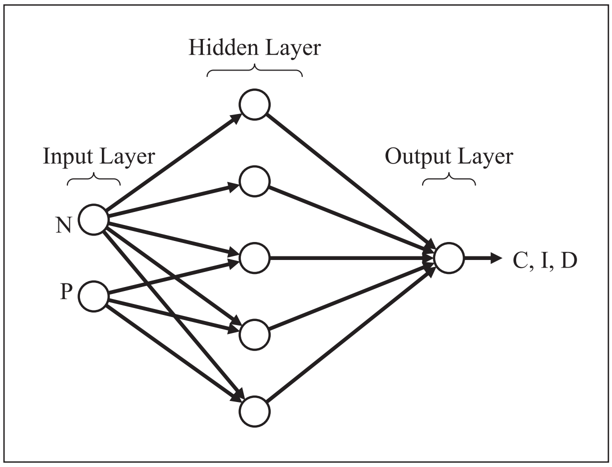

Fig. 2. Architecture of network for accident, injury and fatality

3.2. The Genetic Algorithm Models

In this study, genetic algorithm accident (GAAM), genetic algorithm injury (GAIM) and genetic algorithm fatality (GAFM) prediction models have been proposed for Ankara. During the process of developing these models, P and N have been selected as independent variables. Two different forms of GAAM, GAIM and GAFM including linear and exponential ones were developed among which the best fit models have been obtained in terms of mean square errors (MSE). The linear and exponential forms of GAAM, GAIM and GAFM models are given in Eq. (1) and Eq. (2), respectively.

$$\left.\begin{matrix} GAAM_{lin} \\ GAIM_{lin} \\ GAFM_{lin} \end{matrix}\right\} = w_1 + w_2 \cdot N + w_3 \cdot P, \qquad (1)$$

$$\left.\begin{matrix} GAAM_{\exp} \\ GAIM_{\exp} \\ GAFM_{\exp} \end{matrix}\right\} = w_1 \cdot N^{w_2} \cdot P^{w_3}, \qquad (2)$$

where w_1, w_2, and w_3 indicate corresponding weighting factors.

While developing the linear and exponential forms of GAAM, GAIM and GAFM models, probabilities for crossover (p_c) and mutation (p_m) were selected as 0.6 and 0.01, respectively, and the population size (pz) of 55 and the generation number (t) of 200 were determined as GA parameters.

After applying the GAAM, GAIM and GAFM models, the following equations for accident, injury and fatalities predictions are obtained based on relative errors and minimum mean absolute errors (MAE) between the observed and estimated data. Please, note that variables in Eqs. (3)–(8) are normalized between 0.1 and 0.9. Intervals for normalization ranged between 250.000 and 6.000.000 for P and N, between 16.000 and 200.000 for A, between 6.000 and 25.000 for I and between 100 and 600 for F as lower and upper boundaries.

For the number of accident prediction,

$$GAAM_{lin} = -0.208 + 0.776 \cdot P - 0.120 \cdot N, \qquad (3)$$

$$GAAM_{\exp} = 1.927 \cdot P^{0.300} \cdot N^{1.021}. \qquad (4)$$

For the number of injury prediction,

$$GAIM_{lin} = 0.045 + 0.152 \cdot P - 0.792 \cdot N, \qquad (5)$$

$$GAIM_{\exp} = 1.450 \cdot P^{1.183} \cdot N^{0.569}. \qquad (6)$$

For the number of fatality prediction,

$$GAFM_{lin} = 1.786 - 1.790 \cdot P - 0.671 \cdot N, \qquad (7)$$

$$GAFM_{\exp} = 0.048 \cdot P^{-1.819} \cdot N^{-0.563}. \qquad (8)$$

Similarly to the ANN model, the observed data of the first fifteen years, namely from 1986 to 2000 was used to estimate the weighting factors and the data obtained within the period from 2001 to 2005 was applied for testing the models. The relative errors between the observed and estimated data for the two forms of GA models are given in Table 1. Tables 1a–1c, the exponential model form estimates for the number of accidents and fatality provides better results than linear form estimates. On the other hand, the linear model form of GAIM produced relatively lower errors. MAE values were employed to determine the best performing model for accident, injury and fatality estimates. As shown in Table 2, the exponential model form includes both training and testing periods generating relatively lower MAE values for accident and fatality except injury estimates. Consequently, the exponential model form was used for accident and fatality, whereas the linear form was utilized for injury estimates.

Table 1a. A comparison of the results of the linear and exponential forms of GAAM model with the observed data for the testing period

Years	Number of Accidents (Observed)	$GAAM_{lin}$	Relative Errors (%)	$GAAM_{exp}$	Relative Errors (%)
2001	67 993	52 308	–23.06	62 118	–8.64
2002	68 055	53 939	–20.74	63 132	–7.23
2003	65 712	55 505	–15.53	64 993	–1.09
2004	74 272	56 916	–23.36	68 962	–7.14
2005	69 746	58 308	–16.39	73 168	4.90

Table 1b. A comparison of the results of the linear and exponential forms of GAIM model with the observed data for the testing period

Years	Number of Injuries (Observed)	$GAIM_{lin}$	Relative Errors (%)	$GAIM_{exp}$	Relative Errors (%)
2001	9 610	10 453	8.78	11 248	17.04
2002	9 566	10 522	9.99	11 427	19.45
2003	9 075	10 632	17.16	11 660	28.49
2004	10 136	10 845	6.99	12 026	18.65
2005	10 947	11 067	1.09	12 407	13.34

Table 1c. A comparison of the results of the linear and exponential forms of GAFM model with the observed data for the testing period

Years	Number of Fatalities (Observed)	$GAFM_{lin}$	Relative Errors (%)	$GAFM_{exp}$	Relative Errors (%)
2001	164	310	89	178	9.01
2002	189	299	58	174	–7.80
2003	127	287	125	169	33.12
2004	190	272	43	162	–14.61
2005	171	257	50	155	-8.89

Table 2. The MAE values of all proposed models

	Accident		Injury		Fatality	
	Train	Test	Train	Test	Train	Test
Exponential	7 614	4 049	1 091	1 887	81	37
Linear	10 375	13 760	862	837	89	117

4. Comparison of the Models and Selecting the Best Performance Model

MAE and root mean square errors (RMSE) defined in Eqs. (9) and (10) were utilized to evaluate the model performances. A comparison was made between the model estimates of ANN and GA models. Referring to Table 3, the study results indicate that the ANN approach produced much better estimates than GA models for the given training and testing periods. As shown in the same table, MAE and RMSE values in the testing period are usually smaller than those in the training period. The MAE and RMSE values of GA are almost twice higher that those of the ANN in training and testing periods for accident and fatality estimates. The MAE and RMSE values of both models are relatively close to each other in the training period of injury estimates, whereas the differences between them get proportionally high in the testing period. Therefore, the ANN models were used for future estimates based on various scenarios.

$$MAE = \frac{1}{n} \cdot \sum \left| t_j - o_j \right|, \tag{9}$$

$$RMSE = \sqrt{\left(\frac{1}{n} \cdot \sum_j \left| t_j - o_j \right|^2 \right)}, \tag{10}$$

where t is the actual value, o is the estimate value and n is the number of data.

Table 3. A comparison of errors in ANN and GA models for training and testing periods

Models	Accident				Injury				Fatality			
	MAE		RMSE		MAE		RMSE		MAE		RMSE	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
ANN	3 107	1 973	3 689	2 337	669	404	756	452	41	17	48	23
GA	7 614	4 049	8 612	4 453	862	837	1 171	1 180	81	37	92	93

5. Possible Scenarios of the ANN for Ankara

In this section of the study, two scenarios are considered to estimate *A*, *I* and *F* in Ankara until 2020, the time when Turkey is expected to be a full member of the European Union. These predictions can be useful for creating new plans and strategies to increase traffic safety in the capital city. In the first scenario, the historical growth rates of the population and the number of vehicles are considered 2.0% and 7.5% respectively for model estimations. In the second scenario, the growth rate of the population is still 2.0% while the vehicle ownership rate varies each year reaching up to 60% by 2020. It is expected to be two and a half-fold increase in fifteen years because Ankara has the highest average number of vehicles per capita among Turkish cities. This is consistent with the fact that the average vehicle ownership rate in the European Union ranges between 40% and 60%. The reader is referred to Tables 4 and 5 for data on population and motor vehicle used in the scenarios. For both scenarios, the ANN model estimates of the number of accidents, injuries and fatalities are tabulated in Table 6. The ANN models are able to catch an increasing trend for the number of accidents and injuries and a decreasing trend for the number of fatalities. The differences between the numbers of vehicles in both scenarios steadily increased in fifteen years. While this difference is around 83 000 vehicles in 2006, it increases four and a half-fold reaching up to about 385 000 vehicles. Although there is significant difference in the number of vehicles in the scenarios, the model estimates of the number of accidents, injuries and fatalities are found close to each other. As the study results indicate, by 2020, the estimated number of accidents, injuries and fatalities in Ankara will be about 175 000, 24 000 and 115 respectively.

Although this study covers data up to the year 2005, it was completed at the beginning of 2008. Therefore, it has been possible to compare the observed and estimated values for the years 2006 and 2007. According to the reports of the General Directorate of Public Security (2006, 2007), the number of accidents, injuries and fatalities were 84 794, 11 917 and 207 in 2006 and 93 153, 12 909 and 219 in 2007 respectively. As shown in Table 6, the observed number of accidents and injuries in these years fell in between those of Scenarios I and II. On the other hand, the observed fatality numbers are out of the estimated ranges by the scenarios. This may be due to other parameters such as driver's characteristics, seat belt usage and environmental factors which are not included in the models for the sake of common and practical usage.

Table 4. Variations in the number of population and vehicles used in the scenarios for Ankara

	Population	Motor vehicle number
Scenario I	2.0%	Historical trend: 7.5%
Scenario II	2.0%	Motor vehicle per capita: 0.60

Table 5. Predictions about the number of population and vehicles used in the scenarios for Ankara

Year	Population	Number of motor vehicles Scenario I	Number of motor vehicles Scenario II
2006	4 405 551	1 127 335	1 210 044
2007	4 493 662	1 211 885	1 306 248
2008	4 583 535	1 302 777	1 410 102
2009	4 675 206	1 400 485	1 522 212
2010	4 768 710	1 505 522	1 643 235
2011	4 864 084	1 618 436	1 773 881
2012	4 961 366	1 739 818	1 914 913
2013	5 060 593	1 870 305	2 067 159
2014	5 161 805	2 010 578	2 231 508
2015	5 265 041	2 161 371	2 408 924
2016	5 370 342	2 323 474	2 600 446
2017	5 477 749	2 497 734	2 807 194
2018	5 587 304	2 685 064	3 030 380
2019	5 699 050	2 886 444	3 271 311
2020	5 813 031	3 102 927	3 487 818

6. Conclusions

This study has attempted to estimate the number of accidents, injuries and fatalities in Ankara utilizing demographic and transportation indicators based on GA and ANN approaches. The results of the GA model showed that the exponential model form was suitable to estimate the number of accidents and fatalities while the linear model form was the most appropriate for predicting the number of injuries. The best fit model with the lowest MAE and RMSE between the observed and estimated values was selected for future estimations. The comparison of the model results indicated that the performance of the ANN model was

Table 6. ANN predictions for the two scenarios

Year	ANN					
	Accident estimates		Injury estimates		Fatality estimates	
	Scenario I	Scenario II	Scenario I	Scenario II	Scenario I	Scenario II
2006	75 816	90 188	10 100	13 542	195	176
2007	86 931	117 329	11 694	16 156	188	170
2008	97 345	132 790	12 935	19 358	182	163
2009	104 041	156 936	13 359	22 011	174	158
2010	133 702	168 699	17 461	23 479	170	152
2011	159 488	173 045	20 939	24 077	165	148
2012	171 067	173 980	22 237	24 296	157	144
2013	177 315	174 593	22 877	24 398	150	141
2014	180 503	173 892	23 298	24 480	144	139
2015	181 854	173 240	23 429	24 563	137	136
2016	182 302	172 259	23 447	24 645	134	130
2017	181 943	171 630	23 508	24 718	129	124
2018	181 677	171 504	23 543	24 774	125	119
2019	181 367	171 069	23 581	24 811	120	115
2020	181 022	170 952	23 622	24 826	117	110

better than that of the GA model. The ANN model was the best performing model with the lowest errors in general. In order to investigate the performance of the ANN model for future estimates, a fifteen year period from 2006 to 2020 was employed. Considering the fact that Turkey is likely to enter the European Union by 2020, road safety strategies were evaluated with two possible scenarios. It is assumed that the population of Ankara will reach nearly 6 million and the number of vehicles will range from 3 to 3.5 million by 2020 according to the scenarios. As the study results indicate, by 2020, the estimated number of accidents, injuries and fatalities in Turkey will be about 175 000, 24 000 and 120 respectively. Because of a rapid increase in the number of vehicles, the number of accidents and injuries are expected to increase while the number of fatalities is foreseen to decrease. The tendency towards the number of fatalities mainly results in developing vehicle safety technologies. Here, the increasing number of traffic accidents and injuries can be seen as an indicator of a serious safety problem for road traffic in the city. To overcome this problem, new alternative transportation plans and strategies should be developed. In this respect, a relatively large share of highway transportation in the country should be shifted to air, railway and maritime transportation systems.

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