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Traffic Behavior at Urban Intersection Stop Sign and Blinking Red Signal: The Iranian Experience

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In this paper, an attempt to identify and characterize minor road traffic behavior at unsignalized urban intersections in a city situated in a developing country is described. Information about the particular traffic behavior was collected using video cameras placed at 12 unsignalized intersections connecting minor to major roadways in Tehran. Stop signs and/or blinking red signals provided the stopping message at the minor approaches of the selected intersections. Relevant information about the behavior of more than 2400 vehicles was extracted from the video displays and the database records consisted of 31 variables reflecting driver, pedestrian, passenger, vehicle and intersection characteristics. Four key driver behavior characteristics, including observation of the stop message, departure distance and time from the stopping position and stopping distance from the pavement markings stopping line, were studied and evaluated. Univariate and multivariate statistical analyses of the database were carried out. Inappropriate and proper driving behavior, as related to 4 key characteristics, were identified and modeled. The applied modeling techniques consisted of regression analysis, artificial neural network modeling and discriminant analysis. Although the study findings are based on a rather limited database and are location specific, the same methodology can be applied to any unsignalized intersection.

INTRODUCTION

Intersections are shared areas of joining or crossing roadways which permit pedestrian and vehicular traffic crossing and direction change. Major elements of intersection design and performance include human factors, traffic characteristics, physical elements and economic factors. Traffic control systems are utilized to resolve the right of way conflicts between merging, diverging and crossing traffic streams. This is often achieved by the time separation of different traffic stream movements through traffic control sign and signaling systems. These systems include no control, guide signing, warning signing, yield control, stop control, red and yellow blinking signals and signalization [1-3]. The majority of at grade urban intersections are unsignalized although stop signs and blinking red signals are often installed at the intersections of minor street approaches. This is when the authorization for intersection traffic control devices only mandate a stop sign and/or a blinking red signal. The requirements are related to vehicular traffic volume and platooning, pedestrian volume, accident rate, signal spacing, adjacent land use and environmental characteristics. The physical and installation characteristics of stop signs and blinking red signals are detailed in traffic control device manuals [4-6].

The performance of an unsignalized intersection is directly related to driver and pedestrian behavior, including attributes on the tasks of driving, walking and information handling. Vehicles approaching a stop sign and/or blinking red signal should come to a complete stop and then enter the intersection with due consideration of the appropriate right of way and possible hazards. Pedestrians should use the crosswalk and also enter the intersection with equal consideration. The key to safe, efficient performance is error free information handling and the proper consideration of human factors, which is an important part of intersection design [1,7-12].

At an intersection, a driver, besides control and guidance, has the added navigational task of deciding on one of the available alternative direction and route choices. Drivers do not always observe traffic laws and regulations, especially when law enforcement is not adequate. Errors are caused by deficiencies in

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Table 1. Characteristics of the selected unsignalized intersections.

No.	Major Street Vol. (veh/hr)	Minor Street Vol. (veh/hr)	Stop Sign	Red Blinking Signal (m)	Major Signal Width (m)	Minor Street Width	Major Street Dir.	Minor Street Dir.	Sight Street Right (m)	Sight Dist. Left (m)	Major Dist. Speed (km/hr)	City Street Location
1	2300	310	Yes	Yes	12.0	12.0	2	2	34	62	40	E
2	640	410	Yes	Yes	12.4	10.9	2	2	18	10	35	N
3	850	575	Yes	Yes	7.8	7.3	1	1	12	9	25	C
4	540	360	Yes	Yes	12.3	9.5	1	2	28	26	40	E
5	3430	635	No	Yes	17.5	10.0	2	1	50	60	35	N
6	610	380	No	Yes	12.4	10.3	2	2	17	13	35	N
7	630	110	No	Yes	9.8	6.2	1	1	23	23	30	S
8	2570	430	No	Yes	13.0	8.8	1	1	15	14	35	S
9	1750	350	Yes	No	15.1	8.0	2	1	29	24	35	E
10	560	335	Yes	No	10.9	8.3	2	1	17	11	35	N
11	1270	520	Yes	No	10.0	6.5	1	1	17	16	30	W
12	1115	680	Yes	No	13.0	6.5	1	2	17	18	40	W

pedestrian and/or driver capabilities or by temporary states of incompetence, which, in conjunction with design deficiencies or difficult situation performance demands, produce failure. Driver error occurs due to lack of skill, task overload or inattentiveness and deficient or inconsistent design or information displays which may cause confusion. Driver error also results from adverse psychophysiological states, lack of skill and training, the pressures of time, the complexity of decisions or a profusion of information. The errors can be classified as, 'undetected', 'unrecorded', 'recorded' and 'led to accident' [13-16]. More than half of all traffic accidents occur at urban intersections, where Iran has the highest accident rate per driver in the world [17,18].

Several developing countries have found that using developed countries intersection design and operation manuals without modification can give misleading results and create a high accident rate. This is mainly due to the different behavior and composition of traffic in developing countries. Knowledge of driver behavior is essential in proper intersection design and operation. The objective of the research reported in this paper was to study driver behavior at unsignalized intersections and to characterize appropriate and inappropriate driving behavior. The study focused on 4 key driver behavior characteristics including observation of the stop message, stopping distance from the pavement markings stopping line, departure distance and time from the stopping position. This information was able to shed some light on the similarities and differences between traffic behavior in developing countries as compared with developed countries.

DATA COLLECTION

Tehran is the capital and the largest city of Iran with a population of more than 11 million. Discussion with engineers at the Tehran Traffic Organization led to identification of 36 candidate intersections scattered throughout the city and, due to limited resources, a subset of 12 intersections with typical arrangements and traffic variations were selected from these sites. Using more than 12 sites, especially in different Iranian cities, could have enhanced the study results. Nevertheless, the limited resources confined the study scope to the 12 selected intersections. Major characteristics of the selected intersections are summarized in Table 1. The listed volumes in columns 2 and 3 were the observed values for the morning peak period, based on 5-minute interval measurements and the major street speed was the operating speed. The last column shows the city location of the intersection as north, east, south, west and center with symbols N, E, S, W and C, respectively. The city center reflects the CBD, which is a permit zone. On the working days of the week, only vehicles with a permit can enter the CBD street network from 6 a.m. to 5 p.m. At the selected intersections, curb and pavement markings for pedestrian and vehicle movements were appropriate and no median existed. The stop sign and/or blinking signals were properly operating, located and installed.

Using a video camera with a timer, the traffic behavior was taped during the working days of April 1996. Three hours of video was taped at each intersection, 90 minutes during the morning peak period of 7 a.m. to 9 a.m. and 90 minutes during the off peak period of 9 a.m. to 11 a.m., respectively. During videotaping, the weather was mostly sunny and the temperature varied from 1° to 21°. During the videotaping no unusual event or traffic incident occurred.

The videotapes were reviewed and discernible information about vehicle and pedestrian behavior was extracted from the display on the television screen. The database consisted of computer files containing 2408 records. Each record reflected relevant individual vehicle information when approaching the intersection from the minor street that could have typified its driver behavior. Each record consisted of 31 system characteristics reflecting the following 5 groups of relevant information:

1. Vehicle information, such as case number, type, color and length of vehicle, type and appropriateness of movement, headway with previous arriving vehicle, movement travel time and distance and encountering pedestrians,
2. Intersection information such as location, width, number of lanes, sight distances, parking, markings and signs and signals,
3. Traffic information, such as major and minor street traffic characteristics,
4. Driver and passenger information, such as driver sex and age group and number of passengers,
5. Environment information, i.e., time, temperature and weather type.

Videotaping was a simple and inexpensive way of collecting traffic behavior data and invaluable for data review and verification.

DATABASE DESCRIPTIVE ANALYSIS

The univariate statistical analysis of the 31 variables contained in the database shed some light on driver behavior at unsignalized intersections. The minimum, mean, maximum, range and standard deviation of the variables for 2408 records are summarized in Table 2, including a list of the minimum and maximum values for the ordinal and nominal variables. The mean, standard deviation and dimension are not applicable and/or meaningful for these variables.

The cardinal variables consisted of 16 variables. The variable DAC reflected the departure traverse distance of vehicles from a stopping position at the minor street for three movements of crossing, turning right or turning left. The crossing distance was comprised of the distance the vehicle must travel to clear the major road from its stopped position, which was measured from the rear of the stopped vehicle. The turning distance consisted of the distance the vehicle must travel to complete the turning movement from its stop position, which was also measured from the rear of the stationary vehicle. The DAC was measured from the stop line for vehicles that did not observe the stop message. The sight distance from the left was reflected by a variable DSL and the sight distance from the right was reflected by a variable DSR. The field measurement provided the sight distances. The variable DST reflected the stop distance from the stop line on the minor street pavement. The variable DUR reflected the duration of minor road vehicle movement for the three types of movement used to traverse distance DAC. The variable HDW reflected headway with the previous vehicle of the minor road vehicle moving through the intersection. The variable LGT reflected vehicle length. The variable PAS reflected vehicle occupancy. The variable SPO reflected major street operating speed. The variable SPA reflected average speed during the traversing of distance DAC during time DUR. The variable TIM reflected vehicle arrival time at the intersection. The variable TMP reflected the ambient temperature. The variable VMJ reflected major road volume. The variable VMN reflected minor road volume. The variable WMJ reflected major roadway width. The variable WMN reflected minor road travelway width.

The nominal and ordinal variables consisted of 15 variables. The variable AGE reflected driver age, either young or not young, as perceived from field observation and video display. The age groups of young, with a value of one, and not young, with a value of zero, consisted of 67.1% and 32.9%, respectively. The variable BHV reflected minor street driver stopping behavior, either observing the stop message and stopping or committing traffic violations and not stopping. Driver behavior of not stopping, with a value of zero and stopping, with a value of one, consisted of 77.1% and 22.9%, respectively. The variable CLR reflected vehicle color and included 15 types. The variable DMJ reflected the number of directions in a major street, either one-way or two-way. The variable DMN reflected the number of directions in a minor street, either one-way or two-way. The variable MOD reflected minor street vehicle type and included 8 types. The vehicle types of bicycle, motor cycle, passenger car, pickup, taxi, minibus, bus and truck consisted of 0.2%, 9.3%, 69.3%, 11.1%, 4.6%, 3.8%, 0.9% and 1.0% of the database, respectively. The variable MRK reflected the existence of crosswalks for pedestrians. The variable MVT reflected minor street movement types of crossing straight, turning right and turning left, which consisted of 63%, 14% and 23%, respectively. The variable PED

Table 2. Results of univariate statistical analysis.

Variable	Description	Minimum	Mean	Maximum	Standard Deviation	Dimension
I. Cardinal Variables						
DAC	Departure distance	5.0	15.2	27.1	2.9	m
DSL	Sight distance left	9.0	23.4	62.0	17.1	m
DSR	Sight distance right	12.0	22.5	50.0	10.2	m
DST	Stopping distance	-12.0	-0.8	11.0	3.2	m
DUR	Departure time	1.1	4.6	14.6	1.9	s
HDW	Headway	1.0	13.4	221.1	17.9	s
LGT	Vehicle length	1.6	4.2	16.5	1.1	m
PAS	Vehicle passengers	1.0	2.2	40.0	2.5	pr
SPA	Departure speed	3.0	13.0	37.0	4.8	km/hr
SPO	Operating speed	25.0	34.6	40.0	2.7	km/hr
TIM	Vehicle arrival time	7:00:00	8:34:27	10:30:00	00:28:43	hr:min:s
TMP	Temperature	1.0	9.7	21.0	2.4	C
VMJ	Major road volume	310.0	1116.6	3430.0	342.6	veh/hr
VMN	Minor road volume	110.0	325.7	680.0	104.3	veh/hr
WMJ	Major road width	7.8	12.2	17.5	2.4	m
WMN	Minor road width	6.2	8.4	12.0	1.9	m
II. Nominal and Ordinal Variables						
AGE	Driver age group	0	n/a	1	n/a	n/a
BHV	Driver behavior	0	n/a	1	n/a	n/a
CLR	Vehicle color	1	n/a	15	n/a	n/a
DMJ	Major road direction	1	n/a	2	n/a	n/a
DMN	Minor road direction	1	n/a	2	n/a	n/a
MOD	Vehicle type	1	n/a	8	n/a	n/a
MRK	Crosswalk	0	n/a	1	n/a	n/a
MVT	Movement type	1	n/a	3	n/a	n/a
PED	Pedestrian crossing	0	n/a	1	n/a	n/a
PRK	Corner parking	1	n/a	4	n/a	n/a
RED	Blinking red signal	0	n/a	1	n/a	n/a
RGN	Region	1	n/a	5	n/a	n/a
SEX	Driver sex	0	n/a	1	n/a	n/a
SGN	Stop sign	0	n/a	1	n/a	n/a
SUN	Sunny weather	0	n/a	1	n/a	n/a

reflected the existence of crossing pedestrians during the minor street departure maneuver. The variable PRK reflected the existence of parking in major and/or minor streets. The variable RED reflected the existence of blinking red signals for the minor street. The variable RGN reflected the geographical location of the intersections in the south, east, north, west and central sections of Tehran. The variable SEX showed the gender of the driver as male or female. The male drivers, with a variable value of zero, consisted of 94% of the database. The variable SGN reflected the existence of stop signs for the minor street. The variable SUN reflected the existence of sunny weather.

The departure distance DAC and departure time DUR reflect driver behavior during the task of departure from the unsignalized intersection approach. They are important parameters in required sight distance determination at intersections and have a direct implication in geometric intersection design [1]. The following regression modeling section provides an example of the DUR prediction and reveals its significance in intersection design.

The statistical information variables regarding stopping distance DST and driver behavior BHV shed some light on the extent of inappropriate driving behavior. The observed key statistics of DST and BHV, broken down by type of control and major street movements, are summarized in Table 3. The table shows that most of the drivers observing the stop message passed and stopped beyond the stop line in an

Table 3. Key statistics of stopping distance and stopping behavior.

Stop Sign	Red Blinking Signal	Major Signal Dir.	Minimum Street Distance (m)	Maximum Stopping Distance (m)	Mean Stopping Distance (m)	Median Stopping Distance (m)	Mode Stopping Distance (m)	Std. dev. Stopping Distance (m)	Percent not Stopping (%)
Yes	Yes	2	-7	6	-1.2	-1	0	2.3	70.1
Yes	Yes	1	-5	8	-0.2	0	-3	3.0	81.5
No	Yes	2	-12	8	-1.5	-2	-3	3.5	74.3
No	Yes	1	-8	10	-1.0	-2	-2	2.7	79.5
Yes	No	2	-10	11	-0.5	-1	-1	4.2	79.4
Yes	No	1	-5	9	-0.5	-1	-1	3.2	77.8
All Intersections			-12	11	-0.8	-1	-1	3.2	77.1

improper position and location. Indeed, the last row of the table displaying the intersections' DST mean of -0.8 meter, showed that, on average, vehicles stopped 0.8 meter past the stop line. Its median of -1 meter confirmed that 50% of all vehicles stopped one meter or more past the stop line, which was observed more than any other value. This behavior was irrespective of the type of control, type of movement or city location. The last column of Table 3 also shows that more than three quarters of the drivers did not observe the stop message, irrespective of type of control, type of movement or city location. This behavior is a traffic violation that can be classified as "undetected" by traffic control authorities. Table 3 reflects the severity of the inappropriate and risk-taking behavior of drivers at unsignalized intersections throughout the city of Tehran. Further characterization of this behavior, in order to identify inspiring parameters, was pursued through multivariate analyses discussed in the following modeling sections.

DRIVER BEHAVIOR MODELING

To develop an understanding of the interrelationships between the 31 variables, pairwise parametric and nonparametric correlation analyses were performed. The nonparametric analysis was more useful in depicting relationships with and between 15 nominal and ordinal variables. The size of 31 by 31 correlation matrices prevented their display herein. The matrices revealed a number of interesting patterns and were found useful in the modeling phase of the study. Many pairs of variables were found significantly correlated. On average, each of the 31 variables was correlated, at a 0.05 level of significance, with 68 percent of the others.

To further characterize and model driver behavior, the study focused on the correlation of the 31 variables, with 4 key variables of DAC, departure distance, DST, stopping distance, DUR, departure duration and BHV, stopping behavior, respectively. The results were found to be mostly reasonable and meaningful. The variable DAC was found significantly correlated with 17 variables. The variables with positive correlation were DUR, departure time, DMJ, major road direction, DST, stopping distance, DSL, sight distance left, DSR, sight distance right, LGT, vehicle length, MVT, movement type, PED, pedestrian crossing, PRK, corner parking, SPO, operating speed, SUN, sunny weather, VMJ, major road volume, WMJ, major road width and WMN, minor road, respectively. The variables with negative correlation were MRK, crosswalk, RED, blinking red signal and VMN, minor road volume, respectively. The variable DST, stopping distance, was found significantly correlated with 14 variables. The variables with positive correlation were DUR, departure time, DAC, departure distance, PRK, corner parking, SGN, stop sign and DMJ, major road direction, respectively. The variables with negative correlation were DSL, sight distance left, DSR, sight distance right, MVT, movement type, SPO, operating speed, SUN, sunny weather, VMJ, major road volume, VMN, minor road volume, WMN, minor road width and WMJ, major road width, respectively. The variable DUR, departure time, was found significantly correlated with 17 variables. The variables with positive correlation were BHV, stopping behavior, DAC, departure distance, DMJ, major road direction, DST, stopping distance, DSL, sight distance left, DSR, sight distance right, MVT, movement type, PED, pedestrian crossing, PRK, corner park, SPO, operating speed, SUN, sunny weather, VMJ, major road volume, VMN, minor road volume and WMJ, major road width, respectively. The variables with negative correlation were HDW, headway, MRK, crosswalk, and RED, blinking red signal, respectively. The variable BHV, stopping behavior, was found significantly correlated with 12 variables. The variables with positive correlation were DMJ, major road direction, DSL, sight distance left, DSR, sight distance right, DUR, departure time, MVT, movement type, SEX, driver sex, SGN, stop sign, VMJ, major road volume, VMN, minor road volume, WMJ, major road width and WMN, minor road width, respectively. The variable with negative correlation was AGE, driver age group. Eight variables of PAS, vehicle passengers, SPA, departure speed, TIM, vehicle arrival time, TMP, temperature, CLR, vehicle color, DMN, minor road direction, MOD, vehicle type and RGN, region were not significantly correlated with any of the 4 key variables of BHV, DAC, DST and DUR, respectively.

The developed models predicted DAC, departure distance, DST, stopping distance, DUR, departure duration and BHV, stopping behavior, respectively. For each of these 4 model outputs, the possible model inputs consisted of the rest of the 31 variables. The database was used as a whole or was broken down by a subset of the 15 nominal and ordinal variables in modeling. Breakdowns by variables AGE, driver age, BHV, driver stopping behavior, DMJ, major road direction, MOD, vehicle type, MVT, movement type, RED, blinking red signal, RGN, region and SEX, driver sex, showed interesting results and significant model differences. For cardinal variables of DAC, departure distance, DST, stopping distance and DUR, departure duration, the applied modeling techniques consisted of regression analysis and artificial neural network modeling. For the nominal variable of BHV, stopping behavior, the applied modeling techniques consisted of artificial neural network modeling and discriminant analysis.

REGRESSION MODELING

The first set of models developed predicted DUR, departure time, by regression analysis for different database breakdowns. The second set of models developed predicted DST, stopping distance and DAC, departure distance, with multiple linear regression models. The database was used as a whole and was broken down by a subset of the 15 nominal and ordinal variables in modeling. More than three hundred models with different independent variables and functional forms were evaluated. Evaluation of the developed regression models showed more differences for breakdowns by AGE, driver age, BHV, driver stopping behavior, MOD, vehicle type, RGN, region, and SEX, driver sex. Due to space limitation, only a few examples of the developed models are presented herein.

For cases where the stop message was observed, the followings present a subset of selected models with DAC, departure distance, as the only model independent variable. The t statistic of individual calibrated parameters and the f statistic of the ANOVA table were at 0.05 level of significance for these models.

$$\mathrm{DUR} = -1.02 + 0.41\ \mathrm{DAC}, \tag{1}$$

$$\mathrm{DUR} = 1.56 + 0.031(\mathrm{DAC})^{1.72}. \tag{2}$$

Equation 1 presents departure time as a linear function of departure distance for all vehicles. The square root of the departure time residual mean square or root mean square error, RMSE, and coefficient of determination, R^2, were 1.57 seconds and 0.33, respectively. Equation 2 is the selected nonlinear form, based on least RMSE of 1.54 seconds, developed for all vehicles out of seven nonlinear functional forms. The R^2 for Equation 2 was 0.36. Equations 3 and 4 present similar models for only, passenger car traffic, respectively.

$$\mathrm{DUR} = -1.59 + 0.45\ \mathrm{DAC}, \tag{3}$$

$$\mathrm{DUR} = 1.43 + 0.026(\mathrm{DAC})^{1.81}. \tag{4}$$

The RMSE for Equations 3 and 4 were 1.52 and 1.49 seconds, respectively. The R^2 for Equations 3 and 4 were 0.37 and 0.39, respectively.

Equations 1 to 4 reflect the departure times of local behavior from the stop position at unsignalized intersections. Comparison of models such as Equations 1 to 4, with similar models of developed countries' references, showed significantly longer departure times for Iranian drivers. Models such as Equations 1 to 4 can be used in computing minimum intersection sight distance. For example, the required sight distance for a passenger car departing from a stop position and crossing a major street is computed in two steps. First, the departure time for the vehicle to complete this maneuver is determined by applying models such as Equations 1 to 4. Second, the sight distance is determined by computing the traversed distance of a vehicle traveling with major street design speed during the departure time, plus the perception/reaction time. For a pedestrian crossing at the intersection leg, proper driving requires stopping at some distance before the intersection edge, desirably at least 3 meters, to allow both directions crossing. The appropriate driving behavior of a 5.8 meters passenger car driver, stopping 3 meters from the edge of a 14.4 meters width traveled way, results in a departure distance, DAC, of 14.4 + 3 + 5.8 = 23.2 meters. Equations 3 and 4 predict departure times of 8.8 and 9.3 seconds, respectively. The derived departure time for departure distance of 23.2 meters from the AASHTO curve is 5.5 seconds [1]. Considering a major street design speed of 40 km/hr and a perception-reaction time of 2 seconds, Equations 3 and 4 provide sight distances of 121 and 127 meters, respectively. The AASHTO predicts 84 meters, which is around two thirds of the required values derived from Equations 3 and 4. The AASHTO relations will result in insufficient geometric design. Figure 1 shows Equations 3 and 4 and the AASHTO curve for passenger cars. The figure confirms the under estimation of AASHTO departure time for the observed behavior.

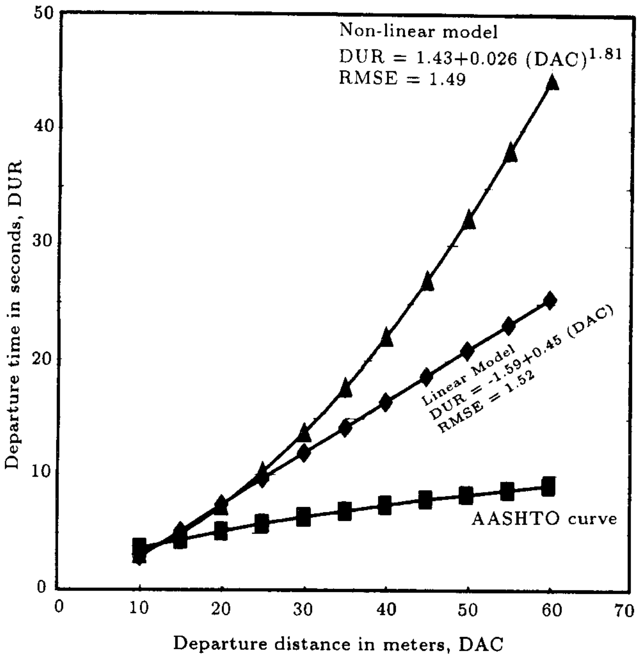

Figure 1. Comparison of the developed departure time models with the AASHTO curve.

For developing multivariable models, stepwise regression analyses were used. The developed models were multiple linear regression models for DUR. The RMSE of these models were smaller than their similar simple linear regression models. Equations 5 and 6 are examples of the selected models. The t statistic of individual calibrated parameters and the f statistic of the ANOVA table were, at 0.05 level of significance, for these models.

$$\text{DUR} = -1.33 + 0.39\ \text{DAC} + 0.00055\ \text{VMJ}, \qquad (5)$$

$$\text{DUR} = -1.61 + 0.41\ \text{DAC} + 0.00046\ \text{VMJ}. \qquad (6)$$

Equation 5 presents departure time as a linear function of DAC, departure distance and VMJ, major street volume, for all vehicles. The RMSE and R^2 of this model were 1.51 seconds and 0.38, respectively. Equation 6 presents departure time as a linear function of departure distance and major street volume for passenger cars. The RMSE and R^2 of this model were 1.47 seconds and 0.41, respectively.

Stepwise multiple linear regression was used to model DST and DAC, respectively. Equations 7 and 8 are examples of the developed models for all vehicles that observed the stop message.

$$\text{DST} = -0.43 - 0.64\ \text{WMJ} + 1.51\ \text{DUR}, \qquad (7)$$

$$\text{DAC} = 4.32 + 2.73\ \text{DMJ} + 0.37\ \text{WMJ}. \qquad (8)$$

Equation 7 presents stopping distance as a linear function of WMJ, major road width and DUR, departure time. The RMSE and R^2 of this model were 1.8 meters and 0.67, respectively. Equation 8 presents departure distance as a linear function of the DMJ, major road direction and WMJ, major road width. The RMSE and R^2 of this model were 1.5 meters and 0.72, respectively.

The developed regression models are useful tools for predicting DUR, DST and DAC. The developed DUR models, such as Equations 1 to 6, can easily determine the intersection sight distance requirements. The study confirms that adjustments should be made prior to use of the developed countries' design and operation manuals, such as the AASHTO references.

ANN MODELING

To improve prediction for reducing RMSE and increasing R^2, artificial neural network modeling was deployed. Artificial Neural Networks, ANNs, are powerful mathematical tools for modeling complex and, sometimes, intractable functions between system inputs and outputs. This is because of the fact that neural networks extract the essence of the relationship between system inputs and outputs through the data made available to them as training information. The key characteristics of an ANN include the number of processing elements in each layer, number of layers, type of transfer function and learning rule, respectively. A variety of ANN architectures, such as back error propagation, kohonen layer, competitive learning, adaline and madaline have been used in transportation [19-22].

The back error propagation refers to the method by which the ANN is trained. A basic backpropagation ANN consists of three layers, namely input layer, hidden layer and output layer, all interconnected with different weights. There are no criteria for determining the appropriate number of layers and processing elements. The backpropagation ANN gets its name from how it handles error. In the training of backpropagation networks, the error information is passed from the output layer to the input layer. Element connection weights are adjusted by comparing the desired outputs with actual outputs using a mathematical rule such as gradient descent method. The Delta rule is generally used as the training algorithm. The function most commonly used for the error is the sum of the square of the difference between the actual and the desired output layer elements' output. For a backpropagation ANN with sigmoid transfer function, the elements' outputs are defined as follows:

$$Y_j = 1/(1 + e^{-\sum_i w_{ij} Y_i}), \qquad (9)$$

where Y_j is ANN's actual output for the jth element, w_{ij} is the weight of connection between the jth element and the ith element in the previous layer of the jth element, Y_i is the ith input for the element j or the output of the ith element in the previous layer.

In the training of backpropagation ANN, the error information is passed backward from the output layer to the input layer. A network learns by successive repetition and training based on the observed information, making smaller errors with each iteration. The most commonly used function for the errors is the sum of the squared errors of the output elements. The w_{ij}'s are adjusted based on the Delta rule which is:

$$E = 0.5 \sum_j (Y_j - Y_{dj})^2, \tag{10}$$

where E is the sum of the square of errors, Y_j is defined as in Equation 9, Y_{dj} is ANN's desired output or the observed data for the jth element. To minimize the error, by taking the derivative of the error in Equation 10 with respect to w_{ij} one has:

$$\partial E/\partial w_{ij} = Y_i Y_j (1 - Y_j)\Omega_j, \tag{11}$$

where $\partial E/\partial w_{ij}$ is the derivative of E, with respect to the weight between elements i and j, Y_i and Y_j are the output of elements i and $j, \Omega_j = (Y_j - Y_{dj})$ for output layer elements and $\Omega_j = \sum_k w_{jk} Y_k (1 - Y_k)\Omega_k$ for hidden layer elements, when k is presenting the number of elements in the next layer that element j is connected to. The error can be calculated directly for the links going into the output layer elements. For hidden layer elements, however, the derivative of Equation 11 depends on values calculated at all the layers that come after it. That is, the value Ω must be backpropagated through the network to calculate the derivatives. For each sample pattern, a forward pass through the network, with some initial values for w_{ij}'s, produces an output pattern. Then, using Equations 9 to 11, the backpropagation algorithm starts with choosing a step size, δ, and, then, updating the w_{ij}'s with the following relation:

$$\Delta w_{ij} = -\delta Y_i Y_j (1 - Y_j)\Omega_j, \tag{12}$$

where Δw_{ij} is the change for w_{ij}, all other variables are defined as in Equations 9 to 11. The algorithm continues until the network is trained and the sum of the square of errors of Equation 10 becomes smaller than a prespecified error limit.

Results from the regression analysis lead to the notion that there are more complex relationships between the 31 database variables. To predict 4 output variables of DAC, departure distance, DST, stopping distance, DUR, departure duration and BHV, driver stopping behavior, among many available options, several ANNs were trained and tested. The developed ANNs, with all the input variables, were not found to be superior to the developed ANNs, with the aforesaid significantly correlated input variables, to output variables, in training convergence and testing results. The selected ANNs would use the selected 19 input variables as inputs to processing elements in the input layer.

With 19 processing elements in the input layer, several one and two hidden layer back propagation ANNs were trained and tested. Indeed, the actual architecture of any backpropagation ANN is problem dependent. The selected ANNs, which had simpler architecture and smaller root mean square of error, RMSE, for the testing data, were basic three layer networks shown in Figure 2. There were 7 processing elements in the hidden layer. In the output layer, the one processing element provided the output estimates. In this study, three types of transfer function, namely, hyperbolic tangent, sigmoid and sine were tried. For each transfer function, the training data were properly scaled. The sigmoid transfer function, given by Equation 9, was selected due to its superiority in training convergence and testing results. The applied learning rule to the hidden and output layers was the cumulative delta learning rule, which accumulated the weight changes over several presentations of the training examples and which were then applied to the weights. The key parameters of the cumulative delta rule include learning coefficients, momentum and epoch. After several trials, the epoch, momentum and learning coefficients of the hidden and output layers were set at 16, 0.5, 0.4 and 0.2, respectively. The momentum and learning coefficients were gradually reduced for a higher number of training iterations for convergence to the preselected RMSE values. After more than 50,000 iterations, by randomly presenting 1800 records as ANNs' training data, the trainings converged to the RMSE of 0.05 for a standardized output. In this way, four ANNs were trained and selected. The trained backpropagation ANNs were, then, tested with the remaining 208 records. For the testing data, the RMSE of the trained ANNs and regression models were compared. The testing data showed an average RMSE reduction of 90%, when four ANNs' predictions were compared with the pertinent regression models. The ANN modeling was also applied and evaluated for database breakdown by a subset of 15 nominal and ordinal variables, namely variables AGE, SEX, MVT, MOD and RGN. The developed ANNs predictions, based on smaller RMSE were found superior to the developed regression models.

DISCRIMINANT MODELING

Discriminant analysis was used to distinguish between two groups of drivers. The first group consisted of drivers who observed the stop message and showed proper behavior. The second group consisted of drivers with inappropriate behavior who did not stop at the intersection. The developed ANNs, with BHV as

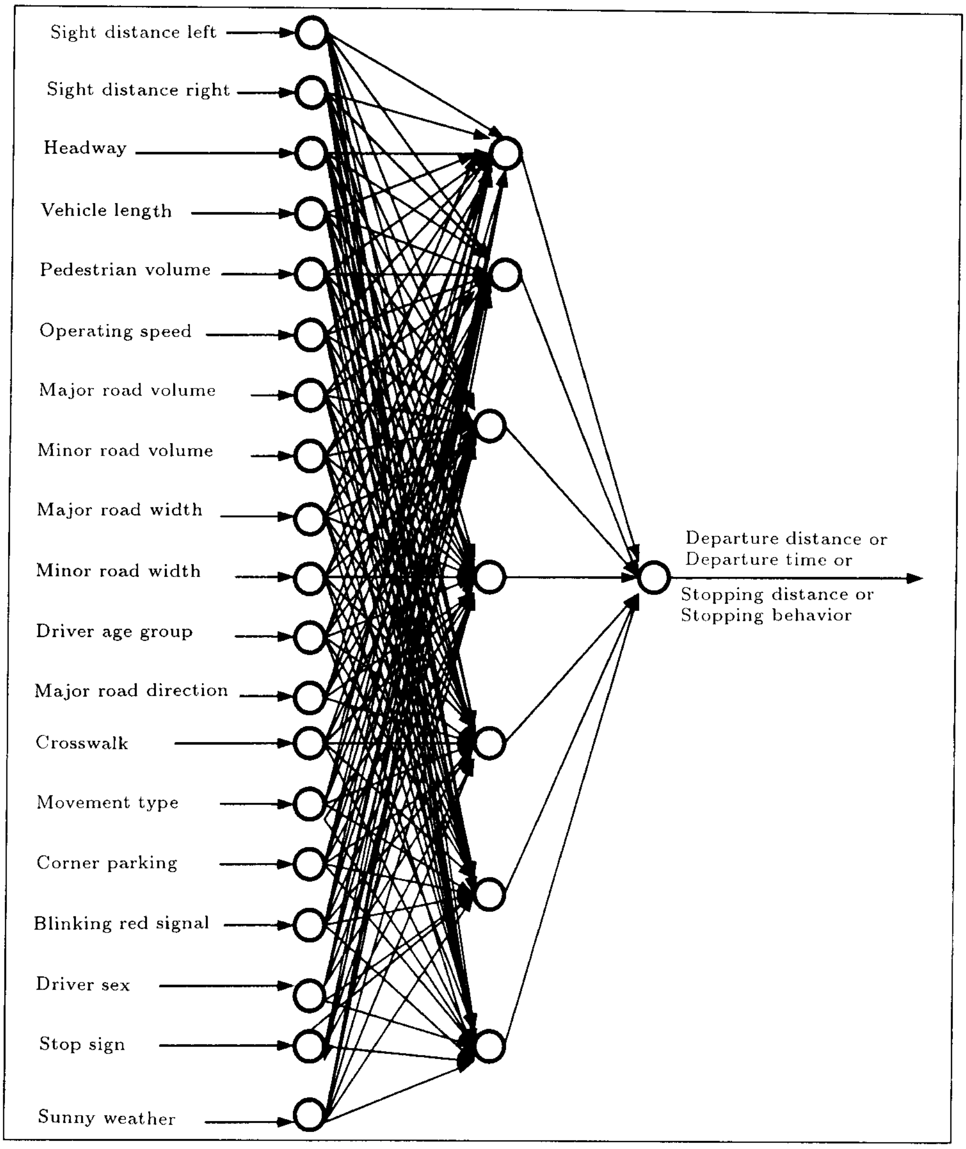

Figure 2. Structure of the selected ANN models for prediction of the driver behavior.

the model output, provided good predictions. Nevertheless, an ANN works like a black box and its practical application is not so simple when compared to discriminant models. The discriminant analysis attempts to form linear functions of discriminating variables in such a way to maximize the separation of the groups. The functions produce discriminant scores, which reflect group membership [23].

To predict BHV, driver behavior for observing the stop message, several discriminant models for the database as a whole and its breakdown by a subset of 15 ordinal and nominal variables were developed. The following equation is an example of the developed models:

$$\begin{aligned} \text{DSC} = {} & 0.46\ \text{ZSEX} + 0.35\ \text{ZVMJ} + 0.21\ \text{ZRED} \\ & + 0.11\ \text{ZSGN} + 0.06\ \text{ZLGT}. \end{aligned} \tag{13}$$

Equation 13 is the discriminant model for driver behavior at an unsignalized intersection. The DSC is the discriminant score. The variables ZSEX, ZVMJ, ZSGN, ZRED and ZLGT are the standardized values of SEX, VMJ, SGN, RED and LGT variables, respectively. The centriod of DSC for a driver group not stopping and a driver group stopping were -0.32 and 0.86, respectively. For any new case, the computed value of DSC determines the behavior closeness to each group centriod. For a DSC value of less than 0.27, it is more likely that the driver behavior be inappropriate and for him/her not to observe the stop message. Equation 13 reflects that the male driver of a small vehicle facing low traffic volume in a major street without a blinking red signal is more inclined to inappropriate behavior.

For the discriminant models, developed for the study, the key discriminant variables were found to be

SEX, VMJ, WMJ, RED, SGN, LGT, DSL, DSR and DUR. The coefficients of variable SEX in discriminant models showed that male drivers are more inclined to commit traffic violations. The coefficients of variables VMJ and WMJ showed that the heavier the traffic is at the major or minor street, the more the number of drivers who observe the stop message. The coefficients of variables RED and SGN showed that the existence of stop signs and blinking red signals are both significant in improving driver behavior. The coefficients of variable LGT showed that drivers of passenger cars are more inclined to commit traffic violations. The coefficients of variables DSL and DSR showed that the larger the intersection sight distances, the larger the number of drivers not observing the stop message. The coefficient of variable DUR showed that those drivers not observing the stop message, drive faster at intersections.

CONCLUSIONS

Traffic behavior at unsignalized urban intersections in the city of Tehran was studied. Information about traffic behavior was collected by video camera at 12 unsignalized intersections connecting minor to major roadways. Stop messages were given by stop signs and/or blinking red signals at minor approaches to the selected intersections. The database consisted of 2408 records of vehicles approaching the intersection from the minor street. Relevant information about each record consisted of 31 variables and was extracted from video displays. The study focused on 4 key driver behavior characteristics, including, observation of the stop message, stopping distance from the pavement marked stop line and departure distance and time from the stop position. Consequently, inappropriate and proper driver behavior, with respect to the 4 key variables, were identified and modeled. Although the study findings are based on a rather limited database, the same methodology can be applied to any unsignalized intersection.

The database descriptive analysis showed the key statistics such as minimum, maximum, mean, range and standard deviation of the variables. The descriptive analysis showed that more than half of the drivers that observed the stop message, passed and stopped beyond the approach stop line. The study also showed that more than three quarters of the drivers did not stop at the intersection. These traffic violations reflect the severity of drivers' inappropriate and risk-taking behavior at unsignalized intersections in the capital city of a typical developing country, in contrast with driver behavior in developed countries. Inappropriate driving behavior results in unsafe driving conditions and increased accident potential. Indeed, traffic safety is a very important problem that has only recently been recognized in Iran. Improvements in public awareness, driver education, traffic control, law enforcement and traffic violation citation can reduce this problem. To efficiently solve this problem, commitments from the public and private sectors are also required. Only through continuous, comprehensive and cooperative traffic safety management can the problem be alleviated.

Pairwise correlation analysis showed that, on average, each of the database 31 variables was significantly correlated with 68 percent of the other 30 variables. The 4 key driver behavior variables were significantly correlated, on average, with around half of the other variables. This showed that driver behavior was often correlated with the driver, vehicle, intersection, traffic and environment attributes.

The modeling focused on predicting the aforesaid 4 key driver behavior variables. The applied modeling techniques consisted of regression analysis, artificial neural network modeling and discriminant analysis. The regression analysis suggested simple models to be used by transportation practitioners for design and traffic management. The developed departure time regression models can easily determine the required intersection sight distance. The computed sight distances were found to be larger than the values derived from the AASHTO curves. This confirms that for developing countries, adjustments should be made prior to use of the developed countries' design and operation manuals, such as the AASHTO references. The developed ANNs predictions, based on smaller RMSE, were found to be superior to the developed regression models. From a transportation practitioner's point of view, the developed ANNs are more like black boxes and their applications are not so simple when compared to regression and discriminant models. The developed discriminant models predicted driver stopping behavior. For the developed models, the key discriminant variables were found to be driver sex, major and minor street traffic volume, existence of stop sign and blinking red signal, vehicle length, approach sight distances and departure time, respectively. Incorporation of relevant information about the discriminant variables can enhance urban traffic safety management. Deployment of transportation system management programs for public awareness, driver education, traffic control, law enforcement and traffic violation citation can significantly enhance the observed unsignalized intersection traffic safety crisis.

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