ANALYSIS OF TRAFFIC BASED ON DRIVERS' LANE CHANGE SEPARATION MODELS TO CALCULATE THE APPROPRIATE POSITION FOR THE MOVEMENT OF VEHICLES ON THE HIGHWAY

AmirMohammad Parvini
PhD Student of Civil Engineering-Payame Noor University-Tehran-Iran

Mahmoudreza Keymanesh

Abstract

Lane changing and car-following models are cell models in which the highways are divided into a series of cells and each vehicle at any time is placed in one of these cells. But unlike the separation model, the movement lanes and their situation are not considered. Therefore, this study defined two different models: integration of lane changing behavior and following based on risk reduction TSR and integration of lane changing behavior and drivers' following based on increasing the speed of TSV and provided their overall relations. Then the macro and micro assessment of TSR and TSV models in analysis of separation based on drivers' lane changing were done. Based on the results of this study, TAV and TSR models can estimate the average speed and the number of lane change satisfactorily at 95% confidence level. The results of assessing these models at the micro level were also provided. The parameters used for micro assessment determine the positions of vehicles in simulation environment and real conditions and decreasing their number is an indicator of more consistency of the model with the real situation. Comparing the results of traffic flow simulation by using the model and the statistical sample taken from the real world showed that the TSV speed increase model simulated the real conditions better than the TSR model. The models were prepared based on optimizing processes of drivers to reduce the crash risk and increase the maximum safe speed for drivers. Based on the results that validated TSV and TSR models at the macro level, and according to the results of micro analysis, in this research TSR model can be used to simulate in other Intelligent Transportation systems.

Keywords: Traffic analysis, separation models, lane changing, highway

1. Introduction

Lane choice means choosing a lane to travel from source to destination, using a typical vehicle in the transport network. Lane change is a very important issue in lane choice behavior. Transportation engineers for decades have tried to check travels and discover the lane choice behavior. Each of the drivers' decisions ultimately affect the traffic system, Khattak et.al (1993) .As a result, traffic behaviors of various drivers is considered in traffic descriptive prediction. Since there is no globally accepted model to be able to predict the random choice behavior or traveling lane change, researchers around the world have tried to construct probabilistic or indefinite models and analyze the type of human behavior, especially when driving on the highways.

The analysis of human behavior as the transport system user is necessary in several ways in choosing and changing the lane. First, the analysis as a useful tool helps building traffic assignment models that by considering the limitations, directs the urban network traffic with the most efficient methods available. Second, this analysis is more useful in the assessment of the operation of existing infrastructure and estimating the need for transport infrastructure. Also analysis of lane choice as an important aspect of the travel, has an important application in network optimized design and information systems for passengers, (Schlaich, 2010)and Rahimov et.al (2016). There are different approaches to modeling the movement of vehicles, each of them established a different balance between the complexity and accuracy. According to the level of details that examined the flow of traffic, simulation models are divided into three groups: macroscopic (macro), microscopic (micro) and mesoscopic (a combination of both). At macro level, traffic congestion variables such as flow, density and average speed of traffic and their relationship will be examined. Macro models are used for modeling a region or a country, if the micro models are used for limited surface or a highway or municipal levels because of the high computational cost.

Micro models study the movement of each vehicles. This means that every vehicle in a transport network moves according to the fundamental laws of motion (the relationship between speed, acceleration and distance) and driver behavioral rules (following and lane change rules, etc.). Micro-simulation models are able to follow the movement of every vehicle in system separately and consider the interaction between vehicles. These interaction are generally expressed by following and lane change models by (Edie,1961). In recent years and with extensive use of computers and efficiency of computer simulation models and their use to simulate traffic flow, much attention was focused on micro behavioral models of vehicles, (Greenberg,1959). In these models, the behavior of each vehicle is considered because the macro behavior of traffic flow can be calculated from the resultant behavior of each vehicle.

In the micro analysis of traffic, the movement of each vehicle is considered and macro traffic variables are obtained from the sum of the performance of these vehicles. The main advantage of traffic micro models is that they are similar to the fact and major drawback of the traffic micro analysis is that the analysis of the motion of each vehicle in the traffic flow requires huge computing and gaining an understanding of the behavior of traffic flow requires a lot of time, Chatterjee et.al (1959) and Gazis et.al (1961). With advances in computer technology and high computing, the use of simulation software which did traffic micro analysis is immense. For this reason, traffic micro models, which are given as input to simulation software, received more attention (Gipps, 1981). Traffic micro characteristics are often expressed with the following and lane change models. In following models, longitudinal movement of vehicles along the path is considered and in lane change models, transverse movement of vehicles in movement bands is concerned. Following and lane change models can be integrated and prepare models that describe the drivers' decision for transverse and longitudinal displacement in their route as a model.

In driver's lane change model, transverse control of vehicles' movement is not considered and vehicles discretely change lane from a lane to another. The decision to change the lane is determined based on a set of rules which determine if the change is desirable and whether the lane change is possible or not. These rules include driving conditions along the way, for example, the target vehicle speed, the expected speed and leader vehicle speed in the same line. Also the acceleration of the vehicle and the driver's desired acceleration are evaluated. Rules concerning the possibility of the driver maneuvers is determined based on the safety of the maneuvers, Krauss et.al (1997) and (May, 1990). Safety of maneuvers is determined based on proper distance between vehicles in a specific band. Since the transverse control has not been considered in MIXIC so far, an interval is considered to simulate the lane changing. In the meantime, the decision to change the lane will be re-evaluated in every simulation period i.e. every 1.0 seconds to provide the possibility of revising the lane change maneuver, (Pursula, 1999). For example, if another vehicle occupied the distance between the vehicles in this case, the driver may change his decision to change lane. This interval considered for lane change can also be useful for realizing simulation of vehicles' movement. Using this simulation model, a highway is equipped with simulated intelligent traffic systems. When the vehicle traffic is increased, as a result, their speed decreases, this intelligent system begins to affect vehicles' movement behavior and can prevent speed reduction in crowded condition as much as possible. Results from intelligent traffic systems in simulation model, show the advantages of using intelligent system. If the movement behavior of the vehicles on highways in Iran is simulated using this system, we can observe the result of various traffic policies in real-world before implementation.

2. ESTIMATION OF THE LONGITUDINAL AND TRANSVERSE POSITION OF VEHICLES IN SEPARATION MODELS OF DRIVERS' LANE CHANGE

In order to analyze traffic based on drivers' lane change separation model, to calculate the appropriate position for the movement of vehicles on highways, the longitudinal and transverse position of vehicle in drivers' lane change separation models must be estimated. On this basis due to the fact that drivers are able to view the position and speed of vehicles around, so they can recognize the speed of other vehicles at the present time, i.e. t time and estimate their longitudinal position in time dimensions given the current speed, but the speed of vehicles doesn't always remain fixed and changes. Changes in speed means acceleration in the vehicle movement. The uncertainty of the longitudinal vehicle speed in time tr seconds after the present time, t, occurs for acceleration, (Wiedemann, 1991). So the longitudinal movement of vehicles is obtained from the following equation:

$$X(i,t+tr) = X(i,t) + V_x(i,t).tr + \frac{1}{2}a_x(i,t).tr^2 \qquad (1)$$

Where ax (i, t) is longitudinal acceleration of the vehicle i at time t and it is obtained from the following equation:

$$a_x(i,t) = \frac{V_x(i,t+tr) - V_x(i,t)}{tr} \qquad (2)$$

Speed and acceleration of the movement of vehicles during their movement is associated with many changes that this is due to braking and acceleration of driver, therefore, acceleration of the movement of vehicles only can be assumed constant within a short timeframe displayed with tr. So the amount obtained for the momentum in a period of time, is constant only for the time interval and the new values will be used for the next time intervals. Given that the uncertain part of the longitudinal movement of the vehicle is their acceleration, the statistical distribution of acceleration of the vehicle is estimated using a statistical distribution. Assuming that the acceleration of vehicles has statistical distribution Normalx (μax, σax), the statistical distribution of longitudinal position of the vehicles will have the following statistical distribution: (Yang and Koutsopoulos,1996) & (Brackstone and McDonald, 1999).

$$X\ (i,t+tr) \approx Normal_x(X(i,t)+V_x(i,t).tr+\frac{1}{2}\mu_{ax}.tr^2,\frac{1}{2}\sigma_{ax}.tr \qquad (3)$$

According to the statistical distribution of the longitudinal position of the vehicle, the likelihood of presence of vehicle i at position X is obtained from the following equation:

$$P(i,X,t+tr)=\int_{X-\frac{l_v}{2}}^{X+\frac{l_v}{2}} Normal_x(x;x_i(t)+V_x(i,t).tr+\frac{1}{2}9tr^2). \qquad (4)$$

Given that the position of each cell is determined by the coordinates of its center and the length of each cell is lv, low limit to high limit of integral of calculating the probability is obtained from X- l_v / 2 to X + l_v / 2.

Just as presented in longitudinal position, the transverse position of vehicles, vehicles transverse movement is obtained from the following equation:

$$Y(i,t+tr)=Y(i,t)+V_y(i,t).tr+\frac{1}{2}a_y(i,t).tr \qquad (5)$$

Where ay (i, t) is the transverse acceleration of the vehicle i at time t and is obtained from the following equation:

$$a_y(i,t)=\frac{V_y(i,t+tr)-V_y(i,t)}{tr} \qquad (6)$$

Just as in the case of longitudinal movement of vehicles, the uncertain part of vehicle transverse movement is created from transverse acceleration, transverse acceleration like longitudinal acceleration means a change in transverse speed of vehicle and is used for measuring the transverse movements of the vehicle, (Daganzo,1994). The statistical distribution of the vehicle transverse acceleration is estimated using a statistical distribution. Assuming that the acceleration of vehicle has a statistical distribution Normaly (μay, σay), the statistical distribution of transverse position of vehicles will have the following statistical distribution:

$$Y(i,t+tr) \approx Normal_y(Y(i,t)+V_y(i,t).tr+\frac{1}{2}\mu_{ay}.tr^2,\frac{1}{2}\sigma_{ay}.tr \tag{7}$$

According to the statistical distribution of the transverse position of vehicles, the likelihood of presence of vehicle i in the Y position is obtained from the following equation:

$$P(i,Y,t+tr)=\int_{Y-\frac{W_v}{2}}^{Y+\frac{W_v}{2}} Normal_y(y;Y(i,t)+V_y(i,t).tr+\frac{1}{2}3tr^2). \tag{8}$$

According to the position of each cell with the coordinates of the center of the cell, and the width of each cell is Wv, the lower limit to the upper limit of the integral of calculating the probability of the presence of vehicle in the cell is determined from Y-Wv/2 to Y + Wv/2, (Daganzo ,1997).

3. PRESENTING THE INTEGRATION OF CAR-FOLLOWING AND LANE-CHANGE BEHAVIOR BASED ON REDUCING TSR RISK

Decision of drivers is done in three steps in the model of lane-change and car-following behavior integration based on risk reduction:

3.1. Determining possible options

At this stage cells that the vehicle in the next step could be placed in them, is identified, and they are called possible cells. If the speed of vehicle ID at time t, is Vx (ID, t) and acceleration of braking and its movement is aID and bID, respectively, the vehicle ID will be in the next time step t + ts in the range below:

$$\begin{aligned} \mathrm{X(ID,t) + ts.Vx(ID,t) - (bID.ts2)/2} &\le \mathrm{X(ID,t+ts)} \\ &\le \mathrm{X(ID,t) + ts.Vx(ID,t) + (aID.ts2)/2} \end{aligned} \quad 9)$$

Cells that are located in this area are called possible cells.

3.2. Determining the risk of possible options

The amount of risk in every possible cell is determined. For each possible cell for each vehicle, its risk is calculated using Equation 8.

3.3. Choosing option due to the lower risk:

At this stage, due to the lower risk, the vehicle selects the new cell randomly.

In Figure below, algorithm for determining the optimum location for the movement of any vehicle in the model TSR can be seen, as can be seen in this figure, in every step of the simulation for each vehicle, the cells there is a possibility to move in them, are determined, then the risk of these cells is calculated and the cell with least risk is selected, Jou et.al (2005).

In fact, in model TSR, it should be noted that decreasing the risk of an accident in a cell, increases the probability of selection. Possibility of choosing the cells on the next time step is calculated from the following equation.

$$\text{RankTS2A(ID,X, Y, t)} = \frac{R(ID, X, Y, t)}{\sum R(ID, i, j, t)} \quad (10) \quad \text{For all feasible cells (i,j)}$$

Where

Rank (ID, X, Y, t): probability of choosing cell (X, Y) by the vehicle ID at time t,

R (ID, i, j, t): risk of accident for vehicle ID in the cell (i, j) at t time. Figure 1 shows Algorithm for positioning for movement of any vehicle in TSR model .

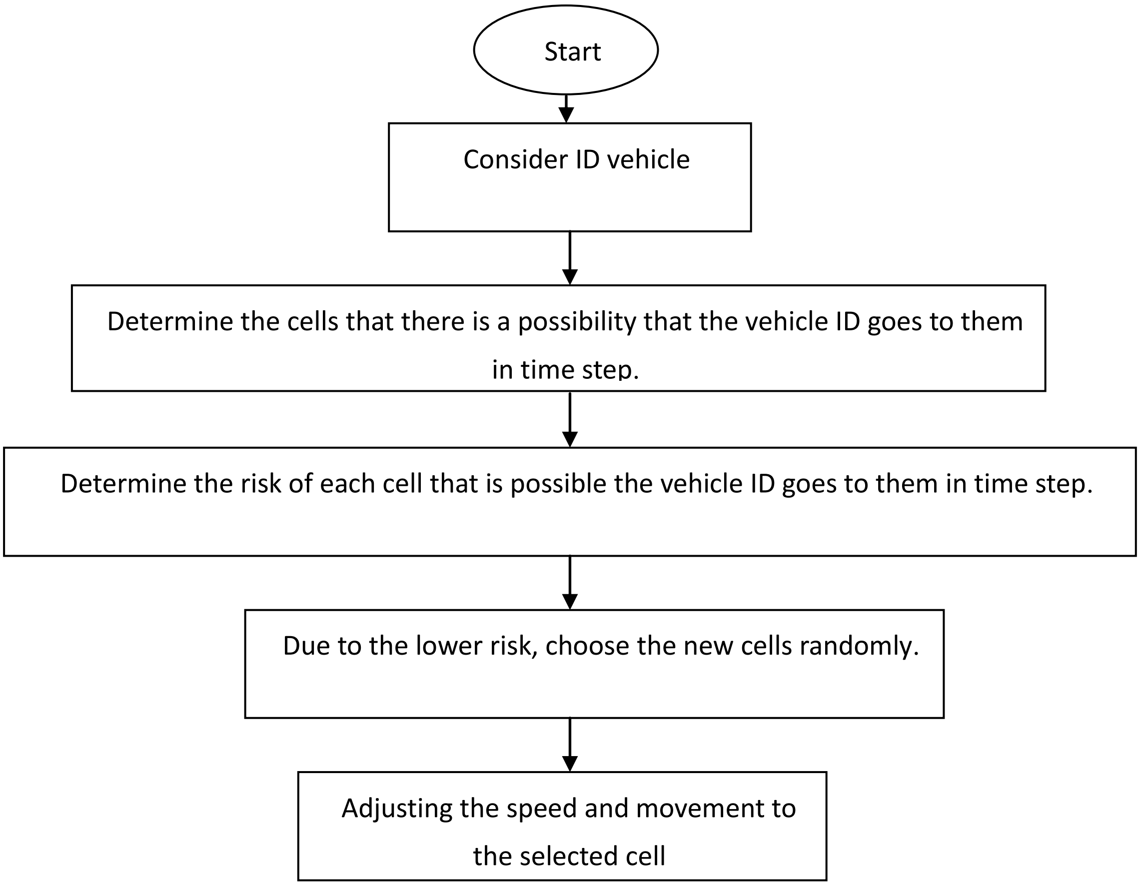

Figure 1: Algorithm for positioning for movement of any vehicle in TSR model

4. INTEGRATION OF THE LANE CHANGE AND CAR-FOLLOWING BEHAVIOR OF DRIVERS BASED ON INCREASING TSV SPEED

This model is essentially similar to lane-change and car-following behavior of drivers based on the reduction of risk that drivers pay attention to increasing speed instead of lowering the risk and every vehicle goes to the same cell that provides the highest speed for him. Drivers' decision in this model is done in three steps:

4.1. Determining the possible options

At this stage cells that the vehicle in the next step could be placed in them, is identified, and they are called possible cells. Limit of the cells is obtained from equation 9.

4.2. Determining the maximum safe speed in the possible options

The maximum safe speed for each cell is determined. For each possible cell, for each vehicle, the maximum safe speed of the cell is calculated using the existing equations.

4.3. Choosing option with respect to the safe speed

At this stage, the target vehicle from the possible cells, in accordance with the safe speed, selects the new cell randomly (which means that whatever the safe speed in a cell is higher, the probability of choosing the cell will be higher).

In Figure below, the algorithm of determining the optimum location for the movement of every vehicle in the TSV can be seen. As can be seen in this figure, in every step of the simulation for each vehicle, first the cells that can move in them, are determined, then the maximum safe speed of the cells is calculated and according to the maximum safe speed, the new cell will be randomly selected. Figure 2 shows positioning for movement of any vehicle in TSV model.

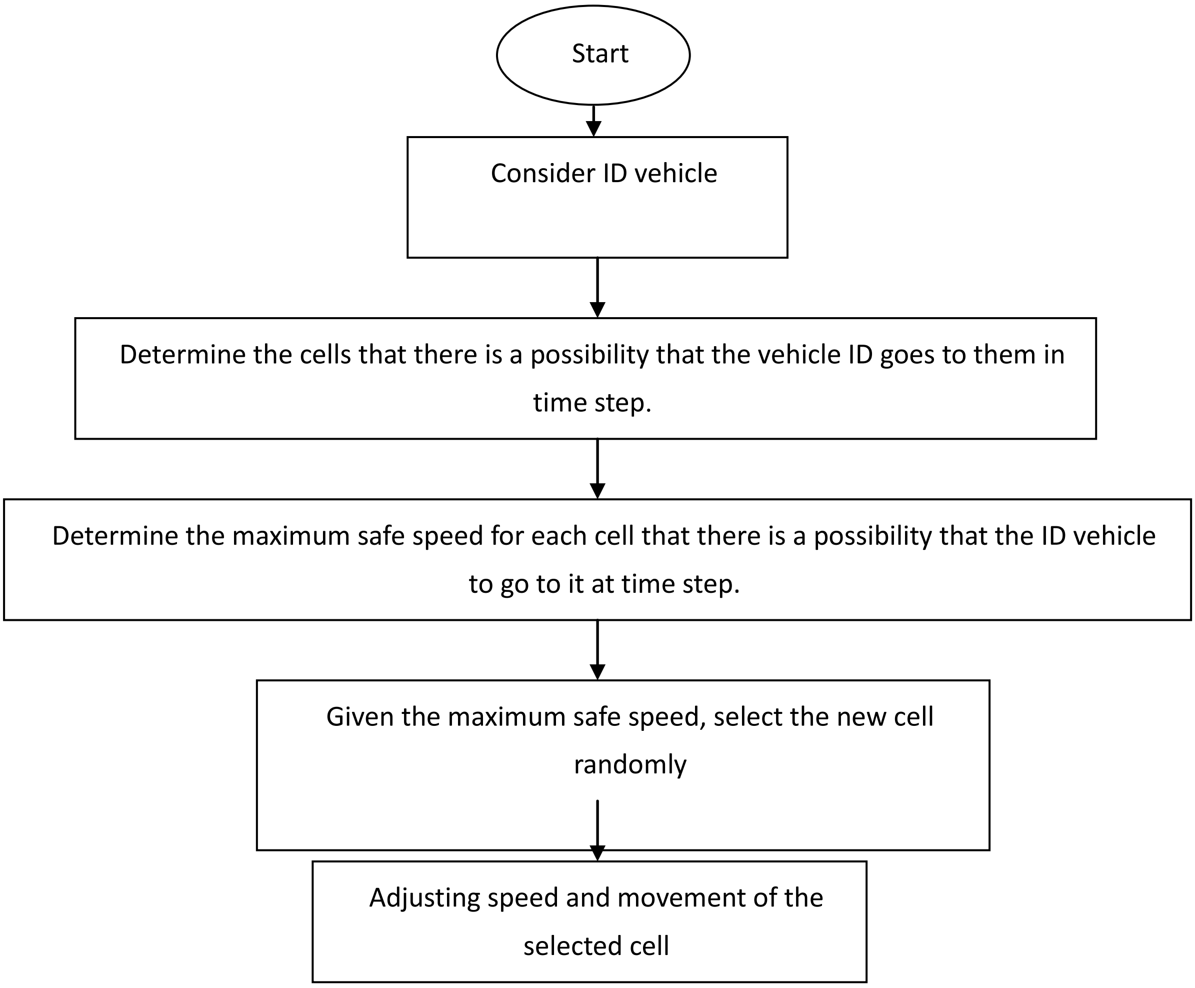

Figure 2: Positioning for movement of any vehicle in TSV model

In fact, in the TSV model, it is noted that by increasing the safe speed in a cell, it is more likely to be selected. The likelihood of selecting cells on the next time step is calculated from the following equation.

$$\text{RankTS2B(ID,X, Y, t)} = \frac{V_{MSS}(ID, X, Y, t}{\sum V_{MSS}(ID, i, j,} \quad (11)$$

For all feasible cells (i,j)

Where

Rank (X, Y, ID, t): probability of selecting cell (X, Y) by the vehicle ID at time t,

VMSS (i, j, ID, t): the maximum safe speed for the vehicle ID in the cell (i, j) at t time.

5. MACRO ASSESSMENT OF TSV AND TSR MODELS IN TRAFFIC ANALYSIS BASED ON SEPARATION OF DRIVERS' LANE CHANGE SEPARATION MODEL

To evaluate each of the separate models of drivers' lane change, modeling application with initial values corresponding to each of the 6 intervals of statistics was conducted in second place and the average speed and the number of lane changes in different performances were calculated as two important indices to be compared with the real condition that is calculated through survey. To evaluate the simulation models, vehicle speed were calculated in real conditions in each of the 6 survey period and the average speed of vehicles in modeling conditions in the corresponding intervals were deducted. Then, the mean and variance of difference values are calculated and from among the various methods to evaluate simulation models, the test for paired observations was selected for this study. The test statistic is obtained from the following equation:

$$t_{po} = \frac{\bar{d}}{S_d / \sqrt{n}} \quad (12)$$

Where

tpo: paired observation test statistics

d: The mean difference of the parameters in the binaries of simulation and real situations,

Sd: standard deviation of the difference between the parameters in the binaries of simulation and real situations,

n: number of samples in a simulated and real conditions

In this test, the degree of freedom is equal to n-1.

If $|t_{op}| > t_{\alpha/2,n-1}$,i.e. the absolute value of the test statistics is more than the statistical distribution of t-student test for accuracy α/2 and degrees of freedom n-1, validation of the model at a confidence level (1-α)% is rejected, and otherwise there is no reason to discredit the model at the confidence level.

In this section, TSR model must be evaluated for separation of drivers' lane change and TSV model is examined. Accordingly, the difference between the average speed in TSR model of the vehicles in the simulation and real environment in 6 survey periods has an average of -2.45 and the variance 2.9. In this way, t_{po} statistics for average speed of vehicles was obtained using the equation $t_{po} = \frac{-2.45}{2.9/\sqrt{6}} = -2.07$. Due to the fact that $2.7 - |t_{op}| = 2.07 < t_{\alpha/2,n-1}$,there is no reason for the unreliability of the model at 95% confidence level to calculate the average speed. The difference between the average number of vehicles lane change in the real and simulation environment in 6 survey period has a mean of 1.27 and variance 2.7, respectively. In this way tpo statistics was obtained for average speed of vehicles using the equation $t_{po} = \frac{1.27}{2.7/\sqrt{6}} = 1.15$. Due to the fact that 2.7=|tpo|=1.15<tα/2,n-1, there is no reason for the unreliability of model at 95% confidence level to calculate the lane change. As mentioned, model reliability is accepted to calculate the average speed and number of vehicles lane change, then evaluation of the model at the macro level shows that TSR is suitable for modeling drivers' behavior in terms of average speed and lane change.

In TSV model, the difference in the average speed of vehicles in the simulation and real environments at 6 survey period has a mean of - 7.25 and the variance of 9.7. In this way, tpo statistics for average speed of vehicles is obtained using the equation

$t_{po} = \frac{-7.25}{9.7/\sqrt{6}} = -1.83$. Due to the fact that 2.7=|tpo|=1.83<tα/2,n-1 there is no reason for the unreliability of the model to calculate the average speed at 95% confidence level. The difference between the average number of vehicles in the simulation and real environment at 6 survey period is a mean of – 1.46 and variance 3.1. In this way, tpo statistics for average speed of vehicles is obtained using the equation $t_{po} = \frac{-1.46}{3.1/\sqrt{6}} = -1.15$. Due to the fact that 2.7=|tpo|=1.15<tα/2,n-1, there is no reason for the unreliability of the model at a confidence level of 95% to calculate the number of lane change. As mentioned above, the validity of TSV model to calculate the average speed of vehicles is acceptable. The evaluation of this model at macro level shows that the model is suitable for modeling the motor behavior of drivers in terms of average speed and the number of lane changes.

6. MICRO EVALUATION OF TSV AND TSR MODELS IN TRAFFIC ANALYSIS BASED ON DRIVERS' LANE CHANGE SEPARATION MODELS

For micro assessment of TSR and TSV models in traffic analysis based on the drivers' lane change separation models, the two following equation are used.

The first equation is the mean root of RMS that is used as a quantitative criterion for determining compliance of the model to real situations. For example, for initial values of longitudinal positions, RMSSEIXi, the mean error of longitudinal position is calculated using the following equation.

$$RMSSEIX_i = \sqrt{\frac{\sum_{ID=F_i}^{N_i+F_i-1} (XR(t_{\min}(ID)+t) - XS(t_{\min}(ID)+t))}{N_i}} \qquad (13)$$

In the above equation

RMSSEIXi: Root Mean Square Error of longitudinal position at t seconds after the first period that each of the vehicles are seen in it at i-th statistical period,

Ni: number of vehicles that are seen in the i-th statistical range,

Fi: Number of first vehicle observed in statistical interval i-th,

XR (t_{min} (ID) + t): longitudinal position of the vehicle ID in real terms t seconds after the first period

XS (t_{min} (ID) + t): calculated value of the longitudinal position of the vehicle ID in the simulation environment t seconds after the first period.

By substituting transverse position or any other desired parameter in this equation, the RMS error parameters for original values of the parameters are obtained.

To obtain another quantitative relationship to compare simulation and real conditions, the RMS error for the all vehicle movements have been used. Thus, in all intervals for each vehicle, the difference between parameters in the simulation and real conditions was calculated and by summing their squares for each vehicle and dividing it by the number of observed vehicles and the square root of the obtained value, RMS error parameter for the total vehicle movements is obtained. For example, root-mean-square error for the longitudinal position of the vehicle is obtained from the following equation:

$$RMSSETX_i = \sqrt{\frac{\sum_{ID=F_i}^{N_i+F_i-1} \sum_{t_m(ID)=t_{\min}(ID)+1}^{t_{mout}(ID)} (XR(t_m(ID)) - XS(t_m(ID)))^2}{\sum_{ID=F_i}^{N_i+F_i-1} (t_{mout}(ID) - t_{\min}(ID))}} \quad (14)$$

In the above equation

RMSSETXi: Root Mean Square Error of longitudinal position of the vehicle in i-th period,

Ni: number of vehicles observed in i-th period,

XR (t_m (ID)): the observed value of longitudinal position of ID vehicle in period t_m(ID) in real condition and

XS (t_m (ID)): the calculated value of ID vehicle longitudinal position in period t_m (ID) in the simulation environment.

By substituting transverse position or any other desired parameter on this equation, parameter of the RMS error for the total vehicle movement is obtained.

To evaluate the TSR model by RMSSEIX parameter, 2 seconds after the first observation of the vehicle is intended. RMSSETX parameter is used to assess how close the longitudinal position of vehicles in the simulated environment with real conditions at all intervals of each vehicle. Similarly, RMSSETY and RMSSEIY parameters are calculated for the transverse position of vehicles and are given in the following table for each intervals. Table 1 shows Evaluation parameters in TSR model.

Table 1. Evaluation parameters in TSR model

Statistical range	1	2	3	4	5	6	Average
RMSSEIX	0.53	0.56	0.62	0.68	0.70	0.56	0.61
RMSSEIY	0.20	0.17	0.13	0.16	0.14	0.18	0.16
RMSSEIX	4.76	6.44	5.62	7.43	4.56	5.78	5.77
RMSSEIY	1.45	3.37	3.11	2.23	2.69	1.46	2.39

As can be seen from the above table, the amount of RMSSEIX is different for different statistical intervals but on average the value is 0.61. In the above table, parameters RMSSETX, RMSSEIY, and RMSSETY were calculated for different intervals and their average was obtained 5.77, 0.16, and 2.39, respectively. These values alone do not share information about the model, but they are used for comparison of TSR with other models to simulate real conditions.

To evaluate TSV model by RMSSEIX parameter, 2 seconds after the first observation of the vehicle is intended. RMSSETX parameter is used to assess how close the longitudinal position of vehicles is in the simulated environment with real conditions observed at all intervals each vehicle. Table 2 shows evaluation parameters in TSV model. Similarly, for transverse position of the vehicle, RMSSEIY and RMSSETY parameters were calculated and given in the following table for each of the intervals.

Table 2. Evaluation parameters in TSV model

Statistical range	1	2	3	4	5	6	Average
RMSSEIX	0.64	0.52	0.57	0.62	0.55	0.60	0.58
RMSSEIY	0.10	0.14	0.10	0.11	0.13	0.09	0.11
RMSSEIX	2.56	1.89	2.22	3.63	2.50	1.98	2.46
RMSSEIY	0.93	0.86	0.72	0.85	0.78	0.097	0.85

As can be seen from the above table, the amount of RMSSEIX is different for different statistical intervals but on average, value is 0.58. In the above table, parameters RMSSETX, RMSSEIY, and RMSSETY are calculated for different intervals and their average was 2.46, 0.11, and 0.85, respectively. These values alone do not share information about the model, but they are used for comparison of TSV with other models to simulate real conditions.

7. CONCLUSIONS

The summary of macro and micro analysis performed in this study is presented below. The proposed models to estimate the average speed and the number of the lane changes were compared with each other and tpo paired observation test for each of the models is shown. Table 3 shows summary of evaluating proposed models at micro and macro levels.

Table 3.Summary of evaluating proposed models at micro and macro levels

Evaluation at micro level			Evaluation at macro level		
TSV	**TSR**	**Model / parameter**	**TSV**	**TSR**	**Model**
0.58	0.61	RMSSEIX	1.83	2.07	Average speed of tpo
0.11	0.16	RMSSEIY	1.15	1.15	Number of lane change of tpo
2.46	5.77	RMSSETX	Acceptable	Acceptable	Evaluation result
0.85	2.39	RMSSETY			

As seen in the above table, statistics, paired observation of models that was prepared based on traffic rules, to estimate the average speed and the number of lane changes is larger than that can confirm the adaptation to real conditions and proposed models and as a result, the model is acceptable. TSR and TAV models could estimate the average speed and the number of lane changes satisfactorily at 95% confidence level. The model proposed in this study has also been evaluated at the micro level. To do this, some parameters were defined and used. In the above table, results of evaluating these models can be seen at the micro level. The parameters that are used for micro evaluation, determine the positions of vehicles in simulation environment and real condition and by decreasing their amount, the model is more consistent with the real situation. Comparison of the results of traffic simulation by using the above model and the statistical sample from the real world, has shown that the speed increase, TVS simulated the real condition better than the TSR model. The models are prepared based on optimizing processes of drivers to reduce accident risk and increase the maximum safe speed. Based on the survey results that have accepted the validation of TSV and TSR models at the macro level, and according to the results of micro analysis, in this study TSR model is used to simulate in other intelligent transportation systems.

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