Predicting Density in Merge and Diverge Areas Based on their Geometry and Traffic Characteristics using Metaheuristic Procedure

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ABSTRACT

In this paper, it was attempted to predict the density (which is a common criterion which represents the quality of flow in every freeway segment) in the merge and diverge areas by simulating 2880 different merge and diverge areas with different geometry and different traffic characteristics. Density was obtained for each merge and diverge area after analyzing trajectory data. A database containing density as a function and geometric and traffic characteristics as its variables was generated after determination of densities in all instances. By using this database, two models were developed by Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) algorithm to predict density in these areas. The models were tested, validated and their errors were checked. The results indicated a good accuracy of similarity between the results of models in predicting density and that of simulations. Case studies were surveyed to verify the accuracy and validity of models. Statistical analysis showed that there were no significant differences between means of densities predicted by models and surveyed densities from case studies.

Keywords— Traffic, Density, merge and diverge areas, Artificial Neural Network, Particle Swarm Optimization

I. INTRODUCTION

Freeways have always played an important role in road transportation. Hence the quality of flow in freeway has been one of the main concerns of researchers. A continuous high-speed flow should be maintained in every freeway and it will be achieved when all freeway segments operate properly. The operation of freeways has been always affected by the operation in the merge and diverge areas. Density is a common criterion which represents the quality of flow in these areas. Thus, in this paper, it was attempted to develop some models to predict the density in merge and diverge areas according to their traffic and geometric characteristics. To do this, density for a specific merge and a specific diverge area with specific traffic and geometric characteristics was calculated based on trajectory data using simulation. By changing traffic and geometric characteristics of the merge and diverge area, 2160 merge area and 720 diverge area were produced. After simulating and analyzing trajectory data, density of every type was computed. After analyzing merge areas, a database was generated with 2160 rows of information which contain seven traffic and geometric variables and one function of density. Another database with 720 rows of information containing six traffic and geometric variables and one function of density was produced after analyzing diverge areas. These rows of information were used to develop the models. One model was developed by Artificial Neural Network (ANN) and another one by Particle Swarm Optimization (PSO) algorithm that both are illustrated in future sections. After checking the accuracy of models, case studies were used to verify them.

II. LITERATURE REVIEW

Density is defined as a concept of real-time and in a limit and can be defined by observing an image of part of vehicles path [1, 2]. Density is the number of vehicles in a specified length of a lane [3]. Gazis et al. proposed a method to count the number of vehicles in a specified segment by measuring the speed and flow rate at the entrance and exits of the segment [4]. Another way to calculate density is to find two simple and principal traffic parameters, flow rate and occupancy [5]. Video monitoring has been very common in recent years. There is three methods to obtain density from video monitoring: 1. the apparent difference: by considering total dimension of vehicles, 2. flow total movement: by surveying speed of vehicles, and 3. keeping background steady: by detecting moving vehicles [6]. Density could be determined by
image processing on photos captured by installed cameras using ANN [7]. Ozkurt et al. applied a three-step model to achieve density. The three steps include 1. detecting passing vehicles by keeping background steady, 2. ANN was used to classify the vehicles by their dimension as big, medium, and small, and 3. calculating density [8]. There are four methods to compute density from photos captured by cameras:

1. The number of vehicles in a specified link is equal to the difference between the number of vehicles enter and exit the link.

   \[ N_i = V_{a,i} - V_{d,i} + N_{i-1} \]  

   Where \( V_{a,i} \) is arrival volume from main line and on-ramps during period \( i \) (vehicles), \( V_{d,i} \) is departure volume from the main line and off-ramps during period \( i \) (vehicles), \( N_i \) is the number of vehicles in segment at end of the time period \( i \), and \( N_{i-1} \) is the number of vehicles in segment at end of the time period \( i-1 \). Iteratively applying equation 1 for the time period \( i-1 \) yields equation 2 as follows.

   \[ N_i = V_{a,i} - V_{d,i} + (V_{a,i-1} - V_{d,i-1} + N_{i-2}) = A_i - D_i + N_0 \]  

   In which \( A_i \) is cumulative arrival volume from main line and on-ramps at time period \( i \) (vehicles), \( D_i \) is cumulative departure volume from main line and off-ramps at time period \( i \) (vehicles), and \( N_0 \) is the initial number of vehicle in the segment.

2. Computing density using occupancy by equation 3

   \[ D_i = 52.80(\text{occ}\%) \times (L_v + L_d)^{-1} \]  

   Where \( D_i \) is the density at detector location \( i \) (veh/mi/ln), \( \text{occ}\% \) is occupancy in percentage, \( L_v \) is average vehicle length (ft), and \( L_d \) is the length of detector (ft). There are two shortcomings in this method. The occupancy is measured in one point and not for total parts and the average lengths of vehicles and detectors are imprecisely assumed.

3. Calculating density from flow rate and speed

   Spot speed detectors measure speeds at time intervals of 20 seconds. Space mean speed is always less than or equal to time mean speed and is calculated by equation 4 [9].

   \[ u_{S,i} = u_{T,i} - \frac{\delta T_{i,2}^2}{u_{T,i}} \]  

   Where \( u_{S,i} \) is space mean speed, \( u_{T,i} \) is time mean speed, and \( \delta T_{i,2} \) is variance of time mean speeds.

   Van Lint proposed equation 5 to calculate space mean speed from time mean speed [10].

   \[ u_T = 0.996u_{S} + 3.541 \]  

   Density could be determined by equation 6.

   \[ D_i = \frac{V_i}{u_{S,i}} \]  

   In which \( D_i \) is density at detector \( i \) (veh/mi/ln), \( V_i \) is traffic flow rate measured by detector \( i \) (veh/h/ln), and \( u_{S,i} \) is space mean speed at detector \( i \) (mph).

4. Combining data from detectors and probe vehicle

   It was assumed that the link consists of two subsegments. The condition of the first subsegment is similar to the condition of upstream detector and condition of the second subsegment is similar to that of downstream detector. Instead of dividing the length between two detectors into two equal subsegments, the length is divided dynamically by speed data from loop detectors and travel time and location of probe vehicle. It was also assumed that travel time in the link is equal to sum of travel times obtained by probe vehicle. Density is then calculated by equations 7 and 8.

   \[ \frac{L}{u_{S,AVI}} = \frac{L_1}{u_{S,up}} + \frac{L-L_1}{u_{S,down}} \]  

   \[ D_f = \frac{\sum_{i=1}^{n} D_i \times L_i \times N_i}{\sum_{i=1}^{n} L_i \times N_i} \]  

   Where \( D_f \) is average density for the segment (veh/mi/ln), \( L \) is total link length (mi), \( L_1 \) is length of the first subsegment (mi), \( L-L_1 \) is length of second subsegment (mi), \( u_{S,AVI} \) is space mean speed measured by AVI (mph), \( u_{S,up} \) is space mean speed calculated on basis of time mean speed at upstream detector by equation 5 (mph), \( u_{S,down} \) is space mean speed calculated on basis of time mean speed at downstream detector by equation 5 (mph), \( D_i \) is density for link \( i \) corresponding with detector \( i \) (veh/mi/ln), \( L_i \) is length of link \( i \) (mi), and \( N_i \) is number of lanes in link \( i \) [11].

   Density could be calculated by using trajectory data and having coordinates of the link. The number of vehicles in a lane divided by the length of link at a moment is the density of the link at that moment. Movement of vehicles during a certain period of time in graphically or mathematically forms could be derived from microscopic simulations which called trajectory [12]. sample graphical trajectories are presented in Figure 1.
SAMPLE GRAPHICAL TRAJECTORIES [12]: (A) INTERRUPTED FLOW ON A SIGNALIZED APPROACH (B) UNINTERRUPTED FLOW ON A FREEWAY

Trajectory indicates locations of vehicles during a certain period of time with a time interval of 0.1 to 1.0 seconds ($\Delta t$) as shown in Figure 2 for vehicle n [12].

III. METHODOLOGY

Using trajectory data, it was attempted to develop models to predict the density in merge and diverge areas based on the geometry and traffic characteristics of these areas. To recognize the effect of variation in the value of every geometric or traffic characteristic on density, simulating different merge and diverge area with different geometry and different traffic characteristic, seems to be a good strategy by which the density could be calculated based on trajectory data. Geometry and traffic characteristics as effective variables in predicting density in merge areas include the length of acceleration lane, number of freeway lanes, number of lanes in on-ramp, freeway volume, on-ramp volume, freeway free flow speed, and on-ramp speed. These variables in diverge areas include the length of deceleration lane, number of freeway lane, number of off-ramp lanes, freeway volume, freeway free flow speed, and off-ramp speed. Tables 1 and 2 present variables description and their range used for simulation.

![Figure 2](https://via.placeholder.com/150)

**Figure 2**

**TRAJECTORY OF VEHICLE N WITH A TIME INTERVAL OF $\Delta t$**

<table>
<thead>
<tr>
<th>Variables</th>
<th>$L_{ACC}$ (m)</th>
<th>$V_{FW}$ (Veh/h)</th>
<th>$N_{FW}$</th>
<th>$V_{R-ON}$ (Veh/h)</th>
<th>$N_{R-ON}$</th>
<th>$S_{FW}$ (Km/h)</th>
<th>$S_{R-ON}$ (Km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range:</td>
<td>100 to 500</td>
<td>750 to 2970</td>
<td>3 to 4</td>
<td>600 to 1600</td>
<td>1 to 2</td>
<td>90 to 120</td>
<td>40 to 60</td>
</tr>
</tbody>
</table>

$L_{ACC}$ is the length of acceleration lane, $V_{FW}$ is freeway volume, $N_{FW}$ is number of freeway lane, $V_{R-ON}$ is on-ramp volume, $N_{R-ON}$ is the number of on-ramp lanes, $S_{FW}$ is freeway free flow speed, $S_{R-ON}$ is the speed of on-ramp

<table>
<thead>
<tr>
<th>Variables</th>
<th>$L_{DEC}$ (m)</th>
<th>$N_{FW}$</th>
<th>$N_{R-OFF}$</th>
<th>$V_{FW}$ (Veh/h)</th>
<th>$S_{FW}$ (Km/h)</th>
<th>$S_{R-OFF}$ (Km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range:</td>
<td>100 to 500</td>
<td>3 to 4</td>
<td>1 to 2</td>
<td>750 to 2970</td>
<td>90 to 120</td>
<td>40 to 60</td>
</tr>
</tbody>
</table>

$L_{DEC}$ is the length of deceleration lane, $N_{FW}$ is the number of freeway lane, $N_{R-OFF}$ is the number of off-ramp lanes, $V_{FW}$ is freeway volume, $S_{FW}$ is freeway free flow speed, $S_{R-OFF}$ is the speed of off-ramp

By combining different geometric and traffic characteristics, 2160 different merge areas and 720 different diverge areas were produced and simulated. The density in the merge and diverge areas was calculated by analyzing trajectory data. Therefore, 2880 rows of information containing density as function and the geometry and traffic characteristics as variables were produced after data analysis.

ANN

ANN was built by the rows of information. To reach the minimum Root Mean Square Error (RMSE), Number of layers, number of neurons, and functions of training, hidden layers, and output layers were determined after a large number of trial and error attempts. By using this ANN, density could be predicted in the merge and diverge areas when there is enough information about the values of geometry and traffic characteristics. The properties of the ANN were as below:

**Merge Area:**
- NO. of layers: 2
- NO. of neurons in each layer: 70
- Train data: 60 % of all data
- Test data: 20 % of all data
- Validation data: Remained data (20 % of all)
equations were proposed and after a lot of trial and error attempts, equation 9 was considered for estimating density in merge area and equation 10 for predicting that in diverge areas.

\[
D_M = b_1 \times 0.143 \times 2^{a_2} \times a_1 e^{2LM} + a_2 a^{2LACC} + a_3 V_{FW}^{a_6} + a_7 N_{FW} + a_8 V_{R-ON}^{a_9} + a_9 N_{R-ON} + a_{11} e^{12SFW} + a_{13} e^{14SFW} + a_{15} S_{R-ON}^{a_8} + a_{17} b_2 + b_3 \quad (9)
\]

\[
D_D = b_1 \times 0.167 \times a_1 L_{DEC}^{a_2} + a_3 N_{FW} + a_3 N_{R-OFF} + a_{5FWA} + a_{7cosaSFW} + a_{9sina10SFW} + a_{11S-OFF} + a_{12b2} + b_3 \quad (10)
\]

In which DM is the density in merge area, DD is the density in diverge area. LACC is the length of acceleration lane, LDEC is the length of deceleration lane, NFW is the number of on freeway lanes, NR-ON is the number of on-ramp lanes, NR-OFF is the number of off-ramp lanes, VFW is freeway volume, VR-ON is on-ramp volume, SFW is freeway free flow speed, SR-ON is the speed of on-ramp, SR-OFF is speed of off-ramp, and ai and bi are constant parameters.

**CASE STUDIES AND MODELS VERIFICATION**

The models should be verified by case studies. Survey results were compared with the models’ outputs. With respect to possible differences between survey results and the models’ outputs, it was necessary to determine that this difference was because of either data distribution and their random properties or a significant difference between the results. Statistical analysis shows that there is a significant difference between densities surveyed and corresponding densities predicted by the models or not. The pooled t - test was used due to the limited number of samples. Statistical t could be calculated by equation 11.

\[
t = (\mu_m - \mu_s) S_p^{-1} (n_m^{-1} + n_s^{-1})^{-0.5} \quad (11)
\]

\[
s_p = (n_m - 1) \sigma_m^2 + (n_s - 1) \sigma_s^2 \quad (12)
\]

In which \( \mu_m \) and \( \mu_s \) are mean of the model population and mean of the survey population, respectively. \( n_m \) and \( \sigma_m \) are the number of samples and standard deviation of model results, respectively, and \( n_s \) and \( \sigma_s \) are the number of samples and standard deviation of survey results, respectively. Computed t should be compared with the tabulated values of the t - distribution table. The tabulated values of t-distribution table depend on the degree of freedom, \( f \), which represents the number of independent parts. The degree of freedom is defined by equation 13 in t distributions.

\[
f = n_m + n_s - 2 \quad (13)
\]

Once the statistical t is determined, the tabulated values of t-distribution table yield the probability of a t value being greater than the computed value. In order to limit the probability to 0.05 of a type I error, the difference in the means will be considered significant only if the probability is less than or equal to 0.05; that is, if the calculated t value falls in the 5% area of the tail, or in other words, if there is less than a five percent chance that such a difference could be found in the same population.
If the probability is greater than 5% (or the computed t value is less than the tabulated values of the t-distribution table) then such a difference in means could be found in the same population and the difference would be considered not significant. Figure 5 shows tabulated values of the t-distribution.

<table>
<thead>
<tr>
<th>df</th>
<th>0.900</th>
<th>0.950</th>
<th>0.975</th>
<th>0.990</th>
<th>0.995</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.078</td>
<td>3.141</td>
<td>3.223</td>
<td>3.276</td>
<td>3.356</td>
</tr>
<tr>
<td>2</td>
<td>1.886</td>
<td>2.092</td>
<td>2.567</td>
<td>3.276</td>
<td>3.980</td>
</tr>
<tr>
<td>3</td>
<td>1.533</td>
<td>1.963</td>
<td>2.262</td>
<td>2.841</td>
<td>3.537</td>
</tr>
<tr>
<td>4</td>
<td>1.415</td>
<td>1.833</td>
<td>2.060</td>
<td>2.571</td>
<td>3.250</td>
</tr>
<tr>
<td>5</td>
<td>1.341</td>
<td>1.746</td>
<td>1.943</td>
<td>2.345</td>
<td>2.947</td>
</tr>
<tr>
<td>6</td>
<td>1.303</td>
<td>1.696</td>
<td>1.860</td>
<td>2.228</td>
<td>2.764</td>
</tr>
<tr>
<td>7</td>
<td>1.279</td>
<td>1.655</td>
<td>1.796</td>
<td>2.131</td>
<td>2.602</td>
</tr>
<tr>
<td>8</td>
<td>1.262</td>
<td>1.628</td>
<td>1.746</td>
<td>2.048</td>
<td>2.452</td>
</tr>
<tr>
<td>9</td>
<td>1.250</td>
<td>1.606</td>
<td>1.708</td>
<td>2.004</td>
<td>2.322</td>
</tr>
<tr>
<td>10</td>
<td>1.240</td>
<td>1.586</td>
<td>1.676</td>
<td>1.971</td>
<td>2.201</td>
</tr>
</tbody>
</table>

IV. RESULTS

Rows of information were generated after simulating and analyzing trajectory data. These rows of information contained seven traffic and geometric variables and one function of density in merge areas and six traffic and geometric variables and one function of density in diverge areas. ANN was developed by using this rows of information. ANN results in merge areas are illustrated in Figs. 6 to 14 and Table 3.
ALL DATA COMPARISON OF ANN OUTPUT AND DENSITY IN ROWS OF INFORMATION AS TARGET IN MERGE AREA

![Figure 9]

TEST DATA COMPARISON OF ANN OUTPUT AND DENSITY IN ROWS OF INFORMATION AS TARGET IN MERGE AREA

![Figure 10]

TEST DATA ERROR DIAGRAM IN MERGE AREA

![Figure 11]

TEST DATA ERROR DISTRIBUTION IN MERGE AREA

![Figure 12]

VALIDATION DATA COMPARISON OF ANN OUTPUT AND DENSITY IN ROWS OF INFORMATION AS TARGET IN MERGE AREA

![Figure 12]
Validation data error diagram in merge area

Validation data error distribution in merge area

All data comparison of ANN output and density in rows of information as target in diverge area

All data error diagram in diverge area

All data error distribution in diverge area

Table 3: Accuracy of ANN outputs for all data in merge area

<table>
<thead>
<tr>
<th>Standard deviation</th>
<th>Error mean</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.721</td>
<td>-0.0669</td>
<td>0.724</td>
</tr>
</tbody>
</table>

ANN results in the diverge areas are also presented in Figure 15 to 23 and Table 4. The results were categorized in three collections of all data, test data, and validation data. For each collection, a comparison between ANN outputs and density in rows of information as the target was described in the first graph. Error diagram and error distribution of data of each collection were presented in second and third graph, respectively. Standard deviation, error mean, and RMSE of every collection are also mentioned in the graphs of each collection.

Standard deviation, error mean, and RMSE of three collections reflect a good development of models by ANN.
TEST DATA COMPARISON OF ANN OUTPUT AND DENSITY IN ROWS OF INFORMATION AS TARGET IN DIVERGE AREA

TEST DATA ERROR DIAGRAM IN DIVERGE AREA

TEST DATA ERROR DISTRIBUTION IN DIVERGE AREA

VALIDATION DATA COMPARISON OF ANN OUTPUT AND DENSITY IN ROWS OF INFORMATION AS TARGET IN DIVERGE AREA

VALIDATION DATA ERROR DIAGRAM IN DIVERGE AREA

VALIDATION DATA ERROR DISTRIBUTION IN DIVERGE AREA
TABLE 4

ACCURACY OF ANN OUTPUTS FOR ALL DATA IN DIVERGE AREA

<table>
<thead>
<tr>
<th>Standard deviation</th>
<th>Error mean</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.139</td>
<td>1.4×10^{-6}</td>
<td>0.139</td>
</tr>
</tbody>
</table>

Constant parameters of equation 9 were also determined by using the PSO algorithm. Results are represented in Figure 24 and Table 5 in merge areas.

FIGURE 24

PSO iteration in merge area (BEST COST = MSE)

TABLE 5

CONSTANT PARAMETERS OF EQUATION 9 IN MERGE AREA

<table>
<thead>
<tr>
<th>a1</th>
<th>a2</th>
<th>a3</th>
<th>a4</th>
<th>a5</th>
<th>a6</th>
<th>a7</th>
<th>MSE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>26.6265</td>
<td>-0.0014192</td>
<td>0.00033446</td>
<td>0.0174315</td>
<td>0.63923</td>
<td>0.450522</td>
<td>-4.83933</td>
<td>3.89</td>
<td>1.972</td>
</tr>
<tr>
<td>a8</td>
<td>a9</td>
<td>a10</td>
<td>a11</td>
<td>a12</td>
<td>a13</td>
<td>a14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-55.4237809</td>
<td>-0.0949753</td>
<td>-0.043941</td>
<td>5.99237E+14</td>
<td>-0.3938234</td>
<td>16.878</td>
<td>0.00030972</td>
<td></td>
<td></td>
</tr>
<tr>
<td>a15</td>
<td>a16</td>
<td>a17</td>
<td></td>
<td>b1</td>
<td>b2</td>
<td>b3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1685010.08</td>
<td>-3.6248276</td>
<td>115.151528</td>
<td></td>
<td>2.31E-11</td>
<td>9.3727654</td>
<td>3.52315875</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The value of RMSE showed a good development of the model. Thus, the equation 9 could be rewritten as equation 14.

\[ D_M = 2.797 \times 10^{-19} \left[ 26.6266 e^{0.0014192} + 0.00033446 e^{0.0174315} + 0.64 e^{0.45} \right] - 4.839 N_{FW} - 55.4237809 \]

All parameters were described previously. As it was mentioned before, case studies were used to verify the models. Figure 25 shows studied merge areas and traffic and geometric characteristics of them are presented in Table 6 in diverge areas.

FIGURE 25

PSO iteration in diverge area (BEST COST = MSE)

TABLE 6

CONSTANT PARAMETERS OF EQUATION 10 IN DIVERGE AREA

<table>
<thead>
<tr>
<th>a1</th>
<th>a2</th>
<th>a3</th>
<th>a4</th>
<th>a5</th>
<th>a6</th>
<th>a7</th>
<th>a8</th>
<th>MSE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>60.430</td>
<td>-0.290</td>
<td>-2.234</td>
<td>-0.171</td>
<td>-546.110</td>
<td>-0.013</td>
<td>-0.390</td>
<td>0.160</td>
<td>1.79</td>
<td>1.34</td>
</tr>
<tr>
<td>a9</td>
<td>a10</td>
<td>a11</td>
<td>a12</td>
<td></td>
<td>b1</td>
<td>b2</td>
<td>b3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.253</td>
<td>0.160</td>
<td>-0.059</td>
<td>561</td>
<td>0.00000467</td>
<td>5.900</td>
<td>-0.770</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The value of RMSE showed a good development of the model. Thus, the equation 10 could be rewritten as equation 15.

\[ D_D = 1.212 \times 10^{-10} \left[ 60.43 L_{DEC}^{0.029} - 2.234 N_{FW} - 0.171 N_{R_{OFF}} - 546.11 V_{FW}^{0.013} - 0.39 \cos(0.16 S_{FW}) + 0.253 \sin(0.16 S_{FW}) - 0.059 S_{R_{OFF}} + 561 \right]^{0.9} - 0.77(15) \]

All parameters were described previously. As it was mentioned before, case studies were used to verify the models. Figure 26 shows studied merge areas and traffic and geometric characteristics of them are presented in Table 7.
Figure 26


Table 7
Characteristics of studied merge areas

<table>
<thead>
<tr>
<th>Location</th>
<th>Characteristics</th>
<th>L_{ACC} (m)</th>
<th>V_{FW} (veh/h)</th>
<th>N_{FW} (-)</th>
<th>V_{R.ON} (veh/h)</th>
<th>N_{R.ON} (-)</th>
<th>S_{FW} (km/h)</th>
<th>S_{R.ON} (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hemmat Freeway W-E: MERGE Asharfi N</td>
<td></td>
<td>145</td>
<td>5023</td>
<td>4</td>
<td>1253</td>
<td>2</td>
<td>90</td>
<td>50</td>
</tr>
<tr>
<td>Niayesh Freeway E-W: MERGE Chamran S</td>
<td></td>
<td>118</td>
<td>3794</td>
<td>3</td>
<td>909</td>
<td>2</td>
<td>80</td>
<td>40</td>
</tr>
<tr>
<td>Tehran-Qom Freeway N-S: MERGE Vahnabad E</td>
<td></td>
<td>173</td>
<td>2252</td>
<td>3</td>
<td>169</td>
<td>1</td>
<td>120</td>
<td>60</td>
</tr>
<tr>
<td>Tehran-Qom Freeway S-N: MERGE Vahnabad W</td>
<td></td>
<td>154</td>
<td>1266</td>
<td>3</td>
<td>440</td>
<td>1</td>
<td>120</td>
<td>60</td>
</tr>
<tr>
<td>Tehran-Saveh Freeway W-E: MERGE Shahriar W</td>
<td></td>
<td>225</td>
<td>2667</td>
<td>3</td>
<td>361</td>
<td>2</td>
<td>120</td>
<td>40</td>
</tr>
</tbody>
</table>

The values of density were predicted by applying two developed models on studied merge areas with characteristics presented in Table 7. Results of statistical analysis between the means of densities predicted by both models versus densities surveyed in the merge areas case studies are represented in Table 8.

It could be found that there are no significant differences between means of densities for models population and real population in merge areas when almost all computed statistical t presented in Table 8 (which are achieved from statistical analysis of the population of models and studied areas) are less than the tabulated values of t-distribution table.

Table 8
Results of statistical analysis between the means of densities predicted by both models versus densities surveyed in merge areas

<table>
<thead>
<tr>
<th>Location</th>
<th>n</th>
<th>D_{M} (veh/km/ln)</th>
<th>ANN Results</th>
<th>PSO Results</th>
<th>Survey Results</th>
<th>Statistical Pooled t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>μ_{m}</td>
<td>σ_{m}</td>
<td>μ_{m}</td>
<td>σ_{m}</td>
</tr>
<tr>
<td>Hemmat Freeway W-E: MERGE Asharfi N</td>
<td>11</td>
<td>30.95</td>
<td>3.40</td>
<td>35.29</td>
<td>7.68</td>
<td>32.51</td>
</tr>
<tr>
<td>Niayesh Freeway E-W: MERGE Chamran S</td>
<td>14</td>
<td>61.56</td>
<td>6.77</td>
<td>85.51</td>
<td>21.03</td>
<td>69.69</td>
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</tbody>
</table>

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Figure 27 shows studied diverge areas and traffic and geometric characteristics of them are presented in Table 9.

The values of density were predicted by applying two developed models on studied diverge areas with characteristics presented in Table 9. Results of statistical analysis between the means of densities predicted by both models versus densities surveyed in diverge areas case studies are represented in Table 10.
Here, it could also be found that there are no significant differences between means of densities for models population and real population in diverge areas when almost all computed statistical $t$ presented in Table 10 (which are achieved from statistical analysis of the population of models and studied areas) are less than the tabulated values of the $t$ - distribution table.

V. CONCLUSION

The influence of variations of traffic and geometric characteristics in the merge and diverge areas on the density of vehicles was assessed in this paper. Two models were developed to predict the density in the merge and diverge areas using ANN and PSO algorithm. The results indicated a good accuracy of models in terms of studying traffic behavior and the range of mentioned variables values, the more reduction in the validity of models. Obviously, the more distance between the values of these characteristics and the range of mentioned variables values, the more reduction in the validity of models. Another conclusion is that models could be developed to predict other traffic parameters such as density, delay, speed, etc. in the merge and diverge areas or other traffic facilities based on their traffic and geometric characteristics using ANN and PSO algorithm.

REFERENCES


<table>
<thead>
<tr>
<th>Hakim Freeway W-E: DIVERGE Sheikh Bahae S Hemmat Freeway W-E: DIVERGE Yadegar S Tehran-Saveh Freeway E-W: DIVERGE Dehshade W Tehran-Saveh Freeway E-W: DIVERGE Robatkarim E Yadegar Freeway N-S: DIVERGE Kouhestan E</th>
<th>$\mu_m$</th>
<th>$\sigma_m$</th>
<th>$\mu_s$</th>
<th>$\sigma_s$</th>
<th>$f$</th>
<th>$t$ (t-dist. table)</th>
<th>$S_{p_{ANN}}$</th>
<th>$S_{p_{PSO}}$</th>
<th>$t_{ANN}$</th>
<th>$t_{PSO}$</th>
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<td>9.92</td>
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<td>11.25</td>
<td>2.45</td>
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<td>1.87</td>
<td>2.31</td>
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<td>13</td>
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<td>1.08</td>
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<td>2.27</td>
<td>11.59</td>
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<td>24</td>
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<td>2.15</td>
<td>2.58</td>
</tr>
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