A Macro-Micro Model under Mixed Traffic Flow Conditions

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Abstract: To simultaneously consider simulation accuracy and efficiency and to acknowledge the prevailing mixed traffics of cars and motorcycles on urban streets, this study proposes a mixed traffic macro-micro model which is able to convert upstream macroscopic traffic flow into downstream microscopic flow with consideration of lateral drifts and transverse crossings of motorcycles by determining the jam density and free flow speed according to car-motorcycle density ratio and lane-changing behaviors on multilane roadways. The proposed model is validated by a field case. The validation results show that the performance and applicability of the proposed model is promising. Additionally, the error rates of simulated motorcycle flows at different lanes are higher than those of simulated car flows. The error rates of traffic flows on inner lanes are lower than those on outer lanes because of the prohibition of motorcycles in traveling on the inner lane.

Keywords: Macro-micro Model, Mixed Traffic, Motorcycle.

1. INTRODUCTION

Traffic flow theory aims to replicate real traffic flow behaviors so as to analyze and predict them under various traffic conditions and to serve as a platform for performance evaluation of traffic control strategies. In terms of level of details, traffic flow models can be divided into three categories: Macroscopic, mesoscopic and microscopic. Microscopic models consider the time-space behavior of individual drivers under the influence of vehicles in their proximity (microscopic models), while the mesoscopic models focus on the behaviors of drivers without explicitly distinguishing their time-space behaviors, and macroscopic models focus on the viewpoint of the collective vehicular flow (i.e. a group of vehicles). Three types of traffic flow models have their own advantages and disadvantages. Researchers choose the appropriate models depending up their research topic and scope.

Generally speaking, microscopic and mesoscopic models can provide more detailed and accurate descriptions of traffic flow behaviors, but they are more time consuming and of higher computation burden in comparing with macroscopic models. However, microscopic and mesoscopic models are rather limited as being applied to a large-scale network or traffic control optimization which requires efficient evaluation of numerous control strategies. In contrast, macroscopic models are not able to replicate the interaction behaviors among vehicles but they are good at efficiently simulating the collective traffic behaviors along a large-scale simple network, such as the basic segment of a freeway. Therefore, to simulate traffic behaviors in a large-scale network, including segments and intersections, macroscopic models are suitable to simulate collective traffic behaviors along segments where vehicles have fewer interactions and microscopic models are appropriate to replicate individual traffic behaviors at intersections where vehicles interactions are more frequent. To integrate and
utilize the advantages of microscopic and macroscopic models, an interface, namely the macro-micro model, for converting microscopic models into macroscopic or vice versa is imperial.

Additionally, most of macro-micro models are proposed for simulating pure traffic flow behaviors and they are not applicable for cases of traffic on Asian streets where mixed traffic composed of cars and motorcycles are prevailing. Especially, for the motorcycle flow which does not follow lane discipline has not been well addressed in previously proposed macro-micro models.

Based on this, this paper aims to develop and validate a mixed traffic macro-micro model. The rest part of this paper is organized as follows. Section 2 briefly introduces and compares macroscopic and microscopic traffic flow models, especially for those can account for mixed traffic. Section 3 presents the proposed macro-micro model. To investigate the applicability of the proposed model, Section 4 presents the model validation results on a field case. At last, conclusions of this study and suggestions for future studies are given.

2. LITERATURE REVIEW

This section first briefly introduces microscopic models, followed by the review of macroscopic models and macro-micro models.

2.1. Microscopic Traffic Flow Model

Microscopic models aim to describe the interactions among neighboring vehicles. Two widely adopted microscopic models are: Car following models and cellular automaton models. The most well-known and generalized form of car following model (Gazis et al., 1961), namely General Motors (GM) model, can be expressed as:

$$\ddot{x}_n(t) = \lambda [\dot{x}_n(t-T) - \dot{x}_{n+1}(t-T)] \frac{[x_{n+1}(t-T)]^m}{[x_n(t-T) - x_{n+1}(t-T)]^l}$$

where, \(\ddot{x}_{n+1}(t)\) is the acceleration/deceleration of the following vehicle at time \(t\). \(\dot{x}_n(t)\) and \(\dot{x}_{n+1}(t)\) are the speeds of the leading and following vehicles at time \(t\), respectively. \(x_n(t)\) and \(x_{n+1}(t)\) are the positions of the leading and following vehicles at time \(t\), respectively. \(\lambda\) is a sensitivity parameter. \(T\) is a reaction time. \(m, l\) are constants.

Numerous modified GM car following models were then proposed, such as Optimal Velocity Model (Bando et al., 1995; Newell, 2002), Generalized Force Model (Helbing and Tilch, 1998), Full Velocity Difference Model (Jiang et al., 2001) and so on.

Another popular microscopic model, Cellular automaton (CA), has been widely used to explicate the behaviors of traffic flows. Nagel and Schreckenberg (1992) first proposed a CA model (known as NaSch model) to reproduce the basic features of traffic flows, wherein the space, speed, acceleration and even the time were treated as discrete variables. The state of the road at any time-step was derived from one time-step ahead by applying acceleration, braking, randomization and driving rules for all vehicles synchronously. Obviously, such a “coarse” description is an extreme simplification of the real world traffic conditions. A considerable number of modified NaSch models have therefore been developed or extended.
in the past decade (e.g., Nagel et al., 1992; 1996; 1998; Chowdhury et al., 1997; Barlović et al., 1998; Knospe et al., 2000; Jiang and Wu, 2003; Bham and Benekohal, 2004; Larraga et al., 2005). Kerner and associates further investigated the field data on German highways and proposed the famous three-phase traffic theory (Kerner and Rehborn, 1996; Kerner and Klenov, 2002; 2004). The aforementioned models mainly dealt with pure traffic (only one type of vehicle such as passenger car). However, Meng et al. (2007), Lan and Chang (2005), Lan et al. (2010), and Lee et al. (2009) further incorporate more realistic CA models into mixed traffic (various types of vehicles such as car, motorcycle, bus).

2.2. Macroscopic Traffic Flow Model

Macroscopic models formulate the relationships among traffic flow characteristics, including density, flow, and speed of a traffic stream. The study of the macroscopic models began at the simple continuum model, also known as LWR model, proposed independently by Lighthill and Whitham (1955) and Richards (1956), which can be expressed as:

\[
\frac{\partial k}{\partial t} + \frac{\partial q}{\partial x} = 0 \tag{2}
\]

\[
q = ku \tag{3}
\]

\[
u = u_e(k) \tag{4}
\]

where, \(k, q, u\) are the density, flow and speed of a traffic stream. \(u_e(k)\) represents the equilibrium speed at density \(k\), while \(t\) and \(x\) represent time and space, respectively. Eq. (2) is a differential equation warranting flow conservation principle. Eqs. (3) and (4) depict the fundamental equation of traffic flow and the relationship between speed and density under equilibrium conditions.

Since the speed in LWR model is determined by the equilibrium speed-density relationship (Eq. (4)), no fluctuation of speed around the equilibrium values is allowed, the model does not faithfully describe non-equilibrium traffic flow dynamics. In order to overcome the shortcomings in the simple continuum model, Payne (1971) introduced a high-order continuum traffic flow model that replaces the equilibrium equation, Eq. (4), by a momentum equation with the following form:

\[
\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} = \frac{[u_e(k) - u]}{\tau} + \frac{v}{k \tau} \frac{\partial k}{\partial x} \tag{5}
\]

where, \(\tau\) is the relaxation time. \(v = -0.5 \frac{\partial u_e}{\partial k}\) is the anticipation coefficient. Afterwards, numerous modified or extended LWR and high-order continuum models were then proposed. For example, Wong and Wong (2002) proposed a multi-class traffic flow model based on LWR model to account for the distribution of heterogeneous drivers characterized by their choice of speeds in a traffic stream, which models the dynamic behavior of heterogeneous users whereby faster vehicles could overtake slower ones under uncongested condition as well as congested condition (though less easily), and slower vehicles would slow down the faster ones. Ngoduy (2011) further extend the multiclass LWR traffic flow model to account for the widely scattered distribution of flow-density relationships by assuming a Weibull distributed capacity variable. The multiclass LWR models proposed by Wong and Wong (2002) and Ngoduy (2011) can accommodate heterogeneous driving behaviors, but the models only limit
to those vehicles following lane discipline, such as trucks, buses, and passengers cars. The mixed traffic including motorcycles is barely considered in the macroscopic models.

2.3. Macro-micro Traffic Flow Model

Macro-micro traffic flow models aim to stitch together the macroscopic (M) and the microscopic (m) descriptions so as to meet the different level of details required for traffic description in various network links. For example, macroscopic models can be used for describing traffic behaviors in simpler links with homogenous traffic to avoid unnecessary computation burden; however, microscopic models are used for describing vehicle behaviors in more complicated links or nodes where vehicles are heavily interacted. To do so, an interface to convert macroscopic models into microscopic models (macro/micro, M2m) or microscopic models into macroscopic (micro/macro, m2M) has to be developed. The interface for both m2M and M2m conversion has to meet the requirements of flow conservation and wave propagation.

Bourrel and Lesort (2003) and Leclercq (2007) proposed LWR-based macro-micro hybrid model. Similarly, they used a finite difference method to spatiotemporally discretize and approximate the LWR model and lead LWR model to Newell’s optimal velocity car following model. As to the interface, Eulerian coordinate is used to describe flow behaviors while Lagrangian coordinate is used to depict vehicular behaviors. It was shown that both macroscopic and microscopic approaches will lead to the same solution.

Although traffic flow models have been well developed, comparatively few studies with regard to macro-micro models have been conducted. Additionally, due to the prevailing mixed traffic in Asian streets, how to extend the macro-micro models to account for mixed traffic conditions deserve a further study.

3. MODEL FORMULATION

To present the proposed mixed traffic macro-micro model, the macroscopic, interface and microscopic models are derived below.

3.1. Macroscopic Model

Since on most of urban streets in Taiwan, motorcycles are limited to use outer lane, while cars are not subject to such limitation, the proposed LWR model treats traffic on each lane separately, which can be expressed as follows:

\[ \frac{\partial k_l}{\partial t} + \frac{\partial k_l u_l}{\partial x} = s_l(x,t) \quad \forall l \]  
\[ \sum_l s_l(x,t) = 0 \]  
\[ s_l(x,t) = \phi \left[ \sum_{i \neq l} (k_i - k_l) - \sum_{i \neq l} (k_{el} - k_l) \right] \]

where, \( k_l \) is the density of lane \( l \), \( u_l \) is the speed of lane \( l \), \( s_l(x,t) \) is the lane change rate at space \( x \) and time \( t \), \( k_{el} \) is the equilibrium density of lane \( l \). \( \phi \) is a sensitivity coefficient describing the propensity that vehicles make a lane change from high density lane to lower density lane (Gazis et al., 1962).

To further consider the mixed traffic conditions, the concept of variable passenger car
equivalent (PCE) proposed by Chiou and Hsieh (2012) is adopted. The variable PCE concept is to dynamically change the PCE of motorcycles depending on the composition of cars and motorcycles. The flow-density relationships can be expressed as:

\[ k = k_a + \eta k_m \]  \hfill (9)

\[ q_i = k_i u_i \]  \hfill (10)

where, \( \eta \) is the variable PCE value of motorcycles, which is defined as an entropy function as shown below:

\[ \eta = \sigma + \left( \gamma H(k) \right) = \sigma - \gamma \sum_i p_i(k_a, k_m) \log p_i(k_a, k_m) \]  \hfill (11)

The core logic of Eq. (11) is that when the densities of two types of vehicles, i.e. cars and motorcycles, are similar, the interactions between two types of vehicles become more significant and the PCE value of motorcycles increases.

Additionally, since frequent lane-changes could disrupt traffic flow and lower down traffic speed, Jin (2010) proposed an “effective total density” to account for the effect of lane change behaviors on traffic flow by introducing a lane-changing intensity variable (\( \varepsilon(k) \)). Therefore, the effective density is defined as:

\[ \bar{k} = k \left( 1 + \varepsilon(k) \right) \]  \hfill (12)

where, \( \varepsilon(k) \) lane-changing intensity. That is, the effective density is equal or large than the real density. To account for mixed traffic context, the lane-changing intensity can be modified as:

\[ \varepsilon = \alpha \frac{k_i t_{c_i}}{kT} \]  \hfill (13)

where, \( k_c \) is the density of lane-changing vehicles (number of vehicles/km). \( t_{c_i} \) is the time required for making a lane-change. \( T \) is the average travel time for traveling one kilometer. \( \alpha \) is a function of density, representing the lane-changing propensity at various traffic density conditions. Eq. (13) is the proportion of total time spent in lane-changes to total travel time for pure traffic. Thus, for mixed traffic condition, Eq. (13) is further revised as:

\[ \varepsilon_{il}(k_a, k_m) = \frac{t_{cen} N_i}{kLT} \frac{k t_{cen}}{kT} = \alpha_i \frac{k t_{cen}}{kL} = \alpha_i \frac{k t_{cen} u}{kL} = \alpha_i \frac{(k_{cen} t_{cen}) u}{(k_a + \eta k_m) L} \quad \forall i \]  \hfill (14)

where, \( t_{cen} \) and \( t_{cem} \) are the time required for a lane-change of cars and motorcycles, respectively. \( k_{ci} \) is the density of lane-changing type \( i \) vehicles, which is derived from the net lane-changing rate: \( k_{ci} = k_s(x, t) \). \( L \) is the length of the study network. \( \alpha_i \) is the lane-changing propensity of lane \( i \). Given a three-lane roadway, the lane-changing propensities of the outer, center, and inner lanes can be respectively expressed as:

\[ \alpha_{outer} = \beta_{outer} + \beta_{1} \left( k_{center} - k_{outer} \right) \]  \hfill (15)

\[ \alpha_{center} = \beta_{center} + \beta_{2} \left( k_{outer} - k_{center} \right) + \beta_{3} \left( k_{inner} - k_{center} \right) \]  \hfill (16)

\[ \alpha_{inner} = \beta_{inner} + \beta_{4} \left( k_{center} - k_{inner} \right) \]  \hfill (17)

Based on Eqs. (15)-(16), the total effective density can be obtained. Travel speed can be further derived by assuming the Greenshields (1935) speed-density relationship:

\[ u = u_f \left( 1 - \frac{\bar{k}}{k_j} \right) \]  \hfill (18)

where, \( u_f \) is the free flow speed. \( k_j \) is the jam density. To further extend the Greenshields model to mixed traffic conditions, the relationship can be expressed as:

1935
\[ u_t = u_{ij} \left( 1 - \frac{k_j}{k_j(k_a, k_m)} \right) \]  
(19)

where, the jam density is assumed as Fig. 1 which depends upon various combinations of numbers of cars and motorcycles. According to our filed observation, even as the number of cars reaches the jam density (e.g. 160 veh/km), few motorcycles can still sneak into the car traffic by taking advantage of the clearance space among cars. Therefore, the relationship is not linear. Thus, the jam density of cars under various compositions of cars and motorcycles can be computed as:

\[ k_{ij}(k_a, k_m) = \begin{cases} 
  k_{aj\text{max}} & \text{if } k_a/k_m \geq k_{aj}/k_{m^*}, \\
  \frac{k_a k_{aj\text{max}} k_{n\text{max}}}{k_a(k_{n\text{max}} - k_{m^*}) + k_m k_{aj\text{max}}} & \text{if } k_a/k_m < k_{aj}/k_{m^*}.
\end{cases} \]  
(20)

where, \( k_{m^*} \) is the remaining density for motorcycles when no more cars can enter the roadway. Additionally, the free flow speed of cars is also lowered down as the number of motorcycles increases, which is expressed as:

\[ u_{fa} = u_{aj\text{max}} \left( 1 - \frac{k_m}{k_{mj}} \right) \]  
(21)

Therefore, the jam density of motorcycles under various compositions of cars and motorcycles can be computed as:

\[ k_{mj}(k_a, k_m) = \begin{cases} 
  k_{mj\text{max}} & \text{if } k_a/k_m \geq k_{aj}/k_{m^*}, \\
  \frac{k_m k_{aj\text{max}} k_{n\text{max}}}{k_a(k_{n\text{max}} - k_{m^*}) + k_m k_{aj\text{max}}} & \text{if } k_a/k_m < k_{aj}/k_{m^*}.
\end{cases} \]  
(22)

3.2. Macro-micro Interface

To convert macroscopic models into microscopic models (M2m) or vice versa (m2M), the target traffic variable is changed from density (macroscopic) to spacing (microscopic). The converting relationship is shown below:

1937

\[ k_i(x,t \rightarrow \Delta t) = \frac{1}{s'_i(x,t)} \] (23)

where, \( k(x,t) \) and \( s(x,t) \) are the density and spacing at space \( x \) and time \( t \) of vehicle type \( i \).

Leclercq (2007) used the upstream demand and downstream supply at both sides of the interface to develop the connection between macroscopic models and microscopic models. The minimum of upstream demand and downstream supply then determines the flow rate at the interface (i.e. Eq. (24)). Taking the M2m interface for example, the upstream macroscopic demand is expressed as Eq. (25) and the downstream microscopic supply is defined as Eq. (28).

\[ q(x,t) = \min \left( \Delta \left( x^-, t \right); \Omega \left( x^+, t \right) \right) \] (24)

\[ \Delta(k) = \begin{cases} kU(k) & \text{if } k \leq k^* \\ q^* & \text{if } k > k^* \end{cases} \] (25)

\[ \Omega(k) = \begin{cases} q^* & \text{if } s_n < s^* \\ kU(k) & \text{if } s_n \geq s^* \end{cases} \] (26)

\[ \Delta(x,t) = \begin{cases} U \left( \frac{1}{s_n} \right) & \text{if } s_n \geq s^* \\ U \left( \frac{1}{s_n} \right) & \text{if } s_n < s^* \end{cases} \] (27)

\[ \Omega(x,t) = \begin{cases} q^* & \text{if } s_n < s^* \\ q^* & \text{if } s_n \geq s^* \end{cases} \] (28)

Since the M2m interface needs to “generate” vehicle one by one according to the upstream demand, a vehicle storage function \( I(t) \) with value of \([0, 1]\) is employed. Once \( I(t) \) reaches 1, a vehicle is generated and reset \( I(t) \) as 0 for pure traffic conditions. The \( I(t) \) is updated according the following equation:

\[ I_i(t + \Delta t) = I_i(t) + q_i(x,t) \Delta t \] (29)

However, in comparing to cars, motorcycles can parallel move forward within one lane; thus, to extend the vehicle storage function to mixed traffic conditions, \( I(t) \) is redefined as the range of \([0, 2]\). Once \( I(t) \) reaches 1, one car or motorcycle will be generated and reaches 2, two motorcycles will be generated simultaneously.

3.3. Microscopic Model

This paper extends Bando’s Optimal Velocity Model (Bando et al., 1995) to mixed traffic conditions for replicating car-following behaviors. As to the lane change behaviors, Logit model is used. The utility functions of cars and motorcycles are respectively represented as:

\[ V_{ai} = \delta_{ai} + \delta_{a1}x_i + \delta_{a2 type_i} + \delta_{a3}x_i + \delta_{a4}u_i + \delta_{a5}b_i + \delta_{a6}btype_i \] (31)

\[ V_{ac} = \delta_{ai} + \delta_{a1}u_i + \delta_{a2 type_i} + \delta_{a3}x_i \] (32)

\[ V_{av} = \delta_{ai} + \delta_{a1}u_r + \delta_{a2 type_i} + \delta_{a3}x_r + \delta_{a4}u_r + \delta_{a5}b_r + \delta_{a6}btype_r \] (33)

\[ V_{ad} = \delta_{ai} + \delta_{a1}u_t + \delta_{a2 type_i} + \delta_{a3}x_t + \delta_{a4}u_t + \delta_{a5}b_t + \delta_{a6}btype_t + \delta_{a7}dist_i + \delta_{a8}dist_r \] (34)
\[
V_{mc} = \delta_{m1} \Delta u_i + \delta_{m2} \text{type}_i + \delta_{m3} \Delta x_i \\
V_{mr} = \delta_{mr} + \delta_{m1} \Delta u_r + \delta_{m2} \text{type}_r + \delta_{m3} \Delta x_r + \delta_{m4} \Delta bu_r + \delta_{m5} \Delta bx_r + \delta_{m6} \text{type}_r + \delta_{m7} \text{dist}_r + \delta_{m8} \text{last}_r
\]

(35)

(36)

where, subscript a and m stands for car and motorcycle. Subscript l, c, r stands for the left, center and right lanes. \(\Delta u\) is the speed difference. Type is the type of the lead vehicle, if the lead vehicle is a car, then type = 1, otherwise type = 0. \(\Delta x\) is the spacing between the following vehicles. \(\text{dist}\) is the distance from the stop line. \(\text{last}\) is the choice decision of last time click.

4. MODEL VALIDATION

To investigate the performance and applicability of the proposed model, case studies on an exemplified example and a field case are respectively conducted. Roosevelt Road Section 3 near the intersection of Roosevelt Road and Heping East Road, Taipei City, a total of 300 meters was chosen. The chosen roadway has four lanes including a bus exclusive lane. To study the mixed traffic of cars and motorcycles, only the outer three lanes were studied and the bus exclusive lane could isolate the bus traffic. The traffic information was collected from the video-taping from a high rising building nearby during 7:00-9:00 am on February 23, 2013. To video-tape the whole study roadway, two cameras were used to simultaneously take seamless consecutive films as shown in Fig. 2.

![Figure 2. Photo of the study roadway](image)

In order to estimate the parameters of the proposed lane-changing model, the samples of lane-changing cars and motorcycles were drawn, including the lane-changing time, location, and change from which lane to which lane. Table 1 shows the estimated parameters. As to the lane choice utility function of the microscopic model, the parameters are set according to Lee (2012) as shown in Table 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_{\text{inner}})</td>
<td>-0.354</td>
</tr>
<tr>
<td>(\beta_{\text{center}})</td>
<td>0.017</td>
</tr>
<tr>
<td>(\beta_{\text{outer}})</td>
<td>0.327</td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>1.21</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>2.78</td>
</tr>
</tbody>
</table>

Table 1. Estimated parameters of lane-changing behaviors
Table 2. Estimated parameters of lane choice utility function

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Car</th>
<th>Motorcycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_r$</td>
<td>-1.49</td>
<td>1.36</td>
</tr>
<tr>
<td>$\delta_i$</td>
<td>-0.66</td>
<td>2.04</td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>-0.16</td>
<td>-0.15</td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\delta_3$</td>
<td>0.03</td>
<td>0.021</td>
</tr>
<tr>
<td>$\delta_4$</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\delta_5$</td>
<td>-</td>
<td>5.13</td>
</tr>
</tbody>
</table>

Source: Hsu and Lee (2012)

To investigate the simulation efficiency and accuracy, six locations of the M2m interface are compared: 300, 150, 100, 50, 10, 0 meters from the intersection as shown in Fig. 3. The upstream and downstream traffic is simulated by macroscopic and microscopic models, respectively.

![Figure 3. Six locations of M2m interface](image)

For 1000 seconds traffic flow simulation, the computation times of various scenarios are reported in Table 3. As expected, the longer roadway of microscopic simulation is, the higher computation time is required. If the whole roadway is simulated by macroscopic model, the computation time is less than 1 second.

Table 3. Computation time under various locations of M2m interface

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Location of M2m interface (m)</th>
<th>Length of macro simulation (m)</th>
<th>Length of micro simulation (m)</th>
<th>Computation time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>300</td>
<td>0</td>
<td>300</td>
<td>5781</td>
</tr>
</tbody>
</table>
To examine the simulation accuracy, the traffic flow of cars and motorcycles of three lanes at two locations, at stop line and at 100m from stop line, are measured. The mean absolute percentage error (MAPE) is used to measure the simulation accuracy. However, since most of time clicks have none of vehicles passing through (i.e. too many zero observations), the symmetric mean absolute percentage error (SMAPE) is adopted instead, which is computed as following:

$$SMAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t + F_t} \right| \times 100\%$$

(37)

where, $A_t$ is the real observed flow at time $t$. $F_t$ is the simulated flow at time $t$. $n$ is total number of time steps.

The results are reported in Tables 4 and 5. As shown in Table 4, since the traffic at the stop line is simulated by the microscopic model under S1 to S5, the accuracy rates are similar, except for S6 which whole roadway is simulated by the macroscopic model and the accuracy of S6 is substantially lower. Additionally, the simulation accuracy of cars is higher than that of motorcycles and simulation accuracies of inner and center lanes are higher than that of outer lane due to illegal roadside parking.

Table 5 represents the simulation accuracy measured at 100m from stop line. The simulation accuracy of both cars and motorcycles at all lanes are substantially higher than those measured at stop line.

The trajectories of cars and motorcycles at various lanes along the study segment under S3 Scenario are depicted in Fig. 4. As shown in Fig. 4, the center lane has the longest queue exceeding the M2m interface (100m). It can be noted that the interface correctly propagate the queue length from the microscopic model to the macroscopic model, suggesting the proposed model can correctly translate the different level of details traffic flow models.
<table>
<thead>
<tr>
<th></th>
<th>Car</th>
<th>Car</th>
<th>Motorcycle</th>
<th>Car</th>
<th>Motorcycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>6.8</td>
<td>8.7</td>
<td>11.5</td>
<td>7.3</td>
<td>15.2</td>
</tr>
<tr>
<td>S2</td>
<td>18.4</td>
<td>21.2</td>
<td>26.7</td>
<td>11.4</td>
<td>20.1</td>
</tr>
<tr>
<td>S3</td>
<td>27.1</td>
<td>33.0</td>
<td>36.8</td>
<td>9.4</td>
<td>44.4</td>
</tr>
<tr>
<td>S4</td>
<td>34.9</td>
<td>46.4</td>
<td>41.9</td>
<td>38.1</td>
<td>47.5</td>
</tr>
<tr>
<td>S5</td>
<td>34.9</td>
<td>46.4</td>
<td>41.9</td>
<td>38.1</td>
<td>47.5</td>
</tr>
<tr>
<td>S6</td>
<td>34.1</td>
<td>45.2</td>
<td>47.3</td>
<td>41.1</td>
<td>49.3</td>
</tr>
</tbody>
</table>

(a) Cars on inner lane

(b) Cars on center lane

(c) Motorcycles on center lane

(d) Cars on outer lane

(c) Motorcycles on outer lane

Figure 4. Trajectories of cars and motorcycles at various lanes under S3 Scenario

5. CONCLUSIONS
To acknowledge the requirements for different levels of detailed descriptions for replicating traffic behaviors along a heterogeneous corridor, a macro-micro model based on LWR model and Optimal Velocity Model is proposed and validated. The proposed model is further extended to account for the mixed traffic of cars and motorcycles.

To investigate the applicability of the proposed model, a case study on a 300m long three-lane corridor near a signalized intersection in Taipei City is conducted. Six scenarios of various locations of M2m interface are compared in terms of simulation computation time and simulation accuracy (SMAPE). The simulation results show the longer corridor simulated by the macroscopic model is, the more efficient the proposed model performs. But the simulation accuracy rapidly deteriorates as the length of corridor simulated by the macroscopic simulation increases. From the simulated trajectories of cars and motorcycles at various lanes, the proposed interface can correctly simulate the queue propagation from micro to macro.

For simplicity, the jam density relationship of cars and motorcycles is assumed to be linear in this study. Nonlinear relationships under various compositions of cars and motorcycles deserve to be developed. Due to the limitation of video-taping area, only 300m long corridor is chosen for the case study. To show the applicability of the proposed model, a longer corridor with assistant of advanced traffic recoding techniques deserves a further study. Last but not least, this study compares the performance of various locations of the M2m interface. However, it is worthy of exploration to conclude a principle for determining the optimal location of the interface toward both efficiency and accuracy.

REFERENCES


