Abstract: Traffic patterns and the associated phase transitions for pure and mixed traffic are explored in this study. Local traffic parameters are defined in a spatiotemporal (3-D) domain so that the cellular automaton (CA) modeling can precisely capture the traffic features. Refined CA simulations are performed under pure and mixed traffic scenarios on a multilane stretch where virtual detectors are placed to measure the 3-D traffic parameters. It is found that the proposed measuring techniques with refined CA modeling can copiously explore the local traffic patterns with associated phase transitions in both upstream and downstream of a bottleneck. Finally, a comparison of the local traffic parameters with the global counterparts is also presented.

Key Words: cellular automaton (CA), mixed traffic, traffic patterns, phase transitions.

1. INTRODUCTION

Cellular automaton (CA) has become an effective tool for reproducing the basic features and for exploring the phase transitions of real traffic since Nagel and Schreckenberg (1992) first proposed a simple CA model—the renowned NaSch model. To date, a considerable number of modified CA models have been proposed, for instance, Nagel (1996, 1998), Rickert et al (1996, 2002), Chowdhury et al (1997) and Barlovic et al (1998), Knospe et al. (2000), Jiang and Wu (2003), Bham and Benekohal (2004), and Larraga et al. (2005). Most of these CA models were for pure traffic on rather coarse cell systems wherein all vehicles are treated as identical size (same length and width). Recently, some CA studies have devoted to mixed traffic scenarios in which vehicles come in various sizes (e.g., Nagel et al., 1998; Ez-Zahraouya et al., 2004; Kerner, 2004; Wang et al., 2007; Meng et al., 2007). However, these studies merely considered different vehicle lengths without factoring different vehicle widths into the models, except for Meng et al. (2007). In reality, a multilane roadway space used by mixed traffic (e.g., bus, car, motorcycle) should take into account the lengths and widths of different vehicles so as to more precisely elucidate their interactive movements, especially the overtaking or lane change behaviors. Besides, using coarse cell systems may oftentimes fail to capture the essential traffic features emerging in a spatiotemporal domain.
for real traffic.

To improve the mentioned weaknesses, Hsu et al. (2007) first proposed a refined CA modelling by introducing a generalized spatiotemporal definition for traffic parameters (occupancy, flow and speed) which can precisely capture the collective behaviors of mixed traffic with different vehicular sizes. One important advantage of the refined CA modeling is that the “resolution” of simulation results is greatly enhanced; therefore, more detailed traffic features can be observed. Lan et al. (2007, 2010) have successfully applied the refined CA modeling to mixed traffic simulations in the freeway (comprising cars and buses/trucks) and surface roadway (comprising cars and motorcycles) contexts.

Because observation of traffic over a long spatial stretch is difficult and expensive, traffic parameters are generally measured in a local (temporal) manner with stationary detectors, rather than in a global (spatiotemporal) manner. Despite this, methodologies for deriving the local traffic parameters, especially on a fine cell system, remain seldom addressed (Mallikarjuna and Ramachandra, 2006, 2008). To fill up the gap, this paper attempts to measure the local traffic parameters and to further explore the local spatiotemporal features of mixed traffic with the refined CA modelling.

The rest of this paper is organized as follows. A short description of the refined CA modelling is given in Section 2, followed by the definition of local traffic parameters in Section 3. The simulations, the derived local traffic parameters and comparisons between pure and mixed traffic are presented in Section 4. Section 5 compares the derived local traffic and their global counterparts for both pure and mixed traffic. Conclusions and suggestions for future studies then follow. In addition, to enhance readability, a notation table summarizing all variables and parameters utilized is given in Appendix.

2. PROPOSED CA MODEL

2.1 Common Unit for Cells and Sites
The concept of “common unit” (CU) was first introduced by Hsu et al. (2007) to gauge different vehicle dimensions (length and width) and their required clearances for safe longitudinal and lateral movements. Following the same concept, this study defines 1×1.25 meters as the CU for cells (representing the vehicles) and sites (representing the roadway spaces).

![Figure 1 Cell/site system utilized and allocations of vehicles of various sizes in the proposed CA model. For demonstration, the virtual local detector is also defined.](image)

For instance, for a two-lane road with 3.75-meter width in each lane, as shown in Figure 1, the road width can be represented by 6 CUs (i.e., each lane is represented by 3 CUs in width, which can be equally divided into 3 sub-lanes). According to Figure 1, for safe movement
with acceptable clearances, a heavy vehicle (bus, truck) can be set as 12×3 CUs, taking 36
CUs of the roadway space; a light vehicle (car) is represented by 6×2 CUs, occupying 12 CUs
of the roadway space; a two-wheel vehicle (motorcycle, bicycle) can be represented by 2×1
CUs, taking up 2 CUs of the roadway space. Other vehicle types can also be defined in
accordance with their lengths and widths. For demonstration, in Figure 1 a local detector
which occupies 1×6 CUs is also depicted.

2.2 Spatiotemporal Traffic Parameters
In conventional traffic flow theory, there are three important traffic parameters—flow (q),
density (k) and speed (v). For a single-lane roadway with length L, the 1-D local traffic
parameters can be defined as:

\[
k(t) = \frac{\text{number of vehicles observed over a road of given length } L \text{ at time } t}{\text{length of observed roadway } L}
\]  

(1)

\[
q(x) = \frac{\text{number of vehicles (m) observed during given time period } T \text{ at loc. } x}{\text{length of observed time period } T}
\]  

(2)

The speed (v) can be calculated by the following equation:

\[q = kv\]  

(3)

It is understood that Eq. (3) was originally developed by scholars in the field of fluid
mechanics upon the assumption that fluid flow is continuous. This formula later was
introduced by Wardrop (1952) for analyzing traffic features and, since then, commonly
utilized for estimating vehicular average speed. However, one may be confused about the
validity of such applicability since traffic flow is not continuous but in essence discrete by
nature. Besides, by definition, the 1-D local traffic flow-\(q(x)\) is a time-based parameter
measured over a period of time at a specific fixed point, whereas the local traffic density-\(k(t)\)
is a space-based parameter measured over a distance of space at a specific time instant. So
although Eq. (3) seems reasonable from dimensional perspective, it has been constantly
criticized in the past. For example, Highway Research Center (2005) argued that this formula
is strictly correct only under some very restricted conditions, i.e., homogeneous state in which
each vehicle equips with identical features (e.g., same headway, identical speed, etc), or in the
limit as both the space and time measurement intervals approach zero. If neither of those
situations holds, then use of Eq. (3) to calculate speed can give misleading results, which
would not agree with empirical measurements.

To overcome this restriction, Daganzo (1997) extended the 1-D local traffic parameters to 2-D
to cover both time and distance and hence defined the 2-D traffic parameters. However, the
2-D definition failed to capture the lateral movements of vehicles in multilane contexts.
Therefore, Hsu et al. (2007) further expanded this concept by introducing the generalized 3-D
traffic parameters, including occupancy \(\rho(S)\), flow \(q(S)\) and space-mean-speed \(v(S)\) over a
spatiotemporal domain \(S\) as follows:

\[
\rho(S) = \frac{\sum N_a(t) \Delta t}{\sum N \Delta t} = \frac{t(S)}{|S|}
\]  

(4)

\[
q(S) = \frac{\sum M_a(x) \Delta x}{\sum T \Delta x} = \frac{d(S)}{|S|}
\]  

(5)
The above generalized 3-D traffic parameters defined by Hsu et al. (2007) will be used in this study to depict the global behaviors of traffic movements in the following CA simulations.

### 2.3 Longitudinal Movements

The forward rules utilized in this study follow those proposed by Lan et al. (2009) who took limited deceleration capability into consideration. The proposed forward update rules apply to both light and heavy vehicles. However, vehicle attributes (e.g., maximum speed, allowable acceleration and deceleration) will be different in accordance with the vehicle category simulated. The forward update rules include the following seven steps.

**Step 1:** Determination of the randomization probability.

\[
p(v_n(t), t_s, t_s, S_{n+1}(t)) = \begin{cases} 
p_b & \text{if } S_{n+1} = 1 \text{ and } t_h < t_s \\
p_0 & \text{if } v_n = 0 \text{ and } t_s \geq t_k \xi \\
p_d & \text{in all other cases}
\end{cases}
\]  

(7)

In this study, \(k=1\) denotes light vehicles, \(k=2\) for heavy vehicles, respectively.

**Step 2:** Acceleration. Determine the speed of vehicles in the next time step.

\[
\begin{align*}
\text{if } (S_{n+1}(t) = 0) \text{ or } (t_h \geq t_s) 
\text{then } v_n(t+1) &= \min(v_n(t) + a_k, v_{k,\max}) \\
\text{else } v_n(t+1) &= v_n(t)
\end{align*}
\]  

(8)

**Step 3:** Deceleration. If \(v_{n+1}(t+1) < v_n(t+1)\), check the following safety criteria to determine speed at the next time step.

\[
x_n(t+1) + \Delta + \sum_{i=1}^{\tau_n(c_n(t+1))} (c_n(t+1) - \frac{D}{2} i) \leq x_{n+1}(t+1) + \sum_{i=1}^{\tau_n(c_n(t+1))} v_{n+1}(t+1)
\]  

(9)

**Step 4:** Randomization.

\[
\text{if } (\text{rand}(r) < p) \text{ then } v_n(t+1) = \max(v_n(t+1) - 1,0)
\]  

(10)

**Step 5:** Determination of vehicle status identifier \(S_n(t)\) in the next time-step.

\[
S_{n}(t+1) = \begin{cases} 
0 & \text{if } v_n(t+1) > v_n(t) \\
S_n(t) & \text{if } v_n(t+1) = v_n(t) \\
1 & \text{if } v_n(t+1) < v_n(t)
\end{cases}
\]  

(11)

**Step 6:** Determination of time \(t_{st}\) stuck inside the jam.

\[
t_{st} = \begin{cases} 
t_{st} + 1 & \text{if } v_n(t+1) = 0 \\
t_{st} & \text{if } v_n(t+1) > 0
\end{cases}
\]  

(12)

**Step 7:** Update position.

\[
x_n(t+1) = x_n(t) + \text{roundoff}\left(\frac{v_n(t) + v_n(t+1)}{2}\right)
\]  

(13)
2.4 Lateral Movements
In real world, most road systems comprise at least two lanes, thus allowing vehicles to change lane or make lateral displacement to overtake a slow vehicle or fixed object in front. Over a two-lane (6 sites in width) roadway, for instance, a heavy vehicle (3 CUs in width) will have only one kind of lateral movement—lane change (either from left lane to right lane or from right lane to left lane). A light vehicle (2 CUs in width) may have one additional lateral movement option: lateral drift, beside lane change. The lateral drift of light vehicle will be triggered if the situation is allowed to overtake a smaller size vehicle (e.g., motorcycle) in front of the same lane and with comparatively slower speed, which refers to moving forward within the same lane but drifting from rightmost two sub-lanes to leftmost two sub-lanes or from leftmost two sub-lanes to rightmost two sub-lanes; provided that each sub-lane is 1-site in width. However, the present paper does not deal with the motorcycle traffic—only pure traffic and mixed traffic that comprised by heavy vehicles (buses or trucks) and light vehicles (cars) are simulated, the lateral positions of light vehicles within each lane will not significantly affect the simulated traffic flow rate. Therefore in this study only lane change behavior is considered for both light and heavy vehicles. The lane change rule for a vehicle locates in the left lane of one two-lane roadway and intends for lane change to the right lane can be described as:

\[ LC_{l\rightarrow r} : \]
\[ v_{l,n}(t) > v_{l,n}(t) \text{ and } v_{n}(t) > v_{l,n}(t) \]
\[ g_{i,n}(t) > \min(d_{i,j}, v_{n}(t + 1)) \]
\[ g_{b,n}(t) > \min(d_{b,j}, v_{b,n}(t + 1)) \]

where \( g \) means the gap and the suffix \( b \) means the vehicle in nearby upstream.

3. LOCAL TRAFFIC PARAMETERS DETECTION
3.1 Local Traffic Parameters
In this section, the method for deriving local traffic flow and occupancy (a proxy of density) is defined. The fundamental diagrams are established to illustrate the traffic features and the coupled phase transitions.

The measurement of local traffic flow rate is conceptually simple and straightforward. According to the definition in Eq. (2), traffic flow rate is collected directly through point measurements and then takes average over the measured time span. This feature coincides with the nature of local traffic conditions on the stationary location. In contrast, it would be complicated when one intends to obtain the local density at a fixed spot. As mentioned before, density is defined as the number of vehicles occupying a certain length of roadway at a given instant by Eq. (1). Basically density is a measure over space; however, it would not be practical (due to too expensive) to continuously take aerial snapshots on a fixed length of road for density measurement, thus occupancy is measured instead. Occupancy is defined as the percent of time a point of roadway is occupied. It can be measured only over a short section (shorter than the minimum vehicle length) with the preset detectors, and therefore does not applicable if we intend to cover a long stretch of roadway.

There are three major reasons putting forward for adopting occupancy as the surrogate of density for local traffic measurement. The first is that there should be improved consistency between theoretical and practical approaches. The second reason is that density, as vehicles
per length of road, ignores the effects of vehicle length and traffic composition. Therefore it would be difficult for implementing into mixed traffic analysis. Occupancy, on the other hand, is directly affected by both of these variables and therefore gives a more reliable indicator of the amount of a road space being used by the vehicles. The last merit for using occupancy instead of density is the easiness for measurement. For pure traffic context, in case that the averaged vehicular length is known, local density can still be estimated from the derived occupancy by the formula (May, 1990):

$$k = \frac{52.8}{l(A) + L_d} O(t) \tag{15}$$

where $L_d$ is the detection zone length, $l(A)$ is the averaged vehicular length. $O(t)$ represents the local occupancy at instant $t$.

Normally occupancy considers single lane only and can vary from 1 to 100 percent. Compared with the traditional definition of occupancy that only taking vehicular length into consideration, the proposed measurement takes both vehicular length and width into consideration, yet basically remains the merit of simplicity. The proposed occupancy $O(t)$ and the local traffic flow rate $q(t)$ are derived via virtual detectors arranged into the simulated road section. In the following, both local traffic flow rate and local occupancy are counted by “occupied cells.” However, they can be transferred into “occupied vehicles” through simple manipulations.

It is worthy noting that since in the refined CA modeling one car occupies only two sites laterally, for a two-lane roadway with 6 sites in width, the maximum occupancy available for pure car traffic would be two-thirds (0.667) only if counted on the CU (cell/site) basis. Only in pure bus (3 CUs in width) traffic can a theoretical maximum occupancy (1.000) be reached, which implies that the lateral 6 sub-lanes (sites) are fully occupied.

3.2 Traffic Detection and Measurement

For a local virtual detector with length 1 site located at position $ms$ on the roadway of width $W$, four possibilities can be identified for one vehicle with width $VW$ and length $VL$ to pass through it within each time-step. All the possibilities are shown in Figure 2. The first possibility is that at time $t$ a vehicle did not arrive the detector but the vehicle “passed through” it at time $t+1$ (Figure 2(a)). The second possibility is that at time $t$ a vehicle did not arrive the detector, but the vehicle “stand” on the detector at time $t+1$ (Figure 2(b)). In the third case, a vehicle remains standing on the detector for consecutive two time-steps (Figure 2(c)), this happens in congested traffic. The final case is that a vehicle touches the detector at time-step $t$ and “passed it through” at time $t+1$ (Figure 2(d)).

![Figure 2 Four possibilities for a vehicle detected by a virtual detector](image)

Upon above, for a virtual detector arranged at the simulated road section, the local flow rate and occupancy can be extracted respectively by Eqs. (16) and (17). Note that both flow rate
and occupancy are counted by number of cells instead of number of vehicles.

\[
O(t) = O(t-1) + \begin{cases}
\frac{VL \times VW}{W \times v_i(t)} & \text{if } T_i(t) > ms \text{ and } H_i(t-1) < ms \\
\frac{H_i(t) - ms \times VW}{v_i(t)} & \text{if } H_i(t) \geq ms \text{ and } T_i(t) \leq ms \text{ and } H_i(t-1) < ms \\
\frac{W}{v_i(t)} \times \frac{VL}{VW} & \text{if } H_i(t) \geq ms \text{ and } T_i(t) \leq ms \text{ and } H_i(t-1) \geq ms \text{ and } T_i(t-1) \leq ms \\
0 & \text{otherwise}
\end{cases}
\]  

\[
q(t) = q(t-1) + \begin{cases}
\frac{VL \times VW}{W \times v_i(t)} & \text{if } T_i(t) > ms \text{ and } H_i(t-1) < ms \\
(H_i(t) - ms) \times VW & \text{if } H_i(t) \geq ms \text{ and } T_i(t) \leq ms \text{ and } H_i(t-1) < ms \\
v_i(t) \times VW & \text{if } H_i(t) \geq ms \text{ and } T_i(t) \leq ms \text{ and } H_i(t-1) \geq ms \text{ and } T_i(t-1) \leq ms \\
(ms - T_i(t)+1) \times VW & \text{if } (T_i(t) > ms) \text{ and } H_i(t-1) \geq ms \text{ and } T_i(t-1) \leq ms \\
0 & \text{otherwise}
\end{cases}
\]  

where \(O(t)\) denotes the cumulated occupancy at time-step \(t\). \(q(t)\) denotes the cumulated flow (in terms of cells) at time-step \(t\). \(ms\) indicates the location of a virtual detector. \(VL\) denotes the vehicle length counted in cells. \(VW\) denotes the vehicle width also counted in cells. \(H_i(t)\) is the head of vehicle \(i\) at time-step \(t\). \(T_i(t)\) is the tail of vehicle \(i\) at time-step \(t\). \(W\) stands for road width counted in sites.

Traditionally, the derived traffic parameters are expressed in arithmetic average (AA) over a fixed time interval to alleviate the drastic fluctuations raised by local noise. For comparison, an unweighted moving average (UMA) of traffic data is also introduced. The moving average technique is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. For example, given a series of traffic data and a fixed time interval (say, 30 seconds), the moving average data can be obtained in the following way. At the beginning, the average value of the first time interval is calculated. Then the fixed time interval is rolling forward to form a new time interval with the same duration and the second average value is also calculated. The process is repeated over the entire traffic data. Thus, a moving average traffic is not a single value but a group of numbers, each of which is the average of the corresponding time interval of a larger set of traffic data points.

The simplest UMA may be the mean of previous \(n\) data points, which can be calculated via the following formula:

\[
V_{ma}(t) = \frac{1}{n} \sum_{i=1}^{n} V_{t-i+1}
\]  

\[
V_{ma}(t+1) = V_{ma}(t) - \frac{V_{t-n+1}}{n} + \frac{V_{t+1}}{n}
\]  

where \(V_i\) is the local parameters \((O(t)\) and \(q(t)\) detected by Eqs. (16) and (17) at time-step \(t\), whereas \(V_{ma}(t)\) is their UMA.

4. SIMULATIONS
4.1 Scenarios
The simulations are performed on a closed track containing 1,800×6 sites (CUs), which represents a two-lane freeway mainline stretch with width 7.5 meters and length 1,800 meters. Pure light vehicle (car) traffic and mixed light/heavy vehicle (car/bus or truck) traffic are simulated. Based on the field observation on Taiwan’s Freeway, the prevailing mixed ratio—80% light vehicles, 20% heavy vehicles—is selected. At time-step 0, all vehicles are set in the front end of the circular track with velocity 0 as the initial condition and simulated for 600 time-steps. The maximum speeds are defined in accordance with the speed limits on Taiwan’s Freeway, that is, 31 cells/sec for light vehicle (around 110 kph) and 25 cells/sec for heavy vehicle (90 kph) respectively. For global (macroscopic) traffic analysis, a warm-up period—the first 60 time-steps, data is discarded, as to get rid of the impact of preset initial parameters setting. However, for local traffic data collection, all the derived data is retained, in light that we intend to evaluate whether the local traffic data derived through the proposed schemes can effectively reflect their counterparts—the global ones.

4.2 Results of AA Traffic Data
To explore the diversified traffic patterns, we arrange a bottleneck in the middle of the right lane of the simulated track. Two local virtual detectors are introduced—one located at 100 sites (meters) upstream and the other at 100 sites downstream of this bottleneck, as shown in Figure 3. Both pure light vehicle and mixed light/heavy vehicle traffic are simulated. It can be clearly identified that the shapes of both x-t plots (Figure 3(a) and 3(b)) are similar, there are sequential traffic patterns transiting around the downstream of the virtual detector from F, F→J, J→S, S→F (denoted by I through IV respectively); while in the upstream, traffic patterns transit from F, F→S, S→J, J→S (denoted by V through VIII respectively). F denotes free flow, J represents jammed flow, and S stands for synchronized flow.

Using the 30s AA traffic data, the above complex traffic patterns and transitions can be further elucidated with a q-O diagram (Figure 4). It can be found from Figure 4 that due to the reduced capacity at the bottleneck and thus the reduced flow rate, vehicles once passing the virtual detectors have enjoyed longer headways, except for the first 200 seconds. Therefore in the fundamental diagram (left panels of Figure 4(a) and 4(b)), the q-O pairs mainly spread in the free flow region. On the other hand, the middle panels of Figure 4(a) and 4(b) provide the q-O information around the upstream detector. Owing to the bottleneck, complicated traffic patterns and transitions in the upstream can be observed (F, F→S, S→J, J→S). As a consequence, q-O pairs sparsely spread in the congested area. It is worthy-mentioned that for the last 300 seconds, synchronized flow prevails, so the q-O pairs reflect this phenomenon in a consistent manner, i.e., it randomly spreads in the congested region. Furthermore, once combining the upstream and downstream data together, an aggregated q-O profile (right panels of Figure 4(a) and 4(b)) that supports Kerner’s three-phase traffic theory (2004) can be clearly identified.
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(a) Pure light vehicle traffic

(b) Mixed light/heavy vehicle traffic

Figure 3 Simulated x-t diagrams with bottleneck for pure and mixed traffic.

Figure 4 Simulated local q-O plots with one bottleneck. (30s AA data)

4.3 Results of UMA Traffic Data

For comparison, the unweighted moving average (UMA) traffic data, as derived by Eqs. (18) and (19), are also calculated to elucidate the same scenarios. For pure light vehicle traffic (Figure 3(a)), we first focus on the downstream of the bottleneck. According to Figure 3(a), traffic patterns around downstream detector will be free flow at the beginning (region I, F phase, also refer to Figure 5(a)) and then pass through the bottleneck to reach upstream of
jam. Vehicles joining the jam will keep stationary (region II, J phase, also refer to Figure 5(b)) until all vehicles in front have left and then start to move (region III, J→S phase transition, also refer to Figure 5(c)). Later on, as the flow rate reduces due to the impact of bottleneck, the traffic transits into free flow (region IV, S→F phase transition, also refer to Figure 5(d)). A clearer picture of these flow patterns and the associated phase transitions can be obtained by aggregating all UMA traffic data into one plot, shown in Figure 5(f).

Similarly, we can describe the upstream flow patterns through the same algorithm, as shown in Figure 6. Also per x-t diagram (Figure 3(a)), traffic patterns around upstream detector will be free flow at the beginning (region V, F phase). When approaching the bottleneck, the flow patterns will transfer to synchronized flow (region VI, F→S phase, also refer to Figure 6(a)) until reaching the upstream front of jam (region VII, S→J phase, also refer to Figure 6(b)). Vehicles stand still to wait for the front condition for movement (region VIII, J→S phase transition, also refer to Figure 6(c)). For the rest of time, because the bottleneck shrinks the road capacity which in turn influences the upstream traffic significantly, the patterns will keep as synchronized flow (region VIII, S phase, also refer to Figure 6(d)). Aggregating all data into one plot, as shown in Figure 6(f), a whole picture of flow patterns and associated phase transitions can be seized exactly. For further comparison, in addition to the above 30s AA and UMA traffic data, the precise 1s local data are also gathered and shown in Figures 5(e) and 6(e), respectively. One can easily find that the 1s data widely scatters in both plots, wherein no significant traffic patterns or transitions can be found. It is clear that a time average traffic parameters is more powerful than the original 1s data created by each time-step (1s) to gain insights into the traffic phenomena.

Per the similar measurement, the $q$-$O$ relationships for the mixed light/heavy vehicle traffic are shown in Figure 3(b). The derived $q$-$O$ plots are shown in Figures 7 and 8. Compared with the pure vehicle traffic scenario, it is surprised to find that although 20% light vehicles are replaced by heavy vehicles, similar results have been obtained, including the traffic patterns and the associated phase transitions. This outcome evidences the validity of the proposed measurement for local traffic parameters.
5. LOCAL VERSUS GLOBAL TRAFFIC FEATURES

As discussed above, it is costly and difficult to observe the global traffic features ($\rho(S)$ and $q(S)$) over a long distance within a long period of time, thus temporal local traffic features ($O(t)$ and $q(t)$) are usually measured via stationary detectors. One criticism arisen as to whether the local traffic data $O(t)$ and $q(t)$ could serve as the appropriate proxies for their global counterparts, $\rho(S)$ and $q(S)$. Because the trajectories of all vehicles during the simulated period can be precisely gauged, CA simulations have excellent capability for monitoring the vehicular behaviors both in space and time frames. In addition, the global traffic features are
in essence the aggregation of all local traffic features; thus, global traffic features can also be deemed as a paradigm for evaluating the effectiveness of locally derived traffic information. As such, this study selects \( q(S) \) rather than \( q(t) \) as the reference index for evaluating the traffic performance.

Upon this, it is interesting to discover the relationship or linkage between global and local traffic parameters, including: (1) Can locally derived traffic data reflect the trends shown in global perspective? If yes, what precision might be achieved? (2) What is the difference between the outcomes of AA and UMA local traffic data? Which one would be better proxy for global traffic data? (3) What are the proper time intervals for taking AA or UMA while measuring the local traffic data? To answer these questions, this study further simulates pure light vehicle traffic scenarios and compares the local traffic features (\( q-O \) plots) with the global counterpart as follows.

Four generalized occupancies (\( \rho(S) = 0.06, 0.12, 0.25 \) and \( 0.50 \)), corresponding to traffic densities (15, 30, 62.5 and 125 veh/km/ln), from free flow to jam are simulated respectively. When simulations initiate, all the vehicles are equally spaced on the circular track wherein a virtual detector is placed in the middle. The derived local traffic data (\( O(t) \) and \( q(t) \)) are taken by AA and UMA with different time intervals (1s, 30s and 60s). Finally, the outcomes for these four simulations are collected and compared with their global counterparts (\( \rho(S) \) and \( q(S) \)). The fundamental diagrams are displayed in Figures 9 to 11.

As shown in Figure 9, as expected, the 1s local flow rate \( q(t) \) significantly deviates from its global counterpart \( q(S) \), especially around the region \( \rho(S)=0.1-0.4 \). The maximum flow rate is overestimated. This is deemed reasonable since the 1s data aims only at the local traffic information for a very short instant; thus, the effect of some extreme situations occurred locally have been exaggeratedly amplified. In conclusion, although the aggregated local 1s data transforms into some traffic patterns that can perfectly match the three-phase traffic theory, it is never sufficient to reflect the traffic conditions in the global perspective.

Figure 10 provides the comparison of 30s and 60s AA local data with the global curves. One may find that there is no considerable difference between them. Basically, both 30s and 60s AA data groups spread in the neighborhood of global \( \rho(S)-q(S) \) curves. However, one may find that the 60s AA data performs a bit better than the 30s data in gauging the global features. In general, the 60s data points scatter within a relatively smaller region along the global \( \rho(S)-q(S) \) curve than the 30s data points do.

![Figure 9](image_url)  
Figure 9 Comparison of global fundamental diagram with local 1s data for four different scenarios (pure light vehicle traffic: \( \rho(S) = 0.06, 0.12, 0.25, 0.50 \))
Similarly, Figure 11 provides the comparison of 30s and 60s UMA local data with the global curves. Again, the 60s UMA data performs a bit better than the 30s data in reflecting the global features because the 60s data tends to be closer to the global $\rho(S)$-$q(S)$ curve. However, when compared with the outcomes of AA data in Figure 10, UMA data in general provides relatively poorer simulation quality than the AA data, regardless of 30s or 60s being chosen. This is because a local fluctuation (noise) of traffic data can influence a series of data points if UMA is used; however, the same fluctuation will affect only one data point if AA is used. In conclusion, the AA local traffic data is excellent in smoothing out the oscillations and henceforth can cope better with the global traffic features as revealed in Figure 10.

Nonetheless, one must agree that, as recalled in Section 4.3, the UMA traffic parameters are more effective than the AA traffic parameters in reflecting the complicated traffic phase transitions. Besides, for each individual simulation, implementation of the UMA technique provides notably more precious data points than that via the AA technique.

In sum, the UMA measurement is effective in reflecting the local traffic phase transitions. However, this merit will reversely turn into a weakness if one is interested in the global traffic features either for pure or mixed traffic simulation. If one is interested in scrutinizing the local traffic data, the AA data would present better simulation quality than the UMA data since the AA data points scatter within a smaller region in the neighborhood of the global curve. It
makes sense because the impact of some local noises of AA data with short lifetime will be few when independent time intervals are considered. In contrast, by the rolling nature of UMA data, the impact of some local noises will yield more expansive influence and henceforth force more UMA local traffic data to deviate from the global curve.

6. CONCLUSIONS

The proposed AA and UMA measurements for extracting local traffic parameters from the refined CA modeling has been successfully validated throughout the complex scenarios under pure and mixed traffic contexts. The UMA measurement is more effective in reflecting the complicated phase transitions; while the AA measurement can better reflect the global traffic features and is also consistent with the Kerner’s three-phase traffic theory. This evidence supports the speculation that three-phase traffic theory is developed through the AA field data. Finally, based on the findings, it is recommended that the time interval for measuring either AA or UMA traffic data would be 30s at least.

For the mixed traffic simulation, this study only considered a mixed ratio of 80 % light vehicles with 20% heavy vehicles. The traffic patterns and associated phase transitions under other mixed ratios require further exploration. In many Asian cities, motorcycles are ubiquitously sharing the roadway space with cars and/or buses on the surface roads. Therefore, it is interesting to conduct more sophisticated CA simulations to capture the traffic features for mixed motorcycle/car or mixed motorcycle/car/bus traffic situations.

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REFERENCES


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**Suffix**
- $i$: The $i$th vehicle
- $k$: Type of vehicles: $k=1$, light vehicle (car); $k=2$, heavy vehicle (bus/truck)
- $ma$: Un-weighted moving average
- $\max$: The maximum value
- $n$: The $n$th vehicle
- $n+1$: Vehicle in front
- $t$: Instant $t$

**Superscript**
- $b$: Downstream
- $f$: The nearby upstream in the next or next second site
- $eff$: Effective
- $r(l)$: The right (left) lane or site considered for lane change or lateral drift