Multiscale Traffic Flow Model Based on the Mesoscopic Lighthill–Whitham and Richards Models

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This article reviews the multiscale modeling concept as an adaptive strategy in traffic flow modeling. The central objective for the multiscale model is to describe and to predict traffic phenomena (e.g., individual accelerations, queuing) that occur at different scales by switching between modeling paradigms. The emphasis in this paper is placed on resolving inconsistencies that arise in the process of integrating models, which are addressed with the mesoscopic Lighthill–Whitham and Richards models—together, widely known as the Lighthill–Whitham–Richards (LWR) model—as the coarse-scale model in the framework. The mesoscopic model is fully consistent at the macroscopic scale with the classic LWR model but does facilitate tracking of individual vehicles. Because of this characteristic, this model can be combined with microscopic models, because no disaggregation or aggregation process is needed. It is thus implied, for example, that travel information (e.g., destination) can be carried over this model without loss of information. Also, vehicle heterogeneity can be incorporated in the mesoscopic model and, as a result, is preserved in the process of switching between models. A brief overview of the mesoscopic LWR model and its solution by the variational theory is presented. General boundary conditions, including internal boundaries (e.g., moving bottlenecks) and interfaces between models, are analyzed and evaluated. The solution of some cases, in which the stationary and moving bottlenecks interact, is provided. The paper concludes with a case study that demonstrates the integration of microscopic and mesoscopic models in a multiscale model and investigates the influence of various boundary conditions on traffic features.

The development of mathematical and computational models for simulating traffic across several spatial and temporal scales is one of the most important areas of traffic study. Advances in tools for forecasting traffic states and methods to assess and compare the impact of new infrastructure and control systems rely on accurate modeling of traffic phenomena. These phenomena occur at spatial and temporal scales that range from vehicle size and seconds (e.g., lane changing behavior) to kilometers and hours (e.g., congestion spread over a network).

Available traffic models largely were designed to model events that take place over a specific spatial scale. These models are not always applicable to reproducing phenomena over larger or smaller scales. First-order traffic flow models [e.g., the Lighthill–Whitham model (1) and Richards model (2)—together, widely known as the Lighthill–Whitham–Richards (LWR) model—], capture large-scale phenomena such as shock waves, while car-following models describe events occurring over much finer scales (e.g., interaction between vehicles). Simulating traffic phenomena at different scales, in general, requires the use of different models. Multiscale modeling is a modeling style that integrates modeling paradigms in a unified framework, so that all traffic phenomena occurring at various scales can be simulated with sufficient accuracy.

This paper classifies the scale at which a traffic model describes traffic operations along two dimensions (3). These are the traffic representation (e.g., vehicle versus flow) and the behavioral laws that govern the dynamics of traffic. Traffic representation relates how traffic and traffic phenomena are described. Continuous models describe traffic analogously to a compressible fluid, whereas car-following models or cellular automata describe the motion of single vehicles. The behavioral law dimension relates to the scale at which a model explains the causes of occurring traffic phenomena. For example, first-order continuous models use steady-state (equilibrium) behavioral rules (the fundamental diagram), whereas most car-following models use more involved behavioral laws that also describe acceleration and deceleration as a function of all sorts of stimuli.

Various multiscale models have been developed recently that integrate traffic flow models that use different representations but are governed by the same (average) behavioral rules. In an example reported by Leclercq, an LWR model in Eulerian coordinates (a continuous flow representation) and an LWR model in Lagrangian coordinates (a vehicular representation, provided a single lane is described and the discretization equals a single vehicle) are coupled in a fixed spatial area (4). In this approach, the descriptive power of the multiscale model increases by switching from coarse-scale (Eulerian) to fine-scale (Lagrangian) models, but the explanatory power of the combined model remains unchanged because the implemented models are based on the same behavioral law and thus reproduce the same traffic dynamics (e.g., congestion patterns). This multiscale modeling approach cannot capture traffic phenomena that emerge because of behavioral rules such as heterogeneous driving style or vehicle classes. In other examples, both implemented models are analytically consistent (5–7).

This article reviews and extends the multiscale methodology developed in earlier works (8, 9). The multiscale model proposed here is based on the mesoscopic LWR model (10). This representation of the LWR model is well suited to integrating different modeling scales because it alleviates some of the numerical inconsistencies that arise in multiscale modeling methodologies. In this
new model, individual vehicles are traceable, and thus the refined vehicle description (microscopic parameters) can be propagated through the coarser-scale model with no loss, that is, no aggregation error is observed. This approach provides a direct solution to the global inconsistency problem that arises in multiscale models (8, 9). Moreover, this mesoscopic approach is computationally more efficient than its macroscopic counterpart because there is no spatial discretization: passing times for all vehicles are directly computed at link boundaries. These unique characteristics of the mesoscopic LWR model make it suitable for a multiscale modeling framework.

The mesoscopic approach also provides a natural solution to local inconsistency problems (8, 9). The general boundary conditions proposed in this paper provide a convenient way to account for the impact of slow vehicles (moving bottlenecks) and to construct the interfaces between models in the form of dynamic or stationary boundary conditions.

In the remainder of this paper, the basic idea of the mesoscopic LWR model is reviewed. Then a modified solution is sketched for a mesoscopic model based on variational theory, and the boundary condition is generalized as a prerequisite for multiscale modeling. Then cases in which boundary conditions interact are discussed with some examples of moving and stationary boundaries. Next, a multiscale methodology based on the mesoscopic model is presented, and solutions are provided to ensure consistency of information that transfers between implemented models. The paper concludes with an experiment that demonstrates the application of the mesoscopic model in a multiscale modeling framework.

MESOSCOPIC LWR MODEL

One of the simplest representations of traffic dynamics is provided by the LWR model (1, 2). Vehicle motion in this model is represented by a conservation equation:

$$\frac{\partial \rho(x, t)}{\partial t} + \frac{\partial q(x, t)}{\partial x} = 0 \tag{1}$$

where \(\rho(x, t)\) is density and \(q(x, t)\) is the traffic flow, with a statistical relationship between flow and density, \(q = Q(\rho)\), which is known as the fundamental diagram. This relationship can be interpreted as a (coarse) behavioral law that relates the average time headway \(1/q\) vehicles maintain (or the speed \(q/\rho\) they drive) to the average distance headway \(1/p\) they experience. The fundamental diagram is a positive function defined on \([0, \rho_{jam}]\), where \(\rho_{jam}\) is the maximal density (jam density). \(Q(\rho)\) represents a flux function of \(\rho\), which depicts the dynamics of traffic flow in terms of aggregated behavior. It is assumed to be differentiable at \(0\) and \(\rho_{jam}\) where \(\frac{\partial Q(\rho)\partial t}{\partial \rho} = \alpha > 0\) is the free-flow speed and \(\frac{\partial Q(\rho_{jam})\partial t}{\partial \rho} = \alpha < 0\) is the congested wave speed.

In this traditional Eulerian formulation of the LWR model, density \(\rho\) and flow \(q\) can be derived from a single surface in \(N(x, t)\) that represents the number of vehicles that have crossed position \(x\) by time \(t\). With the assumption that traffic flow in the direction of increasing \(x\) and vehicles are numbered in the direction of increasing time; if partial derivatives of \(N(x, t)\) exist, then \(\partial N/\partial t = q\) and \(\partial N/\partial x = -\rho\).

The LWR model is a continuous model that is based on an average behavioral law (fundamental diagram). The vehicle characteristics in this model are considered homogeneous, which imposes limitations when the LWR model is combined with microscopic models that account for the heterogeneous traffic characteristics such as different vehicle classes. In such situations, information regarding vehicle and driver characteristics gets lost at the interface between the micro and the LWR model because of the aggregation of discrete vehicle trajectories to a continuum.

A mesoscopic representation of the LWR model offers an intermediate level of traffic representation that will make it easier to interface with the microscopic model. This representation corresponds to the expression in another coordinate system, that is, \((n, x)\), where \(n\) is the vehicle number as defined by \(N(x, t) = n\). The purpose is no longer to determine local density \(\rho(x, t)\) but to determine the crossing time \(T(n, x)\) of vehicle \(n\). Resorting to the variational theory gives a simple expression of the solutions for \(T(x, n)\) in this new system of coordinates when the fundamental diagram is triangular.

Solution of the LWR Model by the Variational Theory

Newell stated that the solution in \(N\) for the LWR model can be derived at any point \((x, t)\) from a minimum principle in Equation 2 (11). This solution is also well known as the three-detectors problem:

$$N(x, t) = \min \left[ N\left(x, t - \frac{x - x_d}{u}ight), N\left(x, t - \frac{x - x_u}{w}ight) + \rho_{jam}\left(x_d - x\right) \right] \tag{2}$$

Daganzo later demonstrated, by introducing the concept of variational theory, that this formulation provides the exact solution of the LWR model given any upstream and downstream boundary conditions, provided that the fundamental diagram is triangular (12, 13). Then \(N(x, t) = n\) defines an implicit expression for \(t\) with respect to \(x\) and \(n\). Solving this equation provides the exact solution of the LWR model in \((x, n)\) coordinates (Equation 2, Figure 1a).

$$T(x, n) = \max \left[ T\left(x, n + \frac{x - x_d}{u}\right), T\left(x, n + \rho_{jam}\left(x_d - x\right) + \frac{x_d - x}{w}\right) \right] \tag{3}$$

An event-based numerical scheme can be straightforwardly derived from Equation 3. One has to discretize \(n\) value in units of vehicles \(n = i\ (i\ \text{is an integer})\). It appears that the time at which a vehicle can cross the boundary \(x\) is then the maximum between its arrival time \(t_a\) and the supply time \(t_u\):

$$t_a(i) = \max\left[ t_a(i), t_u(i) \right] \tag{4}$$

where \(t_u\) corresponds to the time when vehicle \(i\) crosses the upstream boundary \(x_d\) plus the free-flow travel time; \(t_a\) describes the interactions between vehicle \(i\) and downstream traffic in congestion (Figure 1b). The expressions require that the time at which vehicle \(i - \rho_{jam}(x_d - x)\) crosses the downstream boundary be known. Because here only the integer number for vehicles is considered, this time can be interpolated:

$$t_a(i) = (1 - \alpha)t_u(i'') + \alpha t_u(i' + 1) \tag{5}$$

where \(\alpha = i - \rho_{jam}(x_d - x) - i''\).

This numerical expression of the LWR model was originally stated by Daganzo (12) and proved with the variational theory (13).
The next section shows that a simple reformulation makes handling any kind of boundary conditions (including internal boundaries, such as moving bottlenecks or traffic lights) very simple. This boundary handling is especially important for multiscale modeling because interfaces between models act as an external boundary for the mesoscopic model. The influence of the traffic situation in microscopic models on the mesoscopic model can be handled in the interaction between boundaries. The next section solves the mesoscopic LWR model in the presence of general boundary conditions. Situations that interface between models can act as boundary conditions for mesoscopic model are also analyzed in this section.

**General Boundary Condition**

The mesoscopic model calculates traffic flow evolution between two boundary conditions that usually represent link borders. More generally, boundary conditions can also hold for internal flow restriction like moving bottlenecks \(^{14, 15}\). It is then appealing to consider any kind of sequence of successive boundaries.

Consider two boundary conditions \((H\) and \(G\)\) defined by their trajectories \(x_H(t)\) and \(x_G(t)\) (Figure 2). It is assumed that the boundaries do not cross each other. Equations 2 and 3 hold for these two boundaries, which means that the arrival time of vehicle \(i\) at boundary \(G\) \((t^G_G(i))\) follows.

\[
t^G_G(i) = t^G_H(i) + \frac{x_G(i) - x_H(i)}{u} + \Delta x_G \rightarrow H
\]

where \(t^G_H(i)\) is the time when vehicle \(i\) exits boundary \(H\). Solving the implicit equation in \(t^G_G(i)\) provides its value. The supply time of vehicle \(j\) at boundary \(H\) \((= t^H_H(j))\) is provided by

\[
t^H_H(j) = t^H_G(j) = t^H_G(j) + \frac{x_G(j) - x_H(j)}{u} \left(1 - \rho_{jam} \Delta x_G \rightarrow H\right)
\]

Solving Equation 7 is complex because \(\Delta x_G \rightarrow H\) depends on both \(t^H_G(j)\) and \(t^H_G(j - \rho_{jam} \Delta x_G \rightarrow H)\). To solve this problem, the process is reversed so that one calculates the supply time related to the vehicle \(j'\) that exits the downstream boundary at time \(t^H_G(j')\):

\[
t^H_H(j') + \rho_{jam} \Delta x_G \rightarrow H = t^H_G(j) + \frac{\Delta x_G \rightarrow H}{w}
\]
Solving this implicit equation is much simpler, as shown in the following. This calculation is inverse to the way that the mesoscopic numerical scheme works. In this procedure, every time a vehicle exits the downstream boundary, the supply time of the related successive vehicle at the upstream boundary is calculated. This vehicle is not necessarily defined by an integer value. Therefore, the same single linear interpolation is referred to for determining the supply time for the integer number of vehicles and then modifying the vehicle’s arrival time.

The proposed calculation is valid only if positive and negative waves travel within the mesoscopic part from one boundary to the other. This imposes a constraint on the slope of the boundaries, that is, $x'H$ and $x'G$ should always be between $-u$ and $u$. Otherwise, the wave will exit the mesoscopic part sooner than vehicles reach the boundary, and more complex interaction with the microscopic part should be handled (Figure 3).

Finally, the generalization to the reverse boundary condition is straightforward. One only has to apply the previous scheme reversely. The boundary condition also can be a self-constraint, that is, it corresponds to a flow restriction that constrains on the boundary. This is the case, for example, for lane drops, merges, or moving bottlenecks. The flow restriction can vary with time and is defined by $r(t)$. Such boundary conditions may behave as shortcuts within its paths (10). This behavior introduces a third constraint for calculating the effective exit time:

$$
t'(i) = \max\left\{t'(i), t'(i), t'(i)\right\} \quad (9)
$$

where $t'(i)$ represents the exit time when the supply constraint behaves as the boundary. Then $t'(i)$ is defined by

$$
\int_{t'(i-1)}^{t'(i)} r(t) dt = 1 \quad (10)
$$

The constraint flow between the exit time of vehicle $i-1$ and $i$ cannot exceed one vehicle. This fulfills the supply constraint.

### Interaction Between Stationary and Moving Boundaries

To see how the generic solution shown in Equation 8 works, the interaction between a couple of stationary and moving boundaries is calculated. First consider region A in Figure 4, where the stationary and moving bottlenecks are interacting. The time that vehicle $i$ can overtake moving bottleneck, $t_s(i)$, can be calculated by determining the time that vehicle $m$ exits the stationary boundary in $x_i$ as in Equation 8:

$$
t_s(i) = t_L(m) + \frac{\Delta x_i}{w} \quad (11)
$$

with

$$
i = m + \rho_{jam} \Delta x \quad (12)
$$

From the geometry in Figure 4,

$$u_b(t_s(i) - t_0(MB)) = L - w(t_s(i) - t_L(m)) \quad (13)
$$

So

$$t_s(i) = t(m + \rho_{jam} \Delta x) = \frac{L + w t_L(m) + u_b t_0(MB)}{u_b + w} \quad (14)
$$

and

$$\Delta x_i = w\left(\frac{L + u_b (t_0(MB) - t_L(m))}{u_b + w}\right) \quad (15)
$$

It follows that in region B, the following calculation is valid:

$$t_s(i) = t(m + \rho_{jam} \Delta x) = \frac{u_{b2}(t_2(m) - t_0(MB2)) + u_{b1} t_0(MB1)}{u_{b1} + w} \quad (16)$$

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**FIGURE 3** General boundary conditions: (a) speed of boundary is between positive and negative waves and (b) boundary speed is exceeding limits.
and

$$\Delta x_B = \frac{w}{u_{B1} + w} \left( u_{B2} \{ t_{i,2}(m) - t_0(MB2) \} + u_{B1} \{ t_0(MB1) - t_{i,2}(m) \} \right)$$

(17)

Computing the entrance time in region C is simple: just consider $u_{B1} = 0$ in Equations 16 and 17.

MULTISCALE MODEL BASED ON MESOSCOPIC MODEL

This section describes a multiscale modeling approach that uses the mesoscopic model presented in the previous section. The issues to be solved in a multiscale modeling framework relate to the interaction of the two models at the interfaces (boundaries) between the models and to the differences in the number and the type of parameters that each model accepts in its modeling paradigm. On this basis, two categories of inconsistencies between implemented models in the multiscale modeling strategy have been identified (8, 9).

In the context of multiscale modeling, the term “local consistency” is used to describe agreement of traffic features that propagate through the interface between the two models, such as flow and speed. In contrast, “global consistency” refers to preservation of traffic and travel parameters during the process of switching the models, for example, transferring traffic composition and vehicle characteristics from one modeling paradigm to the other (Figure 5).

Resolving the issues of these two kinds of consistency is the main requirement that the integration of different scales of models must satisfy for developing a multiscale model. In the remainder of this section, the local and global consistency concept is reviewed. The review is followed by a discussion of the advantages of the mesoscopic LWR model over the Eulerian LWR model as the coarse-scaled model.

Local Consistency and the Mesoscopic LWR Model

Local consistency describes the agreement of variables, such as flow and speed, that propagate through a local interface $S(x, t)$ between two coupled models. A meaningful synchronization between models at the interface requires the conservation of vehicles. Suppose that model A and model B are integrated in a multiscale model such that model A is applied at the upstream section of the road and model B...
is applied downstream of the interface. The law of conservation of vehicles dictates matching the number of vehicles that are arriving at the interface from model A, $N^{A \rightarrow B}(x, t)$ to the number of vehicles that exit the interface to model B, $N^{B \rightarrow A}(x, t)$.

$$N^{A \rightarrow B}(x, t) = N^{B \rightarrow A}(x, t) \tag{18}$$

If $N(x, t)$ is a differentiable function, the following equation can be derived:

$$q_{A \rightarrow B} = \frac{\partial N^{A}}{\partial t} = \frac{\partial N^{B}}{\partial t} = q_{B \rightarrow A} \tag{19}$$

The LWR model in Eulerian coordinates provides solutions in density and flow, whereas microscopic models provide discrete individual vehicle trajectories. To ensure conservation of vehicles, one should disaggregate or aggregate discrete vehicle numbers to the traffic flow in the process of coupling a microscopic model with the Eulerian LWR model. To avoid this process and its unwanted errors, the mesoscopic counterpart of the LWR model can be applied as an intermediate level of traffic representation. In the mesoscopic model, vehicle trajectories can be easily obtained if the passing time of vehicles from boundaries is known (Equations 3 and 7). The interface between coupled models, in that respect, can be considered as an external boundary for the mesoscopic model.

It has been shown that the location of the interface between coupled models, $S(x, t)$, should be dynamic over time to ensure local consistency when the implemented models have (on average) different behavioral rules (fundamental diagrams) (8, 9). The trajectory of the interface must then follow a path determined by

$$\frac{dS}{dt} = w_{A \rightarrow B} \tag{20}$$

where $w_{A \rightarrow B}$ is the speed of the shockwave that is propagating from model A at the downstream section to model B at upstream part of the road (Figure 3). As mentioned, for calculating the supply time of vehicles at the boundaries with the method that is proposed in this paper, $w_{B \rightarrow A} \leq w_{\text{meso}}$ should hold.

**Global Consistency and the Mesoscopic LWR Model**

Global inconsistency is the loss of information related to the process of switching between the detailed model and the coarser model. In an example, the finer-scale model accepts the traffic composition (e.g., fraction of trucks) as a parameter, but the coarser-scale model does not consider such details in its parameterization. By switching from the finer scale to the coarser model, information about traffic heterogeneity will not be conserved and thus cannot be recovered later in a switch from the macroscopic to the microscopic model. To preserve the vehicle or traveler information ($M$), an advection mechanism is needed that allows quantities $M$ specified in model B to piggyback the average speed $V_A(x, t)$ in model A (8), that is,

$$\frac{\partial M}{\partial t} + V_A \frac{\partial M}{\partial x} = 0 \tag{21}$$

This mechanism works well for quantities that on average travel with the average speed predicted by the coarser model (e.g., the percentage of vehicles with a certain destination further downstream). However, as soon as these quantities are asymmetrically distributed among vehicles with different driving characteristics (e.g., the percentage of vehicles toward a large distribution center or a port, or simply the percentage of trucks), the advection scheme (Equation 21) no longer does the job, which can be explained with a simple thought experiment. Consider a 100-km, two-lane straight road A→B. At a certain period $p$ a platoon of 20 trucks (80 km/h) and 80 person cars (100 kilometers per unit) pass A. Assuming free overtaking conditions, after 60 min, the vehicle mix at B equals 100% person cars, and after 75 min, 100% trucks.

Clearly, advecting the initial vehicle mix (20% trucks) with an average would lead to errors. Aside from the obvious differences in free speed, traffic heterogeneity strongly affects traffic operations in other ways, in effective capacity and congestion dynamics (18). There are various ways to account for the effects of traffic heterogeneity with relatively coarse traffic representations. One can choose continuous multiclass models (17, 18), which endogenously provide a multiclass advection mechanism. The alternative is to use the mesoscopic LWR model with moving bottlenecks (representing trucks).

**EXPERIMENTAL SETUP**

The functioning of a multiscale model based on a mesoscopic LWR model outlined above is demonstrated through a case study. This experiment shows the effectiveness of the mesoscopic LWR model in the multiscale modeling strategy. Particularly, the interaction between interfaces of the microscopic and mesoscopic models and other internal boundary conditions in the mesoscopic model is considered.

In this experiment, the intelligent driver model as a microscopic model is integrated with a mesoscopic LWR model in a multi-scale modeling framework. The intelligent driver model is a time-continuous car-following model for the simulation of freeway and urban traffic. It was developed by Treiber et al. and contains six adjustable parameters (19):

$$\frac{dt_\alpha}{dt} = F \left( 1 - \left( \frac{u_\alpha}{u_0} \right)^{\delta} \right) = \frac{s^\delta (u_\alpha, \Delta u_\alpha)}{s_a} \tag{22}$$

and

$$s^\delta (u_\alpha, \Delta u_\alpha) = s_0 + u_\alpha T + \frac{u_\alpha \Delta u_\alpha}{2 \beta_{ab}} \tag{23}$$

with desired velocity $u_0 = 60$ km/h. The minimum spacing $s_0 = 2$ m; the desired time headway, $T$, is 1.6 s; acceleration, $\alpha$, is 0.73 m/s^2; and the braking deceleration, $b$, is 1.67 m/s^2. The exponent $\delta = 4$ is a dimensionless parameter that determines the relative effect of the speed difference with the leading vehicle on the resulting acceleration. Lane changing is not considered in the microscopic part.

Simulation is carried out in a two-lane link with total length of 1,500 m. The link is divided such that in the 1,000 m upstream of the link, the mesoscopic model is applied, and the downstream
500 m is simulated microscopically. The duration of the simulation is 3,600 s, and the microscopic time step is equal to 1 s.

The demand to enter the link in the mesoscopic part is 1.15 vehicles per second. Jam density of the mesoscopic model is 0.2, and the free-flow speed is 54 km/h. The congestion wave speed is 5 m/s. Two moving bottlenecks are active in the mesoscopic part and are moving with free-flow speed $u_1 = 2$ m/s and $u_2 = 1$ m/s. Moving bottlenecks are inactive in the microscopic model and are considered the same as other vehicles. Furthermore, a disruption in the microscopic part results in the propagation of a shock wave to the upstream road section. To ensure local consistency, the position of the interface between models is dynamically modified by shock propagation. Because the interface complies with the general boundary condition discussed in the previous section, it is the downstream boundary for the mesoscopic model.

**RESULTS AND DISCUSSION**

This section illustrates the simulation results of the experiment. Two slow vehicles having different free-flow speeds act as moving bottlenecks in the mesoscopic part as the demand is high enough to activate the moving bottlenecks (Figure 6a). Because of the capacity restriction that these moving bottlenecks cause, a reduced flow rate of $r_1$ and $r_2$ can pass these two slow vehicles. The moving bottlenecks in the mesoscopic part are shown in Figure 6b, where the trajectories of the vehicles are shown.

To ensure local consistency at the interface between models, the number of vehicles that exit the interface and enter the next model should be consistent. Consistency can be achieved easily in the interface between mesoscopic and microscopic models because the mesoscopic model provides time headway between vehicles that can be used to generate vehicles at the entrance of the microscopic part. Simulation results show a good agreement between numbers of vehicles that pass the interface. Conservation of law thus has been fulfilled (Figure 6b).

A shock wave that is generated in the microscopic model is simulated only by the microscopic model because more information about acceleration or deceleration of vehicles in congestion is desired and a coarse-scale model cannot provide such information for congestion. As a result, the position of the interface is dynamically moving by the propagation of the shock wave. Vehicles passing the dynamic interface have free-flow speed. Thus, the dynamic interface is not constraining the mesoscopic flow. Furthermore, the free-flow speed $u$
and congestion wave speed \( w \) of the microscopic model are not exceeding that of the mesoscopic model (Figure 7). The logical consequence is that the speed of the interface that follows microscopic shock is also not exceeding the congestion wave speed of the mesoscopic model.

CONCLUSIONS AND RECOMMENDATIONS

This paper reviewed and extended a traffic flow multiscale modeling methodology by using the mesoscopic LWR model. The advantage of implementing a mesoscopic model is that the two main inconsistencies that arise when modeling paradigms are combined are alleviated because of the unique characteristics of this model.

First, the mesoscopic model provides a natural solution for global inconsistency problems, which relate to information loss in the process of switching between modeling paradigms. Since the mesoscopic model tracks individual vehicles, in principle all information about vehicles and travelers (destination, route choice, motive, etc.) from the finer-scaled microscopic model can be transported, so that the next microscopic model is provided by the exact same first-in, first-out set of vehicles as entered in the mesoscopic model.

Second, the mesoscopic model provides a natural way to deal with local inconsistency problems (e.g., violation of conservation of vehicles or momentum), which occur at the interfaces between models. There are two sides to this advantage as well. In the combined microscopic–mesoscopic multiscale model, the translation of traffic information over interfaces does not require aggregation or disaggregation of flow and vehicle data, as both provide the same representation of traffic. Furthermore, this paper demonstrated that the mesoscopic model can handle boundary conditions in a generic way. These boundaries may be present at the edges of the mesoscopic model area (i.e., the interfaces with connected models) and in the form of moving bottlenecks.

An implicit advantage in applying the mesoscopic model is that refinement to the model can be introduced fairly easily. For instance, the fundamental diagram can be made dynamic and consistent with vehicle heterogeneity. In this case, the fundamental diagram of the mesoscopic model is dynamically changing through changes in the traffic composition—for example, the presence of trucks.

To demonstrate the performance of a multiscale model based on the mesoscopic model, a case study was presented. In this experiment, the dynamic interface between microscopic and mesoscopic models acted as the most downstream boundary condition for the mesoscopic model. Two moving bottlenecks (such as buses) of different speeds influenced traffic flow in the mesoscopic model. Simulation results showed a good agreement between models in terms of variation of flow that passes through the interface. Further research is needed to quantify the performance of a multiscale model based on the mesoscopic model compared with other integrated macroscopic models (e.g., the LWR model in Eulerian coordinates).

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