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ABSTRACT

We couple EMFAC with a dynamic mesoscopic traffic model to create an efficient tool for generating information about traffic dynamics and emissions of various pollutants (CO_2, PM_{10}, NO_X, and TOG) on large scale networks. Our traffic flow model is the multi-commodity discrete kinematic wave (MCDKW) model, which is rooted in the cell transmission model but allows variable cell sizes for more efficient computations. This approach allows us to estimate traffic emissions and characteristics with a precision similar to microscopic simulation but much faster. To assess the performance of this tool, we analyze traffic and emissions on a large freeway network located between the ports of Los Angeles/Long Beach and downtown Los Angeles. Comparisons of our mesoscopic simulation results with microscopic simulations generated by TransModeler under both congested and free flow conditions show that hourly emission estimates of our mesoscopic model are within 4 to 15 percent of microscopic results with a computation time divided by a factor of 6 or more. Our approach provides policymakers with a tool more efficient than microsimulation for analyzing the effectiveness of regional policies designed to reduce air pollution from motor vehicles.

1. INTRODUCTION

With increasing public concerns about the health impacts of air pollution from motors vehicles, different models have been developed to better assess their emission of air pollutants. However, there is still no efficient model that can accurately estimate traffic emissions on large scale networks. This paper starts filling this gap by combining the Multi-Commodity Discrete Kinematic Wave model (MCDKW) [1, 2] with EMFAC (Emission FACtors) and illustrating its efficiency on a large network that extends between the San Pedro Bay Ports (i.e., the ports of Los Angeles and Long Beach) and downtown Los Angeles.

Based on their working scale, traffic models can be organized in three different categories: microscopic, mesoscopic, and macroscopic. Macroscopic models, which mainly rely on information about average link speed and convex flow-travel time curves, have received a lot of attention early on because they allow analyzing large areas with relatively modest data requirements [3, 4, 5, or 6]. However, as highlighted by Smith *et al.* [7], macroscopic models cannot accurately predict air pollutant emissions, especially for congested traffic conditions, because their description of traffic dynamics is too coarse. As pointed out by André and Hammarström [8], pollutant emissions estimation is sensitive to the quality and accuracy of vehicle trajectories.

Microsimulation, on the other hand, provides second-by-second speed data of individual vehicles so it is able to accurately capture accelerations, decelerations, and stop-and-go phenomena that drive the emission of air pollutants. However, Jha *et al.* [9] point out that most applications of microscopic simulation are limited to small to medium-sized networks because of the data collection burden and time needed to perform simulations. Moreover, building and calibrating large-scale network is quite challenging and it is currently not well understood [7, 9].

Mesoscopic traffic simulation models, on the other hand, offer a compromise between obtaining accurate traffic dynamics and computational complexity. They combine macroscopic supply (e.g., link performance functions and capacities) with microscopic demand (e.g. individual vehicles) to capture the dynamics of congestion patterns, queues and spillbacks on traffic networks. A number of mesoscopic models such as DynaMIT [10] and DYNASMART [11] have been developed, but they typically do not integrate pollutant emissions. DYNEMO by Schmidt and Schäfer [12] is an exception but it tracks individual vehicles so it requires parallelization to reduce simulation time on large networks to manageable levels.

By contrast, the MCDKW traffic model is based on commodities (pairs of vehicle types and paths in a network) so it is insensitive to the number of vehicles, which makes it attractive to simulate large networks. We couple it with EMFAC [13] to estimate vehicular emissions because of the limitations of current microscopic emission models but also because EMFAC is still the model required for regulatory work in California; see Section 2.2 for more details. We then compare its traffic and emission estimates for a range of air pollutants on a large scale network, with results from TransModeler (one of the leading new microscopic simulators).

Our study area extends from the San Pedro Bay Ports (Ports of Los Angeles and Long Beach, SPBP) to downtown Los Angeles. It includes two major freeways (I-710, I-110), several busy cross freeways (I-405, I-105, and I-5), and the SR-91. These freeways carry the bulk of the container traffic for the SPBP, which plays a very important role in the U.S. economy; in 2004, for example, the SPBP handled over 36% of all U.S. container trade [14]. In this paper, we concentrate on traffic emissions from freeways only. Moreover, the SPBP provided over 886,000 California jobs related to the international trade activities, and more than $6.7 billion in state and local tax revenues [15]. However, the economic vitality of this area is threatened by high levels of congestion and air pollution. People living in our study area suffer from chronic air pollution, which is partly due to the thousands of trucks carrying containers from the SPBP to warehouses located downtown Los Angeles and further inland. In addition to its clear economic importance, we selected this area because it was recently studied using microsimulation [16, 17], so we have a basis for comparing our results

The paper is organized as follows. In Section 2, we present the MCDKW model, explain how it was coupled with EMFAC, and introduce TransModeler. Section 3 explains how we generated our data, and Section 4 discusses our results. Finally, Section 5 summarizes our conclusions and suggests directions for future work.

2. MODELING FRAMEWORK

2.1 A multi-commodity discrete kinematic wave (MCDKW) model

Kinematic wave theory has already received a lot of attention (e.g., see Vaughan *et al.* [18]; Jayakrishnan [19]; Daganzo [20, 21]; Leonard [22]; or Buisson *et al.* [23, 24]) because it can efficiently provide aggregate-level traffic conditions such as average travel speed, density, and flow rates using procedures and its computational requirements do not depend directly on the number of vehicles involved. It is therefore a promising model to study large-scale traffic networks. In this section, we summarize the multi-commodity discrete kinematic wave (MCDKW) model, which was developed by Jin [1] and Jin and Zhang [2]. In particular, we will discuss its efficiency, which is a key motivation for this study.

The MCDKW model is obtained through the first-order Godunov method [25, 26]. Consider a network of total length L_{length}, with K links (indexed by $k=1, 2,\dots$,K), such that link k is partitioned into $N_k \geq 1$ cells. Our network has P′ Origin-Destination pairs and P different paths ($\mathrm{P}' < P$), so we have P (p=1,…,P) different commodities. We call commodities pairs of vehicle types and paths in a network; for simplicity, we consider only one vehicle type in this paper. The path of each commodity is predefined. Let us denote total traffic density, travel speed, and flow rate by ρ, v, and q respectively and their value for commodity p by ρ_p, v_p, and q_p. We assume that traffic on all links is additive so $\rho = \sum_{p=1}^{\mathrm{P}} \rho_p$, $\mathrm{v} = \mathrm{v}_p$, and $\mathrm{q} = \sum_{p=1}^{\mathrm{P}} \mathrm{q}_p$. We denote the local proportion of commodity p as $\xi_p = \frac{\rho_p}{\rho}$. To describe the MCDKW model, let us introduce the following notation:

$v_{f,k}$ = free flow speed on link k;
$\Delta \mathrm{x_k}$ = length of a cell on link k;
$\Delta \mathrm{t}$ = duration of a time step;

$\rho_{i,k}^{j}$ = average traffic density ρ in cell i at time step j;

$f_{i-\frac{1}{2},k}^{j}$ = flux through upstream boundary of cell i from time step j to time step j+1;

$f_{i+\frac{1}{2},k}^{j}$ = downstream flux of cell i from time step j to time step j+1;

$\rho_{p,i}^{j}$ = traffic density ρ in cell i at time step j for commodity *p*;

$f_{p,i-\frac{1}{2},k}^{j}$ = upstream flux of cell i from time step j to time step j+1 for commodity *p*; and

$f_{p,i+\frac{1}{2},k}^{j}$ = downstream flux of cell i from time step j to j+1 for commodity *p*.

In the MCDKW model, the total density in cell i time step j+1 is updated with the following equation:

$$\rho_{i,k}^{j+1} = \frac{\Delta \mathrm{t}}{\Delta \mathrm{x_k}}\left(f_{i-\frac{1}{2},k}^{j} - f_{i+\frac{1}{2},k}^{j}\right) + \rho_{i,k}^{j}, \tag{1}$$

which also applies to traffic density for each commodity $p \in \{1,\ldots,\mathrm{P}\}$:

$$\rho_{p,i,k}^{j+1} = \frac{\Delta \mathrm{t}}{\Delta \mathrm{x_k}}\left(f_{p,i-\frac{1}{2},k}^{j} - f_{p,i+\frac{1}{2},k}^{j}\right) + \rho_{p,i,k}^{j}. \tag{2}$$

Equation (2) is used to update the proportion of commodity *p* on link *k* during time step j in cell i:

$$\xi_{p,i,k}^{\mathrm{j+1}} = \frac{\rho_{p,i,k}^{j+1}}{\rho_{i,k}^{j+1}} \tag{3}$$

In a nutshell, the MCDKW model updates the flow and density information in each cell using the procedure below:

1) Given traffic conditions, such as road inhomogeneity, density $\rho_{i,k}^{j}$, and the proportion $\xi_{p,i,k}^{\mathrm{j}}$ of each commodity in the previous step, compute supply and demand in cell i;
2) Compute the flow rates $f_{i-\frac{1}{2},k}^{j}, f_{i+\frac{1}{2},k}^{j}$ in cell i based on the supply-demand method for relevant boundary conditions (e.g., link boundaries, merging, diverging, or general junctions);
3) Find the density $\rho_{p,i,k}^{j+1}$ and commodity proportions $\xi_{p,i,k}^{\mathrm{j+1}}$ for the next step.

From the procedure above, we see that the simulation time for updating commodity *p*'s density for cell i at a time step is nearly constant. We simply denote this time by *T*.

A necessary condition to ensure the numerical convergence of the MCDKW model is given by the Courant-Friedrichs-Lewy (CFL) condition [27], which forbids a vehicle from crossing a cell during a time step. If σ_k denotes the CFL condition for link k, we have:

$$\sigma_k = \frac{v_{f,k} * \Delta t}{\Delta x_k} < 1. \quad (4)$$

If we denote the number of cells on link k by N_k, then

$$\Delta x_k = \frac{L_k}{N_k}. \quad (5)$$

We require that $N_k \geq 1$ so combining Equations (4) and (5) leads to

$$\Delta t < \frac{L_k}{v_{f,k}}, \quad (6)$$

which means that the simulation time step Δt should be smaller than the free flow traverse time on all links. In our simulations, we therefore set

$$\Delta t \leq 0.95\ \delta, \quad (7)$$

where $\delta = min_{k=1}^{K} \frac{L_k}{v_{f,k}}$ is the minimum link traverse time.

After choosing the simulation time step Δt, we find the number of cells on link k from

$$N_k = \left\lfloor \frac{L_k}{v_{f,k} * \Delta t} \right\rfloor \leq \frac{L_k}{v_{f,k} * \Delta t}, \quad (8)$$

where the floor function $\lfloor x \rfloor$ gives the largest integer smaller than *x*. From Equation (8), N_k is the number of time steps in the free flow traverse time of link k, so links with larger free flow traverse times should be divided into more cells. From (6) and (7), $\frac{L_k}{v_{f,k} * \Delta t} \geq \frac{1}{0.95}$ so Equation (8) implies that $N_k \geq 1$, and the CFL condition is satisfied since $\sigma_k = \frac{v_{f,k}}{L_k} \Delta t\ N_k \leq 0.95$.

If the duration of traffic simulation is T_{sim}, the number of time steps is $\frac{T_{sim}}{\Delta t}$. Let T_{total} denote the total time it takes to simulate a time interval T_{sim}. Then:

$$T_{total} = \frac{T_{sim}}{\Delta t} \sum_{k=1}^{K} N_k P_k T = \frac{T_{sim}}{\Delta t} \sum_{k=1}^{K} \left\lfloor \frac{L_k}{v_{f,k} * \Delta t} \right\rfloor P_k T \approx \frac{1}{\Delta t^2} T_{sim} T \sum_{k=1}^{K} \frac{L_k}{v_{f,k}} P_k \quad (9)$$

From Equation (9), we see that the total simulation time T_{total} is roughly inversely proportional to the square of the time step size Δt, proportional to the simulation time duration T_{sim}, and proportional to $\sum_{k=1}^{K} \frac{L_k}{v_{f,k}} P_k$, the total network traverse time of all commodities. Usually the last two terms are predefined, but we can increase the time step Δt to reduce total simulation time. Theoretically, if we double Δt, the total simulation time can be reduced by 75%. Most importantly, the computational efficiency of the MCDKW model is not related to the number of vehicles.

Furthermore, when we combine Equations (7) and (9), we obtain the following lower bound on total computational time:

$$T_{total} \geq \frac{1}{0.95^2 \delta^2} T_{sim} T \sum_{k=1}^{K} \frac{L_k}{v_{f,k}} P_k.$$

Therefore, in order to reduce the total computational time, we can increase the minimum link traverse time, which will increase the length of links whose traverse times are smaller than the desired δ. But by increasing the length of shorter links, we may change the traffic dynamics of the whole network. We illustrate the trade-off between precision and efficiency in Section 4.

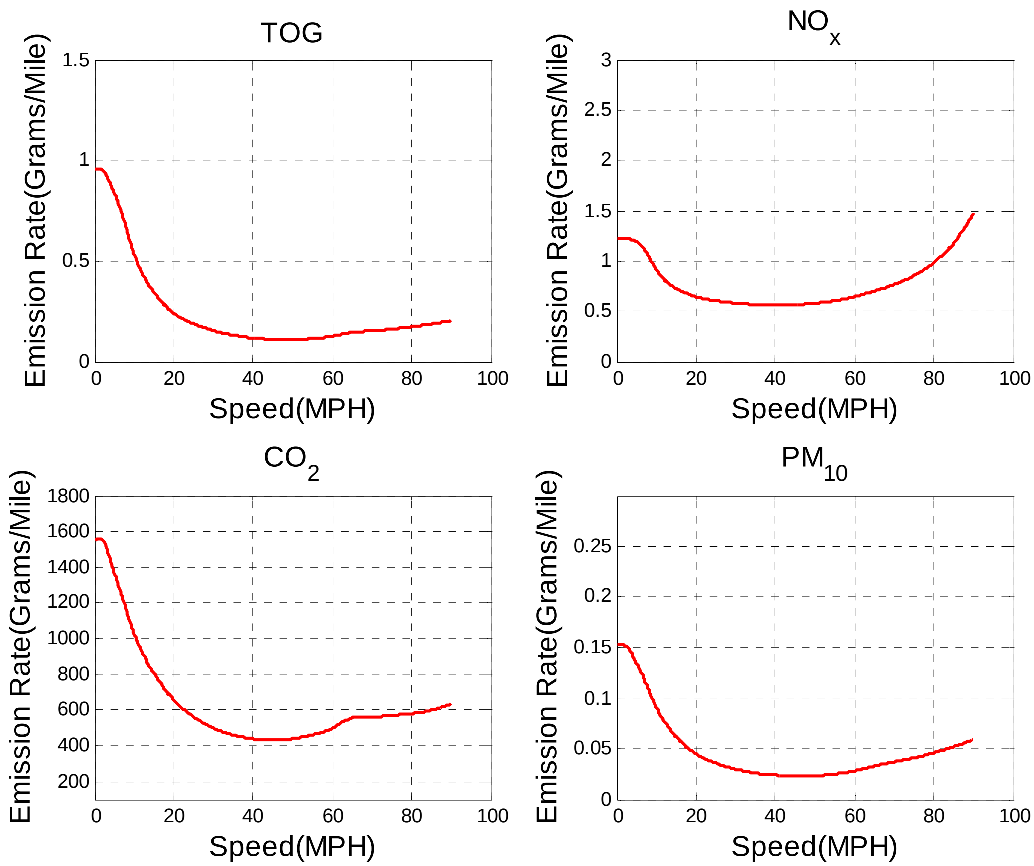

Figure 1. Emission rates for different pollutants

2.2 Traffic emission model - EMFAC

Vehicle emissions models are often classified in two categories: macroscopic (or macro-scale) and microscopic (or micro-scale) emission models. To take full advantage of the trajectory of individual vehicles generated by microscopic traffic simulation models, it would make sense to rely on microscopic emission models such as CMEM [28], developed at the University of California, Riverside, or VT-Micro [29], developed at Virginia Tech. However, neither of these models can currently estimate particulate matter (PM) emissions. The recent release of MOVES [30] offers a good alternative to these two models but it is not approved for regulatory work in California. The model currently approved for regulatory work in California is EMFAC, which was developed by the California Air Resources Board (CARB). EMFAC is an on-road mobile source emissions model that estimates both emission rates and emission inventories for various geographic areas in California. Because it has regulatory approval and also because we are more interested in comparing emissions resulting from a microscopic model with emissions resulting from the MCDKW model, we applied EMFAC to second-by-second vehicle trajectory data to estimate emissions, even though it is not a microscopic model. Note that this imperfect approach was also used by Lee *et al.* [17]. In future work, we are planning on adapting MOVES to California's specific situation to get better estimates of air pollutants.

In our study, we obtained aggregate emission factors for the fleet of vehicles operating in the South Coast Air Basin for the 2005 calendar year. We selected a temperature of 70 F, with a relative humidity of 70% and obtained emission rates every 5 mph for the following pollutants: Total Organic Gases (TOG), carbon dioxide (CO_2), nitrous oxides (NO_x), and particulate matter with a diameter equal to or smaller than 10 μm (PM_{10}). To get continuous emission rates, we relied on cubic spline interpolation, as shown on Figure 1.

2.3 Microsimulation Model: TransModeler

To compare the performance of our mesoscopic model, we chose to rely on TransModeler to perform microsimulations. A couple of reasons justify our choice. First, it allowed us to rely to some extent on previous work in this study area (see Lee et al. [17]). The second reason is the power and the flexibility of TransModeler, which is one of the leading new microscopic simulators. Indeed, TransModeler can easily work with Geographic Information System data (GIS), which is very useful for building our network and defining commodity paths. In addition, it provides us with an easy way to manipulate vehicle trajectory data for all vehicles in our network, which can be used to calculate the emission of various air pollutants.

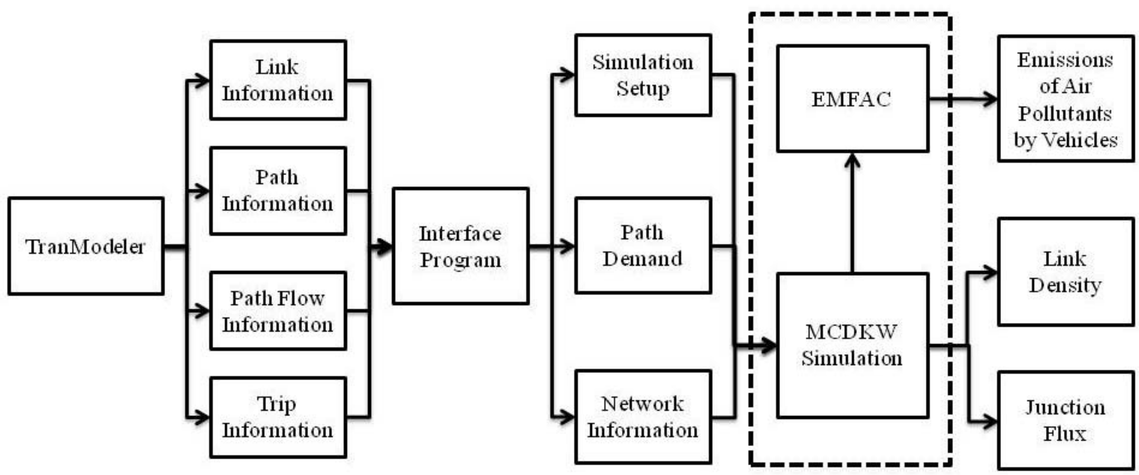

Figure 2. Framework of Mesoscopic Traffic Simulation and Emission Analysis

2.4 Integrated Mesoscopic Traffic Simulation and Emission Analysis

2.4.1 Network representation

Since the MCDKW model does not have a friendly user interface that would be useful for easily creating input files for network geometry and path demand data, we relied on TransModeler's interface. This simply required that we create an interface program to translate network and demand information from TransModeler's format to the MCDKW format. Figure 2 represents the different steps needed to analyze network emissions in our framework.

2.4.2 Calculating Emissions using EMFAC

To calculate the emissions of various air pollutants with the MCDKW model, we need the speed and the number of vehicles for each cell within each link after aggregating them every selected time step. Suppose we have D (*d=1,2,…*,D) different types of pollutants and let $e_d(v)$ designate the emission rate of pollutant *d* at vehicle speed *v*. If N_k^j and V_k^j are respectively the number of vehicles and their average speed on link *k* during the one second interval *j*, then $E_{k,d}^j$, which is the corresponding amount of pollutant *d* emitted, is computed from:

$$E_{k,d}^j = e_d\left(V_{avg,k}^j\right) * N_k^j * V_k^j * \Delta t \tag{10}$$

We can then sum $E_{k,d}^j$ over the whole network (i.e., over *k*) or over time (i.e., over *j*) to obtain aggregate amounts of pollutant *d* emitted during a simulation. Figure 3 summarizes this process.

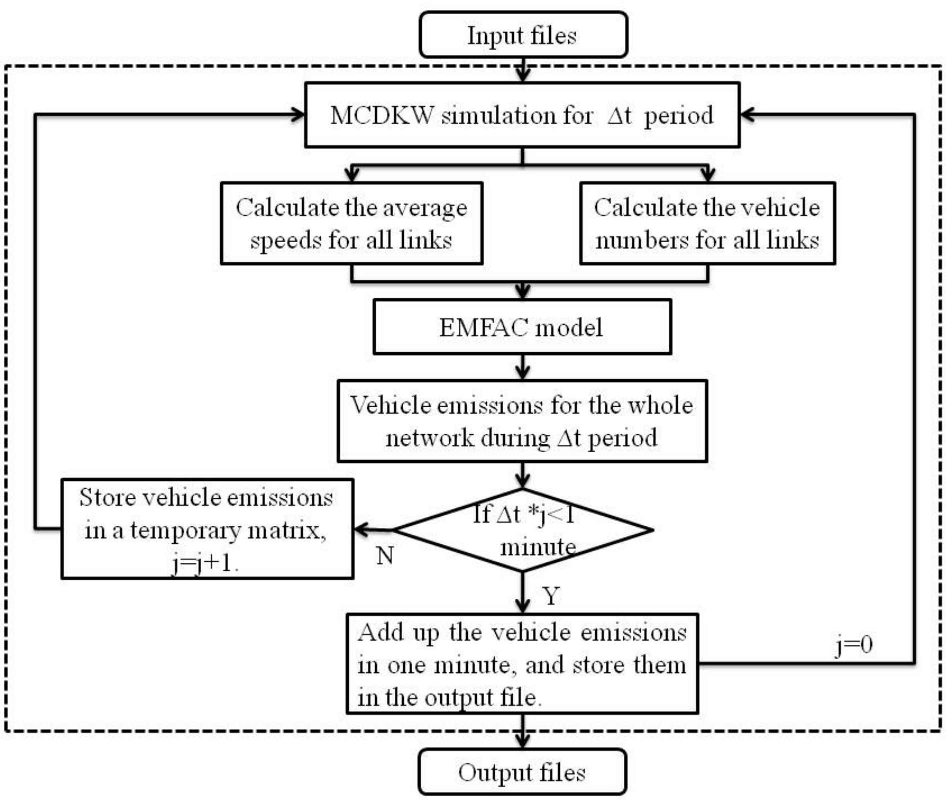

Figure 3. Framework of Integrated MCDKW Model and EMFAC Model

To calculate the emissions of various air pollutants with TransModeler, we simply processed the second-by-second trajectory of each vehicle using EMFAC emission factors and aggregated over all vehicles that took part in the simulation

3. DATA

To represent our network (see Figure 4), we first extracted coordinates for our basic freeway layout from a GIS layer provided by Caltrans and obtained basic freeway characteristics (such as the number of lanes and speed limits) from the Performance Measurement System (PeMS). For additional details, we relied on Google Earth and TerraServer-USA supported by USGS.

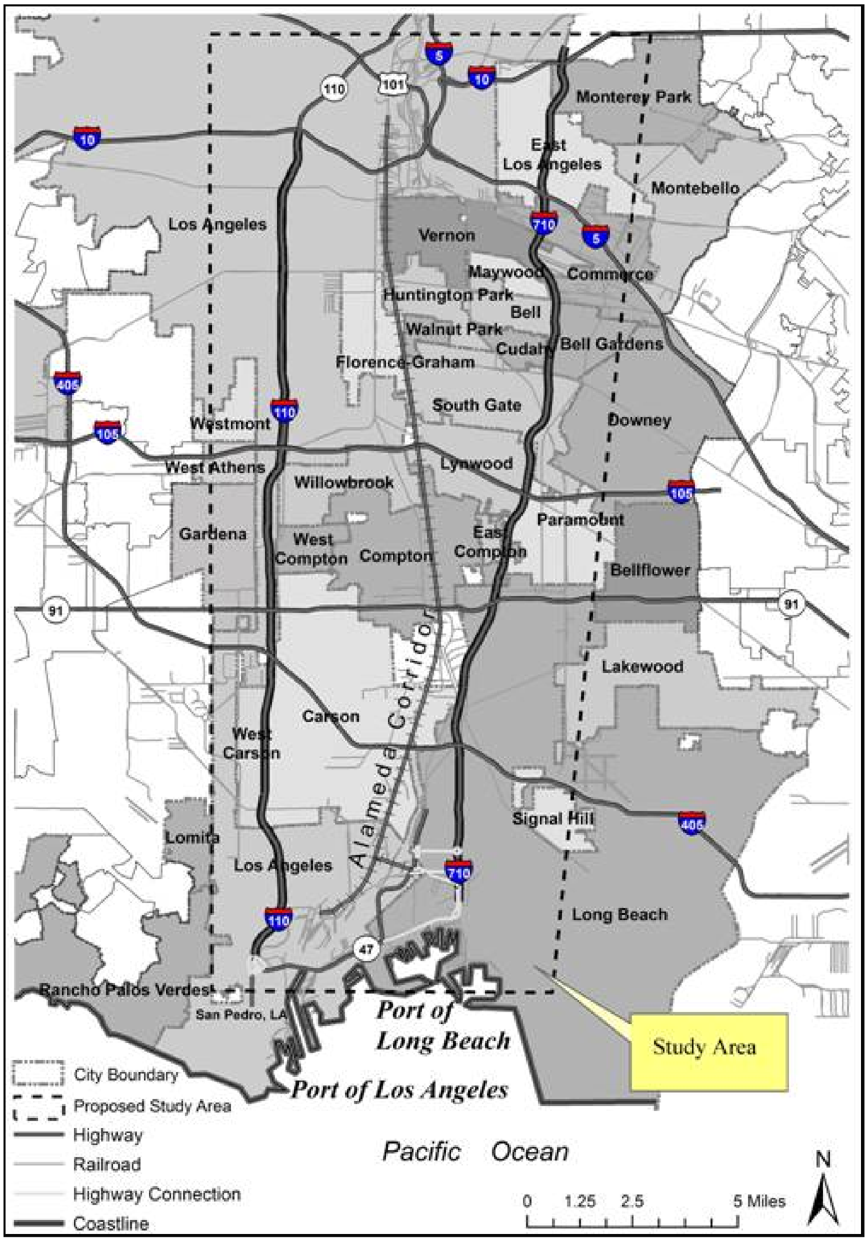

Figure 4. Map of our study area.

For traffic simulation, traffic OD (Origins and Destinations) demand inputs were obtained from the 2000 Southern California Association of Governments (SCAG) traffic study, which is the most comprehensive available for Southern California. To obtain OD demand specifically for our network, sub-area analyses were performed in TransCAD: the study-area network was extracted from the 2000 SCAG data and OD demand was re-assigned.

The OD and path demands were then adjusted to match traffic flow data every hour as measured from PeMS loop detectors. When traffic flow data from PeMS were missing, we used AADT data provided by Caltrans. For O-D estimation, a path-based algorithm was utilized, and the commonly-accepted GEH statistic was selected for assessing goodness of fit:

$$\mathrm{GEH} = \sqrt{\frac{(\mathrm{M}-\mathrm{S})^2}{0.5(\mathrm{M}+\mathrm{S})}}, \tag{11}$$

where M measures traffic flow and S is simulated traffic flow; both are in vehicles per hour.

To obtain a good representation of network traffic conditions, we iterated until the GEH statistic was below 5 (10) for at least 50% (85%) of our loop detectors.

Obtaining reliable simulations every business day of 2005 would be very impractical, so we focused on obtaining calibrated simulation results for two hours on Wednesday, March 9th, 2005 (the day chosen by Lee *et al.* [17]): 7:00 to 8:00 AM, which represents a busy hour during morning peak with significant congestion on our network, and 2:00 to 3:00 AM when there is little traffic on our network.

Each hour was simulated 30 times in TransModeler to obtain reasonable estimates of mean pollutant emissions. Emission estimates were then calculated using EMFAC 2007 for each of these 30 trials.

4. RESULTS

A comparison verified that TransModeler and the MCDKW model produced very similar results and showed the efficiency gains from using the MCDKW model.

4.1 Simulation Accuracy

To maximize the consistence between TransModeler and the MCDKW model, we used the output traffic data from TransModeler as an input to the MCDKW model. A comparison of traffic statistics highlights the similarity of the results for these two models. In TransModeler, 165,778 vehicles per hour entered the road network for the morning peak versus 156,231 for the MCDKW model (a 5.76 percent difference). Average vehicle speed was also quite similar: 35.18 MPH in TransModeler versus 39.64 MPH for the MCDKW model. A comparison of other traffic features (such as average link speed and traffic density at various points of our network) also suggests that, although it relies on a more aggregate approach, the MCDKW model produces similar traffic dynamics as TransModeler.

Table 1 summarizes our estimates of emissions for four air pollutant (TOG, NO_x, CO_2, and PM_{10}) over our network using EMFAC. Interestingly, we note that the MCDKW model tends to slightly overestimate air pollutant emissions in congested conditions (AM peak) but it tends to underestimate emissions in free flow traffic (nighttime). Overall, however, we find that emission estimates from these two models are quite close: differences in emission for all four pollutants are within 10 percent under congested conditions and they do not exceed 15 percent in free flow traffic (when overall emissions are much smaller).

		Total Emission (kg)			
		TOG	NO_X	CO_2	PM_{10}
AM Peak (7:00 AM to 8:00 AM)	TransModeler	141.8	586.8	466,503	30.1
	MCDKW	146.4	620.5	509,535	31.6
	Difference (%)	3.21%	5.74%	9.22%	4.95%
Night time (2:00 AM to 3:00 AM)	TransModeler	20.1	105.5	74,442	4.8
	MCDKW	18.7	90.7	71,832	4.2
	Difference (%)	-7.00%	-14.00%	-3.52%	-12.18%

Table1. Comparison of emission results

4.2 Simulation Efficiency

A key advantage of the MCDKW model is its computational efficiency. In order to obtain mean results from TransModeler, we ran 30 simulations for morning peak traffic, which required approximately 9 hours on an i7-cpu computer. However, for the MCDKW model, the computation time on the same computer (for traffic simulation only) is reduced to less than 1.5 hour with a simulation time step size of Δt=0.451 seconds.

As emphasized in Section 2, the simulation speed of the MCDKW model can be drastically reduced by increasing the simulation time step size. However, the lower bound of the computation time is strongly determined by the network minimum link traverse time δ. In the TransModeler network, approximately 1 percent of the links had a traverse time under 0.6 s. This severely constrained the performance of the MCDKW model, while the computational time in TransModeler remained the same (it is not related to link length). We therefore adjusted the shortest links to allow larger simulation time steps. Figure 5 illustrates the relationship between computation time and minimum link traverse time. After running the MCDKW model on the same network with varying minimum link traverse times, we regressed the logarithm of total simulation time on network minimum link length. We found a strong relationship between computation time (normalized to its original value) and minimum link traverse. The fit was excellent (R^2=0. 9961); the untransformed relationship is given by:

$$T_{total} = 0.3856 * \delta^{-1.23} \tag{11}$$

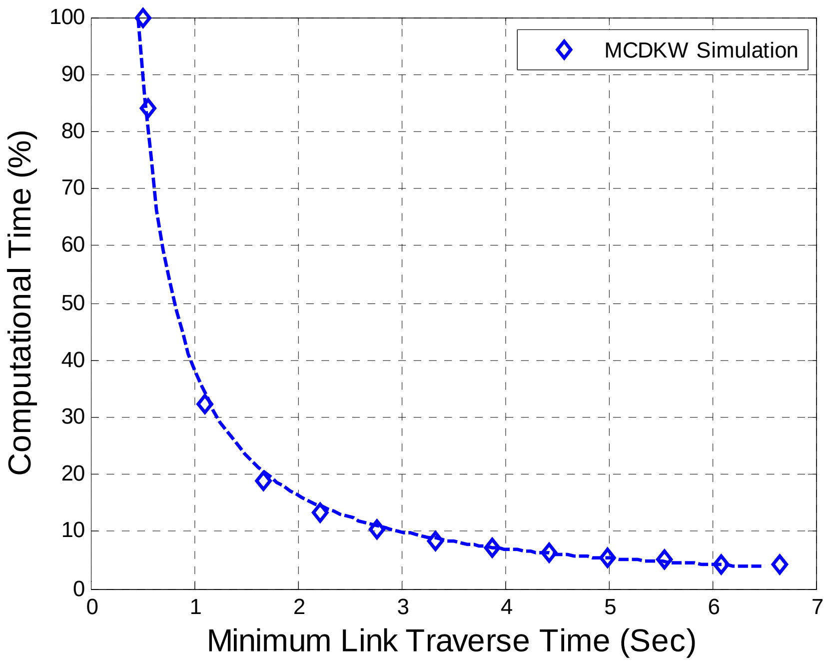

Figure 5. Relationship between computational time and minimum link traverse time

Increasing the minimum link length, which means increasing the minimum link traverse time correspondingly, allows us to decrease simulation time dramatically. However, increasing minimum link length also comes with a cost: it may affect some important network features, change traffic patterns, and bias the resulting estimates of air pollutant emissions. To explore this issue, we estimated total network emissions from our network from 7:00 AM to 8 AM for different values of minimum link length. Table 2 shows that even for a tenfold increase in minimum network link length, estimates of air pollutant emissions compared to microsimulation remain within 10%, with the exception of CO_2 (13.34%). This is understandable since generally such short links are on ramps, so an artificial increase of their links would not significantly change the network topology or the resulting traffic dynamics.

Minimum Link Length (miles)	Total network link length change (%)	Total origin flow rate change (%)	Total Emission Change (%)			
			TOG	NO_x	CO_2	PM_{10}
0.007535 (Original)	0%	5.76%	3.51%	6.15%	9.66%	5.31%
0.01	0.0009%	5.76%	3.72%	6.34%	9.87%	5.52%
0.02	0.0092%	5.84%	4.72%	7.26%	10.84%	6.49%
0.04	0.1713%	5.94%	6.73%	9.11%	12.81%	8.45%
0.08	2.6641%	5.89%	7.04%	9.70%	13.34%	8.83%

Table 2. Impacts of the change in minimum link length on emission estimates

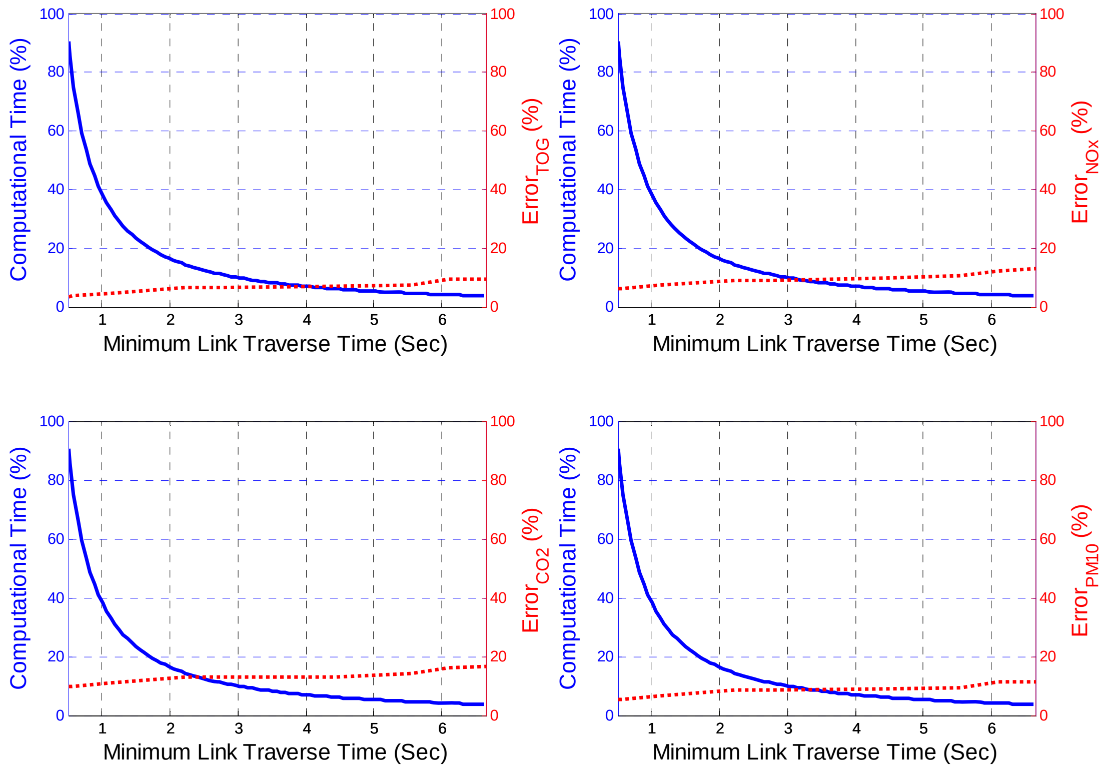

Figure 6. Trade-offs between efficiency and accuracy for different pollutants

Figure 6 further characterizes the trade-offs between computational time and minimum link traverse time. It shows sharp gains in computational time when the minimum link traverse time increases to 2 second with only a moderate loss in accuracy. Increasing the minimum link length from 2 to 4 seconds yields smaller efficiency gains while the loss of accuracy continues at the same rate. Further increases in minimum link length result in smaller efficiency gains but also in smaller increases in differences with microsimulation. These results clearly depend on the characteristics of the network considered but they illustrate the trade-offs between efficiency and accuracy of the MCDKW model on a real-world network.

4.3 Flexibility analysis for large-scale networks

In order to explore the capability of our framework for different networks scales, we split the I-710 from the ports network to form two networks of different size: a smaller one (I-710) with 57 origins, 54 destinations, 320 links, 318 junctions, 624 paths and 36,620 trips; and a larger network (the ports network) with 188 origins, 177 destinations, 1,572 links, 1,435 junctions, 6700 paths and 156,231 trips. Result shows that the computation time for I-710 is ~20 seconds versus 242 seconds for the ports network with a minimum link length of 0.04 mile. Thus, a large increase in network size still led to a fairly small computation time with an adequate minimum link length.

Moreover, to illustrate that our model is not sensitive to the number of vehicles, we increased the demand levels (i.e., vehicle flows) in our network (with a minimum link length of 0.04 mile) from approximately 15,000 vehicles/hour to 156,231 vehicles/hour. We found that the computation time is almost unchanged (roughly 242 seconds). This illustrates that the number of vehicles is irrelevant to the running time of commodity-based models and it confirms that the MCDKW model is more efficient than microsimulation for estimating emissions in congested large scale networks.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we combined EMFAC with the multi-commodity discrete kinematic wave (MCDKW) model, which is a dynamic mesoscopic traffic model, to create a tool that efficiently generates information about traffic dynamics and the emissions of various air pollutants (CO_2, PM_{10}, NO_X, and TOG). Simulation results show that our integrated model yields emissions comparable to those obtained via microsimulation, i.e., using TransModeler combined with EMFAC. Differences in emissions are all within 15 percent, but they can be as low as 3.2 percent for TOG for morning peak simulations. Most importantly, our integrated model cuts total computational time by a factor of at least 6 compared to TransModeler combined with EMFAC. Our results also illustrate trade-offs between total simulation time and accuracy.

Although our approach is very promising, it still takes a lot of time to collect and format network geometry and demand data. We should note, however, that describing the network does not require the same level of details with the MCDKW model (although for the comparisons reported herein we used nearly identical networks). In addition to a faster running time, computational gains are magnified because replications are needed in TransModeler to obtain reliable estimates of mean pollution emissions, but also because emission estimation is currently not integrated in TransModeler so post processing can take a long time.

In the future, we will combine the MCDKW model with MOVES model to obtain better emission estimates. We will also incorporate different types of vehicles to better capture traffic dynamics but also to enhance its ability to perform regional policy analysis. In addition, we will verify the performance of our mesoscopic model on larger networks.

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