Macroscopic relationship between network-wide traffic emissions and fundamental properties of the network

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Emissions from traffic in networks are a growing concern, and there is a need for simple tools to estimate the relationship between network properties, traffic conditions, and the resulting aggregated emissions of pollutants such as greenhouse gases. This paper makes use of a network's macroscopic flow-density relation to approximate the following aggregated components of vehicle driving cycles: time spent cruising at free-flow speed, time spent idling, and the number of vehicle stops. The network-wide emission is estimated by multiplying these driving cycle components with associated emissions factors. The study shows that network emissions are systematically related to the network properties and vehicle density. The proposed analytical model provides an approximation of emissions within 11% of the estimates from a conventional microscopic analysis for all but the most congested traffic states. This approach allows for systematic analysis of network emissions without the need for intensive data collection and simulation.

Keywords: macroscopic fundamental diagram; traffic emission model; drive cycle; network traffic modeling

1. Introduction

Road transportation is a major source of air pollutant emissions. An estimated 1.9 billion gallons (7.2 billion liters) of gasoline and $100 billion are were wasted due to fuel consumption and delays caused by traffic congestion in 2012 within the United States alone (DoT 2012). In addition to wasted energy and time, urban traffic congestion contributes to network-wide emissions of air pollutants, including hydrocarbons, nitrogen oxides, carbon monoxide, and carbon dioxide. It is estimated that the on-road vehicles account for more than half of dangerous air pollutant emissions and over 30% of carbon dioxide emission in the United States (EPA 2013). Reducing these emissions is important for protecting and improving human health as well as reducing production of greenhouse gases, which are associated with global climate change. Emissions from vehicles in traffic are playing an increasingly important role in urban policy making and traffic management in large metropolitan road networks.

Most research on the relationship between traffic and pollutant emissions focuses on individual vehicles and the effect that engine technologies or driving cycles have on emissions from that vehicle. The driving cycle is the pattern of acceleration, cruising, deceleration, and idling as a vehicle traverses distance in the network. In urban environments, the design of the road network and the timing of traffic signals have systematic

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impacts on the driving cycles of the vehicles in the network. The traffic conditions in the network also have an impact on the performance of vehicles, because traffic congestion causes additional stopping and idling, which directly influence the emissions from vehicles in the network. In order to evaluate, control, and reduce network-wide emissions of air pollutants, traffic emission need to be estimated considering the nature of stop-and-go traffic in urban areas.

Although some pollutants have a highly localized impacts, which require detailed models and measurements (e.g., particulate matter), greenhouse gas emissions have a global impact and it is most important to be able to estimate the aggregated emissions from traffic in a whole network. Recent advances in modeling aggregated traffic conditions in urban networks show that a systematic relationship often exists between average vehicle flow and average vehicle density in a network. A macroscopic view of urban traffic provides a basis for making aggregated estimates of air pollutant emissions from the vehicles. This paper shows that emissions factors developed from existing microscopic emissions models can be integrated with models of aggregated traffic variables for urban networks in order to estimate the aggregated network-wide emissions of greenhouse gases from vehicles.

The paper is organized as follows. Section 2 reviews existing literature in the emission modeling and traffic flow fields. Section 3 presents the overall framework for linking aggregated traffic variables that are related to the driving cycle with emissions factors to make an aggregated emissions estimate. A detailed description of how the elements of the driving cycle are estimated from macroscopic traffic model is given in Section 4. An evaluation is presented in Section 5 by comparing the emissions estimates from the proposed model with the results from a more conventional microscopic analysis using simulation. Finally, conclusions are discussed in Section 6.

2. Existing Models

There are a number of existing models in the literature that focus on estimating emissions from vehicle emissions at various levels of resolution. The most detailed microscopic emissions models are based on tracking driving cycles in second by second detail, while the most aggregate models are based on broad averages in order to make regional estimates. Recent advances in traffic models that address the movements of vehicles and congestion patterns at the network level provide useful tools for analysis of aggregated traffic conditions. In the following subsections, some of the most relevant models for modeling emissions and traffic are reviewed. These form the building blocks of the proposed integrated model.

2.1. *Vehicular Emissions*

Existing models for vehicular emissions generally fall into two main categories: microscopic models that focus on specific movements of individual vehicles and macroscopic models that are based on aggregated data and average values. Microscopic models are the most detailed models, and they often provide instantaneous emissions estimates based on concurrent operating conditions of a an equipped vehicle or a simulation. These models typically require extensive data inputs such as second by second trajectories for each vehicle. VT-Micro (Rakha et al. 2000), CMEM (Barth et al. 2000), and the project level of MOVES (EPA 2010) are microscopic models that are widely used in the United States.

In order to analyze the overall effect of changing a signal control system or widening a roadway, microscopic models require that a detailed microsimulation be developed to generate the detailed trajectory of each vehicle which is then used to produce the emission estimate for each vehicle at each second. This is a time-consuming and costly process, and the data intensity and computation time make these microscopic models prohibitively burdensome for estimating emissions in large urban networks. As a result, microscopic models are typically only used in practice for analyzing small-scale projects. For greenhouse gas emissions, such detailed model outputs are not necessary in of themselves except that they tend to be more accurate than emissions estimates from macroscopic models (Rakha, Ahn, and Trani 2003).

Macroscopic emissions models are designed to estimate regional emissions from vehicles based on the average network speed, the total number of vehicles, and some assumed driving cycles (Akcelik 1985; Bai, Eisinger, and Niemeier 2009). These models require relatively few data inputs, so they are much easier to implement for large urban networks. However, these models do not account for the effect of vehicle acceleration and deceleration for stops in a way that is related to what is actually happening in the network. Macroscopic models relate average speed to a single emission rate, but in reality a single average speed could be associated with many different driving cycles ranging from a small number of long stops to a large number of short stops. These driving cycles should be associated with different emissions rates, so macroscopic models have a tendency to oversimplify the relationship between traffic patterns and emissions.

In recent years, a third type of model has emerged: mesoscopic emission models. These models do not require information about the instantaneous movements of individual vehicles, so they are not as complex and data-intensive as microscopic models. Mesoscopic models typically require aggregated traffic data that reflects the traffic conditions and congestion in the network, so they provide more accurate network-wide emission estimation in compare with macroscopic models. One example is VT-Meso, which utilizes link-by-link average speed, the number of vehicle stops, and the stopped delay as aggregated traffic inputs (Yue 2008). The model synthesizes a typical driving cycle, and by using the microscopic VT-Micro model, it estimates the average link fuel consumption and emission rates. Overall network emissions can then be computed by aggregating the emissions on all links. Gori et al. (2012) presents another mesoscopic emission model, which uses a dynamic traffic assignment model to estimate the aggregated traffic parameters, namely distance traveled at free-flow speed, the average speed of vehicles in queues, and the length of the queues. Mesoscopic models improve the accuracy of emissions estimates for larger networks, but they require inputs of aggregated traffic variables, and these need to be obtained either from a simulation or another traffic model.

2.2. *Modeling Traffic in Networks*

Just as emissions can be modeled at varying levels of detail, traffic models also range from microscopic models that track individual vehicle movements to macroscopic models that relate aggregated network-level variables. For the purposes of emission modeling, it is common to use microsimulation tools to construct trajectories for each vehicle that traverses an existing or hypothetical network. Although simulation models are powerful tools for investigating the complex interactions of vehicles, it is costly and challenging to build and calibrate the models appropriately (Dowling et al. 2004). An alternative is to work with the classic kinematic wave model (Lighthill and Whitham 1955; Richards 1956) that makes some simplifying assumptions about the variability of driver and road characteristics but can describe the evolution of traffic states on a road segment by tracking the interfaces between traffic states over space and time. The benefit of this analytical approach is that a wide variety of traffic scenarios can be evaluated in a robust and consistent way with far less data and computational complexity than a microsimulation. At the level of intersections and individual arterials, kinematic wave theory has been a basis of traffic modeling for decades.

For networks that are homogeneous, well-connected, and on which demand is uniformly spread, a consistent relationship between average network flow and average network density has been shown to exist in theory (Daganzo 2007; Daganzo and Geroliminis 2008), in simulations (Ji et al. 2010), and in the real world (Geroliminis and Daganzo 2008; Buisson and Ladier 2009). This relation is often referred to as the Macroscopic Fundamental Diagram (MFD) or network-level fundamental diagram. The size and shape of the MFD depends primarily on the physical properties of the network including the saturation flow rate, block length, and traffic signal settings (e.g., cycle length, duration of signal phases, and signal offsets). This aggregate relation of traffic variables is useful for a network manager, because it can be used to monitor the network performance or implement control strategies to increase throughput and decrease delays in the system (Geroliminis, Haddad, and Ramezani 2013). An additional objective may be to reduce aggregated fuel consumption and emissions in a network, but this application of network-wide traffic models has received less attention in the literature.

Since the critical input for emissions models is an accurate driving cycle, traffic models need to relate the time that vehicles spend accelerating, cruising, decelerating, and idling to the traffic conditions on the roadway. An arterial-level model has been developed to estimate emissions assuming that some traffic data such as flows and number of vehicle stops are measured directly from links in the network and then estimating the other relevant parts of the driving cycle (Skabardonis, Geroliminis, and Christofa 2013). Another recent model uses kinematic wave theory to make analytical estimates of the entire driving cycle for traffic on a single link approaching an isolated intersection (Shabihkhani and Gonzales 2013). The model proposed in this paper is intended to go a step further to estimate emissions based on aggregated traffic characteristics using the MFD and physical characteristics of the network.

3. Integrated Traffic Emission Model for a Network

The proposed modeling framework builds on the Integrated Traffic Emission Model (ITEM) presented in Shabihkhani and Gonzales (2013), which connects an analytical model of traffic approaching an isolated intersection with emission factors from a microscopic emission model. That study shows that reliable predictions of emissions at a signalized intersection can be made using kinematic wave theory to estimate the amount of time vehicles spend idling, the time spent cruising, and the number of times that vehicles stop per vehicle distance traveled. The model of network-wide emissions presented in this paper is structured with the same two components: a traffic model to estimate aggregated traffic parameters and a set of emissions factors to convert the driving cycle into an emissions estimate.

The trajectories of vehicles approaching an intersection or traversing a network have repeating patterns of cruising at the free-flow speed, v_f, idling while stopped, and decelerating and then accelerating between speeds v_f and 0 for every stop. Therefore, three components of the driving cycle that must be estimated from the traffic model in order to account for emissions from the vehicles: the time spent cruising per distance traveled, T_c; the time spent idling per distance traveled, T_i; and the number of times that vehicles must stop per distance traveled, n. The total emissions per vehicle distance traveled, E, is then calculated by multiplying these components by the appropriate emissions factors:

$$E = e_c T_c + e_i T_i + e_s n \tag{1}$$

where e_c is the emission of interest per unit cruising time, e_i is the emission of interest per unit idling time, and e_s is the total emission of interest associated with a complete deceleration from v_f to 0 and a complete acceleration from 0 to v_f.

In order to make accurate emissions estimates, it is important to have accurate estimates of the components of the driving cycle (T_c, T_i, and n) and accurate emission factors (e_c, e_i, and e_s). We will focus the analysis in this paper on investigating simple homogeneous networks in which the MFD is known to be applicable so that we can focus on using the MFD to estimate driving cycles. Then we use these driving cycles to estimate emissions. The details about how to estimate the driving cycle from the macroscopic traffic data are presented in Section 4. Here we will now consider how to obtain appropriate emissions factors, which are important for analysis of isolated intersections or larger networks. Although the method may be applied to measured or simulated vehicle data from any road or network, our investigation will use a simulation approach to study the performance of idealized networks.

3.1. *Traffic Simulation*

The first step to estimating emissions factors with a microscopic emissions model is to obtain high resolution vehicle trajectories that show speed and acceleration a fine temporal resolution (e.g., every second). In the field, trajectories can be measured from equipped vehicles, but a simulation model is useful for considering a wider range of traffic conditions, many of which may not be part of a measured data set. In order to represent the ideal homogeneous network conditions under which a consistent MFD has been proven to exist, a simple ring network has been constructed using Aimsun that is consistent with the theoretical assumptions in Daganzo (2007); Daganzo and Geroliminis (2008). The ring with a single intersection is representative of a long arterial or network with homogeneous traffic conditions and traffic signals with no offset.

In the ring model, a constant number of vehicles in the system correspond to a constant density. The full range of possible densities from an empty network up to a complete jam are systematically analyzed by loading the ring with a specific number of vehicles and then running the simulation to measure aggregated network flow and extract vehicle trajectories. Feeding each trajectory into a microscopic emission model provides a second-by-second estimate of the emissions from each vehicle. Aggregating the emissions from all the individual vehicle trajectories provides an estimate of the network-wide emissions following the conventional detailed microscopic approach. In this paper, the project level of MOVES (EPA 2010) is used as the microscopic emission model, but the same method could be used with any microscopic model that uses vehicle trajectories as the model input.

3.2. *Estimation of Emission Factors*

Our goal is to estimate emission factors for each component of the driving cycle, so a sample of trajectories is parsed into cruising, idling, acceleration, and deceleration. This process requires that thresholds be defined to distinguish between slight oscillations in speed and larger changes that are associated with accelerations and decelerations associated with stopping. The following criteria were used to parse the trajectories in Shabihkhani and Gonzales (2013) and they are used again in this study:

(1) A vehicle is considered to be stopped and *idling* whenever the speed is slower than 1 mph (1.6 km/hr).
(2) A vehicle is considered to be *accelerating* or *decelerating* when the the following

conditions hold: the absolute value of the rate of acceleration exceeds 0.2 mph/sec (0.3 km/hr/sec); the speed changes by at least 5 mph (8 km/hr); the duration of the acceleration or deceleration lasts at least 2 sec; an intermediate period of opposite acceleration does not exceed 1 sec; and an intermediate period of low acceleration does not exceed 3 sec.

(3) The remaining time, the vehicle is moving at steady enough speed that it is considered to be *cruising*.

These criteria were identified because they provided the closest match between the number of stops counted with the automated procedure and the number of manually counted stops from empirically measured and simulated trajectories. Although this parsing process may appear complicated, the important thing is collect observations of enough vehicle trajectories to obtain a good estimate of the average idling, cruising, accelerating, and decelerating behaviors.

Once the trajectories have been broken into each of the components of the driving cycle, each trajectory segment has a duration and is analyzed with a microscopic emission model to estimate the corresponding vehicle emission. For the idling and cruising, the results are simply averaged to obtain an average emission rate for each second of idling and each second of cruising. For the accelerations and decelerations the duration and total emission are both important quantities. Each stop requires that a vehicle decelerate and accelerate, so the sum of the deceleration and acceleration durations are the period of time when vehicles are neither cruising nor idling. The cycle of decelerating and accelerating for a stop is associated with a quantity of pollutants emitted per vehicle stop.

In this paper, we evaluate the proposed analytical model with a number of different network scenarios in which the free-flow speed is $v_f = 53$ km/hr. The project level of MOVES was used to analyze a sample of trajectories extracted from an Aimsun simulation of a ring-shaped network as described in Section 3.1. The emissions of interest for our study are greenhouse gases, because these are global pollutants that are most important to estimate in aggregate for a network. The relevant unit of measure for greenhouse gases is grams of carbon dioxide equivalents (gCO_2eq) because, this represents the global warming of all greenhouse gases emitted from the vehicles in terms of an equivalent amount of CO_2. The emissions factors for this case are $e_c = 2.187$ gCO_2eq/sec, $e_i = 0.881$ gCO_2eq/sec, $e_s = 48.876$ gCO_2eq/stop, and the average duration of an deceleration and acceleration cycle is $\tau = 22$ sec.

4. Analytical Model for Network-wide Traffic Variables

Existing macroscopic models for network-wide traffic conditions relate the average network flow, q, to the average network density, k. These two variables imply the average speed of vehicles in the network, v, by the well known relation:

$$v = q/k. \tag{2}$$

These variables alone provide a lot of useful traffic information about the capacity of a network and the delays that drivers in the network experience. Ongoing research is being conducted to better understand the behavior of the macroscopic flow-density relation for different types of realistic networks. For the proposed model we suppose that the MFD for a network is known or has been measured use it to provide an analytical approximation for the idling time, cruising time, and number of stops for vehicles in the network. The goal is to develop a model with sufficient detail to estimate aggregated emissions in the network without the need to track the details of each vehicle's movements.

As presented in Section 3, the complexities of a second-by-second vehicle trajectory can be simplified into three key parts of the driving cycle that are related to emissions: time spent moving at the cruising speed per vehicle-distance, T_c; time spent idling per vehicle-distance, T_i; and the number of times that vehicle stops per vehicle-distance, n. We will first consider how T_c and T_i can be estimated if n is known. Then we will consider how the number of stops per distance can be estimated as well.

Suppose that traffic on a homogeneous network has a triangular fundamental diagram with free-flow speed of v_f. If we ignore for the moment the range of speeds that are associated with acceleration and deceleration, vehicles will have piecewise linear trajectories with speed v_f while moving (i.e., cruising) or stopped while idling. All travel time for vehicles can be classified as effectively cruising or effectively idling. The kinematic waves associated with these idealized trajectories are the same as the aggregated dynamics of traffic with more realistic acceleration and deceleration patterns (Lighthill and Whitham 1955; Richards 1956).

Every vehicle that stops must decelerate from v_f to 0 and then accelerate from 0 back to v_f. The duration of the deceleration is τ_d and the duration of the acceleration is τ_a, and these values depend on the behavior of drivers in a particular network. If the deceleration and acceleration are at constant rates, then half of τ_d and τ_a is effectively cruising time and the other half is effectively idling time. Figure 1 shows how a piecewise linear trajectory and a more realistic trajectory with constant rates of deceleration and acceleration. For simplicity, we will consider a single time associated with the cycle of deceleration and acceleration for each vehicle stop $\tau = \tau_d + \tau_a$. Therefore the each stop reduces the actual time spent cruising by $\tau/2$ and the actual time spent idling by $\tau/2$. It is important to account for τ when modeling traffic emissions, because the emission rates for cruising and idling should be multiplied by the actual cruising and idling times rather than the effective times.

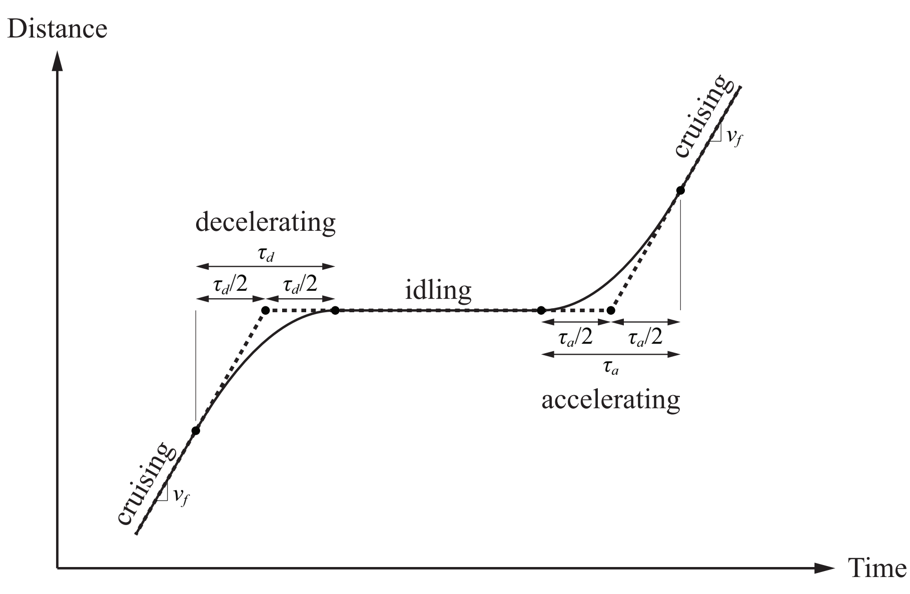


Figure 1. Relationship between a trajectory with constant deceleration and acceleration rates (solid) and a piecewise linear trajectory simplified to effective cruising and effective idling (dashed).

The effective cruising time per unit distance is simply the inverse of the free-flow cruising speed, because no distance is traversed while idling. The actual cruising time per unit distance is then calculated by reducing the effective cruising time by half of deceleration and acceleration time for each stop:

$$T_c = \frac{1}{v_f} - \frac{\tau}{2}n \tag{3}$$

where n is the number of times a vehicle stops per unit distance traveled.

The effective idling time is the difference between the total travel time per unit distance, which is the inverse of the average traffic speed, and the effective cruising time. The actual idling time per unit distance is again calculated by reducing the effective idling time by the other half of the deceleration and acceleration time per stop:

$$T_i = \frac{1}{v} - \frac{1}{v_f} - \frac{\tau}{2}n. \tag{4}$$

In many cases, it may be possible to measure n from the same data source used to obtain the estimated macroscopic traffic state k and q (i.e., traffic data from probe vehicles could provide an indication of this value). In the absence of direct measurements, it is useful to be able to express the number of stops analytically. Although an individual vehicle makes a discrete number of stops per distance traveled, this could vary across vehicles or road segments. Therefore, it is useful to be able to have an analytical approximation for n.

The simplest approximation is simply to suppose that on average vehicles are stopped once per cycle. The average distance traveled during a signal cycle of length C is vC, so the number of stops per distance is given by:

$$n = \frac{1}{vC}. \tag{5}$$

This approximation is appropriate when the signal offset is 0, and especially when the duration of the red signal exceeds the time required to travel the length of a block at free-flow speed: $C - G \geq \ell/v_f$, where ℓ is the length of a block. When the red phase is sufficiently long, a vehicle will always have to stop once per cycle when caught at a red signal. When block lengths or signal times are short enough that thhis inequality is violated, it is possible for some vehicles to traverse the network without stopping during every cycle, which is a possible source of errors.

Since the MFD is a property of a specific network, the flow can be expressed as a function of density, $q = Q(k)$. The shape and size of $Q(k)$ depends on the network characteristcis (e.g., saturation flow, jam density, and block length) and traffic signal settings (e.g., cycle length and green ratio). Therefore the average speed of vehicles in the network can be expressed as a function of density, so (2) becomes $v(k) = Q(k)/k$. The emissions in a network are estimated by evaluating T_c, T_i, and n with $v(k)$ and substituting the resulting driving cycle components into (1).

5. Evaluation with an Idealized Network

The proposed analytical model is evaluated by constructing an idealized network in a microsimulation, and then comparing the emissions estimates with the results of a conventional microscopic emissions analysis. The accuracy of analytical approximations for the MFD itself are beyond the scope of this paper, so the analytical approximations are made assuming that the MFD is measured and known. A ring model is used to represent an idealized homogeneous network as explained in Section 3.1. It is from this simulation that the empirical MFD is measured, and the detailed vehicle trajectories are also extracted in order to calculate the modeling error relative to the conventional microscopic modeling approach.

First a comparison between the analytical modeling approach and the conventional simulation approach is investigated for a base case network. Then, the effect of varying one network parameter – the green ratio – is demonstrated using the analytical model to show how the proposed modeling approach can be used to evaluate changes to the system. Finally, an error analysis if conducted to compare the performance of the analytical model relative to the conventional microscopic approach shows that for a wide variety of network characteristics and traffic states.

5.1. *Comparison of Analytical and Simulation Model Results*

The base case network that is used to illustrate the performance of the proposed analytical model has the following properties: free-flow speed, $v_f = 53$ km/hr; saturation flow, $s = 1900$ veh/lane-hr; jam density, $k_j = 200$ veh/lane-km; green ratio (length of green phase divided by signal cycle length), $G/C = 0.50$; signal cycle length, $C = 60$ sec; block length, $\ell = 0.30$ km; and no signal offset. Running the simulation for a range of densities between 0 and k_j, the average network flow q is plotted for each density k in Figure 2. The points in the figure indicate the measurements from the simulation, and we will suppose that $Q(k)$ is the empirical curve connecting these points (shown as the solid line).

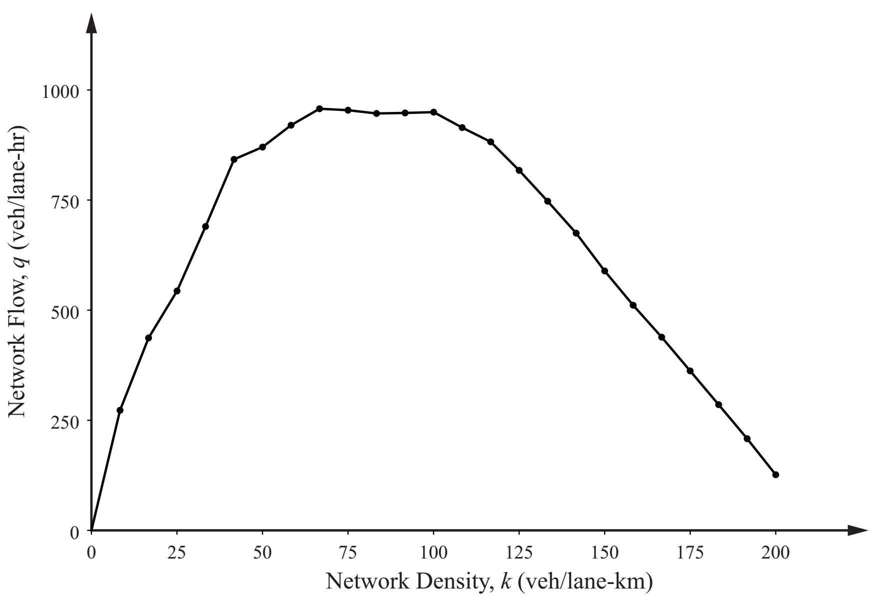
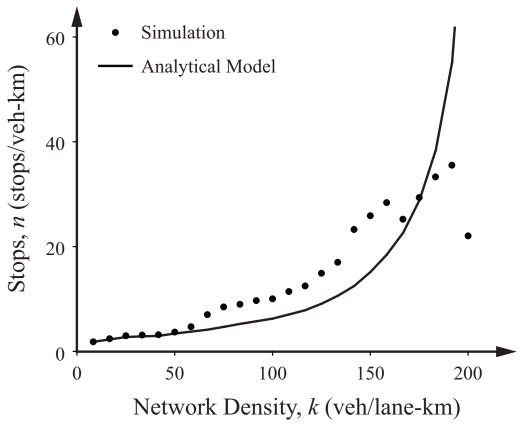
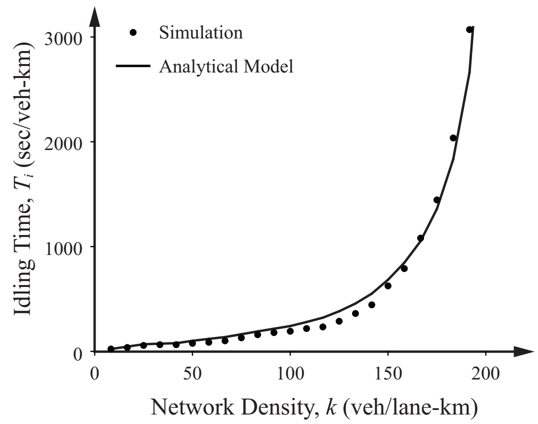


Figure 2. Network flow-density relation (MFD) measured from the simulation of an idealized ring network ($G/C = 0.50$; $C = 60$ sec; $\ell = 0.30$ km).

Using average network speed at each density, $v(k) = Q(k)/k$, the number of stops is estimated using (5). Figure 3(a) shows the analytically estimated value of n (solid line) and the number of stops determined by analysis of the simulated vehicle trajectories (dots) as described in Section 3.2. The plot shows that the analytically estimated number of stops has a similar and close trend to simulated values, especially at low densities ($k <$ 75 veh/lane-km) associated with the free-flow branch of the MFD. At greater densities the number of stops observed in simulation start to grow faster than the analytical prediction, because the interactions between vehicles as conditions become congested create some additional stop-and-go waves that are not accounted for in the simple model. At the highest densities ($k > 175$ veh/lane-km), where traffic is nearly completely jammed, the estimated number of stops per distance soars while the observed number of stops actually declines. This is due to the fact that in extremely congested conditions, vehicles move so little during each cycle that the trajectories do not trigger the necessary thresholds for the stops to get counted.



(a) Number of Stops



(b) Idling Time

Figure 3. Components of the driving cycle estimated using the analytical model and measured from simulation ($G/C = 0.50$; $C = 60$ sec; $\ell = 0.30$ km).

The analytically computed values for n are then used along with the values of $v(k)$ to estimate the time per distance spent cruising, based on (3), and idling, based on (4). Figure 3(b) shows the analytically estimated idling time (solid line) and the idling time measured from the simulated trajectories (dots). The analytically approximation fits closely with the simulated values. Since the idling time and cruising time are calculated by subtracting the duration of the deceleration and acceleration cycles associated with each stop, errors in the estimated number of stops contribute to errors in the estimated values of T_c and T_i. The values of k where stops are underestimated also have overestimated values of T_i and vice versa. The error that affects the idling time (as shown Figure 3) also affects the cruising time estimates (not shown) in a similar way.

The total greenhouse gas emission per vehicle distance traveled is calculated by multiplying each of the estimated driving cycle components by the associated emission factors as show in (1). These results can be compared with the outcome of a conventional microscopic emissions analysis using the simulated vehicle trajectories. A comparison of the analytically estimated emissions (solid line) and the aggregated simulation output (dots) is shown in Figure 4. The close agreement between the analytical macroscopic model and the detailed simulation model occurs because aggregating the emissions from all vehicle trajectories together has the effect of averaging out variations from vehicle to vehicle.

5.2. *Variation of Signal Timing*

The proposed analytical model is particularly useful for comparing the performance of networks with different characteristics. One example is to consider the effect that changing signal timings has on the emissions from traffic in a network. Using all the same network parameters as the base case presented in Section 5.1, an evaluation of the effect of changing the green ratio is conducted by changing only the value of G/C. Figure 5(a) shows the MFD for each of the green ratios $G/C \in \{0.25, 0.50, 0.75\}$. The middle value is the same base case presented in Figure 2.

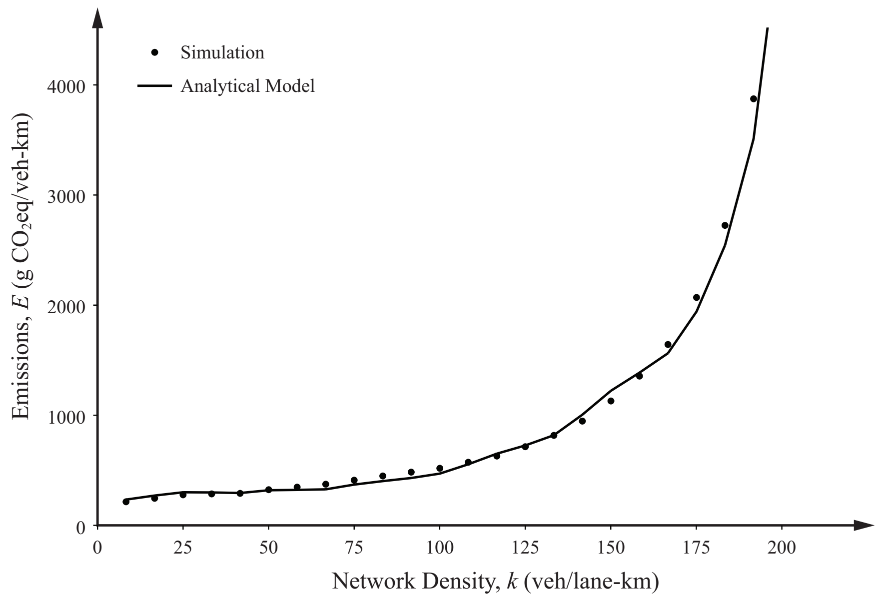
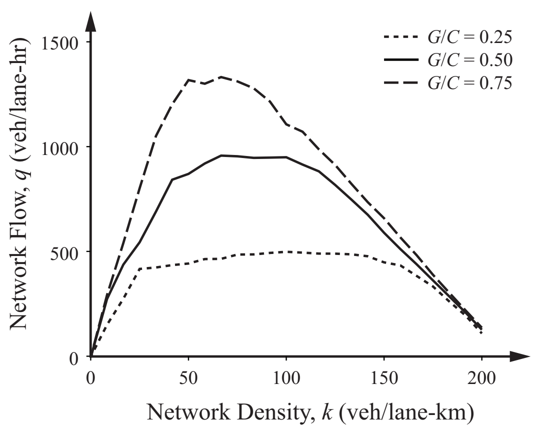
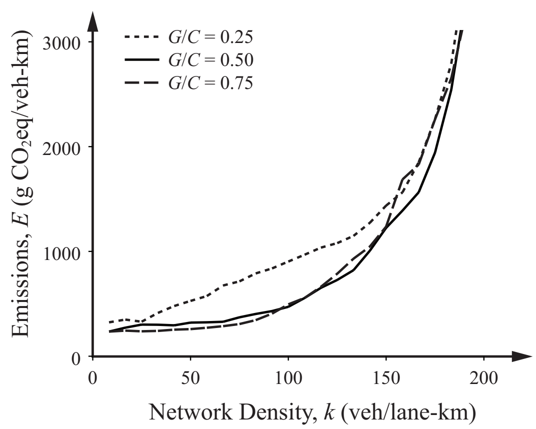


Figure 4. Network-wide emissions estimated using an analytical model based on the MFD and estimated using detailed trajectories from a simulation and microscopic emission analysis ($G/C = 0.50$; $C = 60$ sec; $\ell = 0.30$ km).



(a) Network Flow (MFD)



(b) Network Emissions

Figure 5. Comparison of MFD and analytically estimated emissions for varying green ratios, $G/C \in \{0.25, 0.50, 0.75\}$.

The effect of G/C on the MFD is not surprising, because a longer green phase within the cycle allows a greater flow of vehicles to traverse the network. The most restrictive green time ($G/C = 0.25$) is associated with a low network capacity, and a constant flow that is associated with a wide range of densities. The analytically estimated emissions for each of the cases are shown in Figure 5(b). The results show that the more restricted green ratio is associated with greater emissions per vehicle distance traveled, but there is not a big difference between $G/C = 0.50$ and $G/C = 0.75$.

The ability to compare scenarios based only the MFD is useful because detailed trajectories do not need to be extracted and analyzed with the microscopic emission model for each case considered. A similar method can be applied to changing other network parameters such as the cycle length, C, and block length, ℓ. All of these cases are associated with the same free-flow speed, v_f, so the set of the emission factors (e_c, e_i, and e_s) and the duration of each acceleration and deceleration cycle (τ) remains the same as the base case. If the free-flow speed in the network were to change, these factors would have to be re-estimated.

5.3. *Model Errors*

In order to assess the accuracy and robustness of the proposed analytical model, an error analysis has been performed to compare the estimated emissions from the analytical model with the results of a detailed simulation and microscopic emission analysis. The accuracy is quantified by calculating the percent error of each analytically calculated emission value relative to the simulated result.

Starting from the base case presented in Section 5.1 with $G/C = 0.50$, $C = 60$ sec, and $\ell = 0.30$ km, a systematic error analysis was conducted for each of the following variations in isolation: the green ratio, $G/C \in \{0.25, 0.50, 0.75\}$; the signal cycle length, $C \in \{30, 60, 120\}$ sec; and the block length, $\ell \in \{0.15, 0.30, 0.60\}$ km. For each case a separate ring simulation was constructed to generate the MFD for the analytical approximation and to generate the detailed vehicle trajectories for the conventional microscopic analysis. The percent error of the proposed analytical approach relative to the conventional microscopic simulation approach is summarized in Table 1.

Table 1. Percent error of emissions estimate from the aggregated analytical emission model relative to the microscopic simulation model (Base case: $G/C = 0.5$; $C = 60$ sec; $\ell = 0.30$ km).

Network Properties			Network Density, k (veh/lane-km)				
G/C	C (sec)	ℓ (km)	25	50	100	150	200
Variation of the Green Ratio							
0.25	60	0.30	2.1%	4.9%	0.9%	1.7%	15.9%
0.50	60	0.30	-7.7%	1.3%	10.5%	-7.6%	19.5%
0.75	60	0.30	-8.4%	-5.1%	-7.2%	-17.4%	22.4%
Variation of the Signal Cycle Length							
0.50	30	0.30	9.3%	10.1%	5.5%	0.4%	49.7%
0.50	60	0.30	-7.7%	1.3%	10.5%	-7.6%	19.5%
0.50	120	0.30	-11.0%	-10.0%	0.2%	-1.8%	1.1%
Variation of the Block Length							
0.50	120	0.15	-5.0%	8.5%	6.7%	-1.2%	22.6%
0.50	120	0.30	-7.7%	1.3%	10.5%	-7.6%	19.5%
0.50	120	0.60	-10.3%	-7.5%	1.4%	0.2%	22.4%

The network scenarios are clustered into three groups, each group showing the results of varying one of the network variables. The center row of each cluster is the base case so that the effect on the percent error from increasing and decreasing each variable can be compared one at a time. In almost all cases when the network is not completely jammed ($k < 200$ veh/lane-km), the model is within 11% of the simulated value. These errors do not appear to have a systematic biasand the magnitudes are small relative to the variation in emission rates for different values of k as shown in Figures 4 and 5(b). Therefore, the proposed analytical model provides a good approximation for the detailed microscopic estimates.

Only at the jam density ($k = 200$ veh/lane-km) are the errors very large and consistently positive. These large errors occur when the network is near a state of complete gridlock, because the model predicts a large number of stops but the traffic moves so little with each cycle that the vehicle trajectories in the simulation never move faster than a slow crawl. Fortunately, these extremely jammed conditions are rare, and the model performs well for a wide range of congested traffic conditions and a wide range of network characteristics.

6. Conclusion

A model has been proposed that makes use of the macroscopic relationship between average flow and density known as the MFD to make analytical estimates of the network-wide emissions from traffic. A robust relationship is shown between the components of that driving cycle that are associated with vehicular emissions and the fundamental properties of the network. Aggregated traffic parameters are used to identify a typical driving cycle. The components of the driving cycle per vehicle distance traveled (i.e., cruising time, idling time, and number of stops) are estimated based on the aggregated flow-density relation (MFD), the free-flow speed in the network, the duration of a typical acceleration and deceleration associated with a vehicle stop, and the signal cycle length. These components are then multiplied by emission factors that are developed using a detailed microscopic emission model, such as the project level of MOVES.

The Integrated Traffic Emission Model (ITEM) that has been presented and evaluated in this paper links macroscopic traffic flow models with microscopic emissions models in order to exploit the strengths of each modeling approach. Conventional microscopic traffic emissions modeling requires detailed data for individual trajectories, which must either be measured in the field or generated with a microsimulation, in order make detailed emissions estimates. This is not practical for estimating emissions in large urban networks, but that macroscopic emissions models that are currently available do not adequately account for the effect that properties of the road network have on driving cycles and the resulting emissions estimates. The proposed modeling approach address this challenge by making use of state-of-the-art macroscopic traffic models that are sensitive to properties of the network such as the lane capacities, block lengths, and traffic signal timings. By making use of the MFD, which embodies the effects of network properties on the aggregated flow-density relation, network-wide emissions can be reliably estimated for a wide range of traffic conditions without the need for extensive simulations and trajectory analysis.

The effect of network characteristics and traffic dynamics on real MFDs is currently a topic of extensive research. The flow-density is known to exist and be robust for idealized homogeneous networks, so this was used to demonstrate the potential for using a macroscopic approach to approximate driving cycles in the network. The shape of the MFD has been studied for various types of networks have been developed (Daganzo and Geroliminis 2008; Ji et al. 2010; Gayah and Daganzo 2011), but we suppose that this relation is either measured or determined by some other method. Given the traffic state on the MFD, a few other network characteristics (v_f, C, and τ), and the emission factors (e_c, e_i, and e_s), the ITEM has been shown to approximate the vehicular emissions within 11% of the values from microscopic analysis of simulated trajectories for all but the most congested traffic states.

This proposed model is useful for monitoring emissions in real networks, because traffic states can be monitored using data collected from many different sources, including vehicle probes, mobile phones, and fixed detectors. The same data that is useful for monitoring traffic and implementing efficient traffic control system can also be used to estimate network-wide emissions without simulations or extensive additional data collection. Furthermore, the analytical approach provides a tool for systematically analyzing the effect of changes to the network on emissions by tracking the effect on the MFD. While this paper has focused on demonstrating the potential of this integrated model with an idealized ring-shaped network, additional work is needed to determine how well the modeling approach applies to more realistic networks that may have turning vehicles, signal offsets, or inhomogeneous signal timings and block lengths. Nevertheless, the proposed model has value because it provides a less data-intensive way to estimate aggregated netowrk emissions, which is especially important for tracking pollutants like greenhouse gases that have a global impact.

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