Integration of a speed-dependent emission model in dynamic traffic assignment: a large scale application to the Paris metropolitan area

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Abstract

It is a common practice, when interfacing a traffic assignment model with an average-speed emission model, to use link mean speeds instead of trip mean speeds. Using synthetic traffic data produced by a microscopic model, we show that both approaches do not capture well the effect of congestion on emissions. Instead, using the distributions of vehicle speeds — as opposed to a single average-speed value — can make an average-speed emission model behave consistently with a kinematic emission model. The main contribution of this paper is to show that simple, bimodal, speed distributions, can capture a significant part of the dynamic of congested traffic w.r.t. an average-speed emission model.

1. Introduction

Degradation of air quality is a major concern. In urban areas, road traffic is a prominent source of air pollutants, and traffic congestion makes it harder to predict how traffic flow patterns, and hence traffic emission patterns, evolve with changes in traffic management. To better address this issue, this paper presents the findings of a study in which a dynamic traffic assignment (DTA) model was interfaced with an average-speed emission model.

The paper is divided into four sections, followed by a conclusion. The first recalls the motivations underlying this work. The second section presents two existing different emission models. Both are trip-based. One is an average-speed model, the second requires a finer grain kinematic description of the trip. Section 3 investigates a long-standing debate (see for instance DeCorla-Souza et al., 1994): should the average-speed be the mean speed of a vehicle over a trip (i.e. the trip speed) or the mean speed of vehicles on a link during a lapse of time (i.e. the link speed)? It is suggested, using a counter example, that (i) both practices are equally inadequate and (ii) that using distributions of vehicle speeds — as opposed to a single average-speed value — makes the average-speed model behave consistently with the kinematic model. The comparison between the two models has been performed using synthetic data sets produced by a microscopic traffic model on a ring road. The data sets represent heterogeneous...
stationary states for interactive density levels, i.e. when the actual flow speed is lower than the free-flow speed, because of the formation of platoons. Finally, section 4 contains our main contribution: a simple method to reasonably approximate the distribution of vehicle speeds on a road link, on the basis of the flow density and a few other properties of the link. An example illustrates the changes in traffic emissions that are predicted to occur in the Paris metropolitan area.

2. Background and motivations

A wide range of tools are available for the better management of road traffic. These include dynamic user information, congestion pricing and dynamic speed regulation. However, the occurrence of congestion makes the management of road networks a challenging task. Indeed, trips associated with different origin-destination pairs interact in intricate ways, both in space and time. Because of these complex interactions, a traffic management scheme implemented on a single road link may affect large parts of a congested network: road users may change both their choice of route and departure time. So, even small changes in traffic management may induce noticeable changes in the way the traffic is distributed over the network, and consequently the location and magnitude of pollutant emissions. In current assessment methodologies for urban road networks, static traffic assignment models tend to be used to forecast the traffic flow and speed on each link. But since congestion changes with the time of day, and because congestion is a major determinant of speed, time-of-day modeling is necessary. Using static models separate time periods can be considered, but this approach does not adequately capture the time-continuous reaction of demand to congestion: while congestion levels increase during the day, more and more routes are being used, and at the same time shifts in departure times can be observed. By its very nature, DTA captures these dynamic relationships.

But DTA is usually seen as a computer intensive task that does not scale well to large-scale real networks. As detailed in (Boyce et al., 2001), recent advances in the formulation of link-time-based (as opposed to route-time-based) analytical DTA models has allowed for efficient implementations to emerge. LADTA (Lumped Analytical DTA), together with its software, the LADTA ToolKit (LTK), is one of these. It can handle within a reasonable time frame the road networks of large cities (Aguiléra & Leurent, 2009). Given a dynamic OD matrix (the demand) and a transportation network (the supply), LADTA calculates a dynamic user equilibrium between demand and supply. As an output of the equilibrium, traffic flow and speed are available for every class and every link on the network. Being a link-time-based DTA model, LADTA does not explicitly enumerate the set of trips used at equilibrium. There is a mismatch here with traffic emission models, because most speed-dependant traffic emission models are trip-based. When interfacing an analytical traffic assignment model (whether it is static or dynamic) with a traffic emission model, a common practice is to apply an average-speed model, but to use link speeds instead of trip speeds. On the one hand, some argue that this is a misuse of average-speed models. On the other hand, a trip-based average-speed model cannot distinguish between trips with the same average speed but different speed profiles. In other words, driving conditions encountered during a trip affect emissions. An average trip speed of 50 km/h does not bring the same information if the maximal speed on the link is also 50 km/h (free drive) or if the maximal speed is 130 km/h (congested drive). The driving conditions, the fuel consumption and the emissions vary according to the traffic state. A congested traffic state implies accelerations and decelerations. A free traffic state implies a quasi-constant speed.

For the purpose of integrating a traffic emission model within a link-time-based DTA model, the work presented hereafter presents a simple mean to capture — within an average-speed model — a significant part of the dynamic of traffic on links.

3. Road traffic emission models

The literature on road traffic emissions (see Boulter & McCrae, 2007 and references therein) distinguishes between evaporative emissions, cold start emissions and hot emissions. In what follows, and unless otherwise stated, only exhaust hot emissions (i.e. tailpipe emissions under thermally stable engine and exhaust conditions) are considered. Most emission models are trip-based. Several trip-based models exist, depending on the level of detail of data available for a given trip. For the purpose of our study we compared the two following models. The first was an average-speed model taken from COPERT 4 (Ntziachristos & Samaras, 2009). It requires few inputs: the
duration and the length of the trip. The second was a kinematic regression model proposed by Rapone et al. (2008). Its main input is the speed profile of the trip. Both are described more precisely hereafter, in sections 2.1 and 2.2 respectively.

3.1. COPERT emission factors

The COPERT 4 methodology, included in the EMEP/EEA Emission Inventory Guidebook, is widely used in Europe. It is based upon average-speed emission factors. The quantity $Q_p$ of a pollutant $p$ emitted during a trip of length $L$ and of duration $T$ is given by $Q_p = L \cdot e_p(v)$, where $v = \frac{L}{T}$ is the trip mean speed and $e_p$ is an emission factor. The emission factors also depend on vehicle class. For instance, some of the COPERT 4 emission factors for Euro 1 and later gasoline passenger cars are of the form:

$$e_p(v) = \frac{a_1 + a_2 v + a_3 v^2}{1 + a_4 v + a_5 v^3}$$ (1)

In particular, Equation (1) stands for $p$ in $\{CO, HC, NO_x\}$ and $v$ in the range $[10, 130]$ km/h. The same applies for the fuel consumption $FC$. Note that Equation (1) does not stand for all vehicle classes, nor for all pollutants. For instance, following the COPERT methodology, the emission factor for $CO_2$ is a linear combination of $FC$ and other emission factors. Generally speaking, COPERT emission factors are non-linear U-shape functions, as illustrated by Figure 1.

![Figure 1. Normalized COPERT emission factors for CO, HC, NOx and the fuel consumption FC. EURO 1 gasoline passenger cars and later.](image)

3.2. Kinematic regression model

By definition, an average-speed model cannot distinguish between trips with the same average speed but different speed profiles. To capture the effects of instantaneous speed variations on emissions, Rapone et al. (2008) proposed a kinematic regression model. They define the emission factor $e_{p,n}$ for a pollutant $p$ and a vehicle $n$ during a trip by:
\[ e_{p,n} = \exp\left( a_0 + a_1 \bar{v} + a_2 \bar{v}^2 + a_3 \bar{v}^3 + a_4 \bar{v}^4 + a_5 t_{\text{run}} + a_6 t_{\text{idl}} + \varepsilon \right) \]  

where \( \bar{v} \) is the average speed of vehicle \( n \), \( \bar{v}^\land \) is the product of the instantaneous speed, times the positive part of the acceleration rate, \( t_{\text{run}} \) is the running time, \( t_{\text{idl}} \) is the idle time, \( \varepsilon \) is a Gaussian noise parameter and \( a_i \) to \( a_6 \) are parameters.

4. Using the distribution of vehicle speeds

Let now consider the following situation. \( N = \rho L \) vehicles are distributed on a ring road of length \( L \). The purpose is to estimate the quantity \( Q_p \) of a pollutant \( p \) emitted during a period \( T \). \( T \) is taken long enough so that the system can be supposed ergodic, that is spatial and temporal distributions of vehicle speeds are identical. In particular, this implies that the average speed of every trip is equal to the link average speed (i.e. to the mean value of vehicle speeds along the ring). Under those hypotheses, the output of an average-speed model remains constant whether the trip speed or the link speed is taken as an input. However, given an average-speed, the kinematic model distinguishes between different traffic conditions. In free-flow conditions, the speed of a particular vehicle is expected to remain constant, hence the term \( \bar{v}^\land \) in Equation (2) may be neglected. *A contrario*, if congested traffic conditions occur, large variations of the vehicle speed are likely to happen during the trip, leading to higher emissions.

\( Q_p \) can be expressed in three ways. First, using individual speed profiles and Equation (2), we have:

\[ Q_p = \sum_{n=1}^{N} e_{p,n} \]  

(3)

Second, if the speed-density diagram of the ring is known, then using Equation (1) we have:

\[ Q_p = \rho L \cdot T \cdot v(f(\rho)) \]  

(4)

Third, if the distribution of vehicle speeds is known, with a probability density function \( f(v) \), Equation (1) can be integrated as follows:

\[ Q_p = \rho L \cdot T \cdot \int_v \cdot e_p(v) \cdot f(v) dv \]  

(5)

Equation (5) is supported by standard results from traffic flow theory, which classifies traffic states into two phases: free and interactive. Free traffic states are observed when the flow density is lower than a threshold called the critical density. In the free phase, individual vehicles speeds are independent and almost constant. The flow speed is equal to a constant, the free-flow speed. The flow density is below a threshold called the critical density. Traffic states in the interactive phase are characterized by a density that exceeds the critical density. Individual vehicles speeds are no longer independent (hence the name interactive) and vary significantly with time. The flow speed decreases while the density increases. The analysis of microscopic traffic models (Treiber 2010, Tordeux 2010) shows that a flow of vehicles with homogeneous individual speeds is in a stable state if its density is beyond the critical density. If not, the state is not stable, and one can observe the propagation of kinematic waves (Mahnke, 2008). Those waves induce variations in individual vehicle speeds.

We firstly studied the variations of the distribution of vehicle speeds as a function of the free-flow speed \( \rho \) and of the density \( \rho \). The results are presented in section 3.1. Then, in section 3.2, the emissions computed using the COPERT emission factors are compared to those obtained from the kinematic regression model. The numerical results presented hereafter have been established using synthetic traffic data sets produced by microscopic traffic simulations on a ring road. The microscopic model used is the one proposed by Tordeux (2010). The model assumes a regulation of vehicle time gap according to the performances of predecessors. It is able to produce free and interactive traffic states. In interactive states the propagation of waves induces variations of vehicle speeds between the free speed (close to the maximal value) and the congested speed (close to zero). This model is consistent with detailed physics-based microscopic traffic models such as those described in (Treiber & Kesting, 2010).
4.1. Variations of vehicle speeds distribution

The free-flow speed, denoted $\vartheta$, varied between 90 km/h and 125 km/h. The flow density, denoted $\rho$, varied between 15 veh km$^{-1}$ and 55 veh km$^{-1}$. For each pair $(\vartheta, \rho)$, fifty independent micro-simulation runs were recorded. The initial state of each run was homogeneous: vehicles were equally distributed on the ring. The length of the ring was set to $L = 1$ km. The length of each vehicle was $l = 5$ m. The simulated duration of the run was $T = 1$ h. All vehicles were assumed to be identical and powered with a gasoline EURO 3 engine. In Figure 2 the distributions of vehicle speeds are plotted for $\vartheta = 90$ km/h and $\vartheta = 125$ km/h, as a function of the flow density. In both cases interactive states emerge when the flow density exceeds the critical density $\rho_{c, \vartheta}$. The latter depends on the free-flow speed, and is close to:

$$\rho_{c, \vartheta} \approx \frac{1}{v \tau_\vartheta + l}$$

where $\tau_\vartheta$ is the inter-vehicle time gap. $\rho_{c, 90} \approx 31$ veh km$^{-1}$ and $\rho_{c, 125} \approx 25$ veh km$^{-1}$.

For density less than the critical density, the flow is free. The distribution of vehicle speeds is uni-modal, and centered around the free-flow speed. When the density exceeds the critical density, the flow speed decreases and the distribution of vehicle speeds becomes bi-modal. Kinematic waves appear in the flow. The low-speed mode corresponds to vehicles into a wave of slow traffic. The high-speed mode corresponds to vehicles evolving outside of a wave. A noticeable fact is that for density values exceeding 30 veh km$^{-1}$ the average speed are almost equal for both systems, although the high-speed modes of the two distributions are different.
4.2. COPERT emission factors compared with the kinematic regression model

The emissions computed using Equations (4) and (5), and the same set of simulation runs as those described in section 2.1, are plotted Figure 3. When the density is below the critical density, both equations produce very similar results. In this case, the distribution of speeds is uni-modal, centered around the free-flow speed. Differences appear when the flow density exceeds the critical density. Emissions computed using Equation (5) (i.e. using the distribution of vehicle speeds) are, in interactive states, higher than those computed using Equation (4) (i.e. using the average speed). Figure 4 compares the mass of pollutants computed using Equation (5) (i.e. COPERT emission factor with distribution of vehicle speeds) with the one obtained using Equation (3) (i.e. the kinematic regression model). Emissions are most of the time higher when using the kinematic regression model. At low density levels (less than 20 veh.km$^{-1}$), the dynamics of traffic has little influence on the kinematic regression model, so the observed differences between the two models should (hopefully) vanish if both were calibrated using the same data.

For the four pollutants tested, and a free-flow speed of 90km.h$^{-1}$, the computed emissions are remarkably close between both models. For a free flow speed of 125km.h$^{-1}$, the differences become noticeable. A significant part of the observed differences may be explained by a too high acceleration rate in the dynamics of the simulated traffic flow.
5. Emissions modeling using bi-modal speed distributions

Results in section 2 show that the kinematic regression model and the COPERT emission factors behave consistently when COPERT emission factors are used with speed distributions rather than with a single average-speed value. Those results are coherent with previous results from Smit et al. (2007). Using vehicle speed distributions with the average-speed emissions model reduces the underestimate at super-critical flow densities. However, vehicle speed distributions are not in the set of standard collected traffic data, nor a quantity that every DTA engine may be able to produce. The central question to this section is how to provide a reasonable approximation of the distribution of vehicle speeds on a road link, on the basis of the flow density and some other properties of the link. Section 4.1 investigates the issue of approximating, in a simple manner, the vehicles speed distribution on a road link, using bi-modal speed distributions and a very small set of additional inputs: the flow density and the free flow speed. Section 4.2 presents an application to the Paris metropolitan area network.

5.1. Using bi-modal speed distributions

It is assumed that, on a given road link, one knows the following functions of the flow density $\rho$:

- the flow speed $v(\rho)$
- the high speed mode $v_h(\rho)$
- the low speed mode $v_l(\rho)$

Figure 4. Emissions of pollutants on a ring, as a function of the flow density, using COPERT emission factors with speeds distribution and the kinematic model, for EURO 3, 1,200- to 1,400-cc gasoline passenger cars.
Then, knowing the emission factor $e_p$ of a pollutant $p$, and assuming that the distribution of vehicle speeds is reduced to two Dirac masses (i.e. the distribution is concentrated on two single values), it comes from Equation (5) that the emission rate of the pollutant $p$, denoted $q_p$, and expressed in $kg.km^{-1}.h^{-1}$, is:

$$q_p(\rho) = \rho \cdot (\lambda \cdot v_h(\rho) \cdot e_p(v_h(\rho))) + (1-\lambda) \cdot v_l(\rho) \cdot e_p(v_l(\rho))$$

(7)

with

$$\lambda = \frac{v(\rho) - v_l(\rho)}{v_h(\rho) - v_l(\rho)}$$

the fraction of vehicles in the high speed mode.

In practice, since the high (resp. low) speed mode remains quasi-constant, we can state that $v_h(\rho) = \mathcal{Q}$ (the free flow speed) and $v_l(\rho) = u \approx 10km.h^{-1}$. Equation (7) then becomes:

$$q_p(\rho) = \rho \cdot (\lambda \cdot \mathcal{Q} \cdot e_p(\mathcal{Q})) + (1-\lambda) \cdot u \cdot e_p(u)$$

(8)

Figure 5 illustrates the differences between the emissions computed on a ring (L=1km, T=1h) using either a continuous speed distribution (Equation 5) or a bi-modal speed distribution (Equation 8). The bi-modal speed distribution model allows for a good approximation, while requiring very few inputs.
5.2. Application to the Paris metropolitan area road network

The administrative region that covers Paris metropolitan area is called “Région Ile de France”. Its geographic extent is around 140 km from west to east, and 100 km from south to north. It is divided into eight counties called “départements”. The City of Paris is the central department. The zoning system used for the purpose of traffic assignment was provided by the State Department of Transport for Paris area (DRIEA). It is plotted in Figure 6(a). It covers the eight counties in the Paris metropolitan area plus some extra area in the northern part, and comprises 1,277 zones. Its level of detail varies with the density of population. The road network comprises 39,137 directed arcs and 18,048 nodes. A dynamic OD trip table was setup using data provided by DRIEA. It expresses the demand for an average working day. It has been assigned on the road network, using LADTA. The results are illustrated by Figure 6(b) that presents a map of congestion. The network links that are congested more than four hours during the day are plotted in red. Those congested more than one and less than four hours during the day are plotted in orange. Almost all of the motorways are congested more than one hour during the day. Links congested more than four hours during the day include (a) the main north-south arterials in the Centre of Paris; (b) the first Paris ring road “Le Boulevard Périphérique”; (c) some parts of the second ring road “A 86”; (d) some parts of the third ring road “La Francilienne”; (e) some radial motorways running south; (f) an intermediary ring road used to access the major Business Centre at “La Défense”.

As an output of the assignment, the traffic flow and speed were available for every link and every instant. For the purpose of this experiment, all vehicles were assumed to belong to the same class. The bimodal model exposed in section 4.1 was applied on those data, and compared to the single-value average-speed model, for FC, CO, NOx and HC. The results are plotted Figure 7. Outside peak periods, the differences are negligible. During peak periods, the underestimate bias of the single-value average-speed model appears clearly, at least for FC, CO and HC. Surprisingly, there is no significant difference for NOx.

6. Conclusion

It is a common practice, when interfacing an analytical traffic assignment model (whether it is static or dynamic) with an average-speed emission model, to use link mean speeds instead of trip mean speeds. Using synthetic traffic data produced by a microscopic model, we have shown that both approaches do not capture well the effect of congestion on emissions. Instead, using the distributions of vehicle speeds — as opposed to a single average-speed value — can make an average-speed emission model behave consistently with a kinematic emission model. This is coherent with previous results by (Smit et al., 2007). Our main contribution was to show that simple, bimodal, speed...
distributions, can capture a significant part of the dynamic of congested traffic flow w.r.t. an average-speed emission model. Those bimodal distributions can be easily computed for each link of a road network, knowing the link mean speed and the link free-flow speed. The results presented in this paper are very preliminary, and subject to a number of improvements.

Figure 7. Instantaneous emissions rates on the Paris area road network, as a function of the hour in the day, for FC, CO, NOx and HC, using an average-speed emission model with link speeds. In black, using the mean link speed. In red, using bimodal speed distributions.

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