Are average speed emission functions scale-free?

Delphine Lejri, Ludovic Leclercq

Are average speed emission functions scale-free?

D. Lejri, L. Leclercq

Univ. Gustave Eiffel, Univ. Lyon, ENTPE, LICIT, Lyon, France

Abstract

Although emission models have been designed using vehicle data over driving cycles of a few minutes, they are often applied at large scale to estimate total emission (inventories). In between, there is a range of scales in use in traffic and environmental studies (road sections, sub-areas, etc.). Coupling a traffic microsimulation with COPERT emission factors at different scales reveals scaling biases. We compare network fuel consumption (FC) and nitrogen oxide (NOx) emissions resulting from emission calculations based on different spatial decompositions. The results show that for an area of Paris covering 3 km^2, the differences due to the aggregation scale for emissions range from 5 to 17% depending on the pollutant, spatial partitioning and traffic conditions. These discrepancies can be reduced using a distance-weighted mean speed, which is not a scale-consistent definition of mean travel speed. They can almost be cancelled by using a correction term derived analytically in this paper, thus consistency can be guaranteed between emissions assessed at different scales. Finally, a case study shows that it is possible to evaluate FC and NOx emissions on a large-scale network from a sample of traffic data (probes), and obtain the corrective term to be applied to remove scaling bias. The most critical step is the accurate estimation of the total travel distance. The gaps were successfully reduced to a maximum of 8% in congestion for a penetration rate of about 20%.

Keywords: Average speed model, emission factors, COPERT, scale consistency, driving cycle, mean speed.

Highlights

- Highlighting the scaling inconsistency of emission laws due to the definition of mean speed
- A corrective term is derived to estimate the biases of different aggregation scales
- Floating car data is simulated to estimate unbiased global emissions

1. Introduction

Road traffic is a major source of air quality deterioration in large cities. Despite the advances made in vehicle technologies and traffic management policies, travel needs are increasing and the road sector remains a major contributor to air pollution, with significant effects on public health. These effects on both health and climate change are well established (EEA, 2017; WHO, 2013). Policy-makers are looking for solutions to reduce greenhouse gases and pollutant emissions. To this end, efforts in recent years have focused on the rigorous assessment of emission reduction measures (Fontes et al., 2015; York Bigazzi and Rouleau, 2017).

The challenging issue is therefore to produce a robust "traffic-emission" modeling chain and assess the corresponding uncertainties (Fallah Shorshani et al., 2015). In particular, in urban areas, periods of congestion contribute significantly to fuel consumption and pollutant emissions, which is why traffic dynamics should be estimated accurately (Lejri et al., 2018). Traffic microsimulators are typically used to provide relevant traffic data for emission calculations.

Another issue to be addressed is the way emissions are calculated. Initially, the microscopic scale, which provides the most detailed information seems to be the most appropriate. Indeed micro-emission models such as CMEM (Barth et al., 2001), PHEM (Zallinger, 2009) and CRUISE (AVL, 2018), provide instantaneous consumption and emission data from vehicle trajectories measured or supplied by a microscopic traffic simulator. On a large urban scale, this modeling chain is time and data consuming; moreover, it does not guarantee an experimentally validated evaluation of emissions.

Consequently, aggregate emission models are widely used for the environmental assessment of traffic-related emissions. Macroscopic emission models such as COPERT (Ntziachristos et al., 2009) and HBEFA (Hausberger et al., 2009) require only two traffic variables as inputs: a description of the mean travel speed of the vehicle flow and the corresponding travel distance. Moreover, the COPERT model has shown that it is capable of integrating traffic dynamics and particularly the effects of congestion through average speed or a derived indicator (speed distribution)(Lejri et al., 2018; Samaras et al., 2017). The accuracy of emissions in fact depends on the accuracy of traffic variables estimates.

In this paper, we focus on the COPERT aggregate emission model, which is usually applied at different scales. This macroscopic model is mainly applied at a large urban scale to carry out emission inventories. In this case, highly aggregated traffic variables (i.e. total travel distance and a uniform mean travel speed over the whole city) are used to estimate traffic conditions. In order to estimate emissions more locally, the city can be divided into several sub-areas characterized by different traffic conditions. In this case, the related emissions are then evaluated separately for each sub-area. More recently, given the growing impact of congestion on emissions, COPERT has also been used at the link level (road sections)(Borge et al., 2012; Christos Samaras et al., 2014). In this case, the traffic variables should be specifically estimated for each link in order to derive the corresponding emissions. Finally, with more probe and GPS data available, the question of applying COPERT to a vehicle fleet arises. This last scale is used to estimate the average emissions over a trip, which is the closest to the design of the model. Indeed, the emission laws are established on the basis of measurements made over specific driving cycles, including the ARTEMIS database (André, 2004; Boulter and McCrae, 2007). The set of cycles corresponding to traffic conditions in dense urban areas has the following characteristics: a duration of 5min, a length of 6km, an average speed of 22km/h and a speed standard deviation of around 14km/h.

As noted, to perform emission calculations, spatial decompositions are often used. At all these scales, the results obtained from COPERT are usually considered valid as soon as mean speed and travel distance are deemed accurate. In terms of emissions, the relation between the scales is obvious: emissions are additive. Then, to move from a smaller to a larger scale, sub-area emissions simply need to be added together to obtain the overall emission.

However, it is well known in traffic theory that mean travel speed, the variable at the center of the emission calculations, is not easily transferable from one spatial partitioning to larger one. Mean travel speed is the ratio of travel distance over travel time, which are also both additive variables. But, the mean travel speed of an area is neither the sum, nor the average of the sub-areas mean travel speeds. Therefore, the following questions arise: Could emission laws based on a non-scalable variable, provide scale-consistent results? Are COPERT emission calculations consistent from one spatial partitioning to another?

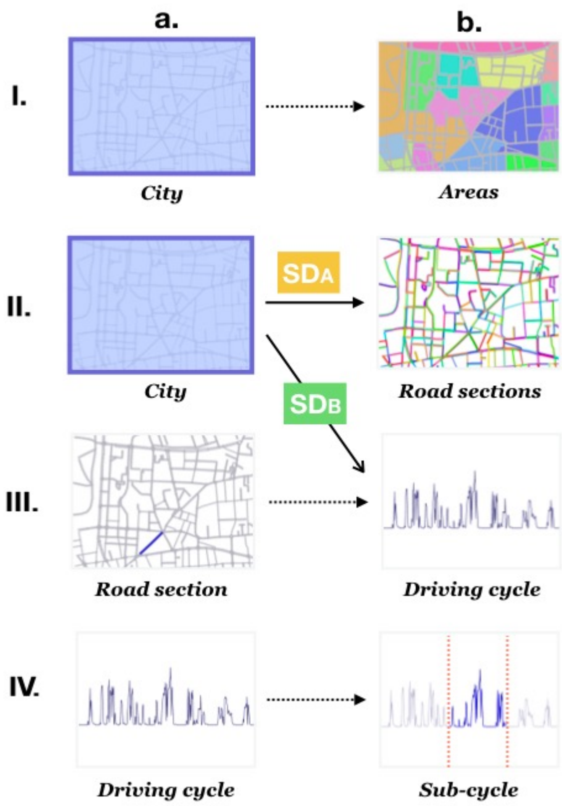


Figure 1 Various spatial decompositions for emission calculations

This work seeks to highlight the discrepancies observed in terms of emissions for different spatial decompositions. Four examples of frequent spatial decompositions in emission calculations are shown in Figure 1. What are the differences on overall emissions between a calculation at a city scale (IIa.) and at link level (IIb.)? This paper points out biases induced by mean speed emission functions when emission calculation scales are different. It focuses on COPERT emission laws, but the issue of scale-inconsistency occurs more generally for any model that uses either non scalable variables, e.g. mean speed, or non-linear emission functions.

The article is organized as follows. The issue is first stated for theoretical and measured driving cycles (section 3). Then, fuel consumptions (FC) and nitrogen oxide (NOx) emission scaling biases are evaluated for the 6th district of Paris (see section 4). This case study focuses on a dynamic traffic microsimulation, which is used to calculate emissions according to different spatial decompositions (individual road sections and individual vehicles). Traffic microsimulation provides all vehicle trajectories. This detailed information is convenient for performing all possible aggregations and then comparative analyses. After highlighting the scaling bias associated with the emission calculations and proposing a method for reducing it, we focus on a practical case for real application (see section 5). The issue addressed here is to evaluate network emissions with only partial local traffic data. We show how it is possible to achieve network emissions consistent with local scale from a sample of probe vehicles (e.g. GPS data). The paper ends with a conclusion (section 6) and a discussion (section 7).

2. Material

This section is devoted to analyzing the way emissions are calculated using COPERT emission functions, depending on the spatial partitioning chosen. We first propose an overview of mean speed definitions in order to facilitate understanding of the following paragraphs and then recall how average speed is involved in the emission calculations.

2.1. Mean speed flow

In traffic theory, it is known that the mean speed of the vehicle flow is not transferable from one spatial decomposition to another. Basically, this means that the mean speed for a set of vehicles is not the average of the mean speed per vehicle, similarly the mean speed for an aggregate of sub-regions is not the average of the mean speed per region. A proper calculation of the mean speed requires the estimation of related travel distance and travel time. These variables are both additive and can be easily transferred from one scale to another.

Let us consider a region [r, $r+\Delta r$] with n vehicles. Each vehicle j (j=1...n) is travelling a distance d_j and stays τ_j in this region during a given interval [t; $t+\Delta t$]. An empirical definition of the spatial mean speed in the region of the space-time diagram of size $\Delta t\ \Delta r$ is given by (Edie, 1965). It is relevant when Δt and Δr are large.

$$V = \frac{\sum_{j=1}^{n} d_j}{\sum_{j=1}^{n} \tau_j} \qquad (1)$$

In the next sections, the space-time regions explored are, for example, the network road sections and 6min time periods. By introducing the vehicular mean speed v_j, formula (1) becomes $V = \sum(\tau_j v_j)/\sum \tau_j$, that is why the spatial mean speed can be considered as the time-weighted average of vehicle mean speeds, and will therefore be noted V_t. This spatial mean speed definition (Lagrangian approach) includes all vehicle entries and exits in the study region, and captures all the dynamics of the vehicles (Lejri et al., 2018). This is the speed relevant for estimating emissions. However, other definitions exist and will be explored later (section 3.2). The most common is the distance-weighted average of vehicle mean speeds (noted V_d), also named punctual mean speed. It corresponds to observations made at a point in the road section (Eulerian approach), that is why it cannot capture all the dynamics of the vehicles. Therefore, it is not a suitable choice for calculating emissions.
Similarly, when considering a region decomposed in m sub-areas, the mean speed V of the whole region is related to the total travel distance d_i and the total travel time τ_i of the sub-areas (i=1...m). Spatial and punctual global mean speed are defined as the time- and distance-weighted average of sub-area mean speeds v_i.
Both these definitions are linked together by the Wardrop formula (Wardrop, 1952):

$$V_d = V_t + \frac{\sigma_t^2}{V_t}, \text{with } \sigma_t^2 = \frac{1}{\sum \tau_i} \sum \tau_i \,(v_i - V_t)^2 \qquad (2)$$

Whatever the spatial decomposition considered, when it comes to characterizing a region mean speed, the right definition is the time-weighted average of the sub-regions mean speeds V_t. In this case, the vehicles' total travel distances and total travel times are properly aggregated at a higher scale without any loss of information. On the other hand, the distance-weighted mean speed V_d, depends on the decomposition considered, as suggested in formula (2), since it depends on σ_t , the time-weighted standard deviation of local speeds. This relationship has been verified using experimental data (Knoop et al., 2009).The way these mean speed definitions interact with emission calculations is highlighted in section 3.

2.2. COPERT construction

COPERT IV has been widely used in most European Countries for compiling national emission inventories (EMEP/EEA, 2016), but it is also increasingly used for emission modeling at the street level (Borge et al., 2012).

This method relies on the fact that average emissions over a trip vary according to the average travel speed. Hot exhaust emissions have been examined on the basis of measurements in several research programs (COST319, FP4 MEET, FP6 ARTEMIS). These measurements were mainly conducted on a chassis dynamometer on which the test vehicle is run over a specific driving cycle while its emissions were collected and analyzed. The emission level was then associated with the mean travel speed over the cycle.
The driving cycle should represent real driving conditions and must therefore be carefully chosen. The New European Driving Cycle (NEDC), a synthetic type-approval driving cycle, has been replaced since 2017 by the World Harmonized Light Vehicles Test Procedures (WLTC), to overcome the shortcomings of the previous test procedure. The Common Artemis Driving Cycle (CAdC) (André, 2004) has also been proposed as being more representative of the behavior of vehicles in real conditions (André and Rapone, 2009). All of these cycles are used to feed the European experimental database that has been developed and examined within the ERMES group for emission modeling.

The emission-average speed relationship is established by combining the results of tests using cycles with different average speeds. Unitary emission factors (EF) consist of continuous speed functions designed using regression analysis to associate the emission level per km with travel speed. These speed curves are drawn for each pollutant and each vehicle class (*e.g.* passenger cars, light duty vehicles, buses and heavy-duty vehicles) and technology (diesel or gasoline, Euro 1 to Euro 6).

To our knowledge, the emission factor values are not established for a unique length but on driving cycles with various characteristics (especially various lengths). This means that (i) mean emission laws integrate a potential internal bias related to multiple (and inconsistent) mean speed values being used, and that (ii) we are actually missing a clear reference scale (resolution at which the relationship between average speed and emission rates are established).
In (Papadopoulos et al., 2018), the authors describe how the resolution affects EF derived from PEMS data and finally propose to establish EF on the basis of a 500m resolution. It also highlights that the extensive use of PEMS data may lead to heterogeneous methodologies for developing EF.

2.3. Using COPERT in the framework

2.4. of an evaluation

Thus, the COPERT model is based on unit emission factors per vehicle and per km travelled. It is therefore possible to estimate the emissions of a vehicle trip knowing its mean travel speed and its travel distance. However, the methodology was designed to produce emission inventories, i.e. to assess emissions from a set of vehicles or trips. It therefore assumes that the relationship remains valid at the scale of a vehicle flow and that the determination of the average speed and the total distance travelled by these vehicles makes it possible to assess the associated emissions.

Defining the most appropriate scale for conducting an environmental assessment with COPERT is a challenging issue. (C. Samaras et al., 2014) considers that segments in the order of 400 m provide good spatial resolution to model emissions in a street network, in relation to the scale for establishing EFs.

In practice, COPERT methodology is applied to various scales and can even be extended to evaluating very large scales such as national inventories over a year. In this case, traffic conditions (average speed) are characterized on a much larger scale than the driving cycle. However, behind this average traffic situation lie very varied traffic conditions, characterized by different average speeds. This is the case in dense urban conditions, where localized congestion phenomena occur. Therefore, it seems appropriate to propose a spatial disaggregation, allowing a more detailed description of traffic conditions (and associated emissions), even in case of monitoring network emissions. Traffic simulations and measurements generally explore two different scales: the road section level and the vehicle level (trajectories). Unlike the global scale, these local scales make it possible to differentiate between streets or routes in terms of traffic and emissions.
However, if we do so, what will be the impact of spatial partitioning on the emissions? Are the total emissions resulting from various spatial decompositions still consistent?

3. Problem statement

3.1. Simple example

Although it is unusual to work at the vehicle scale with COPERT, it seems necessary to start from the operating conditions of the bench measurements used to feed the model. This will help to better highlight the key roleplayed by the speed definition.
For instance, if we consider a vehicle trip of distance D and divide it into two sub-trips of distances d_1 and d_2, we can specify the total emission E_{tot} as the sum of sub-trip emissions e_1 and e_2, because the emissions are cumulative quantities. Knowing the mean speeds of (i) the total trip (V) and (ii) the two sub-trips (v_1 and v_2), these emissions can be assessed using the COPERT emission function f.

$$E_{tot} = e_1 + e_2$$
$$D\, f(V) = d_1\, f(v_1) + d_2\, f(v_2) \qquad (3)$$

Assuming that the emission function f can be approximated with a third order polynomial, relation (3) becomes:

$$a_1 DV + a_2 DV^2 + a_3 DV^3 = a_1(d_1 v_1 + d_2 v_2) + a_2(d_1 v_1^2 + d_2 v_2^2) + a_3(d_1 v_1^3 + d_2 v_2^3)$$
with $f(v) \approx a_0 + a_1 v + a_2 v^2 + a_3 v^3$

Equality is verified if these three conditions are verified:

$$\begin{cases} V = (d_1 v_1 + d_2 v_2)/D \\ V^2 = (d_1 v_1^2 + d_2 v_2^2)/D \\ V^3 = (d_1 v_1^3 + d_2 v_2^3)/D \end{cases}$$

In fact, these conditions cannot be verified simultaneously except if $v_1 = v_2$. This underlines the fact that emissions are dependent on the spatial decomposition considered when calculating them. It is directly related to the definition of emission functions. Indeed, COPERT emission factors have been designed according to a traffic variable that is not transferable from one scale to another: the average travel speed. This effect is enhanced by the convexity of emission function f (Fig. 2). Indeed, if f is convex, then $\boxed{f(\bar{X}) \leq \overline{f(X)}}$.

Also, the second conclusion that can be drawn is that defining the global mean speed as a distance-weighted average (first condition) reduces the gap between the total trip emission and the sum of sub-trip emissions, by cancelling one of the three terms. This result is interesting because it is not the correct definition of the average speed of the trip, which is distance over time. But it is a first step towards achieving consistency between the emission calculation scales.

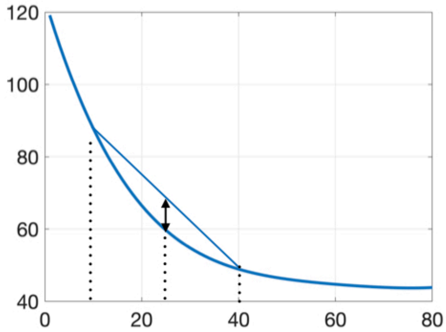


Figure 2 Convexity property of fuel consumption function for Passenger Cars

Measured driving cycle

We now illustrate these effects based on real data. The equipped vehicle was driven in an urban area in the eastern part of Lyon (Fig. 3 - left). The speed profile was recorded using GPS for over an hour (Fig. 3 - right).

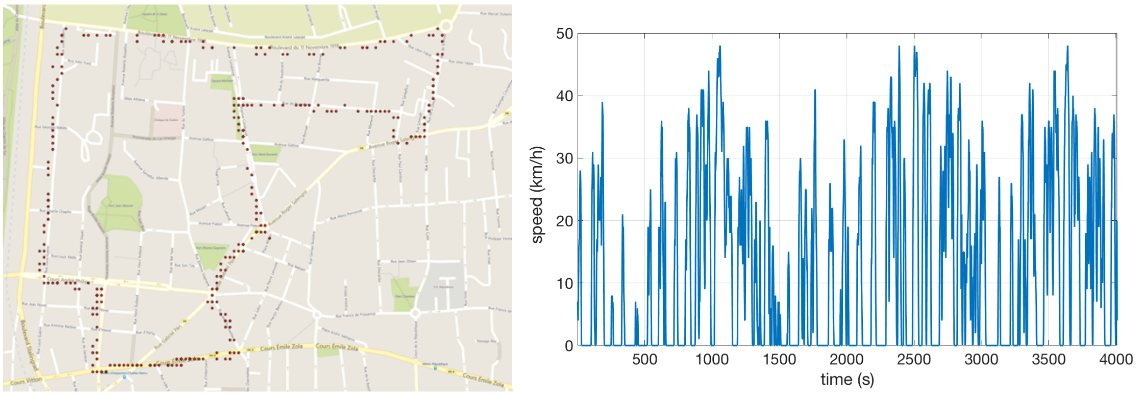
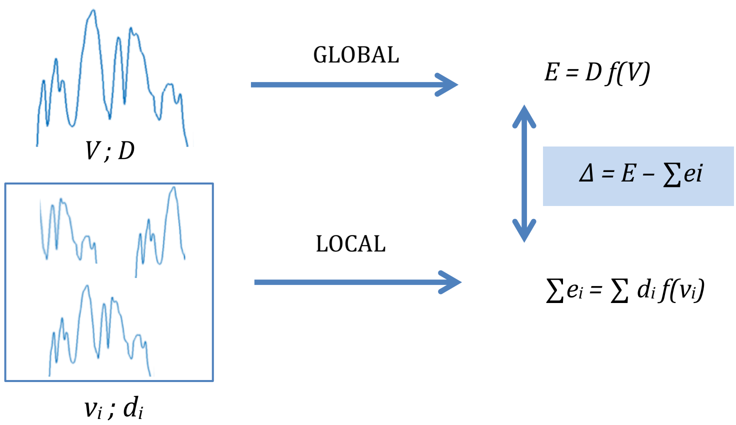


Figure 3: Left: route of the equipped vehicle in the Tonkin district of Lyon.
Right: Speed profile measured with GPS for 4000s.

Fuel consumption and NOx emissions associated with the whole trip are evaluated using COPERT emission functions. This assessment relies on ***global*** traffic variables (V; D). On the other hand, the driving cycle was split into sub-trips. The proposed decomposition leads to the definition of sub-cycles lasting several minutes. For each sub-cycle, the emission assessment relies on ***local*** traffic variables (v_i; d_i). The sum of these local emissions is compared to the global emission. As discussed previously, in order to assess the global emission, we can use the proper mean spatial speed, i.e. the time-weighted average of sub-cycle speeds (V_t) or the distance-weighted average (V_d), which is meant to limit the interscale gap. The global distance D is simply the sum of the distances of the sub-cycles (d_i).

Four decompositions were considered: 15min, 6min, 3min and 1min sub-cycles. Table 1 shows for each sub-cycle decomposition, (i) the global mean speeds V_t and V_d and (ii) the associated gaps Δ between the global emission and the sum of the local emissions. The discrepancies are expressed as a relative deviation from the sum of local emissions.



With the distance-weighted mean speed V_d, the discrepancies between both scales are lower and of the opposite sign. In that case, local emissions are higher than the global emission (Fig. 4). This plot also exhibits the fact that the time-weighted mean speed V_t and the associated emission are insensitive to temporal partitioning.
It finally appears that the shorter the sub-cycle, the larger the gap, which is explained by the greater heterogeneity of local speeds. Thus, for FC assessments, the global/local gaps vary between -1.1% to -3.3%, while time periods are becoming smaller. For NOx assessments, the discrepancies are a little smaller, varying between -0.8% and -1.8%.

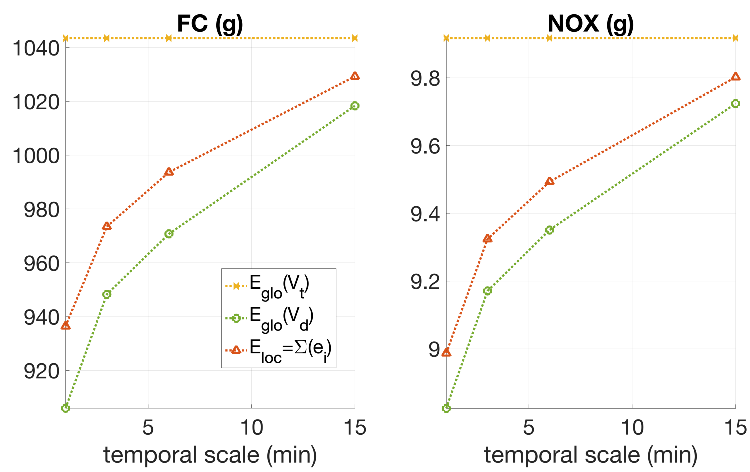


Figure 4 : Fuel consumption and NOx emissions for various temporal decompositions (from 1 to 15min): sum of the local estimations and global estimations with V_t and V_d.

Driving cycle		**V_t (km/h)**	**V_d (km/h)**	**$\Delta(V_t)$ (g)**		**$\Delta(V_d)$ (g)**	
15 min	FC	12.51	13.04	14.22	1.4%	-10.94	-1.1%
	NOX			0.12	1.2%	-0.08	-0.8%
6min	FC		15.21	49.8	5.0%	-22.91	-2.3%
	NOX			0.42	4.5%	-0.14	-1.5%
	FC		16.05	70.00	7.2%	-25.19	-2.6%

3min	NOX			0.59	6.4%	-0.15	-1.6%
1min	FC		18.52	107.02	11.4%	-30.50	-3.3%
	NOX			0.93	10.3%	-0.16	-1.8%

Table 1: Fuel consumption and emission gaps Δ for various temporal partitions (from 1 to 15min) and two different global mean speed definitions (distance- or time-weighted).

Here, the differences of emissions were highlighted for a driving cycle. By adopting the same method in the next paragraph, these gaps are evaluated at the level of a vehicle flow passing through a network.

3.2. From cycles to traffic flow

The construction of the COPERT calculation scale comprises a vehicle and driving cycle lasting several minutes. In practice, the model is applied more extensively to traffic flow (i.e. various vehicle technologies and driving cycles), especially for emission inventories. In terms of kinematics, the average flow speed is then used as an indicator of the amount of emission emitted per km. The total emissions are calculated as the product of the total travel distance and the unitary emission factors.
In terms of fleet composition, unitary emission factors for each vehicle class are defined as a weighted average of vehicle technology unitary emission functions. Here, we will focus on passenger cars. The fleet composition chosen is the French urban fleet for the year 2015 obtained from the IFSTTAR fleet updated in 2013. This passenger car fleet is composed of 30% EURO 5 diesel vehicles and 24% EURO 4 diesel vehicles.
Knowing that the emission curves associated with each vehicle technology hide a wide range of measured emissions, this large scale is often considered more valid because it is meant to reduce the uncertainty on emissions. In this article, whatever the scale, an average vehicle is considered in the sense that the fleet composition is assumed to be homogeneous. On the other hand, dynamic traffic simulation is used to estimate the traffic variables needed to calculate emissions at all scales in an accurate and consistent way.

Considering an urban network, the total emission $\mathrm{E_{global}}$ for pollutant k related to the traffic flow, can be assessed as follows:

$$E_{global}^{k} = D\, \boldsymbol{f}^{k}(V_t)$$

where
$\boldsymbol{f}^{k}$ is the COPERT unitary emission factor (g/km) of pollutant k, D the total travel distance (km) and $\mathrm{V_t}$ the mean travel speed (spatial mean speed, see section 2.1).

From more detailed traffic data it is possible to determine local emissions. The simplest and most natural way to partition a network is by road sections. Emissions are then determined for each link from the local traffic variables: d_i and v_i. The total emissions are then evaluated by summing the estimated emissions on each link $E_{local}^{k} = \sum_i d_i\, \boldsymbol{f}^{k}(v_i)$.

Thus, the gap in emissions between a calculation at the network scale (global) and a calculation with spatial decompositions (local) can be formulated as follows, by including the mean speed V_d:

$$\begin{aligned}\Delta = E_{global} - E_{local} &= D \cdot \Big(f(V_t) - \frac{\sum d_i f(v_i)}{D}\Big) \\ &= D \cdot (f(V_t) - f(V_d)) + D \cdot \Big(f(V_d) - \frac{\sum d_i f(v_i)}{D}\Big)\end{aligned} \qquad (4)$$

The bias Δ is proportional to the total travel distance D and can be seen as a combination of two terms:

i. The first term quantifying the impact of the mean speed definition. This term is positive, because V_d is greater than V_t and f is decreasing at low speeds.
ii. The second term quantifying the convexity of the emission functions is negative.

Using a distance-weighted average speed V_d as an indicator of the mean flow speed, the first term is null. This speed definition is not the right speed definition, but it cancels the first term, which certainly has a positive impact on the result.

Moreover, if we assume that function f can be approximated by a polynomial of order three, the emission gap can then be approached as follows:

$$\begin{aligned}\Delta\,(V_d) &\approx \Delta^* \\ &= a_2\, D\, \left(V_d^2 - \sum_i \frac{d_i v_i^2}{D}\right) + a_3\, D\, \left(V_d^3 - \sum_i \frac{d_i v_i^3}{D}\right) \\ &= D\,[(-a_2 - 3\mu a_3)\mu_2 - a_3\mu_3] \qquad (5)\end{aligned}$$

With the V_d centered moments:

$$\mu = V_d$$

$$\mu_2 = \sigma_d^2 = \frac{1}{\sum d_i}\sum d_i (v_i - V_d)^2$$

$$\mu_3 = \frac{1}{\sum d_i}\sum d_i (v_i - V_d)^3$$

This scaling bias therefore characterizes the heterogeneity of local variables with respect to the global scale. In this paper, we discuss two implementations of these scale transformations: (i) from local to global and (ii) from global to local. In each case, the same theoretical background as described above is involved.
Case (i) is discussed in section 4. We assume that we have access to all local traffic data thanks to microsimulation. When an emission calculation is needed at larger scale (e.g. area, city), there might be a temptation to aggregate traffic data to calculate global emissions (e.g. inventory compilation). The scaling bias introduced when performing a single emission calculation at higher scale is shown. Then, a methodology for consistent global emissions assessment is proposed.
Case (ii) is addressed in section 5. This direction is more challenging. We assume that we have a correct information on traffic variables at large scale, on which we intend to conduct an emission calculation. This scale is not consistent with the reference scale. Indeed, the reference scale is unknown but we believe it is rather local. Thus, the results at large scale will be affected by a scaling bias. The objective is to estimate the total emission that correspond to the integration of local (close to the reference) emissions. But we do not have access to all local data. This is especially the case when using innovative data as floating car data. These partial traffic data are quite efficient for deriving mean speed accurately, but they make the estimation of travel distance challenging. We are therefore faced with two issues: non scalability and total distance estimation.

4. Results

In the context of urban scale inventories and monitoring, it is relevant to perform a single emission calculation for a whole network. This global scale is sometimes also chosen by default, i.e. according to the traffic data available. However, if traffic information is available locally, it may be interesting to make several emission calculations locally, to obtain the emission distribution over the network.

In the following sections, the traffic simulation under study is described, as are the space-time decompositions used to calculate emissions. Finally, the biases between scales are assessed and analyzed.

4.1. Traffic simulation

The network presented in Figure 4 is in the 6th district of Paris. It is composed of 234 links, 93 crossroads, 19 entries, 21 exits, 4 parking areas and 27 traffic lights. The traffic microsimulation was implemented on the Symuvia platform[1], which gives access to the position, speed and acceleration of each vehicle on the network with a 1s-resolution. Vehicle routing choices were governed by a dynamic traffic assignment model, which guided each vehicle in the network on the route that minimized its travel time to its initially assigned destination. Vehicle movements at the microscopic scale were governed by a set of rules, including car-following modelling (Leclercq, 2007a, 2007b), lane-changes (Laval and Leclercq, 2008) and specific movements at intersections (Chevallier and Leclercq, 2007). The question of using the platform outputs for pollutant emission estimations was addressed in (Vieira da Rocha et al., 2013).

The simulation consists of 3 hours representing the morning rush hour. The Origin-Destination matrix was calibrated with hourly traffic flow rates measured on typical weekdays. The total demand evolved by 15-minute steps (Fig.5).
The traffic outputs are the vehicle trajectories, which were aggregated into traffic variables (mean speeds and travel distances) to correspond to the required COPERT inputs, according to the observation scale considered.

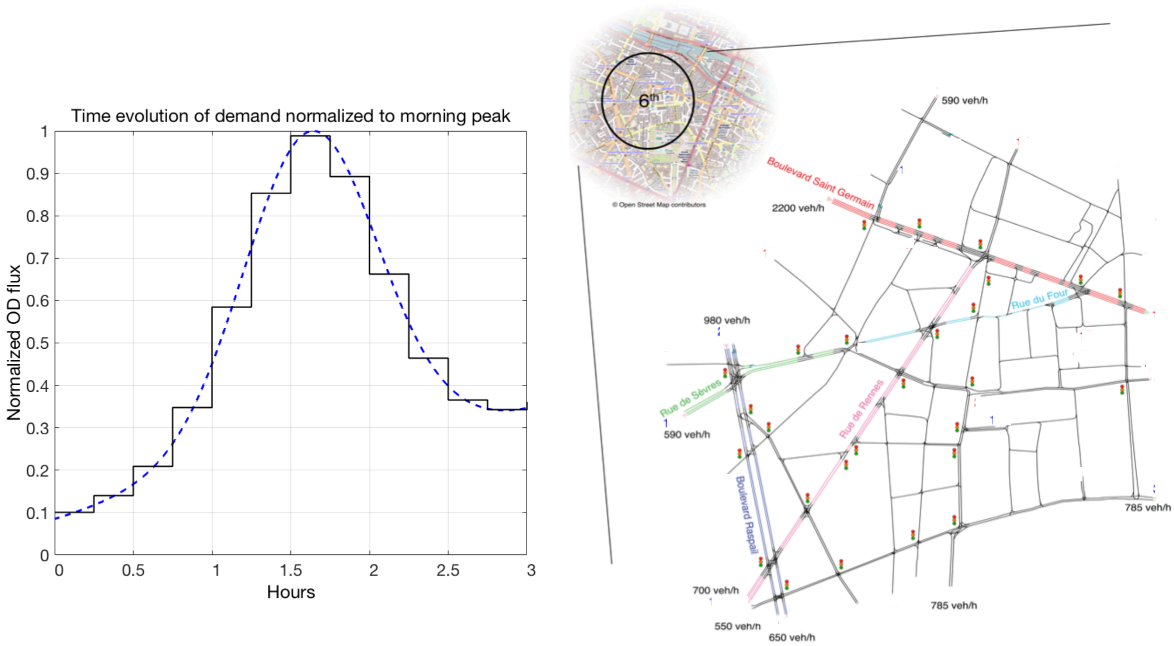


Figure 5: Traffic microsimulation of the 6th district of Paris: evolution over time of normalized input flow (left) and the main peak input flows (right)

4.2. Defining the observation scale

[1] http://www.licit-lyon.eu/themes/realisations/plateformes/symuvia/

The purpose of this study is to evaluate emissions obtained from a dynamic traffic simulation by performing COPERT calculations for different spatial decompositions. Detailed traffic data are available (i.e. 1Hz vehicle trajectories) and can be aggregated spatially and temporally. This section highlights how vehicle trajectories are split and how traffic data are then combined before computing the emissions.

Regarding the traffic microsimulation, the decision was made to set 6-minute time periods throughout the study. This temporal dynamic allows observing the occurrence of congestion and its evolution. A description of this phenomenon is required to accurately assess traffic-related emissions. It is also typical of traffic measurements.
On the one hand, the emissions were determined at the global scale (i.e. one calculation for the whole network). On the other hand, two local spatial decompositions were defined: (i) individual road sections SD_A, (ii) individual vehicles SD_B. These are related to the two types of traffic measurements: stationary measurements (electromagnetic loops) and mobile ones (probe vehicles). In each case, the sum of local emissions is compared with global emissions (all links or vehicles combined) in a more or less congested situation, without favoring one scale over the other.

The *vehicle decomposition* SD_B is close to the scale at which the chassis dynamometer measurements were taken. In this case, the driving cycles are 6 min long at most but can also be shorter because they depend on the time the vehicle entered the network and the time period considered. This coupling does not aim to provide an estimate of the emission associated with a specific vehicle but to describe the emission of an average vehicle (respecting the average specifications associated with the fleet under consideration) presenting such a speed profile.

The *road section decomposition* SD_A is based on a driving cycle per link, combining the trajectories of the vehicles located on this link for a given 6min time period. These speed profile features (mean travel speed and travel distance) are used to determine the associated emissions.

Similarly, the overall calculation is equivalent to establishing a driving cycle based on the speed profiles of all the vehicles on the network for a given period, which can be used to evaluate emissions. Thus, for each emission calculation resolution investigated, the cycle characterizing the traffic conditions must be constructed by splitting and/or combining the individual trajectories.

4.3. Interscale bias for both spatial decompositions

This section presents the results in terms of traffic and emissions for the different scales.

4.3.1. Traffic variables

For each spatial decomposition, the global network traffic variables required to calculate global emissions (mean travel speeds and total travel distance) were determined over the thirty 6-min time periods. As discussed in section 2, the mean travel speed is not transferable from one spatial partitioning to another. In order to observe scale consistency, the right definition of global mean travel speed appears to be the time-weighted average of local mean speeds. $V_t = \sum d_i / \sum \tau_i = \sum(\tau_i v_i) / \sum \tau_i$, where d_i and τ_i are the cumulative travel distance and travel time variables associated with the i^th^ element (a link or a vehicle) and v_i, the corresponding mean travel speed. The distance-weighted average speed V_d will also be evaluated, because it is assumed to reduce the emission gaps between the global and local calculation scales, see section 3.1.

The temporal evolution of these global traffic variables is shown in Figure 6. We observe that the time-weighted speed is lower than the distance-weighted speed, especially when subject to congestion (around period 19). Indeed, this speed definition captures the traffic dynamics correctly. On the other hand, Figure 5 shows that the distance-weighted speed depends on the local scale: the global speed evaluated from the links (SD_A) is higher. This is explained by the Wardrop relationship (formula (2)) and the fact that local speed variance between individual vehicles is smaller than the speed variance between individual road sections. Thus, during congestion the average network speed varies between 7.5 and 16.6 km/h, depending on the speed definition.

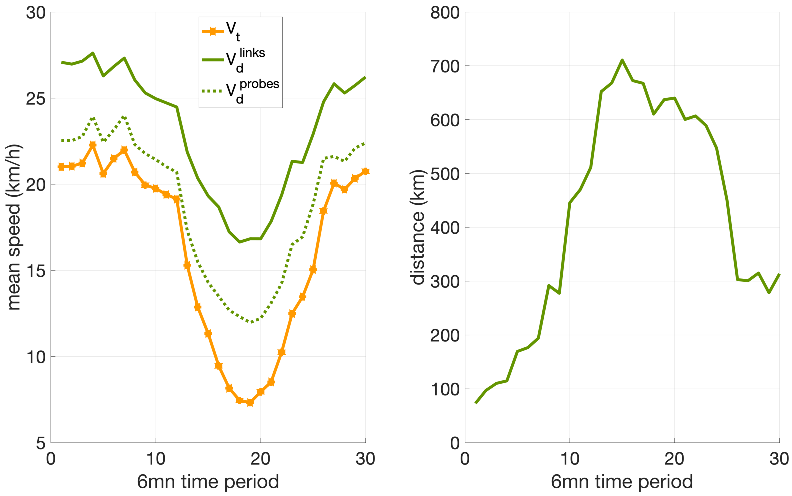


Figure 6: Time evolution of global traffic variables (left: global mean speeds; right: total travel distance)

Figure 7 illustrates the distribution of both traffic variables over both spatial decompositions. The results are presented for a congested time period, for which the discrepancies are obviously more significant. Regarding speeds, the wide dispersion of values on the road section decomposition SD_A is highlighted, which leads to a higher global mean speed V_d (16.8km/h versus 7.9km/h for V_t). For vehicle decomposition SD_B, the speeds are less heterogeneous, which leads to a lower global mean speed V_d (12.2 km/h). As far as the total travel distance is concerned, it is on average 2.7 km for the road sections (SD_A), versus 0.41 km for the vehicles (SD_B).

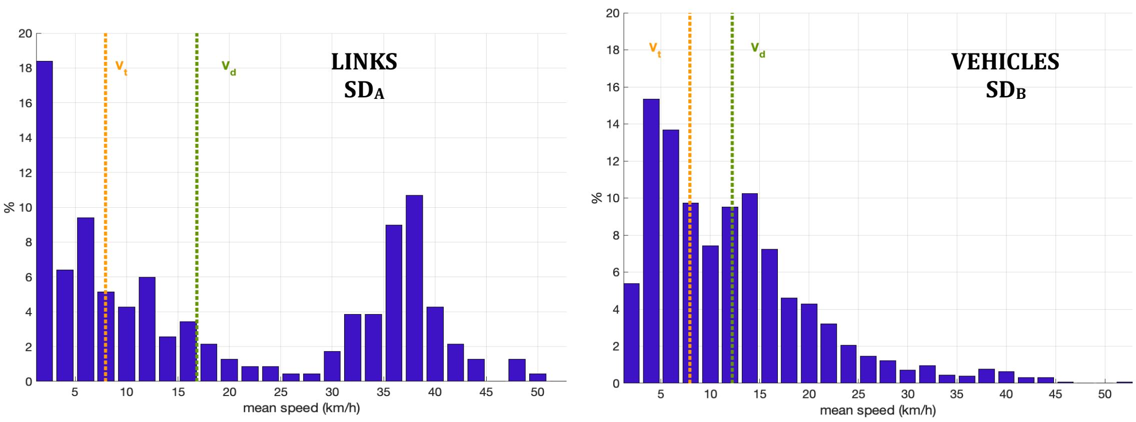


Figure 7: Distributions of local mean speeds subject to congestion for both spatial decompositions (left: SD_A; right: SD_B).

4.3.2. Fuel consumption and NOx emissions

Regarding the environmental assessments, fuel consumption and NOx emissions are evaluated and presented in each case. The local traffic variables described in the previous section were used (i) to assess the associated local emissions, (ii) to evaluate the global traffic variables needed to assess the global emissions, and (iii) to estimate the interscale bias Δ^* using formula (5). Both global mean speed definitions were tested. The corresponding global emissions $E(V_t)$ and $E(V_d)$ were evaluated, such as the gaps $\Delta\ (V_t)$ and $\Delta\ (V_d)$. The discrepancies are expressed as a relative deviation from the sum of local emissions. Table 2 summarizes the results for a congested 6min time period. After removing Δ^*, i.e. the interscale bias estimated from μ, μ_2, μ_3, the relative gaps are lower than 1%.

		V_t (km/h)	V_d (km/h)	$\mu_2\ (V_d)$	$\mu_3\ (V_d)$	$\Delta\ (V_t)$	$\Delta\ (V_d)$	$\Delta\ (V_d) - \Delta^*$
SD_A	FC	7.3	16.8	174.0	1445.9	17.1%	-6.2%	0.9%
	NOX					15.6%	-3.2%	0.7%
SD_B	FC	7.3	11.9	51.2	450.6	9.5%	-1.0%	1.1%
	NOX					8.0%	-0.2%	0.9%

Table 2 Comparison of global mean speeds, aggregated from both spatial decomposition (SD_A and SD_B) for a congested time period. When estimating FC and NOx at both local and global scales, the scaling bias Δ is alleviated by using V_d instead of V_t, and is almost cancelled by using the extensive formulation Δ^*

This means that by integrating the effect of spatial decomposition on emissions in traffic data processing, it is possible to significantly reduce the differences between emission calculation scales. To do this, it is necessary to use the definition of the average speed weighted by distances and to evaluate the interscale bias Δ^*. For spatial decomposition SD_A, the gap is reduced from 17% for FC (16% for NOx) to less than 1% and for SD_B, from 11% for FC (5% for NOx) to less than 0.1%. Figure 8 shows the temporal evolution of these deviations for the two spatial partitions considered (SD_A and SD_B).

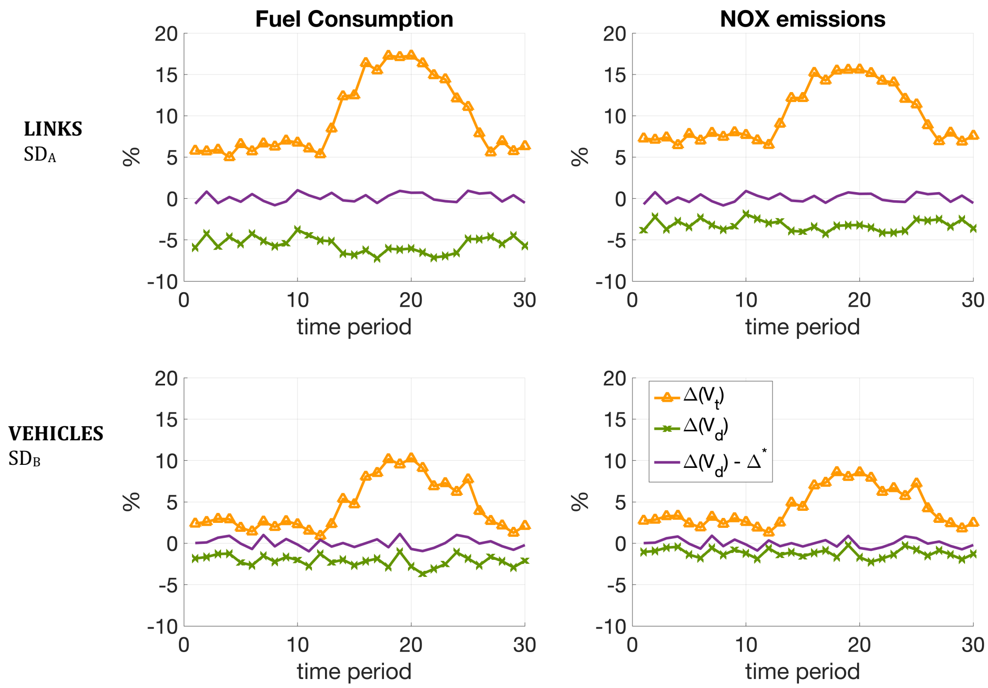


Figure 8 Relative gaps of consumptions and emissions with the links (top) and probes (bottom) approach.

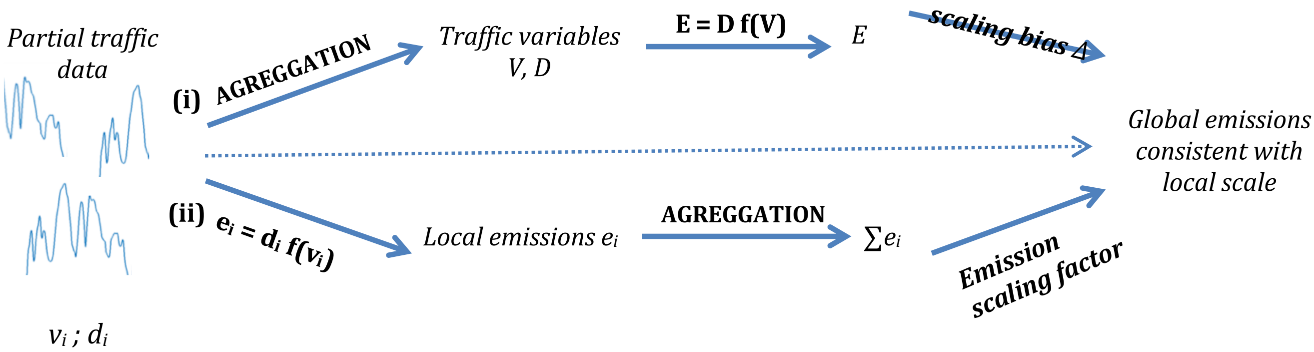
It can be seen that with V_t, the gaps are particularly visible in congestion and can reach 10% and more. On the other hand, with V_d the gaps are reduced and have opposite signs. They are also more or less constant regardless the traffic conditions. Finally, after removing the estimated bias, the gaps between the scales are almost null (under 1%) whatever the traffic conditions.

Thus, based on a global emission calculation and knowledge of the heterogeneity of speeds on the local elements, it is possible to retrieve the emissions evaluated using a local approach and thereby ensure consistent results between scales. To alleviate the scaling bias, we can simply use the distance-weighted average of local speeds. An extensive formulation of the scaling bias is also proposed to restore consistency.

Lastly, final objective is to ensure that emissions are consistent with the COPERT reference scale. As noted in section 2.2, we do not have exact knowledge of the reference scale for the COPERT laws and thus require access to traffic information at that scale. In the following section, we place ourselves in this particular case, knowing that we have partial local traffic data. The reference scale is unknown, but we believe it is rather local. We assume that 6min probe data (corresponding to driving cycles of an average length of 400m) represent our reference scale.

5. Practical application: estimating global emission from a sample of probe vehicles

After having highlighted the scaling bias associated with the calculation of emissions and proposed a method for reducing this bias based on a traffic simulation, we now focus on applying the method to a real situation. In this case, our objective is to characterize the emissions associated with a network (neighborhood, city area, etc.) using a new data source, namely a sample of vehicle trajectories. This type of data is becoming increasingly available thanks to tracking devices in vehicles (in particular GPS).
We then have two options: (i) that of determining the global traffic variables and the associated emissions, or (ii) that of determining the local emissions (i.e. of each vehicle) and add them together.



In case (i), we make an error on network emission due to the introduction of a scaling bias. In case (ii), the scale is in better accordance with the reference scale. However, we do not have access to all vehicle data, so we need to shift from the emissions of partial observations to the full population emissions. Determining this emission scaling factor is very challenging and will certainly introduce large uncertainties. That is why this alternative is not the most reliable and thus not considered here. Finally, option (i) is selected: the emissions are estimated on a global scale, and then corrected using the scaling bias estimates. In this way, the corrected global emissions are rather close to local emissions.
In addition to this scale inconsistency issue, we are faced with the issue of accurate assessment of global traffic variables needed for calculating emissions from probe samples. Here, we draw a

random sample of vehicles from the simulation to represent floating car data. We can therefore test various penetration rates of the probe vehicles (i.e., the ratio between the number of probes and the total number of vehicles on the network) and evaluate the quality of the estimates.

5.1. Mean speed estimation

(Leclercq et al., 2014) compared the methods to estimate the overall mean speed V_t from loops or probe samples. This study showed that an optimal probe sampling rate of 20% allows efficiently capturing the mean spatial speed, with an error of less than 10%. But as mentioned above, it is more appropriate to evaluate emissions from an estimate of the distance-weighted speed V_d in order to reduce the scaling bias. We propose here to evaluate the relevance of new statistical indicators, weighted by distances.

The penetration rate τ (i.e., the ratio between the number of probes and the total number of vehicles on the network) will be considered constant over time. This is a simplification, as in reality the data collected do not represent a constant penetration rate. The effect of variable penetration rate has been discussed in (Lejri et al., 2014). For each period and penetration rate, 100 probe samples are drawn randomly in the traffic microsimulation and the estimators of the variables of interest are assessed for each sample. Their quality is evaluated in comparison to the variable of the total population (all vehicles).

The variability of the results obtained for 100 probe samples is represented in the following figures by the median value (solid line) and the 1st and 9th deciles (dotted lines). Thus, 80% of the data is between the dotted lines. The variables are all expressed as a relative error to the variable of the total population: $(\bar{x} - x)/x \times 100$.

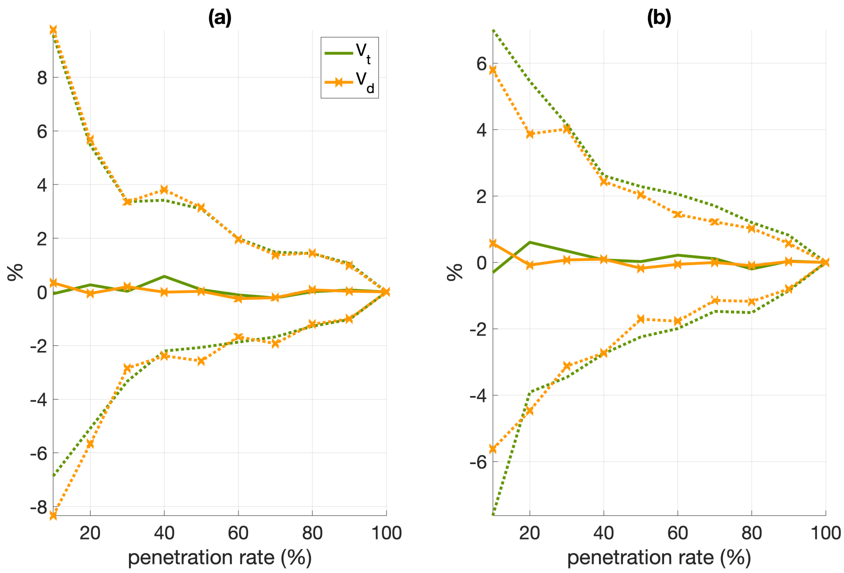


Figure 9 Relative errors on mean speeds V_t and V_d depending on the penetration rate in (a) free flow conditions and (b) congested conditions

Figure 9 confirms previous works: mean speeds may be assessed from probes with good accuracy, whatever the traffic conditions. Thus, with a penetration rate of 20%, we can estimate V_d with an error of less than +/- 5.7% for 80% of the samples in free flow and between -4.5% and +3.8% in congestion.

5.2. Total travel distance estimation

The second variable to be assessed is the total travel distance. The distance travelled by a sample of vehicles is available, but we must determine a scaling factor to obtain the distance travelled by all the vehicles during the time period. In contrast to mean speed estimation, this issue is quite challenging. In the first approximation, this distance scaling factor can be derived from the penetration rate τ, which is reached during the random draw. The total travel distance D is then assessed by d_{probes}/τ , assuming that the number ratio is relevant for estimating the distance ratio.

But in a real case, this rate is variable over time and above all unknown. That is why it will also be estimated by the "probe fishing" method first proposed in (Geroliminis & al., 2008). In addition to the probes, this method requires a minimal number of loop detectors that permit measuring the flows. The penetration rate is then estimated as the ratio of probes crossing the loops over the total observed flow, see eq. (6).

$$\tau^*(T) = \frac{\sum_k N_{probes}^k(T)}{\sum_k N_{vehicles}^k(T)} \qquad (6)$$

where $N_{probes}^k(T)$ is the number of probes seen on loop k, during time period T and $N_{vehicles}^k$ the number of vehicles seen on loop k, during time period T.

Note that the loop requirement is not an issue in practice as loop data are usually available in urban areas, at least in minimal quantity. We identified around twenty detector loops on the real network (Fig. 10), which represents about 10% of the links. For each time period, using microsimulation, we are able to identify the route of the probe vehicles and therefore the loops they cross. We can then estimate the ratio between the number of probe vehicles and the total number of vehicles seen on the loops during a given period. With on-field data, it is also very easy to know which loop is crossed by vehicles based on their GPS coordinates.

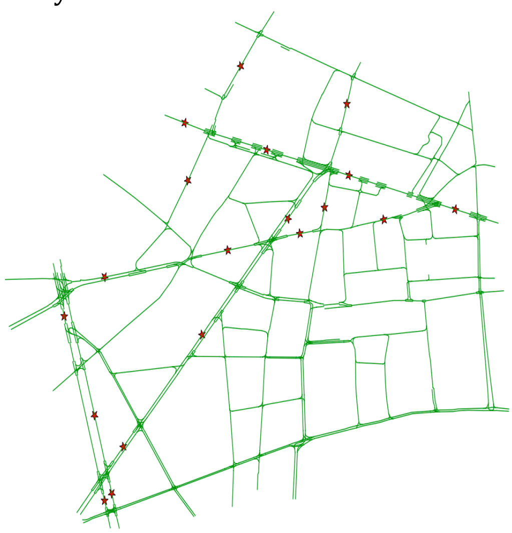


Figure 10 Location of major loops in the sixth district of Paris[2]

Then, the distance scaling factor will be used and its impact on reducing scaling bias will be assessed. Using the fishing method, the penetration rate τ is estimated quite precisely during congestion, whereas in free flow the errors range from 7% to 13% for a 10% sample and from 15% to 24% for a 20% sample (Fig. 11). This is simply because fewer vehicles are traveling in the network in free-flow, rendering the estimate less robust.

[2] https://opendata.paris.fr/explore/?sort=modified&q=trafic (accessed 2019/09/06)

Figure 11 Time evolution of penetration rates: τ and the estimate τ^* (fishing).

The penetration rate is then used to infer the total travel distance, which is a critical parameter for estimating emissions. Figure 12 highlights the relative errors on total travel distance assessed from the sample travel distance and the vehicle number ratio (penetration rates τ and τ^*). Obviously, these estimates are better when the penetration rate increases. We can first observe a break for a penetration rate of 20%, beyond which the relative errors decrease significantly. Using the fishing method and 20% probe samples, it is possible to assess the total travel distance with an error of +/-15% in free flow and +/-6% in congestion.

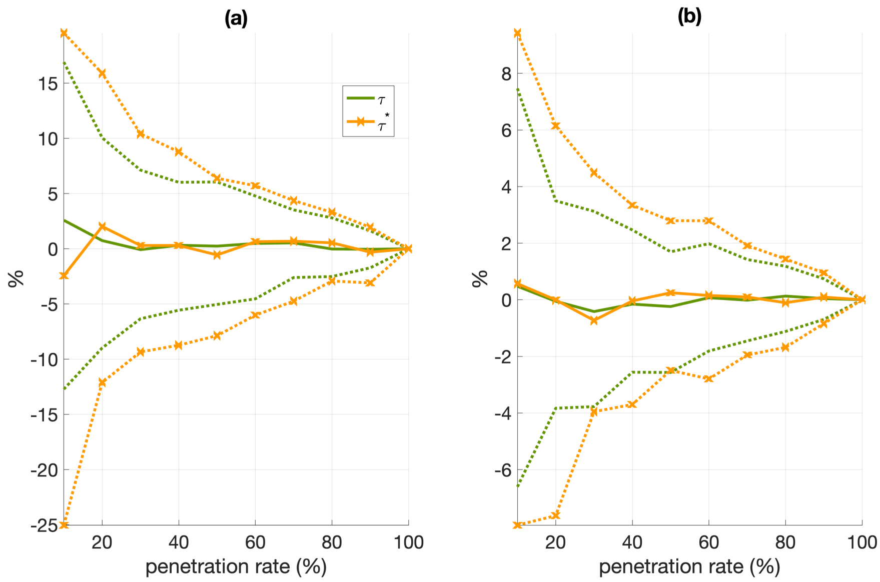


Figure 12 Relative errors on total travel distance with a known penetration rate τ and an estimated penetration rate τ^* in (a) free flow conditions and (b) congested conditions

5.3. Scaling bias estimation

Once the global traffic variables have been assessed, it is possible to evaluate the global emissions. This estimate will be subject to the scaling bias described in section 3.2. The next step is therefore to evaluate the bias to be removed in order to better estimate the results corresponding to the integration of local emissions, which, here, are assumed to be close to the reference scale. The variables V_d, μ_2 and μ_3 and D are first estimated from the probe samples. We then evaluate the scaling bias Δ^* using formula (5). In order to distinguish the influence of sampling on the speed and travel distance assessment, the total travel distance per time period is first assumed known. Figure 13 presents the relative errors on the scaling bias Δ^*. In free flow, with 20% probe samples, the errors are in the range of -29% to 26% and -12% to 11% in congestion. These errors are significant and equivalent for fuel consumption and NOx emissions.

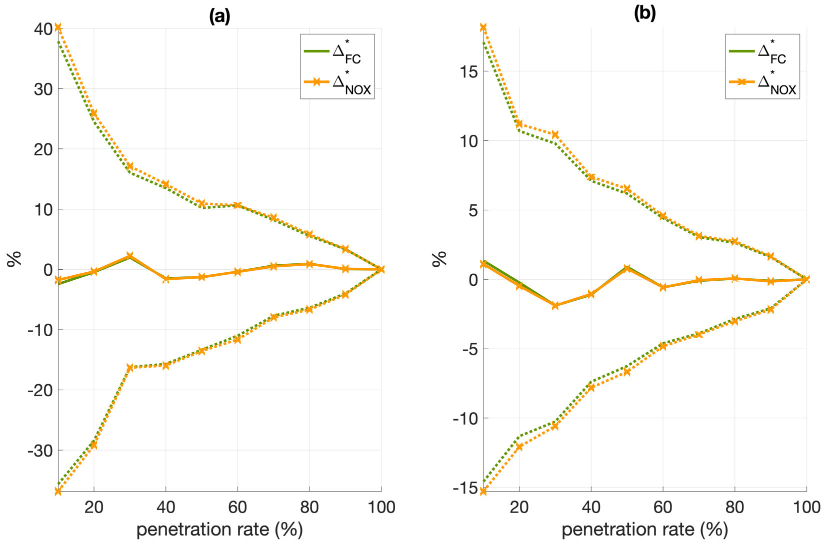


Figure 13 Relative errors on scaling bias Δ* depending on the penetration rate in (a) free flow conditions and (b) congested conditions, assuming the total travel distance is known.

When total travel distance is estimated by the fishing method (Fig. 14), the gaps increase even further, in the range of -37% to 26% and +/-15% in congestion. We note that the outcomes are worse than for speed estimation. A 40% sample is required to estimate the bias with an accuracy of about 10%.

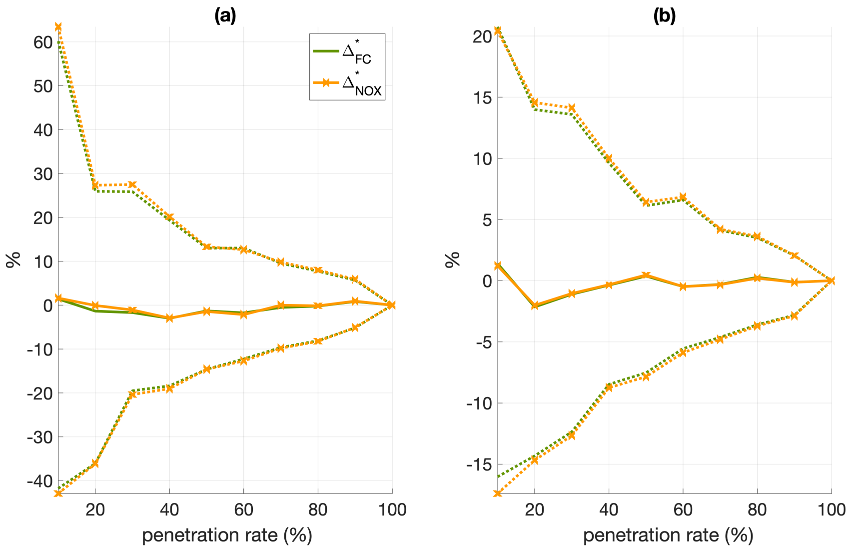


Figure 14 Relative errors on scaling bias Δ* depending on the penetration rate in (a) free flow conditions and (b) congested conditions, assuming the total travel distance is assessed using the fishing method.

5.4. Corrected emission estimation

Finally, the global emissions are corrected by removing the scaling bias $(E(V_d) - \Delta^*)$ and compared to the sum of local emissions. These results are first analyzed as a function of the penetration rate. The estimation of corrected emissions is quite accurate when total travel distance is assumed to be known (Fig. 15). Indeed, the errors here decrease sharply to the range of -3% to 2% in free flow and even less in congestion. This can be explained by the fact that the imprecise estimation of V_d induces errors both on global emissions $E(V_d)$ and on the error on bias Δ^*, that counterbalance each other.

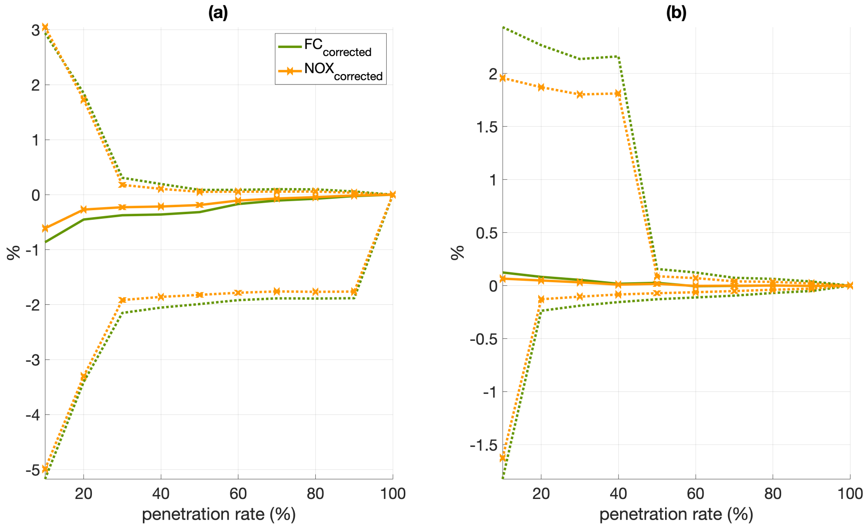


Figure 15 Relative errors on corrected emissions E (V_d)- Δ, depending on the penetration rate in (a) free flow conditions and (b) congested conditions, assuming the total travel distance is known.

Consequently, when total travel distance is assessed by fishing, the relative errors are of the same order as those made on total travel distance (Fig. 16). Again, they are almost similar for both fuel consumption and NOx emissions. These results confirm that the challenging issue is definitively the estimation of total travel distance. The fishing method makes it possible to have a relative error on the residual gap within the range of 10% with 20% probe samples in loaded traffic conditions.

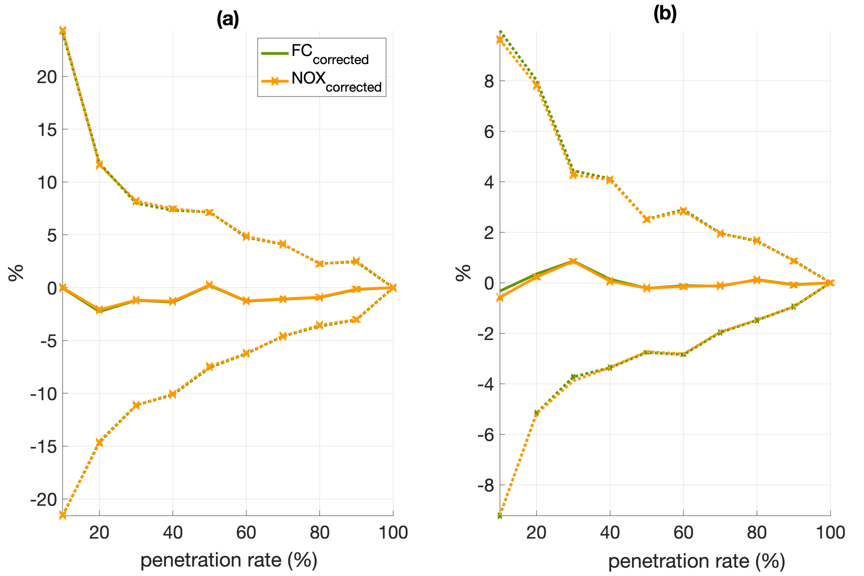


Figure 16 Relative errors on corrected emissions E (V_d)- Δ^*, depending on the penetration rate in (a) free flow conditions and (b) congested conditions, assuming the total travel distance is assessed using the fishing method.

Finally, residual errors are on average very low, even when the distance is approximated: errors are less than 4% on average for 10% probe samples and less than 2% for 20% probe samples. This study shows that in a real case, the ability to reduce bias depends on our ability to accurately estimate total travel distance.

6. Conclusion

To the question "Are average speed emission functions scale-free", the answer is clearly no. Basically, the scaling issues occur (i) because of the convexity of the emission law and (ii) because of the non-scalability of the mean-speed definition. This work pointed out, that the second effect can be minored if distance-weighted speed definition is used. But this is not the correct definition of mean speed, which should be distance over time at all scales.
More generally, the inconsistency issue is not specific to average speed emission models. We focused here on COPERT, an average speed model, because its use is very widespread, particularly at various spatial-temporal scales. However, inconsistency issues occur for any model that either use non scalable variable, e.g. mean speed, or non-linear emission functions.

The purpose of this paper was to make emission modelers aware of the scale-inconsistency in emission calculations and to provide them with a method to restore consistency between the reference scale (resolution at which the relationship between average speed and emission rates are established) and the emission calculation scale (spatial decomposition on which emission factors are implemented). We must specify that the reference scale is not yet properly defined. To our knowledge, emission laws are developed at local scale (driving cycles) but are not established for a unique travel length. The reference scale should be related with the scale at which emission laws are designed, because it is the scale at which mean speed is measured. While we think that new emission laws should be determined based on a clear definition of a reference scale (see the discussion), we currently consider that the local scale is the more reliable because it is closer to the actual driving scale.
In this paper, we discuss two implementations of these scale transformations: (i) from local to global and (ii) from global to local. In each case, the same theoretical background as described above is involved. In case (i), we focused on two spatial decompositions of a network: individual road sections and vehicles (local scales). If traffic data are aggregated to calculate emissions on a larger scale (e. g. district), interscale (local vs global) biases are introduced. This occurs even if traffic data are properly aggregated (using time-weighted mean speed). From the case study, the biases range from 5% to 17%, depending on the pollutant, spatial partitioning and traffic conditions. These discrepancies can be reduced using a distance-weighted mean speed, which is not a scale-consistent definition of mean travel speed. They can almost be cancelled using the extensive formulation proposed in this paper, thus consistency can be guaranteed between emissions assessed at different scales.
In case (ii), we assumed that traffic variables can only be estimated at large scale. Thus, we performed the emission calculations at that global scale. As the emission calculations are not undertaken at a scale consistent with the reference scale, we then introduced a bias. By reversing the method presented in this paper, we significantly reduced this scaling bias and obtained better total emission predictions. This second study is based on probe data. The results are strongly dependent on the probe sample and the penetration rate, which should be high enough in practice to properly estimate all the variables. The most critical step is the accurate estimation of total travel distance. A "fishing" method was applied to this end to improve the estimate of this variable. We finally managed to reduce the gaps to a maximum of 8% in congestion for a penetration rate of about 20%.

7. Discussion

Aggregate emission models are commonly used to calculate total emission at different scales across a country, a region, a city and road sections. The lack of consistency between scales is often attributed to the lack of completeness and/or accuracy of input data. With regard to traffic data, it was shown here that accurate and consistent traffic information between emission calculation scales may lead to different results. This is not satisfactory and we believe that it can be improved.

As working with nuclear information like emission per second is not possible in practice, the only option to alleviate scaling issues, is (i) to properly define the reference scale (where we know that no error occurs because the model has been designed on this particular scale) and then (ii) to find numerical transformations that reduce the scaling bias. This is what we tried to do here with the average speed models despite the absence of a clear reference. This should be the next step and requires reshaping existing emission laws. We would recommend to this end, to set emission laws on driving cycles of same distances. Defining the right distance is out of the scope of this study but the values found in the literature (400 – 500m) seem rather reasonable to us.

A review of macroscopic emission models is currently being undertaken in order to develop emission laws that are more representative of real driving situations (slope, intersections, etc.) and traffic conditions (free, charged, congested, etc.). Previous works showed the need for integrating representative real-world driving cycles in the development of emission models (Fontaras et al., 2017; Franco et al., 2013). Among other issues, the resolution for establishing emission laws is quite challenging. (Papadopoulos et al., 2018) described how the resolution affects emission factors. This study also confirms that the extensive use of PEMS data can enhance the inherent bias of emission functions. Indeed, setting EFs on different lengths means using multiple and inconsistent average speed values. That is we recommend working with cycles of the same distance, in order to average observations that are consistent in terms of mean speed definition. When applying these new emission laws at other scales, we would be able to remove the scale bias by determining the appropriate corrective factors.

Finally, through this study, we mainly focused on emission calculations at large scale. We did not directly address the issue of calculating emissions at the link level. However, calculating emissions at this scale attracts more and more attention as it allows (i) obtaining the distribution of local emissions over the network and (ii) establishing links with traffic model output data and dispersion models. However, links obviously do not have equal lengths over the network. Then, even if a clear reference scale is established, using emission laws directly on links would create a new scale problem. We therefore recommend partitioning the network into virtual links of same length as the reference scale. Then, emission calculations could be done without scaling bias. The emissions related to the real links can finally be evaluated in proportion to the distance travelled in each link. Such a method should be carefully investigated in a future study.

Acknowledgments

This study has received funding from the European Research Council (ERC) in the framework of the European Union's Horizon 2020 research and innovation program (grant agreement No 646592 – MAGnUM project).

8. References

André, M., 2004. The ARTEMIS European driving cycles for measuring car pollutant emissions. Sci. Total Environ. 334–335, 73–84. https://doi.org/10.1016/j.scitotenv.2004.04.070
André, M., Rapone, M., 2009. Analysis and modelling of the pollutant emissions from European cars regarding the driving characteristics and test cycles. Atmos. Environ. 43, 986–995. https://doi.org/10.1016/j.atmosenv.2008.03.013
AVL, 2018. Vehicle Driveline Simulation. https://www.avl.com/cruise.
Barth, M., Barth, M., Malcolm, C., Malcolm, C., Scora, G., Scora, G., 2001. Integrating a Comprehensive Modal Emissions Model into ATMIS Transportation Modeling Frameworks. Transportation (Amst).
Borge, R., de Miguel, I., de la Paz, D., Lumbreras, J., Pérez, J., Rodríguez, E., 2012. Comparison of road traffic emission models in Madrid (Spain). Atmos. Environ. 62, 461–471. https://doi.org/10.1016/j.atmosenv.2012.08.073
Boulter, P.G., McCrae, I.S., 2007. ARTEMIS : Assessment and Reliability of Transport Emission Models and Inventory Systems – final report. 2007 350.
Chevallier, E., Leclercq, L., 2007. A macroscopic theory for unsignalized intersections. Transp. Res. Part B Methodol. 41, 1139–1150. https://doi.org/10.1016/j.trb.2007.05.003
Donateo, T., Giovinazzi, M., 2017. Building a cycle for Real Driving Emissions. Energy Procedia 126, 891–898. https://doi.org/10.1016/j.egypro.2017.08.307
Edie, L.C., 1965. Discussion of traffic stream measurements and definitions., in: 2nd International Symposium on the Theory of Traffic Flow. pp. 8–20.
EEA, 2017. Annual European Union Greenhouse Gas Inventory 1990–2015 and Inventory Report 2017. European Environment Agency Technical Report No 6/2017, Copenhagen, Denmark.
EMEP/EEA, 2016. Air Pollutant Emission Inventory Guidebook- 2016 28. https://doi.org/ISSN 1977-8449
Fallah Shorshani, M., André, M., Bonhomme, C., Seigneur, C., 2015. Modelling chain for the effect of road traffic on air and water quality: Techniques, current status and future prospects. Environ. Model. Softw. 64, 102–123. https://doi.org/10.1016/j.envsoft.2014.11.020
Fontaras, G., Zacharof, N.G., Ciuffo, B., 2017. Fuel consumption and CO2emissions from passenger cars in Europe – Laboratory versus real-world emissions. Prog. Energy Combust. Sci. 60, 97–131. https://doi.org/10.1016/j.pecs.2016.12.004
Fontes, T., Pereira, S.R., Fernandes, P., Bandeira, J.M., Coelho, M.C., 2015. How to combine different microsimulation tools to assess the environmental impacts of road traffic ? Lessons and directions. Transp. Res. Part D 34, 293–306. https://doi.org/10.1016/j.trd.2014.11.012
Franco, V., Kousoulidou, M., Muntean, M., Ntziachristos, L., Hausberger, S., Dilara, P., 2013. Road vehicle emission factors development: A review. Atmos. Environ. 70, 84–97. https://doi.org/10.1016/j.atmosenv.2013.01.006
Hausberger, S., Rexeis, M., Zallinger, M., Luz, R., 2009. Emission Factors from the Model PHEM for the HBEFA Version 3. Univ. Technol. Graz, Rep. Nr. I-20/2009 Haus-Em 33, 679.
Knoop, V.L., Hoogendoorn, S.P., Van Zuylen, H.J., 2009. Empirical Differences between Time Mean Speed and Space Mean Speed., in: Proceedings of Traffic and Granular Flow 07. pp. 351–356.
Laval, J.A., Leclercq, L., 2008. Microscopic modeling of the relaxation phenomenon using a macroscopic lane-changing model. Transp. Res. Part B Methodol. 42, 511–522. https://doi.org/10.1016/j.trb.2007.10.004
Leclercq, L., 2007a. Hybrid approaches to the solutions of the “Lighthill-Whitham-Richards” model. Transp. Res. Part B Methodol. 41, 701–709. https://doi.org/10.1016/j.trb.2006.11.004
Leclercq, L., 2007b. Bounded acceleration close to fixed and moving bottlenecks. Transp. Res. Part B Methodol. 41, 309–319. https://doi.org/10.1016/j.trb.2006.05.001
Leclercq, L., Chiabaut, N., Trinquier, B., 2014. Macroscopic Fundamental Diagrams: A cross-comparison of estimation methods. Transp. Res. Part B Methodol. 62, 1–12. https://doi.org/10.1016/j.trb.2014.01.007
Lejri, D., Can, A., Schiper, N., Leclercq, L., 2018. Accounting for traffic speed dynamics when calculating COPERT and PHEM pollutant emissions at the urban scale. Transp. Res. Part D Transp. Environ. 63, 588–603. https://doi.org/10.1016/j.trd.2018.06.023

Lejri, D., Ibrahim, N.A., Bécarie, C., Leclercq, L., 2014. Estimating pollutant emissions from aggregated traffic variables: the influence of data sources and sampling methods, in: International Symposium of Transport Simulation 2014.
Ntziachristos, L., Gkatzoflias, D., Kouridis, C., 2009. COPERT: A European Road Transport Emission Inventory Model. Inf. Technol. Environ. Eng. https://doi.org/10.1007/978-3-540-88351-7
Papadopoulos, G., Keramydas, C., Ntziachristos, L., Lo, T.-S., Ng, K.-L., Wong, H.-L.A., Wong, C.K.-L., 2018. Emission Factors for a Taxi Fleet Operating on Liquefied Petroleum Gas (LPG) as a Function of Speed and Road Slope. Front. Mech. Eng. 4, 1–13. https://doi.org/10.3389/fmech.2018.00019
Samaras, Christos, Ntziachristos, L., Samaras, Z., 2014. COPERT Micro : a tool to calculate the vehicle emissions in urban areas. Transp. Res. Arena 2014 10.
Samaras, C., Tsokolis, D., Toffolo, S., Garcia-Castro, A., Vock, C., Ntziachristos, L., Samaras, Z., 2014. Limits of applicability of COPERT model to short links and congested conditions., in: 20th International Transport and Air Pollution Conference 2014. 18-19 September 2014. Graz. Austria.
Samaras, C., Tsokolis, D., Toffolo, S., Magra, G., Ntziachristos, L., Samaras, Z., 2017. Improving fuel consumption and CO2emissions calculations in urban areas by coupling a dynamic micro traffic model with an instantaneous emissions model. Transp. Res. Part D Transp. Environ. https://doi.org/10.1016/j.trd.2017.10.016
Vieira da Rocha, T., Can, A., Parzani, C., Jeanneret, B., Trigui, R., Leclercq, L., 2013. Are vehicle trajectories simulated by dynamic traffic models relevant for estimating fuel consumption? Transp. Res. Part D Transp. Environ. 24, 17–26. https://doi.org/10.1016/j.trd.2013.03.012
Wardrop, J.G., 1952. Some Theoretical Aspects of Road Traffic Research, in: Proceedings of the Institute of Civil Engineers, Vol. 1-2. pp. 325–378.
WHO, 2013. Review of evidence on health aspects of air pollution – REVIHAAP Project.
York Bigazzi, A., Rouleau, M., 2017. Can traffic management strategies improve urban air quality? A review of the evidence. J. Transp. Heal. 7, 111–124. https://doi.org/10.1016/j.jth.2017.08.001
Zallinger, 2009. Evaluation of a coupled microscopic traffic simulator and instantaneous emission model. J. Chem. Inf. Model. 53, 1689–1699. https://doi.org/10.1017/CBO9781107415324.004