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# **DYNAMIC ESTIMATION OF URBAN TRAFFIC NOISE: INFLUENCE OF TRAFFIC AND NOISE SOURCE REPRESENTATIONS**

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## **ABSTRACT**

The need for traffic noise prediction models that take traffic dynamics into account has been recently shown for urban areas. Such models couple a dynamic representation of traffic with noise emission laws. The contribution of the paper is to test different traffic and noise source representations for  $L_{Aeq}$  and statistical levels estimation. Tests on four scenarios that reflect urban traffic conditions are carried on. They show that an individualized representation of vehicles with a macroscopic behavior rule is sufficient for noise descriptors estimation. Noise sources have to be aggregated on cells to reduce the calculation time of noise emission propagation. To this end a grid of line source representation appears to be more relevant than a grid of point source representation. Furthermore, large cells do not affect substantially the noise descriptors estimation.

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## **INTRODUCTION**

Traffic noise prediction models are currently used to predict average noise descriptors (e.g.  $L_{den}$ ), as required for example in noise mapping or in legislation [1]. Those models usually consider traffic flow as a steady noise source, whose level depends on flow rate and mean speed. Unfortunately, this static representation does not take urban traffic dynamics into account. An accurate description of average noise levels is bound to dynamic representation of traffic flows [2, 3].

To overcome this deficiency, recent works have coupled a dynamic traffic model with noise emission laws [4-8]. Traffic models are based on either a macroscopic representation (flow is seen as a fluid) [5], or a microscopic one (considering each vehicle singly) [6-8]. Outputs of traffic models (speed, acceleration, gear ratio) are calculated every time step (usually about 1s). They feed noise emission laws [9, 10] to give noise emitted by each vehicle on the network. A sound propagation calculation model is carried out to give noise level at a reception point every time step [11-13]. Acoustic descriptors are then calculated from those levels. Thus, acoustic descriptors reflecting traffic urban noise variation in time can be calculated [6, 14]. This offers a substantial breakthrough since [15, 16] have shown that noise dynamics dimension is important when evaluating physically and perceptively urban soundscapes.

The contribution of this paper is: (i) to test the influence of traffic modeling hypothesis and representation on noise descriptors, (ii) to determine which noise source representation takes profit of traffic dynamics and is computational efficient.

The study is based on four scenarios representative of the urban traffic conditions. For comparison, we assume the same noise emission law for each vehicle [17]. Only geometric attenuation will be considered when calculating noise propagation.

A general review on traffic modeling and noise source representation is given in section 2. Then, the influence of traffic modeling (respectively of noise source representation) on acoustic descriptors is assessed in section 3 (respectively in section 4). Results are discussed in section 5.

## **BACKGROUND**

### **Traffic Modeling**

The aim of traffic models is to predict the evolution of the key variables of traffic, according to boundary conditions (state of the network at time  $t=0$ , disturbances, number of road users...). Those key variables can be the densities, the vehicles speed and acceleration, etc. Different kinds of models can be used according to the variables one want to predict and the level of detail desired. The main traffic models are microscopic and macroscopic ones [18,19].

Microscopic car-following models (mCF models) use vehicles individual representation and aim at reproducing each vehicle behavior. Outputs of mCF models are position, speed and acceleration of each vehicle at each time step.

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Macroscopic conservation law models (MCL models) consider on the contrary traffic as a continuum stream obeying global rules. Outputs are density, flow rate and flow speed evolution on the network.

Some MCL models can also be formulated under an equivalent car-following rule (MCF models). Vehicles are then individually represented while obeying global rules. Outputs of MCF models are position and speed of each vehicle at each time step.

These three classes are considered in this paper. Table 1 summarizes their characteristics.

#### *First order macroscopic conservation law model (MCL model)*

In Macroscopic models, interactions between vehicles are globally studied. Traffic is considered as a homogenous and continuous stream, similarly to fluid dynamics. Macroscopic models are classified into first order and second order models. Only first order MCL models are considered in this study as second order models do not improve urban traffic representation (They are indeed more dedicated to highway traffic representation) [20]. In MCL models, traffic is characterized by three variables: flow  $Q(x,t)$ , density  $K(x,t)$ , and flow speed  $V(x,t)$  [21, 22]. The three variables are linked by the following system:

- The conservation equation :  $\frac{\partial Q(x,t)}{\partial x} + \frac{\partial K(x,t)}{\partial t} = 0$  ;
- The flow definition equation :  $Q(x,t) = K(x,t)V(x,t)$  ;

- An equilibrium relationship  $Q_e$ , called fundamental diagram:  $Q(x, t) = Q_e(K(x, t))$ .

The fundamental diagram represents all the equilibrium situations that the traffic could encounter depending on the road configuration. It is constructed from observations. Two regimes can be distinguished on such a diagram: the free flow and the congested ones; see Figure 1. In free flow, a road can absorb more vehicles (density increase) without saturation (flow increase). In congestion, a road cannot absorb more vehicles and a density increase will increase the saturation (flow decrease). A triangular diagram has been shown to be an accurate representation of urban traffic while being computational [23]. Such diagram is defined by three parameters: the maximal speed  $V_x$  reached when traffic is free, the wave speed  $w$  at which a starting wave downstream of a congestion climbs back the network, and the maximal density  $K_{\max}$  reached when all vehicles are stopped in a queue (then flow speed is null); see Figure 1.

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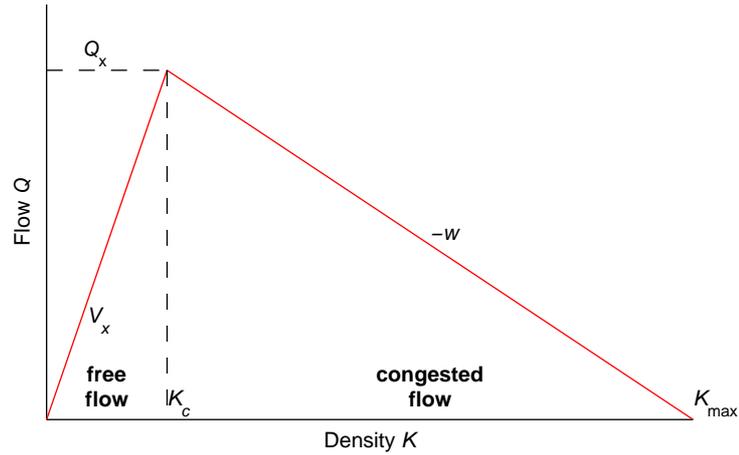


Fig 1: Fundamental diagram for a single lane.  $Q_x=1950\text{veh/h}$ : maximal flow;  
 $K_{max}=200\text{veh/km}$ : maximal density;  $K_c=40\text{veh/km}$ : critical density;  $w=11.8\text{km/h}$ : wave  
 speed;  $V_x=50.4\text{km/h}$  maximal speed

To solve the previous system of equation, each link of the network is discretized into cells, whose length is  $\Delta x$  (see Figure 2). Cell length should satisfy the CFL (Courant-Friedrichs-Lewy) condition  $\Delta x = V_x \Delta t$ , to ensure the scheme stability and to minimize numerical diffusion. Let's introduce the cumulative number of vehicles  $N(x,t)$  that have crossed location  $x$  from time origin to time  $t$ .  $N$  is by definition an increasing function and is related to the flow rate and the density respectively by  $Q = \partial_t N$  and  $K = -\partial_x N$ . The solution of the system in  $N$  can be calculated every time step at each node of the network [24, 25] thanks to the equation (1).

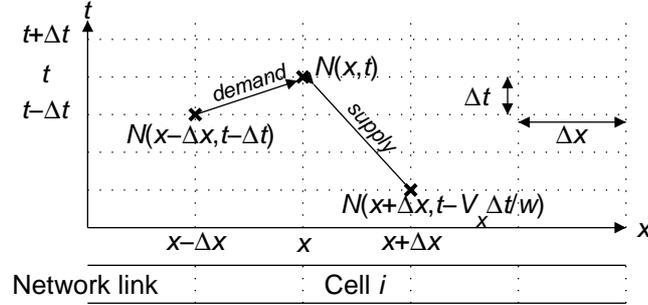


Fig 2: Discretization grid

$$N(x, t) = \min \left( \underbrace{N(x - \Delta x, t - \Delta t)}_{\text{demand term}}, \underbrace{N\left(x + \Delta x, t - \frac{V_x \Delta t}{w}\right) + K_{\max} \Delta x}_{\text{supply term}} \right) \quad (1)$$

where  $w$  is the wave speed,  $V_x$  the maximal speed,  $K_{\max}$  the maximal density.

The  $N$  value is equal to demand term of (1) when traffic is free. When a congestion comes back from downstream, the  $N$  value is given by the supply term.

The flow  $Q = \partial_t N$ , the density  $K = -\partial_x N$  and the speed  $V = Q/K$  are deduced afterwards for each cell of the network at each time step. The main quality of MCL models is that they offer an accurate description of traffic while being very computational since a global rule is used. Moreover, they are easier to calibrate than microscopic models (only the fundamental diagram is required). On the other hand, singularities between vehicles cannot be easily reproduced by such models.



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### *Macroscopic car following model (MCF model)*

Generally car-following models determine speed  $v_i(t)$  of a vehicle  $i$ , according to the relative spacing  $s_i(t)$  and relative speed with the vehicle immediately in front (vehicle  $i-1$ ), which is called the leader vehicle. The relative spacing is deduced from vehicle position by  $s_i(t) = x_{i-1}(t) - x_i(t)$ , where  $x_i(t)$  is the position of vehicle  $i$  at time  $t$ . The specificity of MCF model is that  $v_i(t)$  only depends on relative spacing and is supposed to always correspond to an equilibrium state following the fundamental diagram [26, 27]. Thus MCF model offers an individualized representation of vehicles that still obey to a global mean behavior rule. Numerical developments lead to equation (2) to calculate the position of vehicle  $i$  at time  $t$ :

$$x_i(t) = \min \left( \underbrace{x_i(t - \Delta t) + V_x \Delta t}_{\text{demand term}}, \underbrace{x_{i-1}(t - \Delta t) - w \Delta t}_{\text{supply term}} \right) \quad (2)$$

where  $\Delta t$  should be equal to  $\frac{1}{wK_{\max}}$  (CFL condition), for ensuring the scheme stability and minimizing numerical diffusion.

The position of vehicle  $i$  is equal to the demand term of (2) when traffic is free. This position corresponds to its previous position plus the distance run at  $V_x$  during the time step.

When traffic is congested downstream, vehicle position cannot exceed the supply term.

Thus outputs of the MCF model are speed and position for each vehicle on the network at each time step. The advantage of the MCF model is that it reproduces trajectory of each

vehicle while keeping the same traffic representation as MCL models. Furthermore, it is easy to introduce singularities between vehicles since the representation is microscopic.

*Microscopic car following model (mCF model)*

Contrary to macroscopic models, microscopic models aim at individualizing vehicle behavior and reproducing the driving task through the car-following rule [28, 29].  $v_i(t)$  is no longer associated to an equilibrium state but is derived from microscopic rules that bring into play characteristics of each vehicle. Thus individualized behaviors (nervous driving, slow acceleration...) can be reproduced. The characteristics of vehicle  $i$  (desired speed, acceleration and spacing...) determine how its speed can adapt to his leader vehicle behavior. Large amount of efforts have been involved to calibrate and improve mCF models [19, 30]. The car-following rule used for this study is the AIMSUN microscopic one [31], that distinguishes two different speeds a vehicle can reach whether there is not (case a) or there is (case b) a leader vehicle:

$$\text{Case a)} \quad v_{i,a}(t) = v_i(t-T) + 2.5\gamma_i T \left(1 - \frac{v_i(t-T)}{v_i^*}\right) \sqrt{0.025 + \frac{v_i(t-T)}{v_i^*}} \quad (3)$$

where  $v_i^*$  is the desired speed for vehicle  $i$ ;  $\gamma_i$  is the maximal acceleration for vehicle  $i$ ;  $T$  is the reaction time: note that all the vehicles have the same reaction time.

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$$\text{Case b) } v_{i,b}(t) = \delta_i T + \sqrt{\delta_i^2 T^2 - \delta_i \left[ 2[s_i(t-T) - \lambda_{i-1}] - v_i(t-T)T - \frac{v_{i-1}(t-T)^2}{\delta'_{i-1}} \right]} \quad (4)$$

where  $\lambda_{i-1}$  is the effective length of vehicle  $i-1$ ;  $\delta_i$  is the desired maximal deceleration for vehicle  $i$ ;  $\delta'_{i-1}$  is an estimation of vehicle  $i-1$  desired deceleration. The final speed for vehicle  $i$  during interval  $[t-T, t]$  is the minimum of those two previously defined speeds:

$$v_i(t) = \min(v_{i,a}(t), v_{i,b}(t)) \quad (5)$$

The position of vehicle  $i$  is then updated based on its speed:

$$x_i(t) = x_i(t-T) + v_i(t)\Delta t \quad (6)$$

The mCF model was calibrated in order to fit on average the fundamental diagram of the two previous models.

Car-following models can account for stochasticity in traffic flows by using distribution functions to allocate traffic parameters for each generated vehicle [32] at the entries of the network. We chose a shifted exponential distribution for headways (arrival times between two vehicles) [33], and an exponential one for the desired speeds. Note that stochastic processes need several runs to cover the whole range of the possible traffic evolutions; hence there is an increase in the calculation times.

Outputs of the mCF model are speed and position for each vehicle on the network at each time step. Their main advantage is the individualized description of vehicle behaviors. On the other hand, mCF models involve difficulties in calibration and high calculation costs because of the necessity for replications.

The following table summarizes the characteristics of the three traffic models from our study that can influence acoustic descriptor estimation:

Table 1: Model characteristics

Model	MCL model	MCF model	mCF model
Behavior rule	Macroscopic	Macroscopic	Microscopic
Traffic representation	Macroscopic	Microscopic	Microscopic
Unknown function	$N(x, t)$	$x_i(t)$	$x_i(t)$
Distributed times of arrival	no	possible	possible
Distributed individual speeds	no	no	possible
Need for replications	no	if distribution	if distribution
Associated acoustical representation	aggregated	aggregated or individual	aggregated or individual

### **Noise source representation**

Outputs of the traffic model are used to assess noise emissions every time step by mean of noise emission laws. Such laws give global or spectrum emitted noise for each vehicle or for an aggregated number of vehicles. Then a sound propagation calculation is carried out to give noise level  $L_{Aeq}$  at a reception point P every time step. Acoustic descriptors can then be calculated from those levels.

Emission laws chosen for this study give power noise levels as a sum of a rolling noise  $L_{wr}$  and a propulsion noise  $L_{wpp}$ . The rolling noise  $L_{wr}$  depends on speed and road specificities. The propulsion noise  $L_{wpp}$  depends on speed and cruising mode: accelerating, cruising, or decelerating [17]; see Table 2. The cruising mode is defined by vehicle

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acceleration deduced from differences in vehicle speed between two time steps. Note that we assume in this study that there is no slope on the road.

Table 2: Propulsion noise  $L_{wp}$  for emission law used in the study

Accelerating $a > 0.5 \text{ m.s}^{-2}$	V [km/h]	[5-20]	[20-100]	
	$L_{wp}$ [dB(A)]	111,3 + 24,1 log(V/90)		95,6
Cruising $-0.5 \text{ m/s}^{-2} < a < 0.5 \text{ m.s}^{-2}$	V [km/h]	[20-30]	[30-110]	
	$L_{wp}$ [dB(A)]	86,2		91,9 + 12,0 log(V/90)
Decelerating $a < -0.5 \text{ m.s}^{-2}$	V [km/h]	[5-10]	[10-25]	[25-80]
	$L_{wp}$ [dB(A)]	81,1	98,9 + 18,7 log(V/90)	91,6 + 5,5 log(V/90)

Only a geometric attenuation is considered (propagation effects are neglected). This hypothesis simplifies calculations without affecting noise dynamics for receivers located close to the road.

Different possibilities can be considered when aggregating emitted noise. This mapping influences the accuracy of the model and its computational efficiency. Four mappings are tested in this paper; see figure 3.

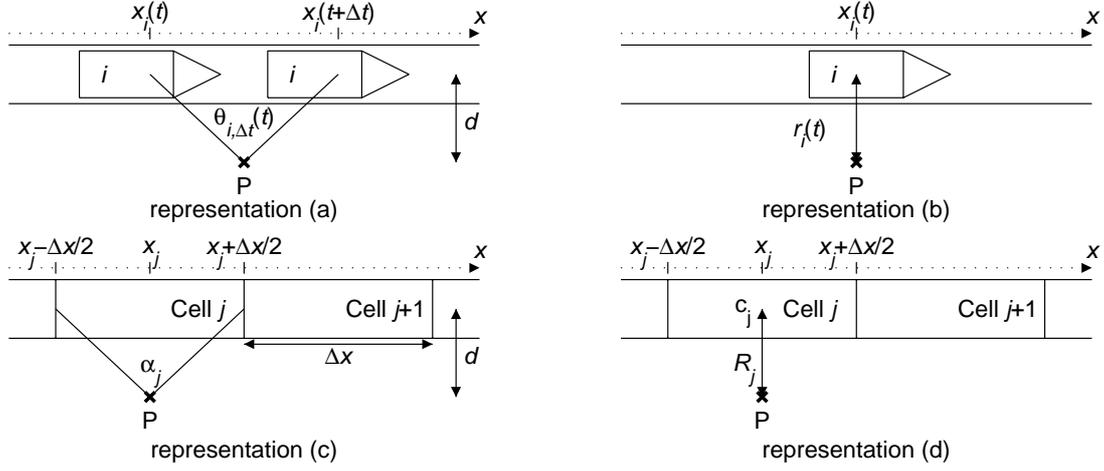


Fig 3: Noise source representations. (a): each vehicle forms a line source; (b): each vehicle forms a point source; (c): each cell forms a line source; (d): each cell forms a point source.

In this section  $i$  will refer to vehicles and  $j$  to cells,  $L_w$  will refer to power noise level of a vehicle, and  $L_w$  will refer to power noise level of a cell, whose length is  $\Delta x$ .

Representation (a): Vehicle  $i$  forms a line source, whose angle  $\theta_{i, \Delta t}(t)$  is defined by the positions of vehicle  $i$  at  $t$  and at  $t + \Delta t$ ; see figure 3a. Let's  $L_{w_{i, \Delta t}}(t)$  be the power noise level of vehicle  $i$  between  $t$  and  $t + \Delta t$ . It is deduced from speed and acceleration of vehicle  $i$  between  $t$  and  $t + \Delta t$ . Equivalent noise level  $L_{Aeq, 1s}(t)$  at a reception point P is given by relation (7):

$$L_{Aeq, 1s}(t) = 10 \log \left( \sum_i \theta_{i, \Delta t}(t) \frac{1}{x_i(t + \Delta t) - x_i(t)} 10^{\frac{L_{w_{i, \Delta t}}(t)}{10}} \right) - 10 \log(2\pi d) \quad (7)$$

where  $d$  is the distance between P and the road.

Representation (b): Vehicle  $i$  forms a point source, taken at its position at time  $t$ ; see figure 3b. Let's  $L_{w_i}(t)$  be the power noise level of vehicle  $i$  at  $t$ . It is deduced from speed and acceleration of vehicle  $i$  at  $t$ . Equivalent noise level  $L_{Aeq,1s}(t)$  at a reception point P is given by relation (8):

$$L_{Aeq,1s}(t) = 10 \log \left( \sum_i \frac{L_{w_i}(t) - 10 \log \left( 2\pi r_i(t)^2 \right)}{10} \right) \quad (8)$$

where  $r_i(t)$  is the distance between P and the vehicle  $i$  at time  $t$ .

Representation (c): Vehicles are gathered on a grid of line sources; see figure 3c. Let's  $L_{w_j}^{\Delta x}(t)$  be the power noise level of cell  $j$  at  $t$ . It is deduced from power noise levels of vehicles on the cell. Equivalent noise level  $L_{Aeq,1s}(t)$  is given by relation(9):

$$L_{Aeq,1s}(t) = 10 \log \left( \sum_j \alpha_j K_j(t) 10^{\frac{L_{w_j}^{\Delta x}(t)}{10}} \right) \quad (9)$$

where  $K_j(t)$  is the cell density at  $t$ ;  $\alpha_j$  is the angle of the cell  $j$  seen from P.

Representation (d): Vehicles are gathered on a grid of point sources; see figure 3d. Let's  $L_{w_j}^c(t)$  be the power noise level at  $t$  of a point  $c_j$  situated at the center of cell  $j$ . It is

deduced from power noise levels of vehicles on the cell. Equivalent noise level  $L_{Aeq,1s}(t)$  is given by relation (10):

$$L_{Aeq,1s}(t) = 10 \log \left( \sum_j 10^{\frac{10 \log(n_j(t)) + L_{W_j}^c(t) - 10 \log(2\pi R_j^2)}{10}} \right) \quad (10)$$

where  $n_j(t)$  is the number of vehicles on the cell;  $R_j$  is the distance between the center of cell  $j$  and P.

The choice of a noise source representation is very important when coupling with a propagation model. Vehicle representations (a) and (b) require a propagation calculation every time step, as vehicles are each time step at a different position. On the contrary, grid representations (c) and (d) require only one propagation calculation, as sources are at a fixed position: sound attenuation between every source and the reception point is stocked and applied every time step to the current emitted noise. Thus grid representations are more computational. Note that first works on dynamic traffic noise modeling have used emission lines or emission points representations [4, 6].

## **Methodology**

In order to point out the influence of each hypothesis, traffic representation and noise source aggregation are singly tested. Simulations are carried out on a 700m length single lane road section. Four scenarios are tested to reflect urban traffic conditions:



- Scenario 1: no traffic signal. Flow rate  $Q = 900\text{veh/h}$ . Large spacing between vehicles. Low flow rate gives intensive dynamics on noise from motion of vehicles.

-Scenario 2: no traffic signal. Flow rate  $Q = 1440\text{veh/h}$ . Small spacing between vehicles. High flow rate gives weak dynamics on noise from motion of vehicles.

- Scenario 3: traffic signal ( $x = 350\text{m}$ , with a 40s green time and a 20s red time). Flow rate  $Q = 900\text{veh/h}$ . Queues vanish over traffic signal cycles.

- Scenario 4: traffic signal ( $x = 350\text{m}$ , with a 40s green time and a 20s red time). Flow rate  $Q = 1440\text{veh/h}$ . High flow rate prevents the queue from discharging during a signal cycle length (overflow rate). The queue spills back on the network.

Received levels are calculated 15m from the section and at 2m height. In the following, other indications excepted, reception point P is located at  $x_P = 350\text{m}$ . Acoustic descriptors are calculated over a 10 minute-period, once the traffic is well-established. Acoustic descriptors calculated are  $L_{Aeq}$  and statistical levels  $L_5$ ,  $L_{10}$ ,  $L_{50}$  and  $L_{90}$ . Time step for traffic simulation and acoustic calculation is  $\Delta t = 1\text{s}$ .

## **INFLUENCE OF TRAFFIC REPRESENTATION**

Effects of traffic representation on noise descriptors are compared with the unbiased mapping of noise sources (b). Results for the four scenarios and every traffic representation are shown on table 2.

Table 2

Averaged and statistical levels [dB(A)] simulated for every traffic model and scenario

Case	Traffic Model	Vehicle generation		noise source representation	Scenario	Simulation results					
		Speed Distribution?	Headway Distribution?			$L_{Aeq}$	$L_5$	$L_{10}$	$L_{50}$	$L_{90}$	$L_{10}-L_{90}$
i )	MCL model	No	No	7m cell	1	63,9	63,9	63,9	63,9	63,9	0,0
					2	65,9	65,9	65,9	65,9	65,9	0,0
					3	64,7	68,0	67,9	64,0	56,8	11,1
					4	65,8	68,0	67,9	67,2	57,4	10,5
ii )	MCF model	No	No	vehicle	1	63,9	65,5	65,5	63,4	62,2	3,3
					2	65,9	66,5	66,5	65,9	65,3	1,1
					3	64,8	68,4	68,2	63,8	56,2	11,9
					4	66,0	68,4	68,2	67,1	57,6	10,6
iii )	MCF model	No	Yes	vehicle	1	63,8	66,2	66,0	63,8	58,7	7,3
					2	65,9	67,0	66,9	66,2	64,0	3,0
					3	64,7	68,3	68,1	63,7	55,9	12,1
					4	66,0	68,4	68,2	67,1	57,7	10,4
iv )	mCF model	No	Yes	vehicle	1	63,8	65,8	65,6	64,2	58,8	6,8
					2	65,2	65,9	65,8	65,5	64,0	1,7
					3	64,5	68,9	68,6	63,2	55,9	12,7
					4	65,9	69,0	69,0	65,6	56,9	12,1
v )	mCF model	Yes	Yes	vehicle	1	62,9	65,9	65,5	62,8	57,0	8,5
					2	64,0	66,0	65,7	64,2	59,5	6,2
					3	63,9	68,7	68,3	62,0	55,4	12,9
					4	65,0	68,8	68,6	64,4	56,8	11,9

### **Influence of resolution when behavior rule is macroscopic: MCL model vs. MCF model**

MCL model and MCF model are based on the same macroscopic behavior rule (the fundamental diagram), and only differ on traffic representation, which is respectively macroscopic and microscopic. Let's see its influence on noise descriptors estimation when there is no headway distribution (cases i and ii in Table 2).

When there is no traffic signal, MCL model coupled with 7m acoustic cells gives the same  $L_{Aeq}$  estimation than MCF model coupled with an individual representation of noise

sources. However, a small part of the dynamic linked with motion of vehicles is smoothed by macroscopic representation, as shown in Table 2 (with MCL,  $L_{10}-L_{90} = 0$  for scenarios 1 and 2).

For the scenarios with a traffic signal (scenarios 3 and 4), MCL model tends to underestimate high levels (0.4 dB(A)  $L_5$  underestimation, compared to MCF estimation), because the aggregation on the cell smoothes peaks of noise.  $L_{Aeq}$  estimation is unbiased.

Thus, with macroscopic behavior rule, traffic representation does not affect  $L_{Aeq}$  estimation but statistical descriptors estimation. Microscopic traffic representation is then more relevant.

### **Influence of behavior rule: MCF model vs. mCF model**

MCF model and mCF model are both car-following models. They differ on behavior rules, which are respectively macroscopic and microscopic. Let's see the influence of the behavior rule, by means of 10 runs with the same headway distributions (cases iii and iv in Table 2).

A more detailed estimation of acoustic descriptors is expected with mCF model, as it can take into account specific behavior of each driver. In fact, that can lead to a different pattern of noise every traffic light cycle, or accentuate the formation of platoons of vehicles formed by slowest ones. But Table 2 shows differences under 1dB(A) for both  $L_{10}$  and  $L_{90}$  estimation for all scenarios, between mCF and MCF estimations. The difference is even under 0.2 dB(A) for  $L_{Aeq}$  estimation for scenarios with a traffic signal.

It seems first that details pointed up by mCF model are smoothed by the aggregation of the acoustic descriptors calculation. Secondly, those details are not necessarily relevant: the dynamics of traffic outflow and its effects on noise are set by the network characteristics, especially when there is traffic signal (vehicle trajectories are then forced by the traffic signal despite their own characteristics).

So an accurate macroscopic behavior rule seems sufficient to assess averaged and statistical noise levels, within hypothesis fixed in this study.

## **Influence of distributions**

### *Headway distributions*

Headway distributions are used to consider variability in the traffic flows (formation of platoons, large headways without vehicles...). Its effects on noise estimation are tested through MCF model (cases ii and iii in Table 2).

When there is no traffic signal, runs with headway distributions show more noise dynamics, especially when flow rate is small ( $L_{10}$ - $L_{90}$  scenario 1 estimation increased by 4dB(A) for case iii compare to case ii). One can see that low levels are more influenced by distributions ( $L_{90}$  decreased by 3.5 dB(A) for scenario 1) than high levels ( $L_{10}$  increased by 0.5 dB(A) for scenario 1). Low levels are indeed related to largest headways (i.e. headways between platoons of vehicles), which depend on distribution. On the contrary, high levels are related to smallest headways between vehicles (i.e. headways inside the platoons), whose are fixed by behavior rule parameters.

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Headway distributions do not affect noise descriptors estimation when there is a traffic signal, as it smoothes arrivals of vehicles.

### *Speed distributions*

Distributions can be performed with mCF model to individualize desired speeds. Table 2 compares noise estimation for the same headway distribution with or without speed distribution (cases iv and v). One can see a slight decrease of noise levels with speed distribution when there is no traffic signal (for scenario 2, from case iv to case v: 1.2 dB(A) decrease for  $L_{Aeq}$ , no influence for  $L_5$  and  $L_{10}$ , decrease up to 5.5 dB(A) for  $L_{90}$  estimation). This can be linked to a decrease in the flow speed, set by slowest vehicles (overtaking is not allowed in the model). Low levels are again more influenced by distributions, as they are linked to headways between platoons which are intensified by differences in speed. Note that this slight decrease of noise might be linked to our hypothesis: no overtaking and the same emission law for each vehicle.

The decrease is less important when there is a traffic signal (e.g. -0.5 dB(A) for  $L_{Aeq}$  and  $L_{90}$  estimation from case iv to case v for scenario 3), as speed is set by the traffic signal.

Headway and speed distributions influence on noise estimation are marked for low levels, but not for high levels, which seem to be set by the network. Note finally the slight decrease of noise levels when performing speed distributions.

### **Influence of replications**

As soon as stochastic processes are used (e.g. with distributions or microscopic behavior rule), replications are needed. Some say it fits reality, as it can take variations between runs into account (note that one has to know if variations between replications are relevant). Main defaults of replications are the difficulty to determine the number of replications needed [34] and computational problems.

Influence of replications on noise estimation is tested through study of standard deviations between 10 runs; see Table 3.

Table 3

Standard deviations [dB(A)] from 10 replications for every scenario

Case	Traffic model	Vehicle generation		scenario	Simulation results				
		Headway distribution?	Speed distribution?		$L_{Aeq}$	$L_5$	$L_{10}$	$L_{50}$	$L_{90}$
vi )	MCF model	yes	no	1	0,2	0,3	0,2	0,3	1,4
				2	0,1	0,2	0,2	0,1	0,6
				3	0,3	0,1	0,1	0,9	0,3
				4	0,0	0,0	0,0	0,0	0,0
vii )	mCF model	yes	no	1	0,3	0,1	0,1	0,3	1,0
				2	0,1	0,3	0,3	0,1	0,4
				3	0,3	0,1	0,1	0,9	0,2
				4	0,1	0,0	0,0	0,2	0,1
viii )	mCF model	yes	yes	1	0,2	0,2	0,2	0,3	0,5
				2	0,2	0,1	0,1	0,3	0,7
				3	0,2	0,1	0,2	0,5	0,1
				4	0,2	0,1	0,1	0,2	0,1

Standard deviations from replications are quite small, especially for  $L_{Aeq}$ ,  $L_5$  and  $L_{10}$  estimations, when aggregating on 10mn period; see Table 3. When there is no traffic signal, low levels estimation is a bit more sensible to replications (standard deviation up to 1.4 dB(A) for  $L_{90}$  estimation of scenario 1 in case vi). Standard deviations are very small (always under 0.2 dB(A) for scenario 4) when there is a traffic signal. In fact, here, pattern of noise is not linked to traffic model parameters but to traffic signal dynamics.

Finally, despite their effects on noise estimation shown above, speed distributions induce a small standard deviation.

Considering those results, there is no need for replications for  $L_{Aeq}$  and high levels estimation calculated over 10mn. This period is sufficient to smooth differences between distributions. Replications might be required if  $L_{90}$  estimation is wanted. Note that this study is based on an averaged emission law. Individualized emission laws could enhance the need for replications; this point will be discussed later.

## **INFLUENCE OF NOISE SOURCE REPRESENTATION**

Noise source representation must be chosen according to the three next points: its ability to reveal traffic dynamics, its computational efficiency and its compatibility with propagation model. Its influence on noise descriptors estimation is tested with mCF model, whose was previously shown to be relevant with urban traffic dynamics. Results are gathered on Table 4-6; influence of noise source representation and cell length are presented.

Table 4

Averaged and statistical levels [dB(A)] for each noise source representation for scenario1 (no traffic signal;  $Q = 900$  veh/h)

Noise source representation	Cell length	Cell configuration	Simulation results					
			$L_{Aeq}$	$L_5$	$L_{10}$	$L_{50}$	$L_{90}$	$L_{10}-L_{90}$
(a) vehicle = line source	-	-	63,9	65,3	65,3	63,1	62,4	2,9
(b) vehicle = point source	-	-	63,9	65,5	65,5	63,5	62,2	3,3
(c) grid of line sources	7m	in phase	63,8	64,8	64,8	62,6	62,6	2,3
		opposed	63,8	65,3	65,3	63	62,3	3,0
	28m	in phase	63,8	64,8	64,8	62,7	62,7	2,1
		opposed	63,9	63,8	63,8	63,8	63,8	0,0
	56m	in phase	63,8	63,8	63,8	63,8	63,8	0,0
		opposed	63,8	63,8	63,8	63,8	63,8	0,0
(d) grid of point sources	7m	in phase	63,9	65,5	65,5	63,5	62,2	3,3
		opposed	63,9	65,3	65,3	64,2	62,3	3,0
	28m	in phase	64,2	65,5	65,5	65,5	62,2	3,3
		opposed	63,6	63,5	63,5	63,5	63,5	0,0
	56m	in phase	65,6	65,6	65,6	65,6	65,6	0,0
		opposed	62,2	62,2	62,2	62,2	62,2	0,0

### **Selection of grid of line sources representation**

Differences between noise source representations are tested on the scenario 1 (scenario with no traffic signal and a low flow rate).

Representations (a) and (b) need a propagation calculation every step, as noise sources are not aggregated on a grid but taken every time step at their position. Those representations are not computational efficient and must be avoided in practice. Thus they just serve as a reference in this study. Table 4 shows a similar noise estimation for these two representations for scenario 1 (only 0.2dB(A) difference between representation (a) and



representation (b) in  $L_5$  estimation). Only representation (b) will be considered in the following, as it is more computational.

Representations (c) and (d) do not require a propagation calculation every time step as sources are aggregated on a fixed grid. Thus they are more computational. Selection between representations (c) and (d) is often based in practice on its compatibility with propagation calculation model. However their different characteristics influence noise descriptors estimation. Table 4 compares noise estimation for scenario 1 (no traffic signal and constant flow): dynamics of noise observed is linked to motion of vehicles. Both representations are tested with different sizes of cells and different alignments: either reception point is in front of the cell (i.e. in phase), or it is between two cells (i.e. opposed); see figure 4.

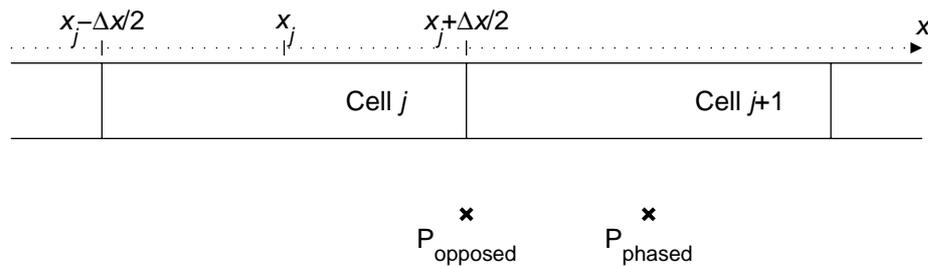


Figure 4: Different alignments for reception point

Line source representation (c):  $L_{Aeq}$  estimation is accurate even with large cells, and is not sensible to problems of alignment (Tables 4 shows no mistake for  $L_{Aeq}$  estimation with 56m cell). However, large cells tend to smooth dynamics from motion of vehicles in free

flowing. This dynamics is also affected by alignments issues ( $L_{10}-L_{90} = 0$  for a 28m line source with opposed configuration).

Point source representation (d): Problems of alignments are more important with point sources. Even  $L_{Aeq}$  estimation is affected by alignment (3.4 dB(A) variations in  $L_{Aeq}$  estimation with representation (d) and 56m cells between phased and opposed configurations). This can be explained by the fact that line source smoothes emitted noise, whereas point source does not. Another study has shown the same alignment problem for  $L_{Aeq}$  estimation with a grid of point sources when cells become larger than 10meters [35].

Thus grid of lines will be preferred, while it can be coupled with the propagation calculation model. Mind that dynamics of motion of vehicle can be altered by aggregation on the cell.

Table 5

Influence of cell length for averaged and statistical levels [dB(A)] estimation with a grid of line sources, for scenario 3 (traffic signal;  $Q = 900$  veh/h). Noise levels given at  $x = 350$ m (right to the traffic signal).

Noise source representation	Cell length	Simulation results					
		$L_{Aeq}$	$L_5$	$L_{10}$	$L_{50}$	$L_{90}$	$L_{10}-L_{90}$
(b) vehicles at their position	-	65,0	68,3	68,2	63,7	58,4	9,8
(c) grid of line sources	7m	64,9	68,2	68,1	64,2	58,2	9,9
	14m	64,7	68,1	67,9	64,3	57,9	10,1
	28m	64,7	68,3	68,0	63,9	56,4	11,7
	70m	64,4	67,6	67,0	63,4	60,5	6,5

### **Influence of the size of line sources for scenarios with traffic signal**

Traffic is very fluctuating near traffic signals. Thus poor noise descriptors estimation was expected with large cells. Actually, estimation of noise descriptors near the traffic signal is surprisingly unaffected by the representation of noise source (Table 5 shows e.g. a 0.6 dB(A) underestimation of  $L_{Aeq}$  with 70m cells or a 0.2 dB(A) underestimation of  $L_{10}$  with 28m cell). Estimation of acoustic descriptors which are aggregated on time seems not to be very affected even if noise pattern is distorted. Moreover, noise emitted by a cell corresponds to the equivalent mean emission of all the vehicles present on the cell. Thus only the localisation of the source is approximated.

Table 6 shows noise estimation for scenario 4 140m upstream to the traffic signal: here flow rate is high, thus congestion spills back on the network. One could think that large cells are not suitable to capture dynamics of this traffic event. In fact, it seems that once again aggregation on large cells is sufficient, while traffic is precisely described (no mistake for  $L_{Aeq}$  or  $L_{10}$  estimation with 70m cells).

Thus accurate estimation of statistical levels can be assessed near traffic signals even with large cells. Note that current works tend to use tight grids near intersections [35, 36].

Table 6

Influence of cell length for averaged and statistical levels [dB(A)] estimation with a grid of line sources, for scenario 4 (traffic signal;  $Q = 1440\text{veh/h}$ ). The reception point is located 140m upstream of the traffic signal.

Noise source representation	Cell length	Simulation results					
		$L_{Aeq}$	$L_5$	$L_{10}$	$L_{50}$	$L_{90}$	$L_{10}-L_{90}$
(b) vehicles at their position	-	66,5	68,3	68,2	66,7	63,4	4,8
(c) grid of line sources	7m	66,4	68,3	68,1	66,7	63,3	4,8
	14m	66,4	68,4	67,9	66,7	63,2	4,7
	28m	66,4	68,3	68,0	66,4	63,5	4,5
	70m	66,4	68,1	68,0	66,3	64,1	3,9

## DISCUSSION

The influence of traffic modeling hypothesis and noise source representation on noise descriptors for dynamic noise assessment has been tested. The study was based on  $L_{Aeq}$  and statistical levels estimation over a 10mn period for four scenarios representative of the urban traffic conditions.

Macroscopic conservation law model seems sufficient for  $L_{Aeq}$  estimation in urban traffic conditions. High levels estimation is improved near traffic intersections with macroscopic car-following model, which represents trajectory of each vehicle.

A microscopic behavior rule is not required for  $L_{Aeq}$  and high levels estimation, when urban traffic conditions homogenize vehicles behavior. Note that this result is obtained with the same emission law for each vehicle. Further investigations will show if introducing

more detailed emission laws (including gear ratio effect, several classes of vehicles...) implies the need for microscopic behavior rule to improve high levels estimation.

If low levels estimation is required, traffic model that does not take headway distributions into account may not be sufficient. This point will need further investigations, to determine if headway distributions are suitable for low levels assessment. Note that low levels estimated by traffic noise prediction models are similar to background noise; hence improvement of low levels estimation is not necessarily required.

If a model that involves stochastic processes (distributions, microscopic behavior rule) is chosen, there is no need for replications for dynamic traffic noise estimation for noise descriptors aggregated over a 10mn-period within the scenarios tested. Noise descriptors calculation smoothes indeed differences between replications; moreover a 10mn-period is sufficient for different traffic situations to occur (what would not be necessarily true with a shorter period).

The recommended noise source representation is a grid of line source, as influence of alignment between cell and reception point is more important with a grid of points.  $L_{Aeq}$  estimation is accurate with large grid of lines (cells up to 56m) whether there is or not traffic signal, provided the dynamics of traffic is precisely assessed. Noise dynamics from traffic signal can be assessed with large cells. On the contrary, noise dynamics from motion of vehicles is lost if cells are large (it is lost with 28m cells for a reception point 15m from the road, within hypothesis of the study). But this dynamics may be neglected: the aim of

our research is to offer tools for traffic management, and traffic management is not concerned by this kind of dynamics.

Hence, a computational model that couples a macroscopic car-following model and 28m grid of lines is sufficient to assess urban traffic dynamics effects on noise that can be revealed through  $L_{Aeq}$  and statistical levels. Note that those results stand for a traffic flow that contains no heavy vehicles. Further research has to be carried out to test the influence of heavy vehicles on dynamic noise estimation. Both emission laws and traffic flow models will have to be modified to take their effect into account. Note finally that conclusions of this paper may vary with other noise descriptors. A more accurate description of urban noise dynamics would involve more specific noise descriptors. Further investigation will have to be done on a selection of descriptors that reflect traffic noise variations in time.

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