Accounting for traffic dynamics improves noise assessment: experimental evidence

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Abstract

This paper compares three traffic representations for urban traffic noise assessment: (i) a coarse static calculation based on mean speeds and flow rates, (ii) a refined static calculation based on mean kinematics patterns, (iii) a whole dynamic noise estimation model that considers vehicle propagation on the network. The three methodologies are applied on real traffic situations and compared to on-field noise levels. Representation (i) is not refined enough to guarantee a precise noise assessment. Representation (ii) can be sufficient for L_{Aeq} estimation in most of cases. However, representation (iii) improves noise estimation since it considers vehicle interactions on the network. Moreover, it allows for specific descriptors to be estimated with a great accuracy, like the $L_{\mathrm{Aeq,1s}}$ distributions or the mean noise pattern that reproduces every traffic cycle. Finally, the dynamic noise estimation appears to be still consistent if the model is fed with data averaged on 2 hour-period. .

I Introduction

Traffic management can be a very efficient policy to fight against urban traffic noise **[1][2]**. It is increasingly implemented in European **[3]** or local **[4]** noise reduction projects. On-field studies have been conducted to measure noise impacts of traffic management policies **[5]**. Noise abatement can be obtained through speed reduction **[6]**. Traffic calming policy also ensures noise reduction since it forbids strong accelerations **[7]**: a 3 dB(A) decrease can be obtained for example from traffic light coordination that homogenize speeds **[8]**. Moreover, simulations show that noise reduction can also be attained by re-routing traffic flows **[9][10]**, or creating quiet zones **[11]**.

To improve noise estimation and prediction, it is crucial to use a precise noise estimation model, able to capture how traffic flow is affected by such strategies. L_{Aeq} or noise distribution estimations can be statistically derived from acoustical and traffic measurements **[12]**. This can be helpful to describe urban noise **[13]**, but this method prevents from evaluating all traffic management policies since it is limited to specific traffic situations. Models based on a coupling between traffic data estimation (flows, speeds, etc.), noise emission laws and sound propagation calculation, are more efficient. Their accuracy is closely linked to the traffic representation. Classical models use a static representation of traffic, which is considered as smooth and homogeneous **[14]**; noise levels are then estimated from flow rates and mean flow speeds. Such models are relevant to assess noise levels in inter-urban conditions. However this traffic representation is less accurate for urban traffic noise estimation **[15]**, especially close to traffic signals, where traffic conditions vary a lot **[16]**. Some classical models have been refined to account for traffic flow characteristics in urban area. Corrections for interrupted traffic flow **[17]** and intersections **[18]** have for example been introduced, deduced from queue lengths determination. Noise estimation close to intersections can also be refined by considering the mean kinematics pattern **[19]**. However, those models are limited to energetic descriptors estimation, like L_{den} or A-weighted sound pressure level L_{Aeq}. Those descriptors are not always sufficient to precisely describe urban traffic noise **[20]**, which is characterized by a strong dynamic linked to traffic signals **[21]**. Specific descriptors have been proposed in **[22]** to capture this dynamics.

The breakthrough in traffic noise estimation comes with dynamic models, which can output L_{Aeq}, but also instantaneous sound pressure levels **[23][24]**. Those models are based on a dynamic representation of traffic that gives at each time-step (usually 1s) position $x(t)$, speed $v(t)$ and acceleration $a(t)$ of each vehicle on the network **[25][26][27]**. Then $L_{\mathrm{Aeq,1s}}$ evolution is estimated, from which classical but also specific descriptors can be calculated.

In practice the choice of the traffic representation should be made in terms of the level of accuracy expected for the results and the amount of data required for calibration. The first studies that have tested traffic representations for L_{Aeq} estimation in urban area **[28]** have pinpointed the need for precise data collection **[29]**. Dynamic traffic representations have been compared in **[30][31]** for classical and specific

descriptors estimation. It was shown that precise noise estimation is bound to a detailed and individualized description of each vehicle trajectory. However, those studies did not confront the different traffic representations to urban acoustical data.

The contribution of this paper is to analyze three traffic representations for urban traffic noise estimation: (i) a coarse static calculation based on mean speeds and flow rates, (ii) a refined static calculation based on mean kinematics patterns, (iii) a whole dynamic noise estimation model that considers vehicle propagation on the network. The three methodologies are applied on real traffic situations and compared to on-field noise levels. Traffic and acoustic measurements are taken at 5 points that depict usual traffic situations: close to a traffic signal, between two consecutive traffic signals, and close to a bus station. The comparisons are based on the abilities of the models to precisely estimate classical and specific descriptors at those points. Note that the correspondence between those descriptors and noise annoyance will be investigated in a future work. Noise emission laws and propagation model are fixed for all calculations to ensure comparison. The amount of traffic data required for the estimation is also discussed.

The experimentation and the three calculation processes will be presented in the first part of the paper. The results will be then presented. Finally the required representations for urban traffic noise estimation will be discussed, according to the descriptors and the level of accuracy needed.

II Method

II.1 Experimentation

The experiment consists in traffic and acoustic measurements from 15.30 h to 17.30 h on a weekday. The site is a major arterial (Cours Lafayette, Lyon, France). This is a one-way three-lane road (the shoulder lane is shared by buses and passenger cars) with 5 signalized intersections. The street is U-shaped with 5-floor buildings. It is quite busy, with about 1400 vehicles per hour during the experiment. The perpendicular arterial Cours Saxe is also busy, with about 1000 veh/h, including 200 veh/h that turn right into the Cours Lafayette. Flow rates on other perpendicular streets are about 250 veh/h. The signal cycle duration is equal to 90 s and traffic signals are coordinated through a green wave. The durations of green and red cycles are given in Fig 1.

The recorded traffic data is the number of vehicles at each intersection for each movement and at each traffic cycle, and the precise bus trajectories (including stopping time at bus stations). Acoustic recordings are $L_{\mathrm{Aeq,1s}}$ evolution for the selected points. The five selected points for noise level measurements are typical of urban situations:

- in front of a bus station downstream of a traffic signal (P_1),
- between two consecutive traffic signals (P_2),
- close to a traffic signal: in front of (P_3) and downstream (P_4 and P_5).

Measurement points are 2m-high. Their exact location is given in Fig 1.

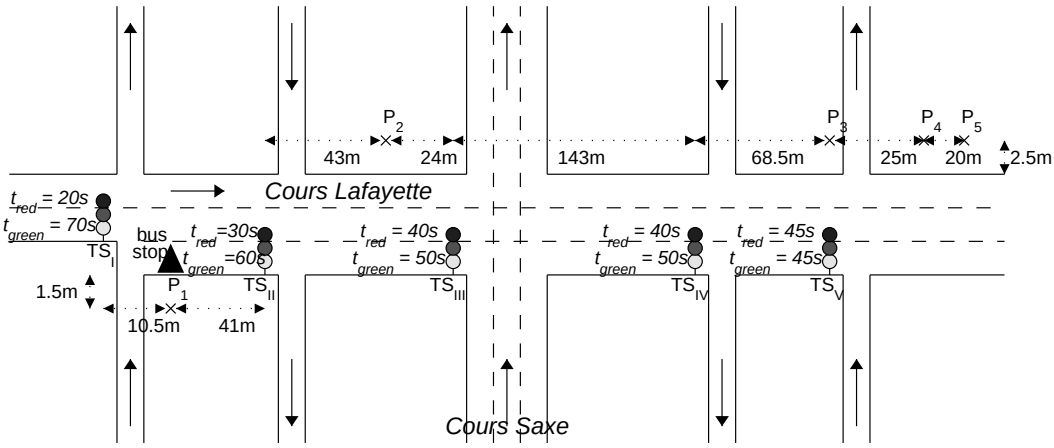

Fig 1: experimental site. Position of traffic signals TS and their green time t_{green} and red time t_{red} durations.

II.2 Noise estimation

II.2.1 Calculation process

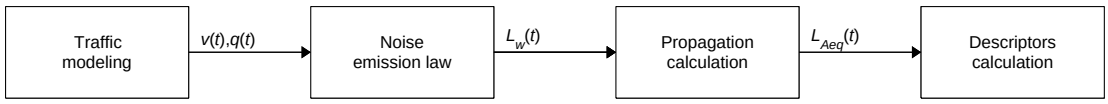

Fig 2: global modeling chain

Noise estimation follows the same modeling procedure whatever the traffic representation is (see Fig 2). The main steps are:

- the site is discretized into cells whose length varies between 9 and 18 m (one cell per lane). This cell length is relevant for noise estimation close to intersections [31]. Moreover, this length guarantees acoustical homogeneous cells, as required in [35] for static noise estimation,
- data given by the traffic model feed noise emission laws to estimate the noise emission $L_{\mathrm{w}}(t)$ of each cell. The laws used in this study distinguish light vehicles and buses, and give L_{w} with respect to speed v and driving conditions (cruising, decelerating or accelerating) [36][37]; see Fig 3. Note that heavy vehicles are not considered in this study since they are forbidden to enter the Cours Lafayette,

- the propagation model NMPB-Routes-96 implemented in Mithra software [38] gives the $L_{\mathrm{Aeq,cell}}(t)$ contribution of each cell for each receiver,
- the contributions of the cells are acoustically summed to give $L_{\mathrm{Aeq,1s}}(t)$ at the receiver:

$$L_{Aeq,1s}(t) = 10\log\left(\sum_{cells} 10^{\frac{L_{Aeq,cell}(t)}{10}}\right), \tag{1}$$

- noise descriptors are finally calculated. If a static traffic representation is involved, traffic variables and thus noise emissions are independent of time, and then only $L_{\mathrm{Aeq,T}}$ can be calculated, where T is the observation period. If a dynamic traffic model is involved, traffic variables are estimated every 1s, and then $L_{\mathrm{Aeq,1s}}$ time evolution but also specific acoustic descriptors can be calculated.

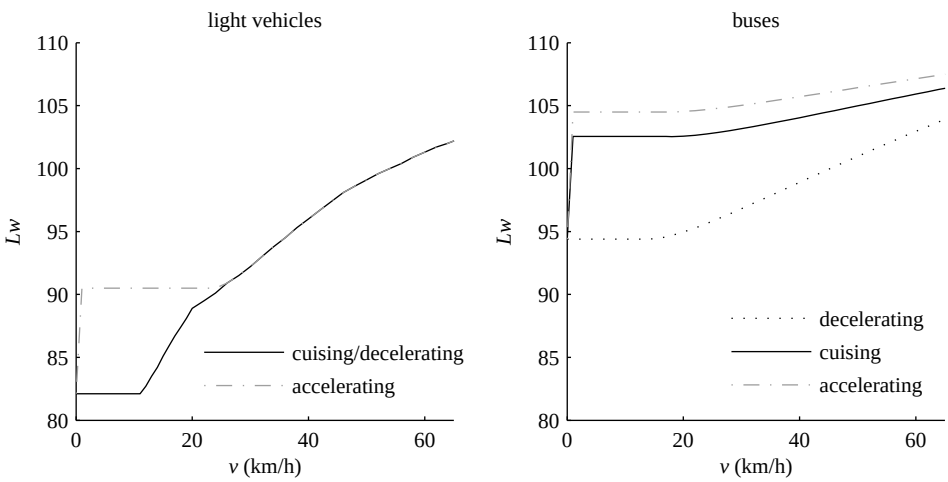

Fig 3: noise emission laws for both light vehicles and buses

II.2.2 Coarse static traffic representation

The flow of vehicles on each cell is divided into two subflows: the light vehicles subflow Q^{lv} and the bus subflow Q^{bus}. No acceleration or deceleration zones are considered: vehicles are supposed to pass through intersections without stopping. Noise emission L_w^i of a given cell is, for each class i of vehicle, deduced from the mean speed v^i, acceleration a^i and flow rate Q^i on the cell:

$$L_w^i = L_w\left(v^i, a^i\right) + 10\log\left(Q^i\right), \qquad \text{with } i = \{\mathrm{lv,bus}\}. \tag{2}$$

Finally, global noise emission L_{w} of the cell is the acoustical sum $\oplus$ of the emissions L_w^{lv} and L_w^{bus} of the cell:

$$L_w = L_w^{lv} \oplus L_w^{bus}. \tag{3}$$

II.2.3 Refined static traffic representation

Stops at intersections are considered. The flow is no longer divided into 2 subflows but into 4 subflows: $Q^{g,lv}$, $Q^{r,lv}$, $Q^{g,bus}$and $Q^{r,bus}$. $Q^{g,i}$ represents the vehicles of class i that pass through the intersection at free-flow speed, when the traffic signal is green ($Q^{g,i}=Q^{i}*t_g/t_c$), and $Q^{r,i}$ represents the vehicles that stop at the intersection when the traffic signal is red ($Q^{r,i}=Q^{i}*t_r/t_c$), where t_g, t_r and t_c are respectively the green, the red and the cycle durations of the traffic signal. Noise emission $L_w^{g,i}$ that corresponds to the subflow $Q^{g,i}$ is calculated as in II.2.2, considering that vehicles move at free-flow speed. Speed on any cell of the network depends on the distance x from the traffic signal for the red subflows: it is the average of the speeds at the upstream and downstream boundaries of the cell, which are deduced from the mean acceleration a, the maximal speed u, and the deceleration d of vehicles. $v=\min\left(\sqrt{2ax};u\right)$ on cells downstream of the traffic signal, and $v=\min\left(\sqrt{2dx};u\right)$ on cells upstream of the traffic signal. Finally, the noise emission L_w of the cell is the acoustical sum of the emissions $L_w^{g,lv}$, $L_w^{r,lv}$, $L_w^{g,bus}$ and $L_w^{r,bus}$ on the cell:

$$L_w = L_w^{g,lv} \oplus L_w^{r,lv} \oplus L_w^{g,bus} \oplus L_w^{r,bus}. \tag{4}$$

II.2.4 Dynamic traffic representation

The dynamic traffic model aims at predicting how key traffic variables evolve along the network. The model used in this study is SYMUBRUIT[1], which is based upon a detailed and individualized vehicle representation. Positions of all vehicles on the network are predicted at each time-step and are governed by three parameters: the maximal speed u reached when traffic is free, the wave speed w at which a congestion spills back on the network, and the minimum spacing $s_{\min}$ between two vehicles, observed when vehicles are stopped for example at a traffic signal. Position of vehicle i at the next time step $x_i(t+\Delta t)$ is the minimum between the position it is willing to reach when traffic is free and the position it cannot overpass when traffic is congested. The time-step is fixed to $\Delta t=s_{\min}/w$ to reduce numerical viscosity. Then:

$$x_i\left(t+\Delta t\right)=\min\left(\underbrace{x_i\left(t\right)+u\Delta t}_{\text{position when traffic is free}}\quad,\quad\underbrace{x_{i-1}\left(t\right)-s_{\min}}_{\text{position when traffic is congested}}\right). \tag{5}$$

Speed $v_i(t)$ and acceleration $a_i(t)$ are then deduced from positions $x_i(t)$ and $x_i(t+\Delta t)$. The model has been refined to take into account the bounded acceleration of vehicles [32], the influence of slow motion

[1] SYMUBRUIT is a simulation tool dedicated to dynamic noise estimation developed by INRETS and ENTPE

of buses [33], and the lane-changing phenomena [34]. Movements at the intersections are handled by assigning proportions of turning and through movements observed during the experiment.

The model requires knowledge of flow rates at each entrance, turning proportions at each intersection, and information on buses trajectories. Two calculations are done in the paper: (i) a first calculation in III.2 using the flow rates and movements recorded per cycle during the experiment, and the precise buses trajectories, (ii) a second calculation in III.3 using the mean flow rates and movements recorded during the experiment, and global information on bus frequencies and waiting times at bus stations.

II.2.5 Calibration

The static models have been calibrated to fit on-field measurements. Vehicle kinematic parameters are: an average deceleration rate d=3m/s^2 and an average acceleration rate a=0.8m/s^2. Note that the low acceleration value could be due to the traffic signal settings, which incite vehicles to accelerate slowly to benefit from the green wave. The other vehicle properties are the wave speed w=-3.33m/s, the minimum spacing $s_{\min}$=5m, and the maximal speed u. The maximal speed of light vehicles depends on the location on the network: u_1 = 17m/s at the beginning of the Cours Lafayette (up to the second intersection), u_2=15m/s at the end of the Cours Lafayette (after the second intersection), and u_3=10m/s on the crossing roads. The maximal speed of buses is u_{bus}=10m/s. Finally, a constant 51 dB(A) noise was added to take into account the background noise.

II.2.6 Descriptors

The descriptors considered in this study are energetic descriptors (L_{Aeq}, $L_{\text{L<80}}$ - that is the noise level after filtration of events that exceed 80 dB(A) -), statistical descriptors (L_1, L_{10}, L_{50}, L_{90}), $L_{\text{Aeq,1s}}$ distributions (that represents the proportion of observed or simulated $L_{\text{Aeq,1s}}$ that fall within each 1dB(A) range), and specific descriptors based on [22] that reveal noise dynamics at the traffic signal scale:

- The mean noise pattern. This is the pattern that repeats on average every traffic signal. It is obtained by selecting, for each instant $t_i \in [0 ; t_c]$, the sample S_i that contains the instants $t \equiv t_i$ $[t_c]$[2], and then operating an acoustical average of the elements of S_i whose level falls between $L_{90,\text{Si}}$ and $L_{10,\text{Si}}$ calculated from S_i.
- L'_g and L'_r, deduced from $L_{\text{Aeq,1s}}$ distribution. This distribution often shows two modes in urban area, which correspond to the green and red phases of the closest traffic signal. The 6 parameters of the bi-Gaussian distribution fit (the standard deviation σ_i, the mode x_i, and its amplitude A_i, with i={1,2}) permit to fit two Gaussian functions to the observed or simulated distribution. L'_g and L'_r, are calculated by operating the acoustical average of the elements between L_{90} and L_{10} of the two Gaussian functions. Hence L'_g and L'_r correspond respectively to the upper and the lower level of the mean noise pattern.

[2] This symbol $\equiv$ stands for modulo

- $N_{L5>75}$: the percentage of cycles whose L_5 exceeds 75 dB(A). This descriptor tells about the periodicity of peaks of noise. A strong value refers to a periodic occurrence of peaks of noise.
- $N_{L95>65}$: the percentage of cycles whose L_{95} exceeds 65 dB(A). This descriptor tells about the periodicity of calm periods. A weak value corresponds to a strong occurrence of calm periods.
- $L_{5/cycle}$: the average of the 5% noisiest events per cycle tells about the intensity of peaks of noise at the traffic signal scale. A high value of $L_{5/cycle}$ means that noise events appear at each cycle.
- $L_{95/cycle}$: the average of the 5% lowest events per cycle tells about the calm of the red phases. A strong $L_{95/cycle}$ means that calm periods are not very marked.

III Results

III.1 L_{Aeq} estimation

L_{Aeq} estimations and measurements are depicted in Tab 1. The coarse static calculation seems insufficient for L_{Aeq} estimation even if a 3 dB(A) error is accepted. The model overestimates noise levels since it considers that all vehicles go at their free-flow speed u on the network. The estimation is correct at the entrance of the network (1.5 dB(A) error at P_1), where vehicle speeds are high indeed. Yet, error is larger farther away, where vehicles are actually slowed down by green wave or stopped by traffic lights. The refined static model improves estimation (with only 2.2 dB(A) mean error) since it takes into account stops at intersections. However, it is still insufficient if a greater level of accuracy is required, since: (i) it supposes that all vehicles move at their free-flow speed during the green phase, (ii) it cannot represent efficiently the queue formation and the waiting time during the red phase, since it supposes that all vehicles stop in front of the traffic signal.

Finally, the dynamic model guarantees a precise estimation of L_{Aeq} (error falls below 2 dB(A) for all the points), since the characteristics of the traffic flow in urban area (queue formation and discharge at each traffic signal, platoons of vehicles behind buses, etc.) are represented. Estimation seems particularly precise in front of the traffic signal: error falls below 1 dB(A) for P_3, P_4 and P_5, what can be linked to a precise localization of accelerating zones. Moreover, the noise decrease at those last three points is underlined by the dynamic model while it is not by static models: it is due to vehicles that arrive from the Cours Saxe and turn right into the Cours Lafayette. Those vehicles slow down traffic flow, which cannot be captured by the static models. Finally, the slight underestimation of noise levels with the dynamic model is due to peaks of noise (such as klaxons), which increase L_{Aeq} and are not taken into account by the model.

	P_1	P_2	P_3	P_4	P_5	mean error
measurement	73.8	73.5	70.3	71.2	71.2	
coarse static representation	75.1	**76.5**	**74.4**	**74.3**	**74.4**	**3.1**
refined static representation	74.5	76.0	73.2	73.5	73.1	2.2
dynamic representation	75.3	71.9	70.6	70.3	70.7	1.1

Tab 1 : L_{Aeq} estimation (in dB(A)) at the 5 points of experimentation through the three different calculations; in clear green: error exceeds 1 dB(A); in dark grey: error exceeds 2 dB(A); in black: error exceeds 3 dB(A)

III.2 Specific descriptors estimation with dynamic noise estimation model

Noise estimation can be refined with a dynamic traffic representation, which allows for specific descriptors estimation. A first calculation of these descriptors is done by using data recorded at each traffic cycle; see Tab 2. Note that such refined data are not easy to collect in practice; the amount of data required for the estimation will be tested in the next section.

Energetic descriptors are precisely estimated. Errors fall under 1 dB(A) as soon as peaks of noise are filtered (see $L_{\mathrm{L<80}}$ estimation), which confirms that the slight underestimation of L_{Aeq} was due to peaks of noise that are cumbersome to capture with a simulation model. The $L_{\mathrm{Aeq,1s}}$ distributions are also estimated with a strong accuracy; see Fig 4. The two modes of the distributions, which are due to green and red phases of the traffic signal and are characteristic of noise dynamics in a one-lane road [22], are well reproduced by the model.

Statistical descriptors are also precisely estimated. Overestimation of L_1 close to the bus station at P_1 may be due to an overestimation of the noise emitted by the bus when staying at and leaving the bus station. This may be due to inappropriate choice of acceleration levels when constructing noise emission laws for buses. Other statistical descriptors are estimated with an error under 3 dB(A) for all points, and with error under 1 dB(A) for most of points.

Moreover, the mean noise pattern is reproduced accurately for the five points; see Fig 4. The succession of calm and noisy periods at the traffic cycle scale (due to the red and green phases) is well reproduced through the mean noise pattern. Moreover, the upper and lower levels of the mean noise pattern L'_{g} and L'_{r} are estimated with an error under 1 dB(A) for most of the points. This can be a valuable result to assess noise dynamics at this scale.

Finally, variations around this mean noise pattern can be estimated. $N_{\mathrm{L95>65}}$ and $N_{\mathrm{L5>75}}$, which tell about occurrences of calm and noisy periods at the traffic cycle scale [22], are estimated with errors under 10% close to the traffic signal, at P_3, P_4 and P_5. Hence variety in noise levels from one cycle to another is captured by the model. However, $N_{\mathrm{L5>75}}$ is overestimated at P_2 (27.5% error): all the cycles are seen noisy by the model at this point whereas some cycles are actually a bit calmer. This point may be improved by

introducing stochastic effects in noise emission laws, for instance by considering a specific class for the noisiest vehicles with a different acceleration rate, instead of a mean law. Finally, $L_{5/\mathrm{cycle}}$ and $L_{95/\mathrm{cycle}}$ are estimated with error under 3 dB(A), except for $L_{5/\mathrm{cycle}}$ estimation at P_1 (due to peaks of noise), which guarantees an accurate representation of noise amplitude.

	Experimental results					Simulation results Model fed with data per cycle					Simulation results Model fed with 2h data				
	P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
L_{Aeq}	73.8	73.5	70.3	71.2	71.2	75.3	71.9	70.6	70.3	70.7	75.0	71.4	70.0	69.6	70.2
$L_{L<80}$	72.5	71.3	69.7	70.3	70.5	72.7	71.9	70.4	70.1	70.5	72.3	71.4	69.8	69.5	70.1
L_1	81.8	80.6	78.3	79.7	79.2	86.3	78.3	78.0	78.1	78.2	86.3	78.3	77.7	77.6	77.7
L_{10}	76.0	74.9	73.6	74.3	74.6	77.7	75.7	74.0	74.1	74.9	77.2	75.7	73.2	73.4	74.6
L_{50}	71.4	69.7	67.1	67.8	67.5	71.8	70.1	68.0	66.8	67.4	71.0	68.4	67.5	66.2	66.3
L_{90}	64.4	63.4	61.1	60.1	58.1	62.0	61.6	62.6	59.4	57.2	64.9	61.8	62.9	59.6	57.4
$N_{L5>75}$ (%)	92.5	68.8	37.5	51.3	51.3	100.0	96.3	38.8	47.5	61.3	97.5	88.8	25.0	28.8	55.0
$N_{L95>65}$ (%)	17.5	11.3	2.5	0.0	0.0	0.0	0.0	5.0	0.0	0.0	31.3	0.0	3.8	0.0	0.0
$L_{5/\mathrm{cycle}}$	77.1	76.2	74.4	75.3	75.5	80.4	76.6	74.7	74.8	75.5	79.8	76.3	74.0	74.3	75.2
$L_{95/\mathrm{cycle}}$	62.9	62.8	60.4	58.9	57.1	60.4	60.5	61.9	58.2	56.3	63.5	60.6	62.1	58.3	56.4
L'_g	73.7	72.2	71.8	72.4	72.7	74.4	73.4	72.5	72.4	72.9	73.1	73.7	71.7	72.0	72.9
L'_r	68.5	65.0	64.4	63.9	61.5	65.9	64.3	65.8	63.3	60.6	69.3	64.8	65.5	63.7	61.7
L'_g-L'_r	5.2	7.2	7.4	8.5	11.2	8.4	9.1	6.8	9.1	12.3	3.7	8.9	6.2	8.3	11.2

Tab 2 : specific descriptors estimation (in dB(A)) with dynamic model at the 5 points of experimentation; in white: error is under 1 dB(A) (or 10%); clear grey: error is between 1 dB(A) (or 10%) and 2 dB(A) (or 20%); in dark grey: error is between 2 dB(A) (or 20%) and 3 dB(A) (or 30%); in black: error exceeds 3 dB(A) (or 30%).

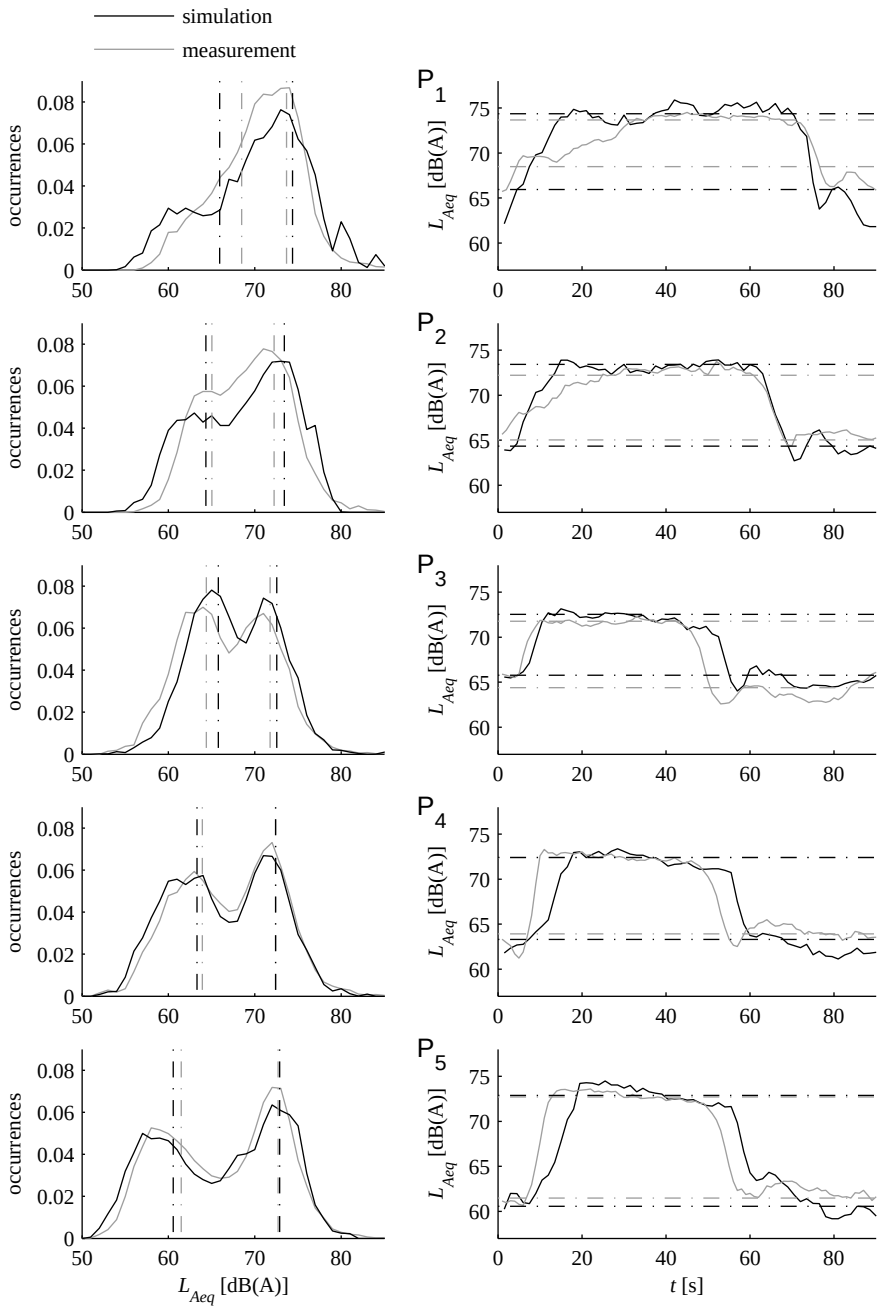

Fig 4: noise characterization of the selected points where the dynamic model is fed by data per cycle.

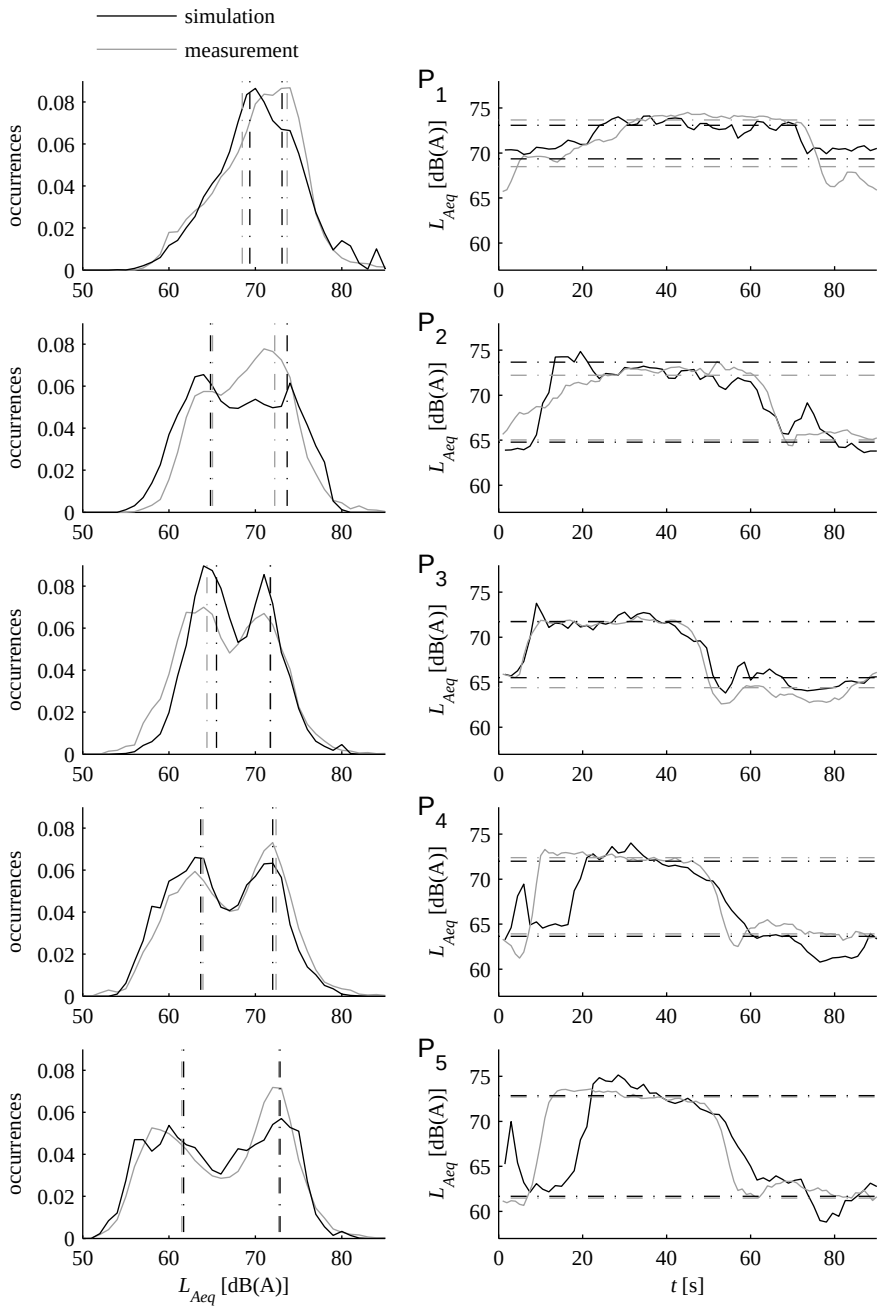

Fig 5: noise characterization of the selected points, where the dynamic model is fed by 2 hour-data.

III.3 Estimation of specific descriptors from coarse data

The dynamic model was shown relevant in III.2 to assess noise dynamics in an urban corridor regulated by traffic signals. However, the model was fed with detailed data which are not easy to collect in practice. The robustness of the dynamic noise estimation model has to be tested with aggregated data to validate its practical use. Hence the same set of descriptors as in the previous section is estimated but with input data aggregated upon the whole 2 hour-period (flow rates, turning proportions and bus frequencies), as it would be done in practice. Flow rate evolution during the experimentation is given in Fig 6: flow values can sometimes vary abruptly from one cycle to the other, but remain constant on average over the two hours.

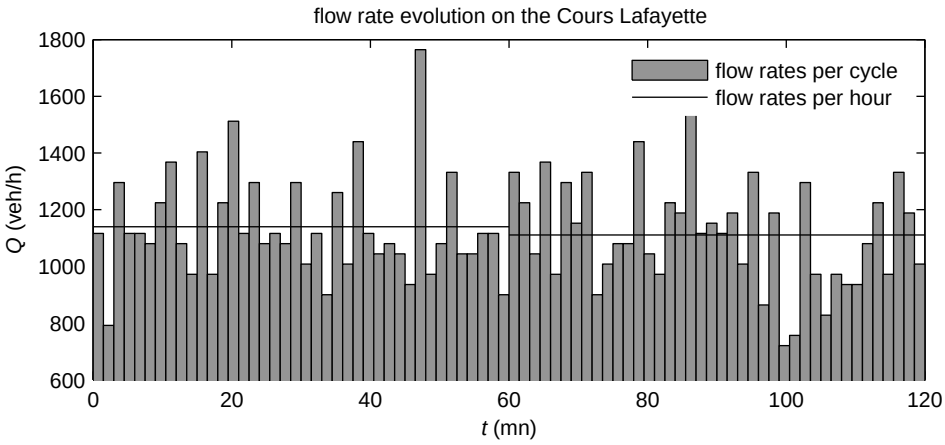

Fig 6: flow rates evolution on the Cours Lafayette during the experimentation (15.30 h to 17.30 h)

Noise distribution and mean noise pattern estimations are depicted in Fig 5. Descriptor estimations are given in Tab 2. Globally, the 2 hour-dataset gives very similar estimations as the cycle database. The main characteristics of noise dynamics can be still deduced from the results given by the model. Noise distributions remain precisely estimated at the five points. They reveal for each point the two modes seen in the previous part, which are estimated with errors under 2 dB(A); see L'_g and L'_r estimations. Moreover, statistical descriptors estimation is not deteriorated: error is under 3 dB(A) except for L_1 estimation at P_1. However, noise levels seem a bit underestimated at the end of the network (P_3, P_4 and P_5): see L_{Aeq} or L_{50} underestimation at P_4.

Furthermore, mean noise patterns still highlight the alternation between the green and the red phases, which is reflected by L'_g and L'_r. However, the shape of the mean noise pattern is a bit distorted at P_1: the low levels of the pattern are underestimated. It is due to the low flow rate on the perpendicular street (about 1 vehicle per cycle). Many cycles actually show no vehicle, which gives a low level when traffic signal is red; this phenomenon is reproduced while working with cycle data.

On the contrary, the 2 hour- data give one vehicle at each cycle, which keeps a relative high red level. The model could be improved by considering distributions for vehicle arrivals on the network.

Finally, estimation of variations around this mean noise pattern is not deteriorated by the 2 hour-dataset: $L_{5/\mathrm{cycle}}$ and $L_{95/\mathrm{cycle}}$ are estimated with errors under 3 dB(A) for the five points.

Hence the model is not sensitive to flow rate variations at the traffic cycle scale: it still captures noise dynamics as long as hourly flow rates are known. Its great accuracy with 2 hour-data enables its practical use for estimation of urban traffic noise.

IV Discussion

Three traffic representations have been tested in this paper for urban traffic noise estimation: (i) a coarse static representation that only considers mean speed and flow rates, (ii) a refined static representation based on mean vehicle kinematics patterns which vary whether the traffic signal is green or red, (iii) a dynamic representation, that aims at reproducing each vehicle trajectory on the network. Representations were compared to on-field data in order to study their ability to precisely estimate noise descriptors. The experimental site is a one way three-lane arterial. Traffic measurements consist of vehicle counting and movement recordings at each intersection for each traffic signal cycle. Acoustical measurements are $L_{\mathrm{Aeq,1s}}$ evolution at 5 points that depict current traffic situations: close to a traffic signal, close to a bus station, and between two consecutive traffic signals. The noise emission laws and the sound propagation calculations were kept constant to ensure comparison.

The coarse static representation can be accepted for L_{Aeq} estimation if a 3 dB(A) mean error is accepted. This representation overestimates noise levels, since it is based on a coarse estimation of vehicle mean speeds. Estimation can easily be refined by considering accelerating and decelerating zones, and distinguishing green and red phases in the kinematics patterns. Errors in L_{Aeq} estimation then fall to 2 dB(A). Hence, this representation can be sufficient in most of cases. However, it fails in taking into account specific traffic flow influence, like flow disruption induced by injection of vehicles from perpendicular streets or by traffic light coordination. Final refinement consists in considering a dynamic traffic model, which reproduces vehicle interactions on the network. This guarantees L_{Aeq} estimation with errors under 1 dB(A) at each point along the network; moreover this is the only available method to estimate specific descriptors, since the output of the model is the $L_{\mathrm{Aeq,1s}}$ evolution.

The $L_{\mathrm{Aeq,1s}}$ distributions and mean noise patterns (i.e. the pattern that repeats on average at each traffic signal) have been calculated with the dynamic traffic representation from traffic data averaged on each cycle. Results are very convincing: the shape of the noise distribution, which highlights two modes, fits the measured ones. Moreover, the simulated mean noise patterns are similar to the

observed ones, and the characteristic levels of those patterns (green and red mean noise levels) are estimated efficiently, with errors under 1 dB(A) for the majority of the points. Hence, noise dynamics along the network can be clearly reflected by the model. Note that future improvements for the dynamic estimation were pinpointed by the study: maximum noise levels estimation could be refined by improving noise emission laws for buses and differentiating the noisiest vehicles; noise level estimation during red phases could be refined by considering distributions in vehicle arrivals.

Finally, the dynamic noise estimation model appears to be still consistent even if the model is fed with data averaged on a 2 hour-period. Note that results are based on an experiment where flow rates remain almost constant with time. The ability of the model to assess the noise impact of a congested period will have now to be tested. If its robustness is confirmed, the model could be used for practical applications. This will be useful to precisely assess the dynamics of urban traffic noise. The impact of this dynamics on human noise perception should finally be investigated, to propose a global tool that greatly improves noise impact assessment of urban traffic management policies.

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VI References

[1] Ellebjerg, L. and Bendtsen H. Possibilities of noise reduction through road traffic flow management. in Inter-noise. 2007. Istanbul. 9p.

[2] Bendtsen, H., Haberl J., Litzka J., Pucher E., Sandberg U. and Watts G. Traffic management and noise reducing pavements - recommendations and additional noise reducing measures (Danish Road Directorate, Copenhagen, 2005). 2005: 90p.

[3] Rust, A. and Affenzeller J. Plans for future european research to reduce transport noise. in Inter-noise. 2007. Istanbul. 10p.

[4] Vancluysen, K. State of the art on noise abatement policies and tools in cities, noise abatement priorities and necessary technologies. WP I.1 Urban Scenarios and Priority Setting. 58p.

[5] Desarnaulds, V., Monay G. and Carvalho A. Noise reduction by urban traffic management. in Journées d'automne 2004, Société Suisse d'Acoustique. 2004. Jona. 4p.

[6] Ellebjerg, L. Effectiveness and benefits of traffic flow measures on noise control (Danish Road directorate, Copenhagen, 2007). Silence project. WP H.1 Methods for Noise Control by Traffic Management, 2007. 50p.

[7] European Commission. The effect of speed on noise, vibration and emissions from vehicles, European commission, Editor. 1998. 80p.

[8] Ellenberg, M. and Bedeaux J.-F. "Calming waves for safety. A time to rethink green waves?" Traffic Technology International, 1999. April/May 1999: p. 55-58.

[9] Kliucininkas, L. and Saliunas D. Noise mapping for the management of urban traffic flows. ISSN 1392 - 1207. Mechanika. 2006. Nr.3(59), 2006.

[10] Thorsson, P.J. and Ögren M. Macroscopic modeling of urban traffic noise - influence of absorption and vehicle flow distribution. Applied Acoustics, 2005. 66: p. 195-209.

[11] Nilsson, N.A. and Stenman A. Creating quiet city zones by noise charges and quiet vehicles. Part two: noise reduction effects. in Inter-noise 2007. 2007. istanbul. 10 p.

[12] Bazaras, J., Jablonskyte J. and Jotauniene E. Interdependance of noise and traffic flow. Transport, 2008. 23(1): p. 67-72.

[13] Barrigon Morillas J.M. et al. Evaluation of urban noise in the city of Caceres (Spain) by two different methods. in 19th International Congress on Acoustics, Madrid, 2-7 September 2007. 2007. 6p.

[14] CERTU. Review of French road and railway noise prediction models (in french : « Catalogue des logiciels de calcul du bruit des infrastructures routières et ferroviaires, un aperçu du marché français »). Centre d'études sur les réseaux, les transports, l'urbanisme et les constructions publiques. 2002. 47p.

[15] Steele, C. A critical review of some traffic noise prediction models. Applied Acoustics, 2001. 62: p. 271-287.

[16] Tajika, T., Tachibana H., Yamamoto K. and Oshino Y. Road traffic noise prediction with the consideration of the relation between traffic volume and vehicle speed. in Internoise. 2000. Nice, France.

[17] Makarewicz, R., Fujimoto M. and Kokowski P. A model of interrupted road traffic noise. Applied Acoustics, 1999. 57: p. 129-137.

[18] De Coensel, B., Botteldoren D., Vanhove F. and Logghen S. Microsimulation Based Corrections on the Road Traffic Noise Emission near Intersections. Acta acustica united with acustica, 2007. 93: p. 241-252.

[19] Picaut, J., Bérengier M. and Rousseau E. Noise impact modelling of a roundabout. in Inter-noise. 2005. Rio de Janeiro, Brésil.

[20] Can, A., Leclercq L., Lelong J. et Defrance J. Descriptors for urban traffic noise dynamic characterization (in French), LICIT, Editor. 2007b. 93p.

[21] Nelson, P., Transportation noise. Reference book. 1987: Butterworth. 520 p.

[22] Can, A., Leclercq, L., Lelong, J. and Defrance, J. Capturing urban traffic noise dynamics through relevant descriptors. Applied Acoustics, 69 : p.1270-1280. 2008.

[23] De Coensel, B., De muer T., Yperman I. and Botteldoren D. The influence of traffic flow dynamics on urban soundscape. Applied Acoustics, 2005. 66: p. 175-194.

[24] Leclercq L., Can A., Crepeaux P., Defrance J., Fournier M., Lelong J., Miege B., Minaudier C., Olny X. and Vincent B., Dynamic prediction of urban traffic noise: a real case study (in French : « Estimation dynamique du bruit de circulation en milieu urbain : étude d'un cas réel »). Rapport INRETS/LICIT N°0703. 2008. 65p.

[25] Leclercq, L. A traffic flow model for dynamic estimation of noise. 2002: Phd report. 317 p. (in french).

[26] Rotranomo. Final conference on 28.09.2005 [on line]. 2005, http://www.rotranomo.com/.

[27] Oshino, Y., Tsukui K., Hanabusa H., Bhaskar A., Chung E. and Kuwahara M. Study on road traffic noise prediction model taking into account the citywide road network. in Inter-noise. 2007. Istanbul. 8p.

[28] IMAGINE. Review of the suitability of traffic models for noise modelling - WP2 : demand and traffic flow modelling. 2004: Project funded by the CE under the sixth framework programme. 132p.

[29] IMAGINE. Collection methods for additional data. 2006, Project funded by the CE under the sixth framework programme.

[30] Can, A., Leclercq, L. and Lelong, J. Dynamic estimation of urban traffic noise: influence of traffic and noise source representations. Applied Acoustics, 69: p.858-867, 2008.

[31] Can, A., Leclercq, L. and Lelong, J. Selecting noise source and traffic representations that capture urban traffic noise dynamics. Submitted for publication.

[32] Leclercq, L. Bounded acceleration closed to fixed and moving bottlenecks. Transportation Research Part B, 2007. 41(3): p. 309-319.

[33] Leclercq, L., Chanut S. and Lesort J.-B. Moving bottlenecks in Lighthill-Whitham-Richards Model: A unified theory. Transportation Research Record: Journal of the Transportation Research Board, 2004. 1883: p. 3-13.

[34] Laval, J. and Leclercq L. Microscopic modeling of the relaxation phenomenon using a macroscopic lane-changing model. Transportation Research Part B, 2008; 42(6): p. 512-522.

[35] Besnard F., Berengier M., Doisy S., Fürst N., Hamet J.F., Lelong J. and Pallas M.A. Vehicle noise emission guide (in French, « Guide méthodologique, Emission sonore des véhicules »), Paris, SETRA, 2009.

[36] Besnard F., Berengier M., Doisy S., Fürst N., Hamet J.F., Lelong J. and Pallas M.A. The procedure for updating the vehicle noise emissions values of the French "Guide du Bruit des transports terrestres". in EAA European Acoustics Association Euronoise. 2003. Naples.

[37] Hamet, J.F, Besnard, F., Doisy, S. and Lelong, J. New vehicle noise emission for French traffic noise prediction. Submitted for publication.

[38] Mithra, Manuel technique Mithra 5.0. 2002: 58p.