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Dynamic approaches for the characterization and mitigation of urban sound environments

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Abstract

Awareness of the health effects of noise gradually became apparent in the second half of the 20th century, in contrast to the parallel urban planning decisions, which left a significant place for the automobile in the city. The high noise levels, combined with the increasing aspiration of city dwellers for a peaceful and environmentally friendly city, have quickly made noise a first-rate nuisance, which must be characterized and mitigated. In this context, this document presents a contribution to research in urban environmental acoustics that attempts to take advantage of a diversity of means to improve the characterization of urban noise environments, and seeks ways to evaluate noise mitigation strategies based on mobility solutions. This research calls for multiphysical couplings to highlight the temporal dynamics of noise.

Chapter 1 focuses on the characterization of urban sound environments. The operational objective of this research is to propose acoustic indicators that capture the specificities of sound environments in their physical and perceptual dimensions and allow impacts to be determined. At the same time, these indicators must be estimable both through measurement and modelling.

Chapter 2 focuses on measurement networks and on combined approaches associating measurement and modelling for the characterization of urban sound environments. The operational objective of this research is to propose strategies for sampling and processing the data collected in order to accurately estimate the indicators of interest. Data assimilation between measures and predictive models also aims to improve the estimation of indicators.

Chapter 3 focuses on multi-physical couplings for traffic noise prediction and mitigation. The operational objective of this research is to develop couplings between noise prediction models and traffic models, to enable the evaluation of strategies to improve urban noise environments by acting on mobility. The models developed must meet different spatial scale requirements according to the strategies considered and be part of a broader multi-criteria evaluation objective.

A discussion on research directions in urban environmental acoustics that present an interest in the medium and long term concludes the document.

Keywords

Environmental acoustics; urban acoustics; multiphysical couplings; acoustic indicators; noise mitigation; measurement networks; dynamic noise; participatory measurement; time interpolations; source recognition; perceptual assessments; traffic modelling; multi-criteria assessments; airbone pollutants; urban environment.

Résumé

La prise de conscience des effets du bruit sur la santé s'est progressivement manifestée dans la seconde moitié du XXe siècle, en opposition avec les décisions d'urbanisme prises en parallèle, qui ont laissé une place importante à l'automobile en ville. Les niveaux sonores élevés, conjugués à une aspiration croissante des citadins pour une ville apaisée et respectueuse de l'environnement, ont rapidement fait du bruit une nuisance de premier ordre, qu'il convient de savoir caractériser et maîtriser. Dans ce contexte, ce document présente une contribution à la recherche en acoustique environnementale urbaine qui vise à améliorer la caractérisation des environnements sonores urbains et à évaluer des solutions de mobilité sur la base des impacts acoustiques. Cette recherche fait appel à des couplages multiphysiques, dont l'un des buts principaux est de mettre en évidence la dynamique temporelle du bruit.

Le chapitre 1 s'intéresse à la caractérisation des environnements sonores urbains. L'objectif est de proposer des indicateurs acoustiques capturant les spécificités des environnements sonores dans leurs dimensions physique et perceptive, et permettant la détermination des impacts. Ces indicateurs doivent dans le même temps être estimables tant par la mesure que par la modélisation.

Le chapitre 2 s'intéresse aux réseaux de mesure, puis aux approches combinées associant mesure et modélisation, pour la caractérisation des environnements sonores urbains. L'objectif opérationnel de cette recherche est la proposition de stratégies d'échantillonnage et de traitement des données recueillies permettant une estimation précise des indicateurs d'intérêt. L'assimilation de données entre mesures et modèles vise à améliorer elle aussi l'estimation de ces indicateurs.

Le chapitre 3 s'intéresse aux couplages multi-physiques pour la prévision et la réduction du bruit de trafic. L'objectif de cette recherche est le développement de couplages entre modèles de prévision du bruit et modèles de trafic, pour permettre l'évaluation de stratégies d'amélioration des environnements sonores urbains en agissant sur la mobilité. Les modèles développés doivent répondre à des impératifs d'échelles spatiales différentes selon les stratégies considérées et s'inscrire dans un objectif plus large d'évaluation multicritères.

Une discussion portant sur les directions de recherche en acoustique environnementale urbaine présentant un intérêt à moyen et à long terme clôt le document.

Mots-clés

Acoustique environnementale ; acoustique urbaine ; couplages multiphysiques ; indicateurs acoustiques ; atténuation du bruit ; réseaux de mesure ; bruit dynamique ; mesure participative ; interpolations temporelles ; reconnaissance des sources ; évaluations perceptives ; modélisation du trafic ; évaluations multi-critères ; polluants atmosphériques ; milieu urbain.

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Introduction

Context

Increasing urbanisation and the high demand for mobility it generates are potential vectors for the degradation of urban noise environments. The direct consequence is that two-thirds of urban dwellers say they are bothered by noise in their homes, with road traffic being regularly cited as the most annoying source of noise. The health stakes are high, with an estimated 1M healthy years lost in Europe (WHO). Urban metropolitan areas, since they are the seat of both the highest noise levels and the highest population densities, concentrate the highest exposures and therefore most of the efforts currently being made to tackle the noise issue.

However, noise control in urban areas is subject to strong constraints. The density of the building prevents the implementation of conventional noise reduction solutions such as noise barriers. The proximity between sources and exposed persons imposed by the urban network calls for reducing noise, particularly traffic noise, at source. Here too, the urban environment imposes a difficulty: the low speeds practiced in the city, and the frequent acceleration phases, reduce the interest of low-noise road pavements, with motor noise often being the dominant factor. Mobility solutions, such as speed reduction, specific facilities (e.g. public transport lane, roundabout, etc.) and the development of silent transport solutions (electric vehicles, bicycles, etc.) exist, but remain difficult to evaluate to date. Finally, these solutions come up against the fact that high noise levels are often due to individual behaviours that are difficult to apprehend (passing of a motorcycle waking up thousands of people, excessive use of the horn, aggressive driving, etc.).

The action to combat noise is also part of a very evolving context:

- Noise environments evolve at the speed of urban renewal. Permanent changes in the mobility offer, urban sprawl, the emergence of new urban practices and new noise sources are all factors that can potentially modify noise environments and that it is therefore necessary to know how to evaluate;
- The expectations of city dwellers regarding their sound environments are much higher than they were in the past, as the desire for calm has spread to most cities. This collective desire for a better environmental quality requires intensified efforts in the fight against noise;
- The technical means of characterizing sound environments are changing rapidly. Technological solutions, such as the emergence of micro-electro-mechanical systems (MEMS), suggest the possibility of dense measurement networks, or even participatory measurement via smartphones, for the characterization and monitoring of sound environments. The permanent increase in computing capacity permits modelisations at urban scales that were unthinkable a few years ago.

Research in environmental acoustics is itself changing. It has been heavily impacted by the Directive 2002/49/EC, which in 2002 required the production of noise maps for all cities of more than 250,000 and then 100,000 inhabitants in the European Community. This directive has served as a lever for operational research applied to urban areas, which has improved knowledge of urban dwellers' exposure to noise and has led to a partial census of the quiet and noisy areas of the cities concerned. However, the approach adopted, which was inevitably simplified to enable the production of maps in a reasonable time, was based on a census of the main negative sources (road, rail and air traffic, as well as the main industries) to estimate the spatial distribution of average energy indicators such as L_{Aeq} or L_{den}. This initially focused applied research on approaches: (i) very reductive in terms of describing sound environments, these average indicators not taking into account the temporal structure of sound environments and their real content in terms of sound sources, (ii) focused on characterization, i.e., making it difficult to evaluate noise reduction strategies.

More recently, research has highlighted the need:

- To develop multi-source approaches, to take into account the complexity of urban sound mixtures in the perceptual evaluation of sound environments;
- To diversify the range of indicators and not limit themselves to energetic indicators to characterize sound environments, in order to fully capture their temporal dimension, which is also important in perceptual evaluations;
- To couple noise prediction models with road traffic modelling, as it is already done in air pollution, in order to assess the impact on noise of traffic regulation strategies;
- To use integrative approaches, in particular through Geographic Information Systems, to facilitate both the data collection and the use of the produced data;
- To promote interdisciplinary approaches, combining engineering sciences and human and social sciences, to involve city dwellers in the processes of proposing noise reduction solutions, to integrate the social contexts and aspirations of city dwellers, and to assess environmental injustices.

These new dimensions of the assessment of urban noise environments invite a paradigm shift that technological advances in measurement and modelling tend to make possible.

In this context, research in urban environmental acoustics must aim to: (i) characterize noise environments through indicators that are sensitive to both their physical and perceptual dimensions, (ii) characterize the impacts such as exposures, impacts on quality of life and health, (iii) propose noise prediction models that allow the assessment, at different spatial scales, of strategies to improve noise environments.

Research activities and document structure

My research activities are in the context described above and focus on the characterization and mitigation of urban noise environments. This research calls for multiphysical couplings to highlight the temporal dynamics of noise. In particular, the coupling between traffic models and acoustic models is developed to assess the impact of mobility on noise environments. My research activities are schematized in Figure 0:1. They have three main components: i) The characterization of urban noise environments through relevant indicators, ii) Combined approaches using both measurement and modelling to characterize urban noise environments, iii) Multi-physical couplings for the prediction and mitigation of road traffic noise.

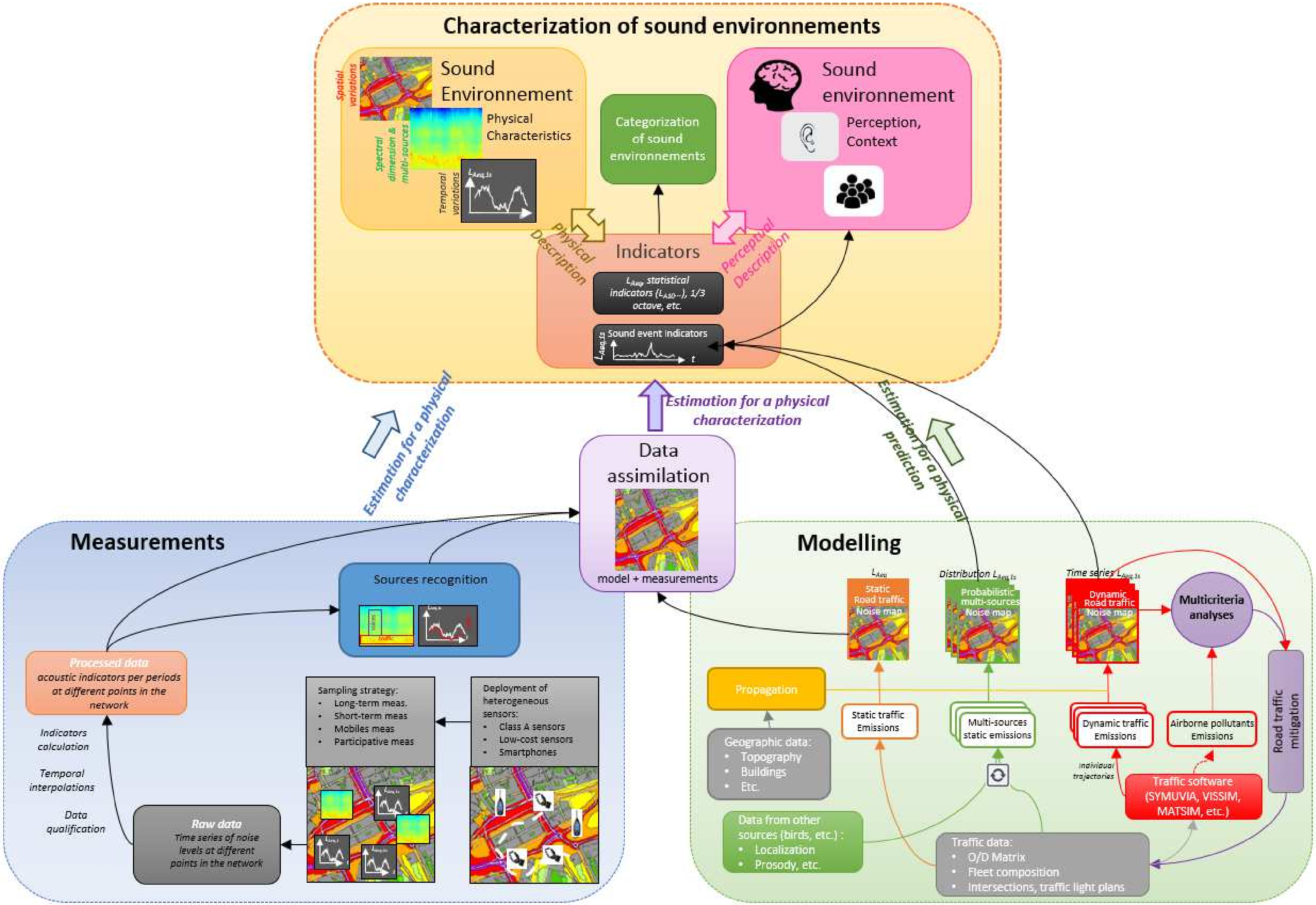


Figure 0:1 Schematic representation of research activities

The document follows this structure, with a chapter devoted to each of these three areas of research. Each of these three chapters forms an entity and can be read independently of the other two; each provides an overview of current research, with a focus on the work to which I have contributed. This research is part of the projects and activities supervision to which I have participated. Finally, each of the axes of research is guided by an operational objective. In summary:

- Chapter 1 focuses on the characterization of urban sound environments. The operational objective of this research is to propose acoustic indicators that capture the specificities of sound environments in their physical and perceptual dimensions and allow the determination of impacts. At the same time, these indicators must be estimable through both measurement and modelling.

  In addition to a literature review, the works presented in this chapter are partly part of the GRAFIC (see details p.139) and EUREQUA projects, and are based on the critical review work carried out as part of the book chapter [OS1] and the conference paper [INV2];

- Chapter 2 focuses on measurement networks and on combined approaches associating measurement and modelling for the characterization of urban sound environments. The operational objective of this research is to propose strategies for sampling and processing the data collected in order to estimate accurately the indicators of interest. Data assimilation between measures and predictive models also aims to improve the estimation of these indicators.

  In addition to a literature review, the work presented in this chapter is partly part of the CENSE and GRAFIC projects (see p.138 and p.139), and is based in part on the theses of Jean-Rémy Gloaguen (Ifsttar / LS2N) on "Estimation of the noise level of sources of interest within urban noise mixtures: application to road traffic" (see p.140), and Antoine Lesieur (Ifsttar / INRIA) on "State estimation and inverse modelling applied to noise pollution in urban areas" (see p.141), which I co-supervised;

- Chapter 3 focuses on multi-physical couplings for traffic noise prediction and mitigation. The operational objective of this research is to develop couplings between noise prediction models and traffic models, to enable the evaluation of strategies to improve urban noise environments by acting on mobility. The models developed must meet different spatial scale requirements according to the strategies considered and be part of a broader multi-criteria evaluation objective.

  In addition to a literature review, the work presented in this chapter is partly based on my thesis work at LICIT (Ifsttar / ENTPE) and my post-doctoral work at Ghent University. More recent collaborations with LICIT (Ludovic Leclercq, Cécile Bécarie, Delphine Lejri), and the work done with Pierre Aumond within UMRAE, have also enriched the chapter. Finally, the thesis started in 2018 by Sidi Mehdi Regragui under my co-supervision on "Estimation of rare events in environmental acoustics" (Ifsttar / Université Cergy-Pontoise, see p.142) is part of this research theme.

A final discussion, focusing on the directions of research in urban environmental acoustics that I believe would benefit from being followed in the medium and long term, concludes the document.

Remarks on the document

- Each chapter contains a summary: reading the three summaries, respectively p.16, 48 and 81, can give the reader an overview of both the context and my research directions;
- Each chapter is self-sufficient and can therefore be read independently (this explains why there is no cross-referencing between chapters);
- References are grouped at the end of the document, p.123;
- The productions to which I have contributed are underlined in the text;
- A summary of the productions to which I have contributed is available at the end of the document, p.145.

Chapter 1 Proposal of indicators for the characterization of urban noise environments

Summary

Increasing urbanization is exacerbating noise exposure problems, simultaneously intensifying emissions and concentrating populations where noise levels are high. The repercussions in terms of deterioration of quality of life and health impacts are significant. The means to address the noise issue exist, but the development of appropriate indicators is needed to describe noise environments and evaluate noise mitigation strategies.

The specificity of the noise pollution problem lies in the complexity of human hearing and the subjective nature of the assessment, as well as in the high spatial and temporal variability and the rich spectral content of the noise generated. The wide variety of sources that compose urban sound mixtures is an additional factor of complexity. At the interface between these different dimensions, it is necessary to rely on indicators that reflect the physical characteristics of sound environments and their perceptual impacts, to improve description and decision-making.

Unfortunately, the indicator used by the legislation, L_{den}, does not meet all the conditions for characterising precisely noise environments. In particular, it fails in underlining various aspects that research in environmental acoustics has recently highlighted, such as the perceptual importance of the temporal structure of sound environments. This justifies the use of new indicators, such as statistical indicators or emergence indicators.

In this context, this chapter aims to compare the indicators from the literature for applications related to the characterization of urban sound environments. We will be particularly interested:

- In the physical description of urban sound environments;
- In a review of the main indicators of environmental acoustics;
- In the categorization of urban sound environments;
- In the perceptive and sanitary dimension of urban sound environments;
- In the operational use of indicators in studies that deal with the improvement of noise environments.

The chapter concludes with a comparison of the main indicators for the characterization of urban noise environments, according to the following three criteria: (i) the ability of the indicators to describe and physically categorize urban noise environments, (ii) the relevance of the indicators to capture how urban noise environments are perceived, (iii) the ability of the indicators to be estimated using conventional or more advanced traffic noise prediction models. The discussion compares the advantages and disadvantages of the selected indicators in an operational context.

Note: *In addition to a literature review, the work presented in this chapter is partly part of the GRAFIC (see p.139 for a detailed description) and EUREQUA project, as well as the critical review work carried out as part of the book chapter [OS1] (see p.155 for a summary).*

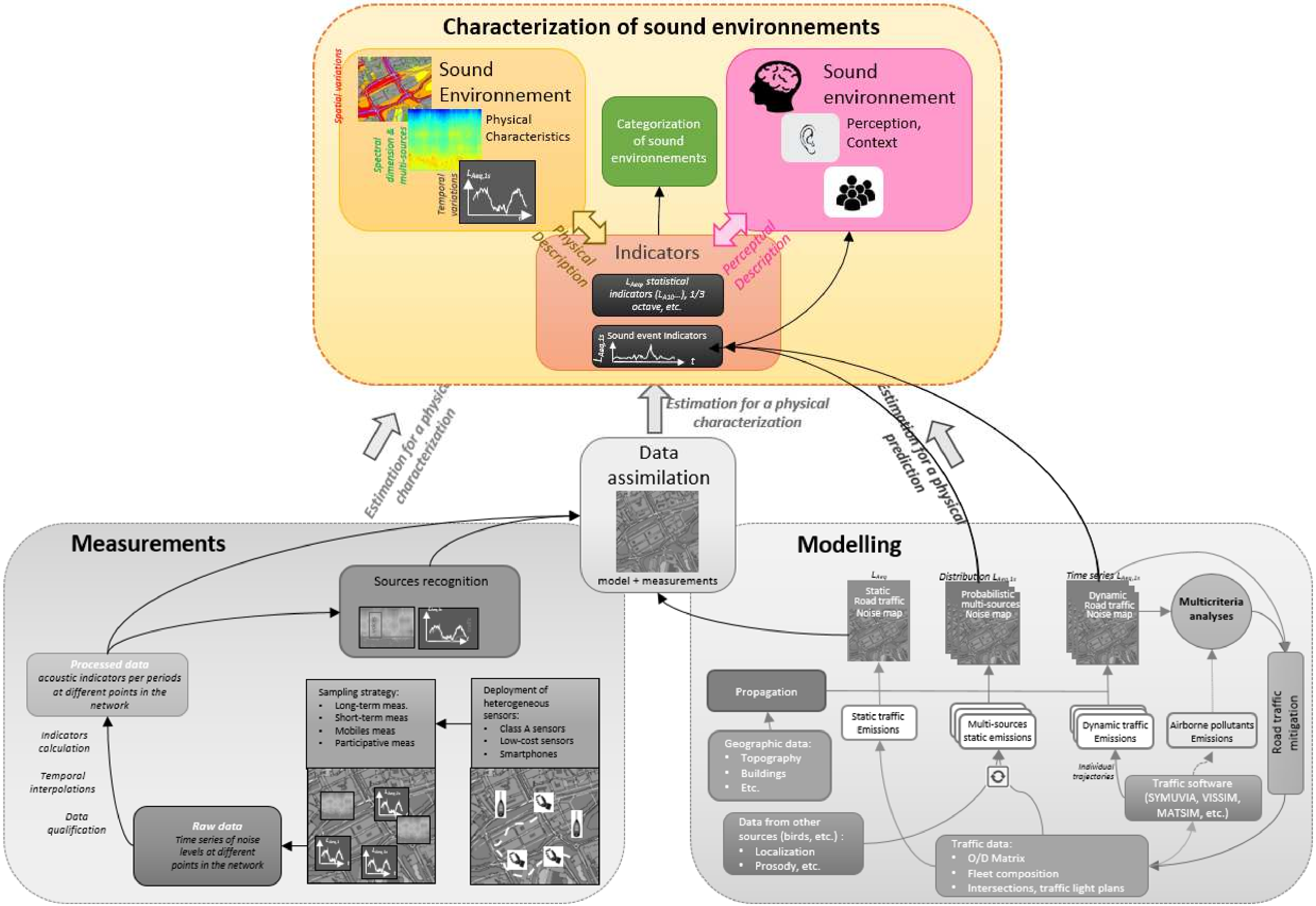


Figure 1:1 Schematic representation of research activities: focus on research axis 1

1.1 Introduction

The repercussions of noise in terms of deterioration of quality of life and health impacts are significant (Lercher, 2011; WHO, 1997; WHO, 2011). In Europe alone, more than 210 million citizens are exposed to harmful noise levels, resulting in a dramatic cost to society, estimated at more than 40 billion euros per year (Den Boer & Schroten, 2007). The means to fight noise exist, but the development of appropriate indicators is necessary to describe noise environments, estimate the effects of noise and evaluate noise control policies.

The complexity of human hearing and subjective assessment (Fastl & Zwicker, 2007), as well as the high spatial and temporal variation and rich spectral content of the noise generated, are dimensions to be taken into account in the description process. Urban sound mixtures are also composed of a wide variety of sources, each perceived differently, which is an additional factor of complexity (Gloaguen *et al.*, 2017). As a result, a wide variety of indicators has been proposed to encompass all these dimensions; the reader can refer to Marquis-Favre *et al.* (2005) or Can (2015) for a detailed review. Choosing among these indicators those that are most relevant in the urban context is a necessary work to improve the description of noise environments and decision-making with a view to reducing noise.

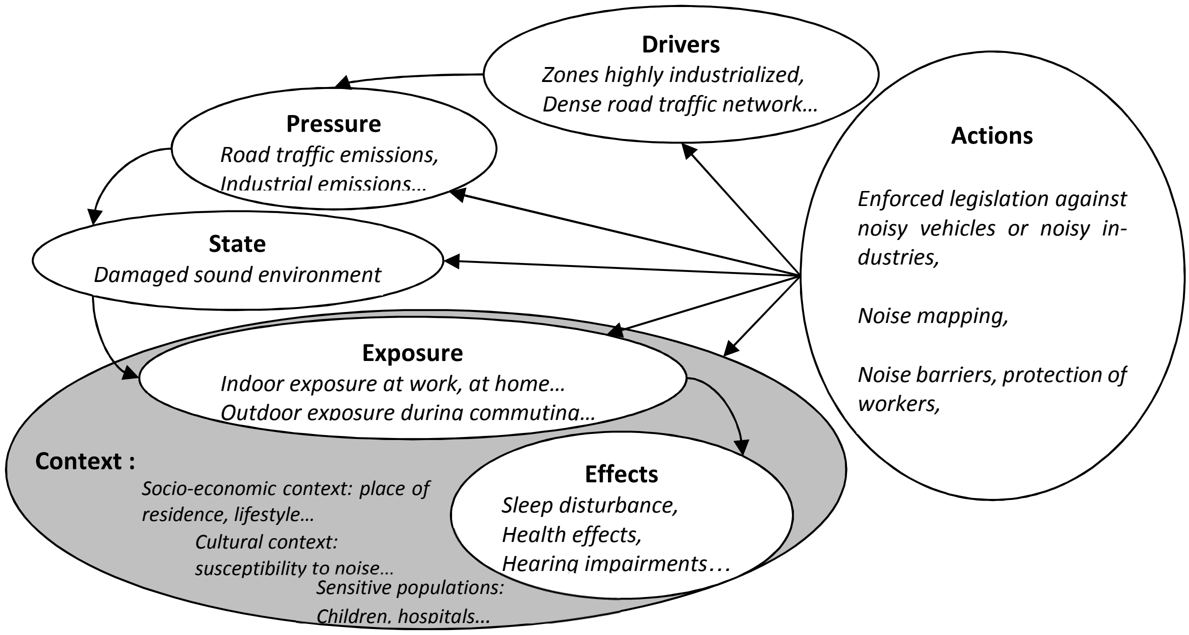


Figure 1:2 DPSEEA Model in the noise pollution context

The DPSEEA model (for "Drivers, Pressure, State, Exposure, Effects, Actions"), which has been proposed to design a system of environmental health indicators in the context of decision-making (WHO, 2004), can guide this choice. The causal chain of noise pollution is illustrated in Figure 1:2 with some examples. It advocates acoustic indicators that can: (i) highlight the characteristics of the sound environment (pressure and state on Figure 1:2), (ii) capture exposures (spatial and temporal distribution of noise, in accordance with the mobility of urban dwellers that are the targets of these exposures) and (iii) quantify the effects. However, these three points can lead to very different indicators. For example, the description of sound environments may use, as shown in section 1.3, indicators that are so refined that no action can be assessed through these indicators. Another example is that there may be a gap between the indicators relevant to describe physically sound environments and those relevant from the point of view of exposures and effects.

A comparison of acoustic indicators was carried out during the implementation of the European Directive 2002/49/EC, which led to the proposal of the L_{den} (European Commission, 2000). However, this comparison focused mainly on evaluations and long-term effects, for which indicators based on energy averages, such as L_{den}, offer satisfactory results (Miedema & Vos, 1998). New paradigms for the evaluation of urban sound environments have emerged since then. There is now a consensus on the need to develop holistic assessments of urban places, including perceptual effects (Kang & Schulte-Fortkamp, 2017). In addition, new noise prediction models have since emerged that make it possible to estimate more refined indicators that are sensitive to temporal variations in noise levels (Leclercq & Lelong, 2001; De Coensel *et al*., 2005; Can *et al.*, 2008; Aumond *et al.*, 2018). Finally, the physical description of urban sound environments has evolved towards integrative approaches, introducing for example sound categorization to spatially or temporally discriminate sound environments (Torija *et al*., 2013; Can & Gauvreau, 2015), or the characterization of noise events (Can *et al*., 2015; Brown & De Coensel, 2018).

This chapter provides a comparison of existing indicators in this new paradigmatic context. The comparison is based on the following three criteria: (i) the ability of the indicators to describe and discriminate physically between urban noise environments, (ii) the relevance of the indicators to capture the perceptual effects of urban noise environments, (iii) the ability of the indicators to be estimated by conventional or more advanced traffic noise prediction models. Before this comparison, the physical characteristics of urban sound environments are presented, as well as the main acoustic indicators (section 1.3). Follows a presentation of the methods to categorize sound environments (section 1.4). A review of the links between these indicators and its effects is then made (section 1.5). This is followed by a review of the use of acoustic indicators in the noise mitigation context (section 1.6). Finally, a discussion on the selection of indicators for the characterization of sound environments closes the chapter (1.7).

1.2 Physical characteristics of urban sound environments

1.2.1 The different physical dimensions of sound environments

“Sound" is the auditory sensation generated by an acoustic wave. By extension, the "sound environment" will be the "sound" heard in a place during a given period; the notion of temporal evolution is thus emerging to describe a sound environment. It should be noted that the notion of sound environment is restrictive compared to that of "soundscape" introduced by Raymond Murray Schafer in (1979) and widely used, which describes "the sound environment as perceived, experienced or understood by one or more persons, in its context" (ISO 12913-1:2014). In contrast, the term "sound environment" describes the acoustic signal independently of the context.

The best way to capture a sound environment is its listening *in situ*. On the contrary, the physical description of a sound environment requires a recording of the acoustic signal, based on which a set of acoustic indicators are calculated. The role of indicators is then to reduce the large amount of information contained in the acoustic signal, in order to allow description and help in decision-making. The objective is then for these indicators to report on the elements that would emerge from the listening.

Describing sound environments through indicators is not trivial: potentially very rapid temporal variations in sound levels, and the very large range of values that sound levels can take, must be captured. In addition, the specificity of sound environments lies in their spectral dimension, as the ear can perceive the pitch of sounds, low or high.

These characteristics of acoustic signals impose the following requirements in the definition of indicators:

- Large amplitude of sound levels: The physical manifestation of sound perceived by our ear, the organ of hearing, is a variation in atmospheric air pressure around its average value. The human ear is sensitive to a very wide range of pressure variation, from the hearing threshold p_0 = 20 µPa to pressures of about 200 Pa, the ear's destruction threshold, that is a range of 10^7. The logarithmic scale has been generalized in the acoustic community to reduce this domain and work with more easily understood quantities. The sound pressure level L_p is expressed in decibels dB as follows: $L_p = 20\log\left(p/p_0\right)$ where *p* is the acoustic pressure. Thus, the noise levels encountered range from 0 dB (human hearing threshold at a frequency of 1000 Hz) to about 140 dB, between which the characteristic noise levels often cited are about 30 dB for a quiet park, 75 dB for a noisy street or 110 dB for a concert.
- Spectral dimension: The specificity of noise pollution, which distinguishes it from any other, is its spectral dimension. Natural sounds have very high frequency pressure variations that can be decomposed into a sound spectrum, distinguishing between low and high frequencies (see Figure 1:3). This decomposition corresponds to the processing of the signal operated by the human ear, which perceives sounds in the frequency range from about 20 Hz to 20 kHz, with maximum sensitivity for frequencies between 1 and 4 kHz (Fastl & Zwicker, 2007). It is crucial to consider this spectral dimension when describing sound environments, as the phenomena of sound emission and propagation are frequency dependent. The norms reduce the spectral component of noise in octave bandwidth or 1/3 octave bandwidth, as defined by AFNOR EN61260 (AFNOR, 1996). Octave bands are defined by their center frequency $f_c = \sqrt{2} * f_{inf} = f_{sup}/\sqrt{2}$, with f_{inf} and f_{sup} the octave band boundaries, and range from 63 Hz to 8 kHz (ISO, 1997). Frequency weighting functions have been introduced to reduce the frequency content to a single value. The most common function is A-weighting, which reproduces the ear's response at 40 dB (Beranek, 1988). Although recommended by legislation, this weighting is often criticized for being based on much lower noise levels than those encountered in environmental acoustics, thus underestimating the impact of low frequencies (Fastl, 1997), which generate increased annoyance (Berglund *et al.*, 1996).
- Rapid temporal variations: Noise exposure durations that cause adverse health effects can be very short (less than 100 ms for gunshots). It is therefore crucial to define carefully the integration time τ on which the noise is evaluated. Environmental noise indicators are generally calculated from the values $L_{eq,\tau}$ (or $L_{Aeq,\tau}$ if the A-weighting is used). The most common integration periods are τ = 1s (S-weighting (for "slow") and or τ = 125ms (F-weighting (for "fast")), ISO (1996).

1.2.2 The spectrogram

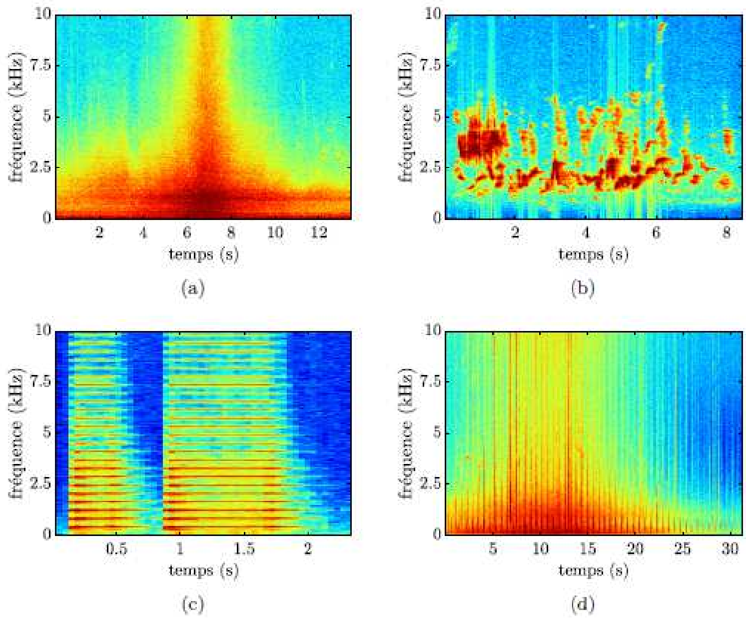


Figure 1:3 Example of spectrograms: a) Car passing by; (b) Birds whistling; (c) Car horn; (d) Footsteps (Source: Gloaguen, 2018).

The most refined representation of a sound environment that can be made is the spectrogram, which represents the sound pressure level (in dB) for each time-frequency pair. Figure 1:3 shows different spectrograms, for example, relating to a car passing by, bird whistles, a car horn and footsteps. The spectrogram allows a precise description of the sounds: the many low frequencies related to the passage of a car, the prosody of the bird whistle, the continuous sound at different pitches for the horn (harmonics), and the repeated activation of all frequencies for the footsteps noise, are information that allows a very clear discrimination between the different sounds.

However, the spectrogram is not an indicator at all. The amount of information it conveys must be reduced for decision making, by capturing essential items. Older measuring instruments *de facto* imposed this reduction because they were unable to capture levels and variations of spectra in the short term and because their storage capacity was limited. These limitations disappear with modern measuring devices (Aflalo & Luquet, 2005), allowing complex noise indicators to be calculated.

1.2.3 Multiple temporal variations in sound environments

This section provides a simple analysis of an urban noise environment to illustrate the need for physical acoustic indicators. Figure 1:4 shows the evolution of $L_{Aeq,1s}$ over a 24-hour period, for a point located at 69 Boulevard Auguste Blanqui, in the 13th arrondissement of Paris, measured as part of the Grafic project. Two elements differ from the $L_{Aeq,1s}$ time series: (i) the high variability of the 1s sound levels, and this in the very short term (black curve), (ii) the slower variations in noise levels (red curve), highlighting the alternation at the daily scale between low and high levels. The temporal evolution of noise levels also highlights the many noise peaks, with the number of peaks exceeding 80 dB(A) appearing high. It should be noted that these emergences also sometimes occur during the night period: this is the case for example for the noise peak observed at 1:09, reaching almost 90 dB(A) during a very quiet period. Note that this peak, by its intensity, has an influence on the $L_{Aeq,1h}$ of the period of interest (see red curve); this element will be discussed in section 1.3.

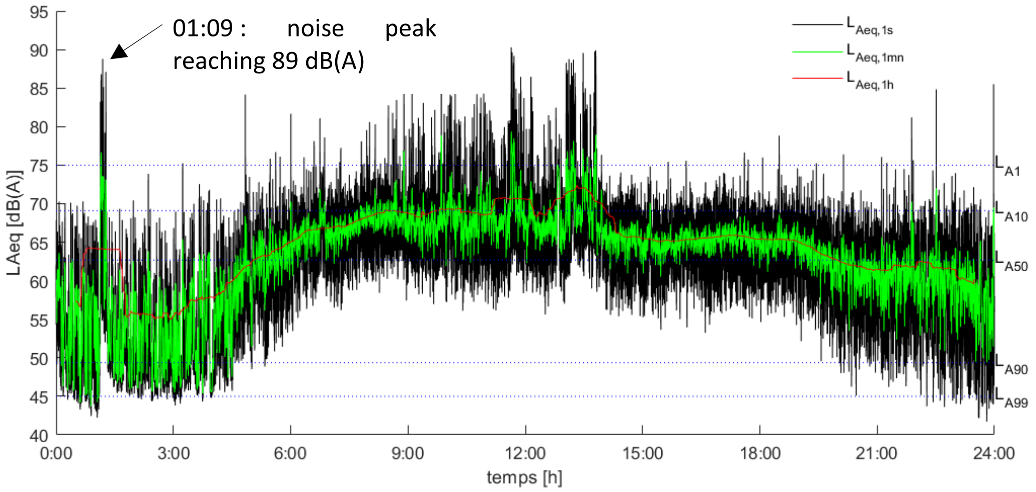


Figure 1:4 Evolution of the $L_{Aeq,1s}$ at a Paris XIII measurement point, over a period of 24-hours (69 boulevard Auguste Blanqui, day of March 2, 2015). Source of measurements: Lavandier *et al.* (2017).

Figure 1:5 shows the same evolution, but focusing on the period [9:00-10:00], during which the average level ($L_{Aeq,1h}$, red curve) is relatively stable. This focus highlights the many noise peaks, one of which even exceeds 90 dB(A) at 9:51. A more detailed analysis of the evolution of the $L_{Aeq,1s}$ shows that an alternation between calm and noisy periods seems to be emerging.

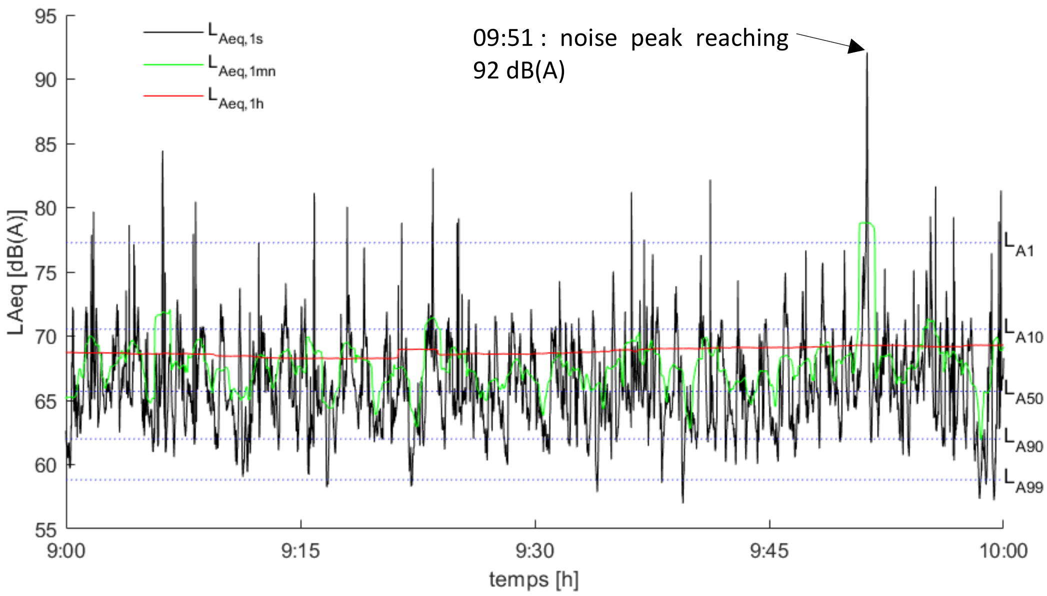


Figure 1:5 Evolution of the $L_{Aeq,1s}$ at a Paris XIII measurement point, over a period of 1 hour (69 boulevard Auguste Blanqui, day of March 2, 2015), period [9:00-10:00]). Source of measurements: Lavandier *et al.* (2017).

Figure 1:6, which focuses on the period [9:45-9:55], highlights the fact that this alternation between quiet and noisy periods is periodic, repeating itself at a period just over 1 mn. This periodicity can be explained very well by the location of the measurement point, placed on a Boulevard where vehicle flows are clocked by traffic lights. This alternation between quiet and noisy periods is characteristic of some urban roads.

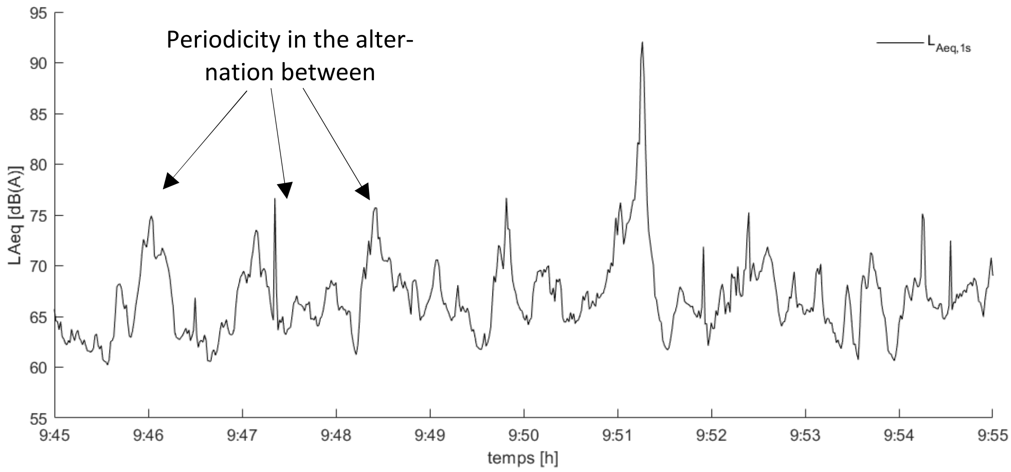


Figure 1:6 Evolution of the $L_{Aeq,1s}$ at a Paris XIII measurement point, over a period of 10 mn (69 boulevard Auguste Blanqui, day of March 2, 2015, period [9:45-9:55]). Source of measurements: Lavandier *et al.* (2017).

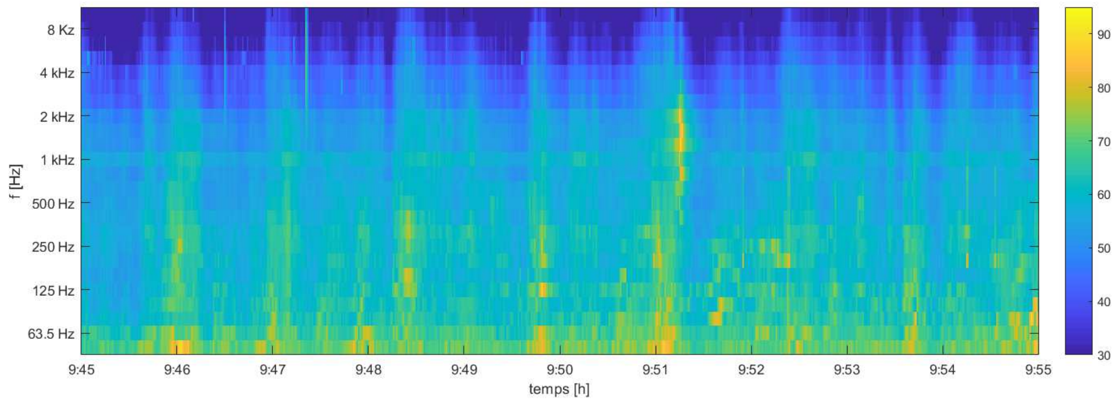


Figure 1:7 Evolution of the $L_{eq,f,1s}$ by octave band *f*, at a measurement point of Paris XIII , (69 boulevard Auguste Blanqui), over a period of 10 mn (day of March 2, 2015, period [9:45-9:55]). Source of measurements: Lavandier *et al.* (2017).

Finally, Figure 1:7 details the evolution of $L_{eq,f,1s}$ for each octave band *f*, with *f* between 50 Hz and 10 kHz. This new representation shows the differences in levels as a function of frequency. Road traffic noise, which predominates at the measurement point, contains a lot of energy at low frequencies. The figure also highlights the fact that variations in overall $L_{Aeq,1s}$ levels may be due to emergences in various frequency bands. For example, the noise peak observed at 9:51 has a maximum energy between 1 kHz and 2 kHz; it may be due, for example, to braking noise from the overhead metro passing near the measurement point. This last remark highlights a point not mentioned so far: sound environments are the juxtaposition of a multitude of sound sources. Perceptual studies show that, beyond sound levels, the sound sources heard play a predominant role when an individual is asked to describe a sound environment (Lavandier & Defreville, 2006). Section 1.5.1.3 will focus on the different ways of including this diversity of sources in the description of urban noise environments.

This simple description of a sound environment highlights the different characteristics of urban sound environments. The indicators described in section 1.3 have been proposed in the literature to capture these characteristics.

1.3 Critical review of the main indicators

A large number of indicators have been proposed in recent decades to measure noise pollution; this review is limited to noise indicators for the outdoor environment:

- The reader can refer to Bradley (2011) or ISO 3382-1 for more details on indoor indicators, developed with more qualitative criteria (speech intelligibility, etc.). A review of the indicators dedicated to building insulation can be found in ISO-717-2;
- The review is limited to physical indicators; psychoacoustic indicators have been developed to better reproduce human hearing. The reader may refer to Fastl (1997) for a detailed description of the loudness, fluctuation force, or acuity indicators. These indicators often provide interesting results for characterizing isolated sound sources, but their contribution to environmental acoustics is often questioned. They also have the disadvantage of being calculated on a very detailed description of the signal (wav format) which is not compatible with all measurement networks and is not accessible yet through modeling;
- Finally, it should be noted that the study is limited to indicators dedicated to the assessment of effects on humans. A wide variety of specific acoustic indicators have been proposed in the context of bio-acoustics, described in Retamosa Izaguirre *et al.* (2018).

The most common general noise indicators are referenced in the following sections, with an analysis of their descriptive power. For a more detailed review of the calculation of indicators, the reader may refer to Picaut (2009). Finally, it should be noted that this review could not be exhaustive, as a large number of indicators are proposed for the specific needs of certain studies, few of which remain with time.

1.3.1 Energetic indicators

Energetic indicators are used to characterize the total noise dose. The equivalent continuous sound pressure level $L_{eq,T}$, defined in ISO 1996-1, expresses the level of a continuous noise that would have the same total acoustic energy as a fluctuating noise measured for the same specific period T:

$$L_{\mathrm{eq,T}} = 10\log_{10}\left(\frac{1}{\mathrm{T}}\int_0^T \frac{p^2(t)}{p_0^2}dt\right) \quad [dB] \qquad \text{Equation 1:1}$$

The indicator $L_{Aeq,T}$ corresponds to the equivalent continuous sound pressure level when the frequency filter A is applied to the pressure levels. This indicator has been widely used, and is supported by studies that have shown its rather good correlation with long-term effects or annoyance (Schultz, 1978; Miedema & Vos, 1998).

Energetic indicators provide information on the total sound level, but they give the same value regardless of the temporal structure of the sound environment. A given indicator value can then correspond to very different sound environments in terms of noise variations and thus in perceptual terms. Figure 1:8 gives an example; the two artificial time series plotted have the same $L_{Aeq,T}$, but correspond to completely different sound environments: the left time series is characterized by very stable levels, while the right time series is characterized by fluctuating levels, continuously increasing with the presence of four marked noise peaks, of different durations and intensities.

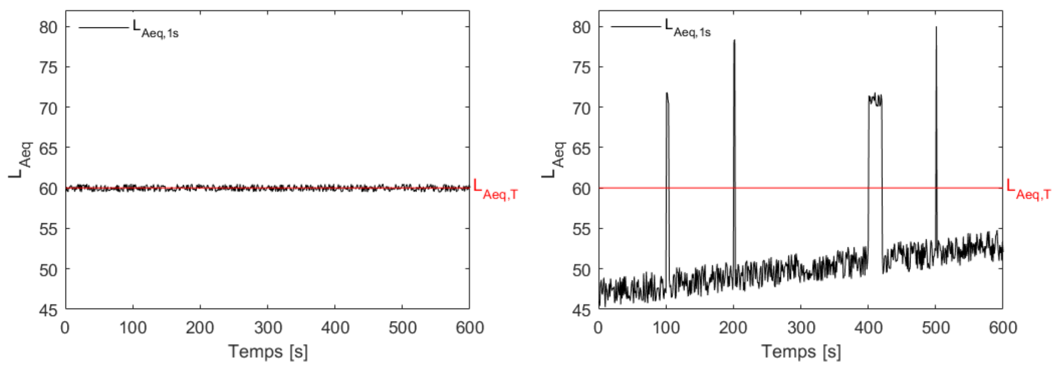


Figure 1:8 Two different $L_{Aeq,1s}$ time series for the same $L_{Aeq,T}$

The equivalence of $L_{Aeq,T}$ over the two time series plotted in Figure 1:8 is largely due to noise peaks, which greatly influence $L_{Aeq,T}$ values due to the energy average used in the calculation of L_{Aeq}. This point of caution in the calculation of L_{Aeq} values calculated over short periods in unstable sound environments is recalled by Alberola *et al.* (2005). Figure 1:4 gives another example: $L_{Aeq,1h}$ over the period [1:00-2:00] are largely impacted by the emergence at 1:09. The impact of emerging noise on the calculated L_{Aeq} is shown in Figure 1:9. For example, a noise emerging of 30 dB(A) compared to the background noise for 0.1% of the time (e. g. the noise of a strong acceleration of a motorcycle for 4s over a period of 1h) increases the $L_{Aeq,1h}$ by 3 dB(A) [1]. This simple calculation illustrates the sensitivity of the L_{Aeq} measured to noise peaks.

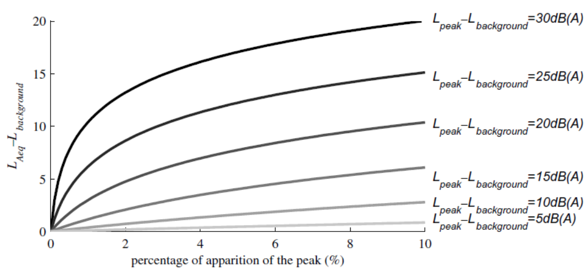


Figure 1:9 Influence of the duration and intensity of an emergence on the value of L_{Aeq}. Source: Can *et al.* (2008).

[1] $L_{eq} = 10.log\left(0.999 * 10^{L_{eq,ini}/10} + 0.001 * 10^{L_{eq,ini}+30/10}\right) \approx L_{eq,ini} + 3$

Composite indicators

Composite noise indicators have been developed from L_{Aeq} to focus on different periods of the day:

- The night level L_{night}, represents the equivalent sound pressure level during the night period (22h-6h in France);
- The equivalent "Day-Evening-Night" L_{den} level, adopted by the European Union within the framework of Directive 2002/49/EC, is calculated on the basis of the equivalent levels over the three base periods: day, evening and night, to which major corrective terms are applied, taking into account a criterion of increased sensitivity in relation to the period. Thus, 5 dB(A) is added in the evening (period [18h-22h] in France) and 10 dB(A) at night (period [22h-6h] in France). The L_{den} is calculated as follows:

$$L_{den} = 10log\left(\frac{12.10^{\frac{L_d}{10}}+4.10^{\frac{L_e+5}{10}}+8.10^{\frac{L_n+10}{10}}}{24}\right), \qquad \text{Equation 1:2}$$

where L_d, L_e et L_n are respectively the equivalent levels during the day, evening and night periods.

1.3.2 Statistical indicators

The percentiles of the $L_{Aeq,1s}$ level distribution are a widely used indicator in environmental acoustics; they are used to describe the range of variation of sound levels. For example, L_{10}, a level exceeded 10% of the time, is often used to characterize road traffic noise. It is interesting to note that the British CRTN ("Calculation Road Traffic Noise") method proposes instead of L_{den} the use of $L_{10,A,18h}$, which is the arithmetic mean of the 18 values of $L_{10,A,1h}$ from 6:00 to midnight, to present road traffic noise exposures (UK, 1988). Relationships have been proposed to link $L_{10,A,18h}$ values to L_n and L_{den} values (O'Malley *et al.*, 2009).

However, each statistical descriptor describes only one point of the $L_{Aeq,1s}$ distribution and therefore a descriptor value can also correspond to very different sound environments. In addition, two criticisms can be made regarding their ability to describe variations in sound levels: (i) statistical descriptors do not allow to characterize the rate of variations in sound levels (slow or fast, regular or irregular, etc.), (ii) analysis of their meaning is often difficult, as the percentile values do not necessarily correspond to elements of the sound environment (Can *et al.*, 2008). The artificial time series drawn in Figure 1:10 illustrate point (i): a high L_{A10} value may for example correspond to a chaotic sound environment (left), a calm sound environment but with a long noise event (middle), or a calm sound environment but with multiple but short noise events (right).

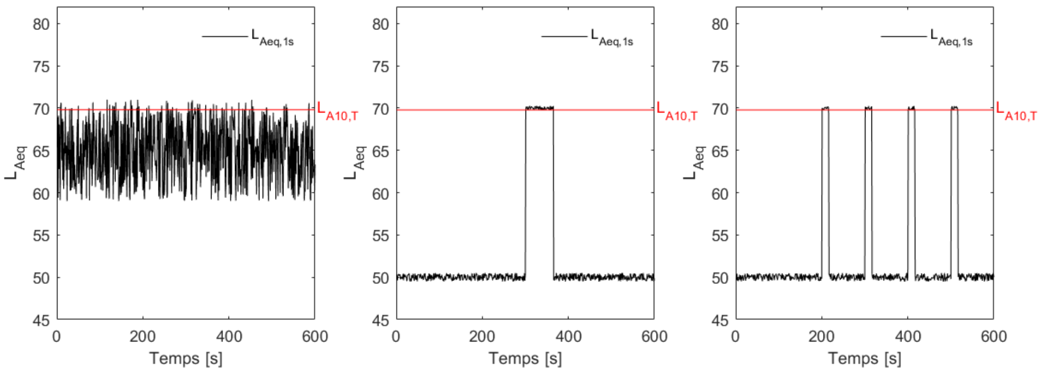


Figure 1:10 Three different $L_{Aeq,1s}$ time series for the same $L_{A10,T}$.

Figure 1:4 illustrates point (ii): if the $L_{A10,24h}$ corresponds approximately to the $L_{Aeq,1h}$ during the daytime period, the $L_{A90,24h}$ is difficult to relate to an element of the temporal evolution of noise levels over the 24h period. This point highlights the fact that it seems irrelevant to calculate statistical indicators over a period of time during which the noise environment is not stable. Their calculation over a shorter period, as presented in Figure 1:5, therefore offers *a priori* more information. However, two limitations are easily highlighted: (i) the L_{A1} is not a good descriptor of noise events, which are much higher; (ii) it seems difficult to describe here the background noise from the L_{A90}.

1.3.3 Event indicators

The indicators "Number of noise events" (NNE) and "Mask Indexes MI" (Mask Indexes MI) are often used to describe noise events. The NNE and MI are respectfully defined as the number of events per unit of time, and the percentage of time that exceeds a given threshold. The threshold can be a fixed value (e.g. 70 dB) or can be adjusted adaptively, for example based on a noise indicator (e.g. $L_{Aeq+10dB}$, $L_{10+10dB}$). Depending on the thresholds chosen, these indicators can be defined to describe noisy or silent periods, and seem more appropriate than the indicators mentioned above to describe variations in sound levels. Nevertheless, each of the NNE or MI offers only a partial view of the noise events: the NNE takes the same value regardless of the duration of the events, and the MI takes the same value regardless of the number of events. For example, the three time series plotted in Figure 1:10 have a MI_{70} of 10% (the $L_{Aeq,1s}$ exceeds 70 dB(A) for 10% of the time since L_{A10} = 70dB(A)), but the number of sound events $NNE_{70,1s}$ is respectively 3.9/mn (39 exceedances in 10 mn), 0.1/mn (1 exceedance in 10 mn) and 0.4 (4 exceedances in 10 mn).

In addition, the calculation of the NNE and MI can take different forms. In the calculation example for Figure 1:10 proposed above, all exceedances were counted, even those with a duration of 1s (i.e. $NNE_{70,1s}$). Different algorithms to detect and count noise events within a $L_{Aeq,1s}$ time series can give very different values of NNE and MI; exceedance times of 1s, 3s, or 5s are regularly encountered. If a duration of 5s is used to account for noise events, the $NNE_{70,5s}$ of the three time series plotted in la Figure 1:10 are $NNE_{70,5s}$ = 0, $NNE_{70,5s}$ = 0.1/min and $NNE_{70,5s}$ = 0.4 /min, respectively. An algorithm for generalizing the definition of noise events has recently been proposed by Brown & De Coensel (2018).

Finally, the two indicators MI and NNE can be merged into a noise events map that also takes into account the threshold (Can *et al.*, 2015). An example of a map is shown in Figure 1:11. This new representation makes it possible to distinguish between short and longer noise events (abscissa axis), as well as the intensity of noise events (y-axis). For example, Figure 1:11 distinguishes between the noise events observed at the two measurement points: the point corresponding to the graph on the left is characterized by a larger number of intense but short noise events ($L_{A50+15dB}$ and duration of 1s), and the one on the right by a larger number of long but not very intense noise events ($L_{A50+3dB}$ and duration of 4s). However, the notion of indicator is lost in such a representation, which would deserve an additional level of information reduction to make it easier to interpret.

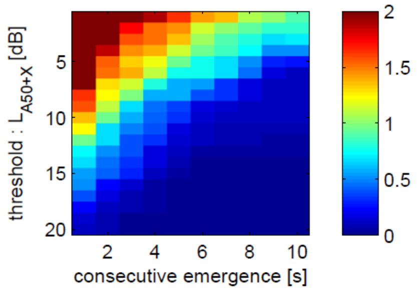


Figure 1:11 Noise events, defined according to the threshold (L_{A50+X}), with X varying between 0 and 20 dB(A) and the duration above the threshold required for the noise event to be counted (with durations varying between 0 and 10 dB(A). 2 measurement points located in the same district of Toulouse are represented; on the left: point located in a noisy street; on the right: point located in a quiet street. Source: Can et al. (2014b).

1.3.4 Specific indicators for road traffic

Specific indicators, dedicated to describing the temporal evolution of road traffic noise, have been proposed over the last two decades. These indicators follow the development of dynamic models for the prediction of road traffic noise, which are able to estimate time series of $L_{Aeq,1s}$ in contrast to traditional approaches. These time series then highlight notions of roughness and rhythm in urban sound environments, due to the traffic flow dynamics, which may have a perceptual impact (Lavandier *et al.*, 2000; Gille *et al.*, 2016).

In particular:

- Indicators were already introduced in the 1970s to describe road traffic noise, which is characterized by high fluctuations, particularly in urban areas (Nelson 1987). Griffiths and Langdon (1968) proposed a specific Traffic Noise Index (TNI) to take into account the increase in annoyance due to these fluctuations: $TNI = 4 * (L_{10} - L_{90}) + L_{90} - 30$. Robinson (1971) proposed to take into account the effect of noise distribution as a whole by using the standard deviation σ_{Leq} of the $L_{eq,1s}$ values, through the "Noise Pollution Level" $NPL = L_{eq} + 2.56\ \sigma_{Leq}$. However, this index is based on Gaussian assumptions about $L_{Aeq,1s}$ distributions, which are not always adapted to urban traffic noise (Don & Rees 1985). These indicators, which are not widely used today, are nevertheless good examples of the desire to take fluctuations into account when assessing road traffic noise. It should be noted that the standard deviation σ_{LAeq} was then only accessible based on measurements; this indicator has regained interest since the development of dynamic models for the prediction of road traffic noise. At equivalent L_{Aeq} level, σ_{LAeq} makes it possible, for example, to discriminate between the noise environment of a ring road, to which a weak σ_{LAeq} will correspond, and an urban boulevard, to which a high σ_{LAeq} will correspond;

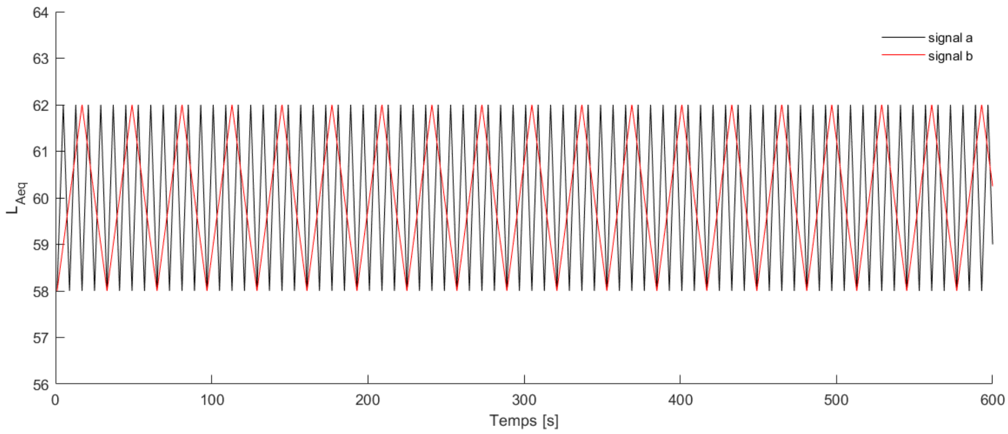


Figure 1:12 Two time series with the same σ_{LAeq} but a different $\overline{\delta_{LAeq,1s}}$.

- Following on from σ_{LAeq}, indicators to highlight the speed of changes in noise levels have recently been introduced. Indicators that highlight changes in noise levels at the second scale (presented as an indicator of sound roughness) have been introduced by Defrance *et al.* (2010), by calculating statistics on noise differences $|\delta_{LAeq,1s}|$ between consecutive $L_{Aeq,1s}$ values. The most commonly used is the average $\overline{\delta_{LAeq,1s}}$ of $\delta_{LAeq,1s}$ values, but the spreading of the distribution of $\delta_{LAeq,1s}$ has also been proposed. Figure 1:12 shows an example of two time series with the same σ_{LAeq} (1.2 dB(A)), but two different values of $\overline{\delta_{LAeq,1s}}$ (respectively 1 dB(A) and 0.25 dB(A) for signals *a* and *b*): so the $\overline{\delta_{LAeq,1s}}$ here highlights the fact that noise variations are slower for signal b than for signal a. However, it may be difficult to highlight this result, observed here on artificial signals, on real $L_{Aeq,1s}$ time series. The criticism can be made that $\delta_{LAeq,1s}$ is highly correlated to σ_{LAeq}, due to the highly structured organisation of urban sound environments, whose noise dynamics are linked to vehicle pass byes and are governed by traffic signals. For the same reasons, the L_{A10}-L_{A90}, describing the amplitude of noise level variations, is sometimes preferred to σ_{LAeq};
- Considering that in many cases the $L_{Aeq,1s}$ time series are very repetitive in urban environments at the scale of traffic cycles, Can *et al.* (2010) have proposed a set of indicators describing the sound environments at this scale. The first proposed indicator is the average noise pattern, of a duration of t_{cycle}, repeating itself at each traffic cycle. This pattern can be reduced to a few indicators, such as average levels during the green and red phases, respectively L_{green} and L_{red} (see Figure 1:13). Additional indicators have been proposed to describe the variations around this average noise pattern, also at the scale of the traffic cycle. For example, $N_{Lmax>80}$ and $L_{max/cycle}$, corresponding respectively to the percentage of cycles for which the maximum level exceeds 80 dB(A) and the maximum average level per cycle, define the noise peaks at the traffic cycle scale. Similarly, $N_{Lmin>60}$ and $L_{min/cycle}$, corresponding respectively to the percentage of cycles for which the minimum level exceeds 60 dB(A) and the minimum average level per cycle, characterize the periods of calm at the traffic cycle scale. Figure 1:13, representing a time series of $L_{Aeq.1s}$ measured near a traffic light intersection, highlights the value of these indicators.

Over the 8 cycles considered, the proposed indicators take the values L_{green} = 71 dB(A), L_{red} = 65 dB(A), $N_{Lmax>80}$ = 37.5%, $L_{max/cycle}$ = 81 dB(A), $N_{Lmin>60}$ = 87.5% and $L_{min/cycle}$ = 62 dB(A), reflecting a noisy noise environment, where in addition the expected quiet periods at each red light period almost systematically disappear, and where noise peaks are very common at the scale of the traffic cycle. This is due to the location of the measurement point, downstream of a traffic light and near a bus stop: restarts and brake noises are regularly added to the more regular noise related to the flow of vehicles downstream of the traffic signal, thus deteriorating the noise environment. It should be noted that, while these indicators provide a very accurate picture of noise variations, they are limited to very rhythmic noise environments, and therefore specific to urban corridors.

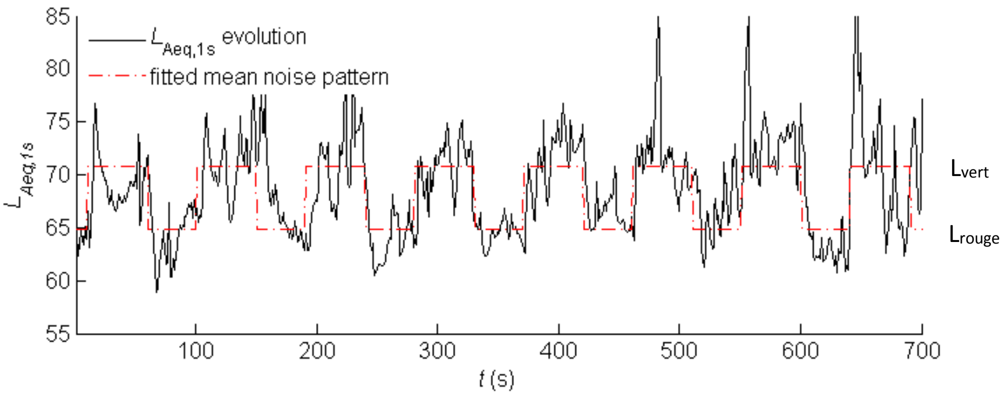
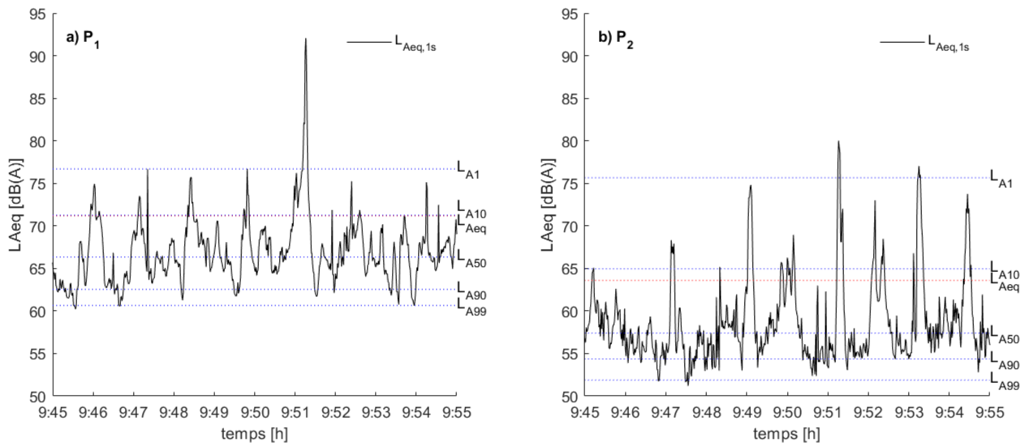


Figure 1:13 Time series of $L_{Aeq,1s}$ measured downstream of a traffic light and near a bus stop. Source: Can *et al.*, 2010.

- The noise rhythm is considered in a global way in (Botteldooren *et al.*, 2006), by calculating the slope of the Fourier transform of the time series of $L_{Aeq,1s}$, based on previous work done in a musical context, which showed that regular spectra were associated with more pleasant sound environments (Voss & Clark, 1978). In the study cited above, the indicator makes it possible to distinguish between sound environments near a roundabout and sound environments near traffic lights, which are more chaotic because of the alternation between stops and restarts;
- An indicator dedicated to the characterization of quiet periods, the CMT (for "Centre of Mass Time") was proposed in Estévez-Mauriz & Forssen (2018), counting the quiet periods (periods during which the $L_{Aeq,1s}$ is lower than the L_{A50} in the proposed example), but giving more weight to long quiet periods than short quiet periods, via the formula: $CMT = sum(a^2)/sum(a)$, where a represents the vector concatenating the duration of quiet periods. The indicator therefore distinguishes between, for example, 10 periods of calm of 1s (which will give a CMT of 10/10=1) and 1 period of calm of 10s (which will give a CMT of 100/10=10). This indicator would benefit from being tested for other thresholds than the L_{A50} in order to qualify periods of calm: fixed thresholds at 55dB(A) or adaptive (the L_{A90} for example), seem relevant.

1.3.5 Example of a description of two sound environments using the presented indicators



	P_1	P_2
L_{Aeq}	71.2 dB(A)	63.6 dB(A)
L_{A1}	76.7 dB(A)	75.7 dB(A)
L_{A10}	71.3 dB(A)	60.5 dB(A)
L_{A50}	66.3 dB(A)	57.4 dB(A)
L_{A90}	62.5 dB(A)	54.4 dB(A)
L_{A99}	60.6 dB(A)	51.9 dB(A)

	P_1	P_2
σ_{LAeq}	3.9 dB(A)	4.9 dB(A)
$\overline{\delta_{LAeq,1s}}$	1.0 dB(A)	1.5 dB(A)
NNE_{75dB}	0.7 / mn	0.2 / mn
MI_{75dB}	3.3 %	1.5 %

	P_1	P_2
MI_{60dB}	100%	26.5%
$NNE_{LA50+5dB}$	1.4	1.6
CMT_{L50}	16.1	13.2
CMT_{60dB}	-	32.3

Figure 1:14 Analysis of the evolution of the $L_{Aeq,1s}$ at two measurement points of Paris XIII, over a period of 10 mn (day of 2 March 2015, period [9:45-9:55]).a) 69 boulevard Auguste Blanqui, b) 3 rue de la Butte aux Cailles. Down: dynamic indicators. Source of the measurements: Lavandier *et al.* (2017).

In this section, we propose to describe two sound environments, whose $L_{Aeq,1s}$ time series are shown in Figure 1:14. Point P_1 corresponds to a point located at 69 boulevard Auguste Blanqui, a busy boulevard in the 13th arrondissement of Paris, crossed by an aerial metro. Point P_2 corresponds to a point located at 3, rue de la butte aux Cailles, a low-traffic street also located in the 13th arrondissement of Paris, not far from the previous point. Although less than 100m apart as the crow flies, the two points present very different sound environments:

- Point P_1 is noisy, with L_{A50} = 66.3 dB(A). It also has pronounced noise events, with 0.7 emergences per minute above 75 dB(A). These noise events have a strong impact on the L_{Aeq}, which is very close to the L_{A10} (71.2 and 71.3 dB(A) respectively). Finally, periods of calm are rare, with the level constantly above 55 dB(A) during the period considered;
- Point P_2 is quiet, with L_{A50} = 57.4 dB(A). The variability of noise levels at the second scale is greater than at P_1, which can be assessed visually by looking at the $L_{Aeq,1s}$ time series; the σ_{LAeq} and $\overline{\delta_{LAeq,1s}}$ are 4.9 dB(A) and 1.5 dB(A) respectively. Point P_2 has some noise events, however

less intense than at P_1, 0.2 noise events per minute exceeding 75 dB(A). However, if an adaptive threshold is used to describe the noise events, such as the $L_{A50+5dB(A)}$, the number of noise events at P_2 reaches 1.6/mn, higher than at P_1. Nevertheless, the L_{A1} at both points is very similar, confirming that this indicator says relatively little about noise event issues. Finally, periods of calm at P_2 are quite common, with MI_{60dB} at 26.5%. In addition, these periods are quite long, with a CMT_{60dB} = 32.3.

This example of characterization of sound environments through some of the indicators presented shows their relevance to describe urban sound environments. However, their large number can make analysis difficult. It should be recalled that this presentation cannot be exhaustive, and that most of the indicators presented here to describe the evolution of the $L_{Aeq,1s}$ can also be calculated for 1/3 octave bands, multiplying the number of indicators available to describe sound environments. For example, 418 indicators are calculated in Can & Gauvreau (2015).

Finally, this presentation highlights the fact that no indicator can be considered as bad or good to highlight variations in sound levels, but that on the contrary each indicator is appropriate to describe one aspect of the $L_{Aeq,1s}$ time series. Consequently, no single indicator can describe a sound environment on its own and it is towards the use of a set of complementary indicators that descriptions must be oriented. The reduction of this large number of indicators into a limited number of indicators, characterizing all the items of interest in the $L_{Aeq,1s}$ and $L_{f,1s}$ time series, can then be based on the strong correlations that may exist between the indicators.

1.4 Categorisation of urban sound environments

The use of categorization methods in environmental acoustics has become more common over the last decade. The primary objective is to reduce the number of indicators used to describe sound environments and to summarize them into a set of indicators that describe all their dimensions. Then, the selected indicators are used to determine classes of homogeneous sound environments. The interest of a classification of sound environments is multiple:

- Make the description of sound environments more readable by replacing indicators that are sometimes not easily accessible;
- Avoid a description based solely on the energetic dimension;
- Spatially categorize a study area into classes with the same physical attributes and thus the same assumed perceptual attributes;
- Understand the temporal structures of sound environments, highlighting which periods are similar.

For example, Liu *et al.* (2013) used a classification method to show that spatial variations in sound environments can be explained by land use characteristics, while temporal variations are due to the temporality of human activities.

1.4.1 Reduction in the number of indicators

The principle of reducing the number of indicators is to rely on redundant information (high correlations) between indicators to reduce the number of indicators used:

- In Torija *et al.* (2013), semantic and physical indicators are used to categorize sound environments. A discriminating technique uses 14 indicators to effectively describe sound environments, namely the Crest Factor (CF), defined as the ratio between the maximum sound pressure and the root mean square value of the sound pressure (Torija *et al.*, 2011b), frequency indicators $L_{eq,25Hz}$, $L_{eq,31.5Hz}$, $L_{eq,125Hz}$, $L_{eq,500Hz}$, $L_{eq,630Hz}$, $L_{eq,800Hz}$, $L_{eq,5kHz}$, $L_{eq,10kHz}$, $L_{eq,16kHz}$ and $L_{eq,20kHz}$, statistical indicators L_{A1} and L_{AImin} (minimum A-weighted sound pressure level with pulse response), and L_{Aeq}. Among these indicators, the study reveals that the CF and $L_{eq,125Hz}$ had the greatest impact on the differentiation of soundscape typologies. It should be noted, however, that the FC does not seem to give rise to repeatable measurements, since it is based on maximum levels, which are known to be very random;
- The number of indicators used to discriminate sound environments is reduced to three in Can & Gauvreau (2015), based on a hierarchical ascendant classification algorithm using the Ward method. This reduction to three indicators is mainly because the frequency indicators are "summarized" in the Spectral Gravity Center SGC, which however does not emerge among the relevant indicators in Torija *et al.* (2013). The three selected indicators are then L_{A50}, σ_{LAeq} and SGC.
- This selection of three indicators is extended in (Can *et al.*, 2015), where a method is proposed to adapt the description and selection of indicators to the spatial scale of interest. To "zoom in" on the noise event indicators, the same classification procedure is proposed, which selects three indicators, namely L_{A1}, $MI_{LA50+10}$ and $MI_{LLF50+15}$[2]. It should be noted that the event indicators, namely $NNE_{L>L\alpha}$ and $MMI_{L>L\alpha}$, are also useful for describing sound environments in Brocolini *et al.* (2013).

Due to the strong correlations between the indicators, this categorization work cannot be read as a selection of the indicators that must be used; it only provides information on those indicators that should not be used together because of a very high correlation between them.

1.4.2 Spatial categorisation

The categorization approach first requires defining what a homogeneous class of urban noise environment is. For the categorization task, a sound environment can be defined as:

- A "location during a given period": the sound environments at this location during a daytime period and a night time period are likely to constitute two different classes; this approach therefore makes it possible to highlight the seasonal variations of sound environments in a place (Can *et al.*, 2015b);
- A "location": two locations with similar noise levels during a daytime period, but very different during a night time period, will then belong to different classes; this is for example the approach followed in Can & Gauvreau (2015).

Figure 1:15 proposes an example of categorization of an urban area based on three indicators (L_{A50}, σ_{LAeq} and SGC), based on measurements taken in a district of Toulouse at different times of the day

[2] $MI_{LLF50+15}$ is th Mask Index for low frequencies (grouping the 1/3 octave bands between 20 and 125 Hz in this study), and having the L_{LLF50} +15 dB threshold.

(Can & Gauvreau, 2015). It should be noted that the originality of the study lies in the fact that here the categorization is based on mobile measurements, thus allowing a continuous categorization of the area. The study highlights four classes of sound environments, distributed over the study area, with singular acoustic properties. Note in this example the distinction between categories G3 and G4, which is not based on the L_{A50} noise level, but on the SGC, which is higher for category G4 because of its proximity to trees (bird noise). The method therefore makes it possible here to highlight singularities of the sound environments to which the energy dimension is not sensitive.

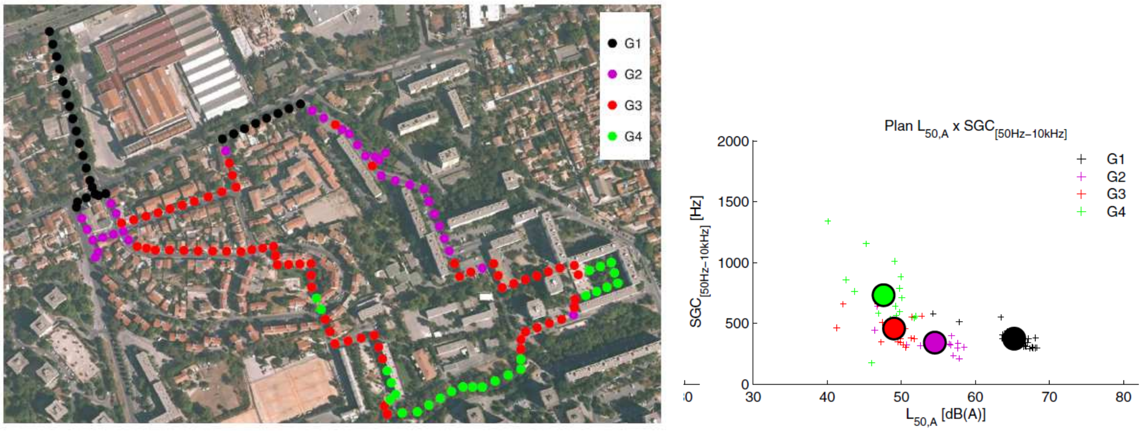


Figure 1:15 Example of categorization of a given area according to sound environments. a) Spatial categories. b) Acoustic description of the categories. Source: Can & Gauvreau *et al.* (2015).

The number of defined sound environment classes can vary from 3 to 20, depending on the starting corpus and the statistical method used. The statistical methods used to categorize sound environments are very varied: variance analyses in Di Gabriele *et al*. (2011), Kohonen's maps in Brocolini *et al*. (2013), discriminant analyses in Torija *et al*. (2013), support vector machines (SVM) in Torija *et al.* (2014), hierarchical ascendant classification in Can & Gauvreau (2015).

In the example presented in Figure 1:15, the classes are highly site-dependent. It is to be expected that by extending the study area to the ring road located near the study area, a new group would appear, defining the noise environment near the ring road that is noisier and with low noise level variations. Some authors advocate the definition of universal sound environment classes with their own characteristics; this is the case, for example, of Rychtarikova & Vermeir (2013), which proposes 20 sound environment classes, such as "sound environment dominated by road traffic noise and sirens" or "noise from fountains and birds".

From a slightly different perspective, Oldoni *et al*. (2013) propose a methodology that allows an "acoustic summary" of a sound environment, automatically classifying the typical sounds heard in a location, based on Kohonen maps: each new element introduced into the sound environment triggers potentially neurons on the map. The stated objective of modelling is then to be able to evaluate the perceptual effects associated with the introduction of new sounds.

Finally, it should be noted that alternative approaches have also been proposed to move away from the calculation of acoustic indicators and directly classify sound environments based on functional variables. The objective is then to define a priori the type of noise environment expected according to these variables: street categories in Barrigon Morillas *et al.* (2005), or landscape indices in Liu *et al.*

(2013). One of the advantages of these approaches is, for example, to define a priori the best locations of sensors within a measurement network, with the aim to avoid putting several sensors in similar spots.

1.5 Acoustic indicators and noise effects assessments

The relevance of indicators to assess the perceptual or health effects of noise should guide their selection for the characterization of urban noise environments. L_{den} is the indicator recommended by legislation to evaluate urban noise environments. Energetic indicators, including L_{den}, are known to show good correlations with annoyance over the long term, and dose/response curves have been established to link the number of annoyed or very annoyed people as a function of L_{den} levels, for different different transportation noise sources: road, rail and air traffic (Miedema & Vos, 1998). However, these curves were constructed based on surveys, in particular those listed by Schultz (1978) and Fidell *et al.* (1991), where only energetic indicators were considered. These results therefore do not allow us to conclude on the relative relevance of the energetic indicators compared to the other indicators for evaluating long-term annoyance, even if these have allowed a first estimate of the number of people annoyed by noise in their homes. This issue will be discussed in section 1.5.2. Section 1.5.1 focuses on the perceptual characterization of sound environments.

1.5.1 Indicators and perceptual characterisations

1.5.1.1 Insufficiency of energetic indicators for perceptual characterizations

Weaknesses of energetic indicators have been highlighted in several studies concerning the perceptual evaluation of urban noise environments. Indeed, they alone cannot explain all the variance in the pleasantness of noise environments:

- They are unable to assess fluctuating sounds (see section 1.3.1), which are very frequent in urban areas and have a negative impact on how noise environments are perceived (Schomer, 2005; Fujii, 2002). In particular, noise peaks should be given more attention according to Björkmann (1988). Labiale (1983), for example, has shown the need to include indicators related to the number of events to describe annoyance in low-noise environments. Another example, Trollé *et al.* (2015) showed the perceptual differences between roundabouts and intersections with traffic lights due to different noise dynamics;
- The spectral dimension is also important when it comes to perceptually assessing sound environments: the presence of low-frequency noise increases annoyance (Berglund *et al.*, 1996), as does the presence of tonal components (Beaumont & Petitjean, 2003). Finally, the A-weighting is not necessarily appropriate to describe the perceived noise pollution, in particular because the annoying levels in environmental acoustics are at much higher levels than those to which the A-weighting has been defined, and the ear is more sensitive to low frequencies at these high levels. Thus, the L_{eq} is often more relevant than the L_{Aeq} for perceptual assessments (Rey Gozalo *et al.*, 2015).

Moreover, the relationship between L_{eq} and the pleasantness of sound environments is far from linear; it is demonstrated in Rey Gozalo *et al.* (2015) that if high L_{eq} values are associated with annoyance, low

L_{eq} values can correspond to both pleasant and unpleasant perceptions, depending on the characteristics of the sound sources. It is therefore not surprising that the L_{Aeq} is often not the most appropriate indicator for estimating the pleasantness of sound environments: the L_{Aeq} is surpassed in this task by the L_{A50} and the N_{10}[3] in Ricciardi *et al.* (2015) and Axelsson *et al.* (2010) respectively.

Starting from the observation that energetic indicators do not capture all the perceptual dimensions of sound environments, several authors have concluded that perceptual evaluation should be based on more qualitative and multidimensional approaches, whether for the evaluation of urban sound environments (Notbohm *et al*., 2004; Raimbault *et al*., 2003; Nilsson & Botteldooren 2007) or rural ones (De Coensel & Botteldooren, 2006). Therefore, just as the physical description of sound environments often highlights three dimensions of noise (see Section 1.4.2), it has been demonstrated that at least three perceptual dimensions, namely intensity, noise variations and noise spectrum, emerge when assessing urban sound environments (Lavandier *et al*., 2000), thus involving a wider range of indicators.

Models have been proposed over the past two decades to link the pleasantness of sound environments to physical indicators, based on linear regressions (Lavandier & Defreville, 2006), principal component analyses (Raimbault *et al*., 2003; Axelsson *et al*., 2010) or neural networks (Ricciardi *et al.*, 2015). They make it possible to define the relevant indicators from a perceptual evaluation perspective. Multi-dimensional evaluation of sound environments often points to L_{50}, Spectral Gravity Center SGC and $\sigma_{LAeq,1s}$ or L_{10}-L_{90} as complementary indicators (Ricciardi *et al*., 2015; Lavandier *et al*., 2000). However, studies have shown that $\sigma_{LAeq,1s}$ is sometimes poorly correlated with the sound pleasantness (Axelsson *et al*., 2010; Aumond *et al.*, 2017).

Finally, specific psycho-acoustic indicators were tested in parallel for the evaluation of sound environments. Rådsten Ekman *et al.* (2015) showed that the force of fluctuation could explain the eventful nature of a soundscape, which is an independent dimension of the "pleasantness" dimension (Axelsson *et al*., 2010). Acuity, generally well correlated with the Spectral Gravity Center, characterizes the presence of fountains for Rychtarikova & Vermeir (2013), but does not allow discriminating between the different types of fountains for Rådsten Ekman *et al.* (2015). However, the use of psychoacoustic indicators for environmental assessment is questionable, because of the often-great difficulty in estimating them: their calculation often requires a finer sampling than the $L_{eq,f,1s}$ time series (the reader can refer to Fastl (1997) for a more detailed review of psychoacoustic indicators). This excludes them from any calculation based on the outputs of a traffic noise prediction model, even a dynamic one, or even a calculation based on the outputs of some measurement networks.

1.5.1.2 Influence of the temporal structure of sound environments on perceptual assessments

Understanding the influence of the temporal structure of sound environments on perceptual evaluations is necessary, since there is a possibility that the aggregated indicators may not capture the assessment of the pleasantness of a sound scene that could depend instead on parameters such as the order of events in the scene. In a dynamic approach, these possible biases may affect the pleasantness of a trip in an urban environment. For example, the same trip taken in the opposite direction may

[3] Zwicker soundness, expressed in sones (ISO 532 :1975B), exceeded 10% of the time.

possibly appear more pleasant. Research in the field of psychology, psycho-acoustics and soundscape has shown that the retrospective overall judgment of a sound scene is not simply an average of instantaneous judgments, but is significantly influenced by the following main temporal effects (more details can be found in Steffens & Guastavino (2015):

- The recency effect, whereby the initial and final momentary judgments of a sequence are more memorized at the time the retrospective evaluation is given, has been observed for sound sequences by Västfjäll (2004) and Susini *et al*. (2002);
- The "peak and end" effect, which stipulates that the overall judgment of an experiment is influenced by the most intense point and the end (negative or positive perception), was observed in (Ponsot *et al.* , 2003; Fiebig & Sottek, 2015);
- The trend effect, which describes the fact that people often make predictions about the future based on trends they have observed in the past, has been demonstrated by Steffens & Guastavino (2015), on a corpus of various 1-minute long samples.

The main studies that have focused on the retrospective evaluation of time-varying acoustic signals have often focused on the perception of sound intensity, on highly controlled stimuli (pure sounds, white noise, specific sound sources, etc.), or on short sound sequences. The evaluation of retrospective global judgments, such as the pleasantness of sound environments during urban travel, were studied in Aumond *et al.* (2017 ; 2017b), showing that recency effects are present for short sound scenes (about 1mn) but tend to disappear for the evaluation of long sound scenes (about 15 mn). Thus, the calculation of indicators over time ranges of around 15 minutes can make it possible to assess the pleasantness of the sound environments over this period.

1.5.1.3 Source-oriented indicators and perceptual evaluations

The description in section 1.4.2 of the sound environment classes, such as the description "sound environment dominated by road traffic noise and sirens" by Rychtarikova & Vermeir (2013), underlines the interest of source-oriented approaches. Indeed, it is often the sound sources rather than the overall sound levels that emerge from perceptual studies *in situ* when people are asked to describe sound environments. Thus, some studies have shown that the pleasantness of sound environments can be advantageously linked to perceived sound sources: high correlations with technological or natural sounds are observed in Nilsson & Botteldooren (2007) and Axelsson *et al.* (2005), and the presence time of road traffic, birds and voices appear in Lavandier & Defreville (2006). Hong & Jeon (2015) show that the evaluation of soundscapes depends on the adequacy between the sound sources present and the functionality of the location.

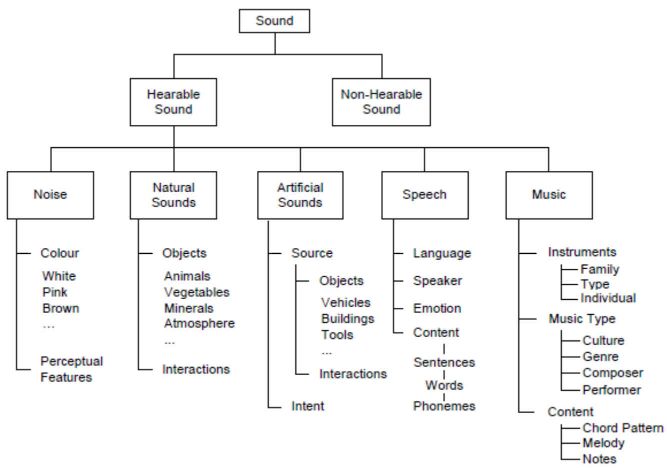
Source taxonomy

An evaluation of sound environments highlighting the sources heard requires a questioning of their classification. For example, is a horn or door slamming noise part of road traffic noise? Work on source taxonomy guides this reflection. The classifications obtained are then very dependent on the context (urban vs. nature, alert vs. atmosphere) and the objectives set by the authors:

- Very precise classification focused on the distinction between biophony, geophony and anthropophony for Krause (2008), whose aim is to observe the impact of human activities on the animal world by going as far as a distinction between the species heard. It should be noted that the distinction between biophony, geophony and anthropophony is very common in the analysis of soundscapes;

- Categorization based on physical phenomena in Gaver (1993): vibrating objects, aerodynamic noises, liquid noises, etc;
- Object oriented categorization for Guastavino (2006) (voices, children, footsteps, etc.), for Dennis (2014) ("vehicles", "animals"), or for Salamon *et al*. (2014 ("cough voice", "drilling noise", "sawing noise");
- Human activities oriented categorization in Brown *et al.* (2011) ("construction noise", "road traffic", "spoken voice", etc.);
- Action-oriented categorization in Liu *et al.* (2013), distinguishing between anthopophonic sounds ("adult voice, rolling bike, etc."), biophonic sounds ("bird song, barking dog, etc.") and geophonic sounds ("rain, blowing wind, etc.");
- Categorization guided by a linguistic approach in Dubois *et al.* (2006), highlighting the fact that some sounds are categorized by sources or actions according to their function or context, even though they correspond to the same sound heard.

In the analysis of sound environments, it seems relevant to rely on an object-oriented description (which is therefore similar to the "action" oriented approach). Guastavino (2006) shows that this is the approach used by people who are asked to describe a sound environment. For example, the taxonomy proposed by Liu *et al*. (2013) seems appropriate: see Figure 1:16.



Main-class	Sub-class
Anthrophony (Anthro)	Airplane flying
	Adult voice
	Bicycle riding
	Bell ringing
	Child voice
	Construction sound
	Emergency
	Footsteps
	Grass mowing
	Motorcycle rumbling
	Music
	Ship moving
	Train moving
	Traffic sound (foreground)
	Traffic sound (background)
	Other anthropogenic sound
Biophony (Bio)	Bird song
	Chicken clucking
	Dog barking
	Insects
	Frog
Geophony (Geo)	Grass rustling
	Raining
	Sea waves
	Tree rustling
	Wind blowing
	Water sound

Figure 1:16 Example of sound taxonomies. Left: Environmental sound taxonomy proposed by Dennis (2014). Right: Urban sound taxonomy proposed by Liu *et al*. (2013).

Source-oriented indicators

The estimation of the presence of sources using physical parameters is necessary to assess the pleasantness of sound environments based on physical indicators. Such indicators are used in the modelling proposed in (Aumond *et al.*, 2017):

- Perceptual variables related to the presence of road traffic can be approximated by indicators such as $L_{50,63Hz}$, $L_{50,125Hz}$ or $L_{50,250Hz}$;
- The presence time of birds and voices can be approximated by $TFSD_{mean,4kHz}$ and $TFSD_{mean,500Hz}$ respectively, which are the second time and frequency derivatives centered on the octave bands at 4kHz and 500Hz. These two indicators were specifically proposed in this study; they highlight variations in temporal and spectral sound levels at a given frequency.

Thus, the indicators dedicated to the description of a given source offer a targeted view that is more representative of the spectral dimension of the sources than the spectral center of gravity. Nevertheless, as with any other indicator, there is the question of their estimation through models.

Towards a recognition of sources

Beyond the source-oriented indicators, which were calculated based on time series of $L_{f,1s}$, the development of source detection models offers the possibility of directly linking the perceptual indicators describing the presence and intensity of sound sources to their actual presence and intensity in the audio signal. Figure 1:17 illustrates two examples of spectrograms made up of several sources: the role of the source recognition model is then to estimate, based on the spectrogram, physical indicators related to the detected sources. It then becomes possible to build a model that directly links the pleasantness of noise environments to indicators describing the sources detected.

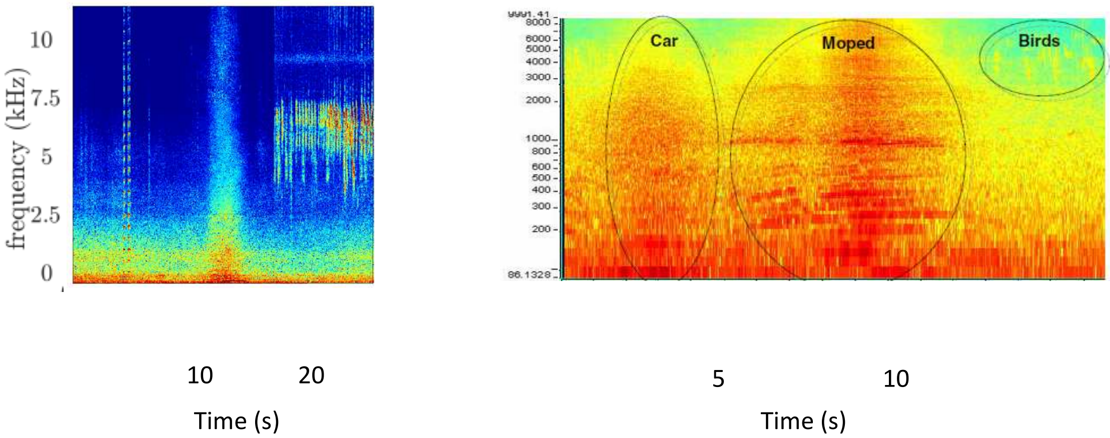


Figure 1:17 Example of spectrograms composed of several sources. Left: spectrogram composed of a vehicle passing noise, a horn, and a bird whistle (Source: Gloaguen *et al.*, 2018). Right: spectrogram composed of a vehicle, a moped and birds (Defréville, 2006).

The most common approach is to describe the signal using a set of descriptors and then train a detector, which often consists of a neural network classifier (Defréville *et al*., 2006) or Gaussian mixture model (Ntalampiras, 2014), based on annotated data. Based on training data, the model learns which source to associate with descriptor values, and is then in principle able to detect in a new signal the presence of learned sources for each time frame (time frames are usually of a duration of about 50 ms). Ntalampiras (2014) thus detects abnormal events such as screams or gunshots. In Masaros (2010), 61 environmental sounds are detected in real audio scenes: applause, horn, dog barking, etc. The detection of abnormal events is also carried out in Socoro *et al.* (2017) or Salamon & Bello (2015), each time oriented towards typical environmental sounds (barking, shooting, sirens). However, while event detection methods can be useful in urban noise monitoring networks (for example, to detect warning signals), they are very often built around characteristic signals that are quite far from the sounds that impact the perceived quality of sound environments. An exception: in Defréville (2006), it is indeed sound sources such as car, moped, voice or birds that are recognized with good performance, but on isolated sounds that do not overlap.

The other disadvantage of detection approaches is that they are not appropriate for urban sound mixtures with strong temporal overlaps. This is the case, for example, of the sounds forming the spectrogram presented in Figure 1:17a: the vehicle's passage is superimposed on footsteps and then on the whistling of birds. In Gloaguen *et al.* (2018 ; 2018b), a method for managing overlaps, based on Non-negative Matrix Factoring (NMF), is proposed to determine the level of traffic noise within urban noise mixtures. The method also has the advantage of determining the relative levels of two overlapping sounds. The extension of the method, currently validated on road traffic noise, to a broader corpus of sources, would allow the estimation of indicators specific to the presence of each source impacting the quality of urban noise environments.

1.5.1.4 Multiphysical indicators and perceptual assessments

Finally, many studies on soundscapes show that perceptual assessments of sound environments are not limited to the acoustic dimension. Ricciardi *et al.* (2015) have shown that external variables, describing visual amenities or familiarity of environments, affect the pleasantness of sound environments. Viollon *et al.* (2002) demonstrated the strong influence on the assessment of a sound environment of the adequacy between the sound and visual environment. Jeon *et al.* (2011; 2013) also highlighted the influence of visual aspects, light and openness (in the landscape sense) in the evaluation of soundscapes. Finally, individual factors are also taken into account in the assessment of soundscapes, such as age or level of education (Yu & Kang, 2010). Although these indicators are outside the scope of acoustic indicators and therefore outside the scope of this indicator review, these results deserve particular attention in perceptual evaluations.

1.5.2 Indicators and characterization of health effects

The health effects of noise are well documented: cardiovascular effects, cognitive impairments, sleep disturbance, tinnitus, annoyance, etc. The author may refer to the WHO report "Burden of disease from environmental noise. Quantification of healthy life years lost in Europe" published in 2011 for a detailed review (WHO, 2011), which also quantifies for each of these effects the "disability-adjusted life year" (DALY).

Health effects are discussed for transport noise in Lercher (2018). From a physiological point of view, transport noise acts as a stress factor for the nervous system (Evans, 2001), generating two responses of the metabolism: a first anabolic transient adaptation and a second prolonged catabolic one (Ursin & Eriksen, 2004). Noise habituation phenomena therefore exist, but they are only surface: for example, night awakenings are less common, but the quality of sleep remains degraded.

The effects of noise on annoyance or sleep disturbance are often assessed using energetic indicators, using dose-response curves using L_{den} for discomfort (Miedema & Vos, 1998) and L_{night} for sleep disturbance (Basner & McGuire, 2018). This approach was motivated in particular by the ease of access to the spatial distribution of the estimated values of the L_{den} or L_{night} indicators, based on the models imposed by Directive 2002/49/EC. However, noise levels are not sufficient to fully explain the annoyance at home: Lercher (2018) reminds us that the variance explained by L_{den} in the estimation of annoyance is sometimes only 10.6%, as many non-acoustic factors can improve modelling: existence of a quiet facade, taking into account noise sensitivity, speed of road traffic flow, etc. (Guski, 1999; Lercher *et al.*, 2017).

Conversely, the evaluation of wake-up probabilities often involves maximum noise levels ($L_{AS,max}$, maximum value of $L_{Aeq,1s}$) calculated over short periods of time, of about 30 seconds (Basner & McGuire, 2018). This difference in approach, on the one side the energetic levels calculated at night and on the other side the maximum levels calculated over short periods, raises questions about the possibility of linking sleep quality to indicators other than energetic indicators. In addition, if the noise dose, characterized by energetic indicators, remains a good indicator of noise effects for high (>65 dB(A)) noise levels, for intermediate (50-65 dB(A)) or low (<50 dB(A)) levels the ratio between the sound level of events and background noise becomes essential to characterize human response to noise (De Coensel *et al*., 2009), a level difference of 10 dB(A) being sufficient to generate a reaction (Chang *et al*., 2015).

The question of the choice of acoustic indicators to characterize health effects therefore remains open, as the modelling choices using energetic indicators are partly due to their ease of access. In El Aarbaoui *et al.* (2019), indicators other than L_{Aeq} are tested to explain the metabolic variations of 78 participants who wore a dosimeter and devices measuring electrocardiographic activity for 7 days. In particular, the study aimed to identify the acoustic characteristics of personal sound exposure that are most predictive of short-term electrocardiographic response in a real environment and primarily the heart rate variability (HRV) parameters that serve as an indicator of the state of the autonomic nervous system. The study showed that:

- The energetic dimension is not the most appropriate dimension when considering non-auditive sound effects on health; the best ranked acoustic indicators were rather those related to the range in noise levels (L_{10}-L_{90}, L_1-L_{90}, etc.), suggesting that temporal variations in sound levels are more closely related to autonomic nervous system reactions. This result could be explained by the fact that these indicators better encompass the presence of sound events that could trigger startle reactions;
- C-weighted acoustic indicators have for the most part performed better than their A-weighted equivalents (e.g. $L_{50,C}$, $L_{1,C}$-$L_{90,C}$). In addition, negative associations between spectral balance indicators (L_C-L_A) and electrocardiographic results indicate a distinct effect of low-frequency sounds on the autonomic nervous system.

The absence of studies investigating the concomitance between acoustic indicators and non-auditory effects (stress, etc.) prevents the generalization of conclusions on the indicators to be used in this context; it is likely that such studies will become more common in the coming years.

1.6 Acoustic indicators and noise mitigation

The third criterion for noise indicators is their relevance concerning the evaluation of mitigation plans that aim to improve sound environments. Unfortunately, no actual model is able to account for all sound sources to permit a global evaluation and improvement of the sound environment. Instead, models focus on road traffic, which is the main noise source in urban environments. Thus, one will focus here on road traffic mitigation plans, which received much attention in last years and generate a high demand from decision makers.

Typical road traffic estimation models, such as the CNOSSOS (Kephanopoulos *et al*., 2014), are based on a static description of road traffic (mainly volumes and average speeds of vehicle flows), combined with geometric sound propagation calculation. This modeling is dedicated to the evaluation of equivalent acoustic pressure levels, but prevents the calculation of sound level variations. Therefore, they cannot provide an estimate of one of the main categories of noise indicators listed in the previous sections, namely noise event indicators. Even statistical indicators cannot be estimated, as this would require knowing the distribution of $L_{Aeq,1s}$ sound levels. Although they have some limitations, static road traffic models are by far the most widely used representation, so it is important to keep in mind the difficulty of basing the assessment of noise mitigation plans on indicators other than L_{Aeq} or its equivalent per frequency band $L_{eq,f}$. This is problematic given the limitations of these indicators mentioned in section 1.3.1. Recent work aims to link L_{Aeq} indicator to more advanced indicators, such as statistical indicators or event indicators, through statistical modelling that takes into account the characteristics of the site (Michel, 2015; Regragui, 2018). While this initial work shows the potential of such modelling, additional investigations are nevertheless necessary to propose reliable relationships.

Recent advances in sound propagation modelling have opened the door to the calculation of more advanced indicators, and thus to a more detailed assessment of strategies for improving sound environments. Temporal sound propagation models, such as the FDTD (Finite Difference Time Domain) or TLM (Transmission Line Matrix) models, allow the estimation of indicators that were previously dedicated to room acoustics, such as reverberation time (Guillaume *et al*., 2012). This allows for a more qualitative analysis, for example in urban areas far from sources (Forssen & Horniks, 2007). However, despite their good results in perceptually describing the acoustics of a room, the use of indicators such as reverberation time is more questionable in environmental acoustics. In particular, they do not make it possible to describe a sound scene as a whole: being calculated based on impulsive noise, they characterize the sound propagation conditions and architectural characteristics of a site rather than the sound environment as a whole.

In parallel, a new generation of road traffic prediction models has emerged for more than a decade. They are based on microscopic traffic models that represent vehicle trajectories on the network: SYMUVIA in Leclercq & Lelong (2001) or Can *et al*. (2009), HUTSIM in Heltimo et al. (2003), PARAMICS in De Coensel *et al*. (2005), DRONE in Bhaskar *et al*. (2007) or AVENUE in Oshino & Tsukui (2006). Since the outputs of the traffic model are the position, speed and acceleration of each vehicle on the network at each time step (typically 1s), such a modeling allows to estimate the $L_{Aeq.1s}$ time series. It should be kept in mind that this evolution of $L_{Aeq,1s}$ is not the expected result, but the basis of advanced indicators calculation. Indeed, as indicated in section 1.3, the evolution of $L_{Aeq,1s}$ is a necessary intermediate for calculating statistical indicators or sound event indicators. As a result, indicators have been proposed to reflect the dynamics of urban traffic noise, such as the dynamic indicators described in section 1.3.4. Studies have shown that these indicators can be used as a basis for evaluating road traffic regulation strategies, with a view to improving noise environments (De Coensel *et al.*, 2005; Chevallier *et al.*, 2009). It should be noted, however, that the output $L_{Aeq,1s}$ time series of these models is still incompatible with the estimation of psychoacoustic indicators, which would require a more detailed description of the audio signal.

1.7 Discussion

1.7.1 Which indicators to characterize sound environments?

The previous sections have shown the difficulty of identifying an optimal set of indicators to characterize and evaluate urban noise environments. Indeed, indicators are rarely relevant for each of the three criteria listed, namely physical description, assessment of the effects, and estimation through modeling. Moreover, studies do not necessarily converge on the same results and the strong correlations between indicators add a certain partiality to the choices made. Finally, the function of the study area, which influences both the expected sound environments and the uses, may imply a need for different indicators from one place to another. Table 1:1 attemps to summarize the advantages and disadvantages of each of the indicators presented in relation to the three dimensions of interest, in order to guide their selection.

If the evaluation of road traffic mitigation strategies is included in the criteria, either dynamic road traffic modelling is available and almost all indicators can be calculated, or only static road traffic modelling is available, and then the L_{Aeq} indicator appears as the default indicator choice. This is unfortunate, as this indicator is criticized by many aspects: (i) it is not the best indicator to estimate the pleasantness of noise environments; (ii) it only covers the energetic dimension of noise and therefore discriminates rather poorly noise environments. It should be noted that, with regard to health effects, the L_{Aeq} explains only a relatively small part of the annoyance, but the number of studies combining other indicators with the health effects of noise is currently insufficient.

In the case where dynamic road traffic modelling is available, or if the assessment of road traffic mitigation strategies is not included in the indicator selection criteria, the choice remains open to all indicators. The L_{Aeq} can then be advantageously replaced by the L_{A50} or L_{50}, which show higher correlations with the pleasantness of sound environments, and emerge more often from categorization work. It seems necessary to complement these indicators with indicators that reflect the other dimensions of sound environments. The work on the categorization and perception of sound environments emphasizes the importance of relying on the three dimensions of energy, time and spectrum:

- The L_{50} appears to be the best descriptor of the energetic dimension;
- To characterize the amplitude of the sound levels encountered, $\sigma_{LAeq,1s}$ and L_{10}-L_{90} have proved useful in a categorization context, but are not often mentioned as relevant indicators in the perception context. However, no better alternative has yet been proposed;
- To characterize the spectral dimension of sound environments, the Spectral Gravity Center emerged in a similar way from categorization work, but not from perception work. In addition, it is criticized for being too sensitive to events. Preferably, low-frequency indicators, such as L_{125Hz} in Torija *et al.* (2013), or indicators dedicated to sound sources $TFSD_{mean,4kHz}$ and $TFSD_{mean,500Hz}$ proposed in Aumond *et al.* (2017b), could be of interest for both categorization and perception. However, the possibility to estimate the latter two by modelling has not yet been proven. Note that in Aumond *et al.* (2017b) the introduction of TFSD indicators made $\sigma_{LAeq,1s}$ irrelevant, possibly making this last indicator uninteresting.

In addition, the recent interest in noise peaks estimation by dynamic road traffic modelling (De Coensel *et al*., 2016; Can *et al.*, 2007), and their known importance in a perceptual context, underlines their possible interest in conjunction with the other indicators. Then, L_{1A}, $MI_{LA50+10}$ and $MI_{LLF50+15}$, which emerged in Can *et al.* (2015b), could be used. These indicators will however have to be confronted to the health dimension and specifically to awakenings issues, since this is not yet clear which thresholds and number of events indicators should reveal.

Thus, the conclusion of this state of the art could be the proposal of a set of indicators that rely for example on: L_{50}, $\sigma_{LAeq,1s}$, L_{125Hz}, $TFSD_{mean,4kHz}$, $TFSD_{mean,500Hz}$, L_{1A}, $MI_{LA50+10}$ and $MI_{LLF50+15}$. As mentioned above, a similar or reduced set of indicators could of course have similar relevance, and further experiments in particular dedicated to health issues are required. In addition, such a set of indicators, if it improves the description and understanding of sound environments and makes it possible to estimate more precisely the perceptual effects associated with a given urban sound environment, has in counterpart the disadvantage of its lack of enforceability.

1.7.2 Towards composite indicators?

The complexity of existing noise indicators sometimes makes them ineffective as a communication tool. The grouping of complex noise indicators into a single dimensionless indicator (ranging for example from 0 to 10), which combines this set of indicators, could solve this problem. The Harmonica indicator is a good example (Harmonica, 2013), much easier to understand than classical acoustical indicators. Sound pleasantness can as well be seen as a dimensionless indicator ranging from 0 to 10 (Aumond *et al.*, 2017b). However, it seems necessary to extend the research on these composite indicators in order to validate their contribution in terms of communication with local residents and to find the optimal combinations from the point of view of describing noise environments.

Finally, acoustic indicators can potentially be combined with other environmental indicators (greenhouse effect, air pollutants, etc.) to form composite indicators, which can summarize multiple environmental data to support the decision-making process and which the public often finds easier to interpret. Their advantages and disadvantages are discussed in Nardo *et al.* (2005). In particular, statistical analysis and weightings should be carefully considered in order to avoid misleading political messages or missing serious shortcomings in some of the environmental dimensions. Another complementary approach is to include noise in an overall assessment system in which it coexists with environmental and socio-economic indicators, as part of a multi-criteria decision-making or economic analysis (Joumard & Gudmunsson 2010).

		Physical descriptive power	Perceptive descriptive power	Noise mitigation
Energetic Indicators	L_{eq}	☹ Highly impacted by noise peaks ☹ Hides the sound levels dynamics ☹ Same L_{eq} value whatever the sound variation are	☺ Correlated to long term health effects	☺ Estimated with Static modelling
	L_{Aeq}	☹ A-weighting often criticized for underestimating low frequencies at sound levels encountered in cities	☹ A-weighting does not fulfil perceptive requirements	☺ Estimated with Static modelling
Statistical indicators	L_{90}	☺ Describes background noise 😐 Low range of variation in urban context	😐 Does not emerge from studies	😐 Estimated with Dynamic modelling
	L_{50}, $L_{50,A}$	☺ Good for discriminating sound environments	☺ Very good correlation with perceived sound intensity and sound pleasantness; outperforms L_{Aeq}	😐 Estimated with Dynamic modelling
	L_{10}	☺ Describes high noise levels	☺ Outperforms L_{Aeq}	😐 Estimated with Dynamic modelling
	L_{10}-L_{90}, L_5-L_{95}	☺ Describes the amplitude of noise variation (Boulevard vs irregular traffic street)	😐 No consensus concerning the perceptual effects	😐 Estimated with Dynamic modelling
noise variations indicators	$\sigma_{LAeq,1s}$	☺ Describes the width of the sound levels distribution ☺ Good for discriminating sound environments 😐 Assumes a normal distribution of $L_{Aeq,1s}$ values	😐 No consensus concerning the perceptual effects	😐 Estimated with Dynamic modelling
	$\delta_{LAeq,1s}$	😐 Discrimination of traffic situation based on 1-s dynamics, although its discriminative power is not proved	☹ Difficult to handle and relate with effects	😐 Estimated with Dynamic modelling
	Slope of 1s-fft	☺ Discrimination of road traffic situations	☺ In musical context acknowledged as a sound quality descriptor ☹ Further studies required to demonstrate link to sound quality	😐 Estimated with Dynamic modelling
Spectrum indicators	**SGC**	☺ Good for discriminating sound environments based on their spectral content ☹ Highly unstable.	😐 No consensus concerning the perceptive effects	😐 Estimated with Dynamic modelling
	TFSD-mean,4kHz	☹ Never investigated	☺ Related to perceived birds time of presence ☹ Only appears in one paper	☹ No current model allows its estimation
	TFSD-mean,500Hz	☹ Never investigated	☺ Related to perceived voices time of presence ☹ Only appears in one paper	☹ No current model allows its estimation
	L_f , **with** f **frequency of interest**	☺ Related to road traffic time of presence (f=65 Hz,125 Hz) ☺ Good for discriminating sound environments frequency content ☹ Spectrum described through a large number of indicators	☺ Low frequencies and tonal components increase annoyance	😐 Estimated with Dynamic modelling
Emergences indicators	$L_{1,A}$,	☺ Good for discriminating sound environments based on emergences	☹ Never investigated	😐 Estimated with Dynamic modelling
	$MI_{LA50+10}$	☺ Good for discriminating sound environments based on emergences	☹ Never investigated	😐 Estimated with Dynamic modelling
	$MI_{LLF50+15}$	☺ Good for discriminating sound environments based on emergences	☹ Never investigated	😐 Estimated with Dynamic modelling
	CF	☺ Good for discriminating sound environments ☹Based on max values so no repeatable measurements	☹ Never investigated	☹ No current model allows its estimation
	$N_{Lmax>80}$	☺ Good for discriminating sound environments in the vicinity of traffic signals	☹ Never investigated	😐 Really specific to urban corridors
	$N_{L95>65}$	☺ Good for discriminating sound environments in the vicinity of traffic signals	☹ Never investigated	😐 Really specific to urban corridors

Tableau 1:1 Comparative table of the main indicators of environmental acoustics.

Chapter 2 Characterization of urban noise environments: comprehensive approaches combining measurements and modelling

Summary

The growing demand of city dwellers for knowledge and control of sound environments was reflected in the birth of noise observatories in the 1990s. These observatories consist of a network of high-precision sensors, providing local access to a description of sound environments (history of noise levels and main acoustic indicators). The characterization of sound environments has since been hampered by an unprecedented expansion and diversification of measurement methods. The emergence of microelectro-mechanical systems (MEMS), and more recently the possibility of making measurements via smartphones, are changing the way in which sound environments are characterized. Current approaches are based on an increasingly dense distribution of low-cost sensors, or even participatory measurement. The availability of a growing number of collected data, and the heterogeneity of the sensors deployed, then invites us to question new methods of data processing in a context of the intelligent city from which acoustics is no exception: parsimonious sampling strategies, coupling between short-term and long-term stations, data qualification and storage.

At the same time, the way in which sound environments are viewed has also changed: recent research on their perception emphasizes the need to characterize not only sources considered negative, such as road traffic, but also more generally all the sound sources that constitute urban sound environments. This new approach involves multi-source approaches, to which measurement can respond with work on source recognition, and to which modelling is directed too.

Finally, measurement can be advantageously coupled with traditional modelling approaches, through emerging data assimilation approaches, to characterize more accurately sound environments.

In this context, this chapter reviews recent research advances in terms of characterization of urban sound environments by measurement, which lead to comprehensive approaches combining measurement and modelling. We will be particularly interested in:

- Parsimonious sampling strategies;
- The rise of participatory measurement in environmental acoustics;
- Methods of sound source recognition within measurement networks;
- Multi-source approaches for modelling sound environments;
- Data assimilation between measurements and models.

All these approaches suggest that in the medium term, the characterization of sound environments will be much finer than the current one. This will raise the question, beyond the characterization, of

the use of the data produced for the control of sound environments. A discussion on the future of measurement in the mitigation of sound environments concludes the chapter.

Note: *In addition to a literature review, the work presented in this chapter is partly part of the CENSE and GRAFIC projects (see p.138 and p.139 respectively for a detailed description), and is based in part on the theses of Jean-Rémy Gloaguen (Ifsttar / LS2N, description p.140) on "Estimation of the noise level of sources of interest within urban noise mixtures: application to road traffic", and Antoine Lesieur (INRIA / Ifsttar, description p. 141) on "State estimation and inverse modelling applied to noise pollution in urban areas".*

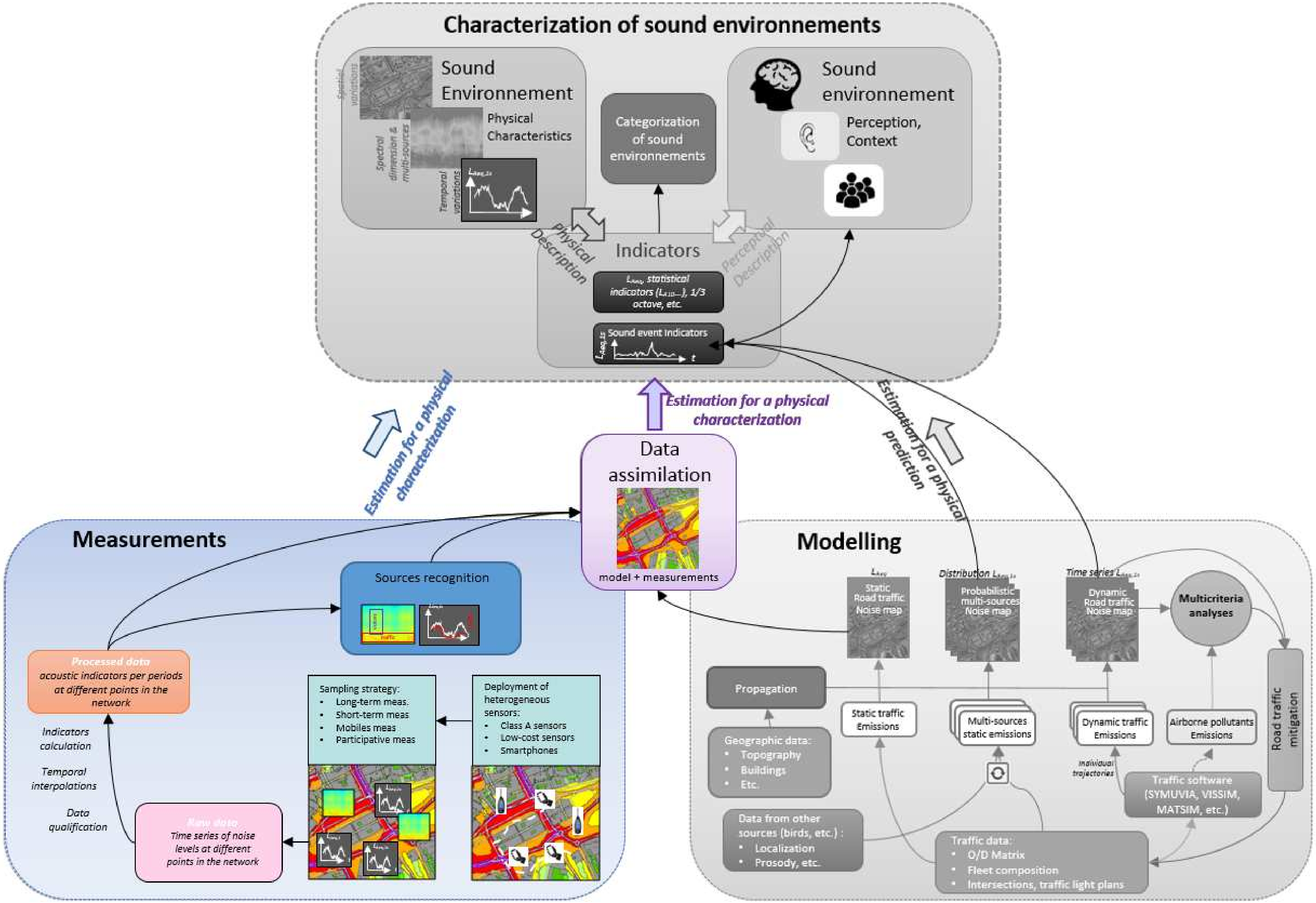


Figure 2:1 Schematic representation of research activities: focus on research axis 2

2.1 Introduction

Awareness of the health effects of noise gradually became apparent in the second half of the 20th century, in contrast to the parallel urban planning decisions, which left a significant place for the automobile in the city. The high noise levels, combined with the increasing aspiration of city dwellers for a peaceful and environmentally friendly city, have quickly made noise a first-rate nuisance, which must be characterized and controlled.

This was followed by a research effort to characterize sound environments and their effects on humans. To characterize sound environments, it is possible to rely on simulation or measurement. The two approaches have always been presented as complementary rather than antagonistic. The "Guide du Bruit des Transports Terrestres" (Road Transportation Noise Guide) (1980) already stressed the complementarity of the two approaches: "Measurement is an irreplaceable instrument for dealing with sites where physical phenomena are poorly known, or for verifying levels estimated in a few points. [...] Simulation is irreplaceable for analyzing large sites or evaluating urban planning" (Cetur, 1980).

The means of characterization, simulation and measurement, have evolved together over time. The simulation has undergone many advances, the phenomena of ground effect, diffraction, topography, being now much better characterized than in the past. But it is above all the advances in terms of computing capabilities that have changed the way in which sound environments are characterized, making it possible to calculate noise maps on a city scale. Measurement has also seen many advances: current measurement instruments make it possible to calculate refined acoustic indicators (statistical indicators, number of noise peaks) that considerably improve characterization, where in the past only aggregate levels were accessible. The miniaturization of measuring instruments and the increase in storage capacity have also played a crucial role in the democratization of urban measurement. The turning point between the 20th and 21st centuries saw the parallel development of noise mapping in urban areas, imposed by Directive 2002/CE/49, and the birth of the first noise observatories, which contribute both to a better knowledge of urban noise environments and to an effort to raise awareness about noise.

It is mainly on their representativeness that the two approaches differ. The measurement is known to capture temporal changes in noise levels, but at the expense of low spatial representativeness. In addition, it essentially captures all the sound sources that compose sound environments. Conversely, the simulation only takes into account the few sound sources modelled and is subject to errors due to the simplifications imposed by the models and the heterogeneous quality of the input data. In addition, the simulation provides access to continuous mapping in space and offers the possibility to test the impact on noise of changes made to the input data.

The current diversification of measurement methods and the associated drop in costs raise the question of the combined use of each approach, with the objective of: (i) a continuous characterization of sound levels both in time and space, (ii) the estimation of acoustic indicators close to the perception that urban dwellers have of the noise environment, (iii) an estimate of the real exposure of city users to noise levels according to their activity profiles. Beyond the technological bottlenecks that will be discussed in this chapter, the question of the scope of these new approaches deserves to be discussed: it is necessary to know what use the different actors in the city can make of the data produced.

2.2 Towards a diversification of measurement modes

The evolution of acoustic measuring devices during the 20th century is described in (Aflalo & Luquet, 2005). Technological advances have made it possible to miniaturize them, as well as to calculate complex acoustic indicators. In addition to traditional microphones, low-cost sensors and even measurements on smartphones have appeared in recent years, diversifying the offer in terms of characterization by measuring sound environments.

2.2.1 Noise observatories

The growing desire of city dwellers to know the noise levels to which they are exposed has been an important factor in the development of noise observatories. The noise observatories, of which the best known in France are BruitParif for the Île-de-France region and Acoucité for the Lyon metropolitan area, are associations with the status of the 1901 law, bringing together members such as local authorities, prefectures, infrastructures, etc. Their activities are mainly centered on a dissemination of observation points in the city, allowing continuous recording of noise levels. Other temporary points are added to measure, for example, the impact of work areas on the noise environment. The observatories' activities are not limited to measuring sound environments. BruitParif, for example, declares three missions of general interest: (i) noise observation in the Île-de-France region, (ii) support for Paris Region stakeholders in taking noise into account in public policies, (iii) information and awareness raising. As such, a website allows BruitParif or Acoucité to communicate on noise levels, through highly educational interfaces: see Figure 2:2 for an illustration. Finally, they also play a strong role in raising awareness of noise, in particular through the development of acoustic indicators that are easily understood by the public (such as the Harmonica indicator), or high-quality educational sheets[4].

The main current limitation of these networks is the number of observation points. Even when disseminating more than 100 fixed stations at the scale of Île-de-France, a network like BruitParif is far from allowing a characterization of sound environments continuous in space. The spatial representativeness area of a measurement point is often estimated at less than 50m (Brocolini *et al.*, 2013), which makes it difficult to spatially interpolate noise levels in urban areas (Can *et al.*, 2014). The costs of the sensors deployed, added to the maintenance costs, amounting to several thousand euros per unit, make it impossible to densify the networks. It is therefore mainly as local captures at strategic locations that these sensors are of interest.

[4] (see for instance the wikiquiet project funded by Ademe to which Acoucité has participed: https://r2b4331330.racontr.com/).

Figure 2:2 illustration of the RUMEUR network from BruitParif (website). Left: localization of the stations. Down: fixed measurement station from RUMEUR. Up right: Harmonica index. Down right: time series of LAeq,1s values available by clicking on a point of interest.

2.2.2 Low-cost measurement networks

2.2.2.1 Principle

In direct line with "traditional" observation networks, low-cost sensor networks (a few tens of euros per unit, compared to several thousand for a sensor from a traditional observatory) are a solution that seems relevant for significantly increasing the density of measurement points. The approach has been made possible by the recent development of MEMS (micro-electro-mechanical systems) microphones. Despite some difficulties related to the intrinsic quality of the sensors (linearity, frequency response), Van Renterghem *et al.* (2011) have shown the possibility of using MEMS sensors to carry out measurements in urban environments, through an anechoic chamber experiment and another one under various meteorological conditions, to which some of the sensors tested have given satisfaction.

Since the first experiments in 2008 (Santini *et al*., 2006), several initiatives have been launched to propose low-cost acoustic measurement networks, such as in Barcelona (Camps, 2015), Milan (Zambon *et al*., 2017) or New York (Mydlarz *et al*., 2015). The technical characteristics of low-cost measurement networks are described in Picaut *et al.* (2017): "The difference with a conventional network lies essentially in the sensor in charge of measurement and pre-processing, as well as in the transmission of data to the server in charge of post-processing and data aggregation. The system generally takes the form of a microphone mounted on a processing card (such as a mini PC), with wired (Ethernet) or wireless (Bluetooth, Wifi, 3G/4G, LORA...) transmission features.

The following sections describe the technical solutions and applications proposed in terms of characterization of sound environments.

2.2.2.2 Technical solutions : example of the CENSE project

A dense network of 150 low-cost sensors (see Figure 2:3) is being deployed in Lorient (France) as part of the CENSE (Characterization of Sound Environments: a Comprehensive Approach Combining Open data, Measurements and Modelling) project, led by Ifsttar. The technical originality of the deployed network is twofold (Picaut *et al.*, 2017):

- The network is built by joining two communicating networks, namely a wireless network that supports sensor nodes and a wired network that supports sensor gateways;
- The wired network is supported by an urban lighting network using the Citybox® technology[5] developed by the partner Bouygues E&S, which constitutes an innovative use of this technology. This mixed-solution offers flexibility in the development of a noise measurement network, taking advantage of already deployed urban infrastructures (lighting network) for data transfer and power supply, with a possible extension of the wired network by using additional "remote sensors".

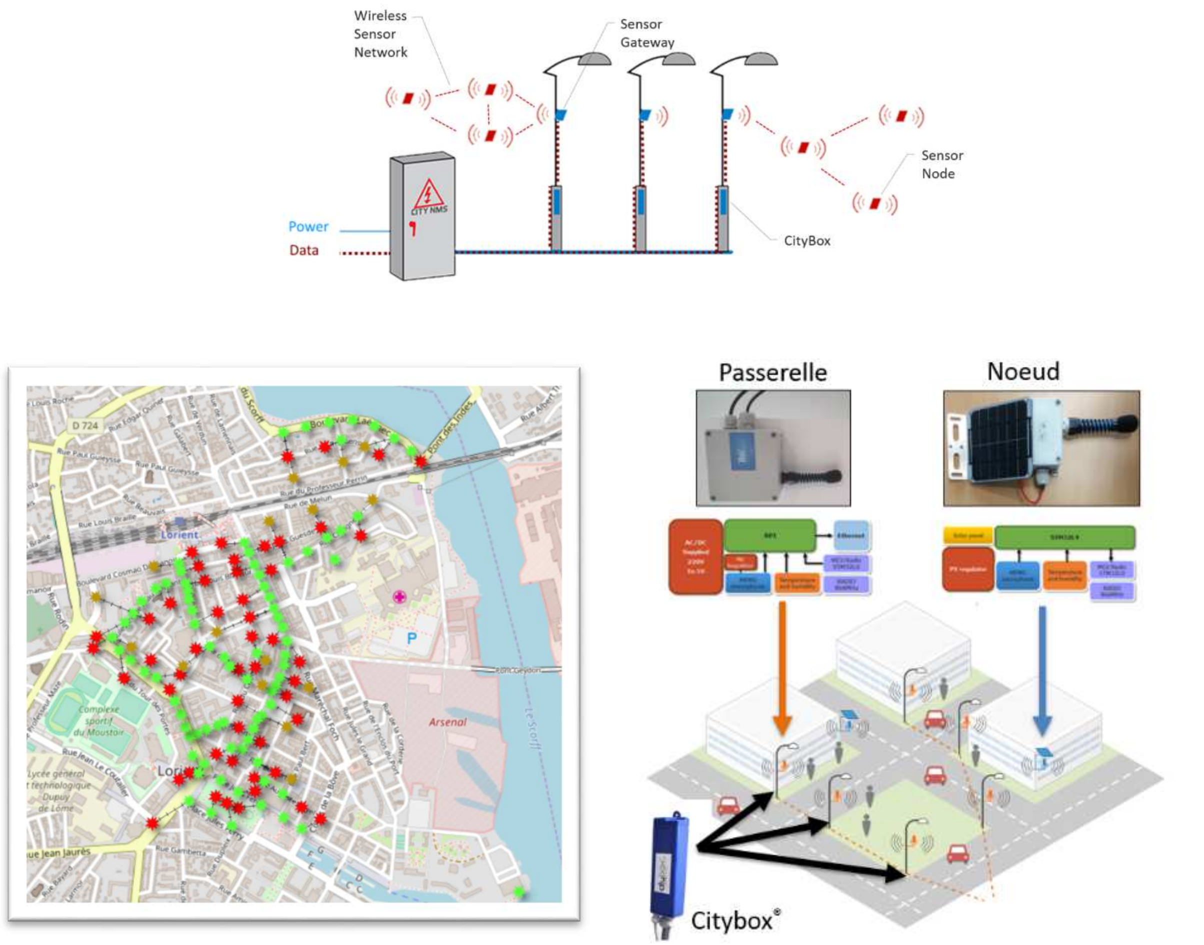


Figure 2:3 Illustration of the CENSE network. Above: communication between sensor nodes, sensor gateways, and power supply. Bottom left: sensor network deployed. Bottom right: sensors deployed as part of the project and infrastructure diagram.

As a result, two kinds of sensors and technologies coexist within the network:

[5] http://www.bouyguesenergiesservices.com/solutions/citybox.php

- The sensors called "nodes" are self-powered, communicate by radiofrequency and are organized in a wireless sensor network. Their noise sampling capability are limited due to energy and data-rate constraints, which allows "basic" noise measurements. On-board processing capabilities allow amplification, normalization, filtering in the sensor before sending data to the network. This reduces the data rate required for the data communication between the sensors, and therefore reduces the power consumption of each device, enabling battery-operated devices. To further reduce power consumption of the devices and increase the autonomy of the network, it is possible to use energy harvesting (*via* solar panel) on each device;
- The sensors called "gateways" are connected on Citybox®, deployed by the partner Bouygues E&S, and access to internet *via* the Ethernet interface of the Citybox®. These gateways are also be powered by the Citybox®. These sensors are able to produce "advanced" noise measurements and to receive radio data from the sensor nodes in the wireless sensor network. They route the data collected by the wireless sensor network to the cloud, hence their name gateways.

The data collected from the sensor network are standardized according to the 6LoWPAN protocol[6] that allows easy addition of sensors to the network, as needed by the deployment, so that the measurement network can be adapted to the studied area. A network server application supervises the sensor network and delivers all the collected data on a specific server.

2.2.2.3 Noise applications

The possibilities offered by low-cost networks have been explored in the research projects Idea[7], Dynamap[8], Sonyc[9] or Cense (see p.138). The projects share the idea that original calculation modules at the server level must accompany sensor densification; however, each approach developed has its own specificities:

- The IDEA project (intelligent Distributed Environmental Assessment, see Figure 2:4) is not limited to the production of standard acoustic indicators (Botteldooren *et al.*, 2011). Three advances are introduced concerning the processing of the data:
    - A module for extracting the acoustic characteristics of sounds is designed at the server level (Oldoni *et al.*, 2013) to select, through a self-organized map (SOM), the characteristic and atypical sounds at a given location. A recording of these sounds is made automatically;
    - The sensor network is multi-physical, with measurements of air pollutants and ultrafine particles being carried out in parallel. A study of the correlations between these quantities has been carried out, with the ambition of using low-cost, less expensive acoustic sensors as a proxy for other environmental externalities (Can *et al.*, 2011; Can *et al.*, 2011b). It should be noted that other studies have shown that despite the strong

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[6] https://fr.wikipedia.org/wiki/6LoWPAN
[7] http://www.idea-project.be/
[8] http://www.life-dynamap.eu/
[9] https://wp.nyu.edu/sonyc/

correlations between environmental externalities, the use of one as a proxy for the other is delicate (Khan *et al.*, 2018);

- The data collected were used to feed short-term (15 mn) prediction models, updating noise maps by adjusting model parameters (Wei *et al*., 2016). More in details, the least mean squares method (LMS) is used for tuning model parameters. To avoid an under-determined system, the number of degrees of freedom is reduced by grouping the sources and propagation paths into different categories. Source strengths and propagation path attenuations in the same category are corrected by offsetting the same small values from their base levels.

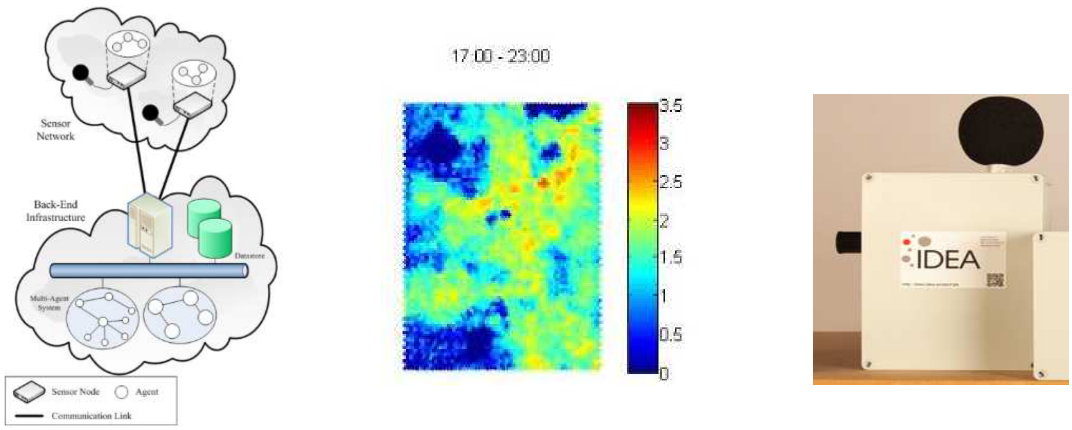

Figure 2:4 Illustration of the IDEA Project network. On the left: network infrastructure. In the center: Self-organizing map describing the occurrence frequencies of each type of sound. Right: low-cost sensor developed as part of the Project

- The Dynamap project proposes two innovative treatments (see illustration Figure 2:5):
  - A module for detecting abnormal events is introduced in Socoro *et al.* (2017) based on Gaussian Mixture Models, to exclude them from the correction module for road traffic noise maps; detection is also useful in a monitoring context, by detecting noise from sources that could represent a danger;
  - A dynamic (hourly) correction module for modelled maps of road traffic noise is introduced: the noise maps are updated, correcting the noise levels of the pre-calculated noise maps according to the observed differences between the measured data and the calculated data. A statistical approach allows road categorization to simplify correction (Zambon *et al*., 2017).

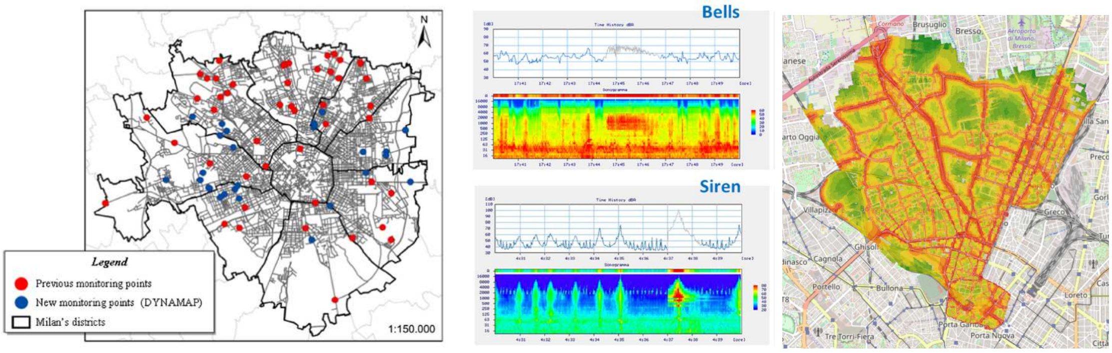

Figure 2:5 Illustration of the DYNAMAP network. Left: Measuring points. In the center: module for detecting abnormal events. On the right: example of a noise map produced. (Source: Zambon *et al*., 2017).

- The Sonyc project (Sounds of New York City) includes a very important part of data mining (Bello *et al*., 2018), focused on source detection as a decision-making aid, see Figure 2:6:
  - A Machine listening module aims to combine techniques from signal processing and machine learning to develop systems able to extract meaningful information from sounds. The objective is to detect, based on deep neural networks, specific sounds such as jackhammers, idling engines, car horns, or police sirens. An annotated taxonomy of urban sounds (Salamon *et al.*, 2015), and various cutting-edge methods for urban sound source identification (Salamon & Bello, 2017) have been developed;
  - A data-driven mitigation module aims to correlate complaints to the sounds recognized by the network (Mydlarz *et al.*, 2017). The system was used over 11 months of data collected from 17 sensors in Manhattan, where it was confirmed the presence of construction noise from 47 localized complaints, when service visits did not identify the source of the violation. The module thus aims to help the services in charge of noise mitigation.

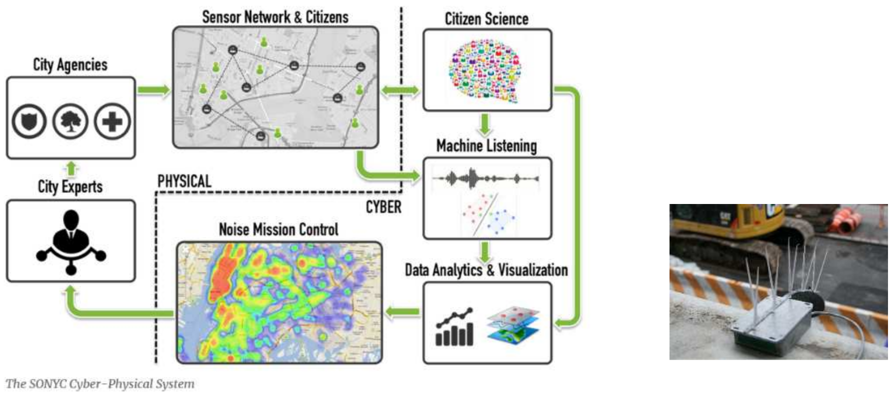

Figure 2:6 Illustration of the SONYC network. On the left: network infrastructure. Right: sensor deployed as part of the project.

- The CENSE project aims at improving the characterization of urban sound environments, by combining *in situ* observations and numerical noise predictions. The project includes four advances in terms of data processing:
    - The project relies on data assimilation techniques, such as the Best Linear Unbiased Estimator presented in Tilloy *et al.* (2013) or the model emulation presented in Mallet *et al.* (2013) in the air pollution context, in order to take profit of both modelling and measurements advantages;
    - The technical solution adopted for the network is innovative, consisting of the deployment of a mixed wired/wireless sensor network, connected to the cloud through a public street lamp network (as a power-line communication based system);
    - The project aims to produce perceptual noise maps, by developing soundscape models that rely on the automatic identification of noise sources;
    - An integrative geographical information system (GIS) platform is developed in order to facilitate the data accessibility (inputs/outputs, measured/simulated), its reuse and its exploitation to build new thematic noise maps.

2.2.3 Mobile measurements

The main criticism of the measurement networks is the lack of spatial representativeness of the measurement points. This measurement protocol therefore has its limits in terms of continuous characterization of the noise environment, unless the density of sensors deployed is very high, what is incompatible with the needs at the scale of a city[10].

A possible alternative to measurement networks is the use of mobile measurements. The principle is either to: (i) perform a large number of short-term measurements with a fine grid pattern of the study area, (ii) directly measure noise levels over a continuous path.

The idea of post-processing is then to use the temporal profiles of noise levels to derive long-term indicators. The protocol consists in equipping an operator with a microphone and a GPS allowing the geolocalization of the measurement, then simultaneously measuring the noise levels and the location. Various versions of the protocol are possible:

- Spot measurements, the idea of which is to carry out short-term measurements in strategic locations. For example, this protocol was used in the SADMAM project, whose objective was to equip a vehicle with a measurement terminal (see Figure 2:7b), to perform short-term measurements at previously targeted locations, and then characterize the sound sources using inverse methods (Manvell *et al.*, 2004);

[10] For example, the network of 150 sensors deployed as part of the CENSE project covers an area of about 0.5km²; it is therefore 3000 sensors that would have to be deployed to cover the entire city of Lorient with the same sensor density, about 400,000 sensors to cover a city like London entirely....

- Continuous measurement. For example, a mapping of sound environments is based on measurements made directly by a walking operator in Can *et al.* (2015) (see Figure 2:7a) or by bicycle in Can *et al.* (2014).


Figure 2:7 Illustration of the different mobile measurement methods. Left: mobile measurement (Can *et al.*, 2015). Right: mobile measurement point mounted on a mobile vehicle of the Sadmam network (Manvell *et al.*, 2004).

The main advantage of the mobile measurement protocol is to provide spatial coverage of the study area at a lower cost. The relevance of the modus operandi was demonstrated in (Can *et al.*, 2014): the method allows a better characterization of spatial variations in noise levels within streets than the use of a fixed measurement network and conventional spatial interpolation methods, such as Kriging or IDW (Inverse Distance Weighting). Nevertheless, the method is subject to points of vigilance:

- The noise made by the operator during his trip can pollute the measurement: footsteps noise, wind noise for a bicycle if the speed is too high, noise of the bicycle in operation (squeaks, wheels). Solutions are proposed in (Dekoninck *et al.*, 2012; Dekoninck *et al.*, 2014). In particular, the authors propose to use a very fine sample of 100 ms, then to retain every second the minimum level $L_{Amin,1s}$ among the 10 values of $L_{Aeq,100ms}$. However, the main purpose of the study was to determine relative levels (in order to correlate these levels with levels of air pollutants), so the link between these $L_{Amin,1s}$ values and $L_{Aeq,1s}$ has not been established, which seems necessary to make the method reliable when estimating L_{Aeq} values;
- Since the measurement is essentially continuous, the production of a noise map requires an intermediate aggregation of the measurements on a spatial grid, which is an essential step in the method. The spatial resolution of this grid is an important parameter: a too fine step (e.g. 5m) requires a large number of pass byes by the operator to have a representative measurement, but conversely a too loose step (e.g. 100m) masks the spatial variations of the noise levels. 50 m steps are used in Can *et al.* (2014) and Dekoninck *et al*. (2014). However, the aggregation function differs, the points being simply aggregated in Dekoninck *et al.* (2014), while in Can *et al*. (2014) a larger weight is given for measurements closer to the aggregation point, a Gaussian filter being applied. Nevertheless, the filter applied was the same at every point in the space. This work needs to be further developed, as the spatial variations in noise levels are likely to be greater in the vicinity of intersections;

- The measurements made are very dependent on the periods in which they are made. It is therefore necessary to know how to propose corrective measures to take into account the time at which the measurement is carried out. Solutions combining mobile and long-term measurements have been proposed in the literature, and are discussed in section 2.3.1;
- Errors on the localization of the measurement can be large. They are potentially more damaging than errors in the acoustic measurement itself. Indeed, under certain conditions, such as in narrow streets, a loss of the GPS signal can allocate an acoustic measurement to the wrong street, for example a very high noise measurement in a quiet street. The qualification stage of the geolocalised data is therefore essential. In fact, each measurement is aggregated on a spatial grid, which is done through a more or less complex mapmatching step. For example, in Aumond *et al.* (2018b), points are snapped point to point in the middle of the nearest street, and by requiring that the map-matched point conserves the same direction of displacement; finally, a maximum distance condition between the origin point and the map-matched point is imposed, failing which the point is not maintained.

2.2.4 Participative measurements

2.2.4.1 Principle et examples

Participatory measurement is an extension of the mobile measurement protocol where each citizen can perform geolocalized measurements via his smartphone, sent to a server where post-processing is performed (Guillaume *et al*., 2016). The user thus becomes both a producer and a consumer of environmental data. The approach is part of a participatory science context common to many disciplines, based on the idea that "the emergence of embedded sensor technologies in the everyday life of citizens could revolutionize the involvement of the population in social, economic or else environmental concerns through the self-assessment of their neighborhood environment quality" (Guillaume *et al.*, 2016).

Many smartphone applications have recently been developed to acquire acoustic data, such as NoiseTube (Maisonneuve *et al*., 2009; D'Hondt *et al*., 2013), WideNoise (Becker *et al*., 2013), NoiseSpy (Kanjo, 2010), NoizCrowd (Wisniewski *et al*., 2010), EarPhone (Rana *et al*., 2010; Rana *et al*., 2015), etc. The best-known French applications are Ambiciti, developed by INRIA (Hashem *et al*., 2015) and NoiseCapture, developed by Ifsttar and the University Bretagne Sud (Guillaume *et al*., 2016[11]).

The possibility of producing noise maps based on participatory measures has been demonstrated (D'Hondt *et al*., 2013). Murphy & King (2016), for example, reconstructed a noise map from individual measurements, with an error below 4 dB(A) for most locations. Despite the metrological difficulties inherent in the measurement protocol, the idea of the method is to bet that the shortcomings of individual measurements are compensated by the large amount of data that can be collected. For example, the Noisecapture application shows nearly 300 days of measurements, divided into 135,000 measurements performed by 33,000 contributors.

[11] http://noise-planet.org/noisecapture.html

The applications are distinguished by the accuracy of the phones and calculation modules, which can be of unequal quality (see section 2.2.4.2). When the conditions for a quality environmental measurement are met, as is the case for example with the EarPhone, Ambiciti and NoiseCapture applications detailed below, the applications focus on various functionalities depending on the scientific origins of the developers:

- In EarPhone, developed in part by the University of New South Wales of Sydney (Australia) (see Figure 2:8), the focus is on data processing. For example, context detection modules have been developed to filter data that do not comply with predefined measurement protocols (Rana *et al.*, 2015).

Figure 2:8 Illustration of the Earphone smartphone application. Left: screenshots of a measurement. Right: map produced (Rana et al., 2010; 2015).

- Ambiciti, developed at INRIA, has a strong background in applied mathematics. $L_{Aeq,T}$ values are measured on-demand or automatically throughout the day in order to provide insights to the user into their own exposure to noise pollution across time:
    - Ventura *et al.* (2017) focused on the calibration of mobile phones. The tested mobile phones show quite linear responses for levels in the 45 to 75 dB(A) range, therefore the mean bias is used as correction to calibrate individually the phones. In addition, various sensing conditions were evaluated. Motion or windy conditions can lead to as much as 15 dB(A) errors. The authors conclude that friction against pockets or bags make measurement unusable, unless the attenuation is correctly estimated during static measurements;
    - The data processing module proposes an assimilation of data between the data produced by the application and the usual noise maps, described in Ventura *et al.* (2018), and based on the best linear unbiased estimator. It merges the simulated map and the measurements based on respective uncertainties so that the analysis map has minimum error variance (see Figure 2:9).

Figure 2:9 Illustration of the Ambiciti smartphone application. Left: screenshot of a measurement. Centre: calibration tests. Right: map from data assimilation. Source: (Ventura *et al.*, 2018).

- Noisecapture, developed by Ifsttar and the University of Bretagne Sud, is based on strong contributions in environmental acoustics and geomatics. The emphasis is on the quality of the measurement as well as on the calibration. Concerning the data collection protocol, the developers proposed the concept of collective participatory measurement events, the "noisecapture parties", organized by municipalities. These events guarantee more reliable data, and are of interest in terms of noise awareness. The produced data is uploaded to a server, feeding a more general platform for mapping sound environments, including noise modeling based on open data[12]. Finally, a data tag module, which can be used for perceptual evaluations, is also included (see Figure 2:10).

Figure 2:10 Illustration of the NoiseCapture smartphone application. From left to right: spectrogram measured in live, tag of sound sources heard, exposure during a journey, and noise map produced on the server that can be displayed on the user's smartphone (http://noise-planet.org/noisecapture.html).

[12] http://noise-planet.org/

2.2.4.2 *Limitations, data qualification*

The use of smartphones for acoustic measurements raises three types of questions about the quality of the data produced, concerning the accuracy, the protocol and the representativeness of the measurements:

- Questions related to the device and the application developed. The use of smartphones for acoustic measurements raises several metrological issues, including the directivity and accuracy of microphones (Manvell, 2016). However, Kardous & Shaw (2014) have shown that while many applications provide erroneous results, some meet the criteria for environmental measurement. In addition, calibration procedures have been proposed:
    - In Can *et al.* (2016), a cross calibration procedure is proposed: measurements made by a smartphone are compared with those made by the fleet of devices, in order to identify and filter operator/device pairs giving imprecise measurements, and to propose corrections for precise but biased measurements;
    - In Picaut *et al*. (2018), an individual calibration procedure is developed: the principle is based on the use of a reference smartphone, previously calibrated, communicating automatically with other smartphones that one wishes to calibrate, by means of an acoustic communication protocol; calibration is primarily carried out in a closed device, generating a diffuse and reference sound field, which allows several devices to be calibrated simultaneously;
    - Finally, an *in situ* calibration procedure is being developed (Rey Gozalo *et al*., 2019b). The objective is for a user to make some measurements of noise levels at the side of the road. A peak detection module implemented in the application makes it possible to define the L_{Amax} values corresponding to the passage of vehicles, which are then compared with the expected theoretical values. The study shows that if an uncertainty of 2 dB is tolerated, measurement at a few sites (about 3) with a few vehicles (about 10) is sufficient to calibrate the smartphone.
- Questions related to the measurement protocol. The participants themselves represent a key point of the measurement protocol. The acquisition can be triggered at a time when the smartphone is held in the palm in the correct measurement configuration or, on the contrary buried in a pocket or carried by the user in a communication situation. It is necessary to design data qualification modules specific to participative measurement to avoid these difficulties, especially when measurements are carried out continuously. In Picaut *et al.* (2018), geolocalized data corresponding to a speed not compatible with a walking situation (speeds above 5 km/h) are filtered. In Rana *et al.* (2015), measurement compliant situations are detected from the telephone accelerometer and a k-nearest neighbor algorithm; in addition, a speech detection module is used to filter data that is not measurement compliant;
- Questions relating to the representativeness of the measures. The brevity of the collected measurement samples, sometimes not exceeding a few seconds, makes them individually difficult to represent the sound environments they are supposed to characterize. This question can easily be circumvented by the large amount of data collected; for example, it is shown in Can *et al.* (2014) that a small number of pass byes in front of a receiver is sufficient to estimate

sound levels with good accuracy. On the contrary, the possible bias introduced by the periods chosen by operators to perform a measurement has never been studied. Indeed, due to the participatory and therefore voluntary nature of the measurement protocol, it cannot be ruled out that some operators may have specific ambitions leading them to carry out a measurement: capturing the calm of a sound ambiance, underlining the noisy nature of the neighbor's motorcycle, etc. Thus, the decision-making process leading an operator to take and share a measurement can potentially bias even the most numerous measurements. This is all the more true if some users become aware of the strategic importance of the measurement carried out.

2.3 Parsimonious sampling strategies

The new measurement protocols, which leave a large part to parsimonious sampling, require determining the spatial and temporal representativeness of the measurement to extrapolate the collected data over space or time. They are also a means of characterizing sound environments based on mixed solutions, combining either short-term and long-term measurements, or measurement and modeling.

2.3.1 Temporal parsimony

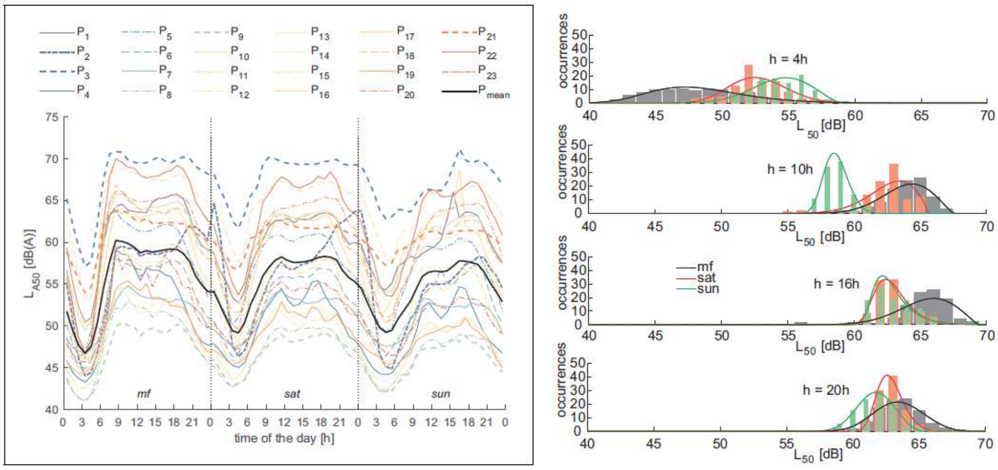

Figure 2:11 Temporal analysis of noise levels evolution at 23 stations located in Paris XIII. Left: L_{A50} Daily Average Noise Patterns. Right: Generalized Extreme Value distributions of the $L_{Aeq,1h}$ values for i = {Monday-to-Friday, Saturday, Sunday} at the monitoring station P_1 for the periods h=4h, h = 10h, h = 16h and h=20h. Source: Can *et al.* (2018).

The principle of parsimonious measurement is to derive long-term indicators based on short-term measurements, relying on the temporal structures of noise levels, which are very pronounced in urban areas. Can *et al.* (2018), for example, highlighted the very regular temporal patterns of noise levels at the weekday scale, made up of an alternation between high levels during the day and low levels at night, with notable differences on Saturday and Sunday compared with the other days of the week (see Figure 2:11). The seasonal trends are also strong. This high repeatability of noise levels also makes it *a priori* possible to determine annual noise levels based on measurements over a few days. Two post-processing strategies are possible:

- To collect data over short periods that are aimed to be representative of long-term ones;

- To adjust the short-term values knowing the noise levels temporal patterns.

This requires an understanding of the temporal structures of noise levels in urban areas, as well as their spatial dependencies. Can *et al.* (2011) investigated the variations of hourly noise levels at the week scale, showing that a matrix of relationships between hourly noise levels can be defined for each measurement point, from which noise levels at any period can be deduced from measurements at other periods. The temporal trends are however different depending on the site. A method for stratifying urban space has been proposed by Borrigon Morillas *et al.* (2002), according to their use in communicating the different zones of the city. The four categories considered were arterial roads outside the central zone, arterial roads in the central zone, two-way roads connecting different zones, and one-way roads. The interest of such stratification lies in the fact that temporal variations in noise levels are correlated from one point to another within the same class.

2.3.1.1 One-day measurements

Based on this high chronicity of noise on a daily scale, sampling strategies have been developed that assume that a few one-day samples could be sufficient to characterize annual noise levels. Brambilla (2002) showed based on measurements in nine urban sites that a one-week measurement period could be sufficient to assess yearly L_{Aeq} values, despite the high noise variations. Gaja *et al.* (2003) found that sampling over non-consecutive days is a better strategy. Then at least 6 days should be used to estimate yearly L_{Aeq} values within a 1 dB(A) uncertainty for 84% of the tested sites. Similar results are obtained in Brambilla *et al.* (2007), in which monitoring lasting 5 to 7 non-consecutive days seems a reasonable compromise between time saving and accuracy.

Beyond these naive sampling strategies, relying on the long-term noise trends can be a lever to reduce sampling durations. Gajardo *et al.* (2016) captured the daily and seasonal noise trends through a Fourier analysis; these trends were found to be very stable from one city to another. Quintero *et al.* (2018) proposed a stratification between weekdays and weekends, validated in the city of Barcelona. The determination of noise differences between both allows reducing the required number of measurement days by 38%, by applying a correction the sample was collected either during one or during the other period.

2.3.1.2 Few-minutes measurements

The high chronicity of noise levels on a daily scale invites to be even more parsimonious in the sampling strategy, by proposing measurements of less than one day to derive either one-hour or long-term indicators. Brocolini *et al.* (2013) showed that 10 or 15 minutes of measurement could be representative of a 1-hour period, since the majority of 10 or 15-minute periods fall within the same range of sound levels during homogeneous periods. Thus, few-minutes measurement strategies seem plausible. The risk then is in the chosen sampling period, which might be unrepresentative of the period of interest that is longer. Ng & Tang (2008) showed that a single sampling can by very risky and that results are improved by simply collecting two samples instead of one. The reliability of short-term measurements highly depends on the sound levels variability, and thus on the function of the street. This should be taken into consideration when defining the sampling strategy:

- Tojira *et al*. (2011) introduced the notion of "stabilization time", which aims at determining the time from which the measurement can be regarded as reliable. This indicator is determined during the measurement, by calculating two indicators characterizing the variability of the signal. The first one, the temporal sound level variability (TSLV), measures the short-term temporal fluctuation of sound pressure level, and is highly sensitive to events that suddenly introduce substantial sound pressure. The second one, the crest factor (CF), deals with the sound-level maxima occurring during the observation interval ;
- In a task of estimating the L_{day} (7am-5pm) from short samples taken during the day, Romeu *et al*. (2011) showed that the error committed was a function of street. The authors conclude that short-term measurement strategies can be acceptable for the main streets (15 min samples were considered), but should not be used for ordinary streets where noise levels are more variable ;
- In complement, Gajardo & Barrigon Morrillas (2015) showed that the stabilization time values were highly dependent on the hour of the day and the measurement station in question. However, according to this analysis, a short-time measurement of 15 min is adequate to estimate $L_{Aeq,1h}$ values with 90 % confidence levels and errors of ±2 dB, with 80 % confidence levels and errors of ±1 dB, and 50 % confidence levels and errors of ±0.5 dB.

These results suggest that short measurements, of the order of 15 minutes, are sufficient to estimate the level of the corresponding 1h-period, but also the daily levels. In contrast to these results, Geraghty & O'Mahony (2016) warn against overly parsimonious sampling strategies. These authors investigated the variability of noise levels at four temporal levels: month, week, day and hour. The results demonstrate a large degree of statistically significant difference between periods, at all of the temporal scales examined, suggesting that caution needs to be taken when assuming that noise measurements taken over very short time periods can statistically capture noise levels over longer periods.

2.3.1.3 Combined short-term and long-term measurements

However, this variability does not make short sampling strategies impossible, but it does require capturing trends and applying appropriate corrections. In the context of dense measurement networks, it therefore seems feasible to rely on both long-term and short-term sampling periods, or even on both long-term and mobile measurements, to estimate indicators over long periods. In this option, the long-term stations aim at capturing long-term noise levels trends, while the short-term or mobile measurements finely grid the space to improve spatial resolution:

- In Can *et al.* (2011), a fixed station installed over a long period is used to capture the average noise levels variations within the day. These captured variations serve as corrections that are used to improve the estimation of L_{den} values at other locations, and allow the reduction of both the number of samples needed and their duration. L_{den} is estimated with an error that does not exceed 1.5 dB(A) to 3.4 dB(A) according to the location, for 90% of the estimations based on 3 samples of 15 min. This sampling strategy also allows for the estimation of average noise levels at one typical 1h-period of the day (for instance average noise levels at 11 o'clock). The estimation of specific indicators, such as L_{A90}, L_{A50} and L_{A10} for these typical 1h-periods is also made possible. On the contrary, the dynamic prediction of time series of 1h-values of L_{Aeq}

or statistical indicators is more difficult. These time series can be predicted easily (with again three samples of 15 min with the help of one fixed station on the network and the proposed modeling) if an accuracy of 3 dB(A) is considered as enough, thanks to the high repeatability of noise levels at the daily scale. However, the prediction cannot reach a greater level of accuracy, because of short-term noise variations, which are not correlated from one street to the other at the one-hour scale;

- Can *et al.* (2018) relied on a wide measurement campaign during 8 month, at 23 measurement stations in Paris, which cover a large variety of urban sound environments, to analyze noise temporal variations. 72 time-slots of interest are defined (24 1h-periods for weekdays, Saturday and Sunday). The statistical analysis determines for each of the 23 stations the Daily Average Noise Pattern (DANP), and for each of the 72 time-slots the 1h-Generalized Extreme Values distributions. In addition, the average sound level differences between these 72 1h-time periods are calculated along with their variability, resulting in 72×72 delta matrices that describe the temporal relations between sound levels. This database is then used to develop two models, which aim to estimate DANP based on a limited amount of measurements. The first model relies on the delta matrices, whereas the second model consists of a weighted average of the DANP that are stored in the database in which the weights are based upon measures of similarity between the stations. A test of both modelling approaches through simulated measurements shows that the first model seems to be more robust in case when measurements are inaccurate.

- Claudio Guarnaccia and his team applied time series approaches to noise levels time series :
  - In Guarnaccia *et al*. (2014), a non-homogeneous Poisson model is considered to study noise exposure. The Poisson process, counting the number of times that a sound level surpasses a threshold, is used to estimate the probability that a population is exposed to high levels of noise a certain number of times in a given time interval. The model proves useful to predict, given the current behavior of the data, the probability of occurrence of high levels of noise in the near future ;
  - In Guarnaccia *et al*. (2017), Time Series Analysis (TSA), are used to analyze datasets of noise levels produced by transport systems over two datasets, namely road traffic in Messina (Italy) and air traffic in Nice airport (France). This approach is based on the analysis of trend and seasonality of the series, and on the implementation of a function of the time that can provide predictions for future periods. Two approaches are compared with both interesting results: the Deterministic Decomposition (DD-TSA), and the Seasonal Autoregressive Integrated Moving Average (SARIMA) technique. This function has fixed coefficients that do not depend on time and, thus, are equally influenced by old and recent data. On the contrary, the second model based on Seasonal Autoregressive Integrated Moving Average (SARIMA) technique, needs in input a certain number of recent data, those that are close to the one under prediction. For this reason, SARIMA can follow the short-term variations of the series, but needs some time to adapt to non-stationarity (such as in the airport case).

- In Guarnaccia *et al.* (2017b), a hybrid predicted model is presented, based on the mixing of two different approaches: the Time Series Analysis (TSA) and the Artificial Neural Network (ANN). The TSA model is based on the evaluation of trend and seasonality in the data, while the ANN is trained on the residuals between TSA estimations and observed data for the previous *n*-periods. Models are tested on measurements in the city of Messina (Italy). Two neural networks are trained, with one or seven days lag periods. The hybrid models improve the prediction performances compared with the TSA. The model predicts with a high accuracy noise levels one-step (one day) ahead in the future. A prediction with a forecast range of 7 days can be performed, although with a small loss of accuracy.

Finally, even shorter measurement periods can be found in the literature, particularly in cases where the participatory measurement context offered by smartphone applications is used. In this case, it is expected that the short measurement times are compensated by the large number of measurements (Guillaume *et al*., 2016), moving from the duration of each measurement episode to the number of sampling episodes, as recommended by Mateus *et al.* (2015) :

- Can *et al.* (2016) proposed a cross-calibration method tested on an artificial sound field, which a set of mobile sensors (also artificial) of different quality tried to reproduce. Different characteristics of the network of mobile sensors are simulated: the systematic error and the deviation of errors over the whole network of mobile sensors, and the dispersion within individual measurements. Concerning temporal interpolations, the proposed cross-calibration method corrects accurately the systematic errors, since individual errors can be evaluated precisely by comparison with the rest of the sensors. To do so, each individual measurement is compared with the measurements collected by other sensors when they passed by the same point during a similar period. The average noise profile at a point is thus estimated by all the mobile measurements made at that point, which in turn are used to correct the values returned by each sensor.;
- Ventura *et al.* (2018) proposed a data assimilation of mobile phone measurements for noise mapping. Each collected data consist of a $L_{Aeq,5s}$ noise level, and the number of collected observation data in the experiment is around 2000. The proposed method relies on the variance associated with measurements. The shortness of the individual measurements, since $L_{Aeq,5s}$ noise levels aim to estimate $L_{Aeq,1h}$ values, increases their variance, which is evaluated by the authors at 22 dB(A)² in their collected data. In addition, the shape of the daily noise profile is also used in the data assimilation process.

2.3.2 Spatial parsimony

Characterizing urban noise environments by measurement requires a sampling strategy that by definition cannot cover the entire territory, and therefore implies, first to ask the question of the spatial representativeness of the measurements carried out, and then to consider ways to interpolate between the measurement points the values of the indicators calculated following the measurement. The limitation of traditional observatories, which is their low coverage of urban space, was presented in section 2.2.1, but questions of spatial representativeness and interpolation also arise for dense low-cost observatories and for participatory measurement.

The aim of spatial interpolation methods is to estimate noise levels at locations where they are unknown, based on nearby points. They are commonly implemented in current GIS tools. This is what can be done to refine the spatial resolution of noise maps derived from modelling for better visual rendering, even though the initial spatial resolution is often already very fine, in the order of 10m. Murphy *et al*. (2016) showed that in this context, the use of Nearest Neighbor, Inverse Distance Weighting (IDW) and Kriging methods had an influence on the maps produced. Park *et al.* (2010) find a similar result by comparing several algorithms for surface interpolation, such as spline, IDW and Kriging methods.

The spatial interpolation of acoustic indicators from a measurement network is more complex due to the low coverage density of urban space compared with simulation. Can *et al*. (2014) showed that interpolation methods were defective when the spacing between sensors was too large (about one measurement point every 250m in the study[13]). The explanation given is that they do not offer a sufficient covering of the network, and assume spatial variations that are not coherent with traffic dynamics or street configurations.

Indeed, in urban areas, a distance of 250m can see a succession of very varied environments. The study of the spatial characteristics of noise variations help defining interpolation functions. Rey Gozalo & Barrigon Morillas (2016) showed that a stratification of roads based on their functionality was helpful before interpolating sound levels. Rey Gozalo *et al.* (2013) showed similarly, based on a measurement campaign in the city of Plasencia (Spain), that the characteristics of sound level variations follow the categories formed with road functionalities. Liu *et al.* (2013) analyzed the sound environments of the city of Rostock, Germany, and observed that spatial variation of urban soundscape patterns was explained by underlying landscape characteristics, while temporal variation was mainly driven by urban activities. Zuo *et al.* (2014), based on measurements in the city of Toronto (Canada), observed that noise variability was predominantly spatial in nature, rather than temporal: spatial variability accounted for 60% of the total observed variations in traffic noise. Finally, Harman *et al.* (2016) showed in the city of Asparta (Turkey), by interpolating from a moderately dense measurement network[14], that noise levels were stratified too from the center to the periphery. This study also showed that interpolation methods, namely IDW, Kriging, and multiquadratic interpolation, were very sensitive to their parameterization.

Two examples of spatial interpolation of noise levels based on a dense sensor network can be found in Segura Garcia *et al.* (2016) and Aumond *et al*. (2018):

- In Segura Garcia *et al.* (2016), a fix grid of 78 sensors was deployed in the city of Algemes (Spain). The network covered 1,8 km², which is about a square grid of 50m on each side[15]. For the purposes of the study, 10 sensors were removed in which levels were estimated at five 3-

[13] That is about 30 sensors per km²
[14] About 10 sensors per km²
[15] That is about 43 sensors per km²

hours periods of the day by an interpolation method, namely an Ordinary Kriging in which noise levels are described by a logarithmic function. The study shows that under this sensors density the kriging method seems an efficient method to interpolate noise levels, within a RMSE of 3.5 dB(A). In addition, the residuals are spatially correlated except for the [19-22h] period, probably because it entails specific noise behaviors (leisure noise activities, etc.);

- In Aumond *et al*. (2018), the impact of the density of observation points and the performance of four spatial interpolation methods were presented. Mobile measurements have been performed while walking multiple times in every street of the XIIIrd district of Paris (France), to construct a reference map, which is estimated by adaptively constructing a noise map based on these measurements. The four interpolation methods were constructed by combining two algorithms: (i) the Kriging method, either Ordinary Kriging or Universal Kriging (which consists in adding a linear trend, defined from the distance between each location and its closest road in each amongst four categories) and (ii) the definition of the distance between locations, either Euclidian or computed from the road network. The linear trend added in the Universal Kriging aims at accounting for the roads stratification whose interest was highlighted in Barrigon Morrillas *et al*. (2005). The road network distance aims to better model errors that come from the traffic. The study shows that the alternative definition of distance along the road network slightly increases the performance of the algorithms, but only for Ordinary Kriging methods. Universal Kriging outperforms Ordinary Kriging. Nevertheless, it introduces an additional calculation of the trend that has a pre-processing cost and can itself be a source of error. Finally, the results show that a high density of observation points is necessary to obtain an interpolated sound map close to the reference map. Approximately 50 observation locations per km² are needed in order to get a correlation coefficient superior to 0.8 and a RMSE value inferior to 2.5 dB between the reference and the interpolated map (see Figure 2:12).

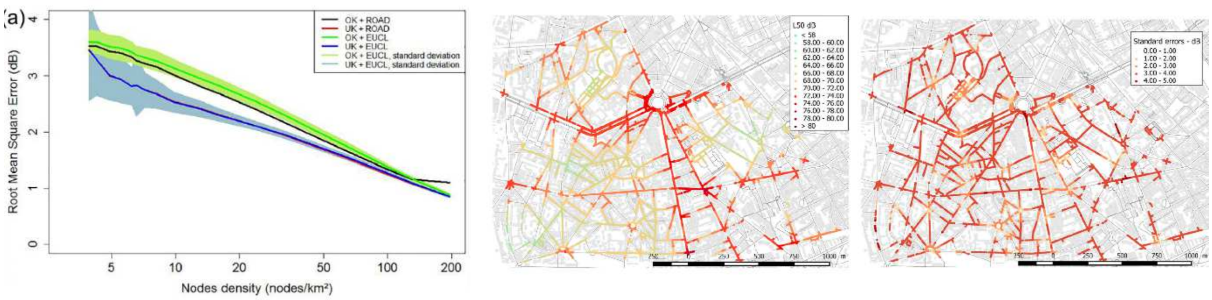

Figure 2:12 Spatial interpolation performed in Aumond *et al.*, (2018). Left: Relation between RMSE and the density of nodes. Center: interpolated sound map from 42 observations with Universal Kriging. Right: associated standard errors map. Source: Aumond *et al.* (2018).

2.3.3 Coupling between measurements and modelling

Beyond relying on simulated maps or measurements, a third approach that merges the two first ones within a common modelling framework is under development, with the perspective to converge towards maps that are more accurate. The idea is to compensate for the spatial parsimony of the measurements by taking advantage of the very fine spatial resolution of the noise maps resulting from modelling.

Introducing observations in combination with simulations is an emerging concern in noise pollution. The first studies follow two different approaches, which consist of using observations to either modify the model parameters or directly correct the produced map.

2.3.3.1 Parameters tuning based on observations

In Wei *et al*. (2016) or De Coensel *et al.* (2015), observations are used to tune a few selected emission and propagation model parameters, in order to produce 15 mn noise maps. The initial number of parameters is reduced by considering one source per road category (following here again the stratification principle), and propagation parameters are supposed uniform over the network, and reduced into three propagation paths, namely horizontal path, vertically diffracted path and scattered path. The correction terms on the parameters are obtained by minimizing the squared error between predictions and observations. In order to prevent unrealistic parameter variations, the minimization is performed not at each time step but on average over longer periods, thus assuming slow change of parameter values with time. The method is validated in Wei *et al.* (2016) in a case study in the Katendrecht district of Rotterdam (Netherlands). The results showed that more than 75% of the L_{Aeq} predictions are closer to the measurement than the initial calculations based on traffic data.

In Murphy & King (2016), a method is proposed to correct the road traffic noise sources initially classically estimated based on inputs such as traffic volumes and heavy/light vehicles ratios. To do so, measurements are achieved with mobile phones at 93 locations close to roads, and inverse modelling is used to go back to the source level. Reverse engineering was already used in Manvell *et al*. (2004), where a set of mobile measurements is used to determine the noise power level of road traffic sources. The presented method requires in principle as many measurement points than sources (thus road segments), but the authors advise that similar roads could be grouped.

2.3.3.2 Data assimilation techniques

Data assimilation is an approach where numerical simulation and field observation are coupled in order to improve the analyses of the past and present states of a system, or to improve forecasts (Bouttier & Courtier, 1999). Data assimilation takes into account model constraints and the spatio-temporal error covariances for both simulations and observations in order to reduce optimally the uncertainties. The approach was introduced for numerical weather forecast in the 80's and was a major source, if not the main source, of improvement in the forecasts over the last 20 years (Kalnay, 2002). The success of the coupling of numerical simulation and field observation has since spread to other geophysical areas, and more recently to many other fields in environment and even biology. At urban scale, the city geometry leads to specific spatial patterns in the errors and in their spatio-temporal correlations, which was successfully dealt with for urban air quality (Tilloy *et al.*, 2013). The use of data assimilation techniques in the field of noise is recent, and was carried out at INRIA under the impetus of Vivien Mallet and his colleagues, from which this paragraph of presentation is inspired.

In Ventura *et al*. (2018), the data assimilation method merges the simulated map and the measurements based on respective uncertainties. The method is illustrated through a neighborhood-wide experiment, as illustrated in Figure 2:13. Measurements consist of mobile phone measurements gathered under the Ambiciti project, while the simulated map (called background) is the time-averaged Paris noise map. The data assimilation method produces an analysis noise map, which is the so-called best linear unbiased estimator (BLUE). An estimate of the noise map containing the exact noise levels that one would like to estimate, called “true state”, is produced by computing the Best Linear Unbiased Estimator. This estimate is an improved state vector x_a, called the analysis, designed to be a linear combination of the background x_b and the observations y, which should be unbiased and with minimal error variance. Therefore, the estimate of the error covariances matrices B (for background) and R (for observations) is an important step of the method in order to obtain the best analysis possible. In this study, the background error covariance matrix depends on both the distance along the road network and the difference in noise levels, while the observational error is the sum of an instrumental error, a temporal representativeness and a spatial representativeness.

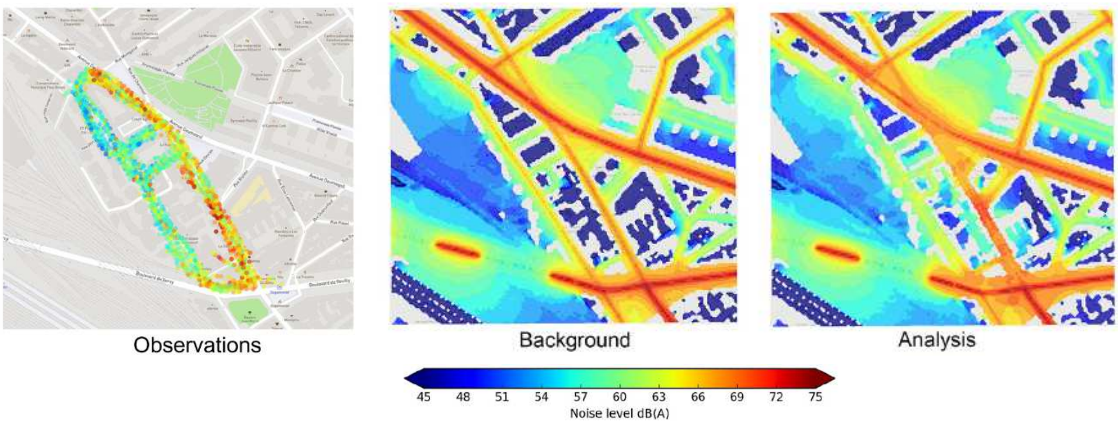

Figure 2:13 Illustration of the data assimilation performed in Ventura *et al.* (2018). Left: observations gathered with mobile phones. Center: simulated map (called background). Right: analysis noise map, which estimates the true state as a linear combination of the two previous ones, with no bias and minimal error variance. Source: Ventura *et al.* (2018).

2.4 Advanced data treatment

2.4.1 Data qualification

While the development of low-cost measuring devices increases the quantity of data available to characterize urban noise environments, it also introduces uncertainty about the quality of the data collected and therefore the need to qualify this data: detection of defective sensors, verification of measurement conditions for mobile phone-based protocols. This qualification can be done on the individual data provided by the sensors, but also take advantage of the mass of data collected, based both on the expected time histories and on the values returned by the surrounding sensors:

- In Dauwe *et al.* (2014), a multi-criteria measurement quality assessment model for detecting anomalies such as microphone breakdowns, drifts and critical outliers was developed. Each of the criteria results in a quality score between 0 and 1. An ordered weighted average (OWA) operator combines these individual scores into a global quality score Q_A. More in details, the method introduces four quality indexes: (i) the intrinsic quality index Q_I defines the quality of the sensor by comparing under anechoic chamber its characteristics to a class-A sensor, (ii) the heuristic quality index Q_H compares each 1-mn the standard deviation to the reference standard deviation on the energetic averages measured during the last four weeks at the same time of the day, (iii) the diurnal pattern quality index Q_D, based on the correlation between the last 15mn noise levels and its average at the same time of the day during the last four weeks, aims to detect drifts, (iv) the SOM quality index Q_S aims to detect unexpected sounds that could indicate a malfunction;

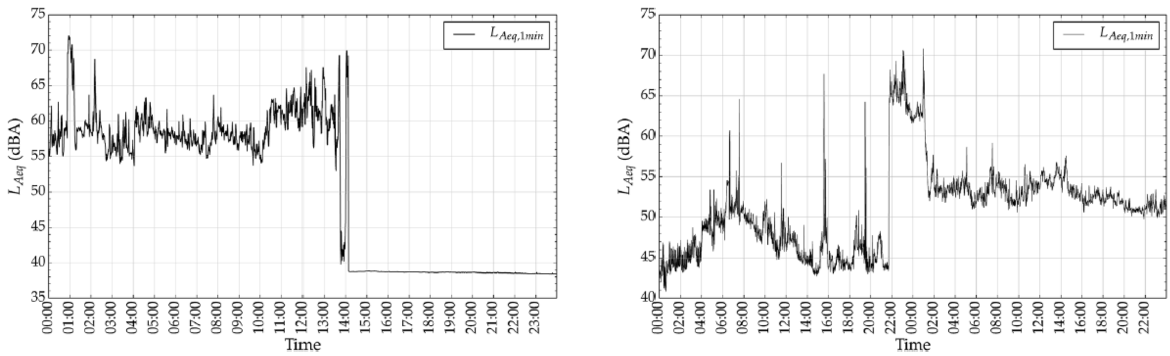

Figure 2:14 Example of microphone failure detection as performed in Dauwe *et al*. (2014). Left: microphone breakdown. Right: incipient failure (windshield detachment resulting in a background noise increase. Source: Dauwe *et al*., 2014.

- In EarPhone, in the context of mobile phone measurements, context detection modules have been developed to filter data that do not comply with predefined measurement protocols (Rana *et al*., 2015). More in details, the method consists of three modules: (i) a call detection module detects whether there is an active call in progress, (ii) a speech detection module compares the measured spectrum to spectra containing conversation noise, (iii) a context discovery module based on the phone accelerometer and proximity sensors and a k-nearest neighbor algorithm detects if the phone is wore at hand;

- In Can *et al.* (2016), a method is proposed to perform simultaneously a fault sensors detection and a bias correction, under the mobile-phone measurement context. The method looks at the discrepancies between the sound levels measured by a sensor and the sound level values given by the other mobile sensors when the latter pass during the same time of the day (not necessarily the same day) and in the same street. If these discrepancies are dispersed, the sensor is flagged as a fault sensor. If these discrepancies are high but not dispersed, the averaged discrepancy is considered as an estimated of its systematic error, which is stored to correct the measurements given by the sensor. The principle is that, if a sensor provides accidentally one measure that deviates from the rest of the mobile sensors, it can be due to the natural variation of the signal, but if it deviates systematically, this deviation can no longer be regarded as random but reveals instead a systematic error of the apparatus.

2.4.2 Towards advanced characterization of sound environments

2.4.2.1 Interest towards soundscape approaches

The limitations of quantitative approaches to characterize sound environments are now consensus. Raymond Murray Schafer's work in the 1970s led to the notion of "soundscape" (Murray Schafer, 1979), now widely used, which is defined as "the sound environment as perceived, experienced or understood by one or more persons, in its context" (ISO 12913-1:2014). Murray Schafer made for instance a distinction between hi-fi and lo-fi sound environments. A hi-fi environment makes it possible for discrete sounds to be heard clearly since there is no background noise to obstruct even the smallest disturbance (typically in the countryside), while in a lo-fi soundscape, signals are obscured by too many sounds, and perspective is lost within the broad-band of noises (typically in cities). These considerations are of interest when it comes to designing urban places with appropriate acoustic qualities. Then, evaluations cannot be evaluated based solely on quantitative ratings.

Research in soundscape concentrates an increasing effort, as underlined in Kang *et al.* (2016). Among the different declinations of the approach, which cannot all be mentioned here, some of the results one can mention are:

- Different dimensions have been reflected in soundscape research. However, majority of available soundscape descriptors are converging towards a 2-dimensional soundscape model of perceived affective quality, e.g. Pleasantness–Eventfulness or Calmness–Vibrancy (Aletta *et al.*, 2016);
- The interest towards restorative places has been demonstrated. It consists of high quality acoustic environments that positively affect well-being and thus requires special care (Van Kamp *et al.*, 2016);
- Soundscape approaches differ from engineering approaches in the fact that environmental sounds are considered as a “resource” more than a “waste”. Research in sounds classification often highlights a distinction between sounds from anthropophony, geophony and biophony. The questions then is the competition between sources of these classes, and their appropriateness to a given environment. Interactions between road traffic noise, water and bird sounds have been extensively investigated in the literature, for instance by Hao *et al.*, 2016, You *et al.*, 2010 or Jeon *et al.*, 2010. De Coensel *et al.* (2011) showed for instance that adding fountain sound reduced the loudness of road traffic noise only if the latter had low temporal variability, and that conversely adding bird sound significantly enhanced soundscape pleasantness and eventfulness, more than what was achieved by adding fountain sound.

This interest towards soundscape approaches reflects in recent attempts concerning both modelling and the use of measurement networks data outputs, although it is one of the main challenges regarding soundscape for the next years, according to Kang *et al.* (2016).

2.4.2.2 Soundscape modelling

Different modelling attempts going beyond the traditional L_{Aeq} indicator have recently been proposed, targeting more qualitative characterizations. Three options can then be followed:

- Collect in a few locations the variables to represent and then interpolate them. For instance, in Hong & Jeon (2017), the presence of sources, classified according to traffic, water, human noise and bird noise, is perceptually assessed at sampled locations and interpolated to create source-based noise maps. This is also the approach retained in Aletta *et al.* (2015), in which soundscape indicators are collected at some locations through soundwalks, and then interpolated to obtain a map, as represented in Figure 2:15;

Figure 2:15 Example of calmness map interpolated from data collected through soundwalk . Source: Aletta *et al.*, 2015.

- Collect in a few locations acoustical indicators and derivate a soundscape indicator map based on both relations and interpolation methods. For instance, in Lavandier *et al.* (2017), the sound indicators of interest are the Time and Frequency Second Derivatives $TFSD_{500Hz}$ and $TFSD_{4kHz}$, which aim to capture respectively voice and bird sounds, and the $L_{50,1kHz}$, which aims to capture the sound level. These indicators are interpolated over the area (the XIIIrd district of Paris) based on mobile measurements performed within each street. Finally, based on a linear re-gression elaborated in Aumond *et al.* (2017), which estimates the sound pleasantness based on these indicators, a sound pleasantness map is produced on the network (see Figure 2:16);

Figure 2:16 Example of sound pleasantness map interpolated from data collected through soundwalk. Source : Lavandier *et al.*, 2017.

- Use only modelling to derivate a sound-source oriented map, which is made more complex by the diversity of sources in urban areas, and the difficulty of characterizing them. Multi-source sound mapping have however recently come into existence. In Aletta & Kang (2015), specific noise maps are constructed for road traffic, fountains and birds, which are placed by default in trees. A probabilistic modelling framework is proposed in Aumond *et al.* (2018) which allows in addition the estimation of statistical indicators and the study of competition between sound sources, in other words the masking effects. The modelling follows a stochastic approach in which a set of sound maps is created that correspond to different representations of the possible instantaneous sound environment for each of the sound sources considered. The main difficulty confessed by the authors in these first attempts is the characterization of sound sources. If this seems easy for fix sound sources such as a fountain or church bells, estimating the sound power level of human voices or birds requires in the first instance strong assumptions. In order to go deeper in this modelling direction, new collaborations with researchers from bioacoustics or mobility will be required.

2.4.2.3 Measurement networks: towards source pleasantness and source-oriented indicators

Measuring soundscape is a tedious task, as it includes non-acoustical parameters (socio-cultural context, listeners' expectations, etc.). Different protocol coexist, described in Aletta *et al.* (2016). The most typical methods are soundwalks, laboratory experiments, behavioral observations and narrative interviews. Beyond this statement, sensor networks deployed can be of great help to access an advanced characterization of sound environments, as by essence it contains the integrality of the sound sources that compose urban mixtures and allows the calculation of any sound indicator.

This requires however:

- Enhancing the collected data with perceptual indicators and societal information. Note that the mobile phone noise application Noisecapture contains a tag module (see Figure 2:10) that goes in this direction. Similarly, the Sonyc project advantageously integrates a data-driven mitigation module that aims to correlate complaints to the sounds recognized by the network; humans are in addition significant part of the data treatment scheme (see Figure 2:6);
- Capturing the sound sources of interest within the signal, and derivating soundscape indicators from it. Main of the first deployed sensor networks include a module for sound source recognition. Oldoni *et al*. (2013) extract the acoustic characteristics of sounds at the server level to select the characteristic and atypical sounds at a given location. The Sonyc project contains a module that aims to detect, based on deep neural networks, specific sounds such as jackhammers, idling engines, car horns, or police sirens (Salamon et al., 2015). Similarly, the Dynamap project contains a specific sounds recognition module (Socoro *et al.*, 2017). Finally, the Cense project aims to produce perceptual noise maps, by developing soundscape models that rely on the automatic identification of noise sources. To this end, (i) a coding scheme that allows the recognition of acoustic events through Random Forest or Support Vector Machine algorithms has been proposed (Gontier *et al.*, 2017), (ii) an algorithm based on the Non-Negative Matrix Factorization has been developed to evaluate the contribution of road traffic in overall sound levels (Gloaguen *et al.*, 2019), (iii) the development of physical indicators that correlate with the perceived time of presence of sources of interest are under development, with the aim to produce sound pleasantness maps.

2.5 Discussion

The recent development of novel low-cost acoustic measurement devices, in a context where city management is moving towards a massive increase in the number of data and greater connectivity between objects, has led in recent years to the deployment of dense acoustic sensor networks and the development of alternative measurement protocols, such as mobile or participatory measurements. Data processing methods, combining the detection of erroneous measurements and temporal and spatial interpolations of measurements collected sparsely, are gradually being implemented. The recent application of data assimilation methods that merge measurement and modelling is a breakthrough in environmental acoustics that will make it possible in the near future to converge towards maps of unequalled accuracy. Finally, the characterization of sound environments is oriented towards perception-oriented approaches that leave an increasing role to the variety in sound sources.

The measurement networks thus created continue to evolve, in particular in the diversity of the produced outputs. Noise measurements have for instance been recently used to produce sound pleasantness maps, which are intended to characterize urban space no longer solely based on sound levels, but by combining indicators describing how noise environments are perceived (Aumond *et al.*, 2017). The CENSE project, for example, includes a task of sound source recognition, which will eventually make it possible to automatically produce multi-source noise maps on the basis of the measurements made, and to refine the sound pleasantness maps produced. Finally, measurement networks are oriented towards multidimensional aspects, the purpose of which is to correlate acoustic quantities with quantities describing traffic conditions (Can *et al.*, 2011), or even with air pollution quantities (Can *et al.*, 2011b). One of the ambitions of these multidimensional treatments is to establish possible confounders in the characterization of the health impacts of noise and air pollutants (Ross, 2011), or noise and fine and ultra-fine particles (Weber, 2009), as expected by epidemiologists. The use of acoustic indicators as proxies for estimating air pollution quantities, motivated by the lower cost of acoustic sensors, faces however many obstacles (Khan *et al.*, 2018), including a different dispersion behavior that leads to very variable correlation coefficients.

Finally, while recent years have seen the development of research on spatial interpolations and parsimonious sampling methods in the field of environmental acoustics, it is likely that these questions will be driven out in the near future by the density of measurement networks and the abundance of generated data. The development of dense sensor networks (one point every 20m in the example of the CENSE project) and continuous noise level measurement possibly makes interpolation issues obsolete. Research on the characterization of sound environments will then, and must already, focus on questioning the use of the data produced:

- In terms of communication with city dwellers, it is likely that the diversity of both the data produced and the means of sharing the data will continue to grow in the coming years. The current development of smartphone applications and dedicated websites, as well as the proposal of simple physical (e.g. Harmonica) or perceptual (e.g. sound pleasantness) indicators are part of this movement.
- Beyond the characterization of sound environments, however important it may be, lies the question of their management. The availability of measurements, continuously and with a high spatial density, must be an important lever of the noise levels reduction and more globally noise environments management. The question then arises as to how city dwellers and decision-makers can appropriate the data produced for noise environments management purposes. Several avenues can be explored:

- The development of smartphone applications that allow individuals to know their exposure, or even to adapt their routes during urban walks according to the noise environments they pass through (Aumond *et al*., 2017b), can allow exposure management at the individual level;
- The produced data can be used to adapt *in situ* the noise mitigation strategies (e.g. vehicle speed limitations) to the calculated noise levels. It is however not sure that dynamic traffic control strategies in the context of noise would be appropriate compared with air pollution, for which meteorology is a strong influential factor and thus dynamic control can be envisaged during pollution episodes. That being said, even under a static use the continuous collection of noise data can be a great help:
  - To better understand the impact of punctual noisy events on sound environments, such as building works, city festivities, etc., by correlating the different data sources, acoustic and other;
  - To test mitigation proposals, either temporary such as speed reduction initiatives, or permanent such as modifications of traffic plans or banishment of quiet zones to noisy vehicles, by directly seeing their impact on the measured noise levels.
- It is desirable that the data produced generate local governance initiatives. Groups of citizens could indeed argue noise reduction policies and make proposals based on shared noise data. For these reasons, it seems important that all the data produced be shared freely and in standard formats.

Finally, the developments discussed above are part of a context of smart city itself in transformation and currently subject to many controversies. Colding & Barthel (2017) list three issues that the Smart City will have to face in the future: (i) address the issues of resilience and cyber security, (ii) determine the benefiters and losers of the Smart City paradigm, (iii) evaluate the risk that the Smart City disconnects humans to nature. If these points may not concern directly the acoustics domain, they however invite to question the technophile approaches under development:

- Point (i) calls for ensuring that anonymity is preserved, in particular during audio recordings, but this is already the case in current measurement networks;
- Point (ii) raises the problems of unequal access to developed technologies (smartphone applications for example) and territorial inequalities in terms of the benefits generated. It is true that the first networks deployed concern hyper-centers, and therefore focus attention on these areas of study. It would be interesting to develop research assessing the disparities in access to information on noise environments, and whether recent noise abatement solutions benefit equitably all urban areas;
- Point (iii) suggests that the smart city may put a distance between human and nature. In the acoustical context, on the contrary the new developed technologies can help reducing this distance, by saving typical sounds and sharing it with city dwellers within dedicated platforms,

thus raising awareness to the diversity of sounds for instance by pointing places with an acoustical interest. The raising connections between research in acoustics and art projects and the growing concern of the impact of noise on fauna may be part of the response to this last issue.

Chapter 3 Multi-physical couplings for road traffic noise mitigation

Summary

Directive 2002/49 /EC, one of the main objectives of which was the production of noise maps, particularly road traffic noise maps, for all agglomerations with more than 100,000 inhabitants, have heavily impacted research in environmental acoustics. The methodology used to produce these maps was based on a static representation of road traffic, using simple vehicle count data to calculate noise emissions on each road section and estimate average noise levels (indicator L_{den}). More recently, the rise of low-cost measurement methods has shifted the focus of research in environmental acoustics to measurement networks. These two approaches, which focus heavily on the characterization of noise environments, explain the near absence of noise prediction models based on detailed road traffic modelling, whereas such couplings have been the subject of much work in air quality. The principle of these couplings is as follows: the traffic model provides kinematic data (more or less fine according to the model: vehicle flows, average speeds or even vehicle trajectories), which are used to calculate acoustic emissions, the road network being discretized beforehand into acoustic cells. This is followed by a calculation of the acoustic propagation giving access to the sound levels in a set of receivers.

The interest of a coupling between a traffic model and an acoustic model is threefold: (i) the traffic model potentially provides access to an accurate description of vehicle kinematics, which refines the estimation of noise levels emitted; (ii) the coupling makes it possible to predict the impact on noise of traffic control strategies to the extent that traffic model outputs take into account traffic conditions, vehicle kinematics and traffic reassignment to streets where traffic is most fluid, based on changes in the network; (iii) the coupling makes it possible to estimate time series of noise levels insofar as the traffic model provides vehicle trajectories, making it possible to calculate acoustic indicators reflecting noise dynamics (noise level distribution, noise event indicators), which are more correlated with perceptual and epidemiological data.

The modularity of the modelling framework presented makes it possible to develop multidimensional approaches, which also introduce other environmental externalities such as air pollution. The questioning around the prerequisites required to allow efficient multi-physical couplings goes beyond the field of acoustics and deserves to be addressed in parallel on all the negative externalities of road traffic.

In this context, this chapter reviews recent advances in research on multi-physical couplings for predicting and reducing road traffic noise. We will be particularly interested:

- In the interest of acting on road traffic to reduce noise levels in urban areas;
- In a review of the different approaches for predicting road traffic noise:
    - Critical review of static approaches,
    - Presentation of recent probabilistic approaches,
    - Presentation of dynamic approaches;

- In the conditions of multi-physical coupling based on traffic modelling, whether for acoustic or air quality assessments;
- In a few case studies using dynamic road traffic modelling to assess the acoustic impact of traffic control strategies.

The latest referenced work highlights the need for multi-criteria assessments, and the use of multi-scale approaches, on which the chapter closes.

Note:

In addition to a state of the art in the field, the work presented in this chapter is partly based on my thesis work at LICIT (Ifsttar / ENTPE) and my post-doctoral work at Ghent University. More recent collaborations with LICIT (Ludovic Leclercq, Cécile Bécarie, Delphine Lejri), and the work done with Pierre Aumond within UMRAE, have contributed to the chapter. Finally, the thesis begun in 2018 with Sidi Mehdi Regragui on "Estimation of rare events in environmental acoustics" (Ifsttar / University Cergy-Pontoise, description p.142) is part of this research theme.

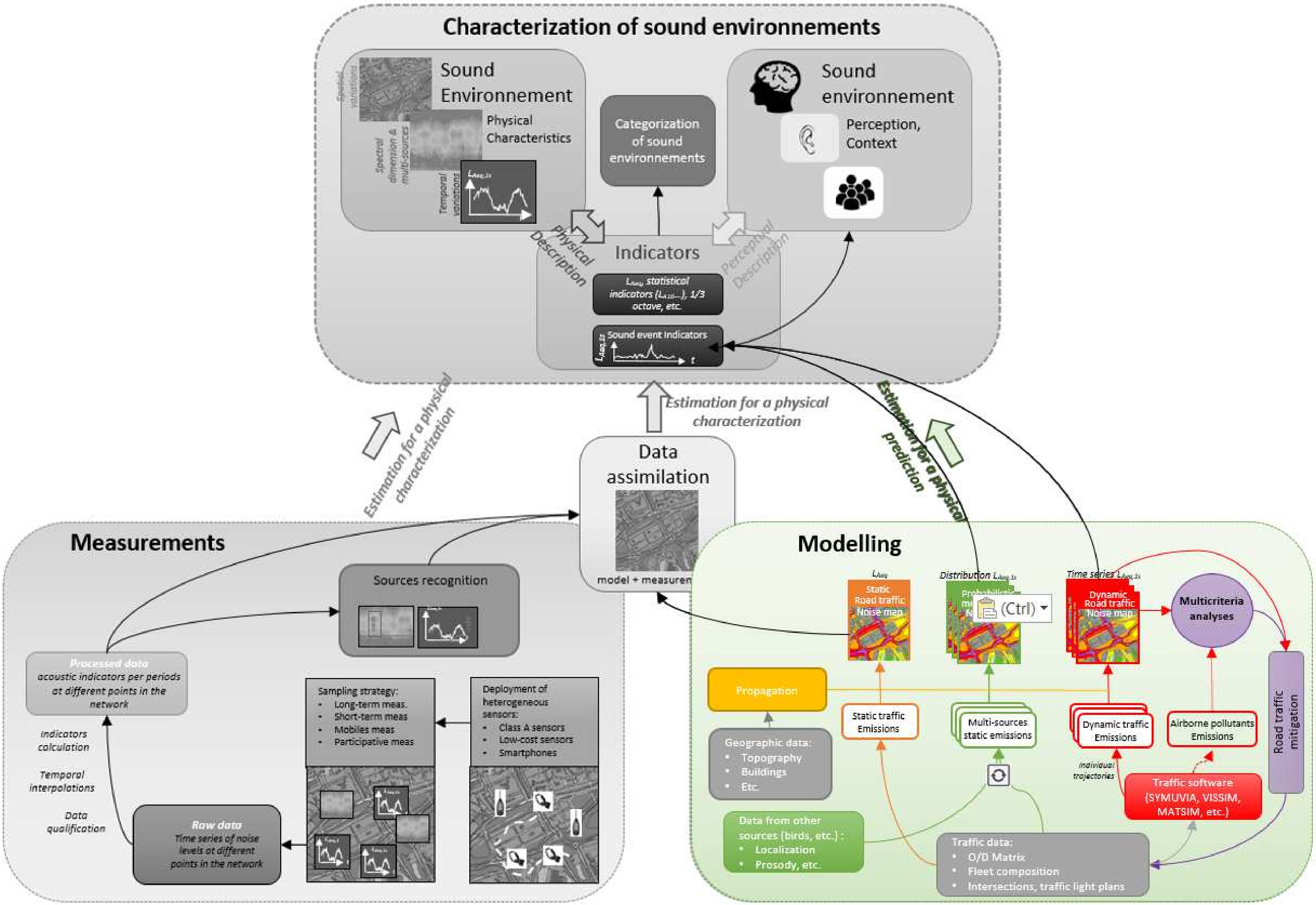

Figure 3:1 Schematic representation of research activities: focus on research axis 3

3.1 Introduction

Increasing urbanization and the high demand for mobility it generates are potential vectors for the degradation of urban noise environments. The direct consequence is that two-thirds of urban dwellers say they are bothered by noise in their homes, with road traffic being regularly cited as the most annoying source of noise. The health stakes are high, with an estimated 1 million healthy years lost across Europe (Who, 2011). Urban metropolitan areas, since they are the seat of both the highest noise levels and the highest population densities, concentrate the highest exposures and therefore most of the efforts currently being made to combat noise. The development of models capable of assessing the impact on noise of urban policies concerning development (e.g. the study of the links between urban density and noise exposure), or mobility management (e.g. the evaluation of road traffic regulation strategies and multimodal transport policies), therefore represents a major societal and environmental challenge.

The context surrounding the use of modelling to characterize urban sound environments is changing. Initially very limited by the European Directive 2002/49/EC, which recommended the evaluation of aggregate acoustic indicators such as L_{den}, the characterization of sound environments is now oriented towards approaches concerned with temporal and spectral variations in noise levels, in response to the results of recent research on soundscapes (Ishima & Hashimoto, 2000; Berglund *et al*., 2002; Lavandier *et al*., 2000). In addition, recent research has highlighted the importance of traffic composition in the perception of sound scenes composed of urban traffic noise; in particular, the presence of two-wheeled vehicles and the strong temporal variations in the noise levels they induce are perceived very negatively (Gille *et al*., 2016b). Beyond noise levels, the number of events becomes a major indicator in the case of heterogeneous traffic (Gille *et al*., 2016).

The problem of road traffic noise in urban areas is therefore part of a multiple context. The very different exposure conditions between silent and noisy places suggest the need for separate treatment depending on the traffic situation. While for the latter the need to reduce noise levels takes precedence over any other consideration, studies conducted on silent neighborhoods again show the importance of the number of events (Abiale, 1983) and the beneficial impact of periods of calm (Gille *et al*., 2016). In addition, the perception of sound environments in quiet neighborhoods is generally perceived differently (more positive) for passers-by than for residents (Rey Gozalo & Barrigon Morrillas, 2017). There is also a consensus on the importance of preserving quiet urban neighborhoods, with modalities for their identification and preservation described in (EEA, 2004). Finally, the abundant literature on nocturnal annoyance again emphasizes the need to focus on noise events modelling (Basner, 2018). The ultimate objective of research on the prediction of road traffic noise must therefore be to propose models, or couplings between models, that allow the estimation of indicators that highlight the physical dimensions of sound environments correlated to perceptual impacts: spectral content, variation in sound levels, noise events.

A description of the potential for reducing noise levels by acting on road traffic is first proposed and then the general modelling principles are given. Then, the different approaches to predicting urban sound environments are examined in this chapter under the prism of this objective: i) static approaches, ii) probabilistic approaches, iii) dynamic approaches. The latest developments of the models and their limitations are discussed.

The dynamic approach, which consists of a coupling between road traffic modelling and conventional models estimating acoustic emissions, is the preferred approach. The problem of multi-physical coupling then goes beyond the field of environmental acoustics. The questions raised by approaches involving road traffic modelling and estimation of the environmental externalities emitted require attention to the modalities of such couplings: fineness and precision required for the traffic variables used, adaptability of the different models, case studies allowed and results. Considerations on these couplings open the way to multidimensional approaches, allowing the evaluation of traffic regulation strategies on a wider range of criteria: noise, air pollutants, energy consumption.

3.2 The importance of taking action on road traffic to reduce noise levels

In an urban context where building density drastically constrains noise reduction initiatives on the propagation path, and in front of the rise of urban space sharing policies that tend to bring together different modes of transport and remove roads reserved for the car, reducing road traffic emissions at source seems the most promising lever to calm noise environments, even if solutions such as low screens or green roofs have recently been developed (Hosanna Project, 2013 ; Sonorus Project, 2016). The means of action seem simple: the factors influencing noise emissions are those on which action should be taken to reduce the noise levels emitted. These factors are:

- **Traffic volumes**: Emissions related to a traffic flow are proportional to the logarithm of the vehicle flow. Thus, it is common to say that a doubling of vehicle flow increases emissions by 10 x log10(2) = 3 dB. Although we will see that in practice the increase is less (the effect of doubling vehicle flow being balanced by a decrease in average speeds), this relationship shows the interest of acting on a decrease in traffic volumes to reduce noise levels;
- **The quality of acoustic road pavements**: vehicle rolling noise is highly dependent on the quality of the road pavements, with attenuations offered by so-called "silent" pavements up to 5 dB(A) compared to reference pavements (Peeters & van Blokland, 2007). However, the gains are not very significant at speeds in urban areas, with the traffic noise component related to engine noise being predominant below 30 km/h for the latest generations of vehicles (Peeters & van Blokland, 2007);
- **Vehicle speed**: speed impacts engine noise as well as vehicle rolling noise. According to the IMAGINE model (Peeters & van Blockland, 2007), for light vehicles the reduction in sound power is about -0.3 dB(A) for a speed reduction of 1 km/h between 30 and 50 km/h, and about -0.2 dB(A) per km/h between 50 and 90 km/h (see Figure 3:2a). However, these figures are often misinterpreted: the reductions per unit of distance, in dB(A)/m, are less significant because slow vehicles stay longer on the network. The reductions in dB(A)/m, which are interesting for the estimation of aggregate acoustic indicators, are given in (Can & Aumond, 2018): they are for example only -0.125 dB(A)/m for a speed reduction of 1 km/h between 70 and 90 km/h (see Figure 3:2b). The potential for reducing noise levels by influencing speed remains real;
- **Vehicle speed variations**: acceleration has an additional effect on engine noise, estimated in the IMAGINE model at 1.7 dB(A) for an acceleration of 1 m/s^2 at a speed of 20 km/h (Peeters & van Blokland, 2007). Let us note that the effect of acceleration varies consequently from one model to another: it is estimated at 15.2 dB(A) for example, if the American FHWA model is used for the same kinematic conditions (Fleming *et al.*, 2005). Traffic smoothing therefore seems potentially effective, but difficult to evaluate;
- **Composition of the vehicle fleet**: emissions vary significantly, for identical kinematic conditions, from one vehicle class to another. According to the IMAGINE model (Peeters & van Blokland, 2007), the sound power of a heavy vehicle is for example higher than that of a light vehicle by 8.3 dB(A) and 6.4 dB(A) for speeds of 50 and 70 km/h respectively. The impact on noise levels of the composition of the vehicle fleet is therefore significant, see Figure 3:2c; however, it should be noted that this impact

is speed dependent. Motorcycle emissions are higher than those of light vehicles, mainly in accelerated mode, by 8.5 dB(A) for example at 50 km/h for an acceleration of 2m/s². On the other hand, perceptual studies tend to show that perceptual indicators such as roughness and the maximum levels reached also explain the increase in annoyance due to two-wheelers (Paviotti & Vogiatzis, 2012). Finally, the rise of electric vehicles seems to be a natural lever for reducing noise levels; however, their effect on the scale of vehicle flow is nuanced by the fact that the percentage of vehicles deployed is still low, and that the contribution is particularly interesting at low speeds where engine noise predominates (Campello-Vicente *et al*., 2017). Moreover, inertia in the renewal of the vehicle fleet is a brake on the reduction of noise levels, with old vehicles contributing significantly to high ambient levels. In fact, the disparity of the levels measured on site is often very large: (Brown & Tomerini, 2011) have, for example, measured deviations from maximum levels of up to 20 dB(A).

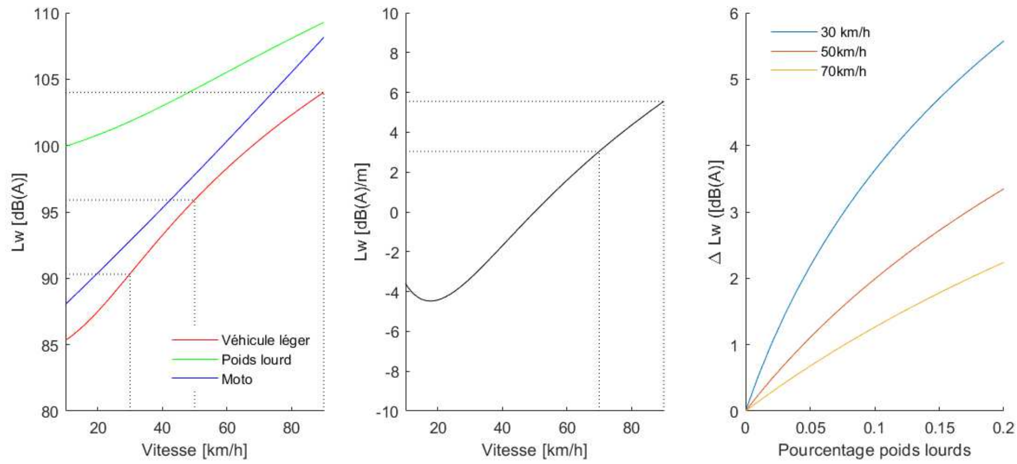

Figure 3:2 Emission laws relating to the IMAGINE model (Peeters & van Blokland, 2007). a) Sound power Lw (in dB(A)) as a function of speed; b) Difference in sound power per unit distance ΔLw (in dB(A)/m); c) Impact of the percentage of heavy vehicles on the sound power of the flow (in dB(A)).

Thus, acting on road traffic to reduce ambient noise levels in urban areas seems promising; it is a solution that is increasingly being adopted (Rust, 2007). Many initiatives in this direction are reported in the literature, see for example (Ellebjerg, 2007) or (Desarnauld *et al*., 2004) for a census. Among the usual solutions, we will remember that:

- The installation of speed bumps aims to reduce speeds, which reduces noise levels. However, the acoustic interest depends largely on the shape of the speed bumps and the composition of the traffic (Ellebjerg 2007), so the results differ widely from one study to another. Reductions of 1 to 2 dB(A) between two speed bumps are predicted by modelling according to (Kokowski & Makarewicz, 2006), due to the decrease in speed. Observations have shown reductions ranging from 4 to 8 dB(A) on daily noise levels (Abbott *et al*., 1997). However, these results must be balanced by the local increase in noise levels sometimes observed downstream of facilities due to vehicle accelerations (Rylander & Björkman, 2002).

- Green waves[16] can reduce noise levels because they tend to reduce variations in speed; the reduction is greater if accompanied by a decrease in average speeds. The probable gain is estimated at 3 dB(A) based on a calculation by (Ellenberg & Bedeaux, 1999). In general, the reduction in high accelerations brought about by driving calming policies tends to reduce noise levels (European Commission, 1998).
- The replacement of crossroads with a traffic signal by roundabouts also tends to reduce speed variations, and therefore noise levels. A reduction in noise levels of 1 to 4 dB(A) is observed by (Bérengier, 2005), depending on the geometry of the intersections.
- Traffic management at the urban scale, including speed reduction, traffic reassignment to main roads or managing the composition of the fleet of vehicles using the network, can reduce noise levels locally (Sonorus, 2016; Ellebjerg & Bendtsen, 2007; Murphy & King, 2011). (Ramis *et al*., 2003) measured decreases in noise levels of 3 to 6 dB(A) in the city of Motilla de Palancar (Spain), for example, following the implementation of a ring. In Dublin City, (King *et al.*, 2011) measured a decrease in average noise levels of 2 dB(A) in a downtown area after its ban on vehicles during peak hours. Traffic reassignment can be aimed at preserving quiet areas (Thorsson & Ögren, 2005), (Nilsson & Stenman, 2007). The banning of noisy vehicle in some areas (Björkman & Rylander, 1997), or the creation of low-traffic areas where only electric vehicles are allowed, are also solutions for preserving quiet areas (Maffei & Masullo, 2014).

A summary of the expected noise reductions on the L_{Aeq} is given in (Bendtsen *et al*., 2005): up to -2 dB(A) for a roundabout, -2 dB(A) for a 30 km/h area, -7 dB(A) for the prohibition of heavy vehicles during night periods. According to the same authors, adverse effects can be observed: up to +6 dB(A) for some speed bumps, or +3 dB(A) for paved areas.

However, the impacts mentioned above are subject to discussion. A census carried out as part of the SMILE project (Smile, 2003) showed that, in addition to the fact that local authorities are already heavily involved in noise abatement, the benefits are most often estimated either based on calculations or on the basis of comparative measurement campaigns, before and after the implementation of the facility. Both approaches have limitations, although first conclusions can be drawn. Calculations made based on emission laws, simply based on expected variations in flow rates or average speeds, neglect the real dynamics of road traffic flow: imposed speed reductions can potentially be accompanied by an increase in speed variations, or unexpected traffic reassignment, which can lead to a real result opposite to that expected. Pre- and post-measurements are reliable, but have a low predictive power, describing only a specific situation, for a given traffic composition and the layout of the study area of interest.

3.3 General modelling principles

Road traffic noise prediction can follow two approaches with different philosophies: statistical modelling or physical modelling. The first aims to link directly acoustic quantities to presumed influential variables through statistical models, while the second seeks to understand and model all the phenomena affecting these acoustic quantities.

[16] Green wave: the traffic lights are synchronized so that a vehicle adapting its speed to the speed of the wave will not encounter any red lights once the first intersection has passed. The green wave can be adjusted at different speeds by playing on the shifts between the green shifts.

3.3.1 Statistic modelling

Statistical modelling consists in linking an acoustic indicator, usually the L_{Aeq}, to input variables, based on observations. The input variables assumed to be correlated with noise levels are then retained. Flow rates by vehicle class are chosen in Gündogdu *et al*. 2005, for example; traffic volume, composition and speed are used in (Rahmani *et al*., 2011). Variables related to horn use, number and width of tracks, slope and surface of pavements are added in (Abo-Qudais & Alhiary, 2007). The diversity of traffic uses and situations can also be implicitly taken into account, as in Rey Gozalo *et al.* (2017) where variables related to the presence of traffic lights, schools or commercial areas appear. Statistical modelling can also be used to estimate acoustic quantities other than L_{Aeq}: an estimation of statistical indicators (L_{10}, L_{50}, and L_{90}) based on light and heavy vehicle flows and average vehicle speed is proposed in (To *et al*., 2002).

In addition to the input variables retained, the approaches differ in the statistical models used, from linear regressions used in Abo-Qudais & Alhiary (2007) or To *et al*. (2002) to more advanced models based for example on genetic algorithms (Rahmani *et al*., 2011). It is shown in Nedic *et al*. (2014) that neural networks offer better results than linear relationships for estimating L_{eq}.

However, the examples cited above all ignore propagation conditions, using only variables describing the sources. In addition, this brief review suggests that the number of potential variables at the input of the models can be extended to infinity, refining the estimation of acoustic quantities but at the risk of an over adjustment problem and a model limited to the study area. To overcome this difficulty, a method is proposed in Torija *et al.* (2010) to prioritize the variables that can be included in the models, aiming to select only the most relevant variables.

Statistical models have also been proposed to link noise levels to urban morphology, thus implicitly taking into account propagation conditions. In Silva *et al*. (2014), noise levels are statistically linked to morphological indicators describing the shape of facades: compactness and porosity indicators, or fractal indicators in Oliveira & Silva (2011). The impact of urban forms on noise levels is also studied in Tang & Wang (2007). Ryu *et al. (*2017) use spatial autoregressive models to highlight influent urban morphology indicators: the authors show the importance of building density, and an indicator combining building density and building height. Finally, Genaro *et al*. (2010) construct the estimate based on a neural network and a set of 24 variables describing the sources (number of light vehicles, etc.) and propagation conditions (building height, street width, etc.).

Finally, it should be noted that statistical approaches could also be used to estimate perceptual indicators. In Lavandier *et al*. (2016), geo-referenced data describing road traffic, the presence of gardens, food shops, restaurants, bars, schools, markets, are transformed into Kernel densities used to construct linear regressions explaining up to 68% of the variance in sound pleasantness in the study area.

To conclude, the variety of models built, and their relevance for estimating physical or perceptual acoustic quantities, especially when they are based on geographical variables such as in Lavandier *et al*. (2016), point to statistical approaches as a locally plausible alternative for the production of sound environment mapping. However, regardless of the quality of the models built and their relevance for estimating noise levels in a given territory, the main limitation of this approach is its high dependence on the corpus of observations, even if this criticism must be tempered by recent results: in Rey Gozalo *et al.* (2016), the robustness of a statistical model is tested on a new corpus of observation points, the error being limited to 2 dB (A) and therefore quite acceptable. However, unless there are very complex models, how can these approaches be used to assess the acoustic impact of road pavement modifications or the installation of noise barriers? How to determine if a decrease in average speed or a modification of the road will have a positive impact on the noise environment? Similarly, the extension of the models built to vehicle fleets or urban morphologies different from those of the observation corpus seems delicate if not impossible. Thus, even if the statistical models constructed are very instructive for understanding the traffic and urban morphology variables that influence noise levels, the limits mentioned above underline the importance of modelling that aims to reproduce each of the physical phenomena, from emission to acoustic propagation.

3.3.2 Physical modelling

Apart from statistical models, the estimation of road traffic noise is systematically based on the calculation process defined in Figure 3:3. The calculation is based on variables describing the flow of traffic on the network in question. These variables are used to estimate acoustic emissions on the network, which is first discretized into acoustic cells. This is followed by a noise propagation calculation, which determines the acoustic attenuation for each "acoustic cell / receiver" pair. This attenuation makes it possible to calculate the contribution of each acoustic cell to the sound pressure level Leq in each of the receivers. Finally, the energy sum of the contributions gives the sound pressure level in each of the receivers.

The robustness of this modelling chain should not overshadow the diversity of approaches that can be used to predict road traffic emissions and noise propagation. The reader may refer to Can & Aumond (2008) or Quartieri *et al.* (2009) for a review of emission models. While the variety in the models is large, their formulation differs little from one model to another, consisting of functions linking spectral band sound power to kinematic variables such as vehicle speed, proportion of heavy vehicles, slope, type of pavement, etc. If different models have been proposed for each country, it is mainly in response to different vehicle fleets.

The variety in propagation models is greater, particularly because numerical solving poses computational problems that the regular increase in computer ressources answers over time, making it possible to take into account new physical phenomena. Time domain modelling has therefore gained interest since the early 2000s; it makes it possible to evaluate new noise reduction solutions, such as green roofs or facades, and to improve the estimation of noise levels inside quiet streets where sound waves undergo a complex propagation path (Van Renterghem & Botteldooren, 2008; Van Renterghem & Botteldooren, 2010). Temporal approaches differ in their numerical discretization scheme and in the solved equations: finite difference time domain method (FDTD) (Ostashev *et al*., 2005; Van Renterghem *et al*., 2006), numerical schemes to reduce computation times such as the line transmission matrix (TLM) (Guillaume *et al*., 2014), or the pseudo-spectral time method (Hornikx *et al*., 2010). However, despite the efforts made on digital resolution schemes and the constant improvement of computing resources, time approaches are currently limited at street level, and therefore do not meet the criteria for traffic noise assessment. High-frequency approximations, neglecting the wave aspect of acoustic waves, have been proposed to allow resolution over larger spatial domains. For a review and comparison of the different models, the reader is referred to Bérengier *et al.* (2003). Most current models, known as engineering models, rely on ray or particle throw methods, which are known to offer a good compromise between accuracy and computation time, despite approximations made at low frequencies (Defrance & Gabillet, 1999; Kephalopoulos *et al*., 2012; Can *et al*., 2015). A detailed review of engineering propagation models is given in Garg & Maji (2014) or De Lisle (2016).

While static, probabilistic and dynamic approaches share the general schematic formulation of Figure 3:3, they differ in the way road traffic is described:

- In the static approach, the traffic model (or on-site measurements) provides access to aggregate data on traffic flows and average speeds, or speed distribution, by vehicle class. These variables are used to estimate the sound power $Lw_{f,k}$ per frequency band f, for each acoustic cell k of the previously discretized road network. The temporal evolution of these emissions is therefore not accessible, and only aggregated indicators can be estimated at the receivers;

- In the probabilistic approach, aggregate data on traffic variables are used to determine the density of vehicles per acoustic cell k, which determines an activation ratio for the cell. Successive iterations then make it possible to estimate, for each instant t, the sound power per frequency band for each acoustic cell k of the road network $Lw_{f,k}(t)$. Note that there is no temporal consistency between the values $Lw_{f,k}(t)$. The estimation of the temporal evolution $L_{eq,f}$ of the pressure levels at the receiver is therefore not possible; but the estimation of acoustic indicators describing the distribution of $L_{eq,f}$ values, yes ;
- In the dynamic approach, the traffic model provides vehicle trajectories, i.e. the position, speed and acceleration of each vehicle on the network at each moment t. The usual time step is $\Delta t = 1s$. These trajectories are used to calculate the emissions of each vehicle at each moment, aggregated emissions per acoustic cell k to form the temporal evolution of the emissions $Lw_{f,k}(t)$. The propagation calculation and the sum of the contributions of each cell allow the determination of the temporal evolution of the pressure level receiver $L_{eq,f}$ (t), allowing the calculation of a wide variety of acoustic indicators.

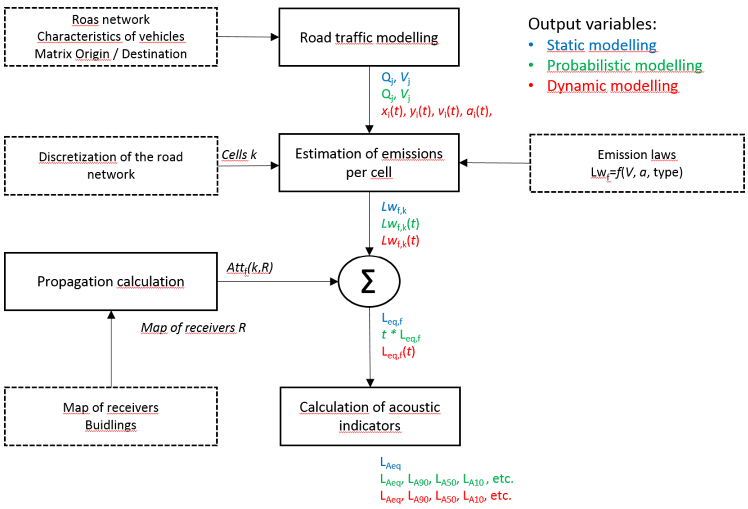

Figure 3:3 Generic scheme of physical models for estimating road traffic noise

3.4 Static modelling: limitations and latest developments

The approach recommended by the European Directive 2002/49/EC for the prediction of road traffic noise is based on a census of average flows and speeds by vehicle class, to estimate the sound power of vehicle flows. Despite the criticisms that may be made of this approach, which will be listed below, the static approach has the undeniable advantage of having made it possible to map the noise of European cities with more than 100,000 inhabitants, thus improving knowledge of the population exposed to excessive noise levels, through a representation that is easily understood by the public (see a sample noise map in Figure 3:4). The product indicator, L_{den}, is also very well correlated with long-term annoyance (Miedema & Vos, 1998).

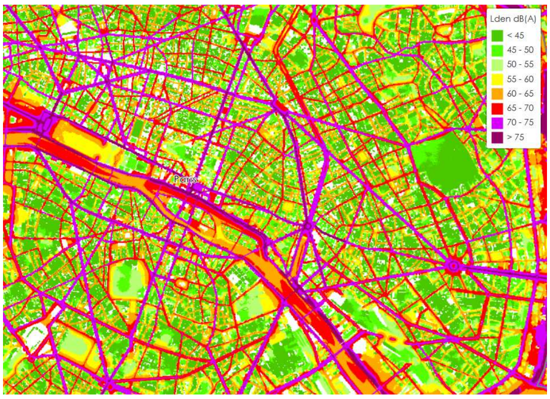

Figure 3:4 Extract from the noise map of Paris. Source: https://carto.bruitparif.fr/

However, since the introduction of the Directive, the shortcomings of the methodology have been highlighted. In particular, it has been criticized for making it impossible to estimate temporal variations in noise levels (Steele, 2001). In addition, even for the estimation of aggregate acoustic indicators, the static approach introduces errors for the estimation of noise levels in an urban context. For example, noise emission models are often limited to speed ranges that do not correspond to urban driving conditions (Melo *et al*., 2015; Hammer *et al*., 2016); models are therefore relatively unsuitable for estimating noise emissions from vehicle flows travelling below 30 km/h, which is quite common in cities. In addition, there are approximations on the input data. In most cases, speed distributions are not considered by models, which favor the average flow speed, even though the impact of these variations on the emitted noise levels is recognized. Iannonne *et al.* (2012), for example, showed that a Gaussian distribution of speeds leads to a variation in the noise levels emitted of about 1 to 2 dB, for standard deviations of 10 and 20 km/h respectively compared to the levels calculated without standard deviation on speeds. Ausejo *et al.* (2010) showed that the uncertainty on speeds is the higher source of error when computing a noise map. Finally, the speed variations on the network, which are very marked in urban areas (repeated stops, acceleration phases, etc.), are neglected by these models in their original form. The chaotic vehicle kinematics imposed by urban traffic flows is then a source of error. Can *et al.* (2009b) estimate the error of a case study of an urban boulevard with traffic lights at more than 3 dB(A). Static models are effectively insensitive to traffic conditions; in particular, they are unable to capture the effects of transient queues under unsaturated traffic conditions and stop-and-go behaviors under saturated conditions (Chevallier *et al*., 2009). Errors are particularly important at low frequencies (Can *et al*., 2010b), which is problematic given the annoyance they cause and the difficulty of effectively mitigating them. Finally, the description of the vehicle fleet is often too simplistic to account for the variability in levels from one city to another due to the percentages of two-wheelers, which can have a significant part in average noise levels and even more so on the maximum levels reached (Paviotti & Vogiatzis, 2012), or due to different driving styles.

3.4.1 Proposals for taking into account vehicle kinematics

As a result, various improvements have since been proposed to better reflect vehicle kinematics:

- In Can & Botteldooren (2011), emission laws are constructed on the basis of driving cycles statistically representative of traffic conditions in urban areas, previously established as part of the development of air pollutant emission models (André, 2004). The model aggregates the sound power emitted during driving cycles, thus implicitly taking into account speed distributions and vehicle accelerations as a function of traffic conditions on the network. The sound power levels estimated with this new approach are significantly different from those estimated simply on the basis of the average speed of vehicles, particularly when traffic is congested: deviations of up to 4dB(A) compared to the actual average speed on the network, and 8 dB(A) compared to the regulatory speed of 50 km/h, are observed. Further tests have shown that the error at low frequencies can even exceed 10 dB. However, limiting the approach is the difficulty in finely spatializing emissions;

- In Iannone *et al.* (2012), a model is proposed to include different forms of speed distributions (Beta, Normal or Chisquare) in the estimation of the acoustic powers of a vehicle flow;
- In Iannone *et al*. (2011), the acoustic powers of vehicle flow are expressed not only as a function of flow rates, but also as a function of vehicle density, using the fundamental diagram of traffic, a key element of road traffic theory that links flows to vehicle densities on a road network (Greenshields, 1935). The proposed approach therefore allows the calculated emission levels to be adapted to traffic conditions, but requires precise knowledge of these variables describing the flow. Makarewicz (2011) uses a similar approach, based on the fundamental diagram, to quantify the reduction in noise levels due to congestion, which can then reach 2 dB in saturated mode. However, these two approaches do not include accelerations induced by chaotic flows;
- In Makarewicz *et al.* (1999), a model is constructed to determine emissions in the context of flows interrupted by a stop line, as a function of the number of vehicles stopping and by integrating their emissions over the entire acceleration phase. This approach is further refined in Picaut *et al*. (2005), where corrections are proposed for estimating emissions at intersections, based on average vehicle trajectories, based on on-site measurements. However, these approaches are limited in their difficulty to adapt to traffic conditions, as queues move the vehicle starting areas for real cases;
- De Coensel *et al*. (2007) use a microscopic traffic model that reproduces vehicle trajectories as a function of traffic conditions (see details on the approach in section 3.6.4) to propose corrections at intersections for different flows at its entrances, and different durations of the green and red phases of the traffic light. The study shows the importance of dissociating the acceleration and deceleration phases in the calculation around intersections. Corrective measures are also proposed, but these depend on parameters such as the size of the queue and the average waiting time at the traffic signal, which are difficult to access;
- Finally, Can & Aumond (2018) introduce additional traffic variables into the modelling to refine the estimation of noise levels in the case of a congested regime: time spent at a standstill by vehicles, average acceleration on the acoustic cell. The study is based on real vehicle trajectories collected on a busy boulevard. Here again, the variables added to the model can be difficult to collect on real cases.

The most recent models used officially partially incorporate the results of this research, and now include a correction that takes into account transient driving conditions and increased noise due to speed variations near intersections (Kephalopoulos *et al*., 2012; Yamamamoto, 2010). The Harmonoise model explicitly introduces a linear correction term that depends on the acceleration value in the range of -2 to 2m/s2 (Watts, 2005); however, this corresponds to data rarely available on a real network.

3.4.2 Contribution of Geographic Information Systems

Beyond the proposals made for improving the consideration of vehicle kinematics, it is above all on the form of the models that recent advances have been most significant. In particular, the contribution of Geographic Information Systems (GIS) to the prediction of traffic noise levels is undeniable. As early as 2003, De Kluijver *et al.* (2003) anticipated the value of using GIS data to facilitate the production of noise maps: in addition to facilitating the collection of the geographical data needed to calculate noise propagation, there is also a reduction in calculation times and a dimensioning of uncertainties. Previously, studies had already used the GIS environment to estimate the effects of traffic on noise or air pollution, but either in a simplified version based on analytical functions (Li *et al*., 2002) or only to modify the input data (Moragues & Alcaide, 1996). Murphy *et al*. (2006) show that the contribution is also undeniable for the communication and rendering of the maps produced. The authors also show, with regard to the rendering of the maps, the impact of the interpolation modes chosen on the results. The modalities for calculating noise maps based on GIS data are discussed in (IMAGINE, 2007), independently of the GIS software used and at different levels of detail: coordinate systems, topological simplifications, minimum size of the buildings to be considered, acoustic characteristics of surfaces, etc. Finally, to further facilitate collection and reporting, Alesheikh & Omidvari (2010) discuss the value of a GIS software prediction model sharing the same data formats. To this end, Kotsev *et al.* (2015) highlight the value of standardized exchange formats, for example based on the INSPIRE directive.

Even if these works lay the foundations for predicting traffic noise in a GIS environment, they keep a decoupled view of the GIS tool, useful for data collection and results restitution, and the prediction of noise levels, carried out externally by a dedicated software. The modularity of GIS software now makes it possible to develop modules for predicting traffic noise within the GIS itself. A major advance in this field is the Noise-modelling module, created at Ifsttar as part of the ANR Eval-PDU project (Eval-PDU, 2012); see Figure 3:5. The proposed approach, which consists of a series of SQL queries compatible with the OrbisGIS software, is described in detail in Fortin *et al*. (2012). For more details, the reader can also refer to the dedicated page: http://noise-planet.org/noisemodelling.html:

- Most of the algorithms in the NoiseModelling module, mainly for the calculation of sound propagation, are based on spatial analysis methods that optimize and reduce the complexity of finding the sound propagation path in an urban environment, and thus reduce calculation times. Each part of the calculation process was divided into several SQL functions using the H2GIS database available in OrbisGIS;
- The rendering integrated into the GIS software facilitates the calculation of exposures, as land use data is often available;
- The method relies entirely on open data for the determination of propagation: topographic data from Open Street Map (http://noise-planet.org/noisemodelling.html). The OrbisGIS software itself is freely accessible (http://orbisgis.org/). Thus, the environment and free data allow the creation of noise maps entirely free of charge. However, a lock remains on access to reliable traffic data, which can be costly;
- The method developed for traffic noise can be adapted to other sources, for the production of multi-source noise maps, according to a methodology described in Aumond *et al.* (2018). The idea is then to use the collection of land use data (shops, residential areas, etc.) to calculate indicators to estimate the presence of certain sources (birds, human voices, etc.), linked to perceptual characteristics of sound environments (Hong & Jeon, 2014). The modeling environment will therefore eventually allow a characterization of sound environments that go beyond traditional noise maps.

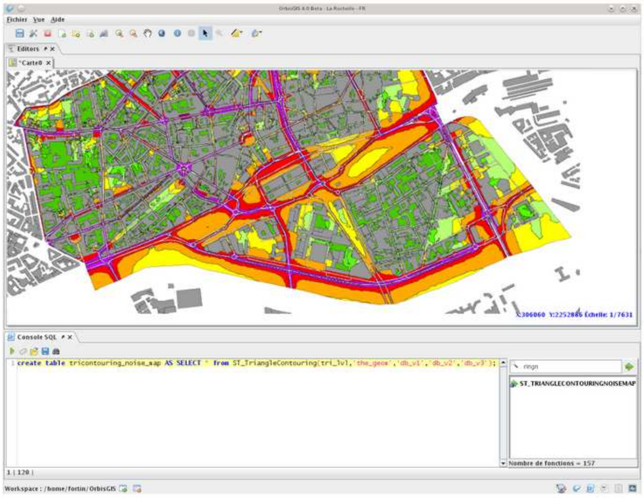

Figure 3:5 Illustration of the Noisemodelling graphical interface. Source: http://noise-planet.org/noisemodelling.html.

3.5 Probabilistic modelling

A major drawback of the static approach to characterizing urban noise environments is that the modelling framework does not account for variations in noise levels, which prevents the production of statistical or noise event indicators, and does not allow the study of competition between typical urban noise sources. The punctual emergence of bird noise is for example dependent on the time evolution of background noise from road traffic. Introducing this variety of sources would improve the characterization of urban noise environments; for example, the masking of bird noises by road traffic noise is potentially detrimental to soundscapes (Hao *et al.*, 2016). This explains the increasing consideration of biophonic sources for the description and management of soundscapes (Kang *et al*., 2016), even if their modelling remains in its very beginning.

In Hong & Jeon (2017), the presence of sources, classified according to traffic, water, human noise and bird noise, is perceptually assessed at sampled locations and interpolated to create source-based noise maps. A modelling approach is followed in Aletta & Kang (2015): specific noise maps are constructed for road traffic, fountains and birds, which are placed by default in trees.

Aumond *et al*. (2018) proposes a probabilistic modelling framework that supports multi-source approaches and allows the estimation of statistical indicators. The approach is stochastic: a set of n x k sound maps is created, corresponding to n representations of the possible instantaneous sound environment for each of the k sound sources considered. Each i_k sound map can be seen as a photograph at a moment of the equivalent sound environment of one second for the contribution of a given sound source. Statistics are performed on a sufficiently representative number of maps to characterize the sound environment where the input parameters of the model are stable (e.g. a constant density of birds during the period in the study area). The objective is therefore to allow the calculation of indicators reflecting the variability over time of the noise environment. The temporal evolution of sound environments, i.e. the coherence between two consecutive iterations i, is not a target output of the model. The same four-step modeling framework is followed regardless of the sound source: (i) a spatial distribution of the potential sound source of interest, (ii) the calculation of a sound propagation matrix, (iii) the stochastic activation of a sound source ratio for n iterations of the noise map, and (iv) the calculation of specific sound indicators:

- For the road traffic source, the interest of the approach lies in the distribution, unlike the usual static approaches, of sound sources on the road network: the road network is discretized into acoustic cells, which are activated or not at each iteration *i*, depending on the density of vehicles on the network. This implementation results in a 1-s emissions map, which coupled with the attenuation matrix allows the calculation of the noise map *i* for road traffic. This stochastic approach therefore makes it possible to reproduce the intermittent sound levels encountered in streets with low traffic densities.
- The same approach is used to calculate *n* noise maps for fountains, human voices and birds. For density estimation, the study is based on free macroscopic data and models available in the literature. For example, pedestrian densities are estimated from Kernel functions around densities of points of interest (shops, stations, etc.), following the approach proposed in Lavandier *et al*. (2016). The emission laws are also based on literature. However, the authors acknowledge that much remains to be done to model sources of noise other than traffic.
- Finally, the *n* maps obtained for each source are compared to study the competitions between sources. A source is assumed to be heard if its sound level exceeds at one point and for a given octave band the other sources (e.g. 4 kHz for birds); however, the authors recognize the need to refine this modelling step as well.

The approach thus makes it possible to produce maps of statistical indicator (e.g. level exceeded 10% or 50% of the time), as well as maps of the emerging sound sources, see Figure 3:6. Here, for example, voices are present in the southwestern part of the study area, which is a pedestrian zone, while birds are heard mainly in the park to the east of the study area.

Figure 3:6 Map of emerging sound sources: a) voices; b) birds; c) road traffic. Source: Aumond *et al.*, 2018.

Thus, the probabilistic approach greatly refines the characterization of sound environments. Its final advantage is that it is only slightly more time-consuming to calculate than the static approach, since the propagation matrix, the most expensive step in the modelling chain, is only calculated once.

3.6 Dynamic modelling

3.6.1 Interest of coupling and feedback on air pollutants

The advantages of the probabilistic approach to improve the characterization of sound environments were described in section 3.5, in particular the new access to the estimation of statistical indicators. However, despite these advantages, the probabilistic approach does not meet the criteria for evaluating mobility strategies more than the static approach, as it is limited to a description of traffic based on aggregate variables, with noise sources simply being distributed differently across the network for each iteration. Static and probabilistic modelling also make simplifying assumptions about the evolution of flows as a function of traffic conditions, ignoring, for example, the links between road traffic assignment (distribution of vehicles on the network) and traffic conditions. The detailed estimation of the noise impacts associated with road traffic presupposes the use of: (i) traffic modelling sensitive to traffic conditions, i.e. reproducing vehicle kinematics (speeds and accelerations) and the dynamic assignment of vehicles on the network according to traffic conditions (individual route selection strategies), (ii) acoustic emission modelling itself sensitive to influential variables (vehicle speeds and accelerations, road fleet composition, etc.) (Can & Aumond, 2018).

The most natural way is therefore to use a road traffic model, designed primarily to assess the impact of traffic control strategies on vehicle flows and kinematics, with the outputs of the traffic model (usually vehicle trajectories) then used to estimate noise emissions; see Figure 3:3. This approach remains quite rare in the field of acoustics, whereas it has been the subject of much work in the field of atmospheric pollutants, following the same modeling framework. This rarity may be explained by the fact that noise reduction methods have long been considered by the acoustic community as the prerogative of disciplinary research: work on road pavement surfaces, motor noise, or the design of noise barriers. It can also be explained by the fact that the gains of action on traffic flows are assumed to be lower in environmental acoustics: a 10% reduction in pollution levels, for example by reducing vehicle flows, is considered beneficial while a similar gain in acoustics is considered to be anecdotal for traditionally calculated aggregate indicators, such as the L_{eq}. It is well known that reducing the flow rates by half results in a 3 dB reduction in noise levels, which may seem marginal because it would hardly be perceived by the human ear; we will see in section 3.6.6.1 that this is not true if we take into account the dynamics of noise. A reduction in the number of vehicles in a quiet street also corresponds to a reduction of half the number of noise events.

The potential for coupling traffic and air pollutant models has been demonstrated and has led to many case studies since the early 2000s[17], which are interesting to focus on. For example:

- Noland & Quddus (2006) use the VISSIM software to study the impact on energy consumption and emitted pollutants (CO, HC and NO_x) of an increase in network capacity: such a measure can be beneficial in that it reduces congestion on the network, but is harmful in that it increases the volume of vehicles on the network in a second phase;
- Boriboonsomsin & Barth (2008) use PARAMICS software to assess the environmental impact (CO, HC, NO_x and CO_2 emissions) of lanes reserved for high occupancy vehicles on motorways;

[17] A simple search on WebOfScience shows, for example, that the number of studies combining VISSIM, the most common traffic model, and vehicle fuel consumption is 41, of which 26 are conducted between 2013 and 2018. Other models are also widely used: SATURN gives 23 occurrences for the same search, and AIMSUN 12 occurrences.

- Barth & Boriboonsomsin (2009) use PARAMICS software to assess the environmental impact (CO_2 emissions) of an eco-driving system on motorways;
- Maddiredy *et al.* (2011) use PARAMICS software to assess the impact on emissions of air pollutants (CO2 and NOx) of two road traffic management measures: reducing speed limits and coordinating traffic lights;
- Fernandes *et al.* (2017) use the VISSIM software to compare the environmental impact of roundabouts and intersections with traffic lights;
- Karioti *et al.* (2017) use AIMSUN software to test the multi-criteria impact, including air emissions (NOx, CO_2, VOC, and PM) of capacity restrictions due to incidents occurring on a ring road;
- Yao *et al.*, (2018) use VISSIM software to study the optimization of traffic light plans based on criteria including vehicle fuel consumption;
- Hülsmann *et al.* (2014) use MATSim software to test the impact of changes in travel demand on emissions of air pollutants (NO_2 and NO_x) across the Munich metropolitan area.

These few examples highlight the importance of imitating these couplings for environmental acoustics, because (i) the modelling chains are very similar, the emissions being based on the kinematic data provided by traffic modelling, (ii) the measures tested echo the noise reduction solutions by acting on the traffic suggested in section 3.2. Beyond the multitude and variety of existing studies on air pollutants, the reading of this research invites us to question the modalities of a coupling between traffic model and emission models of environmental externalities, whether it is the emissions of air pollutants or acoustic emissions that are estimated. Indeed, if the technical implementation of couplings may seem simple, the questions on the modeling choices to be made and the guarantee of the robustness of the obtained results are much more difficult to answer. The problem of multi-physical couplings for the evaluation of environmental externalities attributable to road traffic therefore goes beyond the field of acoustics. An impact study seems reliable if and only if:

- The traffic software used reproduces satisfactorily the impact of the measurement tested on traffic volumes and influential traffic variables (traffic volumes and flow composition, vehicle kinematics, etc.);
- The variables produced by the traffic software are sufficiently detailed for the calculation of externalities (is it necessary to model average speeds, vehicle trajectories, acceleration phases?);
- The outputs of the traffic model are compatible with the emission model used, and the emission model used is sensitive to variations in the traffic variables highlighted: for example, if the measure tested has an impact on vehicle accelerations, but the emission model does not consider accelerations, the impact study will be biased.

It therefore seems useful to focus on the modeling frameworks conventionally used for traffic and the emission of externalities.

3.6.2 General information on traffic modelling and coupling issues for estimating environmental externalities

3.6.2.1 Some general information on traffic theory and existing software

The primary objectives of traffic theory research have been to understand how transport networks operate, in order to optimize their use: predicting the occurrence of congestion after a certain level of demand and understanding how it spreads, factors influencing trip generation and vehicle assignment on an urban network at different time scales, etc. The reader can refer to (Hoogendoorn & Knoop, 2012) for a summary of traffic flow phenomena, and (Calvert *et al*. 2016) for a summary of phenomena related to vehicle assignment on the network.

The research developed therefore focused on segments of the road network of varying sizes (motorway section, network of a few intersections, entire city...) according to the phenomena studied, the models also being dedicated to the scales of the phenomena observed. For example, reproducing the distribution of inter-vehicle spacing in a congested regime does not imply the same level of representation as predicting travel demand on an urban network. Since, although operating on different scales, these phenomena impact all transport networks, software have been developed to unify these research results within integrating platforms, the objective of which is to facilitate the study of the impact of changes made on a transport network. However, these software packages are also relevant at a given spatial and temporal scale, focusing on either vehicle flow or the management of the entire network (travel request management), depending on the objectives sought; see Figure 3:7 for an illustration.

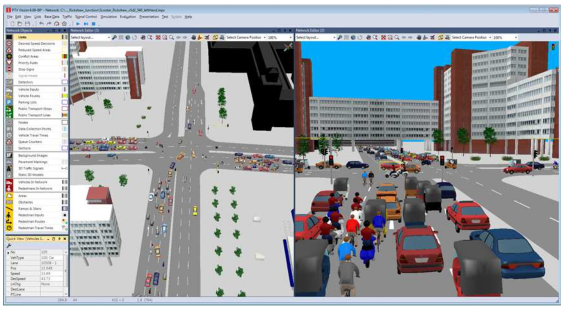

Figure 3:7 Illustration of two traffic software programs. On the left, VISSIM: the software aims to reproduce the trajectories and interactions between each vehicle (Source: PTV, 2011). On the right, MATSim: the objective of the model is to reproduce network and day-scale movements, according to individual activity patterns (Horni *et al*., 2016).

Traffic software therefore include an assignment model and a traffic flow model, both more or less detailed:

- The assignment model determines, according to different environmental variables (localization of activity and residence areas, etc.), the number of vehicles circulating on the network for a given period, and the routes chosen by drivers between their origin and destination, according to the levels of congestion on the network, through the optimization of cost functions. Assignment models include static or dynamic approaches, the latter updating the choices made according to the evolution of traffic conditions on the network during displacement, based on successive iterations. It should be noted that most current software are based on a dynamic route selection model, in which the assignment is processed dynamically over time as a result of successive iterations of the dynamic traffic model;
- The flow model determines the evolution of variables describing traffic conditions (for a vehicle or a vehicle flow), depending on traffic conditions. Traffic flow models have historically been categorized into *macroscopic*, *microscopic*, and *mesoscopic* models:
    - o *Macroscopic* models consider traffic as a continuous flow, by analogy with fluid theory; the variables describing traffic are therefore the flow, the concentration of vehicles present between two points at a given time, and the spatial average velocity of the flow, defined as the ratio between flow and concentration;

- *Microscopic* models represent the movement of vehicles, explicitly simulating their trajectories. This representation makes it possible to deduce the kinematic state of vehicles, characterized by their speed and acceleration, at a given moment (Chevallier, 2008). Recent studies have shown the duality between macroscopic and microscopic representations, both approaches being able to produce vehicle trajectories, and therefore differentiated rather on behavioral laws: they are now rather classified into "*models with individualized behavioral laws*" and "*models with average behavioral laws*", see below;
- Finally, the *mesoscopic* models are based on an intermediate representation: each street is modelled as a queue in which vehicles must wait at least for the free travel time on that street. In addition, the flow rate and storage capacity of each link are limited, in order to reproduce in principle the phenomena of network congestion and the propagation of congestion. However, the approach does not produce detailed vehicle trajectories. The traffic flow model implemented within MATSim (Horni *et al*., 2016) or INTEGRATION (Van Aerde *et al*., 1996) software are for example based on a mesoscopic model.

The use of software developed for environmental assessment is more recent, although already widely used in the context of air pollutants (see section3.6.1); it naturally raises questions about the relevance of the traffic variables produced for the assessment of environmental impacts. It therefore seems important to focus on the characteristics of flow models, insofar as it is the precision of the trajectories produced and the variety of phenomena represented that make it possible to study environmental impacts on the one hand, and on the other hand, that conditions the robustness and calibration of the models. A review of the types of existing flow models is available in Hoogendoorn & Knoop (2012):

- In *individualized behavioral law models*, each vehicle reacts differently to a given environment. These models aim to reproduce in a very detailed way the interactions between vehicles. While different models with individualized behavioral laws have been developed (safety distance models, stimulus-response models such as the one implemented for example in AIMSUN (AIMSUN, 2014)), it is the psychological spacing models that are implemented in most current software, for example VISSIM (PTV, 2011; Fellendorf & Vortisch, 2010), PARAMICS (RTA, 2004) or CORSIM (FHWA, 2006). The basic concept of these models is that the driver of a vehicle begins to decelerate as he reaches his individual perception threshold of a slower vehicle ahead. Since he cannot determine exactly the speed of this vehicle, his speed will fall below the speed of this vehicle until he starts accelerating slightly again after reaching another perception threshold. The result is an iterative process of acceleration and deceleration. The initial model provides for conscious or unconscious reactions depending on the differences in speed and distance between vehicles. Behavioral laws have been refined over time, and are now based on many parameters, most often distributed within the vehicle flow. The models also include specific models describing lane-changing phenomena. A detailed review of existing software can be found in (Algiers *et al*., 1997), or (Saidallah *et al*., 2016).

  Many studies have focused on comparing different software on case studies; see Ratrout & Rahman (2009) for a review. Although the studies generally highlight the convergence between individualized behavioral law models and their ability to reproduce a large number of phenomena, significant differences between them and some shortcomings have been observed: (i) they sometimes struggle to model congestion phenomena, and differences between models occur in congested conditions (Choa, 2004), although it is difficult to say which of the models is correct, (ii) most of the models tested in Ratrout & Rahman (2009) allow the modelling of Intelligent Transport Systems (ITS), although the calibration and validation phase can be more or less complex, (iii) Krause *et al*. (1999)

showed the shortcoming of these models in describing the behavior of transient traffic flows, (iv) they are often criticized for relying on large numbers of parameters, distributed over the fleet of vehicles, which makes it difficult to calibrate the model (Akselik & Besley, 2001);

- In *models with a mean behavioral law*, the hypothesis of an equilibrium relationship linking flow to concentration on a homogeneous section is made (Leclercq *et al*., 2007): it is the fundamental road traffic diagram (introduced by Greenshields in 1935), which describes the fact that after a critical concentration (congested regime), the vehicle flow decreases as the concentration increases on the network. Consequently, the movement of a vehicle on the network is governed by this fundamental diagram, and at each time step (typically 1s), the position of a vehicle is the minimum between the position it could reach if the traffic were free and the position it cannot exceed when the traffic is congested. The movement of vehicles on the network is governed by three parameters: the maximum speed u reached when traffic is free, the speed w at which a starting wave propagates over the network, and the minimum spacing $s_{\min}$ between two vehicles, observed when vehicles are stopped at a traffic light, for example. Different vehicle classes can be introduced to represent the heterogeneity of traffic, but with the philosophy of keeping a limited number of parameters. The SYMUVIA software, developed at LICIT (IFSTTAR / ENTPE), is based, for example, on a model with a mean behavioral law. Improvements were made to the initial model to take into account the bounded acceleration of vehicles (Leclercq, 2007), lane change phenomena (Laval & Leclercq, 2008), and detailed flow modelling at intersections (Chevallier & Leclercq, 2007). SYMUVIA software also includes a dynamic assignment model (Leclercq & Geroliminis, 2013).

To summarize, it is therefore on their ability to reproduce the impact of the measures tested, as well as on the adaptability of the outputs of the traffic model to the emission models, that the choice of traffic software for the study of environmental impacts must be made. This may seem difficult for researchers who are not specialists in traffic theory, and therefore encourages close collaboration between the two communities. The choices must also follow the environmental stakes related to the externalities considered, as described in the next section.

3.6.2.2 Comparison of approaches for predicting different environmental externalities

The estimation of noise impacts, air pollution impacts, or energy consumption are not governed by the same constraints and do not follow the same objectives. It is useful to recall the differences between these externalities, as they will define the key points of the coupling, on the one hand, and condition the multicriteria approaches discussed in section3.6.6.2, on the other. Tableau 3:1 summarizes the differences in terms of indicators to be estimated, spatial and temporal granularities. For example, the acoustician is particularly interested in knowing how to estimate temporal variations in levels, as well as the expected high spatial resolution. Thus, where the estimation of energy consumption can be satisfied with aggregate indicators on the territory of interest, the acoustician is interested in the spatial distribution of noise levels. In addition, unlike exposure to air pollutants, time series of noise levels are desirable at the output of the models. On the other hand, errors in estimating noise levels do not affect subsequent time slots, unlike air pollutants.

	Acoustics	Airborne pollutants	Energy consumption
Health impacts	++ *The impacts mainly concern the deterioration of the quality of life.*	++ *Morbidity related to exposure to air pollutants is a major health issue*	+++ *Energy consumption is linked to global warming, which is not associated with a health impact but for which there is now a consensus on the global risk.*
Spatial granularity	+++ *The expected spatial granularity is very fine, we ideally want to estimate the spatial distribution of noise levels with a spatial resolution of around 10 or 20m.*	++ *The expected spatial granularity is fine. However, many studies are limited to the quantities of pollutants emitted over a rather large area of the territory.*	+ *The impacts are global; the spatial distribution of energy consumption on the network does not matter.*
Temporal granularity	+++ *The estimation of the temporal evolution of noise levels, the estimation of sound events, are target elements of modelling, as they have a great influence on the perception of sound environments.*	+ *The temporal evolution of the estimated pollutant levels is of limited importance, although some studies tend to show the danger associated with exposure to very short (several seconds) pollution peaks above average levels.*	- *Regardless of the temporal evolution of consumption, only long-term periods are important.*
Calculation time for calculating emissions	+++ *The calculation of the acoustic power levels is very fast, following simple functions. It is negligible compared to sound propagation calculations.*	++/- *Two types of models exist:* • *The aggregated models follow simple laws giving emissions as a function of average flow speeds or possibly traffic conditions (congestion level). They are very fast.* • *Modal models estimate instantaneous emissions based on the engine's previous states. They are time-consuming to calculate.*	
Remanence	- *The phenomenon is not persistent: errors made over a time range do not have any repercussions.*	++ *Pollution levels observed over a given time range may be the result of emissions several hours or days earlier.*	+++ *This phenomenon is very persistent in that it is emission balances over long periods that matter.*
Target indicators	*Indicators calculated for a receiver map and a given period, based on the evolution of noise levels: average indicators, statistical indicators, sound event levels.*	*Average levels emitted, average pollutant concentrations in a receptor map for a given period.*	*Overall consumption on the network for a given period.*

Tableau 3:1 Comparative table of environmental externalities

3.6.3 Coupling conditions for estimating environmental externalities

Despite the large number of case studies using traffic software to assess the impact of traffic regulation strategies on energy consumption or air pollutant emissions (see Section 3.6.1), the conditions of these couplings have rarely been explored. This is also true *a fortiori* for the assessment of acoustic impacts based on traffic software, which has been the subject of a smaller number of studies. Addressing these conditions requires research at the interface between the two disciplines, traffic theory and externalities emissions, to ensure that:

- The traffic software used is able to capture the impact of the traffic regulation strategy tested on the influential traffic variables, i.e. vehicle flows and kinematics (for example, it is illusory to test the impact of different traffic light regulation options on the basis of a traffic model that poorly describes vehicle flow at intersections);
- The approximations made within the traffic model, such as the simplification of trajectories, have no impact on emissions (it should be ensured, for example, that micro-accelerations not represented by certain traffic models do not have a too large part in emissions, which would possibly mask the results of the regulation strategies tested);
- The emission model (pollutant or noise) captures well the influence of the kinematic variables produced by the traffic software (for example, many acoustic models take little account of vehicle acceleration).

3.6.3.1 Discussion of acceleration values used in traffic software

The maximum acceleration desired by vehicles is a variable that is difficult to calibrate within microscopic traffic models and set at default values. An acceleration rate of 0.8 m/s^2 is used in Can *et al.* (2010b) for example, while the acceleration rate used in Chevallier *et al.* (2009) and Can *et al.* (2010) decreases with speed: a = 1.5 m/s^2 if $v \in [0 ; 21]$ km/h ; a = 1 m/s^2 if $v \in [21 ; 36]$ km/h ; a = 0.5 m/s^2 otherwise. The default acceleration values used by default remain unknown in most publications, even though this variable has a significant influence on emissions.

In addition, the acceleration values used by default in microscopic traffic modelling only partially cover the range of actual urban driving conditions, which could mask some of the emissions (both for noise and air pollutants) due to speed variations. Urban observations reveal a significant proportion of vehicles evolving during acceleration phases at accelerations greater than 1 m/s^2 or even greater than 2 m/s^2 (Mehar *et al*., 2013). In addition, the average acceleration of a vehicle depends on its speed. Bogdanovic *et al*. (2013) observed that near intersections, even 15% of vehicles exceed an acceleration of 2 m/s^2. Clément *et al*. (2004) have even reported, over more than 2000 km of driving in real traffic conditions, that accelerations below 0.8 m/s^2 are relatively rare and that accelerations between 2.7 and 4.2 m/s^2 are common. At the same time, Viti *et al*. (2008) have shown that microscopic traffic models often misjudge acceleration distributions.

This limitation could compromise the assessment of: (i) the impact of congestion, which is likely to increase the number of acceleration phases, on vehicle emissions, (ii) traffic control strategies that aim to smooth vehicle trajectories, such as the promotion of eco-driving, while the wide diversity of driving behavior suggests the high noise mitigation potential of such a strategy (van Blokland and de Graaff, 2005).

3.6.3.2 Coupling conditions: case of energy consumption and emissions of atmospheric pollutants

- Definition of speeds and calculation of energy consumption and air pollutant emissions at the scale of an urban network

Two classes of models for calculating energy consumption and air pollutant emissions coexist, as highlighted in Tableau 3:1. Aggregate models, such as COPERT (Ntziachristos *et al*., 2009), are initially dedicated to studies on large spatial areas, typically a city or even a region. They are based on aggregated traffic variables, such as the average speed per section. Modal models, such as PHEM (Hirschmann *et al*., 2010) or CMEM (Scora & Barth, 2006), estimate individual instantaneous emissions based on engine history. Built on the same kinematic cycles, the models from both classes converge a priori towards the same aggregated emissions. These are the modal models that are generally coupled to microscopic traffic models, because their resolution (emissions calculated every second) corresponds to the outputs of the traffic models. However, the prohibitive computation times currently limit them to local studies. Studies at the city level therefore focus primarily on aggregate models; there is a strong temptation to use aggregate models on smaller spatial scales than those to which they are initially dedicated. However, the limitations of aggregate models for congested regimes have been highlighted (Smit *et al*., 2008). The question of estimating emissions at the city level, based on aggregate models but finely reproducing the effects of traffic flow dynamics (congestion), is therefore crucial.

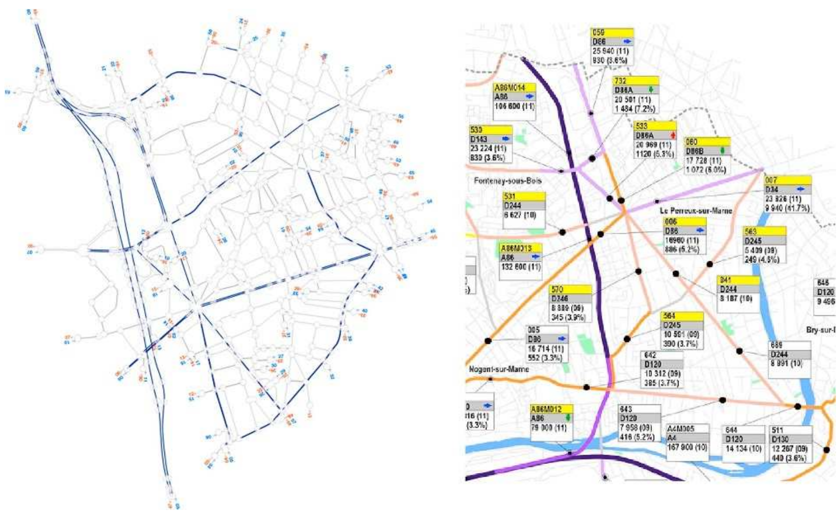

Figure 3:8 Network implemented under SYMUVIA as part of Lejri *et al.* (2018). On the left: network and Origin/Destination matrix of traffic demands. Right: measured average daily flows. Source : Lejri *et al.* (2018).

In Lejri *et al.* (2018), a 3 km² urban network with different levels of congestion is implemented in SYMUVIA; see Figure 3:8. Emissions were calculated with COPERT and PHEM for each road section, every 6 minutes. In addition, three definitions of speed are considered: (i) the network speed limit V_{limit}, (ii) the average of punctual speeds $V_{punctual}$ measured at a sensor, (iii) the ratio $V_{spatial}$ between the distance travelled on the section and the time taken to travel this distance. It should be noted that spatial and punctual speeds generally differ on a network due to the dispersion of speeds practiced by vehicles: slow vehicles staying longer on the network, $V_{spatial}$ is necessarily lower than $V_{punctual}$[18]. Although more appropriate for calculating emissions, the spatial average is more difficult to access, based on data that are not readily available on a real network.

The study shows the high sensitivity of the calculated emissions to the definition of speed. The use of the V_{limit} speed limit leads to an underestimation of 19.8 to 25.3% of energy consumption, and 30.7 to 36% of NO_x emissions. The use of $V_{punctual}$ punctual speed introduces an underestimation of 9.7% to 13.4% for energy consumption, and 13.5% to 17% for NO_x emissions. The greatest differences are observed for periods when the network is congested. The study points out that these errors can be partially compensated by no longer aggregating average speeds, but by relying on the calculation of speed distributions per section, which makes it possible to better capture the actual speeds on the network. However, the study concludes that coupling with the modal model remains the most appropriate, as it is more sensitive to speed variations. It is likely that microscopic model/modal model coupling, even over large spatial areas, will become more widely used in the future.

- Impact of the simplification of trajectories on energy consumption

Viera da Rocha *et al.*, (2014) studied the impact of the simplification of trajectories operated by microscopic traffic models on energy consumption calculated by a modal model (VEHLIB, developed at IFSTTAR). Models are indeed calibrated on macroscopic variables (travel time, etc.), and speed profiles are often simplified; it is therefore important to ensure that the error introduced on the estimated consumption is minimal compared to the expected gains, for example when reducing speeds on a section. To this end, real driving cycles (ARTEMIS cycles described in André (2004)) have been simplified in order to reproduce the expected outputs of a microscopic traffic model, which have constant accelerations per driving phase (a driving phase being defined as a portion of the kinematic profile between two stops; 249 driving phases for the 37 cycles are included in the study). Two levels of simplification have been considered: (i) a first one, C1, where the average accelerations respect those of the real cycles, (ii) a second one, C2, where the average accelerations take two possible values, 0.6 m/s² at low speed (V<20 km/h) and 0.8m/s² otherwise; see Figure 3:9.

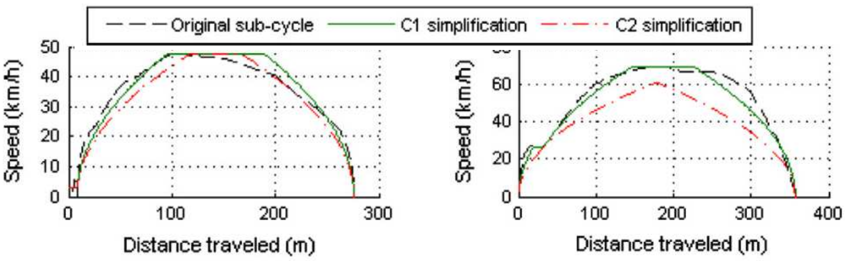

Figure 3:9 Real trajectories (in black dotted line) and trajectories as provided by a microscopic traffic model (simplifications C1 and C2) as modeled in Viera da Rocha *et al.* (2014).

The study shows that the simplification of trajectories, assuming an error-free estimate of average accelerations (simplification C1), leads to an underestimation of energy consumption by about 4%. Errors are greater when the default values of vehicle accelerations are used (simplification C2, the one that most closely corresponds to the trajectories provided by microscopic traffic models), thus not taking into account variations in

[18] A common example is to consider two vehicles travelling a section of length *l* at speeds *v* and 2*v*. The average punctual speed is then $\frac{v+2v}{2} = \frac{3v}{2}$. The average spatial speed is $\frac{l+l}{l/v + l/2v} = \frac{4v}{3}$.

average acceleration from one driving phase to another, or from one vehicle to another; the underestimation of energy consumption then reaches 20% for some cycles.

However, some of these errors are compensated for by considering the entire driving cycles. The study also focuses on influential kinematic variables. It appears that errors on average acceleration have a limited impact if the maximum speed reached during the driving phase is accurately reproduced: indeed, the higher instantaneous emissions for high accelerations are almost entirely compensated by the fact that the acceleration phase is shorter. On the other hand, errors in the deceleration value shorten or lengthen the driving segment at steady speed, causing underestimation or overestimation of consumption that is not compensated during the deceleration phase. It is thus the maximum speed reached, and the deceleration time, which are the two most important kinematic variables, and therefore those that the traffic model must be able to estimate precisely.

It should be noted that this result could not be transposed to other externalities, whose dependence on speed and acceleration are different. It should also be recalled that for acoustics, for example, compensation for driving cycle errors cannot be taken into account since the spatial distribution of noise levels is an indicator of interest, see Tableau 3:1.

3.6.3.3 Coupling conditions: case of acoustics

As highlighted in section 3.3.2, the dynamic approach is the only one that can determine the impact on noise of traffic control strategies that modify vehicle kinematics; however, the conditions for such coupling must be investigated. The specificity of acoustic impact studies compared to other nuisances lies in the fact that they focus on the temporal variations in noise levels and their spectral content (see Tableau 3:1). Another specificity is that the acoustic power summed on the network is usually not a quantity of interest. The acoustician is on the other hand interested in the levels at the receivers (errors on local emissions can however be compensated since several vehicles simultaneously contribute to the level observed at a receiver).

Can *et al.* (2008) investigated the details of the coupling between microscopic traffic model and noise emissions model, for the estimation of L_{Aeq} and statistical indicators (L_{A5} to L_{A90}) along a simplified network (urban corridor with or without a traffic light intersection). The study shows that the reproduction of trajectories is an important element in estimating noise levels around intersections, thus favoring models with vehicular representation (see section 3.6.2.1). The behavioral law has little impact on the estimation of the selected indicators. Concerning the aggregation of emissions on the network, a representation considering at each time step the real position of vehicles on the network is to be avoided, because it would imply a propagation calculation at each time step, leading to prohibitive calculation times. The network can advantageously be discretized into acoustic cells (source points or source lines), to perform only once the propagation calculation. The study shows that the discretization for the calculation of acoustic emissions does not need to be very fine, a 28m step being sufficient to estimate the acoustic indicators at 15m from the road.

This study is extended in Can *et al*. (2009) to different distances to the road, as well as to a set of acoustic indicators describing the noise dynamics around intersections: average noise pattern repeating itself at the traffic signal period, and average levels calculated during the green and red phases of the traffic light. The study confirms the low impact of the behavioral law used to model vehicle flow on the estimated noise levels: the traffic light masks the specificities between the models and imposes the shape of the trajectories. In addition, for the acoustic part, a discretization for the calculation of acoustic emissions with a step of 14m, even 7m, is desirable for the estimation of indicators near the road (5.5m from the center of the road in this study), in such a way as to reproduce the noise dynamics generated by the passage of vehicles.

The estimation of the extremes of the $L_{Aeq,1s}$ distribution, i.e. the very low and very high levels, finally requires more detailed modelling. At the scale of the simplified network modelled in Can *et al*. (2009), traffic modelling should be able to reproduce vehicle platoon arrivals (Poisson distribution of vehicle generations) to estimate very low levels, which correspond to periods without vehicles near the receiver. Finally, the estimation of high levels, or noise peaks, is the subject of current research. A first study by Can *et al.* (2007) showed that introducing into the simulation a percentage of aggressive vehicles (defined as having a higher average acceleration), or distributing vehicle emissions among 9 different vehicles, influenced the L_1 values (noise level exceeded 1% of the time). More recently, De Coensel *et al.* (2016) showed that distributing vehicle emissions by assigning to each vehicle a power level respecting a probability law resulting from measurement campaigns, made it possible to estimate acoustic indicators such as the L_1 or the number of events exceeding a given threshold within a dynamic modelling chain. However, this work concerned non-urban speeds (V > 60 km/h); moreover, the modelling did not dissociate the variability of emissions related to vehicle kinematics from the variability related to the vehicle type. Ongoing work to understand the origin of emission variability on on-site measurements will allow a distribution of each variable influencing emissions, necessary to test the impact of eco-driving traffic strategies, or to estimate noise peaks.

Finally, based on available data on vehicle trajectories collected on an American corridor used as a reference, Can & Aumond (2018) compared different modalities of the coupling between traffic data and acoustic emission models. The study confirms on real data the bias introduced by a punctual measurement of speeds on noise levels calculated under congested conditions, in particular because the proportion of stationary vehicles is not taken into account. The study also identifies areas for improvement in dynamic coupling: (i) acoustic emission models based on binary consideration of vehicle acceleration (a vehicle is accelerating or not, as in the American FHWA model) may be sources of error, (ii) dynamic coupling suggests using acoustic emission models outside their range of validity, especially for low speeds and high accelerations, (iii) there is a need to improve the estimation of noise levels when vehicles are stationary, (iv) the calibration of acceleration values in traffic and acoustic models needs to be improved, as it could affect the results of simulations aimed at assessing the impact of traffic control strategies.

3.6.4 Dynamic couplings in acoustics: experimental validations

Three experimental validations were proposed by three different research teams based on a different modelling framework, Ghent University (Belgium), Ifsttar (France), and Guandzhou University (China), to test the validity of noise level prediction based on a microscopic traffic model:

- In De Coensel *et al.* (2005), a model is constructed coupling PARAMICS for the traffic part, NORD 2000 for the emissions part, and a 2.5 D propagation model based on ray tracing. The model is validated on a case study conducted in the Gentbrugge district, on the periphery of Ghent, Belgium (see Figure 3:10). Measurements were taken over a period of 15 minutes, compared to the simulation results. The error on the 6 points is below 3 dB for the estimation of L_{Aeq}, L_5 and L_{50}. The errors concerning the estimate of the L_{90} are more important, around 10 dB for the two points located in very quiet streets. According to the authors, this error can be explained by the presence of non-modelled sources (ventilation noise, birds, etc.). It can also be explained by the difficulty that traffic models have in generating traffic in low-traffic streets, as algorithms for calculating shorter paths do not often fill these streets. This shortcoming was pointed out in Can *et al.* (2018b).

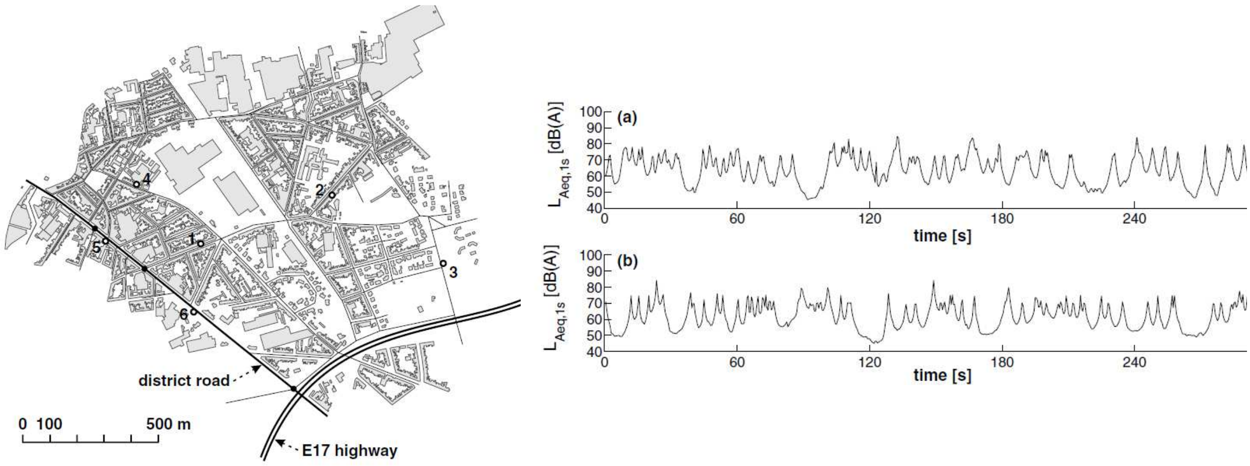

Figure 3:10. Validation of dynamic noise coupling performed by Ghent University. Left: Network implemented in De Coensel et al. (2005). Right: time series extracts of LAeq,1s measured and simulated. Source: De Coensel et al. (2005).

- In Can *et al.* (2009b), a coupling is performed between the SYMUVIA model, the NMPB emission laws, and the Mithra propagation software. The experimental validation is carried out on the Lafayette corridor in Lyon (France), presented on 5 receivers reproducing different traffic situations (a point upstream of a traffic light, a point between two traffic lights, two points downstream of a traffic light and a point near a bus station), consisting of 2 hours of measurements (see Figure 3:11). The average error on the L_{Aeq} estimate is 1.1 dB(A). The error on the estimated L_{A50} is less than 1 dB(A) for the 5 points, and the error on the L_{A10} is less than 1 dB(A) for 4 of the 5 points. The L_{A90} estimate is less accurate but acceptable, less than 2 dB(A) for 4 of the 5 points. The L_{A1} is also estimated precisely, except for the point located near the bus stop, where it is overestimated by 4.5 dB. This raises the difficulty of estimating high noise levels, which here the authors have tried to approximate by adding a class of bus vehicles, whose levels have apparently been overestimated. The coupling also allows the estimation of $L_{Aeq,1s}$ distributions and the estimation of the average noise pattern repeating at each traffic cycle, with relatively good accuracy. The experimental validation is extended in Can *et al.* (2010b), for the estimation of spectral indicators. An additional point is considered, located in retreat of the corridor. The spectral indicators selected, the spectral center of gravity and the spectral emergences (NR curves), are estimated with relative good accuracy (NR value estimated to within 1 dB except for the point behind the corridor, for which the NR value is underestimated by 5 dB). Nevertheless, the model overestimates the low frequencies near the bus stop, and underestimates the high frequencies for the point in retreat of the corridor. However, it remains difficult to understand the reason, which may be related to emissions (vehicle kinematics or emission laws), as well as to propagation calculation (low-frequency approximations for low-frequency overestimation, or insufficient numbers of reflections for high-frequency underestimation). Nevertheless, this validation suggests that the model has the potential to capture not only noise dynamics, but also spectral variations.

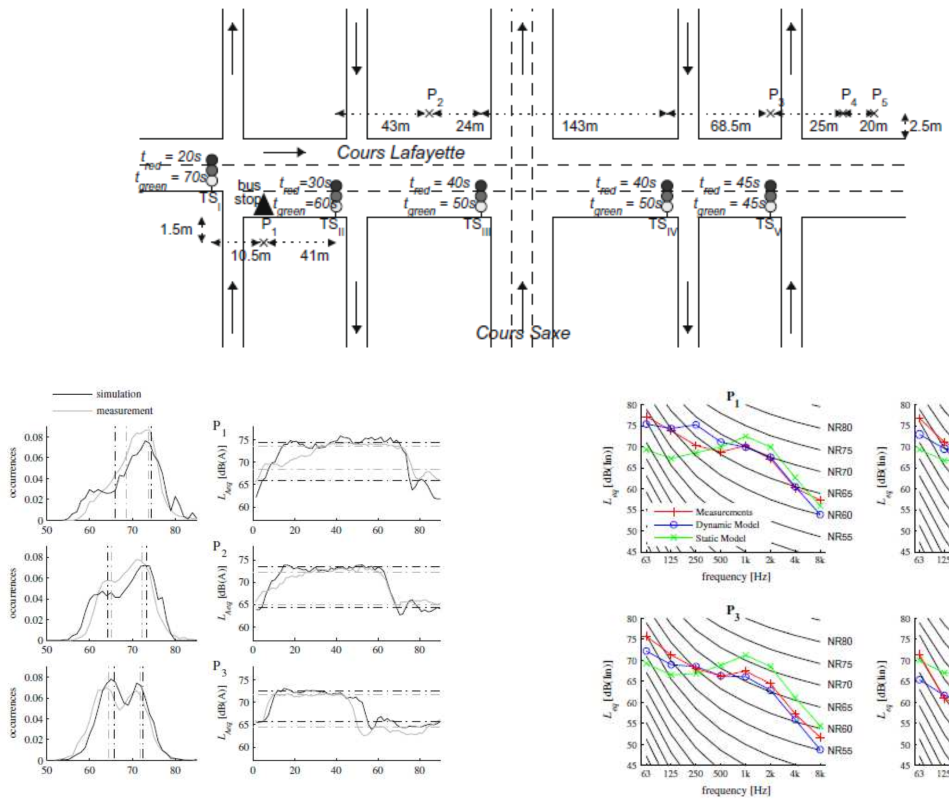

Figure 3:11. Validation of dynamic noise coupling performed by Ifsttar. Top: network implemented in Can *et al.* (2009b). Bottom left: extracts from $L_{Aeq,1s}$ distributions. Bottom right: measured and simulated NR curves. Sources: Can *et al.* (2009b), Can *et al.* (2010b).

- In Luo *et al.* (2012), a coupling is performed between PARAMICS, emission laws constructed as part of the study, and a propagation model using ray tracing. The model is validated on a case study carried out in a high-traffic area of Guandzhou (flows exceeding 9,000 veh/h), with a total area of 540 * 460m. Measurements were taken for 20 minutes at 5 points in the study area, compared to the simulation results. The average of errors on the L_{Aeq} estimate is 0.8 dB(A). The other indicators, L_{A10}, L_{A50}, and L_{A90}, are estimated with an error of less than 1.5 dB(A). Finally, the distribution of $L_{Aeq,1s}$ is accurately reproduced. The study also provides information on calculation times. The parameters used to estimate accurately noise levels are expensive: 3 orders of reflection and one order of diffraction are required, which can be explained by the height of the building in question (163m). Consequently, the calculation time is 32 times the simulated duration.

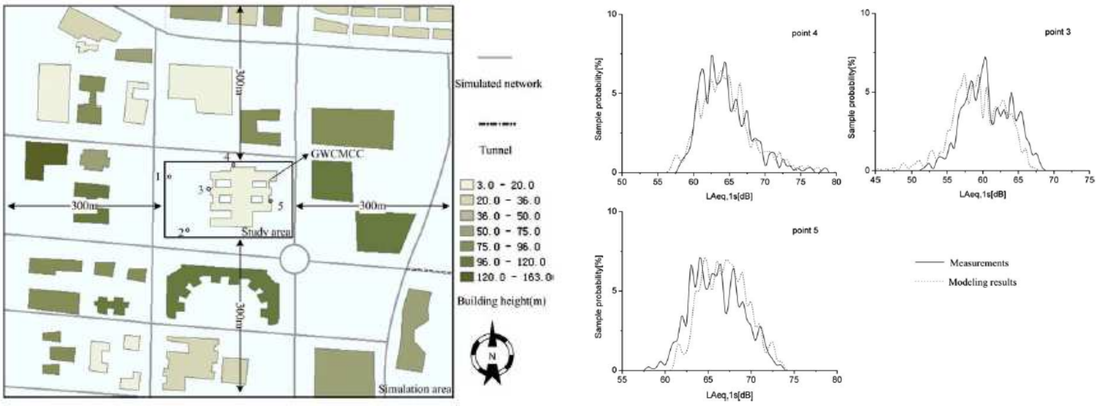

Figure 3:12. Validation of dynamic noise coupling performed by Guandzhou University. Left: network implemented. Right: extracts from measured and simulation distributions of $L_{Aeq,1s}$. Source: Luo *et al.* (2012).

The issues raised by these three experimental validations, such as the difficulty of estimating background noise and noise peaks, or the difficulty of estimating noise levels in low-traffic streets, highlight the need for larger-scale experimental validation. This validation could be performed on the new network implemented in Can *et al.*, (2018b), based on experimental data available as part of the Acoucité Measurement Network[19].

[19] http://www.acoucite.org/observatoire/reseau-de-mesures/

Reference	***Traffic***	***Emissions***	***Propagation***	***Indicators***	***Network***	**Strategies tested**	***Results & comments***
Heltimo et al. (2003)	*HUTSIM (microscopic with behavioral law)*	*Nord 2000*	*Nord 2000*	L_{Aeq}	*One intersection*	*Comparison between a T-intersection and a roundabout with 3 entrances/exits*	*The T-intersection is noisier than the roundabout*
De Coensel et al. (2005)	*PARAMICS (microscopic with behavioral law)*	*Nord 2000*	*2.5 D model (ray tracing)*	$L_5 - L_{95}$ α[20]	*1km² network in the periphery of Ghent (Belgium)*	*Different levels of demand (+20%, +50%)*	*The increase in the number of vehicles modifies the dynamics of noise (in particular the indicator α shows a less chaotic sound environment in congestion) and therefore the soundscape.*
Bhaskar et al. (2007)	*AVENUE (mesoscopic)*	*ASJ Model-1998*	*ASJ Model-1998*	L_{Aeq}	*Area of 5 * 3 km in Tokyo*	*Interdiction of the central area (1km²) to heavy vehicles*	*Noise levels due to the ban on heavy vehicles are decreasing in the central area, but increasing elsewhere due to traffic reassignment.* *Note: coupling presented in (Oshino & Tsukui 2006)*
Chevalier et al. (2009)	*SYMUVIA*	*FHWA*	*Geometric attenuation*	L_{Aeq}	*One intersection between a primary and a secondary road*	*Comparison between an intersection with traffic signal and a roundabout*	*The roundabout reduces noise levels by 2.5 dB(A) compared to the traffic light junction in free flow regime. Both intersections have the same acoustic impact in congested conditions.*
Can et al. (2010)	*SYMUVIA*	*NMPB*	*Geometric attenuation*	L_{Aeq}, L_1, L_{10}, L_{50}, L_{90}, $L_{max/cycle}$, $L_{min/cycle}$	*Network of three intersections*	*Introduction of a specific lane for buses, green wave, replacement of an intersection with traffic lights by a roundabout*	*The introduction of a bus line increases both the* L_1 *and* L_{90}. *The green wave increases noise levels if the speed limit is not reduced. The installation of a roundabout reduces noise levels (*L_{10}*), but increases background noise (*L_{90}*).*
De Coensel el al. (2010)	*PARAMICS*	*Harmonoise*	*Emissions only*	L_w	*Urban network of about 0.5 km² located in Antwerp (Belgium)*	*3 scenarios on the main street: green wave at 50 km/h, green wave broken, green wave at 30 km/h*	*Breaking the green wave has almost no impact on emissions even if the spatial distribution of emissions is modified. The green wave at 30 km/h reduces the emitted levels by about 2 dB(A).* *Note: The study also includes an analysis of the air pollutants emitted.*
Li et al. (2010)	*PARAMICS*	*Emission laws built for the study: Lw = (a.log10(v) +b)*	*Consideration of direct, diffracted, and reflected fields*	L_{Aeq}, L_{10}, L_{50}, L_{90}	*Intersection with traffic signal*	*Test on the Webster function that aims to optimize the durations of traffic cycles in terms of flow rates*	*The different modes of operation of the intersection with traffic signal are equivalent from an acoustic point of view when traffic is fluid. On the other hand, the Webster function increases noise levels when the regime becomes saturated, as it allows an increase in network capacity.* *Note: the study includes an experimental validation (errors of less than 3 dB(A) for each indicator at each of the 3 measurement points)*
De Coensel et al. (2012)	*PARAMICS*	*IMAGINE*	*Geometric attenuation*	L_{Aeq}	*Network of five intersections*	*Different settings of traffic cycles are compared, for different flow rates*	*The introduction of the green wave increases the* L_{Aeq} *by about 0.6 dB(A): 1 dB(A) decrease near the intersection, and 1.5 dB(A) increase between intersections.* *Note: The study also includes an analysis of the air pollutants emitted.*

[20] slope of the sound fluctuation spectrum

Reference	Traffic	Emissions	Propagation	Indicators	Network	Strategies tested	Results & comments
Luo et al. (2012)	*PARAMICS*	*Emission laws built for the study*	*Propagation modeling with ray tracing*	*L_{Aeq}, L_{10}, L_{50}, L_{90}, distributions of $L_{Aeq,1s}$*	*Urban network of 240*160m in Guanzhou (Chine)*	*Speed limitation from 50 to 40 km/h, reduction of the number of vehicles (-40%), intersection with traffic signal*	*The speed reduction and the 40% reduction in the number of vehicles reduce the number of points at which the L_{Aeq} exceeds 65 dB(A) from 37% to 17% and 16% respectively. Replacing a roundabout with an intersection reduces locally the noise levels. Note: Experimental validation on $L_{Aeq,1s}$ distributions in 5 points*
De Coensel et al. (2016)	*AIMSUN*	*IMAGINE Distribution of emissions*	*ISO 9613 propagation model*	*L_{Aeq}, L_{A5}, L_{A1}, L_{Amax}*	*Road segment of 2200 m length*	-	*The study shows that the distribution of emissions allows the estimation of noise event indicators. The discussion focused on the fact that removing the noisiest vehicles from the traffic flow will be much more effective than traffic management measures that target average vehicle speeds.*
Li et al. (2017)	*PARAMICS*	*Emission laws built for the study*	*Geometric attenuation and ground effect*	*L_{Aeq}, L_{10}, L_{50}, L_{90}*	*One intersection*	*Comparison roundabout vs. intersection with traffic signal*	*Little difference downstream of the intersection. Upstream, the levels are higher for the roundabout when traffic flow is fluid, and higher for the traffic light junction (up to 5 dB(A)) when traffic is congested.*
Hou et al. (2017)	*PARAMICS*	*Model from Li et al. (2010)*	*Ray tracing*	*L_{Aeq}, L_{10}, L_{50}, L_{90}*	*Road segment (2* 3 lanes). Noise levels are also calculated inside the buildings.*	*Introduction of an intersection with traffic signal*	*The increase in speed and the number of heavy vehicles increase noise levels. Noise levels are higher upstream than downstream of the intersection. Noise levels are 20 dB higher during the green phase. Noise fluctuations are reduced inside buildings. Note: the study includes an experimental validation on L_{eq}, L_{90}, L_{50} and L_{10}.*
Estevez-Mauriz & Forssen (2018)	*VISSIM (microscopic with behavioral law)*	*CNOSSOS-EU Distribution of emissions*	*Geometric attenuation*	*L_{Aeq}, L_{A10}, L_{A50}, L_{A90}, NE (number of events), CMT[21]*	*One intersection*	*Comparison between roundabout an intersection with traffic signal Introduction of electric vehicles*	*The two intersections are quite similar in terms of acoustics when traffic flows are low. When the demands on the entrance branches are very different, the roundabout can introduce congestion that increases noise levels. The acceleration phases imposed by the traffic light intersection significantly increase noise levels. Finally, the ban on heavy vehicles or the introduction of electric vehicles significantly reduce noise levels.*
Can et al. (2018)	*SYMUVIA*	*CNOSSOS-EU*	*NMPB*	*L_{Aeq}, L_{A10}, L_{A50}, L_{A90}., NNE (number of events)*	*Network of 10 km² in the Lyon - Villeurbanne conurbation*	*Different demands of displacement reproducing the morning commuting hour (3h of simulation)*	*The simulation highlights the increase in noise levels related to the increase in travel demands. It also highlights that the increase in noise levels is not uniformly distributed over the network and has a greater impact on the streets where traffic is reported. In addition, noise dynamics is modified: background noise is particularly sensitive to the increase in vehicle density on the network, as it makes the periods of calm on the network rarer. A more detailed analysis of this dynamic is possible locally through the analysis of specific acoustic indicators.*

Tableau 3:2 Summary table of traffic/acoustic coupling experiments.

[21] CMT (Center of Mass Time), indicator qualifying the periods of calm introduced in the context of this study. The indicator promotes a few large values of quiet periods rather than many small ones.

3.6.5 Dynamic couplings in acoustics: case studies

Tableau 3:2 provides a detailed review of the main case studies in environmental acoustics that have involved dynamic modelling of road traffic. Some conclusions can be drawn, on both the method and the results obtained.

Concerning the modelling aspects:

- The proposed couplings contain a low variability in the traffic models used, unlike the studies listed in air quality (see section 3.6.1). This low variability is due in particular to the limited number of dynamic coupling experiments that have been carried out: of the 14 studies listed, 11 are carried out by three research teams, Ghent University (Belgium), Ifsttar (France) and Sun-Yat-Sen University in Canton (Guangzhou, China). This low variability in traffic models may raise questions about the generalization of the advanced results. However, the fact that the three research teams cited proposed an experimental validation of their model (see section 3.6.4), and the convergence of some of the results, seems to support these approaches;
- Many of the studies identified consist of extremely simple networks, consisting of a single intersection or a road section with no intersection. While these couplings make it possible to understand and reproduce the noise dynamics, marked by vehicle passages and the alternation of calm and noisy periods around intersections, they provide very little information on the acoustic impacts on real cases. Indeed, the simplicity of the implemented networks prevents testing the problems of traffic reassignment and spatialization of congestion areas, which probably also have a strong impact on observed noise levels (see Can *et al.*, 2018). This shortcoming may be explained by the fact that for noise, multi-physical couplings have often been carried out by acoustic research teams, while for air pollutants they have often been carried out by research teams working on transport. Acousticians are then more sensitive to highlighting the temporal changes in levels (calm periods, number of events, etc.) than to the spatial dimension. This point is highlighted by Wang *et al*. (2018) in a comparative study on the use of dynamic assignment models for the assessment of environmental externalities. It is therefore desirable that future studies involving dynamic traffic modelling should be based on collaborations between researchers in environmental acoustics and traffic theory. As such, the approach proposed by Ifsttar seems to be the most advanced to date, with the study presented in Can *et al.* (2018) being the only one that really calls for an analysis on the impact of traffic flow on noise on the scale of an urban network;
- The distribution of emissions seems to be a key point for estimating noise peaks (De Coensel *et al*., 2016). Work will be required to understand better how to distribute emissions within dynamic noise models, discussed in section 3.6.6.1. On the other hand, low levels and periods of calm are mainly due to the form of traffic flow, so they do not require any particular effort in terms of emission distribution within the acoustic model.

Concerning the results produced:

- The generalization of the results produced is difficult due to the differences between the traffic and acoustic models used. Some results are even contradictory. For example, the comparison between roundabout and traffic light junction, which involved 5 studies, leads to significantly different conclusions. The diversity of results can come from the way in which vehicle flow is modelled within intersections, but also from disparities in the intersections represented, sometimes with one lane only, sometimes more complex. The results between fluid and congested traffic flow regimes are for instance different;

- Some very predictable results are converging: the increase in the number of heavy vehicles and the number of electric vehicles, for example, are leading to an increase and decrease in noise levels respectively;
- Traffic regulation strategies aimed at improving network capacity (green wave without speed reduction, traffic flow optimized operation of traffic junctions) are leading to increased noise levels;
- Traffic control strategies aimed at reducing speed variations (green wave with speed reduction, roundabout) allow a reduction in noise levels;
- Finally, all the studies that have focused on indicators other than L_{Aeq} highlight the modification of noise dynamics according to the traffic strategies tested. The introduction of a green wave, or the replacement of a traffic light intersection by a roundabout, results, for example, in a compression of the noise dynamics, reducing high levels and increasing low levels.

To conclude, despite some contradictions in the advanced results, the record of the 14 studies listed are very positive: the couplings between dynamic traffic models and acoustic models suggest the possibility of evaluating, at the network level, the impact of traffic regulation strategies on a set of acoustic indicators. However, it seems necessary to strengthen collaboration between research teams in acoustics and traffic flow theory.

3.6.6 Dynamic couplings: towards combined approaches

3.6.6.1 Towards perceptual evaluations

Access to temporal variations in noise levels through the dynamic approach and the calculation of a varied range of acoustic indicators (see Tableau 3:2), based on the evolution of $L_{Aeq,1s}$, allows a characterization of the temporal dimension of sound environments that suggests the possibility of integrating elements of perception in the study of the impact of noise reduction policies. For example, it is known that the L_{A50} is more appropriate than the L_{Aeq} to describe the sound pleasantness (Aumond *et al.*, 2017b). Studies have also shown the need to take into account the number of events (Labiale, 1983), and the number of quiet periods (Gille *et al*., 2016), to determine noise annoyance in relatively quiet sound environments. Finally, the number and intensity of events would play a role at least as important as the average level in sleep quality (Pirrera *et al*., 2010). These quantities are outputs of the modeling chains presented in the 3.6.4, estimated with a relatively good accuracy.

In parallel, recent studies have focused on the perceptual differences between different urban sound scenes. Morel *et al.* (2012) showed that motorcycle noises were treated cognitively differently and perceived more negatively than other road traffic noises. Finally, Trollé *et al.* (2015) showed on a panel of on-site audio recordings that roundabouts were perceptually preferred to traffic lights, presumably due to less pronounced variations in noise levels and spectral differences as differences in kinematics between vehicle are lesser.

This recent research invites to include elements of perception downstream of the dynamic modelling chain for the assessment of acoustic impacts, by producing indicators such as “sound pleasantness", "number of expected awakenings", etc. The production of indicators such as sound pleasantness based on dynamic traffic noise modelling seems already possible; a relationship is proposed in Ricciardi *et al.* (2015), for example, which estimates this indicator from L_{50}, L_{A10} and L_{A90}. On the contrary, the estimation of indicators such as "number of awakenings" will require the initial reliability of the calculation of sound event indicators. It seems difficult to estimate the number of events exceeding a given threshold if this number is low, even if first proposals have been made in Can *et al.* (2007) or De Coensel *et al.* (2016). The number of events exceeding

90 dB(A) in a relatively quiet street (or during a night period) is not governed by the form of the traffic flow and depends on particular events that are more difficult to model: the passage of a garbage truck, horn, noisy vehicle during a phase of intense acceleration, etc. Specific data analysis work, begun in Regragui (2018), is needed to understand the phenomenology of these noise events, in order to integrate them into the dynamic modelling chain with a view to evaluating policies to reduce noise peaks (banning certain vehicles and driving behavior, etc.). Finally, the work of understanding the impact on the perception of the temporal structure of sound environments must be continued. The role of periods of calm and their structure (recurrence, duration, etc.) would require for instance a particular research effort.

3.6.6.2 Towards multi-criteria evaluations

The modularity of the modelling chain for traffic noise estimation (see Figure 3:3) suggests the possibility of testing the impact of traffic regulation strategies on a set of environmental externalities, based on traffic modelling. The only studies identified to date are De Coensel *et al.* (2010) and De Coensel *et al.* (2012), the first of which presents a case study on a real network (see Tableau 3:2 for more details). The externalities calculated were then the CO_2, NO_x and PM_{10} emissions, calculated with the VERSIT+ model, as well as the noise levels emitted. It should be recalled that for the acoustic part, considering the noise emitted is a limitation, which does not make it possible to understand the dynamics of noise at a reception point or the impact of buildings on noise levels.

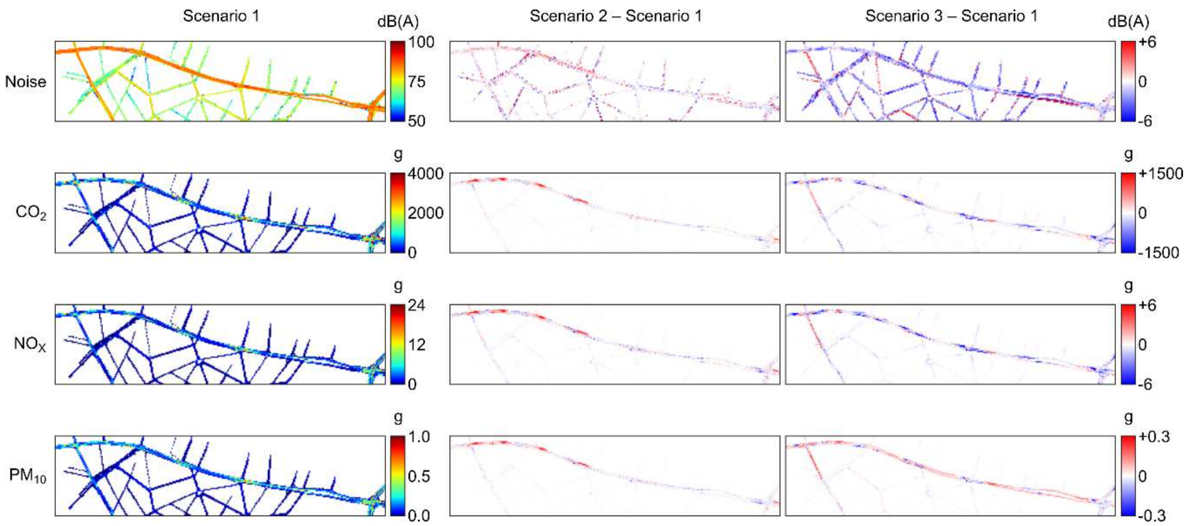

Figure 3:13. Multi-criteria analysis carried out as part of De Coensel *et al.*, 2010.

Figure 3:13 shows the results of the two scenarios tested, Scenario 2 consisting of a break in the existing green wave on the main axis, and Scenario 3 consisting of setting this green wave to 30 km/h, obtained by playing on the offsets between the green crossing times of each traffic light intersection. Scenario 1 represents the initial state, where an east-west green wave, set at 50 km/h, exists on the main axis. The main contribution of this work is to show that the traffic strategies tested have a different impact on the different externalities:

- Breaking the green wave (scenario 2) has little impact on noise at the network level, with the small reduction in noise levels being compensated by the fact that vehicles stay longer on the network. The increase in CO_2, NO_x and PM_{10} emissions, linked to the restart phases, is very stable, varying respectively by +13, +12 and +12%;

- The reduction in speeds (scenario 3) is beneficial from an acoustic point of view (-1.9 dB(A)). The impact on air pollutants is mixed: a 19% and 35% reduction in CO_2 and NO_x emissions is observed, but the number of fine particles emitted (PM_{10}) is increased by 11%.

In addition, the study shows the spatialization of emissions, which underlines for example for the acoustic part that despite an overall reduction in noise levels emitted, Scenario 3 sees a local increase in noise levels on some secondary streets. This may be linked to some traffic reassignment due to the fact that travel times have been increased on the main axis due to the reduction in speed.

The differences observed between externalities highlight the interest of combined approaches: an action taken may potentially degrade one environmental dimension while seeking to improve another. The objective should therefore be to have, within the same simulation platform, modules allowing the calculation of indicators relating to noise impacts, energy consumption and emissions of atmospheric pollutants, possibly attached to indicators describing the traffic dimension (travel times, possibly safety indicators, etc.). The combined estimation of noise and atmospheric pollutants is also an expectation of epidemiologists, because of the correlations sometimes observed between these externalities, which show the interest of such an approach to assess health impacts (Khan *et al*., 2018).

This will raise the question of multi-criteria evaluation, which is not addressed in De Coensel *et al*., 2010. While Tableau 3:1 compares the health elements relating to each of the negative externalities of road traffic, it does not make it possible to decide on the relative weight to be given to each of them in the context of a multi-criteria evaluation, this weight necessarily depending on the objectives sought by the decision maker.

3.6.6.3 Towards spatial analyses and better exposure assessment

Beyond the production of acoustic indicators and the representation of these indicators on the area of interest, the analysis of impacts is facilitated by a calculation of aggregated indicators on the study area. Among the studies listed in section 3.6.5, the use of simple statistics predominated, with the production of indicators such as "percentage of points where the level is higher than 65 dB(A)" or "percentage of points where noise levels have increased". Maps were also produced providing information on the spatial distribution of noise levels. However, these approaches say little about the actual exposure of city users, which also depends on their spatial distribution according to the time of day. In future, impact studies should link the results produced with data describing urban dweller's occupation of the territory, for example through activity models, in order to better characterize exposures. This objective goes beyond the framework of dynamic modelling: the contribution of GIS described in the 3.4.2 concerning static modelling also supports spatial analyses. It should be noted that this contribution would open the door to multidisciplinary studies, for example on environmental injustice in collaboration with environmental economists, since place of residence is a major factor of inequality in exposure to noise pollution (Havard *et al*., 2011).

Finally, on a more local scale, dynamic modelling can provide information on the variability of noise exposures on urban travel (walking or cycling), in a context where environmentally oriented route selection models are emerging. The objective of such models is to propose itinerary choices that minimize noise exposure or maximize the pleasantness of the urban noise environments crossed. The results of dynamic traffic noise modelling can refine or even challenge these models by capturing: (i) the temporal variations in noise levels over a travel, (ii) the variability of noise levels at each point of the travel.

3.6.6.4 Evaluations at the city scale

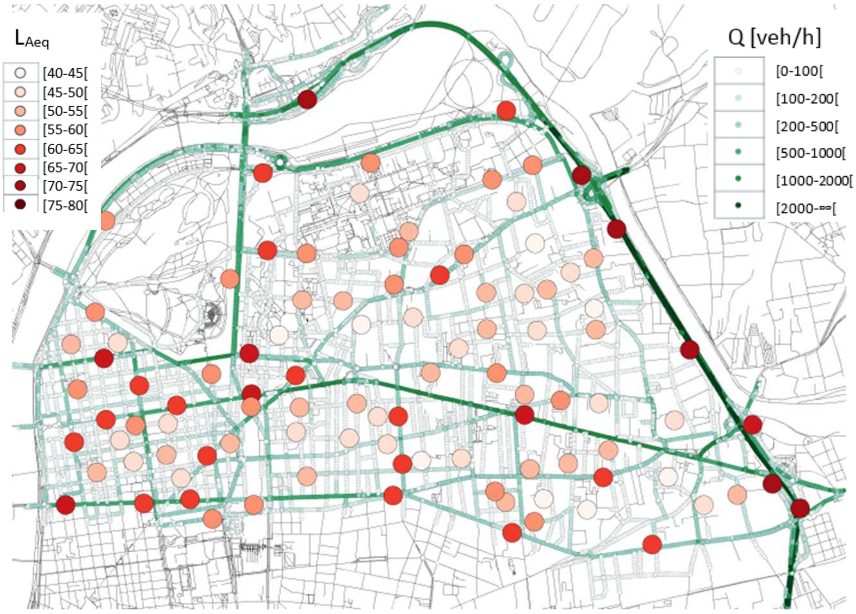

Figure 3:14. Network implemented in Can *et al.*, 2018 and results.

The majority of coupling experiments to date have focused on small networks (see Tableau 3:2). These couplings allow very local impact studies which, despite all the advantages described, say very little about acoustic impacts on a network scale, even though this objective should be a priority. As described in Section 3.6.2.1, actions carried out on a traffic network (speed reduction on an axis, axis reserved for carpooling vehicles, etc.) have local, but also global repercussions at the network level, through traffic reassignment (changes of itineraries, transfers to other modes of transport). It is therefore crucial to develop modeling chains capable of capturing acoustic effects on a large scale. This is the approach followed by recent research: the implementation of large networks, as carried out in Can *et al.* (2018), partly addresses the problem by evaluating the impact on an entire network of traffic regulation strategies, including reassignment. This research is in line with the recent coupling between a LUTI (Land Used and Transport Integrated) model (MibiSim) and a noise module, which was used to show the interest of desynchronization of activity planning on noise at the city scale (Houot *et al.*, 2015).

However, questions remain open: how to assess the acoustic impact of the extension of a tramway line, of deeper modifications caused by a local urban planning plan (relocation of a Hospital Centre, opening of a parcel to construction...?). It is necessary to consider new couplings, based on a larger scale traffic modelling. Multi-agent models, such as the one implemented in Matsim, offer an interesting approach, since their field of study is the agglomeration. It will then be necessary to think on the new conditions of these couplings, which are less relevant to capture local effects such as the modification in vehicle kinematics. New questions on the use of multi-scale models will then be opened up, to guarantee the reliability of acoustic outputs produced that are accurate both to the multiple spatial dimensions of urban networks (neighborhood, city) and to the multiple dimensions of sound environments (energetic and temporal).

3.7 Conclusion

In an urban context where building density drastically constrains noise reduction initiatives, reducing road traffic emissions at source seems to be the most promising way to calm noise environments. The development of models capable of assessing the impact on noise of urban policies concerning mobility management (e.g. the evaluation of road traffic regulation and multimodal transport policies) is therefore a major societal and environmental challenge.

Static models, traditionally used to characterize urban noise environments, struggle to fulfil this role because they do not capture the kinematic variations of vehicles induced by different traffic control strategies, and do not allow the estimation of temporal variations in noise levels even though they have a demonstrated perceptual impact. More recent approaches have been proposed to address partially this shortcoming. In particular, couplings with traffic models producing kinematic data provide access to an estimation of the time series of noise levels that allows a reliable calculation of acoustic indicators sensitive to noise dynamics.

The modularity of the modelling framework presented then makes it possible to develop multidimensional approaches, also introducing other environmental externalities such as air pollution. The questioning around the prerequisites, necessary to allow efficient multi-physical couplings goes beyond the field of acoustics. Research has been carried out to ensure the relevance of traffic/acoustics and traffic/air pollution couplings.

It is to be expected that the dynamic approach will develop in the coming years, since it allows a characterization of sound environments closer to the perception that city dwellers have of them. It also has the enormous advantage of being sensitive to traffic theory elements that have a high acoustic impact, such as impacts on vehicle kinematics or traffic reassignment observed according to traffic conditions. It is therefore necessary that rapprochement be made between the acoustic and traffic communities, as the acoustic impacts come indirectly from benefits obtained on traffic flow by good management of the road traffic network. It is likely that this rapprochement will take place through new research initiatives, for example on dynamic traffic noise modelling at the city scale.

Conclusion

Closing remarks on research in environmental acoustics

Research in urban acoustics is part of a rapidly changing context. Noise environments are threatened by the emergence of new sound sources and the expansion of cities, whereas the transition to new mobility practices is, on the contrary, a potential lever for calming noise environments. At the same time, the desire for calm among city dwellers is increasing, even as city practices are changing towards more mobility and an individualization of rhythms that may conflict with this calm.

Research in urban acoustics itself is changing: recent technological innovations make it possible to improve the characterization of sound environments through both measurement and modelling, and holistic approaches embracing broader disciplinary fields compared with past quantitative approaches become more widespread. It is likely that research in environmental acoustics will continue this mutation; the stakes for the coming years will then be threefold:

- In recent years, research in environmental acoustics has taken a resolutely multidisciplinary path, which also questions the frontiers of this discipline. Some of the notable recent advances in urban environmental acoustics are by the way not the work of acousticians. The data assimilation provided by INRIA, the couplings with the dynamic traffic modelling provided by LICIT (ENTPE/Ifsttar), or the recent proposal of activity-based approaches developed at the University of Berlin devoted to exposure assessment, are three good examples. The work on estimating the health impacts resulting from these exposures is the area of interest of epidemiological researchers who are in demand of collaboration with the acoustic world, in order to take into account more appropriate indicators than those currently used. Finally, many recent projects left a significant place to holistic approaches, bringing together acousticians and researchers in air pollution or climatology, environmental psychology, geography, etc. It seems inevitable, and desirable, that this movement will accelerate in the coming years;
- The very rapid development of new measurement methods suggests a significant improvement in the *characterization* of sound environments, in addition to the many studies on noise mapping carried out over the past two decades. However, it will be necessary to be careful that this does not hamper research on the *improvement* of noise environments. The small number of studies associating traffic/acoustic couplings compared to traffic/pollutant couplings is therefore symptomatic. It seems crucial that research in urban environmental acoustics be directed towards the evaluation of policies to manage noise environments. Some of the solutions can by the way be based on the measurement networks currently being deployed. It seems additionally important to continue to develop research on multiphysical couplings, based on reliable road traffic modelling, at various spatial scales;
- Finally, current societal and technological developments, in addition to the urban renewal, require us to reflect on the sound environments desired for the city of tomorrow, placing the human being

at the center of this reflection. The incipit of the eponym book from Julien Gracq, adapted from one verse of Charles Baudelaire, *« The shape of a city changes faster, as we know, than the heart of a mortal »* (in French: *« La forme d'une ville change plus vite, on le sait, que le cœur d'un mortel »*) illustrates this. In terms of environmental acoustics, this might suggest that urban sound environments change faster than the faculty of adaptation of city dwellers to it. The threat to the sound environments that new vectors of mobility (drones, electric vehicles, etc.) can represent, the absolute need to preserve calm zones in the city, the probable disappearance of cars in the hyper centers, make the noise environment of cities indeed uncertain in a relatively short period of time. This is therefore important to anticipate these changes and assess their consequences. This will again require an opening of the domain of acoustics to new disciplines: cognitive sciences, environmental economics, social sciences, etc.

Closing remarks on personal activities

The research I have been conducting for a little over a decade is part of this context. It attempts to take advantage of a diversity of means to improve the characterization of urban noise environments, and seeks ways to evaluate mobility solutions based on acoustic impacts. This research led me in particular:

- To be interested in all the physical and perceptual dimensions of sound environments in order to define which indicators could be the basis for the characterization and evaluation of urban sound environments;
- To work on the use of different new measurement methods (measurement networks based on low-cost sensors, participatory measurement), and on the necessary treatment of the data produced, in order to offer a continuous characterization in time and space of sound environments;
- To design multiphysical couplings for the evaluation of the impact of mobility and in particular traffic regulation strategies. This research opened up fields other than acoustics for me, to embrace the dimension of atmospheric pollutants, with a view to multi-criteria analyses.

This research has brought me closer to diverse communities: signal processing researchers (Mathieu Lagrange, LS2N, as part of Jean-Rémy Gloaguen's thesis, co-funded by Ifsttar and the Pays-de-la-Loire Region), applied mathematics researchers (Vivien Mallet, INRIA, as part of Cense Project and Antoine Lesieur's thesis, funded by ANR). The work I am doing in collaboration with LICIT (ENTPE/Ifsttar) on multiphysical couplings is also part of this diversity of collaborations. This openness is not an end in itself, but an essential vector for responding to current research questions in environmental acoustics. The collaborations I am currently trying to initiate involve researchers in epidemiology and health, notably through the thesis of Sidi Mehdi Regragui and a project currently under preparation. Finally, the question of the impact of mobility on sound environments, which I wish to examine at different spatial scales, should bring me closer to environmental economists and urban planners in the coming years.

Closing remarks on research ressources and functionning

These last considerations lead me to discuss, and this concludes this document, the means that seem appropriate to me to bring together to answer these questions, namely research projects, the animation of research and the supervision of research.

Research Projects

The current research organisation, which is very much oriented towards project development, seems relevant to address some of these research questions. In particular, research projects are an effective means of accelerating the meeting between different disciplines around common research objects or to answer specific research questions. However, attention should be paid to the well identified risks that this organization may present. In particular:

- The organization of research around time-bound projects can present a risk of sustainability of the actions undertaken; I will give two examples:
    - The analysis of data collected during a project, which could serve as a basis for further research at the end of the project, may be complicated by the difficulty of mobilising the necessary resources for this analysis;
    - The maintenance of software developed during a project can be difficult once the project is completed and the associated funding dried up, which is problematic for an applied research objective.

  This risk is part of a broader problematics of finalised research institutes, described in particular by the problem of RANA (Non-Applicable Applied Research), whose Bruno Latour describes the dysfunctions through some examples: « We can show very concretely with scientometric tools, that we are losing absolutely colossal sums that would be much more usefully invested in new and perhaps very fundamental research programmes[22] » (Latour, 1995);
- The organisation of research in response to calls for proposals can promote fashionable effects. On the other hand, the subjects highly innovative may not be identified as important by the funders. This phenomenon is described by Pierre Joliot: « The domains recognized as priorities are close to maturity and sometimes already in decline [....] Having sufficient recurrent financial resources allows researchers to deviate from the effects of fashion »[23] (Joliot, 2009). It seems essential in parallel to the projects that the use of own fundings be as free as possible.

Research animation

Research animation is also essential to stimulate discussion and generate encounters around identified research questions. It can take different forms:

- The organization of sessions at international congresses is an important challenge for disseminating ideas and bringing together groups of researchers around them. It is, for example, the medium used to discuss environmental acoustics indicators, which include various dimensions of environmental acoustics;

[22] In French, translated with www.DeepL.com/Translator: « On peut montrer très concrètement avec des outils scientométriques, qu'on perd des sommes absolument colossales qui seraient beaucoup plus utilement investies dans des programmes de recherche neufs et peut être très fondamentaux »

[23] In French, translated with www.DeepL.com/Translator: « Les domaines reconnus comme prioritaires sont proche de leur maturité et parfois déjà sur leur déclin […] Disposer de suffisamment de moyens financiers récurrents permet aux chercheurs de s'écarter des effets de mode »

- Research animation is also essential at the institute level. For instance, Ifsttar's current organization, in laboratories (often disciplinary, such as the UMRAE -Joint Research Unit in Environmental Acoustics-) grouped into departments (often built around research objects, such as AME –Planning, Mobilities and Environment Department-) of about 150 pemanent staff[24], can favorize this animation at different scales, in addition to the institute's transversal research axes;
- Finally, inter-institute networks are privileged meeting places for researchers from various disciplines but working around a common object, such as IRSTV[25], which brings together researchers interested in urban questions.

If this animation is a very effective means of sharing methods, making links between questionings, or giving rise to ideas, the difficulty identified for the animation of research is that of the means allocated, whose amounts are sometimes not appropriate to enable the investigation of the identified research subjects. But perhaps this is not the purpose, the enrichment of the questions and the transversal view of the subjects covered by the animation being already highly valuable.

Research supervision

Finally, the supervision of research is obviously a crucial element for the conduct of research. This supervision must also be seen as an exchange, as the arrival of new generations of researchers is constantly changing the way of working. Through their refreshed vision of research contexts, through their new working methods, such as the gradual disappearance of the boundaries between research questions and the technical aspects that make it possible to answer them, or the constant contribution of new statistical tools, doctoral and post-doctoral candidates impose a perpetual reappraisal of working methods, which in many respects is an enrichment. May I finish this document by sending my warm thanks to those I have had the opportunity to work with.

[24] More details about the organization of Ifsttar on the website: https://www.ifsttar.fr/accueil/
[25] IRSTV: Institute of Research in Science and Technology of the City. More details on the website: https://irstv.ec-nantes.fr/.

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Appendices

Appendice1 Cense Project

Project coordination :

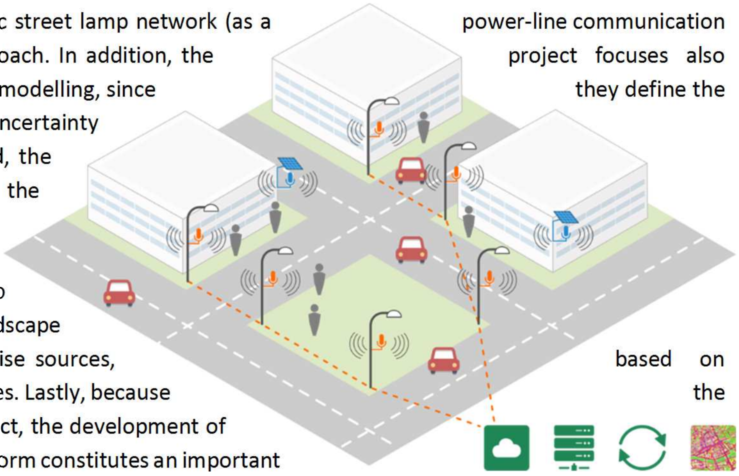
- Judicaël Picaut (project leader, Ifsttar)
- Arnaud Can (scientific coordination, Ifsttar)

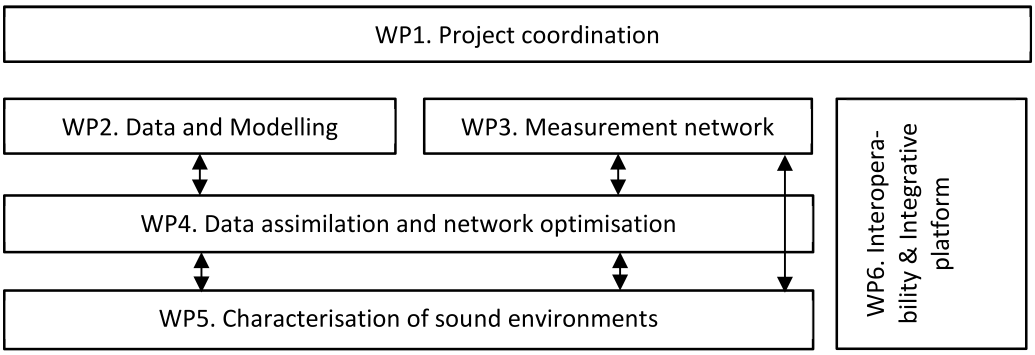
Partners:
Bouygues E&S, BruitParif, Cerema (DTerEst), CNRS (CNRS/LS2N),
INRIA (CLIME PROJECT-TEAM), UBS (Lab-STICC DECIDE TEAM), UCP (ETIS), Wi6Labs.

Funding: ANR
Dates: 01/01/2017 – 31/12/2020

Objectives:

CENSE project aims at improving the characterization of urban sound environments, by combining in situ observations and numerical noise predictions. The project relies on data assimilation techniques, which have never been developed in the environmental noise context yet, in order to take profit of both modelling and measurements advantages. The deployment of a mixed wired/wireless sensor network, connected to the cloud through a public street lamp network (as a power-line communication based system), constitutes an innovative technical approach. In addition, the project focuses also on the quality of the input data that are required for the modelling, since they define the accuracy of the output noise indicators, based on uncertainty propagation approaches. Two aspects will be developed, the first concerning the optimization and improvement of the quality of input data, the second on the estimation of un-certainty of the output data, from the input ones. The CENSE project will also propose an original approach to produce perceptive noise maps, by developing soundscape models that rely on the automatic identification of noise sources, based on models that have never been used for urban noise mixtures. Lastly, because the management of geo-localized data is central to the project, the development of an integrative geographical information system (GIS) platform constitutes an important task, in order to facilitate the data accessibility (inputs/outputs, measured/simulated), its reuse and its exploitation to build new thematic noise maps.





Main publications:

Gontier, F., Lagrange, M., Aumond, P., Can, A., & Lavandier, C. (2017). An efficient audio coding scheme for quantitative and qualitative large scale acoustic monitoring using the sensor grid approach, *Sensors*, 17, 2758;

Picaut, J., Can, A., Ardouin, J., Crépeaux, P., Dhorne, T., Écotière, D., Lagrange, M., Lavandier, C., Mallet, V., Mietlicki, C., Paboeuf, M. (2017). CENSE project: characterization of urban sound environments using a comprehensive approach combining open data, measurements and modeling. 173rd Meeting of the Acoustical Society of America and the 8th Forum Acusticum.

Appendice2 Grafic Project

Project coordination:

- Catherine Lavandier University of Cergy Pontoise

Partners:
Ifsttar, Bruitparif, Ghent University
Participation of the city of Paris

Funding: Ademe
Dates: 01/10/2014 – 31/09/2017

Objectives:

The objective of the GRAFIC research project is to propose a continuous mapping of urban sound environments, coherent from both a perceptual and physical point of view. To do this, the research operation is based on a continuous survey of noise levels, carried out on a network of fixed sensors and geo-referenced mobile sensors, as well as on perceptual surveys conducted both in the neighbourhood studied and in the laboratory. The project results should make it possible (1) to improve the relevance of the acoustic indicators mapped by refining their correlations with the results of perceptual analyses and (2) to interpolate these indicators spatially and temporally from measurements made on fixed sensors. The indicators must then make it possible to reproduce the sound quality of urban journeys. Thus, in this project, it has already been shown that if you want to map sound pleasure using an acoustic measure, it is better to choose the LA50 rather than the LAeq regulatory indicator, since this LA50 is very well correlated with the notion of perceived sound intensity. The perceived presence times of sound sources such as traffic, birds (which reflect the presence of nature in the city) and voices (which reflect the presence of human beings) also have an impact on the quality of the sound environment. While the first two variables can be characterized by the presence of low or high frequencies in the urban spectrum, human presence is, in the current state of this project, still difficult to characterize by a simple acoustic indicator.

Main publications:

Aumond, P., Can, A., De Coensel, B., Botteldooren, D., Ribeiro, C., & Lavandier, C. (2017). Global and continuous pleasantness estimation of the soundscape perceived during walking trips through urban environments, January 2017, *Applied Sciences*, 7(2).

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Aumond, P., Can, A., Mallet, V., De Coensel, B., Ribeiro, C., Botteldooren, D., Lavandier, C. (2018b). Kriging-based spatial interpolation of mobile measurements for sound level mapping, Journal of Acoustical Society of America, 143(5), 2847-2857.

Can, A., Aumond, P., De Coensel, B., Ribeiro, C., Botteldooren, D., & Lavandier, C. (2018). Probabilistic modelling of the temporal variability of urban sound levels. *Acta Acustica united with Acustica*, 2018, 104(1), 94-105.

Filipan, K., De Coensel, B., Aumond, P., Can, A., Lavandier, C., Botteldooren, D. (2019). Auditory Saliency Triggers Change in Pleasantness Assessment of the Soundscape Perceived during Walking Trips through Urban Environments, Building and Environment, accepted for publication.

Can, A., Aumond, P., Michel, S., De Coensel, B., Ribeiro, C., Botteldooren, D., & Lavandier, C. (2016b). Comparison of noise indicators in an urban context, Proceedings of Internoise 2016, Hambourg (Allemagne), 21-24 August, 2016.

Appendice3 PhD of Jean-Rémy Gloaguen

Title:
Estimation of the noise level of sources of interest within urban noise mixtures: application to road traffic

Supervisors:
- Jean-François Petiot (director, LS2N)
- Arnaud Can (co-supervisor, Ifsttar)
- Mathieu Lagrange (co-supervisor, LS2N)

Funding: Ifsttar & Région Pays-de-la-Loire
Dates: 01/10/2015 – 31/09/2018

Abstract:
Acoustic sensor networks are being set up in several major cities in order to obtain a more detailed description of the urban sound environment. One challenge is to estimate useful indicators such as the road traffic noise level on the basis of sound recordings. This task is by no means trivial because of the multitude of sound sources that composed this environment. For this, Non-negative Matrix Factorization (NMF) is considered and applied on two corpuses of simulated urban sound mixtures. The interest of simulating such mixtures is the possibility of knowing all the characteristics of each sound class including the exact road traffic noise level. The first corpus consists of 750 30-second scenes mixing a road traffic component with a calibrated sound level and a more generic sound class. The various results have notably made it possible to propose a new approach, called 'Thresholded Initialized NMF', which is proving to be the most effective. The second corpus created makes it possible to simulate sound mixtures more representatives of recordings made in cities whose realism has been validated by a perceptual test. With an average noise level estimation error of less than 1.3 dB, the Thresholded Initialized NMF stays the most suitable method for the different urban noise environments. These results open the way to the use of this method for other sound sources, such as birds' whistling and voices, which can eventually lead to the creation of multi-source noise maps.

Appendice4 PhD of Antoine Lesieur

Title:
State estimation and inverse modelling applied to noise pollution in urban areas

Supervisors:
- Vivien Mallet (co-supervisor, INRIA)
- Arnaud Can (co-supervisor, Ifsttar)

Funding: ANR (Cense Project)

Dates: 01/10/2017 – 31/09/2020

Abstract:
The estimation of noise levels in a city is based on propagation models acoustic in urban areas and on a large amount of urban data describing in particular the geometry of the city and the sources of emissions including road traffic. The uncertainties, sometimes high in urban data, limit the accuracy of simulations. Observations collected in cities using sound level meters provide the following information additional information. The thesis will propose assimilation strategies of these observations to improve simulations by (1) state estimation, i. e. by merging the simulated noise field and observations, and (2) inverse modelling, i.e. by correcting the input data of the acoustic propagation model. This work will require quantifying the uncertainties propagated in an acoustic model, in particular by exploiting a metamodel to be built. The question of the optimization of the observation network will also be addressed

Appendice5 PhD of Sidi Mehdi Regragui

Title:
Estimation of rare events in environmental acoustics

Supervisors:

- Judicaël Picaut (director, Ifsttar)
- Catherine Lavandier (co-director, Unversity of Cergy-Pontoise)
- Arnaud Can (supervisor, Ifsttar)

Doctoral Scholarship : Ecole Doctorale SPI (Sciences pour l'Ingénieur).

Funding: Ecole Nationale Supérieure de Cachan

Dates: 01/10/2018 – 31/09/2021

Description:
The development of urbanised areas is accompanied by an increase in mobility and high expectations of the population in terms of the environment. Noise pollution is one of the environmental externalities that most affect the quality of life of city-dwellers; it also has significant public health impacts. Road traffic noise maps produced in urban areas respond to both communication and noise pollution management challenges.

The maps produced are based on an averaged estimation of traffic variables and a calculation of noise propagation, which gives access only to averaged noise indicators, such as the day-evening-night sound levels Lden. This approach is relevant to characterize the noisiest areas of the city and the associated annoyance. It finds however its limits in many exposure cases, where the literature suggests the impact of sound level temporal variations and the presence of emerging phenomena on how sound environments are perceived, and the resulting discomfort (Lavandier *et al*. 2011, Basner *et al.* 2014). This is the case, for example, in low-traffic areas where the distinction between low levels (e. g. the sound level exceeded 90% of time L90) and high levels (e. g. the sound level exceeded 10% of time L10) is important, or in the case of night-time exposures, where awakening can be associated with the number and intensity of sound events (e. g. the sound level exceeded 1% of time L1, the number of noise events exceeding 80 dB NNE80, etc.). These cases of exposure are very important because they contribute greatly to the quality of the urban noise environment; however, their estimation is hampered by unresolved scientific barriers.

The purpose of the thesis will be to focus on the estimation of noise distributions, and more particularly on the estimation of distribution queues and sound event indicators related to road traffic in urban areas, and then to study their impact on perception.

Three complementary modelling frameworks are envisaged:

- Stochastic approach: the estimation of the acoustic indicators cited could potentially be carried out within the static modeling chains commonly used for noise maps, such as the platform Noisemodelling developed at UMRAE, but this requires a stochastic modelling framework (Aumond *et al*. 2017). In particular, a reflection will be needed on how to distribute the model input variables (vehicle speed, individual emissions, etc.) according to the indicators to estimate.
- Dynamic approach: the dynamic modelling framework, based on a dynamic road traffic flow model representing vehicle trajectories and sensitive to traffic conditions, is appropriate for estimating noise peaks indicators. This approach also has the advantage of being able to test road traffic strategies that aim to smooth driving conditions and thus reduce the number of peaks of noise. Previous works have shown the interest of distributing input parameters in this modelling framework, but the distributions used were not specific to urban traffic conditions (Can *et al*. 2010, De Coensel et al. 2016). If necessary, a measurement campaign will therefore be carried out to measure the variability of vehicle emissions under real urban traffic conditions, or to add a class of specific vehicles (e. g. motorcycles) to the modelling.
- Statistical approach: the statistical formalism for the modelling of rare events will be applied to the estimation of peaks of noise indicators. Distributing the input parameters of the models probably cannot be sufficient to estimate the highest noise levels (e. g. levels exceeded 1% or 0.1% of the time), because of the interdependence between the input parameters. These rare events have a significant impact, particularly on night-time awakenings. Rare event modelling is a well-documented area of statistics (Van Der Paal 2014). These methods have been used in air pollution, but very little in environmental acoustics, although the forms of distributions have already been characterized (Can *et al*. 2017). The use of specific distribution laws (generalized extreme values distributions, skewed t-distribution, etc.), models using neural networks or support vector machines, which have been proven to predict rare air pollution events, will be investigated.

The estimates made by the 3 above-mentioned approaches will be compared with experimental data collected through a measurement network that will be deployed in 2018 as part of the CENSE project on the city of Lorient (more than 100 measurement points).

Finally, a perceptual test will make it possible to link the estimated indicators to the perceptual dimensions that characterize the places of interest. The corresponding perceptual test will be set up in the immersive laboratory of the University of Cergy-Pontoise, under the direction of Catherine Lavandier, in order to link the perceived discomfort to the number and intensity of the estimated sound events. These results, combined with those from the modelling work, may serve as an entry point for future collaboration with epidemiologists, who are awaiting modelling of acoustic sound events.

The results of this research will be shared with the scientific community through publications in international journals and papers at international conferences. In particular, the results of the modelling work and the results of the perceptual test are highly awaited by the community and will each be the subject of a scientific article.

Curriculum vitae

(as at 10/12/2018)

Arnaud CAN

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Born on 03/12/1980

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Research topics

My research activity focuses on the characterization of urban noise environments, and on the evaluation of the impacts of road traffic on noise. I pay particular attention in this work to dynamic approaches, which highlight temporal variations in sound environments:

- Dynamic coupling between road traffic and noise models to evaluate the noise impacts of traffic strategies.
- Multi-criteria assessments of road traffic environmental impacts, including airborne pollutants.
- Characterization of sound environments through approaches that combine measurements and modelling.
- Description of sound environments through relevant acoustic indicators.
- Perceptual assessments of urban sound environments.

Carreer

- Since 2011 Researcher at Ifsttar (UMRAE).
- 2009-2011 Postdoctoral position at Gent University, Belgium.
- 2009 Postdoctoral position at LICIT (ENTPE / INRETS), France.
- 2005-2008 PhD student at LICIT (ENTPE / INRETS), France.
  Subject: Traffic representation and dynamic noise characterization in urban environments
- 2005 Master degree, « Mécanique, Physique et Modélisation », spécialité « Acoustique ».
- 2004 Diplôme d'Ingénieurs, Ecole Supérieure d'Ingénieurs de Poitiers (ESIP)

Production & management:

- More than 60 publications, including 32 papers in peer-reviewed journals (h-index=12).
- Regular reviewer for Applied Acoustics, JASA, Stoten, Acta Acustica, JUPD, etc.
- Scientific coordination of the CENSE project funded by ANR: http://cense.ifsttar.fr/.
- Responsible of a Work Package within the GRAFIC project funded by Ademe.
- Session organizer for Euronoise 2015, Internoise 2017, ICA 2019, USS 2019.
- Teaching in environmental acoustics, urban acoustics, road traffic noise assessment (≈ 30h / year).
- 1 post-doc supervision.
- 3 thesis co-supervision (including two in progress).
- 5 master student supervision.
- Host of 2 three-months international PhD visitor students & 1 three-months international visitor researcher.
- Member of IRSTV (Institut de Recherche en Sciences et Techniques de la Ville) & SFA (Société Française d'Acoustique).

Summary of personal productions

(List as at 10/12/2018)

Summary of productions

Article dans revue à comité de lecture (répertoriée dans les BDI JCR, Scopus, ERIH ou HCERES (ACL) ou donner le DOI)	**32**
h-index	**12**
Article dans revue à comité de lecture non répertoriée dans les BDI JCR, Scopus, ERIH, AEREL (ACLN)	**8**
Ouvrage scientifique ou chapitre (OS)	**2**
Conférence invitée dans un congrès international ou national (INV)	**9**
Communication avec actes dans congrès international (ACTI)	**20**
Communication avec actes dans congrès national (ACTN)	**5**
Communication orale sans actes dans un congrès international ou national (COM)	**5**
Rapport de recherche	**11**

Abstract of publications

Peer reviewed papers

[ACL 1] GUILLAUME G., AUMOND P., CHOBEAU P., CAN A. , Statistical study of the relationships between mobile and fixed stations measurements in urban environment. Building and Environment, accepted for publication, 2019. (times cited: 0).

Noise predictions are based on both simplified emission and propagation models able to deal with transport and industrial sources only, thus neglecting other sound sources which yet contribute to urban soundscapes. Noise assessment can take advantage of acoustic measurements if a sufficient amount of sensors is deployed to pick up the variety of sound sources. This can be achieved by combining fixed and mobile sensors that offer high temporal and spatial granularities respectively. The paper aims at investigating such a solution by linking up noise measurements issued from moving sensors when passing near receivers fixed to buildings facades. The experimental study is strengthened by a numerical analysis of the noise levels discrepancy between fixed and mobile sensors according to the location of the fixed station in relation to the façade.

[ACL 2] FILIPAN K., DE COENSEL B., AUMOND P., CAN A., LAVANDIER C., BOTTELDOOREN D. Auditory Saliency Triggers Change in Pleasantness Assessment of the Soundscape Perceived during Walking Trips through Urban Environments, Building and Environment, accepted for publication. (times cited: 0).

The sonic environment of the urban public space is often experienced while walking through it. Nevertheless, city dwellers are usually not actively listening to the environment when traversing the city. Therefore, sound events that are salient, i.e. stand out of the sonic environment, are the ones that trigger attention and contribute highly to the perception of the soundscape. In a previously reported audiovisual perception experiment, the pleasantness of a recorded urban sound walk was continuously evaluated by a group of participants. To detect salient events in the soundscape, a biologically-inspired computational model for auditory sensory saliency based on spectrotemporal modulations is proposed. Using the data from a sound walk, the present study validates the hypothesis that salient events detected by the model contribute to changes in soundscape rating and are therefore important when evaluating the urban soundscape. Finally, when using the data from an additional experiment without a strong visual component, the importance of auditory sensory saliency as a predictor for change in pleasantness assessment is found to be even more pronounced.

[ACL 3] GLOAGUEN J-.R, CAN A., LAGRANGE M., PETIOT J-.F. Road traffic sound level estimation from realistic urban sound mixtures by Non-negative Matrix Factorization, Applied Acoustics, 143:229-238, 2019. (times cited: 0).

Experimental acoustic sensor networks are currently tested in large cities, and appear more and more as a useful tool to enrich modeled road traffic noise maps through data assimilation techniques. One challenge is to be able to isolate from the measured sound mixtures acoustic quantities of interest such as the sound level of road traffic. This task is anything but trivial because of the multiple sound sources that overlap within urban sound mixtures. In this paper, the Non-negative Matrix Factorization (NMF) framework is developed to estimate road traffic noise levels within urban sound scenes. To evaluate the performances of the proposed approach, a synthetic corpus of sound scenes is designed, to cover most common soundscape settings, and whom realism is validated through a perceptual test. The simulated scenes reproduce then the sensor network outputs, in which the actual occurrence and sound level of each source are known. Several variants of NMF are tested. The proposed approach, named threshold initialized NMF, appears to be the most reliable approach, allowing road traffic noise level estimation with average errors of less than 1.3 dB over the tested corpus of sound scenes.

[ACL 4] LEJRI D., CAN A., SCHIPER N., LECLERCQ L. Accounting for traffic speed dynamics when calculating COPERT and PHEM pollutant emissions at the urban scale, Transportation Research Part D, 63, 588-603, 2018. (times cited: 0).

Coupling a traffic microsimulation with an emission model is a means of assessing fuel consumptions and pollutant emissions at the urban scale. Dealing with congested states requires the efficient capture of traffic dynamics and their conditioning for the emission model. Two emission models are investigated here: COPERT IV and PHEM v11. Emission calculations were performed at road segments over 6 min periods for an area of Paris covering 3 km^2. The resulting network fuel consumption (FC) and nitrogen oxide (NO_x) emissions are then compared. This article investigates: (i) the sensitivity of COPERT to the mean speed definition, and (ii) how COPERT emission functions can be adapted to cope with vehicle dynamics related to congestion. In addition, emissions are evaluated using detailed traffic output (vehicle trajectories) paired with the instantaneous emission model, PHEM. COPERT emissions are very sensitive to mean speed definition. Using a degraded speed definition leads to an underestimation ranging from -13% to -25% for fuel consumption during congested periods (from -17% to -36% respectively for NO_x emissions). Including speed distribution with COPERT leads to higher emissions, especially under congested conditions (+13% for FC and +16% for NO_x). Finally, both these implementations are compared to the instantaneous modeling chain results. Performance indicators are introduced to quantify the sensitivity of the coupling to traffic dynamics. Using speed distributions, performance indicators are more or less doubled compared to traditional implementation, but remain lower than when relying on trajectories paired with the PHEM emission model.

[ACL 5] AUMOND P., CAN A., MALLET V., DE COENSEL B., RIBEIRO C., BOTTELDOOREN D., LAVANDIER C. Kriging-based spatial interpolation of mobile measurements for sound level mapping, Journal of Acoustical Society of America, 2018, 143 (5), pp.2847-2857. (times cited: 0).

Network-based sound monitoring systems are deployed in various cities over the world and mobile applications allowing participatory sensing are now common. Nevertheless, the sparseness of the collected measurements, either in space or in time, complicates the production of sound maps. This paper describes the results of a measurement campaign that has been conducted in order to test different spatial interpolation strategies for producing sound maps. Mobile measurements have been performed while walking multiple times in every street of the XIIIth district of Paris. By adaptively constructing a noise map on the basis of these measurements, the role of the density of observations and the performance of four different interpolation strategies is investigated. Ordinary and universal Kriging methods are assessed, as well as the effect of using an alternative definition of the distance between observation locations, which takes the topology of the road network into account. The results show that a high density of observation points is necessary to obtain an interpolated sound map close to the reference map.

[ACL 6] AUMOND P., JACQUESSON L., CAN A. Probabilistic modeling framework for multisource sound mapping, Applied Acoustics, 2018, 139, 34-43. (times cited: 1).

The process of modeling noise maps is now well defined: long-term aggregated indicators are calculated based on a collection or estimation of road, air and rail traffic variables. This framework however disregards the sound levels variations, and hence prevents the production of statistical or emergence indicators, and does not allow for the study of competition between typical urban sound sources that can improve the characterization of urban sound environments. A modeling framework in four steps is proposed to answer these issues: (i) a spatial distribution of the potential sound source of interest, (ii) the calculation of a sound propagation matrix, (iii) the stochastic activation of a sound sources ratio for n iterations of the sound map, and (iv) the calculation of specific sound indicators. The stochastic approach proposed in this study enables the estimation of the temporal sound distribution per sound source. It permits in particular to deduce source-oriented indicators such as the percentage of the time when a given sound source emerges from an urban sound mixture. An example of application of this framework is exposed for a district in the city of Nantes, France. It shows the interest of such approaches, in particular for soundscape and urban sound environment studies

[ACL 7] CAN A., AUMOND P. Estimation of road traffic noise emissions: the influence of speed and acceleration. Transportation Research Part D, 2018 (times cited: 3).

This paper relies on vehicle trajectory collection on a corridor, to compare different traffic representations used for the estimation of the sound power of light vehicles and the resulting sound pressure levels. Four noise emission models are tested. The error introduced when the emissions are calculated based on speeds measured at regular intervals along the road network are quantified and explained. The current noise emission models might in particular misestimate noise levels under congestion. This bias can be reduced by introducing additional traffic variables in the modeling. In addition, significant differences within the models are highlighted, especially concerning their accounting of vehicle accelerations. Models that rely on a binary representation of acceleration regimes (a vehicle or a road segment is accelerating or not) can lead to errors in practice. Models under use in Europe have a very low sensitivity to acceleration values. These results help underlying the further required improvements of dynamic road traffic noise models.

[ACL 8] CAN A., AUMOND P., DE COENSEL B., RIBEIRO C., BOTTELDOOREN D., LAVANDIER C. Probabilistic modelling of the temporal variability of urban sound levels, Acta Acustica united with Acustica 2018, 104(1), 94-105 (times cited: 0).

Relying on monitoring networks to compute or improve noise maps is an increasingly used approach. To be able to use this approach to provide adequate temporal treatments, a good understanding of the temporal variations within urban sound level time series is required. This paper provides an in-depth statistical analysis of the temporal characteristics of urban sound environments, on the basis of a wide measurement campaign during 8 month, at 23 measurement stations in Paris, which cover a large variety of urban sound environments. The time series of sound levels were recorded continuously with a 125ms-time resolution, from which LA50,1h values were extracted. In total, 72 time-slots of interest are defined (24 1h-periods covering all days of the week). The statistical analysis determines for each station the Daily Average Noise Pattern (DANP), and for each of the 72 time-slots the 1h-Generalized Extreme Values distributions. The Generalized Extreme Values distributions are found to outperform the normal distributions to model the LA50,1h distributions. In addition, the average sound level differences between these 72 1h-time periods are calculated along with their variability, resulting in 72×72 delta matrices that describe the temporal relations between sound levels. This database is then used to develop two models, which aim to estimate DANP based on a limited amount of measurements. The model M1 relies on the delta matrices, whereas the model M2 consists of a weighted average of the DANP that are stored in the database in which the weights are based upon measures of similarity between the stations. Both models rely on probability density functions, and provide a measure for the reliability of the estimated noise levels. A test of both modelling approaches through simulated measurements shows that the model M1 seems to be more robust in case measurements are inaccurate. Beyond these two models, the proposed database could serve in the development of further models that aim to estimate sound levels based on a limited amount of measurements.

[ACL 9] GONTIER F., LAGRANGE M., AUMOND P., CAN A., LAVANDIER C. An efficient audio coding scheme for quantitative and qualitative large scale acoustic monitoring using the sensor grid approach, Sensors 2017, 17, 2758; doi:10.3390/s17122758 (times cited: 0).

The spreading of urban areas and the growth of human population worldwide raise societal and environmental concerns. To better address these concerns, the monitoring of the acoustic environment in urban as well as rural or wilderness areas is an important matter. Building on the recent development of low cost hardware acoustic sensors, we propose in this paper to consider a sensor grid approach to tackle this issue. In this kind of approach, the crucial question is the nature of the data that are transmitted from the sensors to the processing and archival servers. To this end, we propose an efficient audio coding scheme based on third octave band spectral representation that allows: (1) the estimation of standard acoustic indicators; and (2) the recognition of acoustic events at state-of-the-art performance rate. The former is useful to provide quantitative information about the acoustic environment, while the latter is useful to gather qualitative information and build perceptually motivated indicators using for example the emergence of a given sound source. The coding scheme is also demonstrated to transmit spectrally encoded data that, reverted to the time domain using state-of-the-art techniques, are not intelligible, thus protecting the privacy of citizens.

[ACL 10] AUMOND P., CAN A., LAVANDIER C., DE COENSEL B., BOTTELDOOREN D., RIBEIRO C. Modeling soundscape pleasantness using perceptive assessments and acoustic measurements along paths in urban context, Acta Acustica united with Acustica. Volume 103, Number 3, May/June 2017, pp. 430-443(14) (times cited: 5).

Mapping the pleasantness of an urban environment is an alternative approach, closer to the city dweller's perception, than standardized sound levels cartography. This study reports on modeling pleasantness in urban context using perceptual assessments and sound measurements for specific locations during an urban walk. These assessments have been collected from four groups of approximately ten participants on 19 different assessment locations, along a 2,1 km-long path traveled in both directions. Simultaneously, ⅓ octave band sound levels and audio were recorded. Perceptual and physical models of pleasantness are proposed for specific locations based on multiple linear regressions. A multi-level analysis was performed, and it is shown that a perceptual model that includes perceived loudness joined to the perceived time of presence of traffic, voices and birds explains 90% of the pleasantness variance due to the sound environment variations. Physical models that include the original acoustic indicators that are most correlated with perceptual variables explain 85% of this variance. Thanks to these models, a unique averaged pleasantness value is defined for each assessment location from the perceptual or physical collected assessments. The Pearson's correlation coefficient between the averaged perceived pleasantness and the modeled values from perceptual assessment reaches $r(19)=0.98$, and $r(19)=0.97$, with the modeled values from physical measurements. These results make it possible to consider the use of this kind of models in a cartographic context. As the path was traveled in both directions, the presentation-order effect has also been assessed, and it has been found that path direction did not have a significant impact on the pleasantness assessment at specific locations, except when very strong sound environment changes occurred. Finally, the study gives some insights about the retrospective global pleasantness assessment for urban walks. For very short walks between two assessment locations, a recency effect is shown. Nevertheless, this effect doesn't seem to be significant when longer routes are assessed.

[ACL 11] AUMOND P., CAN A., DE COENSEL B., BOTTELDOOREN D., RIBEIRO C. LAVANDIER C. Global and continuous pleasantness estimation of the soundscape perceived during walking trips through urban environments, January 2017, Applied Sciences, 7(2), 144 (times cited: 0).

This paper investigates how the overall pleasantness of the sound environment of an urban walking trip can be estimated through acoustical measurements along the path. For this purpose, two laboratory experiments were carried out, during which controlled and natural 3-min audio and audiovisual sequences were presented. Participants were asked to continuously assess the pleasantness of the sound environment along the sequence, and globally at its end. The results reveal that the global sound pleasantness is principally explained by the average of the instantaneous sound pleasantness values. Accounting for recency or trend effects improved the estimates of the global sound pleasantness over controlled sound sequences, but their contribution is not significant for the second group of stimuli, which are based on natural audio sequences and include visual information. In addition, models for global and continuous pleasantness, as a function of the instantaneous sound pressure level Leq,1s, are proposed. The instantaneous sound pleasantness is found to be mainly impacted by the average sound level over the past 6 s. A logarithmic fading mechanism, extracted from psychological literature, is also proposed for this modelling, and slightly improves the estimations. Finally, the globally perceived sound pleasantness can be accurately estimated from the sound pressure level of the sound sequences, explaining about 60% of the variance in the global sound pleasantness ratings.

[ACL 12] CAN A., GUILLAUME G., PICAUT J. Cross-calibration of participative sensor networks for environmental noise mapping, Applied Acoustics. Volume 110, September 2016, Pages 99-109 (times cited: 4).

Participatory measurements appear as a promising technique for performing noise mapping and monitoring. However, the confidence in the quality of raw data collected through participatory measurements controls the faithfulness of the output noise maps. In this paper, a cross-calibration method is proposed, which aims at both selecting the best candidate sensors and improving the furnished raw data. The method rests upon four steps: (i) an outlier detection, (ii) the crowd sensors-based correction, (iii) a fixed sensors-based correction, and (iv) the Lden estimation. The efficiency of the approach for different characteristics of the network of mobile sensors is evaluated on its ability to reconstruct an artificial reference sound field, which consists of the one-month L_{10s} evolution, on a twenty streets network. The main conclusions are: (i) the systematic errors of the sensors can be efficiently corrected by a cross-calibration method, and thus do not affect the L_{den} estimation, (ii) the fixed sensor network helps estimating the average error of the network of mobile sensors, (iii) the dispersion in an individual sensor measurements, which is due for example to the operator, stands for a much more critical concern and should be flagged by a rigorous outlier detection method, as the one proposed in this paper, (iv) although individual measures are improved by the proposed cross-calibration, some errors remain on the L_{den} estimation because of the shortness of the collected samples, (v) increasing the number of sensors does not improve the Lden estimation as long as individual measurements dispersions remain too large.

[ACL 13] GUILLAUME G., CAN A., PETIT G., FORTIN N., PALOMINOS S., GAUVREAU B., BOCHER E., PICAUT J. Noise mapping based on participative Measurements. Noise Mapping De Gruyter open journal, 2016, 3, p.140-156. (times cited: 14).

The high temporal and spatial granularities recommended by the European regulation for the purpose of environmental noise mapping leads to consider new alternatives to simulations for reaching such information. While more and more European cities deploy urban environmental observatories, the ceaseless rising number of citizens equipped with both a geographical positioning system and environmental sensors through their smartphones legitimates the design of outsourced systems that promote citizen participatory sensing. In this context, the OnoM@p system aims at offering a framework for capitalizing on crowd noise data recorded by inexperienced individuals by means of an especially designed mobile phone application. The system fully rests upon open source tools and interoperability standards defined by the Open Geospatial Consortium. Moreover, the implementation of the Spatial Data Infrastructure principle enables to break up as services the various business modules for acquiring, analysing and mapping sound levels. The proposed architecture rests on outsourced processes able to filter outlier sensors and untrustworthy data, to cross- reference geolocalised noise measurements with both geographical and statistical data in order to provide higherlevel indicators, and to map the collected and processed data based on web services.

[ACL 14] CAN A., GUILLAUME G., GAUVREAU B. Noise indicators to diagnose urban sound environments at multiple spatial scales, Acta Acustica united with Acustica, 101, September/October 2015, 964-974 (times cited: 6).

The diagnostic of urban sound environments requires noise indicators able to capture its main physical characteristics. However, the more information furnished by indicators, the longer the measurements should be and the lesser immediate their understanding is. In this paper, a methodology in three steps is proposed to diagnose urban sound environments at the neighborhood level, with an increasing level of detail that offers some flexibility to the decision maker when investigating the sound quality of a neighborhood. The first step consists of the calculation of three sound structure indicators, namely the $L_{50,A}$, the $\sigma_{Leq,A}$ and the SGC[50Hz-10kHz], which allow a continuous spatial categorization of the neighborhood. The second step consists of the calculation of sound events indicators, namely the $L_{1,A}$, the $MI_{LA50+10}$, and the $MI_{LLF50+15}$, which are sensitive to the physical dimensions of noise emergences (threshold values, suddenness, occurrences). The third step consists of a map of the emergences, which describes precisely at a given location the number and the duration of the emergences. The procedure is validated over three measurement campaigns achieved in January, April and June, when geo-referenced noise measurements were collected over 18 1h-soundwalks periods in Toulouse (France). A clustering analysis is performed in order to select the subsets of indicators used to describe sound environments. Although these indicators might differ in theory from one location to another, the clustering analysis selects the same indicators than a previous study achieved on another site, suggesting their possible generalization for further use. Moreover, the stability in the indicators values between the three different campaigns validates their calculation over short time samples. Finally, the procedure enables describing in details the time fluctuations of sound environments at both the daily and the seasonal scale. These fluctuations can be explained by the land use of the site.

[ACL 15] CAN A., FORTIN N., PICAUT J. Accounting for the effect of diffuse reflections and fittings on sound propagation within street canyons through a regression analysis, Applied Acoustics, 96, September 2015, 83-93 (times cited: 1).

Diffusion on building facades and fittings within a street can significantly affect sound propagation in urban areas. These phenomena are however not reproduced by the widespread outdoor sound propagation models that are based on ray codes algorithms, because their modeling would induce increased computational costs. In this paper, a set of 32 175 simulations is achieved with a sound particle tracing code to quantify the errors made when neglecting acoustic diffusion within street canyons, according to the street geometry (width, height, distance between the point source and the receiver), the acoustical properties of the street (diffusion and absorption coefficient of the facades, absorption coefficient of the ground), and the acoustical properties of the fittings (mean free path and average absorption coefficient), in the case of a receiver height of 1.5 m. The diffuse reflections can lead to reduction of 2 dB to an increase of 4 dB of sound pressure levels in the absence of fittings, and can lead to an increase of 10 dB of sound pressure levels in the presence of fittings, for the most unfavorable configurations. The influence of the acoustical parameters and the influence of the street geometry on sound attenuation are closely linked to each other. Moreover, acoustic diffusion results in an overall sound level increase if one considers a linear point source distribution. Finally, regressions are proposed that estimate the impact of diffusive reflections and street fittings on sound propagation as a function of the input parameters. These regressions can now be advantageously used to refine sound levels estimations within street canyons, when using classical outdoor sound propagation models, in the range of the parameters tested.

[ACL 16] CAN A., GAUVREAU B. Describing and classifying urban sound environments with a relevant set of physical indicators, Journal of the Acoustical Society of America, 137 (1), January 2015, 208-218 (times cited: 8).

Categorization is a powerful method for describing urban sound environments. However, it has only been applied, until now, to discrete noise data collection, whereas sound environments vary continuously both in space and time. Therefore, a procedure is developed in this paper for describing the variations of urban sound environments. The procedure consists of mobile measurements, followed by a statistical clustering analysis that selects relevant noise indicators and classifies sound environments. Analysis are based on a 3 days+1 night survey where geo-referenced noise measurements were collected over 19 1-h soundwalk periods in a district of Marseille, France. The clustering analysis showed that a limited subset of indicators is sufficient to discriminate sound environments. The three indicators that emerged from the clustering, namely, the $L_{eq,A}$, the standard deviation $\sigma_{Leq,A}$ and the sound gravity spectrum SGC[50 Hz–10 kHz], are consistent with previous studies on sound environment classification. Moreover, the procedure proposed enables the description of the sound environment, which is classified into homogenous sound environment classes by means of the selected indicators. Thus, the procedure can be adapted to any urban environment, and can, for instance, favorably enhance perceptive studies by delimiting precisely the spatial extent of each typical sound environment.

[ACL 17] CAN A., DEKONINCK L., BOTTELDOOREN D. Measurement network for urban noise assessment: comparison of mobile measurement and spatial interpolation approaches, Applied Acoustics, Volume 83, September 2014, Pages 32-39 (times cited: 18).

This paper investigates the relevance of different interpolation techniques to improve the spatial resolution of urban noise maps, in complement to measurements achieved at fixed stations. Interpolation techniques based on mobile measurements are compared to usual spatial interpolations techniques, namely Inverse Distance Weighting and Kriging. The analyses rely on a measurement campaign, which consisted of nearly 8 h of geo-referenced mobile noise measurements performed at random moments of the day, conducted simultaneously with continuous measurements collected at five fixed stations located on the inner city of Gent, Belgium. Firstly, a procedure is proposed to build a noise map with a high spatial resolution (one point every 5 m). The procedure relies on both mobile and fixed measurements: the mobile measurements are used to capture spatial variations on the network, and the measurements at fixed stations are used to capture the temporal variations. The map produced is then used as reference to compare the interpolation techniques based on a significantly more sparse measurement set. The spatial interpolation techniques tested fail in predicting accurately the noise level variations within streets. The explanation given is that they do not offer a sufficient covering of the network, and assume spatial variations which are not coherent with traffic dynamics or street configurations. Inversely, mobile measurements cover the entire network. As a result, they allow a more accurate prediction of noise levels even if very short samples are used, provided that the procedure used to estimate noise levels includes a spatial aggregation, which aims at smoothing the high spatial variations inevitable with short samples. Moreover, mobile measurements can advantageously be used to optimize, through a Genetic Algorithm, the locations where to install fixed stations, promising an efficient noise monitoring at reduced operational costs.

[ACL 18] DA ROCHA T., CAN A., PARZANI C., JEANNERET B., TRIGUI R., LECLERCQ L. Are vehicles trajectories simulated by dynamic traffic models relevant for estimating fuel consumption?, Transportation Research Part D, 24, 2013, p. 17-26 (times cited: 9).

This paper questions the relevance of microscopic traffic models for estimating the impact of traffic strategies on fuel consumption. Urban driving cycles from the ARTEMIS database are simplified into piecewise linear speed profiles to mimic the classical outputs of microscopic traffic flow models. Fuel consumption is estimated for real and simplified trajectories and links between kinematics and the fuel consumption errors are investigated. Simplifying trajectories causes fuel consumption underestimation, from -1.2 to +5.2% on average according to the level of simplification; errors can approach -20% for some cycles. A focus on kinematic phases indicates that the maximum speed reached and the time decelerating are the main influences on fuel consumption. Finally, in the case where maximum speeds are estimated correctly, it is shown that errors committed at each kinematic phase when acceleration distributions are approximated by their mean values, converge towards small errors over complete cycles. A method is developed to quantify and reduce these errors.

[ACL 19] BOCKSTAEL A., DEKONINCK L., CAN A., OLDONI D., DE COENSEL B., BOTTELDOOREN D. Reduction of wind turbine noise annoyance: an operational approach, Acta Acustica united with Acustica, 98, 2012, 392-401 (times cited: 11).

This paper investigates the relationship between wind turbine noise annoyance, exposure indicators, operational characteristics and environmental variables. A six-month field experiment at an industrial site near a residential area includes regular on-line annoyance reports, continuous 1/3-octave band noise level registrations, periodic sound recordings, data on electricity production per minute and meteorological observations. Here the risk of high annoyance does not only depend on the angular blade velocity, but also on the wind turbines' nacelle position relative to the location of the dwellings, i.e. the wind direction. This directivity effect can be captured when noise parameters such as the background noise level caused by other sources and a so-called fluctuation-indicator are introduced, the latter calculated from the 1/3-octave band spectra to quantify the periodic part of wind turbine noise. In addition, the calculated turbine's specific emission levels are closely related to the angular blade velocity, and an important parameter to predict the risk of high annoyance. Finally, these results suggest that operational restrictions based on wind direction together with the angular blade velocity might help to reduce noise annoyance while preserving cost-effectiveness.

[ACL 20] DE COENSEL B., CAN A., BOTTELDOOREN D. Effect of traffic signal coordination on noise and air pollutant emissions, Environmental Modelling and Softwares, 35, 2012, 74-83 (times cited: 20).

Traffic management solutions are increasingly called for to address problems of transport and mobility. In particular, coordinated traffic lights that create green waves along major arterials are an increasingly used strategy to reduce travel times. Although it is usually assumed that an improved traffic flow will result in lower vehicle emissions, little scientific research has been spent on the effects of synchronized traffic lights on emissions. Moreover, because changes in traffic flow do not necessarily influence travel times, noise and air quality in the same way, there is a clear need for a combined approach. This paper reports on a computational study in which a microscopic traffic simulation model (Paramics) is combined with submodels for the emission of noise (Imagine) and air pollutants (VERSIT+). Through the simulation of a range of scenarios, the model is used to investigate the influence of traffic intensity, signal coordination schemes and signal parameters on the noise, carbon dioxide, nitrogen oxides and particulate matter emissions along an arterial road equiped with a series of traffic lights. It was found that the introduction of a green wave could potentially lower the emissions of the considered air pollutants by 10%–40% in the most favorable conditions, depending on traffic flow and signal timing settings. Sound pressure levels were found to decrease by up to 1 dB(A) near the traffic signals, but to increase by up to 1.5 dB(A) in between intersections. Traffic intensity and green split were found to have the largest influence on emissions, while the cycle time did not have a significant influence on emissions.

[ACL 21] CAN A., DEKONINCK L., RADEMAKER M., VAN RENTERGHEM T., DE BAETS B., BOTTELDOOREN D. Noise measurements as proxies for traffic parameters in monitoring networks, Science of the Total Environment, 410-411, 2011, 198–204 (times cited: 12).

The present research describes how microphones could be used as proxies for traffic parameter measurements for the estimation of airborne pollutant emissions. We consider two distinct measurement campaigns of 7 and 12 days, at two different locations along the urban ring road in Antwerp, Belgium, where sound pressure levels and traffic parameters were measured simultaneously. Noise indicators are calculated and used to construct models to estimate traffic parameters. It is found that relying on different statistical levels and selecting specific sound frequencies permits an accurate estimation of traffic intensities and mean vehicle speeds, both for light and heavy vehicles. Estimations of R(2) values ranging between 0.81 and 0.92 are obtained, depending on the location and traffic parameters. Furthermore, the usefulness of these estimated traffic parameters in a monitoring strategy is assessed. Carbon monoxide, hydrocarbon and nitrogen oxide emissions are calculated with the airborne pollutant emission model Artemis. The Artemis outputs fed with directly measured and estimated traffic parameters (based on noise measurements) are very similar. Finally, a method is proposed to enable using a model calibrated at one location at another location without the need for new calibration, making it straightforward to include new measurement locations in a monitoring network.

[ACL 22] CAN A., VAN RENTERGHEM T., RADEMAKER M., DAUWE S., THOMAS P., DE BAETS B., BOTTELDOOREN D. Sampling approaches to predict urban street noise levels using fixed and temporary microphones, Journal Environmental Monitoring, 13, 2011, p. 2710-2719 (times cited: 21).

Requirements for static (prediction of L_{den} and diurnal averaged noise pattern) and dynamic (prediction of 15 min and 60 min evolution of L_{Aeq} and statistical levels L_{A90}, L_{A50} and L_{A10}) noise level monitoring are investigated in this paper. Noise levels are measured for 72 consecutive days at 5 neighboring streets in an inner-city noise measurement network in Gent, Flanders, Belgium. We present a method to make predictions based on a fixed monitoring station, combined with short-term sampling at temporary stations. It is shown that relying on a fixed station improves the estimation of L_{den} at other locations, and allows for the reduction of the number of samples needed and their duration; L_{den} is estimated with an error that does not exceed 1.5 dB(A) to 3.4 dB(A) according to the location, for 90% of the 3 × 15 min samples. Also the diurnal averaged noise pattern can be estimated with a good accuracy in this way. It was shown that there is an optimal location for the fixed station which can be found by short-term measurements only. Short-term level predictions were shown to be more difficult; 7 day samples were needed to build models able to estimate the evolution of $L_{Aeq,60mn}$ with a RMSE ranging between 1.4 dB(A) and 3.7 dB(A). These higher values can be explained by the very pronounced short-term variations appearing in typical streets, which are not correlated between locations. On the other hand, moderately accurate predictions can be achieved, even based on short-term sampling (a 3 × 15 minute sampling duration seems to be sufficient for many of the accuracy goals set related to static and dynamic monitoring). Finally, the method proposed also allows for the prediction of the evolution of statistical indicators.

[ACL 23] CAN A., RADEMAKER M., VAN RENTERGHEM T., VAN POPPEL M., MISHRA V., THEUNIS J., TOUHAFI A., DE BAETS B., BOTTELDOOREN D. Correlation analysis of noise and ultrafine particle counts in a street canyon, Science of the Total Environment, 409, 2011, p. 564-572 (times cited: 39).

Ultrafine particles (UFP, diameter<100 nm) are very likely to negatively affect human health, as underlined by some epidemiological studies. Unfortunately, further investigation and monitoring are hindered by the high cost involved in measuring these UFP. Therefore we investigated the possibility to correlate UFP counts with data coming from low-cost sensors, most notably noise sensors. Analyses are based on an experiment where UFP counts, noise levels, traffic counts, nitrogen oxide (NO, NO_2 and their combination NO_X) concentrations, and meteorological data were collected simultaneously in a street canyon with a traffic intensity of 3200 vehicles/day, over a 3-week period during summer. Previous reports that NO_X concentrations could be used as a proxy to UFP monitoring were verified in our setup. Traffic intensity or noise level data were found to correlate with UFP to a lesser degree than NO_X did. This can be explained by the important influence of meteorological conditions (mainly wind and humidity), influencing UFP dynamics. Although correlations remain moderate, sound levels are more correlated to UFP in the 20-30 nm range. The particles in this size range have indeed rather short atmospheric residence times, and are thus more closely short-term traffic-related. Finally, the UFP estimates were significantly improved by grouping data with similar relative humidity and wind conditions. By doing this, we were able to devise noise indicators that correlate moderately with total particle counts, reaching a Spearman correlation of R=0.62. Prediction with noise indicators is even comparable to the more-expensive-to-measure NO_X for the smallest UFP, showing the potential of using microphones to estimate UFP counts.

[ACL 24] CAN A., BOTTELDOOREN D. Towards traffic situation noise emission models, Acta Acustica united with Acustica, Volume 97, Number 5, September/October 2011, p. 900-903 (times cited: 3).

This article proposes a methodology to account for vehicle kinematics in a fast and efficient way when using single vehicle noise emission models such as the Harmonoise/Imagine, Nord2000 or NMPB. A model is built, which mimics the traffic situation emission models developed in the field of airborne pollutants research. The model aggregates the sound power emitted over driving cycles which are statistically representative of real-world driving conditions. Four different driving conditions are included in the cycles, ranging from free-flowing to stop-and-go traffic conditions. The sound power levels estimated with this new approach are significantly different from the ones estimated with the mean speed approach recommended by the noise mapping guidelines, especially when traffic is congested, suggesting that the method could prove relevant for improving noise map accuracy, in particular in urban context.

[ACL 25] MADIREDDY M., DE COENSEL B., CAN A., DEGRAEUWE B., BEUSEN B., DE VLIEGER I., BOTTELDOOREN D. Assessment of the impact of speed limit reduction and traffic signal coordination on vehicle emissions using an integrated approach, Transportation Research Part D., 16, 2011, 504-508 (times cited: 50).

This paper examines the effects of two traffic management measures, speed limit reduction and coordinated traffic lights, in an area of Antwerp, Belgium. An integrated model is deployed that combines the microscopic traffic simulation model Paramics with the CO_2 and NO_X emission model VERSIT+. On the one hand, reductions in CO_2 and NO_X emissions of about 25% were found if speed limits are lowered from 50 to 30 km/h in the residential part of the case study area. On the other hand, reductions in the order of 10% can be expected from the implementation of a green wave signal coordination scheme along an urban arterial road.

[ACL 26] CAN A., LECLERCQ L., LELONG J., BOTTELDOOREN D. Traffic noise spectrum analysis: Dynamic modeling vs. Experimental observations, Applied Acoustics, 71(8), 2010, p. 764-770 (times cited: 33).

This paper compares two traffic representations for the assessment of urban noise frequency spectrum: (i) a static one, based on mean vehicle speeds and flow rates, (ii) a dynamic one, which considers vehicle interactions along the network. The two representations are compared on their suitability to match real on-field noise levels, recorded on a three lane quite busy street. Representation (i) fails in reproducing spectra envelopes that correspond to this site. In particular, it underestimates low frequencies, what can conceal the real impact of traffic flow on urban sound quality. Representation (ii) greatly improves estimation. It guarantees accurate environmental noise assessment, since it reproduces all traffic situations that are encountered in the site. Moreover, its 1s-based structure allows for the evaluation of spectra variations, with a good accuracy.

[ACL 27] CAN A., CHEVALLIER E., NADJI M., LECLERCQ L. Dynamic traffic modeling for noise impact assessment of traffic strategies, Acta Acustica united with Acustica, 96(3), 2010, p. 482-493 (times cited: 9).

This paper compares static and dynamic traffic representations to assess noise impact of three traffic strategies on an urban main street: (i) introduction of a bus line, (ii) implementation of a green wave, (iii) replacement of a traffic signal by a roundabout. The dynamic noise prediction model is the only one that can capture changes in noise environment due to those strategies, since it explicitly considers interactions between vehicles on the network. Noise impact of the three strategies is compared through the estimation of statistical descriptors (L_1, L_{10}, L_{50} and L_{90}) and the minimum and maximum levels reached per cycle. Within the hypothesis of the study, it is shown that noise levels increase due to buses or speed increase whereas they decrease when a signalized intersection is replaced by a roundabout.

[ACL 28] CAN A., LECLERCQ L., LELONG J. Selecting noise source and traffic representations that capture urban traffic noise dynamics. Acta Acustica united with Acustica, 95(2), 2009, p. 259-269 (times cited: 3).

Considering trafic dynamics greatly improves noise estimation in urban area. This can be achieved by coupling a dynamic trafic model with both noise emission laws and sound propagation calculation. Determining the relevant noise source and trafic representations to estimate classical noise descriptors (L_{Aeq} and statistical descriptors) near trafic signals has been recently studied. This research topic is extended in this paper to more specific descriptors which are able to capture noise dynamics at the trafic signal scale, for usual urban trafic situations (upstream, in front of, and downstream a trafic signal) and different distances from the road (5.5, 10 and 15 m). It appears that 14m-line sources ensure an estimation of all descriptors with errors below 2 dB(A) if trafic dynamics is precisely described. Macroscopic and microscopic car-following models are both relevant to highlight noise dynamics triggered by the trafic signal, but some differences between those traffic representations are observed.

[ACL 29] CAN A., LECLERCQ L., LELONG J., DEFRANCE J. Accounting for traffic dynamics improves noise assessment: experimental evidence. Applied acoustics, 70(6), 2009, p. 821-829 (times cited: 16).

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 $L_{Aeq,1s}$ 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-h period.

[ACL 30] CHEVALLIER E., CAN A., NADJI M., LECLERCQ L. Improving noise assessment at intersections by modeling traffic dynamics. Transportation Research Part D: Transport and Environment, 14(2), 2009, p. 100-110 (times cited: 31).

Three families of road noise prediction models can be distinguished. Static noise models only consider free-flow constant-speed traffic with uniformly distributed vehicles. Analytic noise models assume that all vehicles are isolated from one another but account for their mean kinematic profile over the network. Micro-simulation noise models relax the hypothesis of no interaction between vehicles and fully capture traffic flow dynamic effects such as queue evolution. This study compares the noise levels obtained by these three methodologies at signalized intersections and roundabouts. It reveals that micro-simulation noise models outperform the other approaches. Particularly, they are able to capture the effects of stochastic transient queues in under-saturated conditions as well as stop-and-go behaviors in oversaturated regime. Accounting for traffic dynamics is also shown to improve predictions of noise variations due to different junction layouts. In this paper, a roundabout is found to induce a 2.5 dB(A) noise reduction compared to a signalized intersection in under-saturated conditions while the acoustic contributions of both kinds of junctions balance in oversaturated regime

[ACL 31] CAN A., LECLERCQ L., LELONG J. Dynamic estimation of urban traffic noise: influence of traffic and noise source representations. Applied Acoustics, 69(10), 2008, p. 858-867 (times cited: 15).

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.

[ACL 32] CAN A., LECLERCQ L., LELONG J., DEFRANCE J. Capturing urban traffic noise dynamics through relevant descriptors. Applied Acoustics, 69(12), 2008, p.1270-1280 (times cited: 26).

This paper is dedicated to acoustic descriptors and their ability to capture urban traffic noise dynamics. Analysis conducted in this article is based on acoustical measurements taken at five points which depict different typical urban traffic situations. The relevant scale for assessing the dynamics appears to be the duration of the traffic signal cycle. Existing descriptors fail to characterize urban traffic noise at this scale. A set of descriptors is therefore proposed to fulfil this shortage. It is based on the analysis of the mean noise pattern and the variations around this pattern. The set of descriptors proposed enables a differentiation between traffic noise environments which was impossible through existing descriptors.

Book chapters

[OS1] CAN A. Noise Pollution Indicators, in : Environmental Indicators (Armon, R. and Hanninen, O. Eds), Springer. ISBN 978-94-017-9498-5, p.501-513, 2015.

Noise is a major environmental issue, which gave birth in the last decades to extensive research and consecutively to the development of many estimation and mitigation engineering methods. The specificity of this pollution, which lies in its high spatiotemporal variations, its rich spectral component, its variety of sources, and the complexity of human hearing, explains the abundance of the existing noise indicators. Many energetic, statistical, noise event or emergence general indices have been developed. Complementing these, indicators have been produced to describe specific noise sources (road traffic, railway, aircraft. . .) and their resulting effects on human well-being, which makes the development of indicators directly influenced by the progress in modeling. This review shows the difficulty in finding a set of indicators able to capture both the physical characteristics of noise environments and its effects.

Some invited conference papers

[INV 1] AUMOND P., CAN A., MALLET V., DE COENSEL B., RIBEIRO C., BOTTELDOOREN D., LAVANDIER C. Acoustic mapping based on measurements: space and time interpolation, Proceedings of Internoise 2017, Hong-Kong, 27-30 August 2017.

Noise maps based on measurements gained interest during the last decade. Network monitoring systems are deployed in various cities over the world and mobile applications allowing participatory sensing are now very common. Nevertheless, the sparseness of the collected measurements, either in space or in time, complicates the production of such noise maps. A large measurement campaign has been conducted in the XIIIth district of Paris in order to test different temporal and spatial interpolating strategies. 23 fixed monitoring stations have been deployed during eight months. In parallel, mobile measurements with backpacked stations have been collected walking in every street of the district between 1 and 15 times. The data analysis of the 23 fixed monitoring stations allowed constructing a temporal interpolation model, while the mobile measurements served to construct a spatial Kriging model. The combination of both models is explored in this paper, which enables to produce a fine cartography, both spatially and temporally, of sound levels within the district.

[INV 2] CAN A., AUMOND P., MICHEL S., DE COENSEL B., RIBEIRO C., BOTTELDOOREN D., LAVANDIER C. Comparison of noise indicators in an urban context, Proceedings of Internoise 2016, Hambourg (Allemagne), 21-24 August, 2016.

Noise is a major environmental issue, which gave birth in the last decades to the development of many engineering methods dedicated to both its estimation and mitigation. The specificity of the noise pollution problem lies in the complexity of human hearing and subjective assessment, and in the high spatiotemporal variation and rich spectral content of the noise generated by a wide variety of sources in urban context. Indicators that encompass all these dimensions are required for the description of sound environments and for the evaluation of noise mitigation strategies. This paper compares usual and more specific indicators, dedicated to environmental noise analyses, by means of a literature review. The comparison is based on the three following criteria: i) the ability of indicators to describe and physically categorize the urban sound environments, ii) the relevance of indicators for describing the perceptive appreciations of urban sound environments, iii) the ability of indicators to be estimated through classical or more advanced traffic noise estimation models. A discussion compares the pro and cons of the selected indicators in an operational scope.

[INV 3] GAUVREAU B., GUILLAUME G., CAN A., LEMONSU A., MASSON V., CARISSIMO B., RICHARD I., HAOUES-JOUVE S. Environmental Quality at district scale: A transdisciplinary approach within the EUREQUA project, Proceedings of FICUP, An International Conference on Urban Physics, B. Beckers, T. Pico, S. Jimenez (Eds.), Quito – Galápagos, Ecuador, 26 – 30 September 2016.

This paper presents a research project entitled EUREQUA (Multidisciplinary Assessment and Environmental Requalification of districts) that adopts an original methodological approach relying on a multidisciplinary team of researchers in physics, environmental, human and social sciences (geographers, sociologists, atmospheric physicists, acousticians, architects, etc.) in collaboration with officials of urban living. The EUREQUA project (2012-2017) implements a transdisciplinary approach because it focuses on 3 main observables (climate comfort, air quality and sound environment) and because it combines experimental, numerical and statistical methods. This paper focuses on one district particularly studied within the EUREQUA project, both experimentally and numerically. This paper also briefly expose the methodology and how qualitative and quantitative results are jointly processed and combined in order to make environmental criteria emerge in scenarii conception, through statistical data cross-analysis, feedback meetings with inhabitants and participative workshops

[INV 4] CAN A., GUILLAUME G., GAUVREAU B. Are noise events from surface transport predictable? Insights from a wide measurement campaign, Proceedings of InterNoise 2014, Melbourne (Australie), 16-19 November, 2014.

The negative effect of road traffic noise events on annoyance is now established. However, the assessment and monitoring of road traffic noise remain mainly based on energetic indicators, which are easy to handle but mask noise dynamic structure. Recent developments in dynamic road traffic modelling, and in urban sensor networks, suggest that introducing noise events in urban noise management is possible. This however raises statistical questions: although their inherent random origin (very noisy cars, sirens, etc.) make them hardly predictable, noise events are probably site dependent. In this paper, we rely on a measurement campaign carried out in Toulouse (France), made of 20 1h-measurement periods covering both day and night time slots, to question some statistical matters relative to road traffic noise events. Firstly, some general reflections concerning candidate indicators for describing noise events are given, in line with road traffic noise dynamics. Then, a statistical method is proposed, which selects the frequency bands of interest, and then defines a set of indicators relevant to describe the urban soundscape of the site, in terms of noise events. Finally, some insights about the predictability of noise events are deduced from the spatial distributions of the selected set of indicators.

Some communications with proceedings in international congresses

[ACTI1] GLOAGUEN JR., CAN A., LAGRANGE M., PETIOT JF. Creation of a corpus of realistic urban sound scenes with controlled acoustic properties. Acoustics ’17 Boston, 173rd Meeting of the Acoustical Society of America and the 8th Forum Acusticum, 25-29 June 2017.

Monitoring the acoustic urban environment is beneficial for improving the life of citizens. To do so, the research community in acoustics can benefit from corpora where the acoustic contribution of sources of disturbance such as road traffic is precisely known. In this paper, a set of urban sound mixtures are simulated using an open source tool simScene. Their characteristics (type of sources, density of events, etc.) are inferred from the listening of reference audio scenes recorded in Paris, France. The main advantage of the simulated versions is that several quantities, such as the acoustic level of each source is precisely known, a useful feature for evaluated automated analysis tools. In order to quantify the level of realism achieved by the use of the simulation tool a perceptive test is conducted with 50 subjects. The result show that no meaningful differences can be made between the simulated and the recorded scenes.

[ACTI2] PICAUT J., CAN A., ARDOUIN J., CREPEAU P., DHORNE T., ECOTIERE D., LAGRANGE M., LAVANDIER C., MALLET V., MIETLICKI C., PABOEUF M. CENSE project: characterization of urban sound environments using a comprehensive approach combining open data, measurements and modeling. Acoustics ’17 Boston, 173rd Meeting of the Acoustical Society of America and the 8th Forum Acusticum, 25-29 June 2017.

Urban noise reduction is a societal priority. In this context, the European Directive 2002/49/EC aims at producing strategic noise maps for large cities. However, nowadays the relevance of such maps is questionable, due to considerable uncertainties, which are rarely quantified. Conversely, the development of noise observatories can provide useful information for a more realistic description of the sound environment, but at the expense of insufficient spatial resolution and high costs. Thus, the CENSE project aims at proposing a new methodology for the production of more realistic noise maps, based on an assimilation of simulated and measured data, collected through a dense network of low-cost sensors that rely on new technologies. In addition, the proposed approach tries to take into account the various sources of uncertainty, either from measurements and modeling. Beyond the production of physical indicators, the project also includes advanced sound environments characterization, through sound recognition and perceptual assessments. CENSE is resolutely a multidisciplinary project, bringing together experts from environmental acoustics, data assimilation, statistics, GIS, sensor networks, signal processing, and noise perception. As the project is in launch state, the present communication will focus on a global overview, emphasizing the innovative and key points of the project.