Innovative procedure for measurement uncertainty evaluation of environmental noise accounting for sound pressure variability

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Innovative procedure for measurement uncertainty evaluation of environmental noise accounting for sound pressure variability

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Publications resulting from this work

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Abstract

This study aims to demonstrate the importance of uncertainty evaluation in the measurement of environmental noise in the context of Italian legislation on noise pollution. Attention is focused on the variability of the measurand as a source of uncertainty and a procedure for the evaluation of uncertainty for environmental noise measurement is proposed. First drawing on several real noise datasets in order to determine suitable measurement time intervals for the estimation of the environmental noise, a data-driven sampling strategy is proposed, which takes into account the observed variability associated with measured sound pressure levels. Outliers are eliminated from the actual noise measurements using an outlier detection algorithm based on K-neighbors distance. As the third step, the contribution of measurand variability on measurement uncertainty is determined by using the normal bootstrap method.

Experimental results exploring the adoption of the proposed method drawing upon real data from environmental noise using acquisition campaigns confirm the reliability of the proposal. It is shown to be very promising with regard to the prediction of expected values and uncertainty of traffic noise when a reduced dataset is considered.

Introduction

The World Health Organisation has recognized noise as the most significant health hazard to the working population in terms of the number of people affected (Hansen, 2005). Perhaps the most insidious aspect of noise induced hearing loss is that in most cases damage accumulates over time and is only recognized as a problem when it is too late to do anything about it.

Noise can also affect our daily living away from the work place. This problem is called environmental noise pollution, where noise is usually defined as unwanted sound, an undesirable by-product of society's normal day-to-day activities.

In Italy, the law establishes maximum limits of acceptable environmental noise levels based on the equivalent level, L_{eq}, a parameter expressed in decibels (dB) referred to a 20 μPa pressure, which indicates the level of a continuous stationary noise having the same acoustic energy content of the floating noise under measurement:

$$L_{eq} = 10\,\mathrm{Log}\,\frac{1}{T}\int_T \left[\frac{p(t)}{p_{rif}}\right]^2 \mathrm{d}t \qquad (1)$$

It is important to emphasize that any comparison between a measured value and the maximum levels permitted in law is a complex matter. This is because this is not a comparison between two fixed numerical values since a measurement is only an approximation or estimation of the value of the measurand. It is essential to take into account the uncertainties associated with the measurement, as reported for international technical standards (JCGM 100:2008), because uncertainties are a quantitative indication of the reliability of the result. In the case of environmental acoustic noise measurements, exceeding thresholds may cause health risks for the public and then it becomes essential to find the relationship between measurement uncertainty and acceptable social risk.

Thus, in last decade, the issue of the quantification of the residual doubt associated to the measurement of environmental noise has surfaced as a key issue. The aim of the research described in this work is the realization of an advanced system for the environmental acoustic monitoring and for the assessment of uncertainty associated with measured levels. In particular, there has been close examination of possible sources of uncertainties associated in this area i.e. characteristics of measurement instrumentation, variability of the measurement conditions and instrumentation calibration. But, to provide an adequate estimation of total uncertainty associated with the measurement of the equivalent level of environmental noise, the intrinsic variability of the measurand cannot be ignored.

This thesis is organized as follows. In the first chapter, the main features of sound and noise propagation are briefly discussed, in the second chapter environmental noise monitoring in the context of the Italian legislative framework and on the decision rules is described.

In the third, fourth and fifth chapters the new algorithm for the evaluation of the measurement uncertainty of environmental noise is proposed and analysed. In particular, in the third chapter the influence of the measurement time on the measurement uncertainty of environmental noise is explored and an original procedure based on a bootstrap method is introduced to determine the minimum measurement time, which takes into account the statistical variability of the acquired sound pressure levels.

In the fourth chapter, the specific focus is the study and the estimation of the influence of the occurrence of spot events on the measurement uncertainty and the description of the algorithm which has been applied and experimentally verified with real field data to detect so as to remove these outliers ("Outlier detection").

In the fifth chapter, the uncertainty associated with measurement of 'purified' signals acquired during identified measurement time is determined.

In order to give substance to the proposed strategy, a statistical analysis is carried out on measurement data from several acquisition campaigns and experimental results are shown.

Chapter I
Fundamentals of sound propagation

I.1 Sound fundamentals

As a prelude to the environmental noise pollution problem, a brief description of the nature and propagation of sound is presented in this chapter.

I.1.1 Nature of sound

Perception of sound requires the presence of some simple physical phenomena, in contrast to the very deep physiological and psychological effects.

A sound source oscillates and brings the surrounding air into motion. The compressibility and mass of the air cause these oscillations to be transmitted to the listener's ear. Generally, in this phenomenon one has momentum transportation without a corresponding mass transportation. Pressure fluctuations, referred to as sound pressure p, occur in air (or other fluid) and are superimposed to the constant atmospheric pressure p_0.

A spatially distributed sound field radiates from the source with different instantaneous sound pressures at each moment. The sound pressure is the most important quantity to describe sound fields and is space and time-dependent.

If an air particle is displaced from its original position, elastic forces of the air tend to restore it to its original position. Because of the inertia of the particle, it overshoots the resting position, bringing into play elastic forces in the opposite direction, and so on. Sound is the mechanical vibration of a gaseous, liquid or solid elastic medium through wich energy is transferred away from the source by progressive sound waves. Without a medium, sound cannot be propagated.

The little dots of Figure I.1 represent air molecules. The molecules crowded together represent areas of compression in which the air pressure is slightly greater than the prevailing atmospheric pressure.

The sparse areas represent rarefactions in which the pressure is slightly less than atmospheric.

The small arrows indicate that, on the average, the molecules are moving to the right of the compression crests and to the left in the rarefaction troughs between the crests. Any given molecule will move a certain distance to the right and then the same distance to the left of its undisplaced position as the sound wave progresses uniformly to the right. As a consequence a sound wave is a longitudinal wave, not a transverse wave.

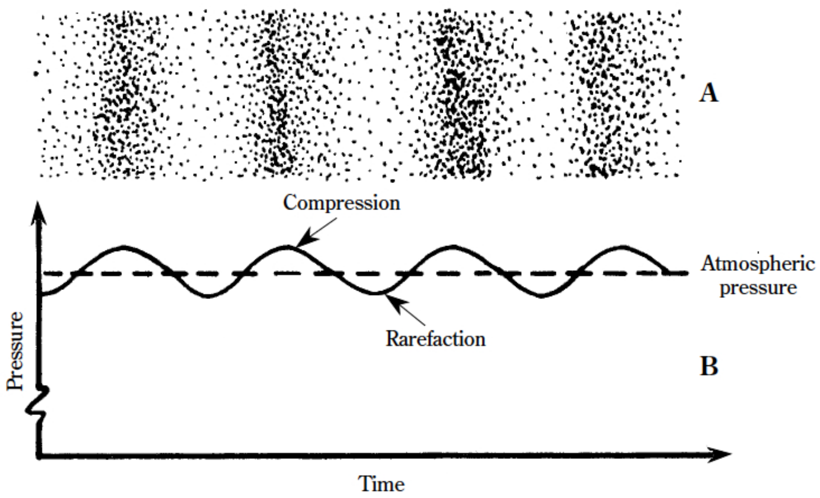

Figure I.1 *Compressed and rarefied regions of a sound wave in air*

I.1.2 Scales for noise – the decibel

Propagation through any elastic medium takes place in the form of a wave, and the most important quantity characterizing its magnitude is the root mean square amplitude A_{rms} defined as:

$$A_{rms} = \sqrt{\frac{1}{T}\int_0^T a^2(t)dt} \qquad (2)$$

where T is the relevant time period over which the averaging takes place and a is the instantaneous amplitude.

A spatially distributed sound field radiates from the source with different instantaneous sound pressures at each moment. The sound pressure is the most important quantity to describe sound fields and is always space- and time-dependent.

The sound has two main distinguishing attributes: `timbre' and `loudness'.

The physical quantity for loudness is sound pressure and the quantity for timbre is frequency f, measured in cycles per second, or Hertz (Hz). The frequency range of technical interest covers more than the range that is audible by the human ear, which is referred to as fihearing level. The hearing range starts at about 16 Hz and ranges up to 16 kHz. The infrasound, which is located below that frequency range, is less important for air-borne sound problems, but becomes relevant when dealing with vibrations of structures (e.g. in vibration control of machinery).

Ultrasound begins above the audible frequency range. It is used in applications ranging from acoustic modelling techniques to medical diagnosis and non-destructive material testing.

The normal method of measuring pressure on a linear scale unfortunately gives rise to certain problems when related to the performance of the human ear. The direct application of linear scales to the measurement of sound pressure would therefore lead to the use of enormous and unwieldy numbers.

Additionally, the ear responds not linearly but logarithmically to stimulus. For these reasons it has been found more practical to express acoustic parameters as a logarithmic ratio of the measured value to a reference value.This reduces the numbers to manageable proportions and the resulting unit, called the Bel (after Graham Bell) is defined as the logarithm to the base ten of the ratio of two acoustical powers or intensities. In practice this unit was found to be rather too large, and a unit of one tenth of a Bel, the decibel dB, is now in general use. As the acoustic intensity, the power passing through a unit area in space, is proportional in the far field to the square of the sound pressure, a convenient scale for acoustic measurements can be defined as Sound Pressure Level:

$$SPL = L_p = 10\ \log\left(\frac{p}{p_0}\right)^2 = 20\log\left(\frac{p}{p_0}\right) \tag{3}$$

where p is the sound pressure being measured
and $p_0 = 20 \cdot 10^{-6} N/m^2 = 20\ \mu Pa$ is the reference sound pressure, that corresponds to the hearing threshold (at a frequency of 1 kHz, because the hearing threshold is frequency-dependent).

So that 0 dB denotes the `just perceivable' or `just not perceivable' sound event. If not otherwise stated, the sound pressure p stands for the root mean

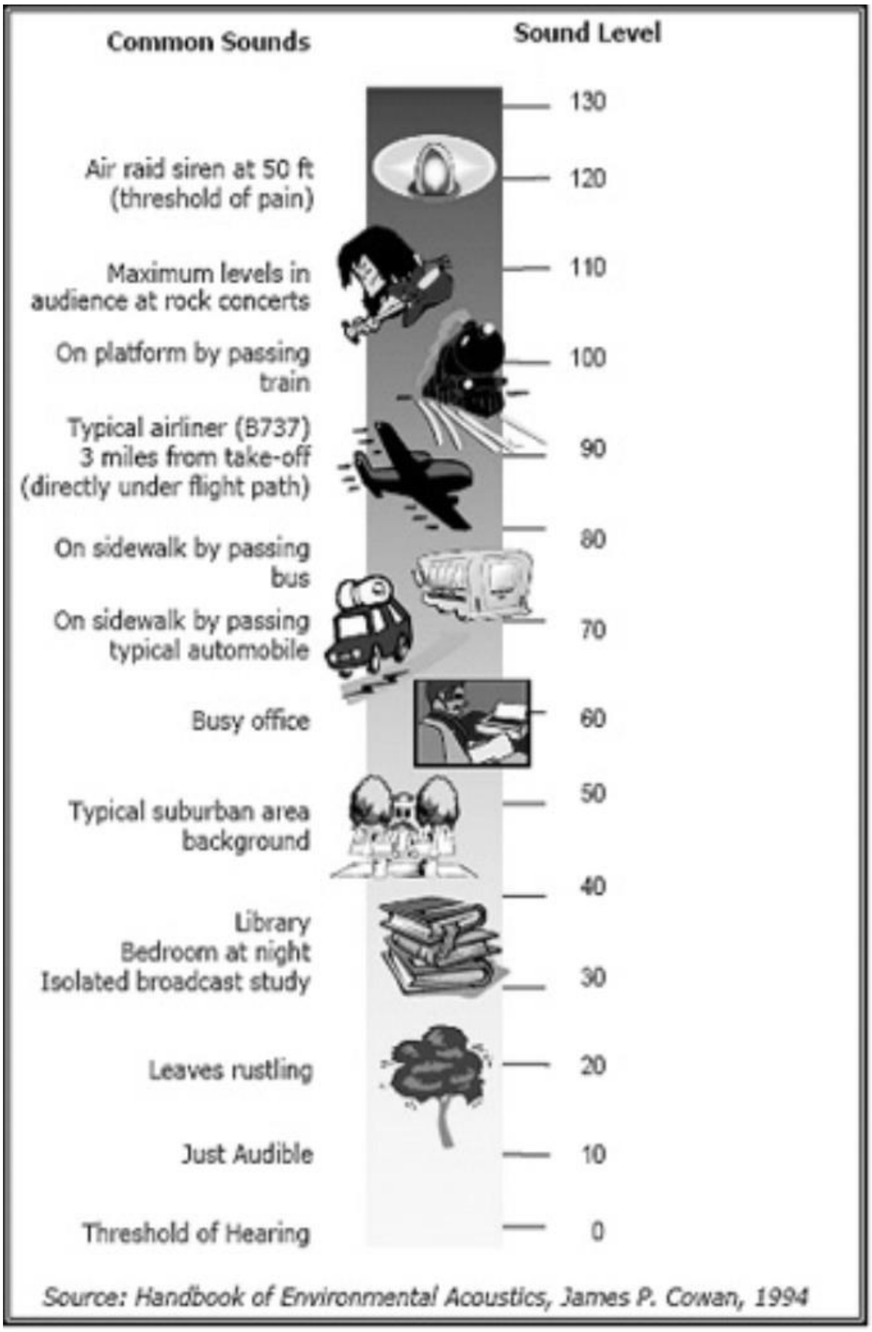

Figure I.2 *Typical sound pressure levels of common noise sources* square (rms-value) of the time domain signal. The specication in decibels (dB) is not related to a specic unit. It indicates the use of the logarithmic law.

Use of the decibel scale reduces a dynamic range of sound pressures from a million to 1 to a more manageable range of sound pressure levels of only 0 to 120, zero indicating the reference minimum threshold and 120 the approximate threshold of pain.

This is far more convenient and easier to deal with as the values lie within a range easily conceived by the layman and one unit (1 decibel) is about the smallest value of significance (Passchier-Vermeer, 2000, pp. 123-131). The big advantage when using sound pressure levels is that they roughly represent a measure of the perceived loudness. Figure I.2 shows many well-known sounds appropriately placed with regard to the sound pressure level at which they are normally heard and their major frequencies.

I.1.3 Octave and third-octave band filters

Sometimes a high spectral resolution is needed to decompose time domain signals. Measurements of the spectral components of time domain signals are realized using electronic circuits, filters, which let a supplied voltage pass only in a certain frequency band. Only filters with a constant relative bandwidth are used for acoustic purposes. The bandwidth is proportional to the centre frequency of the filter.

With increasing centre frequency the bandwidth is also increasing. The most important representatives of filters with constant relative bandwidth are the octave and third-octave band filters. Their centre frequency is determined by

$$f_c = \sqrt{f_{lower} \cdot f_{upper}} \tag{4}$$

For octave band filters:

$$f_{upper} = 2\, f_{lower} \tag{5}$$

which results in $f_c = \sqrt{2}\ f_{lower}$ and
$\Delta f = f_{upper} - f_{lower} = f_{lower} = f_c/\sqrt{2}$

For third-octave band filters:

$$f_{upper} = \sqrt[3]{2}\, f_{lower} = 1.26\, f_{lower} \tag{6}$$

which results in $f_c = \sqrt[6]{2} f_{lower} = 1.12\, f_{lower}$ and $\Delta f = 0.26\, f_{lower}$

The advantage of third-octave band measurements is the finer resolution (more data points in the same frequency range) of the spectrum.

I.1.4 Hearing levels and A-Weighting

The sensitivity of the human ear is strongly dependent on the tonal pitch.

The frequency dependence is depicted in Fig. I.3. The figure is based on the findings from audiometric testing. The curves of perceived equal loudness (which have the unit `phon') are drawn in a sound pressure level versus frequency plot. One can imagine the development of these curves as follows: a test subject compares a 1 kHz tone of a certain level to a second tone of another frequency and has to adjust the level of the second tone in such a way that it is perceived with equal loudness. The curve of one hearing level is obtained by varying the frequency of the second tone and is simply defined by the level of the 1 kHz tone. The array of curves obtained by varying the level of the 1 kHz tone is called hearing levels. It reveals, for example, that a 50 Hz tone with an actual sound pressure level of 80 dB is perceived with the same loudness as a 1 kHz tone with 60 dB. The ear is more sensitive in the middle frequency range than at very high or very low frequencies.

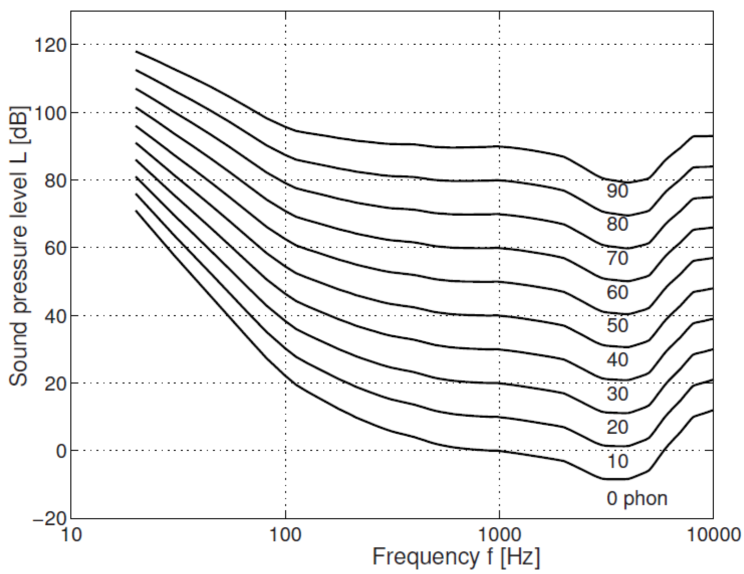

Figure I.3 *Hearing levels*

The relationship between the objective quantity sound pressure or sound pressure level, respectively, and the subjective quantity loudness is in fact quite complicated, as can be seen in the hearing levels shown in Fig. I.3. The frequency dependence of the human ear's sensitivity, for example, is also level dependent. The curves with a higher level are significantly flatter than the curves with smaller levels. The subjective perception `loudness' not only depends on frequency, but also on the bandwidth of the sound incident.

The development of measurement equipment accounting for all properties of the human ear could only be achieved with a very considerable level of effort.

The most common weighting that is used in noise measurement is A-Weighting. A frequency-weighted sound pressure level is used both nationally and internationally, which accounts for the basic aspects of the human ear's sensitivity and can be achieved with a reasonable level of effort. This socalled `A-weighted sound pressure level' includes contributions of the whole audible frequency range. In practical applications the dB(A)-value is measured using the A-filter. The A-filter characteristics roughly represent the inverse of the hearing level curve with 30 dB at 1 kHz (40 phone curve) depicted in Fig. I.3. The A-weighting function is standardized in EN 60651. In Fig. I.4 the frequency response functions of the A-filter, B-filter (inverse of 70 phone curve, rarely used), C-filter (inverse of 100 phone curve, used for peak measurements) and D-filter (used in assessing loud aircraft noise - IEC 537) are drawn.

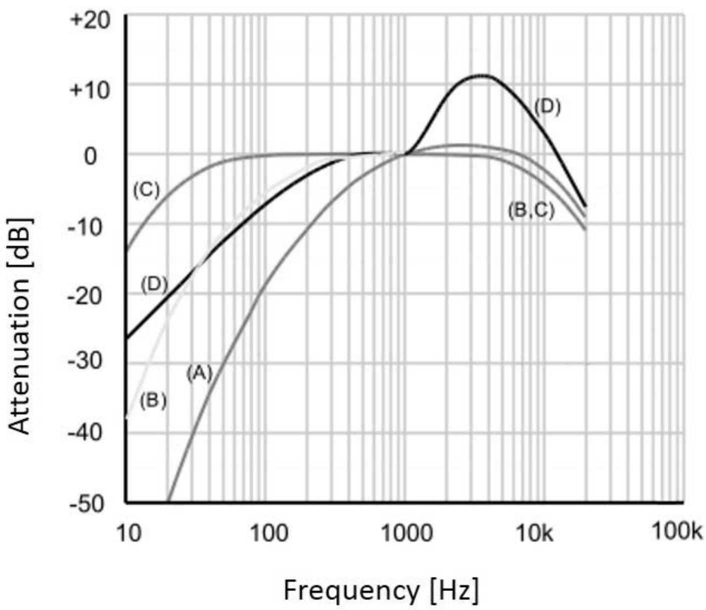

Figure I.4 *Frequency response functions of A (blue), B(yellow), C(red) and D(black) weighting filters*

I.1.5 Equivalent sound pressure level

It is easy to determine the noise level of constant, steady noise, such as from an engine with constant *rpm*. Due to their uniform formations, such noise can be sufficiently described by the A weighted sound pressure level. Otherwise, intermittent signals, such as speech, music or traffic noise, can be described by the level-over-time notation, but this description falls short, because a notation of various noise events along a time continuum makes an otherwise simple quantitative comparison of a variety of noise scenarios, such as traffic on different highways, quite difficult. In order to obtain simple comparative values, one must take the mean value over a realistic average time period.

The most conventional and simplest method is the so-called 'energy equivalent continuous sound level' $L_{eq,T}$. It reflects the sound pressure square over a long mean time T:

$$L_{eq,T} = 10\,\mathrm{Log}\left(\frac{1}{T}\int_0^T \frac{p_{eff}^2(t)}{p_0^2}dt\right) = 10\,\mathrm{Log}\left(\frac{1}{T}\int_0^T 10^{L(t)/10}dt\right) \qquad (7)$$

where $p_{eff}(t)$ indicates the time domain function of the *rms-value* and

$L(t) = 10\,\mathrm{Log}\left(\frac{p_{eff}^2(t)}{p_0^2}\right)$ the level gradient over time.

The square of a time-dependent signal function is also referred to as 'signal energy', so the energy-equivalent continuous sound level denotes the average signal energy.

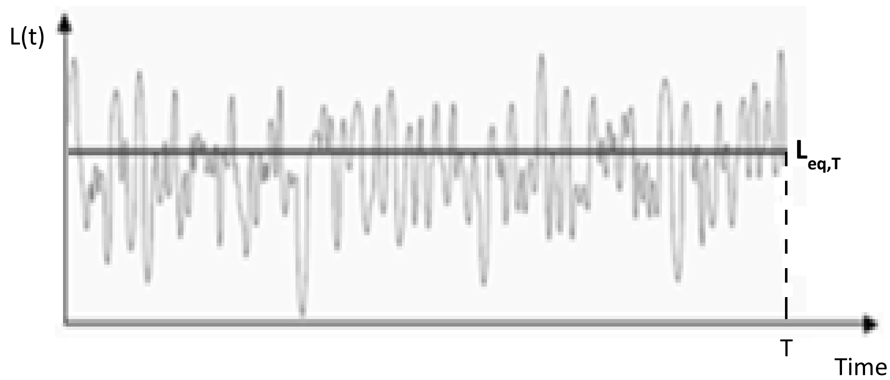

Figure I.5 *Equivalent sound pressure level*

I.2 Wave propagation

The most important qualitative statements about wave propagation can be deduced from everyday life experience. When observing temporary, frequently repetitive sound incidences, such as a child bouncing a ball, hammering at a construction site, etc., a time delay can easily be observed between the optical perception and the arrival of the acoustic signal. This time delay increases with increasing distance between the observer and the source. Indeed, sound incidences sound the same from any vantage point, as the frequency components are the same. The wave form of a sound field (in a gas) is not altered during propagation. The propagation is called `non-dispersive', because the form of the signal is not altered during wave transmission. In contrast, the propagation of bending waves in beams and plates, for instance, is dispersive in gases. In this chapter the physical properties of wave propagation in gases are described. To derive the basic properties, the effects as well as the attenuation with increasing distance and reflections are left out of consideration. The attention is focused on the simple case of one-dimensional sound fields, depending only on a single coordinate. The main properties of sound fields can be deduced from the basic assumption that a perfect gas is an elastically shapeable and mass-adherent medium.

Two investigations are necessary: it has to be discussed how air springs are compressed by the displacement at their boundaries to the left and to the right and the problem of how the air masses are accelerated by the forces of the springs acting on them has to be solved. Small air volumes of length x are used for both investigations. The elements of length Δx (initially assumed to have a finite length for illustration purposes) will finally shrink to the infinitesimal length dx, because the description of the physical facts is a lot easier with functions and their derivatives (Möser, 2009).

The inner compression of one gas element with mobile boundaries is derived by the fact that the mass between the boundaries is constant. If one element is compressed, the density increases. The mass of the element depicted in Fig. I.6 is $S\Delta x\rho_0$ if the medium is at rest (without sound), where S is the cross-sectional area of the column and ρ_0 is the density inside the element at rest. If an elastic deformation takes place (in the presence of sound), the motion of the left boundary defined by $\xi(x)$ and the motion of the right boundary defined by $\xi(x+\Delta x)$ takes place, the mass is given by S $[\Delta x + \xi(x+\Delta x) - \xi(x)]\ \rho_t ot$, where $\rho_t ot = \rho_0 + \rho$ and ρ is the alteration due to the sound field.

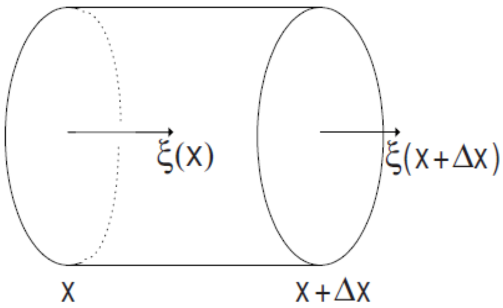

Figure I.6 *Deformation of an element of the gas column leads to a change in internal density*

The mass is equal to the mass at rest, so

$(\rho_0 + \rho)\ [\Delta x + \xi(x+\Delta x) - \xi(x)]\ S = \rho_0\, \Delta x\ S$

or, after the dividing the surface S and multiplying it out,

$$\rho\Delta x + \rho_0 [\xi(x+\Delta x) - \xi(x)] + \rho [\xi(x+\Delta x) - \xi(x)] = 0 \tag{8}$$

The difference $\xi(x+\Delta x) - \xi(x)$ is smaller than Δx, so the sound density in question here can be described by

$$\rho = -\rho_0 \frac{\xi(x+\Delta x) - \xi(x)}{\Delta x} \tag{9}$$

In the limiting case of infinitesimal small gas elements $\Delta x \rightarrow \mathrm{d}x$, the difference quotient becomes the differential quotient

$$\frac{\rho}{\rho_0} = -\frac{\partial \xi(x)}{\partial x} \tag{10}$$

Sound density is directly related to the spatial derivative of the displacement.

The latter is also called `elongation' (or dilatation). This derivation is crucial for the following investigations. It states that the relative sound density is equal to the negative elongation. It should be noted that this fact can also be interpreted as the spring equation. If the sound density, eq (9), is replaced by the sound pressure from $\rho = p/c^2$, where *c* is the speed of sound (343 metres per second), and multiplied by the cross sectional area S,

$$Sp = -S\rho_0 c^2 \frac{\xi(x+\Delta x) - \xi(x)}{\Delta x} \tag{11}$$

is obtained. The left side, *Sp*, represents the force *F* produced by deformation of the gas spring of lenght Δx. Hook's law *F* = - s *Δx*, where *s* represents the stiffness of the spring, can be applied to the case of springs with moving ends, validating

$$F = -s\,[\xi(x+\Delta x) - \xi(x)] \tag{12}$$

Comparing eq (11) with eq (12) it's possible to obtain the stiffness of the spring:

$$s = \frac{\rho_0 c^2 S}{\Delta x} \tag{13}$$

In the case of layers of elastic material, as in a gas element, with a cross sectional area *S* and lenght Δx

$$\boldsymbol{s} = \frac{\boldsymbol{ES}}{\boldsymbol{\Delta x}} \tag{14}$$

is given, where *E* represents a material constant, the so-called elastic modulus.

It should be indicated for the interpretation of eq. (14) that producing a certain change in displacement at the ends requires an applied force which has to be larger. The larger the cross sectional area of the layer is, the smaller the thickness of the layer. The elastic modulus in gases is obviously related to the propagation speed by

$$\boldsymbol{E = \rho_0 c^2} \tag{15}$$

The second phenomenon pertaining to sound wave propagation that needs to be investigated is how gas particles are accelerated by the applied forces of the springs. The answer is found in Newton's law, which is applicable to the (small) volume element of the gas column as shown in Fig. I.7. The acceleration $a_x = \frac{\partial^2 \xi}{\partial t^2}$ of the enclosed mass is caused by the force `pushing from the left' *Sp(x)*, from which the force `pushing back from the right' *Sp (x+ Δx)* must be subtracted. The acceleration caused by the change in force is smaller, the smaller the mass *m* of the element is.

Applying Newton's law (only on *x* coordinate) we obtain:

$$\sum F_x = ma_x \qquad \text{and so} \qquad p(x)S - p(x+\Delta x)S = m\frac{\partial^2 \xi}{\partial t^2}$$

$$\frac{\partial^2 \xi}{\partial t^2} = \frac{S}{m}[p(x) - p(x+\Delta x)]$$

Alternatively, using *m* = volume x density = $\Delta x S \rho_0$,

$$\frac{\partial^2 \xi}{\partial t^2} = -\frac{1}{\rho_0}\frac{p(x+\Delta x) - p(x)}{\Delta x}$$

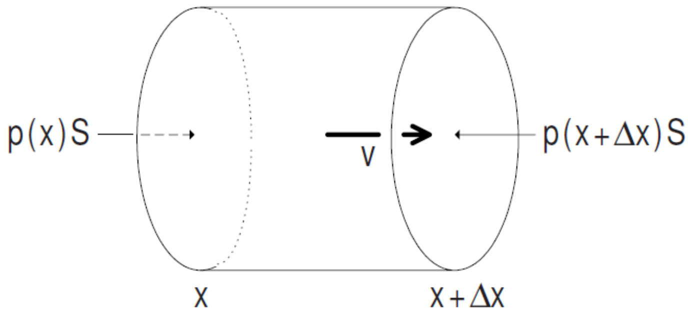

Figure I.7 *Accelerated element of the gas column*

The element is finally compressed, and using

$$\lim_{\Delta x \to 0} \frac{p(x+\Delta x) - p(x)}{\Delta x} = \frac{\partial p}{\partial x}$$

It’s possible to write the inertia law of acoustics

$$\boldsymbol{\rho_0 \frac{\partial^2 \xi}{\partial t^2} = -\frac{\partial p}{\partial x}} \qquad (16)$$

Eqs. (10) and (16) form the basic equations in acoustics. They are able to describe all (one-dimensional) sound incidences. The compression of the elastic continuum ”gas” caused by space-dependent displacement is described in eq. (10); how the displacement is caused by compression, on the other hand, is described in eq. (16). If both observations are combined they yield the explanation for wave propagation. Combining the two observations in terms of equations means inserting one equation into the other. The displacement is consequently eliminated in eqs. (10) and (16). This can be achieved by a twofold differentiation of eq. (10) by time

$$\frac{1}{\rho_0}\frac{\partial^2 \rho}{\partial t^2} = -\frac{\partial^3 \xi}{\partial x \partial t^2}$$

and differentiating eq. (16) by space

$$\frac{\partial^3 \xi}{\partial x \partial t^2} = -\frac{1}{\rho_0}\frac{\partial^2 \rho}{\partial x^2}$$

Hence it follows

$$\frac{\partial^2 \rho}{\partial x^2} = \frac{\partial^2 \rho}{\partial t^2}$$

and finally

$$\boldsymbol{\frac{\partial^2 p}{\partial x^2} = \frac{1}{c^2}\frac{\partial^2 p}{\partial t^2}} \tag{17}$$

Eq. 17 is referred to as the one dimensional wave equation [4]. In general, any function which is exclusively dependent on the argument $t - x/c$ or $t + x/c$ is a solution to the wave equation - eq. (17)-

$$\boldsymbol{p(x,t) = f(t \mp x/c)} \tag{18}$$

In particular $f(t - x/c)$ describes a wave moving in the +*x* direction (progressive wave) and $f(t + x/c)$ describes a wave moving in the -*x* direction (regressive wave).

f(t) stands for a signal form possessing a structure which has been created by the emitter, that is the sound source.

In Fig. I.8 a wave moving in the +*x* direction (progressive wave) for two different times $t=0$ and $t=\Delta t$ is shown: the shape of the perturbation does not change, but it is simply translated of the distance Δx.

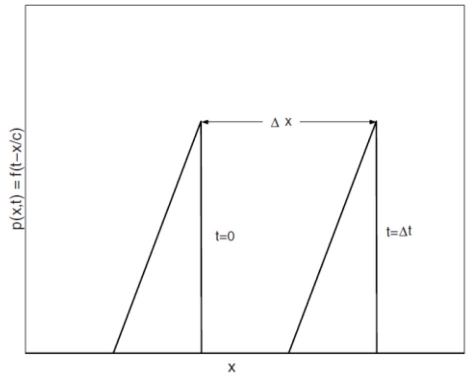

Figure I.8 *Principal characteristics of* $p = f(t - \frac{x}{c})$ *for two different times t=0 and t=Δt*

The graph depicts a set of curves of the same parallel offset space-dependent functions which cross each other. As can be seen from the graph, the state of gas "`sound pressure"' migrates as at constant speed along the *x* axis. This migration of the local states is known as a "`wave"'.

In order to explain the physical meaning of the constant *c* it's possible to imagine a certain value of the function *f* (in Fig. I.8 the maximum of *f* is chosen) which is located at *x* at the time *t* and travels by the distance *Δx* during the time *Δt*.

$$f(x,t) = f(x + \Delta x, t + \Delta t) \tag{19}$$

This is the case if $(t - x/c)$ is the same in both cases, which is equivalent to

$$t - \frac{x}{c} = (t + \Delta t) - \frac{x + \Delta x}{c}$$

and so

$$\frac{\Delta x}{\Delta t} = c \tag{20}$$

Because the speed is calculated by `speed=distance/time to travel', *c* describes the `transport speed of the function', i.e. the propagation speed of the wave.

Obviously, it is independent of the characteristics of the function *f*; in particular, all frequencies travel at the same speed. The fact that the signal characteristics are not altered during propagation is an important feature of sound propagating in gases, which is one of the most important physical preconditions for acoustic communication (e.g. speech).

The one-dimensional wave propagation eq. (17) can be easily transferred to the more general case of three-dimensional wave propagation, using vector differential operators:

$$\nabla^2 p = \frac{1}{c^2}\frac{\partial^2 p}{\partial t^2} \tag{21}$$

where ∇^2 (or Δ), called the Laplace operator or the Laplacian, is a differential operator given by the divergence of the gradient of a function on Euclidean space.

Eq (21) is known as the D'Alembert equation and it permits us to study sound wavefronts propagation in every point of a free field.

Chapter II
Environmental noise pollution and decision rules

II.1 Environmental noise pollution

The current process of urbanization and the associated development of transport and industry in a large part of the world has been accompanied by a number of environmental problems such as greenhouse gas emissions, waste and wastewater and environmental noise pollution.

A publication by the World Health Organization (WHO) points out that noise pollution is ranked second amongst factors that cause environmental stress in terms of public health effects and which has significant auditory and non-auditory heavy health impacts (World Health Organization, 2011).

Noise is derived from the Latin word “nausea” implying ‘unwanted sound’ or ‘sound that is loud, unpleasant or unexpected’. Public health experts agree that environmental risks constitute twenty-four per cent of the burden of disease. Widespread exposure to environmental noise from road, rail, airports and industrial sites contributes to this burden. On the basis of the available scientific evidence and from the results collected in (World Health Organization, 2011), the following key noise pollution outcomes were briefly touched upon to highlight the effects of noise pollution effects the public health:

- cardiovascular disease;
- endocrine responses to noise;
- cognitive disablement (in children);
- sleep disturbance;
- annoyance.

II.1.1 Cardiovascular disease

Epidemiological studies on the relationship between road traffic and aircraft noise and cardiovascular effects was carried out both on adults and on children, focusing on mean blood pressure, hypertension and ischaemic heart diseases as cardiovascular end points. The evidence, in general, of this association was increased during later years (Babisch, 2000, pp. 9-32), (Babisch, 2006, pp. 1-29), (Cavatorta *et al.* 1987, pp. 463-466).

There is increasing evidence that road traffic noise pollution increases the risk of ischaemic heart disease and of hypertension. Very few studies on the cardiovascular effects of other environmental noise sources, including rail traffic, are known but it is logical to assume the same consequences.

II.1.2 Endocrine responses to noise

Exposure to high intensity sound pressure levels was connected in many studies to increasing the levels of noradrenaline and adrenaline [9]. In one study catecholamine secretion decreased when workers wore wearing protection against noise. Other studies showed increase of cortisol in relation to noise exposure (Brandenberger, 1980, pp. 239-252).

The general pattern of endocrine responses to noise is indicative of noise as a stressor, exciting short-term physiological responses, though some inconsistencies between studies were found.

II.1.3 Cognitive disablement (in children)

It is well reported in (Basner, 2014, pp. 1325-1332) and in (World Health Organization, 2011), that postulated mechanisms for noise effects on children’s cognition include communication difficulties, impaired attention, increased arousal, learning difficulties, frustration, noise annoyance, and consequences of sleep disturbance on performance. Some investigators point attention to the effects on children of noise pollutions due to proximity to airports (Evans *et al.* 1995, pp. 333-338), (Evans *et al.* 1998, pp. 75-77), while in (Stansfeld *et al.*2005, pp. 1942-1949) a comparison was made between the effects of road traffic and of aircraft noise on 9–10 year old children. This found some correlation between long-term exposure to aircraft noise and impaired reading comprehension and memory recognition.

II.1.4 Sleep disturbance

Sleep is a physiological state that needs to be respected to allow for normal recuperation of the living organism. Its reduction or disruption is harmful in the long term and it can have a major impact on health and quality of life. Studies have shown (World Health Organization, 2011) that noise affects sleep in terms of immediate effects (e.g. arousal responses, sleep stage changes, awakenings, body movements, total wake time, autonomic responses), after effects (e.g. sleepiness, daytime performance, cognitive function deterioration) and long-term effects (e.g. self-reported chronic sleep disturbance).

II.1.5 Annoyance

Since annoyance varies with persons and situations it can be asserted that what makes a sound a noise is connected with psychology rather than acoustics.

In determining whether a sound is a noise, mental attitude and environment are of major importance and it is interesting to note that groups of people with different backgrounds of work experience have differing annoyance thresholds.

Then, noise annoyance may be affected by psychological or non-acoustical characteristics, primarily on subjective noise sensitivity, attitudes toward noise, gender, age, health status, or socio-economic situation.

The importance of acoustical factors (sound pressure level and frequency, number and time distributions of events) is also well-documented (Miedema and Oudshoorn, 2001, pp. 409-416), and was incorporated into the Directive 2002/49/EC of the European Parliament and of the Council, relating to the assessment and management of environmental noise.

Noise annoyance encompasses broad psychological feelings (among others: irritation, discomfort, distress, frustration, and offence) when noise interrupts one's psychological state or normal life activities (Guski, 1999, pp. 45-56) and could interferes with the quality of life, causing prolonged activation of physiological responses such as increased blood pressure, heart rate and endocrine outputs (Clark and Stansfeld, 2007, pp. 145-158).

II.2 Traffic noise

Traffic acoustical noise is one of the most important components of the environmental pollution in densely populated areas all over the world, because in many countries the car is the favourite means of transportation. In the last years the number of vehicles in circulation has grown, but to this growth did not always correspond an improvement of street networks. This problem can be evidenced by the high growth of the traffic charges on urban, sub-urban and peri-urban roads, with a clear impact on costs, security and environment, even in term of acoustical noise. A similar tendency can be observed in the framework of many European countries. Traffic noise affects areas surrounding roads especially when high traffic load and high speed conditions occur and can lead to a degradation of the quality of life in residential areas. The impact of noise on mental and physical health and on daily activities has been widely documented in the scientific literature (Ouis, 2001, pp. 101-120), (Kryter, 1982, pp. 1222-1242), (Langdon, 1976, pp. 243-282).

With conservative assumptions applied to the calculation methods, it is estimated that Disability Adjusted Life Years (the sum of years of potential life lost due to premature mortality) lost from environmental noise are 61000 years for ischaemic heart disease, 45000 years for cognitive impairment of children, 903000 years for sleep disturbance, 22000 years for tinnitus and 654000 years for annoyance in the European Union Member States and other western European countries (World Health Organization, 2011). These results indicate that at least one million healthy life years are lost every year from traffic related noise in the western part of Europe. Sleep disturbance and annoyance, mostly related to road traffic noise, comprise the main burden of environmental noise. Public health experts agree that environmental risks constitute 24% of the burden of disease. Widespread exposure to environmental noise from road, rail, airports and industrial sites contributes to this burden. One in three individuals is annoyed during the daytime and one in five has disturbed sleep at night because of traffic noise. Epidemiological evidence indicates that those chronically exposed to high levels of environmental noise have an increased risk of cardiovascular diseases such as myocardial infarction.

Thus, noise pollution is considered not only an environmental nuisance but also a threat to public health. In order to inform policy and to develop management strategies and action plans for noise control, national and local governments need to understand and consider this new evidence on the health impacts of environmental noise.

For this purpose, there should be a risk assessment to evaluate the extent of the potential health effects. A key consideration is that risk assessment cannot be carried out (using an exposure specific approach) unless both the exposure assessment and the exposure–response relationship utilize the matching noise indicators. This becomes an issue when there is evidence that the best relationship between a particular health effect and exposure may be based on one indicator, yet data on exposure are only available based on another.

While the work required by Directive 2002/49/EC will increase the availability of exposure assessments using the harmonized noise indicators, available exposure–response relationships may be reported using other indicators.

A number of studies demonstrate that high levels of sound pressure can damage people's health in a variety of ways, making initiatives to control noise a study of key importance to society (Ising and Kruppa, 2004, pp. 5-13), (Hassall and Zaveri, 1979).

II.3 Italian legislative framework on noise pollution

Italian legislation on noise pollution was developed from the beginning of 90's through the establishment of a general law with supporting decrees. There follows a brief description of the main pieces of legislation.

The Decree of the President of the Council of Ministers of 01/03/1991 "Maximum limits of exposure to noise in residential areas and outdoors" is the first piece of legislation act adopted by Italy to regulate and control noise pollution. The Decree of Council of Ministers President of 1 March 1991 was subsequently integrated into the General Law Act N. 447/1995. The decree determined immediate steps required to safeguard the quality of the environment and human exposure to noise across six categories of urban area provides and sets out the basic principles for management of the external and indoor environment. The General Law on noise, in addition to concepts contained in the Decree of the President of the Council of Ministers of 01/03/1991, has 17 articles and establishes the basic principles regarding the protection from noise pollution of external environment and indoor environment; it defines the responsibilities of public administrations, and of public and / or private entities that may be the direct or indirect cause of noise pollution.

A number of other decrees have been promulgated to regulate limits for sound sources, techniques for detecting and measuring noise pollution and management of noise levels from transport infrastructure (Appendix).

In summary, the main decrees and regulations to which we must pay particular attention are:

· Law 26 October 1995, n. 447 "Law on Noise Pollution framework";

· Decree of 11 December 1996 "Application of the differential criteria for continuous production cycle plants";

· Decree of Council of Ministers President of November 14, 1997 "Determination of limit values of sound sources";

· Decree of 16 March 1998 "Techniques for detecting and measuring noise pollution".

· Legislative Decree 81/2008 Title VIII - Chapter II "Protection of workers against the risks from exposure to noise at work"

II.4 Measurements and limit values

The current legislation mainly focuses around the maximum acceptable limits with reference to the A-weighting equivalent level of environmental noise

$$L_{Aeq} = 10\,\mathrm{Log}\frac{1}{T}\int_T \left[\frac{p_A(t)}{p_{rif}}\right]^2 \mathrm{d}t \qquad (1)$$

which indicates the level of a continuous stationary noise having the same acoustic energy content of the floating noise under measurement compared to the average sensitivity curve in terms of frequency of the human auditory system.

It is important to emphasize that any comparison between a measured value and a legal threshold is a complex matter, because this is not a comparison between two fixed numerical values since a measurement is only an approximation or estimation of the value of the measurand. It is essential to take into account the uncertainties associated with the measurement, as reported for international technical standards (JCGM 100:2008), because uncertainties are a quantitative indication of the reliability of the result.

The values below the limit are defined as being in a specification zone, that is range in which different levels below the maximum are tolerated. The uncertainty, associated with a measured value, is known as the confidence zone (Fig. II.1).

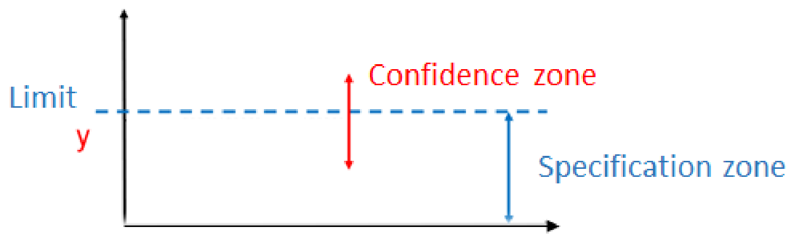

Figure II.1 *Specification zone and confidence zone*

In order to evaluate compliance with near limit values it is necessary to establish some rules, which essentially add or subtract the uncertainty from the limit in order to create an acceptance zone, also known as guardband (ASME B89.7.3.1-2001), (Garai, 2014). Simple acceptance and simple rejection rules are the most basic.

The first establishes that the result of a measurement is compliant if it falls within the specification zone (Fig. II.2: cases 1 and 2) while the second establishes non-compliance if a result of a measurement falls outside the specification zone (Fig. II.2: cases 3 and 4).

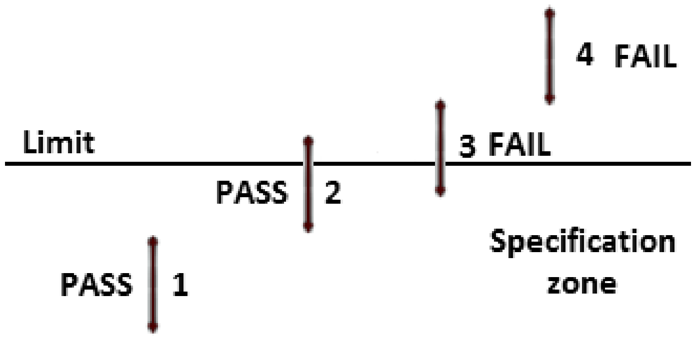

Figure II.2 *Simple acceptance and simple rejection rules*

The probability that a decision based on these basic rules may be erroneous can be very high, up to 50% if the estimated value coincides with a lower or upper limit value (Decree of Council of Ministers President of 14/11/1997).

Stringent acceptance and stringent rejection rules do not take account of ambiguous results, those for which the lower or higher limit value of specification zone is within the range of confidence zone (Fig. II.3: cases 2 and 3). The stringent acceptance rules state that the result is compliant if the entire measurement including the confidence zone lies within the specification zone (Fig. II.3 Case 1), minimizing the risk of a erroneous acceptance.

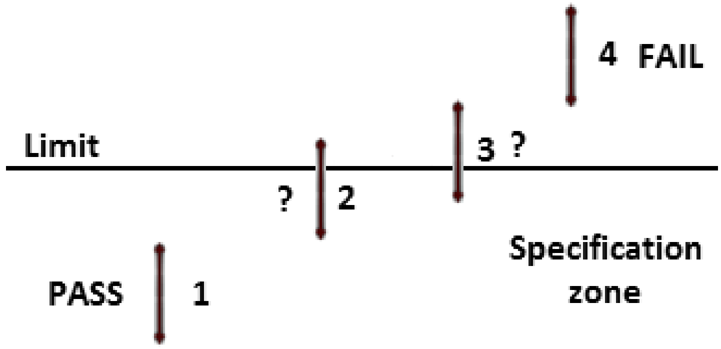

Figure II.3 *Stringent acceptance and stringent rejection rules*

On the other hand, stringent rejection rules only consider non-compliance for those measurement that fall entirely outside the specification zone including allowance for the the confidence zone (Fig. II.3 case 4), minimizing the risk of a false rejection. The relaxed acceptance rules state that the result of a measurement is compliant if it is not outside the specification zone including the confidence zone (Fig. II.4: cases 1, 2, 3), minimizing the risk of a false rejection, The relaxed rejection rules state that the result of a measurement is not compliant if it is outside the specification zone with all the confidence zone (Fig. II.4: cases 2,3,4), minimizing the risk of a false acceptance. The relaxed acceptance and relaxed rejection rules are less precise because they allow for greater flexibility around whether a measurement is compliant or non-compliant, when the lower or higher limit value of specification zone is within confidence zone (Fig. II.4: cases 2 and 3).

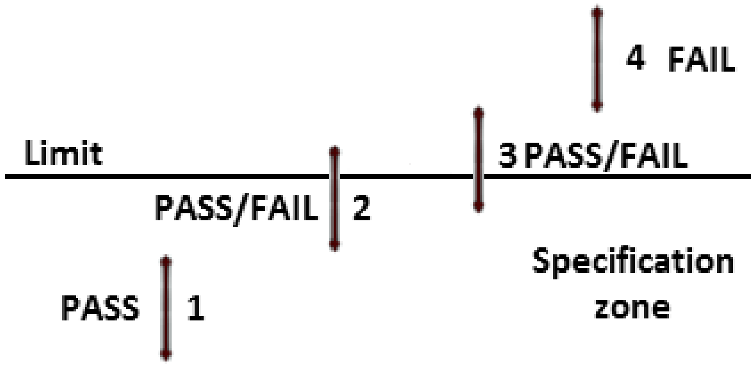

Figure II.4 *Relaxed acceptance and relaxed rejection rules*

In the field of environmental acoustics the choice of decision rules depends on the purpose of the evaluation. In particular, to protect the receiver, stringent acceptance + relaxed rejection rule (Fig. II.5) is chosen, and, to protect the source, relaxed acceptance + stringent rejection rule (Fig. II.6) is chosen (Ruggiero *et al.* 2016b, pp. 74-79).

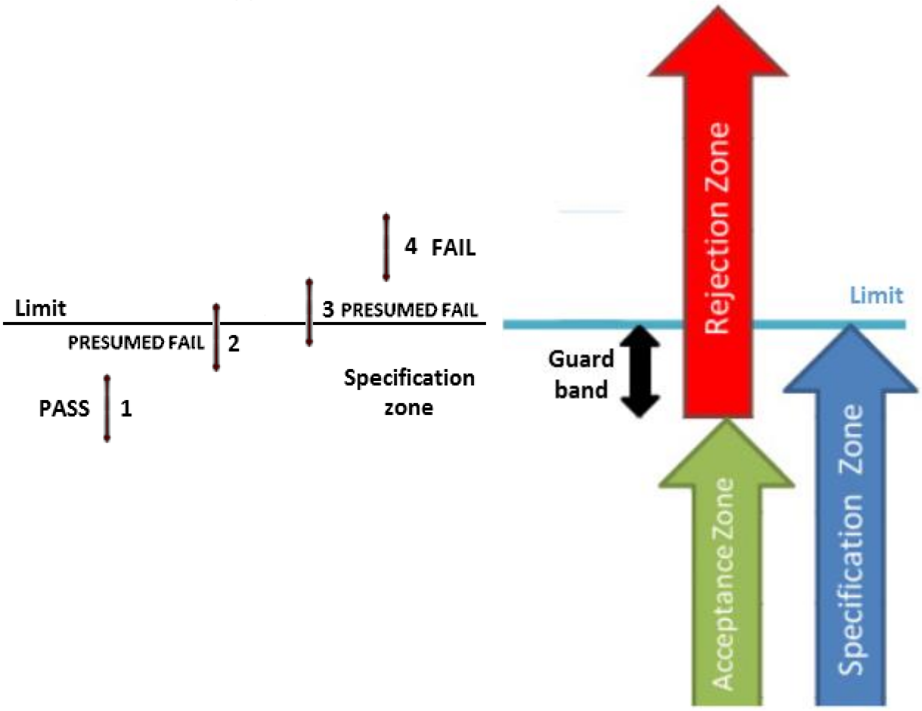

Figure II.5 *Stringent acceptance + relaxed rejection*

An increasing number of decision-making processes, which may have implications not only from an economic point of view, but also on environmental and / or social matters, are based on the outcomes of these comparisons between a measured quantity and a threshold value, The task of establishing the decision-making rules to test the compliance of a product to specifications, taking into account the uncertainty of the measurement, relies on (JCGM 106:2012:2012), (ISO 14253-1:2013), (ASME B89.7.3.1-2001). Both show that the higher the uncertainty of measurement, the smaller the degree of compliance, but neither shows how to assess the level of confidence in the outcome of the comparison, therefore resulting in heightened levels of risk that a wrong decision is being made (JCGM 106:2012:2012).

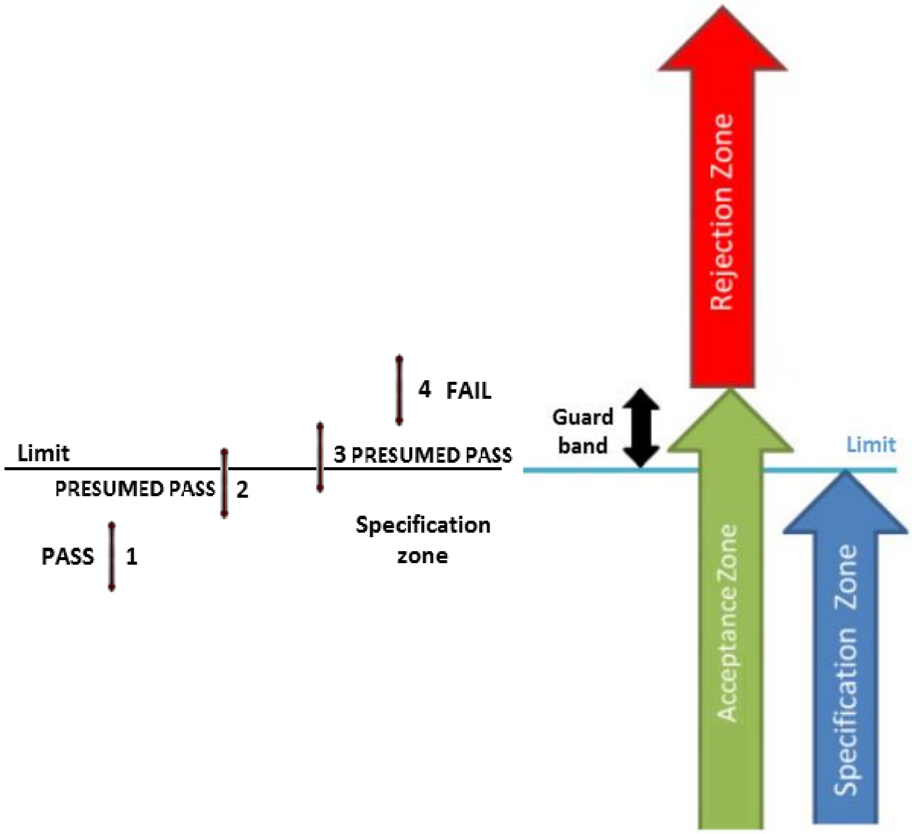

Figure II.6 *Relaxed acceptance + stringent rejection*

For all these reasons, a considered uncertainty statement has to accompany any measurement findings. Only in this way would the comparison between a measurement and a corresponding reference value make sense, and be in accord with current technical international standard (JCGM 106:2012:2012). Any measurement certification has to adhere to this standard.

In the case of environmental acoustic noise measurements, exceeding thresholds may cause health risks for the public and then it becomes essential to find the relationship between measurement uncertainty and acceptable social risk (Liguori *et al.* 2015a, pp. 1238-1242), (Liguori *et al.* 2015b, pp. 13-14), (Liguori *et al.* 2016f, pp. 246-251), (Liguori *et al.* 2016d, pp. 21-24). In addition to the referenced standard, a consistent package of UNI standards is devoted to uncertainty in acoustics (UNI/TR 11326-

1:2009), (UNI/TS 11326-2:2015). However, an adequate technical and procedural reference standard has not been yet available. Even the uncertainty of a noise measurement, in certain cases, may be greater than the reference threshold stated by the standard for that source.

II.5 Sources of uncertainties in environmental noise measurement

In recent years there has been considerable interest amongst the scientific community and experts in the field of acoustics about the quantification of environmental noise measurement uncertainties (Garg *et al.* 2014, pp. 281-288), (Erriu *et al.* 2016, pp. 148-153), (Černetič and Čudina , 2011, pp. 1293-1299), (Khodabandeh and Mohammad-Shahri, 2015, pp. 139-144). In particular, there has been close examination of possible sources of uncertainties associated in this area i.e. characteristics of measurement instrumentation (Guarnaccia *et al.* 2014, pp. 298-306), (Garg *et al.* 2014, pp. 281-288), variability of the measurement conditions (Ohta and Mitani, 1989, pp. 68-76), (Ruggiero *et al.* 2015, 1277-1286), and instrumentation calibration (Daponte, 2013, pp. 3291-3307).

An example of application of the Guide to the Expression of Uncertainty in Measurement (GUM), which involves statistical evaluation and consideration of the technical specifications of the instrumentation and of the technical standards on electro-acoustics, is the uncertainty estimation of a sound level meter class 1. With reference to a generic stationary outdoor source, it is estimated (U20.00.135.1:2008) that value that takes into account the inherent uncertainties contributions, that is the deviation from the nominal value, i.e. weather conditions (temperature, humidity, pressure), linearity, A weighting curve, microphone isotropy, but which does not take into account the positioning of the measuring instruments, is about 0.49 dB [46]. The global uncertainty, assuming that its components are uncorrelated, can be expressed (U20.00.135.1:2008) as:

$$\boldsymbol{u}(\boldsymbol{L}_{Aeq}) = \sqrt{\boldsymbol{u}^2_{instrum} + \boldsymbol{u}^2_{dist} + \boldsymbol{u}^2_{refl} + \boldsymbol{u}^2_{height}} \qquad (2)$$

where:

$u_{instrum}$ is the uncertainty associated to the measurement instrumentation [dB];

u_{dist} is the standard uncertainty associated to the distance between source and receiver [dB];

u_{refl} is the standard uncertainty associated to the distance of microphone from reflective walls [dB];

u_{height} is the standard uncertainty associated to the height of the microphone above the ground [dB];

However, to provide an adequate estimation of total uncertainty associated with the measurement of the equivalent level of environmental noise, the intrinsic variability of the measurand cannot be ignored (Liguori *et al.* 2016d, pp. 21-24), (Liguori *et al.* 2015b, pp.13-14).

Environmental noise is composed of many independent signals, generated from different acoustic sources, but sometimes there are special events that are not characteristic of the environment under observation, although they modify measurement result (Ruggiero and Russo, 2016a, pp.1-9). However, in order to correct the effects of these spot events or outlier it is necessary to identify them.

In literature there are three main approaches to the quantification of the contribution of environmental noise variability on the measurement uncertainty: i) definition of parameters for an optimal configuration of algorithms for the estimation of equivalent noise levels; ii) techniques for the identification of accidental sounds; iii) techniques for the determination of the uncertainty of noise estimations.

II.5.1 Definition of the Measurement Time

Maruyama et al. (Maruyama *et al.* 2013, pp. 317-332) determine the minimum measurement time for estimating the equivalent continuous A-weighted sound pressure level during measurement time interval T, L_{AeqT}, of road traffic noise from the number of vehicle transits through simulation experiments based on the mathematical mode. In particular, they show the influence of four kinds of traffic variables exerted on L_{AeqT}: traffic volume, percentage of heavy vehicles, average vehicle speed, and the number of vehicle transits. In previous works in the literature about this issue, the probability density function of noise level or the traffic conditions are known in advance. Such circumstances, however, may not always be met in the actual measurement sites. According to the results obtained with the proposed model, if the time interval between about 70 vehicles passing the observation point placed at d_0 = 25–50 m from the road is selected as the measurement time interval T, the measured L_{AeqT} falls within ±1 dB around the long time L_{AeqT} with the reliability of 75% or more, even though traffic conditions vary. If the time interval during about 170 vehicle passing is selected as the measurement time interval T, the errors of measured L_{AeqT} may be within ±1 dB with the increased reliability of 90% or more. If the probability distribution of the number of vehicle transits is approximated by the normal distribution, on the one hand, the reliability of estimation of L_{AeqT} may be improved to 95.5% and 99.7% for the same conditions as those mentioned above, respectively. Hence the measurement time interval should be selected from the viewpoint of the reliability required for the estimation.

Same authors in (Maruyama et al. 2014, pp. 150-155) address the issue of minimum measurement time interval to estimate a sound pressure level of road traffic noise with a designated reliability using two types of dynamic statistics. In this case they consider variations in the noise emission from passing vehicles. To verify the validity and availability, simulation experiments based on our dynamic model are examined under various traffic conditions. In the experiments, the mean time interval between two maximum sound pressure levels is consecutively observed during the reference measurement time interval. In both cases, the authors, however, focus on the reliability of the time interval chosen for a measurement of road traffic noise, but do not delve into the quantification of uncertainty.

In (Gaja *et al.* 2003, pp. 45-53), with reference to 5 years of continuous noise measurements of $L_{Aeq,24h}$ carried out in Valencia (Spain), the appropriate period of measurement over a 24-hour noise intervals in order to calculate the corresponding annual equivalent level has been investigated. The findings offer very useful information on traffic noise measurement techniques. In particular, the sampling strategy with a selection of at least 6 randomly chosen days provides an accurate representation of the annual equivalent noise level.

In (Kuehner, 2005), long term equivalent levels of road traffic noise acquired in Ladenburg, Germany, have been considered and different measurement approaches have been discussed. The author demonstrate that a sampling strategy of at least one week leads to the uncertainty of less than +/- 1 dB in noise equivalent levels.

Jagniatinskis and Fiks in (Jagniatinskis and Fiks, 2014, pp. 377-385) focus their attention on a one-year duration noise monitoring experiment in the town of Vilnius (Lithuania) near an arterial road with intensive road traffic. They observe that, under normal weather and source emission conditions, the lowest uncertainty values of Lden occur when a total measurement time of 7 consecutive days is considered.

In (Garg *et al.* 2014, 281-288), (Černetič and Čudina, 2011, pp. 1293-1299), (Khodabandeh and Mohammad-Shahri, 2015, pp.139-144) the authors find that the minimum measurement time interval should be calculated from the error associated with L_{Aeq} on the basis of various vehicle distributions. More specifically, by measuring over intervals of less than an hour, they find it is possible to have an accurate measurement of road traffic noise, within a predetermined uncertainty range for the hourly values of L_{Aeq}.

In (Abbaspour *et al.* 2007, pp.9-16), for the estimation of the traffic noise minimum measurement time interval in the city of Hamadan (West of Iran), the main roads are divided into 54 segments and 94 measuring stations are fixed. Field data obtained from 282 measurements, including 2 daily-hour and one nightly-hour measurements, show that 10-minutes interval measurement of equivalent sound pressure level is able to forecast the hourly values of L_{Aeq} in each station.

Jagniatinskis et al. in (Jagniatinskis *et al.* 2016, pp. 301-308) suggest the replacement of full year measurement by choosing a shorter time interval using the idea of representative time interval that contains an appropriate amount of transportation noise events. In particular, they analyse the representative sample definition for the cases of road, aircraft and rail transport. In Lithuania, for example, a representative measurement time interval for annual urban traffic noise assessment, under normal weather conditions, is one week.

In (Ng and Tang, 2008, pp. 649-661) the authors focus their attention on the effectiveness of using short time span measurements to monitor or assess the acoustical environment. On the basis of data acquired in the high-rise residential areas of Hong Kong, they observe that short time interval results are much lower than the worst scenario of a site, but the energy-based Day–night level and Day–evening–night level are acceptable.

In (Skarlatos and Manatakis, 1989, pp. 47-55), (Skarlatos and Drakatos, 1992, pp. 141-148) and (Skarlatos, 1993, pp. 37-50) a probabilistic method for determining the minimum time of observation for estimate L_{Aeq} is proposed, in cases in which the probability density function of noise level is known.

De Donato (De Donato, 2007, pp. 526-531) discussed a minimum time necessary for measuring the hourly equivalent level of road traffic noise with a designated measurement uncertainty on L_{Aeq} and showed that minimum measurement time interval could be obtained from the expression of error associated with L_{Aeq} according to various vehicle distributions. In particular, the author stated that it is possible to have a correct characterization of road traffic noise, within a predetermined uncertainty range hourly L_{Aeq}, by measuring over times shorter than an hour.

From all research so far reported, it is clear that most of the proposed approaches refer to the estimation of the minimum measurement time about long-term traffic noise indicators. On the other hand, the topic of the measurement of the short term equivalent sound pressure level has not been sufficiently explored. This may be different from the previous research findings of acoustic phenomenon in terms of statistical distribution and/or main influence parameters.

II.5.2 Detection of Unwanted Sounds

The onset of one or more acoustic events during a measurement may cause a significant alteration of the equivalent noise level and then it might induce the analyst not to consider that particular event or to arbitrarily extend the measurement time so as to reach a new stable reading of the equivalent noise level. However, it is not entirely appropriate to allow operator's subjectivity in the identification and elimination of acoustic events, which are maybe only apparently believed not to be characteristic of the sources under examination.

This indeterminateness is then intrinsic to the variability of the measure (i.e. the quantity under measurement) and rather than due to strictly metrological issues.

In literature, there are several works about this theme. Jae- Yee Kim (Jae-Yee Kim, 2008) uses some acoustic patterns to improve accident sound detection in several fields such as traffic noise. He observes that there is a remarkable difference between a pattern of traffic noise and one from accidental sound, like, for example, between vehicle horn sound and special purposed vehicle sirens, which have similar sound pressure to the one of accident acoustic patterns but their frequency waveforms are distinctive periodic type. Thus the author transformed various transmitted sound signals via microphones into frequency bands, then compared them withsound pressure of accident sounds which were saved in a database classified by frequency. With a database of various acoustic patterns and image detection system, which today registers at an accuracy rate of more or less 90%, traffic accident detection rates will be increased at least 2~3 %.

Schröder et al. (Schröder *et al.* 2013) focus their attention on Part-based models (PBMs) for detection of emergency siren sounds in traffic noise. In particular, starting from Hidden Markov Models (HMMs) that are flexible in time but rigid in the spectral dimension, they propose PBMs, widely used in computer vision, in order to detect the sound of sirens. The authors show that, for clean condition training, clean test samples could be classified with higher accuracies than all other approaches.

In (Caligiuri *et al.* 2004) the author states that a lot of acoustic phenomena able to determine annoyance and environmental pollution are represented by non stationary signals. The signals associated to noise levels generated by railway traffic are one of the most important example of non stationary signals.

For this reason it is essential to ensure the validity of the measurements and realize adequate health safeguard actions, to properly recognize and characterize the noise events produced by trains, in particular to distinguish them from those produced by other sources, particularly when the measurements are made in absence of operators. The traditional noise signal analysis techniques based on the Fourier Transform, as Fast Fourier Transform (FFT), and digital filtering show several limitations about highly non-stationary signals because they do not give information about the time location of the frequency components of the spectra.

The authors believe that the solution to this problem is to employ time-frequency and/or time-scale analysis techniques that get the spectra associated to samples of signal which can be considered sufficiently stationary leading to a so-called multiresolution analysis. The Wavelet

Transform (WT) and Wigner-Ville Transform (WVT) represent two of the most important examples of these techniques. They discuss the application of the Wavelet Transform (WT) and Smoothed Wigner-Ville Transform (SWVT) to the noise signals associated to the transits of the most important types of trains travelling in Italy, showing that, with a suitable choice of parameters related to these transforms it's possible to adequately study the main features of railway noise sources.

In (Lutfi and Heo, 2012) the authors compare two approaches to the automated detection of alarm sounds: one based on a change in overall sound level (RMS) and the other on a change in periodicity, as given by the power of the normalized autocorrelation function (PNA). They consider four classes of alarm sounds (bells/chimes, buzzers/beepers, horns/whistles, and sirens) embedded in four noise backgrounds (cafeteria, park, traffic, and music). The results suggest that PNA combined with RMS may be used to improve current alarm-sound alerting technologies for the hard of hearing.

In (Huadong et al. 1999, pp. pp. 1005-1009) the "eigenfaces method," is used to model the sound frequency distribution features. Using this approach, the frequency spectrum of different kind of vehicle sound produced under similar working conditions are classified and identified.

Moschioni et alii in (Moschioni *et al.* 2007, pp. 2478-2485) compare methods based on the coherence and expert system techniques based on the intensity in order to identify the contribution of single sources to global sound levels. Furthermore, a new solution adopting directional sound measurement and consequently implementing both coherence and intensity approaches is proposed.

The methods based on the retrieval of acoustic patterns from a database and their matching with the acquired sound equivalent level may have limitations in their sensitivity, due to the possible incompleteness of the database.

II.5.3 Uncertainty Determination

For the evaluation of the uncertainty associated with the inherent variability of environmental acoustic noise, it is usually assumed that results are associated to a normal distribution. Such an approach raises some doubts or even criticism. T. Wszolek and M. Klaczynski in (Wszolek and Klaczynski, 2006, pp. 311-318) explored this theme examining real statistical distributions of 24-h traffic noise levels registered in 55 reference points. From measurements and analysis the authors, using the Lilliefors test and the Kolmogorov-Smirnov test, showed that for the significance level α=0.05 none of the acoustic data series obtained from measuring reference points, neither for day-time nor night-time, exhibits characteristics of the normal distribution. Additionally, they verified that the measured distributions are not related to any statistical distribution known in the literature. Based on the completed variance analysis, nevertheless, the observed distributions tend to Gaussian distributions both for night-time and day-time data with the increasing traffic intensity observed in a given measurement section. In other words, even if the partial results used for estimation of the uncertainty value have been attributed statistical distributions that are not normal, then the distribution of the resultant variable still tends to a normal distribution.

Some authors, such as M. Paviotti and S. Kephalopoulos in (Paviotti and Kephalopoulos, 2008, pp. 3148-3148), performed studies on noise measurement uncertainty directly assuming a Gaussian model for the originating population. Therefore, given this assumption, they define a probability distribution function for data recorded during a long-term environmental noise measurement session in an urban situation and close to a road with 25000 vehicles pass-bys on average per day as:

$$PDF\ (x) = \frac{10}{\sqrt{2\pi} \cdot x \cdot \ln(10) \cdot \sigma} e^{\left(-\frac{[10 \cdot log_{10}(x) - \mu]^2}{2 \cdot \sigma^2}\right)} \tag{3}$$

where μ and σ are respectively the mean and the standard deviation of the population of values expressed in levels,

$L = 10 \cdot log_{10}(x)$ with $x = \frac{p^2}{p_0^2}$, p being the sound pressure and p_0 being a reference pressure (usually 20 μPa).

Cogorno et al. (Cogorno *et al.* 2008) present a method of evaluation of uncertainty inherent in the acoustic phenomenon in a measure of environmental noise by analyzing the uncertainty arising from the manifestation of specific sound events and using models based on statistical considerations related to a Poisson distribution. In particular, assuming that a single spot event, identified, for example, in a vehicle transit is recorded in the time history, the Poisson statistics allows to conclude that, in the time window of the phonometric measurement, we cannot exclude the possibility of either observing a double transit, or the possibility of not observing any transit at all. These possibilities can be quantified by calculating the Poisson probability.

A different approach to this theme available in literature consists in analyzing the uncertainty of the long-term noise indicators, day-evening-night A-weighted noise equivalent level measured over the 24 hour period (L_{DEN}) and night A-weighted noise equivalent level measured overnight 10:00 - 6:00 a.m. (L_N) with the bootstrap method. This algorithm is a statistical resampling technique does not have limitations in terms of form and properties of considered statistics. The indicators are related to noise annoyance values of the long-term average sound level A in the day-evening-night periods (L_{DEN}) and night periods (L_N) in dB (Batko and Stępień 2010, pp. 11-16).

$$L_{DEN} = 10\log\left[\frac{1}{365}\sum_{i=1}^{365} 10^{0,1*L_{DEN,i}}\right] \tag{4}$$

$$L_N = 10\log\left[\frac{1}{365}\sum_{i=1}^{365} 10^{0,1*L_{N,i}}\right] \tag{5}$$

with:

$$L_{DEN,i} = 10\log\left(\frac{1}{24}(12 * 10^{0,1*L_{D,i}} + 4 * 10^{0,1*(L_{E,i+5})} + 8 * * 10^{0,1*(L_{N,i}+10)})/24\right) \tag{6}$$

$$L_{N,i} = 10\log\left[\frac{1}{K}\sum_{i=1}^{K} 10^{0,1*(L_{Aeq,T})i}\right] \tag{7}$$

where K is the sample size, $(L_{Aeq,T})_i$ is the equivalent sound level for the i^th sample, in [dB], $L_{D,i}$ is the day sound A level, determined from the day–time noise exposure i.e. from 6:00 a.m. to 6:00 p.m., in [dB], $L_{E,i}$ is the evening sound A level, determined from the noise exposures from 6:00 p.m. to 10:00 p.m., in [dB], and $L_{N,i}$ is the night sound A level, determined for the night periods i.e. from 10:00 p.m. to 6:00 a.m., in [dB].

In particular, W. Batko and B. Stepien in (Batko and Stepien, 2010, pp. 11-16) proposed the bootstrap method because it is very difficult to know the probability distribution of the long-term indicators of the noise in the environment. It has a wide applicability and can be very useful in many cases in order to get estimations, which can be difficult to be obtained with other methods.

In (Farrelly *et al.* 2003, pp. 167-175) use also the bootstrap method, that is particularly effective in the real-time estimation of the confidence intervals in environmental noise measurements. Namely, they associate lower and upper extrema of a confidence interval to the measured parameters, thus defining the interval where the "true" value may be found with a given probability.

From all so far reported, it is clear that the estimation of the uncertainty related to environmental measurements can be performed adopting different advanced techniques of statistical analysis. The reason is that the environmental noise turns out to be composed of several independent signals, generated by different acoustic sources, which can be often localized in different places. Due to the large number and variety of these acoustic sources, the noise can be considered a multidimensional random variable.

II.6 The proposal

The aim of this work is the integration of the three different analysed approaches and the realization of a novel procedure, as schematized in Fig. II.7, for the evaluation of measurement uncertainty of environmental noise with reference to measurand variability, verified with real data acquired during measurement campaigns.

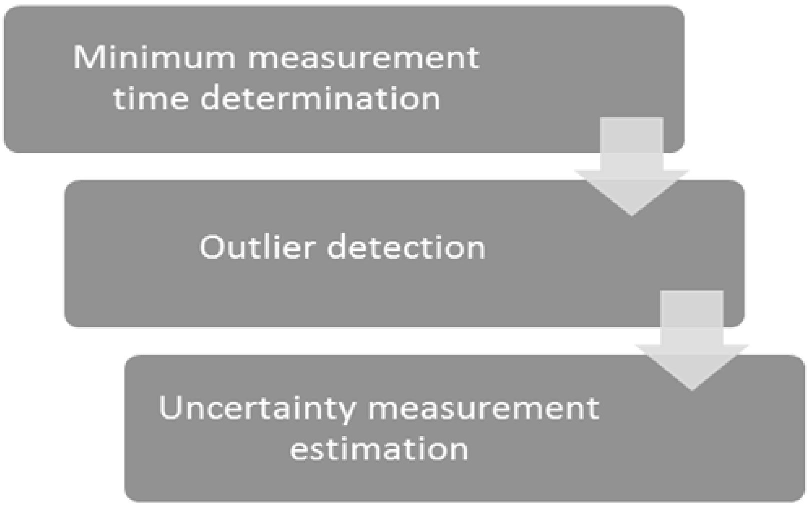

Figure II.7 *Block diagram of the proposal*

In the first stage a comparison was made between the five most commonly used bootstrap methods (normal NORM, basic percentile PER, t-student T, bias corrected percentile CPER, bias corrected and accelerated percentile BCA) using the nonparametric Kruskal-Wallis and Tukey-Kramer test. A more detailed description of the bootstrap methods is given in the next chapter. This first comparison has shown that only the distribution on the t-student method differs from the others from a statistical point of view and that the algorithm used to guarantee maximum replicability is corrected percentile CPER, which estimates the confidence interval of the value in question based on the use percentiles of the bootstrap distribution.

The reliability of the estimate of the environmental noise indicators depends significantly on the temporal variability of the noise, therefore it is essential to accurately choose the measurement time that takes into account the statistical variability of the acoustic phenomenon under observation. To this end, a Matlab procedure was employed, based on the bootstrap method CPER to locate an amount corresponding to the minimum number of sound pressure levels of acquisition time required to ensure statistical significance for the initial set of data. To define this algorithm a statistical analysis of real data was conducted relating to vehicle traffic noise.

Next, a numerical algorithm was produced to ascertain and delete anomalous (outlier) values from a population of real data and, in order to determine the uncertainty associated with the signal measurement, the bootstrap approach was analysed.

Summarizing, at first the measurement time that assures the statistical significance of the starting dataset by applying the CPER bootstrap method is determined, then the algorithm "outlier detection" that removes outlier from the signal is applied and finally the uncertainty measurement is calculated using the bootstrap method.

The results of this method were then compared with the estimate of the expected value for the noise indicator and the corresponding uncertainty by applying the classical method (JCGM 100:2008). Since the quantities calculated with the application of the bootstrap method are very close to those determined with the classical method in the case of reduced number of samples, it can be seen that this procedure is also particularly suited to the indicator forecast of environmental noise when there is little available measurement data.

Chapter III
Estimation of minimum measurement time interval

In this chapter the influence of the measurement time on the measurement uncertainty of environmental noise is explored.

A measurement campaign composed of several measurement time windows randomly distributed can be carried out (ISO 1996-2) for evaluating the environmental noise, as suggested by the legislation.

Each measurement time interval has to contain representative values of noise pressure levels, for calculating accurately the equivalent sound pressure level $L_{A,eq}$, obtained from the sound pressure levels of the fluctuating noise by the cascade of

i) the weighting filter according to a specific profile (for example the A curve, representative of the human ear response),

ii) the time integration

iii) the logarithmical average.

The actual form of the technical standards do not provide practical criteria for the choice of the number and duration of the measurement episodes: ‘‘*to select the measurement time interval to cover all significant variations in sound emission and propagation. If the noise shows periodicity, the measurement time interval should cover an integer number of at least three periods. If continuous measurements over such a period cannot be made, measurement time intervals shall be chosen so that each one constitutes a part of the cycle, so that, together, they represent the complete cycle*’’ (ISO 1996-2). This condition is generally not applicable for environmental noise that is not periodic but random acoustic signal.

The reliability of the estimate of environmental noise indicators depends largely on the time variability of the noise, so it is very important to choose accurately the sampling technique. For this reason, in this thesis, a novel approach is introduced for choosing the suitable measurement time interval that takes into account the statistical variability of the acoustic phenomenon, in particular a data-driven sampling strategy, taking into account the variability associated to the measured sound pressure levels. The data variability is estimated by using the bootstrap technique (Wehrens at al. 2000, pp. 35-52), a statistical resampling method which replicates the initial dataset, without any restrictions in terms of shape and properties of the statistical distributions under consideration.

III.1 Choosing Bootstrap Method

The bootstrap is a computationally intensive statistical technique that allows one to make inferences from data without making strong distributional assumptions about the statistic that is calculated and/or the data.

The main idea is that a number of new data sets, which are referred to as bootstrap samples, can be generated from the initial data set by sampling with replacement. With this resampling scheme, these distributions can be seen as approximations to the true distributions of the estimators, and then a good estimate can be obtained of the distribution of a statistics of interest, such as bias, standard deviation and so on. Given a one-dimensional random variable *X* and a sample (x_1, x_2,..., x_n) which is a realization of

$X = \{X_i, i = 1,2, \dots, n\}$, the hypothesis of this method is that the probability density function *F* of *X* is unknown. Termed *R(x, F)* a certain statistics determined on the sample space, the basic bootstrap procedure has these standard steps:

1. designing the probability distribution by means of the following function

$$\mathrm{P}\ (X_B \ = x_K) = \frac{1}{n}$$

for k = 1,2,...,n
called the bootstrap distribution from sample and denoted by $\hat{F}$, where n is the sample size;

2. sampling, independently, according to the distribution of values $(x_1^*, x_2^* \dots . x_n^*)$, which are treated as the realisation of variable $x^* = (X_1^*, X_2^* \dots . X_n^*)$ and it is called the bootstrap sample;

3. distribution of statistics R is approximated by means of the bootstrap distribution: $\vartheta^* = R\left(x^*; \hat{F}\right)$.

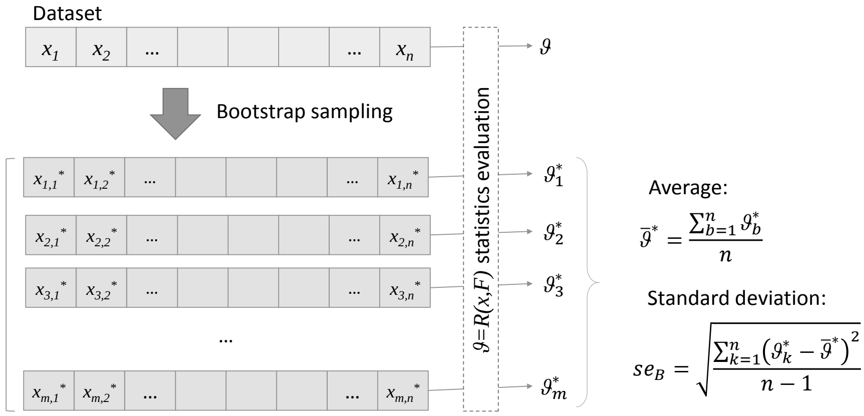

Figure III.1 *Algorithm of bootstrap method*

The distribution of variable ϑ^* is approximated by means the Monte Carlo method. The histogram of statistics ϑ^* is determined as a function of the bootstrap samples repeated m times. The algorithm of the estimation s_{eB} of the expected value and the uncertainty of the long-term noise indicators performed by the bootstrap method is shown in Fig. III.1.

The most important application field of bootstrap method is the construction of confidence intervals.

III.1.1 Bootstrap Methods

In literature there are various bootstrap methods for the determination of confidence intervals, the main ones are:

- normal bootstrap method (NORM), which approximates confidence interval with bootstrapped bias and standard error (Betta *et al.* 2008, pp. 1118-1126);
- basic percentile bootstrap method (PER), which proceeds in a similar way to the normal bootstrap one, using percentiles of the bootstrap distribution. In this case the confidence interval is invariant for monotonic trasformations and is range-preserving, that is its endpoints always fall within the range of variation of the parameter of interest. Confidence interval endpoints (Betta *et al.* 2008, pp. 1118-1126), (Williams and MacKinnon, 2008, pp. 23-51), (Stepien, 2016, pp. 389-397) for the desired confidence level *1-α* are $\left[\vartheta - \frac{\vartheta_{1-\frac{\alpha}{2}} \cdot se}{\sqrt{n}}, \vartheta - \frac{\vartheta_{\alpha/2} \cdot se}{\sqrt{n}}\right]$;

- bias corrected percentile bootstrap method (CPER), which has a weaker assumption and allows the mean of the transformed estimate to differ from the population mean. CPER interval endpoints (Betta *et al.* 2008, pp. 1118-1126), (Williams and MacKinnon, 2008, pp. 23-51), (Stepien, 2016, pp. 389-397) depend on one number z_0 called the bias correction, that is calculated from the bootstrap sampling distribution;
- bias corrected and accelerated percentile bootstrap method (BCA), which is based on knowledge of percentiles of the bootstrap distribution. BCA interval endpoints depend on two numbers: the acceleration and the bias correction (Stepien, 2016, pp. 389-397);
- bootstrap-t method (STUD), which is a more general version of the bootstrap, (Wehrens at al. 2000, pp. 35-52), (Betta *et al.* 2008, pp. 1118-1126), (Williams and MacKinnon, 2008, pp. 23-51), (Stepien, 2016, pp. 389-397), (Polanski, 2000, pp. 501-516), uses a Student's t statistic. In Fig. III.2, a flow chart of the bootstrap-t method is shown. The basic principle of this extension of the bootstrap method is the construction of the confidence intervals by using t-student statistics. For each bootstrap i-th resample, a second level bootstrap gives *h* new samples and the statistics $t_i^* = \left(\vartheta_i^* - \vartheta\right)/se_{i*}$ is calculated by bootstrapping the resample, where ϑ_i^* is the estimate from the i-th bootstrap resample and se_{i*} is an estimate for standard deviation of the same resample. The percentiles $t_{1-\alpha/2}^*$ and $t_{\alpha/2}^*$ are used in order to approximate the confidence interval for the desired confidence level *1-α*, equal to $\left[\vartheta - t_{1-\alpha/2}^* \cdot se,\ \vartheta - t_{\alpha/2}^* \cdot se\right]$ where ϑ is the estimation on the original dataset and *se* is the standard deviation of the original dataset (Liguori *et al.* 2016g, pp. 7-8).

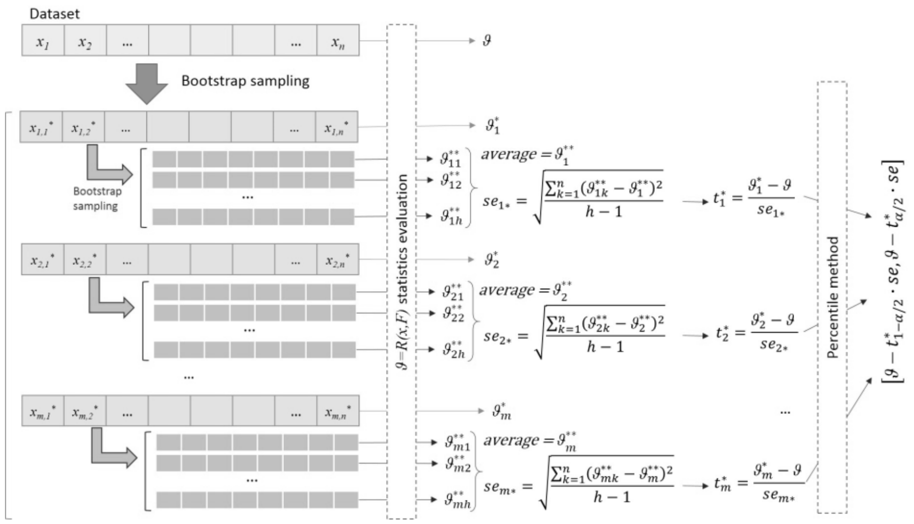

Figure III.2 *The bootstrap-t method*

III.1.2 Comparison of Bootstrap Methods

The standard uncertainty has to be evaluated as a standard deviation of the probability density function (PDF) attributed to the measurand (JCGM 100:2008). In the practice, such a PDF is determined on a finite number of observation, collected in a sample. Moreover, in the area of traffic noise measurement it could be very productive to estimate the uncertainty to be attributed to long time periods by acquiring and processing only time windows of reduced duration. The analysis is carried out on measurements of traffic noise: the Sound Level Meter (Larson Davis 831, Class 1 Environmental Noise & Bulding Acoustics Analyzer) is placed in close proximity to a motorway (at a distance of 1 m from the road and a height of 4 m from the ground). Data collection is performed during one day (wind lower than 5 m/second and witouth rain) by considering the time interval from 9 a.m. to 12 p.m as observation time window. With regard to the instrument setting, the time history logging step and the measurement time have been considered equal to 1 second and 15 minutes respectively. More particularly, a set of 16 acquisitions has been collected, with each acquisition block including 900 equivalent noise levels L_{Aeqi}.

At first, the impossibility that a definite PDF could be attribute to traffic noise data is documented with tests on real data.

To statistically determine the distribution of data, the simulation environment Matlab is used: for each measure, the histograms of the equivalent noise levels are determined as a first step (Fig. III.3) and then the χ^2 tests (Fig. III.4) are applied to these noise level sequences, in order to verify if a Gaussian model can be hypothesized for the originating population.

For the χ^2 tests, the significance level α has changed between 0 and 1, being α the probability of rejecting the null hypothesis when it is true. As a result, for all reasonable values of α, all sequences except the 10th turn out not to be Gaussian (Figure III.4a, 4b).

For each test, the level of statistical significance γ was also determined. Chosen an expected statistical distribution (Gaussian in the present case), the γ value is the probability of observing the given sample or one which is in worse agreement with the expected distribution, given that the null hypothesis is true.

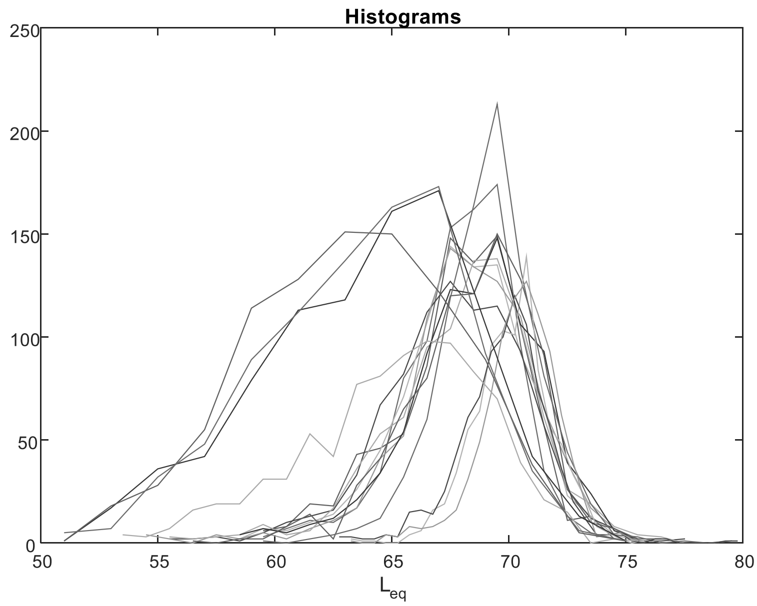

Figure III.3 *Comparison between histograms of the 16 Leq acquisitions*

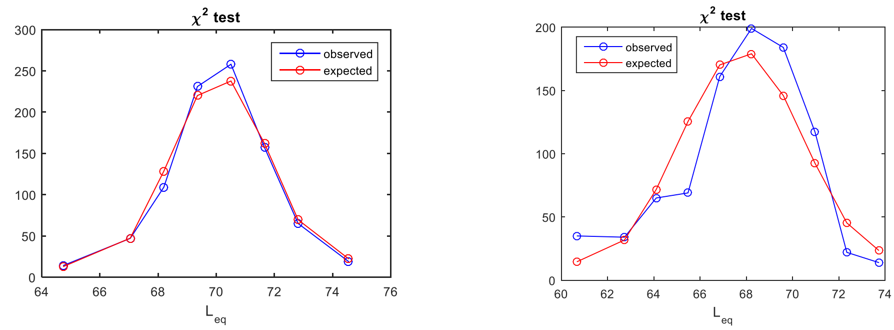

Figure III.4 *Comparison between observed distribution and expected Gaussian distribution in sequences n. 10 (a) and n. 1 (b).*

Then, the smaller the γ value, the worse the agreement with the expected distribution. From Fig. III.5, it is easy to see that only the 10^{th} sequence of data can be considered Gaussian, since the γ value is close to 1: Extremely low values of γ strongly indicate that those datasets are not Gaussian, since when the γ value is less than a predetermined significance level (e.g. 0.05), it means that the null hypotheses (H_0: "dataset is Gaussian") is rejected..

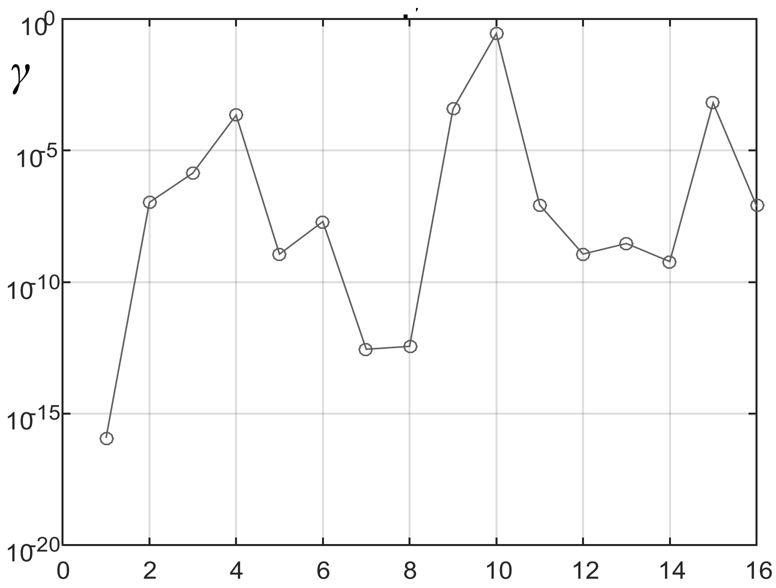

Figure III.5 *Levels of statistical significance γ of all 16 acquisitions*

In the following, a sequence of non-gaussian data has been considered to carry out the comparison of the bootstrap methods previously introduced in terms of the 95% confidence intervals for L_{Aeq}, .

In detail, in Figs. III.6a, III.6b the normal probability plot, that is a graphical technique for assessing whether or not a data set is approximately normally distributed, and histogram of the corresponding L_{Aeqi} are reported for the 13th sequence.

a)

b)

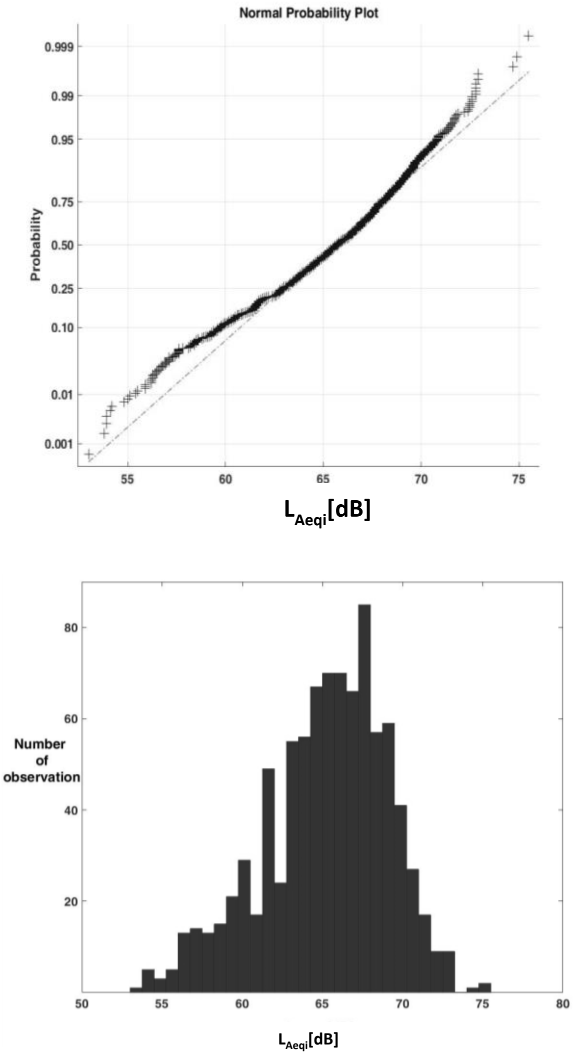

Figure III.6 *Measured L_{Aeqi} for 13th sequence: a) Normal Probability Plot; b) Histogram of occurrences*

One thousand (1000) random samples of size n = 60 are extracted from the considered data; the sample size is chosen with the intention to study the influence on the estimated L_{Aeq} of the population (13^{th} sequence) from a reduced time window.

The reconstruction of the probability density function of the noise indicator is performed separately on the basis of each sample, by considering three different values for the number of bootstrap replications (m = 250, m = 500, m = 1000). In other words, 1000 bootstrap distributions are obtained for each value of m. From these bootstrap distributions 95% confidence intervals are calculated for each of the 5 presented bootstrap methods. Then, focus is devoted to the widths of estimated confidence intervals (the difference between the upper and the lower confidence limits). Thus, 1000-element distributions of 95% confidence interval widths of noise indicator L_{Aeq} are obtained for each combination of bootstrap model and number of replication. Fig. III.7 shows all the obtained distributions in terms of the corresponding histograms (30 class bins are considered), whereas the statistical parameters (minimum, maximum, mean, median, and standard deviation) are reported in Table III.1.

It can be noted that the examined distributions resulting from the application of all the bootstrap methods have statistical parameters very close to each other. Only a slightly greater standard deviation is observed for the distribution computed with STUD method. Thus, a further statistical analysis has been carried out in order to exclude the revealed differences are statistically significant.

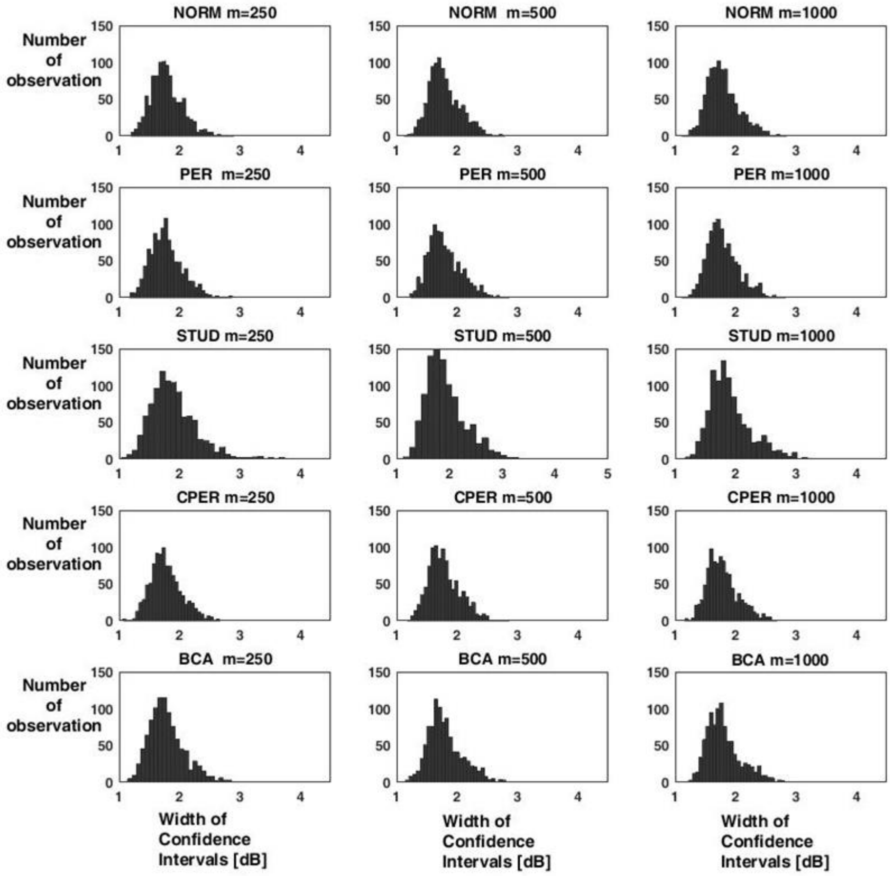

Figure III.7 *Histograms of 95% Confidence Interval widths (based on 1000 repetitions)*

Firstly, the Kruskal-Wallis non-parametric test is performed at confidence level α= 0:05; the obtained probability value (p= 5.8·10-10) indicates that there are statistically significant differences between the bootstrap techniques.

Table III.1 . *Statistical parameters of 95% confidence intervals widths for different bootstrap methods*

	Parameter	Unit	NORM	PER	STUD	CPER	BCA
m = 250	**min**	[dB]	1.20	1.18	1.04	1.06	1.07
	mean		1.78	1.78	1.90	1.77	1.79
	median		1.75	1.75	1.84	1.74	1.74
	max		2.90	2.87	3.74	2.67	3.22
	std		0.26	0.27	0.39	0.26	0.30
m = 500	**min**	[dB]	1.12	1.22	1.01	1.17	1.15
	mean		1.79	1.79	1.93	1.78	1.80
	median		1.75	1.74	1.84	1.74	1.75
	max		2.80	2.87	4.45	2.87	2.92
	std		0.26	0.27	0.38	0.26	0.29
m = 1000	**min**	[dB]	1.11	1.11	1.17	1.17	1.11
	mean		1.79	1.79	1.91	1.79	1.80
	median		1.75	1.75	1.84	1.75	1.75
	max		2.84	2.84	3.69	2.69	2.81
	std		0.26	0.26	0.35	0.26	0.29

Then, the Tukey-Kramer non-parametric test has been performed at confidence level α= 0:05; the corresponding result are reported in terms of the graphical representation in Fig. III.8. The graphs show the average value of rank together with the confidence level for each of the models. Any two compared group averages are statistically different when their intervals are disjoint. Overlapping intervals indicate that there are no statistically significant differences between the compared group averages.

Two main results can be noted:

i) for each bootstrap method, there are not statistically significant differences in the distributions resulting from different number m of replications;

ii) the confidence interval widths determined with the application of the STUD algorithm are significantly statistically different from widths determined by means of other bootstrap methods, whereas there are no statistically significant differences between 95% confidence interval widths obtained by means of NORM, PER, CPER, and BCA techniques. As an example, the probability values obtained from the test for *m*= 250 are summarized in Table III.2.

As a further result, for the determination of Confidence Interval (CI) about the L_{Aeq}, the CPER algorithm is the most suitable one, because it exhibits the greater repeatability (the smaller standard deviation observed for the computed width distribution) (Liguori *et al.* 2016c).

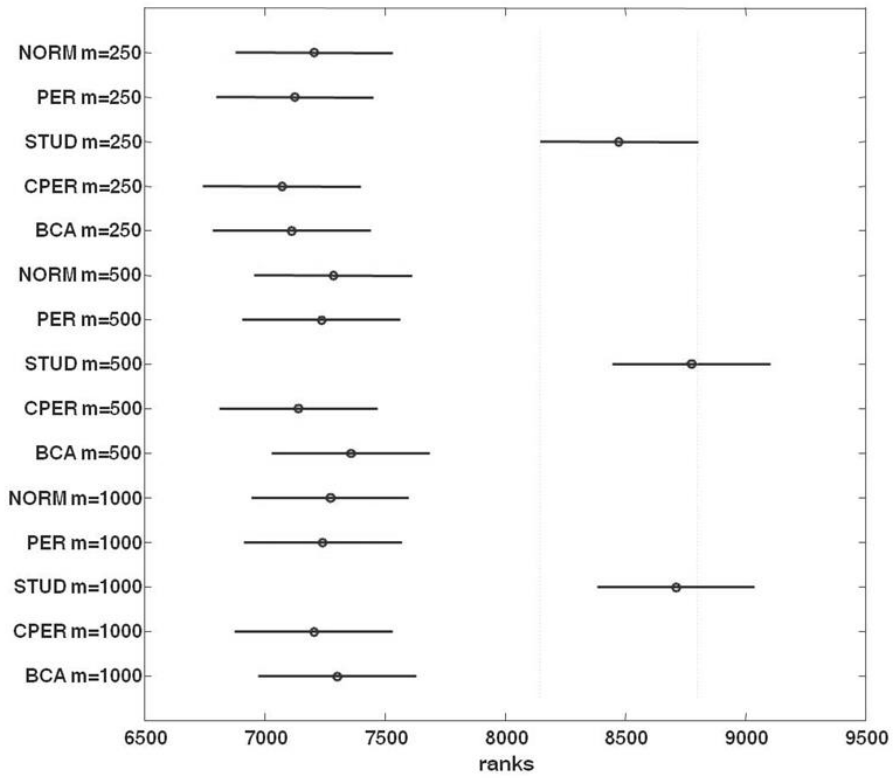

Figure III.8 *Multiple comparison performed through the Tukey-Kramer Test*

Table III.2 *p-values of the Tukey-Kramer Test*

NORM	PER	STUD	CPER	BCA	
-	1.00	4.34E-07	1.00	1.00	**NORM**
	-	4.29E-07	1.00	1.00	**PER**
		-	4.29E-07	4.29E-07	**STUD**
			-	1.00	**CPER**
				-	**BCA**

The results of the proposed approach are compared with the estimation of the expected value for the short term noise indicator and of the corresponding uncertainty by classic method (JCGM 100:2008).

More specifically, the expected value of the equivalent sound pressure level (referring to the observation time = 15 minutes) - in the classical approach - is determined by eq. (1):

$$\bar{L}_{eq,A} = 10 \log\left(\frac{1}{n}\sum_{1=1}^{n} 10^{0,1\, L_{eq,Ai}}\right) \tag{1}$$

where n is the size of the considered sample.

The corresponding uncertainty is determined by eq. (2):

$$u(\bar{L}_{eq,A}) = \sqrt{\frac{\sum_{i=1}^{n}\left(L_{eq,Ai} - \bar{L}_{eq,A}\right)^2}{n(n-1)}} \tag{2}$$

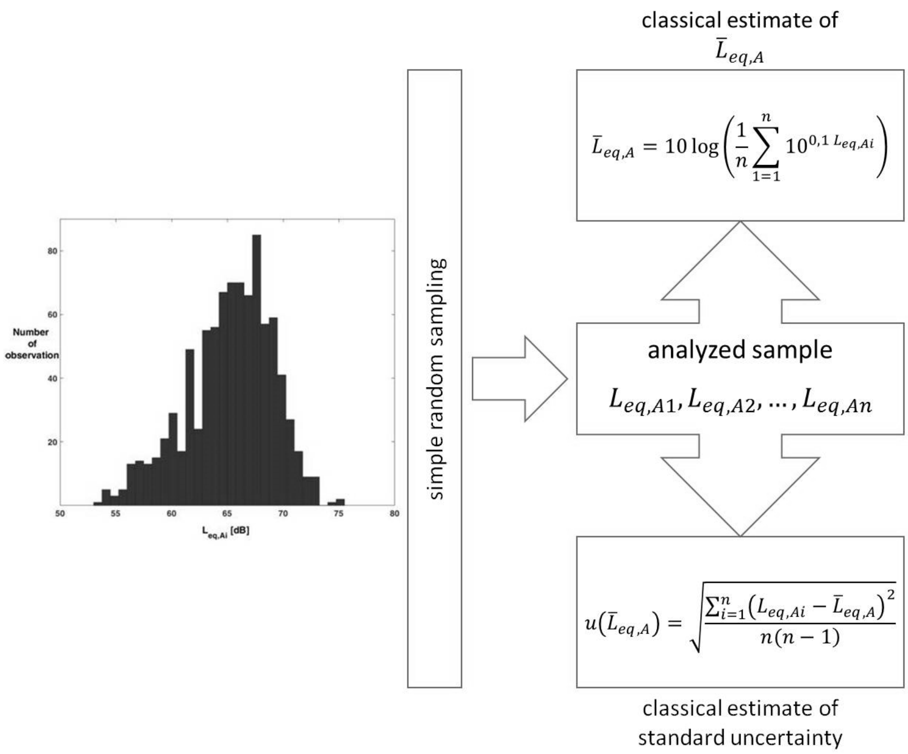

Figure III.9 *Estimation of expected value and standard uncertainty according to the classical method*

The calculation scheme according to the classical approach is depicted in Fig. III.9.

According to the bootstrap approach, the expected value of the equivalent sound pressure level is determined as the midpoint of the CI resulting from the application of the CPER algorithm. The corresponding uncertainty is calculated as standard deviation of the expected values with respect to k iterations of the CPER algorithm, according to the scheme in Fig. III.10.

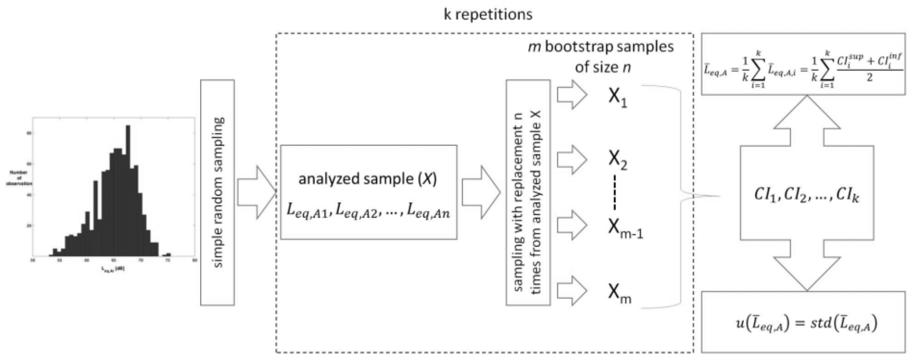

Figure III.10 *Estimation of expected value and standard uncertainty according to the bootstrap approach (CPER algorithm)*

Table III.3 summarizes the comparative results when the classical and bootstrap approaches are applied to the samples (with different size) randomly extracted by 13th sequence. With regard the classical method, for each sample size, both the expected value and uncertainty are achieved as averaged values on k = 1000 repetitions (in order to reduce the influence of the random sampling from the population). The same number of iterations are considered to estimate the uncertainty of the equivalent sound pressure level according to the bootstrap approach. The references are determined by the classical method applied to the whole population (900 samples), resulting in 66.74 dB and 0.14 dB for the expected value and the uncertainty respectively.

As may be observed, both the classical and proposed methods lead to a very good estimation of the expected value for the short term noise indicator when a reduced number of samples are considered. Moreover, the reduced sample size introduces an overestimation of the true uncertainty, that is more evident for the classical method. Consequently, the bootstrap approach seems to be a very promising technique for the prediction of the environmental noise indicator from a reduced set of measurement data.

Table III.3 *Comparison of classical and bootstrap method for the estimation of the equivalent sound pressure level*

	Classical Method			Bootstrap Method		
Sample Size (n)	**Expected Value [dB]**	**Uncertainty [dB]**	**Δu [dB]**	**Expected Value [dB]**	**Uncertainty [dB]**	**Δu [dB]**
50	66.72	0.58	0.44	66.70	0.50	0.35
60	66.72	0.54	0.40	66.70	0.48	0.34
100	66.72	0.42	0.28	66.74	0.35	0.21
120	66.73	0.38	0.24	66.74	0.32	0.18
150	66.74	0.34	0.20	66.74	0.27	0.13

The minimum number of bootstrap replications (m=250) suggested in literature as rule of thumb is enough to estimate an accurate CI for the noise indicator: the adoption of greater values of m does not provide statistically significant differences but it introduces a greater computational burden.

III.2 The proposed procedure

The proposed strategy postulates a minimum acquisition time corresponding to the minimum number (N_{min}) of sound pressure levels for assuring the statistical significance of the starting dataset (typically some hundreds of sound pressure levels should be considered). The minimum measurement time is forced to be an integer multiple of the chosen minimum acquisition time T_{acq} (as well as dependent from the time history logging of the sound level meter).

The N_{min} A-weighted sound pressure levels L_t are considered to calculate the corresponding equivalent level:

$$L_{Aeq} = 10\,Log\left(\frac{1}{N_{min}}\sum_{t=1}^{N_{min}} 10^{\frac{L_t}{10}}\right) \tag{3}$$

The *CI* of the above short time statistic (once the *CL* is fixed) is determined by applying the CPER bootstrap method and considering m

bootstrap samples (resampling the L_t dataset). In order to take into account the random variability introduced by the bootstrap method, *k* repetitions of the *CI* calculation are suggested to determine the (mean) values for the interval width (*ΔCI*) and extremes (CI_{lower} and CI_{upper}).

The proposed strategy for determining the minimum measurement time is schemed in Fig. III.11: the above mentioned steps (for calculating the *CI* information) are continuously applied to consecutive acquisition time windows (next to the starting point), as long as both the actual interval width and extremes show a data variability lower than the one observed in the previous windows (Liguori *et al.* 2017b, pp. 237-242).

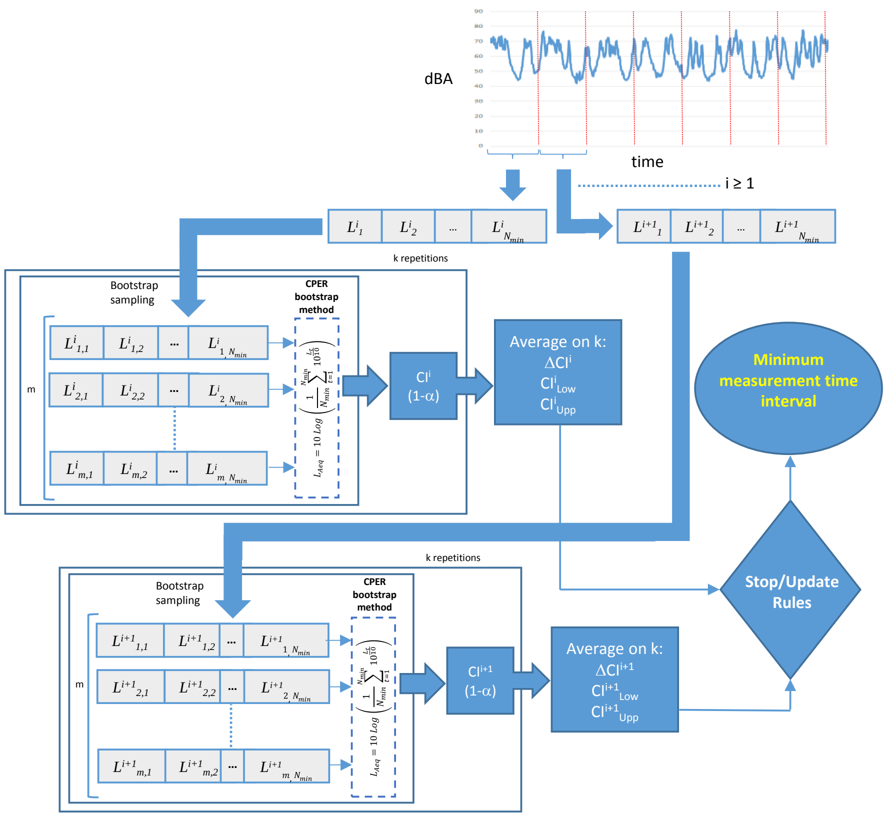

Fig. III.11 *Algorithm used to obtain the minimum measurement time*

More in details, the satisfaction of the following conditions, eq. (4), is considered as the stopping rule:

$$\left(\Delta CI^{j+1} < \Delta CI^{j,MAX}\right)\ AND\ \left(CI_{lower}^{j+1} > W_{lower}^{j,updated}\right)\ AND\ \left(CI_{upper}^{j+1} < W_{upper}^{j,updated}\right) = true;\ \ j \in N \tag{4}$$

where $\Delta CI^{j,MAX} = \max\left\{\Delta CI^{i}: i \leq j\right\}$ is the greatest *CI* width calculated on the observed sound pressure levels, whereas the interval $W^{i,updated}$ takes into account the maximum observed *CI* extremes resulting from the updating rule, eq. (5), applied to the (i+1) time window next to the acquisition starting point:

$$\left(\Delta CI^{i+1} < \Delta CI^{i,MAX}\right) \rightarrow \begin{cases} W_{lower}^{i+1,updated} = min\left(CI_{lower}^{i+1}, W_{lower}^{i,updated}\right) \\ W_{upper}^{i+1,updated} = max\left(CI_{upper}^{i+1}, W_{upper}^{i,updated}\right) \end{cases} \quad i \geq 1 \tag{5}$$

Finally, the minimum measurement time is set to the extent of the consecutive acquisition time windows before the stop rule is satisfied:

$$T_{meas\_min} = j * T_{acq} \tag{6}$$

III.3 Experimental Results (one noise source)

In order to characterize the proposed strategy, a statistical analysis is carried out on measurements of road traffic noise. In particular, the sound level meter (Larson Davis 831, class 1) is placed on the side of A3 motorway near Salerno (Italy) and the chosen dataset is a time series of L_t continuously measured during the time interval from 10 a.m. to 1 p.m. (observation period T_{obs}). Main parameters of the noise source, recorded during the measurement campaign, are reported in Table III.4.

Table III.4 *Main parameters of road traffic*

	Average hourly traffic volume		Mean speed	
	Light vehicles	Heavy vehicles	Light vehicles	Heavy vehicles
Diurnal reference time (6-22 hr)	141 veh/h	49 veh/h	115 Km/h	92 Km/h
Nocturnal reference time (22-6 hr)	40 veh/h	30 veh/h	106 Km/h	89 Km/h

The time history logging of the sound level meter is set to 1 second, resulting in a dataset of consecutive 10800 sound pressure levels. The corresponding normal probability plot is reported in Fig. III.12, whereas the Anderson-Darling Test with 5% significance level leads to refuse the null hypothesis (p=0.0005), showing the examined population is not strictly Gaussian, and so the CPER bootstrap method, for *CI* estimation, is considered.

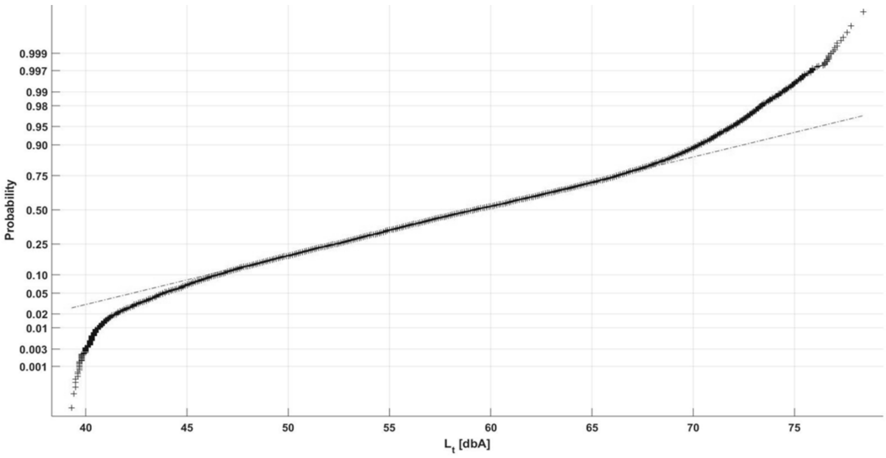

Figure III.12 *Normal probability plot*

The proposed algorithm for determining a significant measurement time has been applied to the chosen dataset according to the following parameters: minimum number N_{min} of sound pressure levels equal to 300 (that implies a minimum acquisition time T_{acq} of 5 minutes and the equivalent A-weighted sound pressure level $L_{Aeq,5\ min}$ as statistic of interest); application of the CPER bootstrap method with m = 1000 bootstrap samples and α= 0.05 for determining the *CI* corresponding to 95% confidence level; k = 30 repetitions of the bootstrap method for each time window.

The proposed strategy has been executed L multiple times (L= 100) for different acquisition starting points within the observation period.

An example of the time evolution is depicted in Fig. III.13, whereas the results are summarized in Table III.5, in terms of the mean value for:

i. minimum measurement time T_{meas_min};

ii. the 95%-CI for the equivalent sound pressure level $L_{Aeq,Tmeas\_min}$ corresponding to T_{meas_min};

iii. the 95%-CI for the equivalent sound pressure level $L_{Aeq,Tobs}$, by taking into account $N_{levels}= N_{min} * (T_{meas\_min} / T_{acq})$ sound pressure levels randomly distributed in the time interval from the starting point to the end of the observation period.

Table III.5 *Minimum measurement time and 95% confidence intervals for the equivalent sound pressure level*

	T_{meas_min} [s]	95%-CI ($L_{Aeq,Tmeas\_min}$)			95%-CI ($L_{Aeq,Tobs}$)		
		Lower limit $L_{Aeq,lower}$ [dBA]	Upper limit $L_{Aeq,upper}$ [dBA]	Width [dBA]	Lower limit $L_{Aeq,lower}$ [dBA]	Upper limit $L_{Aeq,upper}$ [dBA]	Width [dBA]
t_{start}= 1 [s] (10.00.01 a.m.)	**900.00**	65.6	66.5	0.9	65.0	65.9	0.9
t_{start}= 3601 [s] (11.00.01 a.m.)	**900.00**	64.9	65.9	1.0	64.7	65.6	0.9
t_{start}= 5401 [s] (11.30.01 a.m.)	**1200.00**	64.1	65.0	0.9	64.3	65.2	0.9
t_{start}= 7201 [s] (12.00.01 a.m.)	**300.00**	64.6	66.4	1.8	64.2	66.0	1.8

The experimental results show a very good stability of the proposed algorithm. With reference to Table III.4, for each acquisition starting point (t_{start}), the corresponding measurement time (**T_{meas_min}**) is not influenced by the statistical variability of the bootstrap method: the observed repeatability of the estimated minimum measurement time is equal to 100% with the same L= 100.

Moreover, the proposed algorithm is revealed effective in the estimation of the traffic noise from the acquisition of short episodes. Indeed, all the resulting (minimum) measurement times allow the achievement of very accurate estimates of the equivalent sound pressure level $L_{Aeq,Tmeas\_min}$ if compared with the estimates calculated from the whole dataset $L_{Aeq,Tobs}$, both in terms of the *CI* widths (almost coincident) and *CI* midpoints (mean values between Lower limit and Upper limit**)** for which the maximum difference is less than 1%.

It's important to underline that values of T_{meas_min} are different at varying t_{start} : this is due to the measurand variability connected with the real road traffic conditions.

Furthermore, in order to test the proposed algorithm under different conditions, a nocturnal reference measured dataset is considered and the procedure is executed *L* multiple times (*L*= 200) for starting point t_{start} = 01.30.01 a.m. within the observation period T_{obs} (from 0.00 a.m. to 3.00 a.m.). The achieved results show a value of T_{meas_min} = 900 s with $L_{Aeq,lower}$ = 64.2 dBA and $L_{Aeq,upper}$ = 65.2 dBA according to 95%-*CI* ($L_{Aeq,Tmeas\_min}$), while $L_{Aeq,lower}$ = 64.7 dBA and $L_{Aeq,upper}$ = 65.7 dBA according to 95%-*CI* ($L_{Aeq,Tobs}$), confirming the repeatability of the estimated minimum measurement time equal to 100% and the achievement of very accurate estimates of the equivalent sound pressure level like in diurnal reference time case.

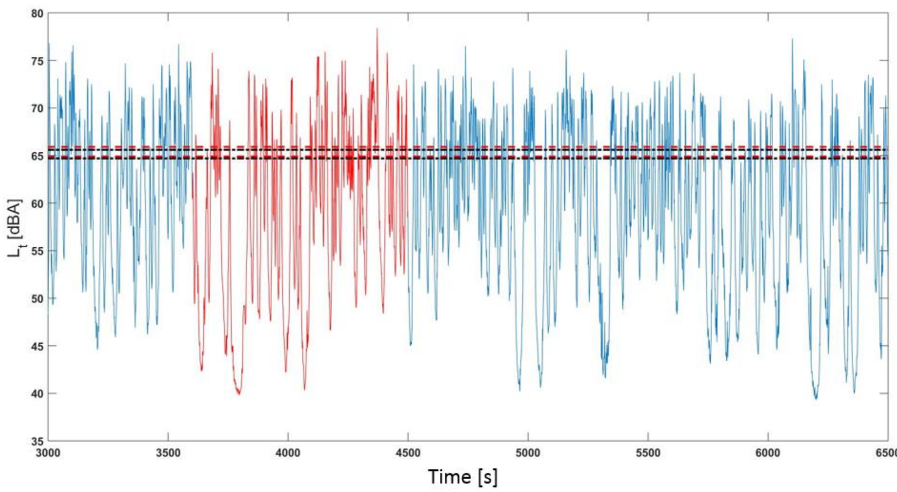

Figure III.13 *Sequence of sound pressure levels during diurnal observation period (solid blue) and resulting minimum measurement time (solid red), observation period 95% CI (dash black), measurement time 95% CI (dash red).*

III.4 Experimental Results (three noise sources)

The procedure, based on CPER Bootstrap Method, is experimentally verified also with other real data acquired in three non Gaussian scenarios (road traffic, outdoor air conditioner fan motor and construction site as noise sources), by adopting the Sound Level Meter Larson Davis 831, Class 1 Environmental Noise & Building Acoustics Analyzer. Then, a statistical analysis is carried out on the measurements of environmental noise.

With regard to the measurement of road traffic noise, the sound level meter is placed in close proximity to a motorway (at a distance of 1 m from the road and a height of 4 m from the ground). Data collection is performed during one day (wind lower than 5 m/second and without rain) by considering the time interval from 10 a.m. to 01 p.m. as acquisition period T_{acq}. With regard to the instrument setting, the time history logging step (T_{const}) is fixed to 1 second, resulting in a dataset of 10800 consecutive sound pressure levels.

With regard to the noise measurement of the air conditioner outdoor fan motor (heat pump and liquid chiller), the sound level meter is placed at a distance of 1 m from the nearest building facade and a height of 4 m from the ground. Data collection is performed during one day (wind lower than 5 m/second and without rain) by considering 50 minutes of the air conditioner fan motor working both at start-up and modulation state. About the instrument setting, the time history logging step is fixed to 0.1 second, resulting in a dataset of 30000 consecutive sound pressure levels.

With regard to the measurement of noise at a construction site, the sound level meter is placed at a distance of 2 m from the noise source and a height of 4 m from the ground. Data collection is performed during one day (wind lower than 5 m/second and without rain) by considering 10 consecutive hours (starting time: 10 p.m.). About the instrument setting, the time history logging step is fixed to 1 minute, resulting in a dataset of 600 consecutive sound pressure levels.

With regard to the CI estimation, focus is devoted to the bootstrap method (CPER) because the examined populations are not strictly Gaussian.

The proposed strategy for determining a significant measurement time is applied to each dataset according to the following parameters: application of the CPER bootstrap method with m = 1000 bootstrap samples and α = 0.05 for determining the CI corresponding to 95% confidence level; k = 30 repetitions of the bootstrap method for each time window.

In order to analyse the stability of the algorithm, the minimum number N_{min} of sound pressure levels is varied in the range [10 ÷ 500]. Moreover, the proposed strategy is executed L multiple times (L=100) for the same acquisition starting point (randomly chosen within the observation period of interest).

Experimental results are summarized in Table III.6, in terms of the mean value for:

i) minimum measurement time T_{meas_min};

ii) the 95%-CI for the equivalent sound pressure level $L_{Aeq,Tmeas\_min}$ corresponding to T_{meas_min};

iii) the 95%-CI for the equivalent sound pressure level $L_{Aeq.}$ corresponding to the whole dataset of interest (by randomly choosing T_{meas_min}/T_{acq} sound pressure levels).

The reported N_{min} represents the minimum value that assures the stability of the algorithm (in terms of the resulting T_{meas_min}) when a sliding window $\left(\pm \frac{N_{min}}{4} \text{ samples}\right)$ is considered around the starting point.

Table III.6 *Minimum measurement time and 95% confidence intervals for the equivalent sound pressure level*

Noise Source	T_{const} [s]	N_{min}	T_{meas_min} [s]	$L_{Aeq,Tmeas\_min}$ Mean [dB]	$L_{Aeq,Tmeas\_min}$ 95%-CI Width [dB]	# Acquired samples	L_{Aeq} Mean [dB]	L_{Aeq} 95%-CI Width [dB]
Road Traffic	1.0	300	1200	65.0	0.9	10800	65.4	0.9
Air Conditioner (Start-up)	0.1	300	120	61.6	0.2	18000	61.1	0.2
Air Conditioner (Modulation State)	0.1	400	360	58.0	0.3	12000	57.1	0.6
Construction site	60	10	3600	70.3	0.6	600	69.7	1.0

A very good stability has been observed for the proposed algorithm. Moreover, for each type of the noise source, the corresponding measurement time (T_{meas_min}) is not influenced by the statistical variability introduced by the bootstrap method: the observed repeatability of the estimated minimum measurement time was equal to 100%.

Furthermore, the strategy is shown to be effective in the estimation of the acoustic noise through data acquisition limited to short time windows. As depicted in Figure III.14, all the resulting measurement times T_{meas_min} allow for the achievement of accurate estimates of the equivalent sound pressure level, that are close to the mean value and width of the 95%-CI of the corresponding collected dataset (Liguori *et al.* 2017a), (Liguori *et al.* under review).

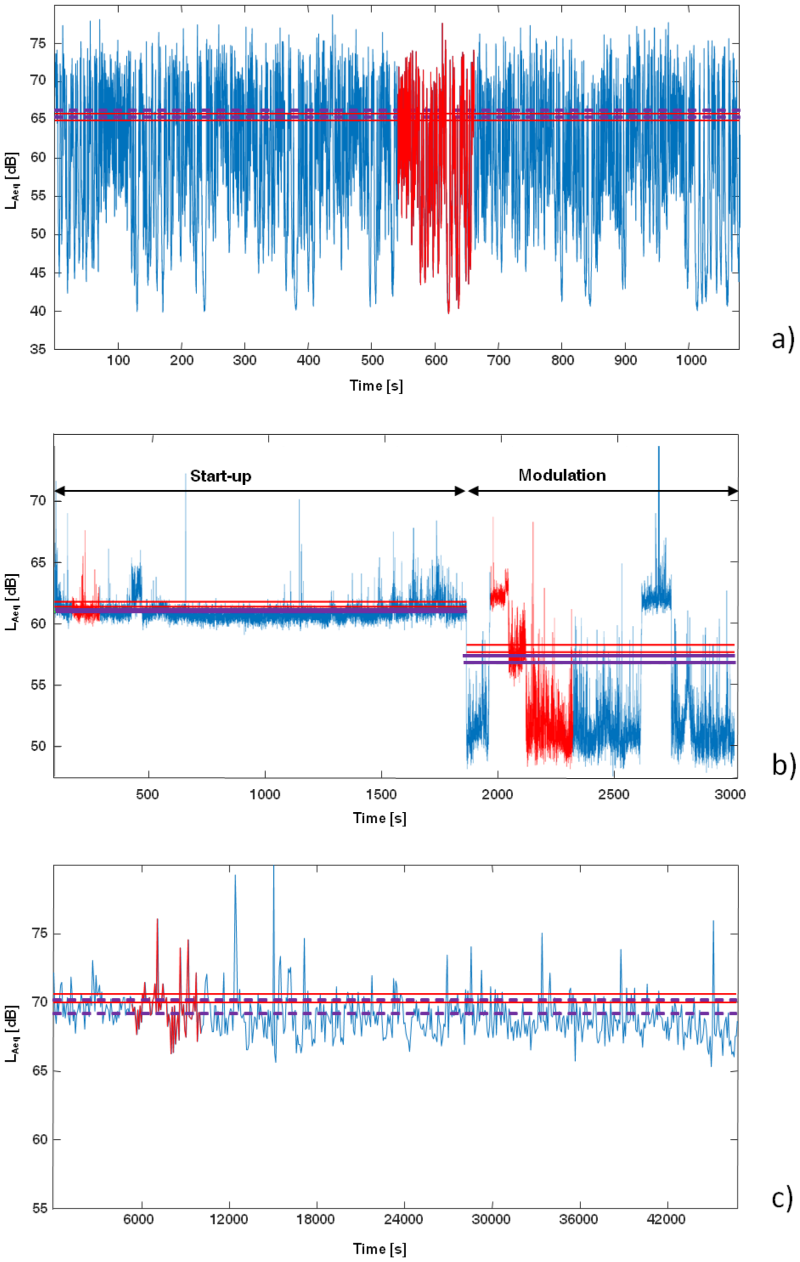

Figure III.14 *Collected sequence of sound pressure levels (solid blue) and resulting minimum measurement time (solid red), L_{Aeq} 95% CI (solid red line) for the measurement time, L_{Aeq} 95% CI (dash magenta line) for the acquisition period about different noise sources: a) traffic road; b) outdoor air conditioner fan motor; c) construction site.*

III.5 Review

In this chapter the influence of the measurement time on the measurement uncertainty of environmental noise is explored. An original procedure based on a bootstrap method is introduced to determine the suitable measurement time, which takes into account the statistical variability of the acquired sound pressure levels.

In order to choose the most effective method for obtaining accurate confidence intervals CI for the indicator L_{Aeq}, at first a comparison of five bootstrap techniques (normal, basic percentile, t-Student, bias corrected percentile, bias corrected and accelerated percentile) has been performed, concluding that the CPER algorithm is the most suitable one, because it exhibits the greater repeatability (the smaller standard deviation observed for the computed width distribution).

The proposal, based on CPER Bootstrap Method, has been experimentally verified with real data acquired both in one non Gaussian scenario (road traffic as noise source) by varying acquisition starting points and in three non Gaussian scenarios (road traffic, outdoor air conditioner fan motor and construction site as noise sources). The results showed a very good stability of the proposed algorithm in determining the minimum measurement time interval as well as its effectiveness in the prediction of the short term noise indicator (mean value and CI). Thus, the suggested data-driven approach may be adopted in the field of the environmental acoustics as guideline in the choice of suitable acquisition windows during the measurement campaign. The proposal can be easily integrated into applied noise measurement instrumentation and is very useful in providing real time information both on the minimum measurement time interval and on the measurand uncertainty estimation.

Chapter IV
Outlier detection

The scope of this first study is to eliminate outliers that occur when measuring signals in real time.

As a matter of fact, these spot events significantly disturb the value of the progressive equivalent level yielded by the measurement task. For instance, a spot event within a measurement in an urban environment with heavy vehicle traffic might be the result of the transiting of a particularly heavy vehicle or of an ambulance. For these reasons, it is interesting to analyse the change of equivalent levels caused by subsequent measurements performed on a given environmental acoustic phenomenon and with the same instrument placed in the same position with the same procedure. This kind of analysis does not depend on the above-mentioned inevitable instrumental, methodological and operating uncertainties and takes into account only the variability of the acoustic phenomenon.

In particular, this study addresses the issues of the identification of the outliers occurring in the time history of an environmental noise signal due to the spot event, following a histogram-based statistical approach, in order to allow the determination of the uncertainty associated to the measurement of the filtered signal.

IV.1 The proposed procedure

In the literature there are several methods for outliers detection with very diverse features, performance and application fields. Although, in general, an outlier is a data point significantly different from others, it is possible read different definitions: Barnett and Lewis in (Barnett and Lewis, 1964, p. 584) propose the definition: "an outlier is an observation (or a subset of observations) which appears to be inconsistent with the remainder of that set of data". Chandola et al. in (Chandola *et al.* 2009, p. 15) define outliers in wireless sensor networks (WSNs) as "those measurements that significantly deviate from the normal pattern of sensed data". Potential sources of outliers in data collected by WSNs include noise, errors and actual events.

Since the first phase of this work is the outlier detection in an acquired signal of environmental noise, among the techniques that could be chosen, the attention is turned to those designed in the context of the networks of sensors and particular attention is focused on non-parametric approach, which assumes no prior distribution (Zhang *et al.* 2010). After a statistical analysis of the acquired signal, which is the result of a measurement session conducted near a motorway, it is suggested that this hypothesis has a particularly fit for this phenomenon of traffic noise. In particular, in order to verify whether a distribution fixed in advance cannot be attributed to acoustic measurements from traffic noise, sequences of 16 acquisitions carried out during one day are considered with the phonometer (Larson Davis 831, class 1) placed on the side of a motorway and span a time interval from 9 a.m. to 12 p.m. Each acquisition block covers a 15-minute interval with equivalent noise levels measured every 1 second. These data do not include unwanted acoustic events in order to observe and verify the background noise.

With regard to the networks of sensors and in particular the non-parametric approach, which assumes no prior distribution, a distance measure is defined between a new test instance and the statistical model, and a threshold on this distance is used in determining whether the observation is an outlier. One of the most widely used approach in this category is the histogram (Sheng *et al.* 2007). This model involves counting the frequency of occurrence of different data instances (thereby estimating the probability of occurrence of a data instance), compares the test instance with each of the categories in the histogram and tests whether it belongs to one of them.

In the case of sensors that generate a significant amount of data, outlier detection is critical to identify and store only the really useful pieces of information. In this context, to optimize communication costs, instead of collecting all the data in one central location for processing, with the model histogram information are collected on the distribution of the data, and, using the hints to filter out unnecessary data, potential outliers are identified.

The outlier detection is based on the distance between two neighboring data points: the distance can be compared with a fixed threshold or with all the other data points.

For a data point x, defined the distance as the absolute difference between two data points, all the other data points can be sorted according to their distances to x in an ascending order. Suppose the sorted list is $x_1, x_2, \ldots, x_k, \ldots$ and $| x_1 - x | \leq | x_2 - x | \leq \ldots \leq | x_k - x | \leq \ldots$.

Let $D^k(x) = | x_k - x |$ represent the distance between data point x and its k-*th* nearest neighbor (KNN) (x_k). An outlier is defined in literature in two different ways (Sheng *et al.* 2007):

- *Definition 1*: A data point x is called an $O(d, k)$ outlier if $D^k(x) \geq d$.
- *Definition 2*: A data point x is called an $O(n, k)$ if there are no more than $n\text{-}1$ other data points y, such that $D^k(y) > D^k(x)$.

Between these two definitions of outlier, the first one was chosen, because it is more inherent in the object of this study: if the second one had been chosen, a minimum of *n-1* points would never been considered, in particular the *n-1* points with the greatest distance. Even though this approach would not significantly affect average and standard deviation of the sample, removing some points reduces the ability to describe the process.

The choice of k parameter in Definition 1 is related to the event duration compared to the period of observation. In the algorithm for the outlier detection, the value that is assigned to the k parameter is very important, because it determines the accuracy of the algorithm. In Fig. IV.1 there are four graphs that illustrate, for two different outliers (case A and case B), how the sensitivity of the algorithm changes when the parameter k changes.

For each case, the top figure shows the sequence of data points and the bottom figure shows the corresponding trends of k^{th} distances. In the Case A, the event consists of two data points. It is clear that the outlier can be detected only if $k \geq 3$ is chosen with a proper threshold d. In the case B, the event consists of four data points. For the same threshold value d of the previous example, the outlier can be detected only for $k \geq 5$.

To establish a criterion of choice of the parameter k, in order to give the user the possibility to decide whether to delete an event or not, an event may be considered such as outlier or as an element characterizing the acoustic phenomenon according mainly to its duration; so the Autocorrelation Function has been studied for each measurement carried out. As a result, the value at which the autocorrelation becomes negligible is considered a valid reference value. For instance, from Figure IV.2, in which the Autocorrelation Function of all the 16 acquisitions is shown, it is clear that, since the time history logging step is equal to 1 s, the events that characterize the phenomenon under observation have an average persistence time of the order of about 10 s: so to characterize a spot event as outlier to be deleted, the user has to choose a value of $k < 10$. The k parameter depends on the measurement period as well.

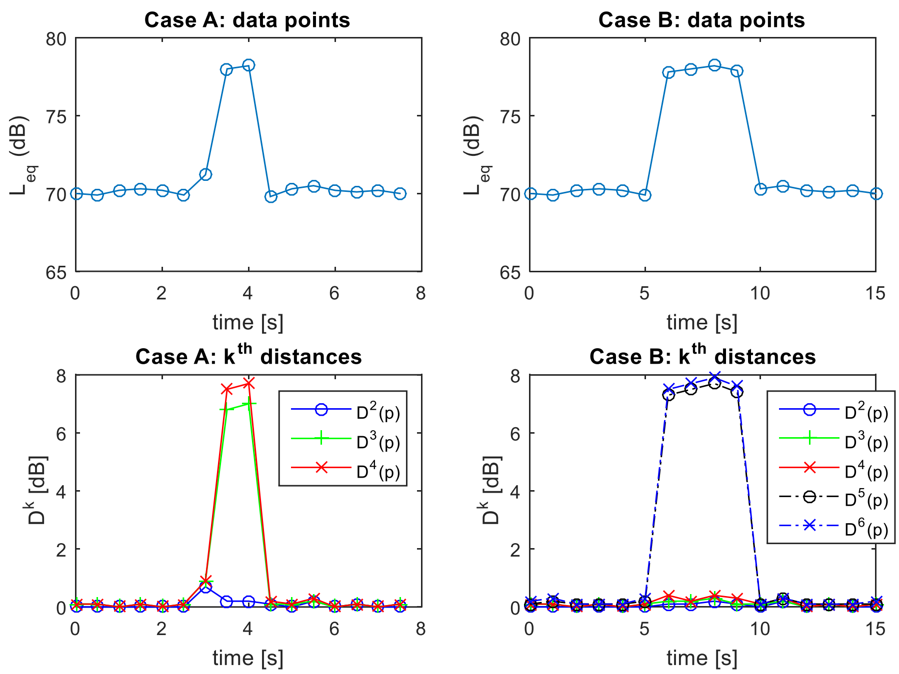

Figure IV.1 *Examples of outlier detection for different k values*

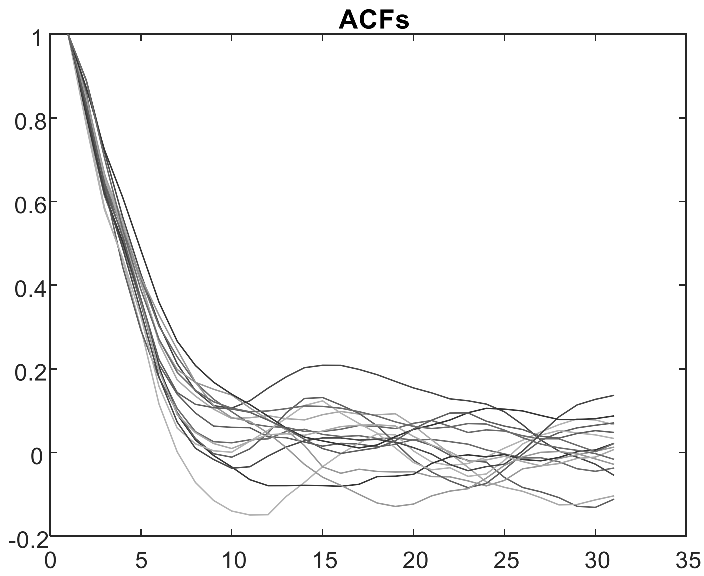

Figure IV.2: *Autocorrelation Functions for all 16 acquisitions (Leq measured every 1 second)*

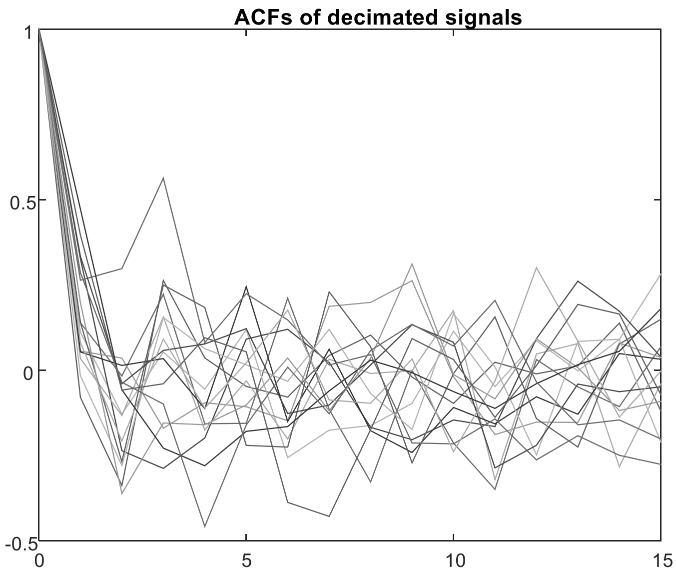

Figure IV.3 *Autocorrelation Functions for all 16 acquisitions (Leq measured every 30 seconds)*

If the data are measured each 30 seconds, the outliers are identified for *k*=1 since the phenomenon duration are comparable with the time history logging step. Fig. IV.3 reports the Autocorrelation Function for the 16 sequences with a time history logging step of 30 s. In this case, the persistence time turns out to be close to one and this can motivate a choice of *k=1*.

IV.2 Experimental Results

In order to experimentally validate the proposed approach, tests are performed on acquired data blocks. Each acquisition block covers a 15-minute interval with equivalent noise levels measured every 30 seconds. The set of 16 acquisitions has been subdivided into 2 subsets collected during the 24 hours of a whole day. The first subset is composed of 11 non-consecutive acquisition blocks that have been used in the tuning of the algorithm. The remaining 5 non-consecutive blocks have been used for the test phase, whose results will be reported in the following.

The $D^k(x)$ has been evaluated with k=1, for each one of the tuning acquisition blocks in order to have indications for the minimum value of the threshold d. Then outliers have been superimposed onto the test acquisition blocks and the percentages of false positives, FP, and true positives, TP, have been evaluated for different values of the threshold d. In the Fig. IV.4 the trends of the false positive ratio (FPR) and of the true positive ratio (TPR) is shown versus the threshold d. In these tests the threshold d has been chosen equal to 2 because in correspondence with this value there is the best trade-off between TPR (100%) and FPR (0.04%).

The performance of the so set-up procedure are evaluated, considering the signal with superimposed outliers and the equivalent levels measured on the sequences:

i) before the superimposition of the outliers;
ii) after the superimposition of the outliers;
iii) after the elimination of the detected outliers.

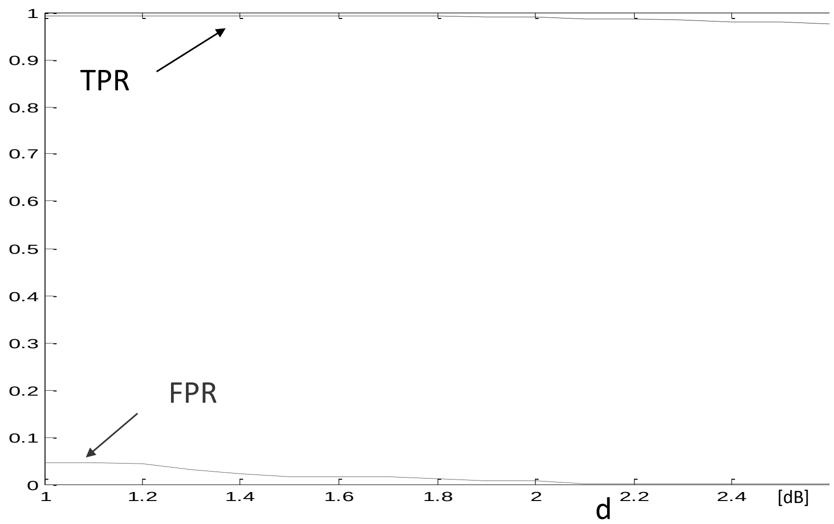

Figure IV.4 *False positive ratio (FPR) and true positive ratio (TPR) versus the threshold d.*

The results are compared in order to quantify the removing capability of the procedure. In detail, the differences $\Delta L_{eq}^{outlier}$ between the data in ii) and i) have been compared to the differences $\Delta L_{eq}^{removed}$ between the data in iii) and i). For each one of these two sets of differences $\Delta L_{eq}^{outlier}$ and $\Delta L_{eq}^{removed}$ the mean and the standard deviation have been evaluated. The normalized histograms of the two sets of mean differences are reported in

Figure IV.5 a), while the normalized histograms of the two sets of standard deviations of the differences are reported in Figure IV.5 b). As can be seen, the difference after the outlier removal, $\Delta L_{eq}^{removed}$, is close to zero for about the 70% of the data, with a worst-case value of 0.37 dB. Without the removal algorithm, the $\Delta L_{eq}^{outlier}$ can reaches 1 dB and consequently L_{eq} may be overestimated up to 1 dB. The analysis of the standard deviations shows that the removal algorithm yields a residual value of the standard deviation of 0.1 dB, which contributes to the overall uncertainty, while there was an overestimation of the standard deviation before the removal up to 4 dB. It is evident that the correction has a greater influence on the standard deviation than on the mean value.

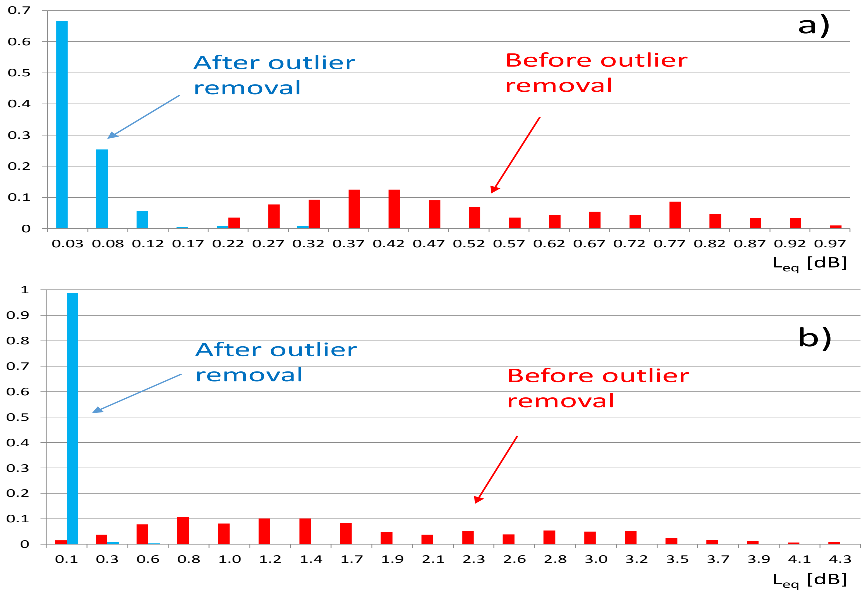

Figure IV.5 *Normalized histograms a) of the mean differences; b) of the standard deviations of the differences.*

Table IV.1 provides a summary of the results of a series of tests performed with different kinds of outliers:

- example I: one outlier with a small value (a few dB above the mean);
- example II: no outlier;
- example III: 2 small outliers;
- example IV: one bigger outlier;

- example V: one small outlier and one big outlier, where the smaller one is <5 dB, and the bigger is >10 dB above the mean.

Only in example 2 does the algorithm find one outlier instead of two, while in all the other cases the number of detected outliers is equal to the expected number. From Table I, it can be stated that the outlier removal algorithm has a minor influence on the mean value and on the standard deviation in the case of one outlier with a small value (example I) and two small outliers (example III). However, it has a significant influence on the standard deviation in the case of one large outlier (example IV) and in the case of one large outlier and one big outlier (example V).

Table IV.1 *Contribution of outlier removal on mean and standard deviation*

# example	mean value (dB)		standard deviation (dB)	
	before algorithm	after algorithm	before algorithm	after algorithm
I	64.4	64.3	1.9	1.6
II	64.9	64.9	1.7	1.7
III	65.4	65.1	2.1	1.6
IV	66.0	65.1	5.2	1.5
V	66.5	65.4	5.4	1.4

A second series of tests are carried out with different parameters of the algorithm. The 11 sequences of data points are collected, with a time history logging step of 5 s. Outlier are added onto these sequences at random time positions and with random amplitudes. The amplitudes of the imposed outliers follow the distribution described in Fig. IV.6 as normalized occurrence histograms.

For the tests, the value of k = 11 is chosen in order to stress the algorithm. The percentages of false positives, FP, and true positives, TP, are evaluated for different values of the threshold d. In the Fig. III.7 the trends of the false positive ratio (FPR) and of the true positive ratio (TPR) is shown versus the threshold d. In these tests the threshold d is chosen equal to 3.5 corresponding to a TPR of 58% and FPR of 0.5%.

For each one of these two sets of differences $\Delta L_{eq}^{outlier}$ and $\Delta L_{eq}^{removed}$ the mean and the standard deviation have been evaluated. The normalized histograms of the two sets of mean differences are reported in Figure IV.8a), while the normalized histograms of the two sets of standard deviations of the differences are reported in Figure IV.8b).

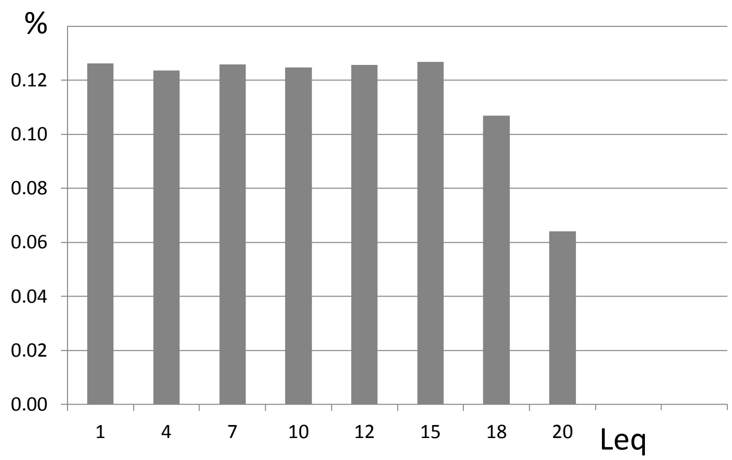

Figure IV.6 *Normalized histogram of the superimposed outliers*

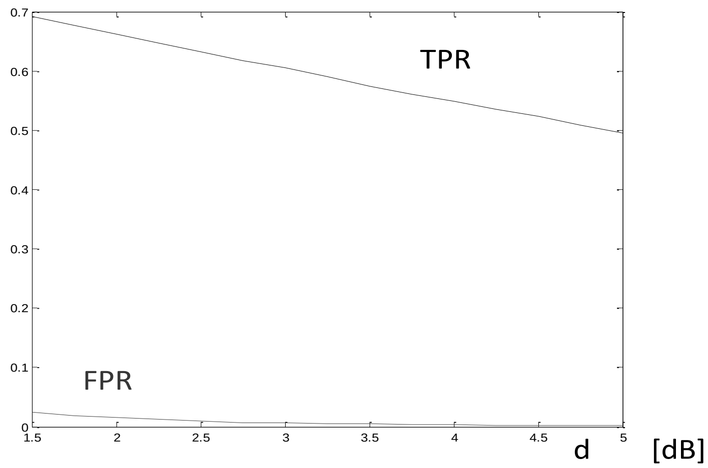

Figure IV.7 *False positive ratio (FPR) and true positive ratio (TPR) versus the threshold d, for the second series of tests*

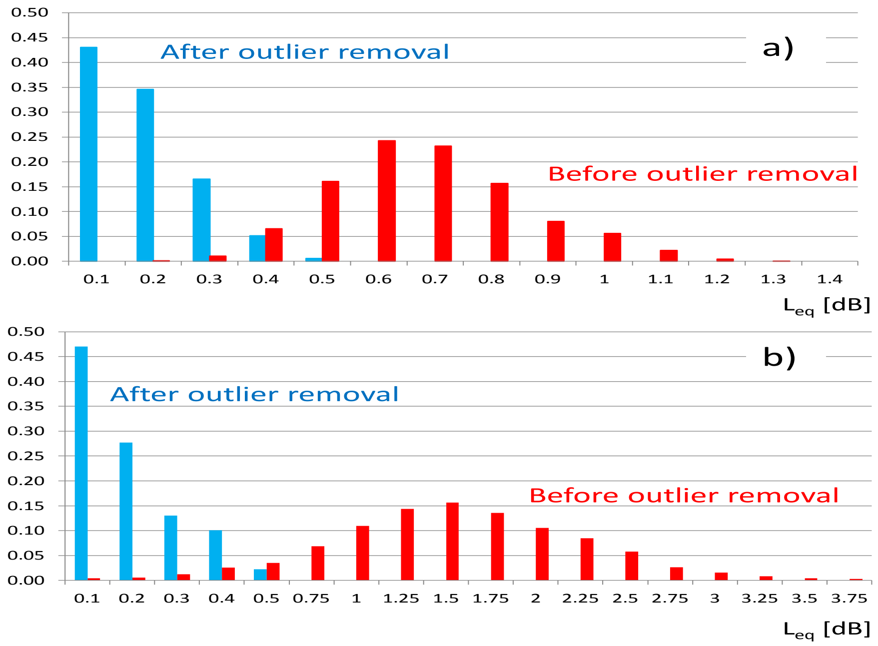

Figure IV.8 *Normalized histograms for the second series of tests: a) of the mean differences; b) of the standard deviations of the differences*

From the analysis of Figure IV.8, one can observe that in this case the difference after the removal, $\Delta L_{eq}^{removed}$, is close to zero for almost the 45% of the data, in 95% of the cases the difference is less than 0.3 dB and in the worst case there is an overestimation of about 0.5 dB.

Vice versa without the removal algorithm, there is an average overestimation of about 0.7 dB, and in the worst case it reaches more than 1.2 dB. The analysis of the values of the standard deviation shows that the overestimation of about 3 dB is reduced by the algorithm down to 0.5 dB. The latter value contributes to the measurement uncertainty (Liguori *et al.* 2016, pp. 234-242).

IV.3 Review

The specific focus of this chapter has been the study and the estimation of the influence of the occurrence of spot events on the measurement uncertainty. An algorithm has been utilized in comparing the distance between data point x and its *k-th* nearest neighbor (x_k) with a fixed threshold and it has been experimentally verified with real field data.

The choice of k parameter, that is related to the event duration compared to the period of observation, is very important, because it determines the accuracy of the algorithm. So, in order to give the user the possibility to decide whether to remove an event or not, an event is considered such as outlier or as an element characterizing the acoustic phenomenon according mainly to its duration. To this end,the Autocorrelation Function has been studied for each measurement carried out. As a result, the value at which the autocorrelation becomes negligible is considered a valid reference value. So, for instance, when the time history logging step is equal to 1 s, the events that characterize the phenomenon under observation have an average persistence time of the order of about 10 s, and to characterize a spot event as outlier to be deleted, the user has to choose a value of $k < 10$.

The results showed that the outlier detection and subsequent removal allow a significant reduction of the systematic bias and of the contribution to the uncertainty of environmental acoustic noise measurement.

In particular, these tests have highlighted that for a measurement time of 1 s and k=1, the residual uncertainty of the algorithm is about 0.1 dB and for a measurement time of 5 s and k=11, the residual uncertainty of the algorithm is about 0.5 dB. These results can be deemed definitely acceptable. This proves that the outlier detection and removal are tasks of utmost importance for the analytical evaluation of the uncertainty in environmental acoustic noise measurements.

Chapter V
Uncertainty measurement evaluation

In this chapter, as a final step of the study, the uncertainty associated to the measured environmental noise is analysed.

In particular, after determining the suitable measurement time for recorded environmental noise signals by adopting the CPER method and applying the outlier detection algorithm, the normal bootstrap method is chosen to calculate the contribution of the measurand variability on measurement uncertainty. The results of the proposed approach have been compared with the estimation of the expected value for the noise indicator and of the corresponding uncertainty using the classical method (according to [2]).

V.1 The proposed procedure

According to the normal bootstrap approach, a number of new data sets (bootstrap samples) can be generated from the initial data set by sampling with replacement. With this resampling scheme, these distributions can be seen as approximations to the true distributions of the estimators, and then a good estimate can be obtained of the distribution of statistics of interest, such as bias and standard deviation. The algorithm of the expected value and standard uncertainty of the noise indicators performed by the normal bootstrap method is shown in Fig. V.1.

V.2 Experimental results

In order to experimentally validate the proposed approach, tests are performed on three real noise datasets (road traffic, outdoor air conditioner fan motor and construction site) by adopting the Sound Level Meter Larson Davis 831, Class 1 Environmental Noise & Building Acoustics Analyzer.

With regard to the measurement of road traffic noise, the sound level meter is placed on the side of A3 motorway near Salerno (Italy) and the chosen dataset is a time series of sound pressure levels continuously measured during one day (wind lower than 5 m/second and without rain) by considering the time interval from 11.30 a.m. to 2.30 p.m. (observation period), whose histogram of occurrences is shown in Fig. V.2.

Main parameters of the noise source, recorded during a measurement campaign, are reported in Table V.1.

Table V.1 *Main parameters of road traffic*

	Average hourly traffic volume		Mean speed	
	Light vehicles	Heavy vehicles	Light vehicles	Heavy vehicles
Diurnal reference time (6-22 hr)	172 veh/h	62 veh/h	113 Km/h	93 Km/h
Nocturnal reference time (22-6 hr)	30 veh/h	25 veh/h	109 Km/h	91 Km/h

The time history logging step of the sound level meter is set to 1 second, resulting in a dataset of consecutive 10800 sound pressure levels.

The minimum measurement time, estimated as previously introduced, is equal to 900 s.

The results of the proposed approach have been compared with the estimation of the expected value for the short term noise indicator and of the corresponding standard uncertainty by the classical method (according to [2]).

Furthermore, the expected value of the equivalent sound pressure level (referring to the measurement time) - in the classical approach - is determined by eq. (1):

$$\bar{L}_{AeqTmeas} = 10 \log \left(\frac{1}{n} \sum_{1=1}^{n} 10^{0,1\, L_{Aeqi}} \right) \tag{1}$$

where n is the size of the considered sample.

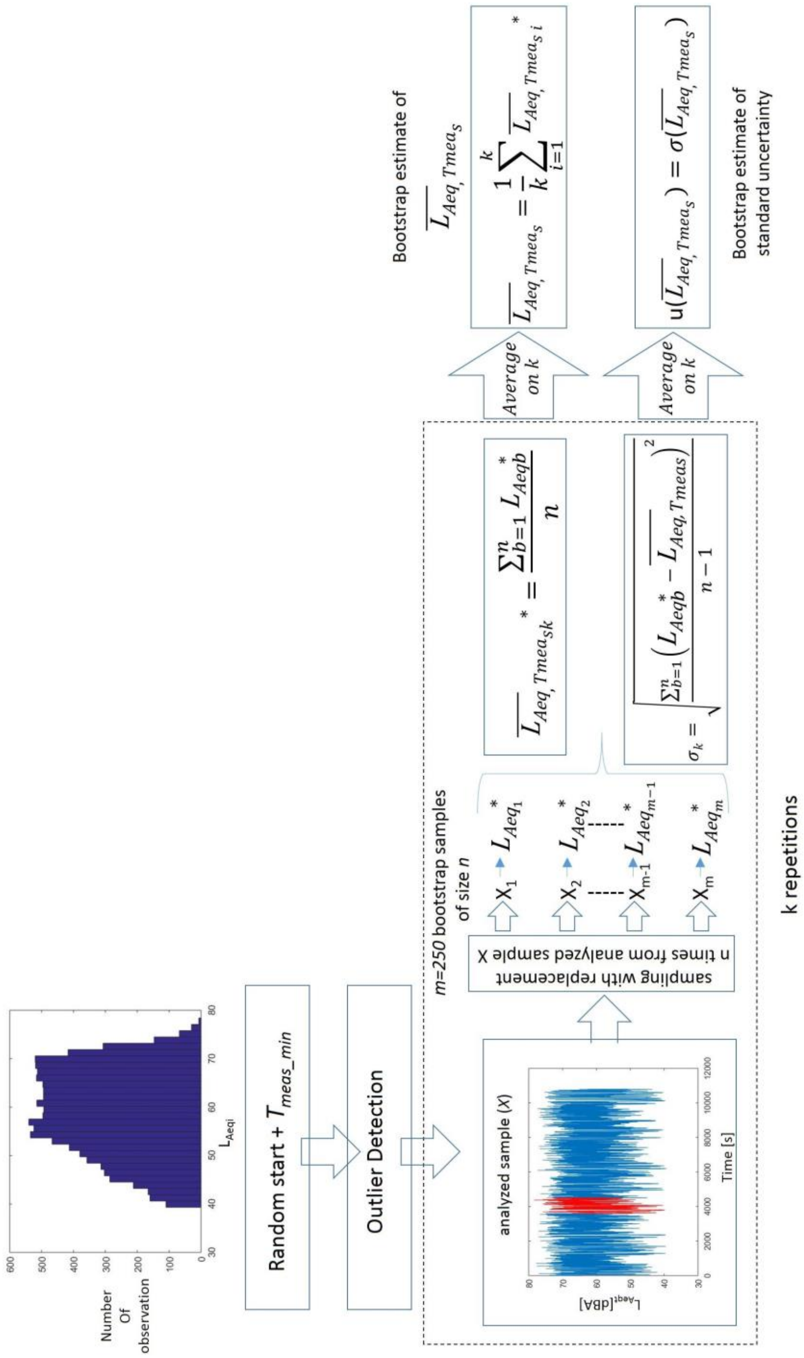

Figure V.1 *Estimation of expected value and standard uncertainty according to the bootstrap approach (NORM algorithm)*

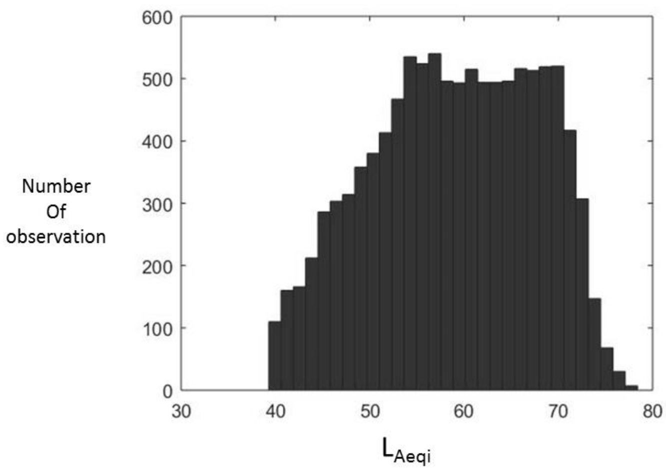

Figure V.2 *Histogram of occurrences*

The corresponding standard uncertainty is determined by eq. (2):

$$u(\bar{L}_{AeqTmeas}) = \sqrt{\frac{\sum_{i=1}^{n}\left(L_{Aeqi} - \bar{L}_{AeqTmeas}\right)^2}{n(n-1)}} \tag{2}$$

The calculation scheme according to the classical approach is depicted in Fig. V.3.

Table V.2 summarizes the comparison results when the classical and bootstrap approaches have been applied to the dataset at varying measurement time intervals (as multiples of the T_{meas_min}).

With regard to the bootstrap method, for each sample size, both the expected value and standard uncertainty are achieved as averaged values on k = 100 repetitions (in order to reduce the influence of the random sampling from the population).

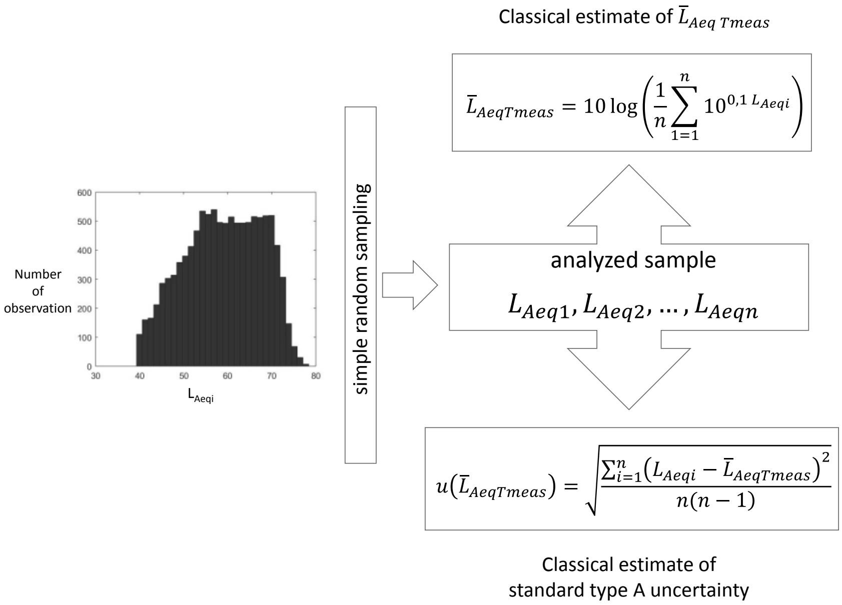

Figure V.3 *Estimation of expected value and standard uncertainty according to the classical method*

Table V.2 *Comparison of classical and bootstrap method for the estimation of the equivalent sound pressure level and standard uncertainty (road traffic as noise source)*

		Bootstrap Method		Classical Method	
Noise source	**Sample Size (n)**	**Expected Value [dB]**	**σ [dB]**	**Expected Value [dB]**	**σ [dB]**
Road traffic	900	65,42	0,27	65,43	0,40
	1800	65,44	0,17	65,45	0,27
	2700	65,16	0,14	65,16	0,21

The uncertainty analysis has been extended to the collected data of the environmental noise from the other noise sources (outdoor air conditioner fan motor and construction site) already introduced in section IV.4.

Furthermore, with regard to noise measurement of the outdoor air conditioner fan motor (heat pump and liquid chiller), the sound level meter is placed at a distance of 1 m from the nearest building facade and a height of 4 m from the ground and dataset is acquired during one day (wind lower than 5 m/second and without rain) by considering 50 minutes of the air conditioner fan motor working both at start-up and modulation state. With regard to the instrument setting, the time history logging step is fixed to 0.1 second, resulting in a dataset of 30000 consecutive sound pressure levels.

The minimum measurement time, estimated as previously introduced, is equal to 120 s during start-up state and to 360 s during modulation state.

Table V.3 *Comparison of classical and bootstrap method for the estimation of the equivalent sound pressure level and standard uncertainty (outdoor air conditioner fan motor and construction site as noise sources)*

		Bootstrap Method		Classical Method	
Noise source	**Sample Size (n)**	**Expected Value [dB]**	**σ [dB]**	**Expected Value [dB]**	**σ [dB]**
Air conditioner (Start up)	1200	61,040	0,016	61,52	0,027
	2400	61,160	0,020	61,16	0,022
	3600	61,130	0,016	61,13	0,016
Air conditioner (Modulation)	3600	57,350	0,075	57,351	0,088
	7200	56,975	0,057	56,977	0,057
	10800	57,115	0,057	57,118	0,055
Construction Site	60	69,65	0,14	69,96	0,14
	120	69,63	0,13	69,63	0,13
	180	69,63	0,12	69,64	0,12

With regard to the noise measurement of construction site, the sound level meter is placed at a distance of 2 m from the noise source and a height of 4 m from the ground. Data collection is performed during one day (wind lower than 5 m/second and without rain) by considering 10 consecutive hours (starting time: 10 p.m.). With regard to the instrument setting, the time history logging step is fixed to 1 minute, resulting in a dataset of 600 consecutive sound pressure levels. The minimum measurement time, estimated as previously introduced, is equal to 3600 s.

Table V.3 summarizes the comparison results when the classical and bootstrap approaches have been applied to the dataset acquired in the two scenarios at varying measurement time intervals (as multiples of the T_{meas_min}).

Generally the bootstrap approach allows for estimation of the equivalent sound pressure level with better precision (smaller measurement standard uncertainty σ) than the results by the classical approach for all types of noise source. As expected, the difference between the performance exhibited by the approaches reduces when an increasing sample size (and measurement time interval) is considered. No differences exist between the two approaches when they are applied to the dataset concerning the construction site, because this particular population, unlike the other noise sources, can not be considered as strictly Gaussian: the Anderson-Darling Test leads to not refusing the null hypothesis (H_0: "dataset is Gaussian"), because the *p* ("probability") value (equal to 0,0786) is major than significance level of 5%.

Finally, Table V.4 shows the synoptic view of the experimental results, in which, with reference to all considered noise sources, the global contribution of the measurand variability on measurement uncertainty is calculated. This takes into account the residual value of the standard deviation of outlier detection algorithm too. In particular, the uncertainty is evaluated considering both the estimated standard deviation and the residual uncertainty of the outlier detection algorithm [2].

These references are determined by the classical method applied to the whole population. As may be noted, both the classical and proposed methods lead to a very good estimation of the expected value for the short-term noise indicator when a reduced number of samples are considered. Moreover, the reduced sample size introduces an overestimation of the true standard uncertainty, that is more evident with the classical method. Furthermore, by increasing the sample size the measurement uncertainty decreases for both approaches and with regard to the bootstrap method the results are closer to that which was expected and the uncertainty is reduced. Finally, it is observed that the measurement results are always compatible with a coverage factor at least equal to 3.

The bootstrap approach seems to be a very promising technique for the prediction of the environmental noise indicator from a reduced set of measurement data.

Table V.4 *Estimation of the equivalent sound pressure level and uncertainty in measurement time and observation period*

		Bootstrap Method			Classical Method				
		Measurement time interval			Measurement time interval			Observation period	
Noise source	Sample Size (n)	Expected Value [dB]	σ [dB]	Global Uncertainty [dB]	Expected Value [dB]	σ [dB]	Global Uncertainty [dB]	Expected Value [dB]	Global Uncertainty [dB]
Road traffic	900	65,42	0,27	0,29	65,43	0,40	0,41	65,41	0,1
	1800	65,44	0,17	0,18	65,45	0,27	0,28		
	2700	65,16	0,14	0,15	65,16	0,21	0,22		
Air conditioner (Start up)	1200	61,040	0,016	0,101	61,52	0,027	0,104	61,1000	0,0050
	2400	61,160	0,020	0,074	61,16	0,022	0,074		
	3600	61,130	0,016	0,060	61,13	0,016	0,060		
Air conditioner (Modulation)	3600	57,350	0,075	0,125	57,351	0,088	0,133	57,080	0,051
	7200	56,975	0,057	0,091	56,977	0,057	0,091		
	10800	57,115	0,057	0,081	57,118	0,055	0,080		
Construction Site	60	69,65	0,14	0,17	69,96	0,14	0,17	69,540	0,070
	120	69,63	0,13	0,15	69,63	0,13	0,15		
	180	69,63	0,12	0,13	69,64	0,12	0,13		

V.3 Review

In this chapter, the global contribution of the environmental noise variability on equivalent sound pressure level measurement uncertainty, after the application of the alghoritms for minimum measurement time evaluation and outlier detection, is explored. This contribution takes into account both the equivalent sound pressure level standard uncertainty (σ) and the residual uncertainty of the outlier detection algorithm.

The proposal, based on normal bootstrap method, has been experimentally verified with real data acquired in three scenarios (road traffic, outdoor air conditioner fan motor and construction site as noise sources).

On the basis of the results analysis, this procedure has been revealed to be effective both for the prediction of noise levels and the corresponding uncertainties characterizing large time intervals by measuring only a short time window of the acoustic phenomena.

Chapter VI
Conclusions

Environmental noise pollution is one of the most significant contemporary health hazards for the working population in terms of the number of people affected.

Current legislation mainly focuses on the maximum acceptable limits with reference to the A-weighting equivalent level of environmental noise.

Most decision-making processes in this area, which may have also implications from an economic point of view, are based on the outcomes of these comparisons between a measured quantity and a legal threshold. The task of establishing decision-making rules to test the compliance of a product to its specifications must take into account the uncertainty of the measurement.

The aim of the research described in this work has been to create an innovative procedure for the assessment of the uncertainty of environmental noise measurement. There are several studies in the literature examining possible sources of uncertainty associated with this area i.e. characteristics of measurement instrumentation, variability of the measurement conditions and instrumentation calibration. However, in order to provide an adequate estimation of total uncertainty associated with the measurement of the equivalent level of environmental noise it is essential to consider the intrinsic variability of the measurand.

The proposal essentially consists of three phases.

In the first, because the reliability of the estimate of the environmental noise indicators depends significantly on the temporal variability of the noise, a Matlab procedure based on the bootstrap method CPER is undertaken to locate a corresponding minimum number of sound pressure levels relating to the minimum acquisition time necessary for ensuring statistical significance of the initial data set.

In the second, a numerical algorithm finds and deletes from a population of real data the anomalous values (outliers).

Finally, the uncertainty associated with the inherent variability of environmental acoustic noise is calculated using the normal bootstrap method.

It’s important to underline that in order to experimentally validate the proposed approach, several measurement campaigns have been carried out acquiring real data from different environmental noise sources, including road traffic, an outdoor air conditioner fan motor and a construction site.

The results are particularly interesting in part from the scientific point of view, because they demonstrate the reliability of the procedure for the indicator forecast of environmental noise when they are available few measurement data. However they are also of interest from a professional point of view, because they allow the experts working in this field to determine the appropriate measurement time range in an objective, automatic and independent (of the operator) way, in compliance with [75] as well as the contribution of the measurand variability on measurement uncertainty [2].

On the basis of this research's results, an advanced electronic measurement system of equivalent sound pressure level, with automatic real-time determination of the minimum measurement time and automatic real-time evaluation of inherent measurement uncertainty contribution, is introduced in the design phase. The principal intent of this is to integrate some additional blocks in the phonometric chain, in order to enhance to the traditional functions of the instrument.

In so doing, it is suggested that the procedure may become a guideline to be applied during measurement campaigns of environmental noise, by optimizing the measurement activities of technical operators.

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Appendix

ITALIAN LEGISLATIVE FRAMEWORK ABOUT NOISE POLLUTION

· Decree of 11 December 1996 "Application of the differential criteria for continuous production Cycle plants";

· Decree of 31 October 1997 "noise measurement methodology Airport";

· Decree of Council of Ministers President of November 14, 1997 "Determination of limit values of Sound sources";

· Presidential Decree of December 11, 1997 "Regulations for the reduction of noise pollution produced by civil aircraft";

· Decree of Council of Ministers President of December 5, 1997 "Determination of the acoustic requirements of buildings";

· Decree of 16 March 1998 "Techniques for detecting and measuring noise pollution";

· Presidential Decree of November 18, 1998, n. 459 "Regulations about provisions of Article 11 of Law 26 October 1995, n. 447, on noise pollution from rail traffic";

· Law ·of December 9, 1998, n. 426 "New environmental interventions"

· Decree of Council of Ministers President of April 16, 1999, n. 215 "Rules for determining the acoustic requirements of sound sources in places of detention in dancing and public entertainment and public exercises";

· Decree of 20 May 1999 "Criteria for the design of monitoring systems for the control of environmental noise levels around airports and criteria for the classification of airports in relation to the level of noise pollution";

· Decree of November 9, 1999, No. 476 "Regulations on amendments to the Decree of the President of the Republic December 11, 1997, n.496, concerning the prohibition of night flights";

· Decree of December 3, 1999 "Noise abatement procedures at airports and respect zones";

· Decree of 29 November 2000 "Criteria for the establishment by the companies and the managers of public services and transport entities or related infrastructure, the plans of containment interventions and noise abatement";

· Decree of April 3, 2001, n. 304 "Regulations on noise emissions produced in the performance of motor tasks, in accordance with Article 11 of the Law of 26 October 1995, n, 447";

· Law of 31 July 2002, 179 "Environmental provisions";

· Ministerial Decree of 1 April 2004 entitled "Guidelines for the use of innovative systems in the environmental impact assessment";

· Presidential Decree of March 30, 2004, n. 142 "Measures for the containment and prevention of noise pollution resulting from road traffic, in accordance with Article 11 of the Law of 26 October 1995, n. 447";

· Legislative Decree of 17 January 2005 n. 13 "Implementation of Directive 2002/30 / EC on the introduction of operating restrictions for the purposes of noise management at EU airports";

· Legislative Decree of 19 August 2005, n. 194 "Implementation of Directive 2002/49 / EC relating to the assessment and management of environmental noise";

· Legislative Decree of 19 August 2005, n. 195 laying -Implementation of Directive 2003/4 / EC on access to environmental information".

· Legislative Decree of 81/2008 Title VIII - Chapter II "Protection of workers against the risks from exposure to noise at work".