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A COUPLED METEOROLOGICAL CLASSIFICATION AND UNCERTAINTY INTERVAL EVALUATION APPROACH FOR LONG-TERM NOISE LEVEL ESTIMATION

Albert Alarcón¹ David Ecotière² Benoit Gauvreau³ Hubert Lefevre⁴

¹ EDF Hydro, 134 Chemin de l'étang 38950 Saint-Martin-le-Vinoux, France

² UMRAE, Cerema, G. Eiffel University, 11 rue Jean Mentelin, 67000 Strasbourg, France

³ UMRAE, G. Eiffel University, Cerema, 44344 BOUGUENAI Cedex

⁴ Cerema Centre-Est, 8-10 rue Bernard Palissy, 63017 Clermont-Ferrand Cedex 2, France

albert.alarcon@edf.fr

ABSTRACT

The prediction of the “long-term” (typically representative of one year period) noise level estimator is a major challenge/issue for the characterization of an environmental acoustic situation, whether it concerns road, rail, industrial or other outdoor noise sources.

In this work we study the possibility of predicting the above-mentioned long-term estimator by combining (i) a classification and variance analysis technique of both observed meteorological and acoustic conditions and (ii) an uncertainty-interval approach in order to calculate the sought estimator for a longer non-observed period of time.

In this context, the theoretical aspects of the coupling of the two techniques are first developed. In a second step, the approach is illustrated through an example using a database of 2-year duration including acoustic and meteorological measurements. In particular, the accuracy and convergence rate of the interval estimator is studied as a function of the duration of the observed conditions vs. the unobserved conditions over the 2-year reference period.

1. INTRODUCTION

Meteorological conditions are of main influence when it comes to atmospheric sound propagation. As a matter of fact, when noise emission from acoustic sources remains steady, the observed variability at receivers is mainly related to meteorological effects. In some cases, however, the influence of the ground effects may play a significant role too [1]. The most commonly assumed meteorological factors are wind-related although, in some specific situations, thermal effects can be of main influence.

Seasonal effects can also be significant over long periods of time, which requires, in certain circumstances, the characterization of suitable indicators.

As the measurement of both long-term acoustic and meteorological conditions is difficult to achieve in practice, we have studied the possibility of estimating this indicator using an uncertainty-interval approach estimation.

For this purpose, we have focused here on the coupling of two techniques proposed in the French NF S 31-120 standard [2], namely:

1. A technique concerning an uncertainty interval evaluation for long-term noise level estimation
2. A meteorological classification on influent parameters/factors for outdoor sound propagation using a variance analysis

In this context, the theoretical aspects of the coupling of the two techniques are presented in section 2. Section 3 is dedicated to illustrate this purpose through the 2-year database including acoustic and meteorological measurements. In particular, the stability and convergence rate of the interval estimator is studied as a function of the duration of the observed conditions vs. the unobserved conditions over the 2-year reference period. As a conclusion, a discussion is proposed concerning the adequacy of this technique to address complex outdoor noise situation where such a long-term estimator is required.

2. METHODOLOGY

This chapter is first devoted to the description of the two techniques mentioned above. In a second time, the steps necessary to combine both of them are specified.

2.1 Uncertainty interval evaluation for long-term noise level estimation

We are interested in estimating a long-term acoustic indicator for a given period LT defined as:

$$L_{LT} = L_{eq,LT} \quad (1)$$

During the LT period, it is assumed that observations of sound and meteorological data during this period are available (observed period). The rest of the time, only meteorological informations are available (non-observed period). The objective is therefore to calculate minimum and maximum long-term indicators in order to perform an interval evaluation of the LT sound level as in Eqn. (1).

We therefore proceed as follows:

- Among the available observations, the observed data are grouped into n distinct groups.

- The equivalent sound level L_{eq}^i is calculated for each group i .
- For each group i , the rate of occurrence of weather conditions over the entire observed period is calculated $p_{i,LT}$.

Considering that the observed period is smaller than the whole LT period we have:

$$\sum_{i=1}^n p_{i,LT} \neq 1 \quad (2)$$

The equivalent weighted level for the observed conditions is then estimated as follows:

$$\tilde{L}_{LT} = 10 \log \left(\sum_{i=1}^n p_{i,LT} 10^{0.1L_{i,eq}} \right) \quad (3)$$

On the other hand, we consider

$$p_0 = 1 - \sum_{i=1}^n p_{i,LT} = 1 - \sum_p \quad (4)$$

as the probability of non-observed conditions to appear on site. Thus, the long-term acoustic indicator sound level can be written as follows:

$$L_{LT} = 10 \log \left(\sum_{i=1}^n p_{i,LT} 10^{0.1L_{i,eq}} + p_{0,LT} 10^{0.1L_{0,eq}} \right) \quad (5)$$

After a few manipulations, the difference between the true (1) and the observed estimator (3) can be expressed as:

$$L_{LT} - \tilde{L}_{LT} = \Delta = 10 \log \left(1 + \frac{(1 - \sum_p) 10^{0.1L_{0,eq}}}{10^{0.1\tilde{L}_{LT}}} \right) \quad (6)$$

Considering the lack of knowledge of the unobserved class 0 noise contribution on the LT level, the adopted approach is to assume that L_{eq}^0 will be included in between the lower and higher levels of the observed groups. Thus, it can be said that:

$$L_{LT} \in [\tilde{L}_{LT} + \Delta_{\min}, \tilde{L}_{LT} + \Delta_{\max}] \quad (7)$$

with

$$\Delta_{\min, \max} = 10 \log \left(1 + \frac{(1 - \sum_p) 10^{0.1L_{\min, \max, eq}}}{10^{0.1\tilde{L}_{LT}}} \right) \quad (8)$$

2.2 Meteorological factors classification for outdoor noise propagation using a variance analysis

The technique adopted for meteorological factors classification is inspired from [3]. This technique aims at establishing a relationship between meteorological factors and noise levels at specific locations within the frame of outdoor noise propagation.

One of the reasons why this technique was chosen in this work is that it is capable of quantitatively associating classes of meteorological conditions with noise levels

statistical descriptors (e.g. means, standard deviations, etc.). Furthermore, these results can be obtained relatively automatically by the implementation of known data analysis algorithms.

For this purpose, it is assumed that a consequent amount of data is available where each sample is composed by values of the main meteorological factors and the corresponding acoustic measurements to be analyzed.

Thus, meteorological data may be analyzed from a statistical point of view and considered as influence factors related to the considered acoustic observations. Therefore, it is possible to classify the observed sound levels in different groups directly related to a cluster of factors.

The general approach of this technique consists of a four-step procedure as follows:

- Define the influence factors;
- Identify clusters of influence factors by means of the k-means algorithm;
- Proceed to a variance analysis test of the acoustic data in-between meteorological clusters. The test is based on a multi-level comparison Kruskal-Wallis statistical test;
- Use the Kruskal-Wallis results as a criteria to regroup the meteorological clusters that can be put together into larger groups.

Although this is a generic method and valid for all kinds of influencing factors and explained variables, in the case of environmental noise propagation, wind-related meteorological factors are often chosen.

Finally, the results of the implementation of this technique into a given dataset, leads to a set of self-consistent groups of weather conditions that correspond to statistically significantly different sound levels. For each group, statistical quantities such as the mean, median, standard deviation or equivalent sound level LA_{eq} can be characterized.

2.3 Combining both methods

Given a long-term dataset during a period LT, the combination of the two methods consists in implementing the following steps:

For the subset data of the observed period:

1. Apply the classification factor technique described in paragraph 2.2 in order to obtain an factor groups and their corresponding sound levels.
2. Compute for each of the groups i :
 - a. the equivalent sound level L_{eq}^i
 - b. a convex-hull of the related weather factors

- Evaluate the maximum and minimum sound levels of all the n groups:

$$\max(L_{i,eq}) \text{ et } \min(L_{i,eq}) \quad (9)$$

For the subset data of the non-observed period:

- For each sample, determine whether or not the sample belongs to a group of observed conditions. For this, test if the sample is inside or outside each convex-hull computed in step 2b.
 - If so, associate this sample to the identified group i and associate the corresponding sound level L_{eq}^i

With this additional information and for the whole dataset:

- Calculate the occurrence rates $p_{i,LT}$ for each one of the n groups.
- Evaluate the equivalent weighted level \tilde{L}_{LT} for the observed conditions as proposed in equation (3)
- Compute the probability of samples associated with unobserved conditions using the expression in (4).
- Compute min and max frame values according to (8)
- Obtain the long-term sound level interval estimation proposed in (7).

3. IMPLEMENTATION OF THE METHOD

3.1 Database description

A database of samples has been set up using the same method than in [4] or [5]. This method consists in the coupling of a sound propagation model [6] coupled to a micro meteorological model [7] and a large meteorological dataset from Meteo-France

The database consists of 17409 samples and covers a 2-year period. Each sample is composed of the following quantities:

$$s_i = \left\{ \overline{wd}, \overline{\nabla ws}, \overline{\nabla T}, LA_{eq,t_i} \right\}^2 \quad (9)$$

where the first three values correspond, respectively, to the average values in the period t_i of the wind direction, the vertical wind gradient and the vertical temperature gradient. The last value corresponds to the A-weighted equivalent sound level integrated in the related period. More precisely, the study shown below considers periods of $t_i=1h$.

The distribution of equivalent sound levels over the 24 months is shown in Figure 1, with a distribution of values in the range of about 21dB(A) to 41 dB(A) approximately.

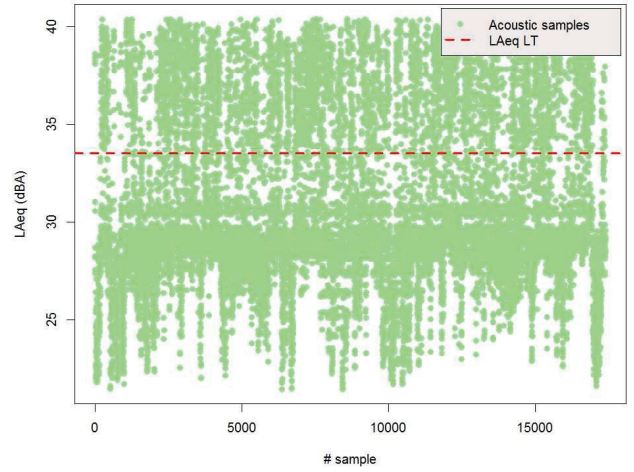


Figure 1. Distribution of the acoustic samples ($LA_{eq,1h}$) through the whole 2-years-span database and its corresponding long-term noise level ($LA_{eq,2year}$)

The long-term equivalent level for this database is represented by a horizontal red line in Figure 1 and corresponds to 33.5dB(A).

3.2 Long-term noise level estimation through interval calculation

In the following simulations, we will consider a variable observation duration. The shortest duration corresponds to 1 month (i.e. 720 samples for the current database under study).

In order to study the capacity of the method to correctly evaluate the sough long-term value and to study its convergence, we will proceed to a variation of the observation length. It will span from 1 month up to 24(total duration) by steps of 1 month.

For each of these observation periods, the method proposed in section 2.3 combining a meteorological factors classification and a long-term uncertainty interval evaluation will be carried out. The main results are given in the following figures.

Figure 2 below shows the evolution of the equivalent weighted level for the observed conditions and the upper and lower framing values as a function of the number of the observed samples.

Several elements are to be noticed in this graph:

- The "true" value of the long-term indicator appears to be always within the estimated interval, regardless of the duration of observation, so the estimate shows good a good convergence behavior towards the real value.
- The correction of the minimum interval value is often very small compared to the equivalent weighted level for the observed conditions \tilde{L}_{LT} , in contrast to the maximum value. It can

certainly be said that it is important to measure high sound levels representative of long-term conditions in order to have a good accuracy of the interval estimation size.

- The speed of convergence seems quite fast for the first few months and becomes very slow after 5-6 months of observation in this particular case.

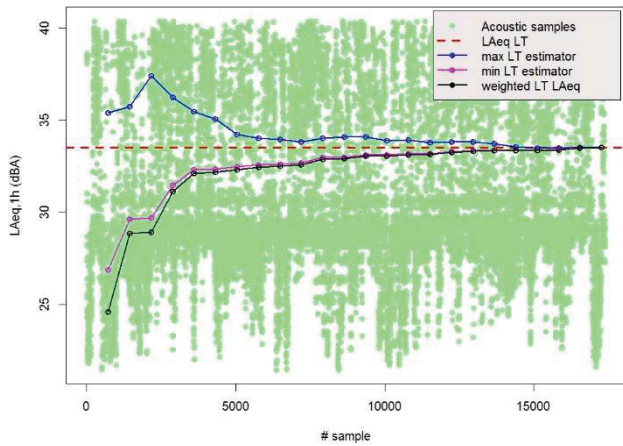


Figure 2. Long-term interval estimation (min, max and weighted observed estimator) as a function of the observed samples length

Figure 3 below illustrates the evolution of the median value within the calculated interval. There is a fairly good correspondence with the sought long-term value, suggesting that the interval is relatively centered with respect to it. A verification of this phenomenon with other acoustic situations would probably be of interest.

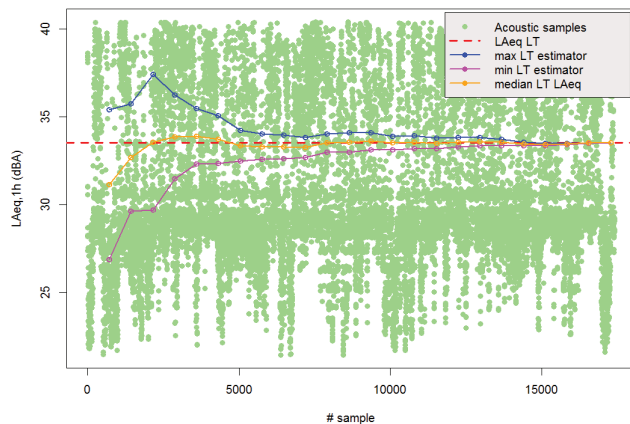


Figure 3. Long-term interval estimation (min, max and median interval estimator) as a function of the observed samples length

In any case, the convergence of this median level towards the target value presents, in the present case, the interest to converge very quickly towards the actual value, which results in a relatively short observation period (2 - 3 months).

In addition to the previous figures, the following figure 4 illustrates the properties of convergence on the

size of the interval as well as the error committed on the median indicator.

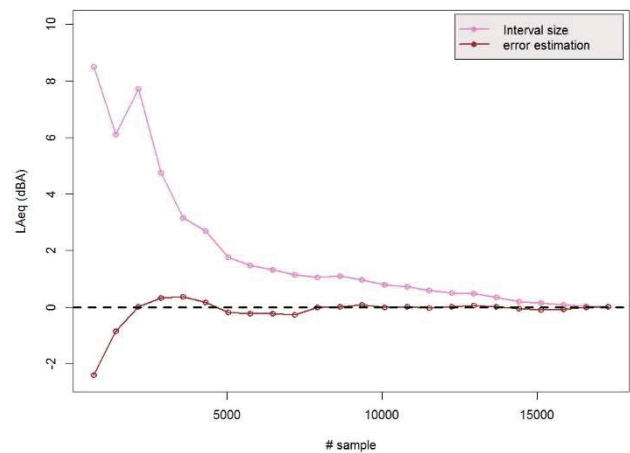


Figure 4. Convergence of the interval size estimator and the median estimator error as a function of the observed samples length

The following figure 5 completes this first experiment with the evolution of the quantities in figure 4 as a function of the % of non-observed conditions.

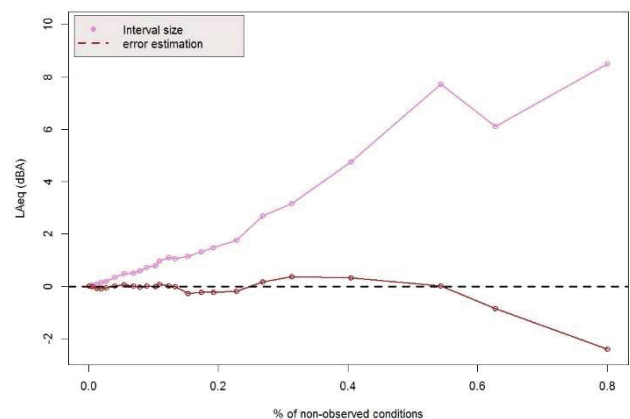


Figure 5. Convergence of the interval size estimator and the median estimator error as a function of the % of non-observed conditions

4. CONCLUSION

This first study proposes the construction of a methodology for a quantitative estimation of long-term acoustic indicators by combining two techniques. The first one is based on a classification and variance analysis technique of both observed meteorological conditions and acoustic situations. The second one is based on an uncertainty-interval approach estimation.

The coupling of these two techniques leads to a first numerical experiment based on a 2-year duration database composed by acoustical and meteorological information.

Results show good agreement between the true long-term noise estimator of the database and its estimation by means of the proposed technique. In particular, it is

interesting to observe that the interval remains centered on the target value. Moreover, the use of the median value of the interval as an LT estimator shows good accuracy and a fast rate of convergence.

In further studies it would be interesting to complete this work with other databases with, for example, a strong influence of seasonal atmospheric conditions or for complex acoustic scenes (e.g. road traffic sound propagation with important local meteorological and ground effects)

In addition, a sensitivity analysis of the weather factors used in the classification step would also be interesting in order to give some practical guidelines for such analysis in an operational context.

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