DOI: 10.61782/fa.2023.1068

STATISTICAL ANALYSIS OF SOUND LEVEL METER MONITORING

Domenico De Salvio* **Dario D'Orazio** **Massimo Garai**
Department of Industrial Engineering (DIN), University of Bologna, Italy

ABSTRACT

Long-term monitoring by means of sound level meters are one of the most common ways of analyzing indoor and outdoor sound environments by technicians. The equivalent sound level $\mathrm{L_{eq}}$ and statistical levels $\mathrm{L_n}$ - where *n* is the acoustical percentile of the statistical population - are the main noise descriptors used in the technical praxis. However, real-world scenarios are complex, and the mentioned metrics describe solely a general view of the monitored acoustic scene. Measurements show how long-term monitoring shape multimodal densities of sound pressure levels. Thus, clustering algorithms can provide deeper tools to perform statistical analyses on sound level meter monitoring. In the present work, the Gaussian Mixture Model (GMM) is used to analyze different synthetic scenarios based on real-world measurements. The comparison among the energetic and the statistical metrics used in the common praxis and the numerical features obtained via GMM highlights the ability of a deeper statistical approach to bring more insights to technicians to analyze active sound environments.

Keywords: *sound level meter, long-term monitoring, gaussian mixture model, noise analysis*

1. INTRODUCTION

In the last years, the acousticians' need for finer noise analyses in real-world scenarios has been growing. As a matter of fact, a noise source could have either positive or negative effects on people experience basing on the context. For instance, in offices the most distracting source is represented by the colleagues' speech [1]. Thus, the noise of mechanical sources, like HVAC systems, could help to disrupt the speech intelligibility and improve the workers' performances [2]. Further, in classrooms, especially in university lecture halls, the chatting among students could represent a robust metric to assess the students' focus levels [3]. Thus, the ability of separating noise sources in real contexts has becoming crucial.

Nowadays, the technical praxis handled by acousticians underlies strong assumptions to evaluate different portions of energy due to noise components. The main noise descriptors used are represented by the equivalent sound level $\mathrm{L_{eq}}$, and statistical levels. The latter indicates the sound pressure levels exceeded for a certain percentage of time indicated by their subscripts. The most used are $\mathrm{L_{10}}$, $\mathrm{L_{50}}$, and $\mathrm{L_{90}}$. Moreover, the physical meaning of statistical levels is not always accurate, except for $\mathrm{L_{90}}$, which is usually referred to the background noise without the source investigated. The assessment of sound environments relies on rule of thumbs.

Previous authors' works investigate and propose a different approach to sound level meter analyses on long-term monitoring. It is based on the analysis of the occurrences curve obtained from a long-term monitoring of the real scenario carried out through machine learning algorithms. Two unsupervised techniques, the Gaussian Mixture Model (GMM) and the K-means clustering (KM), has been used in offices and university lecture halls to identify, separate and measure different kinds of noise sources [4–6]. A deep learning approach, made through a variational autoencoder, assessed the GMM as the best algorithm to perform this kind of analyses [7].

In this work, to visualize better the differences between the two approaches, i.e., the classical praxis and the proposed method, 6 different synthetic scenarios based on real-world measurements are presented. The aim is to obtain useful insights about the possible sources' behavior by varying two main parameters of sound contexts: the signal-to-noise ratio, and the standard deviation of each kind of source. The comparison between the results ob-

****Corresponding author***: *domenico.desalvio2@unibo.it.*

tained via GMM and the equivalent and statistical levels provides useful insights about the lack of details of the common praxis and the use of more advanced statistical methods to analyze long-term monitoring.

2. GAUSSIAN MIXTURE MODEL

The GMM is a clustering technique that describes a generic distribution as a linear combination of Gaussian curves [8]. The assumption is that all data points are generated from a mixture of Gaussian distributions. The Gaussian probability density function $f(x_i)$ of a set of observations $x_1, \ldots, x_n$ can be expressed as a sum of K Gaussian densities $f_k(x_i, \mu_k, \sigma_k^2)$:

$$f(x_i) \cong \sum_{k=1}^{K} \pi_k f_k(x_i, \mu_k, \sigma_k^2) \tag{1}$$

where μ_k is the mean of the cluster, σ_k^2 the variance, and π_k the mixing proportions, non-negative quantities that sum to one. The likelihood function for a mixture model with K univariate normal components is:

$$\mathcal{L} = \prod_{i=1}^{n} \sum_{k=1}^{K} \pi_k \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{-\frac{(x_i-\mu_k)^2}{2\sigma_k^2}}. \tag{2}$$

In this study, the GMM uses the Expectation-Maximization algorithm to fit the original distribution.

3. METHOD

Several works pointed out how the sound pressure levels collected during long-term monitoring shape a multimodal distribution regardless the context [3, 4, 6, 9]. Figure 1 shows two examples of SPLs occurrences collected during a long-term monitoring carried out in two different contexts: a office and a university lecture hall. According to previous studies, the GMM results to be the most flexible and reliable algorithm to analyze a sound level meter long-term monitoring [7]. Thus, it is possible to create synthetic acoustic scenarios combining different Gaussian curves. Here, 6 scenarios has been shaped. As a preliminary analysis, some simplifications must be made to create ideal situations. Thus, the synthetic cases are considered made only by 2 Gaussian components with mixing proportions equal to 0.5. This means that the fluctuations of single components are entirely delegated to the standard deviation (s.d.).

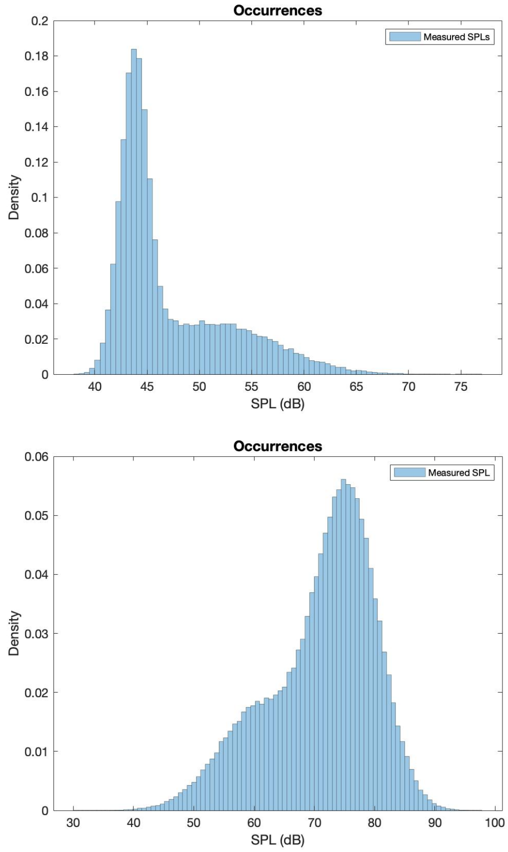

Figure 1: SPLs collected during a long-term monitoring in two different contexts. On the top: a office. On the bottom: a lecture in a university hall.

Previous works confirmed a s.d. equal to 5 dB as a good threshold to separate and identify a mechanical noise from a human source, i.e., speech [4, 7]. Thus, scenarios *a* and *b* depict the condition with two mechanical sources; scenarios *c* and *d* are constituted by the interactions of a mechanical source and a human source; scenarios *e* and *f* represent the case with two human sources.

Then, all scenarios are analyzed with two different signal-to-noise ratios (SNRs), 5 and 15 dB, respectively. The SNR is managed moving closer or farther the means in settings. Table 1 shows the main parameters used to shape the synthetic Gaussian mixtures. A s.d. equal to 7 dB for both sources is needed in scenarios *e* and *f* to evaluate what happens in the rare case of two identical sources. The latter cases are very unlikely in real-world scenarios

Table 1: Main parameters used to create the synthetic scenarios through Gaussian mixtures.

Scenario	SNR	Means	s.d.
	dB	dB	dB
a	15	[35;50]	[2;3]
b	5	[45;50]	[2;3]
c	15	[35;50]	[1.5;7]
d	5	[45;50]	[1.5;7]
e	15	[35;50]	[7;7]
f	5	[45;50]	[7;7]

but are useful to understand the behavior of each Gaussian curve in different kind of mixtures. The statistical populations have 36k samples, corresponding to a monitoring about 1 hour long obtained with an interval time of the sound level meter equal to 0.1 s. Further, the corresponding 10, 50, and 90 statistical levels and the equivalent level of the synthetic populations have been obtained to compare the approach based on the common praxis with the use of GMM.

4. RESULTS AND DISCUSSIONS

The results of the calculations made on the synthetic scenarios are shown in Figure 2. Here, the blue curve represents the mixture obtained from the scenario's settings. The two components are shown in orange and yellow, respectively. The equivalent and statistical levels are indicated in purple, green, cyan, and red. Quantitative results are reported in the plots.

Narrow and large s.d. have been used in different cases to simulate more steady and random sources, respectively. According to the literature and the case studies cited in previous works, L_{eq} and L_{90} are assumed with the same physical meaning as Mean2 and Mean1. In all scenarios, it is possible to notice how L_{eq} is close to Mean2, i.e., the SPL of the highest sound source. L_{eq} is higher than Mean2 in all the cases except scenarios *a* and *b*, where the s.d. of both sources are low. L_{90} is always lower than Mean1. Differences, as seen for L_{eq} and Mean2, are less noticeable when the s.d. is low. More than the SNR, the s.d. seems to affect the results. The range of the statistical metrics varies differently per each one. Considering all scenarios, L_{10} spans in the range 52.5 – 56.9 dB, L_{50} in 37.6 – 47.4 dB, L_{90} in 29.1 – 43.2 dB, and L_{eq} in 48.1 – 53.8 dB.

It is worth noting in scenario *f* how a low SNR of two identical sources shapes a single peak of the occurrences curve. Thus, in real situation this kind of curve would have been fitted with only one component with a mean around 47.5 dB. However, having two identical sources with SPLs equal to 45 and 50 dB, respectively, the total sum of both sources should have had an SPL around 51.2 dB. This case represents the deep difference between the energetic and statistical approach. The sound source is not represented by L_{eq}, which is equal to 53.8 dB indeed, but by means of the most frequent SPL measured. Nevertheless, it must be highlighted that the scenario *f* is an extremely rare situation. It could be possible only with two identical human sources, i.e., speeches. Moreover, the same statistical analysis carried out in the whole spectral domain would have detected some differences in the two different voices. Spectral analyses can be carried out applying the cluster analysis over all the single statistical population obtained each frequency band acquired during the measurement.

In summary, synthetic ideal distributions show how neither L_{eq} nor L_{90} is able to adequately measure the SPL of a sound source. L_{eq} and statistical levels result to be useful to describe the extent of noise fluctuations and depict a general overview of the sound environment. However, they do not seem accurate enough to measure a sound source in a mixture. The combination of the classical approach and the proposed one shows how few features would bring a lot of information to technicians to analyze a sound context.

5. CONCLUSIONS

The present work investigates two different approaches to a sound level meter long-term monitoring. The comparison between the metrics used in the common praxis and the features obtained through the GMM shows how a classical approach to the collected SPLs lacks of real details about the acoustic scene. The GMM allows to detect the most frequent SPL of the single components that shape the mixture. The distribution function of SPLs shows how the classical approach works. It assesses the acoustic scene without considering how the distribution is shaped by the monitored activity. Statistical and equivalent levels do not correspond to any feature of the statistical population. On the contrary, peaks – and points of inflections in the corresponding cumulative visualization of the distributions – of both probability curves seem to give back a more consistent readability of the acoustic environment. All the

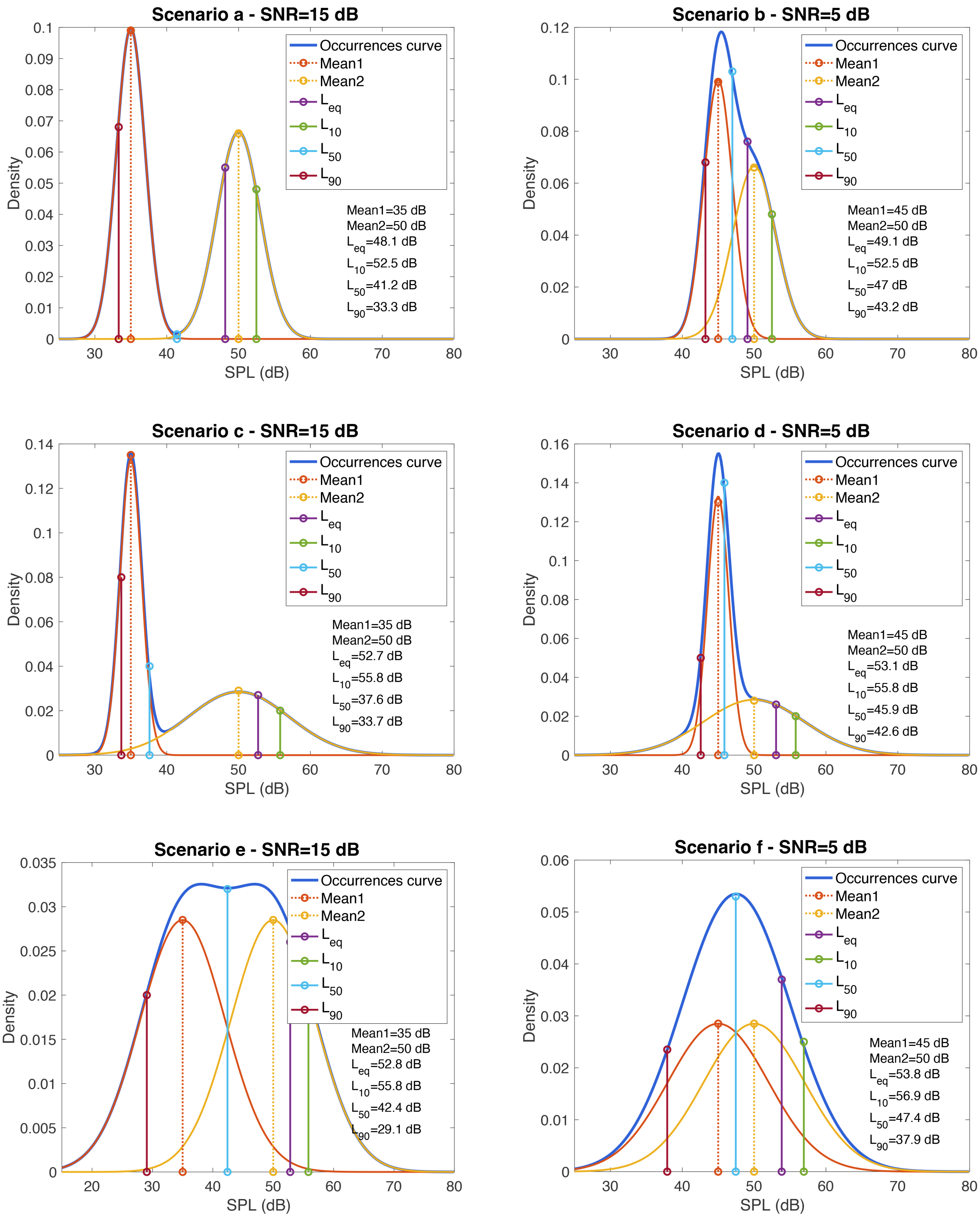

Figure 2: Synthetic scenarios of Gaussian mixtures with different SNR and standard deviations. Means of each component, and the corresponding L_{eq}, besides the 10, 50, 90 statistical levels of each distribution are shown.

synthetic scenarios presented here are based on real-world measurements already analyzed in previous works. The proposed method starts with in-fields applications. After the evaluation of the common characteristics of data distributions, the synthetic scenarios have been replicated. Besides realistic cases, very unlikely scenarios have been assessed to make more general considerations about the method, the distributions, and the conventional metrics used in the praxis. Further works will concern broader and more complex scenarios to investigate the influence of each feature to the resulting mixture.

6. REFERENCES

[1] W. Ellermeier, M. Eigenstetter, and K. Zimmer, "Psychoacoustic correlates of individual noise sensitivity," *The journal of the acoustical society of America*, vol. 109, no. 4, pp. 1464–1473, 2001.

[2] I. Alimohammadi and H. Ebrahimi, "Comparison between effects of low and high frequency noise on mental performance," *Applied Acoustics*, vol. 126, pp. 131–135, 2017.

[3] M. Hodgson, R. Rempel, and S. Kennedy, "Measurement and prediction of typical speech and background-noise levels in university classrooms during lectures," *The Journal of the Acoustical Society of America*, vol. 105, no. 1, pp. 226–233, 1999.

[4] D. De Salvio, D. D'Orazio, and M. Garai, "Unsupervised analysis of background noise sources in active offices," *The Journal of the Acoustical Society of America*, vol. 149, no. 6, pp. 4049–4060, 2021.

[5] D. D'Orazio, D. De Salvio, L. Anderlucci, and M. Garai, "Measuring the speech level and the student activity in lecture halls: Visual-vs blind-segmentation methods," *Applied Acoustics*, vol. 169, p. 107448, 2020.

[6] D. De Salvio, D. D'Orazio, and M. Garai, "Effectiveness of acoustic treatments and pa redesign by means of student activity and speech levels," *Applied Acoustics*, vol. 194, p. 108783, 2022.

[7] D. De Salvio, M. J. Bianco, P. Gerstoft, D. D'Orazio, and M. Garai, "Blind source separation by long-term monitoring: A variational autoencoder to validate the clustering analysis," *The Journal of the Acoustical Society of America*, vol. 153, no. 1, pp. 738–750, 2023.

[8] G. J. McLachlan, S. X. Lee, and S. I. Rathnayake, "Finite mixture models," *Annual review of statistics and its application*, vol. 6, pp. 355–378, 2019.

[9] T. S. Dehlbæk, J. Brunskog, C. M. Petersen, and P. Marie, "The effect of human activity noise on the acoustic quality in open plan offices," in *INTER-NOISE and NOISE-CON Congress and Conference Proc.*, vol. 253, pp. 4117–4126, Institute of Noise Control Engineering, 2016.