



Rectification of wind farm noise monitoring data using effective time estimates

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ABSTRACT

Most wind farm analysis procedures, whether for background noise monitoring or compliance checking, involve collecting 10-minute blocks of data correlated with the wind speed measured at the hub height of wind turbines. The first step in data analysis is rectification, which excludes periods with rain, high local wind speeds, and extraneous noises. While filtering out data for adverse environmental conditions is straightforward and based on available precipitation and wind speed records, detecting data blocks affected by extraneous noises remains challenging. Listening to weeks of audio records is impractical, and there are no widely used procedures for automatically rectifying data affected by extraneous noises. This paper suggests a relatively simple method to detect data blocks significantly affected by extraneous noises. It involves computing the effective time for each block of sound pressure level time histories and comparing them with the effective time estimates of reference blocks. This technique was tested for wind farm data analysis and found to be a promising tool for data rectification.

1 INTRODUCTION

The integrity of noise monitoring data is paramount to ensuring compliance with regulatory standards and addressing community concerns. Several methods have been proposed and developed to rectify noise data and identify periods contaminated by extraneous noises. These methods range from audio records listening to complex artificial intelligence approaches, each with its own strengths and limitations (Bianco *et al*, 2019, Halkon *et al*, 2024, Nguyen *et al*, 2021).

One common approach involves an audiometric analysis, where experts listen to audio recordings to identify and exclude segments containing non-wind farm noise. While this method is still used as a reference method, it is time consuming and impractical for a long term monitoring programme.

Other approaches may involve frequency analysis, using statistical models and machine learning algorithms to classify noise data. These techniques often rely on training datasets and can effectively identify patterns indicative of extraneous noises. However, they require significant computational resources and expertise in data science and still may not provide good effectiveness in segregating monitoring data.

The method proposed in this paper offers a balance between simplicity and effectiveness. By computing the effective time for each 10-minute data block and comparing it with reference blocks, the approach automates the rectification process without the need for extensive computational efforts or complex data post-processing. This technique has shown promise in preliminary tests, indicating its potential for broader application in wind farm noise monitoring.

2 CONCEPT OF EFFECTIVE TIME

In signal processing, effective time is a quantitative measure that characterises the temporal localisation of a signal's energy. It serves as a proxy for identifying the time interval during which the signal is most active or concentrated, offering insight into the timing of dominant features such as transients, bursts, or modulated components.

Traditionally, effective time is defined using the second-order energy moment, based on the squared modulus of the signal. However, in applications requiring higher sensitivity to energy concentration, particularly where transient or impulsive behaviour is of interest, a more selective formulation is beneficial. In this context, we define effective time using the fourth power of the envelope of the analytic signal, denoted as: (Muller *et al*, 2020, ISO, 2017):

$$z(t) = p(t) + j H\{p(t)\}, \quad (1)$$

$$t_{eff} = \frac{\left(\int_{-\infty}^{+\infty} |z(t)|^2 dt\right)^2}{\int_{-\infty}^{+\infty} |z(t)|^4 dt}, \quad (2)$$

where $z(t)$ is the analytic signal of a real valued signal $p(t)$, $H\{p(t)\}$ is the Hilbert transform of $p(t)$, t_{eff} is the effective time. This formulation prioritises short-duration, high-intensity events—such as bird chirps, dog barks, or the brief passage of vehicles—which are typical sources of noise contamination in wind farm acoustic datasets. For continuous periodic signals like sine or cosine functions, the effective time converges to the total elapsed time.

For comparative analysis across varying time windows, it is often beneficial to report the relative effective time:

$$r_{eff} = \frac{t_{eff}}{T}, \quad (3)$$

where T is the elapsed time of the time history.

2.1 Note on effective time estimation

Effective time over a finite time period may be computed using the formulations presented in the previous section. The numerator in equation (2) can be evaluated without explicitly performing the Hilbert transform, by applying known energy relations for analytic signals (Bendat, 2010):

$$\int_0^T |z(t)|^2 dt = 2 \int_0^T p(t)^2 dt. \quad (4)$$

For signals with zero mean, energy can be expressed in terms of variance, bypassing direct integration. Several signal processing platforms, such as MATLAB, provide built-in statistical utilities for computing these properties efficiently.

The denominator in equation (2), however, poses greater computational complexity. It involves fourth-order integrals of both the signal and its Hilbert transform, as well as their squared products. While direct computation via Hilbert methods is one approach, an alternative route leverages statistical moments. Specifically, the fourth-order integral of the signal can be estimated using kurtosis β , defined for a zero-mean continuous signal (ISO, 2017):

$$\beta = \frac{T \int_0^T p(t)^4 dt}{\left(\int_0^T p(t)^2 dt\right)^2}. \quad (5)$$

For specific classes of signals, such as amenable to accurate Fourier decomposition, the integral of the fourth power of the signal and its Hilbert transform may yield similar results. However, this equivalence does not hold universally. Likewise, expressions involving the product of squared signal and Hilbert components may simplify under certain conditions but generally require bespoke analytical or numerical treatment.

In practice, the calculation of effective time may be substantially simplified for signals with known structural properties. Nonetheless, for general signals encountered in wind farm monitoring—often characterised by non-stationarity and impulsive noise—direct integration remains the most robust and broadly applicable approach.

2.2 Suggested procedure to rectifying data blocks

The proposed rectification method builds on regulatory practices outlined in regional guidelines for wind farm noise assessment, which typically involve analysing 10-minute noise data blocks correlated with hub-height wind speed (NZS, 2010; SA EPA, 2021; Queensland Government, 2025). Under these standards, each block is assumed to cover an equal elapsed time. Central to this method is the concept of effective time, defined as the duration within each 10-minute block during which the measured sound pressure levels reflect the operational noise of the wind farm, free from significant extraneous noises.

The initial step involves identifying and excluding data blocks contaminated by rain or high local wind conditions. Specifically, noise records collected when microphone-level wind speed exceeds 5 m/s should be disregarded unless a special wind shield with low wind induced noise has been fitted.

For blocks not affected by adverse environmental conditions, effective time is calculated using time histories of sound pressure level (SPL). These histories, recorded during wind farm operation, are processed using the techniques outlined earlier in Section 2. A reference range of effective time is established from baseline blocks known to be free from extraneous noise, such as transport, fauna, or unrelated anthropogenic sources. This range acts as a benchmark for evaluating other blocks. By comparing each block's computed effective time to the reference range, anomalous blocks are excluded where deviations suggest excessive intrusion from non-wind farm noise. This comparative analysis facilitates systematic data rectification, bolstering the integrity and reliability of the overall noise monitoring dataset.

3 PROCESSING WIND FARM MONITORING DATA

The proposed data rectification technique was applied to time histories acquired from a noise monitoring program conducted in a complex acoustic environment. Measurements were collected at a rural sensitive receiver site, approximately 3 km from the nearest turbine, following protocols outlined in NZS 6808:2010 (NZS, 2010). Wind turbine noise was periodically audible above both natural ambient sounds and household activity.

As standard practice, initial rectification steps excluded data blocks affected by adverse environmental conditions (e.g., rainfall or elevated wind). Notably, data collected during microphone-height wind speeds exceeding 5 m/s were discarded, unless low-noise wind shielding was utilised.

Weather data from the wind farm's meteorological mast facilitated the identification of candidate reference blocks. Downwind conditions during nighttime or early morning hours were prioritized, as these are generally less influenced by wildlife, agricultural operations, or domestic activities. Still, reference blocks were only finalized after confirming audible dominance of wind turbine noise through audio inspection of corresponding records.

Time histories of A-weighted, C-weighted, and Z-weighted (unweighted) sound pressure levels (SPLs) were normalized to a zero mean for each 10-minute block to remove DC component. However, Z-weighted SPL traces exhibited excessive scatter, limiting their utility for rectification. Only A-weighted and C-weighted SPL histories were retained and illustrated in Figure 1.

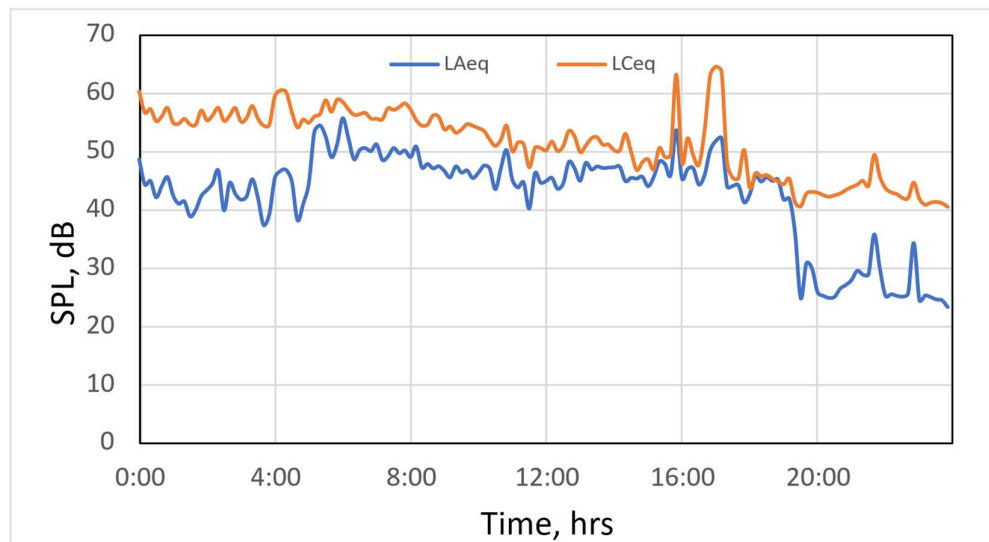


Figure 1: Time history of 10 min SPL estimates

The data was utilised to compute effective times for 10-minute periods. Corresponding effective time estimates are presented in Figure 2.

Effective time estimates were derived for each 10-minute data block, they are shown in Figure 2. Reference blocks yielded a relative effective time range of 0.46–0.61 for A-weighted SPL traces. Blocks falling outside this range

were interpreted as contaminated by extraneous noise events, which introduce SPL “spikes” and thus distort the signal’s effective time.

Examples of 10- minute estimates of relative effective time for one day of monitoring is presented in Figure 2. Analysis of the day’s monitoring data revealed that most “valid” blocks fell within nighttime or early morning periods. Non-wind farm noise sources dominated other periods. From this sample:

- false positives: 4 blocks (2.8%) were incorrectly accepted

- false negatives: 6 blocks (4.2%) with audible turbine noise were missed.

These error rates compare favourably against more computationally intensive post-processing approaches.

There is no significant difference in range of effective time estimates obtained from C-weighted time histories for night, morning or day periods. Both C- and Z-weighted SPLs were more vulnerable to minor extraneous noise, leading to much greater misclassification rates.

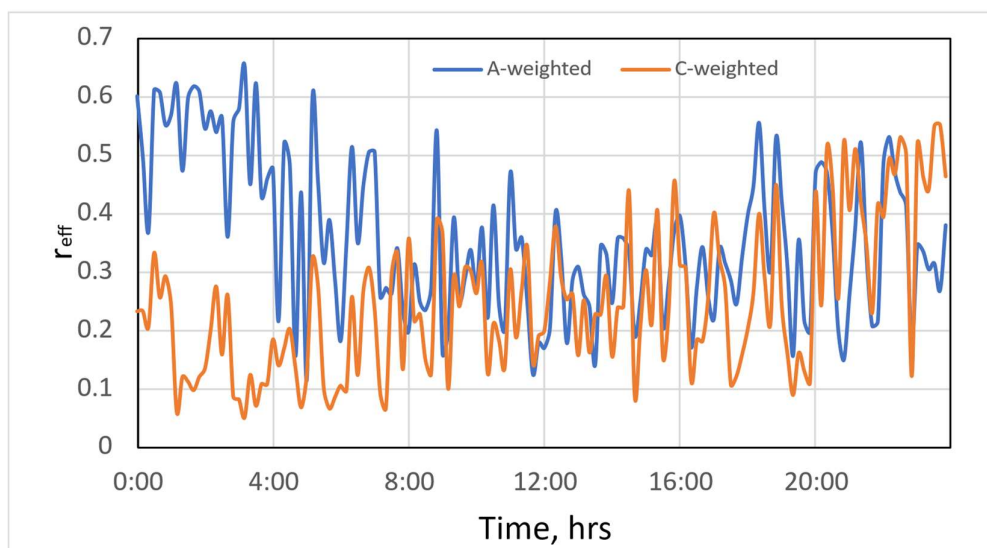


Figure 2: Relative effective time estimates for 10-min monitoring periods

It should be noted that this dataset represents a challenging monitoring scenario, where turbine noise was audible approximately 26% of the time and continuously mixed with background sources. In areas with clearer acoustic dominance by the wind farm, the proposed method may yield improved precision and fewer classification errors.

4 SUMMARY

This study presents a practical and efficient method for rectifying valid data blocks acquired during extended noise monitoring programs. The approach leverages comparisons of effective time estimates computed from time histories of equal elapsed duration against a predefined reference range. Data blocks exhibiting effective times outside this range are likely to contain extraneous acoustic events, such as wildlife activity or domestic noise. Due to its simplicity and scalability, this method is particularly suitable for large datasets, such as those encountered in regulatory compliance assessments of wind farms. It demonstrates favourable error rates and practicability compared to more complex post-processing techniques. The technique can serve as a foundational tool for developing advanced rectification frameworks, especially when integrated with additional acoustic descriptors or statistical parameters. This may enhance accuracy in distinguishing wind turbine-related noise in a complex acoustic environment.

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