

Distracting background noise

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- **1. The basic problem**

At an immission microphone near a dwelling, what you measure is essentially a mixture:

$$x(t) = s_{WT}(t) + s_{background}(t) + n(t)$$

where $s_{WT}(t)$ is the wind-turbine contribution.

In the frequency domain, if the sources are statistically uncorrelated, one can approximately write

$$P_x(f) = P_{WT}(f) + P_{background}(f)$$

and therefore

$$P_{WT}(f) \approx P_x(f) - P_{background}(f).$$

This is the basic principle behind energetic background correction.

The difficulty is that **wind-turbine noise and background noise are both strongly dependent on meteorological conditions**. Wind speed, wind direction, atmospheric stability and turbulence can all affect the received sound. Wind can also generate noise directly at the microphone.

Consequently, a background measurement made at a different time is not necessarily a good estimate of the background that existed while the turbine was operating.

- **2. Turbine on/off measurements**

The simplest approach is:

1. turbine operating $\rightarrow$ measure L_{total} ;
2. turbine stopped $\rightarrow$ measure $L_{background}$.

Then perform energetic subtraction:

$$L_{WT} = 10 \log_{10} (10^{L_{total}/10} - 10^{L_{background}/10}).$$

This is physically sensible provided the background conditions during the two measurements are sufficiently comparable.

The problem is obvious: you have to stop the turbine, and atmospheric conditions may change between the two measurements.

For enforcement this is therefore inconvenient if the objective is **continuous monitoring while the turbine remains operational**.

- **3. Statistical separation using long-term measurements**

A much more interesting approach is to continuously record the sound for weeks or months.

For each short time interval—for example 1, 10 or 60 seconds—you could record:

- broadband sound level;
- 1/3-octave or FFT spectrum;
- wind speed;
- wind direction;
- temperature;
- turbulence;
- turbine electrical power;
- rotor speed;
- pitch angle;
- yaw angle;
- other SCADA parameters.

You can then construct a model such as

$$L(f, t) = F(f, v_{\text{hub}}(t), P(t), RPM(t)\theta(t) \dots) + B(f, t)$$

where F represents the turbine-related component and B the residual/background component.

This is essentially **statistical source separation or system identification**.

The important advantage is that you don't have to declare a particular measurement period to be "background noise". Instead, thousands of observations can establish how the acoustic signal changes systematically with turbine operation.

4. Amplitude modulation and blade-passing frequency

This is particularly interesting for wind turbines.

A three-bladed turbine rotating at N rpm has a blade-passing frequency

$$f_{\text{BPF}} = 3 \frac{N}{60}.$$

For example, at 12 rpm:

$$f_{\text{rotation}} = 0.2 \text{ Hz}$$

and

$$f_{\text{BPF}} = 0.6 \text{ Hz}.$$

The acoustic signal can exhibit periodic amplitude modulation associated with blade rotation.

Thus, instead of merely asking:

Is there acoustic energy at this frequency?

one can ask:

Is the amplitude of the acoustic energy periodically modulated at a frequency corresponding to the *actual* rotor speed?

That gives a potentially powerful **turbine fingerprint**.

Recent research is investigating the use of turbine operational data and modulation frequencies to identify periods in which wind-turbine noise dominates long-term field recordings.

5. Coherence with turbine operation

An even stronger method is to have an independent reference signal from the turbine.

For example:

- rotor RPM;
- tachometer;
- blade-passing frequency;
- generator rotational signal;
- SCADA-derived rotor speed;
- a microphone closer to the turbine.

Let the acoustic signal at the house be $x(t)$, and the turbine reference signal be $r(t)$.

You can calculate the cross-power spectral density

$$S_{xr}(f)$$

and the **magnitude-squared coherence**

$$\gamma_{xr}^2(f) = \frac{|S_{xr}(f)|^2}{S_{xx}(f)S_{rr}(f)}.$$

The coherence ranges from 0 to 1.

Roughly:

- $\gamma^2 \approx 0$: little statistical relationship;
- $\gamma^2 \approx 1$: strong relationship.

This allows you to identify acoustic components that are **coherent with the turbine's actual operation**.

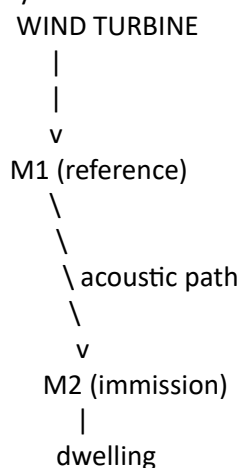
That is particularly attractive for enforcement because it provides a physical discriminator between turbine noise and unrelated sources such as:

- traffic;
- agricultural machinery;
- aircraft;
- insects;
- vegetation/wind noise.

6. Two microphones

Another relatively simple improvement is to use two microphones.

Conceptually:



The two microphones receive the turbine signal at different levels and with different propagation delays.

Local background sources may behave quite differently at the two microphones.

You can therefore calculate:

- cross-correlation;
- cross-power spectrum;
- phase difference;
- coherence.

If a component is coherent between M1 and M2, while another is local and incoherent, the two can potentially be separated.

This can be considerably more informative than simply subtracting two sound-pressure levels.

7. Microphone arrays and beamforming

This is probably the most powerful purely acoustic approach.

Instead of one microphone, use an array:

M1

M2 M3
 M4
 M5 M6



WIND TURBINE

Every microphone receives the same source with slightly different:

- arrival time;
- phase;
- amplitude.

From those differences it is possible to estimate **where the acoustic energy is coming from**.

If the turbine is known to be at, for example,

$$\theta_{WT} = 27^\circ,$$

the array can preferentially identify sound arriving from that direction.

This is the principle of **beamforming**.

There is very relevant experimental work here. Ramachandran, Raman and Dougherty investigated a 24-microphone compact array on a 1.5 MW wind turbine and used advanced deconvolution beamforming methods including **DAMAS** and **CLEAN-SC**. They were able to distinguish aerodynamic and mechanical noise sources and localise blade and nacelle contributions. ScienceDirect

Ramachandran et al. — Wind turbine noise measurement using a compact microphone array

A later study investigated locating and tracking sound sources on a horizontal-axis wind turbine using a compact microphone array and beamforming. ScienceDirect

Locating and tracking sound sources on a horizontal-axis wind turbine using a compact microphone array

8. Direction-of-arrival

You don't necessarily need a large professional acoustic camera.

A smaller four-microphone array could be used to estimate **direction of arrival (DOA)**.

You know the geographical position of the turbine, so you can ask:

Does the acoustic signal contain a component arriving from the turbine's direction?

This can be combined with rotor-speed information.

For example:

candidate turbine noise = correct direction + correct modulation + correct RPM relationship.

That combination becomes much harder for an unrelated background source to mimic.

9. Blind Source Separation

There is also a whole class of signal-processing techniques known as **Blind Source Separation (BSS)**.

You can represent the measurements as

$$x(t) = As(t)$$

where, for example,

$$s(t) = \begin{bmatrix} s_{\text{turbine}}(t) \\ s_{\text{traffic}}(t) \\ s_{\text{agriculture}}(t) \\ s_{\text{wind}}(t) \end{bmatrix}.$$

With multiple microphones, algorithms can attempt to recover the underlying sources.

Relevant techniques include:

- **ICA — Independent Component Analysis**
- **NMF — Non-negative Matrix Factorization**
- **IVA — Independent Vector Analysis**

- **SOBI — Second-Order Blind Identification**
- **RPCA — Robust Principal Component Analysis**

NMF is particularly interesting for acoustic spectra because sound-power spectra are non-negative. One can approximately represent a measured spectrogram as

$$V \approx WH$$

where W contains characteristic spectral patterns and H describes their temporal activity. A persistent turbine signature could potentially emerge as one of those components.

10. Machine learning

The same problem can be treated as a classification problem.

For every short recording, you might extract features such as

$$x = [L_A, L_C, L_{63}, L_{125}, \dots, f_{\text{BPF}}, \text{modulation depth, spectral slope, } \dots].$$

A classifier could then estimate

$$P(\text{WTN} | x).$$

Possible approaches include:

- random forests;
- support-vector machines;
- convolutional neural networks;
- recurrent neural networks;
- transformers.

A CNN, for example, could work directly on spectrograms.

For a regulatory or enforcement application, however, I would be cautious about relying exclusively on a black-box AI model. A **physically interpretable combination of direction, coherence, modulation and turbine-operation data** would be easier to validate and defend.

11. Conditional background modelling

There is another very useful approach that does not necessarily require an additional microphone.

Suppose you have a long-term database of periods where the turbine contribution is known or can be regarded as negligible.

Instead of modelling simply

$$P_{\text{background}}(f),$$

model

$$P_{\text{background}}(f, l, v, \theta, T_{\text{stability}} \dots).$$

In other words:

What background spectrum would normally be expected under *these particular meteorological conditions*?

Then, when the turbine is operating, compare the observed spectrum against the expected conditional background.

This is much more defensible than taking a single "background noise level" measured at some arbitrary time.

12. Reference microphone and adaptive noise cancellation

There is an interesting engineering approach using a reference microphone.

- **Microphone A**

At the actual immission point:

$$x_A(t) = s_{\text{WT}}(t) + b_A(t)$$

- **Microphone B**

Positioned so that it measures essentially the same local background but receives substantially less turbine noise:

$$x_B(t) \approx b_B(t).$$

If the background signals at A and B are sufficiently correlated, an **adaptive noise cancellation** algorithm can estimate the background at A:

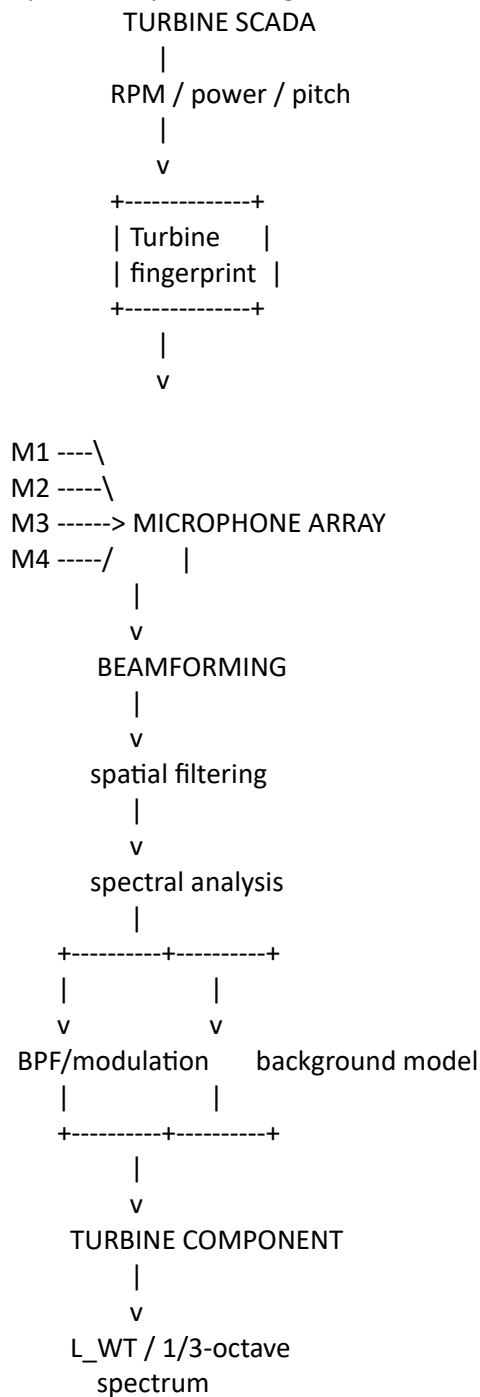
$$y(t) = x_A(t) - \hat{b}_A(t).$$

This is a well-established signal-processing concept, although its suitability for regulatory wind-turbine measurements would require experimental validation.

13. Combining the methods

For an actual monitoring system, I would not rely on just one of these techniques.

A particularly interesting architecture would be:



The crucial point is that four independent pieces of information become available:

1. **Spatial:** does the sound come from the turbine?
2. **Spectral:** does it have the expected acoustic spectrum?
3. **Temporal:** does it show the expected modulation?

4. **Operational:** does it correlate with RPM/power/etc.?

That is considerably stronger than simply observing a high sound level.

14. Relation to the IEC approach

There is an important development here.

IEC TS 61400-11-2:2024 is specifically concerned with measuring wind-turbine sound characteristics at **receptor/immission positions**.

The IEC describes it as providing measurement procedures that enable wind-turbine sound characteristics to be determined at receptor/immission locations, including far-field locations of a wind turbine or wind farm. It explicitly says that these procedures differ in some respects from those used for other industrial sound sources. IEC Webstore

IEC TS 61400-11-2:2024 — Wind turbine sound characteristics in receptor position

This is important because its measurement philosophy is closer to **actual sound immission at the receptor** than the traditional procedure of determining turbine source power and propagating it theoretically to the dwelling.

The standard was published on **27 March 2024** and is currently the first edition of the technical specification. IEC Webstore

15. The Dutch regulatory situation

This is particularly relevant to your original question.

Under the Dutch **Omgevingsregeling**, wind-turbine or wind-farm sound is determined according to **Annex IVi**. The current IPLO guidance explicitly states this. Informatiepunt Leefomgeving+1

IPLO — Determining sound from activities and the environmental plan

IPLO — Wind turbines: use rules and noise

The current Annex IVi describes the standard measurement method as determining the **sound power per octave band as a function of wind speed at hub height**. The wind speed at hub height is derived from the turbine's electrical power using its power curve. Informatiepunt Leefomgeving

Current working version of the Omgevingsregeling — Annex IVi

This is important because it confirms the basic point in your original question: the prescribed methodology fundamentally starts from **turbine emission/source information** rather than trying to identify the turbine component directly in a mixed recording at the dwelling.

There is, however, an interesting provision in the Dutch rules. IPLO states that, in certain circumstances, the competent authority can use another method provided that it is **equally accurate or more accurate**, and that the alternative method is recorded in the decision. Informatiepunt Leefomgeving

That provision could potentially be relevant to the development and validation of a substantially improved direct-immission method.

IPLO — Rules for wind turbines

• **16. A potentially useful measurement concept**

If the ultimate objective is a **technically defensible measurement method for enforcement at a dwelling**, I would concentrate on the following combination:

• **A. Small microphone array**

Perhaps 4–8 microphones rather than a single microphone.

• **B. Turbine operational data**

At minimum:

- rotor RPM;
- electrical power;
- wind speed;
- wind direction.

Ideally also pitch and yaw.

- **C. Coherence analysis**

Calculate the coherence between acoustic signals and turbine RPM/BPF.

- **D. Modulation analysis**

Look specifically for modulation at

$$f_{\text{BPF}} = N_{\text{blades}} \frac{\text{RPM}}{60}$$

and its harmonics/sidebands.

- **E. Direction-of-arrival**

Check whether the relevant acoustic component actually comes from the geographical direction of the turbine.

- **F. Conditional background model**

Estimate what the natural/background sound spectrum should be under the same meteorological conditions.

- **G. Combine the evidence**

Rather than simply saying:

"The measured level is 48 dB(A), therefore the turbine contribution is X",

the measurement system could establish something like:

"During this period the measured signal contains a component arriving from the turbine direction, coherent with the turbine's blade-passing frequency and varying with rotor speed. After spatial and spectral separation its estimated contribution is X dB."

That would be a fundamentally different measurement philosophy.

- **17. Principal sources and further reading**

Here are the sources I would use as the starting library for further work:

Does the acoustic signal contain a component arriving from the turbine's direction?

- **9. Blind Source Separation**

With multiple microphones, algorithms can attempt to recover the underlying sources.

Relevant techniques include:

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- **IEC TS 61400-11-2:2024 — Acoustic noise measurement techniques, measurement of wind-turbine sound characteristics in receptor position.** This is probably the single most important normative reference for the question you are investigating. IEC Webstore
IEC TS 61400-11-2:2024
- **Dutch Omgevingsregeling, Annex IVi — measurement and calculation method for wind-turbine noise.** This is directly relevant for understanding the present Dutch method.
Informatiepunt Leefomgeving
Omgevingsregeling — Annex IVi
- **IPLO — determining sound from activities and the environmental plan.** Useful for the current Dutch legal framework and the possibility, in specified circumstances, of using an equally accurate or more accurate alternative method. Informatiepunt Leefomgeving
IPLO — Determining sound from activities and the environmental plan
- **Ramachandran, Raman & Dougherty — compact microphone array and advanced deconvolution algorithms.** Particularly relevant to microphone-array, DAMAS and CLEAN-SC approaches. ScienceDirect
Scientific paper — Wind turbine noise measurement using a compact microphone array
- **Locating and tracking sound sources on a horizontal-axis wind turbine using a compact microphone array.** Relevant to spatial localisation and tracking of rotating sources.
ScienceDirect
Scientific paper — locating and tracking wind-turbine sound sources

- **The key research question**

I think there is a particularly interesting research project hidden in your original question:

Can the wind-turbine component of an immission recording be reconstructed from the acoustic signal itself, using turbine RPM as a reference, without stopping the turbine?

Technically, I would investigate:

microphone array + direction of arrival + cross-coherence + BPF/modulation tracking + meteorological background

The result would ideally be a **turbine-specific immission spectrum**, rather than simply the total measured spectrum.

That distinction is important: you would no longer be asking "*How loud is the environment?*", but rather "*What component of the sound measured here can be demonstrated to originate from the wind turbine?*"

For the Dutch situation, that could be a very interesting basis for investigating whether a **direct, source-separated immission measurement** could eventually complement or provide an alternative to the present source-power/propagation calculation approach.