Automatic estimation of the wind turbine noise Using deep neural networks

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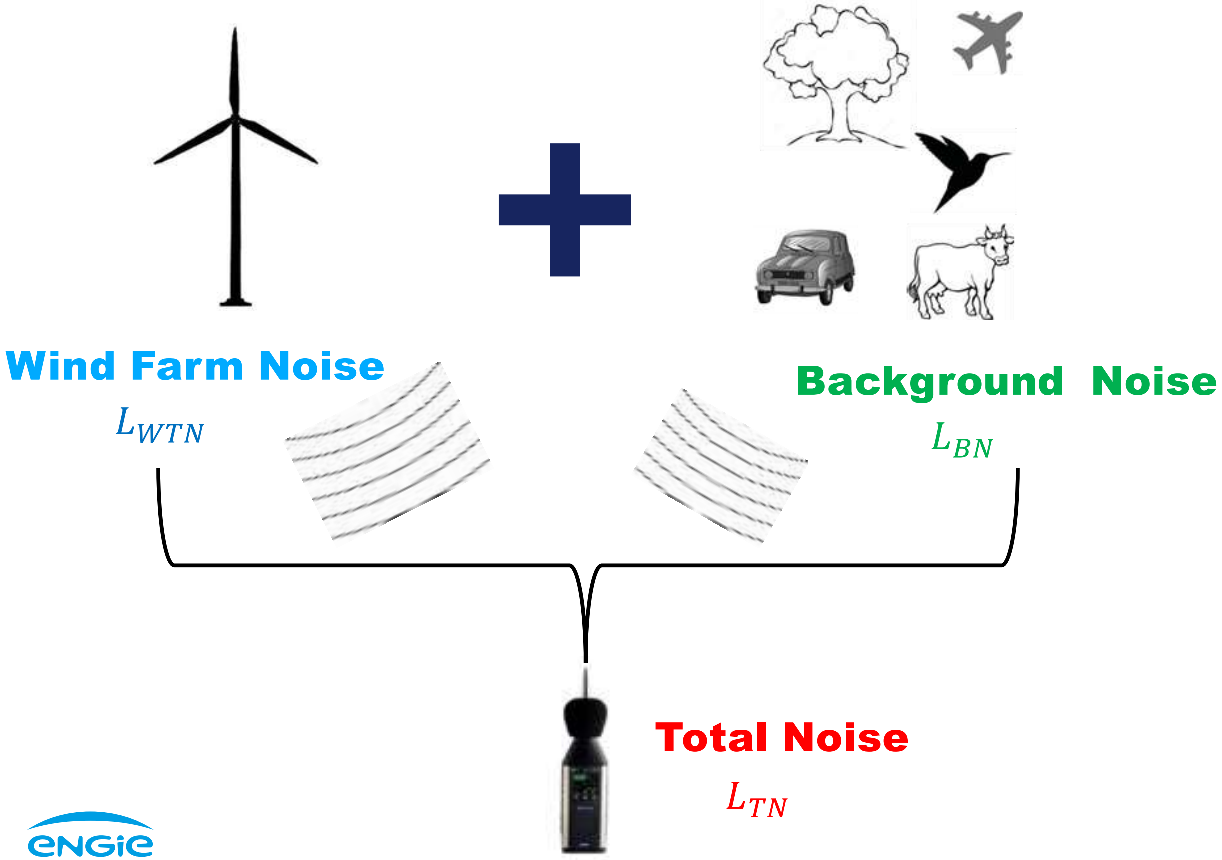
Introduction

Wind farm operators are expected to control noise levels around existing wind farms at several neighboring points.



- In France, the local regulation requires to compare **total noise levels to background noise levels**. Noise limits are set accordingly.
- Emergence = $L_{TN} - L_{BN}$:
  - 3 dBA night [22hoo to 07hoo]
  - 5 dBA day [07hoo to 22hoo]

Introduction

Comparing total noise to background noise requires to stop the wind farm alternating on/off phases for several weeks

- ✗ Severe production losses are encountered during the noise test period (~100 k€ for a french medium size wind farm)
- ✗ Measurement repeatability is not guaranteed due to background noise seasonality & sound scape evolution

→ A signal processing tool to estimate **wind turbine noise levels** from total noise levels would be highly beneficial to wind farm operators and residents.

Previous studies

- No current validated method to address this problem
  - Two microphones + barrier techniques
  - Frequency filtering techniques
  - Machine learning technique to predict background noise from meteo data

Hansen & Hansen, Recent Advances in Wind Turbine Noise Research. Acoustics 2020

Brush & al, 7th International Conference on WTN, 2017

Schomer & al, Internoise 2010

Bigot & Hochard, 8th International Conference on WTN, 2019

- The 2-years project PRESENCE led by ENGIE Green with UMRAE explored Nonnegative Matrix Factorization (NMF) to achieve this separation

Jean-Rémy Gloaguen al. Automatic estimation of the sound emergence of wind turbine noise with nonnegative matrix factorization. JASA, 150:3127–3138, October 2021.

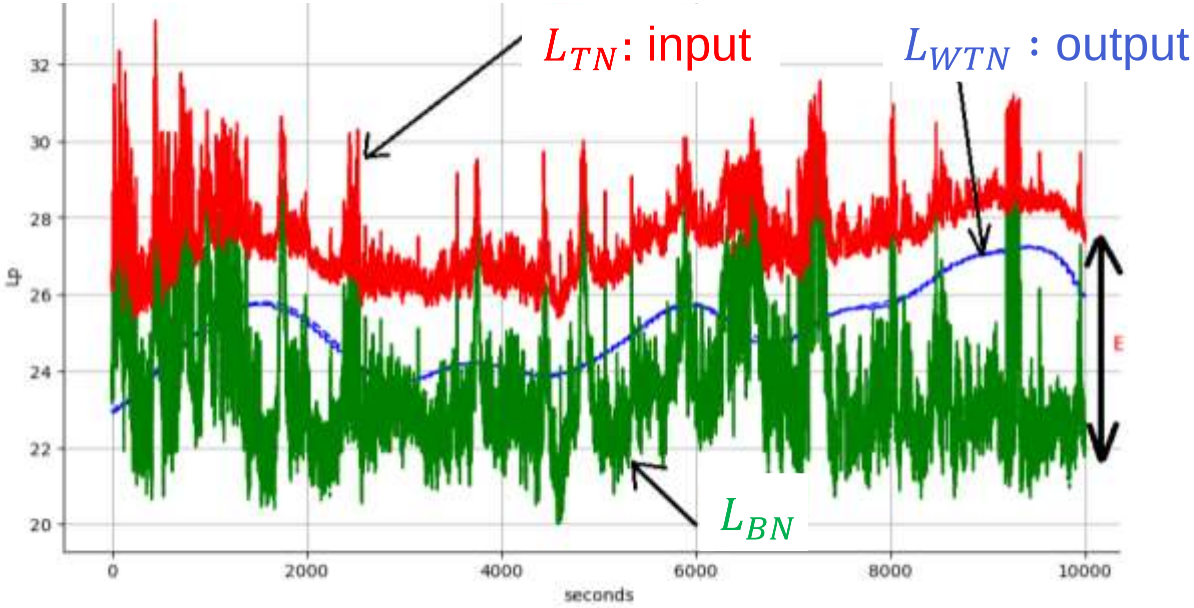
  - Good performances in « medium range » $L_{WT} \cong L_{BN}$ but severe practical limitations in « extreme ranges » $L_{WT} \ll L_{BN}$ and $L_{WT} \gg L_{BN}$
  - High sensitivity against the wind farm noise dictionary

- Several companies in France work on wind farm noise estimation using AI, without knowledge sharing

Proposed approach

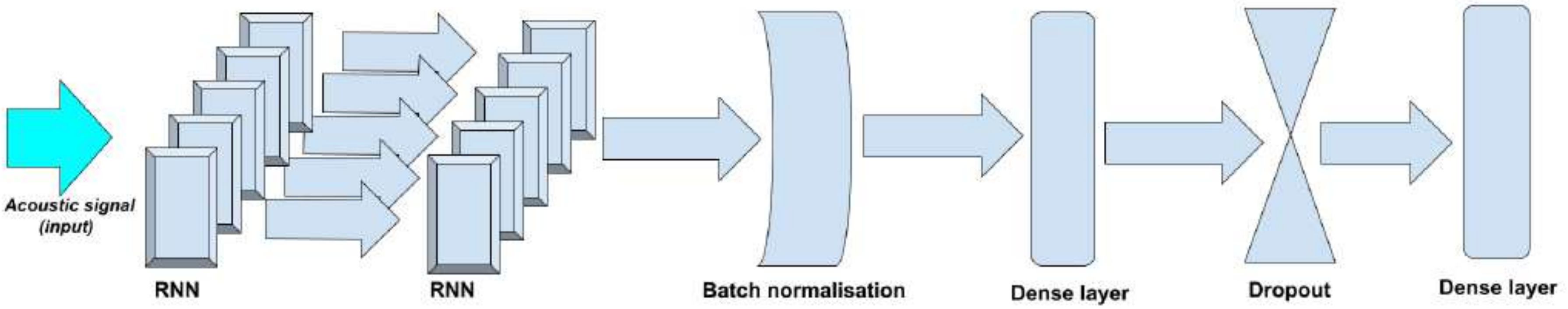
Use deep learning techniques to learn wind farm noise levels from total noise sound scenes

L_{TN}: input
with third octave
details between 31 Hz
and 2kHz



Neural network architecture

Accounting for the specific time signature of wind turbine noise, use is made of Recurrent Neural Network layers (RNN)



Three types of the RNN layers are tested :

- Vanilla : historical « basic » RNN.
- Long Short-Term Memory (LSTM, 1997) : capture long term behaviour while controlling vanishing gradient effects
- Gated Recurrent Unit (GRU, 2014) : lighter version of LSTM

A good learning dataset is key!

Main goal of this task :

Building long and meaningful sound scenes with compatible total and turbine noise data

$$L_{TN}(f,t) = L_{BN}(f,t) \oplus L_{WTN}(f,t)$$

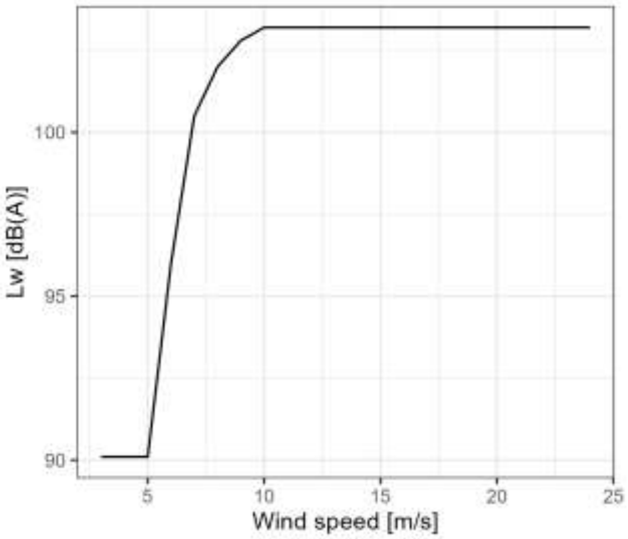
Background noise third octave time series

Directly measured from site assessment in the development phase of the wind farm project

No possible direct measurement at inhabitant distance from wind farm. Needs to be modeled coherently with background noise measurement

In this proof-of-concept study, the specific noise model is chosen as simple as possible.

Simple WT noise model for $L_{WTN}(f,t)$



Met mast measurement*
$V(t)$

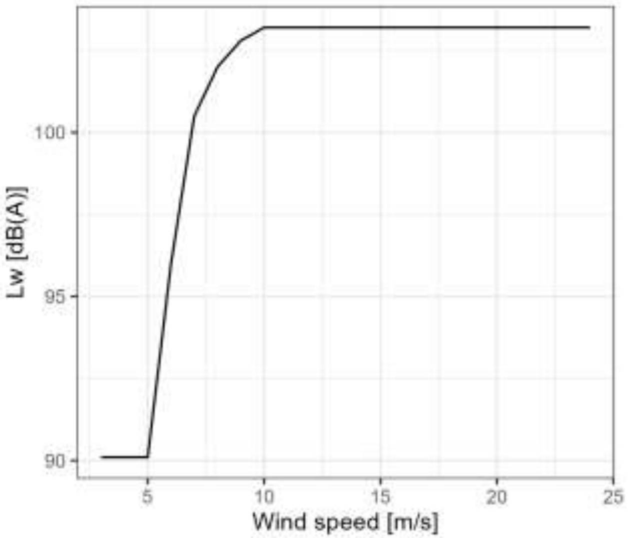
* Sampling period 10 min

Turbine specification*
$L_w(v,f)$

* Only 1 WT is considered here

Sound power time series
$L_w(t,f)$

Simple WT noise model for $L_{WTN}(f, t)$



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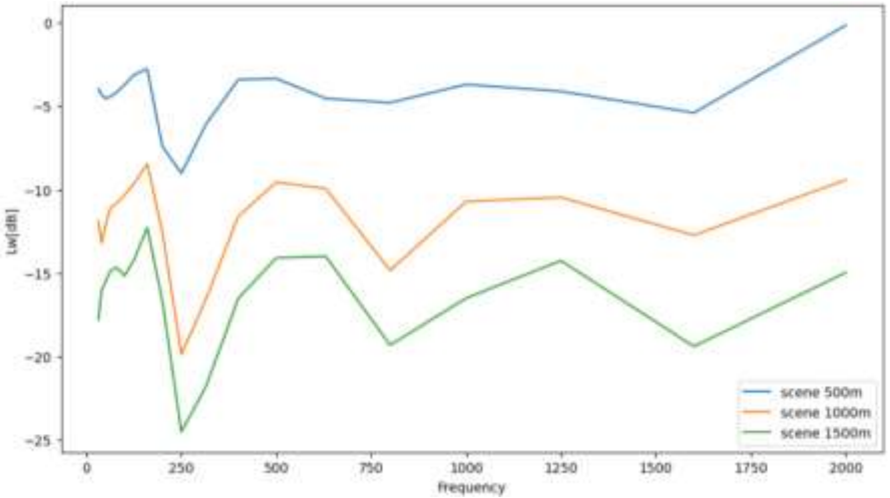
Propagation filters*
$A(f, d, \ldots)$

* Chosen independent of wind shear and direction for now. Calculated with PE from 31,5 Hz to 2 kHz



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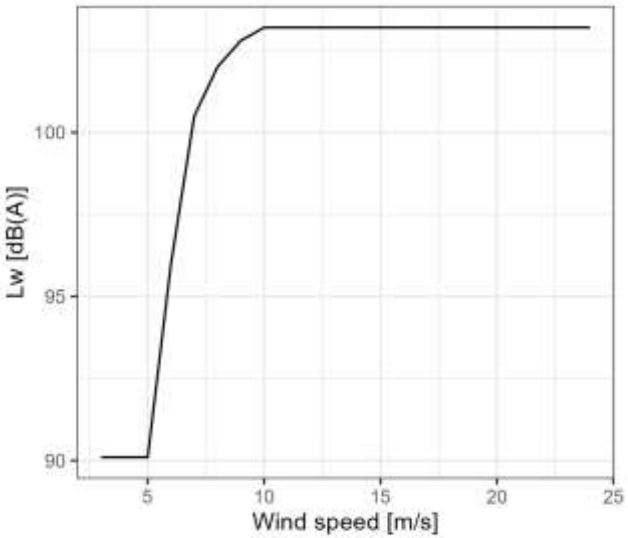

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Sound power time series
$L_w(t,f)$

Sound pressure time series at neighbour distance d : $L_{WT}(t,f)$

Propagation filters*
$A(f,d,\dots)$

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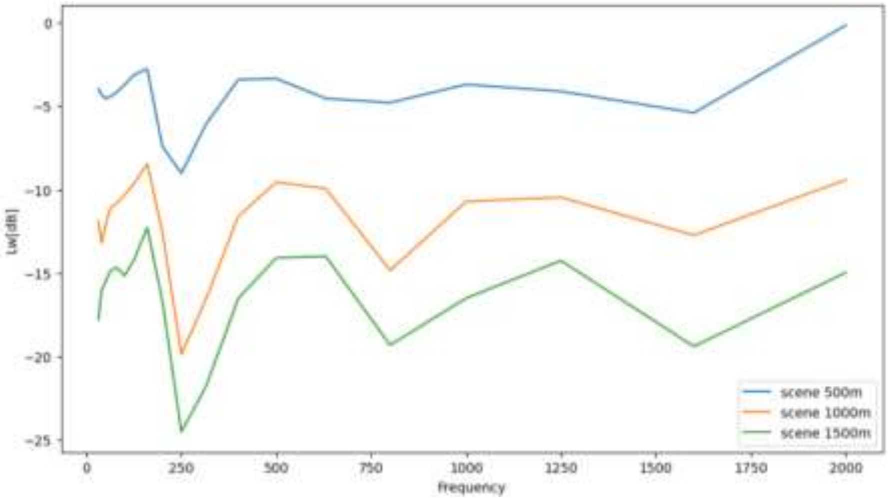

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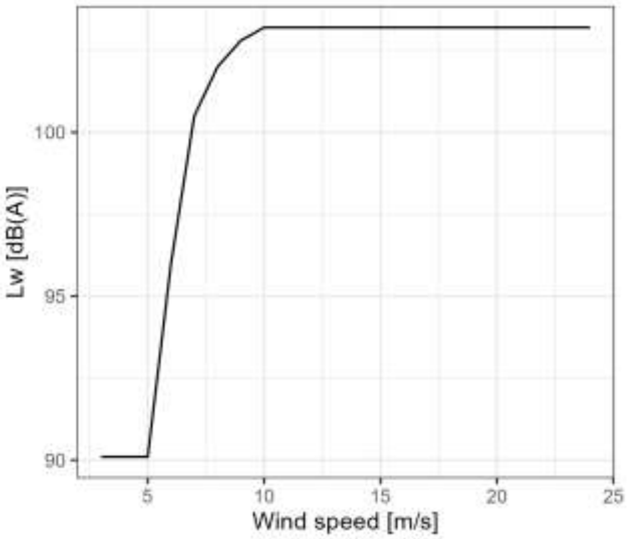

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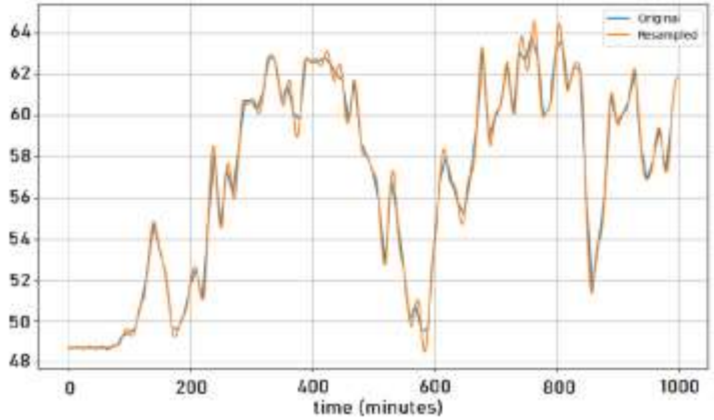
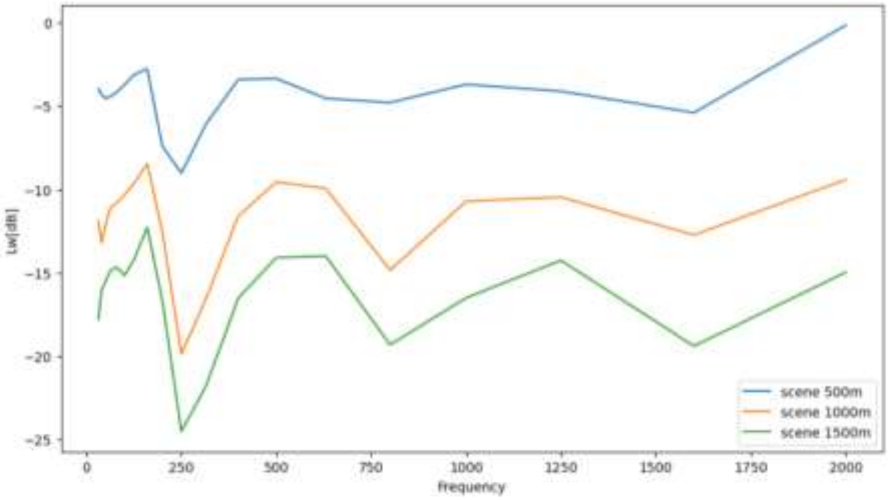
Sound power time series
$L_w(t,f)$



Sound pressure time series at neighbour distance d : $L_{WT}(t,f)$



Propagation filters*
$A(f,d,\ldots)$

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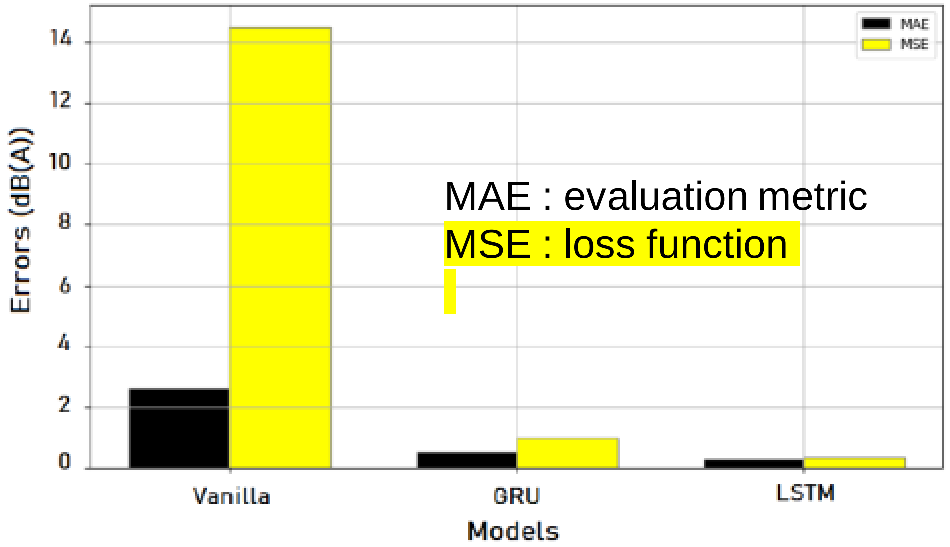
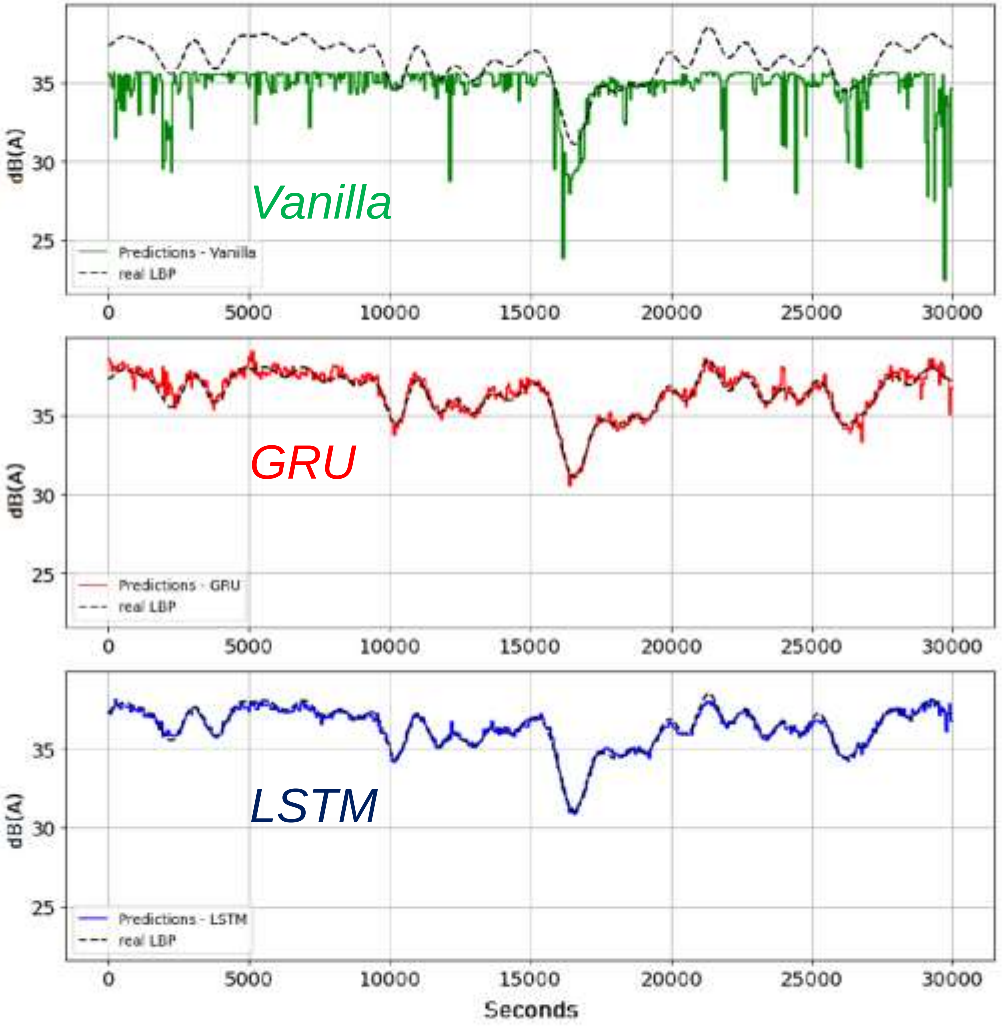
All in all, we obtain a proper dataset of 1 second third octave spectra for both L_{WTN} and L_{TN} and 3 listener distances (500m, 1000m, 1500m).

RNN results

The dataset is divided into 70% for learning and 30% for testing. Mean absolute error (MAE) and Mean Squared Error (MSE) on L_{WT} are evaluated for each RNN type on the test sequence.





➔ **Promising results for LSTM and GRU !**

--- Target L_{WTN}

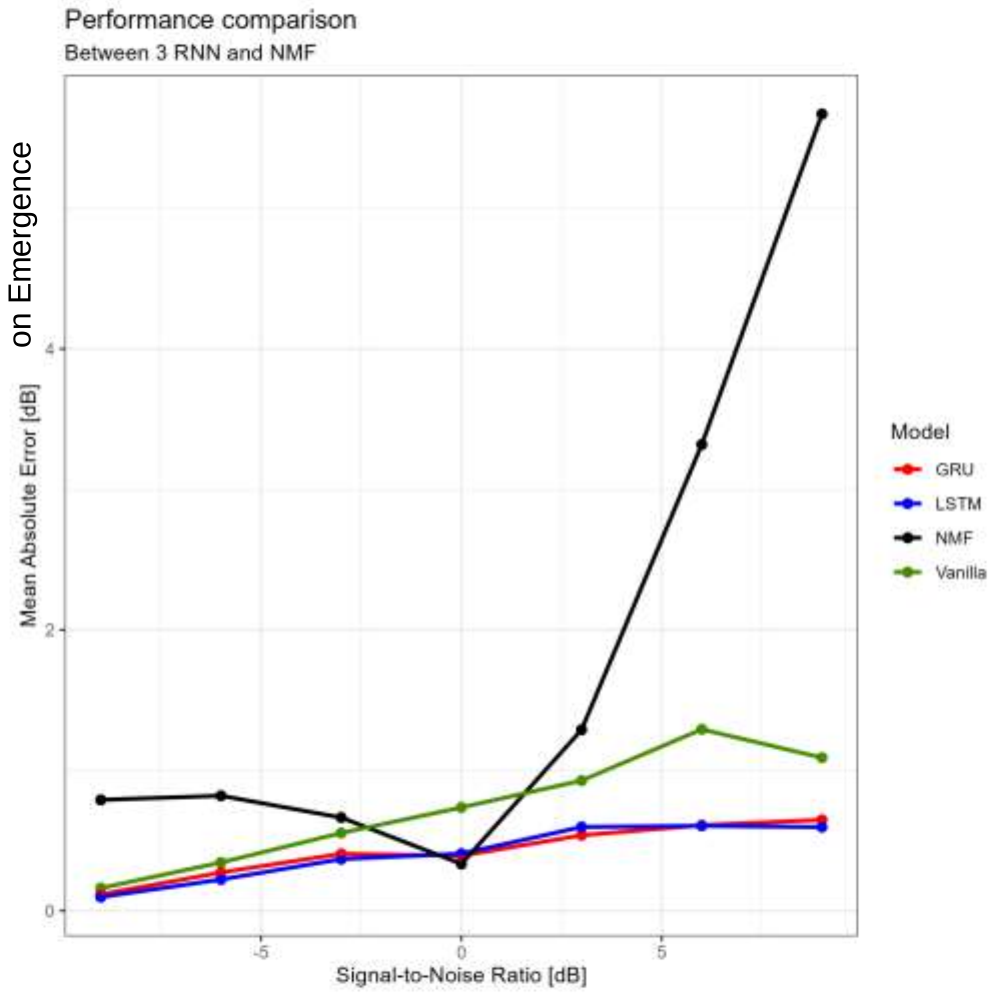
Comparison with published results

Another dataset was constructed in the PRESENCE project in a similar way to evaluate the NMF technique

- With several constructed $SNR = L_{WT} - L_{BN}$: $\{-9, -6, -3,$

Decision :

- use PRESENCE dataset only for “fine tuning” at $SNR = \{-9,\ \ 0,\ 9\}\ dB$ at 500 m (~90h of data)
- test at all other SNR and listener distances



➔ LSTM and GRU provide more stable results against SNR and generally better results than the NMF technique, below 1 dB error.

Conclusion

Summary

RNNs are used to estimate wind turbine noise levels from total noise level measurement in 1sec third octave bands.

- As a proof-of-concept, a simple database is constructed with simplified noise source and propagation models,
- 3 classical Recurrent Neural Network are compared. LSTM and GRU provide equivalently good results,
- The current approach is found to clearly outperform published results obtained with the NMF technique,
- Neural networks are found highly adaptative to new configurations using fine tuning “transfer learning” techniques.

Perspectives

- As there may be a bias due to the use of simple propagation filters, RNN tools will now be evaluated against a more comprehensive and versatile database.

THANK YOU FOR YOUR ATTENTION.