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# **Automatic detection of microphone wind noise : Maximising accuracy of amplitude modulation ratings**

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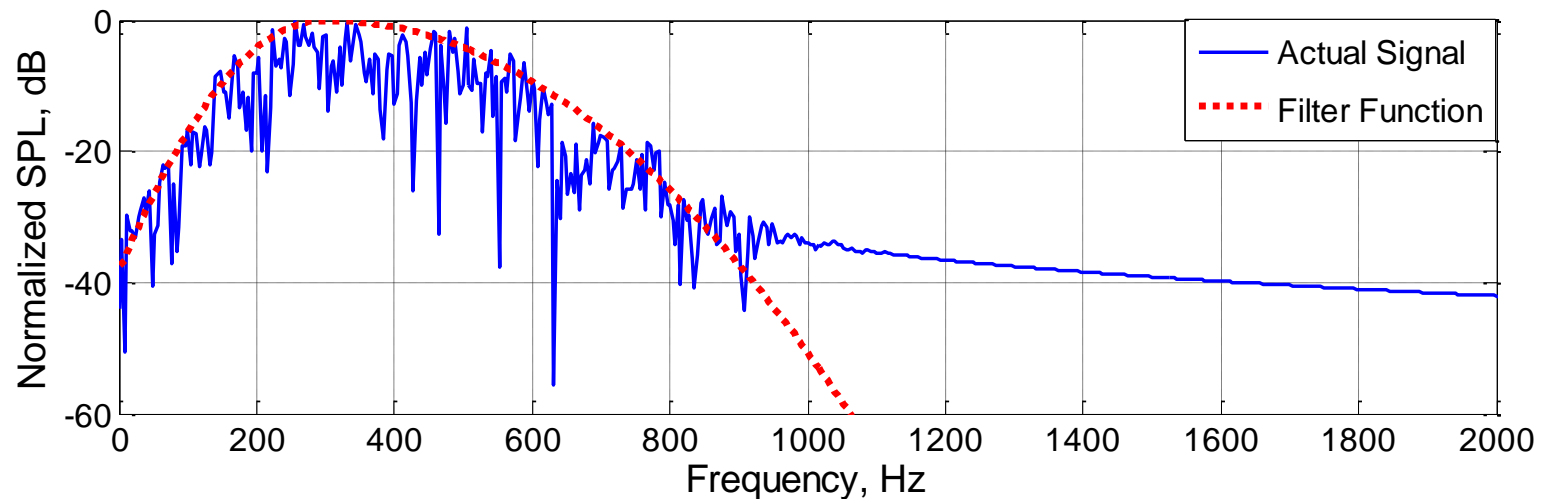
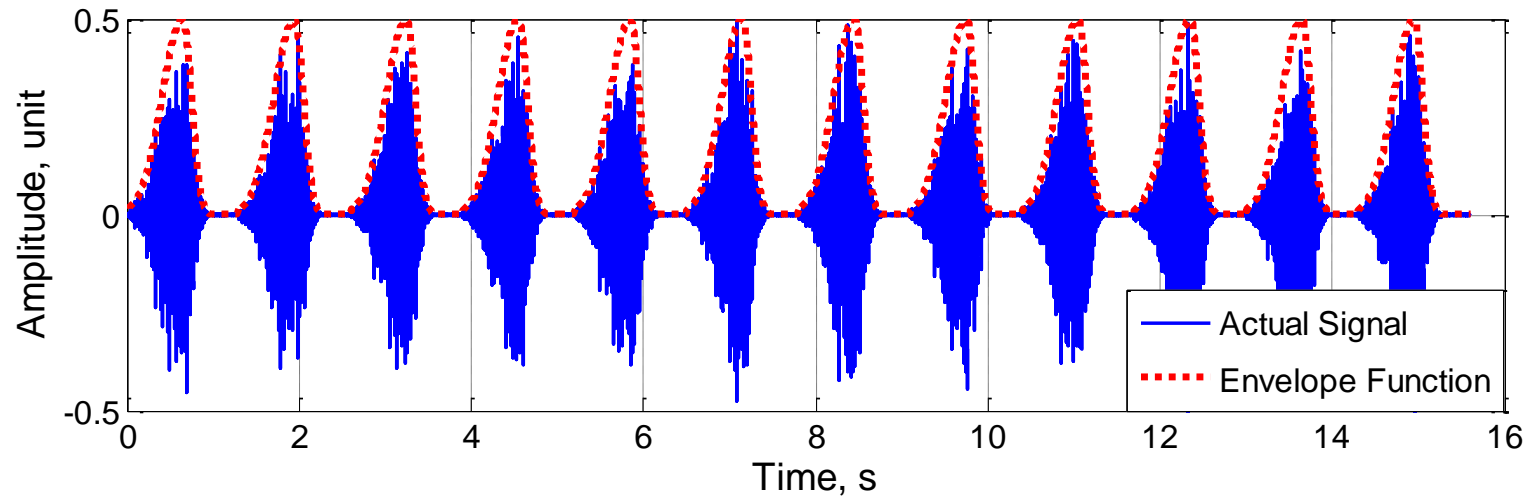


# Introduction

- Microphone wind noise
- Reduced but not removed by wind shield
- Problem for wind turbine noise measurements
- Low frequency, and gusts
- Wind turbine noise – AM metrics
- Improving AM metrics by automatically removing wind noise



# Wind noise simulator(s)



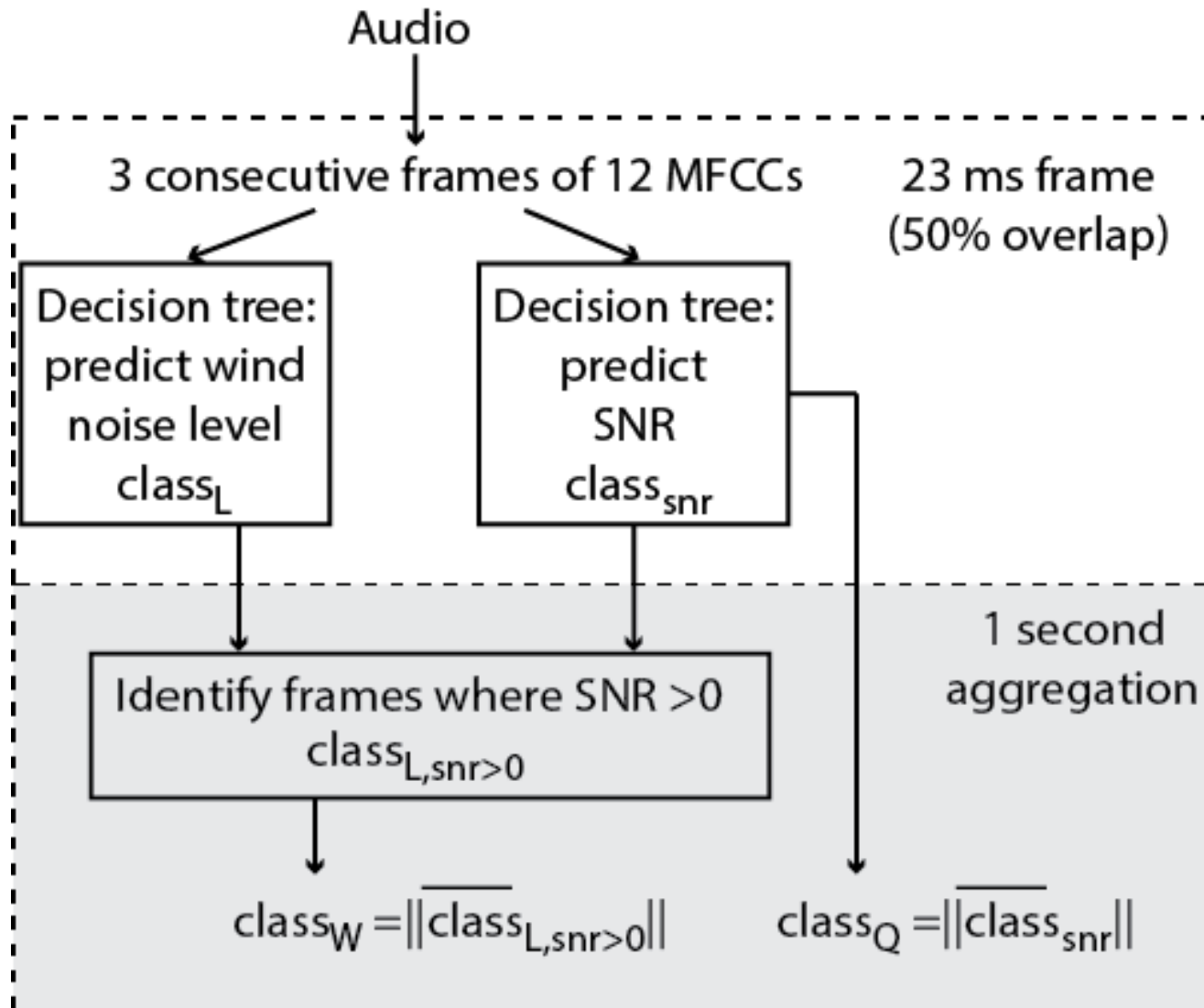


# Amplitude modulation metrics

- Metric one - time series method
- Metric two - modulation frequency domain method
- Currently proposed metric: hybrid between 1 and 2
- Synthesised Wind-turbine noise corrupted by known levels of wind noise.
- Compute AM metrics with varying levels of wind noise – scope of problem
- Run through wind noise detector, remove frames containing wind noise



# Wind Noise Detection Algorithm





# Wind noise test database

- Testing database - real wind noise
  - Wind noise recorded on a number of devices in remote location – low background noise level (37dBA)
  - iPhone, Zoom H2, SM58, B&K Measurement mic (shielded and unshielded)
  - Windy conditions  $>10\text{m/s}$  – poor signal to noise ratio (ideal!)



# Combining wind noise with 'Clean' sounds

- Database of 633 10 s clips, including speech music and other sounds
  - Wind noise added to each example at a broad range of levels and SNRs, includes noise free, and noise only
  - High pass filtered between 30 and 130 Hz, simulating a range of low frequency responses of consumer devices
  - Feature extraction 11 MFCCs + dBA level, 23ms windows, 50% overlap, 3 windows concatenated



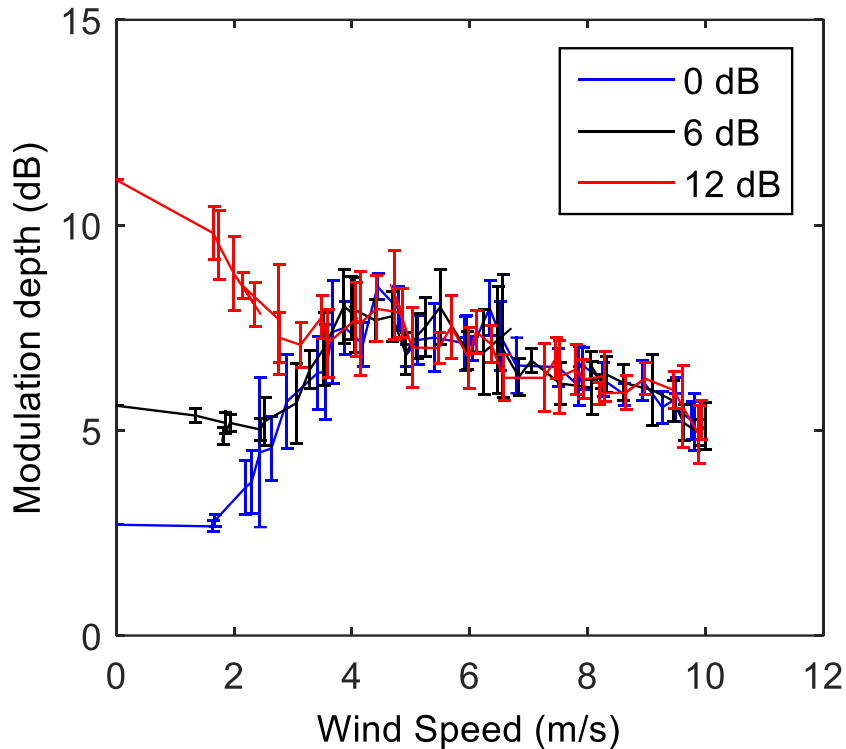
# Detector - overview

- Two **Bagged** Decision trees used to assign two classes to each frame according to;
  - Wind noise level -  $L_{class}$ 
    - **0** – Level < 30
    - **1** –  $30 \geq \text{Level} < 50$
    - **2** –  $50 \geq \text{Level} < 70$
    - **3** – Level > 70
  - SNR -  $SNR_{class}$ 
    - **0** – SNR > 20
    - **1** –  $10 > \text{SNR} \leq 20$
    - **2** –  $0 > \text{SNR} \leq 10$
    - **3** –  $-10 > \text{SNR} \leq 0$
    - **4** –  $-20 > \text{SNR} \leq -10$
    - **5** – SNR  $\leq -20$
- **Bootstrap Aggregation**, is an ensemble of decision trees
- The wind noise level class indicates the presence and magnitude of the wind noise, irrelevant of the level of the foreground audio
- The SNR class indicates the degree of degradation to the audio
- A combination of these two classes can be used to indicate the presence of problematic regions of wind noise

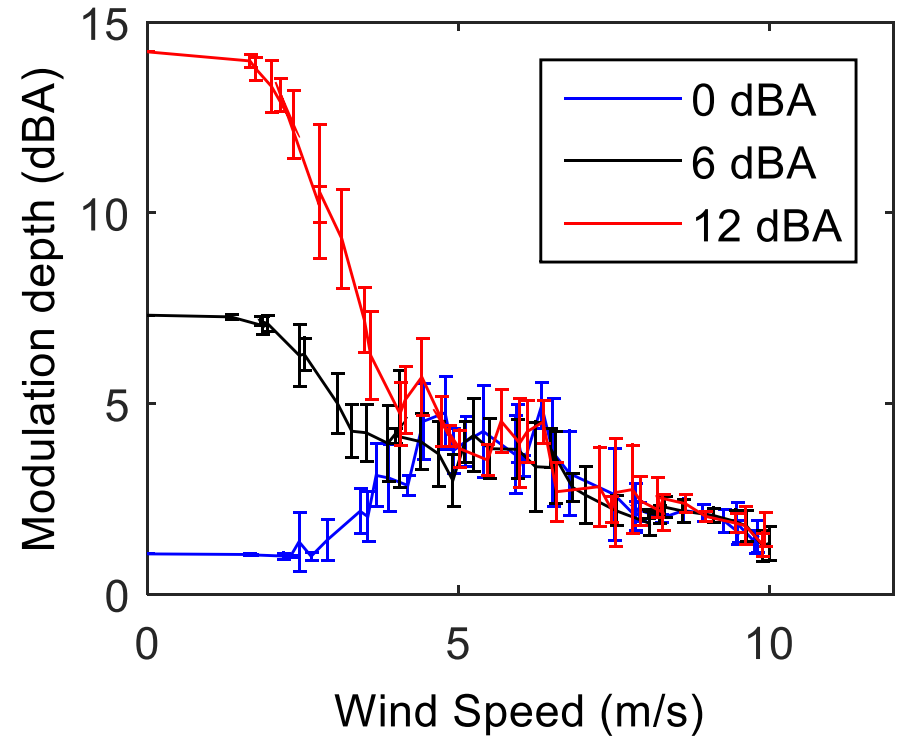




# Effect of microphone wind noise on AM metrics



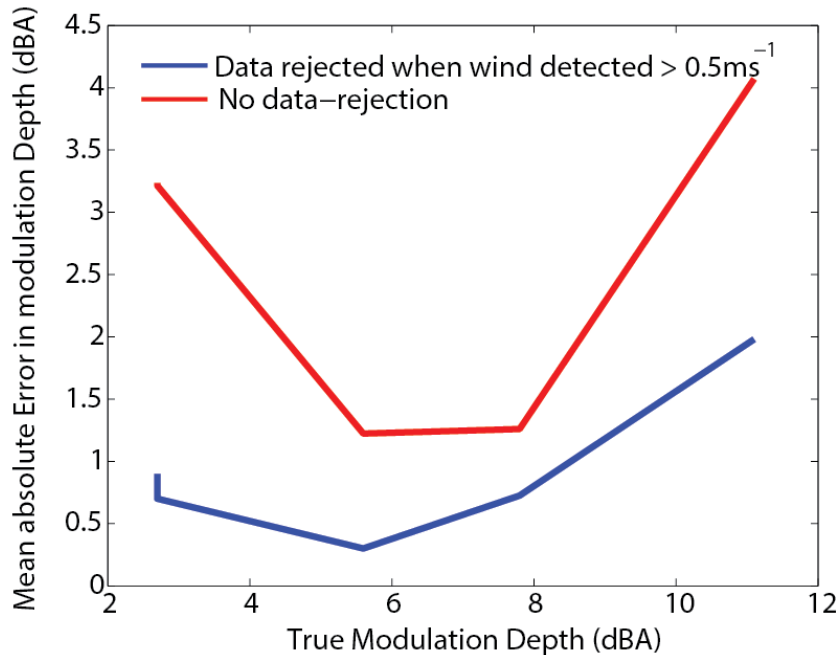
Metric one - time series method



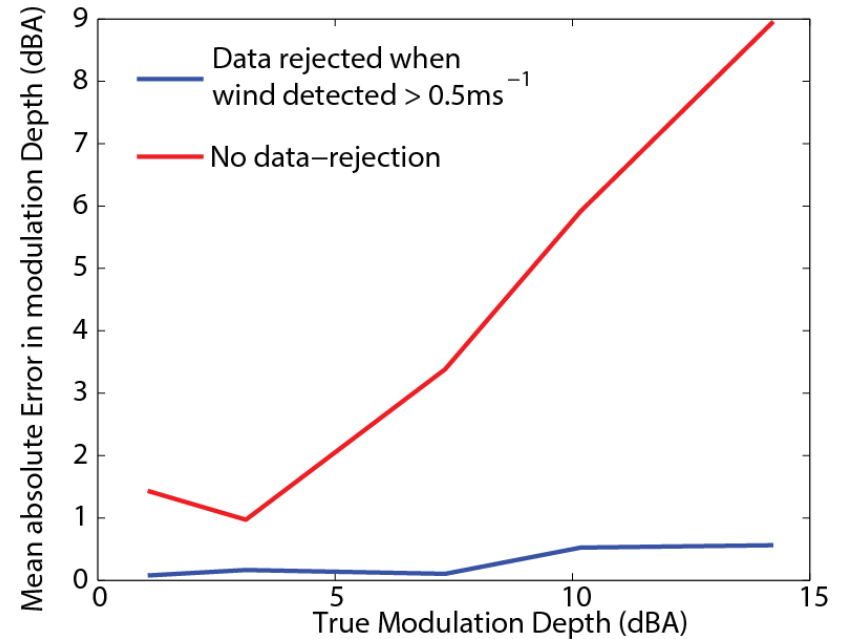
Metric two - modulation frequency domain method



# Automatic wind noise detection results



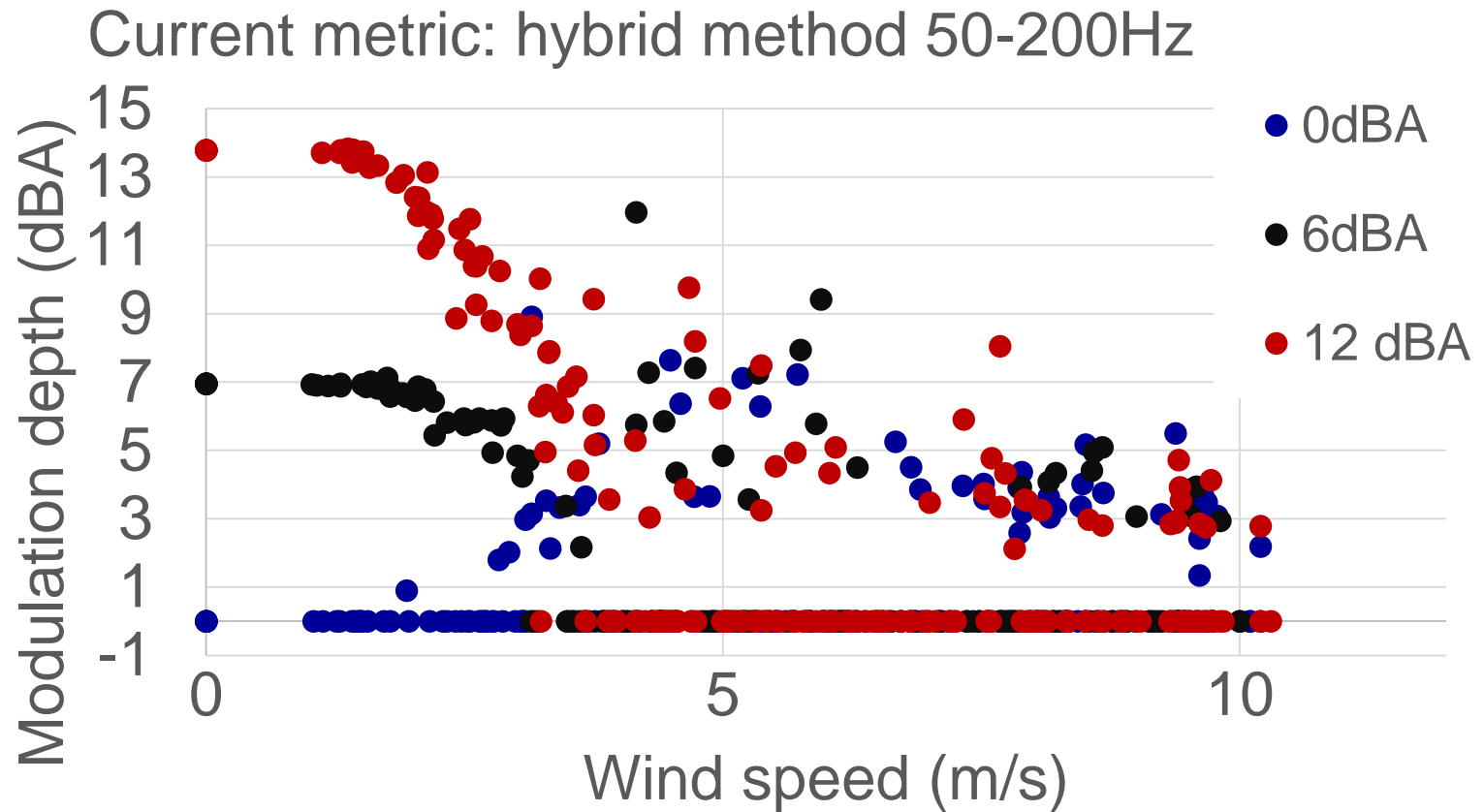
Metric one - time series method



Metric two - modulation frequency domain method

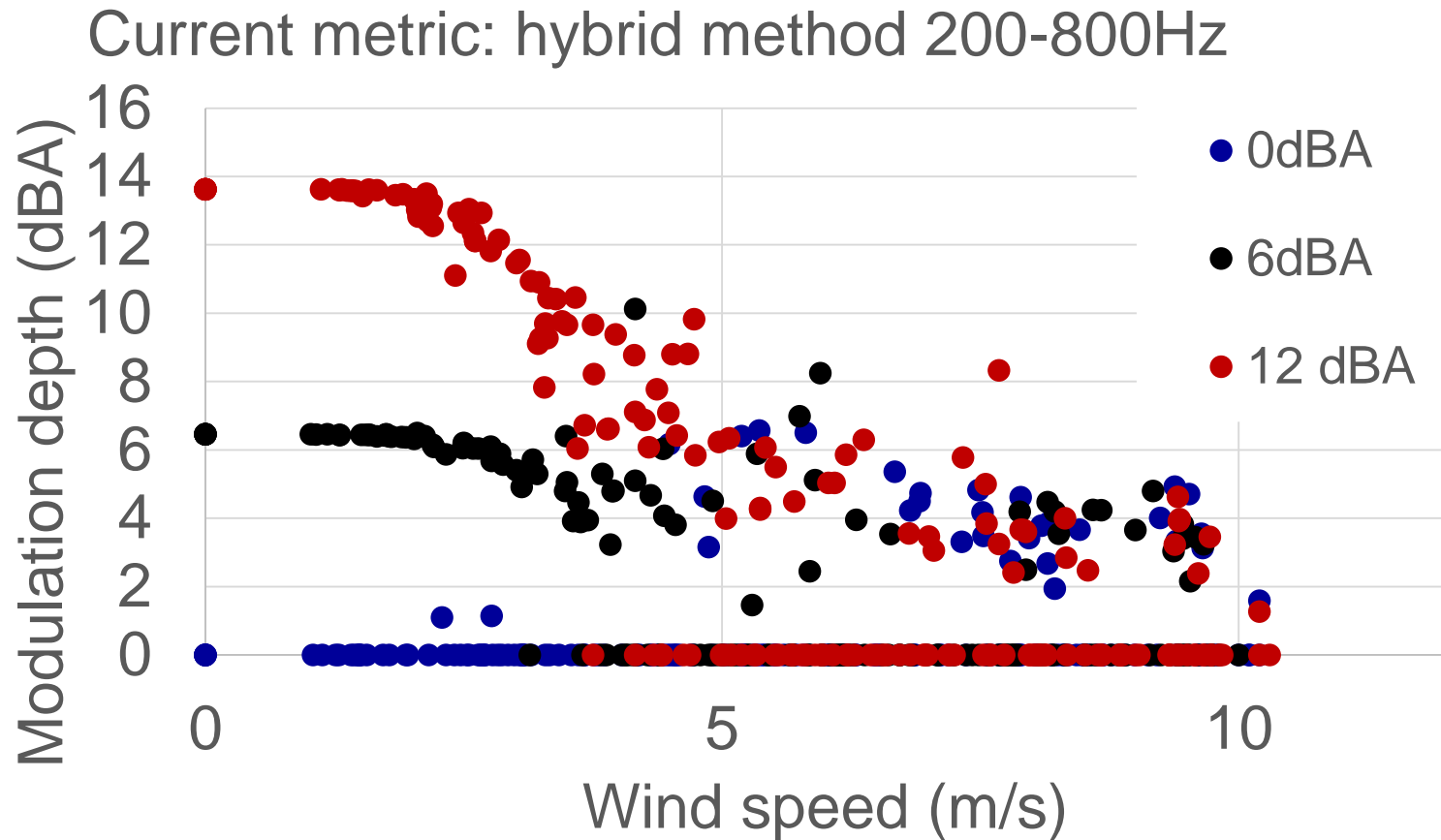


# Effect of microphone wind noise on AM metrics





# Effect of microphone wind noise on AM metrics





# Conclusions

- Wind speeds as low as 3 m/s can cause large errors in the AM metrics
- Microphone wind noise is intermittent, and consequently one solution is to analyse only uncorrupted parts of the recordings.
- Tests showed that doing this can reduce the error to  $\pm 2$  dBA and  $\pm 0.5$  dBA for the time and modulation-frequency domain AM metrics respectively.

# Further Work

- Field test to confirm simulated results
- Test with new Institute of Acoustics AM rating method
- How much is human perception affected by wind noise in the ears?

