CORTEX

Core monitoring techniques and experimental validation and demonstration

# Signal processing methodologies for nuclear reactor data

**CORTEX Workshop**

**Advanced signal processing methods and learning methodologies applied to the monitoring of NPP reactor conditions**

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**Georgios Alexandridis**

**National Technical University of Athens, Greece**

[gealexandri@islab.ntua.gr](mailto:gealexandri@islab.ntua.gr)

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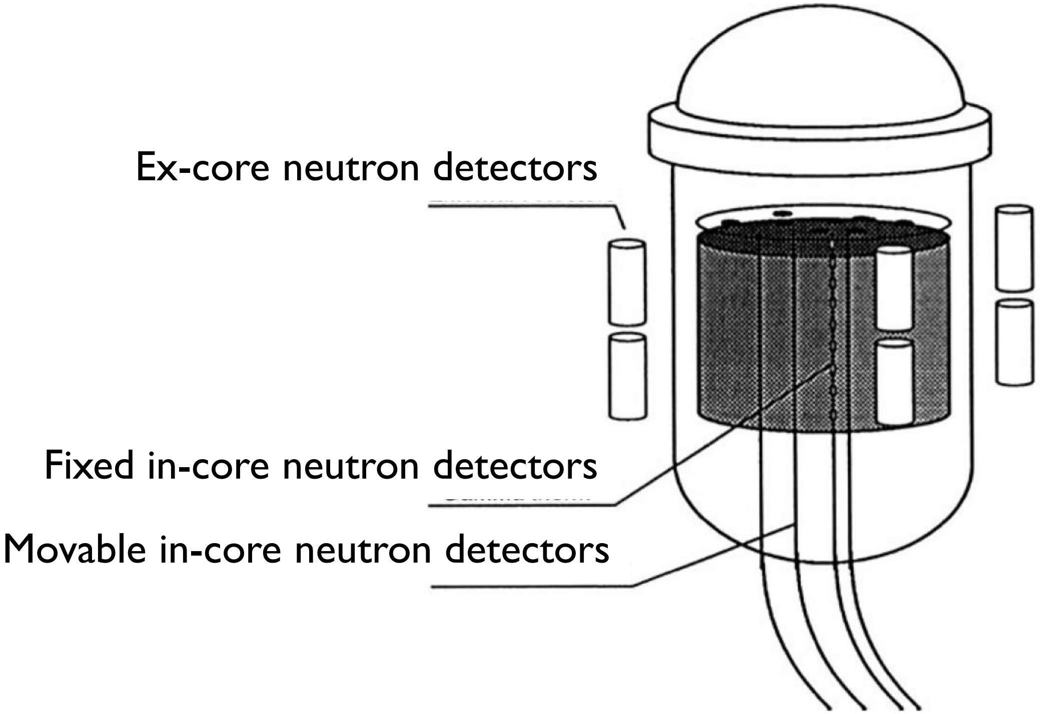
# Main Objective

- Detect **anomalies** in nuclear reactors using **non-intrusive** methodologies
- Anomalies
  - Excessive vibrations of core internals
  - Flow blockage
  - Coolant inlet perturbations
  - Combination of the above
  - ...
- Non-intrusiveness
  - Measure the inherent fluctuations in neutron flux recorded by in-core and ex-core detectors
  - No external perturbation of the system is required

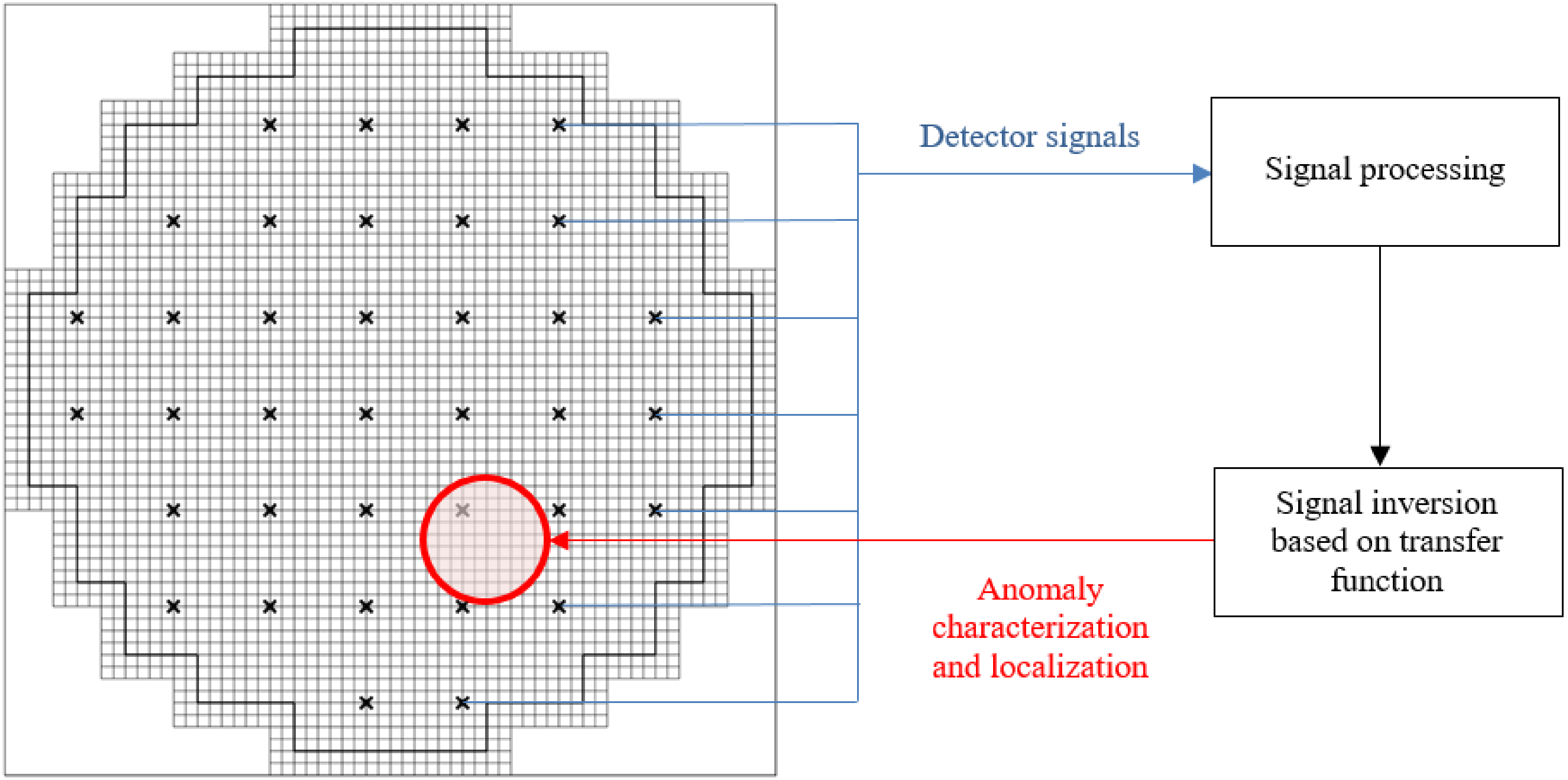
# Location of neutron detectors



# Induced neutron noise

- Identify the driving perturbation(s) measured at the detectors
  - Amplitude and Phase
- Extract the characteristic features
  - Frequency of the perturbation
  - "Relationships" between the induced neutron noise at different locations
    - Spatial variation of the amplitude of the noise
    - Spatial variation of the phase

# Overview of the procedure



# Signal types

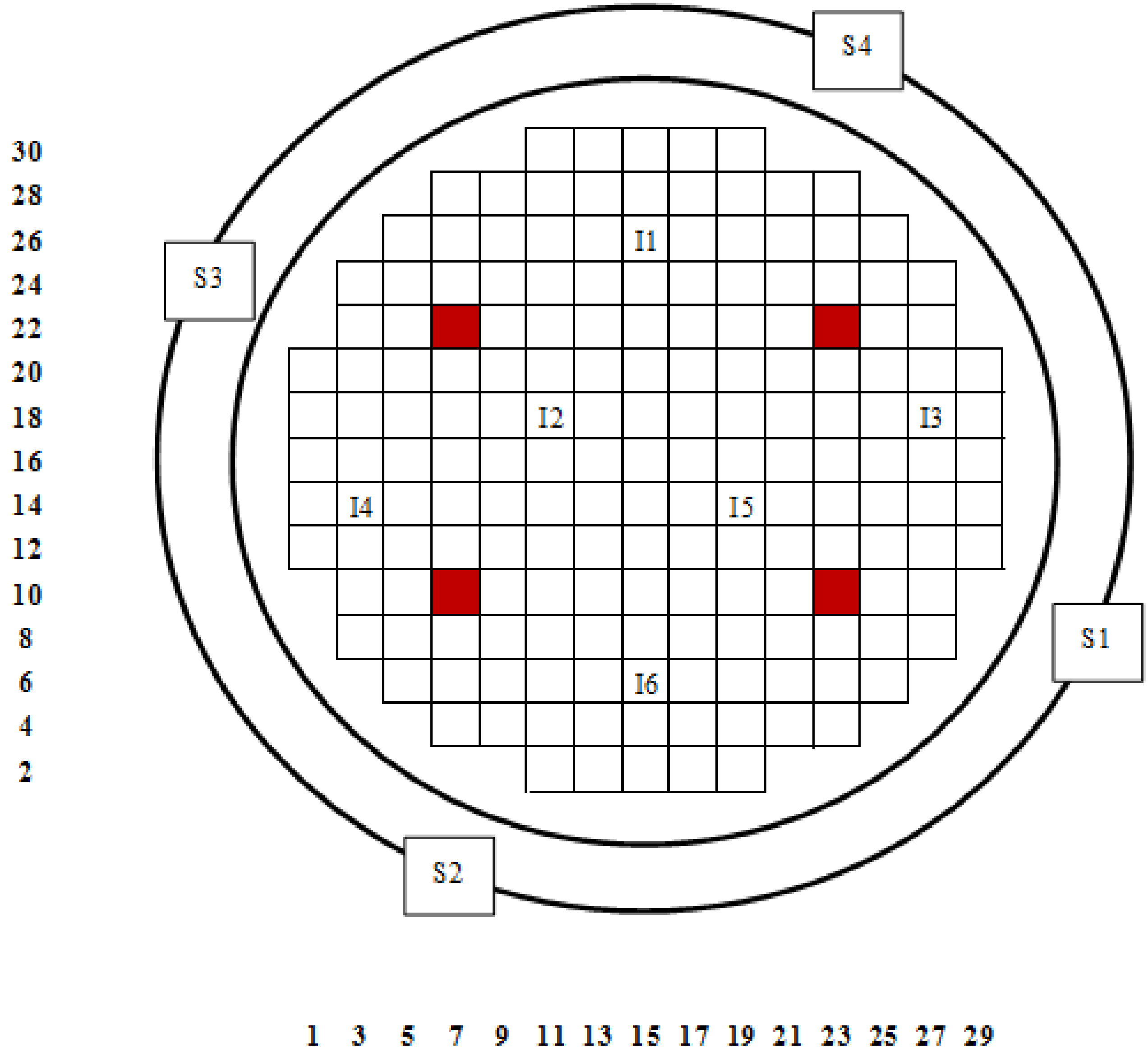
- Real
  - measured at the detectors
  - characteristics
    - may be due to more than one perturbation which are usually unknown
    - noise, trend and intermittencies
    - (possible) detector failure
- Simulated
  - model the fluctuations in neutron flux resulting from known perturbations applied to the system through the estimation of the reactor transfer function
  - characteristics
    - can model a single, known perturbation
    - can model noise, trend and intermittencies
    - no detector failures (unless modelled!)

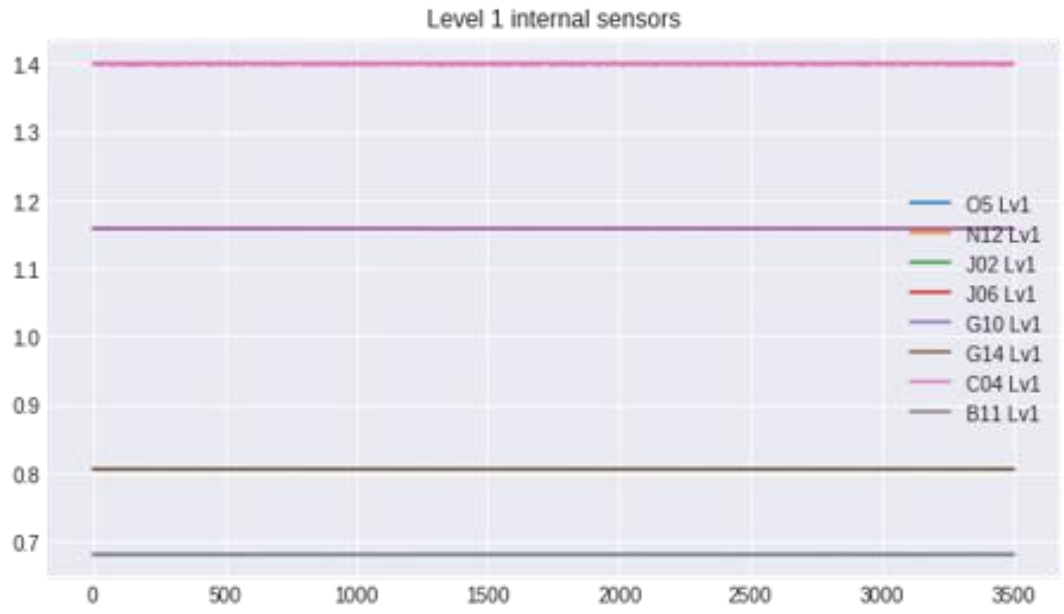
# Signal Processing steps

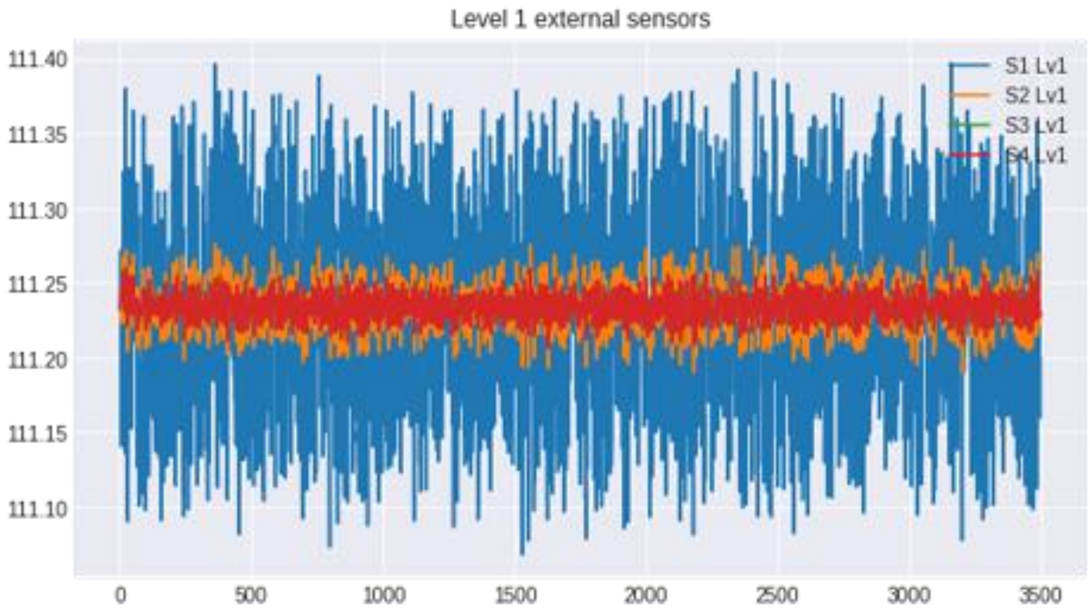
1. Data preprocessing
   - Remove noise, trends and intermittencies
   - Account for possible detector failure
2. Feature Extraction
   - Transformation Methods
     - Discrete Wavelet Transform (DWT)
     - Hilbert-Huang Transform (HHT)
   - Non-parametric inversion methods
     - Artificial Neural Networks (ANNs)
     - Fuzzy logic
3. Feature Selection

# Example perturbation

Single fuel assembly vibrates in one direction





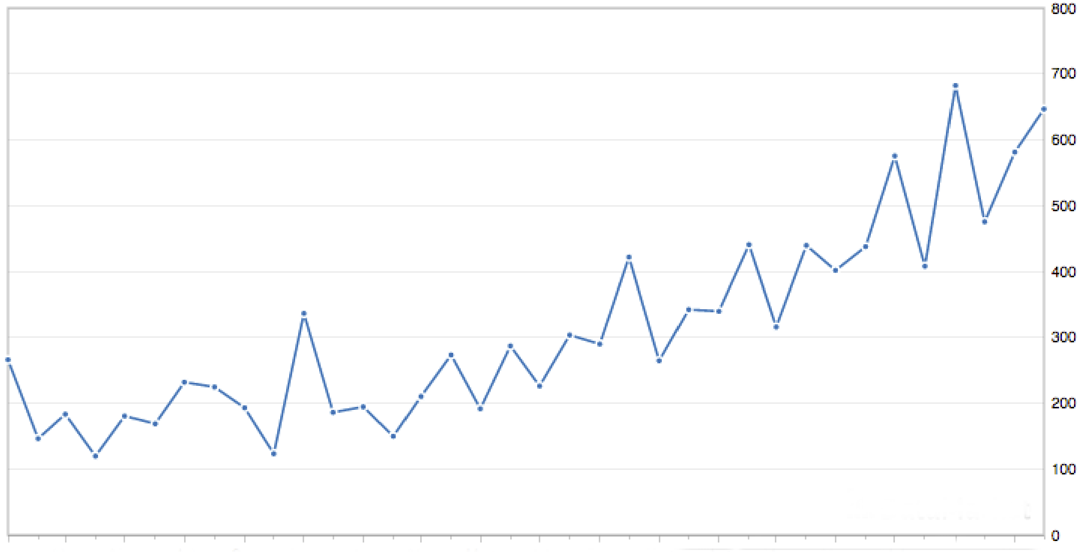

# Example perturbation

measured neutron flux at the in-core and ex-core detectors at the bottom level

# Step 1. Trend detection & removal

# Trend

- Any systematic change in a time series (signal) that does not appear to be periodic
- Types of trends
  - Deterministic
    - increase or decrease consistently
  - Stochastic
    - Increase or decrease inconsistently
- Scope
  - Global
    - apply to the whole signal
    - easier to identify
  - Local
    - apply to parts of the signal

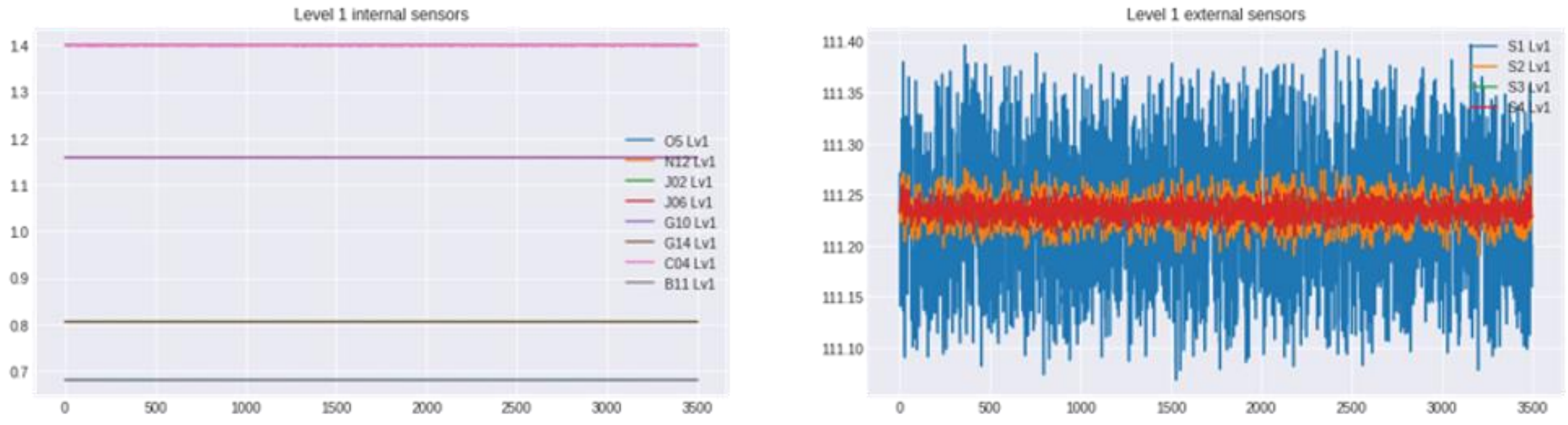


# Removing trends

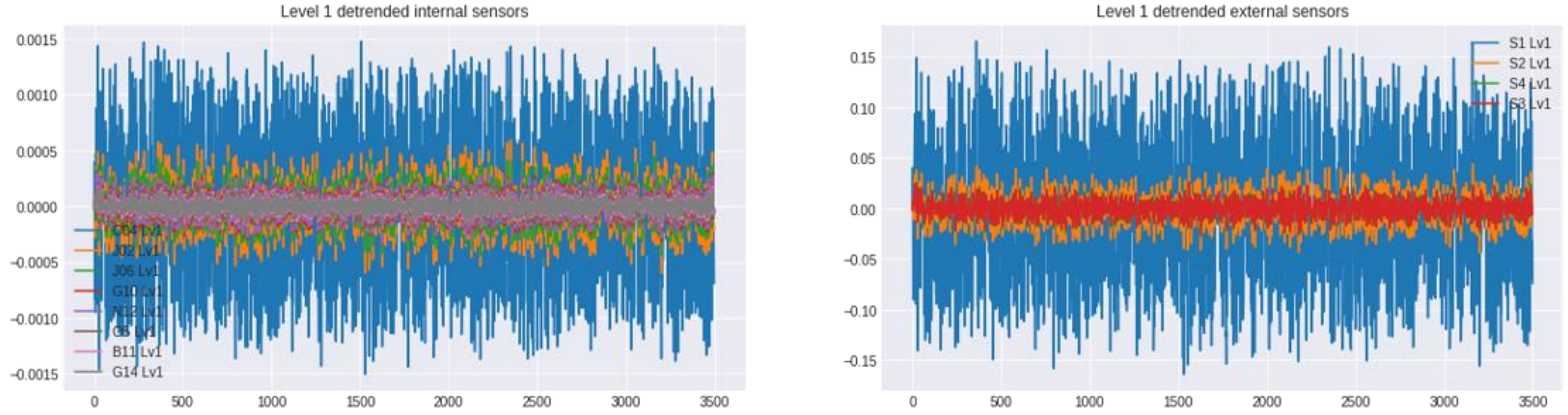
- Signals containing trends are said to be non-stationary
- Detrending
  - The process of removing trend(s) from a signal
  - Simplifies signal analysis
  - Trend(s) has to be modeled in order to be removed
- Trend modelling
  - Deterministic (linear) trends are easier to be modelled
    - e.g. through least-square regression
  - Stochastic trends require more thorough analysis
    - e.g. moving average trend lines can be detrended with the Baxter-King filter
    - e.g. cyclical components can be removed with the Hodrick-Prescott filter
    - …

# Detrending

Before




After

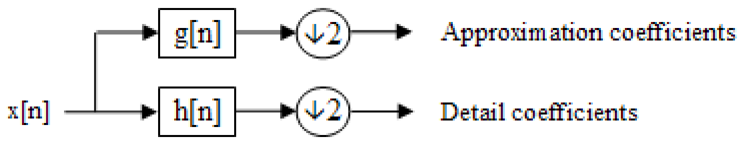


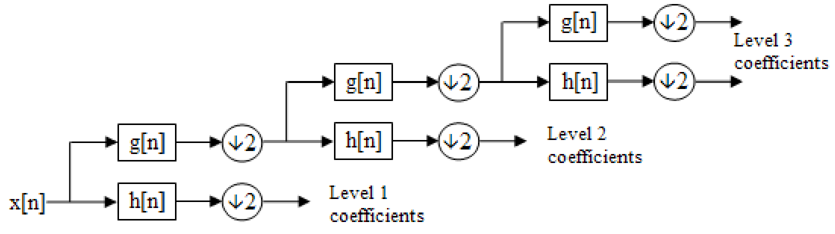
# Step 2. Feature Extraction

## Using transformation methods

# Discrete Wavelet Transform

- An iterative procedure that simultaneously convolutes signal $x[n]$ with
  - a low-pass filter $g$ with impulse response (scaling function): $y_{low}[n] = \sum_k x[k]g[2n-k]$
  - a high pass filter $h$ (wavelet function) : $y_{hi}[n] = \sum_k x[k]g[2n-k]$
- After the filtering, half of the samples can be eliminated (according to Nyquist's rule)
  - Since the signal now has a highest frequency of $\frac{f_{max}}{2}$ instead of $f_{max}$
  - This constitutes one level of the decomposition
  - The signal can now be re-subsampled by 2



# Characteristics of the Wavelet Transform

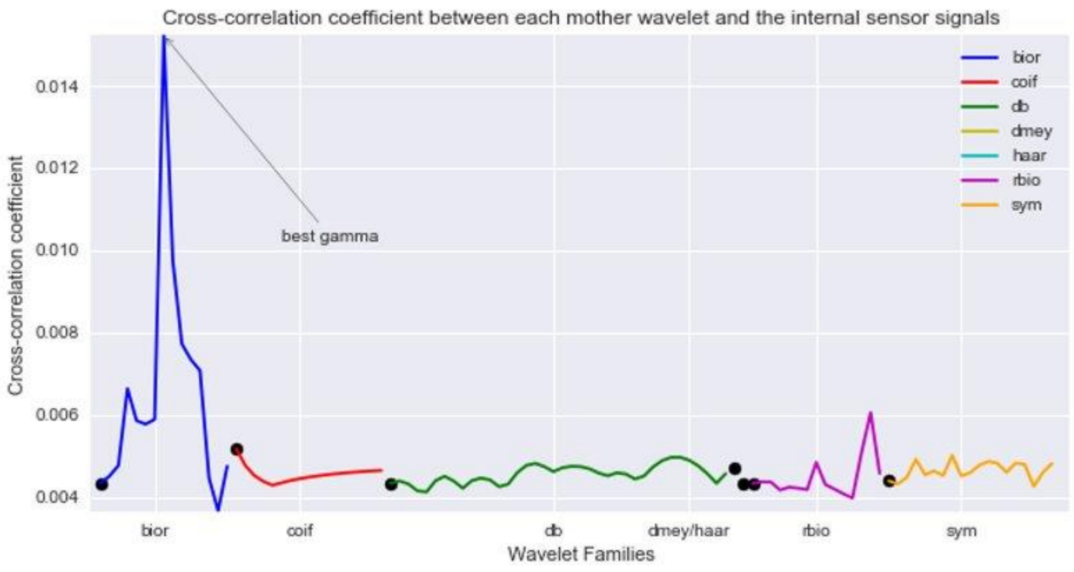
- Suitable for analyzing signals with time-varying spectra
  - Unlike the Fourier Transform (FT), which gives only the spectral details of the signal without considering temporal properties
- Produces varying time and frequency resolutions
  - Unlike FT, which produces a single frequency spectrogram
  - WT scalograms depict transients
- High frequencies
  - Good time resolution, poor frequency resolution
- Low frequencies
  - Poor time resolution, good frequency resolution
- Need to decide on the mother wavelet function used
  - Different wavelets produce different coefficients/scalograms
  - FT uses only sinusoidal functions

# Choice of the mother wavelet

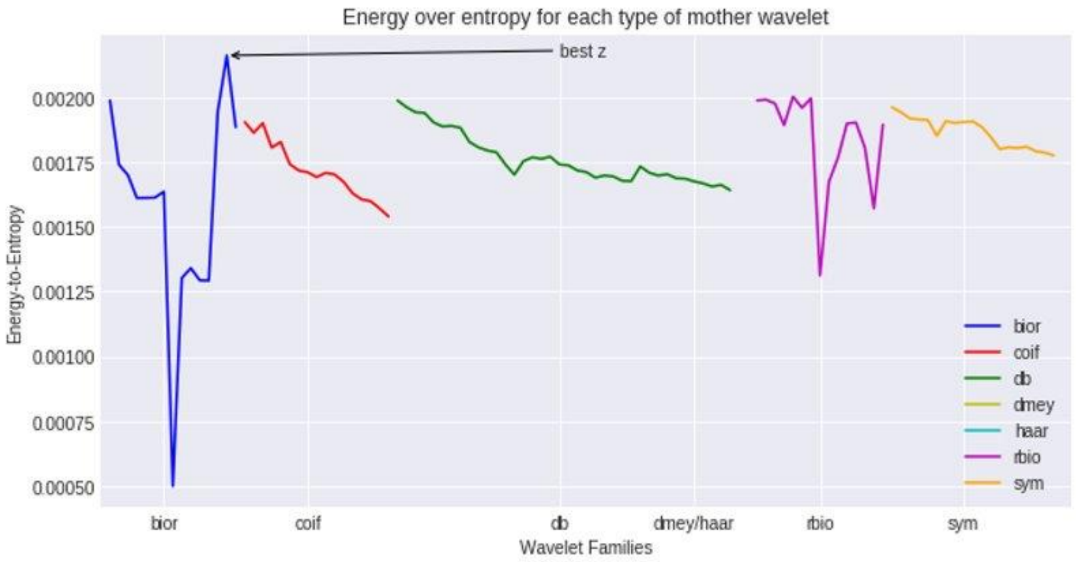
- Mother wavelet families
  - Haar, Daubechy , Symlet , Coiflet , Biorthogonal , Reverse Biorthogonal , Discrete Mayer, ...
- Criterion
  - How "close" is the reconstructed signal to the original?
- Measures of similarity
  - Cross-correlation (statistical)
    - $\gamma(X,Y) = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{(X-\bar{X})^2(Y-\bar{Y})^2}}$
  - Energy to entropy (information-theoretical)
    - $\zeta(n) = \frac{\sqrt{\sum_i s_i^2}}{\sum_i s_i^2 log s_i^2}$

# Cross-correlation vs Energy-to-Entropy for the internal sensors

Best wavelet: **Biorthogonal (3.1)**




Best wavelet: **Biorthogonal (5.5)**



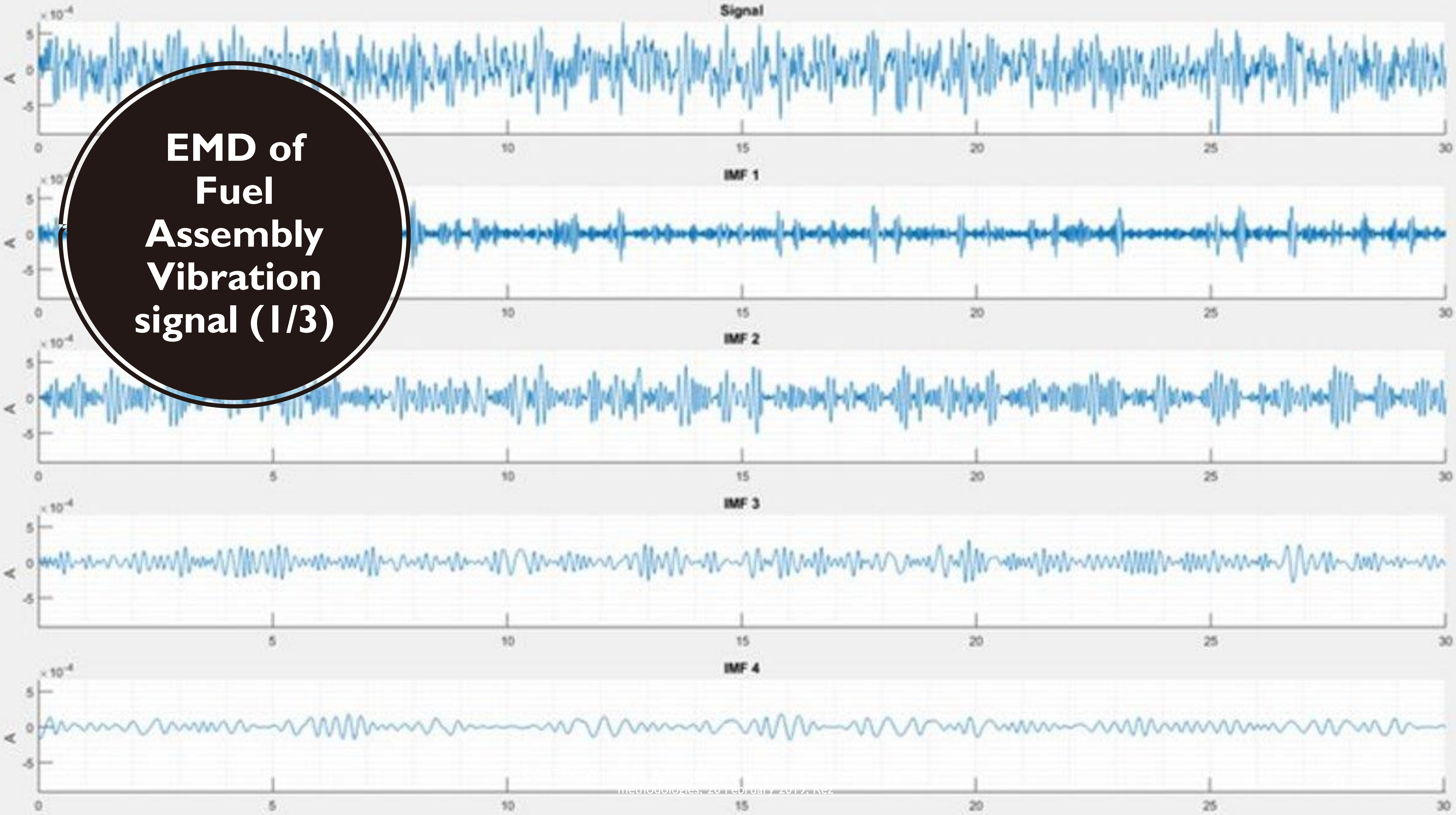
# Hilbert-Huang Transform

- Works well with non-stationary and non-linear signals
- Uses Empirical Mode Decomposition (EMD) to decompose signal to Intrinsic Mode Functions (IMF) along with a trend
  - Unlike WT, no detrending required by HHT
  - The signal is decomposed in the time domain
- IMFs
  - Form a complete and (nearly) orthogonal basis for the original signal
  - Are finite (and often small in number)
  - Have the same length as the original signal
    - can preserve characteristics of varying frequency (transients) like WT
- Apply Hilbert Spectral Analysis (HSA) to IMFs to extract instantaneous frequency and amplitude

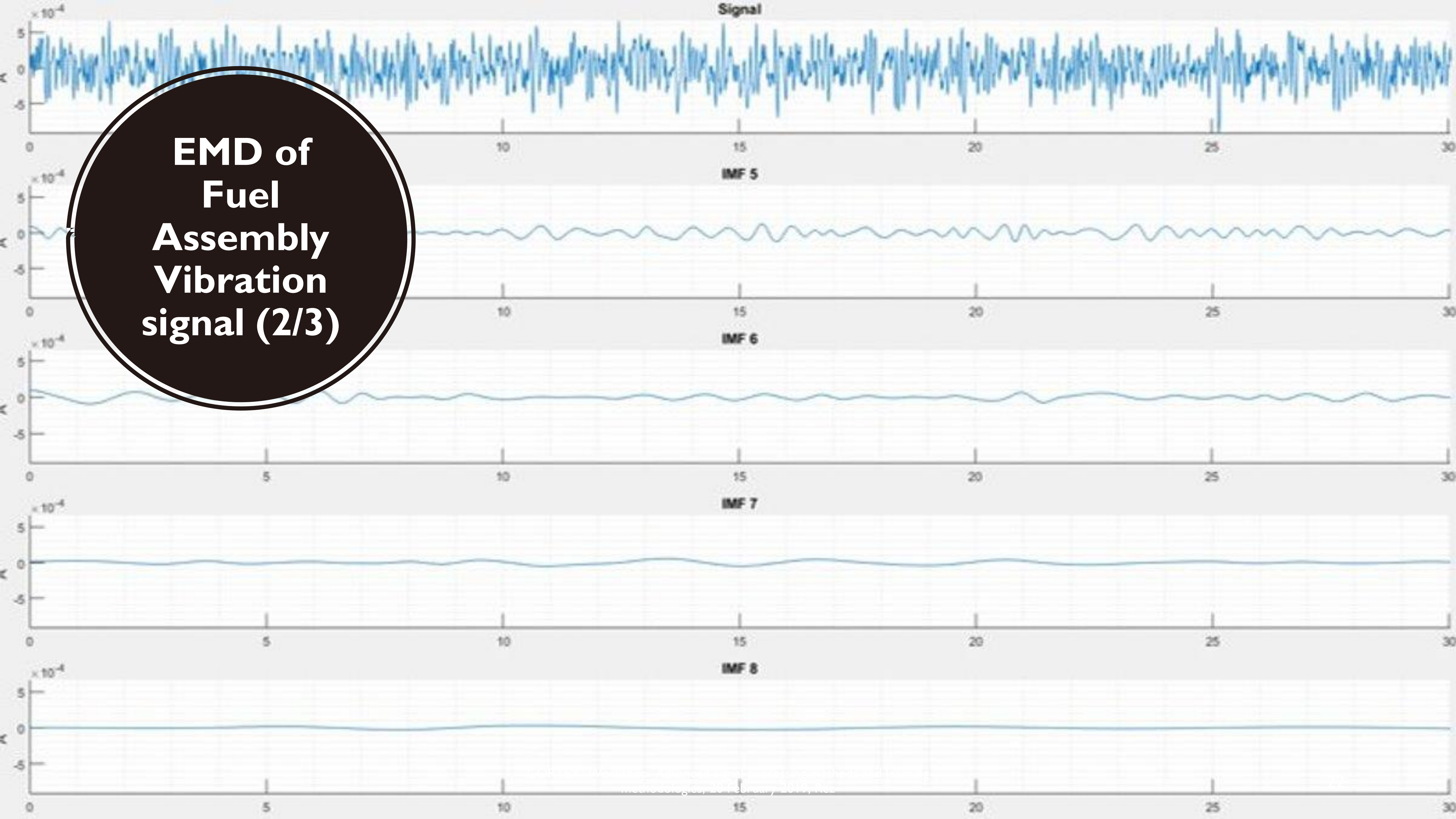
# Empirical Mode Decomposition

- IMF extraction is called **sifting**
  1. Identify the local extrema in signal $x$
  2. Approximate the upper (lower) envelope of $x$ using cubic splines
  3. Compute $m_1$, the mean of the upper and lower envelopes
  4. Let $h_1 \equiv x - m_1$
  5. Repeat steps 1-4 above, treating $h_1$ as $x$
- Stoppage criteria
  - Standard Deviation, S Number, Threshold, Energy Different Tracking
- At $k^{\text{th}}$ iteration
  - $h_{1k} \equiv h_{1(k-1)} - m_{1k}$
  - $c_1 \equiv h_{1k}$ becomes **the first IMF of the signal**, containing the shortest period component in the data
- Separate the first IMF from the signal, computing **residue** $r_1$: $r_1 \equiv x - c_1$
  - $r_1$ contains longer period variations in the signal
- The procedure is repeated for all subsequent residues
  - until residue $r_n$ becomes *monotonic*, having a single maximum and minimum
  - $x = \sum_{i=1}^{n} c_i + r_n$
  - A decomposition of the signal into $n$ empirical modes have been achieved

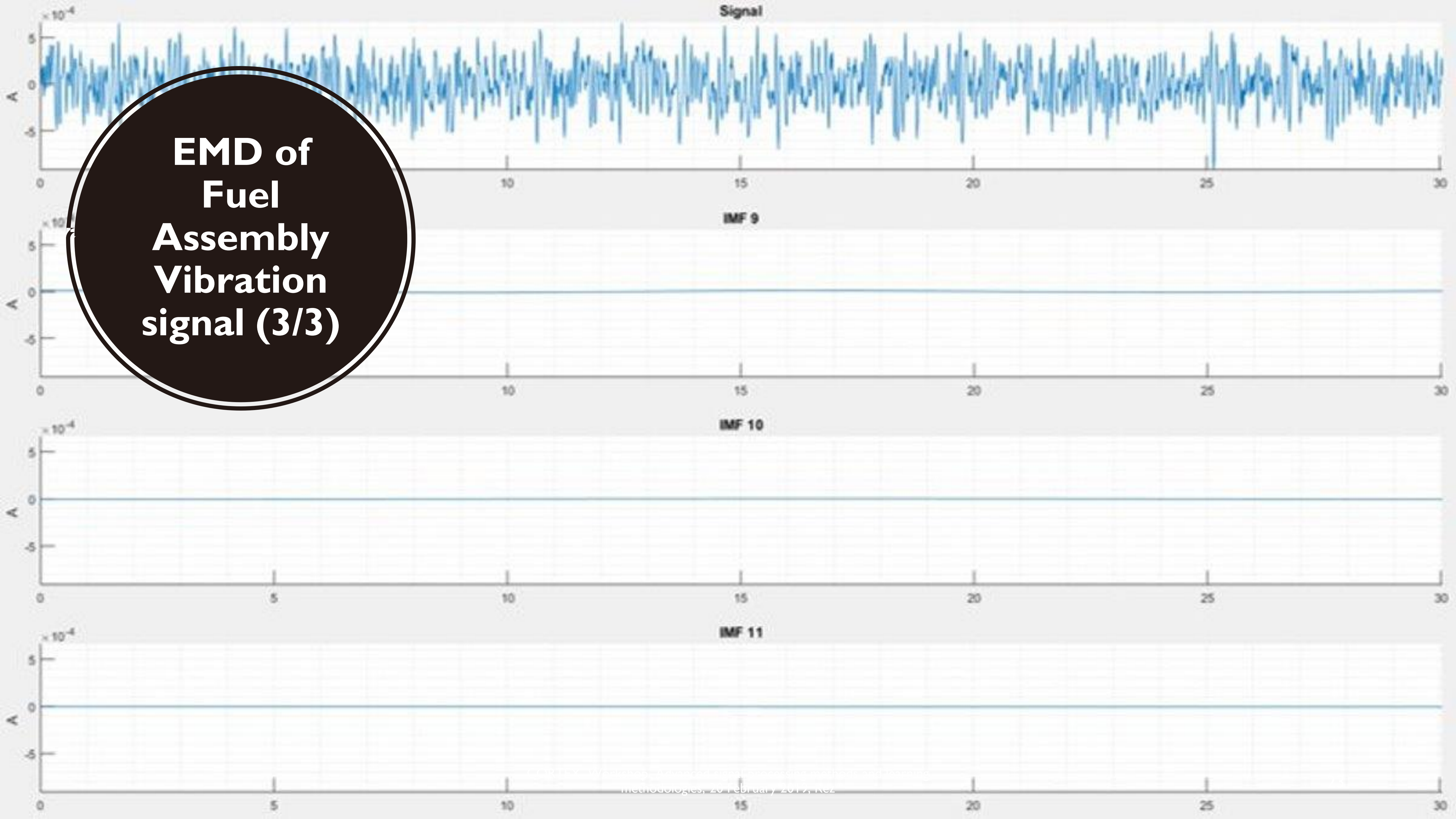
# EMD of Fuel Assembly Vibration signal (1/3)



# EMD of Fuel Assembly Vibration signal (2/3)



# EMD of Fuel Assembly Vibration signal (3/3)

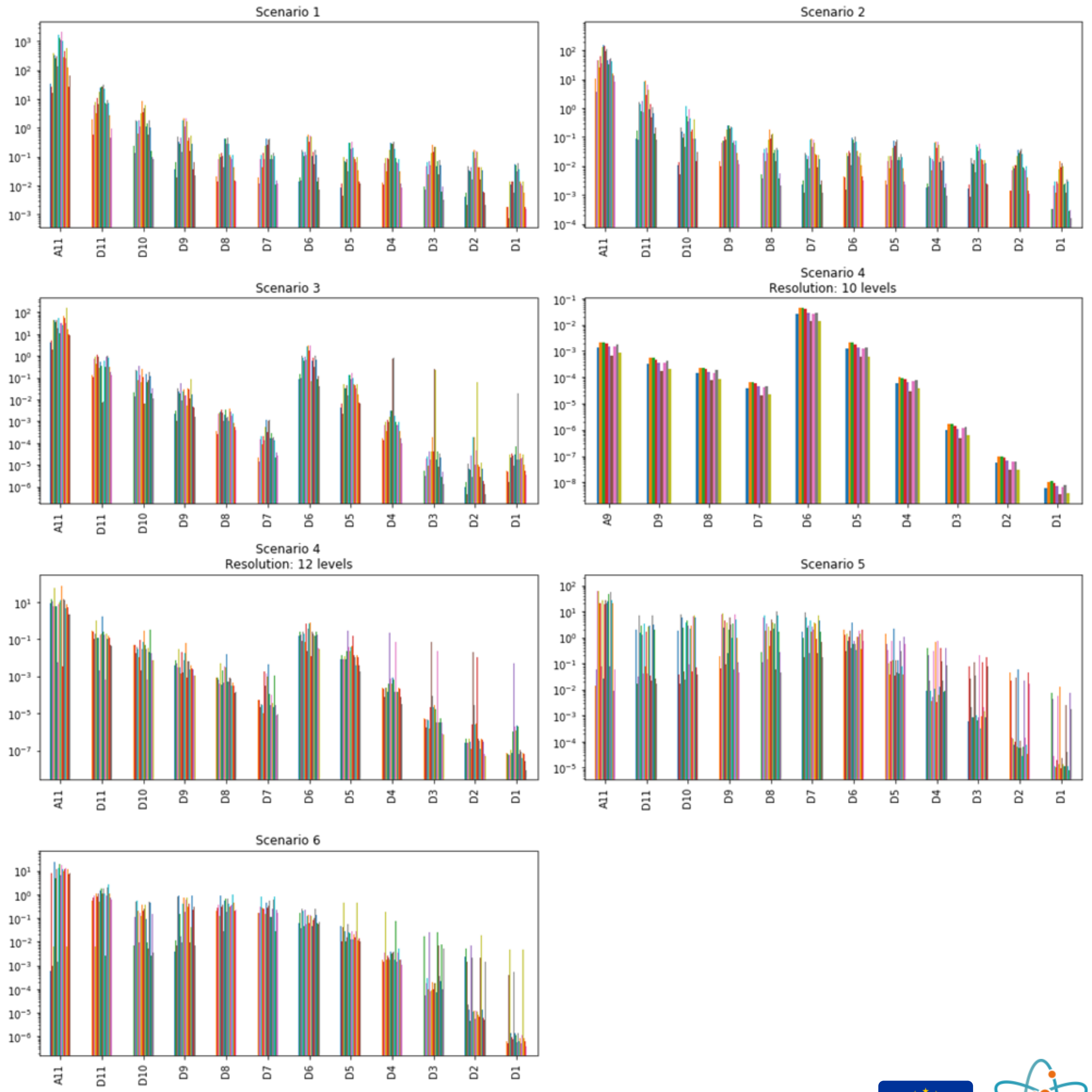


# Comparison of transformations

| | Fourier | Wavelet | Hilbert-Huang |
|---|---|---|---|
| Foundation | theoretical | theoretical | empirical |
| Basis | a-priori | a-priori (adaptive) | adaptive |
| Underlying operation | convolution | convolution | differentiation |
| Spectrum | frequency | frequency & time | frequency & time |
| Feature level | global | regional | local |
| Feature extraction | no | discrete: no<br>continuous: yes | yes |
| Non-linear signals | no | no | yes |
| Non-stationary signals | no | yes | yes |

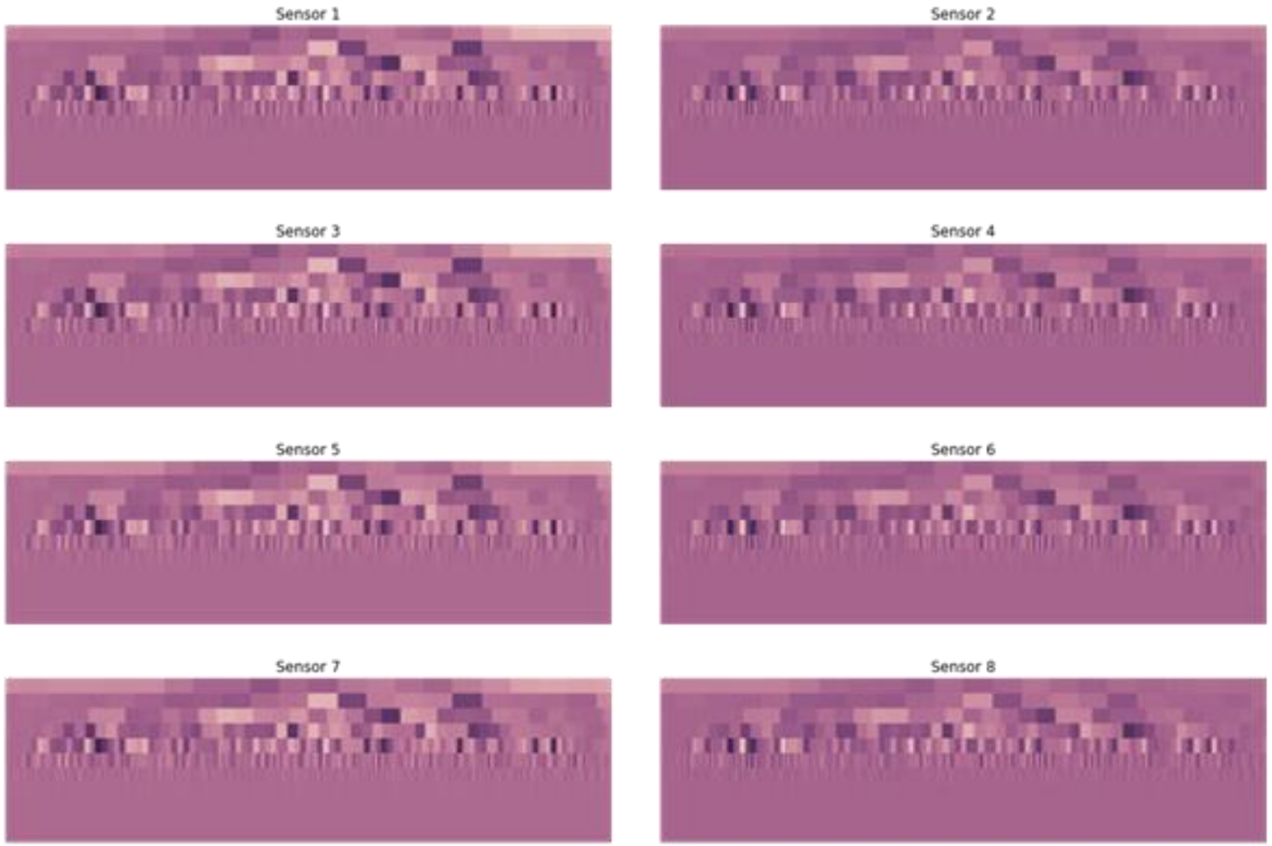
# Step 3. Feature selection

# I st case: Energy distribution of the coefficients of internal sensors

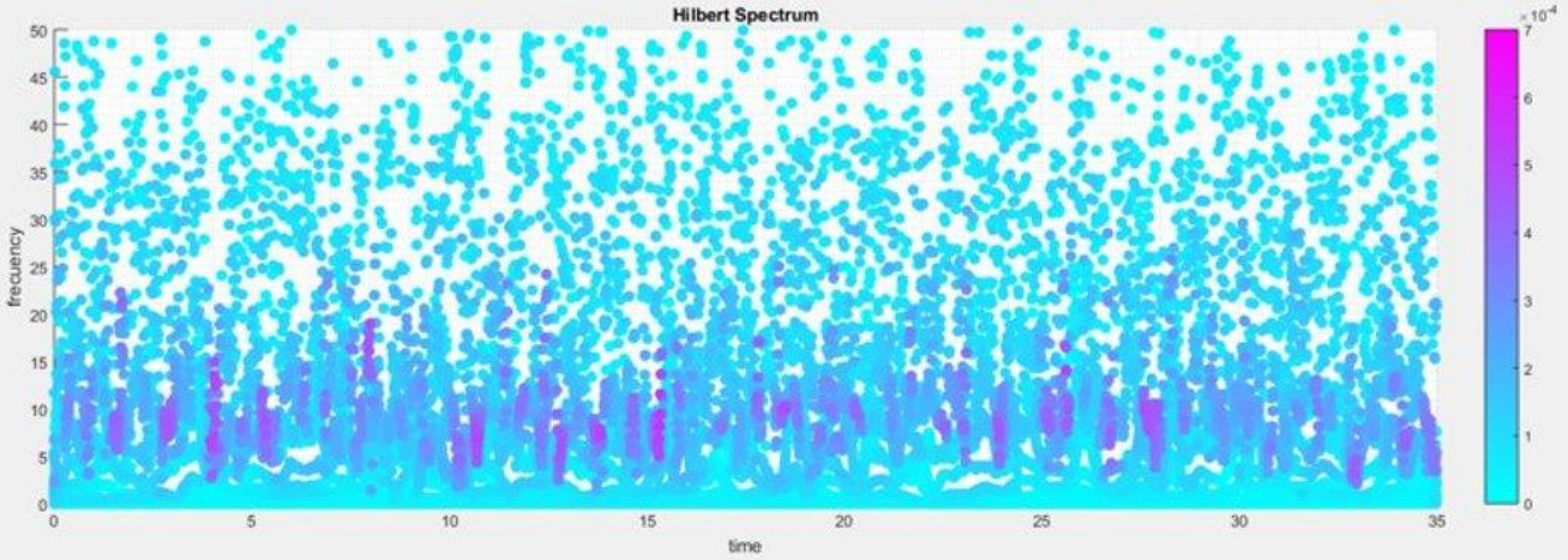


# 2nd case: Scalograms of external sensors

- Combined perturbation of vibrating 5x5 cluster of fuel assemblies and a fluctuation of inlet coolant temperature



# 3rd case: Hilbert Spectrum Analysis of IMFs of Fuel Assembly Vibration signals



# Thank you