CORTEX

Core monitoring techniques and experimental validation and demonstration

Machine learning techniques for anomaly detection and for the alignment of perturbation simulations with power plant measurements

SAINT Workshop on the use of machine learning and artificial intelligence (AI) in radiation science

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Cortex

- Research conducted in the framework of the CORTEX Project
  - Core monitoring techniques & experimental validation and demonstration for improved reactor safety
  - European Horizon 2020 Programme
  - Launched in Brussels on 5-6 September 2017, will last for 48 months
  - Total budget: €5.500.000
  - Coordinated by Chalmers University
  - Gathers 20 partners from 11 countries from across Europe
    - Artificial Intelligence & Learning Systems (AILS) Laboratory, School of Electrical & Computer Engineering, National Technical University of Athens, Greece

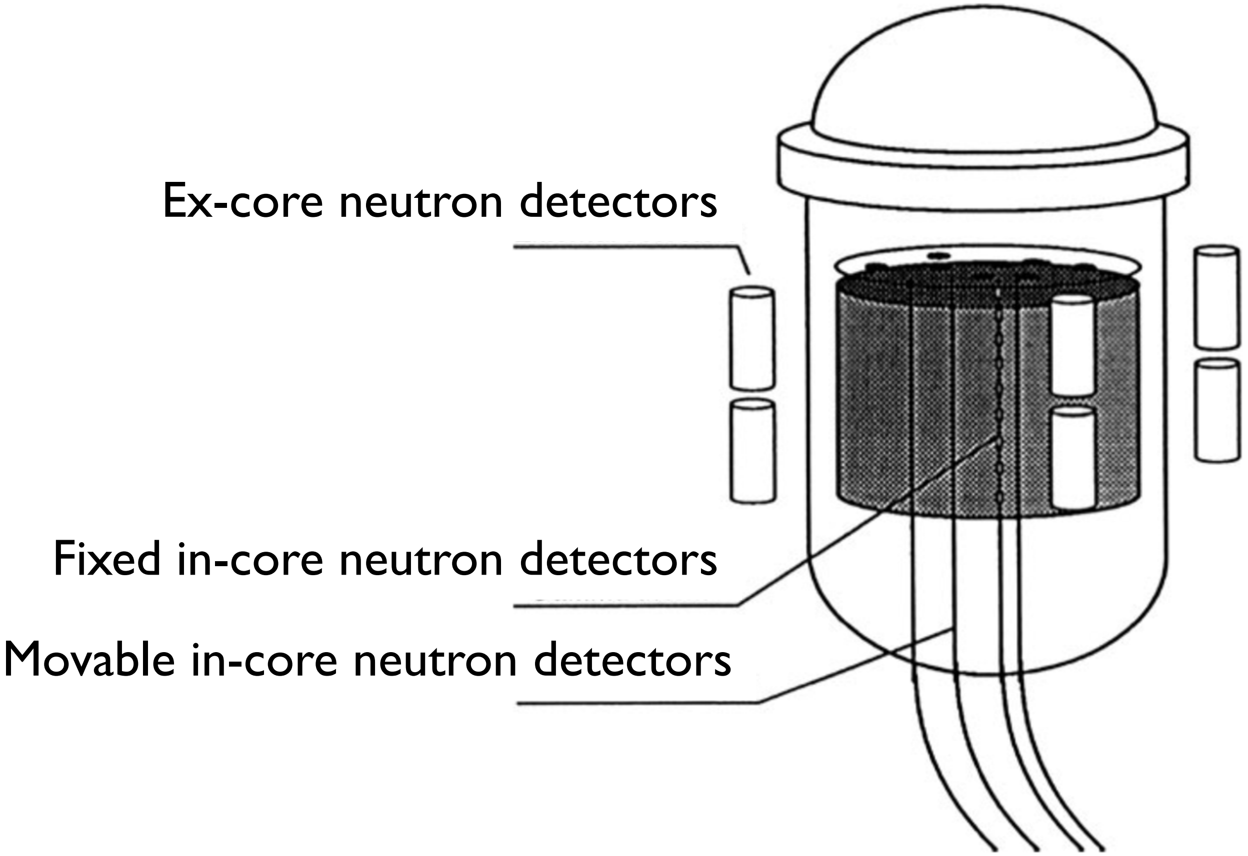
AILS@ECE.NTUA

- One of the main research units of the ECE NTUA
  - directed by Professor Andreas-Georgios Stafylopatis
- Areas of Expertise
  - Machine learning, artificial intelligence, neural networks, multimedia content analysis, human interaction, fuzzy logics, ontological knowledge representation and reasoning, …
- 39 Members
  - 6 faculty, 7 senior researchers, 2 postdoc researchers, 18 researchers and Ph.D students, 6 supporting and technical staff
- Publications
  - Over 200 in journals and over 400 in international conferences
- Myself ☺
  - Teaching & Research Associate (Lab Profile)

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

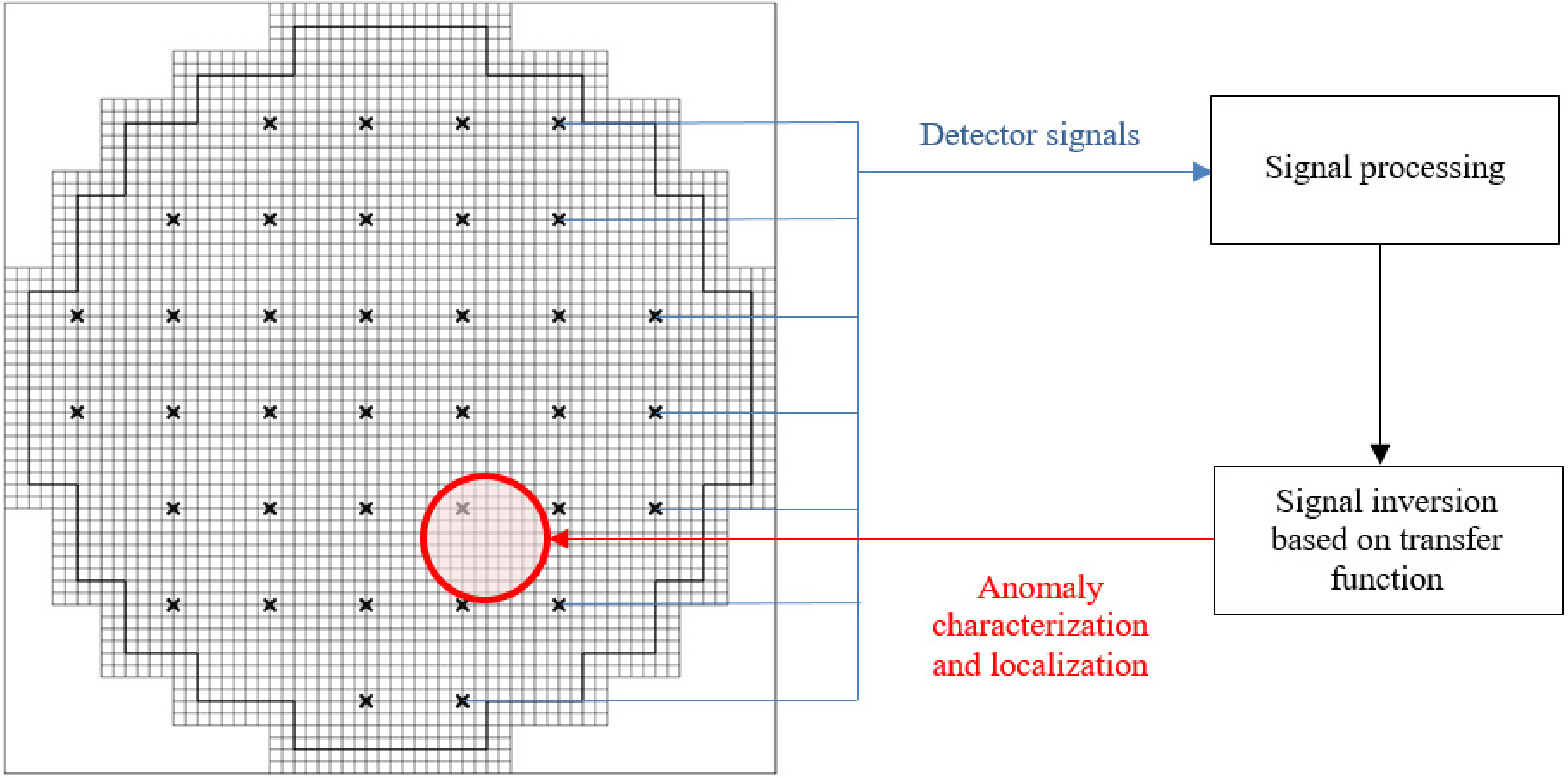
Location of neutron detectors



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

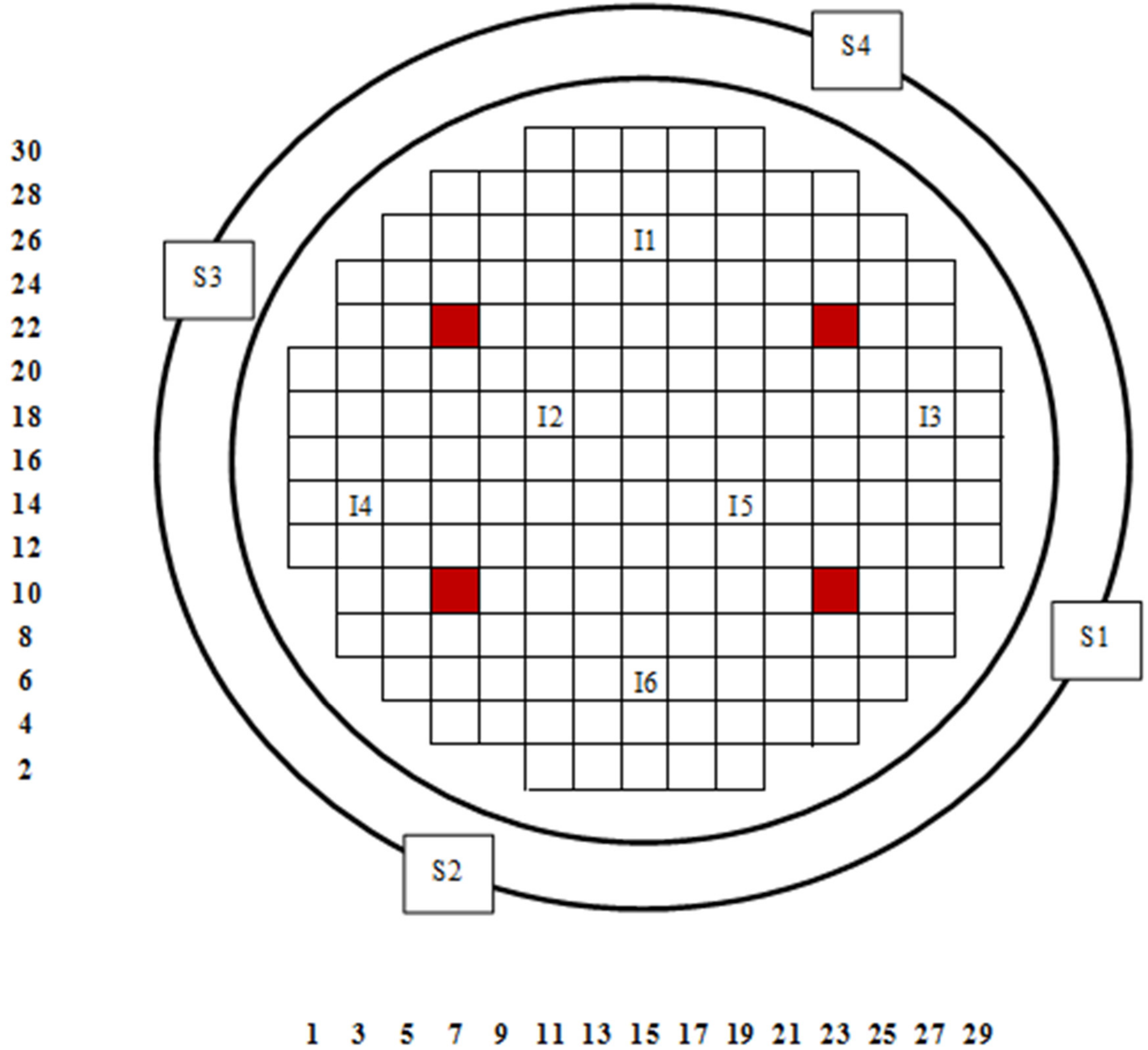
- Real
  - measured at the detectors
  - characteristics
    - may be due to more than one perturbation which are **usually unknown**
    - noise, trend and intermittencies
    - (possible) detector failure
- Simulated
  - model the fluctuations in neutron flux resulting from known perturbations applied 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!)

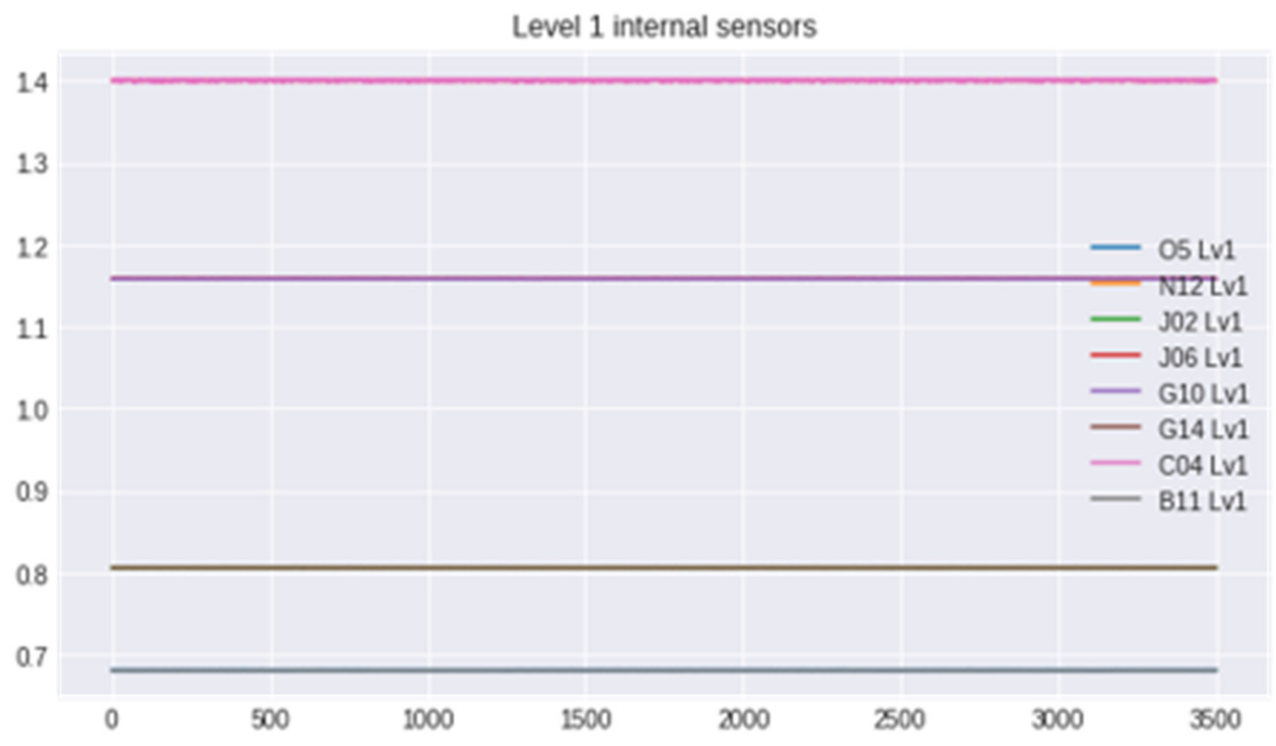
Workflow

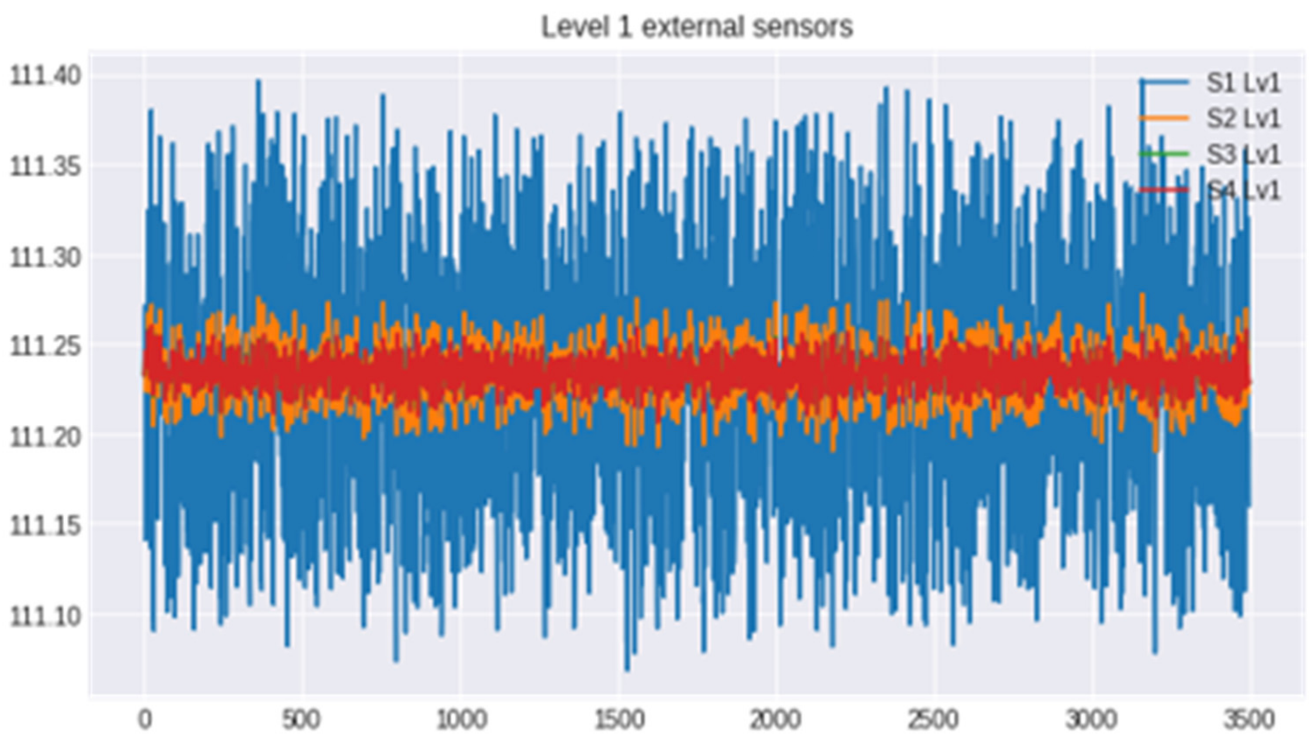
1. Data preprocessing
   - Remove noise, trend and intermittencies
   - Account for possible detector failure
2. Feature Extraction
   - Transformation Methods
     - Discrete Fourier Transform (DFT)
     - Discrete Wavelet Transform (DWT)
   - Non-parametric inversion methods
     - Artificial Neural Networks (ANNs)
     - ...
3. Feature Selection
4. Machine Learning Techniques

Example perturbation

Single fuel assembly vibrates in one direction







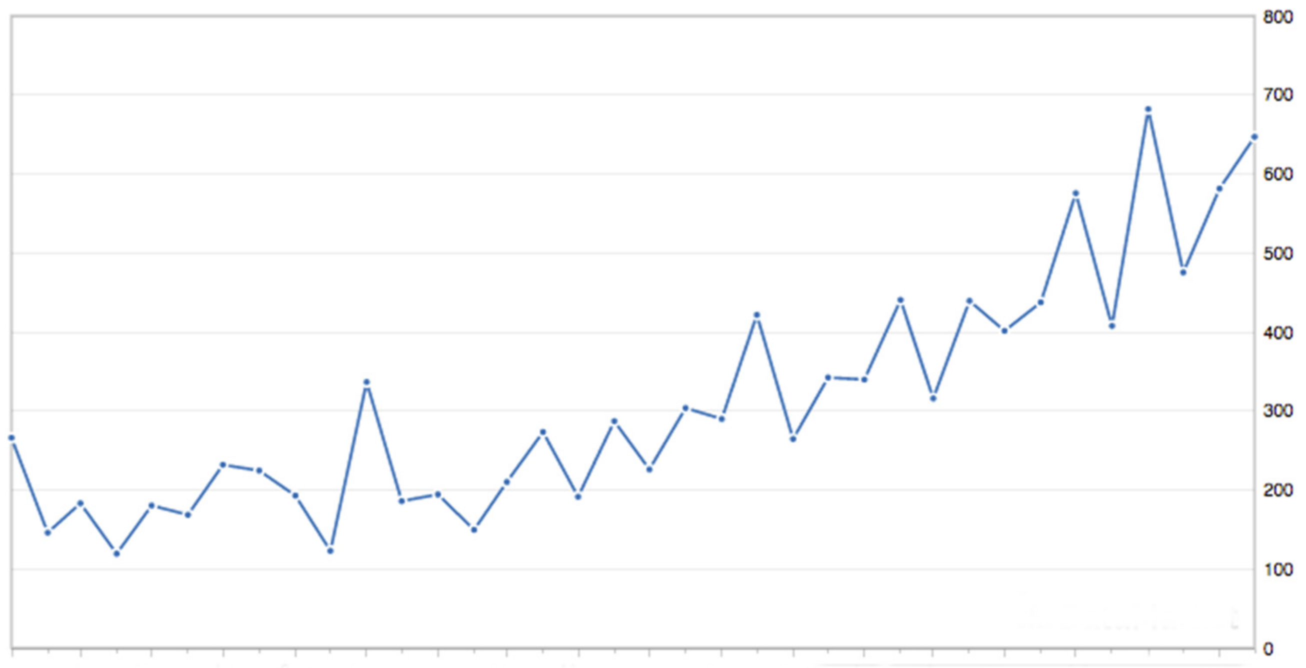
Example perturbation

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

Trend detection & removal

Trend

- Any systematic change in a time series (signal) that does not appear to be periodic
- Types of trend
  - 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

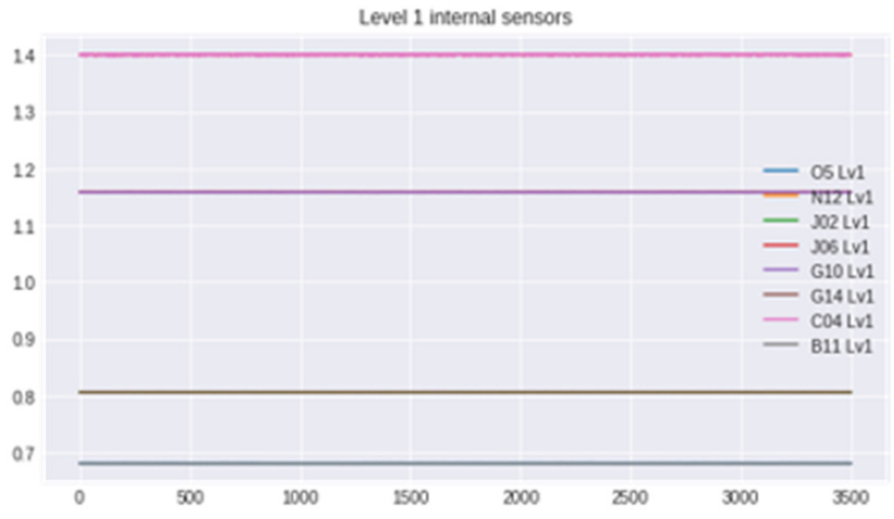


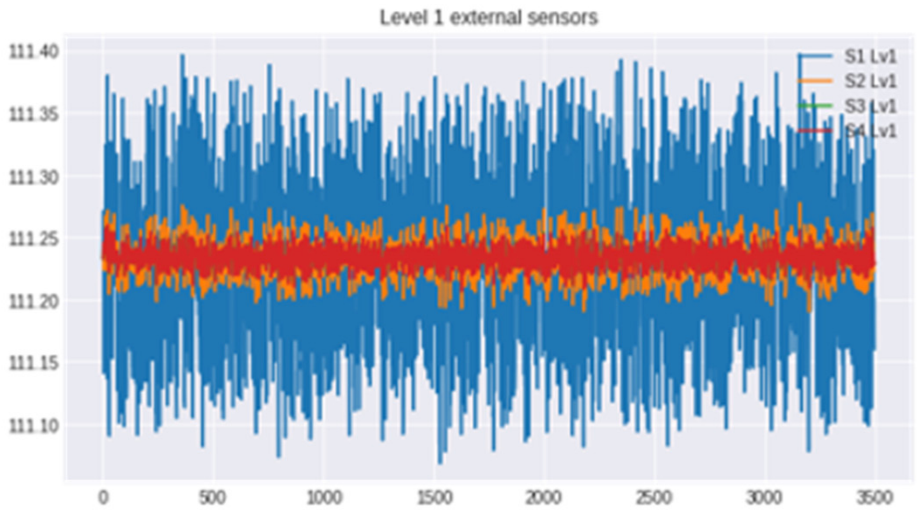
Removing trend

- Signals containing trend are characterized as *non-stationary*
- **Detrending**
  - The process of removing trend from a signal
  - Simplifies signal analysis
  - Trend has to be modeled in order to be removed
- **Trend modelling**
  - <u>Deterministic</u> (linear) trend is easier to be modelled
    - e.g. through least-square regression
  - <u>Stochastic</u> trend 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
    - …

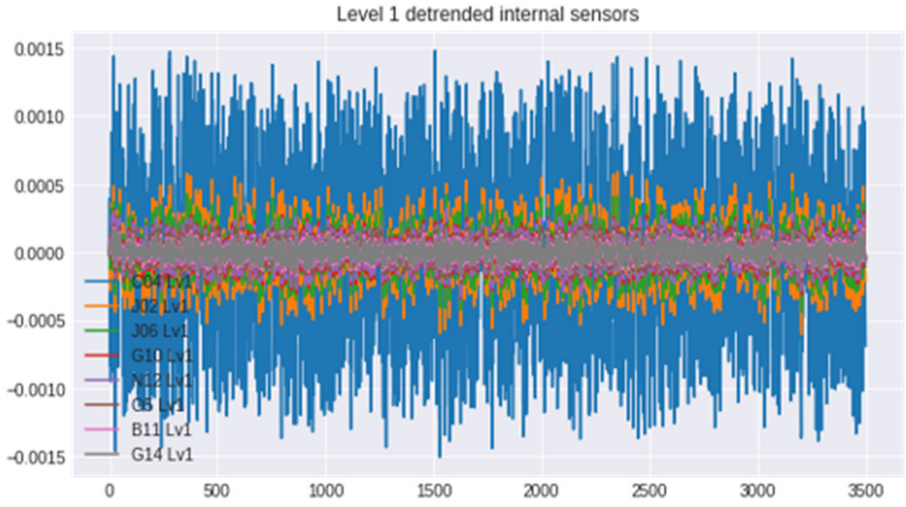
Detrending

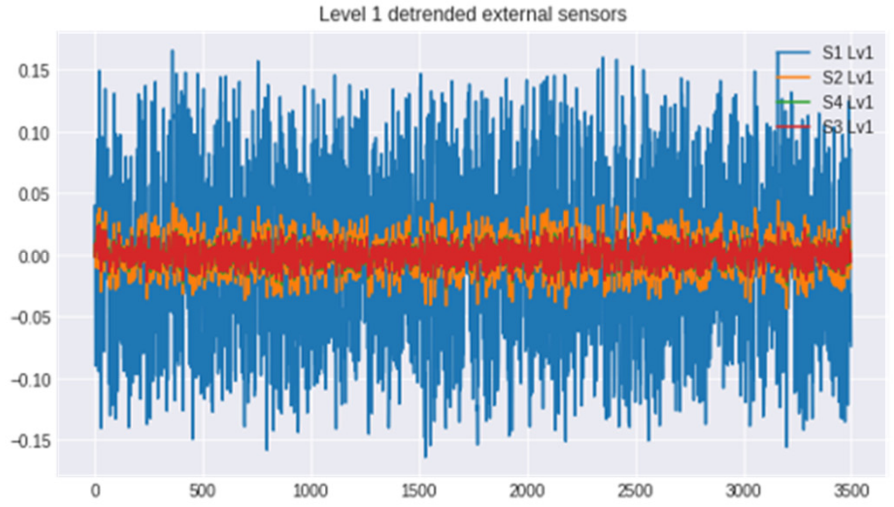
Before





After





Feature Extraction

Using transformation methods

The Discrete Wavelet Transform

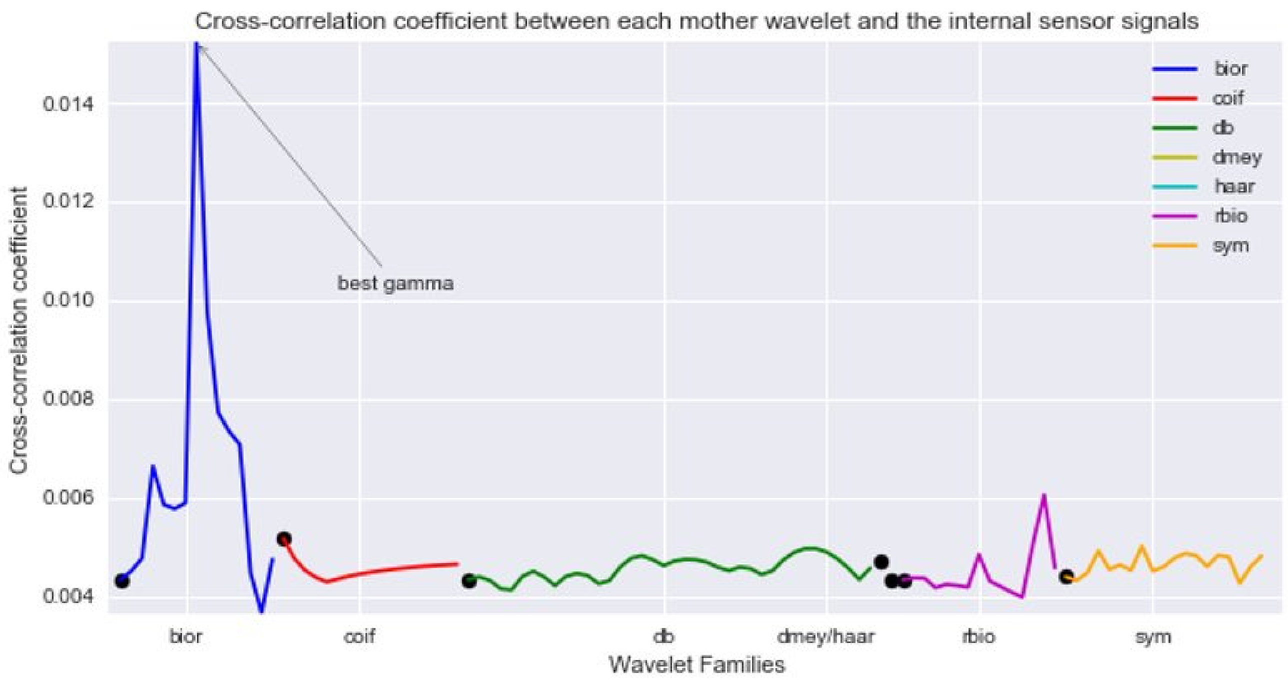
- Suitable for analyzing signals with time-varying spectra
  - DFT gives the spectral details of the signal without considering temporal properties
- Produces varying time and frequency resolutions
  - DFT produces frequency spectrograms
  - DWT scalograms depict transients
- High frequencies
  - Good 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
  - DFT uses only sinusoidal functions

Choice of the mother wavelet

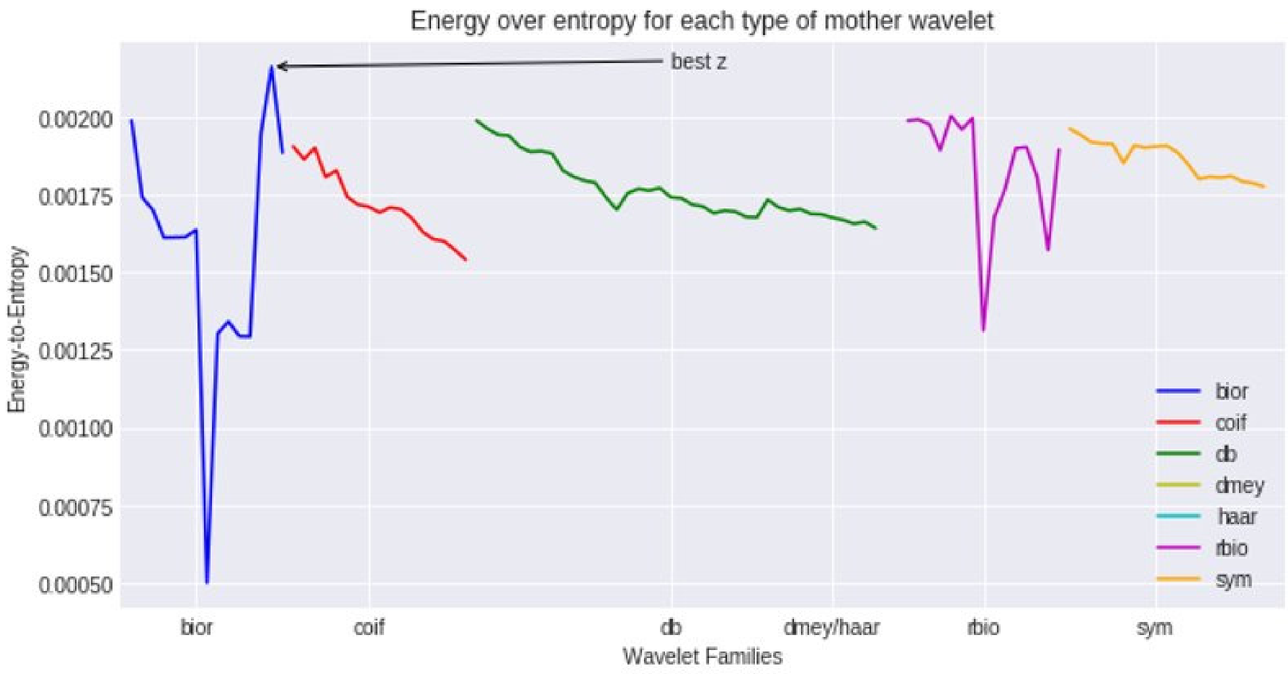
- Mother wavelet families
  - Haar, Daubechy , Symlet , Coiflet , Biorthogonal , Reverse Biorthogonal , Discrete Mayer, ...
- Criterion
  - How "close" is the reconstructed signal to the original?
- Measures of similarity
  - Cross-correlation (statistical)
    - $\gamma(X,Y) = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{(X-\bar{X})^2(Y-\bar{Y})^2}}$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

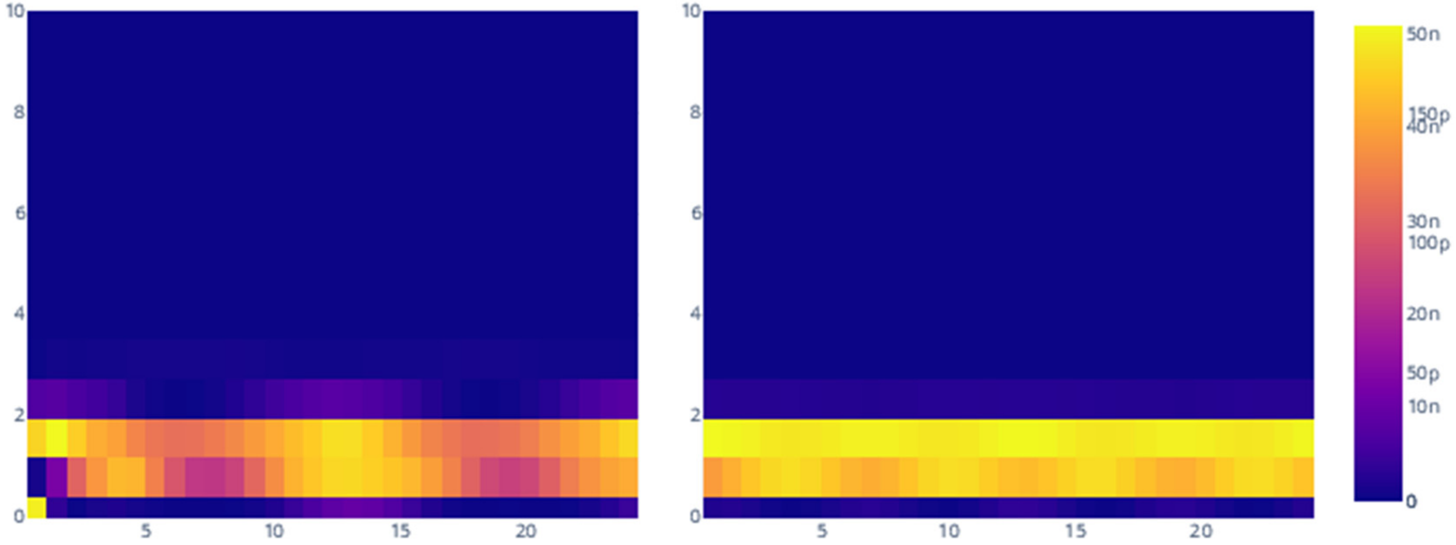
Best wavelet: **Biorthogonal (3.1)**



Best wavelet: **Biorthogonal (5.5)**



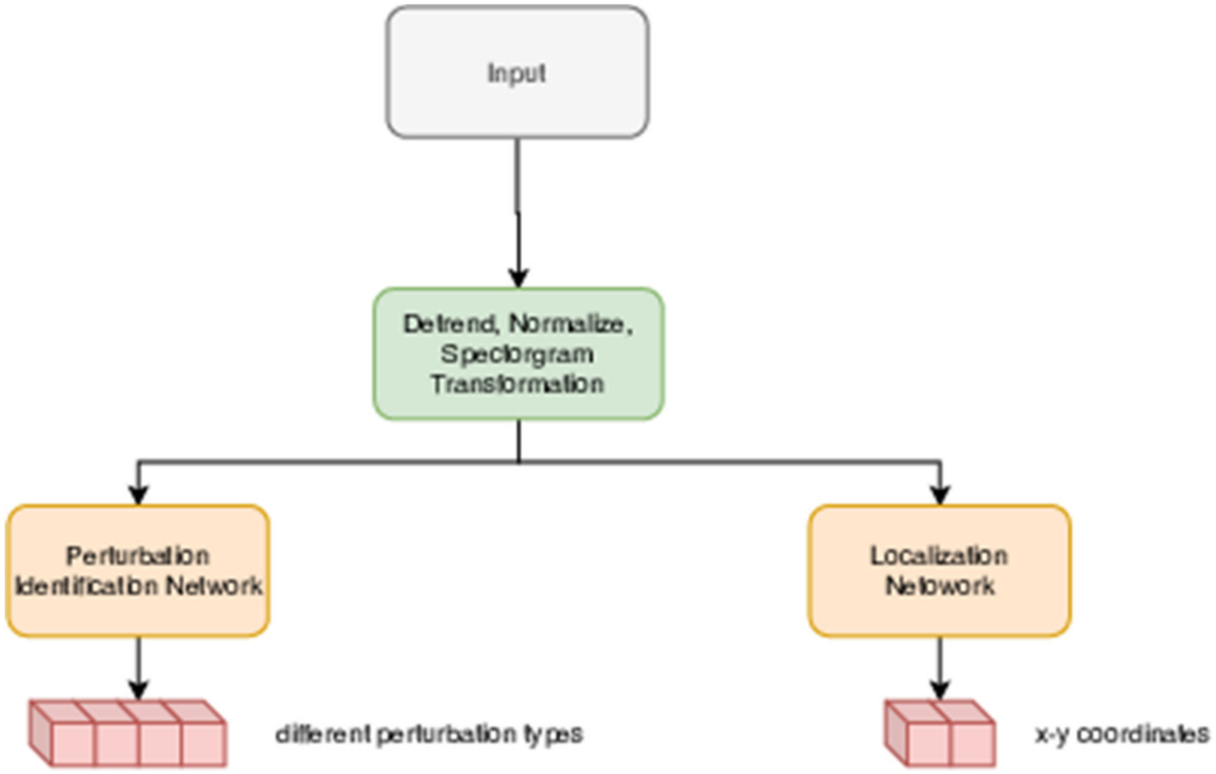
Scalograms



- Detector signals represented as **scalograms**
  - the "spectrogram" of DWT
- x-axis: *time*
- y-axis: *frequency*
- color: *intensity*
- Treated as images by the Deep Learning (DL) techniques discussed next

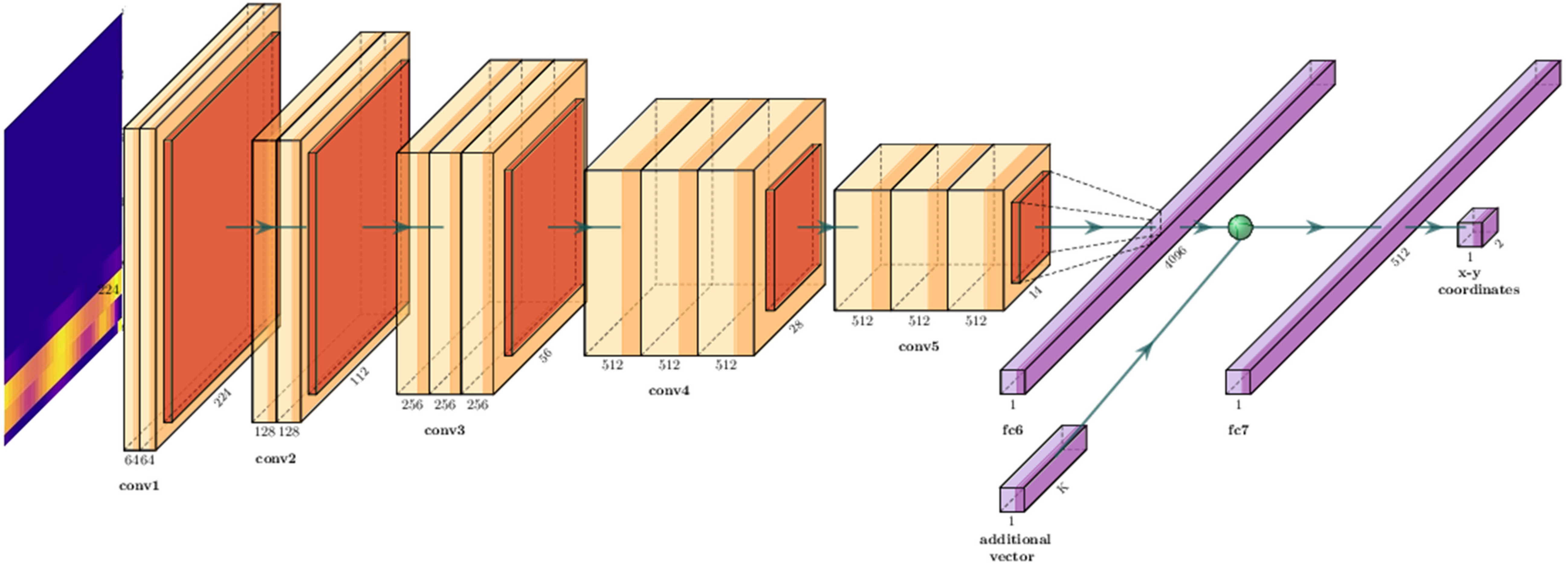
Anomaly Detection

System Architecture



- Two DL Convolutional Neural Networks (CNNs)
  1. Perturbation Identification Network
     - Output a binary vector of the detected perturbation(s)
  2. Localization Network
     - For certain type of perturbations locate them in the reactor core
       - eg single fuel assembly perturbation

Identification & Localization Networks: ResNet



Experimental Implementation

- Swiss pre-KONVOI pressurized water reactor (PWR)
  - 3-loop reactor, 177 FAs
- Simulated data only
  - Provided by the Paul Sherrer Institute (PSI)
    - CASMO-5/SIMULATE-3 code system, coupled with SIMULATE-3K transient nodal code
  - Four perturbation types
    - Individual FA vibrations, inlet coolant, inlet flow & their combinations
  - Three modes of vibration (for the FA case)
    - Cantilevered, C-shaped, S-shaped
  - Three core conditions
    - Beginning, middle & end of cycle

Procedure

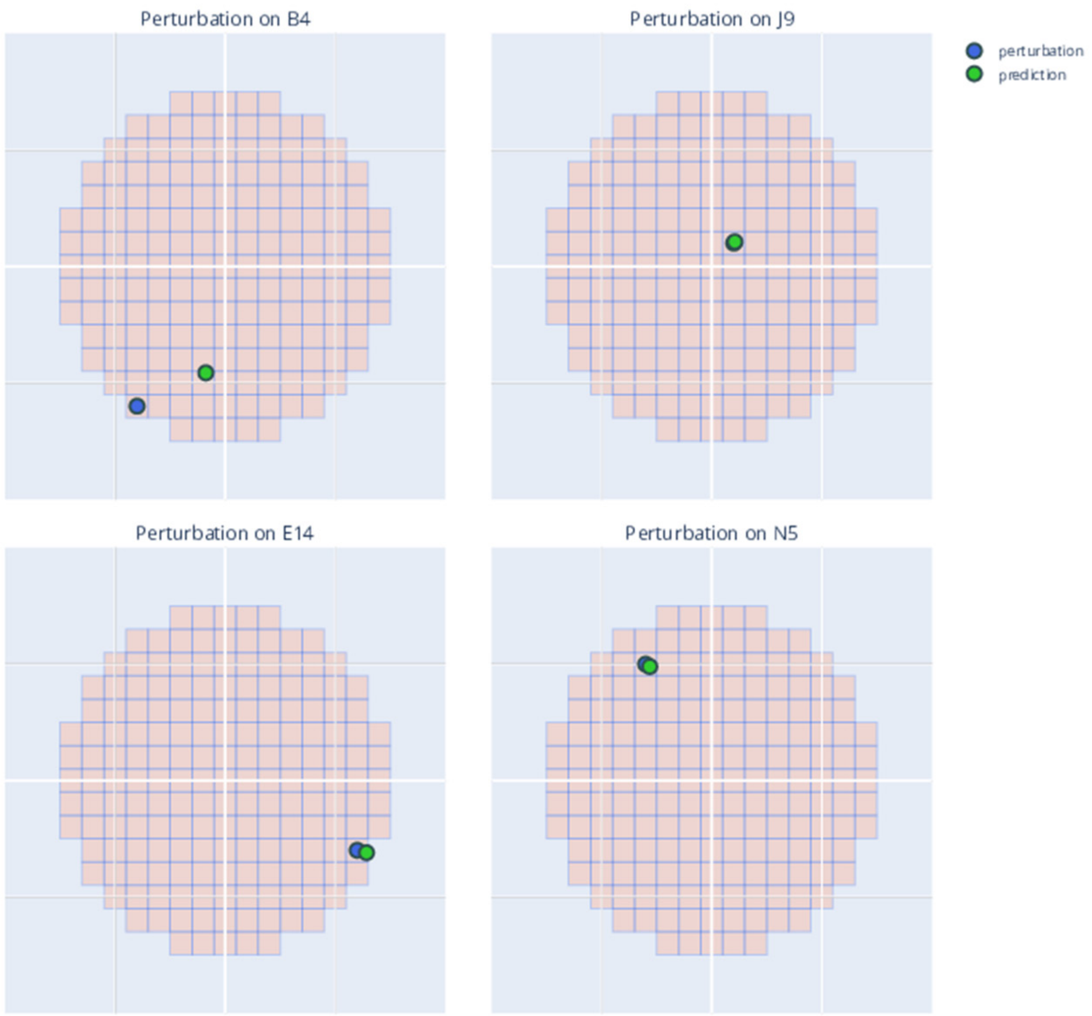
- Preprocessing
  - Detrend signals, compute DWT, construct scalograms
  - Covert scalograms to 1-channel grayscale images
  - Construct a 44-channel image from all detectors
- Results of the identification network on the test data

Perturbation	Precision	Recall	F1-score
FA	0.97	0.96	0.96
Inlet temperature	0.95	0.93	0.94
Inlet coolant	0.94	0.91	0.92
Combinations	0.92	1	0.96

Results of the localization network

- **Accuracy on test data**

Prediction proximity	Proportion
Exact	0.73
± 1 difference	0.21
± 2 difference	0.05
more than ± 2 difference	0.01



Robustness analysis

- Adapt to cases of faulty detectors signals
  - Consider only a subset of incore/excore detectors function normally
  - 6 different combinations
- Accuracy on the test data

Prediction Proximity	Comb 1	Comb 2	Comb 3	Comb 4	Comb 5	Comb 6
exact	0.52	0.58	0.48	0.65	0.43	0.66
± 1 diff.	0.31	0.32	0.32	0.26	0.34	022
± 2 diff.	0.11	0.07	0.13	0.07	0.15	0.09
$> \pm 2$ diff.	0.06	0.03	0.07	0.02	0.08	0.03

- More details on our ANS M&C 2021 submission
  - Thanos Tasakos, George Ioannou, Vasudha Verma, Georgios Alexandridis, Abdelhamid Dokhane and Andreas Stafylopatis - *Deep learning-based anomaly detection in nuclear reactors*

Align simulated perturbations with plant measurements

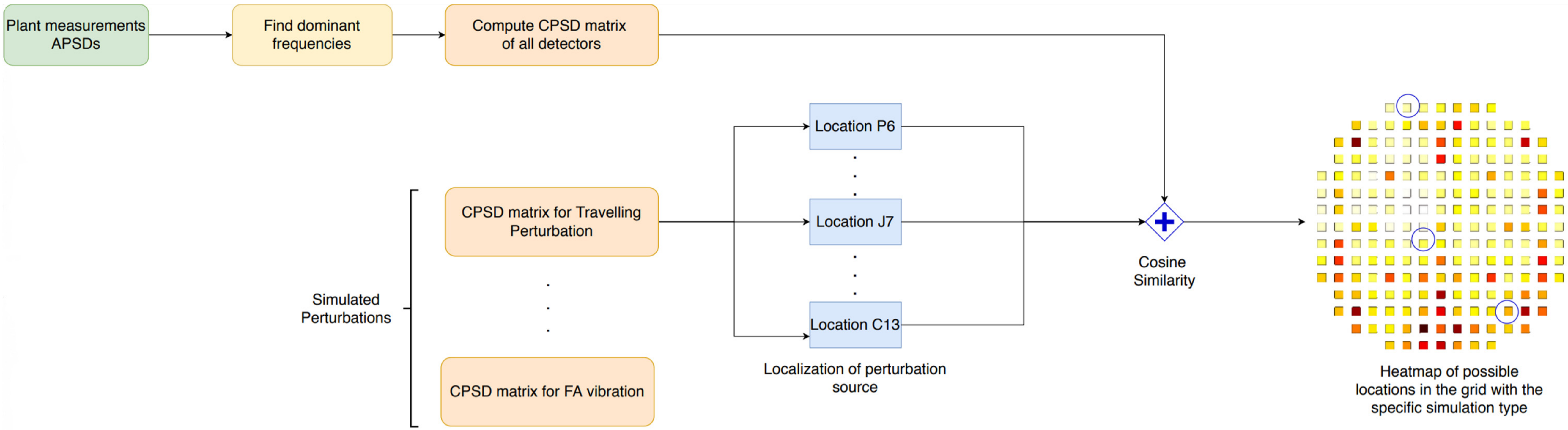
Intuition

- Power plant measurements are usually *unlabeled* data
  - It is not known whether (& which) perturbations occur within the core
- Use modelling tools to simulate the induced noise produced by various "known" perturbations
- Compare the simulated signals with the plant measurements in order to locate similarities & dissimilarities
- These comparisons may form the basis for more advanced machine-learning based techniques
  - eg clustering

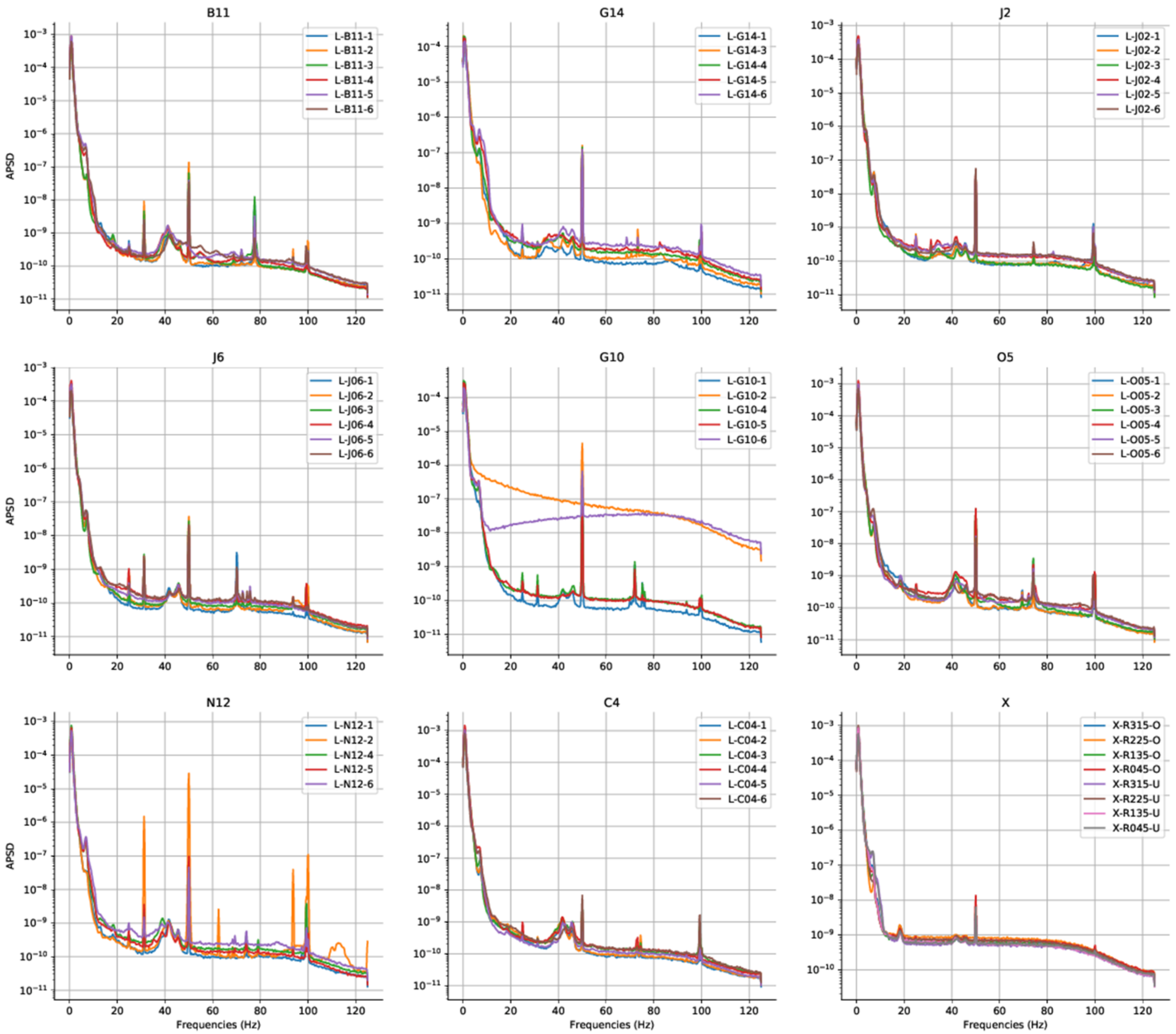
Procedure

- Preprocessing
  - Detrend plant measurements & simulated signals
  - Compute the DFT of the above
  - Compute the Auto Power Spectral Density (APSD) of the plant measurements
- Identify frequency peaks of APSDs
  - Welch algorithm
  - Candidate frequencies for the existence possible perturbations
- Compute the Cross Power Spectral Density (CPSD) between
  - all n detectors of the plant measurements, creating an nxn matrix
  - the corresponding simulated data for the frequency peaks identified above (again creating nxn matrices)
- Compare the CPSDs between real measurements & simulated data

System architecture



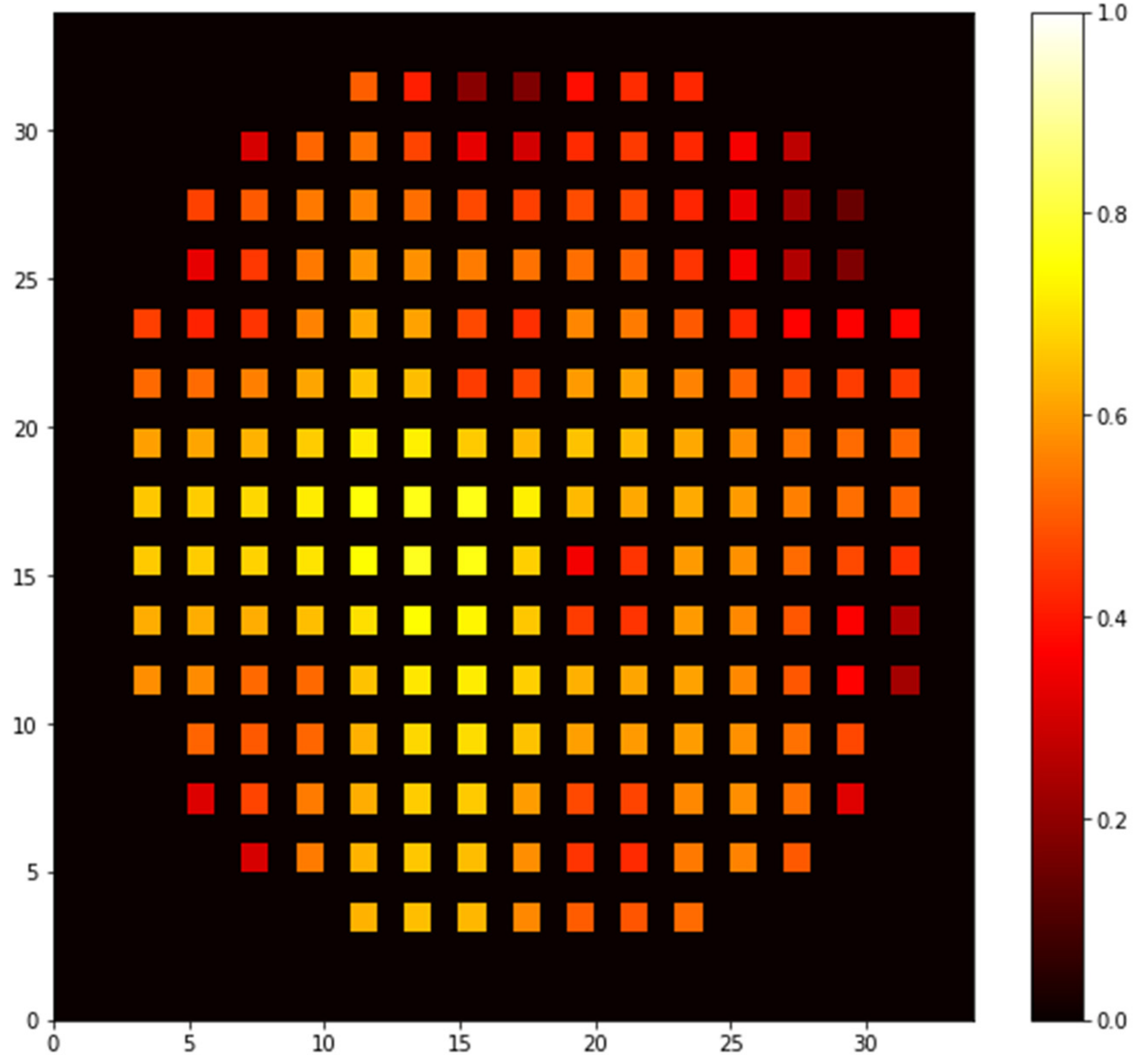
Example APSDs



Experimental Implementation

- German pre-KONVOI PWR
  - 4-loop reactor
- Actual plant measurements
- Simulated data
  - Provided by Chalmers University
    - CORE SIM+ tool
  - Four perturbation types
    - Individual FA vibrations
      - Modes: cantilevered, simply supported, cantilevered & simply supported
    - Coolant flow vibrations
    - Core barrel vibrations
      - Modes: beam, pendular
    - Generic (absorber of variable strength)

Example results



- Similarity Heatmap for axially traveling perturbation at the velocity of the collant flow at 0.3 Hz.
- More details on our ANS M&C 2021 submission
  - George Ioannou, Thanos Tasakos, Antonios Mylonakis, Georgios Alexandridis, Christophe Demaziere, Paolo Vinai and Andreas Stafylopatis – *Feature extraction and identification techniques for the alignment of perturbation simulations with power plant measurements*

Thank you