

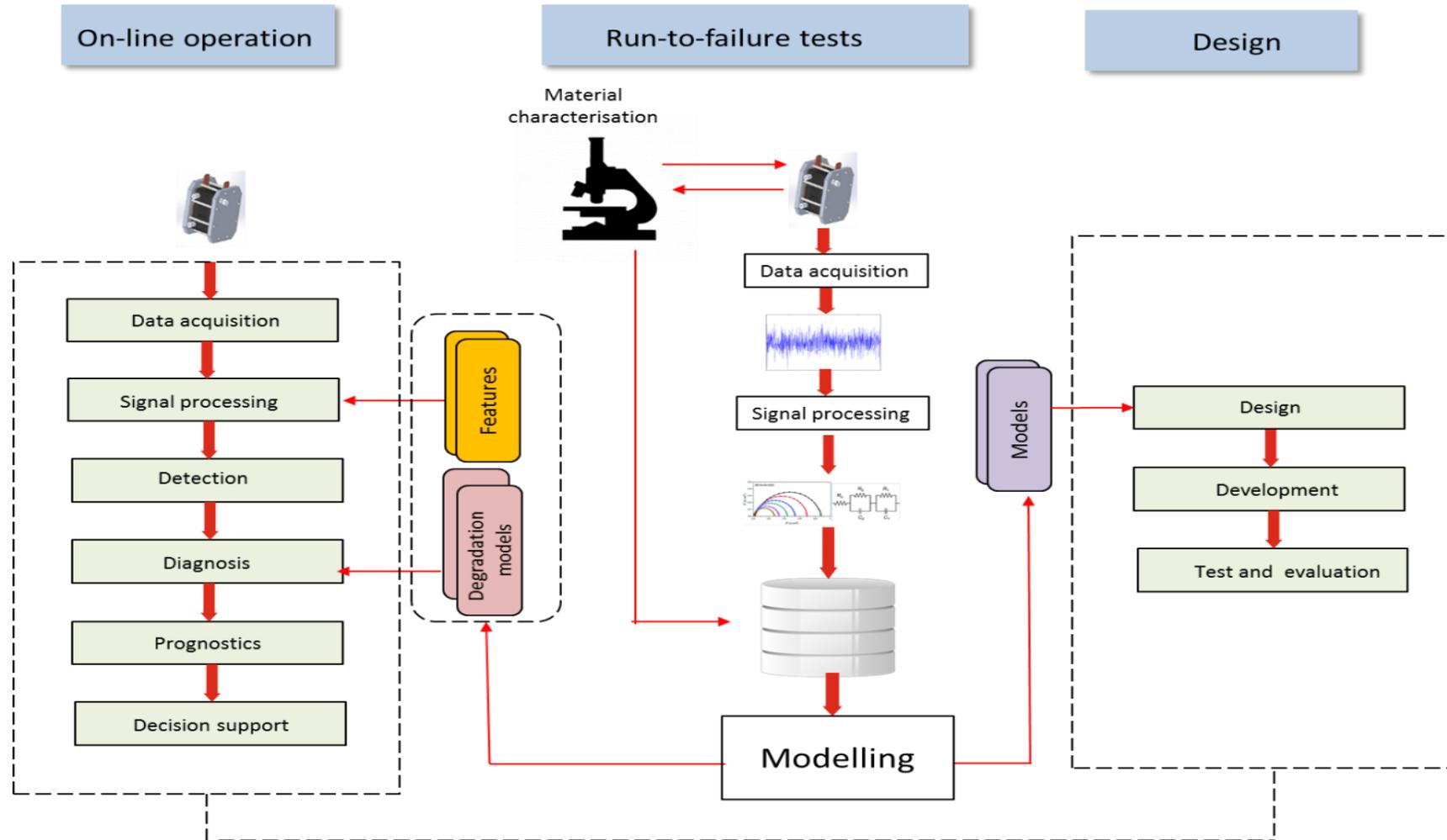


RUBY Project **RUBY**

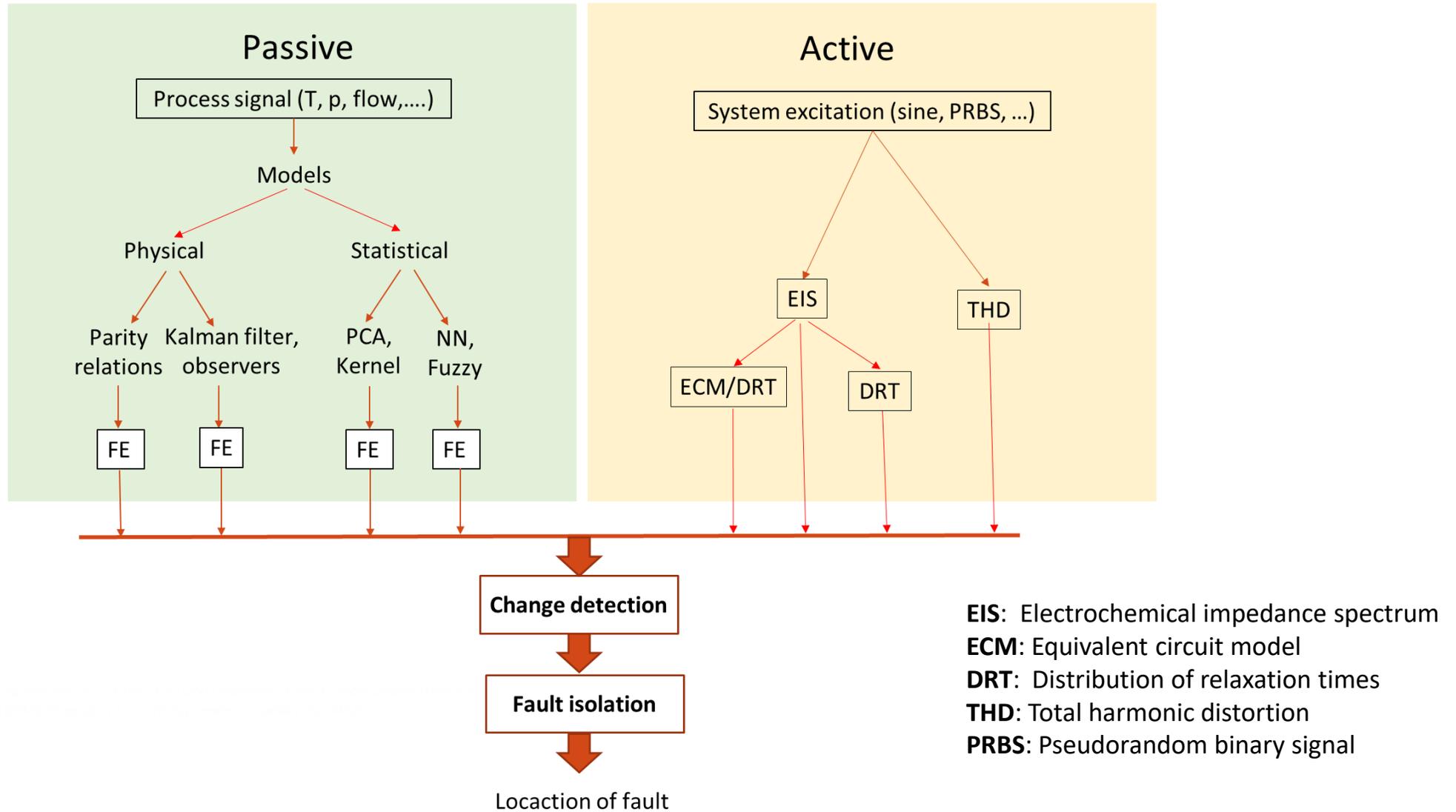
Robust and reliable general management
tool for performance and durability
improvement of fuel cell stationary units

ACTIVE AND PASSIVE DIAGNOSIS OF SOFC CELLS AND STACKS

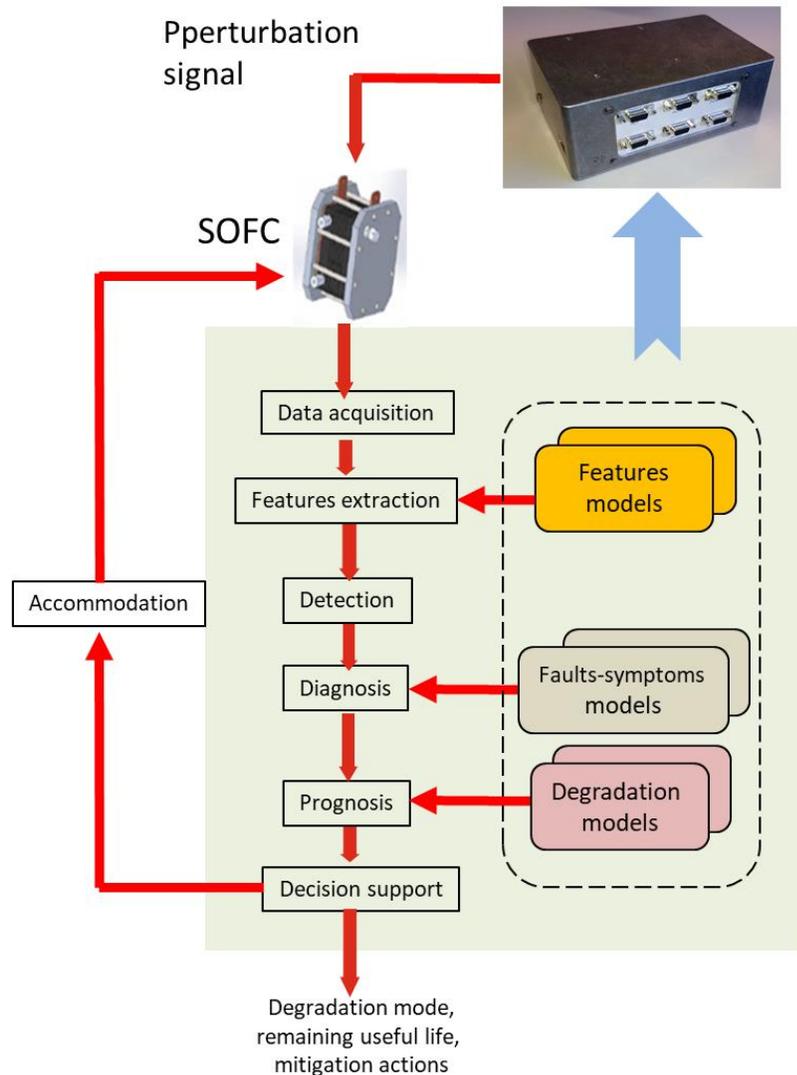




Passive and active diagnosis



Active diagnosis: objectives



- Develop **fault detection and isolation (FDI) algorithms for stack diagnostics**, to be embedded in the **HW**;
- Exploit **EIS, THD and dynamic stack perturbation** together with **model- and signal-based approaches for features (metrics) extraction** ;
- Use knowledge-based approach to derive **Fault-Signature Matrix as the link between metrics and faults** ;
- Identify **features** for fault/degradation **mitigation for future implementation**.
- Provide unified diagnostic framework for active and passive diagnosis

Fast EIS: perturbation by means of DRBS

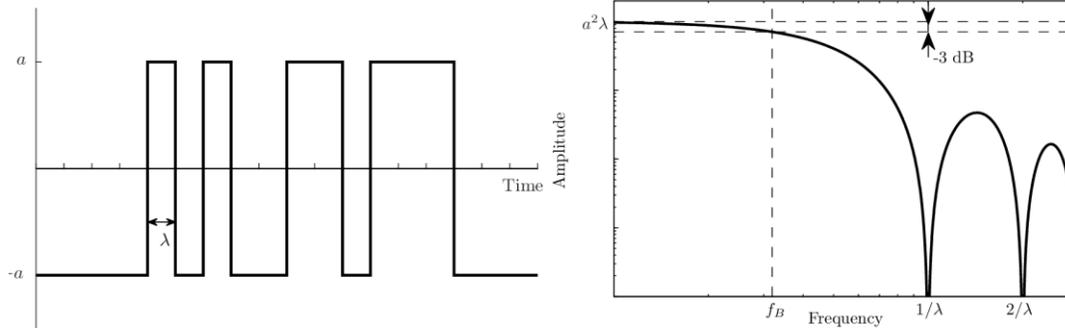
Rationale:

System perturbation with PRBS:

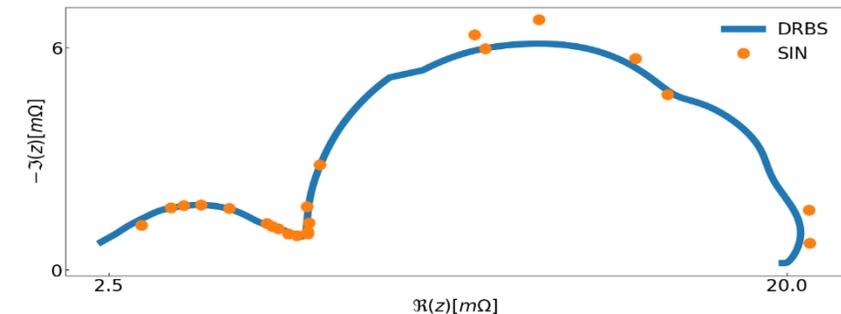
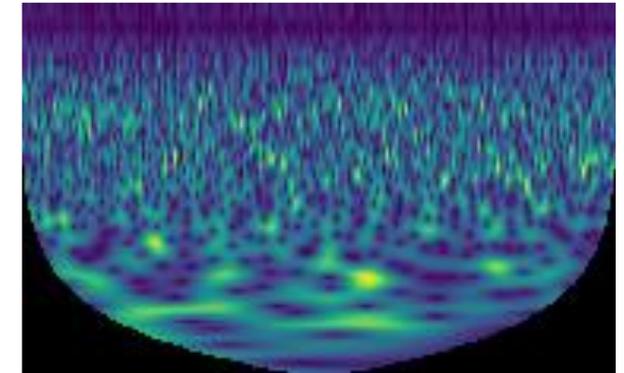
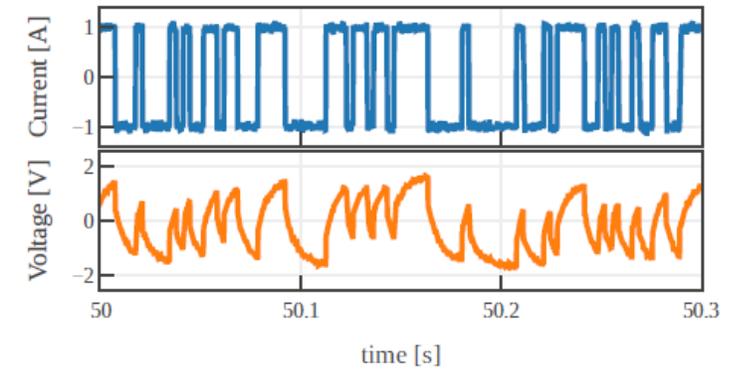
- EIS at **low frequencies** takes prohibitively long times!
- how to assure **stable conditions**?
- Limited signal amplitude** \Rightarrow guaranteed excitation of **linear** mode of SOFC operation;
- Almost **flat power spectrum**;
- EIS characteristic is evaluated on a **continuous frequency interval**, while with (multi/mono) sine approach the impedance is checked only at a limited number of frequency points!

For example

- measurement time for **one point** on EIS curve at $f=10 \mu\text{Hz}$ takes $\approx 10.000\text{s} \approx 2\text{h}47\text{min}$
- scan from **1mHz to 1kHz**, 61 frequencies, equidistant on log scale is $\approx 2\text{h}47\text{min}$
- scan **1Hz to 1MHz**, 61 frequencies, equidistant on log scale is $\approx 7\text{min}$



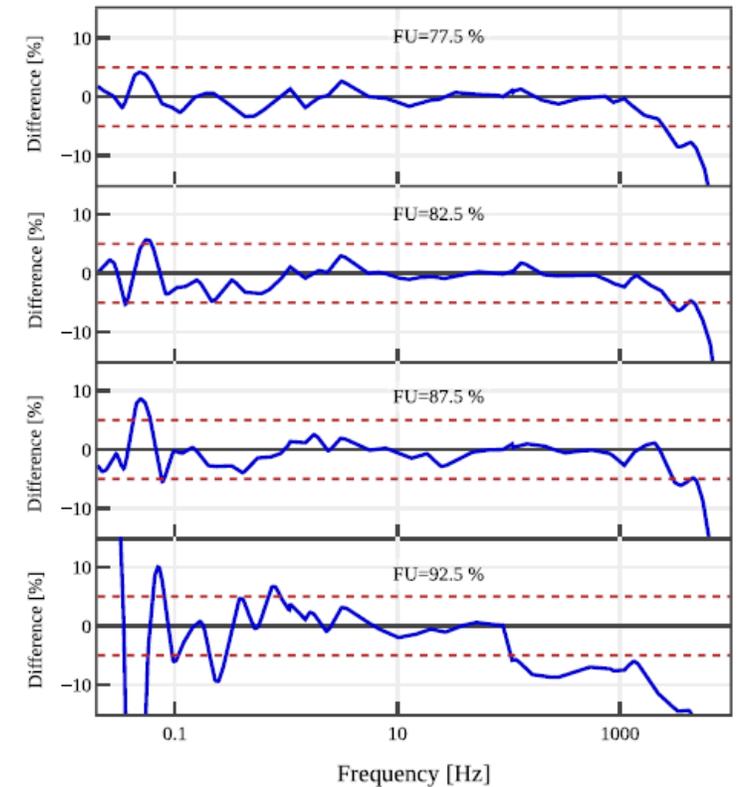
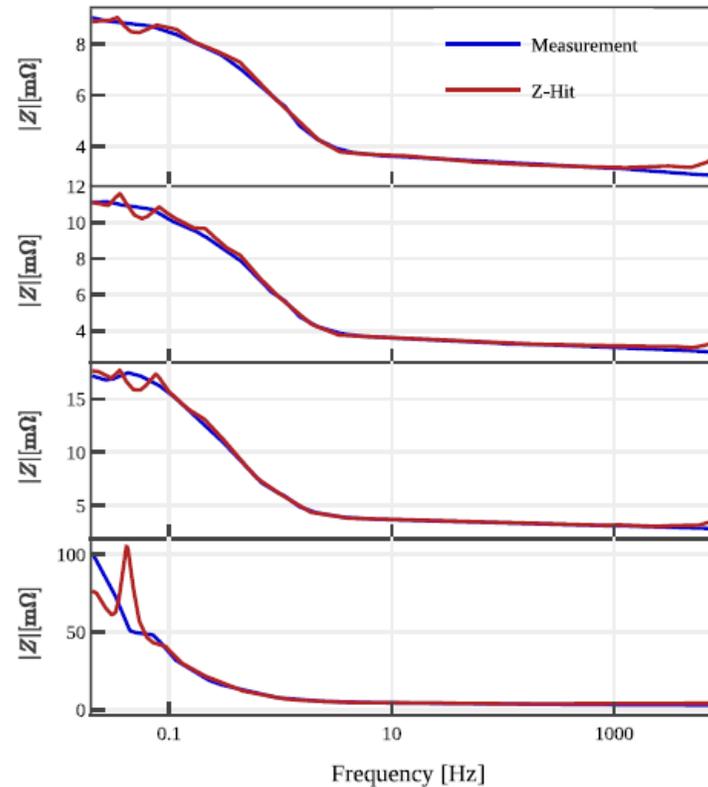
$$\Delta f_{res} \sim \frac{1}{T_s}$$



Impedance Hilbert Transform (Z-HIT)

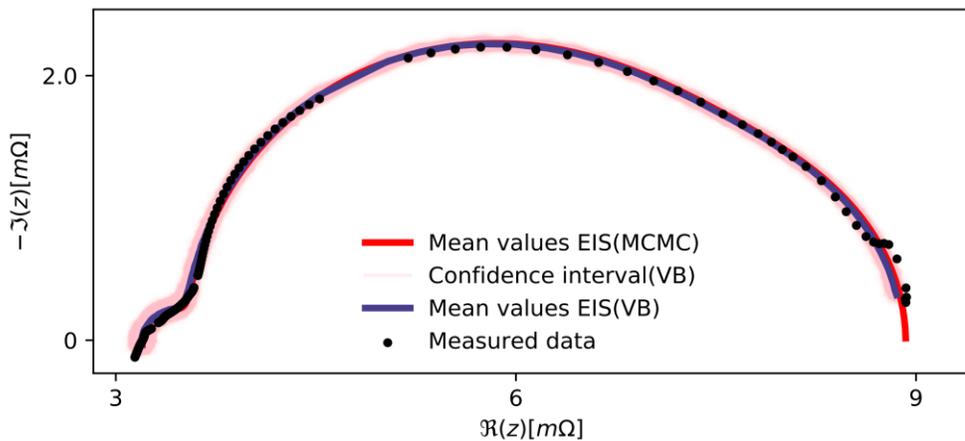
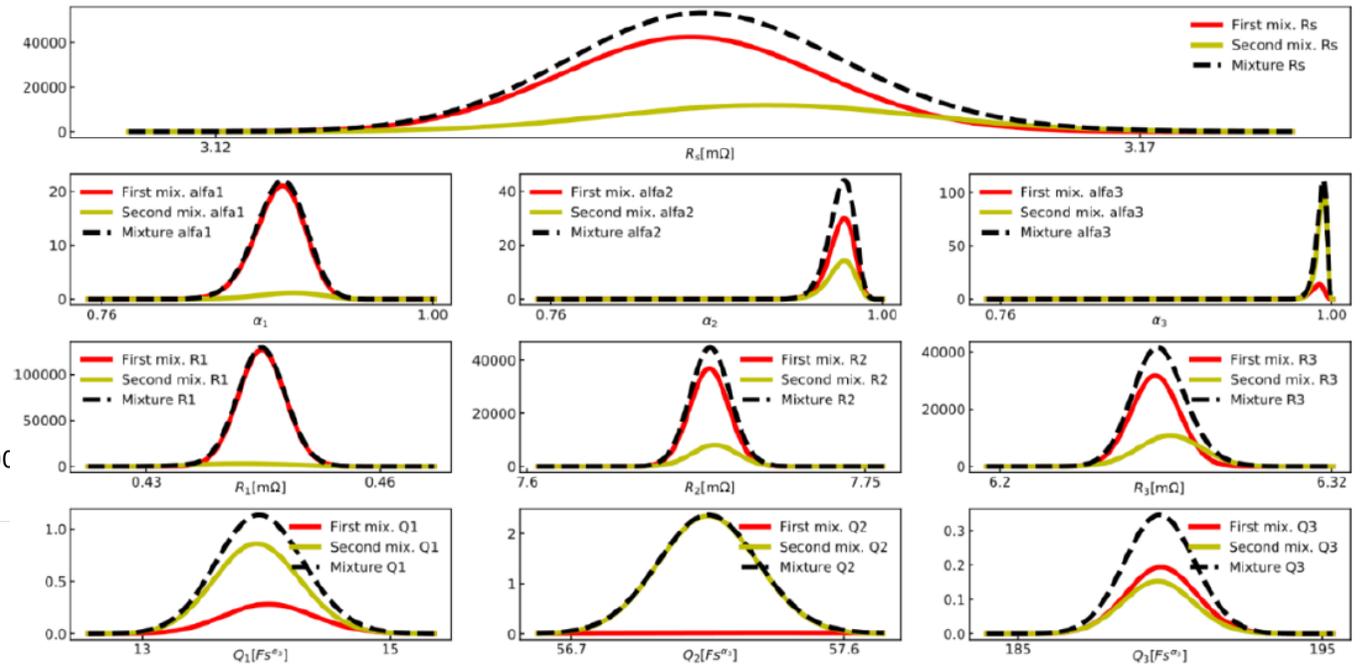
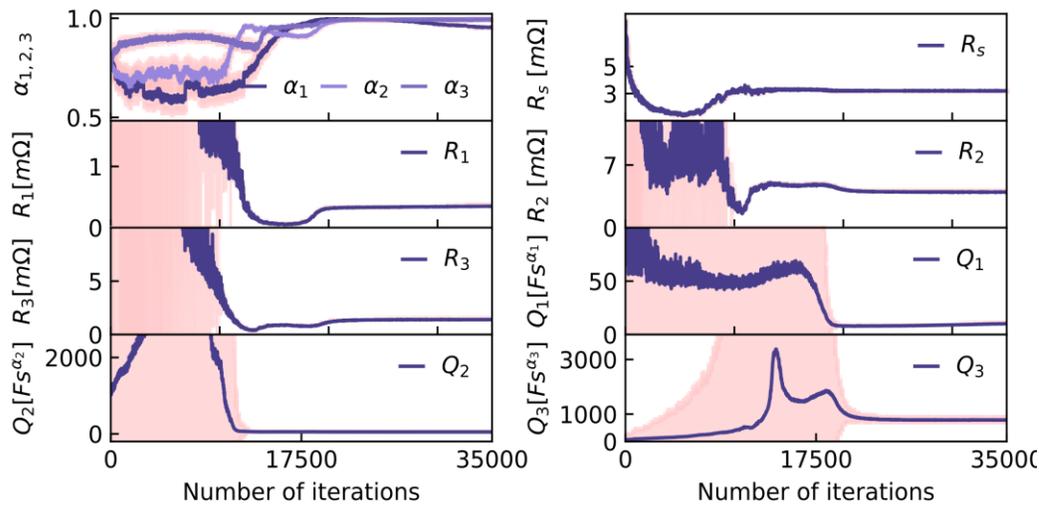
- **linearity**: small amplitudes of perturbations
- **stability**: the overall state of the system should not change during DAQ \Rightarrow minimize **measurement time**
- **causality**: mind the artefacts, nonlinearities \Rightarrow **Z-HIT test**
- eliminate **parasitic** phenomena (e.g. inductivity of cables) not detectable by KK test

Problem with multiplexing in DAQ: detection with Z-HIT test



EIS deconvolution via ECM

Learning ECM parameters with Variational Bayes



Surprisingly low uncertainty in ECM parameters under correct experiment

Characterising the low-frequency part of the EIS curve

Fault-symptom matrix

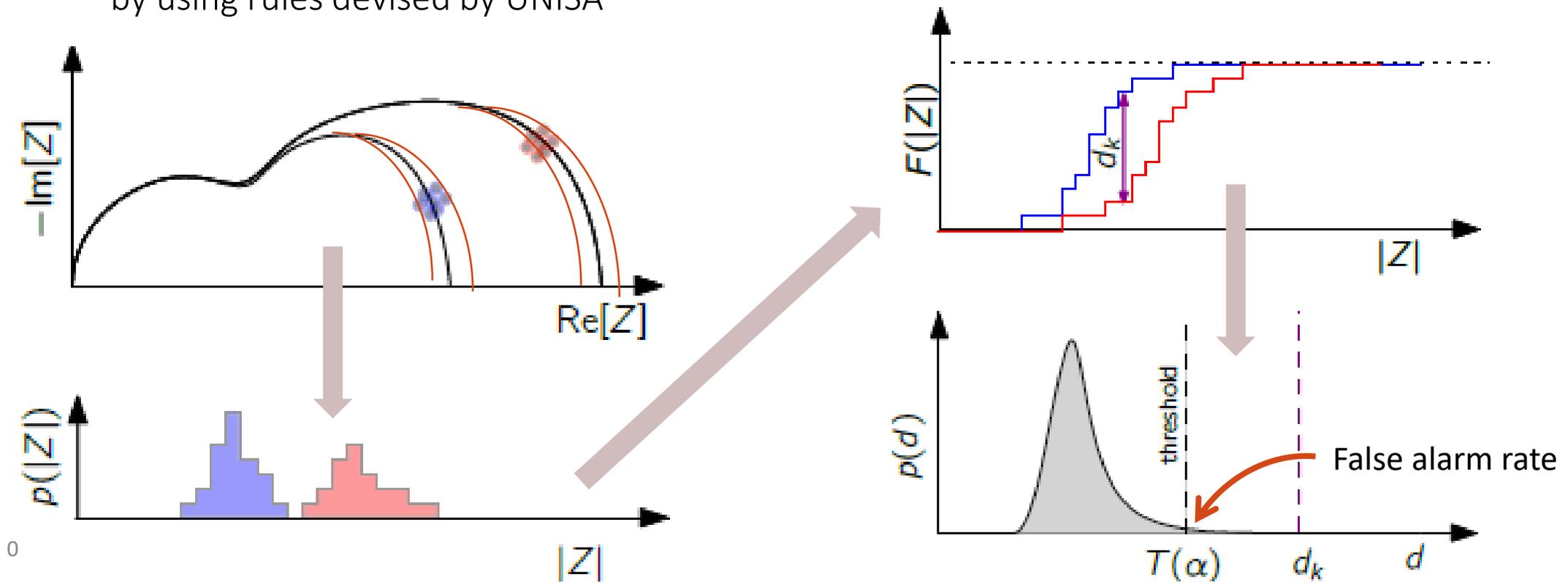
	Low frequency	Mid frequency	High frequency	Rs
Fuel utilisation	X			
Delamination	X	X	X	X
Carbon deposition	X		X	
Leakage	X			X
Ni agglomeration			X	
Cr poisoning		X		X
S poisoning			X	X

Issue:

- efficient characterization of the low-frequency part of the EIS curve by sinusoidal perturbation takes notoriously long perturbations for yet low EIS resolution
- DRBS is better, but going down to the mHz region takes also longer perturbation session

Feature extraction directly from EIS

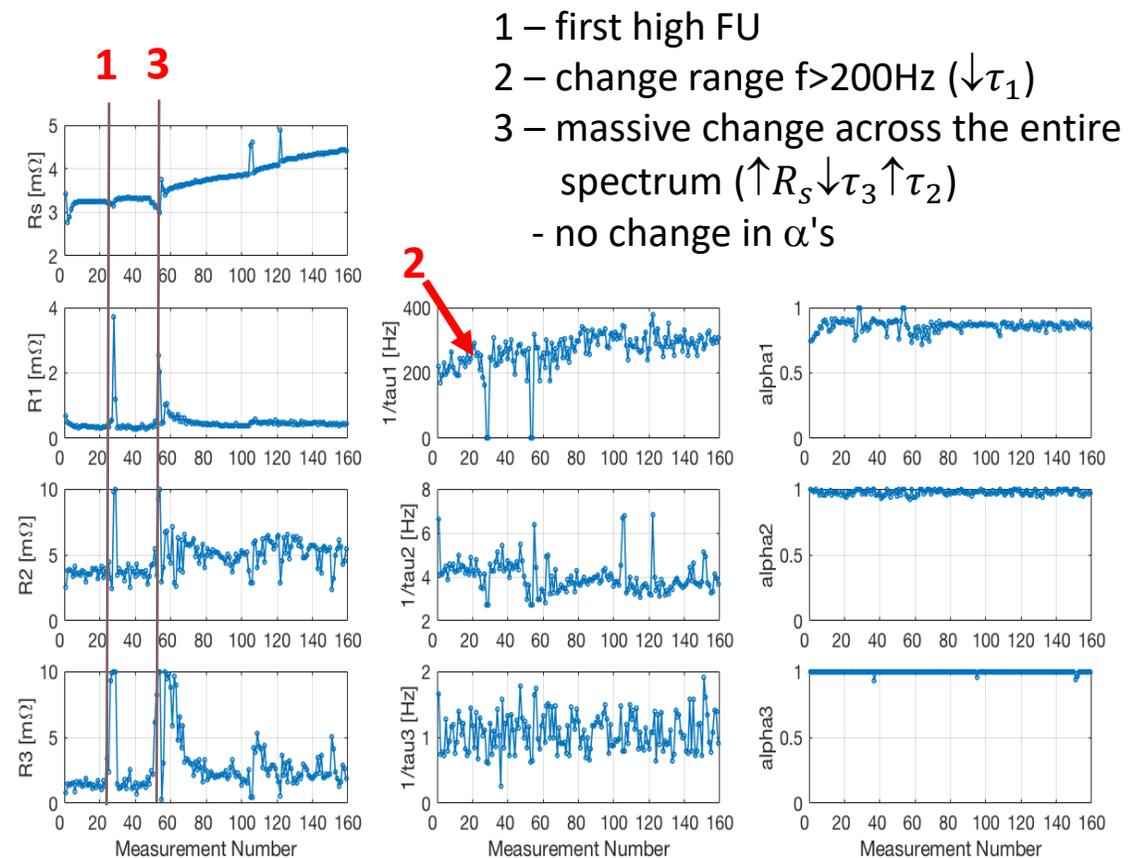
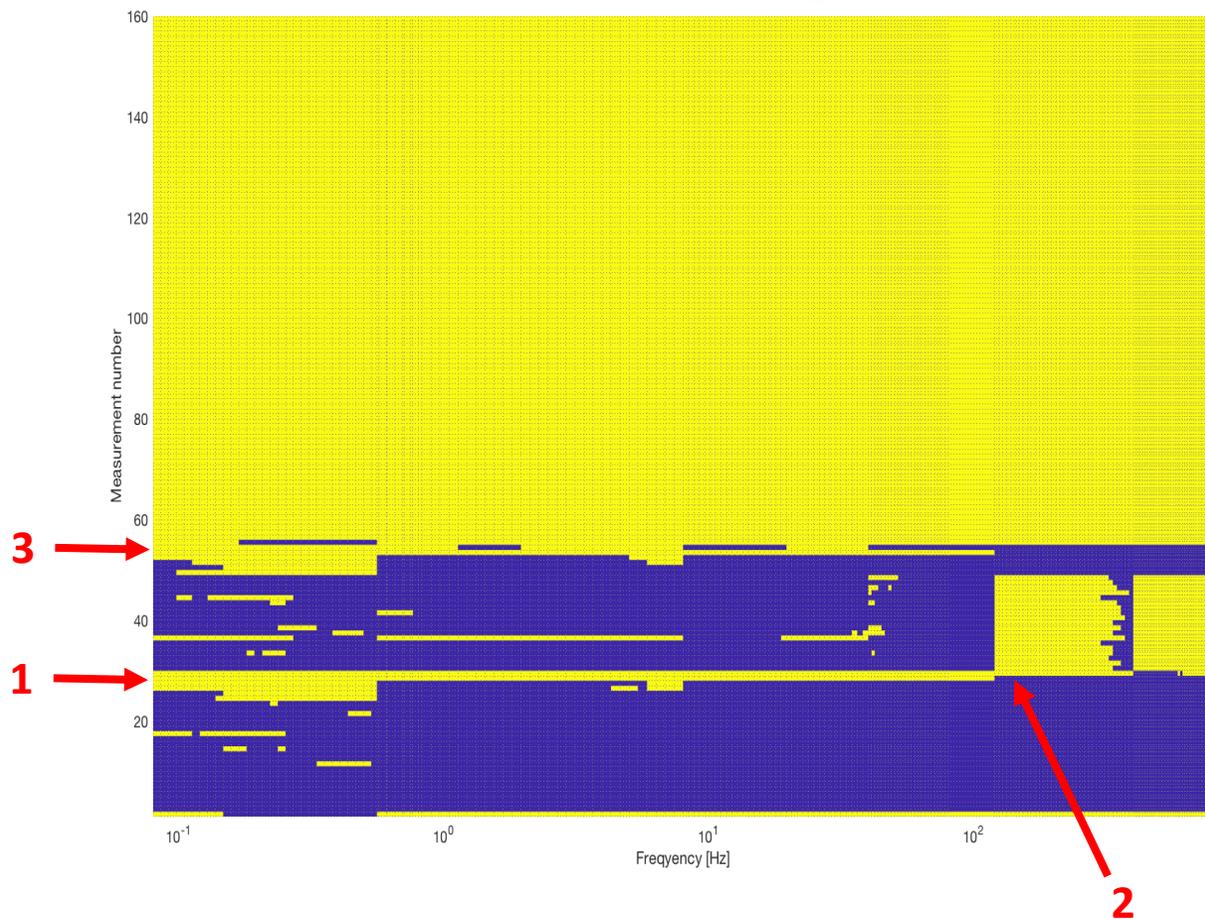
- Change detection based on **Kolmogorov-Smirnov (KS)** test (data-driven approach)
- **Motivation:** **alleviate laborious threshold selection** for symptoms with respect to faults
- **Main idea:** judge upon changes relative to the **reference data**
- **Main achievement:** tolerated **missed alarm rate is the only design parameter**
- **Isolation:** after detection is completed, changes in the particular frequency bands are checked by using rules devised by UNISA



Feature extraction directly from EIS – cont'd

Response of the KS detection algorithm applied to cell 3, short stack CEA:

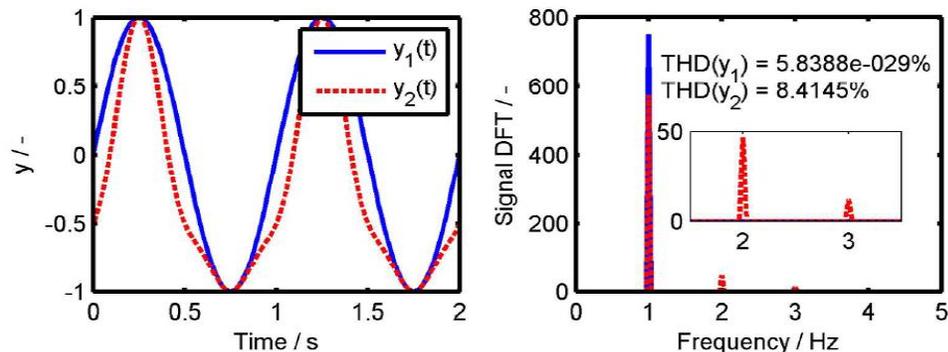
■ nominal ■ change



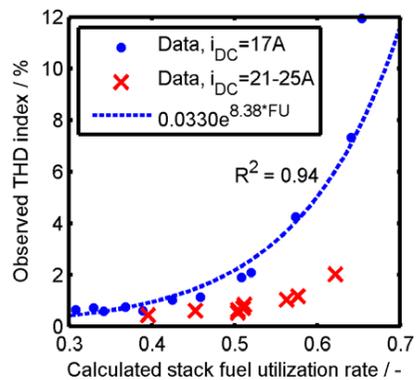
DRT parameters resulting from the fractional order model of the cell

Detection of high FU, various features

Total Harmonic Distortion (THD)

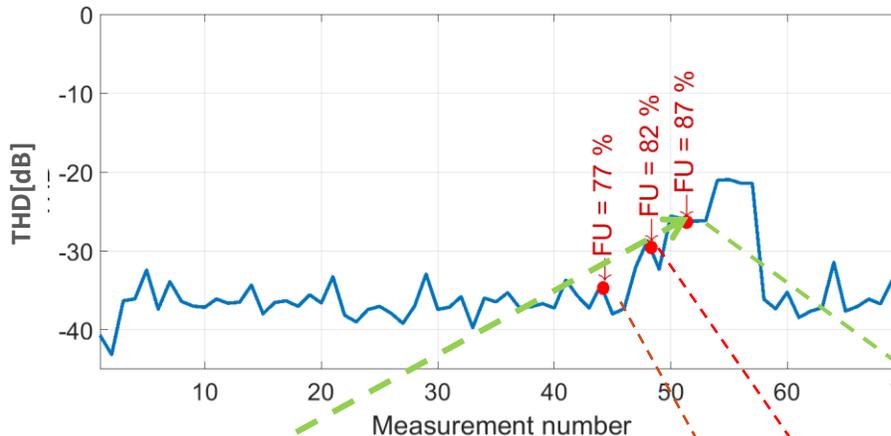


$$DFT(y)_k = \sum_{n=1}^{L_B} y_n e^{\frac{-2\pi j(k-1)(n-1)}{L_B}}$$

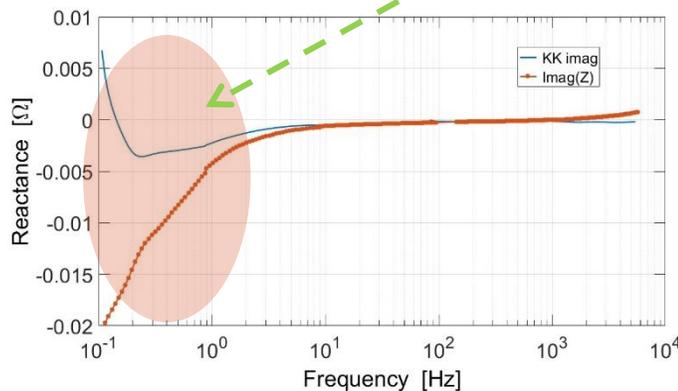


$$THD_{index} = \frac{\sqrt{\sum_{i=2}^{n_H} Y_i^2}}{Y_1} 100$$

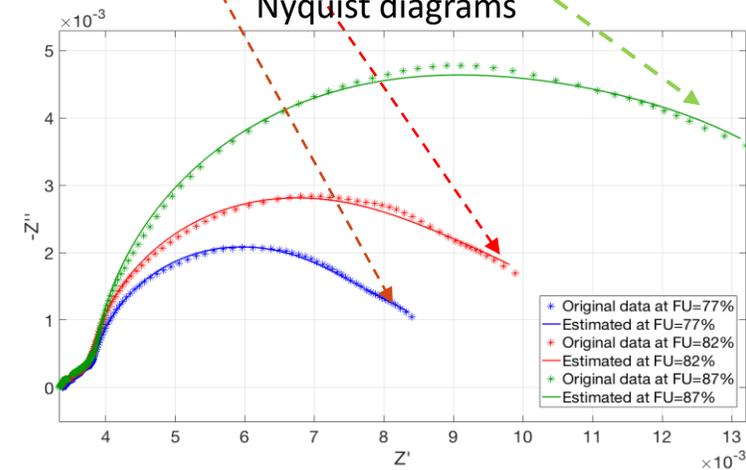
THD index, CEA short stack, cell #3



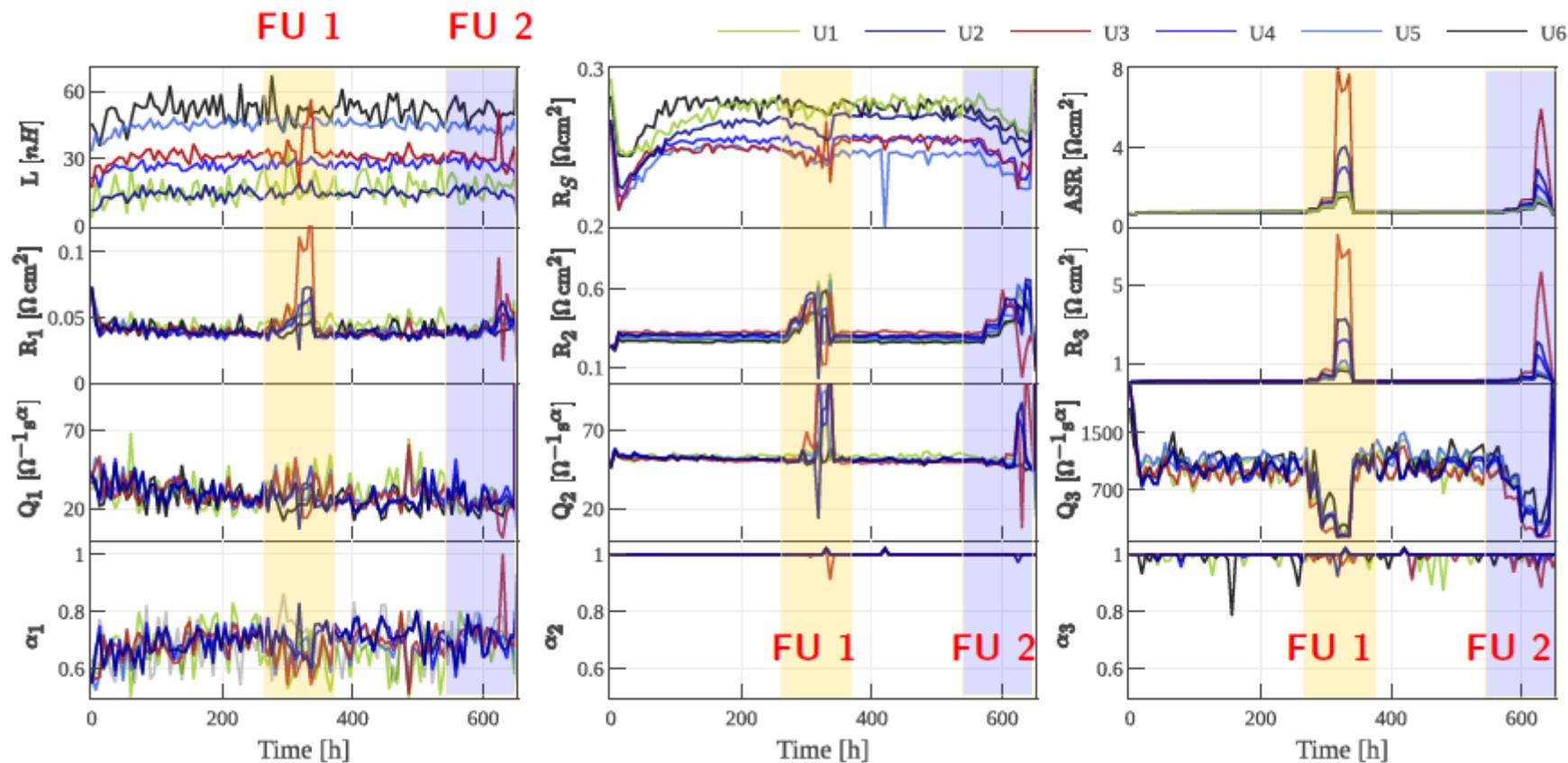
Kramers-Kronig test



Nyquist diagrams



Impact of high FU on ECM parameters



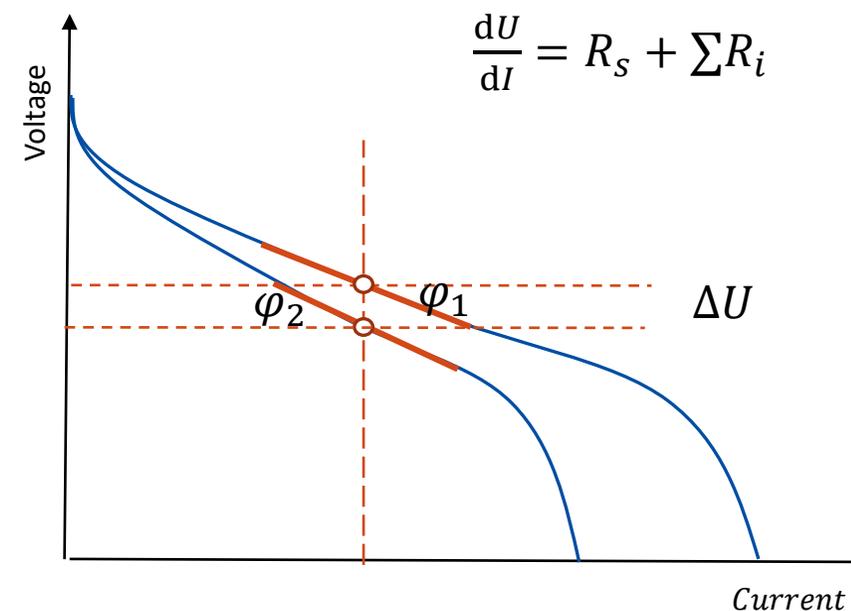
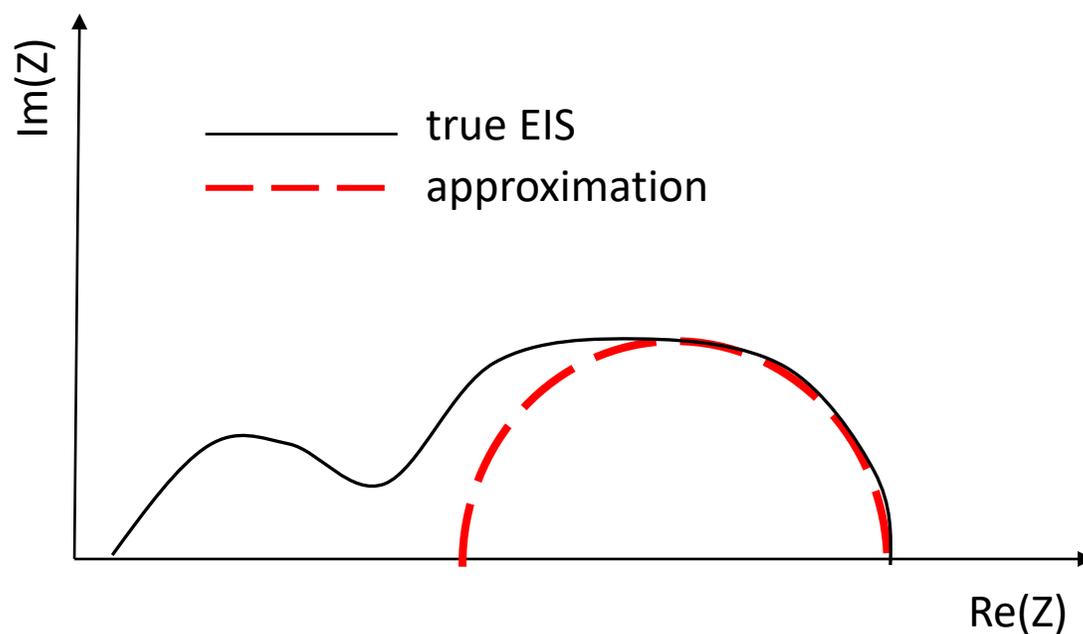
Characterising the low-frequency part of the EIS curve

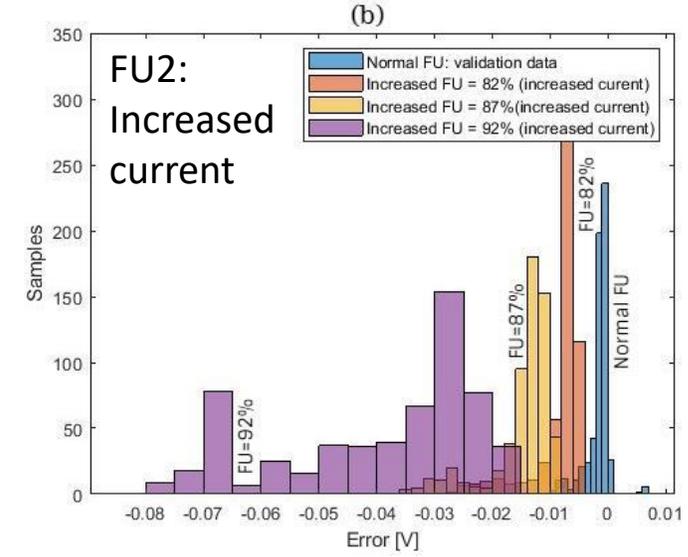
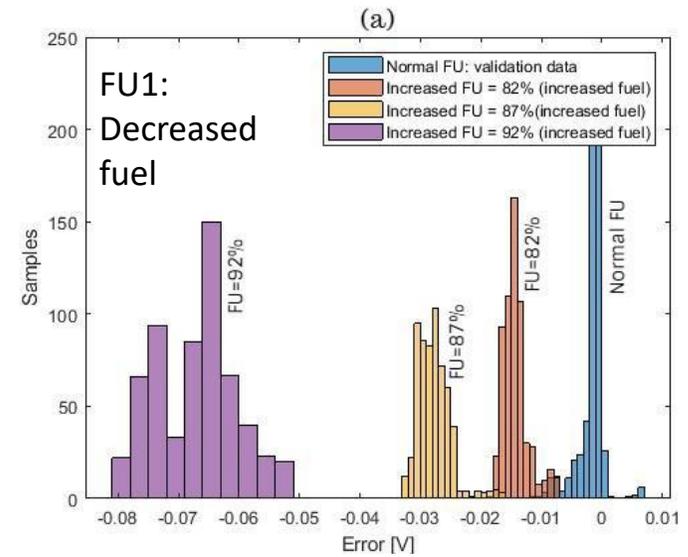
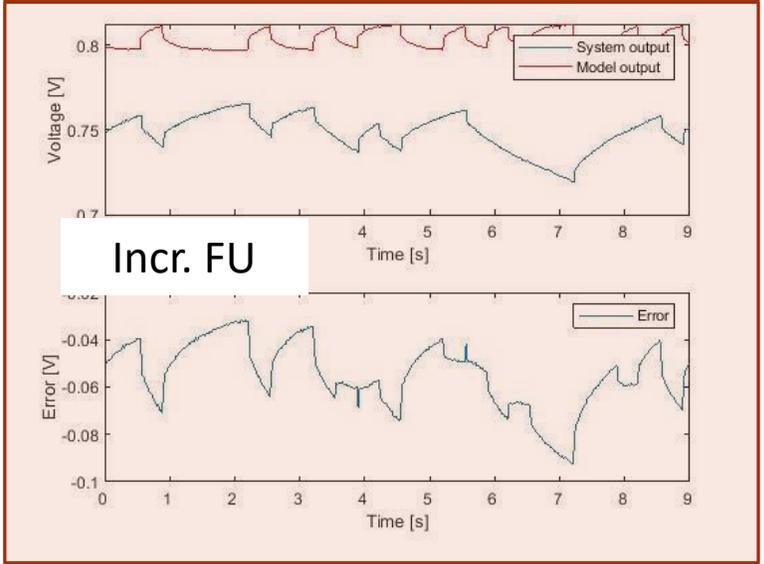
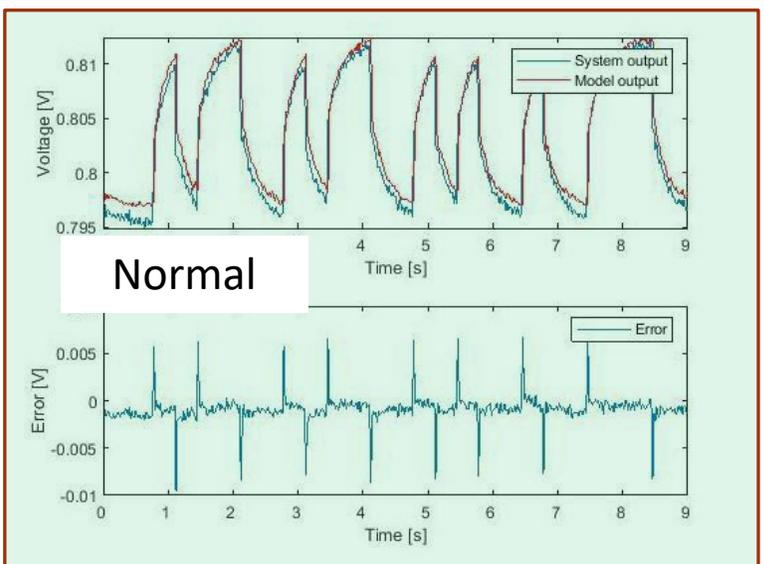
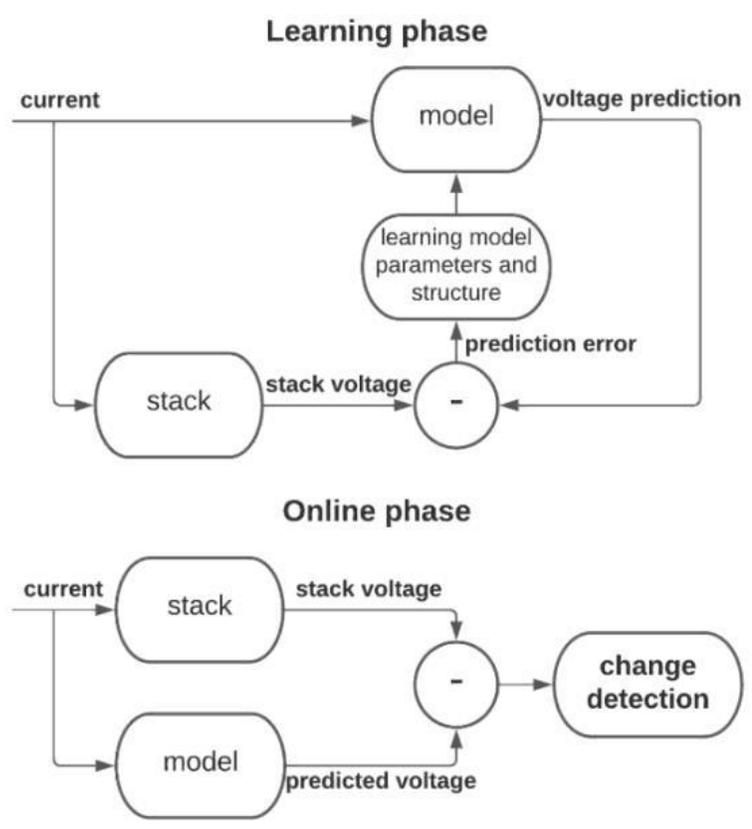
Issue:

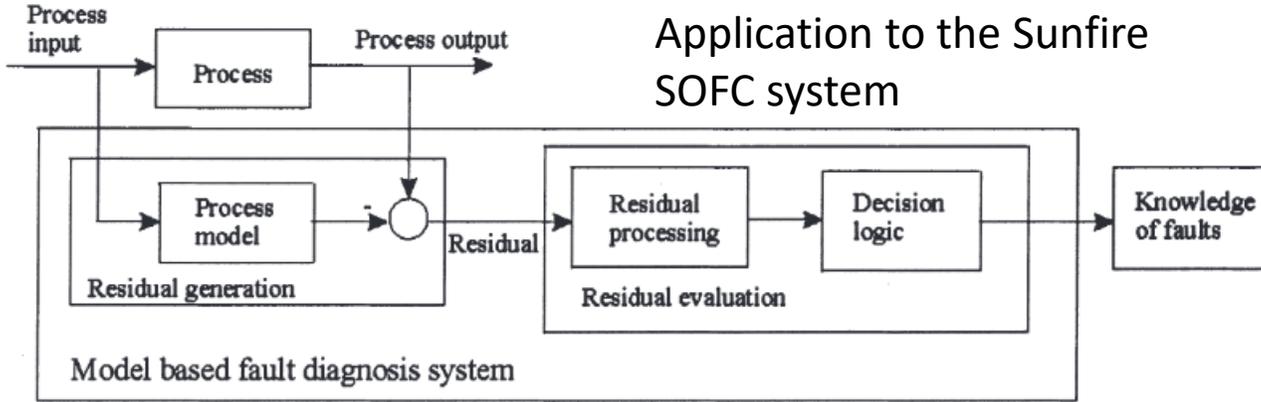
- efficient characterization of the low-frequency part of the EIS curve by sinusoidal perturbation takes notoriously long perturbations for yet low EIS resolution
- DRBS is better, but going down to the mHz region takes also longer perturbation session

Idea: approximate the low-frequency part with a continuous low-order model \Rightarrow high resolution EIS of order of $1/f_s$

Approach: system identification







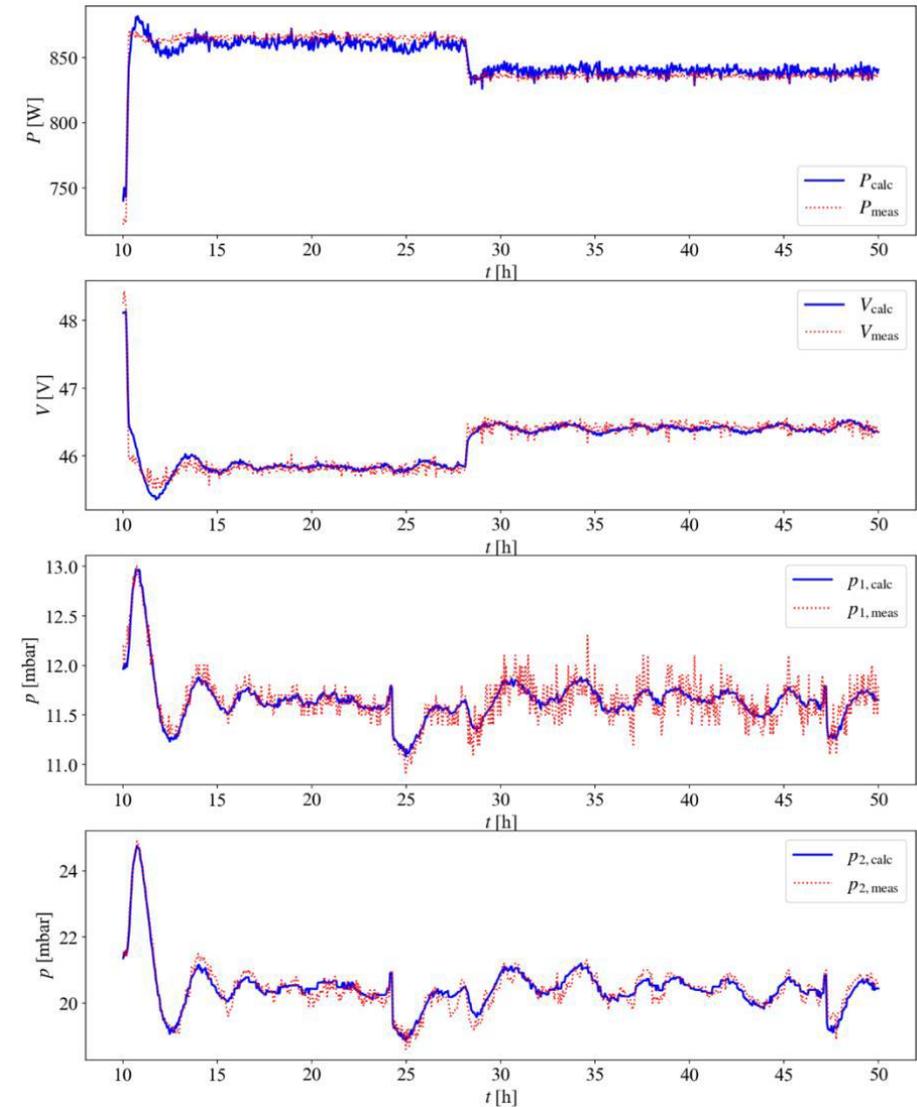
$$k_1 \cdot \frac{\Delta T_{\text{stack}}}{\Delta t} + k_2 \cdot p_{2,\text{air}} \cdot (T_{\text{air, out}} - T_{\text{air, in}}) + \frac{k_3 \cdot T_{\text{stack}} \cdot n_{\text{cell}} \cdot I_{\text{stack}}}{2 \cdot F} = \left(\frac{LHV_{\text{H}_2} \cdot n_{\text{cell}}}{2 \cdot F} - U_{\text{stack}} \right) \cdot I_{\text{stack}} \quad (1)$$

$$\frac{LHV_{\text{H}_2}}{2 \cdot F} - \frac{k_4 \cdot T_{\text{stack}} \cdot I_{\text{stack}}}{p_{2,\text{air}}} - \frac{k_5 \cdot R \cdot T_{\text{stack}} \cdot \arcsin h \left(\frac{I_{\text{stack}}}{I_0} \right)}{2 \cdot F} - k_6 \cdot I_{\text{stack}} \cdot \exp \left(\frac{10300K}{T_{\text{stack}}} \right) = \frac{U_{\text{stack}}}{n_{\text{cell}}} \quad (2)$$

$$k_7 \cdot PWM_1 = p_{1,\text{air}} \quad (3)$$

$$k_8 \cdot PWM_2 = p_{2,\text{air}} \quad (4)$$

Residual #	Sensor Fault						
	T_{stack}	$T_{\text{air, in}}$	$T_{\text{air, out}}$	U_{stack}	I_{stack}	$p_{1,\text{air}}$	$p_{2,\text{air}}$
1	1	1	1	1	1	0	1
2	1	0	0	1	1	0	1
3	0	0	0	0	0	1	0
4	0	0	0	0	0	0	1



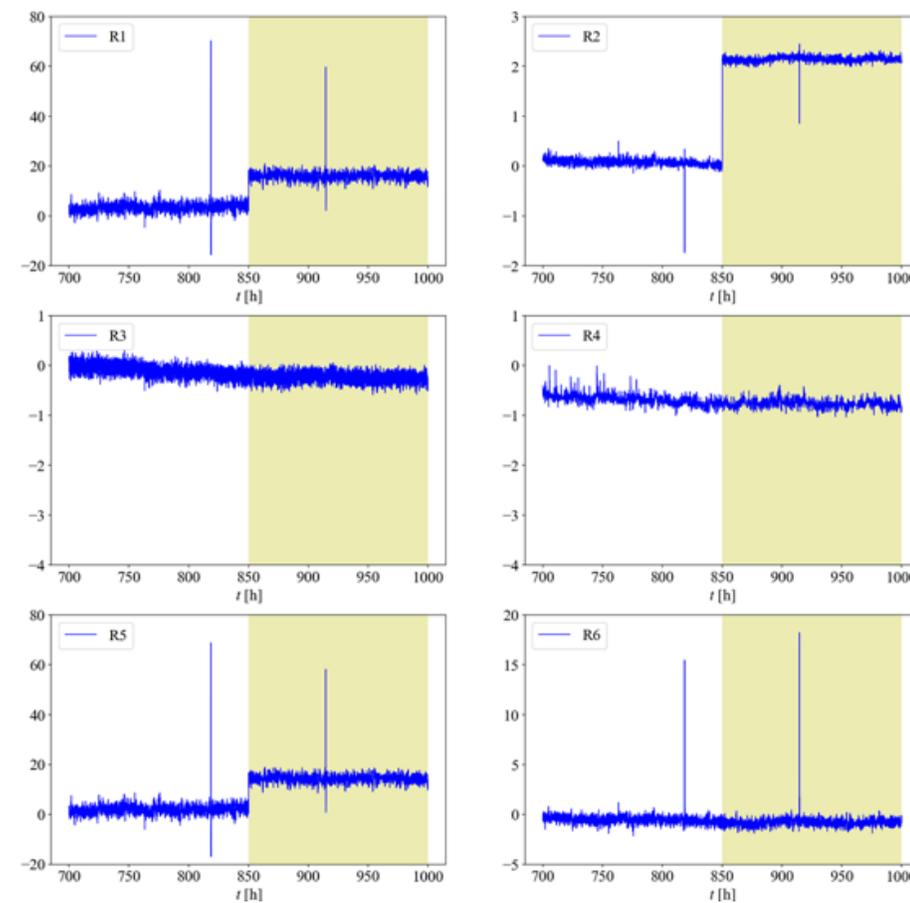
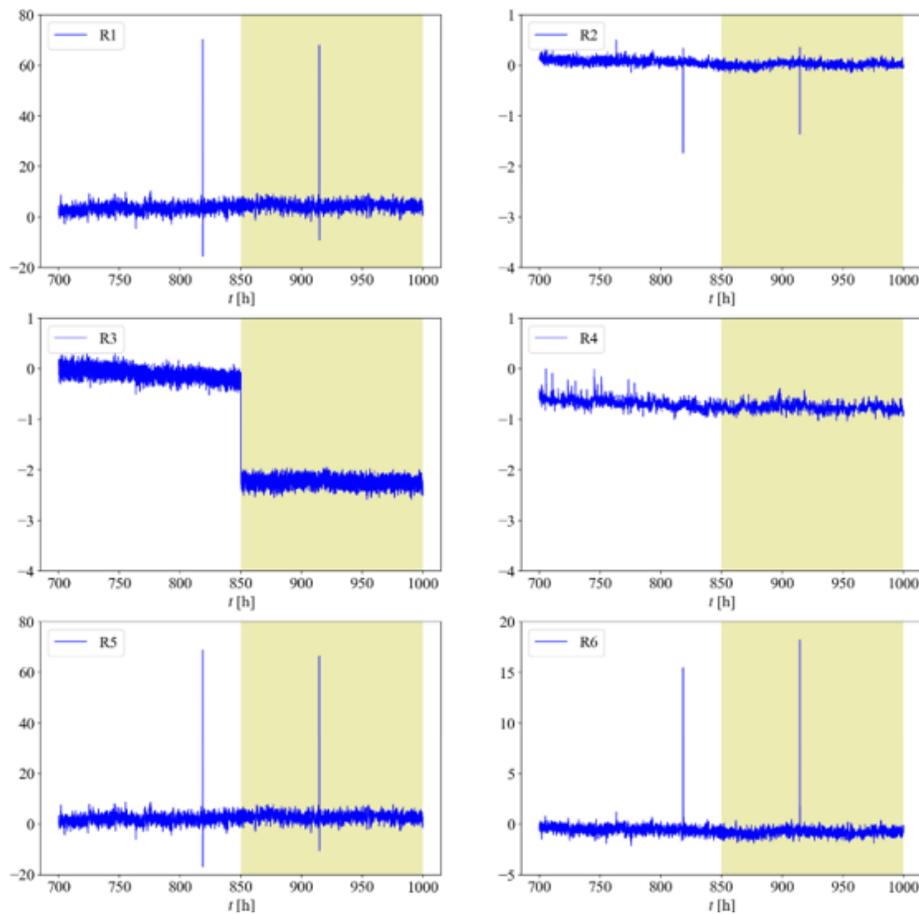
Properties of the residuals

- ❑ 2 groups of non-isolable sensor faults ($T_{air,in}$ and $T_{air,out}$) and (T_{stack} and U_{stack})
- ❑ other faults are weakly isolable
- ❑ for better isolability more sensors are needed

		Sensor Fault						
Residual #		T_{stack}	$T_{air,in}$	$T_{air,out}$	U_{stack}	I_{stack}	$p_{1,air}$	$p_{2,air}$
Primary residuals	1	1	1	1	1	1	0	1
	2	1	0	0	1	1	0	1
	3	0	0	0	0	0	1	0
	4	0	0	0	0	0	0	1
Secondary residuals	5	1	1	1	1	1	0	0
	6	1	1	1	1	0	0	1

- emulated air pressure offset $\Delta p_{1,air} = 2$ mbar
- change only in residual R3 \Rightarrow pressure sensor fault

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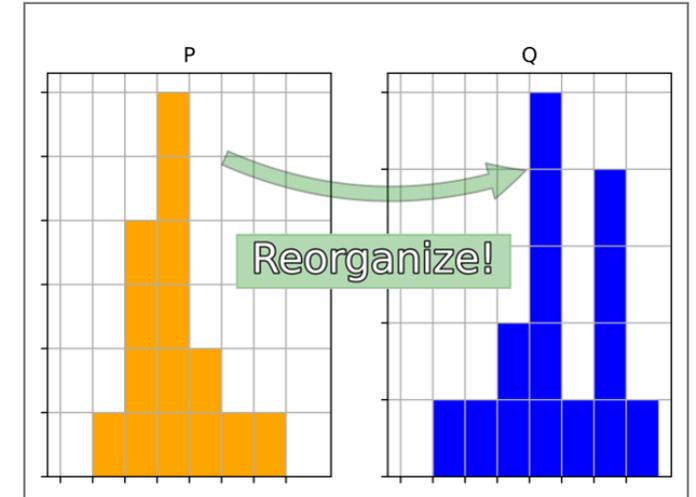
Fault detection

Issues:

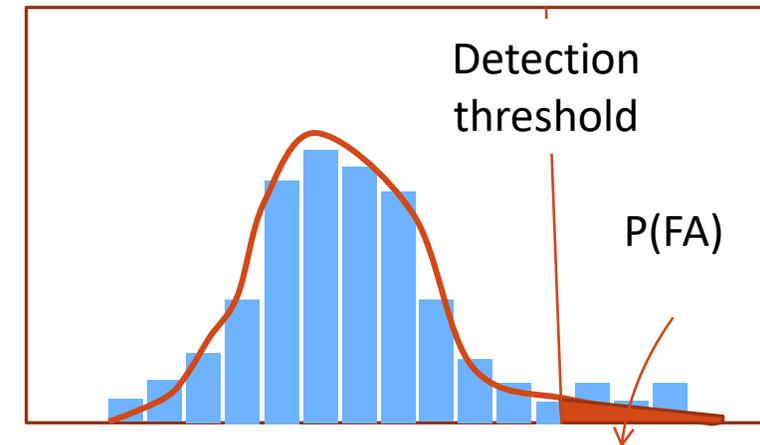
- detection threshold?
- tolerated false alarm rate?
- missed alarm rate?
- minimal detection delay (strongly tied with diagnostic sensitivity)?

Concept of features evaluation:

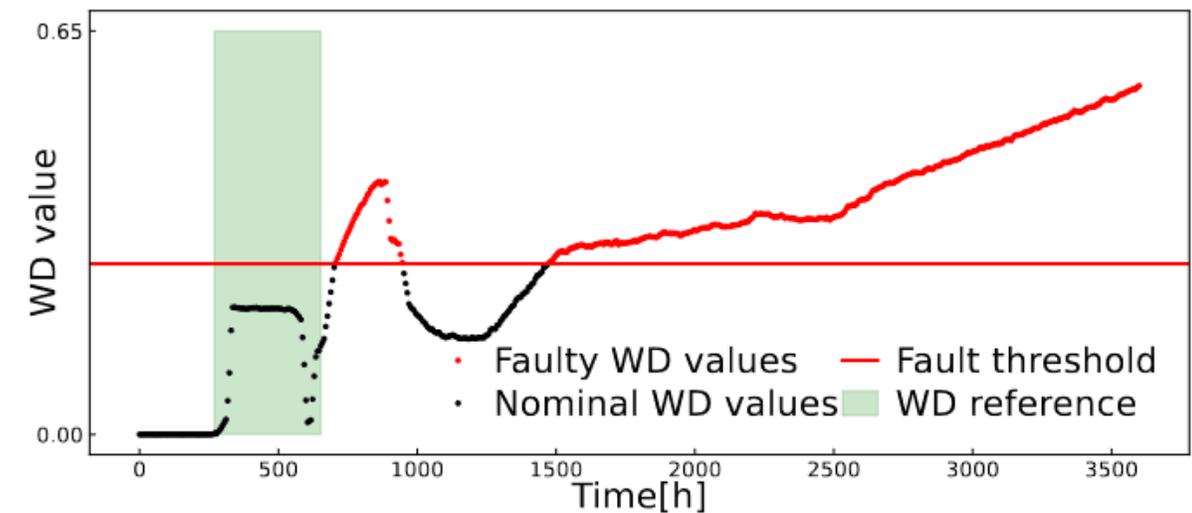
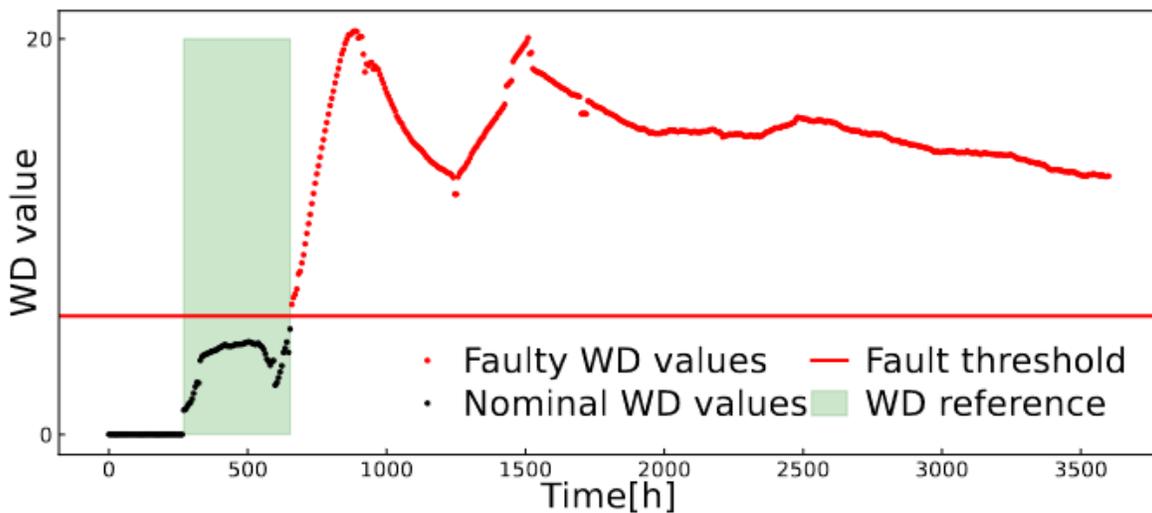
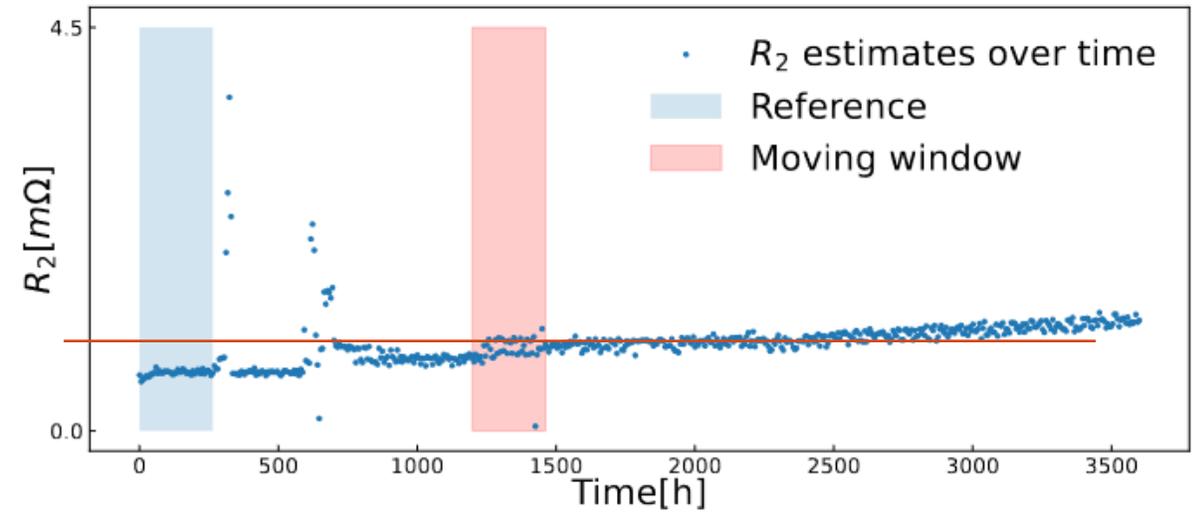
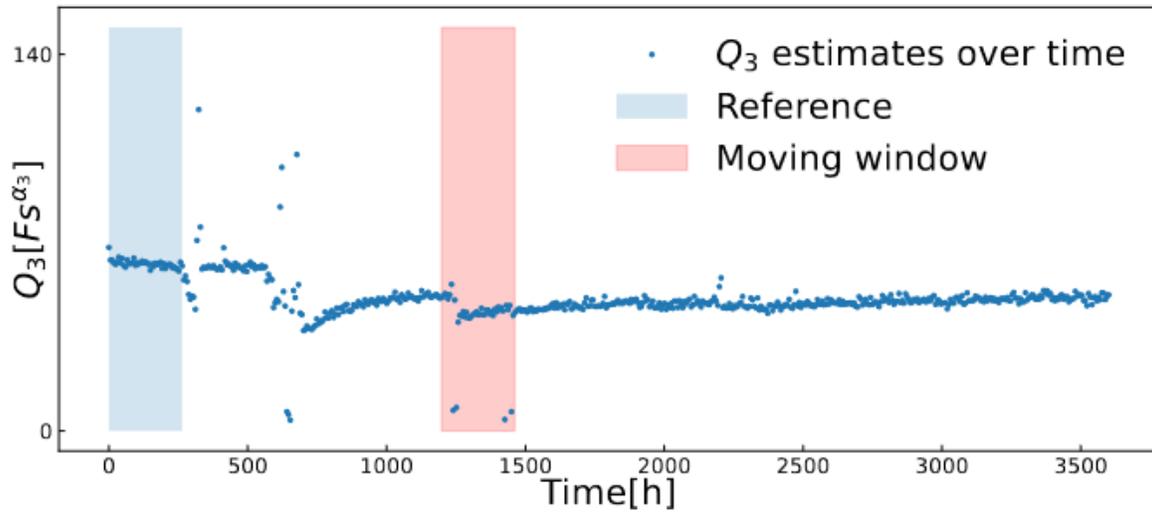
- Features (continuous or discrete) are considered as the realisation of stochastic processes
- change in the features statistic in is assessed through the “**distance**” between their histograms P and Q
- “distance” can be expressed by non-negative divergence measures (Kullback-Leibler, f-divergence etc.)
- “distances” can improve the **diagnostic sensitivity**
- detection threshold can be evaluated from (i) the reference distribution of the distances and the (ii) tolerated false alarm rate



The distribution of distances

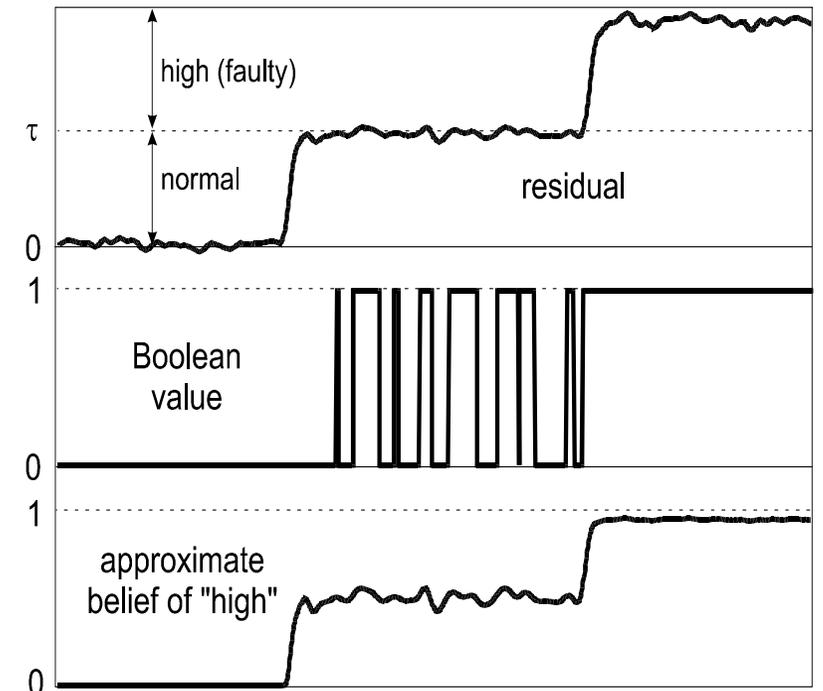
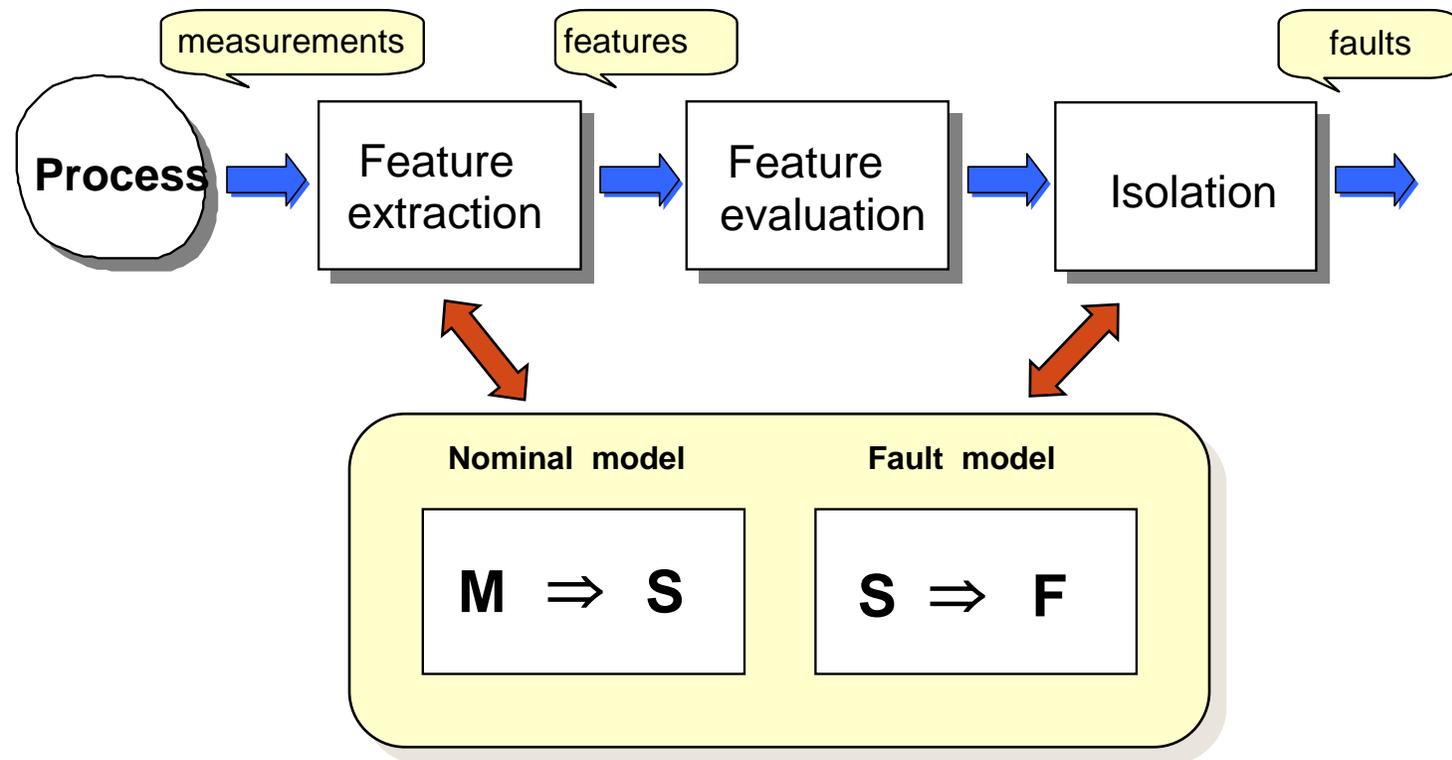


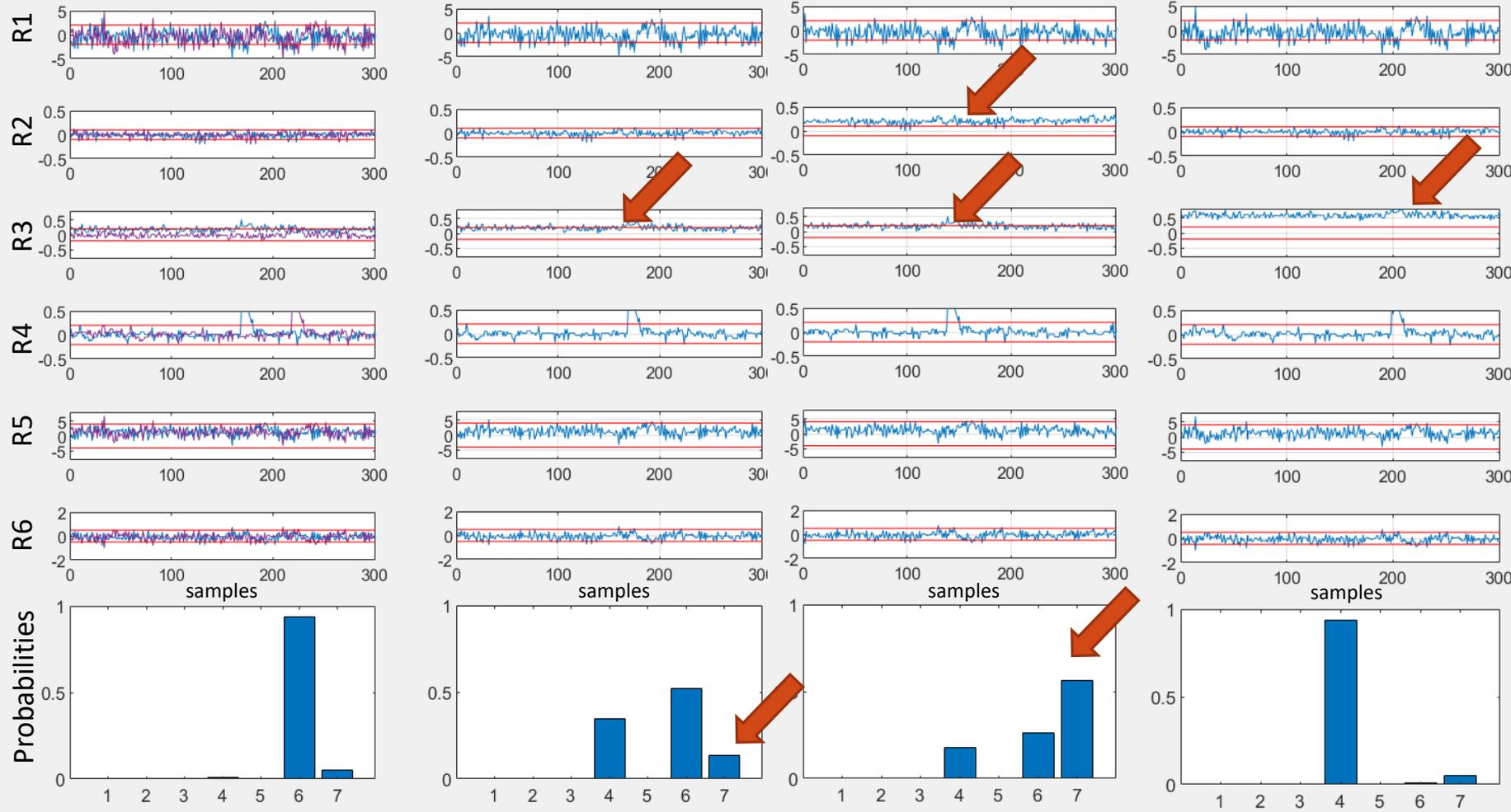
Example: detecting changes in ECM parameters



Fault isolation

- fault isolation is **inverse problem**: from fault-symptom matrix and evaluated symptoms from fault symptom matrix





Demonstration on the Sunfire data

	Description
1	(Sensor T_{stack}) OR (Sensor $T_{air,out}$)
2	(Sensor T_{stack}) OR (Sensor U_{stack})
3	Sensor I_{stack}
4	Sensor $p_{1,air}$
5	Sensor $p_{2,air}$
6	Norma operation
7	Strength of conflict

Conclusions

- Some feature extraction techniques based on active and passive approach have been reviewed;
- passive approach complements active with pointing on problems with BoP
- probabilistic approach to EIS analysis and deconvolution is presented
- A unified framework for fault isolation based on fault-symptoms table by means of the approximate reasoning circumvents the issues related to the disturbances, imprecision in the process model
- Questions:
 - Fault isolation has to be further assessed (with incoming lifelong data);
 - Can we unambiguously distinguish between different faults/degradation modes?



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