CORTEX

Core monitoring techniques and experimental validation and demonstration

Combining simulations and machine learning for neutron noise-based core diagnostics

IAEA Technical Meeting on Artificial Intelligence for Nuclear Technology and Applications
October 25-29, 2021 – hybrid

On behalf of the CORTEX consortium:

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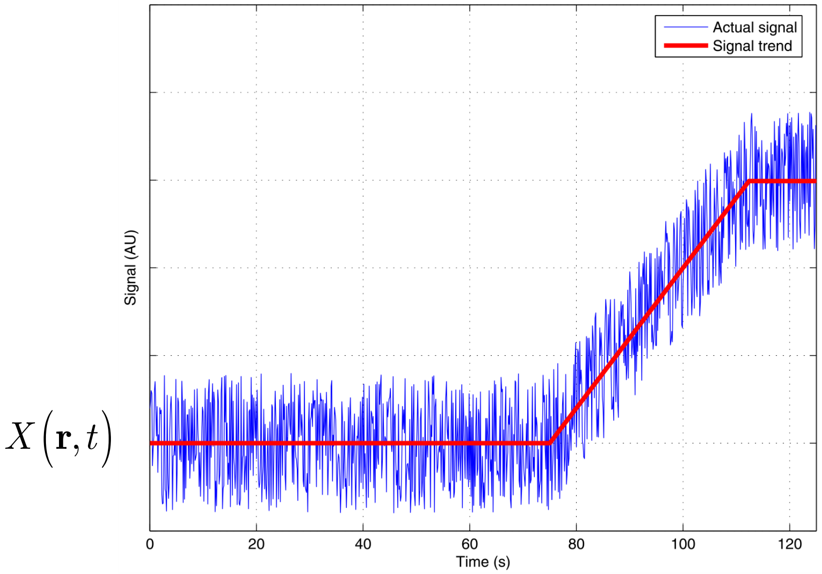
Introduction and background

Introduction and background

- Fluctuations always existing in dynamical systems even at steady state-conditions:



Conceptual illustration of the possible time-dependence of a measured signal from a dynamical system

$$X(\mathbf{r},t) = X_0(\mathbf{r},t) + \delta X(\mathbf{r},t)$$

Introduction and background

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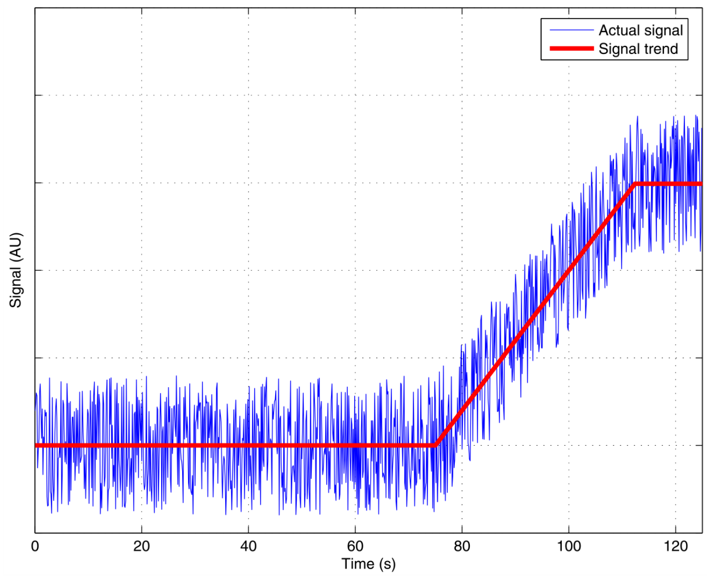
$X(\mathbf{r},t)$



Conceptual illustration of the possible time-dependence of a measured signal from a dynamical system

$$X(\mathbf{r},t) = X_0(\mathbf{r},t) + \delta X(\mathbf{r},t)$$

actual signal

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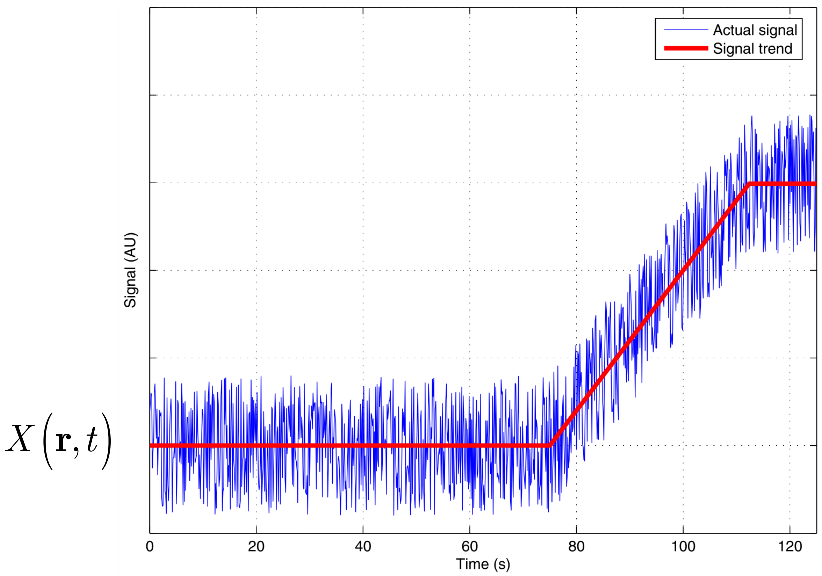

Conceptual illustration of the possible time-dependence of a measured signal from a dynamical system

$$X(\mathbf{r},t) = X_0(\mathbf{r},t) + \delta X(\mathbf{r},t)$$

signal
trend or mean

Introduction and background

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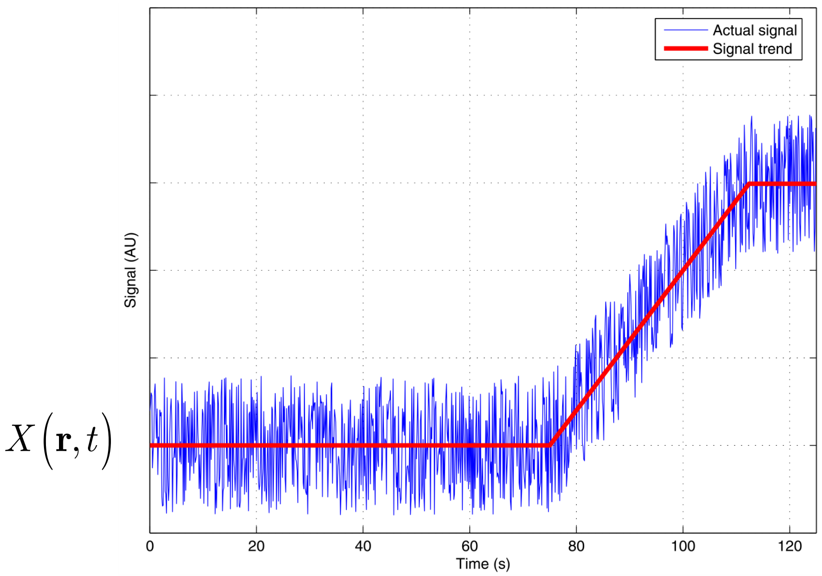


Conceptual illustration of the possible time-dependence of a measured signal from a dynamical system

$$X(\mathbf{r},t) = X_0(\mathbf{r},t) + \delta X(\mathbf{r},t)$$

fluctuations or “noise”

➢ Fluctuations carrying some valuable information about the system dynamics

Introduction and background

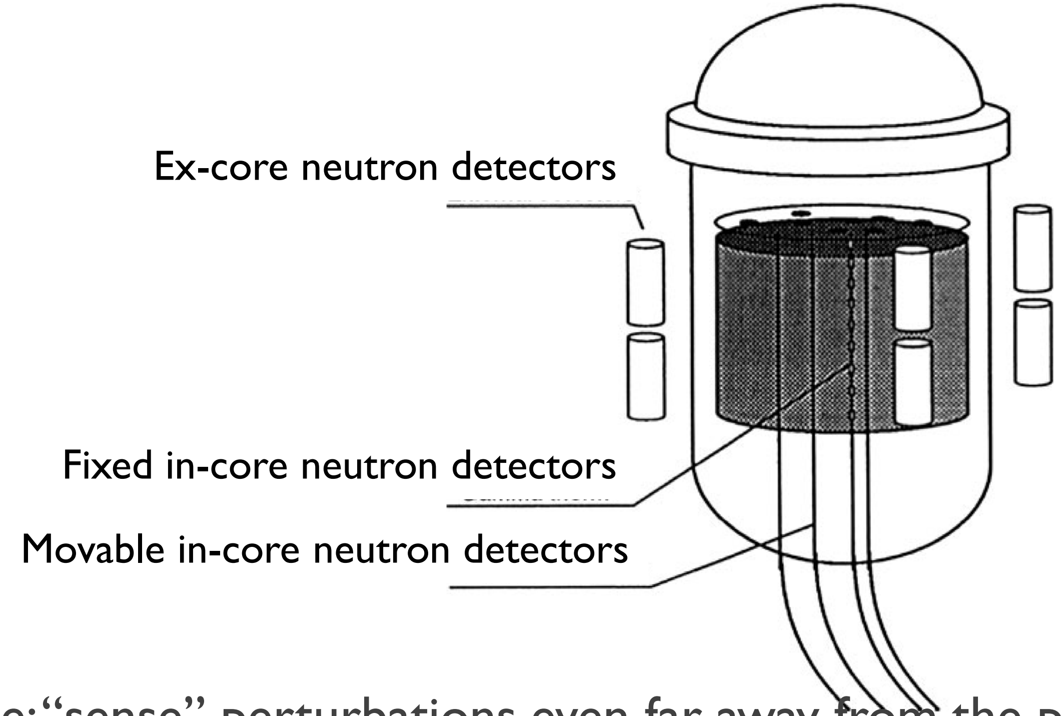
- Fluctuations could be used for “diagnostics”, i.e.:
  - Early detection of anomalies
  - Estimation of dynamical system characteristics

… even if the system is operating at steady-state conditions

➢ Fluctuations in the neutron density in nuclear reactors can be used for core diagnostics and monitoring

Introduction and background

- Neutron detectors present both as in-core and ex-core:

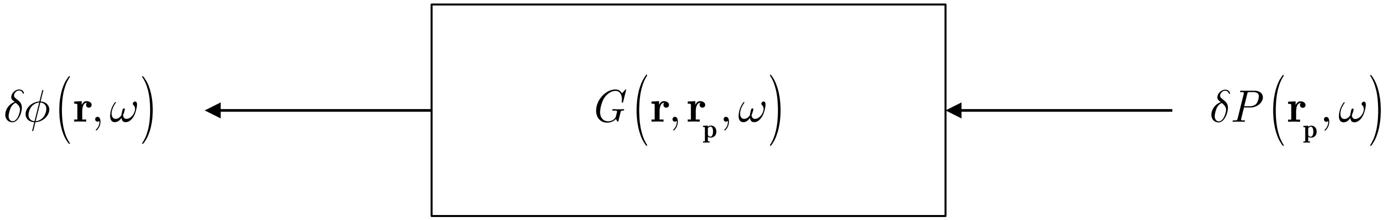


  - ➢ Advantage: "sense" perturbations even far away from the perturbations
  - ➢ Disadvantage: western-type reactors do not always contain many in-core neutron detectors

Introduction and background

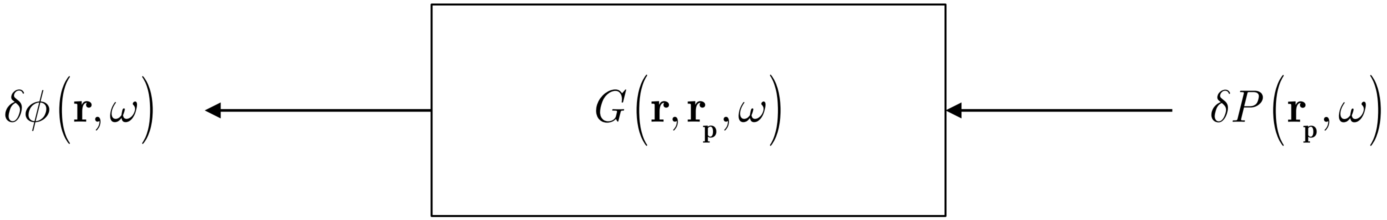
- Neutron noise diagnostics requires establishing relationships between neutron detectors and possible perturbations

➢The "reactor transfer function" $G(\mathbf{r}, \mathbf{r_p}, \omega)$ needs to be determined



Introduction and background

- But noise diagnostics requires the inversion of the reactor transfer function $G(\mathbf{r}, \mathbf{r}_\mathbf{p}, \omega)$



Introduction and background

- But noise diagnostics requires the inversion of the reactor transfer function $G(\mathbf{r},\mathbf{r}_\mathbf{p},\omega)$

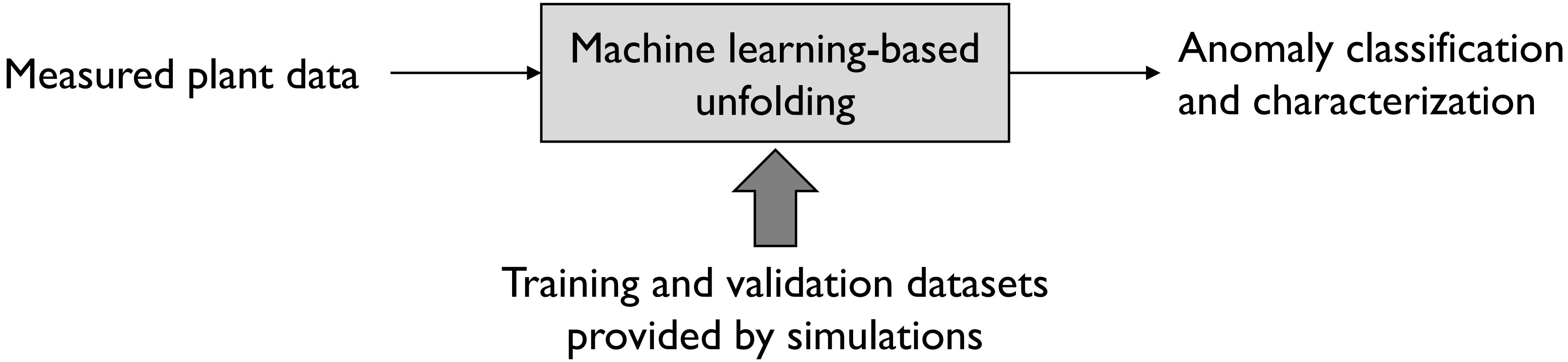
$$\delta\phi(\mathbf{r},\omega) \longrightarrow \left[G(\mathbf{r},\mathbf{r}_\mathbf{p},\omega)\right]^{-1} \longrightarrow \delta P(\mathbf{r}_\mathbf{p},\omega)$$

- ➢ Machine learning could be used for that purpose
- ➢ Unfolding possible even if very few detectors available (due to the spatial correlations existing between a localized perturbation and its effect throughout the nuclear core)

CORTEX project overview

CORTEX project overview

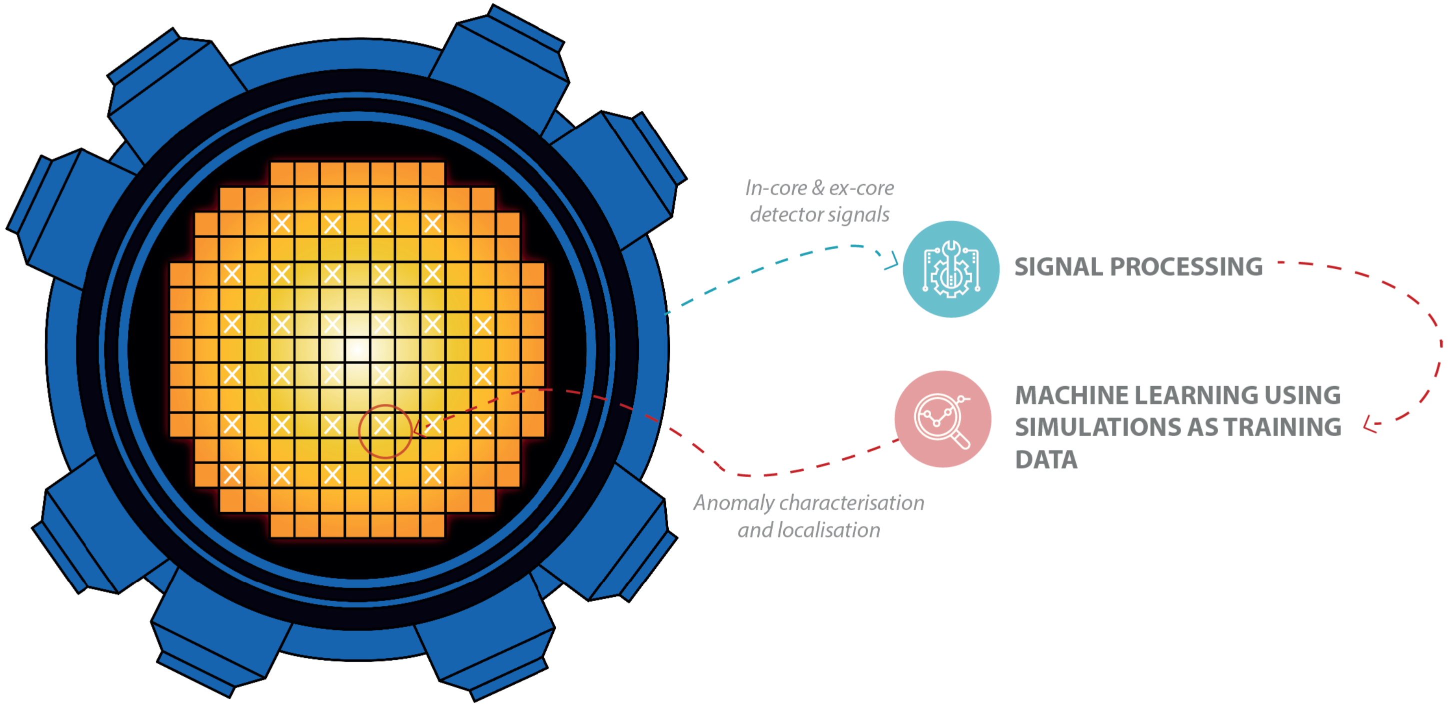
- Basic principle:
  - Annotated data can only be provided by simulations:



CORTEX project overview

- 4-year project financed by the European Union (ended in August 2021)
- 18 European organizations + 1 American partner + 1 Japanese partner
- More than 70 researchers involved

More info at:
cortex-h2020.eu



Theoretical basis of neutron noise and core diagnostics

Theoretical basis of neutron noise and core diagnostics

- Modelling of the neutron noise can be done using the neutron transport equation (Boltzmann equation):

$$\frac{1}{v(E)}\frac{\partial}{\partial t}\psi(\mathbf{r},\mathbf{\Omega},E,t)$$
$$= -\mathbf{\Omega}\cdot\nabla\psi(\mathbf{r},\mathbf{\Omega},E,t) - \Sigma_t(\mathbf{r},E,t)\psi(\mathbf{r},\mathbf{\Omega},E,t)$$
$$+\int_{(4\pi)}\int_0^\infty \Sigma_s(\mathbf{r},\mathbf{\Omega}'\rightarrow\mathbf{\Omega},E'\rightarrow E,t)\psi(\mathbf{r},\mathbf{\Omega}',E',t)d^2\mathbf{\Omega}'dE'$$
$$+\frac{1}{4\pi}\int_{-\infty}^{t}\int_0^\infty \nu(E')\Sigma_f(\mathbf{r},E',t')\phi(\mathbf{r},E',t')\left[(1-\beta)\chi^p(E)\delta(t-t')+\sum_{i=1}^{N_d}\chi_i^d(E)\lambda_i\beta_i e^{-\lambda_i(t-t')}\right]dt'dE'$$

➢ A model to represent the effect of a given perturbation onto the macroscopic cross-section is required

Theoretical basis of neutron noise and core diagnostics

- Modelling of the effect of the cross-section perturbations onto the neutron flux can be done in several ways:
  - Low/high order in angle
  - Low/high order in space
  - Low/high order in energy
  - Time- or frequency-domain
  - Deterministic methods or probabilistic methods (Monte Carlo)

Theoretical basis of neutron noise and core diagnostics

- For diagnostic purposes, one needs to check that the induced neutron noise is significantly different, depending on the type of perturbation and its location

➢ Examination of the amplitude and phase of the neutron noise usually allows differentiating the type of perturbation

➢ Nevertheless, some more intricate responses can arise in some cases
    - ➢ Requires a faithful modelling of the reactor transfer function

Theoretical basis of neutron noise and core diagnostics

- For the identification of the location of a perturbation, an appreciable deviation from point-kinetics is required
- Induced neutron noise in first-order in the frequency-domain:

$$\delta\phi(\mathbf{r},\omega) = \delta P(\omega)\phi_0(\mathbf{r}) + \delta\psi(\mathbf{r},\omega)$$

point-kinetic term

with

$\delta P(\omega)$ fluctuations of the "amplitude factor"

$\delta\psi(\mathbf{r},\omega)$ fluctuations of the "shape function"

$\phi_0(\mathbf{r})$ static neutron flux

Theoretical basis of neutron noise and core diagnostics

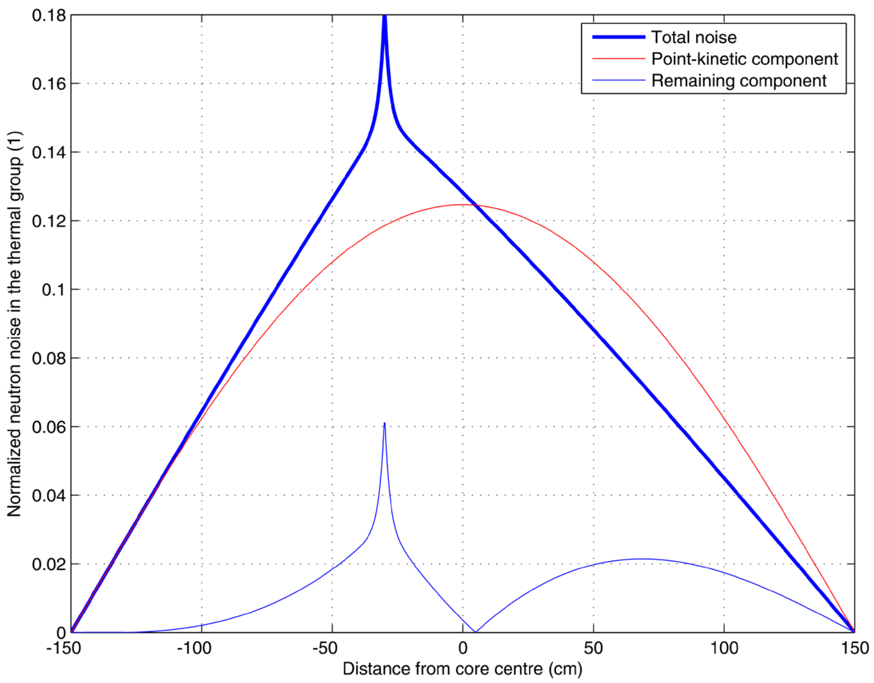


Illustration of the difference between the point-kinetic component and the total induced neutron noise in the frequency domain at 1 Hz, for a perturbation located at -30 cm from the centre of a nuclear core of size 300 cm.

Application to commercial reactors

Application to commercial reactors

- Several machine learning-based architectures developed based on:
  - Either time-domain simulations for training/validation
    - ➢ De Sousa Ribeiro, F., Calivà, F., Chionis, D., Dokhane, A., Mylonakis, A., Demazière, C., Leontidis, G., Kollias, S. (2018), Towards a deep unified framework for nuclear reactor perturbation analysis. *Proc. IEEE Symposium Series on Computational Intelligence (SSCI 2018)*, Bengaluru, India, November 18 – 21, 2018
    - ➢ Durrant, A., Leontidis, G., Kollias, S. (2019), 3D convolutional and recurrent neural networks for reactor perturbation unfolding and anomaly detection. *European Physics Journal Nuclear Sciences and Technologies*, **5**, 20
    - ➢ Tasakos, T., Ioannou, G., Verma, V., Alexandridis, G., Dokhane, A., Stafylopatis, A. (2021), Deep learning-based anomaly detection in nuclear reactor cores. *Proc. Int. Conf. Mathematics and Computational Methods Applied to Nuclear Science and Engineering (M&C2021)*, Raleigh, NC, USA, October 3-7, 2021

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    - ➢ De Sousa Ribeiro, F., Calivà, F., Chionis, D., Dokhane, A., Mylonakis, A., Demazière, C., Leontidis, G., Kollias, S. (2018), Towards a deep unified framework for nuclear reactor perturbation analysis. Proc. IEEE Symposium Series on Computational Intelligence (SSCI 2018), Bengaluru, India, November 18 – 21, 2018
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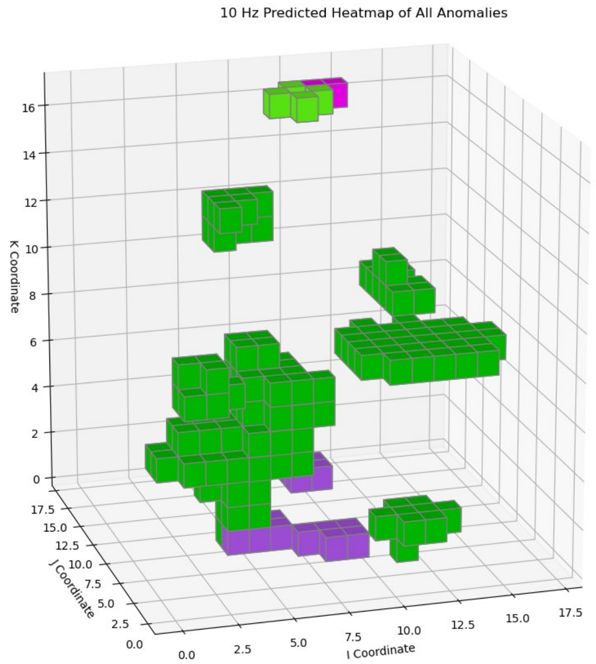
    - ➢ Durrant, A., Leontidis, G., Kollias, S., Torres, L. A., Montalvo, C., Mylonakis, A., Demazière, C., Vinai, P. (2021), Detection and localisation of multiple in-core perturbations with neutron noise-based self-supervised domain adaptation. *Proc. Int. Conf. Mathematics and Computational Methods Applied to Nuclear Science and Engineering (M&C2021)*, Raleigh, NC, USA, October 3-7, 2021
    - ➢ Ioannou G., Tasakos T., Mylonakis A., Alexandridis G., Demazière C., Vinai P., and Stafylopatis A., Feature extraction and identification techniques for the alignment of perturbation simulations with power plant measurements. *Proc. Int. Conf. Mathematics and Computational Methods Applied to Nuclear Science and Engineering (M&C2021)*, Raleigh, NC, USA, October 3-7, 2021

Application to commercial reactors

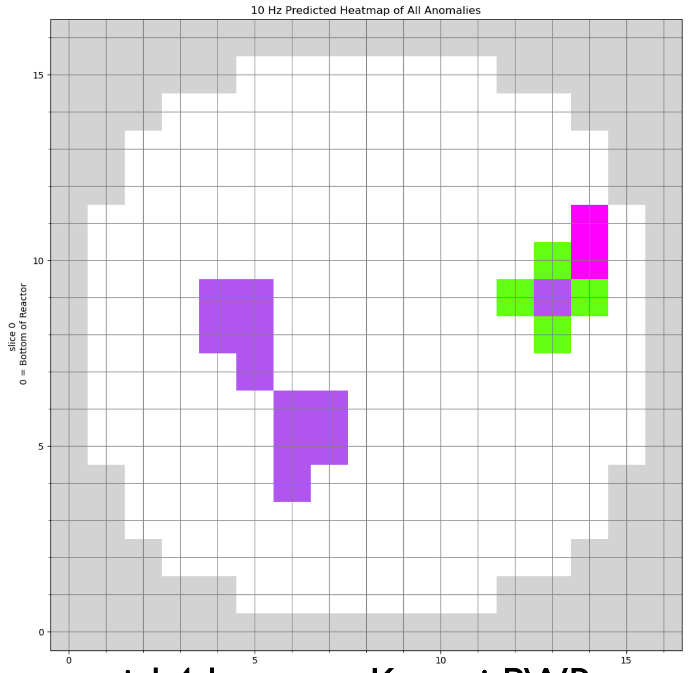
- Overall conclusions:
  - Very good unfolding capabilities, both in terms of classification and localization of anomalies
  - ➢ Significant enough deviation from point-kinetics
  - Satisfactory results:
    - Even when using very few detectors (but more detectors give better predictions)
    - Even when adding uncorrelated noise
  - More evenly distributed detectors lead to more robust predictions

Application to commercial reactors

- Example of machine learning-based unfolding applied to actual plant data:



Fuel assembly vibrations
Travelling perturbation
Absorber of variable strength
Control rod vibrations



Example of machine learning-based unfolding at 10 Hz in a commercial 4-loop pre-Konvoi PWR

Figure from Durrant, A., Leontidis, G., Kollias, S., Torres, L.A., Montalvo, C., Mylonakis, A., Demazière, C., Vinai, P. (2021), Detection and localisation of multiple in-core perturbations with neutron noise-based self-supervised domain adaptation. Proc. Int. Conf. Mathematics and Computational Methods Applied to Nuclear Science and Engineering (M&C2021), Raleigh, NC, USA, October 3-7, 2021

Conclusions

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- CORTEX project demonstrated that machine-learning based unfolding using annotated simulated data can be used for core monitoring
- Could be used by utilities as a decision-making supportive instrument for plant operation and maintenance

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