COMBINING SIMULATIONS AND MACHINE LEARNING FOR NEUTRON NOISE-BASED CORE DIAGNOSTICS

C. DEMAZIÈRE
On behalf of the CORTEX consortium
Chalmers University of Technology
Department of Physics
Division of Subatomic, High Energy and Plasma Physics
SE-412 96 Gothenburg, Sweden
Email: demaz@chalmers.se

Core monitoring techniques represent methods that allow detecting anomalies in nuclear reactors, subsequently characterizing those anomalies, localizing them (if relevant), and classifying them according to their impact on plant safety and availability. One of the most promising core monitoring techniques relies on the measurement of the inherent fluctuations in the neutron flux in a nuclear core, the so-called *neutron noise*. Those fluctuations are the results of perturbations existing in the system, such as mechanical vibrations and perturbations in the cooling medium of the reactor, to name a few. Such perturbations, by modifying the probability of occurrence of the corresponding nuclear reactions in the core, will give rise to fluctuations in the neutron flux. The monitoring of such fluctuations thus makes it possible to detect any abnormal behaviour of the system. The main advantage of using neutrons to detect anomalies as compared to using temperature, pressure or flow rate information is that neutrons propagate through the system via the fission and scattering reactions. Neutron detectors can thus "sense" any perturbation even far away from the actual location of the perturbation.

Using the measured fluctuations in neutron flux for core monitoring nevertheless requires being able to *unfold* from those fluctuations the driving anomalies. In the Horizon 2020 CORTEX project (CORe monitoring Techniques and EXperimental validation and demonstration) [1], this unfolding is carried out using machine learning, as illustrated in Fig. 1. Using numerical simulations, an anomaly is specified, and the neutron noise induced by such a perturbation is estimated. The results of such simulations are then used as training and validation data sets for machine learning. Thereafter, the measured fluctuations are fed to the machine learning algorithm, then returning the type of anomaly existing in the core, its characteristics, and, if relevant, its location.

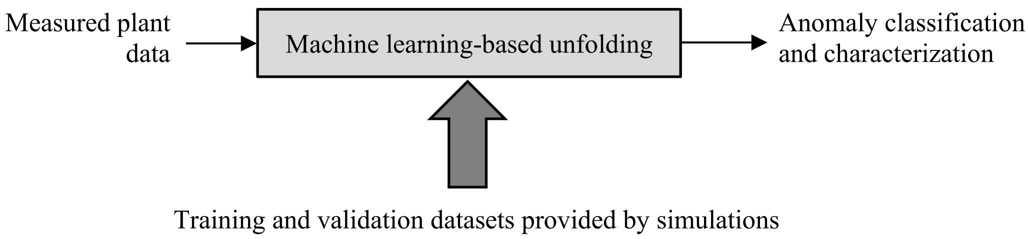

FIG. 1. Overview of the methodology developed in CORTEX.

The performance of the machine learning-based unfolding heavily relies on the simulations used for training and validation. At the frequencies typically considered for core monitoring, the system can essentially be modelled as an open-loop system from a neutronic viewpoint. The modelling of the neutron noise can be divided into two major steps: the representation of the perturbation itself, and the modelling of its effect onto the neutron flux. For the latter, different approaches can be considered: transport or diffusion methods, fine-mesh or coarse-mesh approaches, and time-domain or frequency-domain calculations. The simulations can be performed using either deterministic or probabilistic (Monte Carlo) methods.

Due to the unavailability of annotated neutron noise measurement data for commercial nuclear reactors, as the existence of anomalies is not known, the development and test of different machine learning architectures was carried out in CORTEX using simulation data exclusively.

Using frequency-domain-based simulations, it was demonstrated in [2] that, for large Pressurized Water Reactors (PWRs), machine learning-based unfolding can correctly identify perturbations, and when relevant, successfully localize such fluctuations. Different types of perturbations were considered for two PWRs (a three-loop pre-KONVOI PWR and a four-loop pre-KONVOI PWR): “absorber of variable strength”, core barrel vibrations, fuel assembly vibrations (different types of vibrations), control rod vibrations, and travelling perturbations. When using 45 in-core neutron detectors evenly distributed throughout the core, the classification accuracy was between 79.41% and 99.35%.

Using time-domain-based simulations, it was also demonstrated in [3] that machine learning-based unfolding also works as intended. Numerical experiments on a three-loop pre-KONVOI PWR showed that the accuracy in the classification accuracy, as measured by the F1-score, was between 0.99 and 1.00, when using 44 in-core and ex-core neutron detectors in total. The following types of perturbations were considered: fuel assembly vibrations (different types of vibrations), inlet temperature fluctuations, inlet flow fluctuations, and combinations of those (where the vibrations of the fuel assemblies considered a central cluster of 5x5 fuel assemblies all vibrating in-phase with each other).

In more recent developments of the project, the developed architectures were applied to actual plant data – see, e.g., [2] and [3]. Core maps displaying possible anomalies were created and are of potential great help to the utilities for identifying possible anomalies while the reactors are operating and for taking adequate actions before outage.

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