RECOMMENDATIONS FOR CORE MONITORING TO ENHANCE THE DETECTION AND DISCRIMINATION OF ANOMALIES BY NEUTRON NOISE MEASUREMENTS

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ABSTRACT

In the H2020 CORTEX project, an interdisciplinary team developed neutron noise-based core monitoring techniques implemented as methods and tools based on the approaches of machine learning and artificial intelligence. These methods and tools allow the detection of anomalies in commercial nuclear reactor cores during operation by using the measurements of the fluctuations of the neutron flux – the so-called neutron noise – by very few detectors. The sensitivity of the techniques to changes of different inputs and model parameters were analyzed. Based on these analyses together with the return of experience gained from the operational history of neutron noise measurements, recommendations were derived on how the applicability and the accuracy of the newly developed methods and tools can be improved.

INTRODUCTION

For four years researchers from different disciplines worked together in the H2020 European research project CORTEX to develop new techniques and tools for core monitoring based on the measurement of the neutron noise. These techniques and tools are based on different machine learning approaches, including deep neural networks which are a subcategory of artificial intelligence.

They have several diagnostics tasks at various hierarchical levels. At the uppermost level they should be able to detect anomalous behavior or neutron noise pattern. At the second level they should be able to classify the nature of the detected perturbation. Depending on the nature of the anomaly they should be able to detect parameters of the anomaly like its location at the third level.

They use the existing measurement equipment for the neutron flux, i.e. the neutron flux detectors inside (in-core) and outside (out-of-core) of the reactor pressure vessel. The anomaly detection is done by analyzing measured neutron flux fluctuation and determining the cause of the measured noise pattern.

The newly developed techniques are based on the application of different simulations used for training and validating the machine learning algorithms and on the use of signal processing and signal reconstruction.

The following different generic perturbations possibly causing neutron flux noise were identified [1] and used for the training and validation of the machine learning methods [2].

- Axially travelling perturbations along given channels (such as inlet flow temperature perturbations).
- Lateral vibrations of partially inserted control rods.
- Inlet flow rate perturbations.
- Core barrel vibrations (only the beam or pendular modes were considered).
- Fuel assembly vibrations (cantilevered beam mode, simply supported on both sides modes, cantilevered beam, and simply supported modes).
- Absorber of variable strength, where a spatially localized perturbation exists in a three-dimensional representation of the reactor core.

Different sensitivity analyses were performed within the project at different stages of the model development. The sensitivity of the simulations of the neutron flux noise to changes of different inputs and model parameters was investigated, as well as the sensitivity of the tools to changes in the detector signals [3], [4]. The results of the sensitivity analyses indicated how the detection quality could be improved. Additionally, experience gained from the operational history of neutron noise measurements allowed to derive recommendations on how to improve the applicability and the accuracy of the newly developed methods and tools.

The recommendations were based on analyses and simulations of the fluid structure interactions (FSI) of coolant and reactor pressure vessel internals, on the number, availability, and quality of the neutron flux instrumentation used by the machine learning tools and considerations on the data acquisition systems and results of the data processing and signal reconstruction of different pressurized water reactors. The recommendations are highlighted by using an italic font in the following sections. The details of the derivation of these recommendations were documented in a deliverable [5] of the CORTEX project.

RECOMMENDATION IN VIEW OF FSI PHENOMENA IDENTIFICATION

One source of perturbations during the stationary operation in a power reactor which could result in fluctuations of the neutron flux are oscillations of internals of the reactor pressure vessel (see e.g. [6], [7]). To better understand these kinds of perturbations, different models for the simulations of the fluid structure interactions between the reactor pressure vessel internals and the coolant flow were developed during the CORTEX project [8], [9].

The following first set of recommendations target the identification of those anomalies which could be caused by FSI effects, i.e. vibrations of core internals.

The first recommendation is to *further investigate the correlation of the measured neutron noise with other measurements, like primary pressure gauges, displacement transducers, thermocouples, accelerometers mounted to the RPV head, acoustic instrumentation, or main coolant pump supply current.*

The correlation with those quantities were already successfully used for the identification of other phenomena in the reactor core [10]. The use of those signals by the machine learning tools as developed in CORTEX would require the use of multi-physics models during the learning phase to create corresponding training data.

The next recommendation is *to measure the neutron flux and other quantities under special operating conditions, like commissioning tests, start-up, shutdown, partial load, or the unavailability of one main coolant pump*. An example for measurements during the slowdown of the main coolant pumps were described in [6] showing the excitation of different oscillations with different natural frequencies.

Another recommendation is *to use information from operational experience because defects or wear can be a sign for increased motion in the affected area*. An example for such a correlation was the fretting damages found at the corners of spacers resulting from static and dynamic fuel assembly deformations [11]. It needs to be considered that those correlations are rather vague and do not provide quantitative information.

Beside the use of existing measurement equipment, the installation of new detectors could provide new insight, but would require potential costly work for qualification and integration. Still, another recommendation is to *include in-core accelerometers in the fuel elements and at the core barrel*. An example for this was reported in [12]. In [13] such additional detectors were recommended to understand the phenomenon of changing neutron flux noise amplitudes in German PWRs over different reactor cycles.

Those new detectors would be able to quantify the motions of the core internals, but the question of the driving forces exciting the structures might still be unresolved. Therefore, another recommendation is to *develop and add in-core detectors capable to measure the coolant velocity in axial and radial direction*. The time of commissioning tests of new plants could be used to perform such measurements, e.g. by using fuel assembly dummies during pump tests, because then there will most likely be lower requirements with regard to nuclear safety.

The final recommendation with respect to FSI consideration is *to implement scaled mock-up experiments*. In such experiments, FSI phenomena could be investigated in detail and without nuclear safety requirements, although it would be important to meet relevant dimensionless parameters and other boundary conditions as they occur in real nuclear power plants.

RECOMMENDATION BASED ON THE DEPENCENCY OF THE MACHINE LEARNING-BASED UNFOLDING ON THE CORE INSTRUMENTATION

For recovering the driving perturbation, it is necessary to train and validate the machine learning based core monitoring techniques and tools. This was done by using simulations in time- or frequency-domain and by determining the neutron flux values at the detector locations for postulated anomalies. Those simulated detector readings were then used as input for the machine learning tools. The newly developed tools and techniques were applied to both simulated data and data measured at power plants [2]. But only for simulated data, the so-called ground truth, i.e. the anomaly causing the neutron flux noise, was known. Therefore, only simulations were used to determine the sensitivity of the tools and techniques to modifications of the core instrumentation.

The different anomalies considered as possible causes for the neutron flux noise in power reactors had in common that they induced a space-dependent neutron noise in the entire system. For the determination of the type and location of an anomaly, it was found to be crucial to examine the amplitude and phase at different spatial points inside the reactor core as well as the correlation of these values. Different anomalies showed different characteristic spatial distributions, like a shift of the phase or out-of-phase behavior.

To understand this behavior, the induced neutron noise $\delta\phi(\mathbf{r},t)$ needs to be examined in more detail. In linear theory, it can be expressed as the sum between a point-kinetic response $\delta P(t)\phi_0(\mathbf{r})$ and the fluctuations of a so-called shape function $\delta\psi(\mathbf{r},t)$ [14], i.e.

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

In the equation above, $\delta P(t)$ represents the fluctuations of the amplitude factor and $\phi_0(\mathbf{r})$ is the static flux. The equation shows that the space-dependence of the point-kinetic response is always given by the static flux $\phi_0(\mathbf{r})$ and is thus independent of the applied perturbation. The space-dependence of the fluctuations of the shape function $\delta\psi(\mathbf{r},t)$ can be any. Therefore, the ability to “see” in the measured neutron noise an anomaly specific spatial dependency depends on how overwhelming the fluctuations of the shape function are in comparison with the fluctuations of the amplitude factor. The machine learning-based tools need to be trained in a way, that they recognize with readings of very few neutron detectors a significant enough spatial dependence of the fluctuations of the shape function.

For machine-learning tools, working in either frequency domain [15] or in time domain [16], it was shown that they were able to successfully identify the considered anomalies, based on simulated training and validation data. As mentioned above, the validation was done with simulated data, because only for those the ground truth was known. Results of the quality of the machine-learning based tools for different reactors and anomalies can be found in [5], [15] and [16].

The sensitivity studies reported in [4] for simulations of the vibration of a fuel element with the program CORE SIM+ demonstrated the effect of the space dependency of the phase of the neutron flux noise for small changes in the location of vibrating fuel element. A small change in the location of the vibrating fuel assembly resulted in a change of the spatial phase distribution which could be detected at one of the detector locations in the investigated 3-loop pre-Konvoi reactor (R.P. #5 in Figure 1). Together with the strong spatial dependence of the magnitude of the neutron noise away from the noise source, the amplitude and phase throughout the core significantly deviates from point-kinetics. This means that the resulting space dependence of those quantities is sufficiently correlated to the location of the perturbation to make the unfolding using machine learning possible.

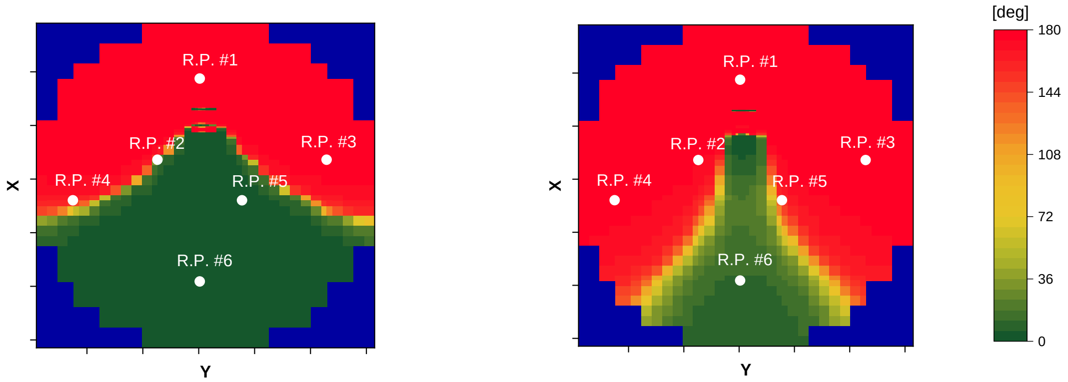

Figure 1: The phase of the thermal neutron flux noise simulated for a 3-loop pre-Konvoi reactor with slightly changed x-positions of the vibrating fuel assembly (left 4.3 mm upwards, right 4.3 mm downwards). The positions of the in-core neutron flux detectors are marked with R.P.#1-6. Results reproduced from [4].

From these observations two recommendations could be derived: The first one is *that the detectors should be homogeneously distributed across the reactor core*. This recommendation was also supported by the experiences gained during the training, validation and testing of the frequency domain-based machine learning tool [15]. The second one is to *have a high in-core detector coverage*. As can be seen from Figure 1, the number of installed detectors in the investigated pre-Konvoi reactors seemed to be at the lower end needed to identify the exact location of a single vibrating FA.

As those results were obtained using simulated data also for validating and testing them, it will be necessary in the future to confirm them using actual measurements in power plants with known perturbations.

RECOMMENDATION BASED ON RESULTS OF DATA PROCESSING AND RECONSTRUCTION

During the CORTEX project different data processing methods as well as data reconstruction methods [17] were applied to the measurements from different pre-Konvoi and VVER reactors [5], [2]. The Fourier analysis was the main technique used to evaluate acquired data from the neutron flux measurements as well as from other detectors, like reactor head accelerometers and the coolant pressure. Also used were joint time-frequency analysis and singular spectrum analysis.

Signal reconstruction methods were applied to the measurements of the self-powered neutron detectors (SPND). By comparing reconstructed and actual detector signals, it is possible to determine faults of the detector signals and to estimate the signal-to-noise ratio. The reconstruction works by using the correlation between different detectors and (re)construct the signal of a detector by estimating it from the measurements at the correlated detectors (see Figure 2). The exact algorithm of signal reconstruction used in the CORTEX project was described in [17].

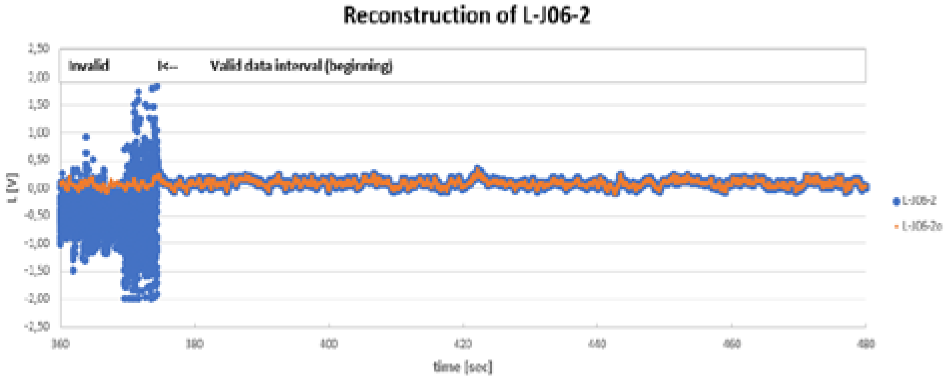

Figure 2: Example for the reconstruction (red) of a partially distorted SPND signal (dark blue). Results reproduced from [5]

Based on the experiences gained by the application of data acquisition, processing, and reconstruction during the CORTEX project the following recommendations were derived.

For SPNDs, it is recommended *to have a high detector density with a uniform distribution throughout the reactor core, to know the transfer function of each SPND, to normalize the signal of each SPND against its concurrent steady state component, and to correct the burnout rate of each SPND individually.*

For ionization chambers, it is recommended *to place them in the upper and lower positions against the reactor head accelerometers for the detection and determination of core barrel movements.*

Also, it is recommended *to record the signals of the accelerometers as well as of pressure fluctuations simultaneously with the reactor instrumentation and to use a uniform time base for all measurements of the whole plant.*

To compare the measurements between different plants, it is recommended *to use the same parameters for the measurements and their analysis (like sampling frequency, spectral resolution, normalization, frequency range).*

The signals of in-core detectors often contain noise or other disturbances. It is therefore recommended *to use reconstructed signals instead of the raw signals as inputs for the machine learning-based tools and techniques.*

CONCLUSION

The recommendations reported here aim at improving the applicability and the accuracy of the methods and tools developed during the CORTEX project. However, they can also improve the applicability of neutron noise analysis for plant surveillance in general. Two groups of recommendations were made. The first one includes measures which can be taken based on the currently installed detectors. Especially measurements during special operational conditions might provide additional insight. As several new reactors are expected to go through this phase in Europe during the next years, this might be a unique opportunity to acquire such knowledge. Alternatively, it might be worthwhile to search for data acquired during the commissioning of already existing reactors. Several of these recommendations were already applied during the measurement campaigns during the CORTEX project.

The second group is about increasing the number of detectors or installing additional detectors measuring complementary physical quantities. The later would not only require the development of new detectors but would also result in changes in the instrumentation & control systems of the reactors, for which licensing through the regulator would be necessary.

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