CORTEX

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Recommendations for modifications, improvements, additional detectors

Authors : Mr. Joachim HERB (GRS), Mr. Christoph Bläsius (GRS), Pr. Christophe Demaziere (Chalmers), Mr. Petr Stulik (UJV), Dr. Jindrich Machek (UJV)

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Author(s)	Mr. Joachim HERB, Mr. Christoph Bläsius (GRS), Pr. Christophe Demaziere (Chalmers), Mr. Petr Stulik (UJV), Dr. Jindrich Machek (UJV)
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Summary

During the CORTEX project methods and tools have been developed and/or applied for sensitivity analyses, different simulations, signal processing, signal reconstruction and machine learning. Also, other experiences gain in the operational history of neutron noise analyses have been analysed. Different recommendations have been derived on the results of these activities and they have been put forward in this deliverable. These recommendations aim at improving the applicability and the accuracy of the developed methods and tools. But they would also improve the applicability of using neutron noise analysis for plant surveillance in general. Two groups of recommendations were found. The first one includes measures which can be taken based on the currently installed detectors. The second group is about increasing the number of detectors or installing additional detectors measuring other physical quantities.

Approval

Date	By
2021-08-25 14:38:39	Mr. Joachim HERB (GRS)
2021-08-25 14:56:00	Pr. Christophe DEMAZIERE (Chalmers)

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Abbreviations

AC	Alternating Current
ADC	Analog to Digital Converter
APSD	Auto Power Spectral Density
AVS	Absorber of Variable Strength
BG	Background / No class
BOC	Begin Of Cycle
BV	Core Barrel Vibrations
CANT	Fuel Assembly Vibrations (FAV) Cantilevered type
CSF	FAV Cantilevered Supported type, First mode
CSS	FAV Cantilevered Supported type, Second mode
COH	Coherence
CPSD	Cross Power Spectral Densities
CR	Control Rod vibrations
DC	Direct Current
DNN	Deep Neural Network
EOC	End Of Cycle
FA	Fuel Assembly
FAV	Fuel Assembly Vibrations
FFT	Fast Fourier Transform
FSI	Fluid Structure Interaction
IRI	Incompatible Rod Insertion
JFTS	Join Time Frequency Spectrogram
JTFA	Joint Time Frequency Analysis
KWU	Kraftwerk Union
MCP	Main Coolant Pump
MOC	Mid of Cycle
NAPSDs	Normalised Auto Power Spectral Density
NPP	Nuclear Power Plant
PSD	Power Spectral Density
PWR	Pressurized Water Reactor
RPV	Reactor Pressure Vessel
RVMS	Reactor Vibration Monitoring System
SSA	Singular Spectrum Analysis
SF	FAV Supported type, First mode
S/N	Signal to Noise
SPND	Self-Powered Neutron Detector
SS	FAV Supported type, Second mode
STFT	Short Time Fourier Transform
TP	Travelling Perturbations

Summary

During the CORTEX project methods and tools have been developed and/or applied for sensitivity analyses, different simulations, signal processing, signal reconstruction and machine learning. Also, other experiences gain in the operational history of neutron noise analyses have been analysed.

Different recommendations have been derived on the results of these activities and they have been put forward in this deliverable. These recommendations aim at improving the applicability and the accuracy of the developed methods and tools. But they would also improve the applicability of using neutron noise analysis for plant surveillance in general. Two groups of recommendations were found. The first one includes measures which can be taken based on the currently installed detectors. The second group is about increasing the number of detectors or installing additional detectors measuring other physical quantities.

1 Introduction

Both signal analysis methods and tools based on machine learning have been developed during the CORTEX project to discriminate between different root causes of fluctuations of the neutron flux. All these methods and tools are based on the signals measured by neutron flux detectors inside (in-core) and outside (out-of-core) of the reactor pressure vessel. Within the CORTEX project it was investigated in different tasks how these tools and methods are sensitive to changes in the detector signals.

This deliverable summarizes the different results of these sensitivity analyses, the applications of different simulation tools, the application of signal processing, signal reconstruction and machine learning, and other experiences gained in the applications of the neutron noise measurements.

The first set of recommendations is derived from the analysis and simulations of the interaction between the coolant and the structures of the reactor pressure vessel internals. Additionally, the experiences gained during the commissioning and the operation history of German PWR is considered.

Then the influence of the number, availability, and quality of the neutron flux instrumentation on results of the machine learning methods is considered. This includes an analysis of the properties of neutron noise in large commercial reactors.

Finally, considerations on the data acquisition systems and results of the data processing and signal reconstruction of VVER and pre-Konvoi reactors are used to derive recommendations for neutron flux detectors as well as for other detectors of other physical quantities and their application.

Based on all these results, recommendations are given for the modification, improvement, and addition of detectors, so that the applicability of the tools and techniques developed within CORTEX can be improved and optimized. These recommendations are not limited to neutron flux detectors but included also detectors for other physical quantities. Additionally, recommendations are derived how to use different operational situations at nuclear power plants to further gain insight in the physical processes and root causes of different neutron noise phenomena.

2 Recommendation in view of FSI phenomena identification

Based on the experience gained during the generation of an FSI model of core internals that have an effect on neutron flux (Bläsius et al., 2020) and the application of different generic excitation scenarios to this model (Alexandridis et al., 2020), recommendations for the enhancement of the reactor instrumentation to improve the identification and quantification of FSI phenomena in the core have been derived. A major driver for these recommendations is the need to identify and quantify potential coherent Fuel Assembly (FA) motions that have been suspected responsible for a phenomenon in neutron flux fluctuations of KWU type reactors (Herb et al., 2017). The first three recommendations come without the need for constructive changes, the latter three will require new kinds of instrumentation and experimental devices. Whether and under which circumstances these recommendations might be helpful identifying and quantifying the phenomenon observed in KWU type reactors as well as other operational and defect-related FSI-phenomena will be discussed in the following.

A first recommendation, which is the intensification of activities to correlate the measured noise with further quantities, bases on a long history of successful application for other phenomena in the core (Thie, 1981). The "fingerprint" obtained by correlation of the neutron flux signal with primary pressure gauges, displacement transducers, thermocouples, accelerometers mounted to the RPV head and among the different neutron flux sensors can be interpreted and compared against existing databases, such as SINBAD (Trenty, 1995). Moreover, unconventional signals like acoustic instrumentation or main coolant pump supply current (Stulík et al., 2019) might be taken into account as well. Using the signals as an additional source for the artificial intelligence approach developed in CORTEX might increase its predicational capability but would require multi-physics models in the learning phase.

A second recommendation is the measurement of neutron flux and other quantities under special operating conditions, like commissioning tests, start-up, shutdown, partial load or 3 of 4 main coolant pumps running. In (Bauernfeind, 1977) measurements after a power-off of the main coolant pumps are described. During the run out of the coolant pumps, mechanical oscillators successively resonated with the falling pump rotation frequency, which allowed the identification of natural frequencies of these oscillators. As the neutron noise level is lower or absent during such measurements, other sensors than full range neutron flux sensors have to be taken into account. Periods of part load can be found at the end of a cycle or at times of lower electricity consumption (end of the year, periods with much renewable energy). Measurement with full range sensors is possible down to about 30 % power. Such measurements have been done in (Fiedler, 2002). Nevertheless, it remains unclear if such measurements can help identifying FSI phenomena, especially as other physical effects, like sub-critical boiling, can arise and increase the complexity of the signal. An operation with 3 of 4 pumps, as it is allowed in some plants, influences the quantity and symmetry of the mass flow profile that is suspected as main driver for some FSI-phenomena.

A third recommendation might be to use information from operational experience, as defects or wear might be a sign for increased motion in the corresponding area. Fretting damages at the corners of spacers have been found in cores that suffered from static and dynamic fuel assembly deformation (Reaktorsicherheitskommission, 2015). Other defects might include broken centring pins or fatigue. Nevertheless, the correlation between those events and increased motion is rather vague and will not allow a sufficient quantification.

A fourth recommendation, which requires additional instrumentation and potential costly work for qualification and integration, would be the inclusion of in-core accelerometers into empty guide tubes, but has actually been done in the past (Laggiard et al, 1995). Especially in view of the suspected phenomenon of correlated FA motions in KWU type reactors, (Seidl et al, 2015) demanded such an instrumentation as gold standard to enlighten the nature of the phenomenon. Similar measurements could be applied to the core barrel. Measurements of the acceleration would be able to quantify the motions but might not be able to give information about the exciting (hydraulic) force. The measurements could be simplified by carrying them out in plants before commissioning, e.g., with dummy FAs and during pump tests, when there are lower requirements regarding nuclear

safety. In VVER reactors there is the opportunity to measure core barrel motions indirectly by measuring the acoustic effects of a specific labyrinth sealing (Liewers et al., 1988).
To obtain the whole picture, the fifth recommendation aims at the development of instrumentations to measure the coolant velocity in axial and radial direction. Nevertheless, besides the problem of costly qualifying and integration of such an instrumentation, a sufficient resolution of the flow field would require numerous measurement locations as global crossflow can be overlaid by other effects such as local eddies (Wanninger, 2018).
A last recommendation aims at the implementation of scaled mock-up experiments, in which FSI-phenomena can be investigated in detail without boundary conditions of nuclear safety. Such potentially heavily instrumented experiments have already been performed in the past (Au-Yang et al, 1995). Well-defined local disturbances could be included, and the experiments can also be used to optimize the number and location of sensors in real plants. Nevertheless, besides the costly construction of such experiments, a major problem is to meet the relevant dimensionless parameters and the conditions in a real nuclear plant.
In conclusion, there are several potential ways to improve the instrumentation of a power plant with regard to FSI-phenomena, some of which were discussed here. Besides the most important problem of costly qualifying and implementing in a nuclear environment, every discussed recommendation has its advantages and drawbacks, which makes it necessary to perform additional accompanying investigations and modelling.

3 Influence of the instrumentation on the machine learning-based unfolding

3.1 Introduction

Neutron noise monitoring can be summarized as several diagnostics tasks to be performed at various hierarchical levels. The uppermost level is simply the detection of an anomalous behaviour or neutron noise pattern. The second level is the classification of the nature of the perturbation existing in the core. The third level depends on the nature of the anomaly. In some cases, the anomaly corresponds to a localized perturbation, for which the identification of the actual location of the perturbation is of importance. In some other cases, estimating some parameters characterizing the anomaly is of interest.

In the CORTEX project, the following types of anomalies were considered:

- 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.

The perturbations above were represented as perturbations of nuclear macroscopic cross-sections (Demazière and Dokhane, 2019) and their effect was thereafter assessed using frequency-domain or time-domain neutronic codes (Dokhane and Mylonakis, 2019). The output of those simulations was then fed to specifically designed machine learning-based algorithms as training and validation data sets. The purpose of those algorithms was to identify, classify and possibly localize perturbations, as explained above, from actual plant data. In CORTEX, the application of the machine learning-based algorithms was both performed on simulated data (Kollias et al., 2019) and actual data (Alexandridis et al., 2020). It is only in the former case that the perturbation existing in the system is known. It thus offers the possibility to verify the correctness of the machine learning-based diagnostics.

3.2 Properties of the neutron noise in large commercial reactors

Stationary fluctuations occurring in a nuclear reactor give rise to an induced space-dependent neutron noise throughout the entire system. The examination of the amplitude and phase existing between different spatial points is crucial for determining the type of anomaly present in the reactor core and for possibly localizing the anomaly.

In some cases, the spatial distribution of the phase alone allows to directly identify the driving perturbation. This is for instance the case when a perturbation is travelling through the core. The induced neutron noise will exhibit, in the most general case, a phase delay in the direction of propagation of the perturbation. This characteristic feature can thus be used to distinguish between this type of perturbation or other possible ones. Likewise, vibrations of structures typically give rise to an out-of-phase response of the neutron noise along the direction of vibrations.

The spatial structure of the neutron noise, even in the cases mentioned above, can nevertheless be more intricate and the examination of the phase alone might not be sufficient. Generally speaking, the induced neutron noise $\delta\phi\left(\mathbf{r},t\right)$ in linear theory can be considered as the sum between a point-kinetic response $\delta P\left(t\right)\phi_0\left(\mathbf{r}\right)$ and the fluctuations of the shape function $\delta\psi\left(\mathbf{r},t\right)$, i.e.

$$\delta\phi\left(\mathbf{r},t\right) = \delta P\left(t\right)\phi_0\left(\mathbf{r}\right) + \delta\psi\left(\mathbf{r},t\right) \quad (1)$$

In the equation above, $\delta P(t)$ represents the fluctuations of the amplitude factor and $\phi_0(\mathbf{r})$ is the static flux. The amplitude factor and shape functions allow retrieving the space- and time-dependent neutron flux as:

$$\phi(\mathbf{r},t) = P(t) \cdot \psi(\mathbf{r},t) \tag{2}$$

where the following normalization condition was used (Bell and Glasstone, 1970):

$$\frac{\partial}{\partial t} \int \phi_0(\mathbf{r}) \psi(\mathbf{r},t) d^3\mathbf{r} = 0 \tag{3}$$

The fluctuations of the amplitude factor are themselves related, in the frequency domain, to the reactivity noise $\delta\rho(\omega)$ via the zero-power reactor transfer function $G_0(\omega)$ as:

$$\delta P(\omega) = G_0(\omega)\delta\rho(\omega) \tag{4}$$

with ω representing the angular frequency.

As Eq. (1) demonstrates, the induced neutron noise is made of two terms having fundamentally different spatial dependence:

- The space-dependence of the point-kinetic response is always given by the one of 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 can be any.

In summary, it means that the ability to “see” in the measured neutron noise a spatial dependency specific to the applied perturbation is dependent on how overwhelming the fluctuations of the shape functions are in comparison with the fluctuations of the amplitude factor. An overwhelming point-kinetic response results in an induced neutron noise always having the same space-dependence (the one of the static flux) irrespective of the applied perturbation.

As a result, the possibility to distinguish between different types of perturbations is related to how different from point-kinetics the reactor response is. It is known that localized perturbations and large reactors correspond to situations where a deviation from point-kinetics is observed (Pázsit and Demazière, 2010). This is exemplified in Figure 1 below. In this figure, the total neutron noise is represented by the thick blue line, the point-kinetic component by the red line and the fluctuations of the shape function (or remaining component) by the thin blue line. Irrespective of the position and nature of the perturbation, the space-dependence of the point-kinetic component is always the same. Thus, this point-kinetic component cannot be used for diagnostic purposes. Only the fluctuations of the shape function (or remaining component) contain some meaningful information, i.e., its space-dependence will be different depending on the location and nature of the perturbation.

As a result, the ability of machine learning-based unfolding to correctly detect and localize perturbations is entirely based on the possibility to measure with very few neutron detectors a significant enough spatial dependence of the fluctuations of the shape function.

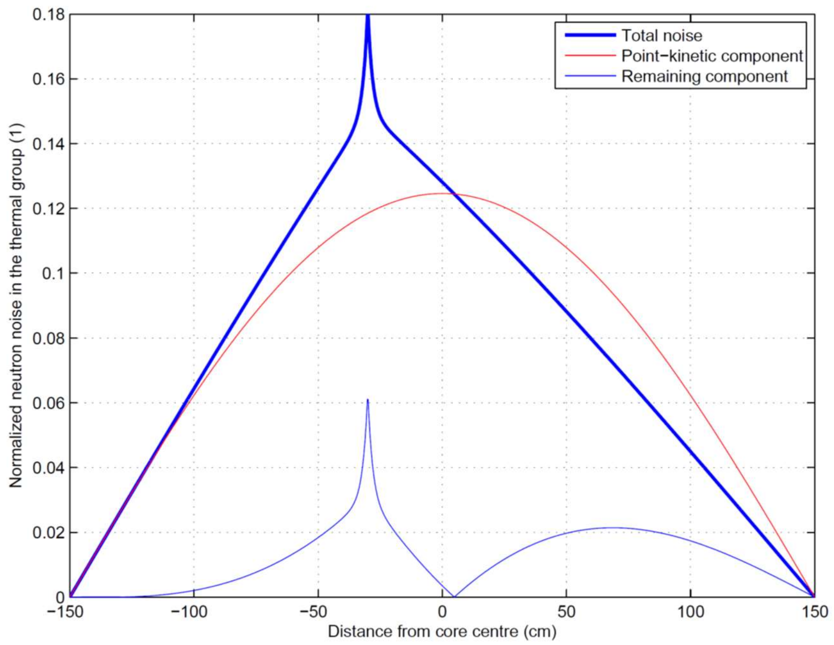


Figure 1: Illustration of the difference between the point-kinetic component and the total induced neutron noise in the frequency domain at 1 Hz, for a perturbation located at -30 cm from the centre of a nuclear core of size 300 cm. The figure represents the amplitude of the various components.

It is demonstrated in (Durrant et al., 2021) that, indeed for large Pressurized Water Reactors (PWRs), machine learning-based unfolding is able to correctly identify different types of perturbations, and when relevant, successfully localize such fluctuations, as summarized in Table 1. This work considers the combination of several postulated perturbations, the effect of which being simulated in the frequency domain for two PWRs: a three-loop pre-Konvoi PWR and a four-loop pre-Konvoi PWR. The various perturbations that are considered are: Absorber of Variable Strength (labelled as AVS), core Barrel Vibrations (labelled as BV), Fuel Assembly Vibrations (FAV) of the Cantilevered type (labelled as CANT), FAV of the Cantilevered Supported type – First mode (labelled as CSF), FAV of the Cantilevered Supported type – Second mode (labelled as CSS), Control Rod vibrations (labelled as CR), FAV of the Supported type – First mode (labelled as SF), FAV of the Supported type – Second mode (labelled as SS) and Travelling Perturbations (labelled as TP). BG refers to no class being detected (background). The exact definition of the scenarios can be found in (Demazière and Dokhane, 2019) and the modelling of their effect in the frequency domain is described in (Dokhane and Mylonakis, 2019). It should be mentioned that the results presented in Table 1 are using simulated data only for training, validation of and testing the machine learning algorithms, with different non-overlapping data subsets used for each task. The advantage of using only simulated data lies with the fact that the actual perturbation existing in the reactor is known. Further details about the analysis summarized in Table 1 can be found in (Durrant et al., 2021). It should be highlighted that the work reported in (Durrant et al., 2021) is based on some earlier work investigating simpler configurations/problems (Calivá et al., 2018; De Sousa Ribeiro et al., 2018; Durrant et al., 2019; Kollias et al., 2019; Demazière et al., 2020). All those investigations reach the same conclusions, namely that the neutron noise in the frequency domain can be used to successfully detect, classify, characterize, and possibly localize anomalies in large PWRs.

Table 1: Per classification voxel accuracies (in %) averaged across the unseen test set using 45 in-core neutron detectors evenly distributed throughout the core of a three-loop, four-loop, respectively, pre-Konvoi PWR. Results reproduced from (Durant et al., 2021).

Reactor model	Type of perturbations									
	BG	AVS	CANT	SF	SS	CSF	CSS	CR	TP	BV
Three-loop pre-Konvoi PWR	99.11	80.95	79.41	82.50	90.79	85.71	90.14	89.86	91.91	100.00
Four-loop pre-Konvoi PWR	99.35	82.28	88.00	87.50	89.23	90.00	92.42	88.99	93.20	100.00

Similar conclusions concerning the possibility to classify and localize anomalies are also drawn in (Tasakos et al., 2021), where the simulations are performed in the time domain. The accuracy in the classification of the perturbation types, as measured by the F1-score, is summarized in Table 2 for the following considered perturbations: FAV (of different types: cantilevered, C-shaped and S-shaped), inlet temperature fluctuations, inlet flow fluctuations, and combinations of those (where the vibrations of the fuel assemblies consider a central cluster of 5x5 fuel assemblies all vibrating in-phase with each other). It should be mentioned that the inlet temperature fluctuations correspond to a TP spatially distributed at the inlet of the core in the previous terminology, whereas the inlet flow fluctuations correspond to an AVS type of perturbations distributed throughout the entire core. The exact definition of the scenarios can be found in (Demazière and Dokhane, 2019) and the modelling of their effect in the time domain is described in (Dokhane and Mylonakis, 2019). It should be mentioned that the results presented in Table 2 are using simulated data only for training, validation of and testing the machine learning algorithms, with different non-overlapping data subsets used for each task. As before, the advantage of using only simulated data lies with the fact that the actual perturbation existing in the reactor is known. Further details about the analysis summarized in Table 2 can be found in (Tasakos et al., 2021). Beyond the ability to properly detect vibrating fuel assemblies (as reported in Table 2), estimating their position is also beneficial. Concerning the localization of individual vibrating fuel assemblies, in 73% of the test cases, the localization network can correctly locate the vibrating fuel assembly. In 21% of the test cases, the identified vibrating fuel assembly is one fuel assembly away from the actual vibrating one. In 6% of the test cases, the identified vibrating fuel assembly is further away. It should be highlighted that the work reported in (Tasakos et al., 2021) aligns with some earlier work investigating simpler configurations/problems (De Sousa Ribeiro et al., 2018; Durrant et al., 2019; Kollias et al., 2019). All those investigations reach the same conclusions, namely that the neutron noise in the time domain can be used to successfully detect, classify, characterize and possibly localize anomalies in large PWRs.

Table 2: F1-score of the perturbation identification network for a signal-to-noise ratio of 10. Results reproduced from (Tasakos et al., 2021).

Reactor model	Type of perturbations			
	FAV	Inlet temperature fluctuation (TP spatially distributed at the inlet of the core)	Inlet flow fluctuation (spatially distributed AVS)	Combination of perturbations (with a cluster of 5x5 FAV)
Three-loop pre-Konvoi PWR	1.00	1.00	1.00	0.99

In (Yum & Perin 2021), a series of sensitivity analyses were carried out assuming the oscillation of one FA in the Swiss 3-loop pre-Konvoi reactor. Three different core conditions were used for the sensitivity analyses using the simulation programme CORE SIM+. It was found that the position of the noise source is the input parameter of the simulations that influences the results most. It was also found, that at the EOC the static neutron flux has a steeper gradient which even increases the sensitivity of the simulation results to the position of the neutron noise source.

It was found that especially the phase of the neutron noise is very sensitive to changes in the position of the noise source. This indicates that the component of the noise which is not caused by the point-kinetic is so large that its contribution can be detected easily.

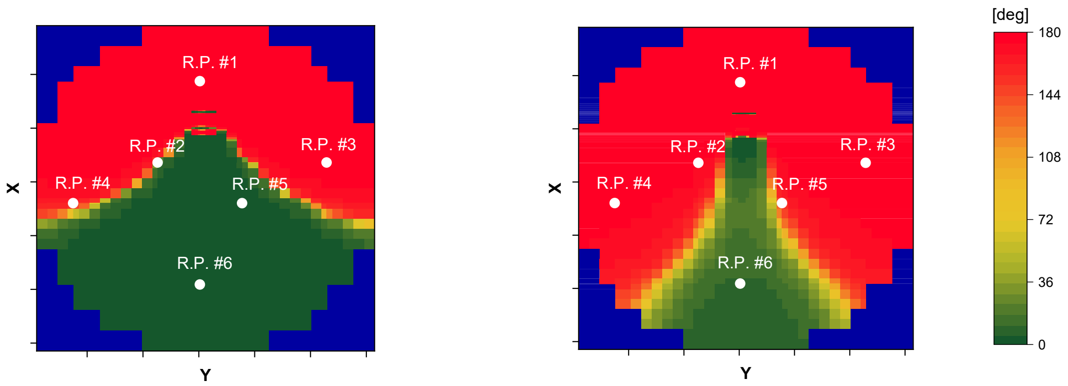


Figure 2: The phase of the thermal neutron flux noise simulated for a 3-loop pre-Konvoi reactor with slightly changed x-positions (left 4.3 mm upwards, right 4.3 mm downwards). The positions of the in-core neutron flux detectors are marked with R.P.#1-6. (Yum & Perin 2021).

In Figure 2, the change in the phase of the thermal neutron noise is largest in the regions where there is a transition from 0° to 180° (about the positions of detectors R.P. #2 and #5). In the other regions, the change of the phase is much smaller.

From this observation, a recommendation which can be derived is that the detectors should be homogeneously distributed across the reactor core. Regarding the number of in-core detectors, the number of installed detectors in the investigated pre-Konvoi reactors seems to be at the lower end needed to identify a single vibrating FA. Another recommendation is, therefore, to have a high in-core detector density. The necessary detector density could be derived from simulations of the anticipated root causes of the neutron noise. This aspect is further dealt with in the following section.

3.3 Dependence of the unfolding on the number of available detectors

The investigations reported in the previous section were based on a rather limited set of neutron detectors, corresponding to the typical number of neutron detectors available in a commercial PWR. It is nevertheless common that some of the neutron detectors are faulty or not available.

The deterioration of the performance of the diagnostics reported in the previous section can easily be assessed by using a reduced set of detectors, as compared to the nominal number of detectors assumed. This effect is summarized in Table 3 for the frequency domain architecture, based on the work of (Durant et al., 2021). As can be seen in this table, the performance is mostly unaffected, even if only using 15 detectors. Such results are again in line with some earlier investigations (Calivá et al, 2018; De Sousa Ribeiro et al., 2018; Durrant et al., 2019; Kollias et al., 2019; Demazière et al., 2020). It should nevertheless be mentioned that having more detectors make it easier to correctly identify and separate the sources of perturbations. Correspondingly, having more detectors also allows providing a more faithful estimation of the actual location of a perturbation, when relevant. Concerning the time domain-based unfolding, the sensitivity on the number of detectors was only investigated by (Tasakos et al., 2021) when localizing vibrating fuel assemblies. When using only 50% of the available detectors in the three-loop pre-Konvoi PWR, in 43 to 52% of the test cases (depending on the chosen in-core detectors), the localization network can correctly locate the vibrating fuel assembly. In 31 to 34% of the test cases, the identified vibrating fuel assembly is one fuel assembly away from the actual vibrating one. In 17 to 23% of the test cases, the identified vibrating fuel assembly is further away. Although the deterioration is appreciable in the time domain case, the prediction capabilities are still more than satisfactory.

Table 3: Per classification voxel accuracies (in %) averaged across the unseen test set using 30 and 15 in-core neutron detectors, respectively, evenly distributed throughout the core of a three-loop, four-loop, respectively, pre-Konvoi PWR. Results reproduced from (Durant et al., 2021).

Reactor model	Number of detectors	Type of perturbations									
		BG	AVS	CANT	SF	SS	CSF	CSS	CR	TP	BV
Three-loop pre-Konvoi PWR	30	99.68	84.45	83.72	92.86	86.54	86.49	81.63	87.85	90.48	100.00
	15	99.43	87.64	89.47	82.14	82.93	89.66	86.11	93.05	91.16	100.00
Four-loop pre-Konvoi PWR	30	99.64	85.97	81.48	90.48	97.37	90.24	95.12	90.21	93.25	100.00
	15	99.08	90.47	92.98	86.49	93.02	97.62	97.22	83.06	94.74	100.00

3.4 Dependence of the unfolding on additional noise

The previous results considered "clean" signals, i.e., signals for which the neutron noise is entirely due to the assumed perturbations. In order to account for the possible presence of additional spatially uncorrelated noise, white Gaussian noise was added to the neutron noise directly coming from the simulations. For the frequency domain-based unfolding, Demazière et al. (2020) reported a drop of the F1-classification score of less than 0.02. Concerning the localization of vibrating fuel assemblies, the drop in the accuracy of correctly locating the vibrating fuel assembly, as measured by the mean absolute error, was less than 1 cm (to be compared to the core size of being larger than 3 m). Those estimations were based on assuming a signal-to-noise ratio of unity. Those results are consistent with the ones earlier published in (Calivà et al., 2018; Durrant et al., 2019; Kollias et al., 2019). For the time domain-based unfolding, using as a reference point the one presented in Table 2 obtained for a signal-to-noise ratio of 10, (Tasakos et al., 2021) reported that the classification accuracy remains excellent for a signal-to-noise ratio of unity, as summarized in Table 4. One then concludes that the unfolding is largely insensitive to the presence of additional noise, irrespective of whether the unfolding is based on time domain or frequency domain simulations. Those results are consistent with the ones earlier published in (Alexandridis et al., 2020).

Table 4: F1-score of the perturbation identification network for a signal-to-noise ratio of 1. Results reproduced from (Tasakos et al., 2021).

Reactor model	Type of perturbations			
	FAV	Inlet temperature fluctuation (TP spatially distributed at the inlet of the core)	Inlet flow fluctuation (spatially distributed AVS)	Combination of perturbations (with a cluster of 5x5 FAV)
Three-loop pre-Konvoi PWR	1.00	0.99	1.00	0.99

3.5 Dependence of the unfolding on the location of the detectors

The influence of the location of the neutron detectors was not analysed systematically as was done for the number of the neutron detectors and the contamination by additional noise. Nevertheless, and as Figure 1 demonstrates, the amplitude of the deviation from point-kinetics is largest in the close vicinity of the perturbation, when localized perturbations are considered. In order to cover all possible locations of such perturbations and to increase the chances of detecting the neutron noise induced by such perturbations, it is highly recommended to have a good coverage of the core with neutron detectors. During experimentations with the machine learning methods on the frequency domain simulations, it was noticed that a uniform spacing of the neutron detectors leads to higher performances of the classification and localization tasks (Durrant, 2021).

3.6 Conclusions based on results of machine learning-based unfolding

As reported in the sections above, the noise pattern in large PWRs differs significantly enough depending on the type of perturbation and its possible location (in case of a localized perturbation). This makes it possible to reliably use machine learning-based unfolding for detecting, classifying, characterizing and possibly localizing perturbations in such reactors.

The accuracy of the classification and localization tasks were demonstrated to be very high, irrespective of whether the unfolding is based on time domain or frequency domain simulations. Moreover, the unfolding is robust with respect to the number of detectors and their possible contamination with additional noise. An even distribution of the neutron detectors throughout the reactor is nevertheless highly recommended in order to more easily detect localized perturbations.

Those results were nevertheless obtained using simulation data for training, validation and testing of the machine learning algorithms. Tests on actual measurement data from which the actual perturbation is known are necessary to corroborate the conclusions drawn in this section.

4 Recommendation based on results of data processing and reconstruction

The subject of this section is to make recommendations based on delivered and processed data of VVER 1000 and the 3-loop pre-Konvoi reactors using the developed tools in CORTEX.

This section aims to extract features of how the developed tools could be applied to the range of plant reactor instrumentation sensors. Attention is put on the achieved measure of fuel and internals vibration evaluation and what quality of the processed signals can be expected.

4.1 Acquisition and processing of VVER 1000, Temelin and 3-loop pre-Konvoi, Gösgen data

4.1.1 Detectors and acquired data

The available detectors of both reactors for signal processing in CORTEX are summarized in Table 5.

Table 5: VVER1000 and 3-loop pre-Konvoi in-core and ex-core detectors used in CORTEX.

Detector		VVER1000	3-loop pre-Konvoi
In-core	SPND	208	36
	Thermocouple	0	6
Ex-core	Ionization chamber	12	8
	Accelerometer	4	0

The investigated reactor core layouts with the radial and axial detector positions for the VVER1000 and 3-loop pre-Konvoi are shown in Figure 3.

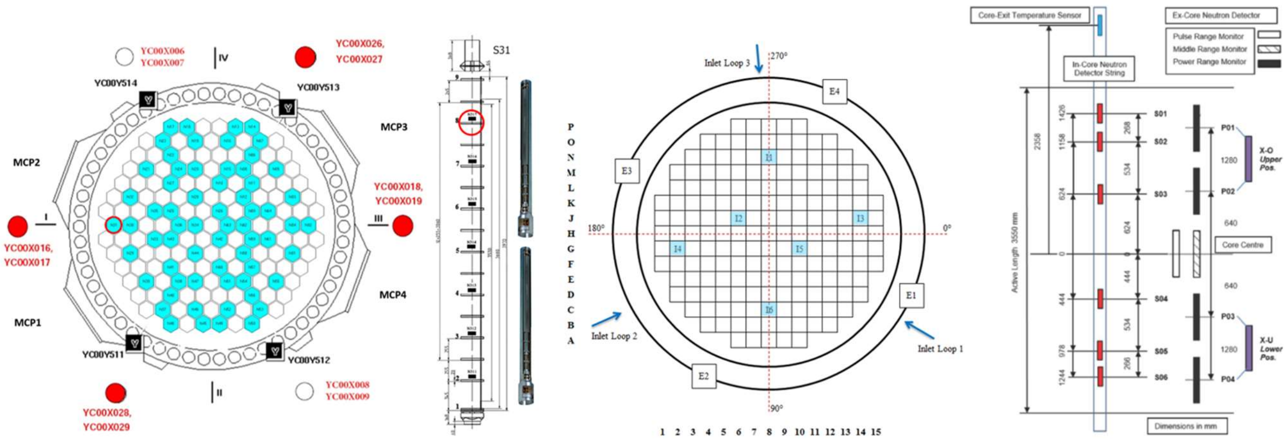


Figure 3: VER1000 and 3-loop pre-Konvoi radial and axial detector positions.

VVER1000 Temelin

Noise data have been measured and gathered with the mobile UJV in-house systems DMTS and RVDT from the standard diagnostic system RVMS (Reactor Vibration Monitoring System) together with records of technological data. The RVMS diagnostic sensors of each unit include 4 accelerometers on the reactor head flange, 12 ionization chambers placed in three vertical planes at two horizontal levels, more than 256 SPNDs across the whole core in four axial heights in non-uniform radial spreading. 5 pressure fluctuation sensors at reactor output and input are available only on the 2nd unit. SPND signals are measured in a group of 16 by the RVMS system which separates noise and DC channels. RVMS measuring chains contain conditioning with isolation and buffer amplifiers, high/low-pass 8-pole Butterworth filters with a minimum of 48 dB per Octave roll-off to form antialiasing filters in several bandpass ranges. Sampling frequency up to 1 kHz with 16/12 bits resolution for noise/DC signals. The diagnostic data acquired by the UJV system DMTS are saved with basic fixed frequency ranges 200 Hz and 300 Hz per channel with typical 0.007 Hz lower cut-off frequency and sampled by 1 kHz frequency with 24 bits resolution at the 5-10 V output signal of standard NPP diagnostic measuring chains. The operation of connected standard RVMS and mobile DMTS/RVDT systems is shown in Figure 4. Systems are connected by special proved cables.

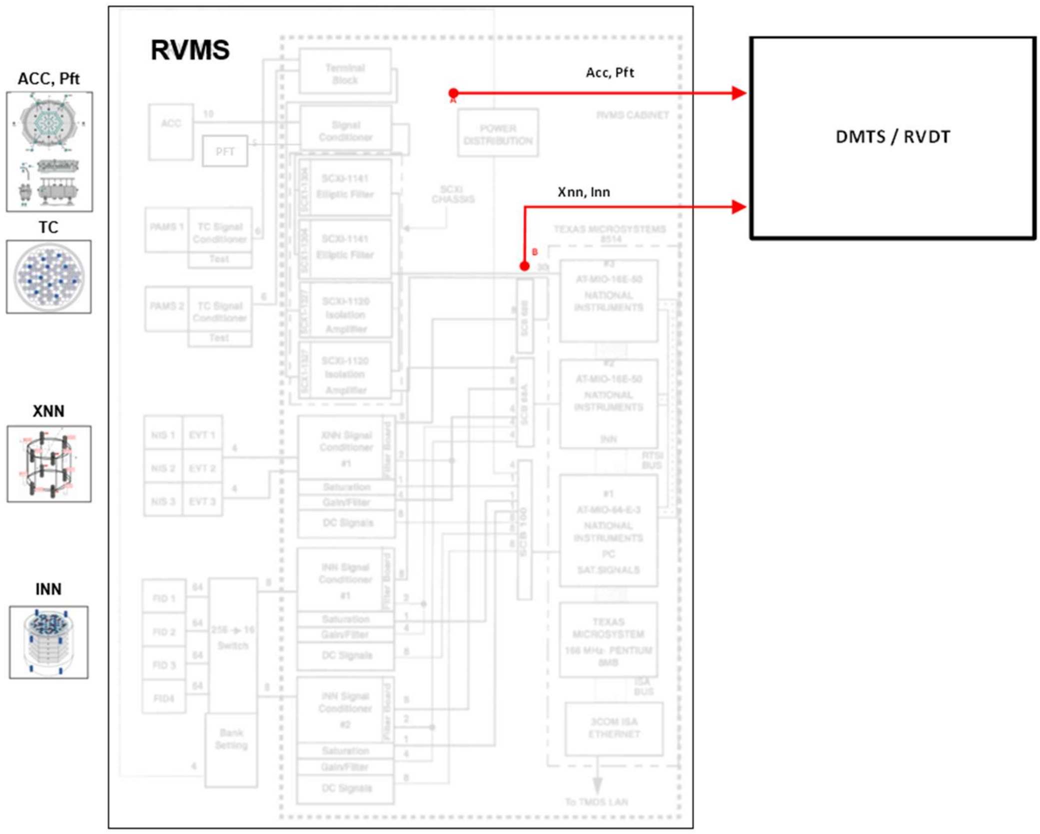


Figure 4: Operation of measuring systems RVMS and DMTS/RVDT systems at NPP Temelin (see (Stulík et al., 2020)).

RVMS systems operate periodically in a daily fashion across the whole fuel cycle and process results only in the frequency domain. Noise time series data were acquired in non-periodic measurements with the UJV mobile in-house systems. All diagnostic data sets are processed and evaluated offline in the time, frequency, and joint time frequency domains together with records of technological data. Relatively long data records under steady-state reactor conditions allow obtaining well-balanced spectral characteristics with less than standard spectral resolution of 122 mHz. The whole data pool of diagnostic data parametrized by technological data is concentrated and maintained by the UIZ database developed in UJV.

The data sets were selected for processing in the work package 4 of CORTEX with the aim to study more closely the symptoms of gradually developed conditions towards the operational situation when the control rod does not pass to the final defined position during free fall test – abbreviated as IRI (incompatible rod insertion). Each data set file contains besides other RVMS operational parameters also a list of 16 SPND sensors which are available at the output of the 256/16 switch. All data has been shortened to the uniform length of 720,000 samples to avoid undesirable transients at the start of original measurements. They are therefore also uniform 12-minute time measurement intervals available for the following processing. DC offsets of all noise data in these sets were removed. All ionization chambers and SPND data are normalized to their DC part of the whole signal.

Data were acquired in 19 configuration sets in each of the U1C09 – U1C12 cycles (October 2010 - September 2013) during physical start-up tests together with the main operational and measurement parameters (Stulík et al., 2020). Altogether, 76 files in the volume of 7,1 GB were prepared for the following processing.

3-loop pre-Konvoi, Gösgen

Five experimental measurements during the normal operation of the Gösgen NPP were performed by ISTec at different burnups and boron concentrations in two cycles: 39 (MOC, EOC) and 40 (BOC, MOC, EOC) (Lipcsei et al., 2018; Pohlus et al., 2018; Pohlus et al., 2019a; Pohlus et al., 2019b). The acquired datasets with recordings of in-core, ex-core detectors, and thermocouples are confidential and serve only for the internal evaluation in CORTEX.

Ex-core detectors at different vertical positions are located at each of the four radial positions in 90° geometry. 16 ex-core power range monitors are also installed but the output of ionization chambers couples is processed together so as the resulting total of eight ex-core signals are available for the measurement and processing.

Six in-core detectors in different axial (vertical) positions are located at each of the six radial positioned strings as can be seen in Figure 3. In total 36 in-core detectors are installed and used in CORTEX.

At the upper part of each in-core detector string, one thermocouple is installed so that altogether six thermocouple signals can be used for the assessment of the core exit temperature.

During all three measurements, the acquisition of all 50 signals has been simultaneously performed by the measuring system SIGMA of TÜV Rheinland ISTec GmbH with a sampling frequency of 250 Hz per signal. The system consists of isolation amplifiers, anti-aliasing low-pass filters, DC signal compensation units, signal pre-amplifiers with 12-Bit-ADC.

Because the used detectors were assigned to different NPP safety channels, it was necessary to connect the detector outputs to the common connector interface by the relatively large cabling and cabinets system in the two-cycle duration of the experiments.

4.1.2 Signal processing

The Fourier Analysis was the main technique used to evaluate acquired data from both plants as described in detail in the deliverables D3.5 and D4.4 (Montalvo et al., 2020; Alexandridis et al., 2020). The NAPSDs of all the detectors together with all combinations of in-core and ex-core detectors for coherences and phases were calculated in all radial and axial distributions. Extensive results in the form of spectral characteristics are stored on the UPM repository as Matlab structure variables. The use of Fourier analysis techniques allowed us to characterize and determine the neutron noise spectral features during normal operation in both reactors like the possible linear phase between in-core detectors of the same string, the possible out-of-phase relationship between opposite detectors, the high response amplitude at low frequencies below 1 Hz. Examples of regions for such investigations are shown in Figure 5.

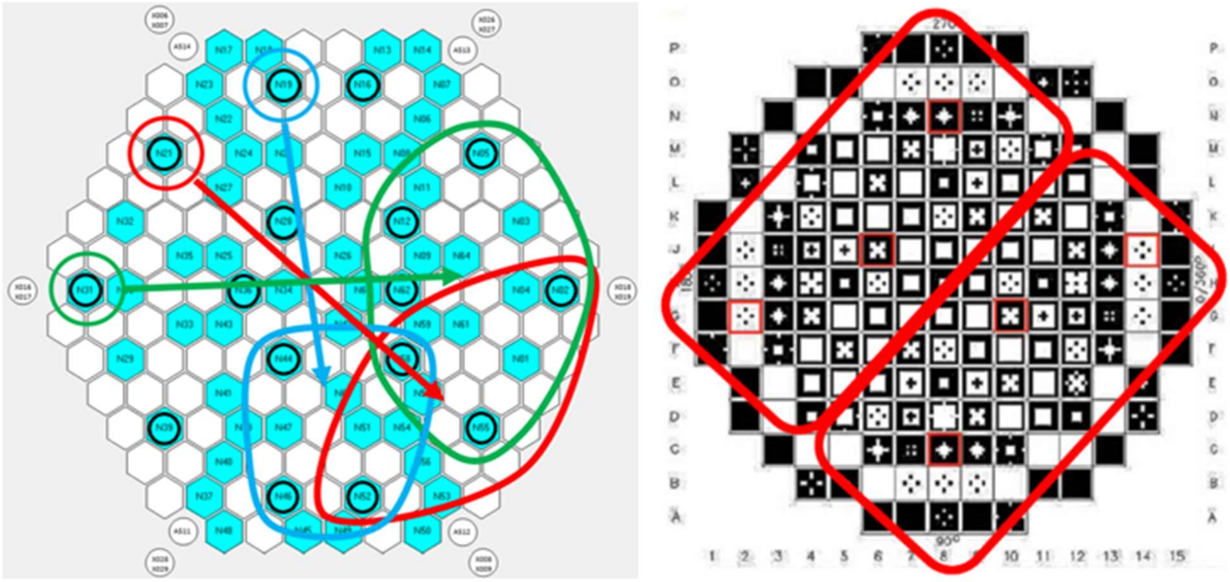


Figure 5: Spectral analysis at NPP Temelin (regions of coherence analysis) and Gösgen (out of phase regions) (see (Montalvo et al., 2020)).

A further technique for evaluation of real plant data in the joint frequency-time domain was explored: the Join Time Frequency Spectrogram (JFTS). The intention of this joint time-frequency method is in solving dynamic phenomena in the core where it is necessary to monitor the development of spectral characteristics over time. Two examples of real noise CORTEX datasets from the VVER1000 Temelín and 3-loop pre-Konvoi Gösgen are shown in Figure 6.

This approach of noise investigation helps to explain namely the historical operational experience of VVER440 Dukovany which was followed by serious operational consequences. In this specific case, vibration beats of pressure vessel and fuel assemblies were associated with pressure and flow fluctuations generated by the main circulation pumps (MCP) with slightly differed revolutions. It was found that the MCP harmonic frequencies are also common to VVER1000 Temelin with a beat character representing a negligible component in overall reactor and core signal behavior (Stulík et al., 2019).

Joint time-frequency analysis (JTFA) tools were used for this purpose when Short Time Fourier Transform (STFT) divides the dataset into time intervals and calculates the power spectral density (PSD) at each time interval separately. The type of sliding spectral windows, frequency, and time resolutions are the parameters of these calculations. The result is then displayed in 2D or 3D spectrograms using a scale in decibels for the PSD value. It was demonstrated that joint time frequency analysis is a helpful tool for better distinguishing between technological irregularities, anomalies, or failures. It provides a quick summary for classifying and localizing possible perturbations before using other advanced signal processing methods (Montalvo et al., 2020).

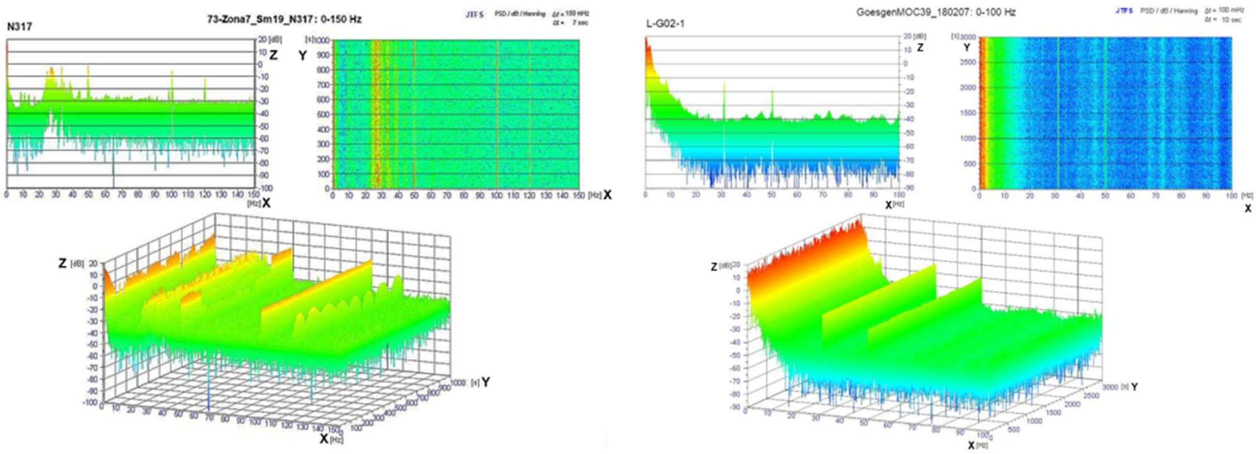


Figure 6: JTFS analysis at NPP Temelin and Gösgen (see (Stulík et al., 2019)).

In addition, the Singular Spectrum Analysis (SSA) methodology was used to explore the time domain of VVER1000 data to extract the trend and the oscillation part of the signals from datasets of all four U1C09 – U1C12 cycles. After revealing the different spectral components of the signal, it was possible to assess the value of the frequencies at an advanced resolution. The parameters were chosen for the SSA, and spectral analysis gives us sometimes many frequencies in a very small range. We have to analyze these results according to the physical investigation. The analysis has been carried out in such a way as to generate a reproducible document automating the data processing. Thus, we can investigate different periodogram smoothing, SSA decomposition (number of eigenvectors), and reconstruction (results of factor classifications). The next step of this work will be to improve the raw data considering the characteristics of the sensors including a physical analysis crossing the features of the signals with the sensor locations and the operating physical quantities (Pantera and Stulík, 2021).

4.1.3 Simulation

Because the core of the described reactors is composed of assemblies with a different geometry, the appropriate simulation tools were used.

VVER1000 Temelin

The FEMFFUSION tool developed at UPV can be used for noise modeling in the time and frequency domain. This tool estimates the effect of macroscopic cross-section stationary perturbations onto the neutron flux using the two-group diffusion approximation. Non-linear terms are explicitly modeled in the time domain, whereas linear theory is used in the frequency domain. Six groups of delayed neutrons are considered. The spatial discretization of the balance equations is based on finite elements, using a high order continuous Galerkin method. Any kind of structured or unstructured mesh is allowed, if the elements are composed of quadrilaterals in 2-D or hexahedra in 3-D. In the case of reactors with hexagonal fuel assemblies, each hexagon is discretized into three quadrilateral cells, as represented in Figure 7.

In the case of the VVER1000 reactor, only the frequency domain was modeled for one cycle. The modeling parameters used in the simulations are representative of the core conditions corresponding to the noise measurements performed in the U1C09 cycle (Lipcsei et al., 2018). Two simulated scenarios in the frequency domain were elaborated, one for a Generic Absorber of Variable Strength and one for a Travelling Perturbation, both modeling the neutron noise for the thermal group. The results enable further FFT calculation of APSD, CPSD, COH, and PHASE spectral characteristics. When comparing with real plant data, it is necessary to normalize by dividing them with the static flux at the position of each SPND detector.

The reactor was modeled using 221 vertical assemblies discretized in 50 planes, representing a total of 10550 hexagonal cells. The numbering of the hexagonal cells is illustrated in Figure 7. Axially, the numbering is carried out incrementally from the bottom to the top of the system.

There are three frequencies of 1 Hz, 3 Hz and 10 Hz modeled in the case of a Generic Absorber of Variable Strength. For a comparison with real data, it is necessary to be aware of the fact that altogether the number of simulated perturbations for one frequency is 50 perturbations per assembly so that for 211 assemblies in the core it generates 10,550 simulated perturbations for the whole core. For three frequencies it means 31,650 simulated perturbations per core.

If one simulated perturbation has the responses in 64 x 4 measured SPND locations, so for three frequencies, we can obtain altogether 8,102,400 simulated SPND responses to be processed in a comparison with the real plant values from the U1C09 cycle. On the topic of localization of absorbers of variable strength perturbation in VVER-1000, a publication is being prepared (Alexandridis et al, 2021).

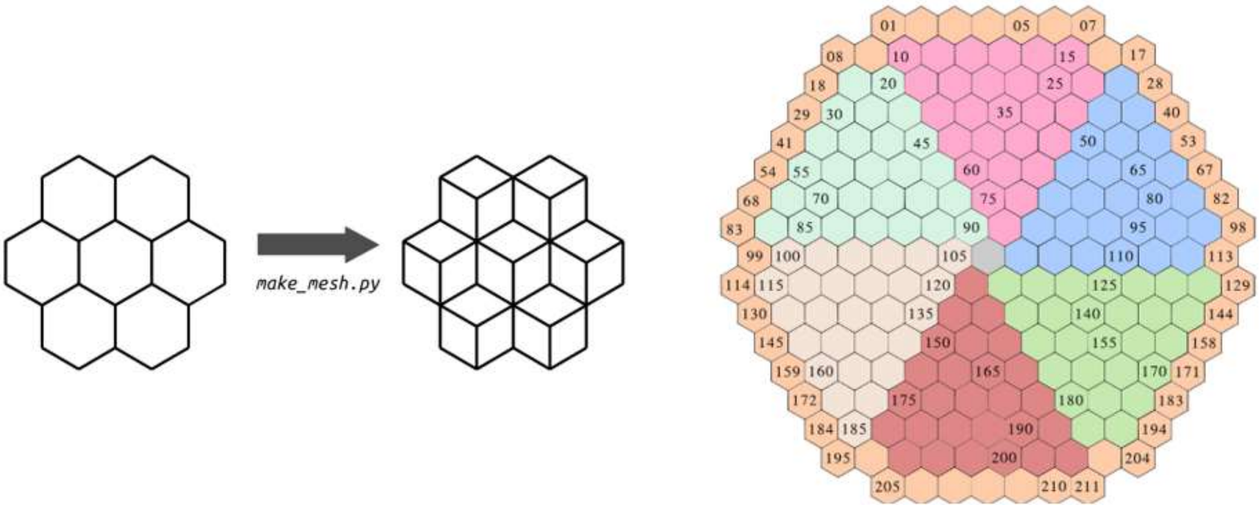


Figure 7: Spatial discretization of hexagonal fuel assemblies into quadrilaterals and numbering of the model cells in the VVER-1000 reactor (see (Alexandridis, 2020)).

3-loop pre-Konvoi, Gösgen

In the case of the 3-loop pre-Konvoi reactor, two simulation tools were implemented in CORTEX: for frequency-domain CORE SIM+ developed by CHALMERS, and for the time domain SIMULATE-3K developed by Studsvik AB (Alexandridis et al., 2020).

In the frequency domain, six scenarios with simulation data were generated:

- generic absorber of variable strength calculated in the frequency range 0.1 to 25 Hz
- axially traveling perturbations at the velocity of the coolant flow for 0.1 to 25 Hz
- fuel assembly vibrations for the cantilevered beam mode: 0.6-1.2 Hz, for simply supported on both sides: first mode 0.8-4 Hz, and second mode 5-10 Hz and for cantilevered beam and simply supported: first mode 0.8-4 Hz, and a second mode for 5-10 Hz
- control rod vibrations for 0.1 to 20 Hz
- core barrel vibrations for 7 to 13 Hz.

In the time domain altogether 336 scenarios were simulated covering a mixture of dynamic fuel assembly's behavior around 1.2 Hz and thermohydraulic parameters for all noise measurements in the cycles 39 and 40.

4.1.4 Lessons learnt

The IRI data were selected by UJV at the start of the CORTEX project to investigate the fuel assembly IRI susceptibility symptoms. At the time of the measurements (2010-2012), the diagnostic tasks realized by in-house system DMTS (see section 4.1.1) (Stulík et al., 2019; Stulík et al, 2020) were performed regularly at BOC during physical tests when strict and repeatable operational conditions are required and maintained for the calibration of plant neutron instrumentation.

The datasets delivered to CORTEX covering the four cycles of the NPP were unfortunately not so optimal for studying this phenomenon because at this time

- there was limited possibility of the then DMTS system to cover more than 16 sensors scanned simultaneously step by step in 19 configuration sets per day
- there was no tool for predicting IRI
- no one could know and predict the occurrence of IRI.

Despite those facts, we decided to provide those data for the purposes and objectives of the project because they contain valuable information about real operational events worth of being investigated in CORTEX.
After primary data modification (normalization, detrending), the data was processed in the frequency domain (APSD, COH, PHASE) for training in DNN (Montalvo et al., 2020). The use of DNN has detected only several non-standard behaving SPNDs through all cycles in relation to the rest. It might nevertheless be only a feature connected mainly with measuring chains that are not directly tied to IRI. We can summarize the DNN investigation in the way that the detection of IRI symptoms was not fully demonstrated (Alexandridis et al., 2020). As the IRI is mainly due to fuel assembly deformation, we can consider the above-mentioned result generally as a consequence of the lack of appropriate spaced core data.
If we compare Gösgen and Temelin's core layout (Figure 3), we can see differences not only in the number of SPNDs but also in their arrangement. The Temelin layout configuration sets such as Fa1-6 and XnnInn1-4 consist of more adjacent fuel assemblies (fours and couples) tight to each other, as can be seen in Figure 8. The red marked sensors with available data in this figure show us also the potential to study further mutual linkages. When we are investigating coherences in one plane of the configuration set Fa1, e.g., for the marked SPND couple N247 – N207 in Figure 9, then for the whole cycle we can obtain the course of quite characteristic behavior for all 15 coherence Fa1 combinations in the U1C09 cycle. Under circumstances that the daily operational measurements were done with fresh new fuel and that, during the cycle, no significant power jumps and operating parameters occurred (e. g. boric acid concentration, pressure, flow, etc.), we can quite reasonably argue that the yellow arrow shows us the time point when the geometry in the mutual position of adjacent fuel assemblies starts to change, due to burnup condition change in the Fa1 itself and its neighborhood (Figure 9). Similar situations were encountered for the remaining cycles. But in these cases, we have to take into account different fuel loads with not homogenous burnup of neighborhood fuel assemblies. This mutual fuel assembly's interaction within cycles for configuration sets Fa1-6 (mid of core) and XnnInn1-4 (core-periphery) is now intensively studied in UJV to give us an idea about geometry changes in fuel assemblies locations.

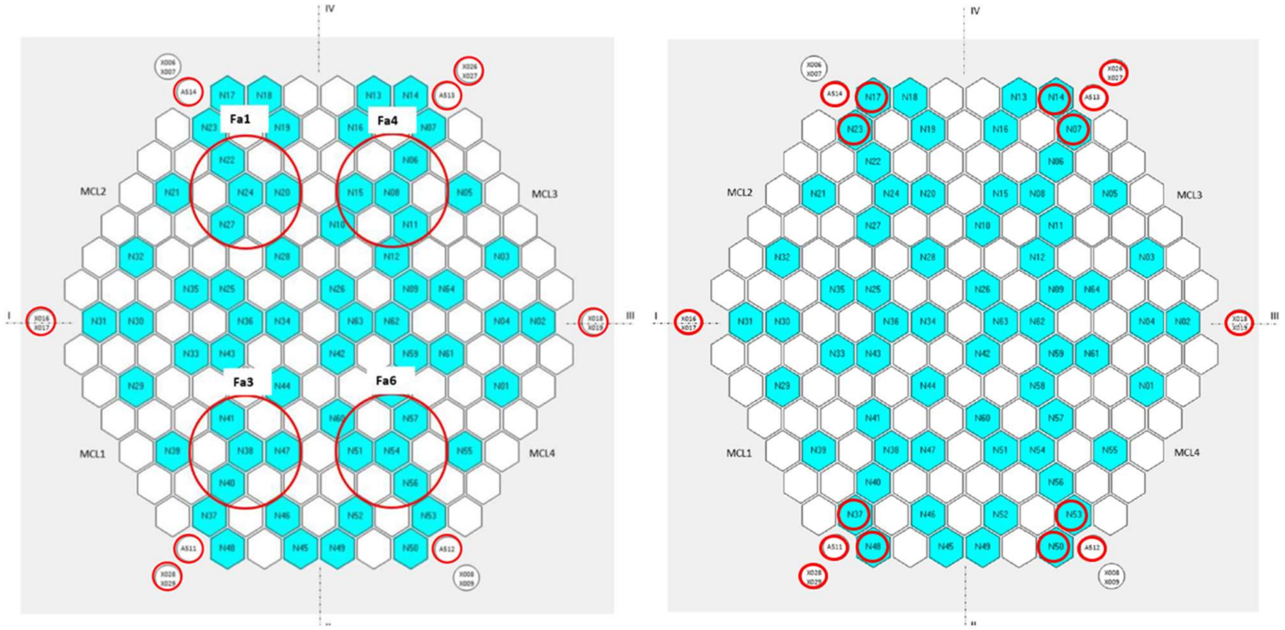


Figure 8: The delivered VVER1000 fuel assembly configuration sets Fa1,3,4,6, and XnnInn1-4.

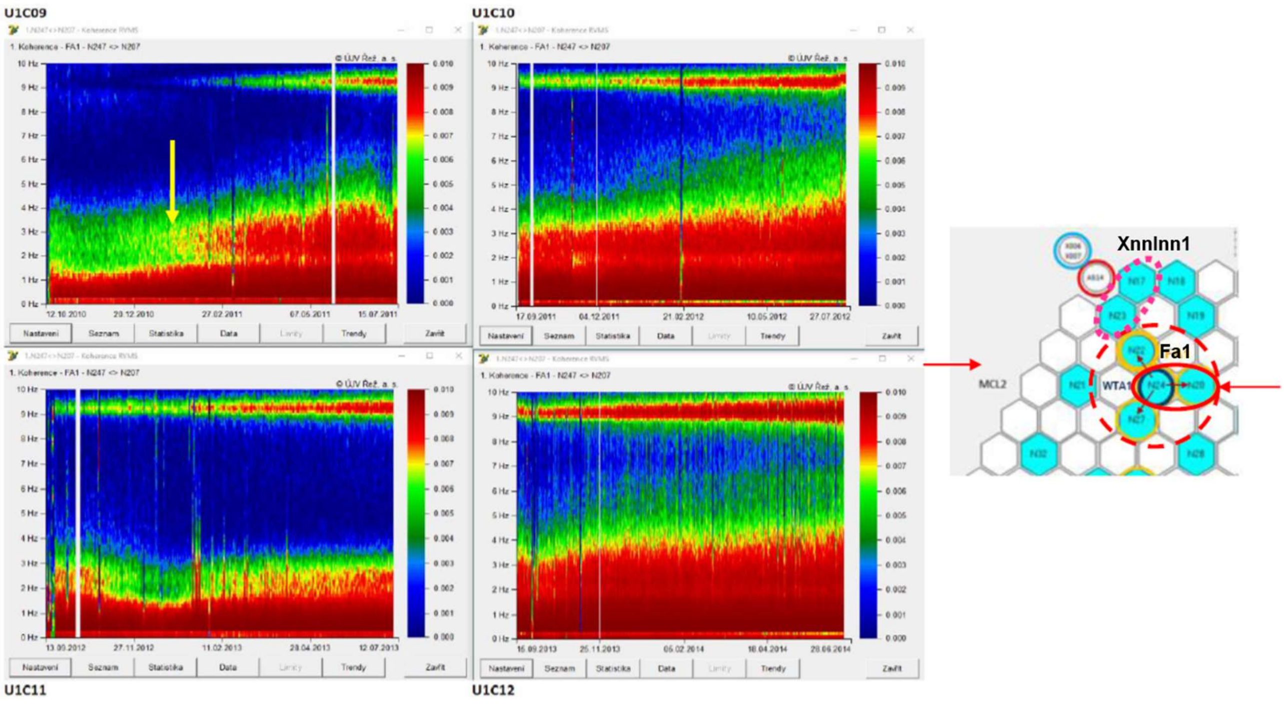


Figure 9: VVER1000 fuel assembly coherences of Fa1 configuration set (N247-207) in U1C09 – U1C12 cycles.

Another possibility for the investigation of core properties is provided by the evaluation of the linkages of reference accelerometers on the reactor cover and in-core SPNDs as can be seen as, an example, in Figure 10. The cumulated PSDs of reference accelerometers and marked adjacent SPNDs of Fa1 and Fa6 are shown with the corresponding coherences for U1C09-U1C11 in the 0-100 Hz range. The study of these features can be important, e. g., in the process of frequency identification and in defining the reduction of the number of detrended signal items of SSA analysis (Pantera and Stulík, 2021).

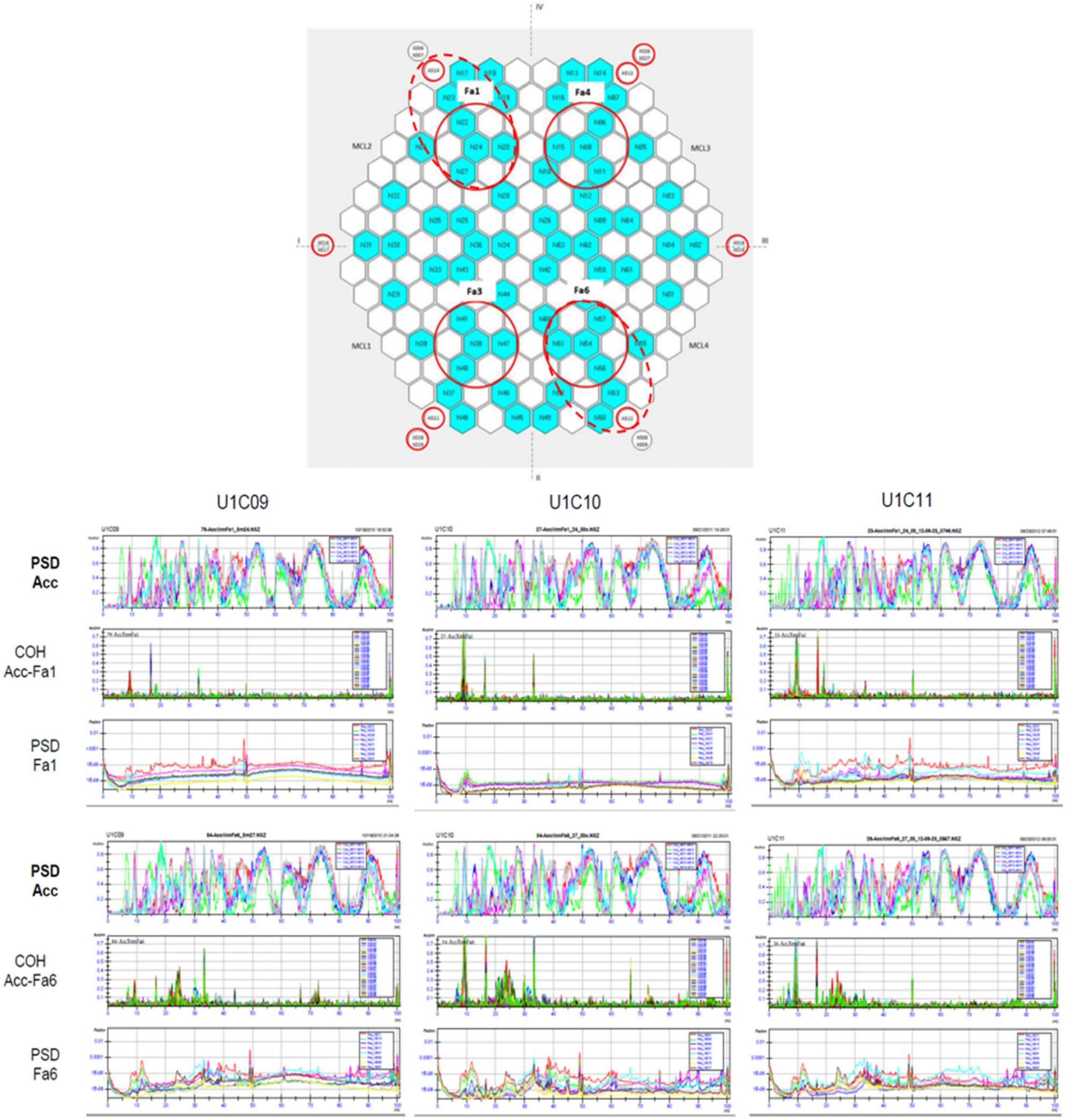
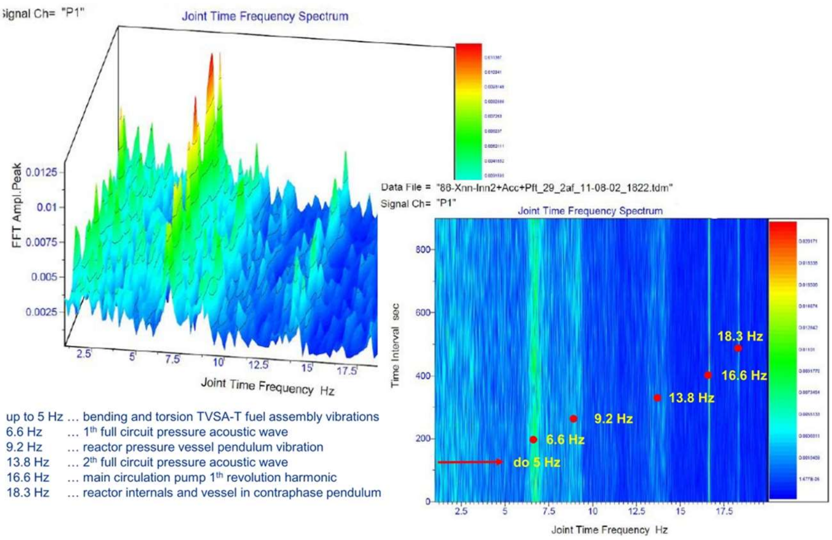
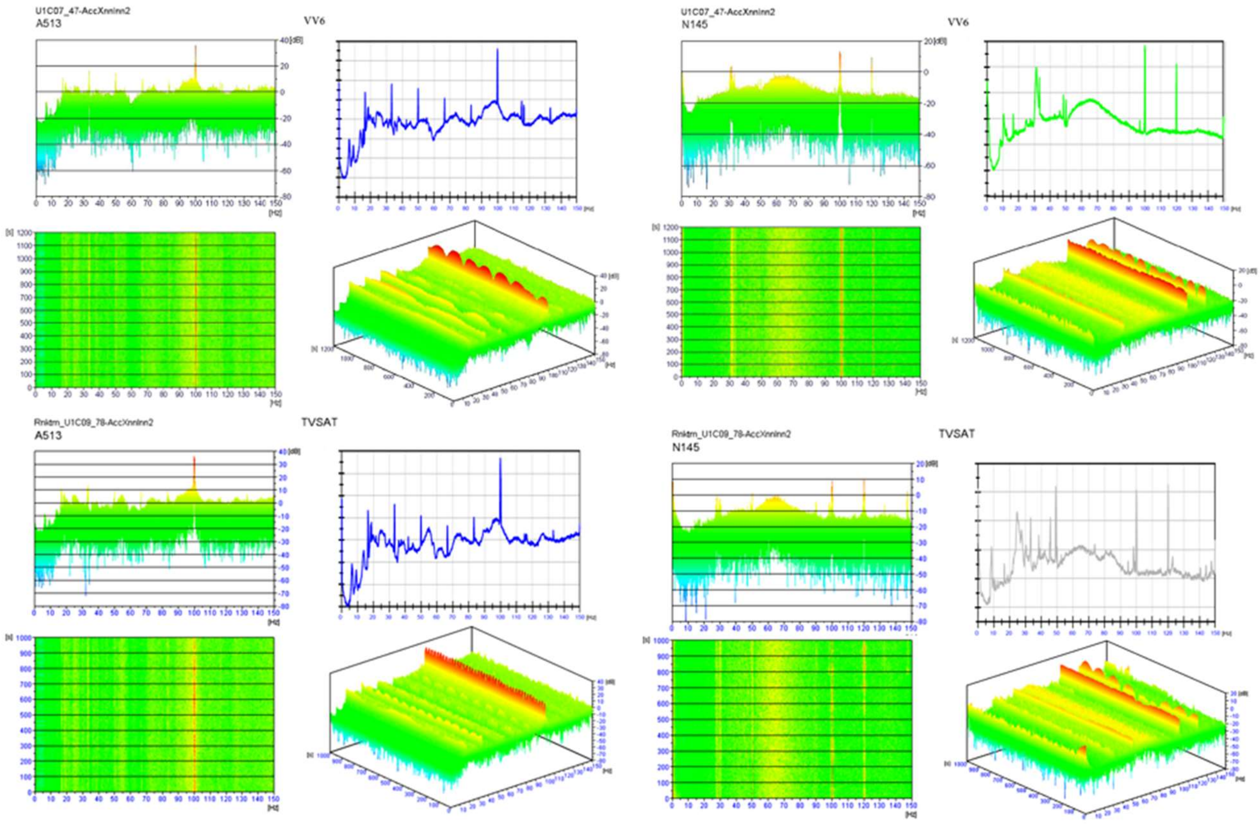


Figure 10: VVER1000 head reactor accelerometers and SPND coherences of Fa1,6 in BOC of U1C09–11.

As mentioned in (Stulík et al, 2019), the significance of operational impacts and effects from the Dukovany NPP is the reason for the corresponding diagnosis of this phenomenon in the core. It turned out that the effects of vibrations at the NPP Temelín and Dukovany are common features of the behavior of a dynamic pressure vessel and core with dependence on the dominant harmonic frequencies of MCP. Figure 11 shows, besides accelerometers, also pressure fluctuations and SPNDs from two fuel vendors with a distinct beat pattern. Comparison of pressure fluctuations with the reference reactor head accelerometers is important because pressure fluctuations are the main direct excitation of internal parts and fuel. This cannot be presented on CORTEX data because the pressure sensors on unit # 01 are not installed. As further detailed described in (Stulík et al, 2019), the nature of the beat effects represents a significant component of the overall signal behavior of the whole reactor.



Pressure fluctuations in Temelin unit #02, VV6, U2C09



Accelerometers, SPNDs in Temelin unit #01, VV6 (U1C07) and TVSAT (U1C09)

Figure 11: Beat effects in pressure fluctuations, reactor head accelerometers and SPNDs (see (Stulík et al, 2019)).

4.2 Signal reconstruction

This chapter contains, in subsections 4.2.1 – 4, comments to the SPND signal reconstructions of all available SPND data. The main goal of the reconstruction is the definition of faults (anomalies) in SPND data and content of the added noise (signal to noise estimate).

4.2.1 VVER-440 SPND signal reconstruction

VVER-440 data from 2nd unit of Paks NPP in Hungary were analyzed. They are organized in 3 data packs, representing the beginning, mean and end of fuel cycle (BOC, MOC and EOC). In-core neutron flux is measured with 36 measuring strings, each containing 7 SPND detectors. Signal of each detector is divided into two parts – DC and AC part. DC part is a slowly changing signal, proportional to the mean neutron flux in its position. The AC signal expresses fluctuations of the neutron flux around the DC value. The sampling period of DC signal is 0.32 sec, the sampling period of AC signal is 0.01 sec. Duration of all packages is approximately 1 hour. All SPND signal values are in mV.

Both AC and DC SPND signals were reconstructed. Concrete identified anomalies of these signals are described in (Machek, 2020), added noise of each individual signal is reported in the appendices of this report. An interesting distortion of some of the Paks AC signals is the signal limitation with ADC (Analog to Digital Converter). These signals were over-amplified and consequently they were totally distorted by ADC conversion, as illustrated in Figure 12.

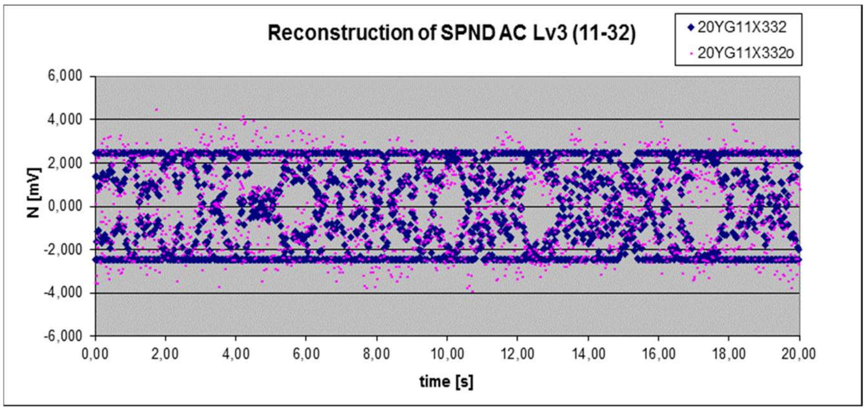


Figure 12: Distorted 20YG11X332 AC signal (dark blue dots).

4.2.2 VVER-1000 SPND signal reconstruction

VVER-1000 is a reactor with high density of SPNDs. It contains 64 measuring strings, each with 7 SPNDs. For the reactor vibrations only signals from odd detectors 1, 3, 5 and 7 are available and evaluated in the Reactor Vibrations Monitoring System (RVMS).

Signals from U1C09 to U1C12 of the Temelin NPP were analyzed and reconstructed. It was found, that due to low correlation between the signals, only approximately ½ of the signals could not be reconstructed. It was the reason for changing strategy in signal selection. While in case of Swiss and German pre-Konvoi reactors for reconstruction of selected signal we used remaining 5 signals of the same string, in case of VVER-1000 for reconstruction we selected 4 most correlated signals out of 15 remaining signals available (simultaneously recorded 16 signals).

Detailed results of selected reconstructed signals are listed in the appendixes in (Libcsei et al., 2018; Machek, 2021).

4.2.3 3 loops pre-Konvoi SPND signal reconstruction

Four data packs were analyzed from Swiss 3 loops pre-Konvoi NPP Gösgen. These data were from MOC39, EOC39, BOC40 and MOC40 fuel cycles. This reactor uses 6 measuring strings, each with 6 SPNDs. In this case, also ex-core neutron flux measurements were available and reconstructed. We concluded our analysis with following conclusions:

- All ex-core measurements from Gösgen NPP are of good quality, their reconstruction fits well with original measurements.
- The quality of in-core measurements was found to be not so good. Signals of the string L-N08 are rather problematic throughout all four measurement periods. But still between 10 to 15 in-core (SPND) signals could be reconstructed well with S/N higher than 20, in some cases even higher than 30. It means that the residuals of the reconstruction are 30x smaller than the standard deviation of the signal itself. Such signals reflect very well processes in the core.
- Among the Gösgen SPND signals. we found one, which illustrates well how the SPND signal can be distorted with additional noise. This is shown in Figure 13, where the distorted signal is visible on the left of the plot, at the beginning of the measuring interval.

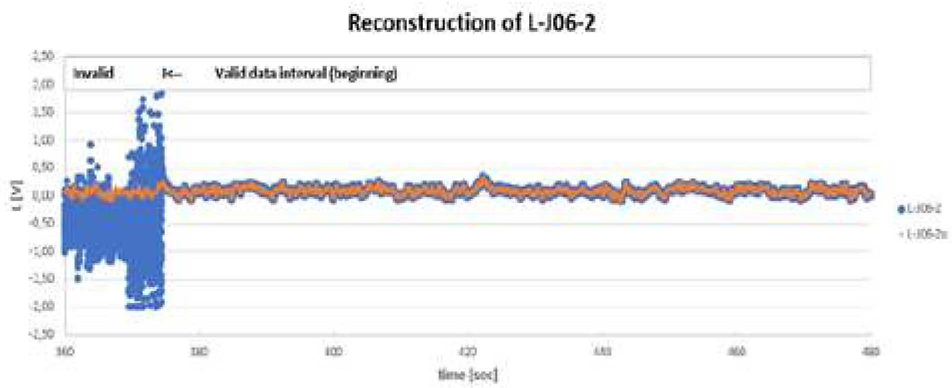


Figure 13: Partially distorted SPND signal (dark blue) and its reconstruction (red).

Detailed information about all reconstructed signals from are given in (Lipsei et al, 2018; Machek, 2021).

4.2.4 4 loops pre-Konvoi SPND signal reconstruction

Both ex- and in-core measured data with notification A30, A31 and A32 were analyzed and reconstructed. The in-core data consists of 8 strings, each string contains 6 detectors. The ex-core data cover 4 lower layer and 4 upper layer detectors.

Analysis and reconstruction of these data was conducted and led to the following conclusions:

- All ex-core measurements from the German 4-loops NPP are of good quality, their reconstruction fits well with original measurements, no problem was identified.
- The quality of the in-core SPND measurements varies. Correlation with other signals is low and their capability to reflect in-core processes is problematic. But still between 10 to 15 in-core (SPND) signals could be reconstructed well with S/N ratio higher then 20, in some cases even higher than 30. This can be interpreted as high-quality measurement, reflecting well the processes in the reactor core.

4.3 Recommendations based on data acquisition, processing and reconstruction

The content of the previous sections will be here summarized into a list of recommendations for the core instrumentation and related applicability.

<u>Detectors</u>

SPND

To make the description of noise anomaly phenomena more exact for the knowledge of inverse reactor function, it would be advisable to fulfill the following conditions:

- to have a maximum number of instrumented SPND with uniform distribution in the core, the optimal solution is to occupy almost all possible places in the core
- to know the transfer function for each SPND
- to normalize each noise SPND signal against its concurrent steady component
- to correct each SPND against burnout rate because there are SPNDs with different burnout rates in the real core through several cycles

Ionization chambers

Ionization chambers should be placed in the upper and lower positions against reactor head accelerometers for the detection and determination of core barrel movements

Accelerometers

These sensors are necessary for the knowledge of referenced vibrations of the reactor pressure vessel, consequently influencing global vibrations of fuel assemblies. It is necessary to ensure their simultaneous scanning with the whole neutron instrumentation.

Pressure fluctuations

It is necessary to know them for the identification of spectral phenomena because pressure fluctuations determine acting forces on internal parts and fuel as a consequence of working main circulation pumps. Identifying all spectral phenomena is also essential for proper signal detrending.

<u>Operating parameters</u>

The influence of flow, pressure, and regimes of main circulation pumps is necessary to investigate and evaluate, in the run of several cycles, for the parametrization of operational diagnostic measurements.

<u>Measurements</u>

- The measurements are to be performed concurrently on all detectors with the connection to the uniform time base of the whole plant.
- For the comparison of different reactors, it is necessary to make the same approximations of the datasets (sampling frequency, spectral resolution, normalization, frequency range, etc.)

<u>Signal reconstructions</u>

The measured in-core data often contain additional noise and other disturbances. This results in the noise source identification and localization very difficult, if not impossible. It is thus strongly recommended to reconstruct in-core signals before they are used for ML / DNN to assure that only correct, uncorrupted signals are used for training.

5 Conclusions

During the CORTEX project methods and tools have been developed and/or applied for sensitivity analyses, different simulations, signal processing, signal reconstruction and machine learning. Also, other experiences gain in the operational history of neutron noise analyses have been analysed.

Different recommendations have been derived on the results of these activities and they have been put forward in this deliverable. These recommendations aim at improving the applicability and the accuracy of the developed methods and tools. But they would also improve the applicability of using neutron noise analysis for plant surveillance in general. Here these recommendations are repeated and duplications between the different subject have been removed.

There are two groups of recommendations. The first one includes measures which can be taken based on the currently installed detectors:

- Investigate further the correlation of the measured noise with further quantities (e.g., accelerometers for referenced vibrations of PRV, pressure fluctuations).
- Measure the neutron flux and other quantities under special operating conditions, like commissioning tests, start-up, shutdown, partial load or 3 of 4 main coolant pumps running, and over several fuel cycles.
- Use information from operational experience, as defects or wear might be a sign for increased motion in the corresponding area.
- Know the transfer function of each SPND.
- Normalize each SPND detector signal with its steady-state value.
- Correct the burnout rate of each SPND.
- Take measurements of all detectors concurrently with connection to a uniform time base.
- Apply signal processing methods and signal reconstruction on the measurements before using them as inputs for machine learning methods/deep neural networks.
- For the comparison between different reactors, the datasets should have as close as possible in terms of measurement parameters (sampling frequency, spectral resolution, normalization, frequency range, etc.).

The second group of recommendations is about increasing the number of detectors or installing additional detectors measuring other physical quantities:

- Include in-core accelerometers into empty guide tubes.
- Develop instrumentations to measure the coolant velocity in axial and radial direction.
- Implement scaled mock-up experiments, in which FSI-phenomena can be investigated in detail without boundary conditions of nuclear safety.
- Distribute detectors homogeneously across the reactor core to detect localized perturbation more easily.
- Increase detector density to have a good coverage.

The first list shows that based on the existing detectors it should be possible to gain additional knowledge about the neutron noise and its root causes. Especially operational conditions 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 the other recommendations in the first list were already applied during the measurement campaigns during the CORTEX project.

The second list contains more ambitious recommendations, as part of these require not only the development of new detectors, but they would also result in changes in the reactor core of power reactors and/or the instrumentation & control systems of those reactors, which would require the licensing through the regulator.

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