

A NEW TYPE OF IN-CORE SENSOR VALIDATION OUTLINE

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ABSTRACT

In this work a new type of in-core sensor validation method is outlined, which is based on combination of correlation coefficients and mutual information indices. First experience with this approach is described and further improvements to enhance the outcome reliability are proposed namely through computational intelligence techniques.

INTRODUCTION

In today's NPPs, the combination of more sophisticated fuel/core design, increasingly longer fuel cycles, higher burn up as well as demands for power upgrades, challenges the core monitoring task. This calls for development of improved core surveillance methods with the ability to detect and diagnose possible unanticipated operational problems. Traditional techniques for core monitoring are based on readings from in-core/ex-core detectors combined with detailed core physics code calculations.

The purpose of this work, which has been started within the OECD Halden Reactor Project joint research programme's effort to investigate the potential of application of new and innovative techniques for core monitoring, is to present the work status in development of new in-core sensor validation methods. The Halden Project intends to concentrate mainly on implementation of computational intelligence techniques (artificial neural networks, fuzzy logic), providing complementary or new information as well as supporting evidence by integrating diverse methods. For signal validation, the promising candidate is the Halden Project's neuro-fuzzy system PEANO that has originally been developed for various process parameters validation, like power, pressures, temperatures, flows, water levels etc. To use it for in-core sensors signal validation is a very challenging task, as its training would normally have to be done each fuel cycle for ever changing fuel load patterns and burn up of both fuel and self powered neutron detectors' (SPNDs) emitters. To overcome this difficulty, the idea arose to train PEANO to residuals, i.e. the differences between core simulator physics code results and experimental values. Thus, in residuals the reactor core physics is implicitly contained. They are supposed to depend on effective days values, control rods position, power, and maybe only few more parameters. Nevertheless, this idea requires a lot of training data acquired simultaneously from both a physics code and SPNDs over a long time period to cover possibly all situations in the reactor core. In the meantime, before we get this data, we have decided to investigate another method based on

correlation between the SPNDs. For this task we have already acquired enough data because in this approach we do not necessarily have to train it over a long time periods and moreover, it is based on sensors' readings only.

Traditionally, the SPNDs readings validation is based on combination of limit checking and statistical treatment of deviations from somehow constructed axialwise or layerwise reference distributions. This approach makes use of the so-called slow component in the SPND sensor signal, which in the WWER-440 case of DPZ-1m sensor comes from 104Rh beta decay (very simplified explanation). In our work we want to test the mutual similarity of signals' prompt component, which comes mainly from (n, γ) reactions. It is assumed that decreasing similarity of signals is the manifestation of a sensor failure.

CORRELATION BASED VALIDATION CRITERIA

The basic idea of using cross-correlation between the SPNDs for validation task comes from the notion that the process noise components in the signals are satisfactorily correlated within some groups of well functioning sensors. This noise component is caused by perturbations in the reactor core, which result in neutron flux fluctuations. Among the most important to mention are e.g. fluctuations in temperature, pressure, flow, fuel rod vibrations. The lack of such correlation most probably occurs due to some detector failure. This part of our work is based on a correlation-based signal validation method for fixed in-core detectors [1], in which the basic assumption was that most of the perturbations in a nuclear reactor core affect the layers of the core containing the in-core sensors and that these perturbations are characteristically correlated. The nice thing on this approach is that we do not have to understand and thus to model the real cause of the noise signal component.

Typically, the SPND detectors are arranged in several (suppose J) detector layers perpendicular to the axial coolant flow in the core with supposed I detectors in each layer, all resulting in $I(I-1)/2$ correlation coefficients for each layer. To decrease the requirements for calculations, in [1] it is proposed to correlate every detector reading with only the average of the readings over the layer where the detector resides. Even more, the layer average is calculated with the detector itself included. It is supposed to be justifiable only for enough detectors in the layer. As it is correctly mentioned in [1], it would be more exact to exclude the detector from layer average. The layerwise linear correlation coefficient at position i of the j 'th layer may be defined as:

$$C_{ij} = \frac{\sum_t (\bar{m}_{j,t} \cdot m_{ij,t}) - \frac{1}{T} \sum_t \bar{m}_{j,t} \cdot \sum_t m_{ij,t}}{\left\{ \left[\sum_t \bar{m}_{j,t}^2 - \frac{1}{T} \left(\sum_t \bar{m}_{j,t} \right)^2 \right] \cdot \left[\sum_t m_{ij,t}^2 - \frac{1}{T} \left(\sum_t m_{ij,t} \right)^2 \right] \right\}^{1/2}} \quad (1)$$

The summations over t are done over the discrete time points $t=k\Delta t$ during the time interval T . The symbol $\bar{m}_{j,t}$ stands for the average of the all i measurements $m_{ij,t}$ in the j 'th layer at the time point t .

The C_{ij} coefficients are random variables because they are created from the measured values. They themselves, due to the superposed process noise, are random variables. If all sensors work properly, we can suppose that all correlation coefficients come from the same statistical distribution. On the other hand, failed sensor's C_{ij} coefficient will unlikely subject to the same distribution. The task of diagnostics will then be a hypothesis testing that the coefficient(s) in question contradict(s) the distribution of majority. The statistical distribution of correlation coefficients is skewed far from the normal distribution to be able to use immediately its confidence levels and quantiles for testing. For this case it is possible to use Fisher's z -transformation [1,2], which transforms the distribution of linear correlation coefficients into a near normal one:

$$Z(C_{ij})=z_{ij}=\frac{1}{2}\ln\left(\frac{1+C_{ij}}{1-C_{ij}}\right) \quad (2)$$

For hypothesis testing in [1] a one-sided confidence level is chosen:

$$k=\frac{1}{\tilde{\sigma}\sqrt{2\pi}}\int_{-\infty}^{\xi_0}\exp\left[\frac{-(\xi-\tilde{a})^2}{2\tilde{\sigma}^2}\right]d\xi \quad (3)$$

where k is the a priori chosen probability (confidence level) of discarding a correct signal and ξ_0 defines the threshold (quantile), above which the z_{ij} values will be accepted. It is to note that estimates of both the mean value \tilde{a} and standard deviation $\tilde{\sigma}$ are layer dependent and thus quantiles ξ_0 are calculated independently for each layer.

ENTROPY AND MUTUAL INFORMATION BASED CRITERIA

The concept of mutual information [2,3,4,5] is based on the information theory developed by Claude Shanon and namely on the so-called Shanon's entropy. Let's define an event x as some interval of values of the data and divide the range of data values into some number of intervals. The data is then binned by assigning each data point to one of the intervals. Let's then define the probability $P(x)$ for each interval as the probability of the data point to fall into the interval x . The entropy for variable X is then defined as follows:

$$H(X)=-\sum_x P(x)\log_2 P(x) \quad (4)$$

Let's now consider another variable Y for which we can compute its entropy $H(Y)$. Further the concept of entropy is extended to include the case of a pair of events, x and y . The joint entropy $H(X,Y)$ is based on calculation of joint probabilities $P(x,y) = P(X=x \text{ and } Y=y)$ and is defined similarly as:

$$H(X,Y) = - \sum_{x,y} P(x,y) \log_2 P(x,y) \quad (5)$$

One of the forms of mutual information definitions is as follows:

$$I(X,Y) = H(X) + H(Y) - H(X,Y) \quad (6)$$

Mutual information is a measure of the dependence between random variables. It is always non-negative and zero if and only if the variables are statistically independent. Unlike the correlation function, the mutual information takes into account also nonlinear correlations.

In this work we used the normalized variation of mutual information index:

$$U_{ij} = U(X,Y) = 2 \left[\frac{H(X) + H(Y) - H(X,Y)}{H(X) + H(Y)} \right] \quad (7)$$

For two completely independent variables $U(X,Y)$ equals zero while for two completely dependent ones it equals unity.

EXPERIENCES FROM TESTING

We have obtained a set of historical data files with signals of SPNDs over a period of several months by the courtesy of Mochovce NPP in Slovakia. The files contained the data logged with 8 sec sampling frequency. The length of the time interval for computing correlation and mutual information coefficients was $T=30\text{min}$ to ensure the sufficient statistics. For the start, to test the behaviour of the method, we used the confidence levels as proposed in [1], namely for suspect level $k_S = 5 \times 10^{-4}$ and for failure level $k_F = 10^{-5}$. These values were recommended as a trade-off between the sensitivity of the method and the occurrence of spurious judgements.

As a standard, the already failed SPNDs were cut off from data logging and there were zeros in place of their signals. Thus, we only could test the good signals. Long testing by both correlation coefficients and mutual information indices just confirmed that signals were correct as expected. Only very seldom warnings of suspect signals appeared when from some reasons the correlation between signals decreased in those respective periods T . It is to say that we originally intended to use the mutual information analysis just as a support to in [1] recommended correlation coefficients approach due to its ability to reflect the nonlinear correlation between signals.

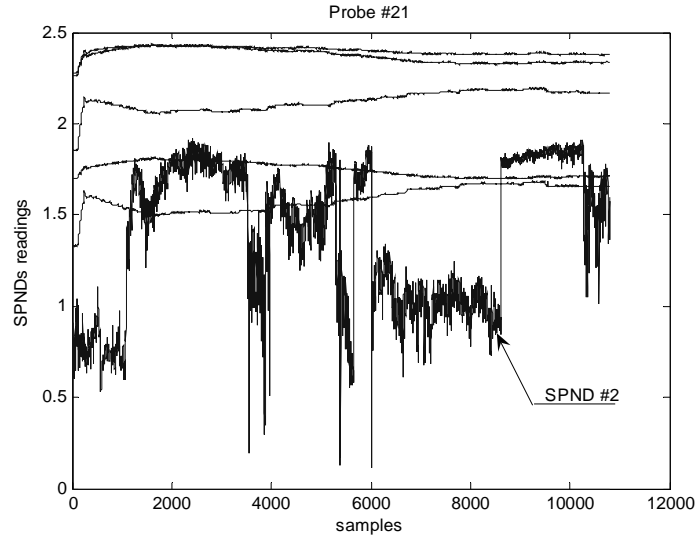


Fig.1 An example of the failed signal 2/21

So far so good. The problem arose when the signal of the 2nd detector in the 21st probe appeared to have failed, see Fig.1. To our surprise, signal 2/21 was labelled as failed only seldom. The reason for this was that the layerwise average was strongly influenced by it and thus well correlated with signal 2/21. Thus, we cannot confirm the experience described in [1].

Fig.2 shows the correlation in layer #2 with and without the signal 2/21 included in layer average. It is obvious that its exclusion from the layer average calculation improves the correlation of the rest of

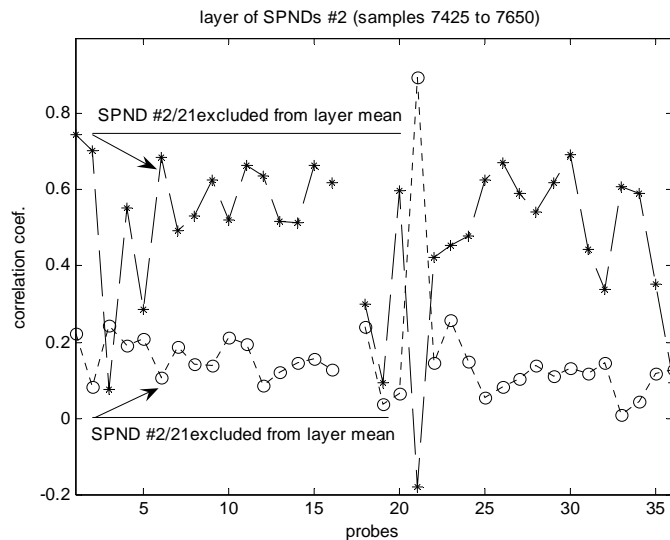


Fig.2 The influence of the failed signal 2/21 exclusion on correlation coefficient

sensors while the sensor 2/21 itself does not correlate well, as expected. Yet, even after its exclusion from layer average calculation, sensor 2/21 was not reliably labelled as failed. The reason might have been in not well chosen confidence levels for our data. Obviously, they will have to be tuned properly. Nevertheless, problem for diagnostics remains because one would first have to label the signal as suspicious what is in fact the

goal of diagnostics itself. As mentioned previously, one way would be to calculate the layer average always without the signal being inspected. However, this is not only computationally more intensive but may deteriorate correlation of other signals when the failed one is included. This might make the diagnostic decisions less reliable.

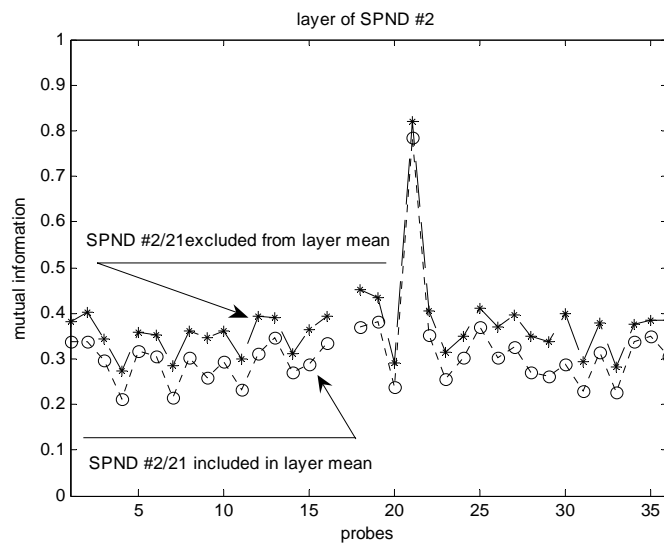


Fig.3 The influence of the failed signal 2/21 exclusion on mutual information index

We have observed very interesting behaviour of mutual information indices. Despite our expectations, the U_{ij} indices were not affected by exclusion of failed signal from the layer average calculation. And even more, they were much higher for the failed signal than for the rest ones, see Fig.3. (note: Probe #17 signals were not available).

Because we do not know what was the real physical cause of the improper behaviour of the sensor 2/21, our explanation is only a pure speculation. As mentioned before, the ever-present perturbations in the reactor core cause the neutron flux fluctuations,

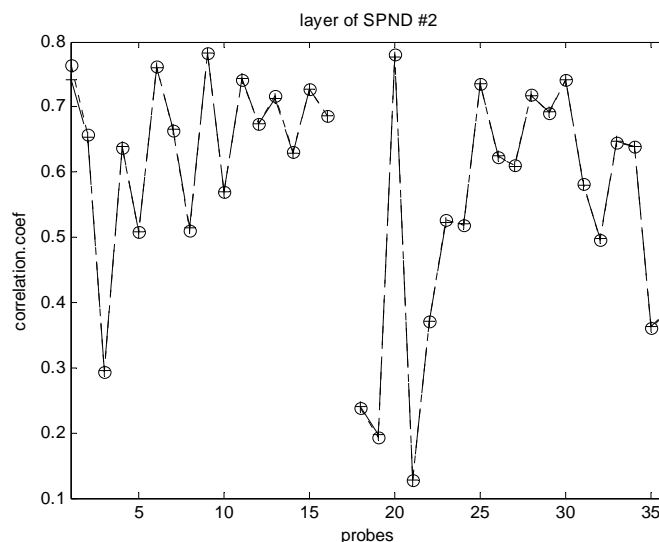


Fig.4 The influence of the right signal 2/1 exclusion on correlation coefficient.

which in result are the reason why the right, well functioning sensor signal is a little bit noisy. The dependence of the signal noise on the neutron flux fluctuations is obviously quite straightforward and supposedly linear. All signals of right sensors fluctuate

according to the fluctuating neutron flux. Their exclusion/inclusion do not influence the layer average substantially, thus having only little impact on correlation/ mutual information coefficients, see Fig.4., where the insignificant influence of exclusion of the correct 2nd sensor of the 1st probe from the layer average is shown. The same holds for mutual information indices as well. The other situation is in case of a failed sensor, having for example a cold junction between the emitter and the leading wire. Then the sensor vibrations may reflect on its signal more severely. This process of vibrations may amplify the signal fluctuations into a nonlinear region. Nevertheless, the mechanical vibrations of the reactor core structures, including the sensor itself, are in certain correlation with neutron flux. Thus, its excluding from the layer average calculation have little impact on mutual information index because of the supposed nonlinearity of the link between the neutron flux and failed sensor's signal. But right due to this supposed nonlinearity the correlation coefficient, which in general captures only the linear dependencies, is influenced substantially when the signal is excluded from the layer average.

The behaviour of the failing signal has distinct influence on C_{ij} and U_{ij} coefficients as apparent from Fig.5-7. The increase in signal noise, physically unsubstantiated by reactor power noise, reflects on their high values, and mainly on U_{ij} ones.

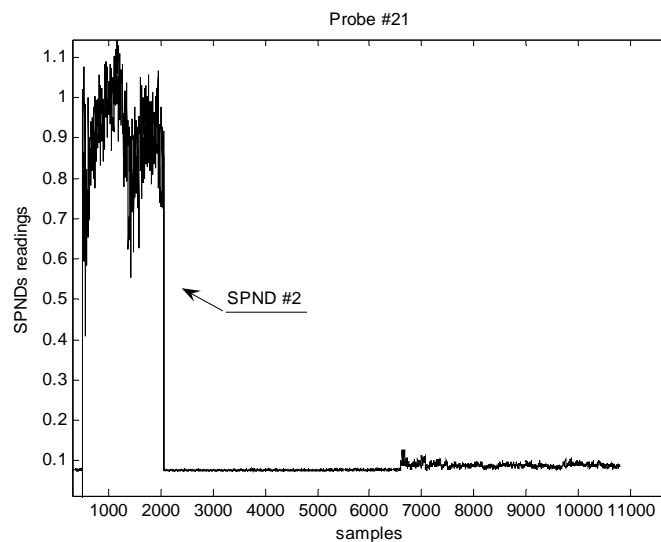


Fig. 5 An example of the failed signal 2/21

It is to say that the high values of both C_{ij} and U_{ij} coefficients in certain time periods do not necessarily have to manifest the failed detector, especially during the situations of high correlation among all signals due to, for example, a ramp change of reactor power. On the other hand, the U_{ij} coefficients going down to zero mean the failed signal, as happened after the 4500th sample in Fig.8.

We have also investigated the option of axialwise average calculation, i.e. the average of signals in their respective probes. Despite the better correlation with the axialwise average especially for bottom detectors, see Fig.9, yet we have decided to rely on the layerwise average calculation. The reason for this decision was that the alterations of mutual information indices after exclusion of a detector from the axialwise

average calculations based on 7 detectors in a probe were bigger than in case of the layerwise average from 36 detectors in a layer.

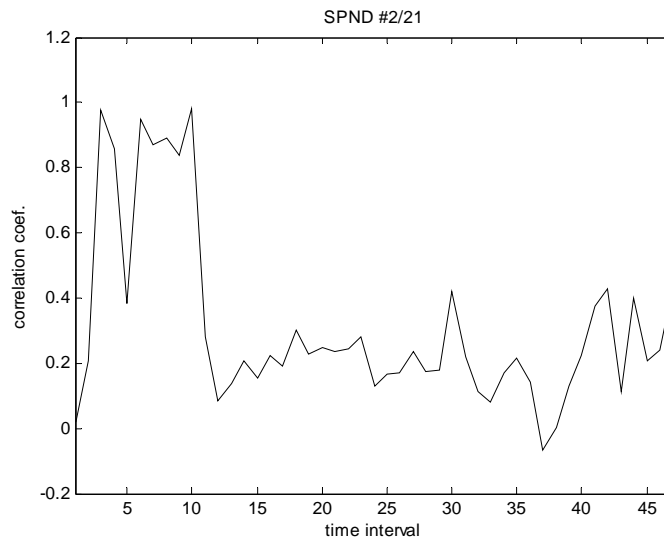


Fig. 6 The course of correlation coefficient along the time intervals T

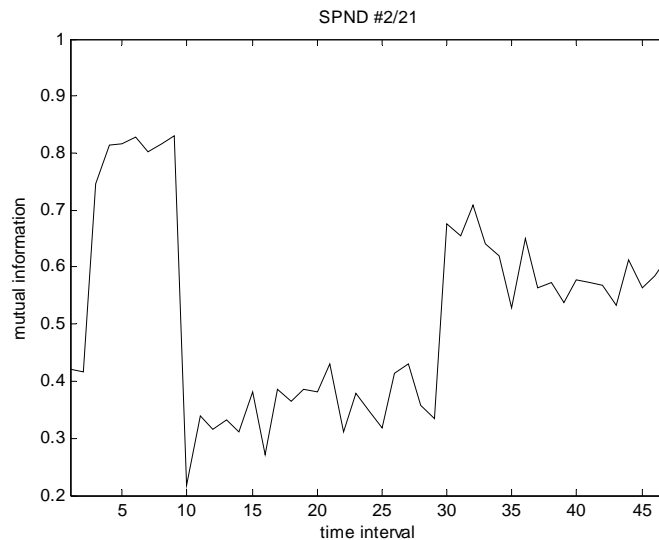


Fig.7 The course of mutual information index along the time intervals T

The other example of failing sensor 2/21 is in Fig.10. This time its noise was quite low and was almost not in any correlation with the rest of the sensors. Both the correlation and mutual information coefficients were low and behaved differently. Despite the situation in Fig.2, the exclusion of the failed signal from the layer average calculation did not reflect on a change of correlation coefficient and mutual information index values, see Fig. 11,12. (*note: Sensor 5/21 failed and was excluded from further processing before*). In reality, this very case of this type of failure might not be of much interest to us, as it would not be left unnoticed by even the basic limit checking methods. Nevertheless, we want our method to be able to capture it in situations when the signal values might be similar to the right expected ones and thus would not be easily recognizable by the classical methods.

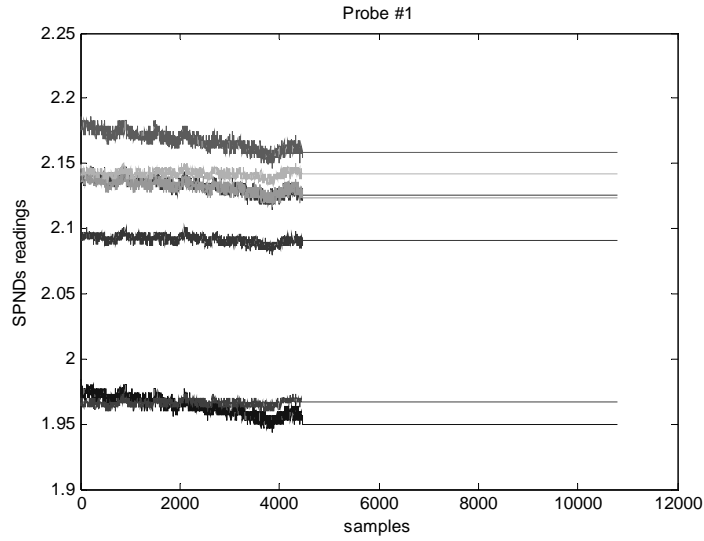


Fig.8 An example of failing signals

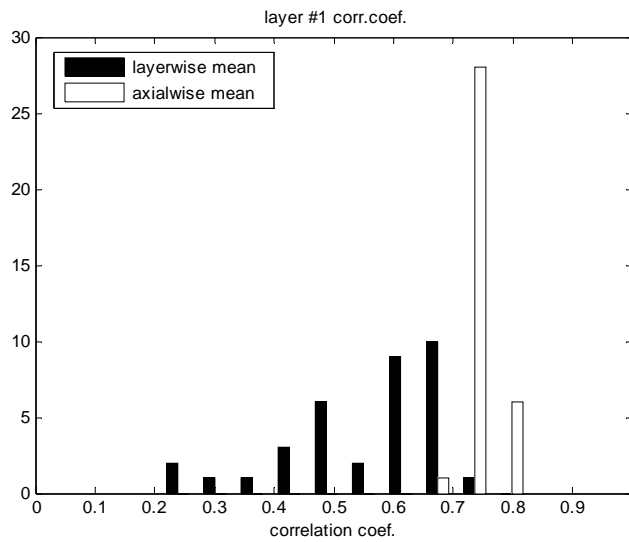


Fig.9 The histogram of layer 1 correlation coefficients

The consequent of various ways of behaviour of correlation coefficients and mutual information indices in different situations is that we cannot rely only on inspection of pure C_{ij} and U_{ij} coefficients. We will have to support our judgements by other methods making use of e.g. signal pattern recognition techniques and/or fuzzy logic based inferential algorithms. For example, the signal features, i.e. the signal patterns, can be constructed based on signal's wavelet transform coefficients [6]. They, we expect, will reflect the correct and failed signal. These patterns then could be easily recognised by properly trained artificial neural networks [7] or other pattern recognition algorithms. The labeling of the failed sensor by statistical hypothesis testing could be in disputable cases supported by judgements from fuzzy logic based inferential engines [7] which would take into account the course of signal itself as well as other parameters.

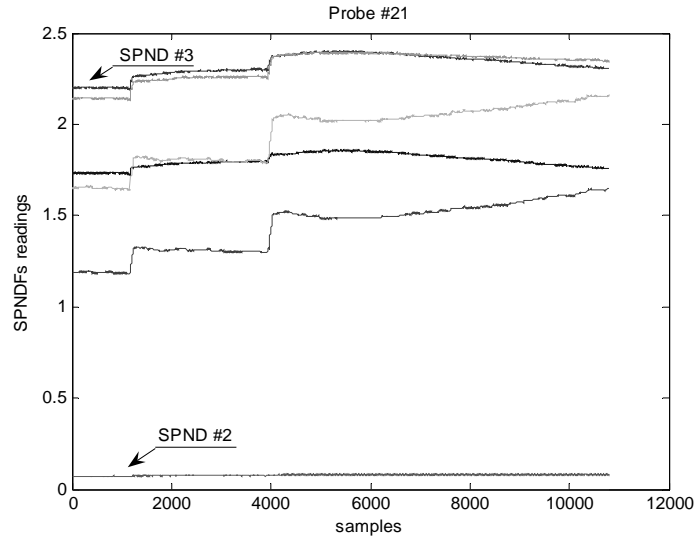


Fig.10 An example of the failed signal 2/21

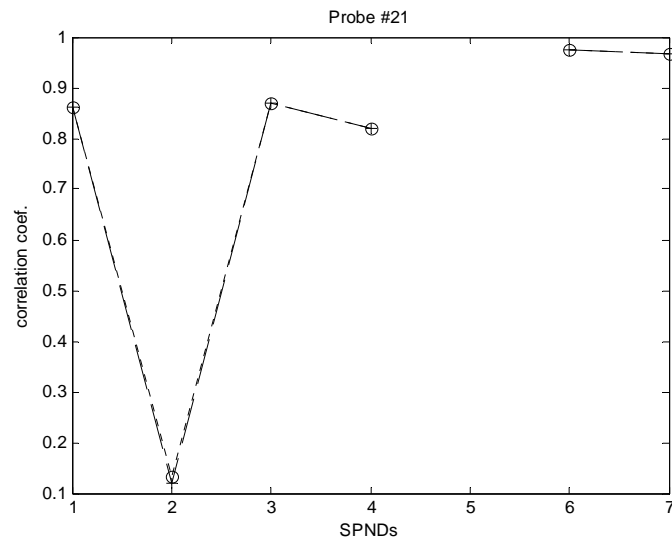


Fig 11 The influence of the failed signal 2/21 exclusion on correlation coefficient.

CONCLUSIONS

In this work we outline a new type of in-core sensor validation approach and present our first experience. The method is based on correlation of signals, both in linear and nonlinear regions, and makes use of the fluctuations in signals' prompt component, which have their source in perturbations present in the reactor core. It is assumed that decreasing similarity of signals' prompt components is the manifestation of a sensor failure.

The proposed approach makes use of correlation coefficients and mutual information indices between the SPNDs signals and their respective layerwise averages. The experience shows that in case of the strong fluctuations in the failed signal both the correlation coefficients and mutual information indices were usually high. After the

exclusion of the signal from layerwise average calculation the correlation coefficients were falling down towards zero while the mutual information indices remained practically intact. On the other hand, when the signal's fluctuations were low, then both correlation and mutual information coefficients were lower than usual and the signal exclusion did not reflect on their values so much. It has also been observed that in the situations of high correlation between all the signals during e.g. the ramp change of reactor power, the mutual information indices were high also for the right signals.

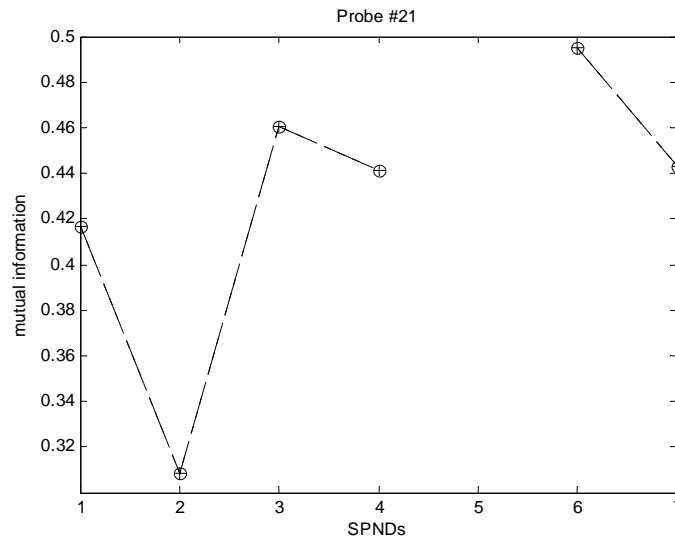


Fig. 12 The influence of the failed signal 2/21 exclusion on mutual information index

The consequent of different behaviour of both correlation coefficients and mutual information indices in different situations is that we cannot rely only on inspection of pure C_{ij} and U_{ij} coefficients. We will have to support our judgements by other methods making use of e.g. signal pattern recognition techniques and/or fuzzy logic based inferential algorithms. For example, the signal features, i.e. the signal patterns, can be constructed based on signal's wavelet transform coefficients. They, we expect, will reflect the correct and failed signal. These patterns then could easily be recognized by properly trained artificial neural networks or other pattern recognition algorithms. The labeling of the failed sensor by statistical hypothesis testing could be in disputable cases supported by judgements from fuzzy logic based inferential algorithms, which would take into account the course of signal itself as well as other parameters.

Our work on the development of the proposed method is in progress and will in the nearest future concentrate on tuning the proper values for the confidence levels for both correlation coefficients and mutual information statistical distributions. The work will continue with proper signal feature extraction methods and fuzzy logic algorithms to solve the possible disputable situations. The final phase will be to train the neuro-fuzzy validation system PEANO after having obtained enough data from various situations in the reactor core. Nevertheless, it seems indisputable that the only reliable approach to the signal validation is the combination of various techniques, the classical and state-of-the-art ones to ensure that failures sneaked through one method will not be left unnoticed by the other one.

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