IMPLEMENTATION OF COMPUTATIONAL INTELLIGENCE METHODS IN DIAGNOSTIC SYSTEMS IN THE NUCLEAR POWER PLANT

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Abstract

The aim of this overview paper is to present the new approaches elaborated at VUJE, Inc. to make the diagnostic systems in the environment of a nuclear power plant more robust and reliable. The systems in question are the sensor signal validation, denoising, early detection and identification of anomalies in chemical regime, time prediction of plant process parameters, and loose part monitoring in the reactor primary circuit. The techniques used are based on the computational intelligence and modern signal processing methods. The development of these systems was very much facilitated by variety of methods that can be used in MATLAB environment together with the toolboxes like Signal processing, Fuzzy Logic, Neural Networks, and Wavelet toolbox. This paper is of an overview character and does not focus on a detailed description of the methods used.

1 Real-Time Process Signal Validation Based on Neuro-Fuzzy and Possibilistic Approach

The operation of each industrial plant is based on the readings of a set of sensors. Their reliable functioning is essential as the output of sensors provides the only objective information of the process. The task of the signal validation is to confirm whether the sensors are functioning properly. Signal validation must be enough robust to multiple sensor faults as well. This requirement is crucial especially in case of an accident when the abnormal changes of the process together with possible severe damage of the sensors can occur. The only information about the actual state the plant or process is in can be obtained from the values of technological variables, which describe the plant or process. The condition monitoring of the plant or the process is based on monitoring of technological variables' deviations from their expected values. These deviations represent the degradation of the plant/process properties. Condition monitoring is thus an important step towards the optimization of the plant/process operation efficiency with impact on operation and maintenance costs. In the sector of power industry or industry at all this is the main goal and challenge for upcoming decade.

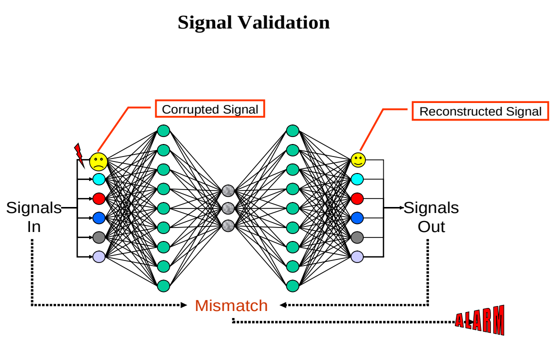

Figure 1: Signal validation by ANNs

Figure 2: PEANO user interface- drift in signal

The signal validation model is based on the set of the artificial neural networks (ANN), each driven by a pattern recognition algorithm. This classifier, based on the fuzzy and possibilistic clustering technique [1] identifies the incoming signal pattern (a snapshot of process signals) as a member of one particular cluster from a set of clusters. They are recognized to cover the entire operating range represented by the possible combinations of steady-state and transient values. Each cluster is associated with one ANN previously trained only with data belonging to this cluster. During the operation the classifier provides an automatic switching mechanism to allow the best tuned ANN to be used. The maximum membership grade of the sample in the particular cluster and the maximum signal mismatch in the neural network module input into the Mamdani type fuzzy model to estimate the reliability level of the validation. The ANN architecture is the typical feedforward five layers structure trained by either Levenberg-Marquardt or conjugate gradient backpropagation algorithms at a choice of a user. The number of nodes in three hidden layers form a bottleneck shape, see Fig.1. To capture the process dynamics, the past samples of the time series in addition to the current ones may be added to the input nodes. The transfer function of the output layer is linear.

This model has originally been developed in MATLAB environment within the joint research program at the OECD Halden Reactor Project, Norway, which VUJE, Inc. is a member of. Later on, it has been compiled into C++ run-time library and is delivered as the signal validation and condition monitoring system under the marketing name PEANO, see Fig.2. It does not require any special and additional type of measurement or equipment (common e.g. in noise diagnostics) as it utilizes only the standard measurements available in the plant. Different kinds of multiple faults were simulated - noise superposed on the signal, drop and drift in the signal. During the normal operation scenarios all faults were recognized correctly, with the reliability level of high or medium. The alarm was triggered either instantly (drop) or after few samples (drifts) as soon as the mismatch between the signal and the estimated values exceeded the error band, which was calculated separately for each signal and each cluster during training phase.

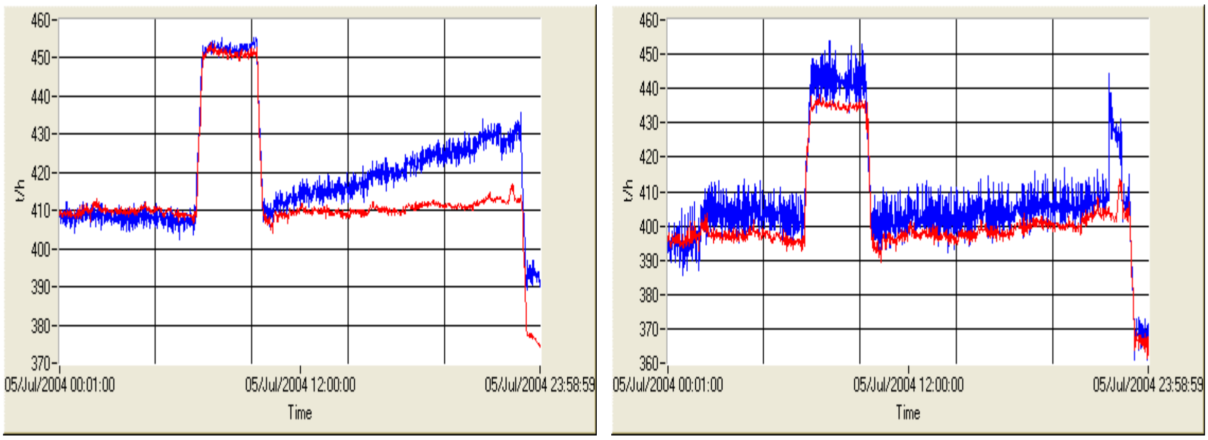

Figure 3: Simulated simultaneous drift and step change in steam-generator steam and feed-water flow as recognized by PEANO

The proposed model has been developed and tested on a simulated data from the PWR type of a nuclear power plant, to monitor safety-related reactor variables over the entire power-flow operating map and also implemented in the real environment of BWR plant in Halden, Norway. It has also been trained to recognize the possible degradation of the steam generator feedwater flow measurement at the NPP Mochovce, see Fig.3 and in-core sensors – self-powered neutron detectors and thermocouples – at the NPP Bohunice , both being the VVER-440 type. PEANO can be successfully used for early fault detection also in the situation of multiple failures simultaneously. In case of unknown situations in the plant or process or too many faulty signals the model correctly warns the user about the low reliability of the analysis. This is very important especially for the safety related applications, e.g. in nuclear or chemical industry.

2 Modern Methods of Signal Processing in the Loose Part Monitoring System

The loose part monitoring system in the primary circuit of the WWER-440 type as in any other PWR or BWR type of NPP is one of the fundamental and essential to safety diagnostic tools. VUJE, Inc., has more than 20 years of experience with the LPMS of its own production. Our systems are installed at nuclear power plants in Slovakia, Czech Republic and China (in cooperation with Westinghouse Electric Company, USA). The purpose of the system is to detect, localize and analyze detached or loose metal pieces. The prompt and reliable detection of loose parts dragged along the primary circuit by the flow of coolant may prevent the subsequent potentially severe damage to the internal structures. When the impacts are detected in the primary circuit, the system is supposed to trigger an alarm and give an assessment of loose part mass and localization of impact. The subsequent decisions are then taken whether to shut down the reactor or wait until the next refueling period. The LPMS is typically composed of a set of 15-22 accelerometers mounted on the reactor vessel, main circulation pumps and steam generators, Fig.4.

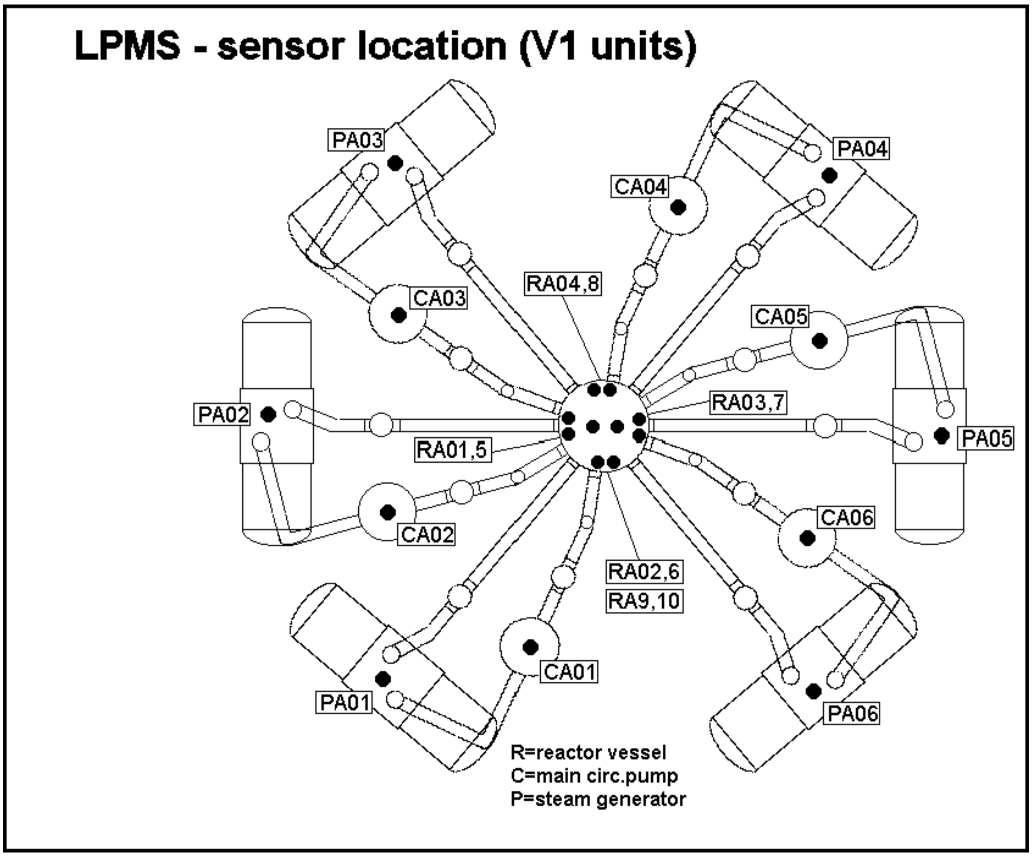

Figure 4: Layout of primary circuit components and LPMS sensors

When the metal impact occurs, it causes the mechanical vibration of the structures and a sensor/sensors detect a burst signal. Information about metal impact properties is primarily contained in the peak amplitude and frequency content of the initial impact wave. These characteristics of the detected signal are affected by gradual attenuation and the losses are a complex function of distance, component thickness, and frequency. Transmission through structural discontinuities such as pipe-to-vessel connections, in-line valves, and between the steam generator shell, tube sheet etc. introduces additional losses and reflections. In a typical installation, the measured analog signals are transferred to preamplifiers, and to the input of a monitoring unit where they are filtered and digitized in parallel by sampling frequency of 100 kHz. Bursts, i.e. signals caused by loose parts, are automatically detected in a measured background signal (noise) using a ring memory and thresholds. Bursts are automatically recognized using a specialized fast algorithm of linear prediction that takes into account the characteristic properties of a background noise. When present in more than one measurement channel, bursts are localized using time delays between the beginnings of the same burst in two or more measurement channels. For bursts with a maximal amplitude larger than a given threshold, the mass of a hypothetical loose part is estimated based on the Hertz theory and results of an experiment conducted before the installation of the LPMS with metallic spheres of various masses and kinetic energies.

2.1 Signal de-noising by digital wavelet transform

The operation of the NPP is associated with a background noise. The ever-present vibrations of the primary circuit structures are caused by the coolant flow, by the operation of the main circulating pumps and other components such as valves and control elements. When the metal loose part impacts on the internal walls or fittings within the primary circuit structures, additional structure-borne vibrations are excited. It results in the loose part burst signal being noisy, especially when the point of impact is far from the sensor. The individual bursts must be unambiguously distinguished from the background noise with respect to the start time, real rising edge, amplitude, duration and shape (envelope) of the burst in order the mass of the impacting part and the correct time of burst arrival for localization of impact might be determined correctly. This requires the signal to be first cleaned off the noise. It also results in improvement of the signal-to-noise ratio. In practice the noise cancellation is performed by linear or non-linear filters. The prerequisite of the LPMS signal de-noising is that the real front rising edge and the shape of the burst should not be distorted which can hardly be assured by the classical band-pass filtering. In this respect a very good candidate for noise cancellation is digital wavelet transform (DWT) based de-noising: First the whole signal is decomposed up to the level five of details by MATLAB function *wavedec*, using Daubechies db2 wavelets. Experiments have shown that the result of de-noising depended on the type of wavelets only insignificantly. Then the default soft threshold is calculated by the MATLAB *ddencmp* function only on the initial part of the signal before the burst arrived. Next the *wdencmp* function is called to threshold the wavelet coefficients from which the new signal is reconstructed. Related to thresholding, two issues must be addressed: how to choose a threshold and how to perform the thresholding.

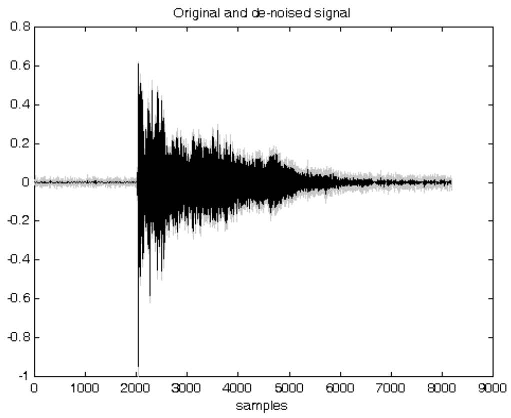

Figure 5: Original (dimmed) and DWT based de-noised signal (solid)

First the threshold value was estimated based on Stein´s Unbiased Estimate of Risk (SURE), then the soft thresholding was applied, in which the wavelet coefficients with absolute values lower than the threshold were set to zero, and then the nonzero coefficients were shrunk towards zero. The above-mentioned de-noising relates to the so-called global thresholding when one threshold coefficient is calculated for all scales. The other approach with a threshold coefficient magnitude dependent on the respective scale was also tested with little impact. Results show that the front rising edge and the shape of the burst is practically intact, see Fig 5. This makes the wavelet based noise removal by a soft thresholding a very suitable approach for the LPMS system. For other signal de-noising tasks also the multiresolution based approach can be used. In this case the decomposition of the original signal by high-pass and low-pass filters yields the approximation and detail wavelet coefficients from which two signals – an approximation as the part of the signal at the large scale, and a detail as the part of the signal at the low scale. The decomposition process can be iterated so that the original signal is broken down into many lower resolution components. The multiresolution based de-noising of a signal refers to signal reconstruction by the inverse DWT process, omitting some of the levels of detail wavelet coefficients.

2.2 Time of arrival detection

The accurate detection of the burst arrival time, i.e. the start of the transient, is crucial for localization of impact. The delay time depends on the distance between the sensor and the location of impact (and the speed of sound in the structures). Knowing the burst arrival times to different sensors installed one can localize the impact either of a loose part when the delay times observed are constant or of a detached part when the delay times observed are of varying values. The previous chapter closely relates to this task as the burst emerges from the background noise and presence of peaks can impair the detection of the real start.

In practice, the burst arrival time can be detected by the stationary background noise modeling using the autoregressive process. For resolving the beginning of burst the actual forward prediction error of the signal is compared to a threshold. When the waves reach the sensor, the substantial increase in the magnitude of this error will be observed.

Very promising and accurate results are offered by the algorithm having been tested at VUJE in a recent time. It relies on the wavelet transform ability to perform the local analysis of a signal – that is to analyze a localized area of a larger signal with respect to changes or discontinuities:

1. The whole signal is decomposed to the level one of details, using Haar wavelets.

2. The default soft threshold is calculated only on the initial part of the signal before the burst arrived and the wavelet detail coefficients are soft thresholded.

3. The beginning of burst coincides with the first non-zero value of the level one detail coefficients, from which we can pinpoint the start of the burst, see Fig 6.

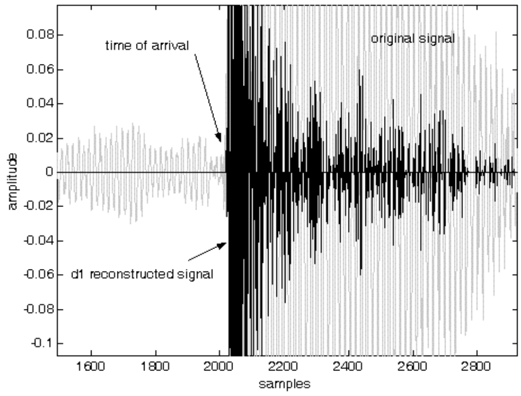

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Figure 6: Original and d1-reconstructed signal.

2.3 Discrimination between real and false alarms

The requirement, which an LPMS system must fulfil, is to launch an alarm whenever a burst signal appears. In the real implementation the triggering is evoked when the level of signal exceeds a certain threshold over the background noise. From that moment all the subsequent processing starts resulting in identification of the burst and alarm launched. The problems are encountered when the signal is logged in the real industrial environment. The false alarms appear due to the various electrical or electromagnetic interferences the consequence of which is the signal exceeding the threshold.

The burst signal shape – amplitude and form - varies depending on the energy of impact and sensor location: reactor, steam generator or main circulating pump. Yet, it is much different from an interference signal. The wavelet coefficients, representing the features of the signal, see Fig. 7, can be used as an input to the classifying algorithm, e.g. fuzzy c-mean clustering or artificial neural networks, both available in the MATLAB environment, which can discriminate the false alarm from a real one.

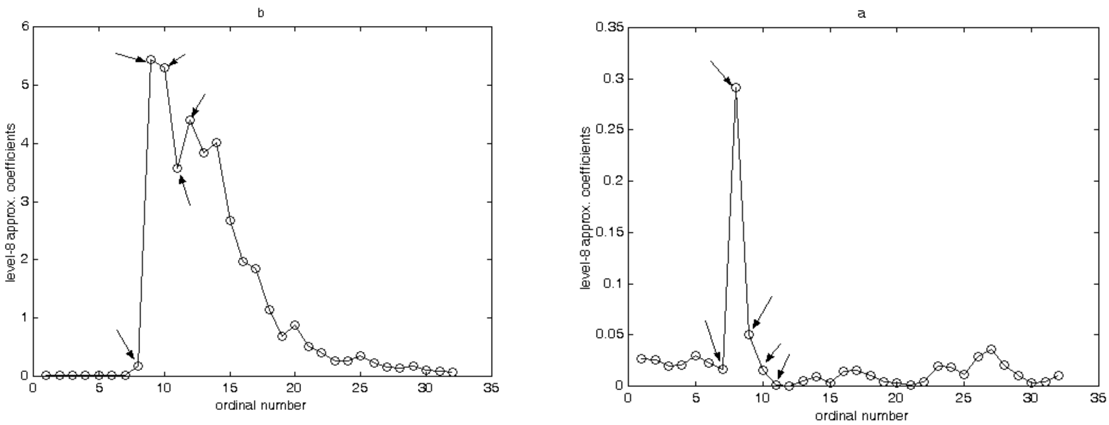

Figure 7: Level-8 approximation coefficients of the burst signal (left) and interference (right)

The easy recognition is based on the substantial difference between the shape and magnitudes of the eighth level approximation a8-coefficients of real and interference signals - note their typical difference in both cases.

2.4 Impacting mass estimation

The sensor response depends on the impacting loose part mass (and energy). This is also reflected in the shape of the fast Fourier transform (FFT) spectrum of the burst. The heavier the impacting part is the more low frequencies can be found in the spectrum. In other words, the spectrum is shifted towards the low frequencies with the mass increasing. In practice this dependence is expressed through the spectral index as a quantity characterizing the shape of the spectrum. The spectral index is the ratio of power spectral density (PSD) of low frequency band to PSD of high frequency band. The mass of impacting part is one of the most important characteristics. It directly affects the decisions about the urgency of next steps to be taken to resolve the situation. The mass of the impacting part can be determined from a curve fitted to the spectral index values, which yields only a rough estimation of the impacting mass. Instead, the artificial neural network properly trained to recognize the shape of the PSD represents a more accurate estimation.

3 Early detection and identification of anomalies in chemical regime.

VUJE Inc. develops a new diagnostic system for early detection and identification of anomalies incoming in the water chemistry regime. This system, called SACHER (System of Analysis of CHEmical Regime), which is being installed within the major modernization project at the NPP-V2 Bohunice, has been developed fully in MATLAB environment. The availability of prompt information about the chemical conditions of the primary and secondary circuit is very important to prevent the undue corrosion and fouling build-up.

The typical chemical information systems that exist and work at the NPPs give the user values of the measured quantities together with their time trends and other derived values. It is then the experienced user's role to recognize the situation the monitored process is in and make the subsequent decisions and take the measures. The SACHER system, based on the computational intelligence techniques, inserts the elements of intelligence into the overall chemical information system. It has the modular structure with the following most important modules:

watchdog module- its aim is to recognize that the situation of the process starts to deviate from the normal one. It is based on the possibilistic fuzzy clustering approach. The clustering algorithm must be able to generate the representative clusters which the patterns of process parameters values belong to. As the pattern vectors may have the characteristics of several classes, the classification must assign any single pattern to the representative clusters through the membership degrees or discard the pattern if not represented in any cluster. Another requirement on the clustering algorithm is the smooth transition between the clusters as the situation represented by process signals evolves due to the power manoeuvres or transients. For this reason, the possibilistic fuzzy clustering approach has been used in this module. This means that patterns not reflecting any of the identified cluster prototypes, i.e. not belonging to the clusters of normal situations, are discarded as unknown if not fitting into any cluster. The low membership degree to all clusters of normal situations is the indication of an incoming anomaly and serves as the early warning to the staff to take the adequate measures.

fuzzy identification module- its aim is to identify the anomaly on the basis of a set of fuzzy rules of Takagi-Sugeno-Kang type, into which the excessive knowledge of an expert-chemist has been incorporated. Each anomaly is defined by a specific fuzzy if-then rule, e.g. :

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if (P1 is HIGH) or (P1 is ASCENT) and (P2...............) then ANOMALY_i

if (P1 is LOW) or (P1 is DESCENT) and (P2..............) then ANOMALY_j

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The firing strength of each rule determines the strength of the corresponding diagnostics.

time-prediction module- its aim is to predict the behavior/trend of selected chemical quantities 8 hours ahead in 15 min step from the moment of request. The model uses properly trained artificial neural networks, each giving the prediction to the specific time step. This means, that for one quantity to be predicted 8 hours ahead there are 32 networks engaged and even more as the entire operating range of each quantity has been partitioned into 3 or 4 fuzzy clusters to avoid training of the neural networks to capture all situations at once. It has been proven that the neural networks perform better if they are trained each capable to recognize only a specific type of situations. During the prediction task, first the cluster most reflecting the given situation is found and then the prediction is done by neural networks having been trained to situations of that respective cluster.

validation module- its aim is to validate the measured quantities. It is based on the autoassociative kernel regression method [2]. The true expected value of the measured quantity is calculated as the weighted average of the values obtained from the nearest clusters in a certain vicinity to the most representative one. The centers of these clusters have been found in the training phase in advance. The mismatch between the measured values and their true expected calculated counterparts can be estimated whether not exceeding the properly chosen error band.

4 Summary

This overview paper briefly describes the new approaches elaborated at VUJE, Inc. to make the diagnostic systems in the environment of a nuclear power plant more robust and reliable. The systems in question are the sensor signal validation, de-noising, early detection and identification of anomalies in chemical regime, time prediction of plant process parameters, and loose part monitoring in the reactor primary circuit. The techniques used are based on the computational intelligence and modern signal processing methods. The all presented techniques have been developed and tested on data from the real process. Some of them have already been implemented in the NPP; the implementation of others is being prepared in the upcoming projects. Their development was very much facilitated by variety of methods that can be used in MATLAB environment together with the toolboxes like Signal processing, Fuzzy Logic, Neural Networks, and Wavelet toolbox.

References

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