SURVEILLANCE AND FAULT DIAGNOSIS FOR POWER PLANTS IN THE NETHERLANDS: OPERATIONAL EXPERIENCE

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Abstract

Nuclear Power Plant (NPP) surveillance and fault diagnosis systems in Dutch Borssele (PWR) and Dodewaard (BWR) power plants are summarized. Deterministic and stochastic models and artificial intelligence (AI) methodologies effectively process the information from the sensors. The processing is carried out by means of methods and algorithms that are collectively referred to Power Reactor Noise Fault Diagnosis. Two main schemes used are failure detection and instrument fault detection. In addition to conventional and advanced modern fault diagnosis methodologies involved, also the applications of emerging technologies in Dutch reactors are given and examples from operational experience are presented.

1. INTRODUCTION

The Netherlands has two nuclear power plants. The first Nuclear Power Plant Dodewaard started its production of electricity of 54 MWe (163.4MWth) in March 1969. This is a small BWR reactor is cooled by natural circulation. Power increased to 60.4 MWe (187 MWth). During the 1997, the owner (SEP, Dutch Electricity Production Companies, GKN N.V.) of the plant decided to stop the operation although it was licensed until 2004. Reactor is shut down and preparations are being made for its decommissioning.

The second NPP is the Borssele owned by EPZ-NV (Electriciteits Productie-maatschappij Zuid-Nederland). The reactor is built by KWU-Siemens and first core cycle started at the beginning of 1974. It is a Pressure Water Reactor (PWR) with two coolant loop and two steam generators and a pressurizer. The reactor thermal power is 1360 MWth with electric production of 480 MWe. Borssele NPP had major plant modifications in 1997 in order to meet advances in technology and regulatory requirements, after operation of 23rd core cycles [1]. At the beginning of 1998 the reactor started again its electricity production.

The Netherlands Energy Research Centrum ECN started with reactor noise studies as early as in 1962 with noise measurements at zero-power on an Argonnaut type low flux reactor; these

these studies were extended to power reactors after 1970. Borssele NPP experiments were started in 1974. The Dodewaard reactor noise measurements were started by KEMA in 1976 and later jointly conducted by TU-Delft Interfaculty Reactor Institute (IRI) and GKN N.V.

Both power plants mentioned above played an important role in the reactor noise analysis, monitoring and development of advanced techniques for diagnosis. Data obtained from the reactors have been a driving force for the reactor noise analyses. It gave a feedback to benchmark analysis for measuring power reactor noise at PWR (SMORN-III in 1981), core physics parameters estimation (SMORN-IV in 1985), anomaly detection and testing benchmark (SMORN-VI in 1992) and testing the Neural Network Methodology (SMORN-VII, 1995).

The Dodewaard reactor also became a very important facility to study stability in (natural circulating) BWRs and its monitoring. The BWR reactor can be unstable under unfavorable conditions and circumstances caused by a feedback between neutronics and thermal hydraulics, which may result in excessive oscillations of the flow rates or the reactor power.

In this paper, achievements from both reactors are presented in power reactor noise analysis during first decade of operation and developments in fault diagnostics in the second decade.

2. BORSSELE NPP NOISE MEASUREMENTS, ON-LINE MONITORING AND DIAGNOSTICS

The Borssele NPP noise measurement started in 1974 after a request of the Directorate of Labor of the Ministry of Social Affairs (KFD). Aims of these measurements have been to determine the noise patterns of the reactor as completely as possible. During the period of 1975 and 1981, that is in first ten core cycles, periodic measurements were done until tenth core in three days measuring campaigns. The increasing number of sensors are employed and analyzed off-line. After the 10th core cycle in 1981 until the end of 23rd core cycle in 1997, measurements were carried out with an on-line system.

These measurements are reported in SMORN (Specialists meetings on reactor noise), up to 1995 in seven meetings, IMORN (regular informal meetings), until '97 in 27 meetings, and POWER PLANT DYNAMICS, CONTROL and TESTING Symposia until 1995, in nine meetings and numerous IAEA (-TCM) and other meetings including a number of publications.

2.1 BORSSELE PRIMARY SYSTEM INTEGRITY AND SENSOR TESTING MEASUREMENTS

The main interest is to measure the reactor noise at reactor power by ex-core and in-core neutron detectors, thermocouples and pressure signals of the primary system. The main emphasis is to develop measuring techniques and the methodology to understand core behavior during the operation. Using ex-core neutron detectors at four different axial levels and at four different detector positions the method for Core Support Barrel Motion analysis was developed [2]. Also the inlet and outlet temperature noise signal, primary pressure signal are investigated. For neutron detectors, the low-frequency spectrum determines the total r.m.s value of the noise,

which is highly dependent on the boron concentration of the primary coolant. The reactor noise contributions are measured and results reported to the reactor operation. In some cases super intended of the reactor control and maintenance group requested further information about specific events and sensor testing. During the stretch-out operation, where boron concentration is zero, we observed effects on reactivity and noted that pressure noise is linearly dependent on temperature of the coolant. From these measurements the temperature dependent pressure coefficient is derived. In-core and ex-core neutron detector signals and their relation to primary pressure signals are investigated at different operational conditions. These measurements formed a very large database as AC/DC signals, information files and resulted in fingerprints of the spectral patterns.

A new technique was developed to measure core support barrel motion (CSBM). This technique uses at least four ex-core neutron detector signals. From linear combinations of CPSD's of all neutron detector pairs the reactivity noise spectrum and the core motion spectra are separated from each other and the absolute motion amplitude and direction of the motion is derived [3]. Later this technique was implemented on-line and also a special PC-version was developed for real-time measurements.

In-core self-powered neutron detector signals are measured and several spectral peaks are investigated with relation to ex-core, incore, primary pressure and main coolant pump vibration signals [3,4,5].

The changes on the standing waves depending on the temperature of the primary coolant system are investigated through pressure signals. These standing waves extend over the whole coolant circuit, with nodes inside the pressure vessel and the two loops oscillating in opposite phase. The wavelength derived from these experiments the total average length of the two loops could be estimated; Its value - 142.6 m – corresponds to the actual length.

Temperature noise signals of the core-exit, the core–outlet and the core-inlet noise signals are investigated and the response time of the thermocouples are derived. Core inlet thermocouple response times are about 1.20 ± 0.10 s., core outlet 2.32 ± 0.12 s. and core exit thermocouple response times range from 0.31s to 0.92 s.

2.2 ON-LINE MONITORING AND HIGHLIGHTS OF DIAGNOSTIC STUDIES FOR THE BORSSELE NPP

In 1981, the first patch panel was built for 90 signals, on which 32 signals are directly connected to the on-line system. An on-line data acquisition system provides programmable signal conditioning and conversion. The converted data can be used locally or transmitted through the data transmission system to ECN for signal analysis, monitoring and failure detection. Information on the structural integrity thus obtained gave rise to:

- predictive maintenance;
- early detection of failures and minimizing the detrimental effects on the internal parts and diagnostics of the failure;

- reduction on inspection cost and direct possibility for in-situ testing of measuring channels;
- remote control possibilities in case of unforeseen difficulties.

This system has ability of continuous monitoring of 32 selected DC and AC signals and circular database of three elapsed days. System used on-line multi-channel signal processing in both time and frequency domain. Real-time data and the processed results are block-wise transferred to a large block of shared memory every 2 s. or 4 s., which is accessible commonly to several users and other real-time diagnostic applications. The part of the calculations for further analysis is performed in the distributed network system in other PC- or workstation-based systems through the Ethernet. The on-line analysis for testing complete measuring electronics and sensors in situ is enhanced. The test of thermocouples and other sensors response time and frequency and time characteristic are worked out for model-based analysis. The real-time core support barrel motion analysis is carried in routine base [6,7]. Most important is the monitoring of the secondary system, therefore measuring channels were extended by steam generator steam flow, steam temperature, steam pressure, water level and the feedwater flow, temperature, pressure.
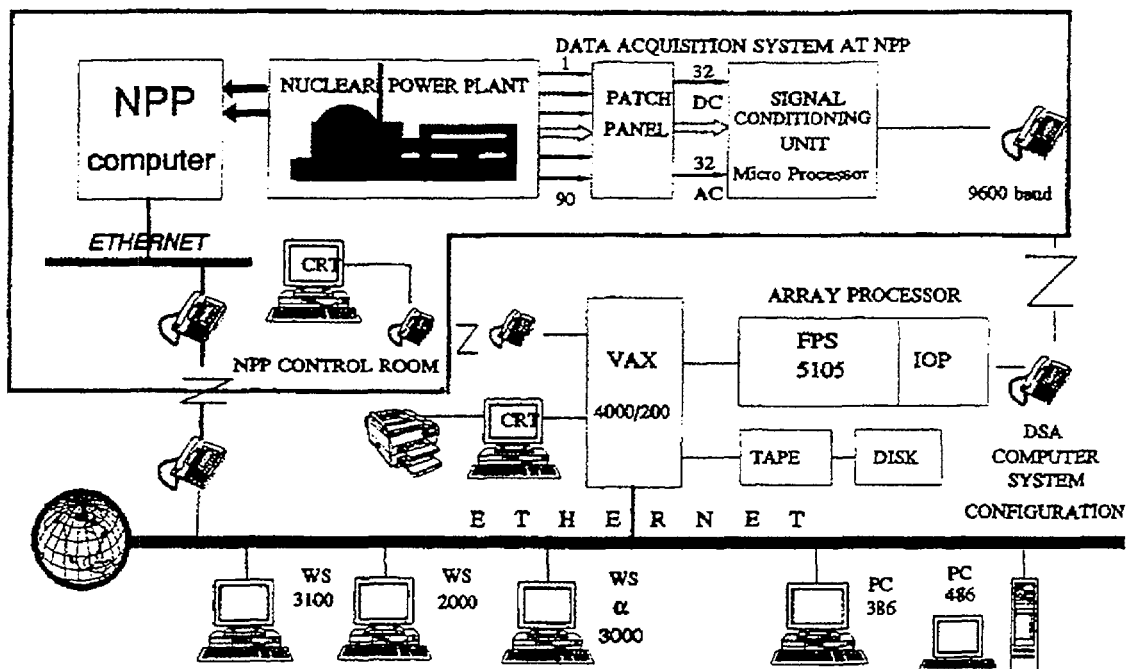

Fig.1: Real-time NPP (Borssele) monitoring overview..

In case of emergency, it is important to be able to access all dynamic measurement channel information determined earlier for comparisons. The database is made until the end of the core cycle 23rd, while, database is created for the whole core cycle of operation between 1982-1997.

In the course of time, model and method developments and computer enhancements succeeded to work in parallel. In the beginning of the years '90, early failure detection techniques, decision making and reliability became important issues. Therefore, a general sequential decision reliability concept and a failure rate assessment methodology is introduced for systems in which decision making is an integral part of the operational [8].

The effectiveness of the failure detection by adaptive Lattice modeling using Kalman Filtering methodology is introduced and implemented in Borssele NPP [9].

Lattice parameters calculated in real-time are used to calculate the Mahalanobis distance for discrimination, which is termed as feature selection in the pattern recognition terminology. The Mahalanobis distance in essence is sensitive to the changes in the system dynamics through the change of the pdf of the multivariate normal distribution. This implies that the failure sensitivity analysis of the failure detection system can be carried out on a statistical basis. Also DC signals are used for the failure detection by using cumulative sum test (CUSUM) by accumulated information [10].
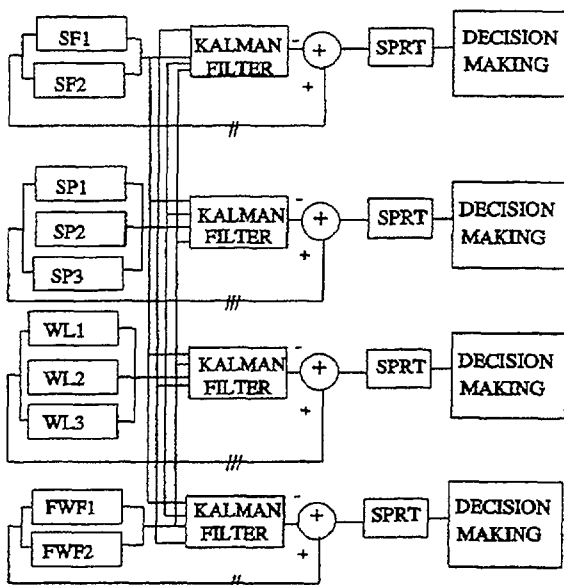

Fig.2: *Block scheme of the sensor failure detection for steam generator sensors [12].*

model parameters are assessed for Borssele NPP and the sensor failure detection method for dynamic system presented for steam generator water level, pressure, feed water flow and pressurizer pressure, water level [11,12] and incore signals [13]. Failure detection is based on monitoring of the residuals corresponding to each measurements.

In case where residual exceeds a predetermined bound, the estimator indicates the possibility of failure according to a certain decision making scheme. To this end a sequential failure detection technique is implemented.

Studies are performed for signal validation together with sensor failure by modeling the steam generator and pressurizer of Borssele NPP separately in state space using Kalman filtering methodology [11,12,13]. The method used in studies involves both sensor redundancy and analytical redundancy so that the number of Kalman filters each of which is dedicated to a particular state; it is equal to the number of states defined. The states are estimated by means of the signals from the measurement channels and the redundant sensor signals are applied to the input of the Kalman filter assigned to them with appropriate desensitization so that the redundancies involved give the possibility of detection of the sensor failure. The method is applied to Borssele NPP. Sensor failure detection method for dynamic system presented. Simplified pressurizer and steam generator
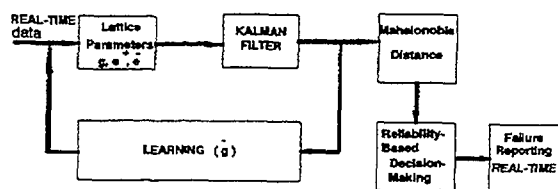

Fig.3: *Failure detection by pattern recognition using statistical measure of Mahalanobis distance [9].*

Nneural network (NN) studies and applications started in about 1991. The first application was implemented for the pressure signals spectra measured at the different temperatures. A
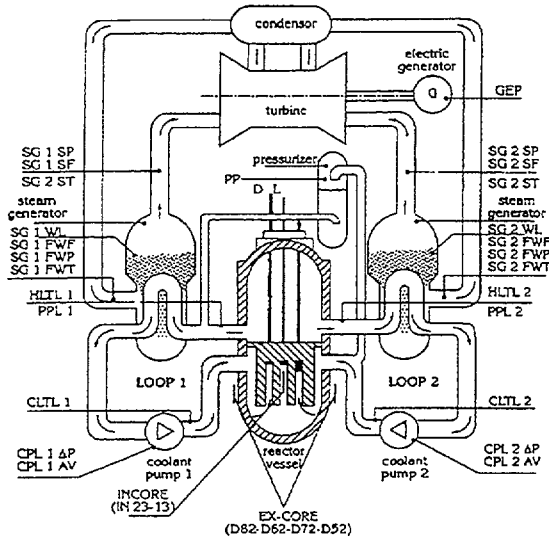

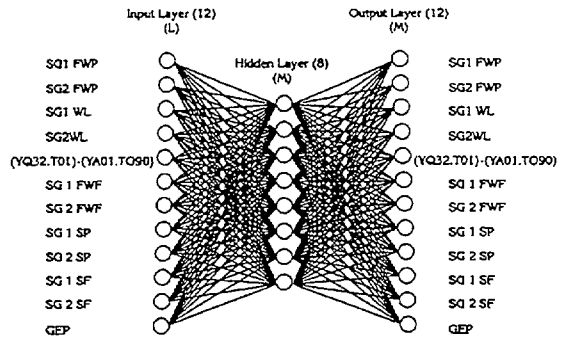Fig.4: *Schematics of the Borssele NPP and measured signals.*

Fig.5: *Example of Feedforward neural network topology.*

neural network was used to identify the average temperature from the measured peak position which appeared due to a standing wave [14]. The potential of NN for sensor validation and plant monitoring was noted. For these studies the autoassociative NN structure was extensively used [15,16,17,18]. The type of network was feedforward and the training algorithm was standard backpropagation (BP). Neural network structures can be modified according to the information provided at its input, in a temporal base so as to train the network with changing process environment. This can be carried out in real-time [19,20]. As the surveillance process is an important information source for the predictive maintenance procedures which are especially important for NPPs, investments were made for improvements of monitoring systems [21]. However, since the BP algorithm was not efficient and effective enough, advanced training algorithms were also considered and employed [22,23].
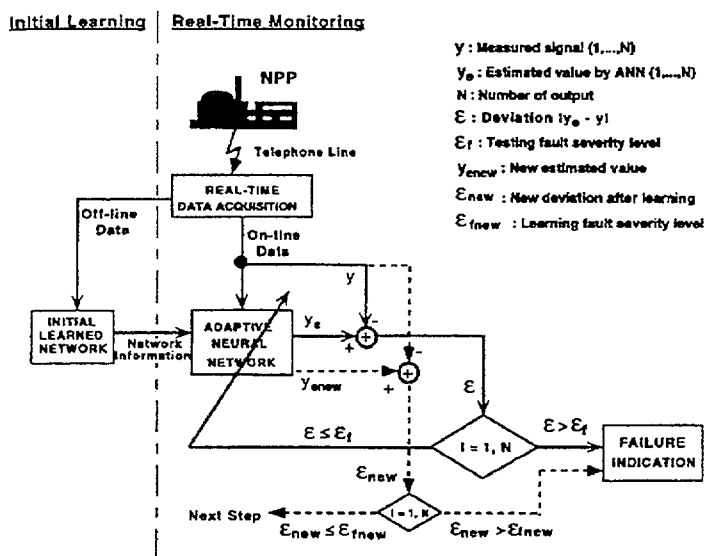

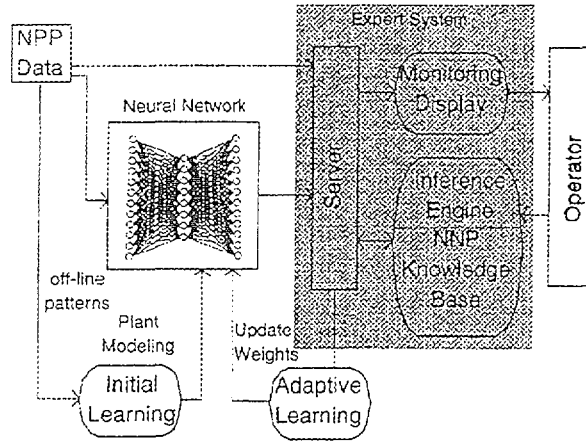Fig.6: *Block diagram of adaptive neural network.*

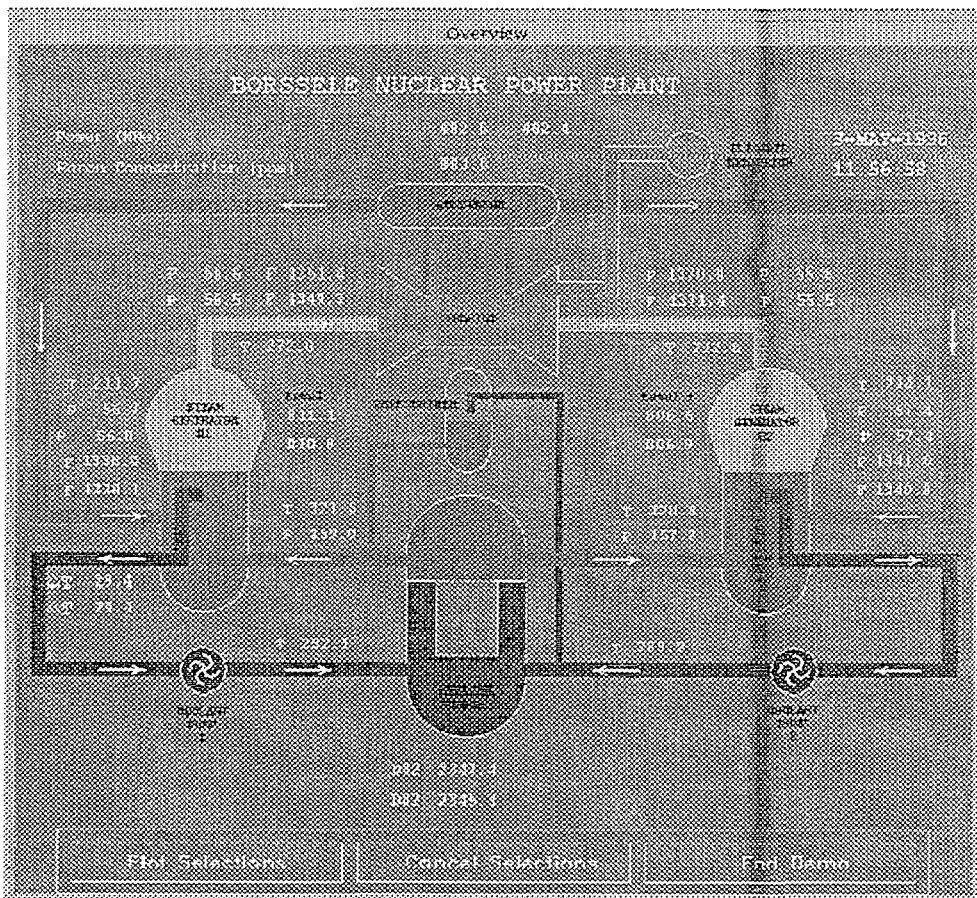Fig.7: *Diagram of Hybrid AI Systems [24].*

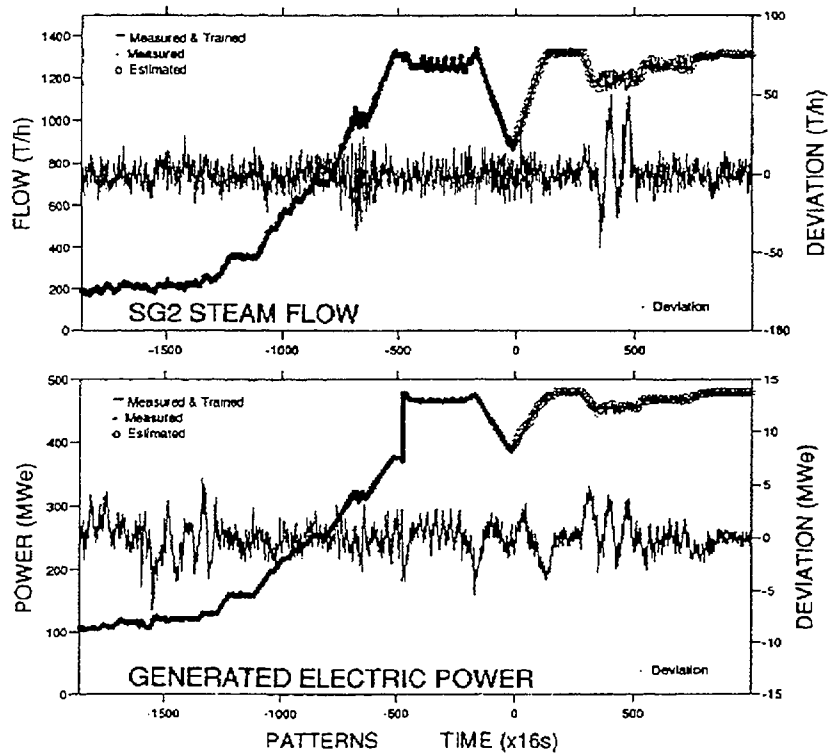Fig.8: *Monitoring display by real-time neural network; Measured and NN estimated (light) values.*

Fig.9: *Monitored steam flow and generated electric power by neural network. The network was trained using the data presented before time equal zero.* [25].
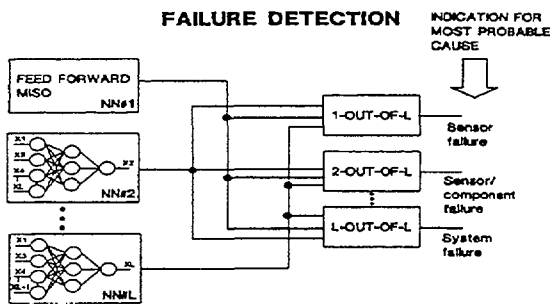
Fig.10: *The MISO structure and failure detection structure* [26].
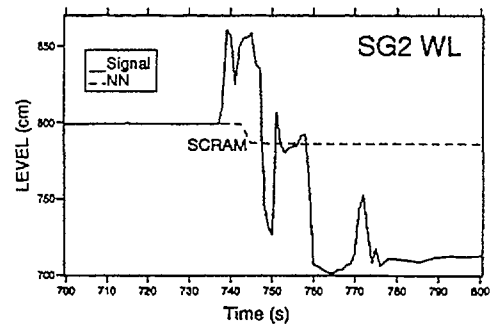

Fig.11: *Fast sensor failure estimation by neural network for the steam generator water level signal* [26].

The studies were later integrated into two European projects on severe accident management and in these projects self-organizing neural networks were employed to the big volume of the data subject to processing [24,25,26,27,28,29]. By means of this, data reduction is performed and

the task is formed into a shape suitable for execution by feedforward NN afterwards. This work eventually resulted in an on-line NN plant monitoring system applied to the plant.
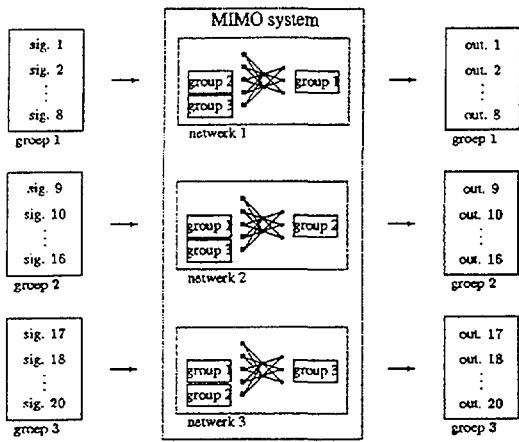

Fig.12: *Scheme of MIMO for monitoring a system with 20 sensors in 3 groups. The first and second groups 8 sensors (in SG1 and SG2) and the third group has 4 sensors (reactor core) [29].*
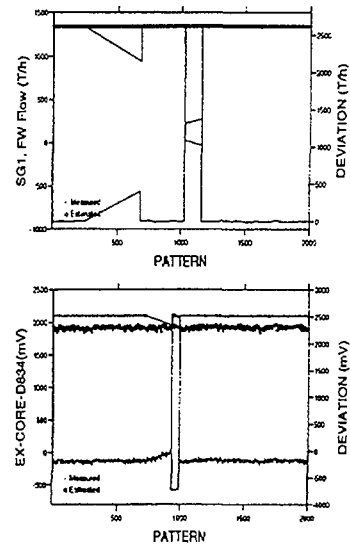

Fig.13: *Results of test with MIMO system with 20 signals in group 3 and 8 neuron in the second layer. Two different failures identified SG1, FW Flow signal(above) with two failures and ex-core neutron detector sensor signal (below) [29].*

In parallel with the advent of new technologies, new methods are being developed for the effective utilization of the techniques involved in these technologies. With respect to advanced data analysis, specially, in addition to powerful Fourier transform techniques, a relatively recent development appeared in the applied mathematics as a new technology. This method introduce some new potentialities in data analysis since they can detect and analyze localized structure in signals in contrast with Fourier transform, which spreads the information throughout the time interval used. The new mathematical tool for signal analysis is the wavelet transform. This powerful tool analysis the dependence of signal on scale, position and signal dimensions. The adaptability property of wavelets is especially useful in plant monitoring where the signal energy is concentrated at lower frequencies in slow developing transients as well as in rapid transients where the signal energy is concentrated at higher frequencies. During the last few years it is explored in many areas of application for NPP signal analyses [27,30,31,32,33].

2.3 HARDWARE/SOFTWARE SYSTEMS FOR SIGNAL PROCESSING AND PROCESS MONITORING

Condition monitoring was one of the spin-offs of ECN's ongoing research program at the beginning of 90's. Successful system monitoring through the multi-user system used in on-line monitoring of Borssele NPP gave idea in parallel developments in WorkStation and powered PC line. A series of single user PC based systems were developed and used for condition monitoring.

The first system build was DSA-1: it is a graphical enhanced real-time data acquisition system based on PC with A/D converter and Digital Signal Processing Card DSP using upto four signal channels. This system has the ability of calculating in time and frequency domain, all combinations of signals in same time. Also real time AR-modeling up to four channels using the Levinson-Durbin algorithm is addead to software. Model orders can be selected depending on Akaike's information criterion with minimum of 20. Measured and model-based spectra can be compared and displayed simultaneously. Real-time display of step response, impulse response function and optional calculation of decay ratio. System was later upgraded and selectable alarm settings on the identified functions or parameters, e.g., RMS values, response time, decay ratio (DR) and damping coefficients were added. A special unit was built and installed at the Dodewaard NPP in 1994 for the on-line monitoring of stability of the reactor using three reactor safety channel signals for operator support.

The next signal analysis and monitoring system is the DSA-2 system. It has 8- analogue measuring channels with advanced ADC card of sigma-delta technology (CAD8F), which is able to achieve signal to noise ratio of 90 db antialias filtering and digitizing the analogue signals with 16 bits accuracy. DSP card (SPIRIT30) using TMS320C30 processor is used for multichannel signal processing. This system is operating two main programs: the first program is multichannel reactivity calculation using the solution of inverse kinetic calculations in real-time. The second program is a general real time noise analysis in time and frequency domain. The system is able to calculate all available 8-channels with all their possible cross combinations in time and frequency domains for 256 time and frequency resolutions and a maximum frequency up to 1 kHz. It uses exponential averaging with selectable given time window for forgetting the pasted time. Coherence and Phase calculations are added to real time operation after every spectral calculation and the exponential averaging. The system is used in various types of reactors in the Netherlands and also in Switzerland PSI and Indonesian Multi-Purpose reactor of 30 MWth. In the very near future the system will be used during the start-up experiments of HTTR (High Temperature Engineering Test Reactor of Japan (JAERI-Oarai) [34].

The third up-grade is the DSA-3, based on previous systems; is called "Primary System Integrity Monitoring Device". The system is designed for the on-line and real-time measurements of Core Support Barrel Motions "CSBM" in PWR type NPPs, using radial pump vibrations signals. DSA-3 measures in real time all cross information (28 in total) as well as phase and coherence information and in the same time it calculates decomposed spectra of the neutron detector signals to the CSBM analysis. The system displays in real-time resulting core motion amplitude and direction as well as the reactivity spectrum and all measured functions on request.

The fourth upgrade (DSA–4) was built and tested for instantaneous boiling detection or any type of anomaly detection for observing specific out-of-core experiments. It is specially designed for use at High Flux Reactor (HFR) experiments. It has the same functionality as the DSA-2 system only all measured functions are preserved with pre-defined and alarm bands and alarm indication for any sudden change in the monitored patterns.

DSA-5 system is a combination of DSA-2 basic functions with addition of real-time spectral pattern recognition using adaptive neural network for condition monitoring [35]. The neural networks are known as powerful pattern classifiers. They are able to respond in real-time

to the changing system state descriptions provided by continuous sensor outputs. This on-line spectral pattern recognition system uses various frequency functions (PSD, CPSD, Coherence, Phase and Transfer functions) obtained from a variety of signals of the reactor. Adaptive learning facility makes it possible for the network to learn (new) real-time patterns and to extend its generalization power. This can happen if the error relay between the predefined desired and testing error. The system is able to follow 256 spectral points in real time measured and predicted functions by adaptive autoassociative neural network and the deviations between measured and predicted patterns with allowed error limits. When these alarm limits are exceeded adaptive learning stops and prediction continues while the severity level of the exceeded alarm is given as fault identification. It has fast learning capability and display facility for selected function.
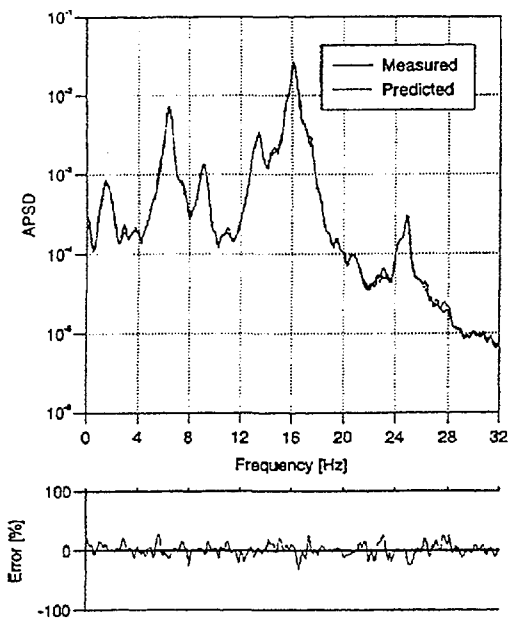
Fig.14:*Real-time neural network monitoring for spectral pattern recognition for primary pressure signals with error indication [35].*
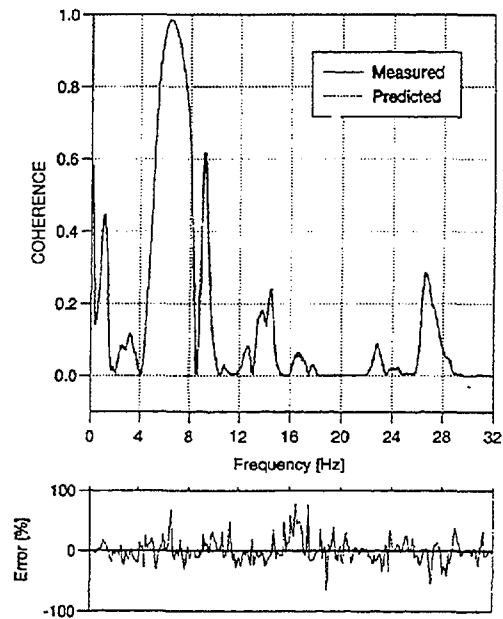
Fig.15:*Real-time neural network monitoring for coherence between primary pressure signal 1 and 2 with the error indication between measured and predicted signals.*

3. DODEWAARD NUCLER POWER PLANT MONITORING AND DIAGNOSTICS

The Interfaculty Reactor Institute (IRI) in Delft has a rather long history in using noise analysis for obtaining information on the status of nuclear reactor. In the past 20 years, research on Dodewaard reactor demonstrated that noise analysis is a powerful and convenient tool for studying the characteristics of a boiling water reactor. Analytical studies comprised the optimum way of using the noise signals available for an early and adequate detection of an anomalous situation.

3.1. BOILING WATER REACTOR NOISE AND STABILITY MEASUREMENTS

In 1978, during the eight-core cycle, noise measurements started to characterize the noise patterns of the principal reactor parameters and to identify the noise sources in the reactor. These identifications form an essential part in improving the knowledge of the overall dynamic stability of the reactor system [36]. In these measurements, ex-core and incore (LPRM) neutron detector signals, reactor pressure and steam flow, temperature signals were used and their mutual coherence and phase information were studied. Research was carried out for in-core feedback effects where information was deduced from neutron noise measurements [37]. Incore power feedback effects have been studied by radial coherence measurements where the coherence was found to be dependent on detector distance and frequency. The result indicated that even such a small core reactor does not behave as a point reactor [38]. The sub-channel coolant flow rate measurements have been carried out using noise signals of both in-core neutron and gamma detectors [39]. It has been found that the measured velocities were different from those obtained by neutron sensitive twin detectors. These measurements with two sets of detectors indicated that the noise correlation measurements in BWRs measure the velocity of steam bubbles. However, a correction must be made for void drift between different sub-channels. Difference is explained by the larger field of view of the gamma detectors compared to the neutron detectors [40]. A fairly large discrepancy remains between the recirculation flow as obtained by the incore measurements and by thermocouple noise correlation in the downcomer. The coolant velocity profile over the core is measured by means of twin self powered neutron detectors [41]. The challenging study has been carried out experimentally and theoretically for the study of effective time constant related to heat transfer from fuel to coolant which is a very important parameter for dynamic behavior and thus the stability of the reactor. Here, the measured fuel time constant was found to be 2.0 ± 0.4 s.

Instabilities can result to excessive oscillations of the reactor power or of the coolant flow rate, therefore extensive attention is paid for BWR stability and numerous of experiments model calculations were made. Several methods have been tried in time and frequency domain analyses of the neutron detector noise signals at different experimental conditions [41]. The impulse response of the ARPM signal can be estimated from the AR-model and it is observed that system has not a pure second-order oscillatory behavior but superimposed on it a exponential decay which leads to third-order system. Decay ratios and the frequencies, the impulse response and NAPSD are obtained by least-squares-fitting. Least-squares fitting of the impulse response and NAPSD function resulted in the decay ratio. From the experiments the r.m.s ratio of the APRM signal of 0.8-1.3 Hz and 0.4-0.8 Hz is a linear function of decay ratio. This gives also very quick check for the measured decay ratio by other means. From the measurements the maximum outlet void fraction as a function the decay ratio is derived by spectrum fitting [41]. Data of the noise measurements were used to validate computer codes and studies of the physics of the reactor especially with respect to natural circulation, the oscillatory behavior observed during the start-up measurements [42].

Measurements, taken in the Ringhals-I BWR, show that instability occurred at high power and low core flow. It was found that both global (in-phase) and regional (out-of phase) oscillations occur, the global with low DR but large signal amplitude. Methods for obtaining the stability characteristics of both modes separately from neutron noise signals were developed. The DR of the out-of-phase mode appears to be a good indicator of the margin to instability [43].

3.2. DEVELOPMENT OF ANOMALY DETECTION TECHNIQUES

Safe operation of NPP can only be guaranteed in case of a timely and reliable detection of anomalies, followed by a proper corrective action. In sophisticated anomaly detection, several distinctive tasks have to be performed successively by signal processing, feature extraction, feature compression and decision making [44,45,46]. During the first process, the information contained in the noise signals is presented as a function of time in a more suitable way. Thereafter a relevant feature of this new time signal is extracted and compared to 'normal' feature values such as DC value, standard deviation, AR parameters, residual noise etc. Finally, a reliable decision has to be made whether the system is still normal. Deviations of the system from the AR model show the change of characteristics (feature extraction) which can be observed in the residual noise. Here three ways of feature extraction and comparison of residual noise have been studied and compared; the first way is to compare extremes of the residual noise with thresholds based on the standard deviation under normal condition. Secondly, comparing the distribution of the amplitude of the residual noise with the expected distribution. Finally, using sequential probability ratio tests (SPRT).

The performance of an anomaly-detection method has been studied by three detection parameters, namely: the false alarm probability (FAP), the alarm failure probability (AFP) and average time to alarm (ATA). These rates can be determined from the probabilities. The important difference between the SPRT and the former methods is that a decision about the state of the signal is not taken every time step of the signal. Moreover, the number of time steps between two decisions is not constant. For optimization of the anomaly detection method, the false alarm rate (FAR) should be as low as possible and the average time to alarm (ATA) as short as possible. Study showed that the SPRT method gives the fastest response to a change in standard deviation of the residual noise for given false alarm rate (FAR).
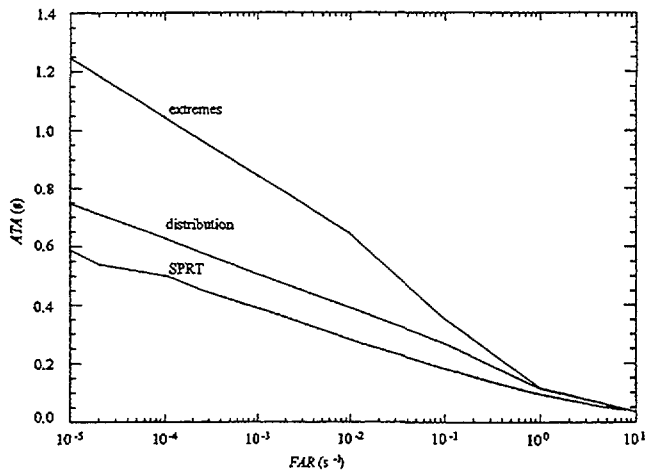

Fig.16: *Comparison of the average time to alarm (ATA) for the three anomaly detection methods as a function of the false alarm rate (FAR) ($f_c =100 Hz$; anomaly: 50% increase in standard deviation) [44].*

The application of an artificial neural networks (ANN) for the Dodewaard reactor stability monitoring was studied [45]. A three-layer perceptron was trained on synthetic autocorrelation functions to estimate the decay ratio and the resonance frequency from measured neutron noise. Training of the ANN was improved by adding noise to the training patterns and by applying non-conventional error definitions in the generalized delta rule. The performance of the developed ANN was compared with those of conventional stability monitoring techniques. It is found that the training is capable of monitoring the stability of the Dodewaard. The ACF of the second order system and the Dodewaard neutron noise are given in the Fig.17.
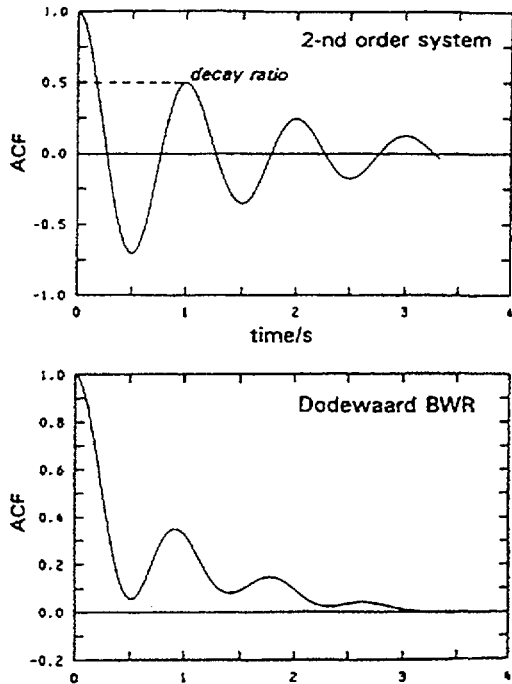
Fig.17:*Autocorrelation function (ACF) of the output signal of a second-order system fed with white noise (upper graph) and the Dodewaard neutron noise (graph below) [44].*
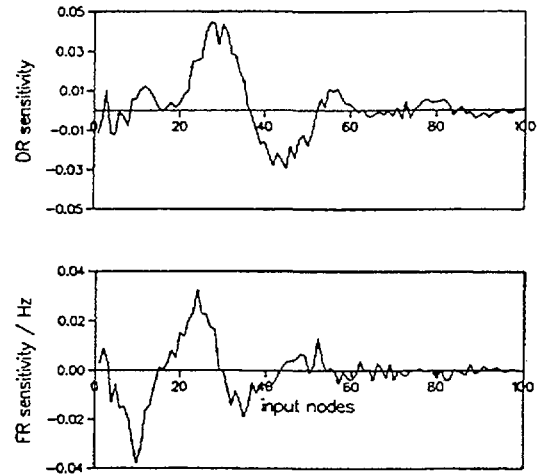

Fig.18:*Sensitivity of the NN estimation of the DR and the F_R, resonance frequency, on the value of the input nodes, [44].*

In the neural network topology auto associative network with three layers was used. In the first layer the ACF of 60 time lags as a number of input node 60 is filled, in the hidden layer 30 nodes are used and at the output layer DR and resonance frequency are estimated. Study of the sensitivity analysis is carried for this application [Fig.18]. It is found that the neural network gives a very accurate estimation of the resonance frequency, network performs very well in stability monitoring (DR estimation) and also network is more robust than the ACF method.

4. CONCLUSIONS

In this paper a review is given for Borssele NPP noise measurement, real-time applications, advance methodologies, systems and their applications. The on-line system used for Borssele NPP has extensive capabilities for comprehensive monitoring of the total power plant. The processed information is made available by the main computer to various peripheral computers connected . The system has the capacity of multi-level monitoring as well as multi-tasking provides the users with a distributed computer system environments. Signal processing is performed for the following distinctive goals, namely,

• forming a database of signals for the purpose of investigations on earlier serve core cycles,
• information stored during the on-line thirteen fuel cycles can can be used for further new analyses or emerging researches in PWR NPP diagnostics.

- early detection of failures or failure trends results in reduction of inspection and maintenance expenditure.

The multi-level distributed structure of the system has ample flexibility to perform any signal processing task in the most efficient way. It provides the user with the same degree of flexibility to implement emerging applications for surveillance.

In the coarse of time several deterministic and stochastic methods have been implemented and tested in real-time base. The importance of Kalman filtering in the dynamic system may be regarded as an optimum observer. The optimality of recursive Kalman filter estimates with the equivalent recursive information update form, provides a modern approach to time series analysis for sample by sample real-time information processing.

Neural networks are extensively tested and used in real-time operation and the high performance of these applications are very encouraging.However, the reliability of the neural network estimations are not yet explicitly addressed yet. Still they can be considered as rather robust and reliable auxiliary supporting tools for NPP operation; adaptive learning should be carefully treated during the application. The first applications of the MISO (sensor failure) and MIMO (sensor/ system failure) system approach has the ability of indicating failed signals at different components where this feature can be used for detecting failed component and the failing sequence. Applications are spread over a wide range of support areas in literature, including plant parameter estimation, transient event classification and many others.

The multiresolution signal decomposition in real-time implies that the signal is splitted up into several orthogonal components, so that each component signal can be treated effectively for enhanced information processing in NNP operation. The signal as well as the spectral decomposition can be performed in real time for the purpose of enhanced plant monitoring.

The reactor noise study yields very good achievements in the development of the BWR noise analysis understanding. Several theoretical and experimental results gave well understanding of the physical phenomena. In spite of the fact that the Dutch Dodewaard reactor is shut down, there is a wide set of experimental data available for further analysis and understanding in two-phase flow phenomena as well as stability monitoring.

Three anomaly detection methods, namely the extremes, the distribution and the SPRT method, were studied and compared with each other . It is found that the SPRT method performs best under all circumstances studied. The distribution method is superior to the extremes method in this respect. The performance of neural networks for BWR stability monitoring was studied; results obtained in the study gives the trade of the implementation but never the less very good performance was achieved in DR and resonance frequency estimation.

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