



A SYMPOSIUM ON NUCLEAR REACTOR SURVEILLANCE AND DIAGNOSTICS

May 19-24, 1991, Gatlinburg, Tennessee, U.S.A.

organized by

OAK RIDGE NATIONAL LABORATORY

and

THE UNIVERSITY OF TENNESSEE, KNOXVILLE

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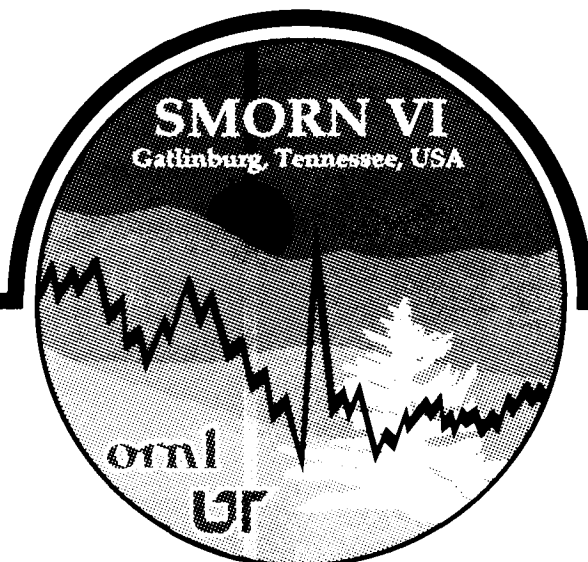
O.E.C.D. NUCLEAR ENERGY AGENCY

COMMITTEE ON REACTOR PHYSICS

COMMITTEE ON THE SAFETY OF NUCLEAR INSTALLATIONS

in cooperation with the

**IAEA INTERNATIONAL WORKING GROUP ON
NUCLEAR POWER PLANT CONTROL AND INSTRUMENTATION**



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FOREWORD

Oak Ridge National Laboratory and the University of Tennessee, Knoxville are pleased to organize the Sixth Symposium on Nuclear Reactor Surveillance and Diagnostics (SMORN VI). We wish to acknowledge the sponsorship of the symposium by the O.E.C.D. Nuclear Energy Agency and the cooperation provided by the IAEA International Working Group on Nuclear Power Plant Control and Instrumentation.

This symposium is a follow-up to SMORN V (held in Munich in 1987) but with an expanded scope focusing on the development and application of surveillance and diagnostic techniques to nuclear power plants for the purpose of assuring the operational readiness of components and systems important to plant safety and economic operation. The papers published in these two volumes deal with the following topics: operational experience with surveillance and diagnostic systems, BWR stability monitoring, leak and boiling detection in fast reactors, modeling and monitoring the motion of PWR and BWR structures, advances in signal processing methods, parameter estimation techniques, application of neural networks and pattern recognition, sensor monitoring and signal validation methods, and advances in machinery diagnostics and loose-part monitoring.

We thank the contributors for their excellent technical papers and the attendees for their participation. It is our hope that others reading the contents of these volumes will find the work reported enlightening and useful.

Robert C. Kryter, Oak Ridge National Laboratory
Belle R. Upadhyaya, The University of Tennessee

Symposium Co-Chairmen
Gatlinburg, Tennessee, U.S.A.
May 1991

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A SIMPLE WAY OF FITTING ARMA MODEL TO STATIONARY NOISE

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ABSTRACT

ARMA models appear as useful tools in the fitting of time series, since the signal is characterized by using few parameters. The usual methods have the difficulty of involving a great amount of calculations.

A new simple method is proposed and developed to fit the MA parameters, once the AR part is solved by the Yule-Walker equations. It leads to very accurate solutions and, furthermore, can be implemented as the start point to get initial conditions for other methods.

1. INTRODUCTION.

It is well known that a stochastic process can be modeled using the idea that a time series, in which sucesive values are strongly dependent, can be generated from a series of independent shocks of impulses (Wold's Theorem).

These are random impulses from a fixed distribution, usually Gaussian with zero mean and σ_ε^2 variance (white noise). We may thus consider this signal or noise as the output of a linear filter when the input is a white noise. In practice (1), for such a model to be useful, is convenient to reduce the number of filter parameters as much as possible. That is the parsimony principle.

Autoregressive moving-average (ARMA (p,q)) stationary time series modeling, full accomplish with the parsimony principle, and is able to establish a relationship with the transfer linear input-output function model, containing the possibility of poles identification and hence the parameters calculation (2).

ARMA (p,q) modeling appears thus in many applications, as in control theory as in signal proccesing. For instance, the linear dynamics of a BWR can be reduced to a set of five differential equations. This leads to a power/reactivity transfer function that can be reduced to a three zeroes and four poles rational function (3). By means of an ARMA fitting of the stationary neutron noise from average power range monitors, the poles can be obtained, and then the parameters of the physical model can be calculated.

In the ARMA modeling, the AR part is the deterministic one, and it

corresponds to the denominator of the transfer function, and is calculated in a straightforward way. But the MA part is a very different case, it corresponds to the numerator of the transfer function and, in order to calculate the q parameters, a set of $q+1$ non linear equations must be solved.

By the invertibility principle, an ARMA model may be converted in a pure AR model of high order. Due to the difficulties of an ARMA fitting, this option is sometimes considered, and it exists powerful algorithms for AR fitting, avoiding the resolution of non linear equations that can lead to spurious results.

In this paper, the problem of the MA part fitting is considered and an iterative process is proposed. It works properly if initial conditions are well chosen.

2. ARMA EQUATIONS.

Let $y(t)$ be a stationary noise signal from which a discrete series of N equally spaced points, y_i , is extracted. This series can be fitted to an ARMA (p,q) model in the form (4):

$$y_i = \sum_{k=1}^p \phi_k y_{i-k} + \varepsilon_i - \sum_{l=1}^q \theta_l \varepsilon_{i-l} \quad (2.1)$$

where ε_i is a Gaussian white noise with σ_ε^2 variance; ϕ_k are the AR parameters and θ_l the MA ones. The notation can be modified using the backshift operator $B^k y_i = y_{i-k}$:

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) y_i = (1 - \theta_1 B - \dots - \theta_q B^q) \varepsilon_i \quad (2.2)$$

or

$$\Theta(B) y_i = \Theta(B) \varepsilon_i$$

The possibility anticipated in the introduction of converting an ARMA model to a AR or MA pure is clear in this representation, when the $\phi(B)$ and $\Theta(B)$ polynomial roots lie out of unit circle. Then the model is said to be invertible.

The AR part can be calculated by the Yule-Walker equations. If we consider the autocorrelation function:

$$C_\tau = E[y_i, y_{i-\tau}] = C_{-\tau} \quad (2.3)$$

taking expectation values $E[y_i, y_{i+q-\tau}]$ $i=1, \dots, p$ in both sides of equation (2.1) and considering that ε_i is a white noise it is obtained easily:

$$C_i = \sum C_{i-k} \phi_k ; \quad i=q, q+1 \dots q+p-1 \quad (2.4)$$

having a straight solution.

After the AR part is solved, subtracting this to the signal y_i , a pure moving-average problem is got

$$y_i = \varepsilon_i - \sum_{n=1}^q \theta_n \varepsilon_{i-n} \quad (2.5)$$

where

$$y_i^* = y_i - \phi_1 y_{i-1} - \dots - \phi_p y_{i-p}$$

calculating the expectation value $E[y_i^*, y_{i-\tau}^*]$

$$\begin{aligned} C_0^* &= (1 + \theta_1^2 + \dots + \theta_q^2) \sigma_\varepsilon^2 \\ C_\tau^* &= \begin{cases} (-\theta_\tau + \theta_1 \theta_{\tau+1} + \dots + \theta_{q-\tau} \theta_q) \sigma_\varepsilon^2 & i=1, 2, \dots, q \\ 0 & \end{cases} \end{aligned} \quad (2.6)$$

where σ_ε^2 is the white noise variance. Therefore we have $q+1$ non linear equations to calculate σ_ε^2 and q moving-average parameters.

In the simplest case MA(1), equations (2.6) can be solved in an analytical form; setting two solutions θ_1 and θ_1^{-1} . If an invertible model is desired, with the roots of characteristic polynomial outside the unit circle, the solution with absolute value less than one is taken. In the MA(2) case four solutions appear, and in great orders the situation is worse.

3. RECURSIVE METHOD TO OBTAIN THE MA PARAMETERS.

A new method to solve the equations (2.6) is proposed. This leads to unique solution, by means of the assumption of a initial reference value for one of the variables, σ_ε^2 , and the construction of a iterative process, concluding when steady values are obtained for the search parameters.

In order to clarify ideas, first at all, the 1 and 2 order models will be studied, as a previous step to the more general case.

a) MA(1) model

The MA(1) temporal series model is:

$$y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} \quad (3.1)$$

calculating the autocorrelation function:

$$C_\tau = E[y_t - y_{t-\tau}] = E[(\varepsilon_t - \theta_1 \varepsilon_{t-1})(\varepsilon_{t-\tau} - \theta_2 \varepsilon_{t-\tau-1})] \quad (3.2)$$

for $\tau=0$

$$C_0 = E[(\varepsilon_t^2 + \theta_1^2 \varepsilon_t^2 - 2\theta_1 \varepsilon_t \varepsilon_{t-1})] \quad (3.3)$$

assuming ε_t to be white noise of σ_ε^2 variance:

$$C_0 = (1 + \theta_1^2) \sigma_\varepsilon^2 \quad (3.4)$$

in the same form, considering $\tau=1$:

$$C_1 = -\theta_1 \sigma_\varepsilon^2 \quad (3.5)$$

we have a two non linear system of equations with two unknowns quantities σ_ε^2 and θ_1

$$\begin{cases} C_0 = (1 + \theta_1^2) \sigma_\varepsilon^2 \\ C_1 = -\theta_1 \sigma_\varepsilon^2 \end{cases} \quad (3.6)$$

the equation for θ_1 is:

$$\theta_1^2 + \theta_1 (C_1/C_0) + 1 = 0 \quad (3.7)$$

which has two solutions, θ_1 and $1/\theta_1$. As we indicated before, in order to obtain a invertible model the solution with absolute value <1 is chosen.

The σ_ε^2 calculus is straightforward.

b) MA(2) model.

$$y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} \quad (3.8)$$

now the system of equations is:

$$\begin{cases} C_0 = (1 + \theta_1^2 + \theta_2^2) \sigma_\varepsilon^2 \\ C_1 = (-\theta_1 + \theta_1 \theta_2) \sigma_\varepsilon^2 \\ C_2 = -\theta_2 \sigma_\varepsilon^2 \end{cases} \quad (3.9)$$

is needed to find initial aproximate values. They can be obtain from the MA(1) model which can be solved analitically. From this model we have σ_ε^{2*} and θ_1^* , taking the third equation of (3.9)

$$\theta_2^* = -C_2/\sigma_\varepsilon^{2*} \quad (3-10)$$

and from the second:

$$\theta_1 = C_1/\sigma_\varepsilon^{2*} + \theta_1^* \theta_2^* \quad (3.11)$$

now σ_ε^2 can be recalculated with these new values

$$\sigma_\varepsilon^2 = C_0/(1 + \theta_1^{*2} + \theta_2^{*2}) \quad (3.12)$$

and a cycle can be built (3.10 $\rightarrow$ 3.11 $\rightarrow$ 3.12) until steady values of parameters and σ_ε^2 were encountered.

c) MA(m) model.

In the general case the system of equations is more complex

$$\begin{cases} C_0 = (1 + \theta_1^2 + \dots + \theta_m^2) \sigma_\varepsilon^2 \\ C_k = (-\theta_k + \theta_{k+1}\theta_1 + \dots + \theta_m\theta_{m-k}) \sigma_\varepsilon^2 \\ C_m = -\theta_m \sigma_\varepsilon^2 \end{cases} \quad (3.13)$$

we need also initial values to start the iteration. These are the σ_ε^2 and parameters, θ_i , $i < m$, values obtained in the order MA(m-1). The iterative process is:

$$\begin{cases} \theta_m = C_m / \sigma_\varepsilon^2 \\ \theta_{m-1} = C_{m-1} / \sigma_\varepsilon^2 + \theta_m \theta_1 \\ \theta_{m-2} = C_{m-2} / \sigma_\varepsilon^2 + \theta_{m-1} \theta_2 + \theta_m \theta_1 \\ \dots\dots\dots \\ \sigma_\varepsilon^2 = C_0 / (1 - \theta_1^2 + \dots + \theta_m^2) \end{cases} \quad (3-14)$$

that is to say, in order to solve the MA(m) model, we need to find initial values, which may be obtained from preceding orders and then the iterative process (3.14) is executed until steady values were encountered. It is not necessary to solve completely the previous orders, we are only looking for approximate solutions for setting the initial values and, only a few iterations are needed.

4. EXAMPLES.

Let us consider an ARMA (4.3) series directly generated, that is to say, proposing several parameters and taking a white gaussian noise of unity variance and zero mean, by the formula

$$y_i = \sum_{k=1}^p \theta_k y_{i-k} + \varepsilon_i - \sum_{l=1}^q \theta_l \varepsilon_{i-l}$$

in our case (see Figure 1) we take 4000 points from the series

$$y_i = 2.5y_{i-1} - 3y_{i-2} + wy_{i-3} - .7y_{i-4} + \varepsilon_i + .4\varepsilon_{i-1} + .5\varepsilon_{i-2} - .2\varepsilon_{i-3}$$

the AR values are calculated by the Yule-Walker equation, resulting

$$\phi_1 = 2.51 \quad ; \quad \phi_2 = -3.02 \quad ; \quad \phi_3 = 2.014 \quad ; \quad \phi_4 = -.7$$

the MA part is calculated using the previous iterative method

$$\theta_1 = -.396 \quad ; \quad \theta_2 = -.48 \quad ; \quad \varepsilon_3 = .213$$

and for the variance $\sigma_\varepsilon^2 = .997$ (Fig. 2).

The results, as can be seen, are very accurate. Other examples yield to similar results.

4. CONCLUDING REMARKS.

ARMA (p,q) modeling appears as a useful tool in many applications (5), in science, technical works and, in a particular form, in the domain of Power Plants.

The AR fitting is not difficult to obtain and, several procedures exist in order to do that (Yule-Walker, Kalman filter, etc.) (6). In the other hand, the MA part is more complex to get. It leads to the solution of non linear equations and although very powerful methods exist (4) they have several objections, since they requires a great amount of calculations and a big computer is needed, or the initial conditions must be elected very accurately.

The method here proposed is useful because its simplicity. With a few iterations a unique solution for the MA parameters is found and, in the other case, when this is not possible, it can be implemented with other methods as an aproximation to the initial conditions.

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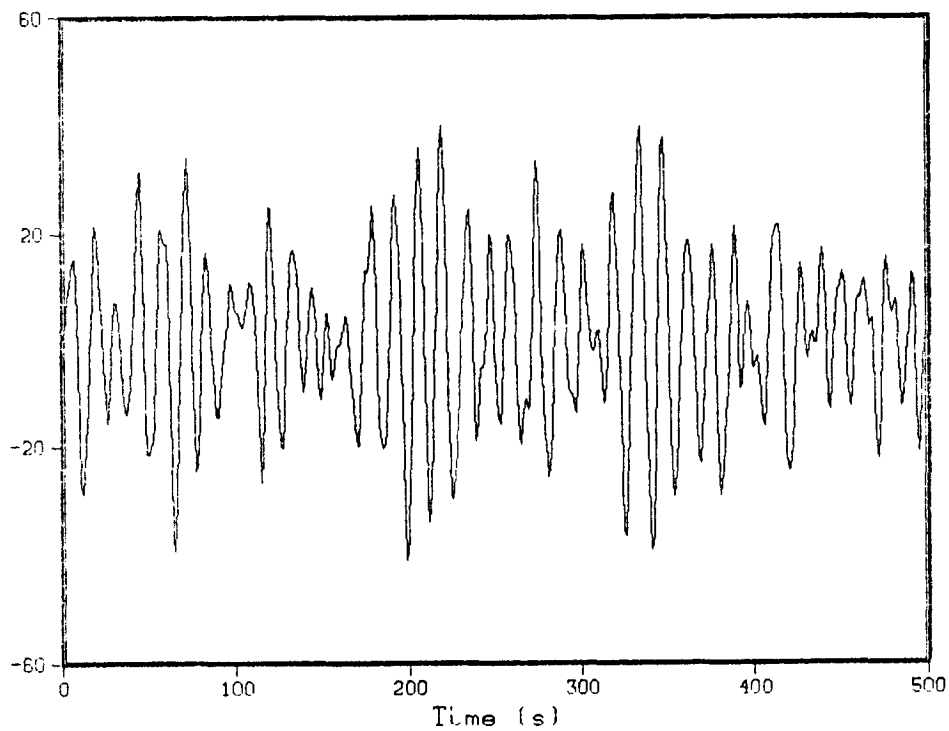


Figure 1. Computational ARMA(4,3) noise data.

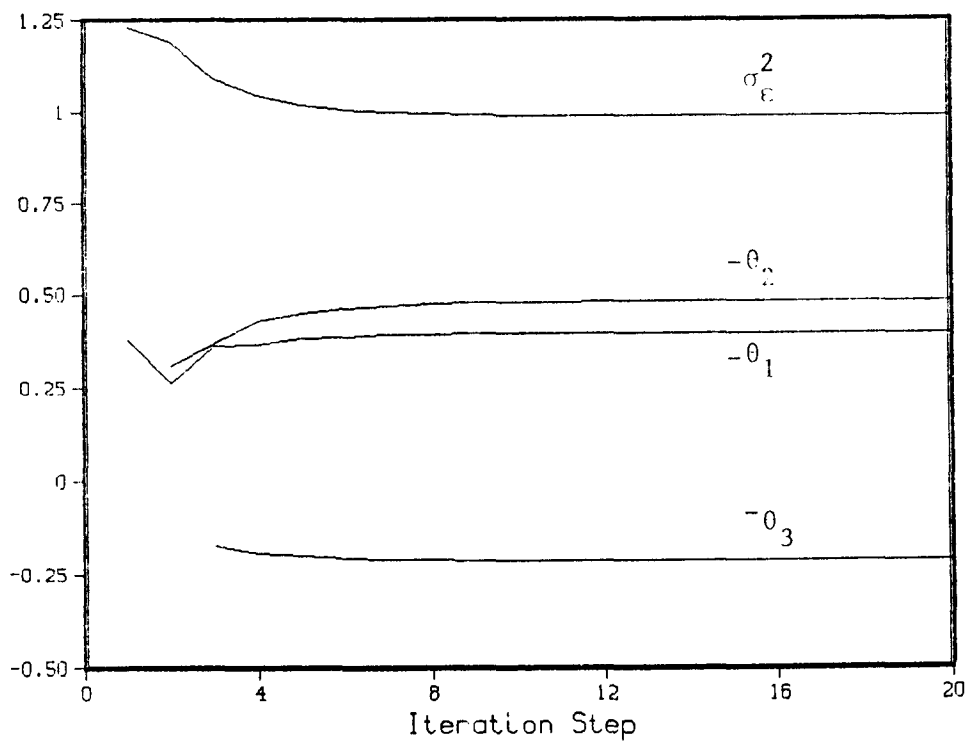


Figure 2. Evolution of MA parameters and variance with iteration step.

THE RESEARCH ON INCIPIENT FAILURE DIAGNOSIS FOR PWR USING NOISE ANALYSIS TECHNIQUE

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ABSTRACT

This paper presents the Research Program on PWR Incipient Failure Diagnosis sponsored by the NNSA and undertaken by the Diagnosis Research Group for Nuclear Power in the Nuclear Power Institute of China (NPIC). The items completed include the development of a computer-based 16-channel data acquisition/analysis system for noise signals, modelization of neutron detector response to vibrations of in-core components, calculation of scale factor for core-barrel motion and corresponding codes, and experimental studies on internals vibration and local boiling detection. The results obtained are summarized.

1. INTRODUCTION

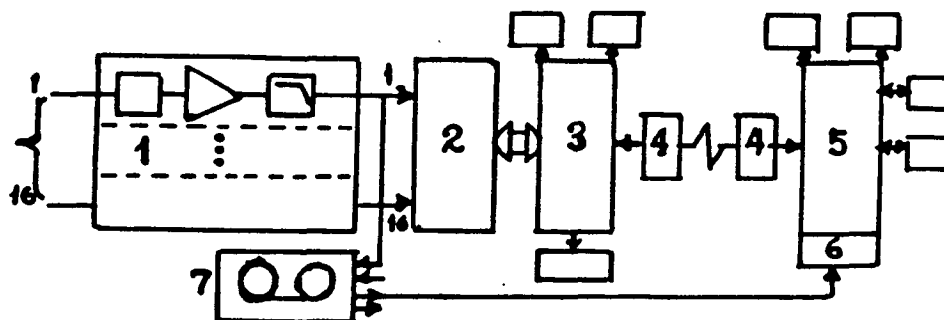
Along with nuclear power plant getting its beginning in China, we have shifted the goal of reactor noise to the applied research on diagnosis for PWR. A program on this purpose, sponsored by the National Nuclear Safety Administration (NNSA) in 1987, was undertaken by the Diagnosis Research Group for Nuclear Power in NPIC. The program includes the following items:

- Development of a computer-based 16-channel data acquisition/analysis system for reactor noise signals
- Theoretical aspects about the diagnosis of in-core component vibration and core-barrel motion
- Experimental studies on recognition of abnormal vibration of in-core components and on the detection of local boiling

Since there was no nuclear power plant operating in China by that time, we had set the experiments in laboratory conditions to test the data acquisition/analysis system and to verify the analytical model developed for abnormal vibration recognition of internals. In this paper, the main results obtained will be briefly presented.

2. DATA ACQUISITION AND ANALYSIS SYSTEM FOR REACTOR NOISE SIGNALS

A system was developed on the idea that an on-line, continuously operating, data acquisition/analysis system for reactor noise could be useful both in practical power plant surveillance in the future and in the diagnosis technique study in laboratory conditions. The hardware configuration of the system is shown in Fig.1.



1. Analog channels 2. Digitizer 3. IBM PC/286 4. Modulator/Demodulator
 5. VAX11/730 6. LPA11-K 7. Tape recorder

Fig.1 Hardware configuration of the data acquisition/analysis system

Each of the 16 channels consists of:

- An isolative amplifier for interfacing the channel with plant signal, which can effectively buffer the channel input from interference introduced on some sensor lines
- Automatic zero-stabilizer/amplifier for removing the DC component from the noise signal and for amplifying the signal to a appropriate level to fit the dynamic range of the A/D converter
- Low-pass filter for resistance to aliasing effect, with cut-off frequency from 0.1Hz to 20kHz, adjustable by computer command or by manual.

The digital portion of the system comprises the following units:

- A 12 bit-resolution, $\pm 5V$ dynamic, separate-clock timed and separate-powered, 16 channel simultaneously-sampling digitizer, in which 16 channels share one A/D converter by simultaneously-controlling 16 sample/hold circuits
- An IBM PC/286 micro-computer with 640KB RAM and 20 MB disk storage, which is used to control the sampling unit and to process the noise data at first level
- A VAX11/730 mini-computer, as host computer, with 2MB RAM and 40MB user disk storage, and equipped with VAX/VMS laboratory peripheral accelerator LPA11-K. this unit is utilized for controlling the system and analysing the data transferred from IBM PC/286.

The physical connection between IBM PC/286 and VAX11/730 is made by asynchronous communication interface, and the communication control is performed by the net-control software packet DECNET-DOS. The maximum communication distance is about 5 km.

In addition to digital data acquisition, a 7 channel (plus one channel for sound label) AF recorder of type RS 306 is used to record analog signals for resampling and analysis afterwards.

The data acquisition and analysis system is supported by three code packets:
 -SPCP, operating on the IBM PC/286, performs sampling control (to set up channels, sampling rate, data length and cut-off frequency of the LP filter) according to the user's commands, and calculates APSD, CPSD, COHERENCE and PHASE for selected channels. The SPCP can also be run at the host computer through the network;

- CACRTR, operating on the VAX11/730, is an expanded analysis code. Its function, in addition to that of SPCP, also includes digital filtering (LP, HP, or BP for specified cut-off frequency), and correlations, transfer function and probability distribution calculations;
- MNTR, operating on VAX11/730, performs the following tasks:
 - (1) Mean and variance calculations of time-sequent signals
 - (2) Calculation of PSD or CPSD calculation and their averaging for desired statistics
 - (3) Monitoring of PSD's trends using the statistical discriminators reported by Piety (Piety K.R. Progress in Nuclear Energy, 1, 781, 1977), and real-time screening of the trends on a color terminal VIL25
 - (4) Documentation both for routine operating and for abnormal informations.

3. MODELING OF NEUTRON NOISE INDUCED BY VIBRATING COMPONENTS IN CORE

Since it is difficult to mount vibration sensors directly on some components such as fuel assemblies and control rods in operating PWR, neutron noise analysis has become an attractive way to monitor the vibrations. Experience and calculations had shown that the vibrations of internals in PWR could be observed through their influence on the noise signals received by in-core as well as ex-core neutron detectors. The purpose of modeling is to establish the relation between the two physical phenomena, by which the data acquired from neutron detectors can be interpreted and some important vibration parameters may be estimated.

The force arising from coolant passing through the core can excite and sustain vibratory motion of fuel elements and control rods and of any other structure component. And the in-core vibrations influence the noise signals received by neutron detectors. For practical use, we considered the PSD of the vibration-induced neutron noise, taking the following assumptions:

- The force generated by turbulent flow of coolant is Gaussian, White noise;
- The displacement of vibrating component is so small that the vibratory motion can be referred to a linear system;
- The vibrating component perturbs the neutron field through Boltzman operator perturbed by the exchanges of the nuclear cross sections of the component and original medium in the region of motion. And the fluctuations of neutron flux around the stationary level can be treated by Langevin technique;
- If more than one driving source exist, the linear superposition theorem shall be followed.

With these assumptions, the following formulae were derived:

$$PSD = \sum_{i=1}^N \frac{P_{ii}}{Q_{ii}} + 2 \sum_{i=1}^{N-1} \sum_{m=i+1}^N \frac{P_{im} Q_{im} + G_{im} H_{im}}{Q_{im}^2 + H_{im}^2} \quad (1)$$

where N is the number of noise sources for different components or different modes; and

$$Q_{jm} = (\omega_{oj}^2 - \omega^2)(\omega_{om}^2 - \omega^2) + C_j C_m \omega^2 \quad (2)$$

$$H_{jm} = [(\omega_{oj}^2 - \omega^2) C_m - (\omega_{om}^2 - \omega^2) C_j] \omega \quad (3)$$

$$P_{jm} = \gamma_{jm} D_F^j D_F^m [Re(a_j) Re(a_m) + Im(a_j) Im(a_m)] \quad (4)$$

$$G_{jm} = \gamma_{jm} D_F^j D_F^m [Re(a_j) Im(a_m) - Re(a_m) Im(a_j)] \quad (5)$$

where ω_j and C_j are the characteristic angular frequencies and the dampings respectively; γ_{jm} is the correlation coefficient for vibration j and m ; D_F^j are the mean squares of the forces; and a_k are complex functions, defined as follows:

$$a_k = \sum_{j=1}^2 \int_{-1}^1 (-1)^{j+1} dv \int d\bar{\Omega} \phi^+ (B_M - B_C) \phi \quad (6)$$

where v is neutron velocity; $d\bar{\Omega}$ is the cubic angle element; B_M and B_C are the unperturbed Boltzmann operators evaluated at the original medium and at the component respectively; ϕ is the static flux at the perturbation location; and ϕ^+ is the solution of the detector adjoint equation in frequency domain:

$$\left(\frac{i\omega}{v} - B^+ \right) \phi^+ = \Sigma_d \quad (7)$$

where B^+ is the adjoint Boltzmann operator in frequency domain.

The a_k functions given by equation (6) are space- and frequency-dependent, and represent the response of neutron detector to vibrations of in-core components. To estimate the detection sensitivity, a_k can be computed using appropriate codes. But the computation of a_k is not often necessary, and we would rather take them as semi-empirical parameters. In fact, the a_k functions display a very weak frequency dependence comparing with Q_{jm} and H_{jm} given by equation (2) and (3) respectively, and it is a good approximation to consider a_k as constants in the narrow frequency ranges of peak K ($K=1, 2, \dots, N$). so we take the P_{jm} and G_{jm} , given by equation (4) and (5) respectively, as constants in the estimation of the vibration parameters for given detector

position and given components in the core. In this sense, we can apply equation (1) to fit the measured data of neutron detector PSD with ω_k, C_k, P_m, G_m as the parameters to be estimated and ω as the variable. It should also be noted that the cross-correlation coefficients between pairs of different components, for Gaussian, white forces, are negligible, and some of cross terms in the second part of equation (1) will vanish. But those between different modes of one component will still be retained.

In addition, for low frequency, we have the global reactivity contribution to the neutron PSD, modelled by the formula (March Leuba J. et al., Trans. Am.Nucl.Soc.39,951,1981)

$$PSD_o = b_o / [d^2 + (\omega + e)^2] \quad (7)$$

where b, d and e are the parameters which better fit the PSD in this frequency range.

The fitting of vibration-induced neutron noise PSD by the model given by equation 1 is to solve the following optimization problem:

$$S^2 = \sum_{i=1}^L W_i [PSD_i^e - PSD(\omega_i, B)]^2 = \text{minimum} \quad (8)$$

where PSD_i is the value of measured PSD at frequency ω_i ; and $PSD(\omega_i, B)$ is that of calculated by the model with the parameters given by vector B ;

$$B = (b_k) = (b_o, d^2, e, p_{ii}, p_{im}, G_{im}, C_i, W_{oi}) \quad (9)$$

$$k = 1, 2, \dots, 3 + N(N+2)$$

$$i = 1, 2, \dots, N \text{ for } P_{ii}, C_i, \omega_{oi}$$

$$i = 1, 2, \dots, N-1; m = i+1, \dots, N; i \neq m \text{ for } P_{im}, G_{im}$$

For this purpose, two codes MFIF and NPSDFT were compiled. The code MFIT was used to estimate the initial values of the parameters for code NPSDFT by profiling the measured PSD on screen. And the NPSDFT is a hybrid global optimization code which combines random searching, space narrowing, the strategy of changed domain, and local optimization algorithm in a optimum way. The MFIT/NPSDFT show a good numerical stability and fast convergence in PSD fitting.

4. COMPUTATIONS ON CORE BARREL

It is well known that for the beam mode of core barrel vibration the neutron signal PSDs from two opposite-placed ion chambers display a high coherence and a 180 difference in phase, and provide a convenient way for the recognition and diagnosis of failures of core-barrel as well as its structures. In order to establish quantitative relation between neutron noise and the rms-amplitude of barrel motion, a coefficient, SF, known as scale factor for frequency domain analysis, was introduced.

To compute the SF, a special code, DTF7, had been developed. The DTF7 uses 1D transport code to compute the source term and P1S4 approximation to compute neutron attenuation. The SF for a typical PWR (Xue, Y.W et al., Nucl.Sci., 20(2), 81, 1983) was computed by the code DTF7, and obtained $SF=1.497(\%mm^{-1})$

Furthermore, a finite element code was compiled and was used to compute the vibration modes of core-barrel for frequency identification. This computation will be useful for the shell mode vibration recognition when neutron noise is applied for barrel monitoring.

5. EXPERIMENTS

According to the demand of the research program, we had conducted two experiments with the purpose:

- to test the newly-developed data acquisition and analysis system;
- to verify the theoretical model and codes; and
- to gain knowledges on incipient failure diagnosis by noise analysis

5.1 Experimental Research on Vibration Monitoring of In-core Components by Neutron Noise

The experiment was carried out on a U/H₂O critical assembly containing 1584 fuel elements in 36 fuel assemblies each of which contains 44 elements and is 72X72(mm) in dimension. The diameter of the fuel element is 8mm, and the enrichment of ²³⁵U is 3%. The control rod used is Cd-Ag-In rod of 14mm in diameter. Both the fuel assembly and the control rod at desired position can be excited by a PR9270 10kg exciter through a pre-tightened spring and coupling structures. White Gaussian as well as pink Gaussian force and/or periodic exciting forces were used to simulate the forces arising from coolant passing through a power reactor core.

The signals from 4 channels including 3 neutron ion-chambers (2 in the reflector and one in the core) and a accelerometer mounted on the vibrating component were sampled and analyzed by means of the data acquisition/analysis system mentioned in section 2.

50 sets of measurements for different core arrangements and different driving forces had been conducted. The data were analyzed in frequency domain. Also, the vibration parameters, including amplitudes, frequencies and dampings were estimated by fitting the measured neutron PSDs using the theoretical model introduced in section 3. Some typical results will be given in this section.

- Neutron noise response to component vibration

Fig.2 shows the PSD and the coherence between the neutron detector and the accelerometer from measurement #11, in which the fuel assembly was excited by a 16 Hz periodic force. It can be seen that besides the peak at the driving frequency, 16Hz, another peak of about 8Hz which is the half-frequency harmonic appears. The high coherence confirms that the peaks in neutron PSD are caused by the vibrating assembly.

In measurement #42, the assembly was driven by a mixture of periodic force of about 27Hz and pink Gaussian force. The PSD of neutron detector and the coherence between neutron and accelerometer signals are shown in Fig.3. Two evident peaks at 7.3Hz and at 27.0Hz are observed, which correspond to the characteristic frequency of the assembly and the frequency of the periodic force respectively.

To study the response of neutron detector to fuel element rod vibration, in measurement #58, we introduce white force to a fixed fuel assembly. Fig.4 shows the result obtained in this condition. It is evident that the neutron PSD gets peaked in a wide range of about 200-700Hz while the higher coherence in this range appears. Fig.5 gives the accelerometer spectra of fuel rods in the condition of white force exciting, which shows a coincidence with the coherence in frequency range.

The measurements for vibrating control rod give similar results that the PSDs of neutron detector show evident response to the vibration of control rod.

- Estimation of the vibration parameters

The analysis in frequency domain shows that the existence of in-core components vibrations can be detected by neutron noise. For the purpose of incipient diagnosis, however, more informations about vibrations are needed. To estimate the vibration parameters, the theoretical model introduced in section 3 was used to fit the measured PSDs, so that characteristic frequencies, corresponding amplitudes and dampings were obtained. This task was carried out by means of the codes MFIT and NPSDFT. Some typical results are summarized in table 1. The comparison between the vibration amplitudes from neutron PSD fittings and those from accelerometer measurements are given in Fig.6. Fig.7 and 8 are the examples of the fitting curves. The deviations in Fig.6, come from both the neutron PSDs and the accelerometer measurements. In PSD computations the data were weighted by a Hanning window and averaged for 36-48 blocks, so that the statistical error was about 12-14 percent. Besides; the directly-measured amplitudes obtained from the amplified and double-integrated signals of accelerometer also introduced some uncertainties.

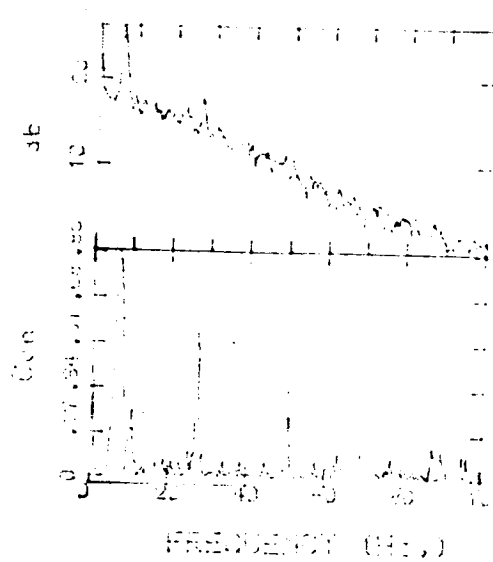
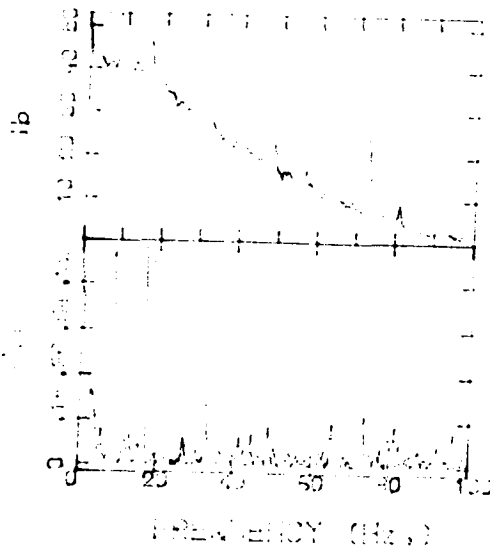


Fig.2 Data plot of measurement #11 Fig.3 Data plot of measurement #42

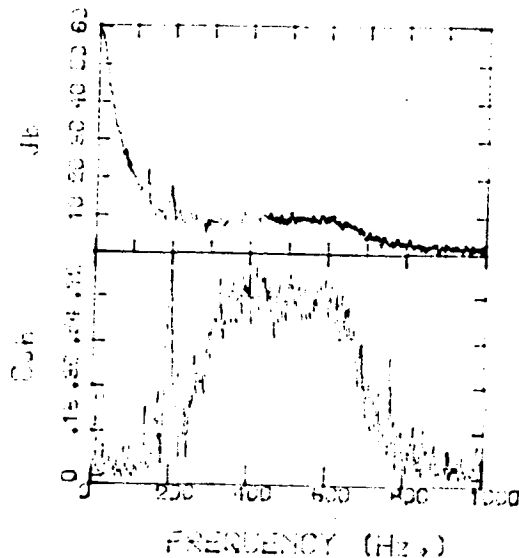


Fig.4 Data plot of measurement #58

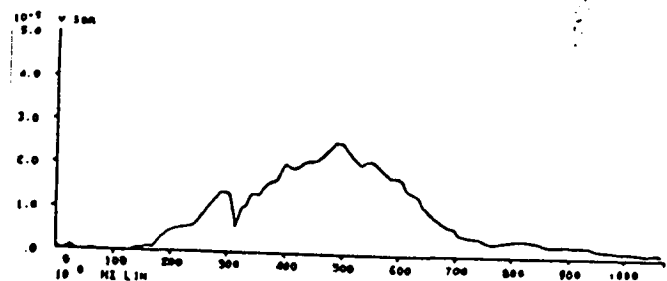


Fig.5 Accelerometer spectra of fuel rods excited by white force in water

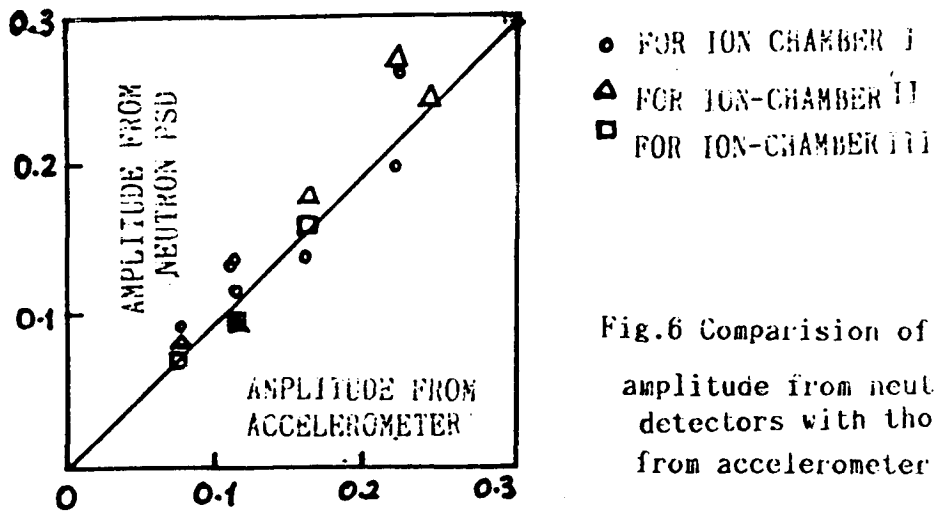


Fig.6 Comparison of the amplitude from neutron detectors with those from accelerometer

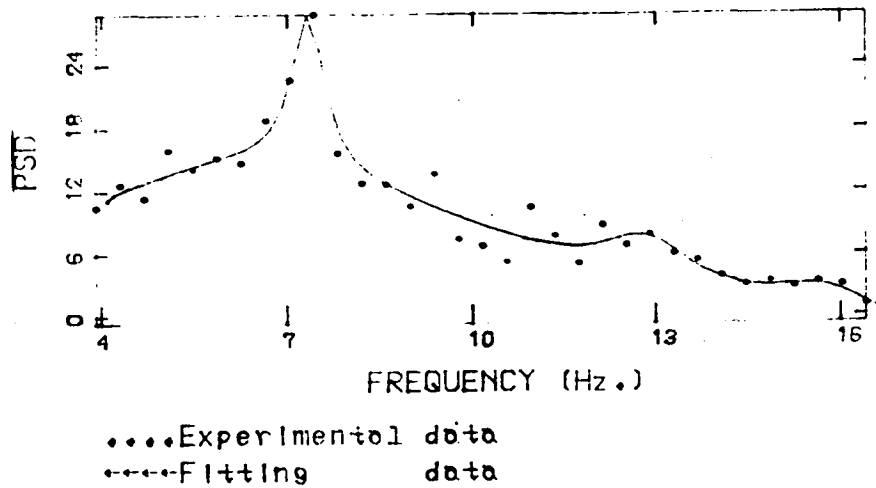


Fig.7 Model fit to the neutron PSD from measurement #06

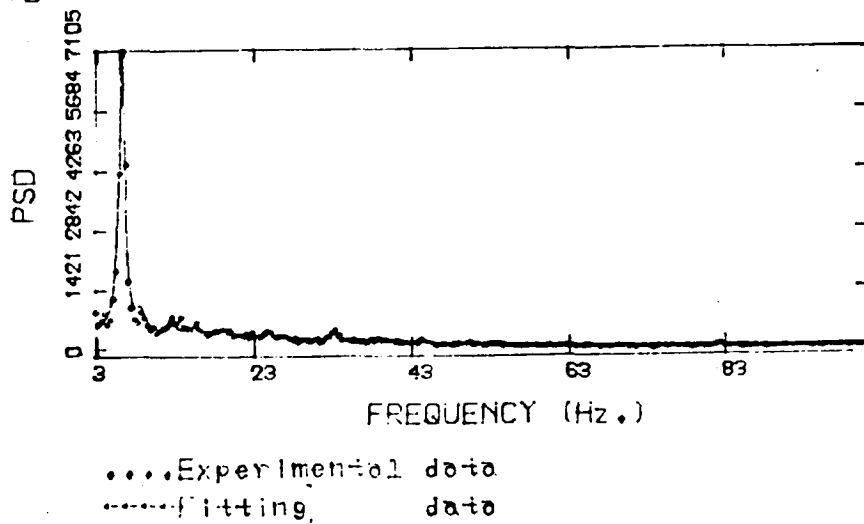


Fig.8 Model fit to the neutron PSD from measurement #47

Table 1. Vibration parameters from neutron PSDs

	First Mode		Second Mode	
	f (Hz)	C	f	C
Fuel Assembly	6.90	4.91	14.70	5.49
Control rod	11.54	9.76	21.58	6.83

* $C = \frac{1}{M}$, = damping force, M =Mode Mass

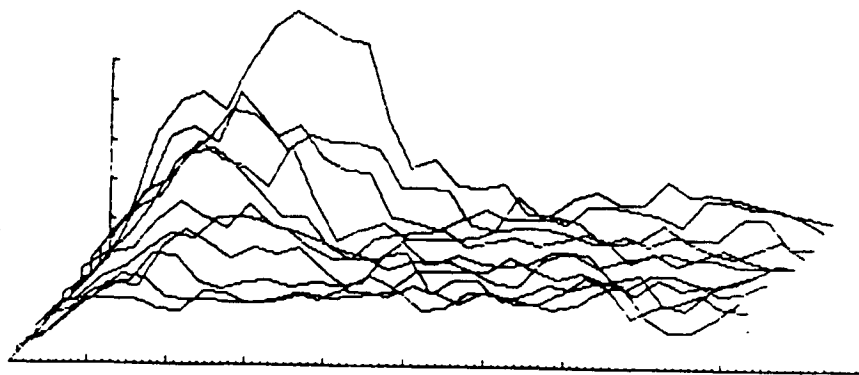
5.2 Simulated Experimental Study on Local Boiling Detection by Neutron Noise

In PWR, onset of local boiling which might develop to film-boiling under advanced conditions, can lead to superheated fuel surfaces and may result in a local burn-out situation. Therefore the monitoring of local boiling scale is a safety-related problem. To study local boiling detection by neutron noise, we conducted a simulated experiment on the U/H₂O critical assembly described in above section. A pressurized N₂ system was used to inject gas bubbles into the core quantitatively, and the bubble flow rate was adjustable from 0 to 160 ml/s. Neutron noise signal were measured and analyzed using the data acquisition/analysis system presented in section 2. PSD calculations were carried out by the code CACRTR and the Piety's discriminator trend monitoring was performed using the code MNTR.

The experimental results show that the detectors both in- and ex-core have evident responses in the range below 5Hz. This can be clearly seen from the spectrum series in Fig.9 where the horizontal axis represents frequency while the deep direction and the vertical axes are the bubble rate introduced and the PSD amplitude respectively. the Piety's discriminators vs. bubble rate are shown in Fig.10.

It is also observed that the in-core detector has also a distinct response to the bubbles in the range of several hundred hertz. Fig.11 shows the spectrum series drawn in this frequency range. The peaks of amplitude increasing with bubble rates appear in the range of about 400 to 480Hz. The Piety's discriminators vs. bubble rate are shown in Fig.12. To investigate this behavior, we set an additional experiment in which the fuel rod vibration excited by gas bubble flow was measured, and the accelerometer spectra showed a coincidence with the peaked frequency region of the neutron PSDs. So we can owe the behavior of the neutron PSDs in this frequency range to the local neutron flux perturbations caused both by the bubbles themselves and by the bubble-excited vibrations of fuel rods.

Furthermore, correlation analysis between some discriminators and bubble rate were made using suitable statistic models which fit the data best. Most of the correlation coefficients are better than 0.98.



PLOT OF PSD vs. N_2 , DET. 1, $N_2=0-10$ L/M, $FC=10$ HZ, $DF=0.32$ HZ, $F=0-10$ HZ

Fig.9 Neutron PSD series from bubble experiment
out-core detector, 0-10Hz

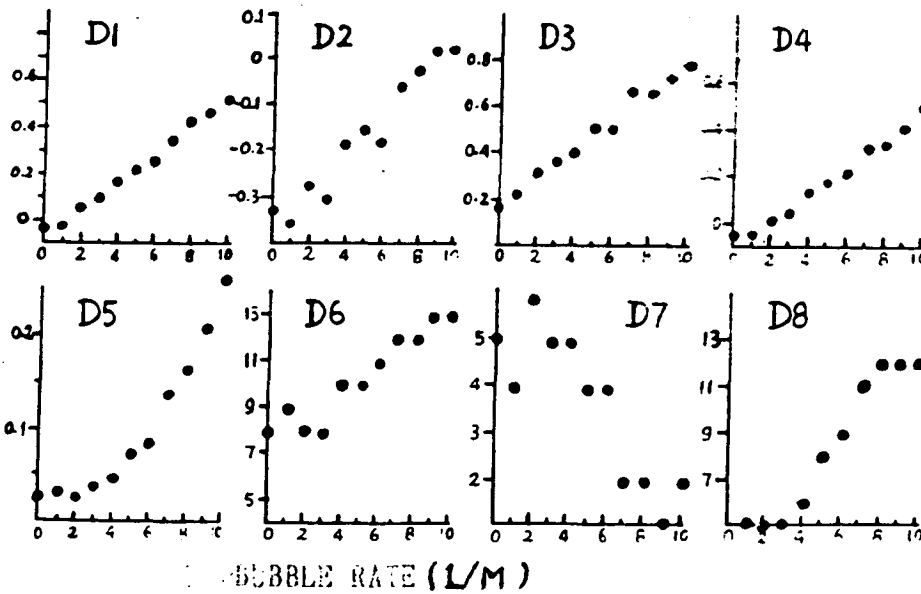
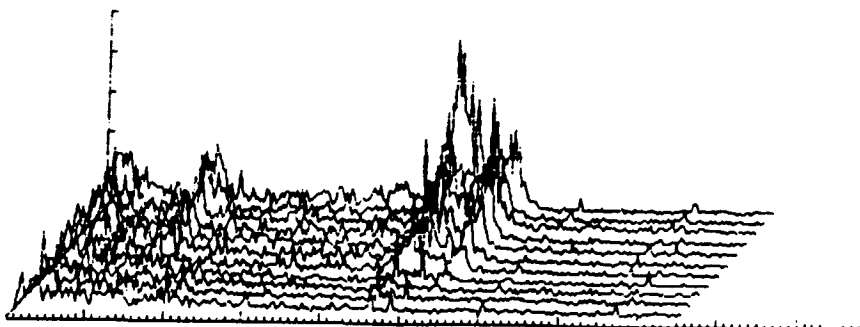


Fig.10 Piety's Discriminators vs. the bubble rate, ex-core detector, 0.3-4.4Hz



PLOT OF PSD vs. N_2 , DET. 1, $N_2=0-10$ L/M, $SR=2000$ HZ, $DF=1$ HZ, $F=300-600$ HZ

Fig.11 Neutron PSD series from bubble experiment.
in-core detector, 300-600Hz

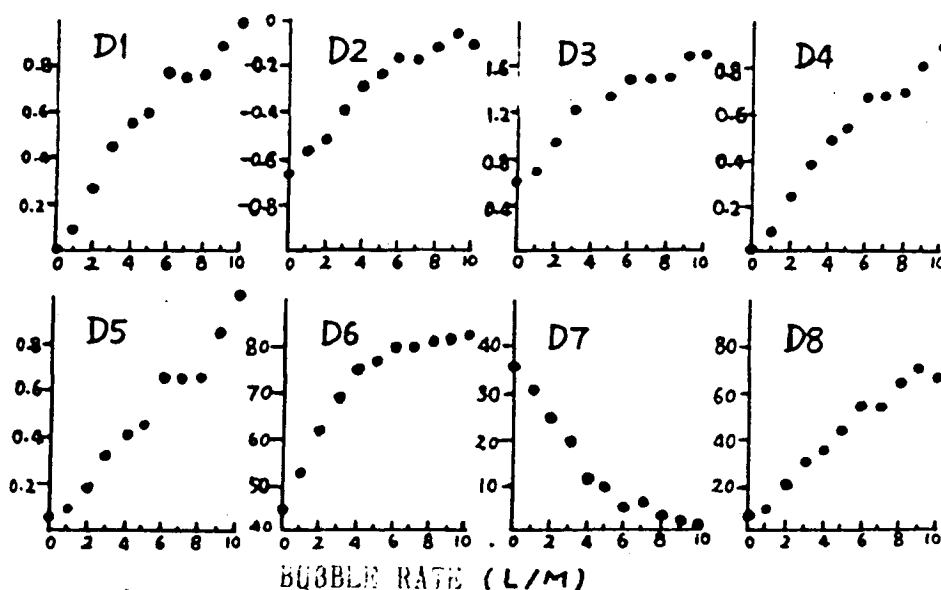


Fig.12 Piety's Discriminators vs. bubble rate, in-core detector, 400-430Hz

6. CONCLUSIONS

Summarizing the results achieved in the research program, we draw the following conclusions:

- The hardware as well as the software of the data acquisition/analysis system developed can meet the requirements of reactor system noise signal sampling and analysis.
- The simulated experiment for the vibrations of in-core components show that not only the onset of abnormal vibration can be detected by neutron noise, but also the important vibration parameters including characteristic frequency, damping and amplitude can be quantitatively estimated by fitting the measured neutron PSD using the analytical model introduced in section 3. This will be useful for incipient failure diagnosis.
- The simulated boiling experiment confirms that neutron PSD has distinct response to the appearance of bubbles in core, and that suitable statistic model can be found to describe the response for a given core arrangement and detector position. Therefore, the scale of boiling may be estimated. With additional information of linear phase dependence of the PSDs from vertically-distributed neutron detectors, onset of local boiling may be recognized. So we can expect neutron noise analysis to be useful to the thermal pipe surveillance for PWR.

The research had been performed in laboratory conditions. In PWRs, practical conditions are much more complex. Nevertheless, we believe that the results obtained will be helpful for the development of pragmatic diagnosis system for PWR in the future.

NEUTRON NOISE SURVEILLANCE IN INET TEST HEATING REACTOR

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ABSTRACT

A neutron noise surveillance system was installed in China INET Test Heating Reactor and has been operated since Nov. 1989. In the present paper, the surveillance system, identification about the mini-vibration of the hydraulic-driving control rods system, and an algorithm for onlined BWR stability monitor are described.

KEYWORDS

Reactor Noise, Stability, Control Rod, Vibration

INTRODUCTION

A Test Heating Reactor (THR) had been operated in the Institute of Nuclear Energy Technology (INET) of Tsinghua University of China during the winter of 89-90. In this reactor, the whole primary loop with natural circulation is placed in a vessel at a rating pressure of 1.47 MPa and used for district heating. Chief parameters and structure of the reactor is given in Table 1 and Fig.1. Two of the operational manners were designed, a, the PWR manner with 12°C core exit subcooled temperature; b, low steam quality BWR manner with 25% core exist void fraction. Thermohydraulic analysis and experiment had shown that the BWR manner was probably associated with the low steam quality BWR stability. Therefore two assemblies of self-powered neutron detectors were inserted in the core for monitoring the BWR stability and other operational faults.

Table 1, Parameters of 5 MW THR

	PWR	BWR
Thermal Power (MW)	5	5
Pressure of Reactor (MPa)	1.47	1.47
Core Inlet Temperature (°C)	147	186
Core Exit Temperature (°C)	186	198
Core Height (M)	0.69	0.69
Chemney Height (M)	2.31	2.31
Core Flow (Kg / s)	29	75

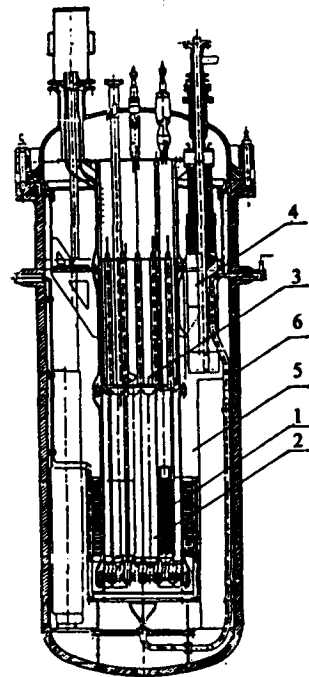


Fig.1, 5MW Test Heating Reactor
(1,Fuel Element 2, Core 3, Chemney 4, Heat
Exchanger 5, Downcomer 6, Pressure Vessel)

NEUTRON NOISE SURVEILLANCE SYSTEM

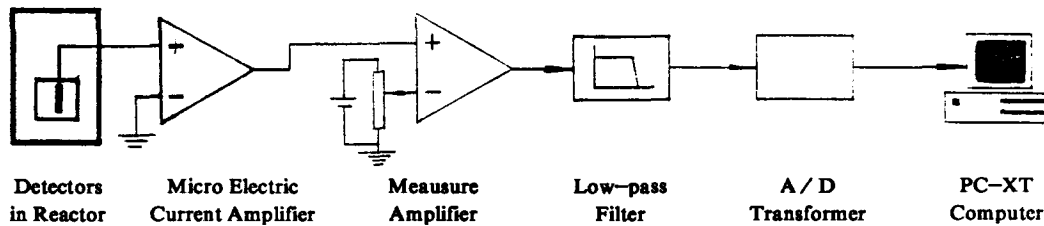


Fig.2 Neutron Noise Surveillance System in 5MW THR

As illustrated by Fig.2, the neutron noise surveillance system was made up by parts as follows:

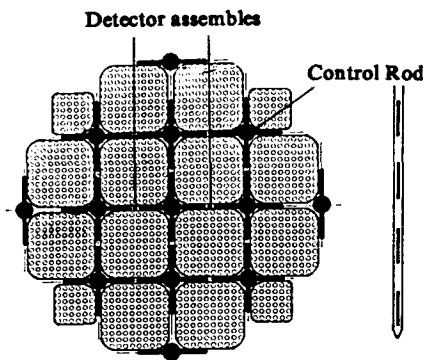


Fig.3, Location of Detectors

- Two assemblies of cobalt self-powered neutron detectors were located between the fuel element boxes as Fig.3. Each of them were installed by four detectors of 112mm length and 2.5mm diameter along core height. The detectors are fast response.
- Low-noise transportation cables and signal amplifiers.
- A / D transformers and a PC-XT computer.

Through the careful work on signal filtering, power supplying, grounding, shielding, etc., the background noise of the system was effectively lowered. The system had been operated since Nov. 1989, and the noise data been recorded in diskettes during the different period.

IDENTIFICATION OF THE MINI-VIBRATION IN HYDRAULIC-DRIVING SYSTEM OF CONTROL RODS

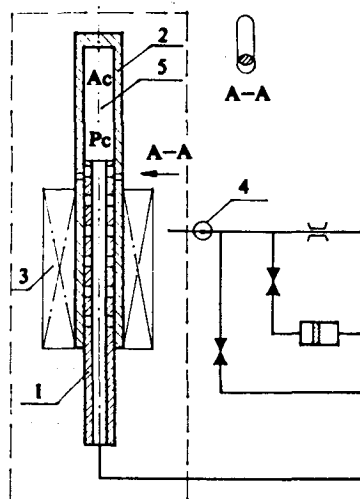


Fig.4. Control Rod System
(1, Inner Tube 2, Outer Tube 3,
Absorber 4, Pump 5, Hydraulic Cylinder)

5 MW THR is the first reactor to use hydraulic system for driving control rods in the world. As illustrated in Fig.4, the system consists of an inner tube, outer tube and neutron absorber. The fixed inner tube has several rows of long round holes and the movable outer tube has a row of round holes. The absorber is fixed to the outer tube. Like a float meter, a certain flow is corresponding to a defined equilibrium position of outer tube. After injecting a flow impulse, the outer tube is moved a distance between two rows of holes relative to the inner tube and step movement of control rods is realized in order to control fission reaction. The excellent operation and safety features were demonstrated by lots of experiments about this system.

During the PWR operation of 5MW THR in 1989-1990, a 17 HZ resonance was found in total auto power spectral density (APSD) diagrams of the noise at different operating powers and detectors, as shown in Fig 5 and Table 2, where the APSD is calculated by the parameter spectral method of Burg AR series and of a 5ms sampling time step, 1000 data length which is averaged 6 times.

The same resonance was also found by using different spectral calculating methods, sampling time steps and data lengths.

Table 2. Frequences of Reasonce

Time	Power	Peak Frequency
Dec.17,1989	5MW	17.2HZ
Dec. 20,1989	5MW	16.4HZ
Feb. 26,1990	3MW	17.7HZ

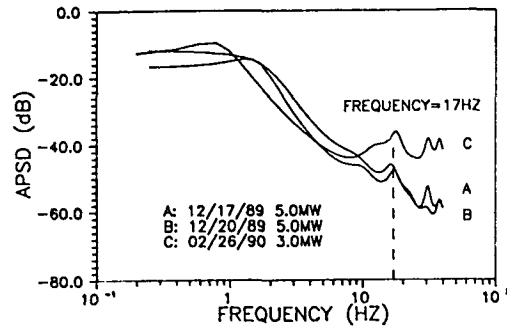


Fig.5, Auto Power Spectral Density of 5 MW THR Noise
(A2 Detector, Sampling Time Step= 5 ms, 6 × 1000 Data)

In order to identify the source of the reasonce, the hydraulic-driving system of control rods was studied. Since of the exciting of physical noise such as fluctuation of water flow, the floating outer tube and neutron absorber is of a mini-vibration that can't been found by sight around an equilibrium position and then the mini-vibration of neutron flux is driven. The equation of motion can be written as the following differential equation:

$$M \cdot \ddot{X} = Pc \cdot Ac + M \cdot g \cdot \frac{\gamma_w}{\gamma_t} - M \cdot g - Rm \cdot \dot{X} \quad (1)$$

where M is the mass of outer tube and neutron absorber, Pc the pressure of the cyclinder, Ac the inner area of outer tube, Rm the friction coefficient between the outer and inner tubes, γ_w the density of water, γ_t the density of outer tube and neutron absorber, x the position of outer tube.

Under a constant pressure drop of the pump, take a fluctuation around the equilibrium position:

$$x = x(0) + \delta x \quad (2)$$

a second order linear differential equation describing the mini-vibration of control rods is induced. The frequency of the mini-vibration f_c is arrived through the characteristic equation, as indicated by Fig.6. It shows that the f_c decreases when the flow of the system increases and is varied between 8–20 HZ under the operational range of the system.

The rating flow of the hydraulic-driving control rod system is 0.8 ton / hour per control rod. Since the control rods are of prior importance for the operation and safety of the reactor, we can not observe directly the drift of reasonce by changing the flow in 5 MW THR for further demonstration of the source, an experiment on a 1:1 outer reactor facility was performed. The pressure in hydraulic cyclinder was recorded by considering the measuring difficulty for the position of outer tube. The frequencies of reasonce in the two singals are identical since the system is linear. The recorded parameter spectrum is indicated in Fig.7, a reasonce of 17 HZ is existed, where A curve is the response of a step pertubation of control rod while B is the noise without any pertubation. On the right of the 17 HZ reasonce there is background noise since their energy were lowered relatively after pertubation. On the left of the 17 HZ reasonce, there is a reasonce which are referred to be caused by the pressure sensor and the measure system during the construction and experiments of the system.

Through changing the flow of the system, drift of the 17 HZ reasonce was measured, as shown in Table 3. Similar to the results of theoretical calculation, the frequency of reasonce decreases as well as the flow increases, but the same drift of the left reasonce was not observed. The results of reactor, outer reactor facility and theory are illustrated in Fig.6, their agreements are found in spite of the difference between the test and theory since of uncertainty of the resistant coefficients.

Since the mini-vibration frequency of the control rods indicates the status of parts in whole control rods driving system such as pump, flow pipe and hydraulic cylinder, the surveillance of abnormality of the frequency by neutron noise is helpful to early discovery of the faults of the system and valuable to the safety and operation of the reactor.

Table 3. Frequency of Reponse in Outer Reactor Facility

FLOW(T / h)	UPWARD			AVERAGE	DOWNWARD			AVERAGE	TOTAL AVERAGE
	FREQUENCY (HZ)	FREQUENCY (HZ)	FREQUENCY (HZ)		FREQUENCY (HZ)	FREQUENCY (HZ)	FREQUENCY (HZ)		
0.64	18.0,	18.0,	18.0	18.0	17.2,	17.2,	18.0	17.5	17.8
0.80	18.7,	18.0,	18.0	18.2	18.0,	18.7,	18.1	18.5	18.4
1.00	15.6,	15.6,	15.6	15.6	14.8,	14.8,	14.8	14.8	15.2
1.18	14.1,	14.1,	14.1	14.1	13.3,	13.3,	13.3	13.3	13.7
1.40	10.2,	10.2,	10.2	10.2	10.9,	10.9,	10.9	10.9	10.6
1.60	7.8,	7.8,	7.8	7.8	7.8,	8.6,	7.8	8.1	8.0

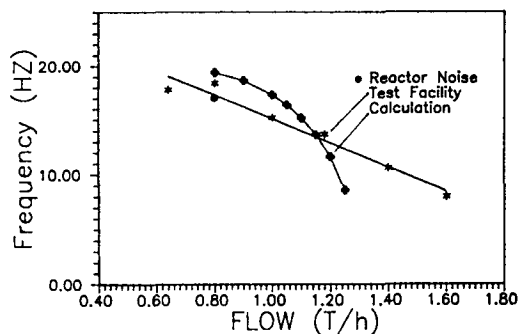


Fig.6 Frequency of Mini-vibration of Control Rods System

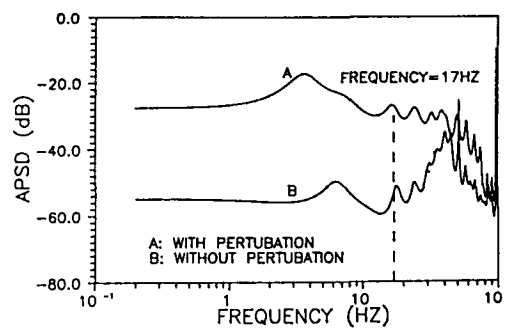
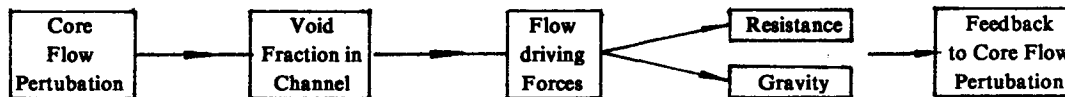


Fig.7 Auto Power Spectral Density of out Reactor Test

BWR STABILITY MONITOR

BWR stability is referred to the two phase flow density wave oscillation generally, it is excited in a chain as follows:



Frequency: 0.1-1HZ

Fig.8. Mechanism of BWR Stability

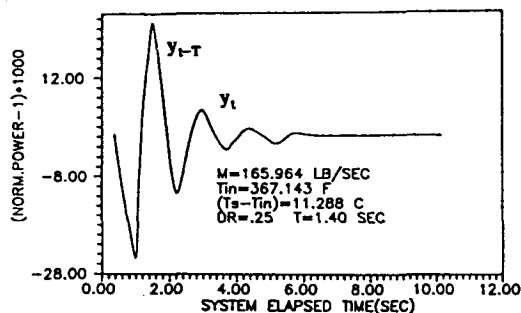


Fig.9 Normal Power of 5MW THR Rating Operation after Perturbation

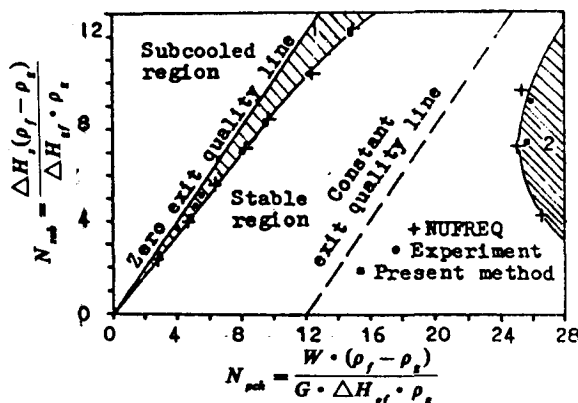


Fig.10 Stability Diagram of 5 MW THR

Different from the general BWR stability excited by resistance, the BWR stability of 5MW THR is excited by gravity and occurred in low pressure and low steam quality region. Experimental and theoretical research about this type instability had been performed in INET. In Fig.9, the impulse response of power at rating operation is shown by using the thermohydraulic code. The stability boundary map coming from the experiment and calculation is illustrated in Fig.10, Where W is power, G core flow, ΔH_s core inlet subcooled enthalpy, ΔH_{gr} potential enthalpy, ρ_g, ρ_l density of gas and liquid. The results have demonstrated the excellent stability of 5 MW THR rating operation. It is also found that the decay ratio of the system decreases when core inlet resistant coefficient or operation pressure increases, or riser height decreases.

The parameter to describe stability of a system is decay ratio DR defined as belows:

$$DR = \frac{y_{t-\tau}}{y_t} = e^{-2\pi\zeta/\sqrt{1-\zeta^2}} \quad (3)$$

where ζ is damping ratio. The reported decay ratio estimating methods may be classified as follows:

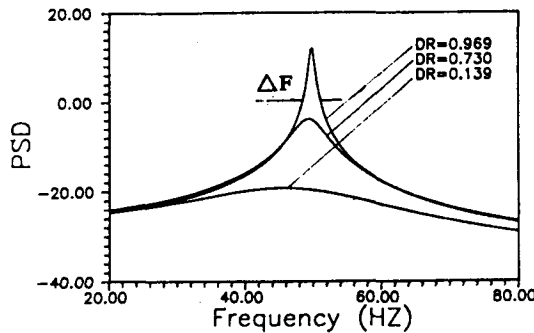
a, Impulse Response Method The method is unable to calculate the DR with a sufficient accuracy if low frequency parts of signals are existed.

b, Characteristic Roots Method The decay ratio is induced from the roots of characteristic equation as follows:

$$Z^n + a_1 \cdot Z^{n-1} + a_2 \cdot Z^{n-2} + \dots + a_n = 0 \quad (4)$$

where, $a_1, a_2, \dots, a_n$ are AR parameters. Accuracy of the method should be the best one in all of DR estimating methods if the structure of the system analysed such as AR order is known and limited only by the accuracy of AR modeling method. However, the order of the system is difficult to know exactly and then the method is not very useful in practice.

c, The method Based on PSD Diagram The extended bandwidth (EBW) method is one of them. A real second order system is of different PSD shape with respect to different DR, as shown in Fig.11. The PSD of a second order system can be written as:



$$PSD[y] = \frac{\sigma^2}{(\omega^2 - \omega_r^2)^2 + \omega_0^4 - \omega_r^4} \quad (5)$$

It reaches maximum when frequency $\omega = \omega_r$. The $1/k$ peak should meet:

$$\frac{\sigma^2}{k(\omega_0^4 - \omega_r^4)} = \frac{\sigma^2}{(\omega^2 - \omega_r^2)^2 + \omega_0^4 - \omega_r^4} \quad (6)$$

defines the bandwidth ΔF ,

$$\Delta F = 2(\omega^2 - \omega_r^2) \quad (7)$$

Fig.11 PSD Diagram at Different Decay Ratio

and parameter

$$\lambda = \frac{\omega_0^4}{\omega_r^4} - 1 = \frac{1}{(1 - 2\zeta^2)^2} - 1 \quad (8)$$

we have:

$$\lambda = \frac{1}{(k-1) \cdot \omega_r^4} \left(\frac{\Delta F}{2} \right)^2, \quad \zeta = \sqrt{\frac{1}{2} \left(1 - \sqrt{\frac{1}{1+\lambda}} \right)} \quad (9)$$

From the PSD diagram, the bandwidth ΔF of $1/k$ peak can be measured and the parameters λ and ξ of 9 be calculated, then the DR be reached finally. That is the so called EBW method. The method is practice since of its good fitness and sufficient accuracy.

However, in practice a second order resonance is frequently modeled by more than two of AR roots, an example is a PSD diagram in Fig.12 which comes from the computer synthetic data under defined parameters. A defined 50 HZ resonance is fitted by four of AR roots at frequencies of 44 HZ and 58 HZ. The parameter spectrum of 50 HZ resonance is not an exact second order loop and then the decay ratio at different resonance peak $1/k$ is different according to the EBW method. Table 4 is the results of EBW method for the spectrum of Fig.12.

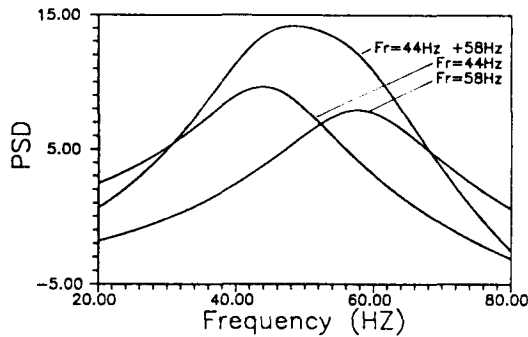


Table 4. Results of EBW Method at Different Peak Height

i	k_i	λ_i	ξ_i
1	1.3862	0.2186	0.2169
2	1.9217	0.1834	0.2009
3	2.6639	0.1530	0.1853
4	3.6928	0.1288	0.1714
5	5.1192	0.1099	0.1594
Average		0.1588	0.188

Fig.12. A Resonance is modeled by 4 Roots of AR Series

In another aspect a resonance is probably covered by various litter resonances due to background noise. Therefore the method that only the information on a defined peak height is used will not be very suitable and the method that the information of whole resonance is used should be noticed. Two of the ways are as follows:

- In a defined frequency bandwidth the resonance are fitted by least square method. The method should consider a way to prevent nonlinear algorithm. The calculation test showed that the method is of great dependence to the defined bandwidth of frequency.
- Average of results of EBW method at different peak heights. As shown in Table 4, the damping ratio of average is 0.188, very close to the exact one 0.190.

In order to make the method robust in practice, the latter method is used. Because a selected resonance is frequently perturbed by other resonance at different frequency, an operation to reform the selected resonance only is used. The whole algorithm in our stability monitor is as follows:

- AR modeling by using Burg method and AIC.
- Searching the characteristic roots in a defined frequency bend from AR parameters.
- Reforming a PSD diagram using the searched characteristic roots.
- Average of several EBW results.
- Displays.

Table 5 is the results of verification by AR (2) synthetic Data. The results of characteristic roots method is considered as an exact value since it is of the greatest accuracy at a known order.

Table 5. Verfication by AR(2) Synthetic Data

	1	2	3	4	5	6	7
DR defined	0.969	0.939	0.730	0.531	0.277	0.139	0.064
DR* by Characteristic method	0.960	0.939	0.749	0.553	0.296	0.149	0.076
DR by the method presented	0.960	0.939	0.749	0.553	0.296	0.160	0.082

ARMA (5,4) synthetic data is generally modeled by a long order AR series. In Fig.13, the results of decay ratio under

different orders demonstrated that the AIC criterion is suitable to estimate the AR order and robust 2-3 orders around the order by AIC. Table 6 is the results at different decay ratio by using AIC. It showed that good agreements is existed if $DR > 0.2$. Since the stability of a system in which $DR < 0.2$ is very good, the bias of DR is not of importance for the practice surveillance of stability. The same results were mentioned too.

Table 6, Verification of ARMA(5,4) Synthetic Data

	1	2	3	4	5	6	7
Exact DR *	0.969	0.939	0.730	0.531	0.277	0.139	0.069
DR Presented	0.965	0.933	0.731	0.528	0.300	0.203	0.191

A monitor that is able to sample, calculate, and display automatically has been completed and should have a further verification in reactor once our test reactor enters the BWR operation. Its display is shown in Fig.14.

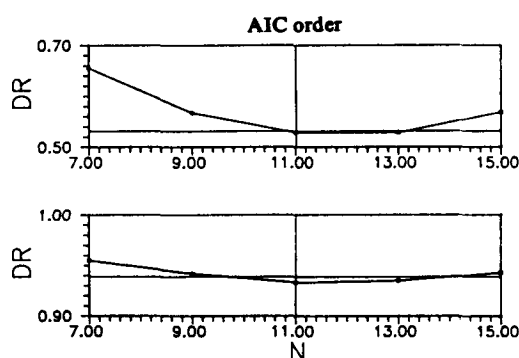


Fig.13. Decay Ratio at Different AR Orders

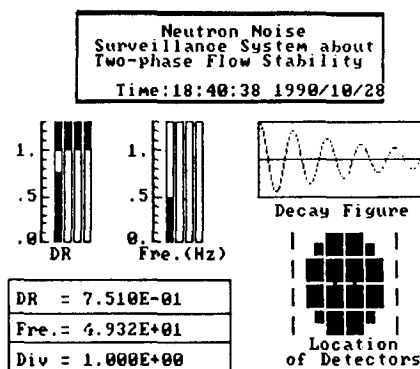


Fig.14. Terminal Display of Onlined Stability Monitor

CONCLUSIONS

- 1) Two assemblies of cobalt self-powered neutron detectors were installed in the core of INET THR and consist of a neutron noise surveillance system with signal amplifiers, A/D transformer and a PC-XT computer. The system has been operated since Nov. 1989.
- 2) During the PWR operation of the reactor, a resonance of 17 HZ was found in PSD diagrams of recorded noise. After research on theoretical model, experiments on a 1:1 outer-reactor facility, the resonance was identified to be caused by the mini-vibration of the hydraulic-driving system of control rods in the reactor.
- 3) On the basis of existed EBW method, an advanced algorithm is presented to calculate the decay ratio for BWR stability monitoring. The verification using AR (2), ARMA(5,4) synthetic data shows its sufficient accuracy and good fitness. An onlined BWR monitor by using this algorithm is completed.

Currently the neutron noise surveillance in INET THR is continued. We expect to get enough experience in order to use the technology in the operational surveillance of a commercial 200 MW heating reactor, which will be finished in 1995 in the north-east of China.

ACKNOWLEDGMENT

The authors wish to acknowledge prof. Wu Yuanqiang, Prof. Li Zezhong, Prof. Yang Nianzu, Mr. Anjian for their support to use facility of control rods system and prof. Wang Dazhong, prof. Lin Jiagui, prof. Dongduo and prof. Gao Zuying for helpful discussions and continuous encouragement throughout this project.

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IMPROVEMENTS IN SIGNAL PROCESSING FOR PRIMARY COOLANT FLOW MEASUREMENTS IN POWER REACTORS USING N-16 GAMMA NOISE

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ABSTRACT

Primary coolant flow rate measurements have been carried out in DHRUVA reactor using N-16 gamma noise for studying various features of signal processing. Cross-correlation method of signal analysis has been used to determine transit time of coolant by placing two gamma detectors near the pipe line of one of the primary coolant loops. Measurements have been carried out for various detector-spacings and at different reactor power levels by using AD-3525 FFT analyser. It has been found that the transit time peak in cross-correlation function (CCF) has improved by three times in amplitude by using ac-coupled amplifiers as compared to the peak obtained with dc-coupled amplifiers used in the earlier measurements. The flow measurements have also been carried out at different low power levels to assess the power level above which the N-16 technique can be successfully utilised. The effect of filtering high frequencies from N-16 noise signals on the transit time peak in CCF has also been studied.

The main advantage of the N-16 noise signal is that no penetration of the system piping is required and measurements are carried out during normal operation of the reactor.

INTRODUCTION

N-16 activity is formed by fast neutron activation of O-16 of the coolant in the reactor core. N-16 decays with a half life of 7.35 sec emitting high energy gammas (6.13 and 7.12 Mev). The N-16 activity formed throughout the reactor core is not uniform as the formation is proportional to the neutron flux levels which are varying from channel to channel and also varies axially within a channel. As the reactor power level can also fluctuate on account of reactivity perturbations, there is an additional contribution to N-16 fluctuations. The reactor coolant from the outlet header to the individual coolant loop pipes is not homogeneously mixed and sufficient N-16 noise remains for the flow measurements by noise analytic transit time technique.

In power reactors, various methods of transit time determination, by analysing the noise signals of two sensors placed along the flow path of the coolant, have been reported by Lubbesmeyer (1984), Horanyi et al. (1985) and Joshi et al. (1985). For on-line determination of mean coolant transit time, the method of cross-correlation is the simplest. The peak in CCF yields the transit time.

The coolant flow measurements have been carried out in DHRUVA (100 MW thermal, heavy water moderated and cooled) research reactor. In this reactor heavy water coolant is pumped into a plenum located at the bottom of calandria, from where it gets distributed and flows upwards through the fuel assemblies located inside the coolant channels in the reactor vessel. The coolant exits at the top into a common outlet header through individual tail pipes. The coolant from the header is divided into three separate loops. Each loop has a main coolant pump, an auxiliary pump and a heat exchanger. The measurements

were carried out by placing two gamma detectors near the pipe line of one of the primary coolant loops. N-16 signals were analysed by using a dual channel, AD-3525 FFT analyser and cross-correlation method of analysis. The measurements were carried out for various distances between detectors and at different reactor power levels.

MEASUREMENTS AND RESULTS

The coolant flow rate measurements were carried out on 300 mm dia pipe line of one of the primary coolant loops in the shielded room, near the suction of main coolant pump No.3 of DHRUVA reactor. Fig.1 shows the schematic of detectors location. Two NaI(Tl) gamma detectors, operating in current mode, were placed along, and perpendicular to the axis of coolant pipe line. Only the detectors were located near the pipe line. The instrumentation was located in the reactor hall and connected to detectors by about 60 m long cables. The detectors were shielded with lead bricks. Signals from gamma detectors were fed to ac-amplifiers (band filtering between 0.04 Hz to 1 KHz at 3 db/octave). The amplified signals were fed to the analyser to generate the cross-correlation functions from the signal pairs. The peak in CCF gave the mean coolant transit time. The flow rate 'G' was determined using the expression, given by Bazerghi et al.(1977) :

$$G = k \cdot d \cdot a / t, \quad (1)$$

where k = theoretical correction factor for the velocity profile

$$= 1 / (1 + 0.19 \cdot Re^{-0.1}), \text{ where } Re = \text{Reynold's number}$$

d = distance between the detectors

t = transit time of coolant

a = pipe cross-sectional area

The main errors associated with velocity measurements by cross-correlation technique are the statistical and resolution errors. The statistical error, defined by Bendat and Piersol (1971) is :

$$e = \sqrt{n / (T \cdot f)} \quad (2)$$

where n = no. of sample points per function

f = sample frequency used in the analysis

T = measurement time

The resolution error, given by Lubbesmeyer (1984) is :

$$r = v / (f \cdot d) \quad (3)$$

where v is the measured velocity. f and d are defined above.

Fig.2 shows the circuit diagram of the ac-amplifier used for flow measurements in DHRUVA reactor. In the flow measurements which were carried out on the recirculation loop of Tarapur Atomic Power station (200 MWe, BWR) by Joshi et al. (1985), signals from gamma detectors were first converted into voltage signals by using dc-amplifiers and then amplified by ac-amplifiers. A scatter was observed in the CCF and the transit time peak was not very distinct. With the use of ac-amplifiers for the measurements in DHRUVA, the transit time peak in CCF has improved by three times as compared to the peak obtained with dc-amplifiers used in the earlier measurements. For comparison, Figs.3 and 4 show

the CCF obtained with dc and ac amplifiers, respectively at DHRUVA.

As N-16 concentration in the primary coolant is proportional to the reactor power, the transit time measurements have been carried out at different power levels to assess the power level above which the N-16 technique can be successfully utilised. These measurements were carried out at a detector-spacing of 125.5 cm. Figs.5 to 10 show the CCF obtained at various power levels. No transit time peak in CCF was observed at 0.6 MW. A clear indication of peak was observed beyond 10 MW and the peak amplitude increased with increase of reactor power.

The coolant flow in power reactors is mainly turbulent. Turbulence acts as a low pass filter and affects the shape of cross-correlation between the two signals. The cut-off frequencies are not well defined and depend on the local conditions. The effect of filtering high frequencies from N-16 signals has been studied. The signals were filtered using low pass filters (24 db/octave). Table 1 shows the effect of filtering N-16 signals on transit time peak in CCF. These measurements were carried out for a detector-spacing of 80 cm and at the reactor power of 80 MW. It is observed that filtering the higher frequencies results in shifting the peak position to higher transit times and hence measured flow is found to be lower.

Table 1 Effect of Low Pass Filter on Transit Time

Sr. NO.	Low pass Filter at Frequency, Hz	Transit Time Peak msec
1	1	175.8 $\pm$ 2.0
2	2	156.3 $\pm$ 2.0
3	3	148.4 $\pm$ 2.0
4	5	140.6 $\pm$ 2.0
5	20	138.7 $\pm$ 2.0
6	200	140.6 $\pm$ 2.0

The sensitivity of the N-16 technique was confirmed by repeating the measurement for a detector-spacing of 153.6 cm. The flow was increased by about 3% by opening the pump discharge valves and consequently the peak in CCF has shifted to lower transit time by about the same percentage (i.e., from 280 to 270 msec).

Transit time measurements have been carried out for various detector-spacings. In order to get the statistical errors to about 0.5%, N-16 signals were analysed for about 12 minutes. Figs.11 and 12 show coherence and cross-power spectral density (CPSD)-phase angle respectively for the measurements carried out at a detector-spacing of 80.0 cm. It is observed that coherence and CPSD-phase exist upto about 20 Hz and large scatter is observed in CPSD-phase beyond 20 Hz. Due to this, Phase-slope method results in an incorrect transit time determination.

Figs.13 to 16 show CCF for detector-spacings of 40.0, 80.0, 99.7 and 153.6 cm respectively. As seen from the figures, the transit time peak in CCF is very distinct. The flow rates have been calculated using the expression given in Eq.(1) and are given in Table 2, where the coolant flow results are given together with corresponding readings from venturi channels. The total flow in

a loop is the sum of core inlet flow and structural cooling flow, as given by the respective venturi channels. As seen from the table, the errors on the measurements increase with decrease in detector-spacings. The flow variation observed is due to variation of mains frequency which varied from 49.25 to 51.0 Hz during the course of measurements.

Table 2 Primary Coolant Flow Rate for Various Detector-Spacings

Sr. No	Detector-Spacings cm	Reactor Power MW	Flow rate * 10 ⁴ lpm			
			By N-16 Technique	By Venturi Channel		
				A	B	C
1	153.6	99	2.26 ± 0.02	2.22	2.16	2.26
2	153.6	82	2.28 ± 0.02	2.24	2.21	2.29
3	153.6	82	2.32 ± 0.02	2.29	2.24	2.31
4	125.5	52	2.25 ± 0.02	2.15	2.17	2.22
5	125.5	80	2.25 ± 0.02	2.17	2.20	2.27
6	99.7	72	2.29 ± 0.03	2.17	2.20	2.25
7	80.0	80	2.31 ± 0.03	2.28	2.22	2.32
8	80.0	77	2.28 ± 0.03	2.25	2.22	2.29
9	40.0	70	2.38 ± 0.06	2.32	2.34	2.39
10	30.5	72	2.35 ± 0.09	2.20	2.22	2.27

CONCLUSIONS

1. The transit time peak in CCF is more distinct with the use of newly developed ac-coupled amplifiers. The peak amplitude has increased by three times as compared to the peak obtained with dc-coupled amplifiers used in the earlier measurements.
2. The primary coolant flow rates obtained by the N-16 technique have agreed with the flow rates indicated by venturi channels.

ACKNOWLEDGEMENTS

Authors are thankful to Dr. V.C. Deniz, Head, Experimental Reactor Physics Section for his keen interest in this work. Thanks are also due to Shri R. Chowdhuri, Reactor Superintendent, and other personnel of DHRUVA reactor for their help in making the measurements possible. Special thanks are due to Shri A.R. Gore of Nuclear Power Corporation for useful discussions.

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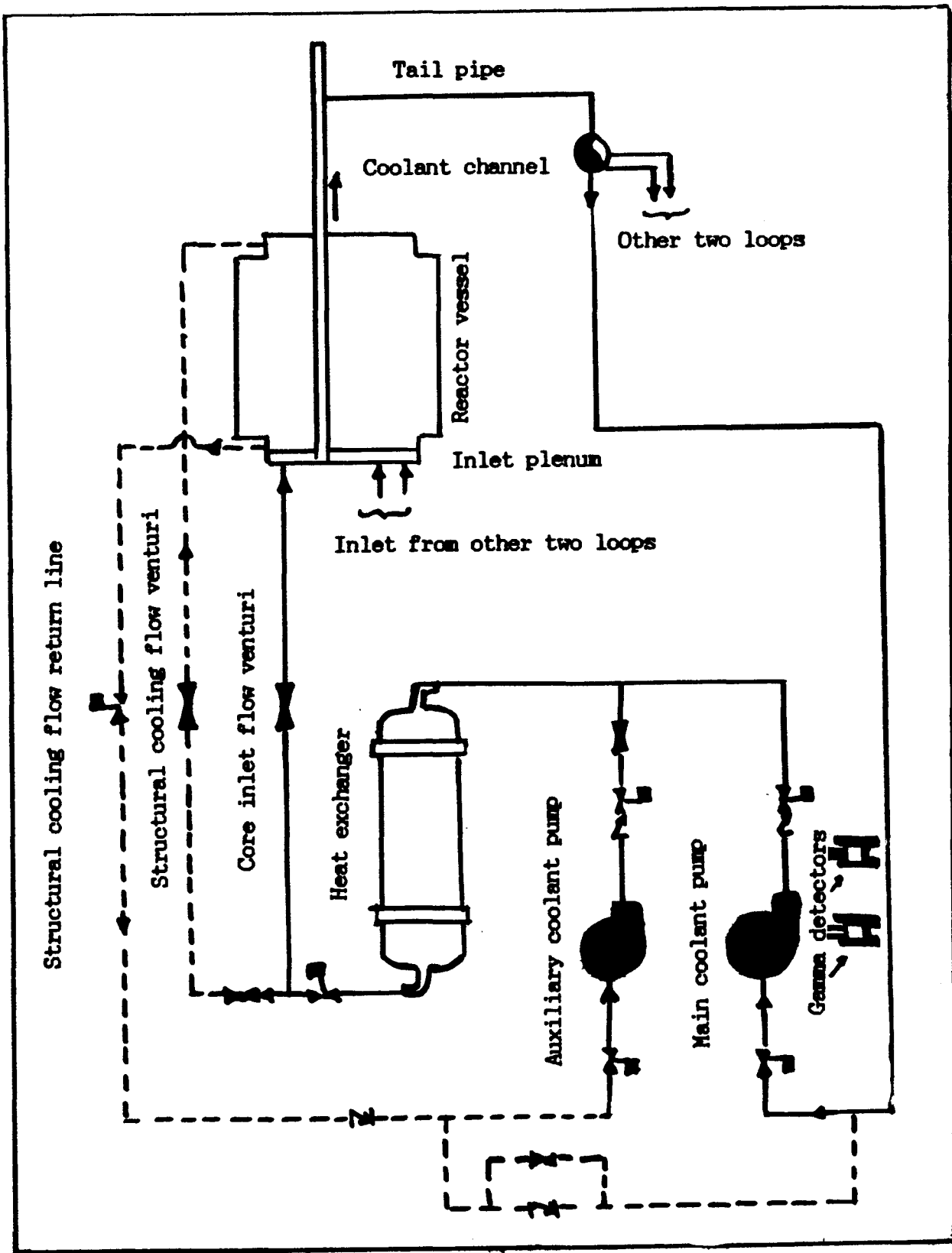


Fig.1. Schematic of detectors location and simplified flow diagram of Main Coolant System of DHRUVA Reactor

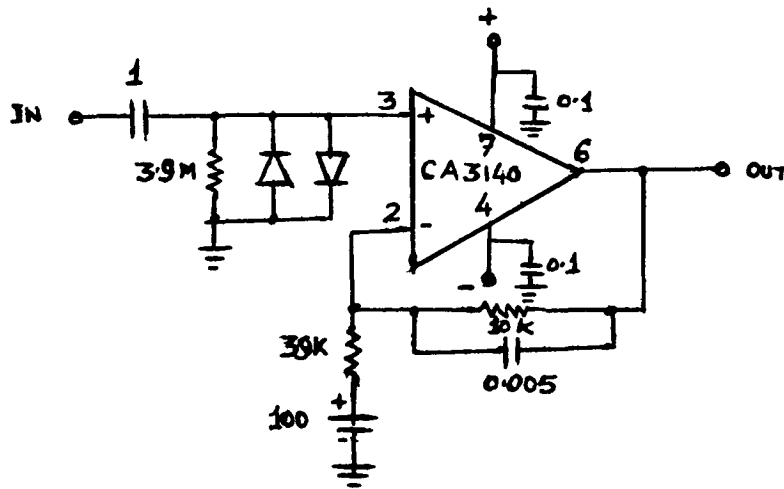


Fig.2. Circuit diagram of ac-amplifier

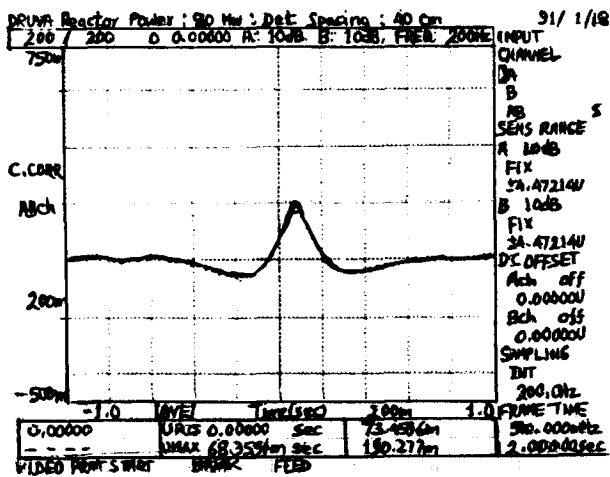


Fig.3. OCF of N-16 signals by using dc-coupled amplifiers

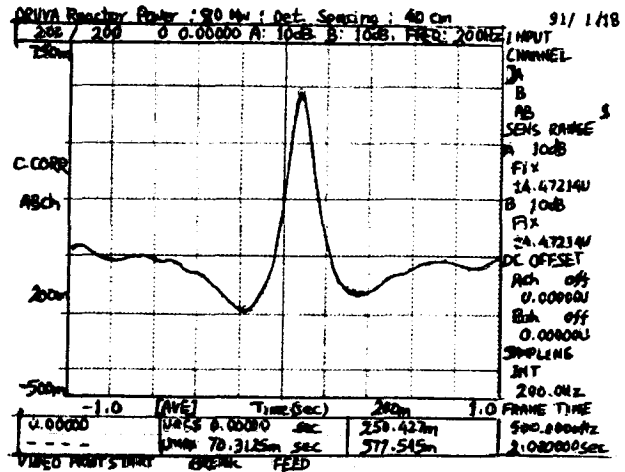


Fig.4. OCF of N-16 signals by using ac-coupled amplifiers

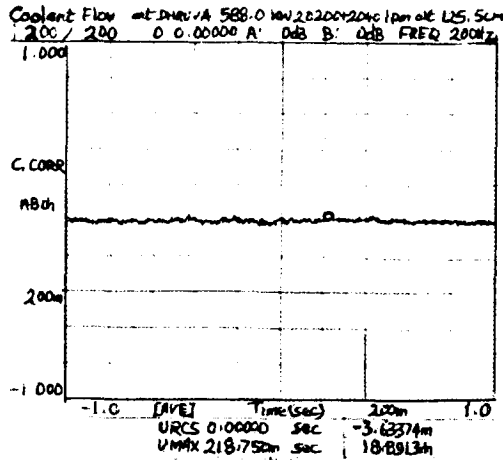


Fig.5. CCF for 0.6 MW power

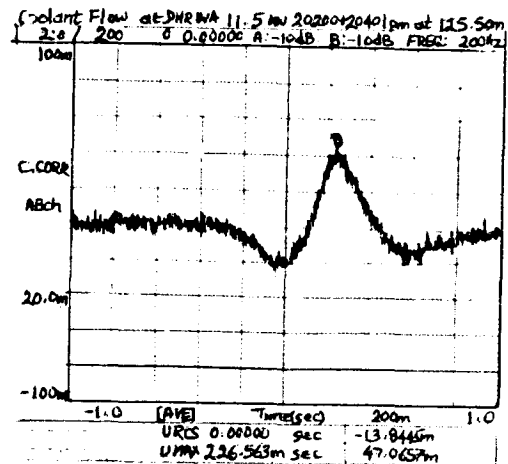


Fig.6. CCF for 11.5 MW power

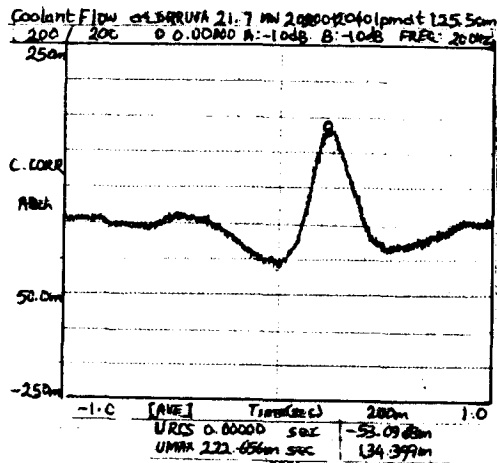


Fig.7. CCF for 21.7 MW power

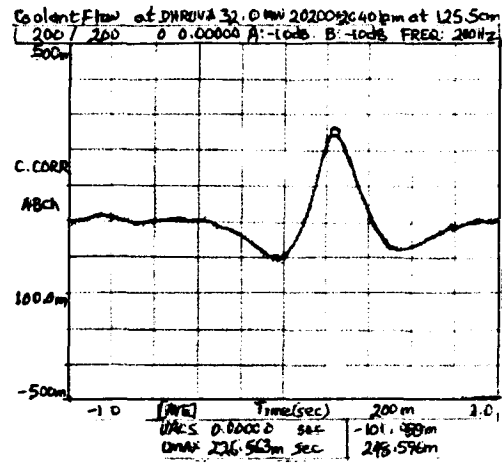


Fig.8. CCF for 32.0 MW power

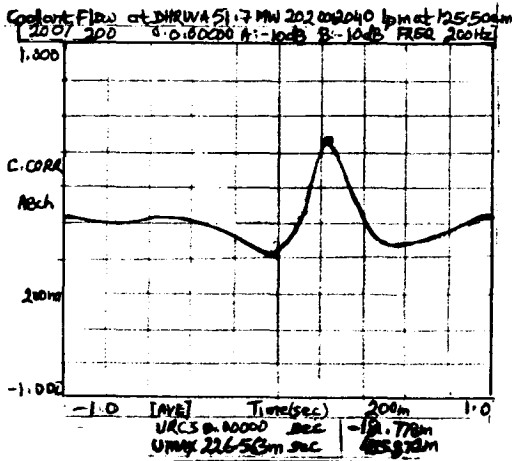


Fig.9. CCF for 51.7 MW power

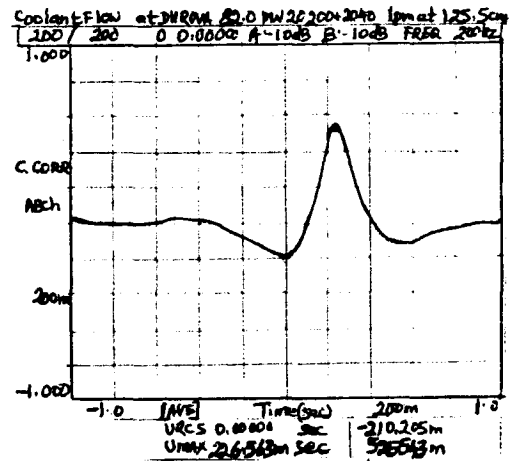


Fig.10. CCF for 82.0 MW power

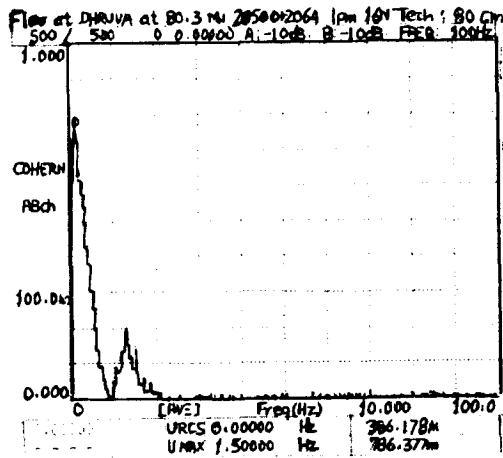


Fig.11. Coherence for 80 cm detector-spacing

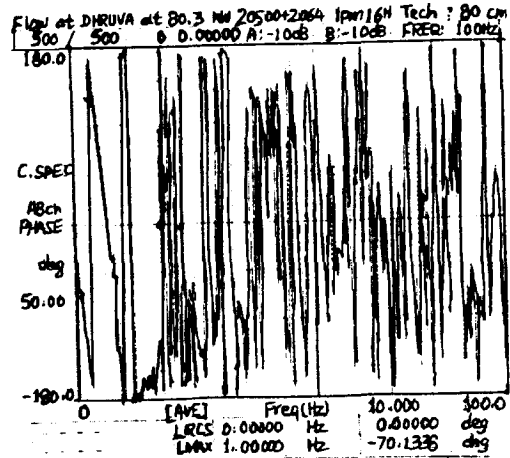


Fig.12. CPSD-phase for 80 cm detector spacing

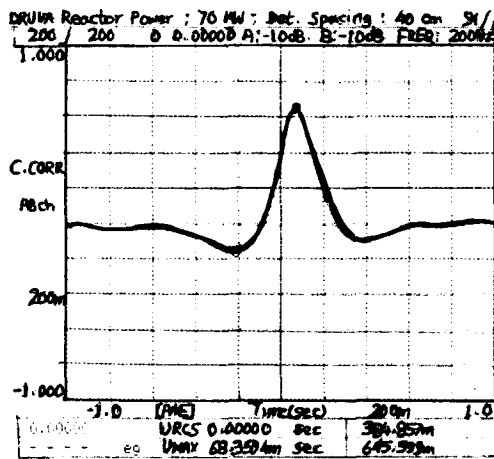


Fig.13. CCF for 40 cm detector-spacing

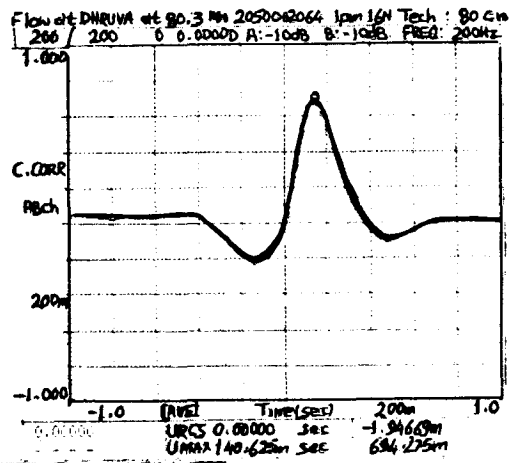


Fig.14. CCF for 80 cm detector-spacing

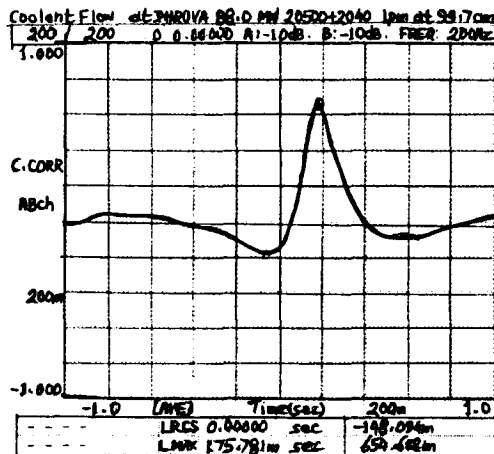


Fig.15. CCF for 98.7 cm detector-spacing

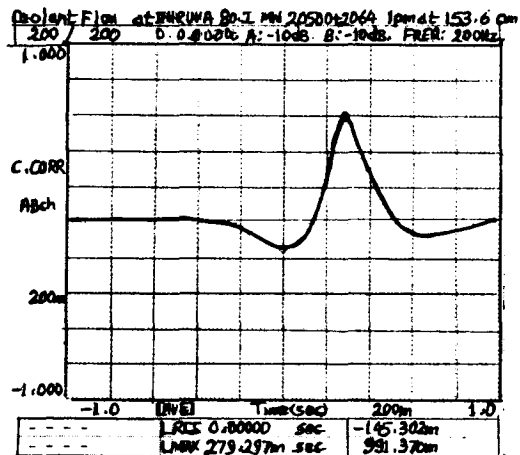


Fig.16. CCF for 153.6 cm detector-spacing

KALMAN FILTERING OF SELF-POWERED NEUTRON DETECTORS FOR NEUTRON NOISE ANALYSIS

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ABSTRACT

Fixed ex-core detectors have been the traditional instrument of choice for the application of neutron noise analysis techniques to determine specific reactor core parameters and identify reactor internals vibrations in pressurized water reactors. However, the use of ex-core detectors is limited by the fact that the detectors are far from the source of the flux perturbations, so that the random fission process and other global noise sources tend to mask the deterministic flux variations of interest. Fixed in-core rhodium self-powered neutron detectors are located close to the source of the flux perturbations. Unfortunately, only a small fraction of the detector signal is able to follow the neutron flux variations. This paper describes a software algorithm, based on Kalman filtering, which converts the delayed-responding rhodium detector into a prompt-responding detector by amplifying the small prompt component of the detector signal without the introduction of measurement noise sources inherent in traditional analog methods. Further, the Kalman filter offers the potential of separating out the deterministic portion of the noise signal from the random process noise, thus enhancing the capabilities of reactor noise analysis by permitting more accurate determination of reactor core parameters and detection of smaller scale reactor internals vibrations at lower reactor powers than is currently possible.

INTRODUCTION

Pressurized water reactors (PWRs) employ both in-core and ex-core instrumentation to demonstrate that the core behaves as designed and predicted and to help identify and diagnose any anomalies that may occur. Specifically, the in-core and ex-core instrumentation are used for (1) protective functions to trip the plant if the deviation from expected behavior is large or grows rapidly, (2) monitoring functions to warn operators immediately if certain Limiting Conditions of Operation (LCOs) are exceeded, (3) surveillance functions to periodically verify that the LCOs are not exceeded, and (4) control functions to provide input to reactor control systems. The in-core and ex-core instrumentation are also used for miscellaneous functions such as core power distribution determination, methods verification, determination of specific core parameters, and detection of core anomalies.

Protective functions in PWRs are generally fulfilled by linear power range ex-core detectors. Monitoring and surveillance are accomplished using either fixed in-core detectors or a combination of fixed ex-core and movable in-core detectors. Core power distribution measurements are achieved

using either fixed or movable in-core detectors. Determination of specific core parameters and anomaly detection are performed by both in-core and ex-core instrumentation.

Neutron noise analysis is one of the techniques used to determine specific core parameters (core coolant flow velocity, moderator temperature coefficient) and to identify core anomalies such as fuel assembly vibration modes and excessive control rod assembly vibration. Generally speaking, the noise analysis techniques have been applied to ex-core detectors, since a prompt-responding, fixed detector is needed to follow the neutron flux variations associated with these parameters and phenomena. However, use of ex-core detectors alone for neutron noise analysis presents limitations. The detectors are few in number and are positioned far from the source of the flux perturbations. As a result, the random fission process and other global noise sources tend to mask the deterministic flux variations, thus making the interpretation of ex-core detector noise signals difficult.

Fixed rhodium self-powered neutron detectors (SPNDs) are used extensively in Combustion Engineering and other PWRs to provide on-line monitoring and on-demand surveillance of core power distributions and related parameters. Further, the extensive presence throughout the core, high detector sensitivity and high accuracy of rhodium SPNDs offers the potential of using neutron noise analysis techniques in conjunction with these detectors to more accurately calculate core parameters measured by neutron noise analysis and to detect and locate small local motions that cannot be seen by the ex-core detectors due to the presence of large global noise sources.

However, since rhodium SPNDs are primarily delayed-responding detectors, only a small fraction of the detector signal (the prompt component) is fast enough to follow the dynamic neutron flux variations. Most of the detector signal (the delayed component) has a long response time and contributes only to the average (DC) current. Therefore, neutron noise analysis techniques have not been widely applied to rhodium SPNDs. In cases where rhodium SPNDs have been used for neutron noise analysis,¹ traditional analog band-limiting and amplification techniques have been applied to the rhodium detector signals. The results indicate that rhodium detectors have a dynamic response up to approximately 25 - 30 Hz.¹ However, the small prompt component of the rhodium detector (approximately 6.5 percent²) means that the noise sources introduced by traditional analog band filtering and amplification methods can be significant compared to the deterministic signals of interest, making interpretation of neutron noise spectra from rhodium detectors difficult, particularly at low reactor powers.

This paper describes a software algorithm, based on Kalman filtering, which converts the delayed-responding rhodium SPND into a prompt-responding detector by reconstructing the dynamic signal sensed by the detector from the prompt and delayed components. Using this algorithm, the Kalman filter amplifies the prompt component without the introduction of measurement noise sources inherent in traditional analog methods. Further, the Kalman filter offers the potential of separating out the deterministic portion of the noise signal from the random process noise by modeling the deterministic portion in the filter, thus enhancing the capabilities of in-core neutron noise analysis and permitting more accurate determination of core parameters and detection of smaller scale vibrations at lower reactor powers than is currently possible.

DETECTOR DESCRIPTION AND OPERATION

A typical rhodium self-powered neutron detector, shown in Figure 1,³ is comprised of a rhodium emitter, high density insulation, an electrically-grounded collector sheath and a signal lead wire. The signal lead wire transmits the emitter signal to an electrical connector (not shown in Figure 1). The

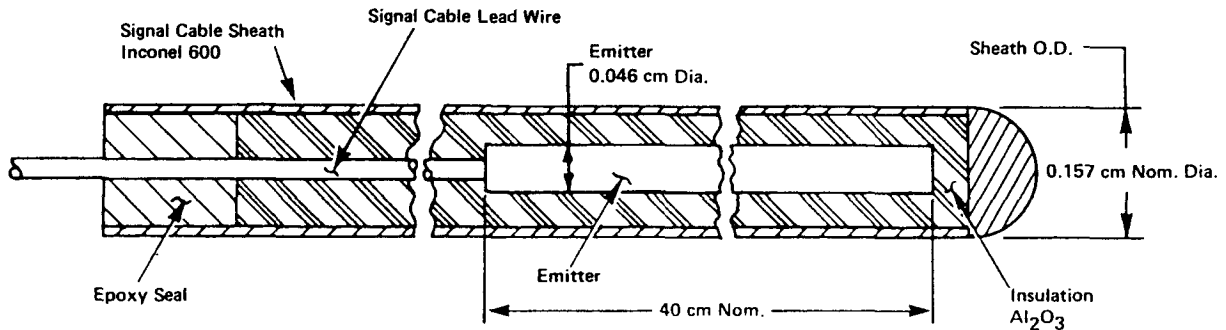


Figure 1. Typical rhodium self-powered neutron detector.

signal is carried from the detector connector through well-shielded cables to the signal conditioning equipment, and then to the plant computer system for signal processing. The processed signals can then be used as input for power distribution monitoring and surveillance and/or reactor control systems. Several individual detectors (typically 4, 5 or 7), spaced uniformly along the active core height, are contained in each in-core detector assembly. Detector assemblies are located in approximately 25% of the fuel assemblies in a reactor core.

The self-powered neutron detector operates on the principle of neutron activation of the detector emitter material. For rhodium SPNDs, the detector signal is produced primarily by neutron-beta reactions within the emitter. Incident neutrons are captured by nuclei in the emitter, from which energetic negative beta particles (electrons) are released in a statistical decay which is delayed in time and characterized by a half-life which is uniquely identified with the type of emitter material. A fraction of the energetic beta particles escape the emitter and are collected in the detector sheath. Free electrons then flow from ground through the signal conditioning equipment to the emitter to replace the electrons that originally escaped, producing an electric current signal which is directly proportional to the neutron flux incident on the detector emitter.

The beta decay scheme of rhodium⁴ involves two radioisotopes of rhodium-103. The predominate mode, contributing 92.3% of the (n,β) signal, is the beta decay of rhodium-104 with a 42 second half-life. The remaining 7.7% of the (n,β) signal results from the two-stage decay of rhodium-104m, first by gamma emission to rhodium-104 with a 4.4 minute half-life, followed by beta decay with a 42 second half-life.

In addition to the signal generated from (n,β) reactions, a small but significant portion of the overall rhodium detector signal is generated by capture gamma reactions (n,γ) in the emitter and external gamma flux reactions (γ,β) with the emitter and the detector sheath which produce electrons through either the Compton or the photoelectric effect. The capture gamma and external gamma flux signal is prompt, as its mechanism is identical to the reactions in prompt-responding detectors. For rhodium SPNDs, the prompt component is approximately 6.5 percent² of the total detector signal.

The total signal obtained from rhodium detectors also includes a signal generated by a multitude of reactions with the detector cable itself. The primary reactions are (n,γ) and (n,β) reactions with the detector cable materials. This "background" signal is not related to the signal produced by the

emitter; rather, it is a function of the cable geometry, material and length of cable in the active core. The exact models for the reactions contributing to the background signal are quite complex. However, the background signal amounts to only a few percent of the overall detector signal. Further, the use of background detectors enables one to directly measure the cable contribution to the emitter signal and to correct the total detector signal for cable-related reactions, thus producing a signal due only to neutron reactions with the emitter.

KALMAN FILTER

The Kalman filtering technique⁵ can be used to convert delayed-responding rhodium detectors into prompt-responding detectors (in effect providing a significant prompt component gain) without the introduction of measurement noise. As shown in Figure 2, the Kalman filter is a feedback system which predicts an estimate of the neutron flux based on previous information and corrects that estimate based on the difference between the detector response generated by the estimate and the new measurement.

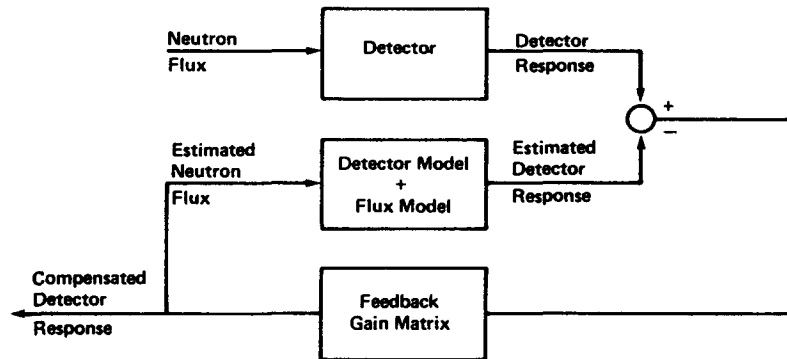


Figure 2. Schematic of Kalman filter.

The formulation of the Kalman filter is based on a discrete realization of the state equations which describe the neutron flux and the detector response. The state equations consist of a pair of first-order linear differential equations for the detector states (derived from the detector transfer function) plus a Wiener process model for the neutron flux. In addition, a measurement equation which relates the state variables to the actual measured quantity (the detector response) is also required.

The discrete realization of the state equations and the measurement equation form the basis for the Kalman filter with driving noise, which is given by the following:⁵

$$X_{n,n-1}^* = \Phi(n,n-1) X_{n-1,n-1}^* \quad (1)$$

$$S_{n,n-1}^* = \Phi(n,n-1) S_{n-1,n-1}^* \Phi(n,n-1)^T + Q_{n,n-1} \quad (2)$$

$$H_n = S_{n,n-1}^* M_n^T (R_n + M_n S_{n,n-1}^* M_n^T)^{-1} \quad (3)$$

$$S_{n,n}^* = (I - H_n M_n) S_{n,n-1}^* \quad (4)$$

$$X_{n,n}^* = X_{n,n-1}^* + H_n (Y_n - M_n X_{n,n-1}^*) \quad (5)$$

where

$X_{n,m}^*$	=	the estimate of the state vector at time step n due to information up to time step m
$\Phi(n,n-1)$	=	the transition matrix which carries the state vector from time step n-1 to time step n based on information up to time step n-1
$S_{n,m}^*$	=	the covariance matrix of random errors in $X_{n,m}^*$
$Q_{n,m}$	=	the covariance matrix of random driving noise of $X_{n,m}^*$
H_n	=	the filter gain matrix at time step n
R_n	=	the covariance matrix of observation errors at time step n
Y_n	=	the observation at time step n
M_n	=	the observation matrix at time step n.

Equation (1) predicts the new value of the state vector estimate (and hence the neutron flux) at time step n based on information up to time step n-1. Equation (5) then corrects this estimate in light of the new observation made at time step n. The correction to the estimate predicted by Equation (1) is the difference between the actual observation at time step n and the predicted value of that observation based on the most recent estimate of the state vector, multiplied by the filter gain matrix at time step n. The optimal gain matrix at each time step for a particular noise level and sampling rate is calculated by Equations (2) - (4).

FILTER PERFORMANCE

In a previous paper,⁶ it was shown that, for the 1 - 10 second sampling intervals typical of plant monitoring systems, both the Kalman filter and the direct inversion dynamic compensation filter currently employed in Combustion Engineering plants^{7,8} can be used to improve the response time of rhodium SPNDs. For each filter, there is an inverse relationship between the noise gain of the filter and the response time of the filter. Also for each filter, the value of the prompt component of the rhodium detector signal used to construct the filter (p_F) can be utilized as a "tuning parameter" to adjust the noise gain and response time of the filter. As p_F increases, the noise gain of each filter decreases and the response time increases; as p_F decreases, the noise gain increases and the response time decreases. In addition, the Kalman filter can also be tuned by varying the amount of driving-noise (Q). Increasing the value of Q decreases the "memory" of the filter, placing more dependence on the most recent measurement and increasing the noise gain of the filter while decreasing the response time. Conversely, decreasing the value of Q increases the memory of the filter, placing more dependence on past estimates of the state vector and decreasing the noise gain of the filter while increasing the response time.

More importantly, however, the Kalman filter can achieve combinations of acceptable noise gains and rapid response times not possible with the direct inversion filter. Specifically, the Kalman filter can provide significant improvement in the rhodium detector response time while maintaining an acceptable noise gain or, conversely, provide significant improvement in the noise gain while maintaining an acceptable response time. For comparable noise gains, the improvement in response time is approximately a factor of 3 - 6, depending on the sampling interval. For comparable response time, the improvement in noise gain is approximately a factor of 2 - 8 for the range of sampling intervals. Moreover, these improvements can be achieved even when the true value of the prompt component of the rhodium detector signal is not known exactly. These results, shown in Table 1 and illustrated graphically in Figure 3, were obtained using simulated rhodium detector signals generated from known flux inputs typical of those occurring in operating reactors, and verified using real plant data.

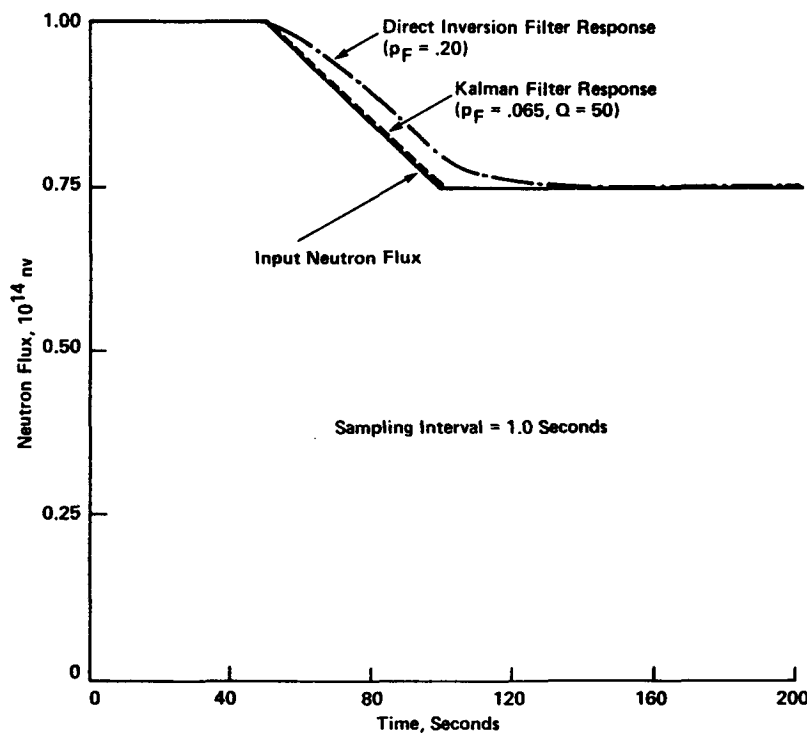


Figure 3. Comparison of Kalman and direct inversion filter responses using known flux inputs.

In Table 2, these results are extended to more rapid sampling frequencies (50Hz) typical of those used in neutron noise analysis. The results in Table 2 also support earlier work¹ which concluded that rhodium SPDs have a dynamic response up to at least 25 - 30 Hz, and can be used to detect dynamic neutron flux variations caused by void propagation in the core and by reactor internals vibrations. Further, the results in Table 2 demonstrate that Kalman filtering can be used to achieve response times from delayed-responding rhodium detectors typical of those from prompt-responding detectors. In addition, amplification of the prompt component of the rhodium detector signal can be achieved through Kalman filtering without introducing additional measurement noise sources, as is the case with traditional analog methods.

Table 1

Comparison of Currently Used Direct Inversion Filters
with Possible Replacement Kalman Filters

Filter	Sampling Interval (Sec)	P_F	Q	Noise Gain	Delay Time* (Sec)
D. I.	1.0	.20	-	4.9	9.4
Kalman	1.0	.065	50	4.8	1.5
Kalman	1.0	.065	1	0.6	9.1
Kalman	1.0	.070	50	4.8	1.7
Kalman	1.0	.070	1	0.6	9.1
D. I.	2.0	.15	-	6.4	7.0
Kalman	2.0	.065	100	5.9	1.8
Kalman	2.0	.065	5	1.3	7.8
Kalman	2.0	.070	100	5.9	2.0
Kalman	2.0	.070	5	1.3	7.8
D. I.	10.0	.10	-	7.6	7.8
Kalman	10.0	.065	400	7.6	2.9
Kalman	10.0	.065	60	3.3	8.5
Kalman	10.0	.070	400	7.5	3.2
Kalman	10.0	.070	60	3.4	8.5

*Delay time is defined as the delay associated with a ramp charge in the input neutron flux.

Table 2

Comparison of Kalman and Direct Inversion
Filter Noise Gains and Delay Times
($P_F = .065$)

Filter	Sampling Interval (Sec)	Ramp Rate (% Power/Sec)	Q	Noise Gain	Delay Time* (Sec)
D. I.	1.0	0.5	-	14.6	.474
Kalman	1.0	0.5	5000	14.6	.052
D. I.	0.1	5.0	-	15.3	.037
Kalman	0.1	5.0	5000	14.7	.009
D. I.	0.02	25.0	-	15.3	.003
Kalman	0.02	25.0	5000	14.7	.002

*Delay time is defined as the delay associated with a ramp charge in the input neutron flux.

A further advantage of the Kalman filter is its capability of allowing more intelligence to be built into the filter by increasing the number of state equations which describe the neutron flux and the rhodium detector response. For example, a more sophisticated model for the rhodium detector response can be used to explicitly account for deterministic noise signals within the filter. Similarly, the filter can be improved by using a more sophisticated (higher-order) model to describe the neutron flux.

These characteristics of the Kalman filter offer the potential of recovering valid data from neutron noise analysis when the valid data and background noise share the same frequency content. Of particular interest is the separation of the deterministic portion of the noise signal from the random process noise. The importance of this separation is illustrated in Figure 4,⁹ which shows the auto power spectral density (APSD) versus background noise for an ex-core detector in a typical PWR at several different power levels. The APSD was constructed from ex-core detector signals which were band-filtered and amplified using traditional analog techniques. The background noise, made up of uncorrelated noise sources, has an APSD which is constant at all frequencies and independent of reactor power level. On the other hand, the deterministic noise due to core support barrel/thermal shield vibrations has an APSD which is linear with reactor power. Therefore, as the power level decreases, the background noise becomes a progressively larger percentage of the measured detector signal, making identification of specific vibration modes increasingly difficult. For example, in Figure 4, the beam mode frequency of vibration of the core support barrel/thermal shield (at approximately 7 Hz) can be easily identified at all three power levels. However, identification of the first shell ($\cos 2 \theta$) mode (at approximately 12.5 Hz) becomes increasingly difficult as the power level decreases. Use of a Kalman filter which models the deterministic portion of the ex-core detector noise signal could reduce the background noise relative to the deterministic noise, making identification of specific vibration modes considerably easier, particularly at low power levels.

CONCLUSIONS

In summary, Kalman filtering can be used to convert delayed-responding rhodium self-powered neutron detectors into prompt-responding detectors (e.g., fission chambers) by amplifying the small prompt component of the rhodium detector signal. Further, this amplification can be achieved without the introduction of measurement noise sources inherent in traditional analog methods. Since the rhodium SPNDs are in the core and hence closer to the source of the flux variations than are the ex-core detectors, the rhodium detectors are able to detect small local flux variations often masked from the ex-core detectors by the random fission process and other global noise sources. Also, the Kalman filter allows explicit modeling of the deterministic portion of the noise signal within the filter, thus enabling the reduction of background process noise relative to the deterministic noise of interest. As a result, the Kalman filter offers the potential of enhancing the capabilities of reactor noise analysis by permitting more accurate determination of specific reactor core parameters and detection of smaller scale reactor internals vibrations at lower reactor powers than is currently possible using traditional noise analysis methods.

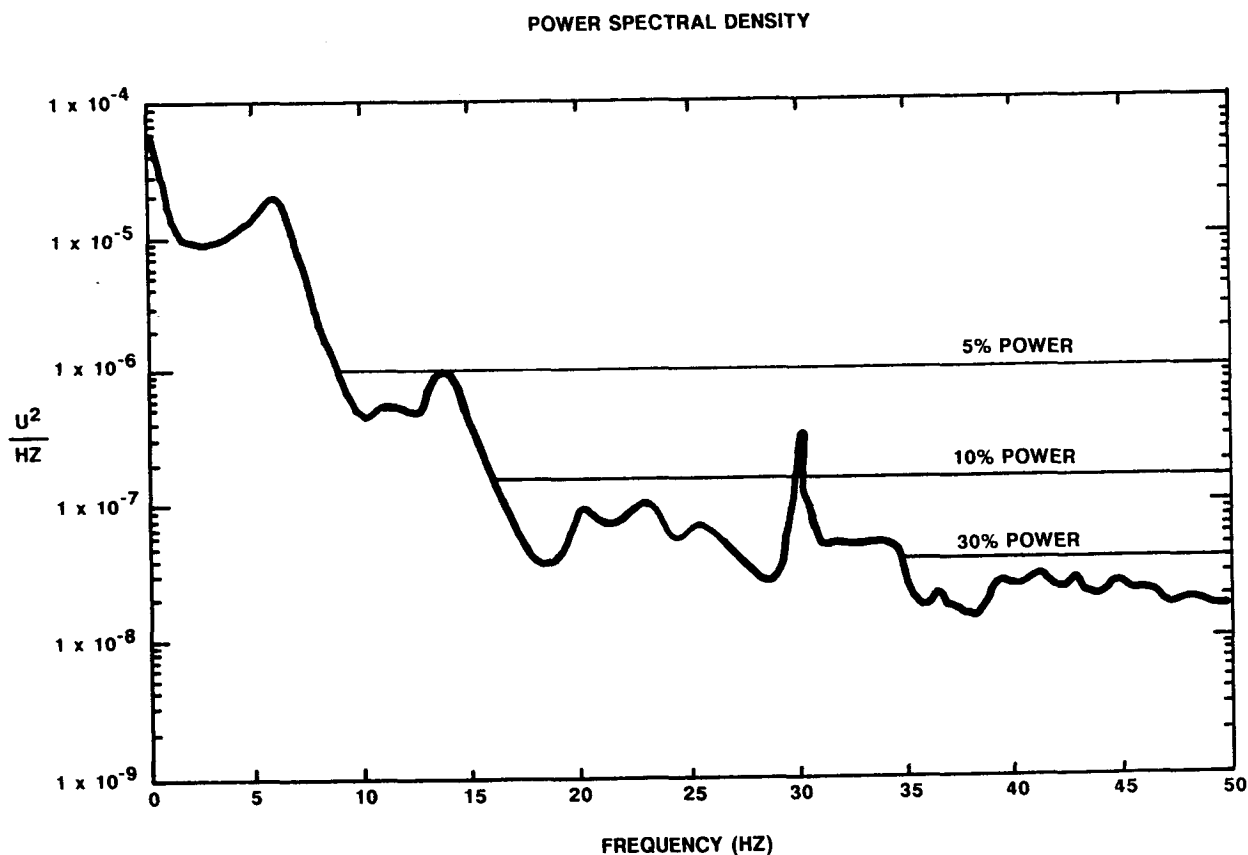


Figure 4. Auto power spectral density versus background noise for an ex-core detector in a typical PWR as a function of power level.

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THE STANDARDIZATION OF NUCLEAR REACTOR SURVEILLANCE AND DIAGNOSTICS TECHNIQUES FOR SAFE AND OPTIMAL PLANT OPERATION

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ABSTRACT

Some thirty-five years ago Professors Moore and Kemeny, then working at the University of London, England, developed and tested a two channel analogue signal correlation and power spectral density analyzer. At this time the "state of the art" in this area of plant surveillance could be best summarized by recalling that the key components of this system consisted of an ultra violet galvanomotor recorder and the British Institute of Oceanography's optical correlator and Fourier Transform analyzer. This equipment consisted of a large, one meter diameter drum on which the analogue signals were placed. A servo-system braked the drum, initially rotating at high speed, to stand-still in an exponential mode, bringing the Fourier frequencies in the original records into "ringing frequency" with the amplifiers which scanned the signals read by an optical transducer.

The technique and the equipment led to the first papers on "reactor noise" and its link with plant surveillance and safety. Those papers, published in "Nature" showed that important plant parameters could be measured by recording neutron density fluctuations and that the approach could link this fundamental phenomenon with virtually every phase of reactor behavior, including hydroelastic vibration, void fraction, core barrel motion and thermal and acoustic signals generated during plant operation.

The present paper describes a 1990 "state of the art" device, operated "on line" and in "real time" which incorporates the leading edge of hard-wave and soft-wave but still retains some, of the basic concepts of noise signal analysis.

Twenty channels of information from the reactor are recorded. The algorithms for stochastic signal analysis include power spectral density analysis, the Hilbert transform, auto-regression analysis, zero-crossing analysis and Bode, Nyquist and transfer function plots.

Five display units in the reactor control room display standardized forms of the above algorithms and automatically compare the up-dated results with three prior results using a pattern recognition algorithm. The five displays are easily recognizable by control room staff. The artificial intelligence algorithm of the computer gives an alert signal when the variance between the four data buses exceeds 5%. An automatic shut-down option is available to the shift supervisor if a 10% variance is detected. These options exist for all combinations of the signals from the twenty transducers of which ten measure neutronic fluctuations while the remainder collect temperature, flow, acoustic and mechanical data. The system is patented and in a process manufacture.

A UNIFIED NOISE SOURCES CATALOGUE FOR NPP WITH WWER REACTORS AS A DATA BASE FOR A NOISE DIAGNOSTIC EXPERT SYSTEM

Omar Aguilar, Valentina Badia and Javier Santos

**Advanced Institute for Nuclear Sciences and Technology, AINST
Republic of Cuba**

ABSTRACT

Considerable investigations have been devoted to the problem of noise sources in PWR of WWER types. Specially related to the first loop of NPP the following contributions have been pointed out

- Fluctuations of the neutron flux density arising from power changes in the reactor.
- Pressure fluctuations containing a low frequency resonance at nominal power reactor conditions, mainly influenced by changes of water level in pressurizer.
- Vibration of the pressure vessel and the mechanical structure inside it.
- Effect of subcooled boiling, power fluctuation and inlet temperature fluctuations in the reactor.

The international experience received from monitoring of the main parameters in a WWER type NPP gives possibility to systematize in a well suitable frequency range the existence of different noise sources characterizing the WWER reactor operational work.

With this aim was developed the Unified Noise Sources Catalogue (UNoSoC) for WWER type NPP. Contributions included in the UNoSoC can be applied to detect deviations from patterns of normal effects throughout the pattern recognition technique.

In this work description of UNoSoC is presented and the possibility to apply it to Noise Diagnostic Expert System as a Data Base is commented.

Full manuscript not available

**ELECTRICAL SYSTEM CONDITION MONITORING
AND TROUBLESHOOTING AT
SAN ONOFRE NUCLEAR GENERATING STATION
USING THE ECAD TEST SYSTEM**

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ABSTRACT

This paper describes the utilization of the ECAD test system at San Onofre Nuclear Generating Station for condition monitoring and troubleshooting of electrical systems. A discussion of the technical basis for ECAD is presented followed by a description of the system. The use of the ECAD System at San Onofre from its initial application in 1986 to present use in the cable monitoring program is described. Use of the system is supported by presenting case histories of degraded circuits through periodic monitoring and baseline evaluations.

Case histories include trending of power and instrumentation cables to identify insulation degradation, identification and location of degraded connections, grounded shields, noise injection points and moisture intrusion paths. Actual ECAD data is presented to support findings.

The paper concludes with a discussion on limitations of the ECAD System, overall benefits realized and future uses of the system at San Onofre.

INTRODUCTION

Predictive maintenance programs in the power industry mainly focus on monitoring degradation in major system components. Monitoring techniques used include:

- ultrasonics
- vibration analysis
- lubrication oil analysis
- dielectric oil analysis
- infrared thermography

While these techniques generally reflect the state-of-the-art methods, their application tends to be limited to discrete components. Until recently, there have been no widely accepted techniques for monitoring the condition of electrical circuits, including cables and their end devices. Rather, electrical testing methodologies have established functionality based only upon pass/fail criteria such as insulation resistance and circuit continuity. These parameters are usually measured individually using manually operated instruments, typically the Megger\ and multimeter, with results recorded on a data sheet. This type of testing may determine circuit functionality and identify gross circuit faults, but it cannot efficiently detect the cause and location of circuit degradation prior to, or after failure.

The ECAD System 1000 was developed to fill the void in electrical system condition monitoring technology, and to provide the basis for an effective predictive maintenance and troubleshooting program.

TECHNICAL BASIS FOR ECAD

ECAD is an acronym for "Electronic Characterization and Diagnostics", and is applied to the testing of instrumentation and control and power circuits. The ECAD approach is based on viewing the plant circuit as an r-f transmission line with a load, and analyzing the lumped and distributed circuit elements. Typical transmission lines include parallel wires, wire over a ground plane, and coaxial cable. Direct current and radio-frequency testing techniques can be applied to determine and monitor those electrical characteristics necessary for circuit functionality assessment. The direct current or low-frequency measurements provide the lumped values of circuit loop resistance, shunt resistance, inductance, and capacitance. These measurements provide the best indication of circuit degradation, but cannot determine where the degradation is occurring. Using the radio frequency technique of analyzing reflected electromagnetic pulses in the time domain, the circuit is analyzed as an r-f transmission line, consisting of a series of resistors, inductors, and capacitors. This technique, known as Time-Domain Reflectometry (TDR), identifies the distributed resistance, inductance, and capacitance of the circuit, and can accurately detect the location of circuit degradation.

The information acquired by these two testing techniques not only reveals the degree of circuit degradation, but also the nature and location of the problem.

ECAD SYSTEM DESCRIPTION

The ECAD System 1000 is a completely automated data acquisition system consisting of state-of-the-art electronic test equipment and a computer. The computer provides complete control of the test instrumentation through the IEEE-488 interface bus utilizing specially designed software. The basic measurements acquired by the system include AC/DC voltage (noise), insulation resistance, DC loop resistance, impedance, inductance, capacitance, and time-domain reflectometry signature. These measurements, along with circuit identification information and testing history, form the ECAD database.

The ECAD System conducts all measurements remotely using a 2-wire connection to the circuit under test. Figure 1 illustrates a one-line diagram for a typical RTD circuit. To completely characterize this RTD circuit a total of nine (9) ECAD tests would be performed. Time per test ranges from 1 to 3 minutes depending on the circuit configuration and if an insulation resistance test is required. For example, a test across an RTD element would show a low ohmic value and would not require an insulation test resulting in a one (1) minute test duration. A test from the shield to ground would indicate an open circuit at the end device and an insulation resistance test would be automatically conducted at an operator specified voltage.

Upon test completion a "quick-look" data chart is produced as shown in Figure 2. This chart displays circuit descriptive information, lumped element data and the TDR signature. If previous data exists for the device under test, the ECAD computer automatically recalls and prints the baseline data for trend comparisons.

INTRODUCTION OF ECAD AT SOUTHERN CALIFORNIA EDISON

The San Onofre Nuclear Generating Station is a three (3) unit nuclear site. Unit 1 is a Westinghouse Pressurized Water Reactor, and Units 2 and 3 are Combustion Engineering Pressurized Water Reactors. Unit 1 began commercial operation in 1968, while Units 2 and 3 entered commercial operation in 1983 and 1984 respectively.

In November of 1985, San Onofre Unit 1 experienced a trip followed by a water hammer causing damage to components on the secondary side of the plant. The root cause of the trip was the degradation of a 4 Kv cable that was part of the original installation; construction on Unit 1 started in 1964.

As a result of the trip, Southern California Edison (SCE) searched for a method on monitoring long term cable degradation. One of the promising new technologies discovered was the ECAD System under development by the ECAD Division of Pentek, Inc. (Pittsburgh, PA).

After several successful demonstrations of the system at Unit 1, SCE purchased the first commercial ECAD as a research and development project in the fall of 1987.

APPLICATION OF THE ECAD SYSTEM: CONDITIONING MONITORING

The intent of purchasing the system was to provide the basis for a program of predictive maintenance on cables. To accomplish this, SCE has established a Cable Monitoring Program. The intent of this program is to detect long term degradation of cables before they become a problem.

Currently, SCE has selected approximately 450 cables and electrical equipment to be tested during refueling outages. These cables will be tested at 1, 2, and 3 outage intervals based on an estimate of their relative importance and/or past history in the plant. Circuits were selected for testing based on the following:

- circuits with a history of problems
- circuits important to safety
- circuits important to power production
- a sampling of other circuits for development of a diagnostic baseline

The predictive maintenance program has not yet fully matured. While the first data taken revealed some unanticipated equipment problems (see CASE STUDIES below), other potential problems will continue to be trended over time. SCE believes that the ability of the ECAD System to store and retrieve accurate readings taken years apart should yield valuable information in the long run.

APPLICATION OF THE ECAD SYSTEM: TROUBLESHOOTING

The ECAD System represents a different approach to traditional testing and troubleshooting methods. If it is reasonably certain that the cable is the source of the problem, then the ECAD System is brought in. Currently, maintenance personnel use the ECAD System to look at problem areas once or twice per month. They prefer to use the ECAD System since it is easy to connect; the system is currently set up to test a cable without disconnecting the circuit's end device. This gives the advantage of learning

more about a problem in containment before sending someone to investigate, thus reducing radiation exposure. The ECAD System can often provide sufficient information to show that a problem is not in a cable. If the problem is in the cabling, the ECAD System can usually provide more useful information than through use of traditional techniques.

CASE STUDIES

To date, the most dramatic results from use of the ECAD System have been obtained during troubleshooting. The best way to demonstrate this is to discuss selected case histories of problems that have been solved with ECAD. In discussing these problems, we have necessarily simplified some parts of the discussion and have left some questions unanswered, since they would require detailed presentations outside the scope of this paper.

Cable Splice Problem In An RTD Cable

In the summer of 1987, ECAD was at the site to give a demonstration of the system. At the time, SCE suggested that they look at a primary system Resistance Temperature Detector (RTD) circuit that had been giving intermittent problems for over six months. After taking a single set of data, the ECAD System was able to identify a point on the RTD cable inside the containment in a cable tray that had a few ohms of increased resistance where there should have been no resistance. An investigation identified a deteriorated cable splice in the cable tray.

This single demonstration produced a savings that would nearly have paid for the entire system and convinced SCE to purchase an ECAD System to use directly at San Onofre and to provide a platform for developing new applications for our future benefit.

Leaking RTD Thermowell

During the winter of 1988, while taking initial readings for the Cable Monitoring Program, one of the RTD's showed a high dissipation factor, indicating moisture in the system. Disconnecting the RTD caused the high dissipation factor to disappear. An investigation showed that the thermowell was leaking. A spare RTD was connected and the problem thermowell was capped.

This RTD would probably have caused problems in the future, potentially causing a unit shutdown.

Nuclear Instrumentation Cable Problems

During the winter of 1988, SCE replaced the Nuclear Instrumentation System at Unit 1. On March 10, 1989, after installation was complete, baseline data was obtained on all of the new cables. At that time, the system was operating satisfactorily and the ECAD data did not reveal any problems. Subsequently, one (1) of the channels on the intermediate range began to show noise problems. With plant startup fast approaching, SCE brought in the ECAD System and requested assistance from ECAD. The testing ran over several days and several problems were found and resolved. The most significant problem was an apparent minor change in the TDR trace, when compared to the baseline, at a connector near the Bioshield. It appeared that the shield connection on a Triax cable had a slight increase in impedance. These cables are difficult to disassemble and reassemble reliably, so an extra braided shield was strapped over the existing connector; the noise disappeared immediately.

Troubleshooting this problem was difficult, but it would have been much more difficult had SCE not performed baseline testing with the ECAD System. The importance of obtaining baseline data cannot be over emphasized.

RCS Low Flow Reactor-Trip (1)

On August 3, 1989 at about 6:00 p.m., Unit 1 tripped due to a low flow signal in the Reactor Coolant System (RCS). The design of Unit 1 did not (in this case) identify which of the three (3) loops caused the problem. Standard troubleshooting techniques were used but did not identify any problems. By noon the next day (August 4, 1989), SCE discussed the need to restart the unit without finding the cause of the problem. At 3:00 p.m. we brought in the ECAD System and started testing. At that time, baseline data was only available for the loop "A" flow transmitter. No problems were found on loop "A" or "B". However, loop "C" showed a high dissipation factor (.9 vs .07) and a high capacitance (.31 nf vs .11 nf). By comparing the TDR traces for loop "A" and "C", the maintenance foreman identified a slight capacitive dip in the signature out near the transmitter. The TDR data is shown in Figure 3 and clearly identifies the point of degradation. By 6:00 p.m. that evening, a crew was on its way to check that section of the cable. When the cable was pulled out of the conduit near the transmitter, it could be seen that it had been wet for some time. The cable section was replaced and the Unit was restarted on August 5.

Subsequent testing of the circuit in May of 1990 indicated that the cable section is remaining dry and in good condition. Table 1 lists ECAD data with the wet cable section and data acquired after replacement.

The cause of the failure was attributed to water intrusion during the previous outage. The cable was analyzed and found to be heat and/or radiation damaged over the 20 years it had been installed. All cable of this type in critical locations was replaced during the June 30, 1990 outage.

Based upon this finding, SCE believes that the ECAD System has probably prevented at least one (1) reactor trip and saved at least a couple of days of generation.

RCS Low Flow Reactor Trip (2)

On April 30, 1990 Unit 1 tripped again due to a low flow signal in the Reactor Coolant System. This incident was very similar to the previous RCS low flow trip. The ECAD System was immediately brought in to obtain data on all of the flow transmitters for comparison with the data taken in August, 1989. This time, the data for Loop "B" showed a difference from the previous data, but it did not clearly point to a known problem.

The data was sent back to ECAD for their analysis. ECAD hot-line support personnel analyzed the data and suggested that it did not appear to be a cable problem. ECAD had similar data from another plant which indicated that the transmitter had been the problem. Subsequent disassembly and microscopic analysis of the transmitter showed that the trip was caused by insulation degradation of the force balance coil in the transmitter.

New Pressure Transmitter Installation-Problems

During the Unit 2 Outage in October, 1989, SCE installed four new pressure transmitters. Prior to the station accepting them from construction, the ECAD System was used to obtain baseline data. Three (3) of the transmitters were good, but one (1) showed a low resistance from the shield to ground. By comparing the TDR traces it could be seen that the low resistance was at the transmitter. Inspection showed that the shield had not been completely wrapped with electrical tape when it was terminated in the junction box at the transmitter. The shield was repaired and the problem was resolved.

While this problem could have been solved by traditional methods, the ECAD data allowed SCE to go directly to the source of the problem instead of spending a couple of days lifting leads searching for the ground.

SCE'S THOUGHTS ON THE ECAD SYSTEM

ECAD continues to improve system performance through development efforts which strive to incorporate customer feedback; SCE has recently employed Rev. 5.0 of the software. In addition, SCE will exploit continuing improvements in instrumentation technology through periodic upgrades. SCE is still learning the applications and limitations of the system.

At San Onofre, we have a significant amount of noise on our power cables; instrumentation and control cables are usually not affected due to cable shields. Currently, the ECAD System cannot acquire impedance data on excessively noisy circuits; however, neither can any other commercially available instrumentation used at San Onofre.

The equipment and software is designed so that it takes little experience to operate and obtain data. However, as with any diagnostic tool, it takes experience and training to fully comprehend the data. SCE understands that it may take several years of experience to become self-sufficient at this task. ECAD has provided on-going support on a 24-hour per day, as needed basis to assist us throughout this process.

Finally, application of the ECAD System is becoming a useful condition monitoring technique, and represents another good addition to SCE's diagnostic toolbox. We anticipate that it will become more useful as we continue to learn more about the technology as applied to trending circuit condition over time. SCE feels that the system has paid for itself and all of SCE's efforts many times over, and currently credits the system with some stunning successes; it has saved at least one reactor trip and several days generation on one occasion, and a shutdown on another (both on Unit 1). SCE has made a commitment to the continued use and improvement of the system for applications at San Onofre Nuclear Generating Station. Recently, ECAD Division of Pentek, Inc. has sold several other systems to major industrial users. We hope to be able to work with these new users to our mutual benefit as members of a formal ECAD Users Group.

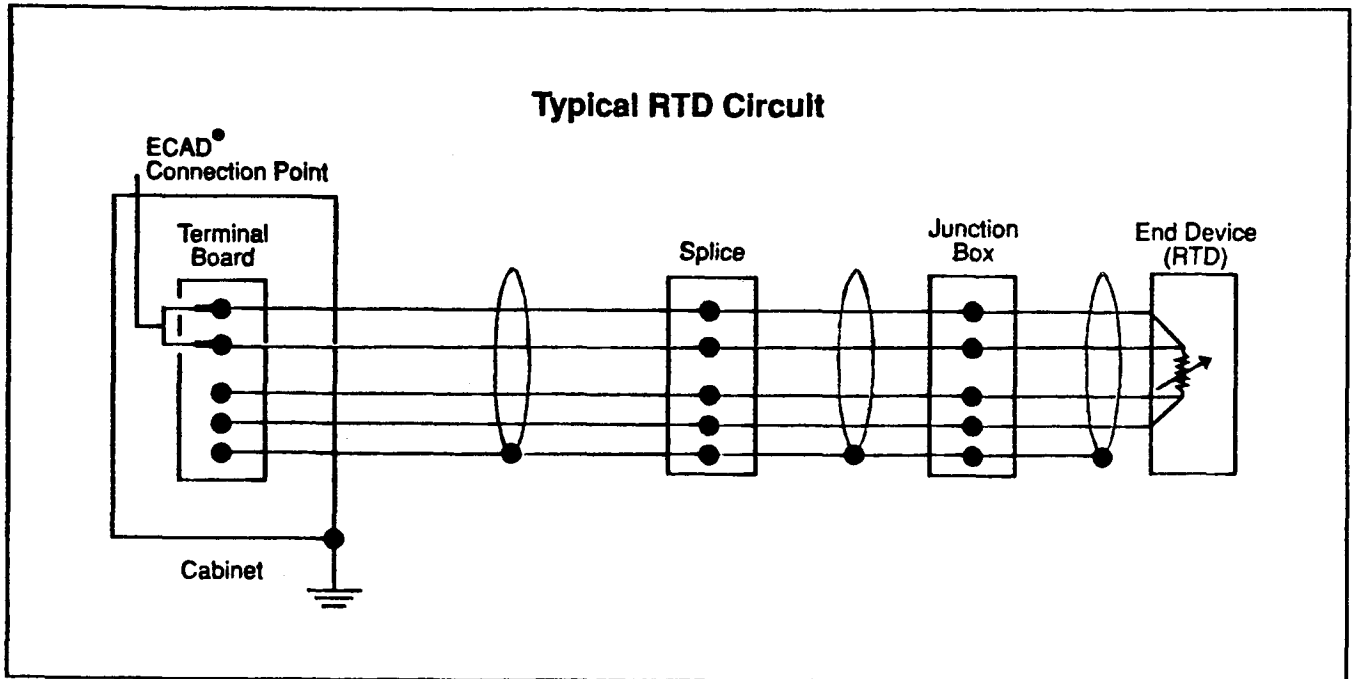


Figure 1. One-Line Diagram Showing ECAD Testing Connection

ECAD SYSTEM 1000 DATA CHART

ECAD SERVICES INC.

EF 100

CIRCUIT IDENTIFICATION

DEVICE CODE: 11E101

DESCRIPTION: 4 WIRE RTD TRAINING MODEL

DEVICE TYPE: RTD4 CONFIGURATION: A

OPERATOR IDENTIFICATION

LAST NAME: SERENA

LAST NAME:

FIRST: KEN

FIRST:

SS#: - -

SS#: - -

TEST AREA: ECAD SHOP

TERMINATION: TERM. BLK.

ID CODE: TB-A

MOD: 00000000002

HIGH TEST POINT: TB

ID CODE: A

PIN: 1

LOW TEST POINT: TB

ID CODE: A

PIN: 2

VOLTAGE (V)	DC RESISTANCE (OHMS)		AC RESISTANCE (OHMS)		REACTANCE (OHMS)		U	MEASUREMENT UNDEFINED
							L	INDUCTANCE/QUALITY (H/UNITY)
VAC + VDC	FIRST	FINAL	1 KHZ	10 KHZ	1 KHZ	10 KHZ	C	CAPACITANCE/DISSIPATION (F/UNITY)
(R) 6.44 n	1.50	1.50	1.53	1.57	111.00 n	1.09	L 17.67 u/ 72.60 n	L 17.40 u/ 697.51 n
(I) 4.77 n	11.69	11.69	11.72	11.76	109.00 n	1.08	L 17.35 u/ 9.30 n	L 17.11 u/ 91.39 n

IR Test Voltage: 0 V

Polarization Index: 1.00

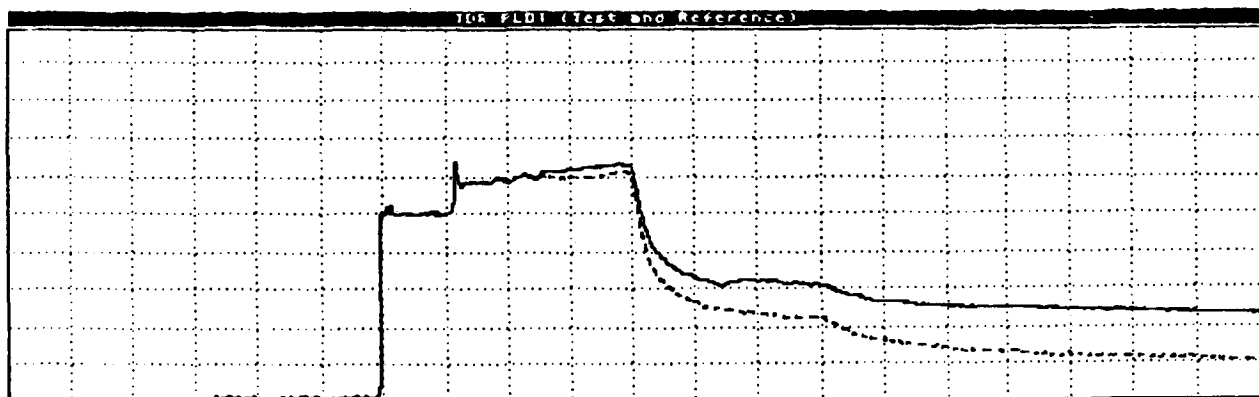
IR Test Duration: 0 Seconds

(R) REFERENCE DATA -- DATE: 08/29/90 TIME: 16:15

G = Giga M = Mega K = Kilo

(I) CURRENT DATA -- DATE: 08/30/90 TIME: 13:44

n = milli u = micro n = nano p = pico



Horizontal Distance

Test 1 (Solid)

Instrument Cables: 32 ft/div (approx)

Power Cables: 25 ft/div (approx)

Time Base: 100 nS

Reference (Dashed)

Instrument Cables: 32 ft/div (approx)

Power Cables: 25 ft/div (approx)

Time Base: 100 nS

Vertical Rho = .2/div

Figure 2. ECAD Data Chart

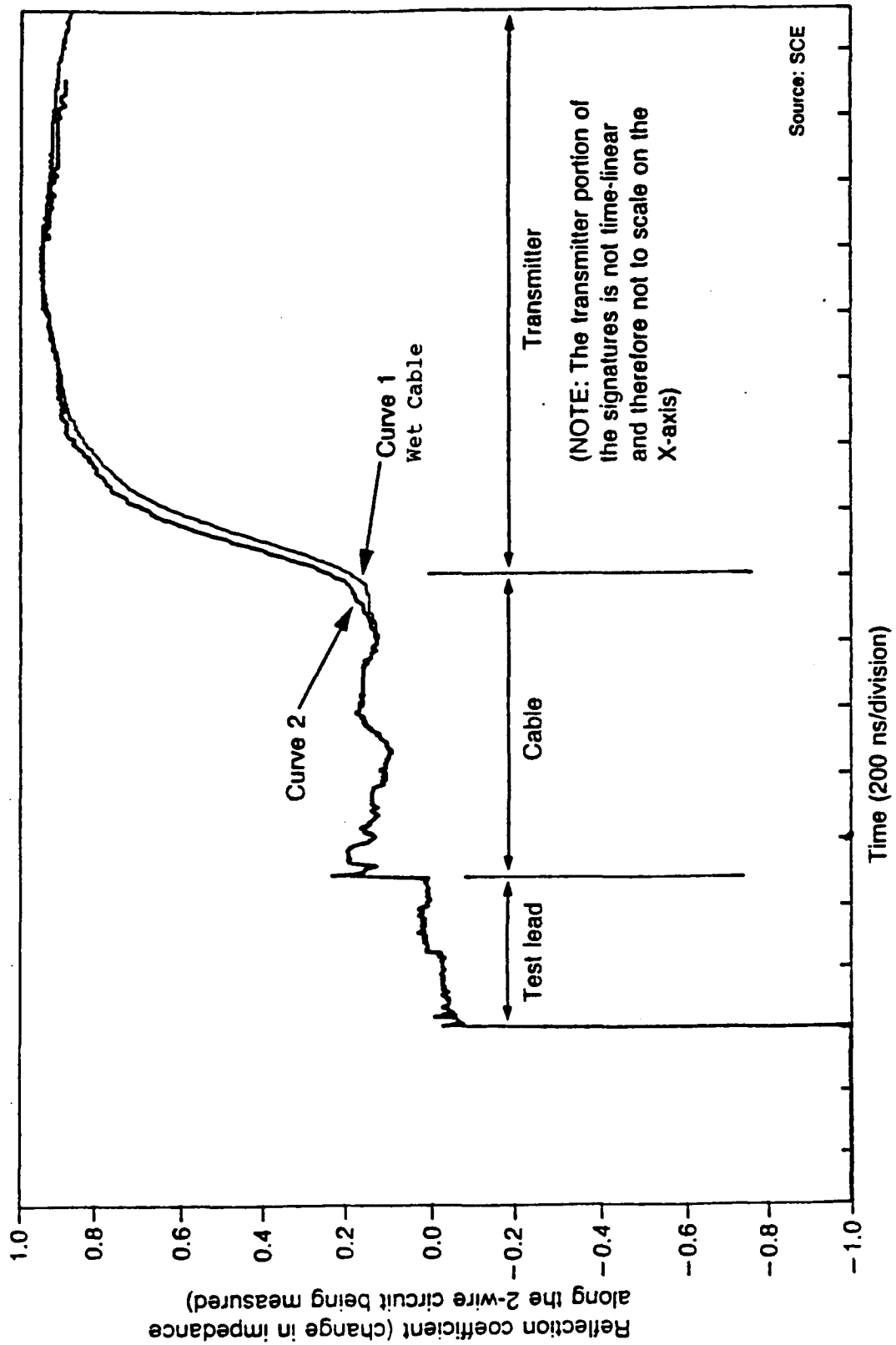


Figure 3. TDR Data Showing Location of Wet Cable

ECAD SYSTEM 2000

Page: 2
Date: 05/05/90

Date	Time	Test Voltage	DC Resistance	1 KHz AC Resistance	10 KHz AC Resistance	1 KHz Capacitance/Dissipation	10 KHz Capacitance/Dissipation
08/04/89	17:22	< 6.5	0.00	4.85K	98.63	31.36 nf / 954.89 m	16.56 nf / 102.64 m
05/01/90	12:32	< 6.5	31.00 M	1.05 K	33.32	11.20 nf / 74.00 m	10.89 nf / 22.80 m
05/01/90	12:35	100	3.78 G	9.61	6.31	16.24 nf / 0.98 m	16.28 nf / 6.45 m
05/01/90	12:38	100	3.84 G	9.48	6.23	16.35 nf / 0.97 m	16.38 nf / 6.41 m
05/01/90	12:42	100	26.45 M	2.43 K	151.49	11.63 nf / 177.39 m	9.60 nf / 91.41 m

DEVICE: S1-RCS-FT-420

DESCRIPTION: RCS FLOW XMITTER LOOP C

August test with wet cable
Current test with good cable

08/04/89	17:22	< 6.5	0.00	4.85K	98.63	31.36 nf / 954.89 m	16.56 nf / 102.64 m
05/01/90	12:32	< 6.5	31.00 M	1.05 K	33.32	11.20 nf / 74.00 m	10.89 nf / 22.80 m
05/01/90	12:35	100	3.78 G	9.61	6.31	16.24 nf / 0.98 m	16.28 nf / 6.45 m
05/01/90	12:38	100	3.84 G	9.48	6.23	16.35 nf / 0.97 m	16.38 nf / 6.41 m
05/01/90	12:42	100	26.45 M	2.43 K	151.49	11.63 nf / 177.39 m	9.60 nf / 91.41 m

Table 1

FLOW TRANSMITTER DATA FOLLOWING CABLE REPLACEMENT

DIAGNOSTICS OF FIRE HAZARDS SITUATION
IN NUCLEAR POWER PLANT

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ABSTRACT

The paper deals with the data systematic approach on fires and fire damage in Nuclear Power Plants (NPP). Fire causing factors and fire hazards analysis have been performed. Organization and technical design consideration items aiming on fires mitigation in NPPs are discussed.

INTRODUCTION

Among problems determining ways and perspectives of nuclear technologies development one of the key items is the problem of fire prevention thus a prognostic fire damage in a nuclear plant demands of a high risk. An extensive research is needed into new non-conventional ways and means of fire protection development.

Referring data /1-2/ from 40 to 50 fire incident occur in the mean in world's NPPs per year. This consideration makes it urgent to study the problem of NPP fire protection therefore. Similar data have been obtained from INIS data analysis, catalogues and abstract journals. Included data base comprise 1214 sources /3/, covering the period from 1980 till 1990.

FIRE INCIDENTS DATA ANALYSIS IN NPP

Fire incidents occurrence in a NPP operation is a random event resulting coincidence of a number of independent events such as combustible medium and oxidizer presence, ignition

TABLE 1. FIRE EVENTS IN NUCLEAR POWER PLANTS

Item	: USA	: USSR	: FRG	: UK	:FRANCE
	: /4/	: /5/	: /6/	: /7/	: /8/
No.of recorded inci- dents	354	156	59	46	34
<u>Causes of fire (%)</u>					
Component failure	5.9				
O i 1 leakage		13	30.4	28.3	11.7
Welding	1.5	22	27.1	4.2	5.8
Electrical failure	17.5	40	22.1	19.6	35.3
Heating	11.9	8	6.8		32.5
Explosion	7.8	12		32.7	
Component and elec- tricity failure	9.1				
Component failure and overheated material	11.25				
Others	21	5	13.6	15.2	14.7
<u>Fire fighting (%)</u>					
Shift personnel	27.6	35.8	25.6		
Fire brigade	20.4	60.8	64.4		
Automatic system	5.9	3.4			
Others	46.1		10		

source and a mechanism of energy transfer. The results of output data analysis of a recent 10 years in world's NPP operation showed that there occurred over 600 fire incidents. Severe fire incidents with radioactivity release behind plant territory accounted 0,5%, mean severity incidents (with radioactivity release within the station limits 9%) and the rest are insignificant fires regardless radioactivity release into the atmosphere.

In table 1 fire incidents data in world's NPPs are presented regarding the reasons of their origin.

Comparative evaluations of fire origin in NPP buildings show that design imperfections account for 18% of all number of fires, mounting failures - 10%, equipment malfunction - 20%, operator failure - 42% and the rest are external causes.

Therefore as a number of fires is changed from year to year the percentage ratio of fire causes exhibit stability.

In Fig. 1,2 change of dynamics in fire number relations (N) to (m) value is shown.

In the Soviet Union of late 10 years there occurred 73 fires in RBMK and 83 fires in VVER reactor respectively /5/. It must be pointed out that the highest number of fires is referred to construction and starting period of reactor operation.

Then 10 - year period of stabilization and hereafter comes a gradual growth of fires.

In early stages of plant construction and pre-operational period fires are explained by equipment mounting failures and fire engineering regulations violation.

There enters a long period in plant operation with stable amount of fires and constant in time. Though on passing 10-15 year period in plant operation fires appear again regarding as a rule equipment failure due to a premature aging. Equipment failure due to elements aging occur regarding long term radiation and temperature exposure, corrosion and erosion processes etc.

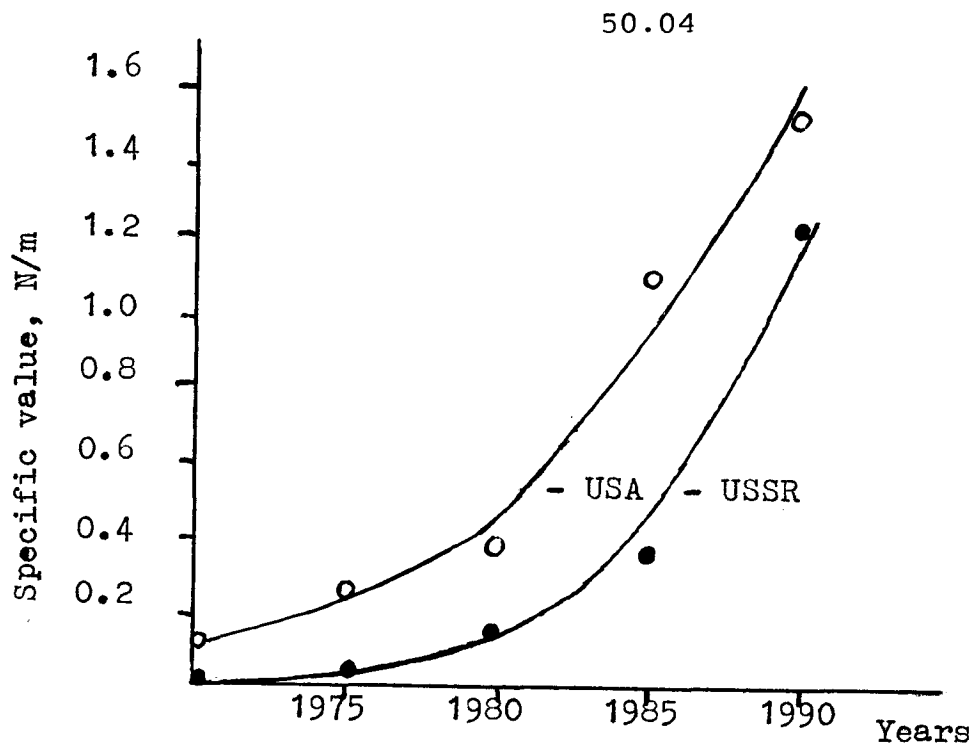


Fig.1 Dynamics of specific value change

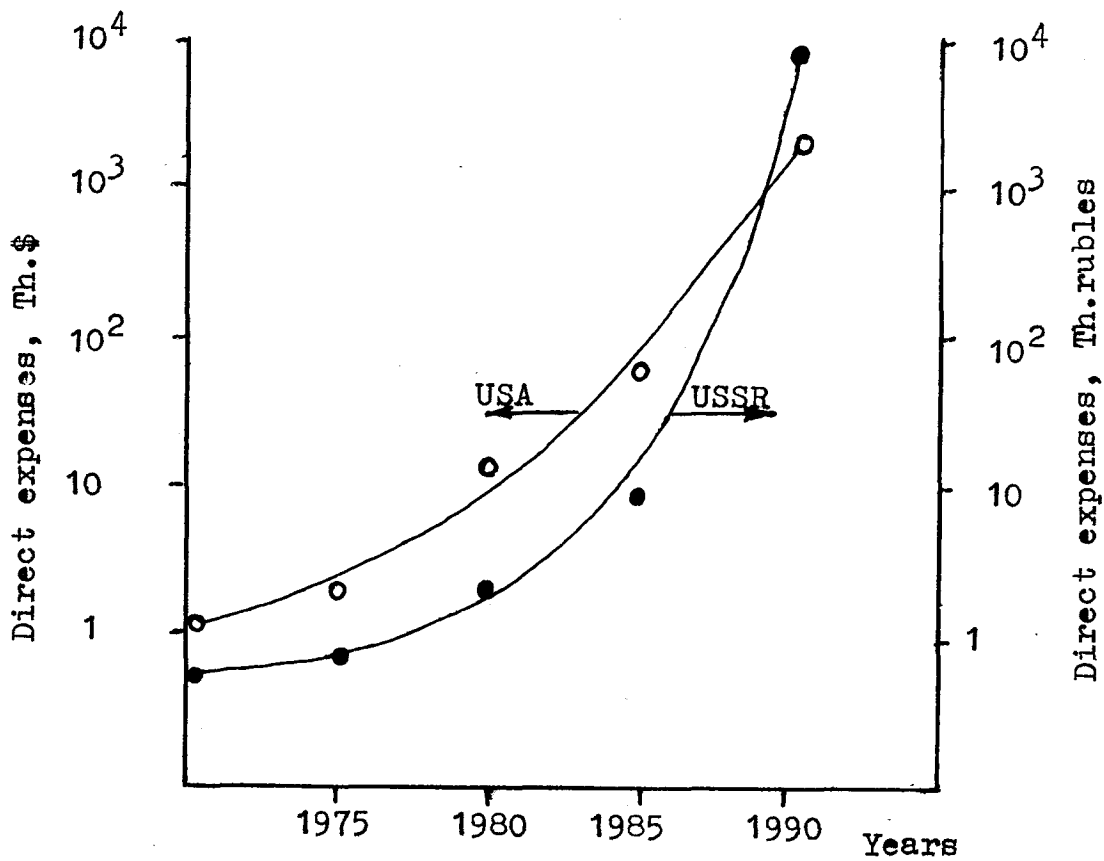


Fig.2 Material damage resulting NPP
fires occurrence in % regarding fires

Table 2. Comparative fire and ignition distributions in NPP equipment (%)

Country	Equipment type						
	Cables	Electrical	Turbine	Pumps	Control	Cooling	Other
	: make-up	: generator	: compartment	: towers			
USA	28	31	10	13	2	1	15
USSR	31	37	16	6	3	2	5

Table 3. Comparative fire distributions regarding the place of their origin (%)

Country	Place ignition					
	Reactor	Turbine	Deaerator	Sealed	Auxiliary	
	: buildings	: halls	: rooms	: zones	: compartments	
USA	39	36	8	7		10
USSR	41	38	6	3		12

Table 4. Comparative fire and ignition distribution regarding the causes of their origin

Country	Fire ignition causes						
	Short	Oil hot	Equipment	Fire	Fire	Not established	
	: circuit	: surface	: failure	: regulation	: protection	: cause	
	: leakage	: failure	: failure	: failure	: failure		
USA	25	12	20	18	13		12
USSR	34	13	12	19	11		6

We mainly reffer here as fire dangerous equipment pumps, valves, cable insulation, oil ducts, electronic equipment etc.

Fire and ingnition distribution occured in NPPs (USSR, USA) in various equipment is shown in table 2. Out of total 156 fires in the USSR 113 or 72% occured in main plant buildings and 43 or 28% occured in auxiliary.

In the USA out of total 214 fires 74% occured in main plant buildings and 26% in an auxiliary.

In table 3 a comparative evaluation of fire distribution is given (USSR, USA) regarding the place and the cause of their origin respectively. From the data introduced in tables 1-4 a conclusion may be derived that regardless type of a NPP, function regime and technological properties mean fire and ignition distribution values in % are practically the same as regarding type of equipment, place and causes of fire origin.

FIRE HAZARDS FACTOR IN NPP

We rely to Fire Hazards Factor (FHF) an indication or an array of indications whose change in time may cause fire or ignition if not to suppress the dynamics of the event. Fire category is determined of specifications and depends upon standards of protected object.

Thus FHF identify possible fire causes (combustible media, oxidizer, ignition source, energy transfer mechanisms) and the character of consequences. As an information term FHF include two parts - "a priori" (characterising possible fire causes and sources) and "a posteriori" (identifying fire hazards level and consequences). "A posteriori" part in FHF is derived by prognostic simulation or real fire damage estimation /9/.

Typically a NPP differs in structure of FHF from other objects in "a priori" (specific technologic media, nuclear fuel, moderator, coolants, radioactive elements etc.) therefore in "a posteriori" (ecology, social and material damage from fires in NPPs is much higher than in other objects). Presently there

exist various methods for classification and analysis of FHF indication. In Fig. 3 we introduce the FHF classification indication for NPPs. The inner events introduced in Fig. 3 are: 1) technical or technological outcoming e.g. in core reactor processes (loss of coolant, water and cable insulation radiolysis, radiation heating of structure materials, Wigner's effect, positive reactivity coefficient etc.); 2) in - plant management events (personnel failure, inadequate reactor maintenance, design and mainting failure, inadequate regulations and guidelines).

External events which may cause fire are kept with natural phenomena such as earth quake, water-spout storm, flood, lightning, tornado etc. and events of technological origin - aircraft accidents, transport accidents, gas clouds of chemical origin, shock wave impact etc. We also reffer here nuclear plant fires geared with sabotage and terrorism. Ignition source indications are divided into nuclear (radiation heating, radiolysis, reactor run etc.), heat (open fire, lightning etc.), thermal (self-ignition, heated surface), mechanical (friction, strike, wear), electric (lightning strikes, electrostatic charges, spark discharges, short circuits etc.), chemical (vapour zirconium reaction explosive mixture origin etc.).

Combustible items media exhibit the following substance status: nuclear fuel (hard form), structural material, graphite, cable insulation etc.), liquid items (transformer oil, lubricant oil, acids, alkalies etc.) and gas items (oxygen, hydrogen explosion mixture etc.).

In nuclear plant fire occurrence there should take place an energy transfer from ignition source to combustible media. Energy transfer may be conducted through heat transfer, convection and radiation transfer. These processes are also considered for FHF indication classification (See Fig. 3).

Fire Hazards Factor "a postriority" indication in nuclear plant fall into four categories: factors impacting nuclear safety, factors impacting nuclear safety indirectly, factors impacting

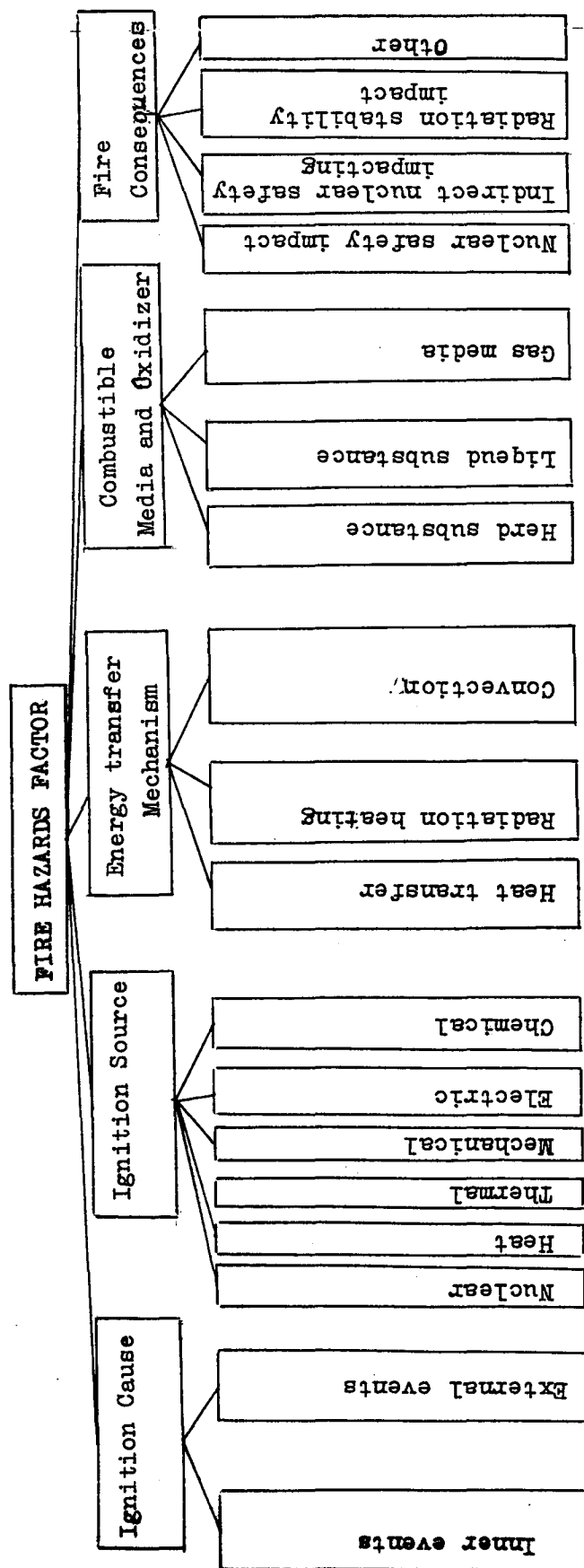


Fig. 3. Fire hazards factor indication classification in NPP

number in FHF for j - category ($j = 1, 2, 3, 4$) and
 L - Order number in LHF value.

The range arrangement of levels in LFH will list

- $i = 1$ preventive level
- $i = 2$ repair level
- $i = 3$ incident level
- $i = 4$ process shut down level.

3. PHYSICAL MODELS OF FIRE OCCURANCES (MFO) in each NPP compartment and fire scenarios progress in time have been working out.
4. Information Base for System of Pre-Fire Diagnostics (SPFD) in NPP run as:
 - conventional systems of current nuclear plant control of informational sources determining indications of hazards factor;
 - system of specified fire alarms for current fire hazards indication control;
 - prognostic results of MFO for definite value calculation indications of fire hazards factor.
6. SPFD NPP functions separately from other plant safety systems and its life and reliability must be preserved at design accidents.
7. SPFD NPP is connected by informational channel to other plant systems and on the upper levels of fire hazards it belongs the priority in decision making at nuclear power plant operation. At exceeding LFH - L_4 - 4 a NPP shutdown must be occurred in automatic regime.

CONCEPTION OF SPFD IN NPP

Configuration and structure of the system of diagnostics of pre-fire situation in nuclear power plant is much to be determined by functional role of protective buildings and equipment maintenance /12/. For early fire detection various sensor types of technological control are mounted within the region of fire

radiation safety. The first and the second categories should be listed in guideline regulations accounting individually each nuclear plant.

Though preserving nuclear safety fire may cause radiation safety failure therefore assuming radionuclides release and encompassing of urgent measures performance (repair, technological, deactivation, rescue etc.) in radiation dangerous conditions.

Fire Hazards Factor analysis introduced manifest that in VVER-1000 there exist almost 100 indication of fire hazards factor and more than 40 scenarios of fire ignition and layout.

Fire layout may be easily restored by consequent retrospective events analysis or by computer simulation.

Computer simulation problems of fire layout on early stage of ignition in nuclear plant building may be formulated as follows:

1. Formulation of dynamical equations, treating the behavior of protected object and its components.
2. Interrelation installation between equations.
3. Distribution function $F(x, t)$ evaluation for object protected.
4. Entropy determination as a time function

$$S(t) = K \int F(x, t) \ln F(x, t) dx,$$

where $X = \{X_1, X_2, \dots, X_N\}$ parameter object characteristics
 K - Boltzman constant.

Regarding FHF indication a conclusion may be derived accounting basic principles of the system of pre-fire diagnostics conception situation in NPP :

1. Pre-fire situation in a NPP must be identified on an early stage of its progress development (dynamic parameter items change control must be performed of fire hazards factor in time)
2. Several Levels of Fire Hazards LFH - L_j - i are established regarding each indication of FHF where L_j - indication

Table 5. Technical characteristics for infra-red Fire Sensor (FS)

Parameter FS type	Operational : temperature : range, : K	Spectral : range, : mm	Ignition : place de- : tecton : length, : m	Supply : voltage, : V	Size, : mmxmm	Mass, : kg	Maximal : exposure : rate, : Gray
Infra-red unit	253+328	2+75	60	± 12	50x250	0,3	2.10 ⁶
Fire detection	253+333	1+2,5	25	± 15	40x100	0,5	10 ⁵
Infra-red sensor	263+323	1+15	20	± 5	30x30	0,1	8.10 ⁵

Table 6. Technical characteristics for fire indication temperature

Parameter FS type	Performance : temperature : range, : K	Constant : time, : sec	Supply : voltage, : V	Size, : mmxmmxmm	Mass, : kg	Maximal : exposure : rate, : Gray
Foil thermoresistor	223+523	0,4	± 0,5	3x3x0,1	0,01	5.10 ⁷
Temperature excess sensor	213+400	1,0	± 9	4x4x0,1	0,04	3x10 ⁷
Opticofibrous point temperature sensor	243+513	10	± 15	1x1x1000	0,3	80
Fusible optical fibre sensor	243+523	10	± 15	1x1x10 ⁵	10	10

dangerous equipment.

Fire detection sensors must keep the requirement of severe function condition (temperature 300 K, pressure 0,1 mP, humidity 90%, vibration amplitude 0,1g with the base frequency 30 Hz, radiation exposure etc.). In tables 5-7 fire sensors parameters are given standing severe operation conditions operating in sealed zone, turbine hall and cable channel. Non-conventional types of fire sensors /13/ exhibit higher sensitivity to compare with conventional ones and allow to obtain information of the surrounding media and the proper state of sensor itself. It must be noted so far that the measurement accuracy of each fire sensor is determined not as an instrumental error but as a deviation caused by external condition of measurement and the main sensor parameter is defined as start - on coefficient not equipment failure items.

In Fig. 4 a version of functional structure of SPFD is considered comprising three hierarchy levels. In the lower system level technological control transducers, sensors of fire indication of various types, alarm dosimeter and radiation meters are distributed. An array of sensors serve to justifiable measurement. Direction control numbers comprise 8,16 and 32 items depending sensor location and NPP type. The maximal configuration of the SPFD reasonably embrace 32 directions and may treat over 3000 signals on-line.

Intellectual blocks of fire indication comprise three modules: Unit Control Crate (UCC), Chip Processor Unit (CPU), Programmable Crate Controller (PCC), Diagnostics Module (DM) and output of alarm signals management (blocking). In the middle level of SPFD (see Fig. 4). Minicomputer (MC) of high fidelity and high-duty performance, Fine Tuning Panel (FTP), Display (Ds.), Printer (Pr.), Random Access Memory (RAM), Interface (In.) and Connection Object Unit (COU) are utilized.

Middle level system equipment assure to avoid false actuations using various types of fire sensors, through different methods

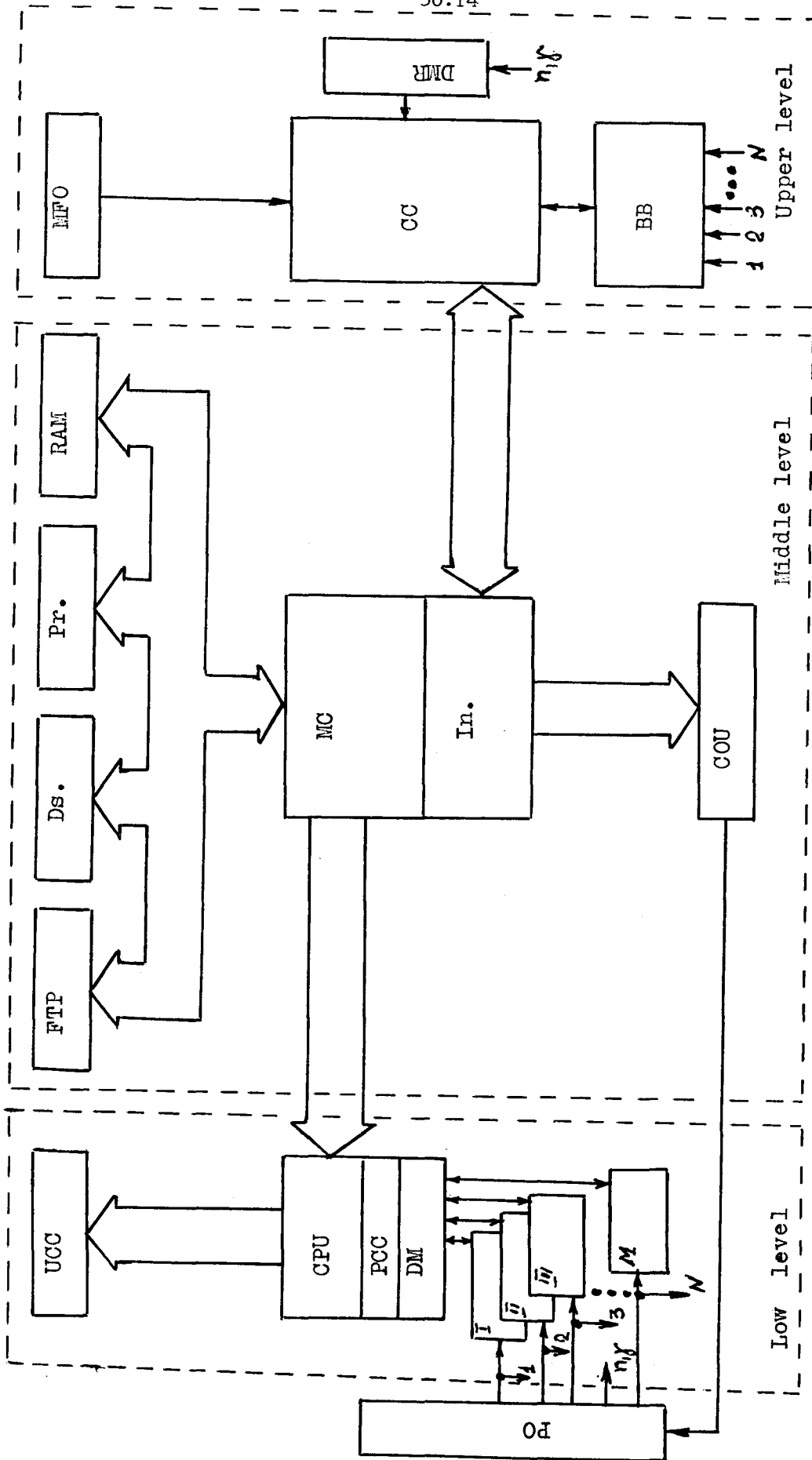


Fig. 4 Structure scheme for pre-fire hazard situation system

of discrimination FHF indications and development (absolute value method, differential method, heuristic etc.). Central Computer (CC) located on a higher hierarchy level provides the MFO calculations and prognostification FHF indications, diagnostics and identifies LFH values for selected scenario of fire layout. This level contains a "Black Box" (BB) and Dose Meter Rack (DMR) for accident condition workout. A proposed configuration of SPFD NPP assure to maintain control performance of Protected Object (PO) having large spatial distribution therefore in time perform actions of management requests.

CONCLUSIONS

A proposed statistic data approach in determining fire and ignition causes in nuclear power plants and material damage evaluation cleared the problem of nuclear power plants fire protection as of international value. Therefore its solution put forward an international scientists effort coordination in the field of creation and development of new systems for pre-fire diagnostics and determination regarding non-conventional types of fire sensors, computer models for early ignition detection in radiation dangerous objects. It stands clear the problem of further development and modification of already existed statistic probability approaches in prefire risk evaluation in nuclear power plants.

In spite of various approaches to NPP fire protection in various countries common features are outlined among:

- growing regulations to fire protection in nuclear power plant, development of new safety standards, licensing and regulations;
- actuation of principles of multi-barriers for fire protection;
- strict observation and follow of engineering and technical fire protection regulations including IAEA recommendations;
- regular test and maintenance operation regarding equipment and building fire protection prevention;
- non-conventional methods and means for pre-fire situation diagnostics and prognostification in early stage of fire occurrence.

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BWR VIBRATION MEASUREMENTS BY IN-CORE NEUTRON NOISE ANALYSIS

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ABSTRACT

Noise Analysis is established as a reliable tool for vibration surveillance in PWR's. Based on this method the signals of the standard reactor instrumentation of the 1300 MW BWR Gundremmingen (KRB C) have been analysed in order to identify vibrations of the reactor components. The signals of 176 in-core miniature fission chambers, a reactor pressure sensor, steam rate meters as well as some signals of accelerometers and absolute displacement transducers mounted at the reactor pressure vessel have been analysed. All signals were recorded during different reactor power levels and burn up conditions. Vibrations of some reactor structural components, for instance a displacement of the pressure vessel, fuel bundle vibrations and different modes of instrumentation string vibrations, could be identified. The paper also presents results of some special measurements to find out the origin of a particular core lattice cell vibration.

INTRODUCTION

Surveillance of mechanical vibrations by neutron noise analysis is usual in PWR's. This analysis is more difficult to implement in BWR's due to the fact that the boiling process is the dominant noise source. The general behaviour of BWR noise was investigated by some authors [1, 2] and reviewed in [3]. Additionally neutron noise has been used to detect BWR in-core instrument tube vibrations in [4, 5].

In this paper neutron noise analysis of signals from the 1300 MW BWR Gundremmingen has been performed. Also other signals of the standard reactor instrumentation have been analysed.

The principal aim of this work is to demonstrate that mechanical vibration monitoring in BWR's is possible to carry out using this method without any interference to the normal plant operation and with no need of any additional instrumentation.

CORE INSTRUMENTATION

The core arrangement of the BWR Gundremmingen and parts of the lattice configuration are shown in Fig. 1. In-core neutron flux monitors are arranged in fortyfour instrumentation strings. Each instrumentation tube houses four miniature fission chambers, located at different axial positions of the active core height.

The signals from all the 176 standard in-core power range neutron flux detectors have been analysed in various frequency ranges. Additionally the signals from one absolute reactor pressure sensor, four steam flow rate meters, two absolute displacement transducers mounted at the flange of the pressure vessel and twelve accelerometers have been available. The last belong to the loose part monitoring system and are placed on the pressure vessel at three levels.

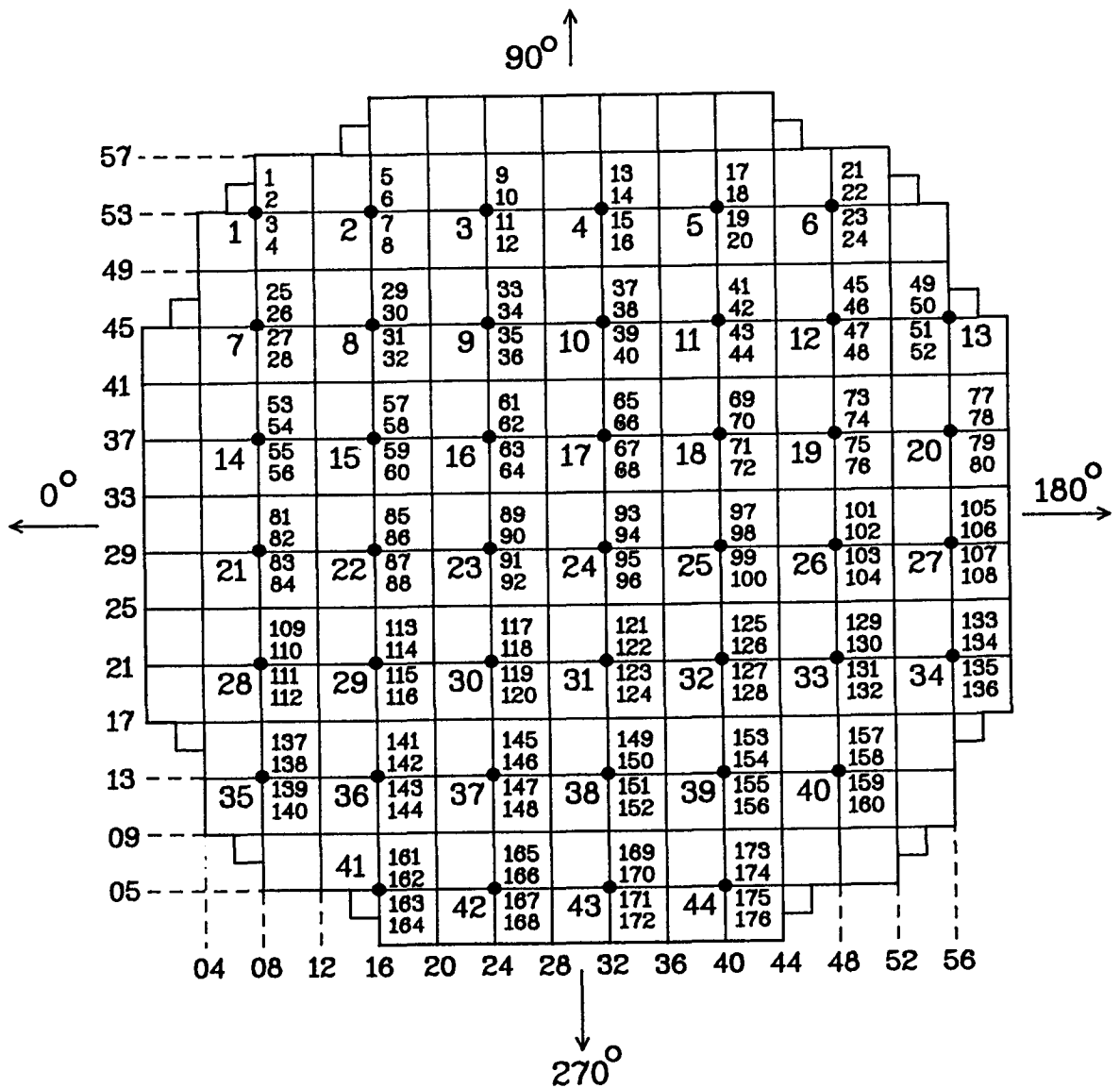


Fig. 1. Core Arrangement of the 1300 MW BWR Gundremmingen

IDENTIFICATION OF MECHANICAL VIBRATIONS IN IN-CORE NEUTRON NOISE SIGNALS

The NAPSD's shown in the upper part of Fig. 2 represent the typical behaviour of the in-core neutron noise spectra during one fuel cycle. In the frequency range from about 2 Hz to 100 Hz boiling is the dominant noise source, mainly in the upper part of the core. This influence decreases during core life due to the decreasing void fraction in the coolant flow. For this reason the peaks described in the following can be observed more clearly at the end of a fuel cycle.

Using a linear one dimensional model eigenfrequencies of some reactor components have been estimated.

Instrumentation Tube

The peak around 2.5 Hz can be associated to the fundamental mode of the instrumentation tube vibration, while the peak between 9 and 10 Hz corresponds to its second mode. Pressure fluctuations are identified as the driving force of the 2.5 Hz vibration by a minimum value of 0.6 in the coherence between pressure and neutron noise.

Fuel Channel Box, Fuel Bundle

The peak in the NAPSD's between 5 and 6 Hz is related to the fundamental cantilever type vibration mode of the fuel channel boxes. The other peak between 3.5 and 4 Hz is assumed to be due to the fuel bundle vibration.

Up to about 8 Hz all these peaks are present in the coherence function between signals from different planes in one string (lower part of Fig. 2) and the corresponding phase behaviour indicates the mechanical origin of them.

Pressure Vessel

The fundamental vibration of the pressure vessel causes a peak in the APSD's and coherences of the signals from absolute displacement sensors and accelerometers around 6.5 Hz (Fig. 3), which has already been found out during the preoperational tests. This displacement affects the signals of the in-core neutron sensors at the outer core position too, but has no influence on the signals of the inner detectors. This fact is shown by the coherence between two neutron detectors (det. 3, string 1, core edge and det. 59, string 15, inner core position) and the vibration sensors A3 and M01 (Fig. 3).

Control Rod

The comparison between neutron noise spectra obtained while the control rods were partially inserted in the core and while they were pulled out gives no hint on control rod vibrations.

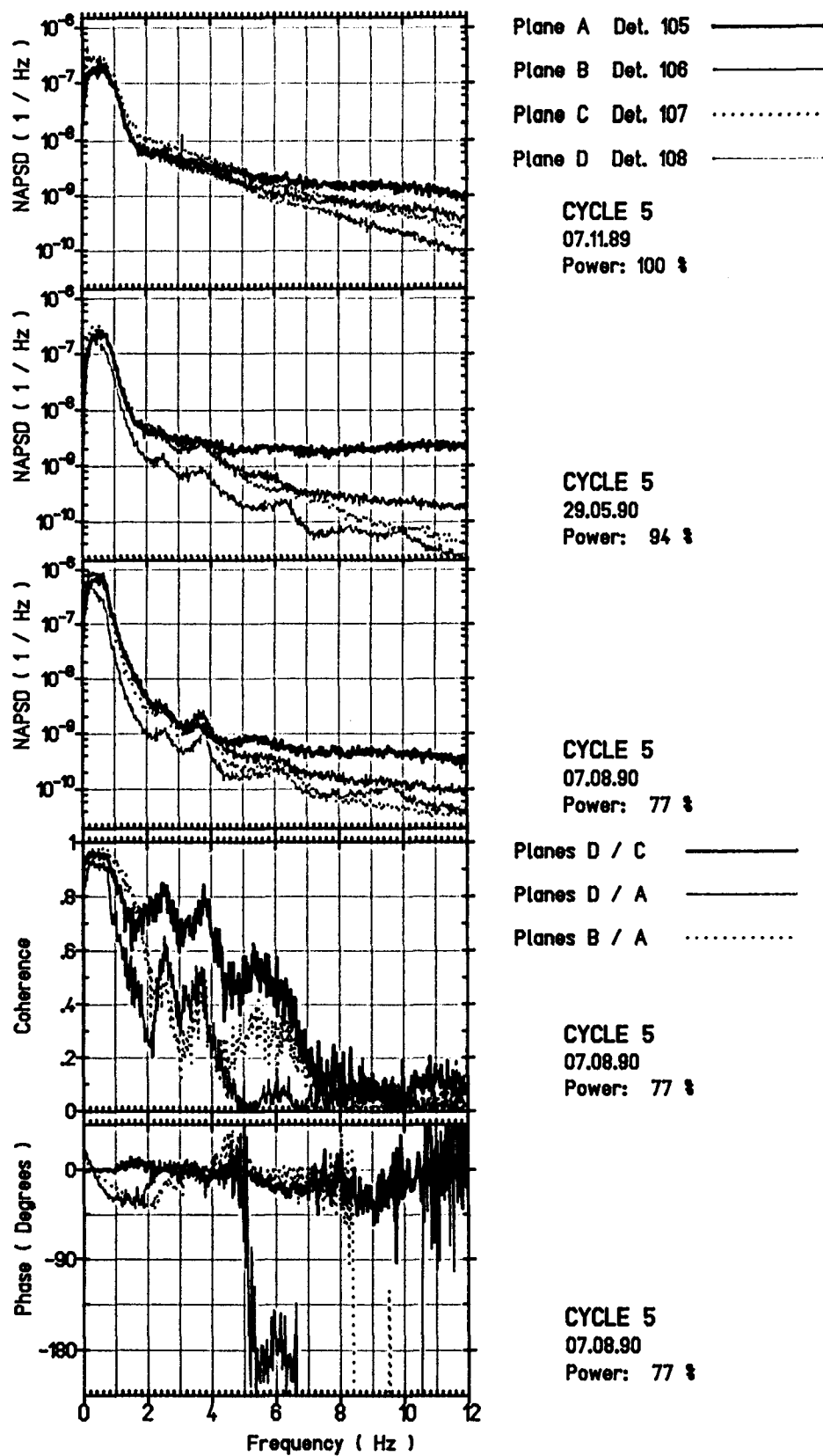


Fig. 2. NAPSD's, Coherences and Phases of Signals from String No. 27

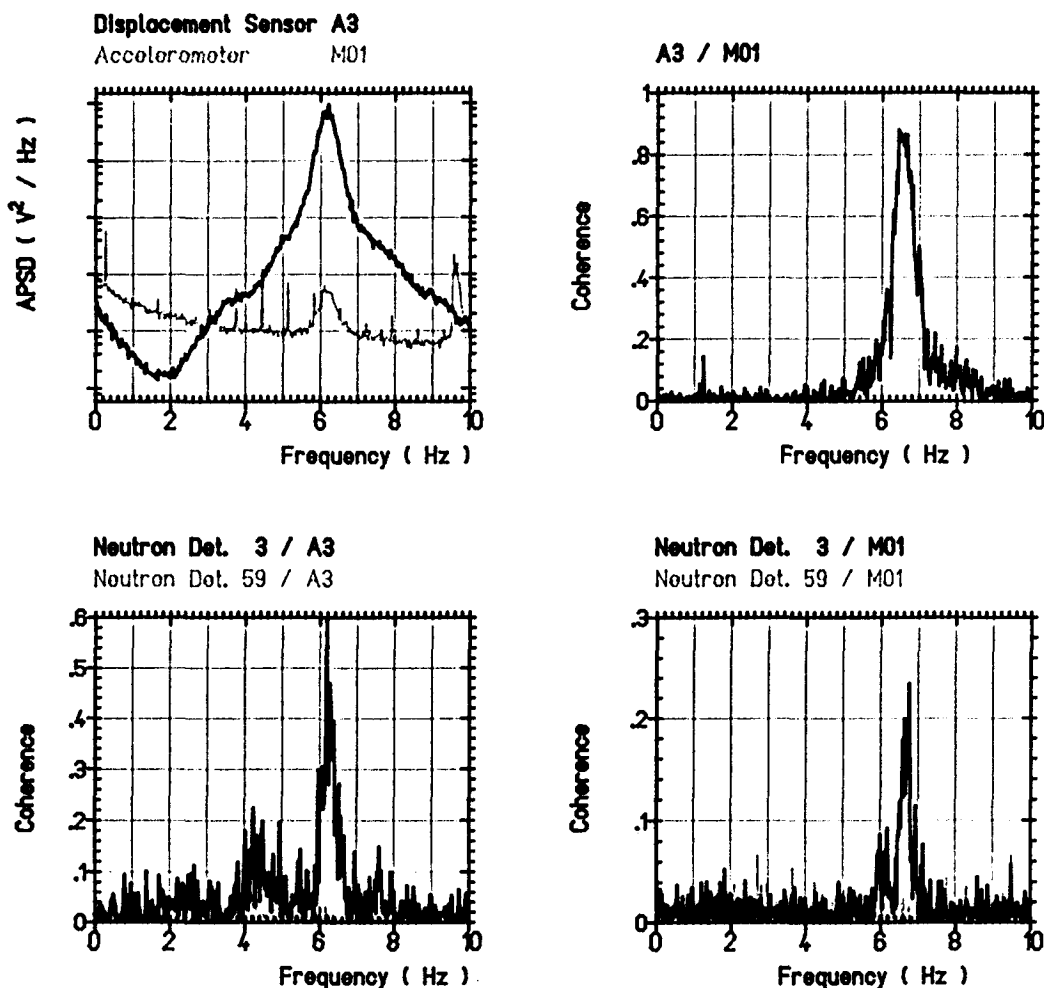


Fig. 3. Identification of Pressure Vessel Displacement

PARTICULAR VIBRATION BEHAVIOUR

Beside the typical vibrations described above, particular vibration behaviours have been observed at some core positions.

Instrumentation string vibration

In Fig. 4 the development of the NAPSD's of the signals from instrumentation string No. 8 during three consecutive cycles can be seen. The magnitude of the 2.5 Hz instrumentation tube vibration was approximately one decade higher in cycle five than in cycle six. It is assumed that this is due to a change in the supporting conditions of the tube from one cycle to another during refueling.

String No. 26 is another example for a more intensive instrumentation tube vibration (Fig. 5.). In this case beside the NAPSD's the NCPSD's between the signals from plane A (det. 101) and plane B (det.102) are additionally drawn.

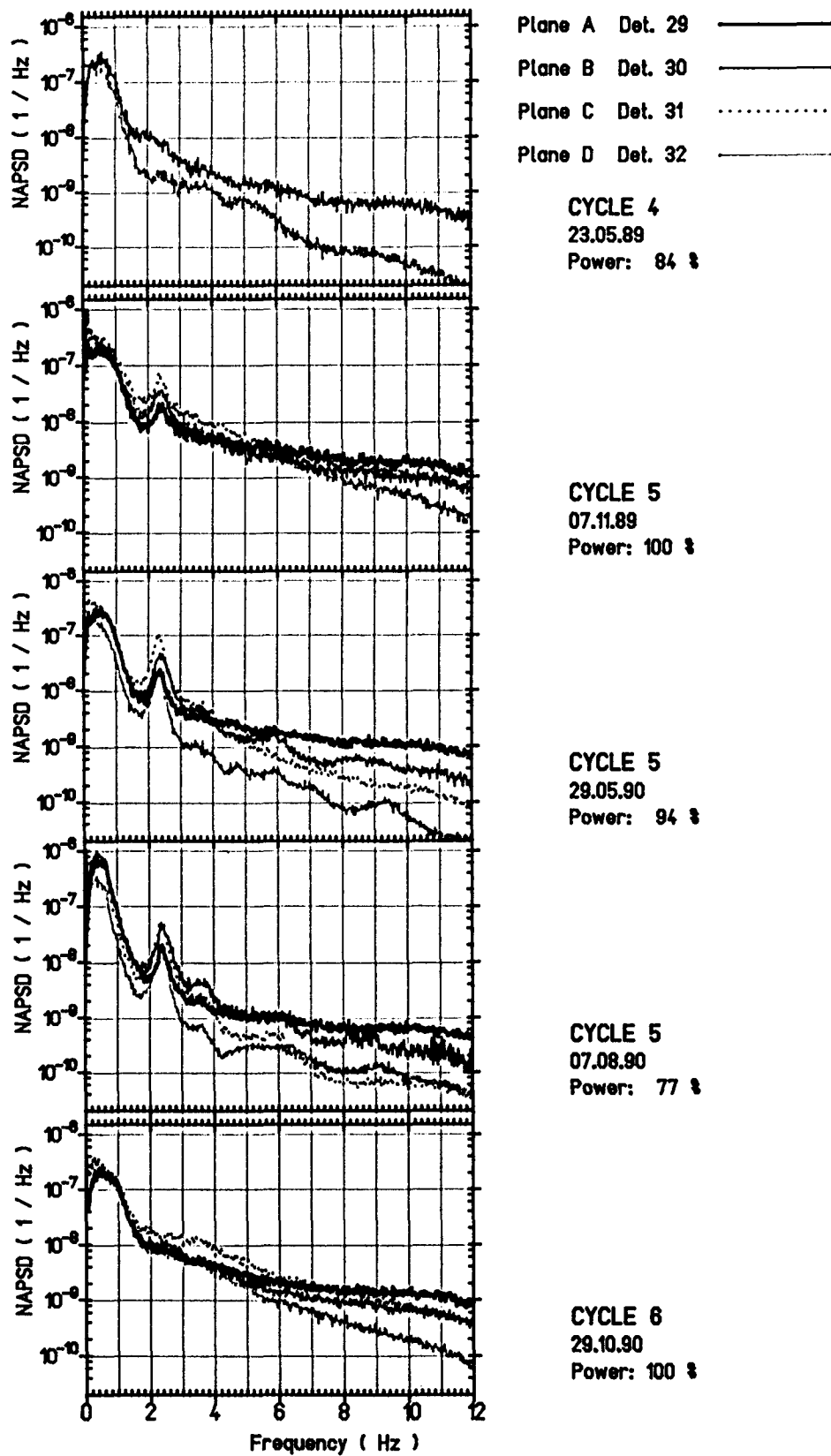


Fig. 4. NAPSD's of Signals from String No. 8

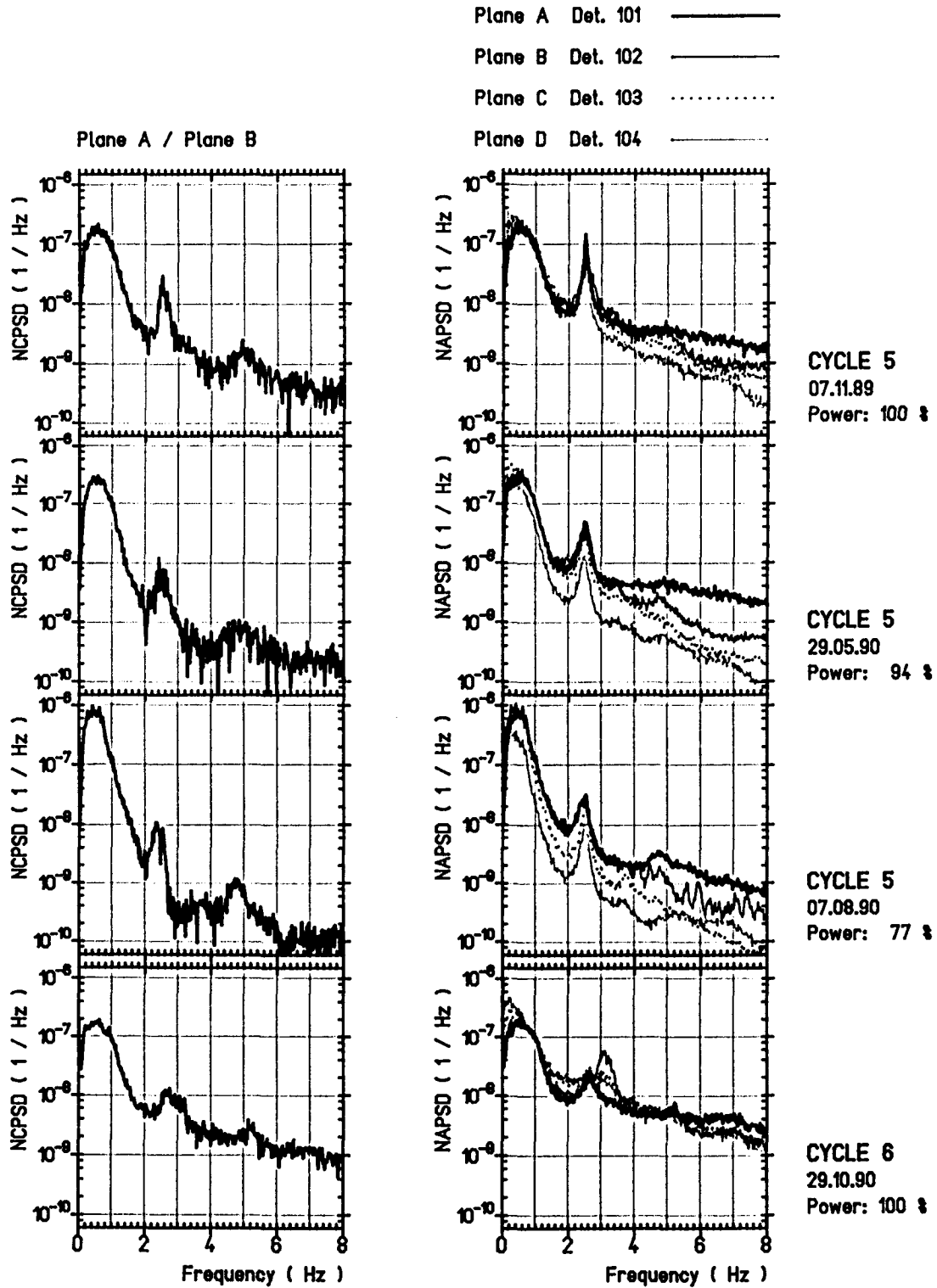


Fig. 5. NCPSD's and NAPSD's of Signals from String No. 26

In the NAPSD's during cycle six the peak at 2.5 Hz is lower than in cycle five which may be related to a change in the mounting conditions, but it remains higher than in other core positions. Also the peak around 5 Hz which was associated to the fuel channel box vibration can be visualized in the NAPSD's. Therefore the NCPD between signals from the two upper neutron sensors were calculated to investigate these vibrations more in detail. Within cycle five a small shift to lower frequencies due to changing thermohydraulic conditions has been observed in both peaks.

It is possible that these two particular vibrations of the instrumentation tube and the surrounding fuel boxes are favored by a specific mounting condition at this core position and that they are related to each other.

Core lattice cell vibration

The vibration of the core lattice cell components at string position 42 deviate from the corresponding vibrations at other core positions. Fig. 6 shows the development of these vibrations in the NAPSD's of five measurements during three cycles. After refueling the spectra obviously change between cycles four and five in the frequency range between 2 and 6 Hz.

The 2.5 Hz peak, observed in cycle four shifted to a lower frequency around 2 Hz while its amplitude increases in the following cycles. In the frequency range from 3 Hz to 4 Hz, where the influence of the fuel bundle vibration can be expected, the magnitude of the upper detector's spectra rises between cycle four and the following cycles. The magnitude of the peak around 5 Hz is higher than in other core positions, but does not change remarkably in all measurements (Fig. 6.). The coherence between signals from plane A and B in cycles five and six (Fig. 7.) has a peak around 5 Hz, which is very low in cycle four. The NCPD in this frequency range rises from cycle four to five. The phase indicates mechanical movements in the analysed frequency range.

The coolant flow through the core is driven by eight circulation pumps, located in the lower part of the reactor. Because pump No. 7 is the closest to the instrumentation string No. 42 pump No. 7 was supposed to excite the core lattice cell vibration described above. To prove this, the signals of string No. 42 have been analysed at two different coolant flow conditions (Fig. 8): first all pumps running at 2000 revolutions per minute and second pump No. 7 switched off and all other pumps running at 2000 revolutions per minute. It is seen that one of the exciting forces of the measured vibrations is generated by the coolant flow from circulation pump No. 7 because the corresponding peaks in the spectra decrease drastically.

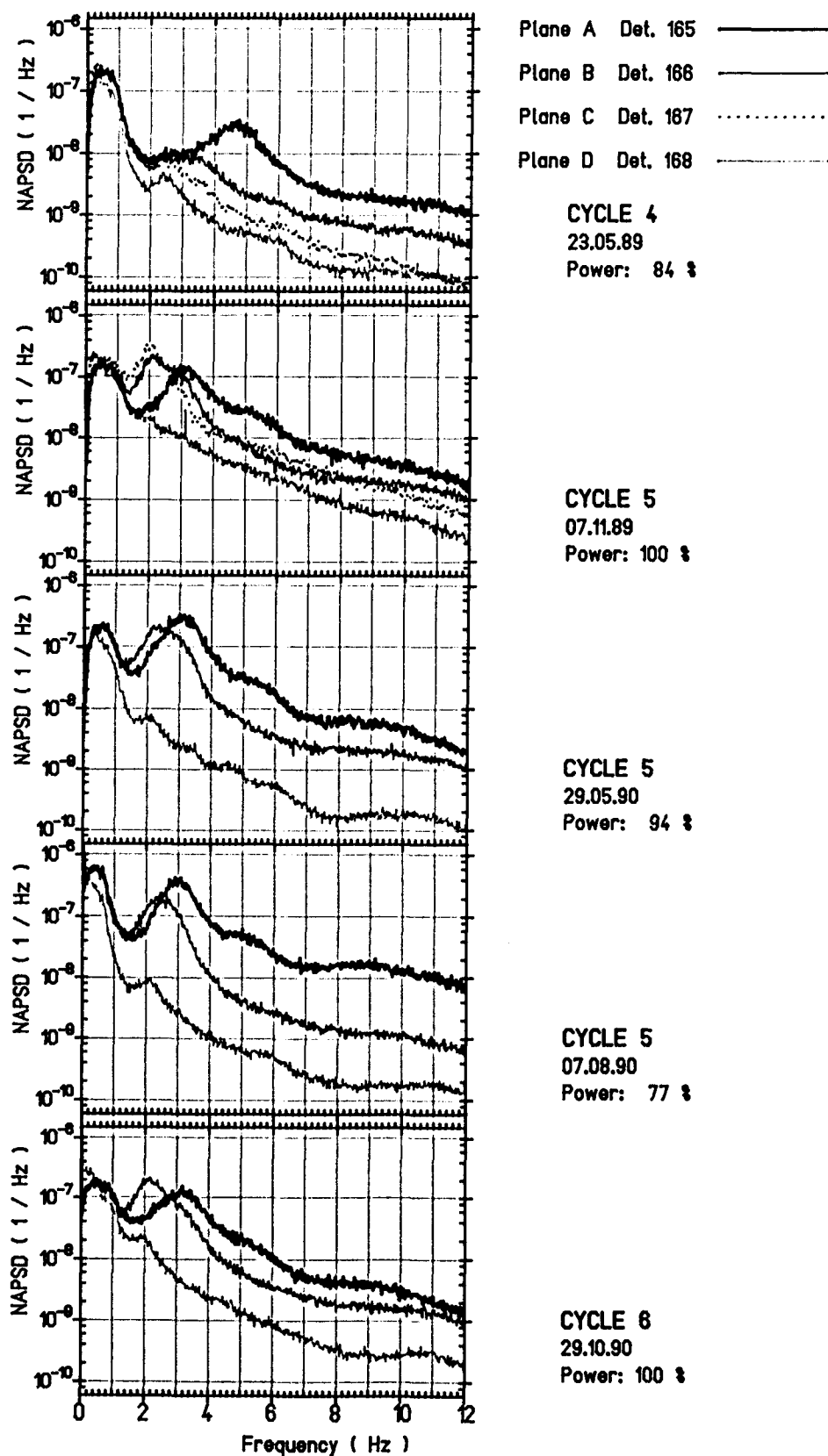


Fig. 6. NAPSD's of Signals from String No. 42

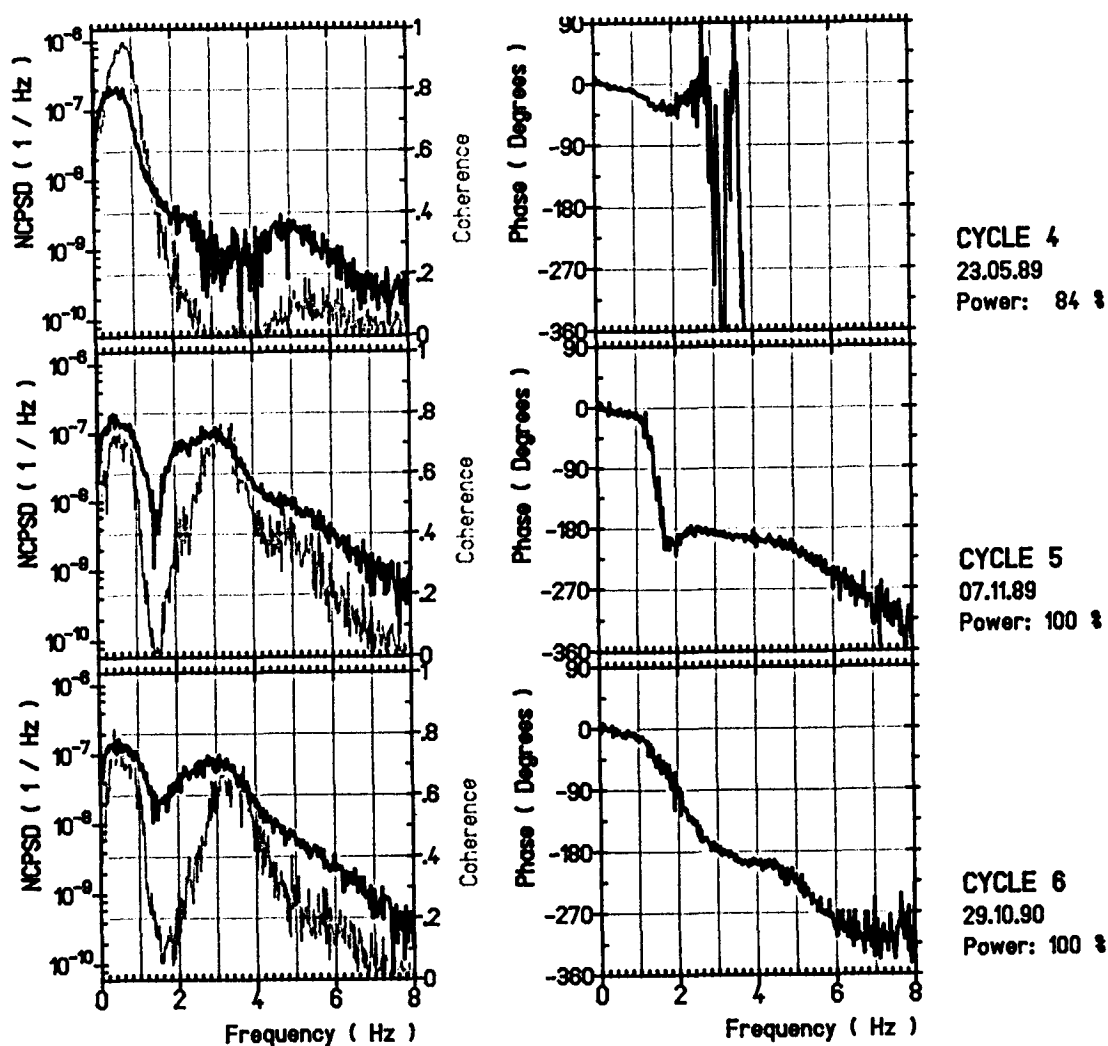


Fig. 7. Correlations between Neutron Signals from Planes A' and B of String No. 42

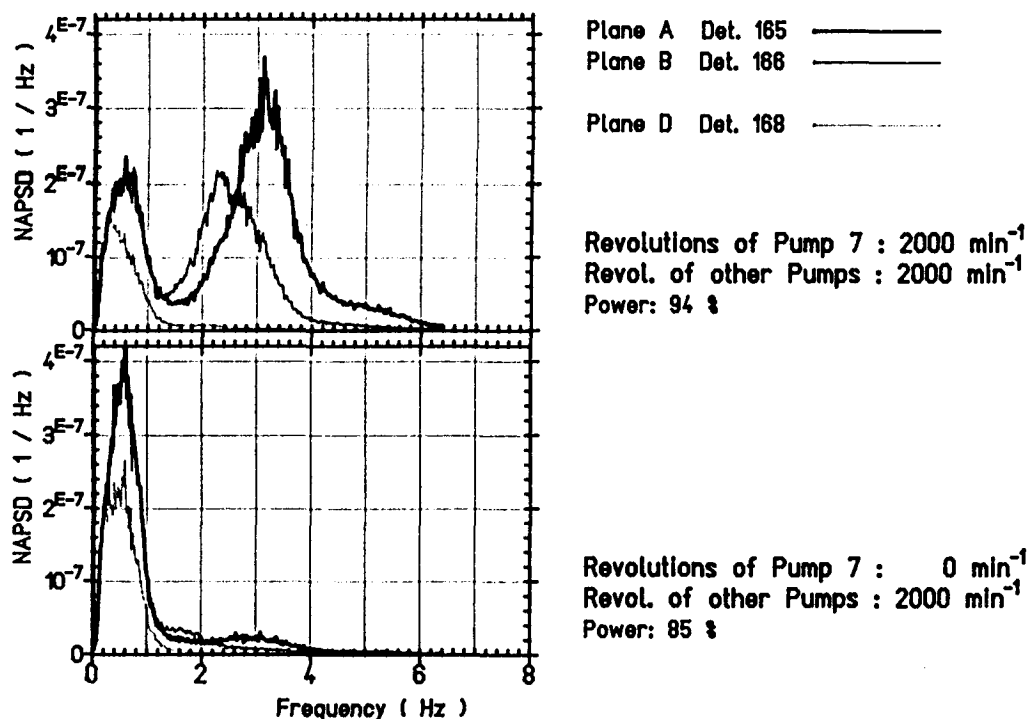


Fig. 8. Influence of Circulation Pump No. 7 on the Core Lattice Cell Vibration at String Position No. 42

CONCLUSIONS

The boiling process and other thermohydraulic phenomena are the main source of the in-core neutron noise especially in the upper core region. Also the influence of mechanical effects can be found in the neutron noise clearly. Using a linear one dimensional model, eigenfrequencies of some reactor components have been estimated. Typical vibration conditions can be seen in neutron signals and particular vibration behaviour at some core positions has been detected.

Spectra of in-core neutron noise signals indicate the following vibrations:

- fundamental and second mode of the instrumentation string vibration,
- fuel bundle vibration,
- fundamental cantilever type mode of the fuel channel box vibration,
- pressure vessel displacement.

Changes of some vibrations could be explained considering changing mechanical supporting conditions.

It was found that the operating conditions of one circulation pump have an influence on a weak core lattice cell vibration at a particular core position.

The comparison between neutron noise spectra obtained while the control rods were partially inserted and while they were pulled out gives no hint on control rod vibrations.

It is concluded that it is possible to monitor mechanical vibrations of some components of the 1300 MW BWR Gundremmingen using the in-core neutron noise analysis.

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CHECK VALVE MONITORING USING
LOOSE PARTS MONITORING TECHNIQUES

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ABSTRACT

Loose part monitoring techniques are utilized to periodically verify the structural integrity of the Sequoyah Nuclear Power Plant main steam check valves (MSCVs). Valve acoustic response data are monitored and trended for indication of shifts in internal structural resonance and metallic impacting caused by degradation of valve internals. The modified amplitude probability distribution (MAPD) is used to detect the onset of disc impact against the back stop and to trend the relative impact amplitude and impact rate. This paper describes and demonstrates the use of these techniques using data acquired from the Sequoyah MSCVs.

BACKGROUND

On September 21, 1990, Sequoyah Nuclear Power Plant staff reported a loud metallic noise in the unit 1 main steam lines between the east steam valve vault and the turbine building. Because of a previous main steam check valve (MSCV) failure, MSCV failure was considered possible. Typical loose part data were acquired at each of the four MSCVs on October 3, 1990. These data indicated that the acoustic response of MSCV 1-624 was significantly higher than the rest and that the MSCV 1-626 disc was impacting against the back stop. Lack of baseline data, however, rendered further interpretation inclusive.

Two east valve vault MSCVs were radiographed on October 8, 1990. The composite pictures clearly indicated the MSCV 1-624 disc was separated from the hinge arm. Since the MSCVs perform a safety related function (they isolate reverse flow and permit main steam isolation valve closure in the event of a main steam line break inside containment), the unit was removed from service in accordance with plant Technical Specifications.

Subsequent valve inspections conducted October 9 and 10, 1990, indicated that the disc was detached from the hinge arm in three of the four MSCVs. Only the MSCV 1-626 disc assembly was found intact. MSCV 1-623 and 1-625 discs were discovered approximately 500 feet downstream, and the MSCV 1-624 disc was lodged in the valve body. In each case, the failure resulted from fatigue fracture of the disc post. A simplified illustration of the MSCV design and failure location is shown in Figure 1.

INITIAL DATA ANALYSIS

Initial acoustic data measured at both the hinge pin and the back stop on October 3, 1990, indicated three distinct response characteristics (Figure 2). These data were more easily interpreted after the valves were inspected.

1) MSCV 1-626 data contained low-level flow noise with occasional (once every few seconds) low-frequency bursts in the range between 1-2 kHz. The initial interpretation of the bursts as disc impacts against the back stop was determined to be correct.

2) MSCV 1-624 and 1-625 data were dominated by frequent (once every 100 msec) high-frequency bursts in the 5-10 kHz range. The frequency and occurrence rate of the bursts indicated turbulent flow conditions and possibly the formation of localized cavitation in low pressure areas of the valve. The overall energy level at MSCV 1-624 was twice the level at MSCV 1-625 and, therefore, was initially suspected as having a detached disc. Inspection revealed that both discs were detached; however, the 1-624 disc was lodged in the valve body restricting flow and increasing the level of turbulence in the valve.

3) MSCV 1-623 data primarily contained flow noise with occasional (once every few seconds) high-frequency bursts similar to MSCV 1-624 and 1-625. The overall response level was approximately one-third the level at MSCV 1-624 and no problems were suspected. Inspection of this valve also revealed that the disc was detached from the hinge arm.

In retrospect, the absence of disc impact against the backstop in MSCVs 1-623, 1-624, and 1-625, was indication of disc separation. Further, flow turbulence initially thought to be caused by the projection of the valve internals into the flow was later determined to be primarily caused by the upstream piping configuration. The piping configuration is very compact; MSCV 1-623, 1-624, and 1-625 are welded directly to the corresponding isolation valve and within 5 equivalent straight pipe diameters downstream of a short radius elbow. The proximity to the elbow and to the isolation valve causes a turbulent, asymmetric flow distribution through the MSCVs. The distribution creates an eccentric loading about the disc centerline causing it to wobble and impact against the stop at 100% steam flow. The distribution through MSCV 1-626 is improved because it is 2.5 pipe diameters downstream of the isolation valve.

MONITORING PROGRAM

Although the failure mode was identified and modifications were made to improve valve reliability, long-term monitoring was considered prudent. The primary goals of the monitoring program were to detect catastrophic failure of the valve internals, to identify and trend parameters related to valve internals degradation, and to provide guidance, based on the results of the trending program, for periodic valve inspections. Both loose part experience and current development work in check valve monitoring indicated acoustic monitoring as the best course of action.

One high-temperature, radiation-hardened accelerometer is installed at the hinge pin and one at the back stop of each unit 1 and unit 2 MSCV. The hinge pin accelerometer is stud-mounted to a block bolted around valve at the hinge pin protrusion, and the back stop accelerometer is stud-mounted to a saddle block strapped to the valve body immediately above the back stop.

The conditioned signals are periodically recorded on magnetic tape, analyzed, and trended. Analysis and trending is accomplished using the Technology for Energy Corporation (TEC) Smart Meter, Intelli-Trend predictive maintenance and Intelli-LPM loose part software, and the LPM Surveillance Intelli-Card.

STRUCTURAL RESPONSE ANALYSIS AND TRENDING

Both loose part and neutron noise analyses have frequently relied on resonant frequency shifts as an indicator of structural relaxation or degradation. In considering the initial valve failure process, the valve internals would have shown marked resonant frequency changes. Therefore, narrow frequency bands based on internal resonances of the rebuilt valves and based on power spectral density (PSD) differences in failed and rebuilt valves were established for computer trending.

Valve resonances were determined through in-air and in-situ structural response testing before the unit was returned to service. Typical data (Figure 3) indicate that the disc/hinge arm/hinge pin assembly resonant frequency is between 1.0 and 1.2 kHz. A simulated in-service impact was also performed by manually impacting the disc against the back stop. These data (Figure 4) again indicated disc resonance at approximately 1.2 kHz and a back stop mounted resonant frequency at 2.1 kHz. Difference PSDs (baseline PSD from a rebuilt valve minus detached disc PSD) show significant spectral response between 0-500 Hz and 1-1.5 kHz. Based on these considerations, the spectral bands selected for trending are:

- 1) 10-500 Hz - unidentified valve internals resonances,
- 2) 0.6-1.75 kHz - disc/hinge arm/hinge pin assembly resonances,
- 3) 1.75-3.5 kHz - disc impact energy and impact rate at back stop, and
- 4) 5-10 kHz - broad band flow noise.

MODIFIED AMPLITUDE PROBABILITY DISTRIBUTION ANALYSIS AND TRENDING

The slope of the modified amplitude probability distribution (MAPD) is used to provide a statistical measure to reliably detect the onset of disc impact against the back stop, to trend the relative impact amplitude and impact rate, and to detect metallic rattles caused by valve internals degradation. The MAPD slope is a quantitative measure of the Gaussian characteristics of a given signal. The MAPD is derived by taking the logarithm of the APD function, thus creating a linear relationship with a constant slope equal to

$$\text{MAPD Slope} = \log(e^{-0.5}) = -0.22$$

for a purely random signal (References 1, 2 and 3). The introduction of any periodic process into the signal will change the slope. Therefore, as the MAPD is applied to MSCV monitoring, flow noise is assumed to be purely random, and the slope would be -0.22. The introduction of rattles or metallic impacts will effect a positive change in the MAPD slope. MSCV failure analysis indicates that impacting would have increased markedly as the valve internals loosened and began to fatigue and would have been followed by a sudden reduction in impacting after disc separation. By measuring and trending the MAPD slope, the presence of impacts and changes in amplitude and occurrence rate of impacts can be determined.

MONITORING PROGRAM RESULTS

The MSCV acoustic monitoring program was implemented October 24, 1990. To date, no trends have developed which would indicate significant degradation. The basic results of the trending program are summarized below.

1) PSDs (Figures 5 and 6) show that the predominant response at the hinge pin accelerometer is in the 0-500 Hz and 1-1.5 kHz ranges, and that the back stop accelerometer response is predominantly at 2.1 kHz, as expected by the impact data. These resonances are excited by relatively constant disc impact against the back stop.

2) MAPD slopes at MSCV 1-625 and 1-626 (Figure 7) indicate that little disc impacting was present when the system was initially returned to service. After 3 months of operation, the trends indicate a steady change in the MAPD slope indicative of increased impacting. This is considered the result of normal valve packing loosening rather than internals degradation.

3) The change in MAPD slope coincided with proportional changes in the narrow band PSD response indicating all trend parameters are detecting the onset of and increase in disc impact.

Based on the program results, it would be expected that significant degradation or catastrophic failure of the MSCVs can be readily detected by one or more of the trended parameters. Therefore, conventional acoustic and loose part monitoring techniques are effective tools for non-intrusive check valve monitoring programs.

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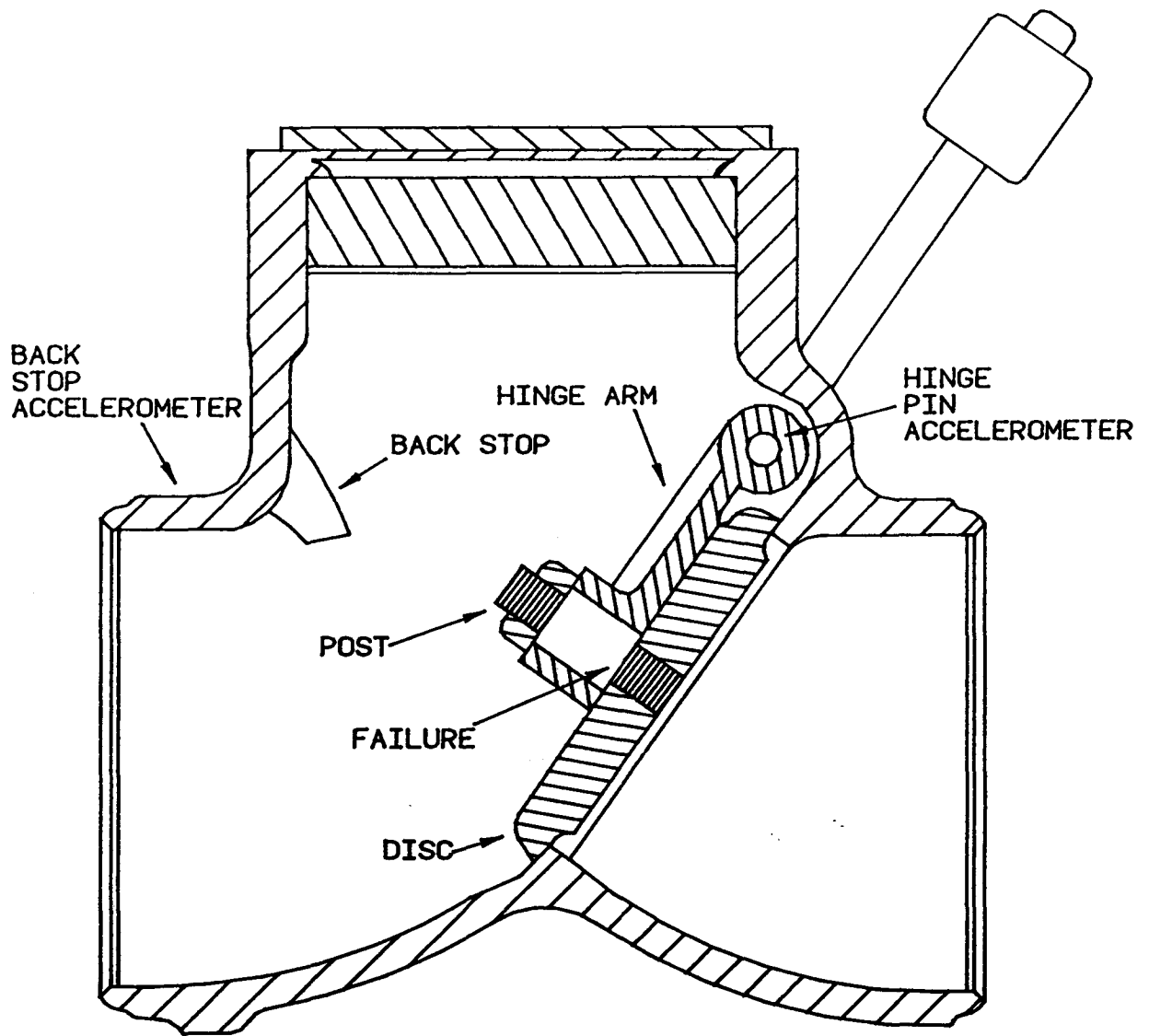
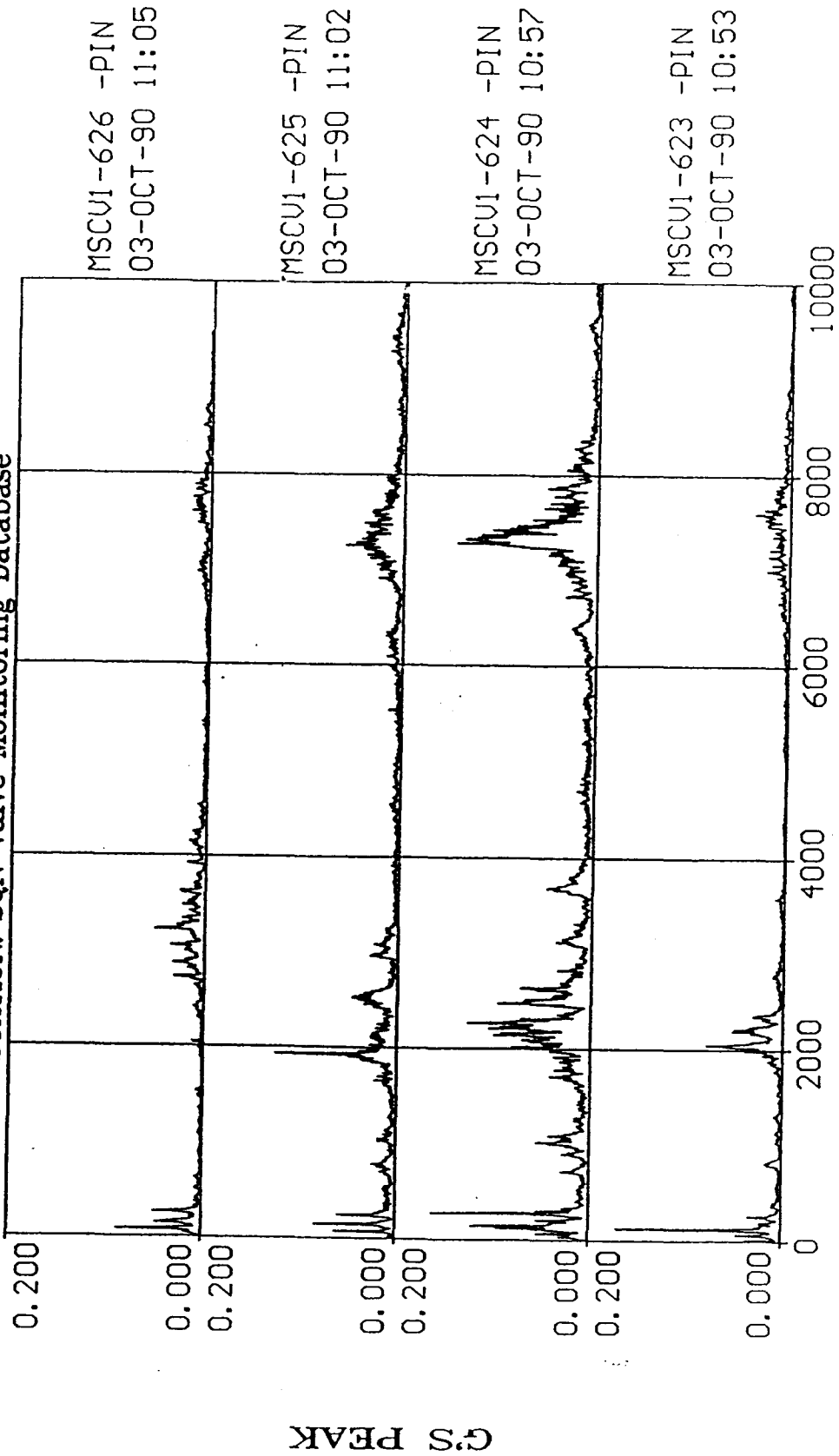


Figure 1. Main Steam Check Valve

Intelli-Trend(R) Multi-Spectra Display

STATION: SQN Valve Monitoring Database



Frequency in Hz

Figure 2. PSDs Before Plant Shutdown

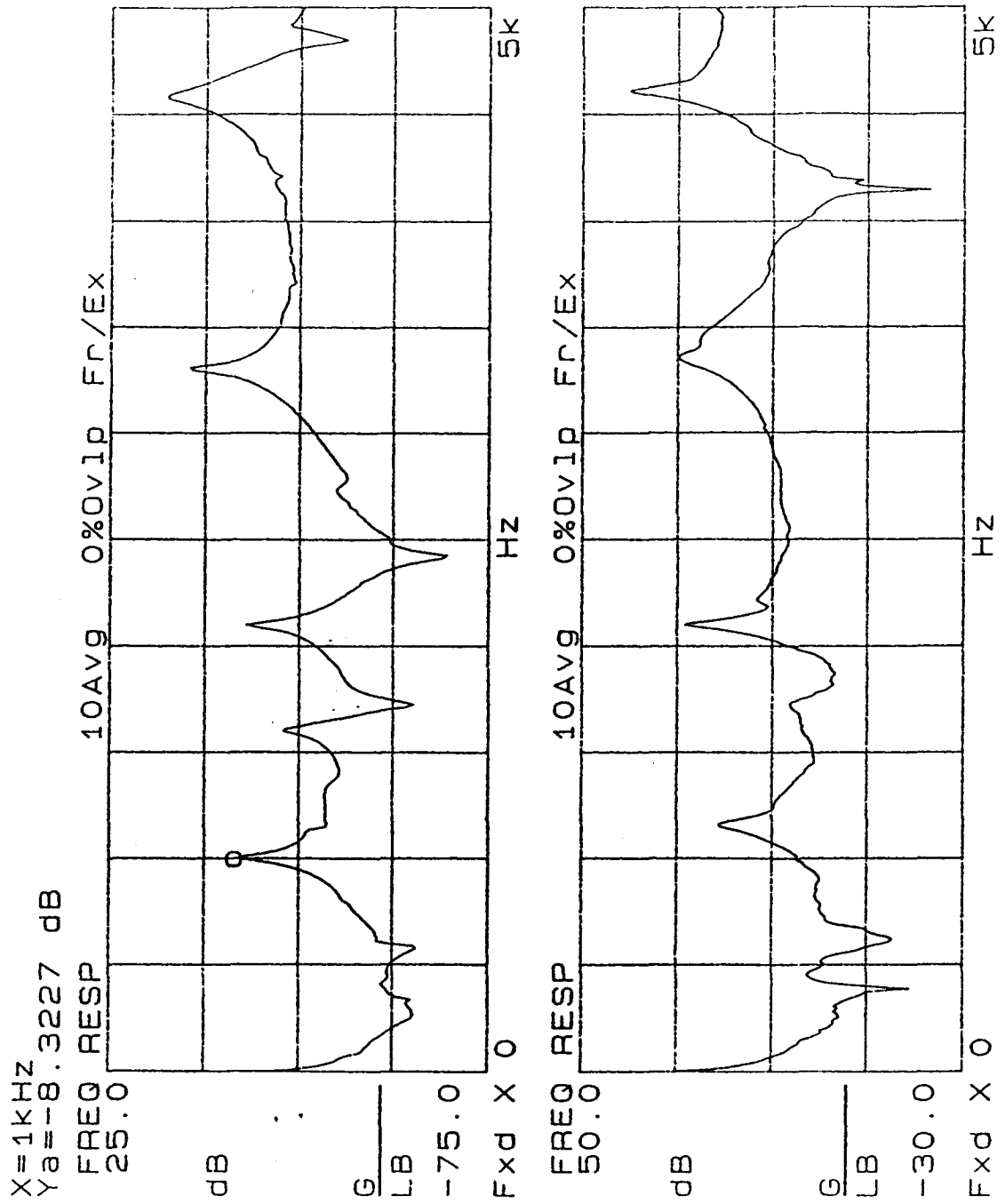


Figure 3. In-Air and In-Situ Structural Response

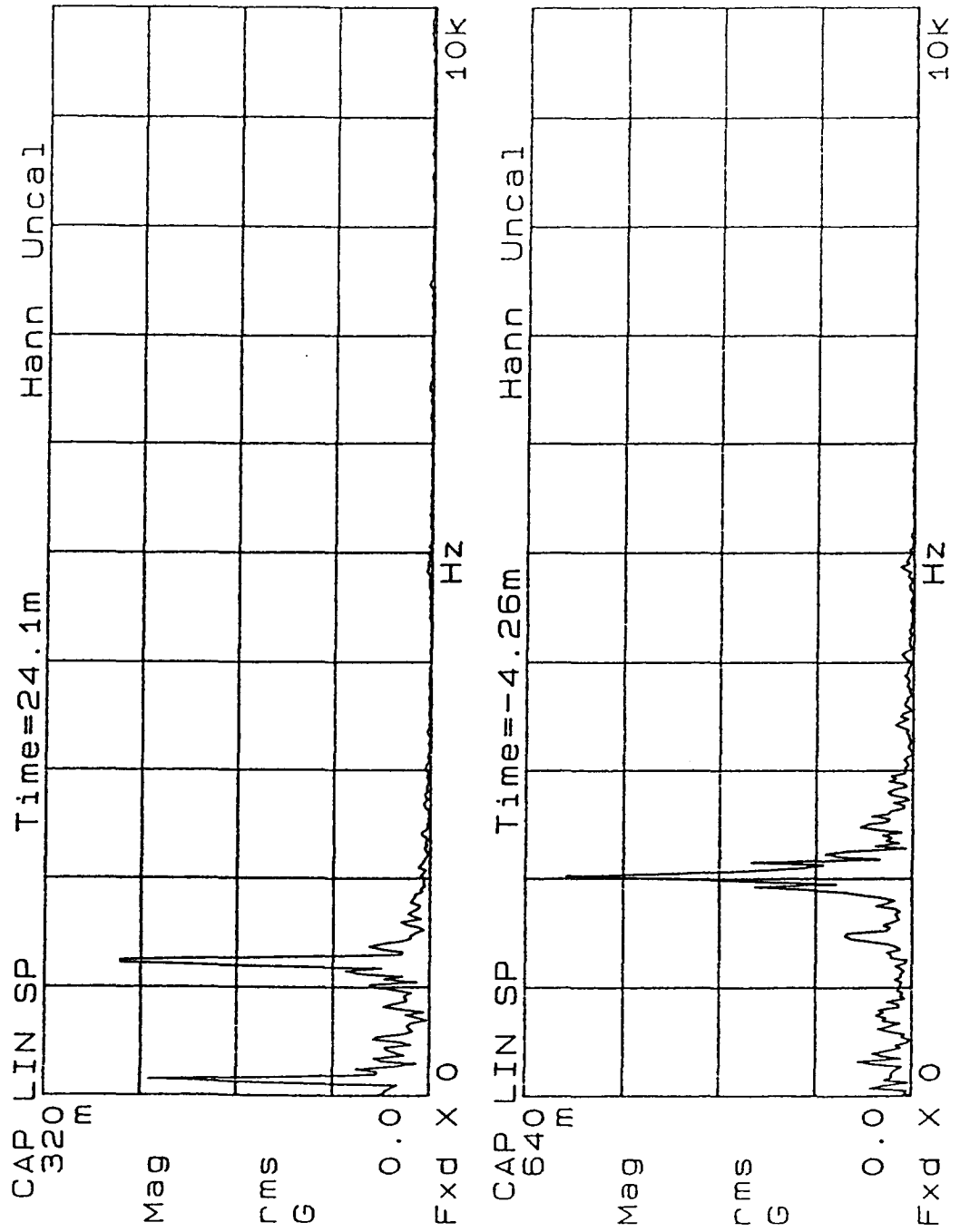
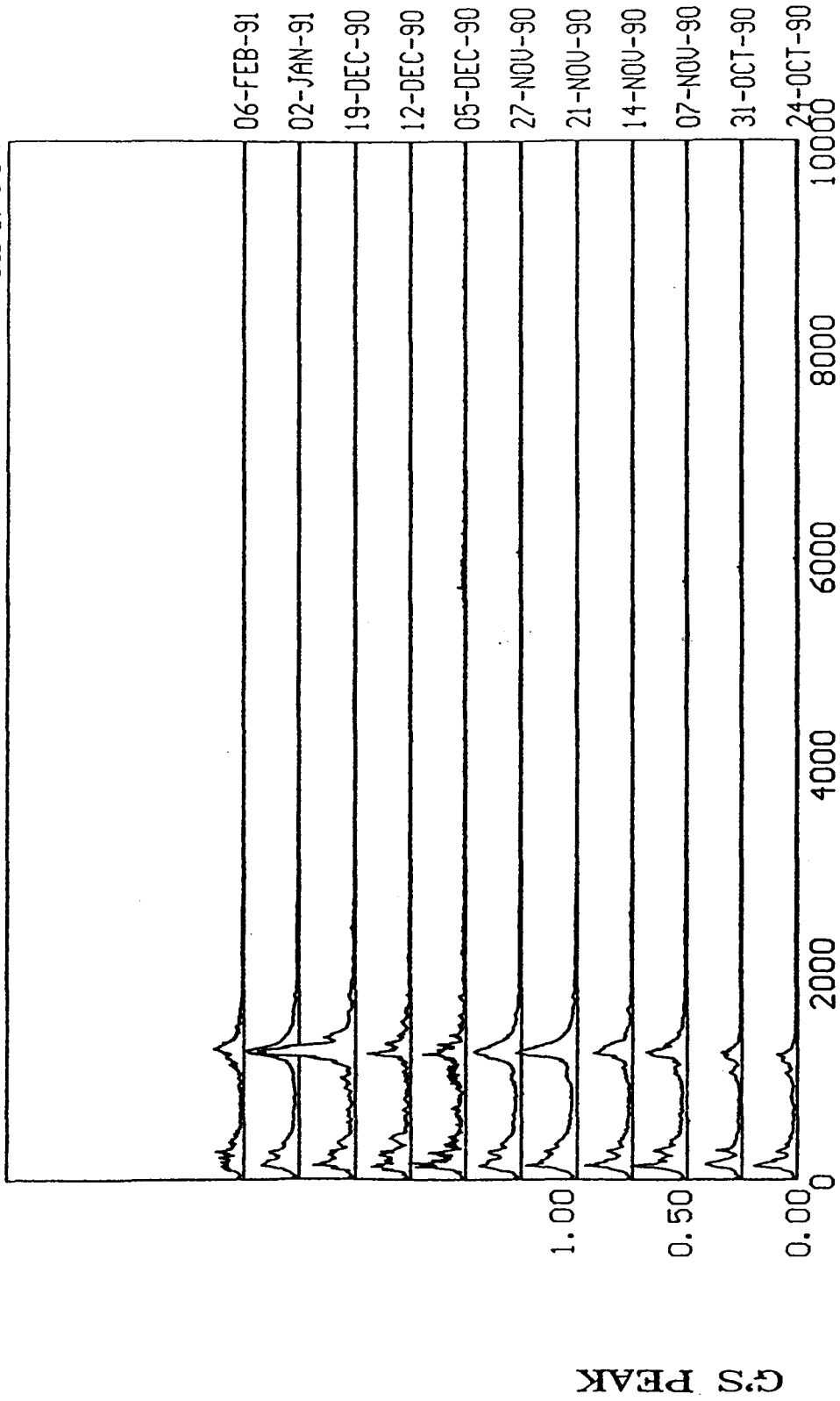


Figure 4. Hinge Pin and Back Stop Response to Manual Impact

STATION: SQN Valve Monitoring Database

MACH: MSCV 1-VLV-1-625

MPT: PIN



Frequency in Hz

Figure 5. MSCV 1-625 Hinge Pin PSD History

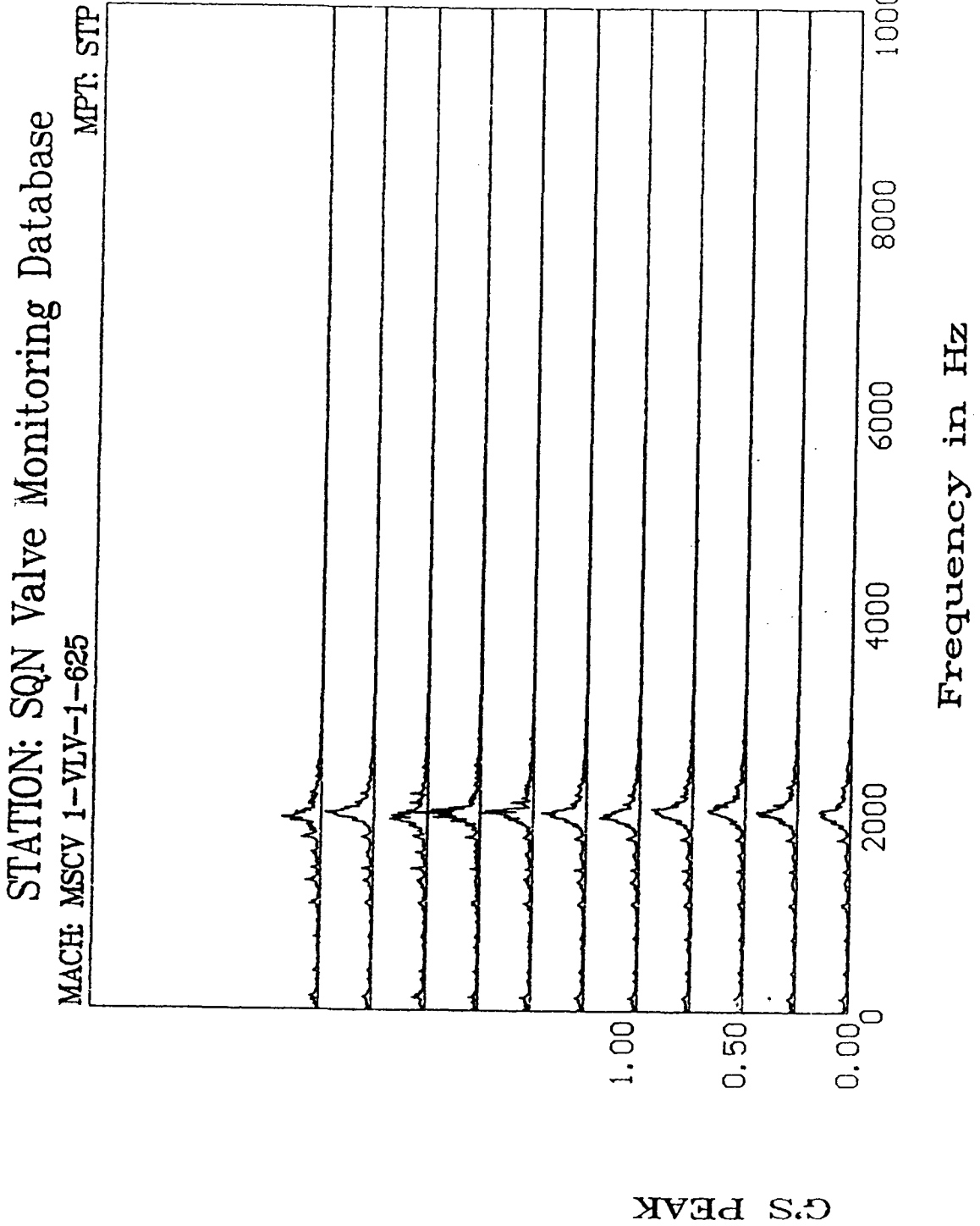
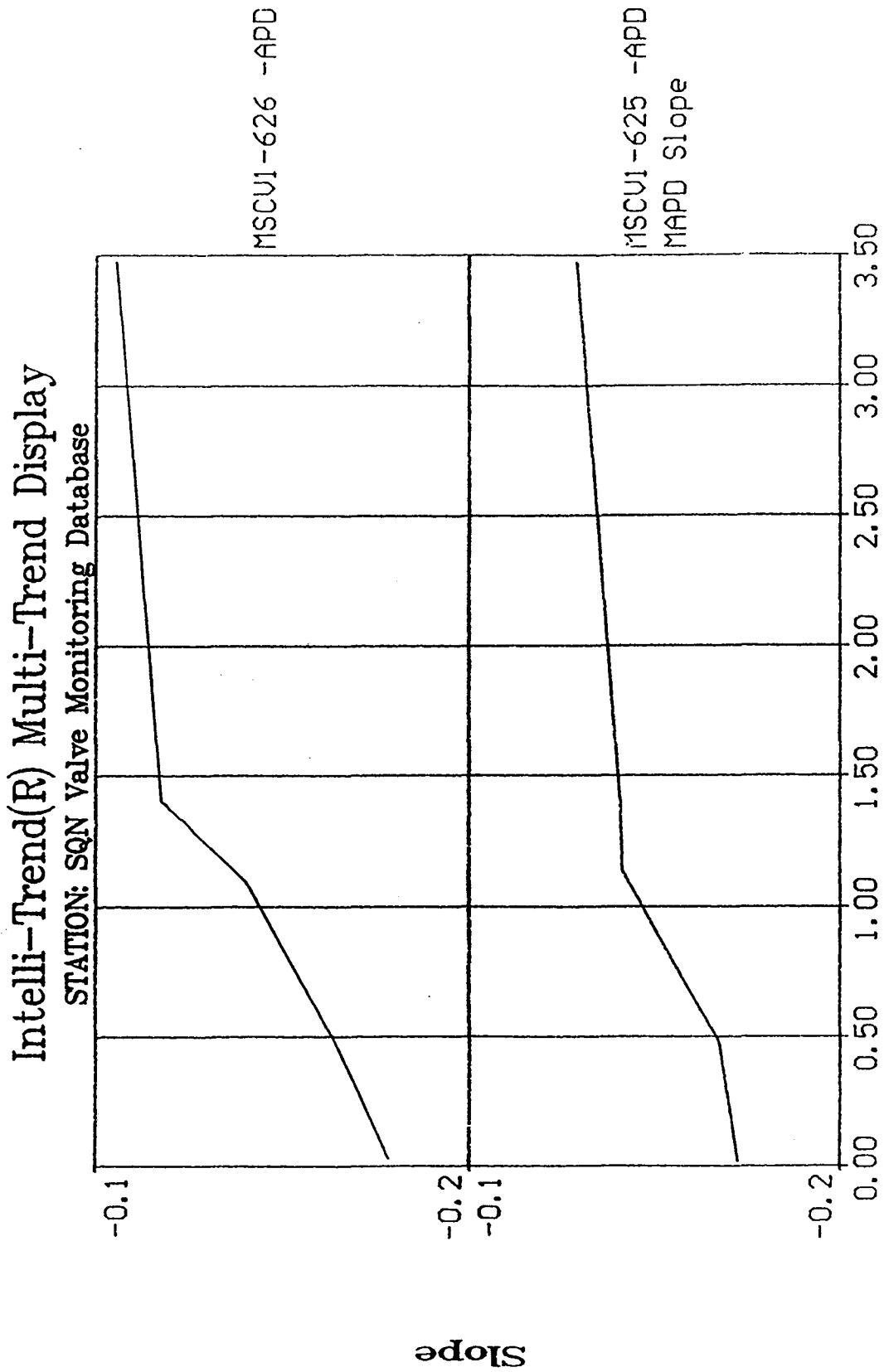


Figure 6. MSCV 1-625 Back Stop PSD History



Months: 24--OCT--90 to 06--FEB--91

Figure 7. MSCV 1-625 and 1-626 MAPD Trend

ON-LINE ACOUSTIC MONITORING OF EDF NUCLEAR PLANTS IN OPERATION AND LOOSE-PART DIAGNOSTICS

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Abstract

In order to detect incipient failures in nuclear power plant components, EDF has now put into operation more than 50 loose-part monitoring systems, on its 900 MW and 1300 MW units.

This paper first reviews the experience gained on the 900 MW reactors in recent years. It then focuses on the 1300 MW loose part monitoring system (IDEAL) and to the tools developed for the diagnosis off site within a specific Expertise Laboratory at the Research and Development Division.

New studies have been undertaken within the Monitoring and Aid to Diagnosis Station (PSAD) in order to extend the capabilities of loose part diagnostics on site. The new tools here presented integrate the recent progress in acquisition technology (SMART system) and in artificial intelligence (MIGRE expert system).

Introduction

Early detection of loose parts in the primary systems of nuclear plants has been a major concern of Electricité de France since the start-up of the nuclear program. [ref 1]. Therefore, monitoring systems have been developed and installed in EDF nuclear plants. Their main objective is to perform a reliable detection of abnormal acoustic situations. The two systems developed up to now meet this need :

- on the 34 units of 900 MW, the DEVIANT system [ref 2] has made possible the detection of all loose parts to date.
- on the 20 units of 1300 MW, the IDEAL system (Impact DEtector and Aid to Localization) has brought new capabilities in aid to diagnosis.

These two systems are described in the first part of the paper, their principles of detection are recalled as well as the diagnosis processes for each family of reactors, and the most recent incidents are briefly reviewed. Then in a second part, the developments made for diagnostic purposes off site within a specific Expertise Laboratory at the EDF Research and Development Division are presented.

For the immediate future, a new concept will soon see the light, the PSAD on-line Monitoring and Aid to Diagnosis Station [ref 3]. Its main objectives are to give an easy access to the existing monitoring functions (vibration monitoring of structures and big rotating machinery, loose part detection), and to allow the interpretation of unidentified situations by the plant personnel, in easy connection with off site specialists. The development of the new integrated loose-part monitoring system SMART, in connection with the expert system MIGRE will be presented in the last part of the paper.

1. The detection of abnormal acoustic events on site

Feedback experience acquired since the start-up of the first French nuclear PWRs using a simple acoustic monitoring system has pointed up the importance of certain criteria for the design of an on-line Loose Part Monitoring System (LPMS). These include :

- sensitivity and reliability of detection,
- easy maintenance,
- simplicity of the system,
- post-alarm analysis capability,
- quality training and technical assistance from specialists.

Monitoring of loose parts includes the **detection, characterization and diagnosis** of anomalies. At Electricité de France, these various tasks are performed on two levels:

- on each nuclear site, operators of the plant are responsible for the detection process whereas the technical staff intervenes after an alarm and makes the initial evaluation. But assistance by specialists is judged necessary because it is difficult to maintain a proper level of expertise for all different systems installed in the plant.
- at the Research and Development Division in Chatou, specialists see to diagnostics for the plants, as well as to extending knowledge and developing new systems.

Detection of loose parts in 900 MW reactors

The first detection systems consisted in conventional devices able to process in a simple way the signals from piezoelectric accelerometers mounted on the walls of the primary system, such as audiomonitors, scopes and voltmeters. In 1982, after the first loose-part incident occurred at full power, it became clear to EDF that continuous monitoring should be performed, and that the plant should be stopped, just after a loose part diagnosis [ref. 1].

The loose-part detector unit **DEVIANT** had been designed before this incident for monitoring of the plant from the control room during the start-up period. It is now used continuously. Its principle is based upon the detection of transient signals whose amplitude is higher than a predetermined threshold: detection is based upon the crest factor of the signal, which is the ratio between the peak instantaneous value of the signal and its long-term RMS value (time constant between 5 and 10 seconds). An instantaneous alarm is produced. Feedback experience has shown that the choice of a value of 12 for the threshold crest factor was adequate. However, in order to prevent undesirable isolated spikes, which could produce high crest factors, a specific procedure is applied to those signals which go over the threshold, resulting in the detection of repetitive signals only. This eliminates the risk of false alarms.

DEVIANT includes 5 channels, connected to the steam generators and to the bottom of the vessel. It also indicates date of the loose-part alarm and RMS peak voltage and peak factor measurements. Activation of the alarm automatically triggers a perturbation unit for post-alarm analysis. In addition to the on-line detector of mechanical impacts, a Control and Audio Monitoring Unit enables the technical operator to evaluate the signals.

This continuous loose-parts detection procedure has now been in operation for more than 8 years, representing a feedback experience of more than 250 reactor years. Operating experience with this monitoring system has clearly demonstrated that major incidents have been avoided, because all loose parts which had been impacting the structures have been detected. The global balance between benefits and costs was highly positive: from '75 to '86, it represents about US\$ 30M, or approximately a saving of the energy generated by a 900 MW nuclear unit in 1 year [ref. 4].

We list below all the incidents which have occurred in France since the start-up of the first 900 MW unit and review the most recent ones, in Fessenheim 1 (85-86), Tricastin 4 and Gravelines 1 (88).

Fessenheim 1, September 1985 : During the restarting of Fessenheim 1 in September 1985, a loose part alarm appeared on the control room panel : it could have been interpreted as a false alarm because no abnormal noise was observed some minutes later. Fortunately, the magnetic recording which had been automatically started after the alarm activation revealed the presence of shocks. The figure 1 reproduces typical signals perceived on the SG water box (AG 21 and AG 22), on the upper part (AG23) and on the vessel head (AC5). The expertise of the signal concluded to the presence of a loose part : its mass was evaluated to less than 85 g, with use of an experimental curve plotting the amplitude versus the energy and taking into account an estimate of the water velocity. The loose part manifested quite curious behaviour inside the waterbox, since it did not continuously impact the walls: instead it remained fixed by suction against the tube plate over long periods of time, and produced no damage. Taking into account the duration of those periods when impacts did occur as against the quiet periods and in comparison with a previous incident in 1982, the total number of shocks to the end of the cycle was calculated and it was shown that the damage would be about the half of that for the previous incident. As a result, the French Safety Authority allowed EDF to continue the operation of the plant.

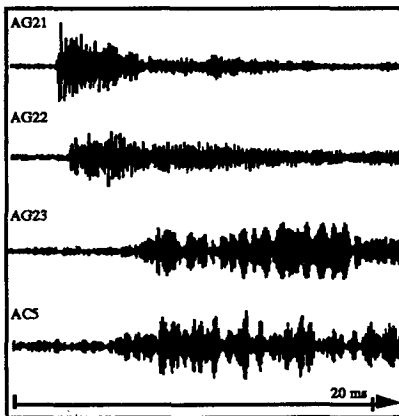


Figure 1: FSH 1985 loose part high pass filtered signals

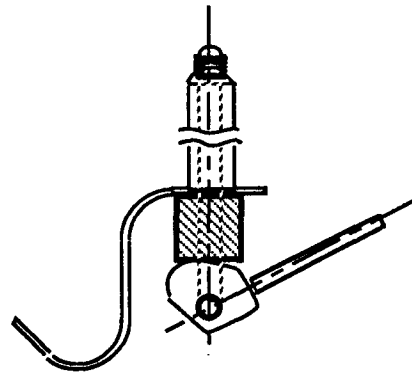


Figure 2 : loose part at Fessenheim 1 (1985-86) : hatched section represents the detached part from an inspection lamp fastening device.

At the end of the cycle, in August 86, an object was found inside the waterbox: it was a part of fastening device for an inspection lamp (fig. 2) and had been left inside the waterbox before it was closed. Its mass was 75 g.

This incident has led to a change in the operation procedure : for the future, the risk of damaging the structures will be taken into account before making the decision of shutdown.

reactor	phase	date	origin	location	damage	comments
FSH 1	cold test	1976	temporary device	SG water box	no	
BGY 4	cold test	1978	<i>temporary device *</i>	SG water box	slight	
BGY5	cold test	1978	temporary device	SG water box	no	
SLB1	cold test	1980	<i>temporary device *</i>	SG water box	severe	
BLA 1	cold test	1980	temporary device	vessel bottom	no	
FSH 1	100%	1981	<i>forgotten objects</i>	lower internals	no	immobile object
GRA 1	restarting	1981	<i>guide tube pin *</i>	auxiliary circuit	no	
FSH 1	100 %	1982	guide tube pin	SG water box	yes	delayed shutdown
BGY 2	restarting	1982	guide tube pin	SG water box	no	
PAL 1	hot test	1983	forgotten objects	SG water box	no	
BLA 2	90% power	1982	anti-rotation bar	SG secondary	no	
FSH 1	100 %	1985/86	guide tube pin	SG water box	some	delayed shutdown
TN4	100 %	1987	guide tube pin	SG water box	slight	
GRA 1	100 %	1988	guide tube pin	SG water box	yes	delayed shutdown
GRA 1	100 %	1988	guide tube pin	SG water box	no	

undetected objects are in italics

* monitoring not in service

SG: steam generator

Table 1: loose parts and defects detected in France (1976-1990: 52 reactors, 250 reactor-years)

Tricastin 4 (1987) and Gravelines 1 (1988) : Both incidents occurred after an unscheduled shut-down. The reactors were thus put at zero power and the signals were recorded : loose parts were diagnosed in the hot water boxes of the steam generators, with masses around 100 g. The expertise made for Gravelines incident will be presented in part 2 (fig 12, tables 2, 3). In one case, circulation of the fluid was not stopped immediately in the loop, causing some damage in the tube plate. In each incident, a guide tube pin was discovered inside the waterbox : 125 g at Tricastin (fig. 3) and 77 g at Gravelines.



Figure 3 : loose part found at Tricastin

Detection of loose parts in 1300 MW reactors

At the beginning of 1987, due to the increasing number of reactors in operation, it was becoming necessary to decentralize a part of the diagnostic process on the nuclear sites. The starting of a new series of 1300 MW PWRs was an opportunity to take advantage of feedback experience and of recent technological improvements. Development of a new system had begun as early as 1985. IDEAL is now installed on all 1300 MW reactors in operation (18 plants). It introduces a new principle of detection and offers capabilities for diagnostics to plant personnel [ref 5, 6].

The principle of detection

Detection is performed by acoustic sensors mounted on the walls of the primary system (fig. 4). These sensors are grouped by three or four, each group representing one zone of the reactor, these zones being the loop, the head of the vessel (some units only) and the bottom. Six groups provide the description of one reactor. The purpose is to detect repeated shocks which have significant amplitude and which appear almost simultaneously in the same zone.

The procedure of detection comprises 4 steps:

- **Detection of transient events** is based on the crest factor: a pulse is detected if its amplitude is greater than K times (K between 8 and 12) the long-term RMS value of the background noise.

- **Detection of elementary events.** A single sound event is detected if several pulses issued from sensors in a single zone are observed within a specified time interval. This interval is determined by the maximum time of propagation of acoustic waves in that zone. Only the transients occurring in coincidence are considered. This principle enables the separation of isolated shocks which could be due to other phenomena (thimble rattling, acoustic impacts from control rod driving mechanism).

- **Detection of significant elementary events.** In order to discriminate casual coincidences, (valve actuation, stress wave relaxation, thimbles rattling, for instance), events are judged significant only in cases of repeated occurrence, typically, when the number of events per unit of time surpasses a threshold. These situations produce a local alarm relating to the zone of the reactor where the event occurred.

- **Alarm activation.** An alarm is also produced in the control room, unless it is inhibited by external signals related to the operation of the plant, such as movement of the control rod driving mechanisms, or the pressure of the primary system.

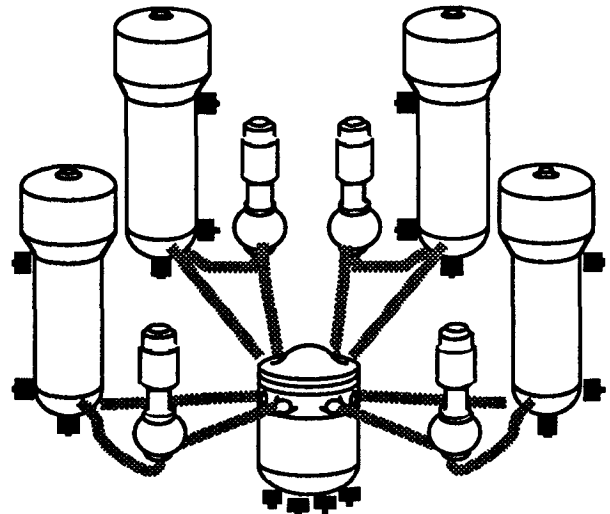


Figure 4 : implantation of sensors

Aid to diagnostics

Predagnosis is now possible with the new system, IDEAL. This is performed in two steps:

Step1 : global automatic predagnosis

- **Acquisition of level 1 descriptors for the characterization of single sound events.** IDEAL elaborates the main parameters of each event, such as the peak amplitude, RMS value of the background noise, the time intervals between impacts, the time difference between the arrival of separate waves on the different sensors in a single area, the sequence of these arrivals. These parameters are the

level 1 descriptors of the phenomenon. The system automatically processes at least 256 successive events or 15 minutes of signals.

• **Acquisition of level 2 descriptors.** After having obtained all level 1 descriptors, the system elaborates level 2 descriptors, such as the histogram of time intervals, and the related descriptors (mean, mode, standard deviation).

The pre-diagnosis is available some minutes later on a printer, in the following form:

- probability or lack of probability of a loose part,
- localization of the phenomenon (reactor sub-area or SG waterbox, according to the number of available sensors).

Step 2 : complementary characterization of the phenomenon

An analysis of some single sound events is useful to confirm the results obtained by the IDEAL processing unit. Specific software has been developed to allow such analysis using the main computer and a 4-channel scope memory. The graphs obtained can be printed and sent to experts for analysis.

Aid in normal surveillance of the plant

A loose-part monitoring system should also facilitate surveillance of the background noise generated by the normal operation of the plant. As a matter of fact, it is essential not only to recognize abnormal noise, but also to identify operational noise. This is not possible to do that automatically, because one would need to connect all noisy components of the plant to the LPMS and to take into account an extended knowledge base. Some progress has been made however with IDEAL, as it is possible to detect some typical classes of noises, such as isolated transients, or changes in background noise. The objective is to save time for the technicians so that they can spend more time on analysis. But training remains necessary : with that purpose, a specific simulator has been developed (GECHO). Four signals can be generated with known characteristics, enabling one also to verify the correct behaviour of the LPMS.

The architecture

IDEAL comprises an acquisition system connected to a micro-computer. The acquisition system detects the transients, measures the RMS and peak values and delivers envelopes of the signals: these can be used at any time for monitoring by means of a graphic recorder. The microcomputer runs several devices, a graphic monitor, a simplified keyboard, a printer and a cassette recorder. The display of the primary system synoptic is the main interface with the operator : in the event of an incident this permits one to visualize the movement of a loose part in the primary circuit. Important messages are automatically printed. Furthermore, the defective sensors are directed to the recorder, which is automatically activated.

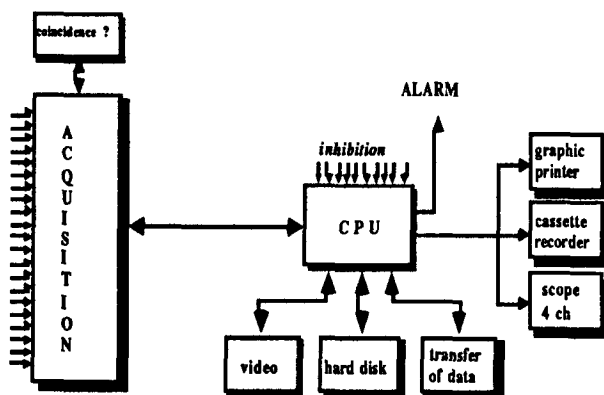


Figure 5 : architecture of IDEAL

Some results

Simulation of a loose-part incident in a 900 MW reactor : we show hereby (fig. 6) the message delivered on line by IDEAL. The situation concerns the loose part at Fessenheim 1 (1985-86), already described. We see that 3 sensors are sensitive to the phenomenon, 55% of the impacts are first seen by AG21 at the SG bottom, most frequent arrival order of waves is AG21/AG22 (45%), arrival time differences on AG21 and AG22 is around 0.9 ms. We also get the maximum amplitudes on these sensors and the histogram of intervals between events : the maximum value (34 sec.) shows that the phenomenon is not continuous and that the object stays immobile during a long time. The diagnosis concludes there is a loose part in loop n°2, in the area "water box".

Acoustic phenomena detected on 1300 MW plants: IDEAL has enabled the automatic detection of disturbing noise on some loops in 1300 MW units. Below is an example of the signatures obtained (fig. 7) in Cattenom 3 : the shape is similar to that produced by a loose part but the time scale is different: duration may reach several hundred ms and rise times are longer. These signals are first seen on the steam generators and then propagate to the vessel : delay is not easy to measure but it roughly corresponds to a propagation speed of about 900 m/s, which is the velocity of sound in water at that temperature. A frequency analysis has shown that the energy of the signal was situated at around 4200 Hz, with modulation peaks spaced at multiples of the blade rotation frequency (173 Hz). In order to confirm that the pump was the true source of the noise, we performed tests on some plants which showed a strong dependance of the amplitude of noise on the injection flow at the pump seal n° 1 (fig. 8). The origin of the noise was explained by a cavity resonance at the injection point . In order to isolate this phenomenon and focus on detection of loose-part impacts only, the detection thresholds of IDEAL were changed.

05/29/90 10:51:32		
ALARME in ZONE n°02		
255 Coinc. within 3 mn		
<u>Arrival order</u>		
	first	second
AG21	55 %	39 %
AG22	44 %	55 %
AG23	0 %	5 %
AC 5	0 %	0 %
AG21/AG22 : 45 %		
<u>Time difference</u> AG21/AG22		
average (µs)	880	
mini	1	
maxi	5818	
<u>Shocs amplitude</u>		
	AG21	AG22
creast	2.1 g	2.8 g
rms	0.9 g	1.4 g
<u>Intervals distribution</u>		
class width	1.07 s	
max. events number	50	
average	1.8 s	
sd	3.5 s	
mini	0 s	
maxi	34.4 s	

DIAGNOSIS :		
Loose part in loop n°2		
in the area "water box"		

Figure 6 : example of diagnosis message by IDEAL (Fessenheim 1985-86)

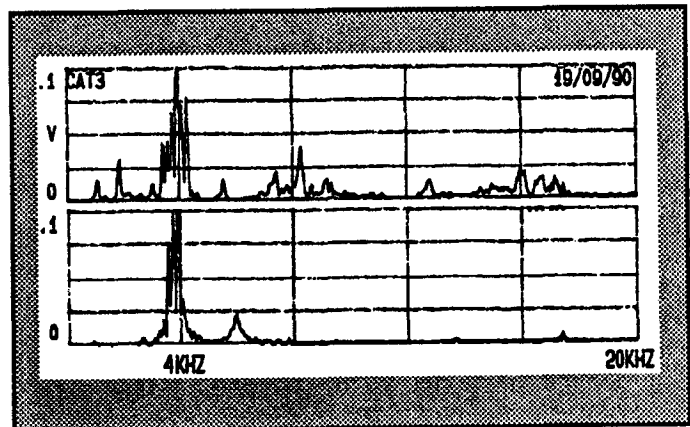
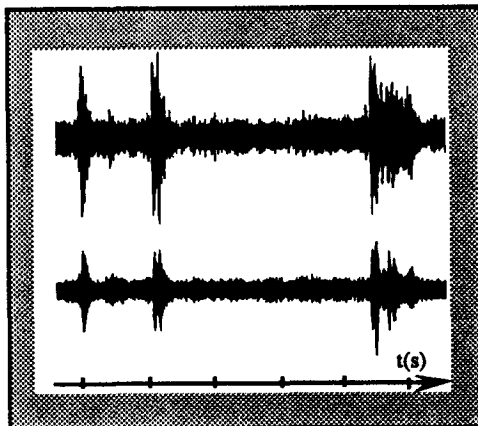


Figure 7 : Zoom at the signal versus time and frequency

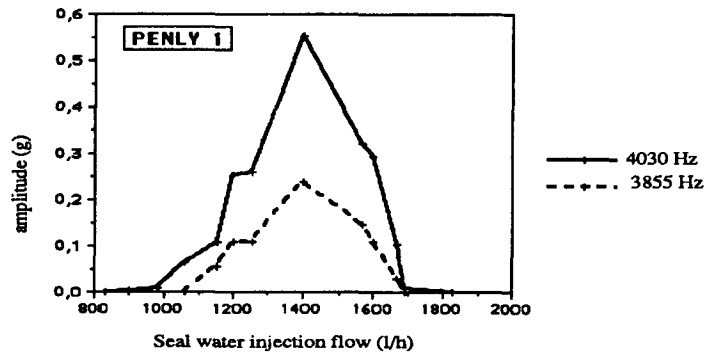


Figure 8 : RMS background noise amplitude versus seal water injection flow

2. The diagnostic phase off site

In order to carry out diagnosis and confirm the presence of a loose part or identify the phenomenon, as rapidly as possible, a specific expertise laboratory has been set up in Chatou. It comprises (fig 9) :

- an 8 channel acquisition system connected to data-processing equipment (fig. 10) : it is possible to acquire transients and background noise in real time, with 12-bit resolution at 50 kHz sampling per channel and to transfer them continuously to a hard disk.
- a 4 channels frequency analyser .
- a transient graphic recorder equipped with 8 channels.
- a loud speaker and a scope.

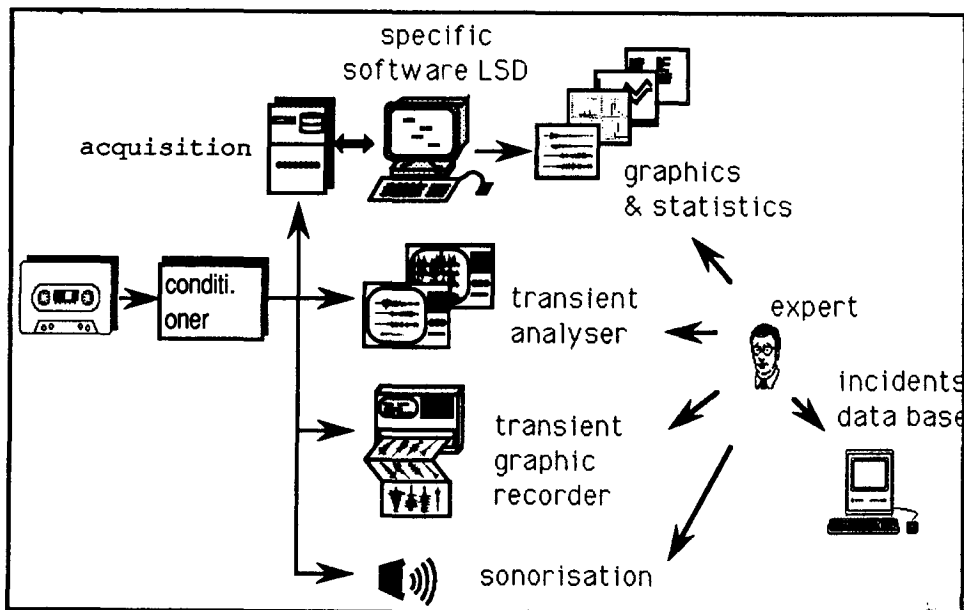


Figure 9: specific expertise laboratory

The transient signals stored on the hard disk are then processed and the time parameters of the events are automatically calculated : rise time, amplitude, duration, order of arrival of waves on the sensors, delay between sensors, time interval between single sound events. Statistical processing of these parameters is

then performed and some new descriptors are obtained, such as chronograms of these parameters, histograms (fig. 11), 2-dimensional graphs for each event of the different combinations of parameters (rise time versus duration, correlation tables, etc...).

For aid to diagnosis, a database has been constructed which permits the calling up of the 80 anomalies and incidents which have occurred since 1970. For each of these, we can retrieve the following information : name of plant, phase of operation, date, nature of anomaly, damage incurred, diagnosis, records of the signals, report of incident and background, etc.

Figure 12 is a graphic display of one event with all the corresponding descriptors.

Example of diagnostic

The example refers to Gravelines 1 (88), already mentioned : The four processed signals originate from the bottom of the steam generator (AG31, AG 32) and from the bottom of the vessel (AT1, AT2). The following tables have been automatically obtained :

- Table 2 indicates the sensors most frequently impressed at first, second, third, fourth, or more and the sequence most frequently encountered : all the events are first seen by the SG sensors (76% first seen by AG31).
- Table 3 gives elaborated descriptors concerning both most impressed channels and issued from statistical analysis : minimum, maximum, mean and standard deviation (sd).

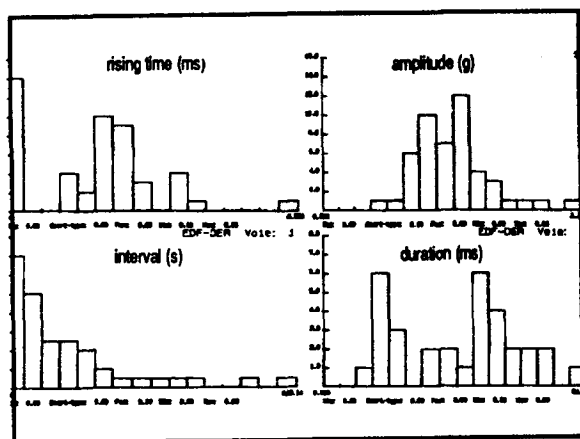


Figure 11 : example of histograms from the expertise station

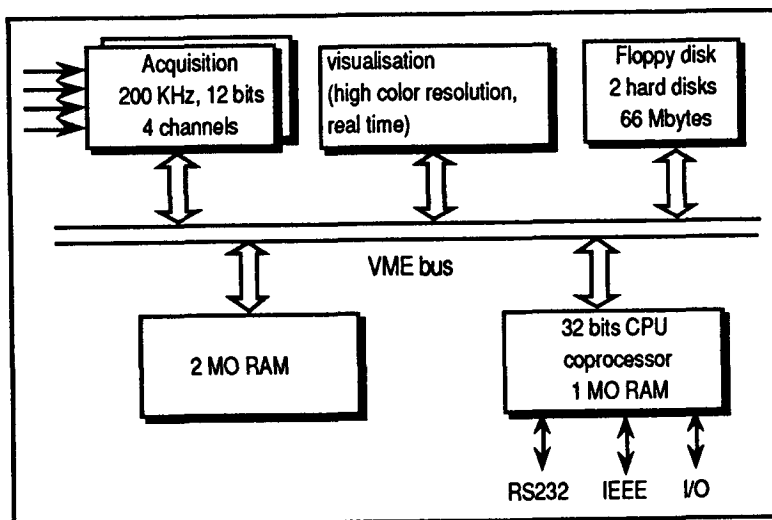


Figure 10 : acquisition and processing system for loose part diagnosis

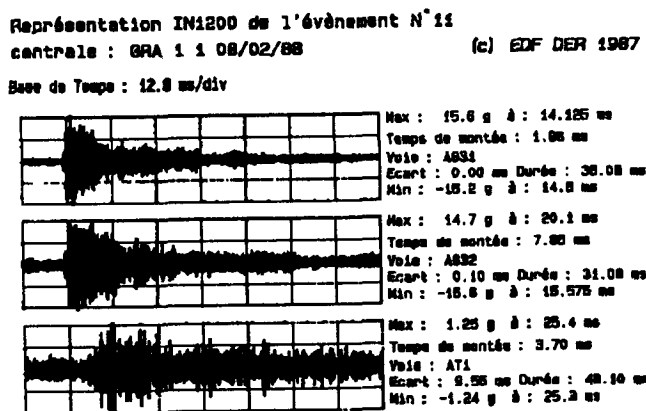


Figure 12 : processing and graph of one individual event

coincidence logic : 2
events - total number : 41

channel name	1st (%)	2nd (%)	3rd (%)	4th (%)	more (%)	number of events(%)
AG31	75.6	24.4	0	0	0	41
AG32	24.4	75.6	0	0	0	48
AT1	0	0	9.8	0	0	2
AT2	0	0	0	0	0	1

Most frequent arrival order :
AG31, AG32 (68.3%)

Δt channels (ms)	mini	mean	maxi	sd
AG32/AG31	0.03	0.68	2.23	0.44

Table 2 : statistics about arrival orders

channel 1 : AG31	mini	maxi	mean	sd
amplitude (g)	3.7	16.1	8.2	3.2
rise time (ms)	0	13.6	3.2	2.8
duration (ms)	2.4	70.5	31.0	19.6
intervals (s)	0.2	3.5	0.9	0.7
Δt / AG31 (ms)	0	0	0	0

channel 1 : AG32	mini	maxi	mean	sd
amplitude (g)	8.2	17.0	13.4	1.8
rise time (ms)	0	14.4	5.2	3.3
duration (ms)	1.2	70.6	41.5	15.7
intervals (s)	0.2	3.5	0.9	0.7
Δt / AG31 (ms)	-8.3	2.2	-0.1	2.0

Table 3 : statistics about parameter values

3. The future and decentralization of diagnostics on site

Increasing needs for diagnostics on the part of power plants, especially during start-up, confirm the appropriateness of decentralizing diagnostics on the sites. This is the objective of the PSAD Monitoring and Aid to Diagnostics Station, now under development [ref 5]. It doesn't only concern loose part detection, for which this requirement was already filled by IDEAL, but all the other monitoring systems. All should be connected to a main computer, thus allowing to facilitate operation and maintenance by the plant personnel.

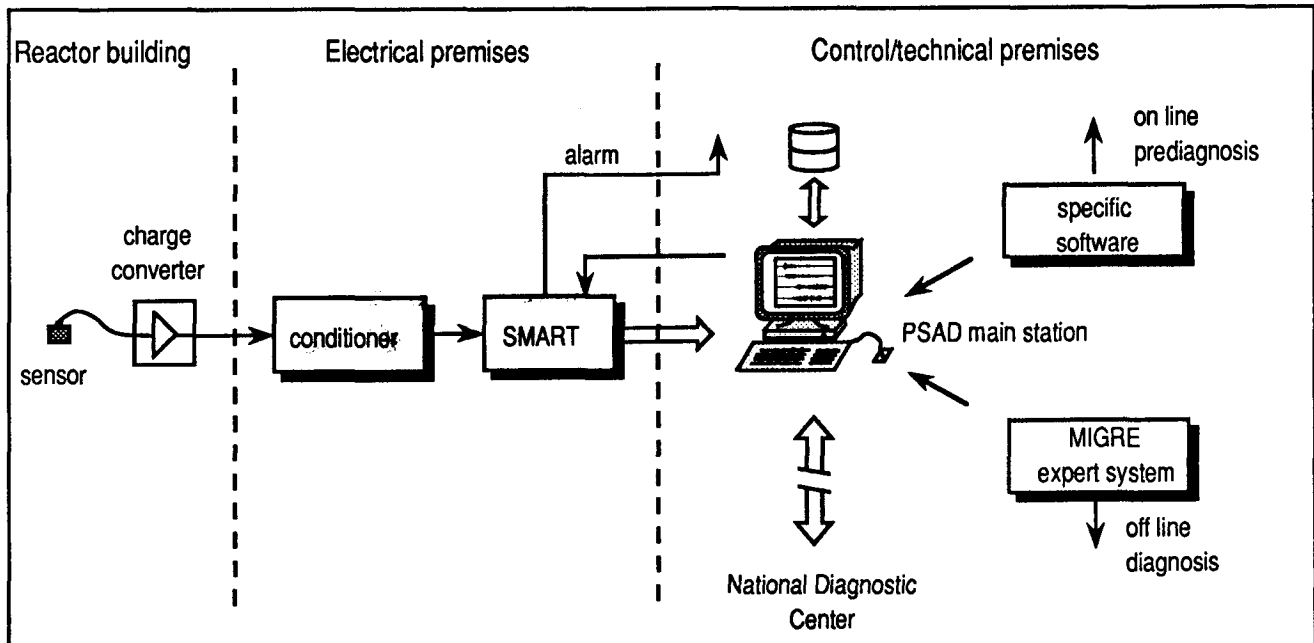


Figure 13 : general architecture of the loose part function inside PSAD

In the PSAD structure, the Loose-Part Monitoring and Diagnostic System will be divided into 3 parts (fig. 13) :

- an acquisition system, SMART, on the electrical premises,
- a specific processing and pre-diagnosis software near the control room,
- an expert system MIGRE on the control or technical premises.

Acquisition of descriptors

A new conditioner has been developed : it provides output signals for on line processing and for local monitoring or evaluation needs. The raw signals from accelerometers are directly used by SMART after charge to voltage conversion and high pass filtering (1 kHz).

Thanks to a high dynamics of the conditioner and SMART, there is no more intervention of the operator (range adjustments). SMART is thus a "black box" which is remotely run and configured from the PSAD main station. Its main functions are (fig. 14) :

- to detect abnormal events and activate an alarm in the control room,
- to elaborate descriptors of abnormal events (up to 8 channels) after improvement of signal noise ratio,
- to detect anomalies in background noise such as instationarity or abnormal spectrum and to filter undesirable frequencies on line.
- to elaborate descriptors of normal noise of the plant (random noise, isolated impulses) and of background noise anomalies.
- to acquire raw signals from single sound events, for vizualization and diagnostics by the experts, in case where it would not be possible on line.
- to transmit all the descriptors to the PSAD main station for subsequent analysis.

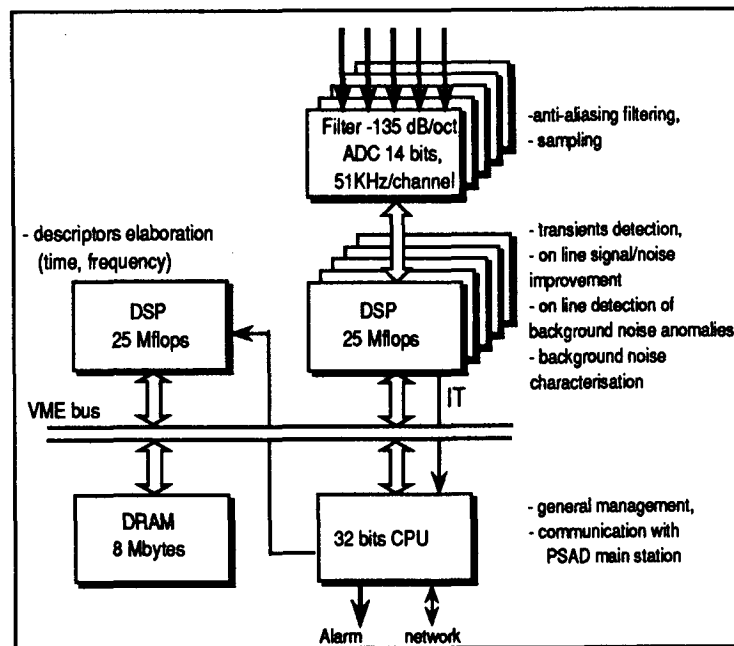


Figure 14 : SMART architecture.

A prototype is now under realization. Its main technical characteristics are a very high dynamics (more than 80 dB), a high slope anti-aliasing filter to reduce frequency sampling (51 KHz) and six powerfull Digital Signal Processors to allow on line digital filtering (for signal/noise improvement and abnormal frequencies filtering).

Some other developments concern the improvement of the detection during the reactor startup : as a matter of fact, at low pressure the background noise is high, and transient signals due to loose part impacts are not detectable. One of the methods now under evaluation consists in whitening the raw signal using the linear prediction method in order to improve the signal to noise ratio. Tests must be performed to make sure that real time processing is possible.

Specific processing and pre-diagnosis software

The software in the PSAD main station has three principal functions : automatic elaboration of a pre-diagnosis, visualization of descriptors of the incident and operator-interface with SMART.

Automatic pre-diagnosis is provided to the operator immediately following an incident, or at most 15 minutes after the beginning of an incident. This pre-diagnosis uses the parameter of "interval between events" to identify the source of shocks (loose part or vibrations between structures), as well as the parameter "delay between channels" to localize the point of impact.

Visualization of the descriptors of an incident enables the technical personnel in the plant to have a clear, overall image which will allow them to estimate the time-distribution of impacts. From this global visualization, they can "zoom" to obtain the shape of transient signals as well as the PSD of each transient . One can also generate various curves (histograms, chronograms, point clusters, correlations) representing typical parameters : amplitude, rise time, duration, time delay, interval.

Operator interface allows to change the SMART configuration and start acquisition of signals if necessary.

The MIGRE expert system [ref. 3]

An expert system MIGRE has been built to assist the technical staff of the plant and confirm the on line pre-diagnosis. MIGRE was developed in Prolog language between 1985 and 1988. The natural-language interpreter and the inference engine were designed especially for the loose-part application. It now runs on several microcomputers and Unix work-stations. The knowledge base contains now approximately 100 objects and about 500 rules to describe the domain.

At present, MIGRE works in a conversational mode but requires some manual and tedious processings to access the relevant data. For the future, MIGRE will be connected to the PSAD station and the access to theses data should be automatized.

Conclusion

Loose-Part Monitoring has now reached industrial "maturity". Acoustic anomalies are detected in time and no major damage has occurred. Henceforth, the challenge consists in making on-site diagnostics a reality . Our prime objective is to automate the detection process as much as possible, and to aid plant personnel in identifying defects. The PSAD concept, connecting several expert systems, should render possible this major evolution. Close cooperation has been initiated with the final users of the system, especially to encourage this new outlook. Of course, the ideal is not possible and the skilled advice of specialists remains essential. We must therefore concentrate our efforts on the future expertise center and its rapid link-up with the PSAD stations, as well as on new diagnostic methods.

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On-line Vibration Monitoring at the Koeberg Nuclear Power Plant

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Abstract

The noise analysis system at the Koeberg nuclear power plant has recently been upgraded by expanding the noise signal array and by replacing the regular off-line measurement campaigns with a multi-channel on-line noise analysis system. Three micro-computer based on-line noise analysis systems were subsequently installed at Koeberg : one system for the monitoring of six main coolant pumps and the primary components belonging to units one and two and two systems for on-line vibration monitoring of the two 900 MWe turbines.

Prior to the installation of the on-line noise analysis systems, a series of off-line noise measurements were made at Koeberg during the periode 1985 to 1991(i.e. since the first fuel cycle of unit one). In the first part of this paper the results of these measurements are summarized.

The second and major part of this paper is dedicated to a description of the surveillance scheme which forms the basis of the monitoring systems. The proposed surveillance scheme utilizes a pattern recognition scheme to cope with the stochastic nature of noise signals and uses a priori knowledge of the system being monitored to extend the diagnostic potential of the system.

The general design philosophy, hardware and software concepts of the surveillance system is discussed.

1 Introduction

Noise analysis techniques are used to obtain information concerning the mechanical integrity of components at any time during the power operation of a plant, without causing any disturbance to plant operation. The detection of mechanical degradation, the monitoring of further degradation, an assessment of its severity and influence on plant operating procedure are the main aims of vibration monitoring.

An on-line microcomputer-based surveillance system for

- shaft crack monitoring on MCP's
- vibration monitoring of primary reactor components
- vibration monitoring of turbines

utilizing noise signals and plant parameters was recently installed at the Koeberg nuclear power plant. Although the surveillance scheme and hence the hardware and software for both primary component and turbine chain vibration monitoring are similar, only the former will be discussed in this paper.

The noise instrumentation will be discussed, followed by a summary of noise measurements since commissioning. The surveillance scheme, as well as hardware and software requirements will be highlighted.

2 Noise instrumentation

In figure 1 the locations of transducers used for noise analysis in the Koeberg plant are shown, namely 8 ex-core neutron detectors belonging to the reactor safety instrumentation, 7 accelerometers on the pressure vessel and one accelerometer on each of the three MCP's. The direction of measurement is indicated.

The signal array was recently extended by adding five additional vibration signals for each of the six MCP's, namely: one keyphasor, two x-y proximity probes and two velocity probes mounted between the pump coupling and shaft seals.

3 Signature interpretation and measurement results

In table 1 and figure 2 the results of a correlation analysis for Koeberg-1 are shown. The signature interpretation, conducted by EdF [4] for PWR's of a similar structural design, were verified for the Koeberg plant, prior to implementation of the surveillance scheme [6].

In figure 3 the results of the noise measurements during the first two fuel cycles are summarized. The trends marked 1, 2 and 3 can be explained as follows:

1. The downward shift in the fuel assembly beam mode is due to the relaxation of the fuel assembly springs during a fuel cycle due to irradiation of the fuel elements. This effect is prominent for fuel cycle 1 but became less apparent during subsequent fuel cycles due to the fact that only one third of the core is replaced during refuelling.
2. The increase in frequency observed for the fluid resonances is caused by the decrease of outlet coolant temperature as indicated.
3. The corresponding decrease in frequency of the core barrel shell mode for measurements at reduced power is also caused by the decrease of outlet coolant temperature. This effect cannot be observed equally well for all mechanical resonances due to a poor frequency resolution and due to the fact that such frequency shifts are expected to be smaller for lower frequency resonances.

Summary: No undue change in vibration has been observed in either of the units of the Koeberg nuclear plant. A number of accelerometers have been replaced due to sensor degradation.

4 The Surveillance Scheme.

In figure 4 the surveillance scheme for the recently installed monitoring systems is shown. Three items can be noted: a general pattern recognition scheme, a diagnosis block, and the influence of the a priori knowledge base on the surveillance scheme.

In [8] a mathematical framework for the total surveillance scheme is presented and the surveillance scheme is tested in a finite element simulation calculation.

4.1 The Pattern Recognition Scheme

Process The block *process* represents all the physical phenomena which can occur in an operating nuclear power plant, i.e. either during normal operating conditions or in abnormal situations. These phenomena can be roughly classified as deterministic or as stochastic. The *Plant (process) signals* used in the surveillance system consist of noise signals and plant parameters.

Preprocessing Signal conditioning is done during *preprocessing* and the statistical (noise) parts of respective noise signals are analysed. At this stage, FFT's of noise signals are calculated and subsequently APSD's, and CPSD's and coherencies for a number of pre-defined signal combinations is calculated. Prior to commencement of the surveillance task, a set of reference signatures, referred to as *baseline signatures*, is calculated.

Let the set of calculated APSD's and CPSD's and baseline APSD's and CPSD's be denoted by

$$\{F_i/i = 1, \dots, M\}$$

and

$$\{F_i^b/i = 1, \dots, M\}$$

respectively. Here

$$F_i = (f_{i1}, \dots, f_{iN})^T$$

and

$$F_i^b = (f_{i1}^b, \dots, f_{iN}^b)^T$$

Feature extraction In principle, the statistical functions obtained in the preprocessing phase could be used directly in the *classifier* phase as input *feature vectors*. However, the large number of sensors (typically 20 to 60) and the possibility of many signal combinations used to calculate correlation functions, could lead to a problem of unacceptably high dimensionality. Subsequently an essential block in the surveillance scheme is the *feature extraction* block of which the main purpose is to reduce the dimensionality of the problem.

In this application three parameters are calculated for pre-selected frequency intervals in APSD's and CPSD's. The choice of frequency intervals is based on the information content in noise signals. For each selected noise signal i , and each selected frequency interval j , the following is calculated:

- Correlation discriminant:

$$d_i^j = \frac{\sum_k (f_{ik} - \bar{f}_{ik})(f_{ik}^b - \bar{f}_{ik})}{[\sum_k (f_{ik} - \bar{f}_{ik})^2 \sum_k (f_{ik}^b - \bar{f}_{ik})^2]^{\frac{1}{2}}}$$

where $\sum_k$ denotes summation over frequency interval j

- Amplitude:

$$a_i^j = \max_{p_{ij}^{min} \leq k \leq p_{ij}^{max}} f_{ik}$$

where p_{ij}^{min} and p_{ij}^{max} denote lower and upper limits of frequency interval j in noise signal i .

- Frequency:

$$f_i^j = \text{frequency value at } a_i^j$$

Using these values, the *feature vector* X_i is built:

$$\begin{aligned} X_i &= (f_1^1, a_1^1, d_1^1, \dots, f_{P_1}^1, a_{P_1}^1, d_{P_1}^1, \dots, f_{P_M}^M, a_{P_M}^M, d_{P_M}^M)^T \\ &= (x_1, \dots, x_P)^T \end{aligned}$$

Classification The *feature vector* is then subjected to a *classification* phase. Due to the statistical nature of the feature vector, *classification* is based on a comparison of the feature vector with a *training set* (i.e. a set of reference feature vectors (defining the reference state) which is obtained during the *learning phase* prior to commencement of surveillance). In the case of reactor noise, the training set is *incomplete* (i.e. the training set does not contain feature vectors which represent all possible plant states).

It is therefore clear that a versatile diagnosis cannot be obtained by using a statistical pattern recognition approach alone. Furthermore, treating the components x_i of feature vector X_j as statistically independent will result in the generation of false alarms.

4.2 Diagnosis

The purpose of the *diagnosis* block is to distinguish between those feature vector deviations indicating failure development and those deviations of the feature vector due to plant operating state changes or due to spurious or pseudo changes (eg. disturbances of the measurement process). Furthermore, it is required that the diagnosis contains specific information, i.e. pertaining to a specific failed component. This block should prevent false alarms and state the development of failure only when justified. A versatile diagnosis can be obtained utilising the a priori knowledge base as described in the next section.

4.3 The A Priori Knowledge Base

In the proposed surveillance scheme, the a priori knowledge base contains:

- Facts concerning the process and plant signals e.g. considering the system behaviour and the particular placing of sensors, there is a redundancy in the information supplied by different sensors.
- The interpretation of spectra, i.e. the physical significance of resonances in spectra. Due to the complexity of the monitored system, a substantial effort is necessary to allow an interpretation of noise spectra. The interpretation of spectra is the result of: correlation analysis of a well-instrumented prototype plant [1], experimental modal analysis and shaker tests [9], experimental work on mechanical mock-up facilities, [7] theoretical investigations of system behaviour by means of computer codes [2],[3].
- System process behaviour during normal plant operation. This information goes beyond the learning phase in a particular plant, and includes relevant information from past experience in plants with a similar structural design. This will include information concerning due changes in vibrational behaviour, e.g. due to changing operating conditions or due to increased irradiation time of components.
- Experience of plant vibrational behaviour during failure development, includes:
 - experience throughout the total past lifetime of the monitored plant.
 - experience gathered during the past lifetime of other plants, may often be applied qualitatively in justified cases.

Heuristic knowledge uses information specific to particular problems. It will generally be pertinent and effective only for those particular problems, and cannot be immediately generalized to other problems. Heuristic knowledge therefore does not constitute a means of reducing the complexity of a problem in a methodological way.

4.4 Utilizing the a priori knowledge base

Although the a priori knowledge base often contains fragmented bits of information, it increases our knowledge about the monitored system and, if properly applied, results in a more versatile surveillance system.

In figure 4 the influence of the knowledge base on the surveillance scheme is shown:

- The selection of frequency bands containing known resonances in the surveillance scheme, results in the incorporation of the interpretation of spectra.
- The use of amplitude, frequency (and correlation discriminant) for these resonances as components of the feature vector gives these components x_i of the feature vector physical significance.
- The formulation of diagnostic rules allows the application of information pertaining to mechanical degradation (i.e. undue deviations from normal state) and due mechanical changes, and results in the versatile diagnostic block as shown in figure 4

5 Knowledge representation

The finite random sequence

$$\{X_n\} \subset \mathbb{R}^P$$

represents the evolution of the system in state space. The last element, X_n , of this sequence represents the state of the system obtained from the most recent measurement.

With each component $x_i \in \mathbb{R}^1$ of X_n is associated:

- a quantifying real number x_i
- a notion as to whether x_i denotes frequency, amplitude, or discriminant
- the lower and upper limit of the frequency interval for which the above was calculated.
- the signal number and hence signal name to which x_i belongs
- the peak number and a semantical expression indicating the physical significance of the resonance found in the monitored frequency band i.e. the noise source (vibrating component) and vibration mode.
- a lower and upper alert level to indicate the normal range of x_i .

Changes in the components x_i of X_n is evaluated in conjunction with components which are related to x_i in terms of the semantics of the problem.

Diagnostic rules are used to specify those combinations of components of X_n with physical significance. Hence only physically significant diagnostic rules are applied in the diagnostic stage of the surveillance scheme.

5.1 A logic for the implementation of diagnostic rules.

A diagnostic rule is a symbolic expression of operating knowledge. It is a means of concisely representing knowledge applicable for diagnosis. Such knowledge is often not quantitative (and hence not representable in numbers) but may contain qualitative indication of system or process behaviour which can be described symbolically in *IF – THEN* rules. The syntax used to define rules is presented in table 2

Metarules To preserve consistency in rules, so called metarules (i.e. rules about rules) are used to specify the correct use of the above semantics. These metarules are integrated in the surveillance software in the form of an interpreter which checks the consistency of diagnostic rules when they are fed into the a priori data base.

Let $R = \{R_k | k = 1, 2, \dots, T\}$ be the set of diagnostic rules in the a priori data base.

Each rule R_k is presented by a sequence of symbols

$$“ \dots l(xS_{ij}@)l \dots \Rightarrow S_k ”$$

where

- $x \in \{d, f, a\}$
- $@ \in \{\square, *, \uparrow, \downarrow\}$ or any equivalent form as presented above
- S_{ij} : noise signal i , frequency band j
- $l \in \{\wedge, \vee\}$
- S_k : a semantic expression containing pertinent diagnostic information.

The metarules will preserve this basic form of the rules and prevent illogical inputs and check the existence of the input noise signal and the specified frequency band. The semantic expression S_k is not interpreted as this is merely a message or diagnosis output by the surveillance scheme.

A number of vibration monitoring problems may require the inclusion of deterministic plant signals (plant parameters). These signals will not be preprocessed as described above and can be included in the feature vector X_n by simply increasing the dimensionality of X_n .

Hence signature linkage can be applied and diagnostic rules specified to include deterministic plant signals, if necessary, in the diagnosis phase.

6 Surveillance system hardware

The hardware configuration used in the implementation of the proposed surveillance scheme is shown in figure 5. In table 3 the system hardware features are summarized.

The analog noise signals are fed through programmable anti-aliasing filters (one per noise signal) with a cut-off steepness of 180 dB/octave and a 80 dB dynamic range. These filters were manufactured by the Noise Analysis division of the AEC. Noise signals are sampled with the 112-channel ADC and multiplexer card and data is transferred to a powerful 55 MHz processor card for FFT-production. This card is used to calculate APSD's, CPSD's and Coherence of a software-selectable number of signal pairs.

The controller is a 33MHz 386 PC with 2 MB RAM, equipped with a high-resolution color monitor, color printer and 150 MByte hard drive and backup facilities.

The system is equipped with a 9600 baud modem card with refined fault correction capabilities for remote access to the system.

Although plant parameters can be obtained by sampling analog signals with the ADC card, in this application plant parameters is obtained via RS-232 link directly from the Emergency Responce Facility (ERF-computer).

Multiples of the add-in cards are available for extension of the number of channels to be monitored.

7 System software concept

The software is configured in two systems (one for each unit). Each system runs in two modes: mode 1 for MCP vibration monitoring, which runs permanently, and mode 2 which handles the general problem of primary component vibration monitoring. Mode 2 runs on a weekly basis.

The software runs in a multi-tasking environment as shown in figure 6.

Four software tasks run simultaneously:

- Background process

In this process, the data sampling (ADC) is controlled. Noise signals are sampled and multiplexed and data is sent to the numbercrunching card through direct memory access. This card performs FFT production, calculates APSD's and CPSD's for a software-selectable number of signal pairs and calculates the feature vector. Data is then stored on the hard disc but when disc space is exhausted, the oldest data files will be deleted first after having been backed up to streamer tape automatically.

- Remote communication

This software allows remote access of data on the hard disc, as well as access to the surveillance system in general, i.e. noise data can be obtained, rules can be experimented with and system setup changes can be made.

- Reporting software In this process regular updates of noise measurements is displayed on the CRT. Newly obtained signatures and baseline signatures is shown. The feature vector is trended. A hardcopy and summary of

measurement results is printed daily. The outcome of a search through the rule base is printed.

Similar reporting is done on a weekly basis for mode two for each unit.

- User interface

This software allows total system control and general system setup. The number of averages, frequency resolution, signal names and spectral content can be specified, reporting date and time is set and rule base entries can be made.

A graphics menu is included to allow two and three dimensional displays.

8 Summary

In this paper the on-line vibration monitoring system at the Koeberg nuclear power plant is discussed. The surveillance system can:

- monitor all types of noise signals and be capable of unattended on-line monitoring and interpretation of large volumes of noise data
- perform trending, logging and updating of noise data automatically
- allow for operator interaction with the computer in order to obtain additional information
- maintain an extremely low false alarm rate and be sensitive to changes in the vibrational behaviour of primary components
- diagnose a variety of primary reactor component and turbine vibration malfunctions

The system, based on the proven COMOS concept [5], includes the following further developments:

- a lower level of hardware is used resulting in a more modular and cost-effective system
- the system can be expanded by adding ADC and processor cards
- plant parameters (digital or analog) can be included without additional hardware costs
- the system is multi-tasking and allows simultaneous calculation of FFT's of up to 110 noise channels per ADC card
- the diagnostic part of the software has been further developed to allow more comprehensive diagnostic rules
- the system is equipped with a modem to allow remote access to data and diagnostic rule base.

9 Future perspectives

Before the end of 1991, four VIMOS systems (Vibration Monitoring System) will be running as indicated in table 3.

These systems should allow a comprehensive correlation between plant parameters and vibration signals of the MCP's, primary reactor components and turbine chains of the abovementioned stations.

Additional monitoring parameters, such as the phase angle, is being investigated as an addition to the feature vector. The event-initiated measurement of transients, such as run-up and coast-down, will be further developed.

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Table 1: Interpretation of Koeberg-1 vibration signatures. ¹: confirmation of interpretation necessary. *: peak seen in signal type as indicated. N: Neutron sensors. A: Accelerometers. P: Proximity probes. V: Velocity probes

NO	N	A	P	V	FREQ.	INTERPRETATION
1	*				2.6-3.2	Fuel Assembly Beam Mode (Fundamental Mode)
3 ¹	*				5.6	Fluid Resonance
4	*				6.1-6.4	Fuel Assembly Beam Mode (First harmonic)
5	*				8.1	Core Barrel Beam Mode
6	*				10.2-10.5	Fuel Assembly Beam Mode (Second Harmonic)
7		*	*	*	11.0-12.0	MCP Oil-Whip (weakly perceived)
8		*	*	*	12.5	MCP-Shaft Vibration Subharmonic
10		*			17.5	Vessel Rocking Mode
11		*			18.0	Vessel Rocking Mode
12		*			18.5	Vessel Rocking Mode
13	*				19.7-20.4	Core Barrel Shell Mode (n=2)
14	*	*	*	*	24.8	MCP Rotation (1x)
15 ¹		*			32.5	Fluid Resonance
16			*	*	49.9	MCP rotation (2x)
17			*	*	74.9	MCP rotation (3x)
18			*	*	99.9	MCP rotation (3x)

Table 2: Syntax used to define rules.

SYMBOL	MEANING	USE
(), [], { }	Separators	Help to structure an expression.
$S_{i,j}$	Noise signal number i, peak number j	to identify component x_i of X_n
f, a, d	frequency, amplitude discriminant	To specify monitoring parameter for $S_{i,j}$
$\wedge$	Conjunction <i>AND</i>	Used as connectors
$\vee$	disjunction <i>OR</i>	
*	alert level exceeded	To describe system state
$\square$	alert level not exceeded	
$\uparrow$	value increased $\vee *$	
$\downarrow$	value decreased $\vee *$	
$\neg$	negation <i>NOT</i>	
$\Rightarrow$	implication	
$\Leftrightarrow$	mutual implication	

Table 3: Surveillance system hardware features

SYSTEM HARDWARE FEATURES	
ANTI-ALIASING FILTERS	
Filter type	● switchable/programmable
Filter range	● 1,2,5,...,5000,10000,20000 Hz
Filter steepness	● 180 dB/octave
Dynamic range	● 80 dB
ADC-CARD	
Total no of channels (N)	● 16/48/64/96/112 per ADC card
Frequency range (all channels)	● 40/100/167 kHz
Two scan frequencies for	● noise signals and plant params
Max number of noise signals	● two less than N
Max number of plant parameters	● two less than N
BACKGROUND PROCESSOR	
Backplane processor card	● 32 bit, 55 MHz CPU, 2 MByte RAM
CONTROLLER	
PC-compatible micro-computer	● 32 bit, 33 MHz CPU, 2 MByte RAM
PERIPHERALS	
Monitor and Printer	● high resolution, colour
Hard Disc, Streamer Tape	● 150 MByte
Modem and modem card	max 9600 BAUD, fault correction

Table 4: Installed and planned vibration monitoring systems.

System	Station	Application	Noise signals	Plant parameters	Status
VIMOS 1	Lethabo coal fired power station	600 MWe turbine chain unit 1	17 inductive shaft vibration probes 9 proximity probes (on bearings) 6 accelerometers on gen. housing 1 key phasor	80 analog	operating since March 1991
VIMOS 2	Koeberg nuclear power station	6 MOP's and primary components of 1 and 2	for each unit: 8 neutron sensors, 7 accelerometers. For each pump: 2 proximity probes, 2 velocity probes, 1 keyphasor, 1 accelerometer	digital, all parameters available on ERF lable on ERF	operating since April 1991
VIMOS 3	Koeberg nuclear power station	912 MWe turbine unit 1	20 proximity probes 1 key phasor	digital, all parameters available on ERF lable on ERF	operating since April 1991
VIMOS 4	Koeberg nuclear power station	912 MWe turbine unit 2	20 proximity probes 1 key phasor	digital, all parameters available on ERF lable on ERF	to be commissioned during August 1991

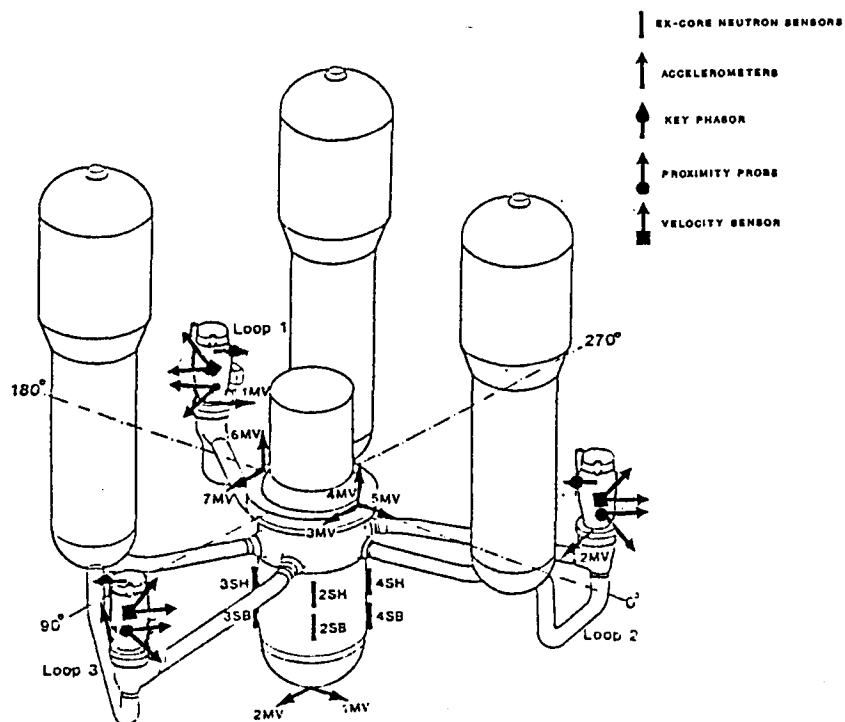


Figure 1: Koeberg noise instrumentation

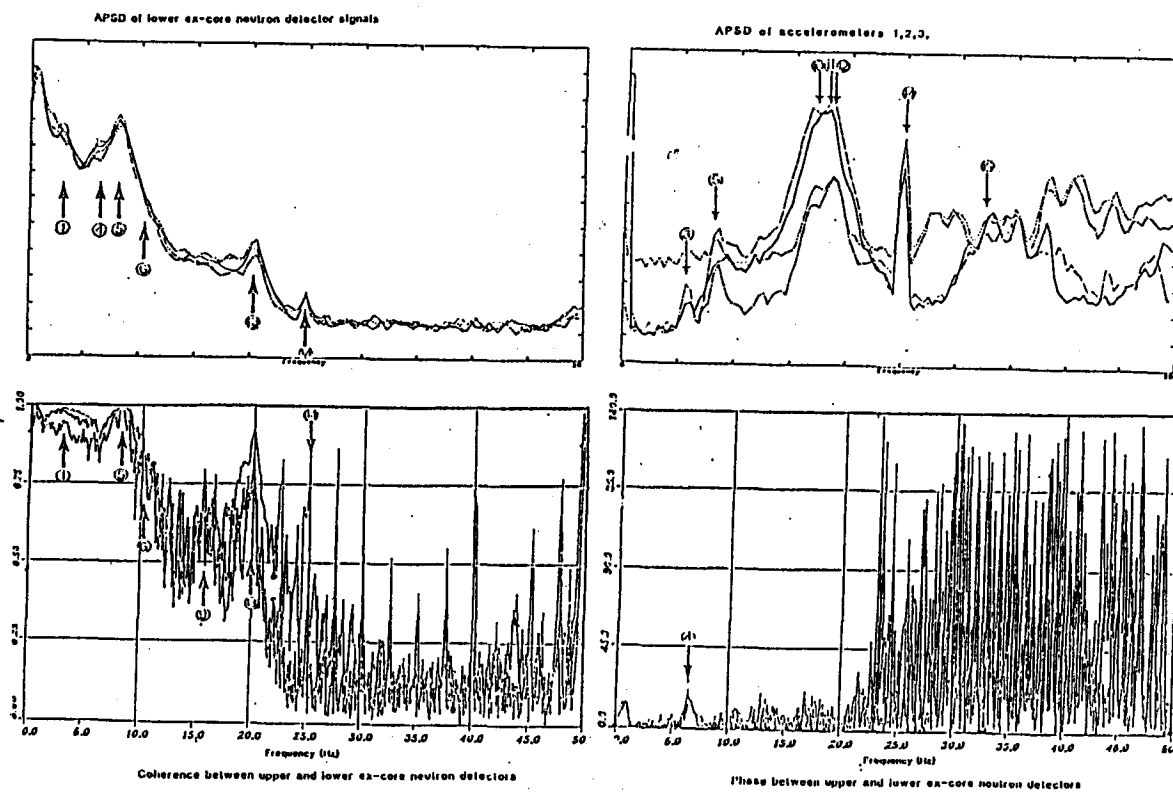


Figure 2: Koeberg-1 vibration spectra. Resonances are numbered according to table 1.

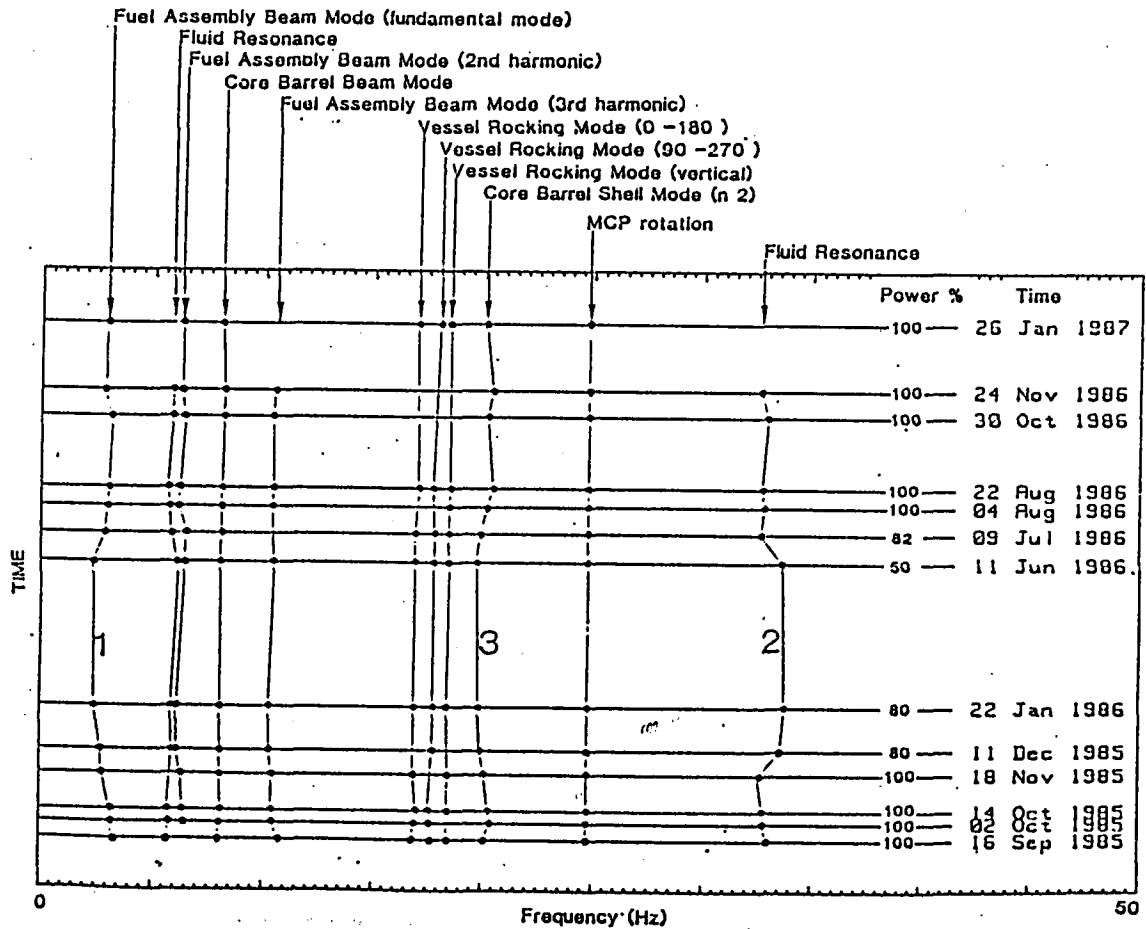


Figure 3: Summary of noise trends during fuel cycle one and two of unit one.

TOTAL SURVEILLANCE SCHEME

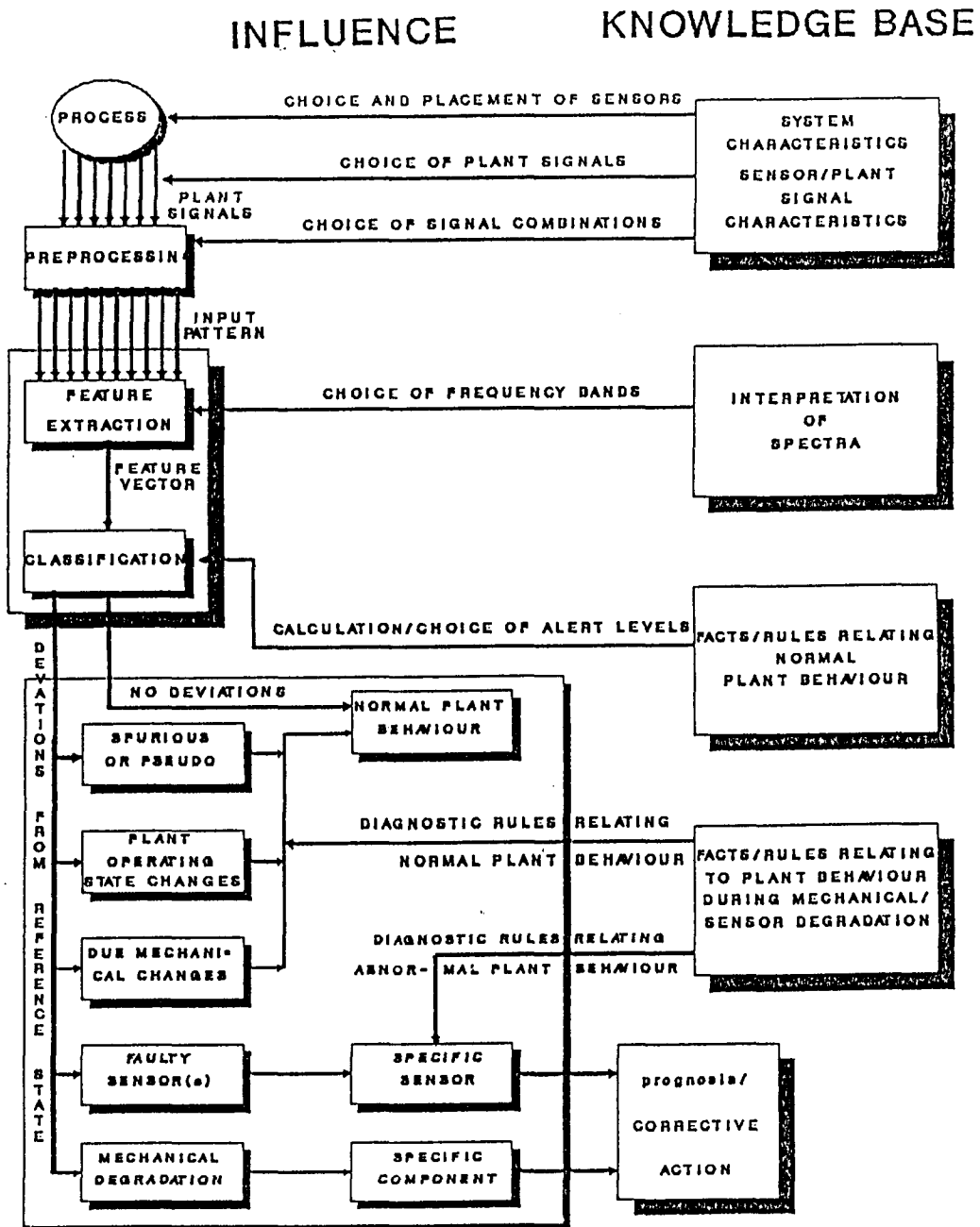


Figure 4: Influence of the a priori knowledge base on the surveillance scheme

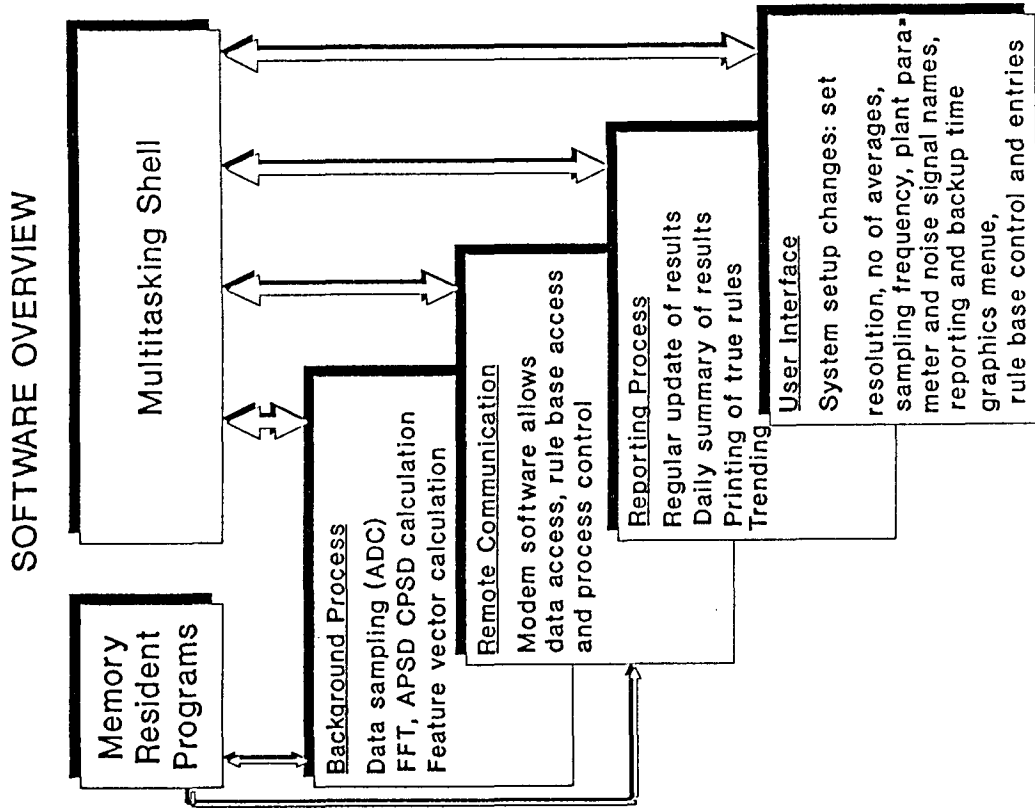


Figure 6: The surveillance system software.

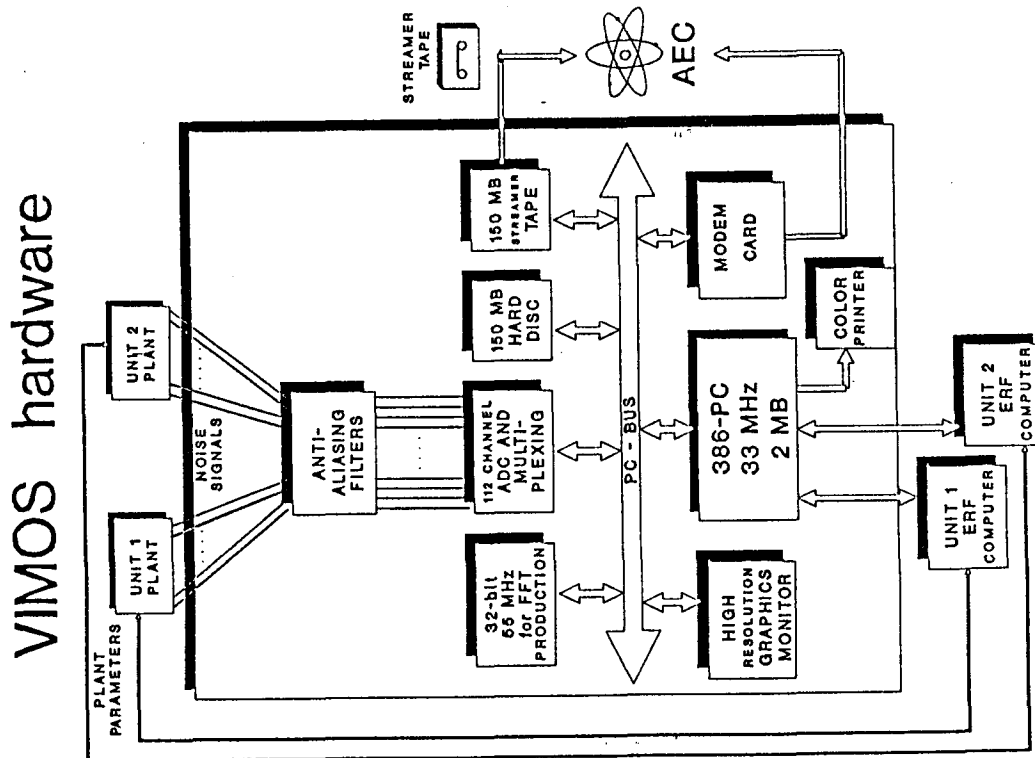


Figure 5: The surveillance system hardware.

APPLICATION OF NEURAL NETWORKS TO THE OPERATION OF NUCLEAR POWER PLANTS

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ABSTRACT

Application of neural networks to the operation of nuclear power plants is being investigated under a U.S. Department of Energy sponsored program at the University of Tennessee.[1] Projects include the feasibility of using neural networks for the following tasks: (a) diagnosing specific abnormal conditions, (b) detection of the change of mode of operation, (c) signal validation, (d) monitoring of check valves, (e) plant-wide monitoring using autoassociative neural networks, (f) modeling of the plant thermodynamics, (g) emulation of core reload calculations, (h) analysis of temporal sequences in NRC's "licensee event reports", (i) monitoring of plant parameters, and (j) analysis of plant vibrations. Each of these projects and its status are described briefly in this article. The objective of each of these projects is to enhance the safety and performance of nuclear plants through the use of neural networks.

INTRODUCTION

Monitoring and decision making in the operation of a nuclear power plant involves the handling of great quantities of numeric, symbolic, and quantitative information by plant personnel, even during routine operation. The large number of process parameters and systems interactions poses difficulties for the operators, particularly during abnormal operation or emergencies. During such situations, individuals are sometimes affected by stress and emotion that may have varying degrees of influence on their performance. Taking some of the uncertainty out of their decisions by providing real-time diagnostics has the potential to increase plant availability, reliability and safety by avoiding errors that lead to trips or endanger the safety of the plant. The emerging technology of neural networks offers a method of implementing real-time monitoring and diagnostics in a nuclear power plant.

NEURAL NETWORKS

A network of artificial neurons (usually called a neural network) is a data processing system consisting of a number of simple, highly interconnected processing elements in an architecture inspired by the structure of the cerebral cortex portion of the brain. Hence, neural networks are often capable of doing things which humans or animals do well but which conventional computers often do poorly. Neural networks exhibit characteristics and capabilities not provided by any other technology.

Neural networks may be designed so as to classify an input pattern as one of several predefined types (e.g., the various fault or transient states of a power plant) or to create, as needed, categories or classes of system states which can be interpreted by a human operator. Neural networks have the ability to respond in real-time to the changing system state descriptions provided by continuous sensor inputs. For complex systems involving many sensors and possible fault types (such as nuclear power plants), real-time response is a difficult challenge to both human operators and expert systems. However, once a neural network has been trained to recognize the various conditions or states of a complex system, it only takes one cycle of the neural network to detect a specific condition or state.

Neural networks have the ability to recognize patterns, even when the information comprising these patterns is noisy, sparse, or incomplete. Unlike most computer programs, neural network implementations in hardware are very fault tolerant; i.e., neural network systems can operate even when some individual nodes in the network are damaged. The reduction in system performance is about proportional to the amount of the network that is damaged. Thus, systems of artificial neural networks show great promise for use in environments in which robust, fault-tolerant pattern recognition is necessary in a real-time mode, and in which the incoming data may be distorted or noisy.

DIAGNOSTICS: STATE OF THE PLANT

When a nuclear power plant is operating safely, the readings of the hundreds, or even thousands, of instruments in a typical control room form a pattern (or unique set) of readings that represent a "safe" state of the plant. When a disturbance occurs, the instrument readings undergo a transition to a different pattern that represents a different state that may be safe or unsafe, depending upon the nature of the disturbance. The fact that the pattern of instrument readings undergo a transition to a new state that is different for every given condition is sufficient to provide a basis for identifying the state of the plant at any given time. Such identification requires a rapid (real-time), efficient method of "pattern recognition", such as neural networks, to implement a diagnostic tool based on this phenomenon.

Steam Generator Transients. Identification of transients in a U-tube steam generator (UTSG) has demonstrated the ability of a neural network to diagnose specific abnormal conditions in a nuclear power plant.[2] Six transient conditions were introduced into the operating conditions of a simulated UTSG, and ten samples of each of the traces of four variables were used as the 40 inputs to the neural network. The output of the neural network was a three-bit binary representation to identify each of the six transients. The hidden layer contained twelve artificial neurons. Backpropagation was used to train the network to give the proper three-bit designation for each of the six perturbations. After 500 training cycles, the numerical outputs of the neural network approximated

the binary designations for the six transients. When the number of input variables were reduced to three, and subsequently to two, the deviation of the outputs from the binary representations increased, (e.g., an output that should have been a one might change from 0.98 for four inputs to 0.91 for two inputs.) However, the transients were always identified correctly, because there was never any ambiguity as to whether the output should have been a one or a zero. Increasing the number of training cycles to 1000, and subsequently to 1500, further reduced the deviation. Furthermore, the neural network also continued to give the correct output even when the input data was corrupted with very large levels of uniformly distributed noise (up to $\pm 90\%$.) An index of performance of the neural network under different conditions was obtained by averaging the deviations between the actual network values and the correct values (one or zero.) This index deteriorated as the number of training cycles decreased, as the number of input variables decreased, and as the input noise level increased.

Diagnostics using Watts Bar Training Simulator Data. A new "auto-adaptive" stochastic learning technique was developed and applied to a special neural network with a dynamic node structure (e.g., the number of nodes in each of the three hidden layers used was optimized.)[3] The training of a neural network requires the near optimization of the inter-neural connections. In this project, a new method for the stochastic optimization of these inter-connections was developed. The method uses auto-adaptive biased sampling techniques to improve the efficiency of the optimization process. A generalized, fully interconnected network of perceptrons incorporated four variables that were optimized; nodal bias, gain, the output activation constant, and the usual connection weights for each artificial neuron. The network contained three hidden layers that initially contained only one artificial neuron each. Neurons were added individually in the hidden layers until an overall index of performance approached a limiting value. When compared with a typical neural network trained with the conventional backpropagation procedure, the optimized neural network produced by this procedure trained more rapidly and generalized more effectively.

A Monte-Carlo training procedure was used to train this network to identify seven different nuclear power plant transients. The new (1989 installation) Singer-Link training simulator at TVA's Watts Bar Nuclear Power Plant provided data for some 27 variables (reduced from 80 by combining data from the four loops into an equivalent single loop) for seven different accident transients. These time records constituted the input vectors to the neural network. The Monte-Carlo training procedure was very effective in training the neural network to differentiate between the seven different transients (loss of coolant in the hot leg of the reactor coolant system (RCS), loss of coolant in the cold leg of the RCS, main steam-line break in containment, main feedwater line break in containment, total loss of off-site power, control rod ejection, and steam generator tube leak), as well as the steady state condition. In two of the seven cases, the network was able to diagnose the problem before the plant shut down. In all cases, even when noise was introduced into the signals, the neural network was able to diagnose the problem within two minutes of the initiation of the transient.

This work is being extended by using genetic algorithms to optimize the neural network configuration and by increasing the number of variables monitored. Eventually, it is expected that the variables available from the safety parameter display system (SPDS), typically about 500 variables, will provide the input vectors to the neural network and that the number of accident transients for which the neural network is trained will be increased to cover all those accident conditions normally used in the training of nuclear plant operators. The goal will be to detect all accident conditions before the plant is tripped, so that mitigating action (such as a power reduction) can be taken if it is appropriate for that particular condition.

Detection of the Change of Mode in Nuclear Power Plants. During operation of a nuclear power plant, it is desirable to identify changes in the state of operations at the earliest possible time. With the fluctuations that take place during normal operations, there is often a period of minutes before the initiation of deviations from the prior behavior is identified clearly, even when the operators continuously watch the appropriate instruments. The goal of this project is to train the neural network to discriminate among data patterns that describe operational states of the plant. The technique has been reduced primarily to a two-category problem, i.e., the neural network must discriminate between data collected during steady-state conditions and data collected during transient conditions.

In this project, two neural network techniques were applied to data (time records) from a commercial pressurized water reactor (PWR) nuclear power plant to detect changes in the states of the plant's operation, i.e., when the power level changed from a constant level and starts to increase or decrease.[4] The two different neural network techniques used were the polynomial discriminant method (PDM) and the backpropagation network (BPN) method.

PDM is a pattern classification technique for multiple-category problems developed by Donald Specht[5] in 1967 that uses polynomials to define accurate decision boundaries among classes. The technique performs rapid matching, exhibits great extrapolating ability, and can be applied to problems of arbitrary complexity. However, its computational requirements for training are high. BPN is a multilayer, fully connected, heteroassociative neural network that computes the weights between pairs of artificial neurons such that the difference between the actual output and the desired output is minimized in a least-squares sense.

The state of the plant was represented by data from sensors, power level, pressurizer pressure, RCS hot-leg temperature, RCS cold leg temperature, steam generator main feedwater flow, and steam generator pressure. All sensor readings were column-wise normalized in the range 0.1 to 0.9 by dividing the values in each column by the maximum value, multiplying by the interval size (0.8) and adding 0.1. Each vector was presented to the neural network as an independent event. Although training times for both methods were long, recalling values during normal monitoring requires only a few milliseconds using personal computers and less time using work stations.

The PDM and the BPN both were able to classify correctly over 97% of the patterns for a two-category problem (i.e., for normal and transient conditions,) thereby identifying the correct mode of the plant over 97% of the time.[5] Most of the misclassifications occurred immediately after the time the transient state started and the values of the variable being monitored were similar to those during steady state. Once the neural network is trained, on-line detection of different modes of operation appears to be feasible because the pattern can be identified in one cycle of the neural network.

MONITORING OF NUCLEAR POWER PLANTS USING NEURAL NETWORKS

Sensor Validation. The usefulness of information provided to plant operating personnel is dependent upon the validity of the signals coming from sensors as well as the ability to convert such data into meaningful information, presenting it in an understandable format, and providing a diagnosis of the problems. A neural network paradigm has been developed for automated sensor validation during both steady-state and transient operations.[6] The use of neural networks for signal estimation has the advantage that the functional form relating a set of process variables is

by the neural network system (model of the process) and is implicitly nonlinear. Once the network is properly trained, future predictions can be made in real-time. Furthermore, the state estimation using a neural network is less sensitive to measurement noise compared to direct model-based techniques.

For signal validation, a neural network model of the process (or a portion of the process) is developed. The input layer of artificial neurons correspond to the input signals, and the output layer usually has just one signal which is to be predicted or estimated. The neural network is trained over the range of anticipated operating conditions while the system is known to be operating properly. Then the neural network model repeatedly predicts the output value, based on the actual inputs. As a sensor deteriorates or fails, the predicted output value from the neural network deviates from the measured value.

Tests with data from the Experimental Breeder Reactor-II (EBR-II), a liquid metal fast breeder reactor at the Idaho National Engineering Laboratory and a commercial four-loop PWR power plant have shown that this technique can be used to validate data from sensors placed in nuclear power plants.[5]

Monitoring of Feedwater Venturi. The techniques discussed above for sensor validation can be extended to monitoring a specific variable for drift or change over time. A project being initiated by the University of Tennessee involves monitoring the fouling of the throats of the venturi flow meters that measure the feedwater flows to the steam generators in a PWR power plant. Since these measured values are directly related to the calculation of thermal power, which is limited by the NRC license, fouling that erroneously indicates a higher velocity effectively causes a derating of the plant from the licensed power level, unless it can be evaluated and compensating steps taken. Even when compensating adjustments are made, there is the possibility that the crud could break loose, causing the thermal power to exceed the licensed power. Hence, monitoring for changes, either gradual or abrupt, is an important step. An analysis of the situation shows that the sensor validation technique is sensitive enough that it can be used to monitor the fouling. The University of Tennessee is now gathering data from two nuclear power stations, each with two four loop PWR plants, to determine the feasibility and practicality of monitoring and evaluating this fouling.

Plant-Wide Monitoring Using Autoassociative Neural Networks. The technique for sensor validation has been expanded into a plant-wide monitoring system[7,8] by using an autoassociative neural network where the inputs and the outputs are identically the same variables. The number of artificial neurons in the intermediate layer is selected to minimize the training time and maximize the ability of the neural network to generalize. The network is trained over the range of operation using the same data for the input vector and the desired output vector. Backpropagation using a sigmoidal function with an adjustable coefficient was used to train the network. Once the network is trained, its outputs represent estimates of the instantaneous values of the output variables. When the system is operating properly, all of these estimates are virtually identical to the actual outputs. When a sensor begins to drift or an error is introduced into a data channel, the predicted value and the actual value differ. Hence, monitoring the differences between the estimates predicted by the neural network and the actual values from the system provides a method of identifying drift or instrumentation (or other) failure.

This technique was applied to data from ten signals from the EBR-II during ascension in power from 45% to 100%. Two separate networks were used, one for the variables related to the primary system and the other for the variables related to the secondary system and balance of plant, to

reduce the training required. Errors between estimates predicted by the neural network and the actual values were usually less than 0.5%. Further reduction of this difference should be possible by removing the mean values of the signals prior to introducing them into the neural network.

Monitoring of Check Valves. Check valve failures at San Onofre Unit 1 on November 21, 1985 led to the Nuclear Regulatory Commission (NRC) issuing NUREG-1190 that discussed the reasons for the failures of the five check valves and how the check valve failures induced water hammers to the feedwater system. In a parallel effort, the Institute for Nuclear Power Operations (INPO) issued a Significant Operating Experience Report SOER-86-3 on October 15, 1986 that discussed the San Onofre check valve failures as well other previous industry experience with check valve failures. Subsequent activities include the formation of a Nuclear Industry Check Valve Group that funded an EPRI managed test program on check valves at the Utah State University Water Resources Laboratory in Logan, Utah in early 1990.

Although there are many failure possible mechanisms for check valves, the most common problems associated with check valve failures are due to system flow oscillations or system piping vibrations. These vibrations and oscillations induce check valve component wear and thus component failure. The most common types of physical damage in check valves (disk separated from the hinge pin, disk stud broken, disk nut loose, disk partially open, disk caught on inside of the seat ring, antirotation lug lodged under hinge arm, cracked disk, seat ring or bushings, worn hinge pin and bushings, missing bushing, elongated hinge pin holes, bent hinge pin disk and hinge arm) give some kind of evidence of their existence. Many of them emit sounds that can be detected by monitoring acoustical emissions from the valve body. Inappropriate movement of the disk can be detected by magnetic or ultrasonic measurements or through movement (displacement, velocity or acceleration) sensors attached to the disk.

Neural networks have the ability to recognize patterns and extract complex statistical features from the data they process. A program involving the use of neural network techniques for the analysis of acoustical data from check valves has been initiated at the University of Tennessee under support of the Electric Power Research Institute (EPRI.) It involves training neural networks to recognize predefined conditions and using the system for data clustering based on the inherent statistical features of the data. However, the success of this project is directly related to securing data from many check valves of different sizes and types that are both operating properly and malfunctioning in order to associate patterns with the known condition of the check valves.

The monitoring and analysis of data from check valve measurements can be addressed by breaking the problem into three parts: feature extraction, matching, and patterning recognition. The ability of neural networks to handle these types of problems is well known. The process of feature extraction involves the analysis of the data coming from sensors during an interval of time. This requires that the neural network be able to incorporate time dependency and recognize the trends, amplitudes and frequencies that the data reflect. Matching involves the comparison of the signatures collected from the machine with signatures for normal operation. A neural network can recognize significant deviations from the original signature to detect faults and recognize deviations of frequency components associated with possible faults. Finally, the output of the matching system can be fed to a network for pattern recognition. The networks could be trained, using data available from severity charts, to recognize instances of severe deviation that may require attention by maintenance personnel.

The collection of data from monitoring check valves by utilities and from the tests conducted by EPRI under sponsorship of the Nuclear Industry Check Valve Group at Utah State University in 1990 is underway. In the EPRI tests, acoustical, ultrasonic, and magnetic measurements were taken under both normal and flawed conditions (defective valve seat, hinge pin machined undersize, disk hinge pin hole drilled out, etc.) Most of the data available from nuclear power plant check valve tests utilize acoustical measurements taken from piezo-electric sensors. Some types of information (e.g., leakage through the seat or the disk hitting the backstop) can be taken during normal steady state operation, while other types of information (e.g., hinge pin or hinge bearing wear) require that the disk move during the measurement.

Monitoring of Thermodynamic Performance. Of approximately 130 quantities used to calculate the heat rate (inversely related to efficiency) at TVA's Sequoyah Unit-1 Nuclear Power Plant, only 26 actually change with time. The others are related to the design of the plant. Records of these 26 variables for about 45 weekly measurements were used as inputs to a neural network to develop a model of the thermodynamic processes of the plant.[1] The training of the network involved the use of a Kohonen neural network technique to cluster the data into 22 clusters with an Euclidean distance of 1.0. Then the centroids of these clusters were used as inputs to a neural network. Functional links were used to speed up the training of the network using backpropagation and provide a system error of about 0.01%. When the original data (not the centroids of the clusters used in training) were introduced into this model for recall, the results were usually within 0.1% of the measured values. When the same thermodynamic data from Unit-2 (a very similar, but not identical unit) was put into the network for recall, the output heat rates usually agreed within 0.5% of the measured values. This indicates that the neural network models of the thermodynamics of these two nuclear power plants are very similar. These neural network models are superior to any mathematical models since they involve no assumptions (e.g., linearity) or approximations and are based on actual data from the plants.

The neural network model was then used for a sensitivity analysis in which the partial derivative of the output variable with respect to each individual input value was evaluated. The larger this partial derivative, the more influence the particular input variable has on the output (efficiency or heat rate.) The sensitivity of the heat rate with respect to different variables can give guidance to the utility as to which efforts to improve efficiency are likely to be most effective. In some cases it may not be possible to change the input variable, even though it may be very important to efficiency (e.g., it is virtually impossible to control the river or ocean temperature.) It is also useful to compare the importance of a particular input variable with the cost of controlling it. Sometimes it may be more cost-effective to control a less important variable because it can be done quicker and for less money.

An additional iteration of this procedure was introduced by revising the network to use the most sensitive quantity determined by the first sensitivity study as the output of a neural network while retaining the rest of the variables as inputs. This then identifies the variables that are most important to the variable that was initially most important to efficiency and heat rate.

Design of Nuclear Fuel Cycle Reload. This project combines an expert system and neural networks to improve the efficiency for obtaining optimal candidate reload core designs. The neural network modeling captures the essential physics of the neutronic calculations by training the networks to produce the same results as conventional calculations. Separate neural networks are used to emulate the LEOPARD code, the neutronic statics calculations, and fuel depletion calculations. An expert system then performs fuel shuffling that produces an improved core loading. Several iterations of this process will give a near optimal candidate fuel loading. Although NRC approved calculational

methods must still be used for licensing this approach, when developed, promises to be much faster and less expensive than present methods.

Results from this study, in conjunction with theoretical considerations, indicate that neural networks can be trained to capture the essential physics of neutronics calculations. Although it appears rather evident that arbitrary accuracy for approximating any continuous function should be obtainable, this claim has been recently established.[9] Thus, if one accepts the fundamental theory, the question of feasibility for duplicating neutronics with neural networks is simply a matter of having suitable neural network software and training data for achieving this task. It may also be necessary to tailor the network structure to in-core fuel management physics to obtain a numerically feasible formulation of the problem. Recently-developed software permits patterns of connections among the nodes between layers. This feature will permit the neural network to represent the neutron physics in a natural way. It will also limit the number of connections to a numerically tractable problem.

Results from recent work at the University of Tennessee[1] to predict relative power distributions as a function of average burnup have been very encouraging. The network for this evaluation uses 56 inputs, one for each assembly in one-quarter of the core, and 3 inputs that specify initial burnup, final burnup and the change in burnup. The output layer consists of 56 nodes, one for each assembly, and the hidden layer uses seven nodes. All of the 56 predicted results are within 5% (and many within 1%) of the calculated values, and the training time was about 5 minutes for a convergence tolerance of 0.01. Although this study uses a fully-connected architecture, it is expected that patterned connections will be needed when testing networks with all of the fundamental neutronics data specified as input since several hundred inputs will be required.

Review of "Licensee Event Report" Data Base. When there is an incident of any sort at a commercial nuclear power plant in the United States, the utility must send a "licensee event report" (LER) to the Nuclear Regulatory Commission (NRC.) Oak Ridge National Laboratory (ORNL) has processed thousands of these reports for the NRC in the past several years by encoding the sequence of events from each incident into a computerized data base called the Sequential Coding Search System (SCSS.) The SCSS is a large database that stores information about all the incidents that occurred since 1980 in all nuclear plants in the USA. The information stored in the SCSS database has the form of causal relationships organized into a chronological order. A causal relationship is defined by a cause and its effect where both are represented by symbolic data. Because the causal relationships are embedded in the temporal information, the SCSS is a temporal database.

A large part of the knowledge stored in the database is not explicit. It is rather implicit and lies in the form of patterns and relationships. Once extracted, this implicit knowledge can be used to detect erroneous data stored in the database, and possibly reconstruct missing data. In this research, a neural network technique is applied to extract implicit knowledge from the SASS. The goal of this work is to elicit implicit knowledge stored in the SASS database to identify erroneous data, such as causes that are declared in association with inappropriate effects, and to infer missing information such as existing casual relationships not explicitly reported in the past or possible casual relationships that were unknown to the database users.

A two-phase approach is being proposed to address subsequently the spatial aspect embedded in the cause/effect relations, and the temporal aspect of the problem embedded in the chronological order of the cause/effect relations. In the first phase, a self-organizing semantic neural network is used to categorize casual relationships in order to extract typical relationships. A metric distance is used to identify erroneous relational information. In the second phase, a competition based multilayer neural

network is used to recognize sequences of occurrences, and possibly classify the sequences into categories in order to detect unusual ones. This approach should allow engineers to improve the reliability of the data stored in the SCSS, to better analyze human errors, and possibly to infer unknown causes of incidents.

Self-organizing neural network techniques are now being applied at the University of Tennessee[1] to determine if hitherto undiscovered correlations can be identified. At the present time, a prototype network has been developed and several hundred events are being studied. This project constitutes a "mining of the database for 'nuggets' of knowledge." The goal of this work is to elicit implicit knowledge stored in the SCSS database and to identify erroneous data and infer missing information (such as existent casual relationships not explicitly reported in the past experience or possible casual relationships that are unknown to the database users.)

Analysis of Vibrations. Although the flow of fluids (water and steam) can induce vibration and shock, the primary source of vibration in most power plants is rotating machinery. Vibration per se is not necessarily bad if its amplitudes and the associated forces are within acceptable limits. Indeed, vibration in machinery can be the source of much information about the various systems involved. Analysis of vibration data can identify the operational problems of rotating machinery. Such analyses have proven very effective in identifying potential failures before they occur. Indeed, it is now possible to estimate the remaining life of certain systems, once a fault has been detected. Hence, there is considerable motivation to design systems to automatically perform this analysis on a real-time basis in a reproducible manner.

A program for the analysis of vibration data has been initiated at the University of Tennessee under the sponsorship of Electricite de France that involves the application of neural network technology to the interpretation and the automation of the processes that typically require expertise to interpret the measurements. This approach involves both training the neural networks to recognize predefined conditions and using the networks for data clustering based on the inherent statistical features of the data. The preliminary work has emphasized the reduction of the dimensionality of the spectral density measurements taken on rotating machinery. Emphasis will be placed on applying the neural network techniques to enhance and automate the existing procedures used in vibrations measurements and analysis today.

CONCLUSION

In the light of the experience described above, it is clear that neural networks offer an interesting and productive means of addressing many of the problems that occur in nuclear (and fossil) power plants. Although much of this work is still in the feasibility stage, the results are encouraging and indicate that the techniques can be used to enhance the performance and safety of nuclear power plants.

ACKNOWLEDGEMENT

Much of this research was supported by the U.S. Department of Energy under contract #DE-FG07-88ER12824, entitled "Enhancing the Operation of Nuclear Power Plants through the Use of Artificial Intelligence." This support, as well as the support of Electricite de France and the Electric Power Research Institute, is gratefully acknowledged.

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APPROACH TO IDENTIFICATION AND ADVANCED CONTROL OF PWR USING NEURAL NETWORKS

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ABSTRACT

The paper demonstrates that neural networks can be effectively used for identification and control of nonlinear systems. Indeed many works as seen in reference [1,2] have recently shown the ability of neural networks to approximate large classes of nonlinear functions. And more accurately, it has been demonstrated that for any continuous function f belonging to the $C[R^n \times R^p]$ over a compact subset R^n , one can find a neural network with a hidden layer that can approximate the function f .

This provides motivations in order to deal with the tricky problems of identification and control of plants, and especially nonlinear systems in which classical methods are not well efficiency. On the other hand the learning and classification capabilities of neural networks may supply some means to solve identification and adaptive control problems in time variant plants. We present a new kind of control learning architecture fitted to adaptive control on nonlinear dynamical systems.

Using neural networks, some results of simulation of nonlinear identification problems in PWR are presented. Processed examples concern the calculation of correlations in a PWR's assembly between power distribution, flow distribution, primary temperature, critical axial height and critical flux.

1. INTRODUCTION

Recently, Hornik, Stinchcombe and White [1] showed that multilayer feedforward networks may be seen as universal approximations. This kind of networks are capable of arbitrarily accurate approximation to any mapping, provided that a sufficient number of hidden units are available.

Very few results exist in nonlinear systems theory which can be directly applied in nonlinear identification problems. So, from demonstrated capabilities of neural networks to approximate large classes of nonlinear functions, our interest in this paper is in the study identification problems for nonlinear systems, such as PWR plants, using neural networks [4].

An overview of identification problems is given in Section 2. Section 3 describes Multilayer Neural Networks and the backpropagation algorithm. In Section 4, we describe different kinds of neural controllers [2, 7], and their associated learning architecture and we propose a new kind of learning architecture. Main results of our application to nonlinear identification problems in PWR are shown in Section 5. Concluding remarks are given in section 6.

2. IDENTIFICATION

In this section our aim is not the presentation of the identification theory. Our purpose is to present the place of the connectionnist approach in the identification problems. Most details and basic

concepts are clearly described in the Narendra and Parthasarathy's excellent paper [2].

The objective of identification theory is to construct a suitable model which when subjected to the same input U as the plant, produces an output Y^* which approximates the output Y of the plant, in sense of a suitably defined norm. The basic concepts of the connectionnist approach in the identification problems is to substitute a neuronal model for the identification model and the learning procedure of the network for the classical adaptation algorithms, as shown in Figure 1.

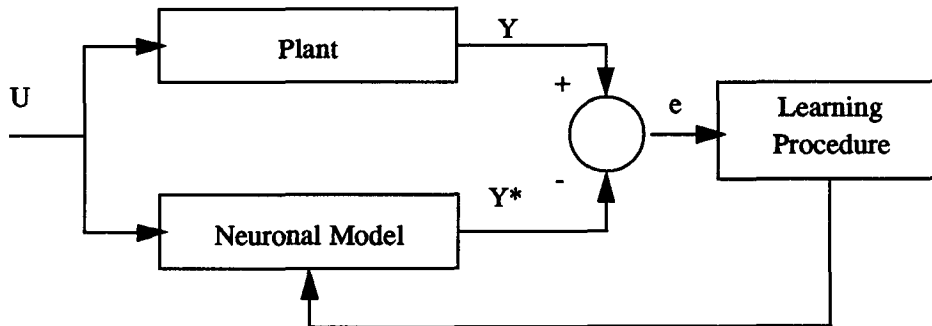


Figure 1 : Identification by connectionnist approach

The aim of identification schemes by neural networks is to try to deal with the tricky problems in the case of nonlinear systems for which classical methods cannot be used with very efficiency.

3. MULTILAYER NEURAL NETWORKS

An example of a multilayer network is given in Figure 2. Its architecture is formed by an input layer with 3 units, an output layer with 2 units, and one hidden layer with 5 units. Transmission of information between units of two neighboring layers is performed through oriented links. These links are level-headed by connection weights. In this kind of network, the information coming to the input units is recoded on the hidden layer into an internal representation and the outputs are generated by the internal representation rather than by the original pattern. Input pattern can always be encoded, if there are enough hidden units, in a form so that the appropriate output pattern can be generated from the corresponding input pattern.

The role of the hidden layer is fundamental. A network without hidden units (i.e., without ability to internal representation) will be unable to perform the necessary mappings from input patterns to output patterns, in particular on the problems nonlinearly separable as such the famous boolean function XOR.

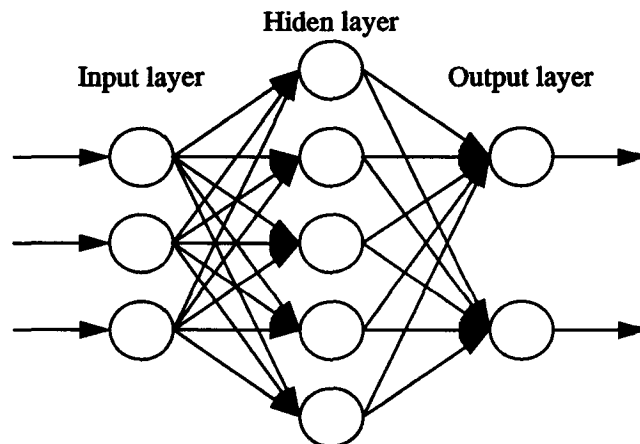


Figure 2. A Multilayer Neural Network

The processing cellular unit (PCU) is the basic building block of the network and is shown in Figure 3. The PCU sums the products of the inputs with their corresponding connection weight from the previous layer

of PCU's and then applies a sigmoid activation function f in which a threshold is introduced. The value of the threshold can be represented just like any other weights from a unit that is always equal to 1.

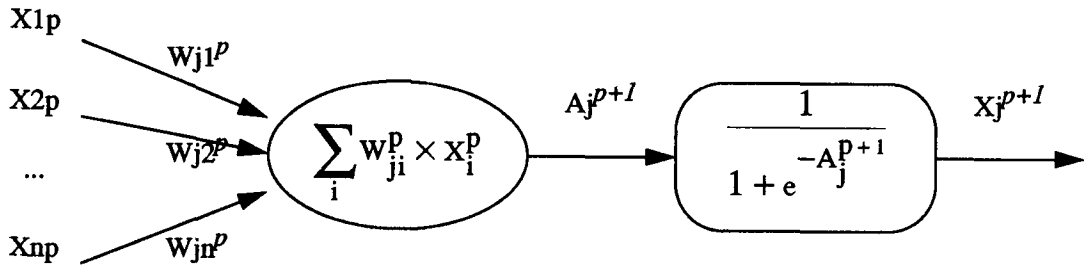


Figure 3. The Processing Cellular Unit

If X_j^i represents the state of the unit j of the layer i , N_i the number of units of the layer i , and W_{hk}^i the synaptic weight between the unit k of the layer i and the unit h of the neighboring layer $i+1$, we obtain the following relations defining the state of each unit in relation to the synaptic weights and the input units :

$$X_h^i = f(A_h^i) \quad A_h^{i+1} = \sum_{j=1}^{N_i} W_{hj}^i \times X_j^i$$

From a set of examples, the learning of the network consists in the modification of the synaptic weights in order to minimize an objective function in relation to the set of examples that will be presented to the network. If the subscript o represent the output layer, the objective function is the norm quadratic of the difference between the output vector X^o of the network and the desired vector Y for the l -th example. With N_o , the number of the units of the output layer, i.e., the same value of the dimension of the desired output vector Y , we can obtain for each the l -th example, the l -th part of the objective function :

$$C_l = \sum_{j=1}^{N_o} (X_j^o - Y_j)^2$$

The Widrow-Hoff's law is used to modify synaptic weights, i.e., the variation of synaptic weights is defined and applied for each example. The variations are defined from gradient method. For instance when the l -th example is applied to the network, we obtain the following relation defining variations of synaptic weights:

$$\Delta W_{hk}^i = -\eta \times \frac{\partial C_l}{\partial W_{hk}^i}$$

The gradient descent requires that infinitesimal steps be taken. The constant of proportionality η is the learning rate. Practical applications requires a learning rate that is as large as possible without leading oscillations. A way proposed by Rumelhart [3] to increase the learning rate consists to include a momentum term which filters out high-frequency variations of the error in the weight space :

$$\delta W_{hk}^i(n+1) = -\eta \times \Delta W_{hk}^i + \beta \times \delta W_{hk}^i(n)$$

Where n indexes the presentation number and β is the moment constant which determines the effect of past weight changes on the current direction of variation in weight space, analogous to conjugate gradient methods.

So, the aim of the backpropagation algorithm is to define the partial derivative of C_l according to the synaptic weights :

$$\frac{\partial C_l}{\partial w_{hk}^i} = \frac{\partial C_l}{\partial A_h^{i+1}} \times \frac{\partial A_h^{i+1}}{\partial w_{hk}^i} = \frac{\partial C_l}{\partial A_h^{i+1}} \times x_k^i$$

With the following notation :

$$D_h^{i+1} = \frac{\partial C_l}{\partial A_h^{i+1}}$$

We finally obtain :

$$\Delta w_{hk}^i = D_h^{i+1} \times x_k^i$$

The terms D_h^i are defined by the following way :

$$D_h^i = \sum_{j=1}^{N_{i+1}} \frac{\partial C}{\partial A_j^{i+1}} \times \frac{\partial A_j^{i+1}}{\partial A_h^i} = \sum_{j=1}^{N_{i+1}} D_j^{i+1} \times \frac{\partial A_j^{i+1}}{\partial A_h^i}$$

Because of the dependency of the terms D_h^i of the layer i , function of terms D_j^{i+1} of the previous layer $i+1$, this algorithm is a backpropagation algorithm from the output layer to the input layer.

$$\frac{\partial A_j^{i+1}}{\partial A_h^i} = \frac{\partial A_j^{i+1}}{\partial f(A_h^i)} \times \frac{\partial f(A_h^i)}{\partial A_h^i} = \frac{\partial A_j^{i+1}}{\partial f(A_h^i)} \times f'(A_h^i)$$

From the following relation :

$$\frac{\partial A_h^{i+1}}{\partial f(A_h^i)} = w_{jh}^i$$

We finally obtain :

$$D_h^i = \sum_{j=1}^{N_{i+1}} D_j^{i+1} \times w_{jh}^i \times f'(A_h^i)$$

This procedure that implements gradient descent in sum-squared error involves two phases. During the first phase the input is presented and propagated forward through the network to compute the output value for each unit. The outputs are then compared with the targets, resulting in an error signal for each output unit. The second phase involves a backward pass through the network in order to define appropriate weight changes.

4. CONTROL

Since the Widrow's works in 1962 using a neural network called Adeline to balance a pole on a cart [5], many new concepts have extended the potential of neural networks for control applications [6, 7, 8]. In this section, we briefly mention three kinds of learning architecture to solve control problems and we investigate a new type of neural controller combining advantages of the previous neural controllers.

4.1. Indirect Learning Architecture [7]

The basic principles of the indirect learning architecture is given by Figure 4. The desired response d is propagated through the net producing the plant input u . The neural controller is a simple copy of the network that approaches the inverse operator of the plant.

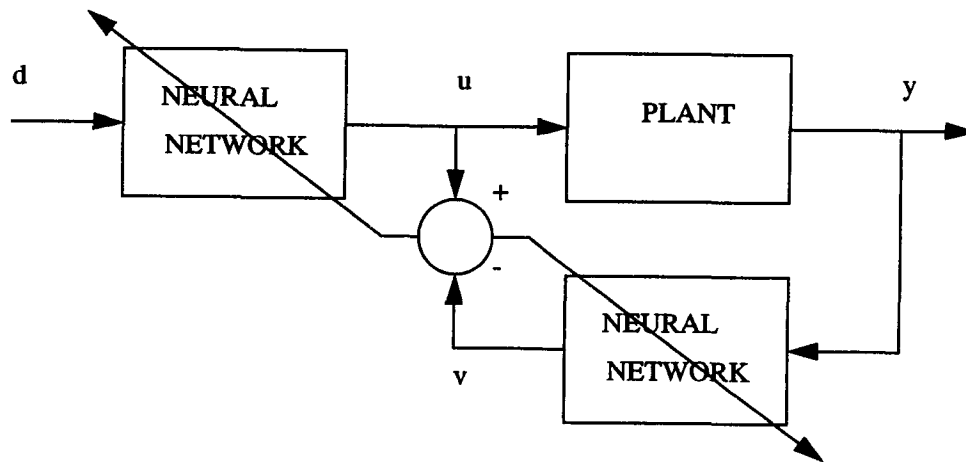


Figure 4 : Indirect Learning Architecture

The difference between the outputs of the network and its copy is the indirect error, $e_i = u - v$, used in correcting the network. The idea is that by driving e_i to zero, the total error, $e_t = d - y$, also goes to zero. However this method requires restrictive conditions on the operator modeling the plant and in particular the existence of an inverse operator in both region of interest. In general case we can have an indirect error equal to zero and a nonzero total error.

4.2. Specialized Learning Architecture [7]

As seen in Figure 5, in specialized learning architectures, the network learns to find plant inputs that drive the system outputs to the desired responses by using the error between desired and actual response of the plant. In relation to the previous architecture, the advantage is that there is not inverse model to be approximated. But the weakness of this architecture is that the training of the plant involves the knowledge of the plant which normally is only approximately known and perhaps variable in time.

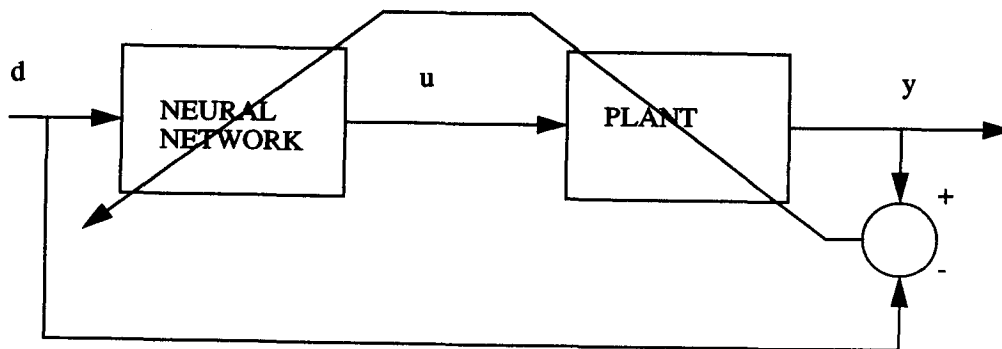


Figure 5 : Specialized Learning Architecture

The backpropagation algorithm requires the jacobian of the plant in relation to the input control u .

4.3. Narendra's architectures [2]

The Narendra's neural controllers can be used to deal with dynamical systems but only for those in which linear or nonlinear dependence of the output on the state vector and control vector is assumed to be separable.

$$y_{k+1} = f(y_k, y_{k-1}, \dots, y_{k-n+1}) + g(u_k, u_{k-1}, \dots, u_{k-p+1})$$

The output y_{k+1} of the plant at the time $k+1$ depends both on its past n values y_{k-i} ($i = 0, 1, \dots, n-1$) and the past m values of the input u_{k-j} ($j = 0, 1, \dots, p-1$). The aim of the learning is to identify a net that approximates the plant operator f , and another net that approximates the inverse of the control operator g .

The control input in this case is chosen as :

$$u_k = g^{*-1}(-f^*(y_k, y_{k-1}, \dots, y_{k-n+1}) + y_{k+1}^d)$$

In the previous equation, y_{k+1}^d is the desired response at the time $k+1$, f^* is the neural network of the plant operator f and g^{*-1} is the neural network of the inverse control operator g . We find again same assumptions as the indirect learning architecture concerning the existence of the inverse control operator. However Narendra has shown in several examples, that this neural architecture have real abilities of identification and adaptive control on nonlinear dynamical systems of neural networks.

4.4 Adaptive Learning Architecture

With the relative advantages and disadvantages of specialized learning architectures and Narendra's neural controllers schemes, a combination of these techniques can produce new learning architectures. We propose first performing the identification of the plant by training the Neural Network Model (NNM) of the plant and we use the specialized learning scheme to identify the Neural Network Controller (NNC), as seen in Figure 6. In relation to Narendra's approach we will attempt to solve problems for which the operator state f and the operator control g can be not separable.

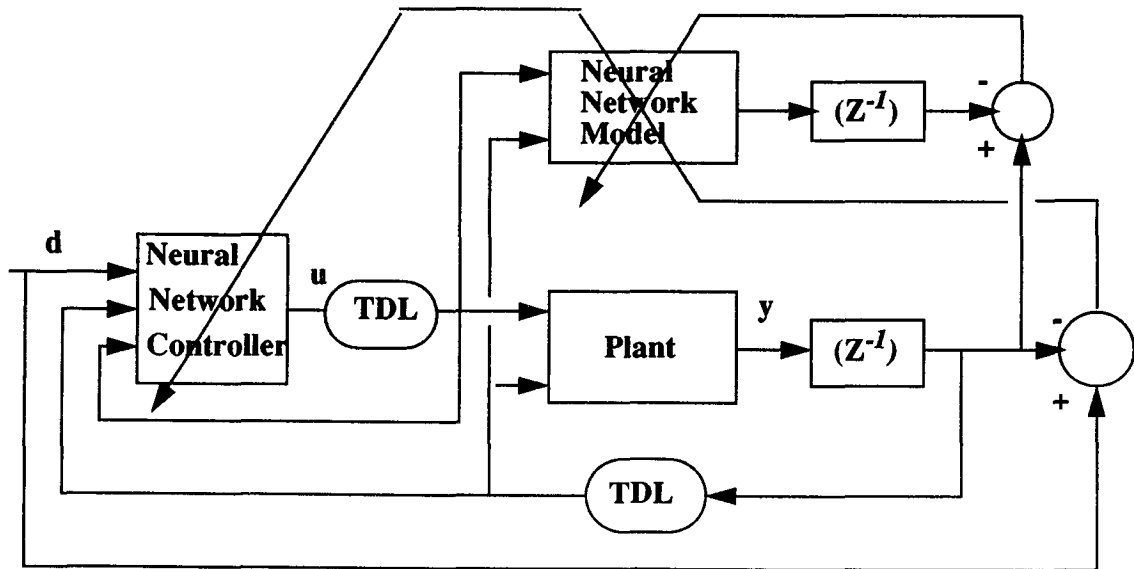


Figure 6: Adaptive Learning Architecture

In Figure 6, TDL denotes a tapped delay line whose output vector has for its elements the delayed values of the input signals :

$$TDL(w_k) = (1, z^{-1}, z^{-2}, \dots, z^{-p})(w_k)$$

During the training of neural networks, in relation to the specialized learning architecture in this case the jacobian dy/du is approximated by the backpropagation algorithm through NNM that is assumed having constant synaptic weights during the learning phase of the NNC. For on-line procedures, identification and control must proceed simultaneously. This fact involves the use of a classical controller in order to train the neural network model and the neural network controller.

5. MAIN RESULTS IN IDENTIFICATION

In identification problems, the tested application concerns a thermal-hydraulic problem. We have dealt with the local conditions concept relative to the boiling crisis in a PWR core, i.e. relations between local values of mass flow, pressure, temperature, critical axial height, canal geometry and axial heat flux shape along the canal.

The calculations has been performed by FLICA 4, a CEA computer code devoted to the thermal analysis of nuclear reactor core, from results provided by experimental conditions in tube bundle. The axial heat flux along the canal is not uniform, it has a sine shape. The concerned geometrical parameters are in the one hand constant hydraulic and thermal diameters and in the other hand a variable position of the grid upstream the boiling crisis point.

For this simulation, we have used a 3-layer feedforward network with real units. The input layer has 6 units : mass flow, pressure, vapor quality, critical axial height, integral flux, position of the grid upstream the boiling crisis point. The hidden layer includes 8 units and the only unit of the output layer fits the value of the critical heat flux. This network was trained from 57 prototypes, i.e. each cycle of learning procedure includes 57 various examples. All the values given by FLICA 4 has been normalized to range 0 to 1.

Simulations results, as shown in Figure 4, reveal that the identification schemes suggested, for this kind of problems, are very efficient and practically feasible. In Figure 7, the x-coordinate corresponds to numbers of examples and the y-coordinate to the normalized of the critical flux. The dotted line corresponds to the target while the unbroken line corresponds to the out of the network.

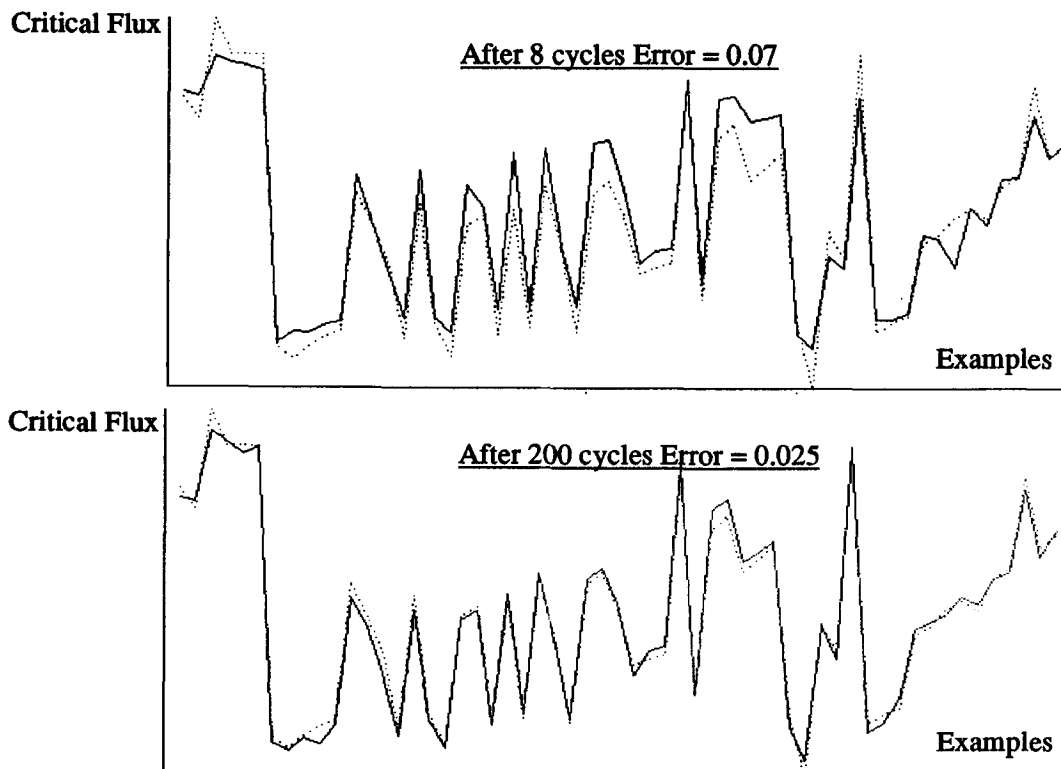


Figure 4 : Identification Procedure

5. CONCLUSION

The simulation studies on nonlinear system reveal that identification using neural network can be very effective. Neural networks can be seen as universal simulators thanks to their capabilities of approximation and generalization. In identification, connectionist approach provides suitable methods to built models of "black box" type, i.e., models that reproduce the behavior of the system from a set of input-output state vectors. These neural models have a Multi Layer Architecture.

Backpropagation methods determine an adaptive algorithm which adjust the parameters, i.e. synaptic weights of the neural network as referred as neural simulator. After the learning step the neural network internal representation is fitted to the system behavior. After this first learning step, the neural simulator has integrated knowledge on the plant, and it can be used in control loop to perform an adaptive control of the plant.. These properties might allow their use in problems of adaptive control, prediction and early diagnosis faults. In relation to neural networks which have been proposed by many authors, we have presented a new learning architecture fitted to adaptive control on nonlinear dynamical systems.

Future work will attempt to develop interpretation methods from the synaptic weights, methods seen like an aid to classical data analysis methods. The study of the synaptic map may be a means of interpretation of the correlations between parameters and data of the studied problem. Indeed, the objective of the learning phase is to extract the implicit knowledge included in the set of examples and to distribute it in the set of synaptic weights. From an analysis of correlations between the units of the network via the values of the synaptic weights, an approach more qualitative may be performed.

ACKNOWLEDGMENT

We are very grateful to C. Capillon, student at "l'Ecole Nationale Supérieure des Télécommunications de Paris" for his efficient contribution to this work..

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AN EVALUATION OF NEURAL NETWORKS FOR IDENTIFICATION
OF SYSTEM PARAMETERS IN REACTOR NOISE SIGNALS

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ABSTRACT

Several backpropagation neural networks for identifying fundamental mode eigenvalues were evaluated. The networks were trained and tested on analytical data and on results from other numerical methods. They were then used to predict first mode break frequencies for noise data from several sources. These predictions were, in turn, compared with analytical values and with results from alternative methods. Comparisons of results for some data sets suggest that the accuracy of predictions from neural networks are essentially equivalent to results from conventional methods while other evaluations indicate that either method may be superior. Experience gained from these numerical experiments provide insight for improving the performance of neural networks relative to other methods for identifying parameters associated with experimental data. Neural networks may also be used in support of conventional algorithms by providing starting points for nonlinear minimization algorithms.

INTRODUCTION

Mathematical models of systems and instrumentation are often used in conjunction with numerical algorithms to identify parameters that obtain optimal fits of models to data. These methods are essential since they provide pertinent information on reactor systems and instrumentation. Occasionally, however, they fail to produce physically realistic information when the data contain information that is not included in the model of interest.

Neural networks are recognized to be robust, and they can approximate any continuous function to any specified accuracy^(1,2). Thus, parameter identification with neural networks is feasible since functions of interest that map data to parameters are continuous. However, the practical realization of a network that identifies parameters of mathematical models requires that it

utilize an optimal number of appropriate linearly independent basis functions and that the training data contain parametric information over the domain of interest.

Data analyzed for results reported herein were preprocessed to obtain inputs for several single-output backpropagation neural networks with nine, nineteen or thirty-two inputs and three, five or ten hidden layer nodes. These networks were trained and tested on analytical functions and on noise data with outputs established by alternative methods. They were then used to predict first-mode eigenvalues which were, in turn, compared with those obtained from a nonlinear minimization algorithm.

A substantial number of data sets have been processed with several neural networks that utilized a variety of methods for representing the input. A relatively small portion of these results are presented in this paper, but the ones reported are typical of those associated with this study. All results from neural networks listed in this paper were trained on analytical functions. However, better agreement between results from neural networks and other methods can be obtained if the networks are trained with results from the methods used for the comparisons.

RESULTS

Evaluations of the feasibility for using neural networks for predicting first-mode break frequencies are presented for the following: 1) laboratory data from a Rosemount pressure transmitter, 2) a neutron power range signal, 3) reactor coolant temperature, and 4) subcritical noise data on commercial reactor fuel.

Laboratory Data

Power spectral density data for a typical Rosemount pressure transmitter were obtained from a pressure loop at the University of Tennessee. These data, along with analytical fits, are illustrated in Figures 1 and 2. Break frequencies listed in Figure 1 were obtained by optimizing a visual fit to the data. The first mode break frequency shown in Figure 2 is identified by a nonlinear minimization algorithm, and the higher modes are from the visual fit. Note that there is little difference in the quality of the fits. A neural network with nine inputs and five hidden layer nodes obtained a first mode break frequency of 4.4 Hz, compared to the 4.0 Hz for the visual fit and 4.8 Hz by the nonlinear minimization algorithm. This fairly pleasing agreement is credited to the relatively good quality of the data.

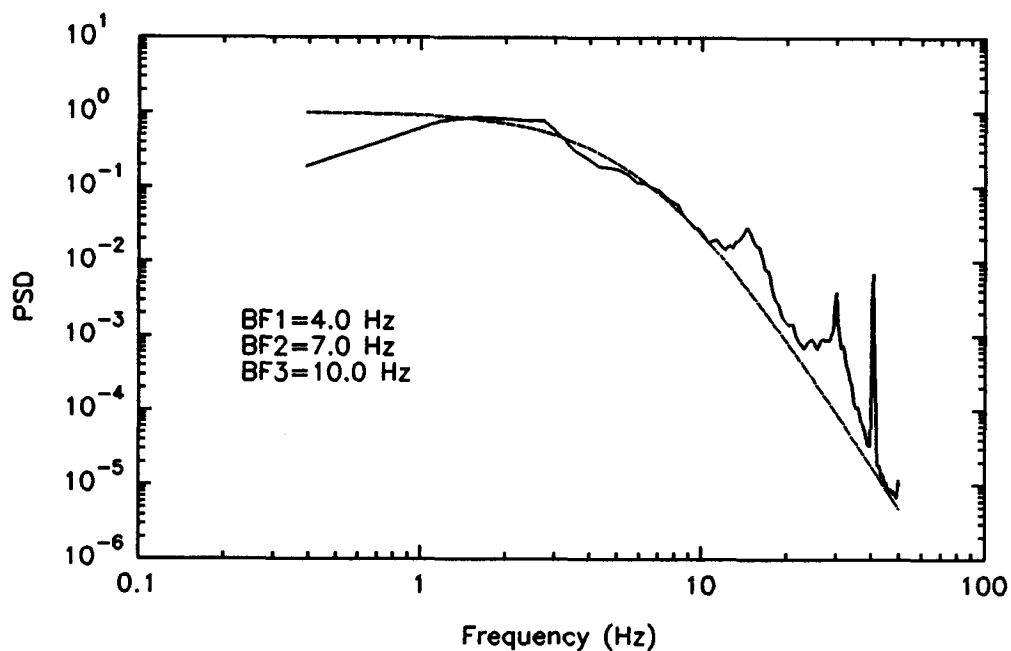


Figure 1. Power spectral density and visual fit for a Rosemount pressure transmitter.

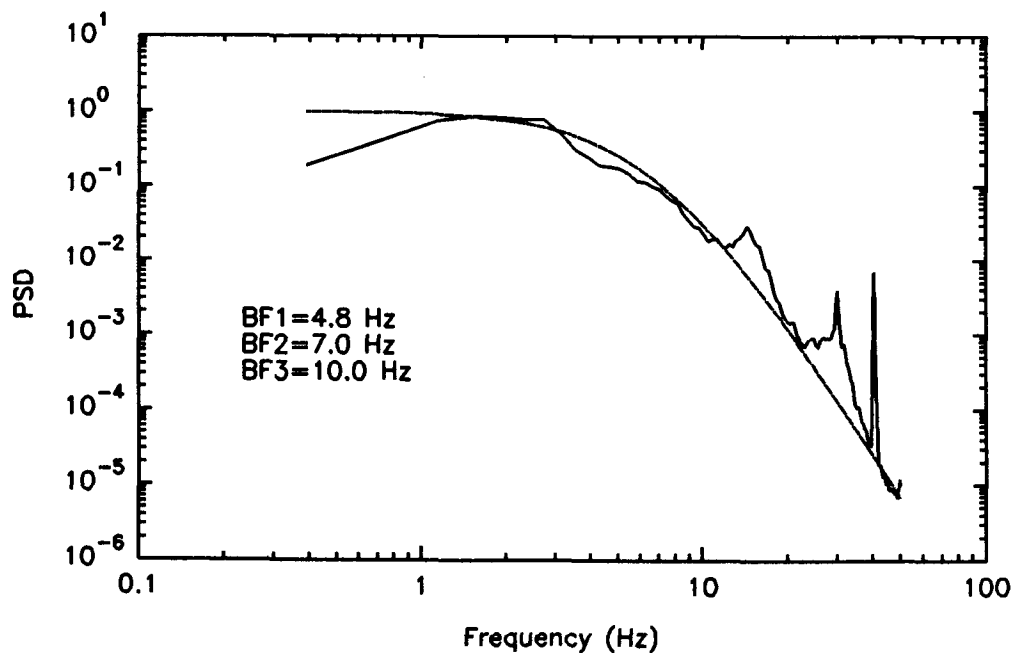


Figure 2. Power spectral density and nonlinear fit for a Rosemount pressure transmitter.

Sequoyah Plant Data

The data shown in Figures 3 through 6 are from the Sequoyah Nuclear Power plant and were obtained from Oak Ridge National Laboratory. Figures 3 and 4 illustrate the data from a power range instrument and Figures 5 and 6 show data from a resistance temperature detector on the steam generator inlet of loop 4. Fits based on visual optimization are shown in Figures 3 and 5, whereas results from a nonlinear minimization algorithm are shown in Figures 4 and 6. It is evident that these data do not directly correspond to the shape of a first or second order analytical function for power spectral density. However, they do provide an opportunity to evaluate the robustness of alternative parameter identification methods.

Three networks were evaluated with this data, and all were trained on the first mode break frequency with the inputs determined from analytical functions. One used nine inputs with five hidden layer nodes, another used nineteen inputs with five hidden layer nodes, and the third used nineteen inputs with three hidden layer nodes. These respective networks obtained 0.44, 0.05 and 0.1 Hz for the power range data, and they obtained 0.51, 0.001 and 0.005 Hz for the temperature data. The first and second mode results from the nonlinear minimization algorithm were (0.187,0.188), and (0.039,0.438). None of these results are accurate, but they illustrate difficulties encountered when trying to fit models to data that contain information that is inconsistent with the model used for the fit.

Subcritical Noise Data

A group of twenty-six data sets from measurements on subcritical assemblies were analyzed with several neural networks and with a nonlinear minimization algorithm. A comparison of these results for two neural networks is shown in Table 1. About one-half of these data sets are of relatively poor quality, and both the neural network and the nonlinear minimization fail to produce accurate results in several cases. Data set number seven is of very poor quality, and both methods failed. In addition, the nonlinear minimization algorithm erroneously identified low-frequency modes in data sets twenty-one through twenty-seven whereas the neural network identified them accurately.

Results from a network with nine inputs, five hidden layer nodes and one output performed very well on several data sets, but it did not generalize as well as networks with more inputs and fewer hidden layer nodes. Analyses of neural network results from data evaluated for this paper, and other data, indicate that one should keep the number of hidden layer nodes to a minimum for parameter identification. However, there should be no fewer nodes than the number of linearly independent functions known to exist in the data.

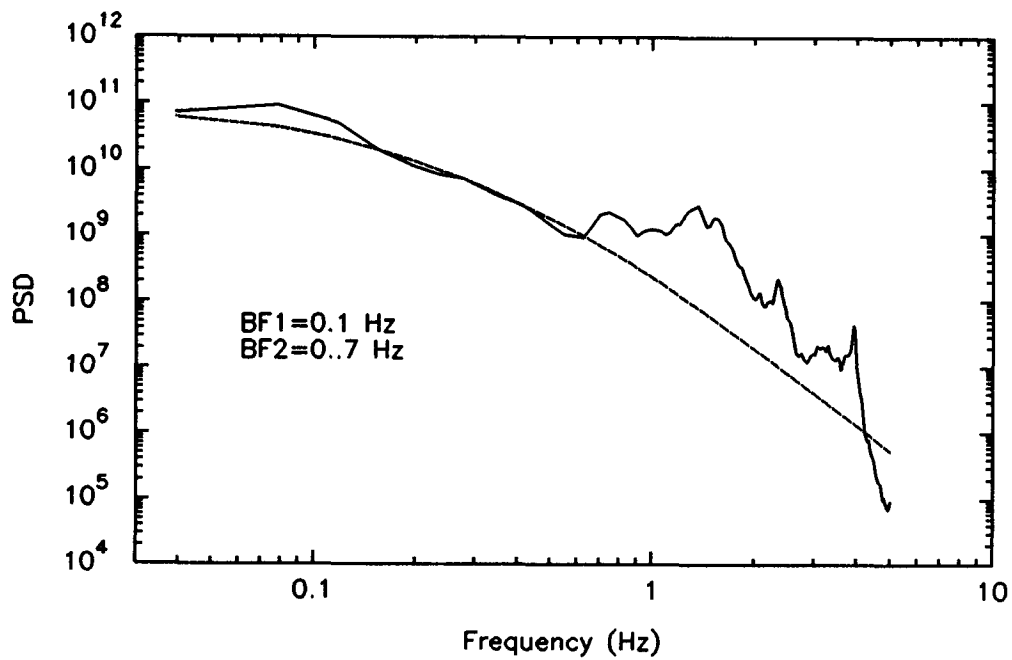


Figure 3. Power spectral density and visual fit for a Sequoyah power range signal.

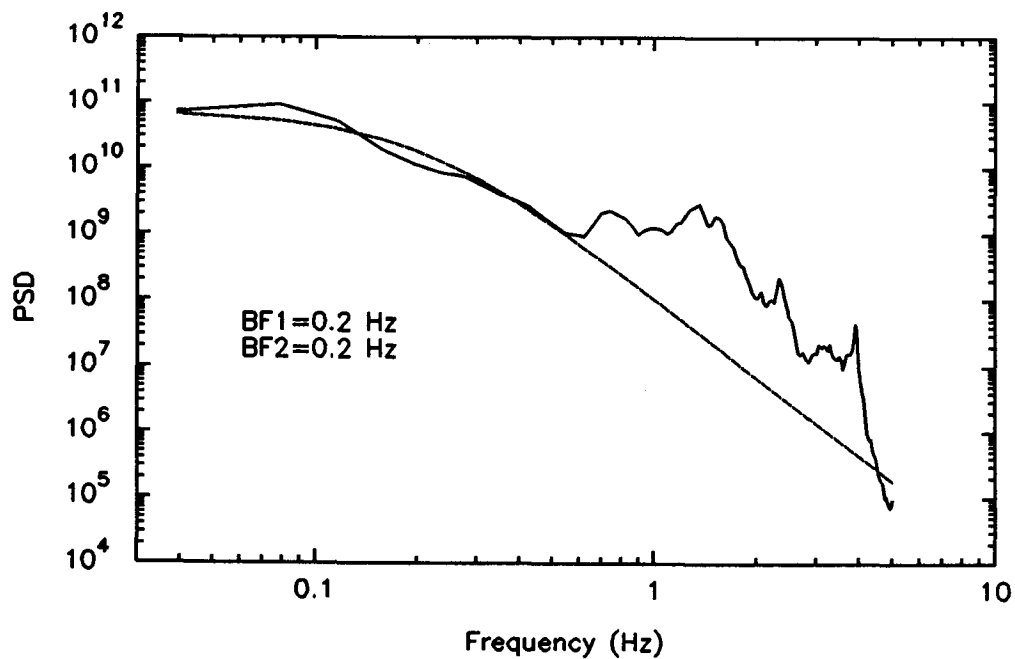


Figure 4. Power spectral density and nonlinear fit for a Sequoyah power range signal.

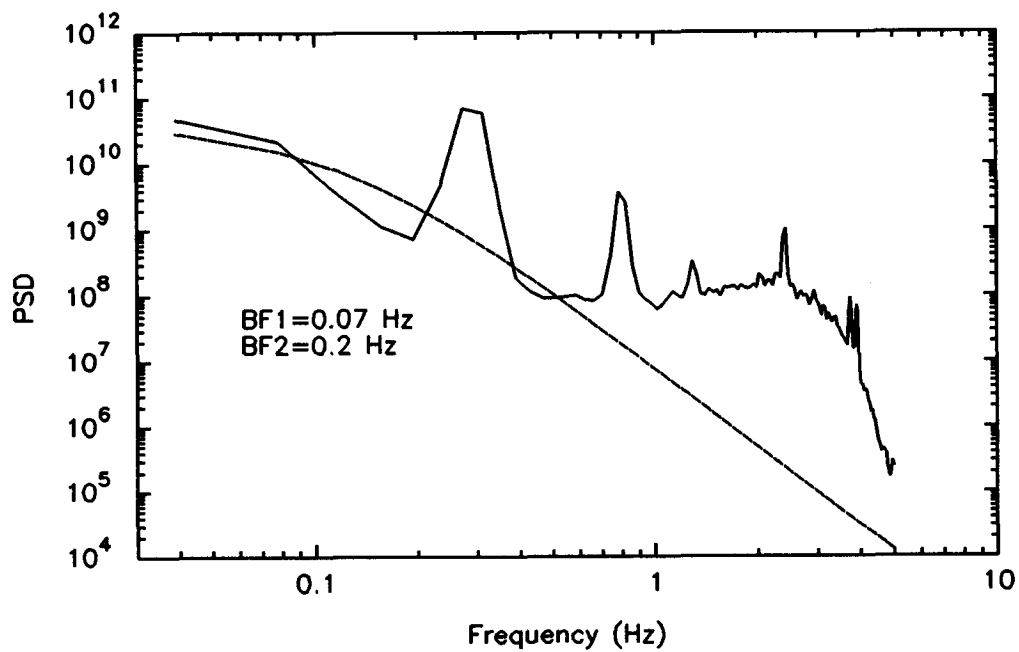


Figure 5. Power spectral density and visual fit for a Sequoyah hot leg temperature.

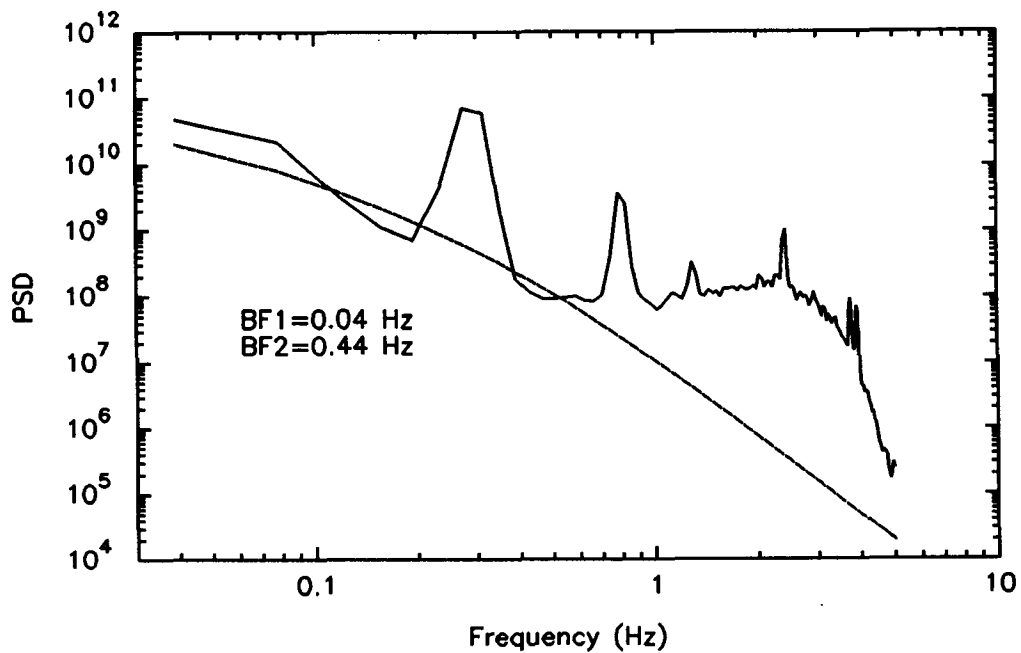


Figure 6. Power spectral density and nonlinear fit for a Sequoyah hot leg temperature.

Table 1. Break frequencies (BF) obtained from neural networks and from nonlinear minimization. Superscripts (a and b) denote networks with 19x5x1 and 19x3x1 input, hidden and output nodes. BF-1 and BF-2 designate first and second mode break frequencies.

File	Neural Network		Nonlinear Minimization	
	BF-1 ^a	BF-1 ^b	BF-1	BF-2
1	44.74	46.24	47.31	521.43
2	40.02	44.58	50.57	651.17
3	39.52	41.74	46.89	521.43
4	25.36	29.72	46.48	622.87
5	43.86	46.65	71.52	88.14
6	42.65	47.93	78.87	82.46
7	385.10	328.62	34.66	183.50
8	45.27	49.96	73.46	83.93
9	35.64	40.08	58.82	1061.69
10	49.30	54.55	62.04	1213.10
11	49.22	51.40	60.14	1109.93
12	55.61	60.45	72.81	1386.11
13	73.38	71.77	72.81	1386.11
14	59.25	59.72	71.21	1325.86
15	62.23	62.64	70.89	1325.86
16	68.95	68.54	71.52	1325.86
17	69.25	70.34	70.89	1325.86
18	64.04	64.76	70.58	1325.86
19	67.86	68.60	69.95	1268.22
20	69.78	68.82	70.26	1325.86
21	93.70	91.98	6.86	96.76
22	97.05	92.14	6.80	96.76
23	90.22	93.74	7.01	92.56
24	88.42	91.92	6.99	93.38
25	117.96	112.13	6.87	96.33
26	88.82	89.90	6.91	97.19

CONCLUSIONS

It is concluded that neural networks may be, in some cases, more robust for identifying parameters than conventional methods and that equivalent accuracies can be obtained from neural networks and from conventional methods. It may also be computationally efficient to use neural networks to provide initial parameter estimates for conventional parameter identification methods.

The number of hidden layer nodes should be minimized for parameter identification applications, and it is expected that networks with a variety of linearly independent transfer functions will be more useful for parameter identification than those with only sigmoidal functions.

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ESTIMATION OF FEEDBACK PARAMETERS IN PRESSURIZED WATER REACTORS USING NEURAL NETWORKS

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ABSTRACT

The moderator temperature coefficient of reactivity (α_c) is an important parameter related to the operational safety and plant availability of pressurized water reactors (PWRs). A combination of spectral-domain signatures and neural network paradigms is used to estimate α_c . Preliminary results of estimating this parameter demonstrate the feasibility of applying this technique for the prediction of α_c provided the domain of prediction is within or close to the training domain for neural networks.

INTRODUCTION

The hybrid technique of digital signal processing and neural networks (parallel distributed processing) is very useful in overcoming problems related to physical or empirical modeling. In the present study, this approach is extended to the estimation of the moderator temperature coefficient of reactivity (α_c) in PWRs. The theory of relating α_c to PWR neutron noise-coolant temperature signals was first presented by Shieh et al [1] and later extended to the estimation of α_c by other investigators [2,5,10]. Properly "trained" multi-layer neural networks can be used as substitutes for models and thus be applied for interpolating (and extrapolating) continuous parameters [3,4].

The work reported here is part of a collaboration between the University of Tennessee and the Central Research Institute for Physics, Budapest, Hungary (sponsored by the U.S. National Science Foundation and the Hungarian Academy of Sciences).

Several issues need to be considered in applying neural network methodology for the estimation of a continuous parameter. These are (a) the choice of a spectral signature which varies as a function of the parameter, (b) the choice of measurements for computing the spectral signature, (c) the domain used for training the neural networks, and (d) the application of established networks for parameter interpolation and extrapolation. In an ideal situation the plant personnel would like to use a neural network that has been developed using data from one or two fuel cycles of a PWR, for prediction during future fuel cycles. In general this approach will not be feasible, unless the extrapolation or prediction domain is very "close" to the trained domain. In this work we present the results of both interpolation and extrapolation and suggest guidelines for using this methodology for α_c estimation. The spectral signatures in this study are derived directly from a multi-channel model of a PWR core [5], using the design data for the 440 MW(e) Paks PWR. An adaptive backpropagation network is used for parameter estimation and is implemented in a VAX workstation.

Due to the nonlinear physics of core neutronics and heat transfer model it is not possible to obtain an explicit relationship between α_c and for example, the ratio between neutron power-coolant temperature cross power spectral density (CPSD) function and the auto-power spectral density (APSD) of coolant temperature noise. It is for this reason we want to study the effectiveness of multi-layer neural networks for the estimation of α_c . Moreover one or more neural networks may be updated on-line as the system properties change from cycle to cycle, so that a complete operational regime may be captured by such paradigms.

APPLICATION OF NEURAL NETWORKS TO POWER PLANT DATA

Neural networks are intrinsically parallel and non-algorithmic methods; these features of neural networks make real-time processing of data and information feasible. Some of the applications of neural networks include nuclear fuel management, multi-sensor information fusion, sensor validation, control problems, plant-wide monitoring, and pattern recognition for diagnostics of plant malfunctions [6].

Neural networks have been traditionally used for pattern classification and similar applications. Such networks perform reliably even when used with noisy and incomplete data [3,6]. Neural networks may also be used to adaptively control a system by optimizing control parameters to minimize the difference between model response and desired system state. Another useful feature of neural networks is the ability to respond in real-time to changing system states whose descriptions are provided by the process sensors. For complex systems involving many sensors and possible fault types, estimating real-time response is a challenging problem in the nuclear industry [4]. Once the networks are trained they can be implemented for fast recall. Unlike most other computer programs, neural networks can give high performance even when there is a failure in the network structure, such as a missing processing element which is the fundamental component of a neural network.

THE BACKPROPAGATION ALGORITHM

The backpropagation network (BPN) algorithm is used to estimate the connection weights of a multi-layer, fully connected, heteroassociative network [7]. The algorithm minimizes the global error between the desired output and the calculated output of a network using the steepest descent method. An interactive algorithm has been developed in a VAX workstation which has the feature of adapting the learning parameters during the training period, thus leading to the terminology adaptive BPN [4].

Studies have shown that progressively adjusting the shape of the activation function during learning and gradually increasing the learning coefficient, accelerate the convergence and improve the accuracy. Another important parameter in backpropagation network, the so called the momentum term, is also employed in this study. The momentum term not only accelerates the convergence but prevents the network from getting trapped at local minima. In multi-layer networks hidden layers have significant importance in convergence and accuracy. Hidden layers are used to represent the nonlinear properties of the data. Experiments have shown that using one hidden layer is sufficient to solve many nonlinear problems. The size of this layer is very important for reaching sufficiently small error and for fast convergence. For solving signal validation problems, an experimental formula has been developed using Shannon's information [8], and is used for estimating the hidden layer nodes [4,9].

The BPN algorithm computes the connection weights between pairs of processing elements such that the difference between the actual output and the network output is minimized in a least-squares sense. It is also important to note that this architecture accepts analog signals, thus binary representation is not necessary. Three-layer networks have been employed throughout this study to estimate the feedback parameters. Figure 1 shows a typical topology for a three-layer perceptron.

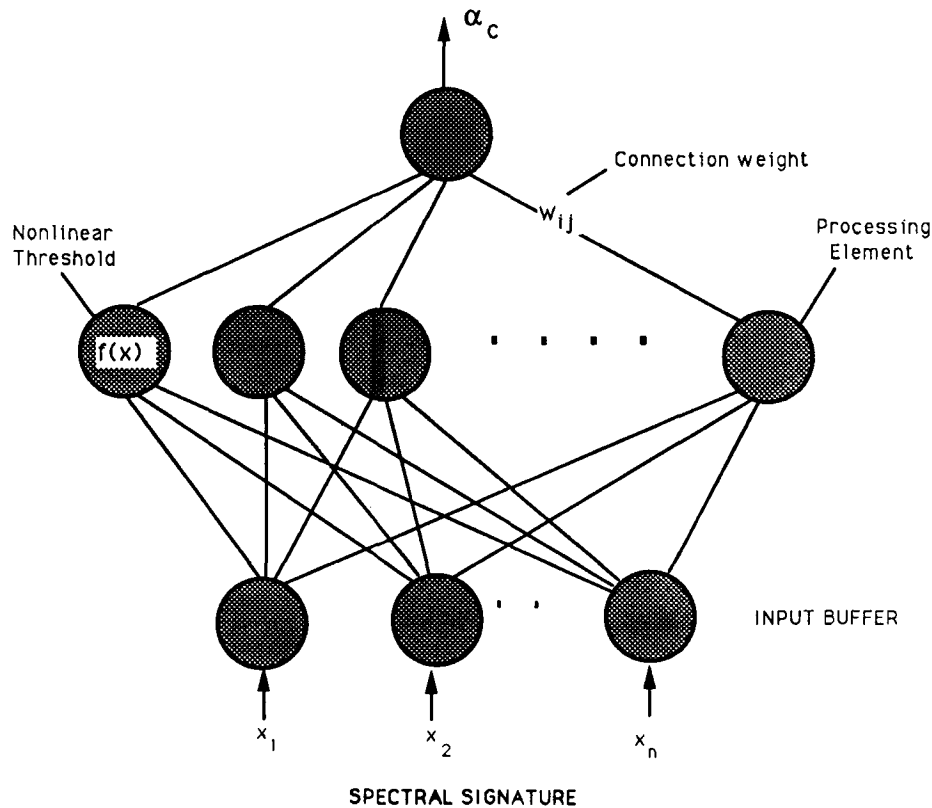


Figure 1: Topology of a three-layer perceptron.

The first layer receives the information, and feeds it to the inner layers. The second layer, which is commonly known as the hidden layer receives information from the input layer, modifies it with the connection weights and propagates this forward. Hidden layer size and the number of hidden layers are one of the important issues in the development of network architecture. The hidden layers are used to characterize the nonlinear properties of the system to be analyzed. The last layer is the output layer where the desired parameter values are observed. In this study, the number of input nodes is equal to the number of frequency points selected for the spectral signature. The number of hidden nodes in the hidden layer is determined based on the complexity of the problem. An empirical formula, based on Shannon's information [8], has been developed and used for signal validation and plant-wide monitoring type of problems [4].

One of the requirements of the BPN algorithm is the normalization of the training data to the range (0,1). The algorithm developed in the VAX workstation has the feature of automatic data normalization between 0.1 and 0.9 which enables the network to reach the extremities. This type of normalization gives the advantage of interpolating and especially extrapolating the data. In the present study, normalization is necessary because the magnitudes of the feedback parameters are very small. In order to minimize the numerical error, the normalization is performed before the training.

REACTOR DIAGNOSTICS APPLICATIONS

For sensor validation, plant-wide monitoring, and parameter estimation, neural networks offer several advantages when compared to traditional empirical models. It is not necessary to define a functional form relating a set of variables. The functional form is implicitly nonlinear in multi-layer networks. It is also not necessary to know the system specifications in detail. To a certain extent neural networks are robust in the presence of noise.

The parameter estimation feature of neural networks is used to determine the moderator temperature coefficient of reactivity. Neutron power-coolant temperature CPSD/coolant temperature APSD is the spectral signature used to estimate the parameter α_c . This decision is also based on earlier theoretical and experimental studies [1,2,5,10].

Some of the important issues related to the estimation of α_c values are stated below. These are concerned with the basic assumptions made during this study.

- (a) The exact formula which would give us a scalar value for α_c as a function of the measured CPSD/APSD complex transfer function is not known, or does not exist. Physical models and actual measurements at NPPs suggest that the information about α_c is hidden somewhere in the CPSD/APSD complex transfer function [5,10].
- (b) Also, we have only a conjecture of the frequency range in which the change in α_c affects the CPSD/APSD transfer function. This conjecture is based on simple physical models.
- (c) Since the change in α_c may not cause proportional change in the magnitude of CPSD/APSD function, it is not enough to look for only a scalar constant which would relate the two changes. Instead, we have to determine a network of constants capable of modeling nonlinear relations between the whole ratio function and the scalar value of α_c . The neural network technique provides a general mapping necessary in this problem.
- (d) It should be noted that even if the best neural network model is found for the given training set, the method of estimating α_c by using the CPSD/APSD function is still not an exact one. This means that the success of α_c estimation is limited by not only the errors in the neural network training but also by the CPSD/APSD - based method itself.

A noise-based estimation of α_c over a complete fuel cycle was performed at the second unit of the Paks nuclear plant in Hungary [10]. The technique involved the analysis of core-exit thermocouple and ex-core neutron detector signals. The moderator temperature coefficient of reactivity was estimated using the relationship

$$\alpha_c = \frac{1}{G_o(f)} \frac{CPSD_{NT}}{APSD_{TT}} \quad (1)$$

where $G_o(f)$ is the neutron density to reactivity transfer function. The authors estimated α_c using the magnitude of CPSD/APSD function in the frequency range 0.3 - 0.9 Hz for seven separate measurements during the fuel cycle. The trend and the numerical values of estimated α_c were close to the design values of the VVER-440 type reactors ($-10^{-5}/\text{deg C}$ at the beginning of the fuel cycle, and $-6 \times 10^{-4}/\text{deg C}$ at the end of the fuel cycle). It is important to note, that in general, the relationship between α_c and the neutron-temperature transfer function is not linear (Eq. (1)). In the present paper the application of neural networks is considered to overcome the difficulty of mapping spectral signatures to the feedback parameter.

ESTIMATION OF MODERATOR TEMPERATURE COEFFICIENT OF REACTIVITY

Several sets of CPSD/APSD functions have been generated by an analytical multichannel core model of a PWR [5]. The α_c values were changed in the model in 25 steps from $-5 \times 10^{-5}/\text{deg C}$ (beginning of the fuel cycle) to $-5 \times 10^{-4}/\text{deg C}$ (end of the fuel cycle), and the 25 corresponding CPSD/APSD ratio functions were calculated for 100 frequency points in the range 0 - 2 Hz. During the calculations all the other model parameters, such as fuel temperature coefficient of reactivity, fuel and coolant time constants, spectrum of inlet coolant temperature noise, spectrum of in-core coolant velocity noise, spectrum of independent, external reactivity noise were kept constant over the 25 cases. Typical CPSD/APSD ratios are shown in Figures 2 and 3. In order to generate the transfer functions in the numerical tests the following approximate values of plant

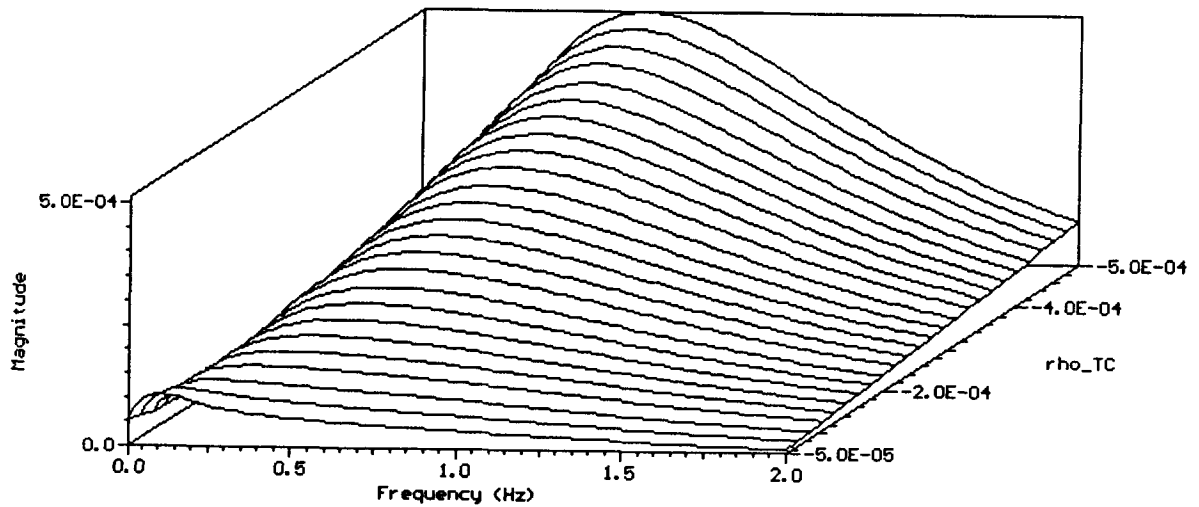


Figure 2. Ratio between reactor power - core-exit coolant temperature CPSD and coolant temperature APSD for the case of ex-core neutron detector. The plots correspond to 25 different values of α_c .

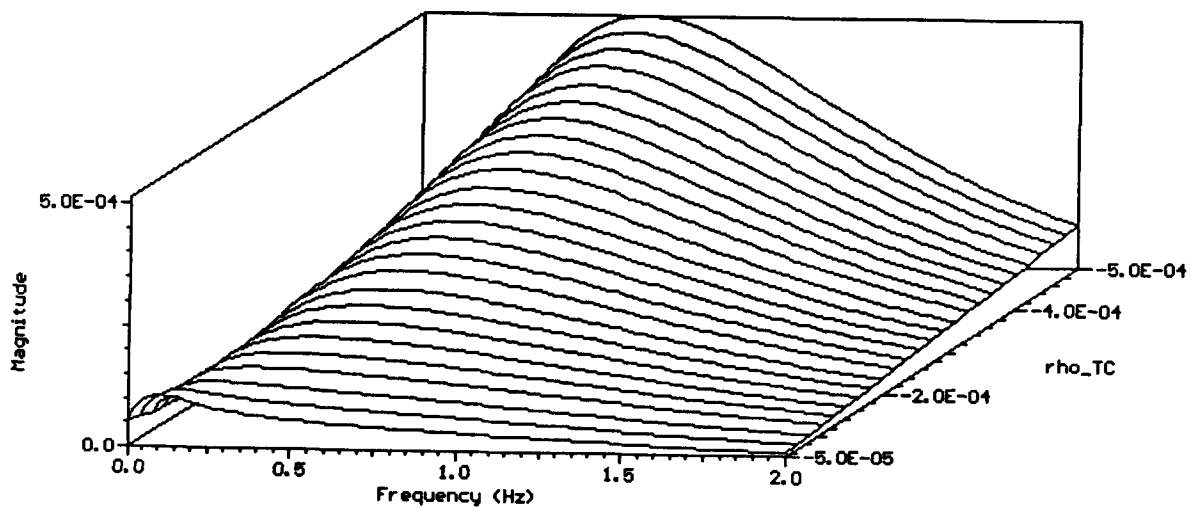


Figure 3: Ratio between reactor power - core-exit coolant temperature CPSD and coolant temperature APSD for the case of in-core neutron detector and temperature measurement in different channels. The plots correspond to 25 different values of α_c .

parameters were used in the developed model [5]. These represent the parameters of the 440 MWe Paks PWR in Hungary.

Active core height: $H = 2.5$ m.
 Number of fuel assemblies: $K = 349$.
 Vertical coolant velocity inside the reactor core: $V = 3.5$ m/s.
 Thermal power: $P = 1350$ MW.
 Horizontal fuel cross-section in a fuel assembly: $A = 7.9 \times 10^{-3}$ m².
 Fuel time constant: $\tau_f = 5$ sec.
 Coolant time constant: $\tau_c = 5$ sec.
 Fuel temperature coefficient of reactivity: $\alpha_f = -5 \times 10^{-6}$ / °C.

The ratio neutron-coolant temperature CPSD/coolant temperature APSD is shown for two cases in Figures 2 and 3. As stated earlier these frequency-domain signatures are generated from a physical model in the 0-2 Hz region. Three different detector configurations are analyzed.

1. Ex-core neutron detector and core-exit thermocouple (TC).
2. In-core neutron detector and core-exit TC located in the same channel.
3. In-core neutron detector and core-exit TC located in different channels.

The network configuration has 50 input nodes (corresponding to 50 spectral values), 15 hidden-layer nodes and one output node. Two experiments have been performed. For the first case CPSD/APSD patterns for 12 different values of α_c (taken alternatively from pattern number 2 through 24) are used for training the network. The remaining 13 patterns are used to interpolate α_c . The results of network performance for the training set and test set are shown in Tables 1-4. Tables 1 and 2 use CPSD/APSD with ex-core neutron detector signal, and Tables 3 and 4 use CPSD/APSD with in-core neutron detector. The in-core neutron detector and the core-exit temperature are taken from different channels. The results of interpolation are excellent and indicate that a good network mapping has been developed. The results also indicate that the use of in-core ND and core-exit temperature noise measurements from different channels give better estimates of α_c compared to the case where the two measurements are in the same channel. Furthermore, in-core ND-temperature combination is superior to ex-core ND-temperature noise.

A second neural network was trained to study the pure extrapolation capability of parameter estimation. The first 12 patterns are used for training and the remaining 13 patterns are used for testing the extrapolation beyond the trained domain. The result is shown in Figure 4. It is clear that for patterns close to the trained domain the prediction of α_c is close to the actual values. As the test patterns deviate away from the training set, the estimation error increases and the results are not acceptable. This indicates that the network need to be updated as new information becomes available so that its overall prediction capability is not compromised.

CONCLUSIONS

The parameter estimation capability of neural networks is exploited in determining the moderator temperature coefficient of reactivity, α_c , in a PWR. Previous studies have shown that spectral signatures derived from in-core signals in a PWR are closely related to the variations in the moderator temperature coefficient of reactivity, α_c [1,5,10]. The spectral signature CPSD/APSD ratio is found to be the best signature for parameter estimation. The neural networks may be used for on-line estimation of reactor performance parameters, provided the domain of training covers the operating regimes of interest. It is also concluded that the estimation error increases when the test domain deviates far from the training domain of the network models.

In applications to operating PWRs one or more neural networks may have to be generated for on-line parameter prediction. Data from several fuel cycles may be used to establish an effective neural network model. This study will be made in the future using neutron and core-exit coolant temperature noise data from a commercial PWR.

Table 1. Estimation of α_c using the Ex-Core ND - Core-Exit TC CPSD training data in the frequency range of 0-2 Hz. APSD

<i>Network prediction</i>	<i>Actual value</i>	<i>Absolute error</i>
- 8.40E-05	- 6.87E-05	1.52E-05
- 1.07E-04	- 1.06E-04	1.72E-06
- 1.37E-04	- 1.43E-04	5.88E-06
- 1.72E-04	- 1.81E-04	8.30E-06
- 2.12E-04	- 2.18E-04	6.67E-06
- 2.53E-04	- 2.56E-04	2.62E-06
- 2.95E-04	- 2.94E-04	2.09E-06
- 3.37E-04	- 3.31E-04	5.81E-06
- 3.75E-04	- 3.68E-04	7.21E-06
- 4.11E-04	- 4.06E-04	5.40E-06
- 4.43E-04	- 4.43E-04	5.72E-06
- 4.71E-04	- 4.81E-04	9.30E-06

Table 2. Estimation of α_c using the Ex-Core ND - Core-Exit TC CPSD recall data in the frequency range of 0-2 Hz. APSD

<i>Network prediction</i>	<i>Actual value</i>	<i>Absolute error</i>
- 7.44E-05	- 4.99E-05	2.44E-05
- 9.52E-05	- 8.75E-05	7.71E-06
- 1.22E-04	- 1.25E-04	2.78E-06
- 1.54E-04	- 1.62E-04	6.68E-06
- 1.92E-04	- 2.00E-04	7.89E-06
- 2.32E-04	- 2.37E-04	4.84E-06
- 2.74E-04	- 2.75E-04	2.32E-06
- 3.16E-04	- 3.12E-04	4.17E-06
- 3.56E-04	- 3.50E-04	6.86E-06
- 3.94E-04	- 3.87E-04	6.74E-06
- 4.28E-04	- 4.25E-04	3.14E-06
- 4.58E-04	- 4.62E-04	4.21E-06
- 4.84E-04	- 5.00E-04	1.53E-05

Table 3. Estimation of α_c using the In-Core ND - Core-Exit TC CPSD (different channels) training data in the frequency range of 0-2 Hz. APSD

<i>Network prediction</i>	<i>Actual value</i>	<i>Absolute error</i>
- 8.12E-05	- 6.87E-05	1.24E-05
- 1.06E-04	- 1.06E-04	7.16E-07
- 1.38E-04	- 1.43E-04	5.34E-06
- 1.74E-04	- 1.81E-04	6.79E-06
- 2.13E-04	- 2.18E-04	5.00E-06
- 2.54E-04	- 2.56E-04	1.48E-06
- 2.96E-04	- 2.93E-04	2.29E-06
- 3.36E-04	- 3.31E-04	5.10E-06
- 3.74E-04	- 3.68E-04	5.99E-06
- 4.10E-04	- 4.06E-04	4.31E-06
- 4.43E-04	- 4.43E-04	3.10E-07
- 4.73E-04	- 4.81E-04	8.03E-06

Table 4. Estimation of α_c using the In-Core ND - Core-Exit TC CPSD (different channels) recall data in the frequency range of 0-2 Hz. APSD

<i>Network prediction</i>	<i>Actual value</i>	<i>Absolute error</i>
- 7.07E-05	- 4.99E-05	2.07E-05
- 9.33E-05	- 8.75E-05	5.81E-06
- 1.22E-04	- 1.25E-04	2.96E-06
- 1.55E-04	- 1.62E-04	6.56E-06
- 1.93E-04	- 2.00E-04	6.20E-06
- 2.34E-04	- 2.37E-04	3.36E-06
- 2.75E-04	- 2.75E-04	4.54E-07
- 3.16E-04	- 3.12E-04	3.88E-06
- 3.55E-04	- 3.50E-04	5.83E-06
- 3.93E-04	- 3.87E-04	5.50E-06
- 4.27E-04	- 4.25E-04	2.38E-06
- 4.58E-04	- 4.62E-04	3.78E-06
- 4.86E-04	- 5.00E-04	1.30E-05

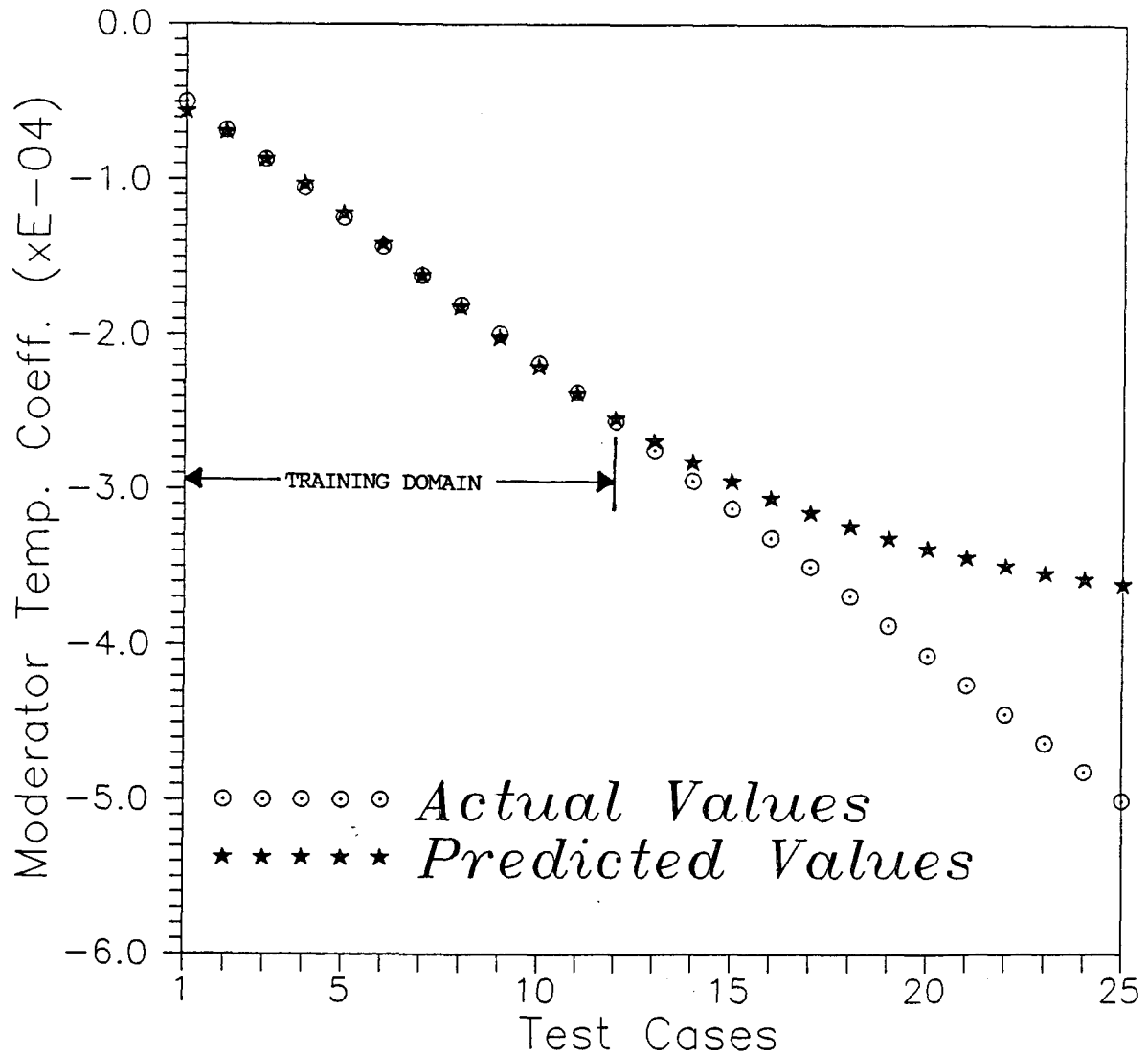


Figure 4. Estimation of moderator temperature - coefficient of reactivity using in-core ND - core-exit TC CPSD/core-exit TC APSD. Extrapolation (prediction) of α_c deteriorates as the test cases deviate from the training domain.

ACKNOWLEDGMENT

The assistance provided by Evren Eryurek in developing the various neural networks is greatly appreciated.

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VIBRATION MONITORING WITH ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Vibration monitoring of components in nuclear power plants has been used for a number of years. This technique involves the analysis of vibration data coming from vital components of the plant to detect features which reflect the operational state of machinery. The analysis leads to the identification of potential failures and their causes, and makes it possible to perform efficient preventive maintenance. Early detection is important because it can decrease the probability of catastrophic failures, reduce forced outage, maximize utilization of available assets, increase the life of the plant, and reduce maintenance costs.

This paper documents our work on the design of a vibration monitoring methodology based on neural network technology. This technology provides an attractive complement to traditional vibration analysis because of the potential of neural networks to operate in real-time mode and to handle data which may be distorted or noisy. Our efforts have been concentrated on the analysis and classification of vibration signatures collected from operating machinery. Two neural networks algorithms were used in our project: the Recirculation algorithm for data compression and the Backpropagation algorithm to perform the actual classification of the patterns. Although this project is in the early stages of development it indicates that neural networks may provide a viable methodology for monitoring and diagnostics of vibrating components. Our results to date are very encouraging.

BACKGROUND

A power plant (nuclear or fossil) is fundamentally a thermodynamic system that includes a heat source (fission or combustion), flowing fluids, valves, control systems, and rotating machinery (pumps, fans, motors, gear boxes, turbines and a generator.) Although the flow of fluids (water and steam) can induce vibrations and shock, the primary source of vibrations is rotating machinery. Vibration per se is not necessarily bad if its amplitude and the associated forces are within acceptable limits. Indeed, vibration in machinery can be the source of much information about the various systems involved.

There is a great deal of literature available that describes the type of vibration signals to be expected for faults in typical systems and the analysis techniques that can be used for early detection of faults. Angelo[1] presents a discussion on actual phenomena and their individual characteristics. For example, the low frequency domain contains information about unbalance, misalignment, instability in journal bearing and mechanical looseness; analysis of the medium frequency range can render information about faults in meshing gear teeth; while the high frequency domain will contain information about incipient faults in rolling-element bearings. In addition, trend analysis may be performed by comparing the vibration spectrum for each machine with a reference spectrum and evaluating the vibration magnitude changes at different frequencies. Standards, such as the ISO 2372 and 3945, may be used to determine the severity of the changes.

This form of analysis for diagnostics is often performed by maintenance personnel monitoring and recording transducer signals and analyzing the signals to identify the operating condition of the machine. This method has proven to be effective in identifying potential failures before they occur. With the advent of portable fast Fourier transform (FFT) analyzers and "laptop" computers, it is possible to collect and analyze vibration data on site and detect incipient failures several weeks or months before repair is necessary. Indeed, it is often possible to estimate the remaining life of certain systems once a fault has been detected. Hence, there is considerable motivation to design systems to automatically perform this analysis on a real-time basis in a reproducible manner.

METHODOLOGY

Vibration data are usually collected with accelerometers attached to plant machinery. The sensors are placed at locations where the signals are expected to be reliable, and the data is recorded for an interval of time. From these data, spectra are generated using FFT techniques and the coefficients stored in a database to be analyzed later by expert personnel in an effort to identify faults.

RMS velocity, acceleration, displacements, peak value, and crest factor readings can be collected from vibration sensors. However, to exploit all the information embedded in these signals, a robust and advanced analysis technique is required. Our goal is to design such a diagnostic system using neural network technology. A system such as this would automate the interpretation of vibration data coming from plant-wide machinery thus permitting efficient on-line monitoring of these components.

Neural Networks

A network of artificial neurons (usually called a neural network) is a data processing system consisting of a number of simple, highly interconnected processing elements in an architecture inspired by the structure of the cerebral cortex portion of the brain. As a result, neural networks are often capable of doing things which humans or animals do well but which conventional computers often do poorly. Neural networks exhibit capabilities difficult to achieve using other technologies. Neural networks have the ability to recognize patterns, even when the information comprising these patterns is noisy, sparse, or incomplete.

Perhaps the most important characteristic of neural networks is the ability to model processes and systems from actual data. The neural network is supplied with data and then "trained" to mimic the input-output relationship of the process or system. Neural networks have the ability to respond in real-time to the changing system state descriptions provided by continuous sensor inputs. For complex systems involving many sensors and possible fault types, real-time response is a difficult challenge to human operators; neural network technology may provide a viable alternative to the solution of this problem.

Neural Networks for Vibration Analysis

For the analysis of spectral signatures, neural networks may be used both as classifying and clustering systems. To perform classification it is necessary to attach to each spectral signature a label which describes the operational state of the machine at the time of collecting the signature. The input to the network is a spectrum (a set of FFT coefficients) and the output is the class label. The network is trained to identify an arbitrary pattern as a member of a state among a set of possible states. Clustering involves the grouping of patterns according to their internal similarity and requires no labels. The aim is to separate the set of patterns into classes such that the patterns in each class have similar statistical and geometrical properties.

We are addressing the problem of identifying and classifying vibration signatures in two phases. Phase I includes compression of the spectral signatures using Recirculation networks. Phase II of the project comprises the classification of the compressed patterns using the Backpropagation algorithm. Compression is an important issue in the context of this analysis because we deal with a very large data set and reducing the dimensionality of the patterns decreases significantly the training time and computer resources needed.

The vibration levels recorded at each sensor for each machine differ depending on the fault. The vibration levels may differ also because of sensor positioning and overall neighboring vibration. These divergences among sensor readings for each machine make it difficult to produce a "typical" vibration signature for a particular fault and type of machine. We have decided to address this problem by designing a multiple-network system that performs classification on readings collected at each sensor/location separately. Each network is trained on data collected from a single sensor and a solution (class or malfunction) is generated by taking a majority vote among network responses. This approach has proven robust for problems in a number of other areas[2] and may prove very useful in cases of drastic sensor failures since the failure of one sensor is only reflected in one network of the system. Figure 1 illustrates the architecture of the multi-network system.

Recirculation Networks

The Recirculation Network algorithm was developed by Geoffrey Hinton and James McClelland.[3] The network is autoassociative in nature and in its simplest version has only two trainable layers, a visible layer and a hidden layer. The input and output layers act simply as buffers for input and output (Figure 2.)

The purpose of the training phase is to construct in the hidden layer a representation of the data presented at the visible layer (the input vector.) If the number of hidden units is less than the number of visible units and if the network is trained successfully, the hidden representation may be considered as a compressed implementation of the visible representation. For this project we built a network with a hidden layer containing half the nodes of the input layer in order to reduce the dimensionality of the input vector set by a factor of two.

The aim of training is to reduce the error between the original input vector and the reconstructed vector. The reconstructed vector is built by running the compressed representation through the set of weights. This error is an accurate indicator of performance because it is calculated as the sum of the squared error at each node. The algorithm calls for a minimization of this error using a gradient descent strategy. A description of the algorithm and the derivation of the weight adjustment equations may be found in reference.[4]

Backpropagation Network

The Backpropagation network (BPN) is a multilayer fully connected, heteroassociative network. The BPN algorithm computes the weights between pairs of processing elements such that the difference between the actual output and the desired output is minimized in a least-squares sense. The generalized delta rule is used for calculating the error between the actual output and the desired output and for generating the weight adjustment coefficients. The basic algorithm is discussed by Rumelhart and McClelland.[5]

It has been established that three-layer networks are capable of representing arbitrarily complex decision surfaces.[6] Figure 3 shows the architecture of a typical three-layer network. The first layer receives the input, modifies it using the set of weights, and passes it to the hidden layer; the hidden layer in turn propagates the modified inputs to the output layer where the overall error is calculated. The hidden layer is used to represent the non-linear characteristics of the data and its size is determined by the complexity of the problem. Although the determination of the size of the hidden layer remains an art, several studies have been conducted which suggest empirical formulas for calculating the dimensions of the hidden layer.[7] Approaches have also been proposed for improving the performance of the algorithm.[7,8]

The BPN is a fully connected network in which every neuron is connected to all neurons in adjacent layers with no lateral connections. During training the information flows forward from the input layer to the output layer and the error is propagated backwards through the weights to calculate the weight adjustments. Training involves the modification of the weights until the error is reduced to an acceptable limit.

SPECTRAL SIGNATURES

To perform spectral monitoring of components in an operating engineering system, signatures are collected from plant machinery and analyzed to detect features which reflect the operational state of the machinery. We have secured vibration data from a steel sheet manufacturing mill consisting of measurements of "laminar flow" table rolls in the facility. There is a total of 246 rolling elements monitored. Data were collected at 9 different locations on each machine. From these data, spectra are generated using FFT techniques and the coefficients stored in a database. Each spectrum contains 100 points and only one data set per machine was collected to perform the diagnostics. The general problem areas are misalignment, improper lubrication, looseness, wear in motor brushes and damage to inboard and outboard bearings. Although the raw data correspond to rollers in a steel sheet manufacturing mill, the behavior of these components is comparable to vibrating equipment in power plants. These techniques should be applicable to a power plant setting without major redesign.

The range of the spectral data was (0.0, 1.0). The input vectors were not normalized or enhanced by any method, and neither were the compressed versions collected from the Recirculation network after training. Figure 4 depicts a typical spectrum with 100 points and its compressed 50-point representation. The Recirculation network had as its input the 100-point spectra and produced a compressed version of the signatures containing only 50 points. The 50-point compressed pattern was then fed to the Backpropagation network to perform the classification.

The 50-point signature produced by the Recirculation network has a different geometrical shape than the original pattern (Figure 4.) However, the patterns retain their statistical characteristics after training. We tested the effectiveness of the compression by clustering both the original patterns and the compressed patterns using standard clustering techniques. These results are included in the Results section of the report.

The data was separated into 9 sets, each set corresponding to readings collected at each location/sensor. The readings collected at different locations for a roller at a particular time t are correlated but not identical (Figure 5) because the vibration levels are different throughout the machine, and because the effect of neighboring vibration levels is not uniform. In addition, faults which are particular to a bearing located near a sensor are not necessarily recorded by other sensors. Other factors such as sensor mounting position and roller location on the table may affect the level of vibration detected by each sensor.[9] Each one of the 9 sets constitutes a training set for a different network.

RESULTS

For this project, we used the version of the Recirculation network included in the NeuralWorks™ development package which runs on a Zenith 386 machine. Each vector representing a spectrum was an input to the network. The resulting compressed vectors had 50 inputs, thus achieving a 2/1 compression ratio.

The recirculation network was trained for 10,000 iterations until it reached the pre-established error threshold (0.001.) On the average, the training speed was 100 epochs/minute, so the training time was roughly 100 minutes. The effectiveness of the compression was tested by clustering the original and compressed patterns using the K-means algorithm.[10] The results were consistent except in 5 cases out of 31. The agreement translates to a degree of consistency of almost

84% which was beyond our expectations. Given the sensitivity of the K-means algorithm (or its instability), we feel that these results could be improved by using other clustering or self-organizing algorithms. Additional training may help improve the performance of K-means by further tuning the compressed representation.

For the classification of the patterns we used the version of Backpropagation included in PLEXI™[11] which runs on a SUN SPARC IPC workstation. The entire system is comprised of a series of 9 networks trained independently on data from each sensor. A solution is generated by taking a majority vote among network responses (Figure 1.) The potential advantage of this approach is that it could aid in cases of drastic sensor failures or in cases where a machine may be experiencing more than one fault that could not be detected at all locations.

Each network has as input the 50-point compressed spectrum and five output units corresponding to each possible fault. The responses of the individual networks do not always agree for a particular testing case. This is due possibly to the fact that all faults are not always detected at all locations, and also because the neighboring vibrations contaminate the signatures differently at every location. For these reasons, we feel confident that the classification by majority counts is a reasonable and sensible technique.

To train the networks we are exploring a variety of techniques for preprocessing the spectral values. Since the aim of preprocessing is to enhance the individual features of the signatures to reflect clearly the state of the machine, we are using not only the raw coefficients but also their first, second and third order differences as training data. The set of differences is a better training set in some cases but our results are not conclusive at this stage. Our results appear to indicate that in cases where patterns are very similar but belong to different classes, using the raw data for training requires longer training sessions. In some cases convergence was not achieved at all. Using the differences forces the network to focus on the severity of the changes and not on the absolute values of the vibration levels. The changes in magnitude are a more unique feature relating to each fault.

CONCLUSIONS

We are working on the implementation of a methodology for interpreting vibration measurements based on neural networks. The anticipated advantage of developing such a system is the possibility of automating the monitoring and diagnostic processes for vibrating components, and building diagnostic systems which complement traditional PSD analysis by dealing with the non-linear characteristics of the signals.

We have studied the performance of neural networks for monitoring applications in other areas.[12,13,14] Our experience leads us to believe that to implement reliable monitoring systems using neural networks, it is best to utilize multiple independent networks to address several phases of the problem, than to design a large network capable of performing all analysis. The major consideration is training time. Training time increases according to the complexity of the network and affects directly the accuracy of the results.

The feasibility of using Recirculation networks for compression of spectral data has been established. Under this study we have achieved compression ratios of 2/1 while maintaining the statistical properties of the original patterns. The original and compressed patterns were clustered using the K-means algorithm and the results obtained are consistent in 84% of the test cases. The Recirculation network used to compress the data had 100 input units and 50 hidden units. The

network was trained for 10,000 cycles taking approximately 100 minutes on a Zenith 386 microcomputer. The results of the compression surpass our original expectations and we believe that additional training may improve the representation.

Our results indicate that the multi-network architecture for classification is a robust and viable approach. Using differences of the spectral coefficients as the training set enhances the unique characteristics of the data for each class. Differences seem to force the network to concentrate on the changes in magnitude of the vibration levels instead of their absolute values. We are not able to assert at this stage how many differences are necessary in the preprocessing or to evaluate exactly how much each higher derivative is able to contribute to the enhancement of the data.

Although our project is in the preliminary state of development we feel that neural networks can provide a methodology for improving the analysis of spectra, and may provide a viable alternative to PSD analysis for monitoring and diagnostics of vibrating components. Our results to date are very encouraging.

ACKNOWLEDGMENTS

The authors wish to acknowledge the financial support of Electricity de France and the Department of Energy (contract # DOE-DE-FG07-88ER128124) for this research. Also the assistance of Technology for Energy Corporation (TEC) is gratefully acknowledged.

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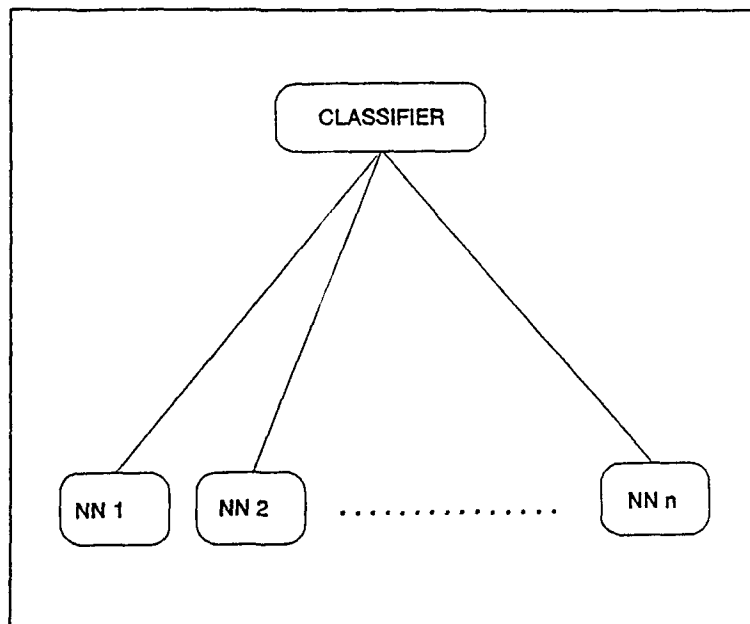


Figure 1. Multi-Network System for Classification.

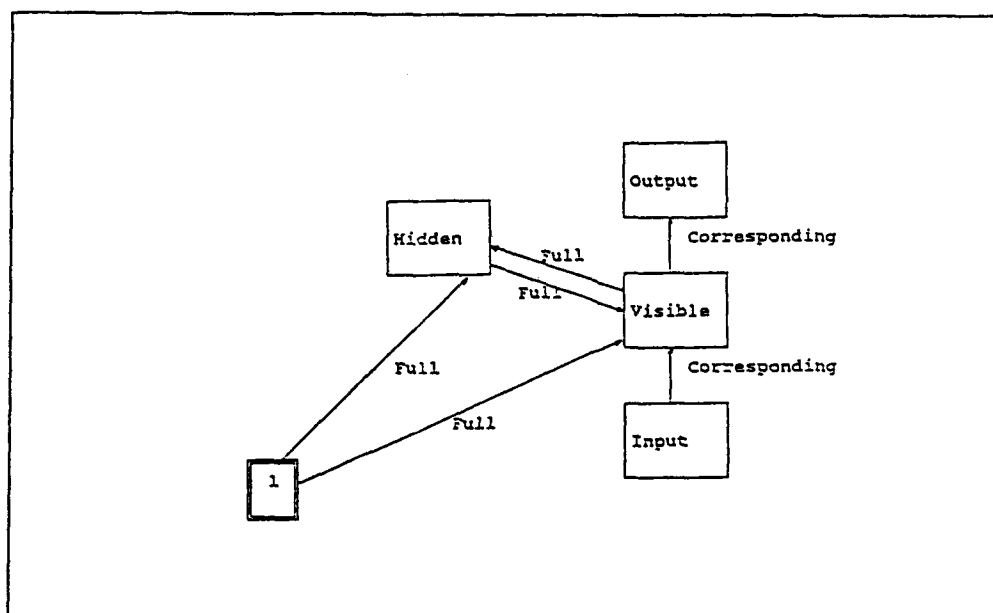


Figure 2. Recirculation Network Architecture.

Note: Connections marked "Full" indicate fully connected layers. Connections marked "Corresponding" have one-to-one connections.

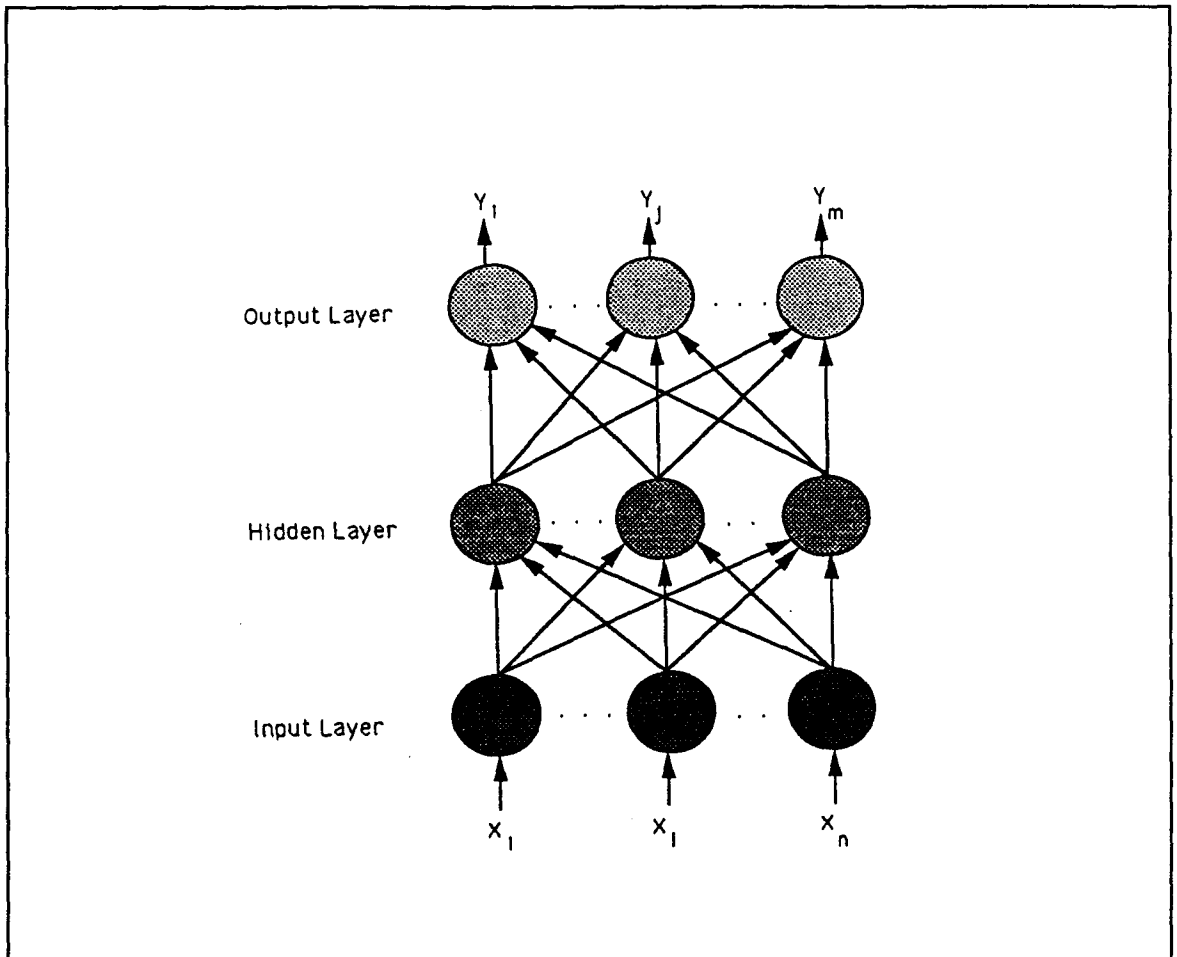


Figure 3. Three-layer Neural Network Architecture.

a) Original Spectrum

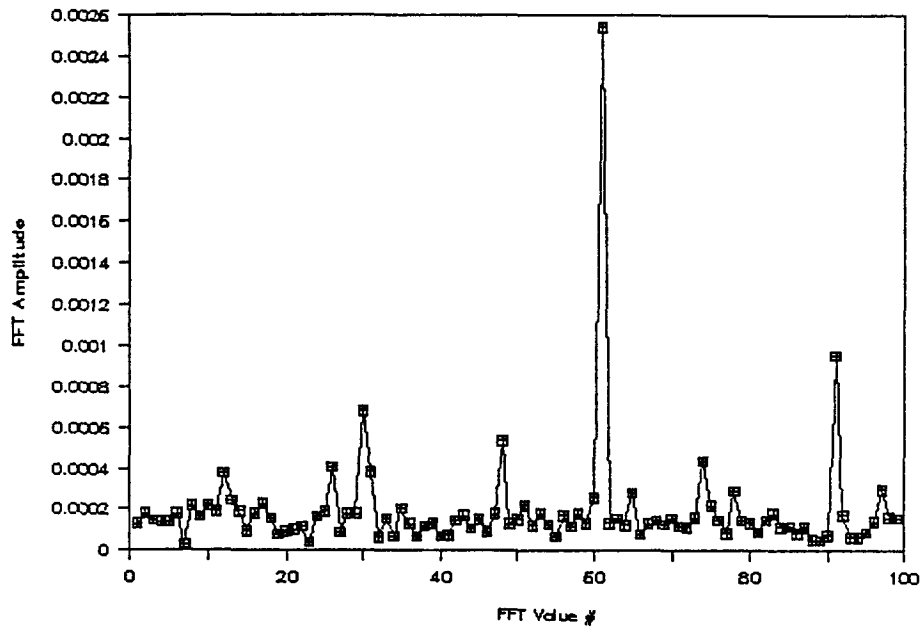


Figure 4a. Original Spectral Signature.

b) Compressed Spectrum

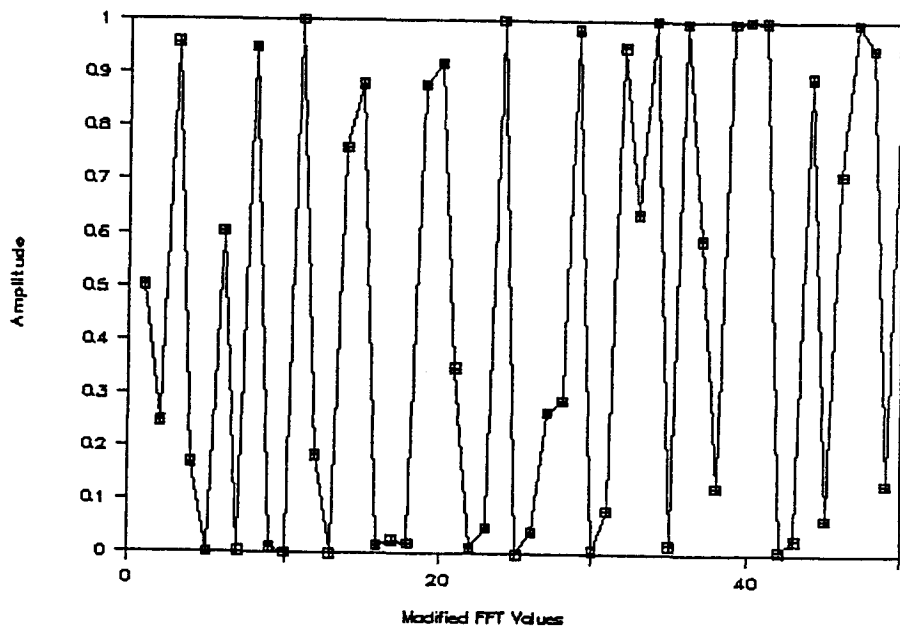


Figure 4b. Compressed Spectral Signature.

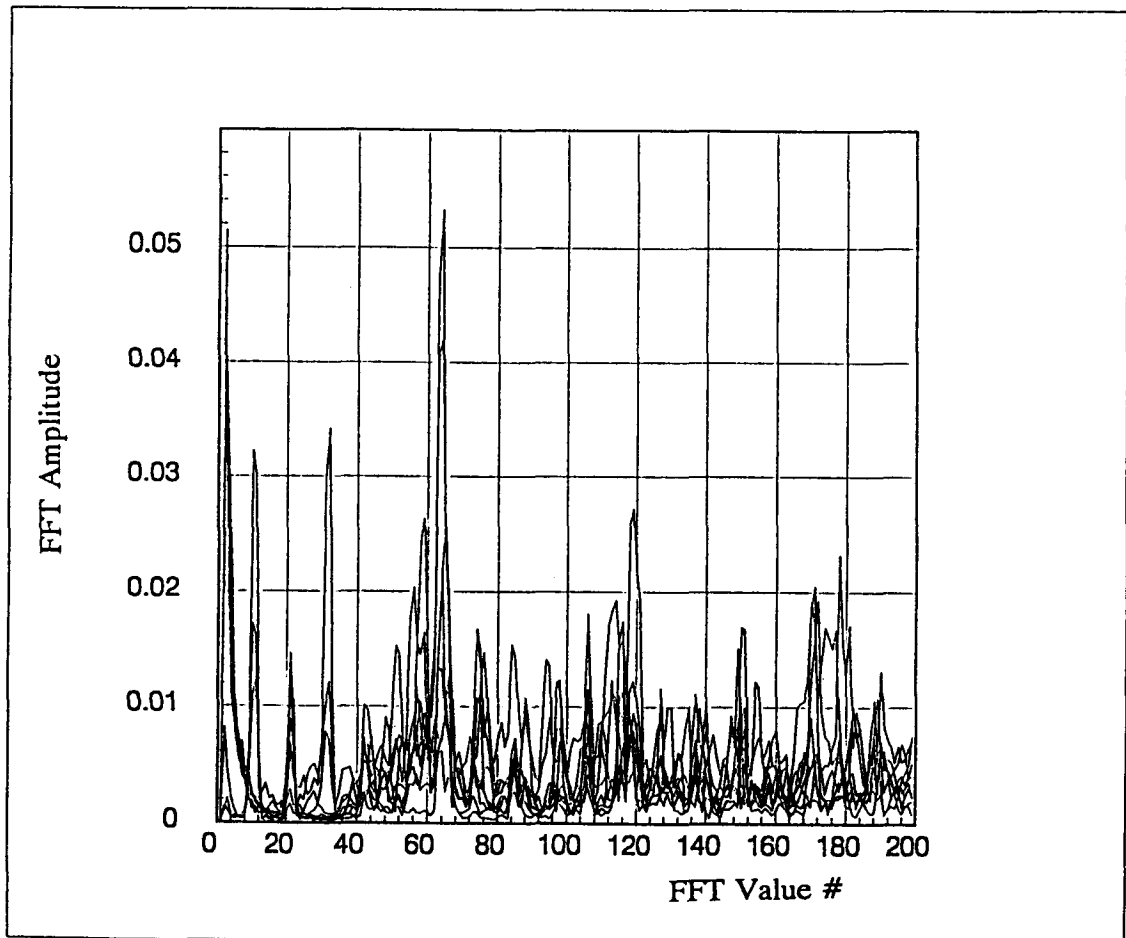


Figure 5. Vibration Levels Recorded by Different Sensors on the Same Machine.

**INVESTIGATION OF NEURAL NETWORK PARADIGMS
FOR THE DEVELOPMENT OF AUTOMATIC
NOISE DIAGNOSTIC/REACTOR SURVEILLANCE SYSTEMS***

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ABSTRACT

Results are presented from investigations into the use of neural networks for the recognition and analysis of neutron noise data. A Spectral Feature Detector network based on the backpropagation paradigm is described, and its potential for use in the development of automatic noise diagnostic systems is discussed.

INTRODUCTION

The use of artificial intelligence (AI) techniques as an aid in the maintenance and operation of nuclear power plant systems has been recognized for the past several years, and several applications using expert systems technology currently exist.¹⁻³ Research efforts in the application of neural networks in this area have been reported.⁴

We investigated the backpropagation paradigm for the recognition of neutron noise power spectral density (PSD) signatures as a possible alternative to current methods based on statistical techniques.⁵ Our goal is to advance the state of the art in the application of noise analysis techniques to monitor nuclear reactor internals. Continuous surveillance of reactor systems for structural degradation can be quite cost-effective because (1) the loss of mechanical integrity of the reactor internal components can be detected at an early stage before severe damage occurs, (2) unnecessary periodic maintenance can be avoided, (3) plant downtime can be reduced to a minimum, (4) a high level of plant safety can be maintained, and (5) it can be used to help justify the extension of a plant's operating license.

The initial objectives were to use neutron noise PSD data from a pressurized water reactor, acquired over a period of ~2 years by the Oak Ridge National Laboratory (ORNL) Power Spectral Density RECOgnition (PSDREC)⁵ system to develop networks that can

1. differentiate between normal neutron spectral data and anomalous spectral data (e.g., malfunctioning instrumentation); and

*Research sponsored by the U.S. Department of Energy under contract DE-FG07-88ER12824 with Martin Marietta Energy Systems, Inc., and The University of Tennessee.

[†]Managed by Martin Marietta Energy Systems, Inc., for the U.S. Department of Energy under contract DE-AC05-84OR21400.

2. detect significant shifts in the positions of spectral resonances while reducing the effect of small, random shifts [in neutron noise analysis, shifts in the resonance(s) present in a neutron PSD spectrum are the primary means for diagnosing degradation of reactor internals].

LIMITATIONS OF STATISTICAL PATTERN RECOGNITION METHODS

The limitations of reactor surveillance systems based on statistical pattern recognition techniques⁵⁻⁹ are exemplified by PSDREC,⁵ which has been used to acquire a library of power spectral density data for many reactor signals from the Sequoyah-1 nuclear power plant. The system provides a set of eight statistical descriptors (called discriminants) for each monitored signal. Each discriminant is designed to detect a specific feature in the PSD. By comparing the discriminants obtained from current PSD with those obtained from baseline data, the system can detect changes in the noise signals. The approach used in PSDREC is to place statistical limits on normal discriminant behavior at the beginning of operation. These limits are then modified as the system gains experience from monitoring the plant. An acquired signature is then classified as suspect if any one discriminant exceeds the set limit.

PSDREC was designed for the acquisition of power spectral density data of various signals (e.g., ex-core neutron detectors, reactor cooling system pressure) for subsequent off-line analysis. Analysis of such data revealed the following.

1. Although much data reduction is possible (for nine of the signals monitored, only ~10% of the signatures observed were classified as suspect), visual comparison of some of the plots of (neutron noise) suspect spectral signatures with baseline signatures showed little difference in the spectral shapes (Figure 1). This result suggests that the system in an on-line environment could be triggered when in fact the plant is operating normally. We hypothesized that this problem is due to the inherent statistical nature of the recognition process.
2. For a constant operating power level, some discriminants trigger much more frequently than others (Figure 2), even though plant operation is normal. The discriminants can be considered to be the statistical features extracted from the signal. Thus, we hypothesized that not all of these features are necessary for characterization of the noise signals. Also, because triggering modes are based solely on statistical considerations, the more discriminants present, the greater the likelihood of at least one of them going beyond its set limit.
3. Nonstationary components in some of the reactor signals resulted in a greater percentage (>20%) of the observed signatures being classified as suspect.

To improve on the performance of PSDREC for the development of the next generation of on-line surveillance systems, alternative recognition methods closer to human cognition are being investigated. The objective is to combine AI techniques with some of the statistical techniques employed in PSDREC. A methodology using the backpropagation paradigm has been developed. In this paper, preliminary results obtained with the method are presented. Neutron noise data acquired by PSDREC were used in this work because this method is the primary means of monitoring reactor internals vibration.

PATTERN CLASSIFICATION USING NEURAL NETWORKS

Neural network theory is an approach to parallel computing based on an architecture inspired by the structure of the cerebral cortex portion of the brain. Hence, neural networks are often capable of functions that humans do well but conventional computers often do poorly. A particular attraction of neural networks is their ability to recognize patterns, even when the information comprising these patterns is noisy, sparse, or incomplete. Neural networks can therefore be said to perform "approximate reasoning," a technique frequently used by humans and simulated in other AI-related technologies such as fuzzy logic. Neural networks have been used to identify causes of perturbations in the steam generator of a nuclear plant,⁴ for the classification of industrial spectral signatures,¹⁰ and as a data encoder in the analysis of acoustic emission of jet engines.¹¹

In a typical application, a neural network can be used to classify an input pattern as one of several predefined types on which the network has previously been trained. Unlike many pattern classification applications, however, where representative patterns from each class of interest are available, obtaining patterns characterizing abnormal behavior in the components of a nuclear plant is difficult. Obtaining abnormal patterns by planned failure of components is not feasible because of implementation costs and/or governmental regulations.

In this work, the approach taken has been to train networks to recognize the general features a human would use to characterize a normal neutron noise spectral pattern (such as resonances appearing in appropriate regions) and compare the network response to baseline data with responses to subsequent spectral data to detect deviations from normal behavior.

SPECTRAL FEATURE DETECTION

A typical PSD plot consists of only a few features, any one of which can be identified in a sufficiently small region: (1) a resonance (peak), (2) a valley, (3) a monotonically increasing spectrum, (4) a monotonically decreasing spectrum, or (5) a flat spectrum. The occurrence of these features at particular frequencies enables a spectrum to be recognized by a human as "a normal neutron noise spectrum." Similarly, a neural network's ability to perform "approximate reasoning" should allow it to recognize these features even under noisy conditions. To demonstrate their feasibility, these concepts were tested with a backpropagation network consisting of 16 neurons in the input layer; 2 hidden layers with 8 and 16 neurons, respectively; and 3 neurons in the output layer (Figure 3). The network was trained to differentiate between the 5 idealized spectral features shown in Figure 4—an output of "111" represented a resonance feature, "000" represented a valley-like feature, "011" represented a monotonically increasing feature, "100" represented a monotonically decreasing feature, and a binary output of "101" represented a flat feature. Patterns with slightly distorted features were then presented for network recall, as shown in Figure 5. The results show that the network could correctly classify the test patterns in much the same way a human would categorize them.

These concepts were extended to the recognition of neutron spectral data using a multiple neural network system with an overlapping window structure (Figure 6). A 4-Hz window was used with 2-Hz overlapping (i.e., the window widths were 0 to 4 Hz, 2 to 6 Hz, 4 to 8 Hz, etc). Each "spectral feature detector" (SFD) consisted of a 10-neuron input layer (representing ten frequency bins in a 4-Hz window); two hidden layers with 5 and 3 neurons, respectively; and a 3-neuron output layer. Two hidden layers were used because this architecture was found to make

the system less sensitive to background. Performance of the networks did not degrade appreciably when the number of neurons in the hidden layers were reduced from 8 and 16 (as in Figure 3) to 5 and 3 respectively. (In this case, performance is defined as the percentage of resonances that were correctly classified as such when neutron noise spectral patterns at different reactor operating power levels were presented for network recall.) Ten neurons were used in the input layer because this number represents the minimum window width such that, at most, one simple spectral feature will be recognized in a window. The (binary) output from the set of networks constituted a "binary feature signature" (BFS), which was used to detect the resonance regions in the spectrum. Each 3-bit pattern represents a particular feature seen by a network.

To reduce the system's sensitivity to background, a set of each simple feature was generated at different amplitudes, and a slightly different distortion was introduced in each by adding a small amount of noise prior to network training.

In all the tests described below, a 14-network system in an overlapping window structure was used. This arrangement represented a spectral range of ~ 30 Hz. For the actual plant data, spectral data from the ORNL neutron noise library were used.

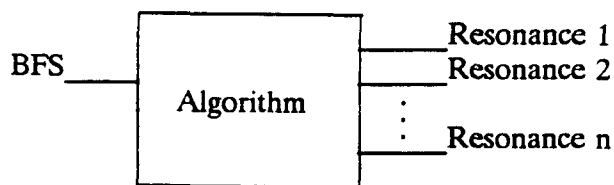
TEST RESULTS

(1) Recognition of Abnormal Spectra

An intelligent recognition system should be able to screen the PSD signature to determine its validity before using it in an analysis procedure. Validity can be determined by presenting the PSD data to the SFD system and comparing the resulting set of binary spectral signatures to that obtained from baseline data. Tests with both simulated and actual plant data showed that the method is effective in validating spectral data. Examples of simulated spectral data compared with a typical normal neutron spectrum are shown in Figures 7 and 8. Extensive tests showed that, while interpretation of the binary feature signatures was straightforward for $\sim 90\%$ of the data tested, a knowledge of the positions of all resonances in a test spectrum can, in general, be obtained by only a more careful analysis of the BFS set. Consider Figures 7a and 7b, for example, in which the spectral shapes look similar. Inspection of their BFSs, however, shows some discrepancy where the resonance appears. A simplistic interpretation of the BFS for Figure 7b will result in nonrecognition of the resonance. In Figure 7a, the BFS in this bin range (56-65) is "111" (a simple resonance feature); and in Figure 7b, the BFS is "011" (a monotonically increasing feature). The reason is that each network responds to the most predominant feature in its field of view. In this case, many of the data in this region in Figure 7b are, in fact, monotonically increasing, and the data in the same bin range (in Figure 7a) have a significant amount of data points that dip below a peak. Therefore, to interpret the feature in Figure 7b correctly, the adjacent binary signatures also have to be considered. In this case, the binary signature in the 61-70 bin range (right of the feature under consideration) is "100," signifying a monotonically decreasing feature. A monotonically increasing feature followed immediately by a monotonically decreasing feature strongly suggests a maxima at the center of the region. Based on such reasoning, an algorithm has been developed to interpret a BFS set from neutron PSD data. This algorithm consists of a small set of IF then ELSE rules such as

IF region i has a monotonically increasing feature,
 AND region $i + 1$ has a monotonically decreasing feature,
 THEN a resonance is at the center of i and $i + 1$.

The algorithm thus deduces the positions of the resonances from the binary feature signature, as depicted in the figure below.



Given the resolution in the plant data used [FDELTA ~ 0.4 Hz (Figure 8)], the algorithm could correctly interpret the positions of resonances to within ± 0.8 Hz. (Widths of resonances in the spectral signatures used were typically of the order of 3 to 4 Hz.)

(2) Detection of Shifts in the Position of Resonances

The supervision of complex systems can be performed at one of two levels: (1) the surveillance level, in which the behavior of the system components is classified as either normal or abnormal without regard to the source of the abnormality; and (2) the diagnostic level, in which after an abnormal behavior is detected, an attempt is made to diagnose the cause. In the supervision of reactor systems using noise analysis, part of this diagnostic process involves identifying individual resonances in a PSD spectrum that are associated with the vibrational behavior of the reactor components (e.g., core support, primary pump). Current spectra are then compared with baseline spectra to detect any shifts in the positions of resonances associated with normal behavior, for example, and an attempt is made to interpret these changes.

The neural network approach discussed in this paper has been applied successfully to detect shifts in and the appearance/disappearance of resonances in PSD data from ex-core neutron detectors. An example is shown in Figure 8. The diagram shows a neutron spectrum and its BFS along with a neutron spectrum (and its corresponding BFS) in which the resonance in the neighborhood of bin 30 has disappeared and the position of the resonance in the neighborhood of bin 50 has shifted to a higher frequency.

APPLICATION

Current work is directed toward using the described technique in an embedded network as part of an expert system for analysis of reactor internal conditions. The methodology employed in PSDREC for the acquisition of baseline and trend spectra is being followed. However, instead of using eight statistical discriminants, detection of anomalies is performed by comparing the feature (F) from current spectral data to some baseline data. F is defined as

$$F = \{f(\text{BFS}), e, u\} \quad , \quad (1)$$

where

$f(\text{BFS})$ represents the position of resonances in a spectral signature as extracted from its binary feature signature; and e is given by

$$\frac{1}{W} \sum \log \left(\frac{P_i}{R_i} \right), \quad (2)$$

where W is the window width in which a resonance is found, and P_i and R_i are the test and baseline PSD within the window. It is a measure of the mean difference between the two PSDs on a log scale. The u is given by

$$\frac{1}{W} \sum \left[\log \left(\frac{P_i}{R_i} \right) \right]^2, \quad (3)$$

which is a measure of the variance of a set of W log ratios.

The monitoring approach is to watch the behavior of resonances as reported by the BFS and to allow an expert system to make decisions/suggestions concerning likely sources of anomalies, line of action to pursue, etc.

CONCLUSION

This paper describes a method based on the backpropagation paradigm that has been employed to recognize the positions of resonances in power spectral density data. Although the emphasis of this work is the eventual development of an expert system for automatic surveillance and diagnostics of reactor internals using neutron noise data, the method has also been demonstrated to be applicable to other PSD data (e.g., ex-core temperature) in the ORNL PSD library. Advantages of using neural network paradigms are that they are less susceptible to noise (statistical variations) in the data than are statistical pattern recognition systems and have (the potential for) much faster response.

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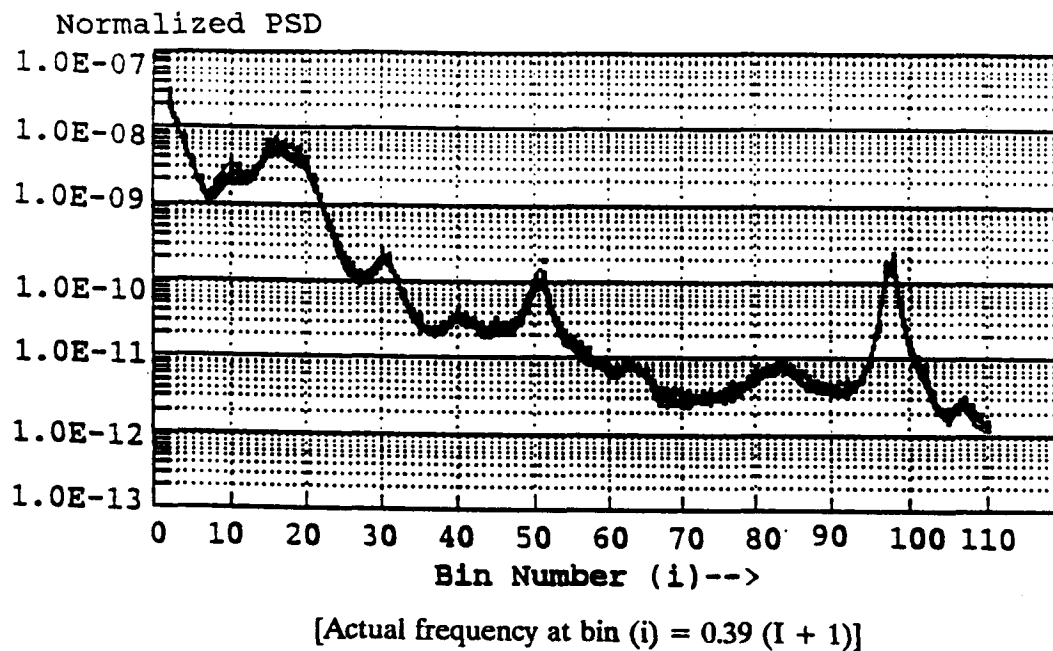


Figure 1. Plot of several baseline and suspect neutron power spectral density data. Although the computed discriminants went beyond limits after extended learning, comparison with baseline data showed little difference.

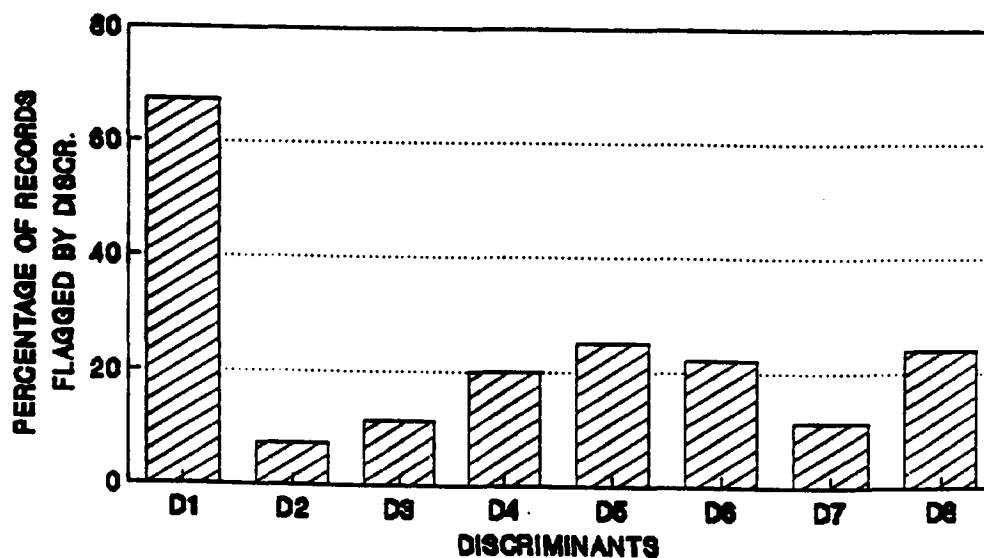


Figure 2. Frequency of discriminants flagged by the Oak Ridge National Laboratory Power Spectral Density Recognition system.

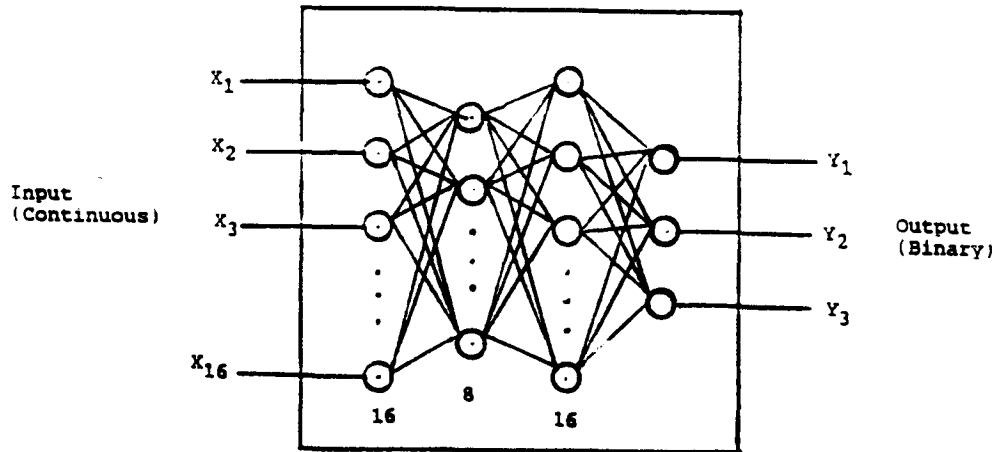


Figure 3. Basic architecture of the spectral feature detector used in the initial investigations.

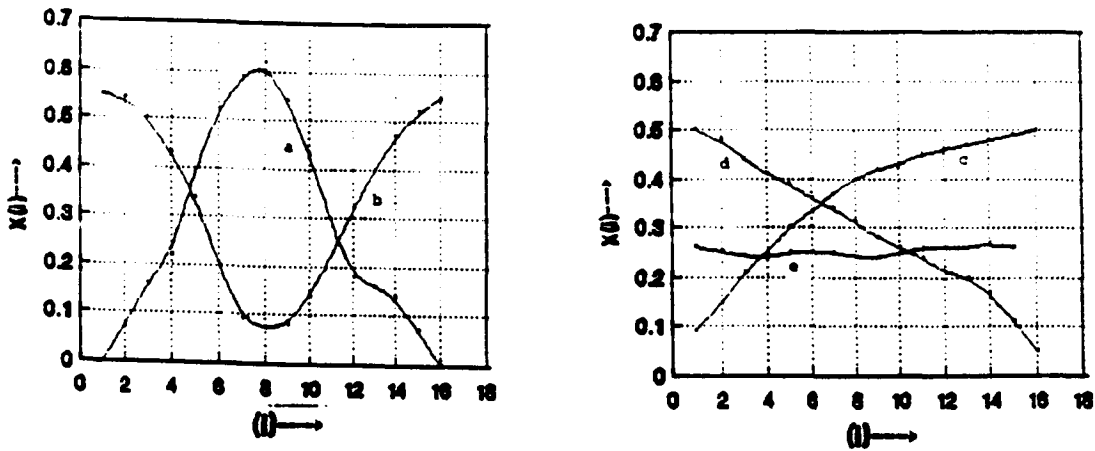


Figure 4. Simple features used in training the backpropagation network used in the initial investigations: (a) resonance feature, (b) valley feature, (c) monotonically increasing feature, (d) monotonically decreasing feature, (e) flat feature.

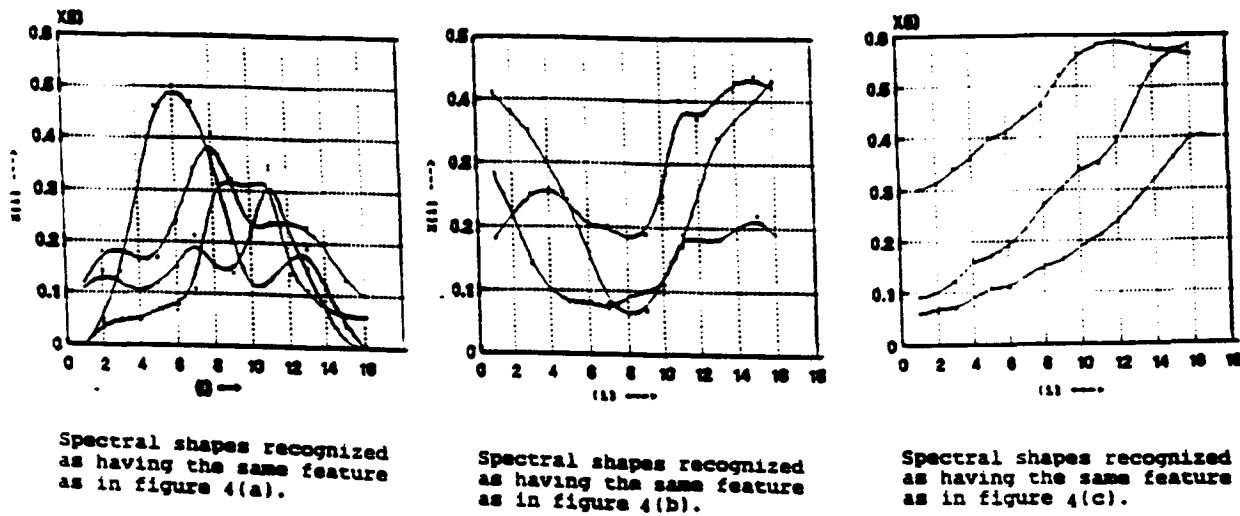


Figure 5. After training the network with the simple features shown in Figure 4, the network was able to correctly classify these simple spectra.

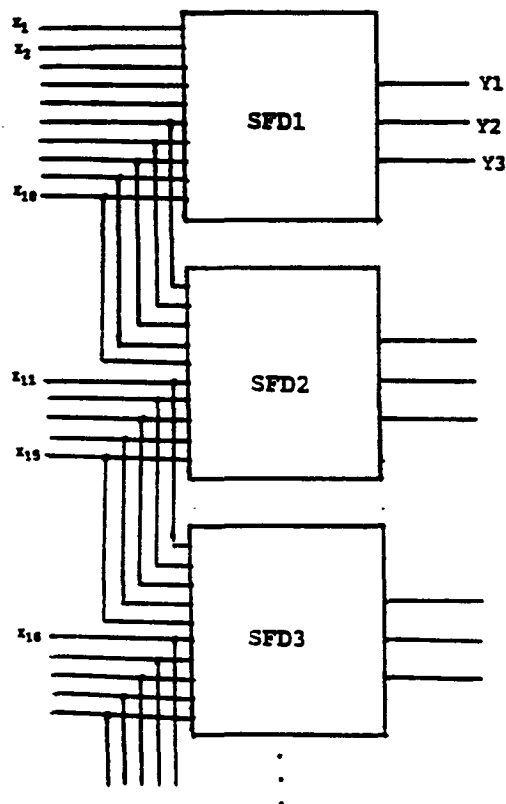


Figure 6. Interconnections of the spectral feature detectors (SFDs) developed for recognition of pressurized water reactor neutron power spectral density signatures (only 3 are shown). The SFDs are identical in their architecture, learning, and recall behavior.

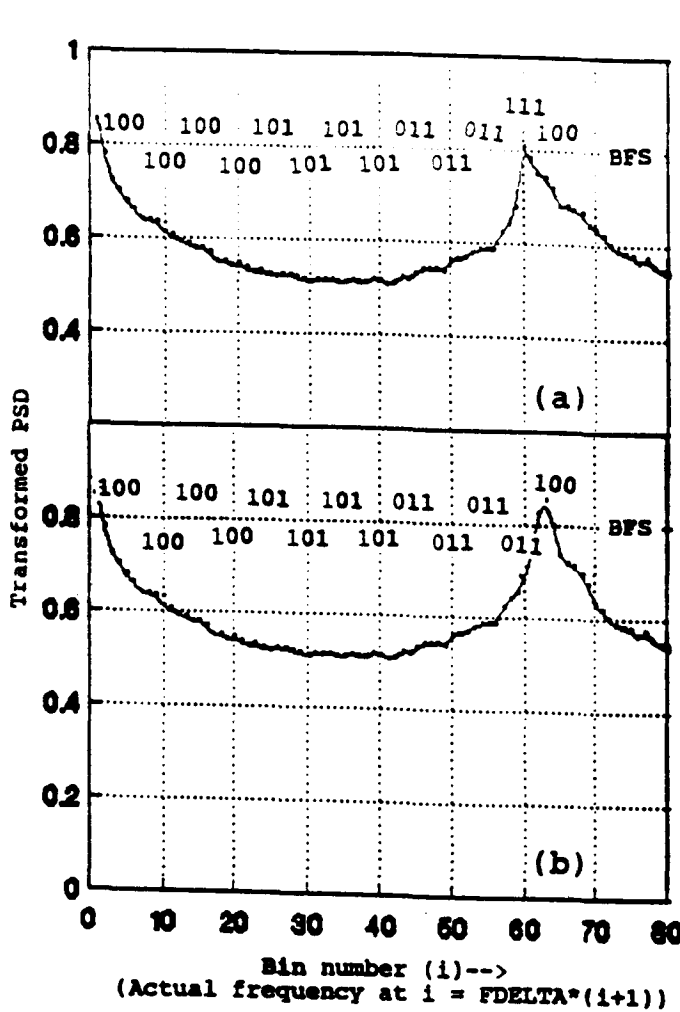


Figure 7.

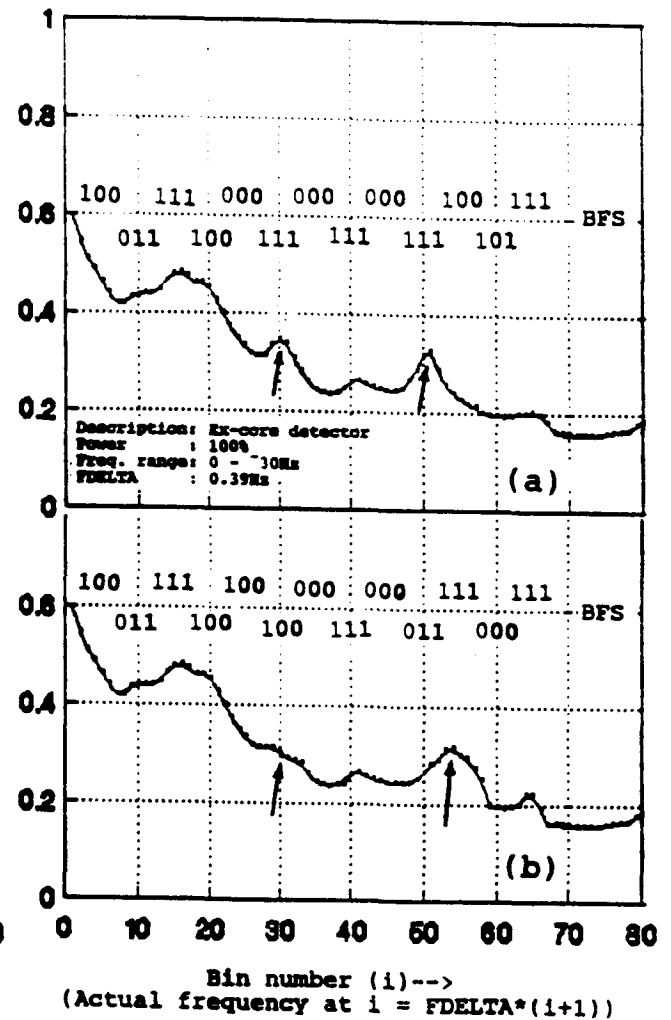


Figure 8.

Figure 7. Spectral pattern [and corresponding binary feature signature (BFS)] obtained for a simulated sensor failure. In general, the BFS has to be interpreted to correctly locate resonances. Comparison of (a) and (b), for example, shows a discrepancy in the BFSs in the resonance region.

Figure 8. (a) Ex-core neutron power spectral density and the resulting binary feature signature. (b) The changes in the spectrum (arrowed) were seen by the neural network system.

PATTERN RECOGNITION SYSTEM FOR THE NUCLEAR REACTOR NOISE IMAGE ANALYSIS AND DIAGNOSTICS

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ABSTRACT

The system reported is aimed at diagnostics of the medium- and long- term behavior of the nuclear reactors, the abnormal operations monitoring and prognoses. The pattern recognition methods: clustering, features selection and mapping of patterns, in combination with classical noise image analysis techniques constitute, the methodological base of the system. Modern standards applied for data acquisition, data processing and human-machine interface allow an operator to observe the reactor behavior using the IBM PC workstation. In addition to the methodological and technical aspects, the reliability, portability, cost effectiveness, system possibilities and its future development are discussed. The results obtained and experiences acquired in the application of the system to the IBR-2 Dubna pulsed reactor diagnostics are exemplified.

INTRODUCTION

As the exploitation experiences show, the nuclear reactor abnormal behavior, as a rule, occurs under unforeseen in the theoretical models scenario, and the probability of the already known abnormal situation recurrence is minute. That is why the conception of the diagnostic system presented in our paper assumes the reactor as the "complex" system. According to G.C.Fox and S.W.Otto [1]: "A complex system is a large collection of, in general, disparate members. Those members have, in general, a dynamic connection between them; a dynamic complex system evolves by a statistical or deterministic set of rules which relate the complex system at a later time to its state at an earlier time.". The set of rules will never be complete and even for this incomplete set the available mathematic and computer techniques might not be sufficient to give the satisfactory results. For such a "complex" system exists an *a priori* non zero probability of its unforeseen behavior in abnormal or earlier unknown situations.

As the diagnostics of the "complex system" using classical computer

simulations based on theoretical models are not reliable in the accidental situations the nuclear reactor diagnostics problem on the first stage can be solved by means of the reactor state identification in accordance with the simple rules: "typical- untypical", "right- wrong". On this purpose the diagnostics system should have:

- build-in heuristic procedures based on the experience and knowledge of an operator,
- effective ways to detect the abnormal or untypical situations in the early evolution stage,
- appropriate informative capacity for the analysis of the long- time (years) tendencies of the reactor behavior,
- convenient for developing and modifications architectural configuration and portable software.

The system is valued additionally by its easy handling and user friendly interface.

As the character of spectral densities of the power fluctuations and the other random processes taking place in the reactor core are tightly coupled with the current reactor state [2], their combination may be considered as a noise image of the reactor. The subsequent noise images, where an instant noise image is added to a host of images registered well before, determine the dynamic changes of the reactor state. In accordance with this fact and the diagnostics system conception presented above, pattern recognition techniques, namely, clustering and clusters analysis can be fruitfully used as a methodological base of the system.

Each of noise images, corresponding to the instant measurement of a respective reactor parameter may be represented as a point in M-dimensional Euclidean space, where each of its subsequent coordinates is equal to the value of the spectral density amplitude for a subsequent discrete value of frequency. Clustering methods allow one to reveal the M-dimensional structures constituted by all the points, which are periodically recorded. The tendencies of changes in various characteristics of clusters i.e. an abrupt change in the position of an instant cluster center, a change in its shape or initiation of a new cluster, give information on the reactor anomalous operation.

On the basis of this general idea, the diagnostics system elaborated by Nuclear Reactor Safety Section staff in the Joint Institute for Nuclear Research (Dubna, USSR), is being improved and modified. Simultaneously each of its current versions is tested at the pulsed reactor IBR-2 at the beginning of 1987. The actual version which can be considered as the commercial one is presented in this paper. In the first section more methodological and technical details are reported. In the second one some results referring to the IBR-2 diagnostics are presented. The ways of the system development in the near future are discussed in conclusions.

METHODOLOGICAL APPROACH AND TECHNICAL APPEARANCE

The detailed description of the system methodology reflecting its development from the earliest versions are presented in reports [2,3,4] and papers [5,6]. The diagnostic process is fully user controlled by means of the program package, directly from the workstation. Two regimes are available. The first-

"extended" one- is destined for detailed investigations and the second- "suppressed" one- for an operator purposes. In this section the former one, covering all the system possibilities, is presented. The software part of the system has a tree structure, each of its branches accessed easily by the window handling program. The iconic representation of the root menu (see Fig.1) shows the main sequence of actions which must be followed by the user to perform the process of reactor diagnostics. Technical appearance and the system methodology can be easily described following the software system organization.

DATA ACQUISITION

The data acquisition process is supervised by the program which handles the interface between the workstation and external devices responsible for registering the reactor "raw noise" signals. As shown in Fig.2 the interface is rather standard and simple. The system hardware consists of the IBM PC/386/387 (20MHz, 1MB) microcomputer and its environment (printer, plotter, streamer, EGA display) with input data acquisition blocks in the CAMAC standard and PC-LABCARD (PCL-718). Such an approach to the system architecture allows one to adjust easily indispensable number of measurements channels, using for this purpose two independent classes of equipment. The chosen signals which are simultaneously registered as the time series and collected on the workstation hard disk, represent the current reactor state under the measurement period. Such a "raw noise image" of the reactor is rather illegible for numerical analysis and must be additionally preprocessed. The subsequent data acquisition and its preprocessing is automatic, however the period length can be controlled by an operator.

DATA PREPROCESSING

The classical procedures as the FFT transformation (with the Keizer- Bessel data window), fast Walsh transformation and normalization, transform the "raw" fluctuations of all the measured reactor parameters to the respective spectral densities which represent the final input data for further processing. The set of instant measurements transformed to the respective spectral densities can be analyzed using classical techniques. However, the process of long term diagnostics refers not only to the current reactor state determination, but to its relation to the states registered earlier. The analysis of the full data set covering the long (years) period of reactor operation involves the new techniques for data analysis like pattern recognition methods. For this purpose each of the subsequent spectral densities for the respective reactor parameter fluctuation is treated as a point in M-dimensional Euclidean space, where each of its subsequent coordinates is equal to the value of the spectral density amplitude for a subsequent discrete value of frequency.

On this stage of diagnostics the correlation analysis can be optionally performed and coherence functions and phase between each pair of reactor parameters instant measurements can be computed.

DATA TYPE TO PROCESS

The number of reactor parameters which fluctuations are registered for diagnostics purposes are usually greater than one. As the diagnostics system is destined for the sequential workstations, the respective set of spectral

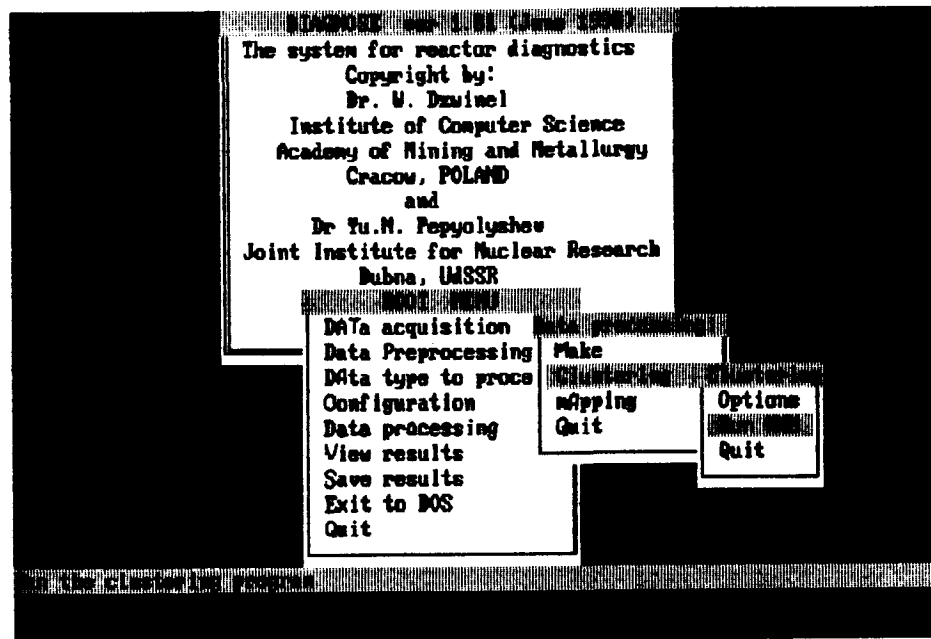


Fig.1 The system root menu, data processing, and clustering sub-menus (display hard copy).

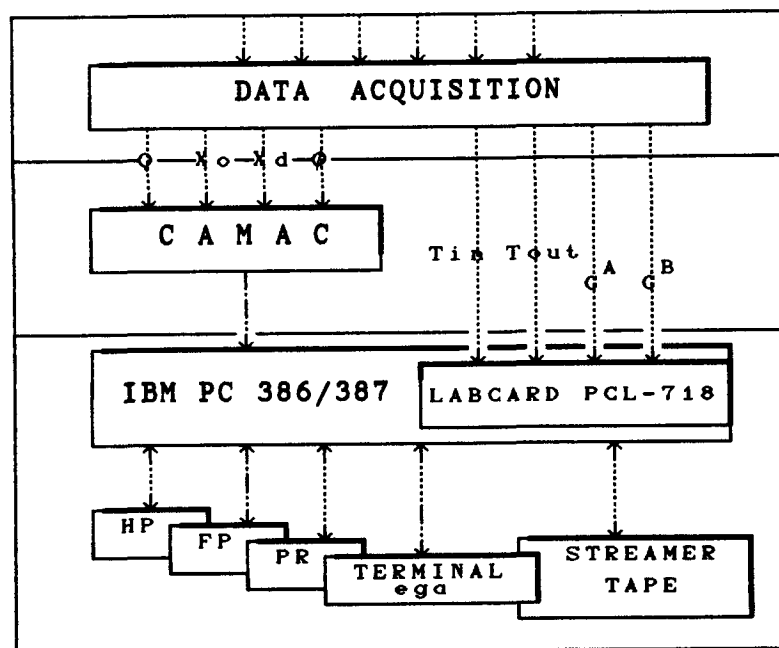


Fig.2 Block schematic of the diagnostics system hardware configuration (HD- hard disk, FD- floppy disk, PR- line printer).

densities for each of the parameters is processed separately and consistently with the succession established in the system initiation stage. However, in the "extended" version of the system the user can decide which one of the reactor parameters processing is necessary for further investigations.

CONFIGURATION

The files configuration for the data processing programs is set-up automatically. However, as our experiences show, the "extended" version of the system involves sometimes its change.

DATA PROCESSING

The periodically recorded spectral densities of the chosen reactor parameter establish a clusters structure in M dimensional Euclidean space [4,5]. When the instant data are added to the host of images registered before, the tendencies of changes in various characteristics of clusters i.e. an abrupt change in the position of an instant cluster center, a change in its shape or initiation of a new cluster, give information on the reactor untypical operation. The clustering and other pattern recognition methods allow one to reveal both current clusters structure and observe its changes during reactor operation. Additionally, if the instant data falls directly to the well established cluster (the cluster which characteristics are known earlier) the current reactor state can be immediately determined. When an untypical reactor behavior is detected, the correlations between all the reactor parameters clustering results must be investigated to reveal the reasons responsible for the reactor operation changes. If such correlations do not exist, the investigations external to the diagnostics system techniques tool are necessary.

The data processing action consists of two programs runs (see Fig.1). For the "suppressed" system version its options are set-up automatically and full processing is performed (the "Make" action, see Fig.1). For the "extended" system version each of programs can be handled independently and options must be set-up manually. The first program comprises clustering procedures with cluster analysis techniques and two independent feature selection algorithms. The hierarchical clustering algorithm based on the mutual nearest neighborhood conception (MNN) presented in [7], improved and adapted to the diagnostics problem by the authors ([5,6]) appears to be more convenient and reliable than non-hierarchical ones e.g. the ISODATA applied earlier [4,8]. The comparisons of the MNN algorithm against the non-hierarchical ISODATA for diagnostics purposes, are discussed in our earlier works ([5,6]).

Although, the clustering program output can not be underestimated, the valuable details as the clusters shapes and their mutual localizations remains hidden for an operator. The mapping of patterns techniques allows one to some extent to resolve this problem. In order to visualize the M -D (M dimensional) clusters structure preserving its real characteristics, the sophisticated algorithms performing M -D to 2(or 3)-D transformations are used. Two of them, namely, classical Karhunen- Loeve transformation algorithm [8] and improved Niemann technique [6,9] can be optionally chosen in the second pattern recognition program. As the authors experiences show, the Niemann method gives better clusters separation, consistent with the clustering results. As will be shown in the next section the mapping of patterns procedure enriches the

information obtained by the clustering and gives an operator the opportunity to observe visually the reactor operation changes.

VIEW RESULTS

The package of graphical programs let one to visualize both the current raw data, its respective spectral densities, coherence functions and phase between each of pairs of the reactor parameters and results of data processing i.e. the clusters statistical analysis results, clusters centers, time diagrams which show in time the reactor operation changes, 2-D and 3-D clusters structures.

SAVE RESULTS

All the spectral densities for the respective instant measurements are automatically saved and added to the data base after the system quit. The remaining results can be saved on the hard disk for further investigations as necessary, or removed otherwise.

EXIT TO DOS

Sometimes the user needs to leave temporarily the diagnostics system and return to the operating system with the opportunity to come back to the system menu afterwards.

QUIT

This action finishes the full diagnostic process.

As shown above, the diagnostic system is constructed on the basis of standard devices like IBM PC microcomputer and CAMAC or/and PC- LABCARD products. The authors recommend, however, to obtain the proper system efficiency to use the IBM PC 386/387 (or higher versions as the IBM PC 486) microcomputers with the memory not less than 1MB and hard disk capacity greater than 40MB. The minimum EGA driver is recommended. The system software runs under the DOS operating system versions higher than 3.10. The configurations more modest than those pointed above can be taken into account too, but the proper system efficiency is not guaranteed. The full software portability is limited to the IBM PC products and DOS operating system. However, all the pattern recognition programs sources are written in the FORTRAN77 under OLYMPUS standard and can be used without limits on the optional general purpose computer.

THE RESULTS OF DIAGNOSTICS SYSTEM APPLICATION

The system briefly described above is used to the IBR-2 pulsed reactor (Dubna USSR) diagnostics and the results presented below are treated as an example of its application.

The IBR-2 reactor is used as a pulsed neutron source for performing the physical investigations on the neutron beams. Its main characteristics are as follows:

- average power regime: - 2 MW,

- maximum pulse power: - 1500 MW,
- power pulse width: - 215 μ sec,
- frequency of reactor pulses: - 5 Hz,
- fuel load (PuO_2): - ≈ 100 Kg,
- coolant (Na) flow rate: - $\approx 100 \text{ m}^3$ per hour,
- reactivity modulator: - two moving reflectors: the main (OPO) and additional one (DPO).

The fluctuations of the eight most valuable in reactor safety parameters are recorded. They are as follows:

- energy of the pulse (reactivity) - Q (R),
- axial OPO and DPO vibrations - X_o , X_d ,
- desynchronization of the OPO/DPO angle - ϕ ,
- coolant temperature on the reactor core input and output - T_{in} , T_{out} ,
- coolant flow rates in A and B loops, - G^A , G^B .

The first one, namely, the pulse energy (reactivity) is the most general reactor parameter. Its fluctuations are measured by means of the vacuum and ionization fission chambers placed mainly in the center of the reactor core and on the neutron beam. The X_o and X_d vibrations are detected using capacity sensors. The T_{in} (T_{out}) and G^A (G^B) are measured using the Cr-Co thermocouple and induction sensors respectively.

The pulse signals (Q , X_o , X_d , ϕ) are transmitted by means of the respective CAMAC blocks. The remaining ones i.e. (T_{in} , T_{out} , G^A , G^B)- by the LABCARD module PCL-718. The statistical error of the power spectral density (PSD) for the measured time series length equal to 8192 and 256-points PSD discrete channels, is estimated at 13%. As the sampling frequency of the pulse signals is given by the reactor pulse frequency (i.e. 5Hz) the reactor control period must be not less than 30 minutes, and the width of PSD discrete channels ≈ 0.01 Hz. The control period and statistical PSD characteristics turn out to be, the optimal ones to obtain appropriate results for the following clusters analysis.

Up to now, during the period of diagnostics system exploitation (in various its versions) from 1987 to the beginning of 1991, the four main clusters representing four noise reactor states can be distinguished. In Fig.3 the subsequent energy fluctuation spectral densities are presented at the end of the time period mentioned above. The reactor state transition from the former to the following one is reflected by the cluster number change on the time diagram presented in Fig.4. The illustrative and comprehensive information about: the spectra- to- clusters distribution, spectra- and- clusters localizations and the tendencies of the clusters forms changes gives Fig.5. The picture was obtained using the Niemann transformation of the real 256-D clusters structure to 3-D space, where each point corresponds to the respective spectral density.

The results presented above show that during more than 2 years the reactor is operating in stable regime. Additionally, taking into account the clusters statistical analysis results and the correlation between all the recorded parameters, it can be concluded that:

- the spectral frequency width and absolute level of both the full and partial

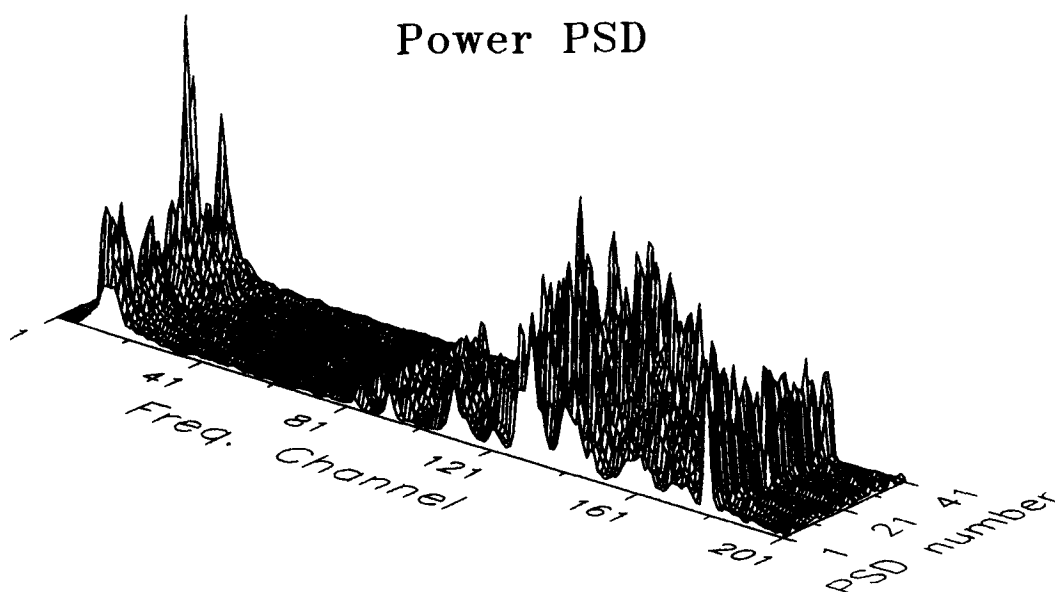


Fig.3 The power spectral densities obtained at the end of 1990.

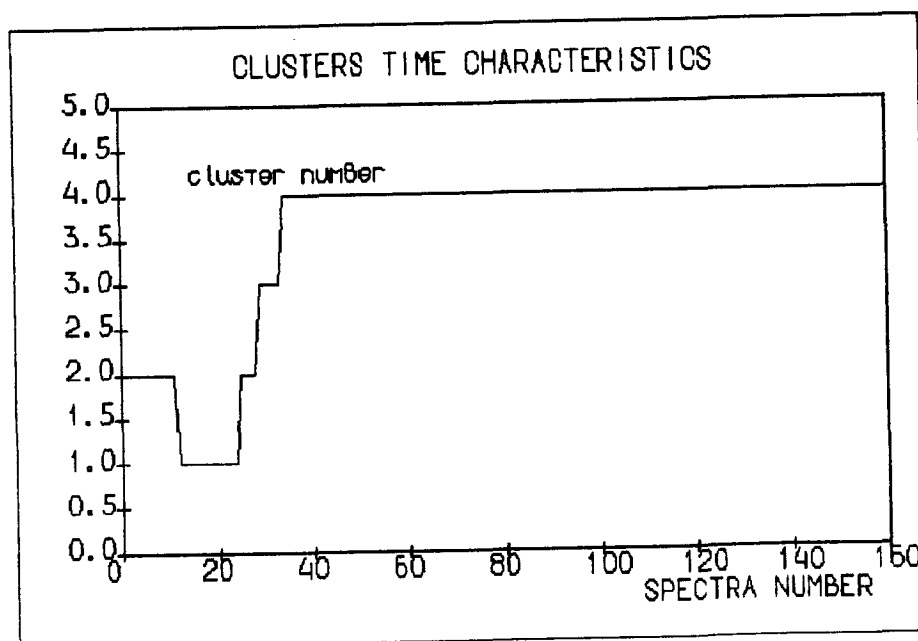


Fig.4 The time diagram (display hard copy) which shows the cluster number each subsequent PSDs belongs to (where X- subsequent spectra number and Y- cluster number). The clustering was carried out for the full [0,2.5] Hz frequency interval.

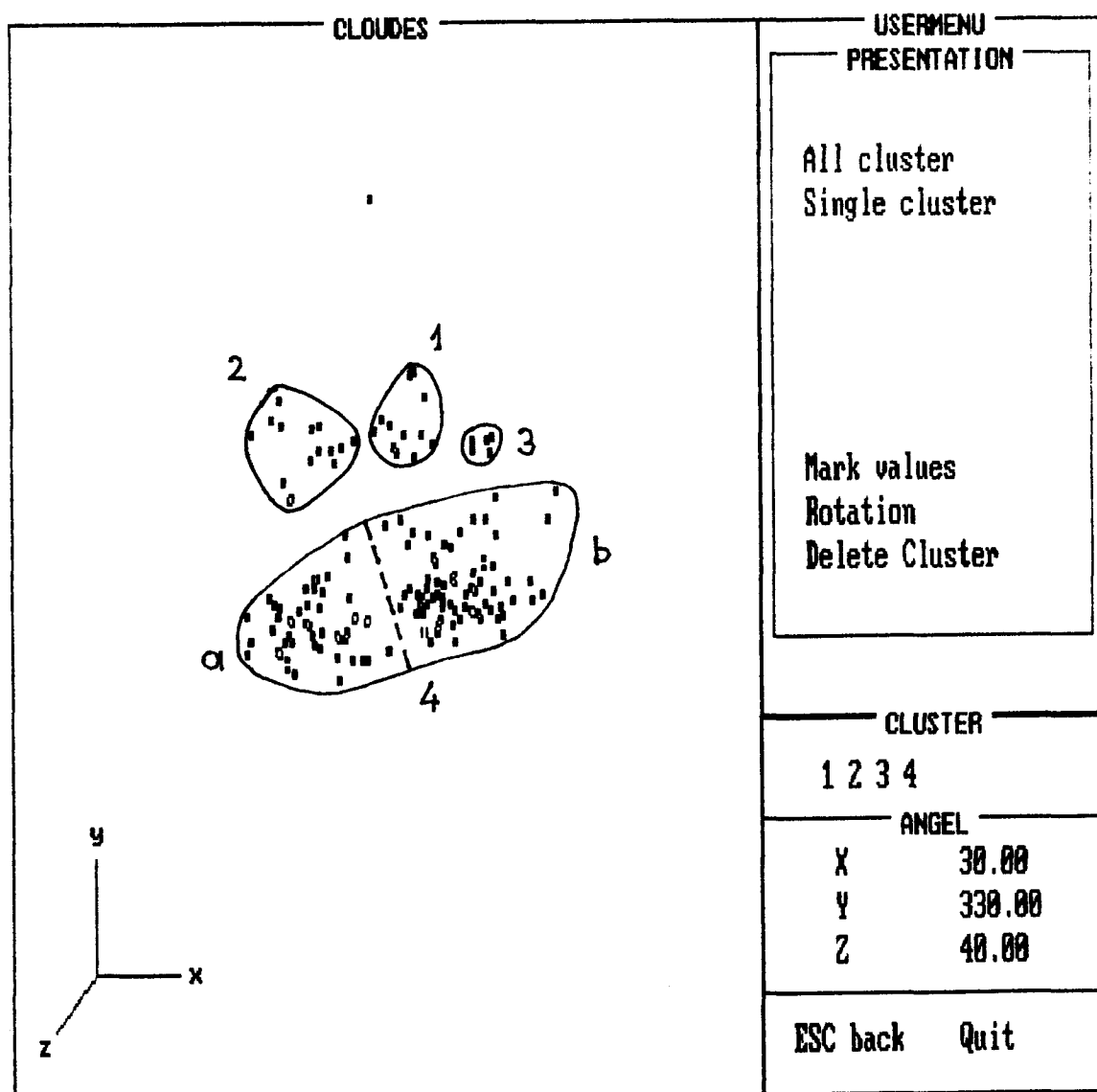


Fig.5 The Niemann 3-D pattern (display hard copy). The clusters boundaries and numbers were drawn manually (the points belonging to the respective clusters have different colors on display). The fourth cluster substructure is apparent (4a, 4b) though not detected by the clustering program (see Fig.4).

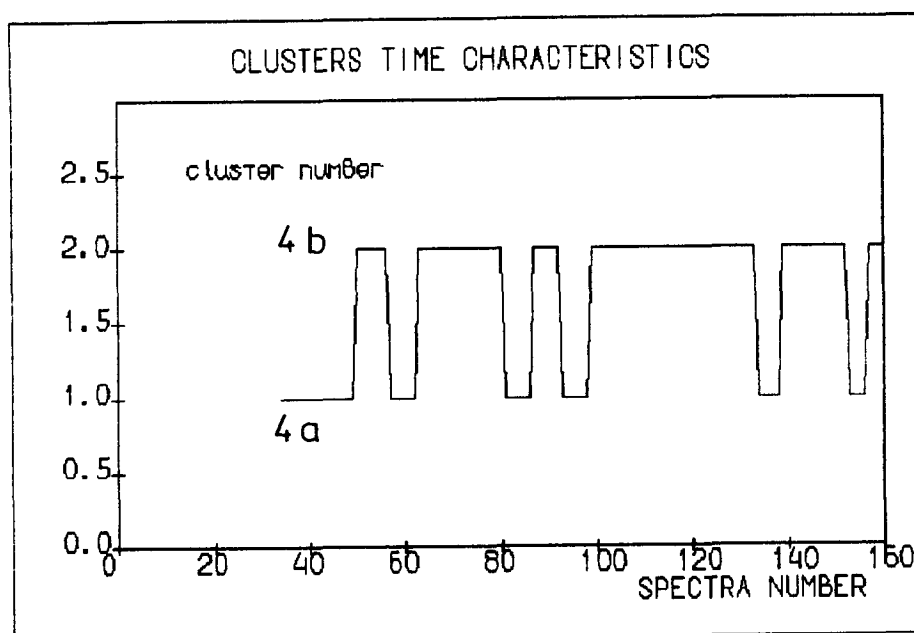


Fig.6 The time diagram display hard copy for the fourth cluster PSDs "members". The [1.7,1.8] Hz PSD's frequency interval was considered. Two reactor operation states are apparent.

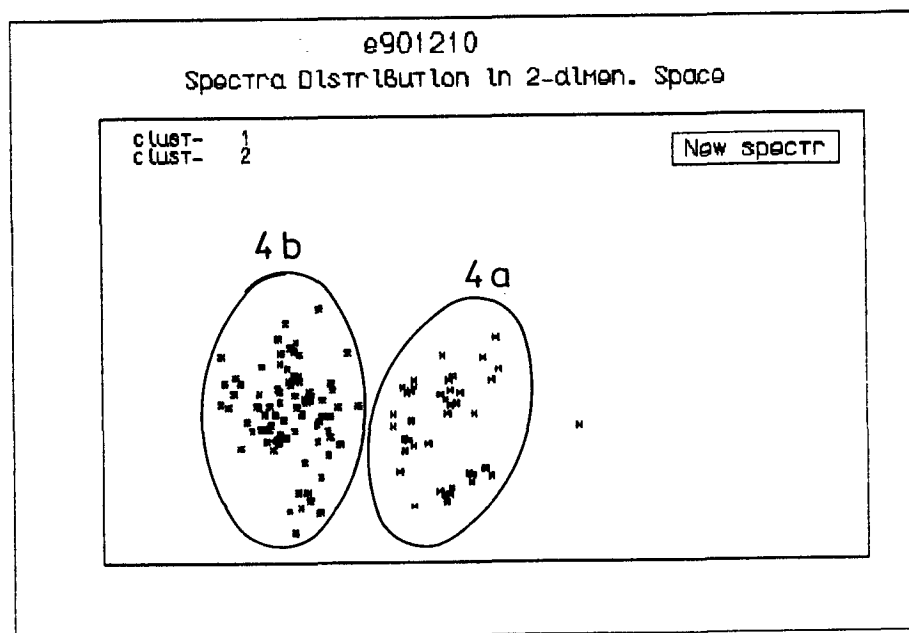


Fig.7 The Niemann 2-D pattern (display hard copy). The subclusters boundaries and numbers were drawn manually (the points belonging to the respective clusters have different colors on display). The [1.7,1.8] Hz PSD's frequency interval was considered.

fluctuations of the reactivity remain unchanged,

- the characteristics of the main fluctuation sources of the external reactivity (the OPO, DPO vibrations and the effects evoked by the coolant flows through the reactor core) remain unchanged too,
- the mechanical and dynamic reactor characteristics changes i.e. transfer function change, are negligible.

These conclusions illustrate some internal diagnostics system opportunities. It is worth mentioning additionally, that the fourth cluster appearance is caused by the negligible moving reflector construction vibrations as the whole.

The fourth cluster in the full frequencies interval ($[0, 2.5]$ Hz) space has internal "subtle" structure. It is not detected by the clustering program but visually distinguished as two subclusters 4a and 4b in Fig.5. However, in the "features space" of the power fluctuation spectral densities ($[1.7, 1.8]$ Hz), associated by the correlation relations with OPO and DPO vibrations (X_o , X_d , ϕ), this substructure gets apparent both for the clustering and on the 2-D Niemann pattern (see Fig.6 and Fig.7). Since all the power spectral densities referring to the respective measurements during single reactor cycle (the regime of the long term reactor operation is periodical one i.e. in the single cycle it works non-stop two weeks then waits one week with zero power) fall into the one out of two subclusters, we can assume that two various reactor states exist. They are connected with the minute (10^{-3} mm.) moving reflectors mutual location changes on the subsequent reactor cycle start. However, this effect, because of its negligible influence on reactor operation, is still not particularly investigated and serves us to the system accuracy estimation. So, we can conclude that using the presented system for a reactor diagnostics, the anomalous effects, initiating accidental disturbances on a 10^{-7} - 10^{-6} $\Delta K/K$ level can be distinguished.

CONCLUSIONS

The system presented here is destined rather for the long term reactor diagnostics than on-line supervision. The CPU time, needed for each of the reactor parameters processing for $N=250$ (where N the number of spectral densities) and $M=256$ is ≈ 10 minutes on the IBM PC 386/387 using RMFORT compiler (for NDP FORTRAN compiler the computational time efficiency is two times higher). The clustering program scales as N , however the $o(N^2)$ program part contribution, negligible for $N < 10^3$ gets apparent when N is greater than 10^3 order. In turn, the mapping of patterns Niemann procedure scales as N^2 . The memory increases simultaneously as N^2 for both of programs. In order to make the system capable to perform on-line diagnostics ($N \approx 10^3$) the considerable increase of system efficiency is needed. As the operating memory of the system can be easily extended, the time efficiency appears to be the crucial point for such a type of reactor diagnostics. As the applied algorithms and programs codes were optimized in time and are almost ten times faster than their beginning versions reflecting the "raw" ideas presented in respective references (i.e. MNN clustering [7] and Niemann processing [9]), two ways remains only to increase the system efficiency.

The first one consists of the clustering procedure alteration to the more efficient one (e.g. the ISODATA, the "learning with teacher" algorithms) and

resigning the mapping of patterns idea. However, in such a case, the system would be inferior (see [6]) for long term investigations in comparison with that presented above. The results visualization would be considerably poorer and its time efficiency for on-line diagnostics insufficient yet. Application of the most efficient discriminant analysis approach may, in turn, decrease the reliability of the whole diagnostics system.

The second way, namely, parallel processing, seems to be more profitable. The concurrent computations of each reactor parameter data and internal possibilities of the FFT, clustering and mapping of patterns procedures parallelization, point to the direction of the system development in the near future. In order to cut the costs of such system modification the PC Plug-in TRAM boards are planned to be applied.

Simultaneously, the existing system modifications are necessary. They concerns the more convenient and automatic clustering results analysis of the whole set of the reactor parameters data using the "expert" approach. Up to now it is done using classical correlation methods and needs additional operator experience and knowledge. On the other hand however, the portability of the expert systems based on the specific for a given reactor, sets of heuristic rules is strongly limited. The system presented in this paper can be used to the diagnostics of an optional reactor type or other complex objects without any changes. Because of its simplicity the diagnostics system presented here can be easily modified and developed.

ACKNOWLEDGEMENTS

The authors wish to thank Dr. J.Kitowski from Institute of Computer Science, Academy of Mining and Metallurgy, Cracow, Poland, for valuable contributions both to the "birth" stage of the diagnostics system and to its constant development. Thanks are due to Dr. Norma Michel from Zentralinstitut für Kernforschung, Rossendorf bei Dresden, Germany, for her direct help in graphic system output elaboration. Mrs. T.A.Filimonycheva assistance in manuscript preparation is appreciated.

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KNOWLEDGE REPRESENTATION AND INFERENCE IN NOISE DIAGNOSTIC EXPERT SYSTEMS

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ABSTRACT

Nowadays several noise diagnostic systems for nuclear power plants have been designed to support early failure detection and increase availability and safety. This paper considers an approach (the so-called *general* one), where the system was designed to solve any signal processing task and provides a general environment (in a shell form) to solve specific noise diagnostic tasks. A natural way to combine several types of knowledge is suggested and a possible scheme to exploit them is given. The structure of the system can be represented by objects in the sense of object-oriented programming, and deep knowledge appears as the internal structure of the objects and the procedures added to them. An inference mechanism operating on production rules expressed in connection with the system objects makes diagnoses. A prototype of a realized Noise Diagnostic Expert System - being in operation on the 3rd and 4th reactor units of NPP Paks - and the experiences of its development is described. A real-time data acquisition system and an extended set of signal processing and pattern recognition methods are available to supply the expert system with input information. The main features of the knowledge acquisition, representation, and validation process is discussed, as well as the mechanism is outlined, how the expert system can use the knowledge in making diagnoses.

Keywords: noise diagnostics, failure detection, parametric modelling, feature extraction, pattern recognition, knowledge representation system, expert system

INTRODUCTION

The extraction of information contained in the noise processes of a nuclear reactor and the utilization of this information for surveillance and diagnostics received increasing interest in the recent years (see SMORN IV-V). Several noise diagnostic systems have been elaborated to support the problem solving in the above area. These stems from simple FFT based signal processing till automated diagnostic systems. It has recently been recognized that the efficient use of modern signal processing methods applied on digital computers requires a special expertise seldom owned by noise analyst people. At the same time the combination of domain specific knowledge with the results of signal processing, feature extraction e.t.c. results in a necessity to obtain reliable diagnostics. These problems can be attached by building special knowledge based and/or expert systems where the synthesis of numeric and symbolic computation and combination of algorithmic (often called procedural) and domain specific diagnostic knowledge have to be realized.

Various approaches about the basic philosophy and structure of these systems can be found in the literature, see e.g. Suda et al (1989) where the so-called *general*, *specific* and *hybrid* approaches are characterised. This paper considers the first, *general* approach, where the system was designed to solve any signal processing task and provides a general environment (in a shell form) to solve specific noise diagnostic tasks. We only refer to the signal processing technology applied in the system (see Kitamura et al, 1985; Nagy et al, 1988; Veress et al, 1988; Keviczky et al, 1988; Bokor et al, 1987) and concentrate on the problem of knowledge representation and inference elaborated for solving the diagnostics.

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An exact diagnostics obtainable from the signals of various sensor groups has to be the result of a complicated inference process, that has to be based on the diagnostic knowledge available about the system. Human diagnostic inference uses a great variety of knowledge:

- special domain-knowledge, e.g. structural and functional considerations, models of operations of the system, and receipts how to find several type of failures,
- meta-knowledge e.g. mathematical, physical, technical, etc. considerations and rules of logic in inference.

The representation of this knowledge is a principal task when a computerized form of diagnostics must be realized. Classical expert systems have limited their scope on representing production rules, and inferences based on forward or backward chaining on them. The origin of rules have usually been the experience. Contemporary expert systems aim to combine rule-based knowledge and deep model-based knowledge.

Our paper is organized in the manner described as follow: The first part of the paper proposes a natural way to combine several types of knowledge and gives a realization in a Lisp-based object oriented programming environment. The second part describes the prototype of a realized Noise Diagnostic Expert System (being in operation on the 3rd and 4th reactor units of NPP Paks), and the experiences of its development, and testing. Finally the main features of the knowledge aquisition, representation, and validation process, as well as the mechanism of applying knowledge in making diagnoses is discussed.

KNOWLEDGE REPRESENTATION SCHEME

Knowledge and mental processes of a human expert in failure diagnostics of a complex physical system (e.g. a nuclear power plant) serve as paradigms in developing our approach. A human expert who seeks for diagnoses on a complicated physical system never uses a unified complete model of the system. Rather he uses an extremely complex and diverse mixture of knowledge which contains both elements strictly associated with the system under consideration - so-called *domain knowledge* -, and general, multipurpose knowledge, e.g. mathematical, logical rules, physical, chemical, etc. laws - the so-called *meta-knowledge*. A combination of the domain- and meta-knowledge applied to the given state of the several system components can lead to a solution of the given problem. Combination means here the construction of appropriate sequences of applying several items of knowledge, i.e. operating on models, evaluating criteria or applying rules.

Let us see how an expert on nuclear reactor noise diagnostics makes diagnoses: which type of knowledge does he use, and what kind of processes leads him to a diagnosis of any failure in the reactor unit. First of all let us note the trivial thing: no any overall model of a nuclear reactor is available. (This is not trivial for some types of systems, e.g. for purely electronic circuits, where the connections diagram and the electrical specification of the parts constitutes a satisfactory overall model). Instead, that expert can exploit several types of knowledge such as follow:

- He has a good knowledge on the structure of the reactor, he knows all the components and the mode of their connections.
- He uses rules - originated from practical experience of noise measurements - to infer presumed faulty parts from general symptoms (for example: *If* the reduced data of the daily checking measurements of a given MCP vibration signal shows changes, and the vibration amplitude of double rotation frequency of given main coolant pump exceeds the alert limits, *then* the defect of the clutch unit with inside and outside toothing connecting the motor and the pump can be supposed and a detailed vibration analysis is needed (Turi et al., 1988).
- He knows - at least qualitatively - the function of the components, and their behaviour in correct and errorous states.
- He knows (or he can look it up in manuals) parameters which can be set or relations which can be met in a normal operation.
- He knows - at least qualitatively - basic physical laws, for instance the laws of nuclear physics, thermohydraulics, mechanics etc.
- He knows the basic laws of logical inference, or he is rather able to use them intuitively.
- He has experience on the frequencies of occurrence of several faults and he is able to use this knowledge in choosing the most promising alternative in the diagnostic process.
- An experienced diagnostician applies standard procedures, measuring methods and tests to check the operation of system components, and to diagnose the most frequent failures.

These types of knowledge are applied in the diagnostic process without making any effort to unify and integrate them in a total system model, however there is no doubt that the complex of this knowledge constitutes a special comprehensive model of the total system whose purpose is to find diagnoses to symptoms originated from failures.

The diagnostic process realized by the noise diagnostics expert has specific features as follow:

- The diagnostician - after some initial considerations - limits his scope from the total system to its components using some basic rules and the hierarchical structure of the system (the knowledge types mentioned above as the first two items). The objective of this activity is to focus on system components which possess rules and models fittable to the symptoms, and are promising in the respect of finding diagnosis. This activity is made continuously and recursively in the course of the diagnostic process, and *backtracking* is performed if the branch of process which has previously chosen has been found unsuccessful.
- After focusing on a system component several types of knowledge can be used:
 - rules can be applied whose origin is the experience, for example: *If the amplitudes of in-core SPND signals at 1.1 Hz are increased, then undue vibration of one or more control rods can be supposed* (Glöckler et al., 1986.).
 - qualitative models of the system parts operation can be applied, for example a qualitative explanation of the core support barrel (CSB) motion is as follows: if a pendular movement of CSB occurs, then the water gap between the CSB and the reactor pressure vessel (RPV) changes. If the water gap between CSB and RPV varies, then the neutron attenuation varies too, leading to the fluctuation of neutron flux in the biological shield. If the neutron flux fluctuates in the biological shield, then a peak appears in the APSD of the ionisation chamber signal (Thie, 1981).
 - quantitative models of processes in the system, for example the measurement of average coolant velocity in the reactor core using in-core neutron signals (Wach and Kosály, 1974; Albrecht, 1982, etc.) or in-core SPND signals and out-of-core thermopar signals (Sweeney et al., 1985a).
 - qualitative and quantitative meta-models representing physical laws as described previously.

These types of knowledge are used to make decisions on the true or false state of diagnostical assumptions, i.e. the application of this knowledge shows conformity to the rule-based framework where it is used.

- The human diagnostician is intuitively able to perform *jumps* in the diagnostical process: to interrupt the process and to choose a more promising way; to neglect some alternatives in advance; to return to any stage of the process, etc. Heuristics is a very significant factor in a succesful diagnostics.

Our goal is to imitate this process by using machine intelligence in order to obtain an automated diagnostic process which come near to the human one in success .

Our starting point in modelling a very complex and inhomogenous physical system is, that an extremely great amount of knowledge can be gathered of several components - subsystems, parts, elements - of the system due to the great variety of describing methods produced by several disciplines of science and the practical experience. In addition to these, physical elements obey general laws and principles of physics and rules of common mind. However this indefinite conglomerate of models cannot be integrate in a unified large scale model (e.g. a set of differential equations) of the system because of the diversity, redundancy, and lack of knowledge.

The conventional mode of describing the behaviour of a physical object is the construction of quantitative models. These can be input/output type or criterion type models, static or dynamic models, deterministic or stochastic models, etc. By our point of view the most important distinction is the first one:

- input/output type models describe how the object answers the effects of its environment,
- criterion type models define predicates which hold true or false value, for example answer the question whether the system is stable (see Liapunov's criteria for nonlinear system) or observable, controllable etc. (see criteria expressed by Kalman on linear systems).

The input/output models - more precisely their procedural representation on digital computers - are usually unable to make directly decisions on the basis of them, they are rather suitable to compute a specific output value depending on the actual values of inputs. A human user, whose goal is to make decisions, when he uses input/output models, combines these models with some criteria, for instance compares the model output to predefined patterns or measurements. The criterion type models are suitable for direct decision making. Both input/output and criterion type quantitative models can be expressed in digital computers by procedures or procedural programs, and they are usually realized in algorithmic computer languages such as Fortran or Pascal.

Qualitative explanations are used in describing the behaviour of physical objects and systems from time immemorial, and that is usually a qualitative explanation which must precede the quantitative formalization. However the formalization of the qualitative modelling itself has not been happened up to the recent time, and what is more, a qualitative explanation was not appreciated as thing of scientific worth unless a quantitative support reinforced it. Nevertheless the everyday practice proves the excessive worth of qualitative explanations or models, for example the electronic engineers - despite of the availability of several delicate analysis and synthesis methods - apply some very primitive rules and relations in the design of analog circuits (e.g. the basis-emitter

voltage of a Si transistor is 0.7V; when the potential on basis increases, the collector current also increases; a resistor on the emitter results in a negative feedback etc.), and this design method is more effective in the solution of everyday problems than the usage of complicated circuit analysis and synthesis methods.

Another type of knowledge is the so-called *rule based knowledge*. The rule-base associated with any physical object contains production rules of the form

If <condition on assertions> then <fact>

The rules in classical rule based expert systems are expressed on the basis of assertions, which are objects holding true or false values. The facts are the assertions proved to be true, i.e. the assertions which was found in the right side of a rule whose left side was proved to be true. An extensive set of that type rules is suitable to represent a phenomenological description of a system. The physical systems - being usually continuous in state - can only be described very superficially, a more or less exact description requires an extremely great number of rules. The rules of that type are rather suitable to express *rules of thumb*, knowledge originated purely from the practical experience.

A slight modification of the form of rules make them suitable to describe deeper knowledge of a physical system. The new form of the rules:

If <an expression to be evaluated true or false>
then <fact or action>

The left side of the rule consists an expression which hold boolean value. It can be a composite expression containing

- logical expressions of assertions and further boolean type sub- expressions,
- relations forming boolean type expressions,
- arithmetical expressions taking part in relations,
- references to variables representing the state of the system, and functions operating on them, etc.

The right side of the rules can contain - besides the facts - actions which can modify the state of the system. By means of these modifications the rule-base associated with a physical system (or rather a component) becomes suitable to operate on a set of quantitative or qualitative models connected to the system. The operation means both the exploitation of the model outputs or criteria defined on them and the alteration of the system state.

As we have seen there is rule-based and model-based knowledge associated with the system components. The form of the rules allows us to treat qualitative and quantitative models embedded in the rules itself. Therefore the comprehensive model of the system can be a rule base which realizes

- focusing on a given component,
 - sequencing the promising alternatives and backtracking at unsuccessful actions,
- i.e. realizes a diagnostic or a control process similarly as a human diagnostician or operator. The only difference issues in the exploitation of heuristics: human intuition will be replaced by a systematic search process.

The structure of a complex physical system can conveniently be represented in an object oriented programming environment. Class definitions and inheritance offers a very convenient way to define a hierarchical structure of any complexity. The notion of object offers a good means to restrict the scope of the inference process in a well-defined environment thus keeping away from a combinatorical explosion, besides the objects realize protection on data structures encapsulated in them. Contemporary Lisp programming environments - Common Lisp or Scheme - reinforced by an object oriented environment give very good means for realizing our system. Model representation becomes very simple in Lisp because of the mode of procedure representation: procedures can be represented equivalently as data. The hierarchical nature of lexical scoping offers a good basis for the separate treating of subproblems thus reducing the complexity.

The structure of the system is realized using the notion of *object*. In the object-oriented programming environment the objects can be defined as instances of classes. The class definition contains definitions of instance variables, a specification of variable treatment, and an enumeration of component classes. The properties of any given class are composed by the properties defined in the class itself and that ones inherited from the component classes. The values associated with instance-variables can be any Lisp object including procedures or sets of rules as well (fig.1.). Deep models mean sets of variables and procedures (functions) operating on them. The Lisp programming language treats procedures equivalently as data, i.e. a procedure can be assigned as a value to any variable. The procedures can be described as lambda expressions (e.g. the squaring function can be represented as the expression (lambda (x) (* x x))). The rules associated with any given object can be represented as constant lists connected with special object slots.

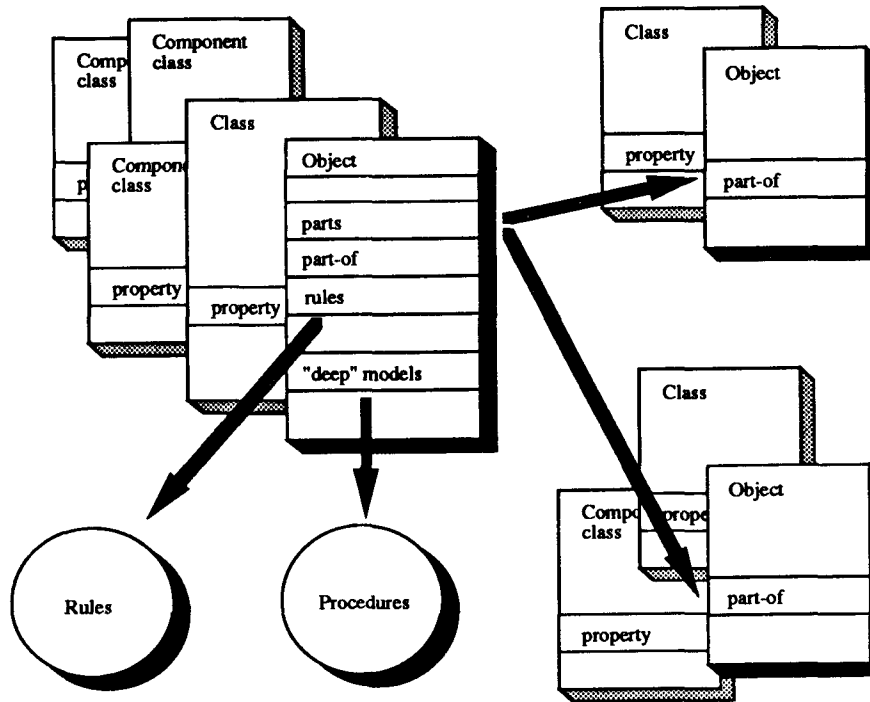


Fig. 1.

The structure of the physical system to be described can be represented as a hierarchical network of components. For instance a *reactor unit* consists of components as the *reactor* itself, and the *coolant loops*, the *reactor* consists of sub-components as the *vessel*, the *head*, the *core*, etc., one of the *coolant loops* consists of the *main coolant pump*, the *hot-leg* and *cold-leg pipes* and *valves*, the *steam-generator*, etc. This hierarchical decomposition can be refined until *atomic* components are encountered or further decomposition is not necessary in respect of the given problem.

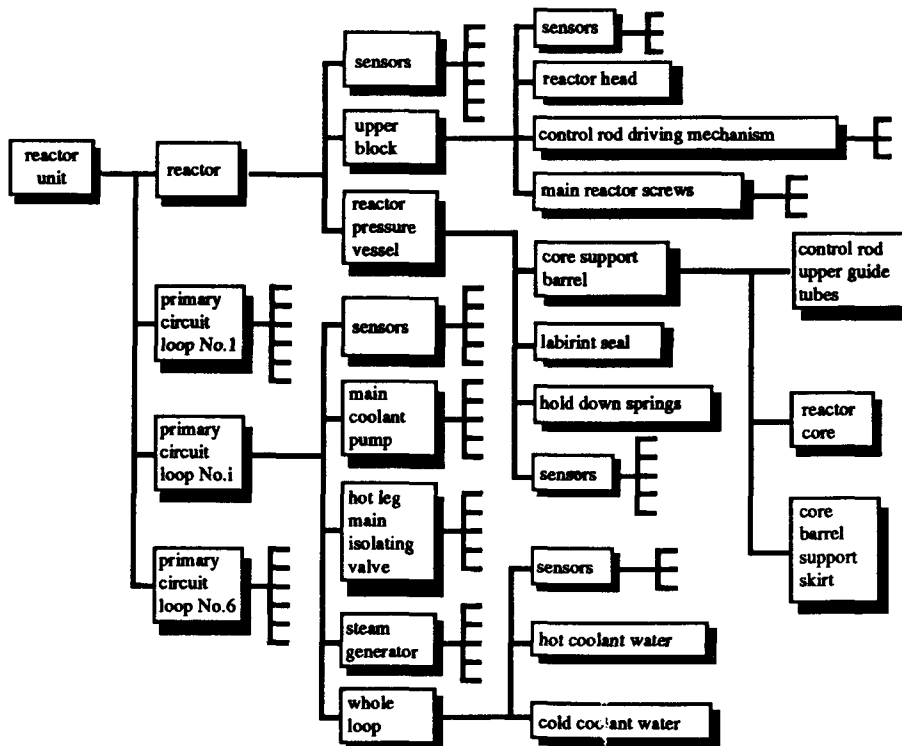


Fig.2.

The purpose of modelling is to make a decision to find a diagnosis, which can be achieved by running an *inference process*, which operates on the sequence of rules. The basic operation in this process is the following:

1. evaluation of the *if*-expression of a given rule
2. if the result is true, then the evaluation of the *then*-expression will be done.

The expressions which can be found on the if and then part of any rule can be very complex ones consisting procedure calls, logical and arithmetical functions, special forms, as well as assertions having no procedural meaning. The handling of assertions requires a modification in the Lisp's evaluation mechanism: a pattern matching to the existing *facts* (also belonging to the given object) will be performed if an assertion is found, and a TRUE boolean value will be associated to it at success, FALSE otherwise. The normal procedure evaluation scheme of the Lisp language serves to activate deep models expressed by object variables and procedures.

The selection of an object in a given stage of the inference process - i.e. focusing on an object, backtracking in the case of unsuccess, etc. - can be organized by rules defined in a global environment. Many algorithms of object selection can be applied, e.g. depth-first or breadth-first movement down on the hierarchy; jump to the object which has been most frequently quoted; jump to the object whose facts have grown, etc. The rule-based approach of organizing this process can combine these algorithms, which results in the flexibility and safety of solving the given problem.

PROTOTYPE OF A NOISE DIAGNOSTIC EXPERT SYSTEM

Hardware connection: The Nuclear Power Plant Paks consists of four operating WWER-440 (PWR) type reactor units, additionally equipped by *standard noise diagnostics surveillance systems* (Valko et al, 1985). For the development, control, and testing of noise diagnostics expert systems under real reactor condition, all random signals of the 3rd and 4th reactor units were transferred into a separate junction via a MUX-FILTER-S&H-A/D unit and connected on-line to the *prototype system*. The sensors used are accelerometers located on the control rod driving mechanisms, the reactor pressure vessel head and on the housing of the main coolant pumps, steam generators and hot leg main valves (altogether 28 detectors/unit); pressure fluctuation sensors located in each loops, at the reactor inlet and outlet and at the pressurizer (14 sensors/unit); ex-core ionization chambers of the safety instrumentation (6 chambers around the core); 3 additional ionization chambers, in-core SPN detectors (6 strings/unit, each consisting of 7 detectors placed at different core high); and 3 core outlet coolant temperature fluctuation sensors. The prototype system under development is able to reach on-line 2x96 noise signals independently, and without disturbing the operation of the standard noise diagnostics systems. The principles and realization outlined above have been applied in the diagnostics of failures in the primary circuit of the pressurized water nuclear reactor units.

The general scheme: A schematic representation of the prototype reactor noise diagnostics expert system is shown on the Fig.3. The main parts of the system are as follow:

- Real-time data acquisition and on-line monitoring system
- Signal processing system containing parts as follow: Supervisor; Identification of parametric models; AR/ARMA spectral estimation; Nonparametric spectral estimation; Signal processing data base;
- Diagnostic expert system

The main features of the system components are outlined as follow.

Real-time data acquisition and on-line monitoring system: the real-time front-end data processor of the overall noise diagnostic system. It ensures reliable acquisition and preprocessing of signals, makes choices on the set of input channels of the analog multiplexer, and through the programmable process interface unit - handles the analog filters and channel amplifiers. It has two operational modes: on-line continuous monitoring; and package acquisition i.e. batch processing mode. In continuous monitoring mode the system performs continuous trend monitoring and limit checking on FFT-based spectral features of signals or set of signals chosen by the expert. In this way low-level anomaly detection methods are realized. In the package acquisition mode the system performs on-line measurements according to the special requirements of the off-line signal processing system, and sends data packages to it for detailed off-line analysis. The real-time data acquisition and on-line monitoring system is realized on a separate computer which is connected to the machine containing the signal processing and diagnostic expert subsystems by an Ethernet network.

Supervisor: a frame-program which

- serves as a suitable environment which makes the development and testing of signal processing strategies - which are expressed in action-plans - possible and
- ensures the safe and efficient execution of these strategies, while coordinating the activities of system

components in time and presenting an interactive user interface.

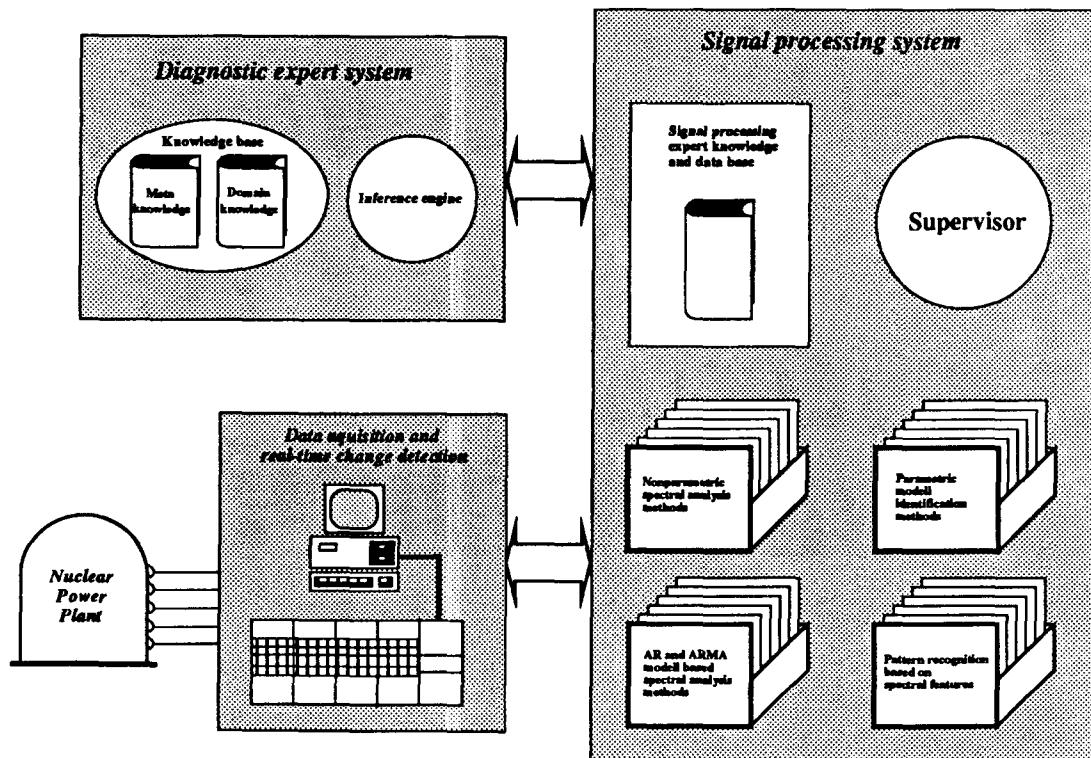


Fig.3.

Identification of parametric models: This subsystem is to identify the AutoRegressive /AR/, AutoRegressive Moving Average /ARMA/, AR with exogenous input /ARX/ and transfer function models for the measured reactor noise processes. These AR, ARX, ARMA etc. models are used in the subsequent parametric spectral analysis and change detection processes. Methods implemented:

- Methods for AR and ARX model identification:
 - Least-squares method
 - Whittle-type recursive in order method
 - Levinson-Wiggins-Robinson type lattice method
- Methods for ARMA and transfer function model identification:
 - Extended Least-squares method
 - Generalized Whittle-method
 - Maximum Likelihood method

AR and ARMA spectral analysis: This system is to provide frequency domain informations based on the identified AR and ARMA models. Basic frequency domain characteristics (features) related to the dynamic properties of the plant or its components are extracted from the computed frequency functions. The following spectral functions are computed for a prespecified frequency range and resolution:

- Spectral density and related functions:
 - APSD
 - CPSD
 - Phase
 - Coherence
 - Cepstrum
- Signal Transmission Path /STP/ analysis:
 - Noise Power Contribution /NPC/ functions (Oguma, 1982)
 - Partial Noise Power Contribution /PNPC/ functions
 - Common Noise Power Contribution /CNPC/ functions (Nagy et al., 1988)
 - Input Noise Power Contribution /INPC/ functions
- Signal Effect /SE/ analysis:
 - Global Signal Effect /GSE/ functions (Veres et al., 1988)
 - Partial Signal Effect /PSE/ functions

Nonparametric spectral analysis: The purpose of the system is to transform the vibration signals of

reactor- and primary loop components to power-density spectrum or frequency functions associated with it. The adequate and robust tool to perform this task is the spectral estimation based on Fast Fourier Transformation (FFT). Several types of windowing techniques enhance the significant characteristics and reject the insignificant ones, therefore the power density functions can be determined using limited number of characteristics, which can efficiently be used in change detection. The spectral reference, which determines the vibration properties belonging to the several states of system operation, is built up of these types of characteristics. The frequency-domain pattern-recognition compares reference to the actual spectrum computed from the measured signals, and gives information about the measure of differences. The methods applied:

- Spectral estimation:
 - periodogram method
 - indirect method
- Windowing methods:
 - Tukey
 - Kaiser
 - Blackman
 - Hamming
 - Bartlett
 - Hann
 - Priestley
- Spectral functions:
 - autospectrum
 - cross-spectrum
 - phase
 - coherence
- Feature extraction:
 - location and neighbourhood of given frequencies
 - location and neighbourhood of extremal values
 - number of crossing alert and alarm levels
 - integral on a given interval
 - number of sign-alterations rated to median
- Pattern recognition:
 - distance measures (discriminants)
 - Euclidean
 - Canberra
 - correlation
 - quadratic
 - Benzecri
 - Minkowski
 - Mahalanobis
 - Piety 1-5

(Piety, 1977; van Niekerk et al., 1988; Fu, 1976; Behringer et al., 1985)

Signal processing data base: the action-plans, the reference functions and features, as well as the results of actual measurements are handled by a data base management system.

Diagnostic expert system: The purpose of this system is to generate diagnoses of nuclear reactor failures, i.e. to determine the faulty components of the system or to give an advise to the operator how to correct them, on the basis of the facts resulted in by the signal processing system and the knowledge base. The diagnostic expert system

- uses production rules as a general conceptual framework of representing domain- and meta-knowledge,
- provides the possibility of modelling the state and the behaviour of the physical system components,
- describes the physical system structure using the object-oriented programming approach,
- applies actions to represent the procedural aspects of making diagnoses,
- uses a forward chaining inference engine to conclude from symptoms (detected using signal processing algorithms) to diagnoses,
- holds the possibility of backward chaining in explanation and hypothesis testing,
- provides the possibility of altering the system objects, modifying and testing knowledge bases by applying symbolic editors and debuggers.

The mode of representing several types of knowledge is realized upon the principles discussed above by using an object oriented Lisp-based general purpose expert system shell. This shell provides methods for rule- and model-based knowledge representation and several types of inference engines.

DESCRIPTION OF THE PROCEDURE OF DIAGNOSTICS

The main purpose of noise diagnostics or vibration monitoring of reactor units is to discover deficiencies or malfunctions of systems and equipments, the further observation of the development of anomalies, the judgment of their severity and making decisions about plant operation. The monitoring of time and event dependent vibrational characteristics of mechanical components is the basis of the failure and malfunction detection. The detection of deviations of features of actually measured signals (or group of signals) from reference values is the first step of monitoring procedure. The statistical discriminants for determination of changes in the local characteristics of APSDs and some global characteristics are used for diagnostical purposes. Using feature extraction and data reduction - based on exact interpretation of spectral characteristics -, the results obtained from pattern recognition gives a powerful input for diagnostics, for analysis the reason of undue deviation. The *domain specific knowledge* of noise diagnostics concerning to passive and active components (van Niekerk et al., 1988) on the one hand involves:

- the set of symptoms and/or syndromes of concrete failures, mechanical degradations or anomalies of systems and equipments and their time behaviour (materials of SMORN and IMORN conferences give a lot of examples),
- information about the essential eigenfrequencies and modes of vibration of systems and components, complete

- understanding of various spectral functions (Bastl et al., 1985),
- their changes in normal operational stage without the occurrence of damage to the component using idea of *tolerable (allowable) frequency deviation* defined by Wehling and Warnemünde (Wehling et al., 1988),
 - the set of main characteristics of frequency functions and its *normal* changes due to the system parameter (reactor power, coolant temperature/pressure etc.) changes (Wehling et al., 1985),
 - the set of alert and alarm limits of frequency functions, characteristics, features and their changes (Bastl 1985),
 - the effects of slow changes due to fuel burn up, solute boron concentration changes, material fatigue, etc. processes (Türkcan, 1982, Sweeney et al., 1985b)
- and concerning to the process anomalies and distinct physical phenomena on the other hand such as:
- subcooled boiling in the reactor core (Bernard et al., 1982; Pór et al., 1988)
 - coolant flow velocity (Kostic et al., 1988; Sweeney et al 1985a; Kosály et al., 1982)
- It is very important to know the influence of operational changes on the vibrational behavior of selected primary components to avoid the false alarms.

The information, the data and the special knowledge of reactor diagnostics have to be well structured according to the hierarchy of objects. All objects have a set of phenomena (failures, deviations from the normal stage, degradation or damage of components as well as simple physical phenomena, etc), which monitoring and examination is needed. All phenomena have one or more rules, set of rules or *deep* models (see Fig. 4.).

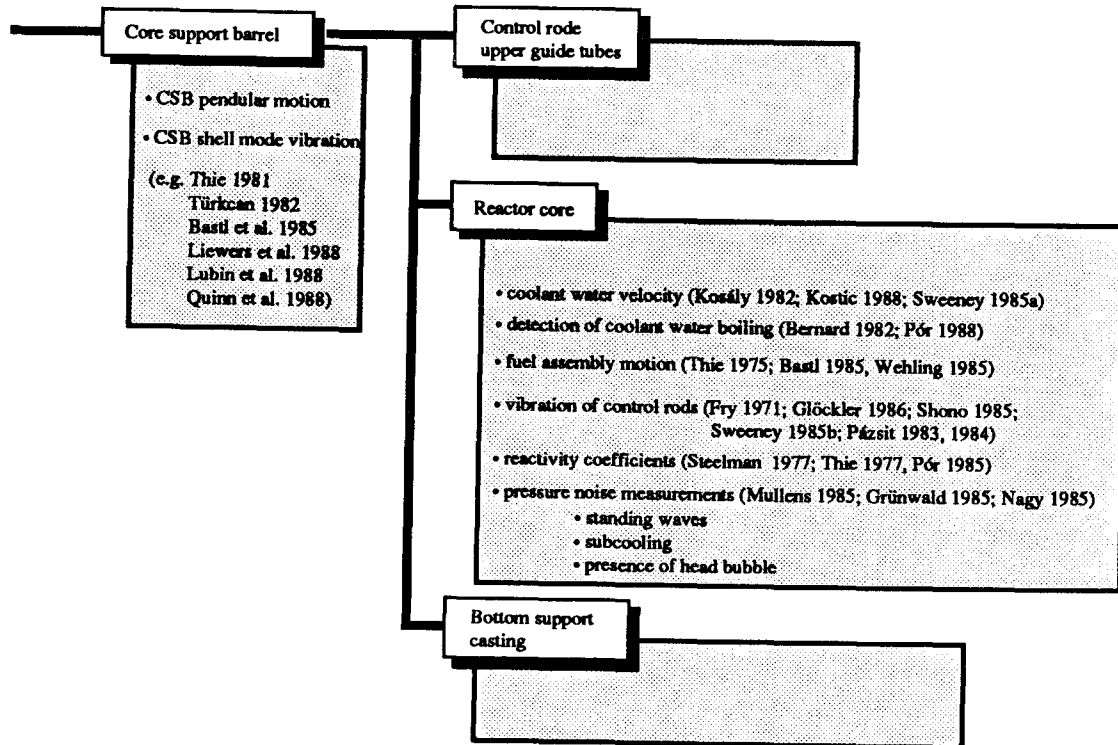


Fig.4.

The rules are created practically in such manner, that the failures could be identify on the strength of symptoms on syndromes. The frequency of examination of phenomena are defined by the probability of occurrence and/or severity of consequences as well as velocity of failure evaluation. The order and frequency of measurements aiming special examinations arranged and settled by noise diagnostics expert in the schedule of signal processing system. All measurements are made under the control of this system on the basis of action plans orientated to the phenomena. Examinations of phenomena realized by execution one or more action plans. The action plan is a sequence of activities, which define conditions of measurements of time signal (sample time, filter selection, number of samples) methods of preliminary analysis of time signals (trendelimination, normalization etc) methods

of structure and parameter estimation of parametric models, conditions of parametric spectral analysis (frequency limits, resolution etc), conditions of STP and Signal Effect analysis, methods and conditions of nonparametric spectral analysis (periodogram or indirect method, frequency limits etc) feature extraction of parametric and nonparametric APSD functions and the method of statistical distance measures for detection of deviations from reference.

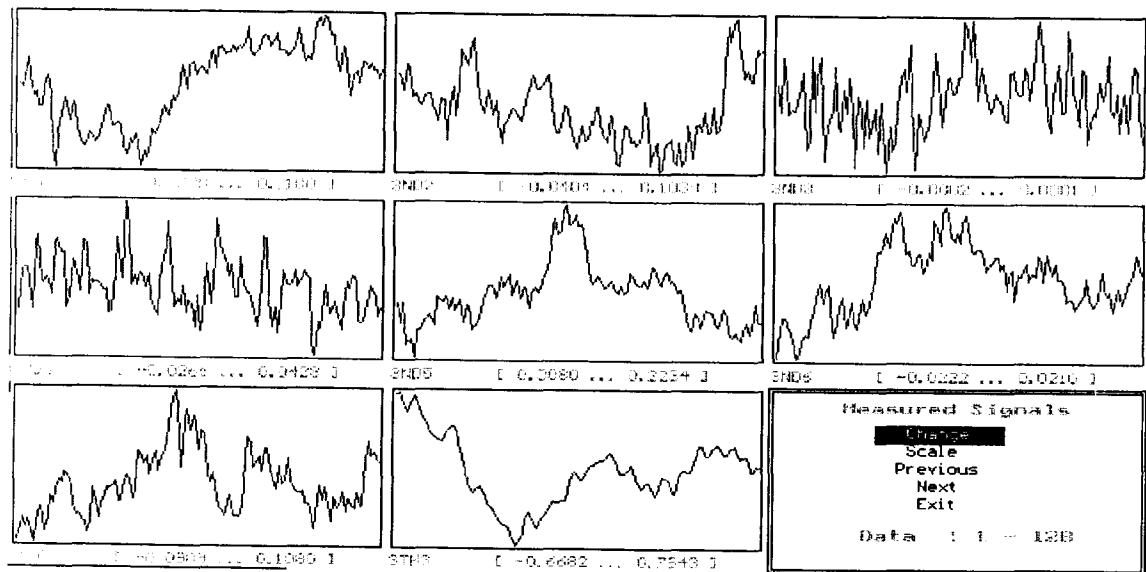


Fig. 5.

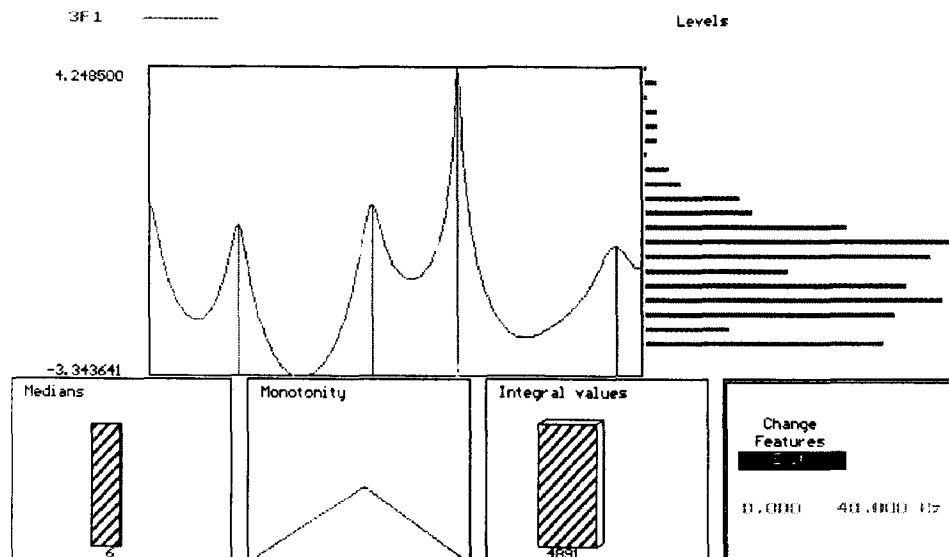


Fig. 6.

The results of actions:

- single or multivariate time series and its transformed form (Fig.5.),
- single or multivariate parametric models,
- spectral functions of parametric spectral analysis: APSDs, CPSDs, phases, coherences, NPCs, partial coherences, PNPCs, global- and partial signal effect functions,
- spectral function of nonparametric spectral analysis: APSDs, CPSDs, phases, coherences,

- results of feature extraction: global and local characteristics of APSDs (Fig. 6.),
- results of pattern recognitions: deviations of features and characteristics of actually measured APSDs from reference values.

The above results are stored in a temporary file, after all actions, and from it the expert diagnostics subsystem sorts out the necessary for the diagnoses characteristics of deviations from the reference, which create symptoms or syndromes of phenomena. The examination always concerns to the control condition of an object which could have more possible failures or phenomena. For the sake of the evaluation of rules concerning to the certain failures (phenomena) the diagnostics expert subsystem generates facts from above results and using them begins its work. Evaluation of rules may result:

- calling of a "deep" model (subroutine with a procedural calculation),
- start a new action, or
- call a human expert to make a detailed analysis supplementing the knowledge base.

SUMMARY

The presented reactor noise diagnostics expert system is under development. The prototype system is in operation on the 3rd and 4th reactor unit of NPP Paks, having on-line connection with the noise sensors of standard noise diagnostics systems through a signal conditioning equipment unit. Some shortcomings make more difficult creating the knowledge base:

- there is not gathered, completed and systematized the diagnostical methods and knowledge for WWER type reactors,
- the complete interpretation of APSDs of measured noise signals is lacked
- the sets of tolerable deviations of actual signal characteristics from references are not complete.
- the alert and alarm limits concerning to the main features and characteristics of spectral functions exist only partly.

The authors plan to reduce some parts of above shortcomings in the near future by means of regular purposeful measurements and trend analysis. But the continuation and success of R&D works aiming the complete understanding of spectral functions they could only expect, as it is determined the level of knowledge and ability of expert system developed by them.

ACKNOWLEDGEMENT

The authors are indebted to Prof. L. Keviczky for his advices, discussions and encouragement, to Mr. J. Szabó, deputy gen. director of NPP Paks for his support, to Ms. M. Tanyi, Mr. P. Gáspár, and Mr. A. Edelmayer for their help and joint R&D work with the authors.

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THE USE OF NOISE ANALYSIS TO DETECT BUBBLES' APPEARANCE
INTO THE PRESSURE TRANSMITTER SENSING LINE

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ABSTRACT

Autoregressive analysis of stationary noise from pressure sensors can be performed on-line and are useful tools for its surveillance and maintenance. Moreover, it doesn't perturbate the operation of the plant.

The aim of this paper is to detect and quantify bubbles appearance in the sensing line of a pressure sensor through noise analysis in the time domain. Pressure noise has been simulated for a capacitive pressure sensor and its line using different void fraction values. Autoregressive analysis of these noises reproduce the initial values of void fractions and sound speed in the line.

Pressure noise analysis in the time domain can be effectively used to monitoring the appearance of bubbles in the detector sensing line.

1. INTRODUCTION.

Sensors are the eyes of the nuclear reactors lying in a rather adverse environment. Their surveillance is considered as important from several points of view: Nuclear Safety, Plant Availability and, recently, sensors degradation matters in Life Management too.

The analysis of stationary noise from pressure sensors do not perturbate the operation of the plant and it can be performed on-line. Usually, the surveillance to degradation is being made measuring the sensor response time by means of autoregressive methods. The procedure is accurate enough when hypothesis it lays on are fully accomplished: linear noise, white driving noise. It has been also proven as helpful quantifying sensing line degradation and sensor calibration [1].

Malfunctions in the sensing line arise mainly from: air bubbles, blockages by sludge or boron or leakages in the line, leading to calibration errors.

The aim of the present work is to show how the on-line stationary noise analysis, both AR and ARMA, in the time domain may detect the appearance of bubbles in the sensing line of a capacitive pressure sensor (Validyne type).

The methodology used for this development is as follows: the physical system fluid-line-sensor was simulated by an electrical network, characterized by a transfer function depending on the physical para-

meters, void fraction (α) and sound speed in the line. Artificial pressure noises were generated for different values of the void fraction, using the state variable method [2] for the derived transfer function. Later AR and ARMA analysis of the noises should return the initial values of α for each one.

Using the AR analysis is possible to obtain the void fraction in the line through a criterium based in the distance between two frequency peaks in the PSD, corresponding to the sensor and sensing line.

The ARMA analysis, without knowledge on the PSD and taking advantage from the fact that the dynamical system is known, may determine some line characteristics as its capacitance or sound speed in it.

2. SYSTEM TRANSFER FUNCTION IN PRESENCE OF BUBBLES.

The system fluid-line-sensor can be simulated as an equivalent electrical circuit as [4] in Figure 1:

being

- P_0 = pressure on the diaphragm
- P_i = pressure outside the line
- R^i = resistance of the line = $\rho Fl/A$
- L = inductance of the line = $\rho l/A$
- C_d = sensor capacitance = diaphragm stiffness = Ax_d/P_0
- C_l = line capacitance = $Al/\rho c^2$

and

- A = sensing line cross section area
- x_d = fluid displacement
- F = friction coefficient between fluid and line wall
- ρ = fluid density
- c = speed of sound in the fluid

The transfer function in the Laplace domain is:

$$H(s) = \frac{P_0}{P_i} = \frac{1}{\left[\frac{LC_d}{2} s^2 + \frac{RC_d}{2} s \right] \left[1 + LC_1 s^2 + RC_1 s + \frac{C_1}{C_d} \right] + \frac{LC_d}{2} s^2 + \frac{RC_d}{2} s + 1} \quad (1)$$

which may be converted using:

$$\omega_d^2 = \text{detector frequency} = 1/LC_d$$

$$\omega_1^2 = \text{line frequency} = 2/LC_{1R}$$

$$\xi = \text{damping constant} = \frac{\sqrt{C_d/L}}{2}$$

$$H(s) = \frac{\omega_d^2 \omega_1^2}{s^4 + 4\omega_d \xi s^3 + (\omega_d^2 + \omega_1^2 + 4\omega_d^2 \xi^2) s^2 + (2\omega_d \xi \omega_1^2 + 2\omega \xi \omega_d^2) s + \omega_d^2 \omega_1^2} \quad (2)$$

Everyone of the physical properties in the line may be affected by the appearance of the bubbles. Two-phases fluid density becomes:

$$\rho = \rho_L (1 - \alpha) \quad (3)$$

where ρ_L is the liquid phase density.

The line capacitance, through the sound speed, is highly sensitive to the void fraction. The relationship between c and α is not linear because the former depends on bubble position that is not known in advance [3]. Using the approximation to a "separated phases" model for the fluid and bubbles in the line, an expression for the sound speed may be derived:

$$\frac{1}{c^2} = \frac{(1-\alpha)^2}{v_L^2} + \frac{\alpha^2}{v_G^2} + \frac{2\alpha(1-\alpha)}{v_L v_G} \quad (4)$$

where v_L and v_G are the velocity of sound in liquid and gas phases respectively. The physical effect of bubbles is a drastic reduction of c , because the two-phase medium is more compressible (because of gas) and still dense (liquid), so C_1 have to grow sensitively.

According to expressions (3) and (4), the line capacitance becomes:

$$C_1 = A.1 \left[\frac{1-\alpha}{\rho_L v_L^2} + \frac{\alpha^2}{\rho_L (1-\alpha) v_G^2} + \frac{2\alpha}{\rho_L v_L v_G} \right] \quad (5)$$

Because of the appearance of bubbles, the normalized distance between the line and detector frequencies should change and so, we define the following parameter depending on the void fraction:

$$\frac{D}{D_0} = \frac{\omega_1 - \omega_d}{(\omega_1 - \omega_d)_{\alpha=0}} \quad (6)$$

Values for this relationship (column 2 in Table 1 and Figure 2) have been found in the case of a capacitive pressure sensor (Validyne), with the following features taken from literature [4]:

$$l = 5 \text{ m}$$

$$A = 18.9 \times 10^{-6} \text{ m}^2$$

$$C_d = 0.83 \times 10^{-12} \text{ m}^3 \text{ Pa}^{-1}$$

$$\rho = 1000 \text{ Kg cm}^{-3}$$

$$R = 0.5 \times 10^{10} \text{ Kg m}^{-4}$$

which can be fitted as:

$$D/D_0 = 0.993 - 2.413 \alpha$$

showing as the peaks get closer when α grows.

Also in Table 1 we show the frequencies ($f = \omega/2\pi$) for the line and the detector, sound speed in the line and an integrated parameter useful for the future ARMA analysis, as a function of void fraction.

α	D/D_0	f_l	f_d	c	$c/\sqrt{1-\alpha}$
0.00	1.00	64.63	33.94	1435.0	1435.0
0.01	0.97	63.99	34.11	1420.7	1413.6
0.02	0.95	63.36	34.29	1406.7	1392.6
0.03	0.92	62.74	34.46	1393.0	1372.0
0.04	0.90	62.13	34.64	1379.6	1351.7
0.05	0.87	61.54	34.83	1366.4	1331.8
0.06	0.85	60.96	35.01	1353.5	1312.2
0.07	0.82	60.39	35.20	1340.8	1293.0
0.08	0.80	59.82	35.39	1328.3	1274.1
0.09	0.77	59.27	35.58	1316.1	1255.4
0.10	0.75	58.73	35.78	1304.0	1237.1
0.11	0.72	58.20	35.98	1292.3	1219.1
0.12	0.70	57.68	36.18	1280.7	1201.4
0.13	0.68	57.17	36.39	1269.3	1183.9
0.14	0.65	56.66	36.60	1258.1	1166.7
0.15	0.63	56.17	36.82	1247.1	1149.8
0.16	0.61	55.68	37.04	1236.4	1133.1
0.17	0.58	55.21	37.26	1225.7	1116.7
0.18	0.56	54.74	37.48	1215.3	1100.5
0.19	0.54	54.28	37.72	1205.1	1084.6
0.20	0.52	53.82	37.95	1195.0	1068.8

Table 1 - Distance criterium, frequencies for line and detector and sound speed for a Validyne type sensor (see text).

3. NOISE SIMULATION

Using equation (2) and the validyne system features, a set of simulated noises varying the void fraction from 0.0 to 0.20 at intervals of 0.05, have been generated.

State variable method was used to simulate the noise, sampled at 5 ms. Figures 3 and 4 show two extreme cases, $\alpha=0.0$ and $\alpha=0.20$.

4. AR ANALYSIS.

Noises generated in the previous chapter have been analyzed by means of an AR fitting method. The objective was to determine the optimum AR order (using the Akaike criterium) for each noise and the corresponding AR parameters. System poles and frequencies may be derived from these parameters as well as from the PSD.

Optimum order for noise with $\alpha=0.0$ was 11, descending to 7 for $\alpha=0.20$. Derived frequencies and D/D_0 parameter may be seen in Table 2, all of them obtained using the optimum order for $\alpha=0$.

Relationship between D/D_0 and α values is represented as dots in Figure 2. So, through the AR analysis of the noise coming from that system, a value for the void fraction in the sensing line may be derived:

$$\alpha = \frac{1}{2.4} (0.990 - D/D_0) \quad (7)$$

The PSD built up from the AR parameters provides two broad peaks, corresponding at sensor and line. As Figure 5 shows, both peaks get closer when α grows.

Errors in determining α through the whole process arise mainly from two sources: not to use the proper optimum AR order for each α [1] (estimated nearly as $\alpha/6$ by simulation) and the accurate peak position determination (nearly 0.01, depending on the frequency resolution). Both errors provide a value for $\Delta\alpha$ ranging from 0.01 for $\alpha=0$ to 0.04 for $\alpha=0.20$.

α	f_1	f_d	D/D_0
0.00	64.07	33.87	1.
0.05	60.11	34.43	0.85
0.10	58.31	35.60	0.75
0.15	55.93	36.40	0.65
0.20	52.62	37.42	0.50

Table 2 - Results for the AR analysis of noise.

5. ARMA ANALYSIS.

Fitting the pressure noise, the optimum AR order is found to be high and, although it provides an accurate enough value for the void fraction, it does not make use the fact that the system transfer function is known. Direct control on other physical features of the system may be gained using the Dynamic Data System and an ARMA (p,q) analysis.

For our purposes, equation (1) may be written as:

$$H(s) = \frac{P}{s^4 - s^3 \Sigma + s^2 B - sT + P}$$

This equation has four poles; so we may fit the generated noises by an ARMA (4,q), adjusting q for to get the best fit. After that, we shall have the poles: p_1 , p_1^* , p_2 and p_2^* , in such a way that:

$$\Sigma = -(p_1 + p_1^* + p_2 + p_2^*)$$

$$B = \text{sum of binary products of poles}$$

$$T = \text{sum of ternary products of poles}$$

$$P = p_1 p_1^* p_2 p_2^*$$

Identifying terms with (1), and combining equations, we shall have finally:

$$B = (2P)^{1/2} \left(\frac{C_d}{C_1} \right)^{1/2} + \frac{(2P)^{1/2}}{2} \left(\frac{C_1}{C_d} \right)^{1/2} + \frac{\Sigma^2}{4}$$

a non-linear equation which can be solved obtaining a value for the capacitance of the line:

$$x = \frac{2C_d}{C_1} = \frac{2C_d c^2 (1-\alpha)}{l^2} L(\alpha=0)$$

or

$$c\sqrt{1-\alpha} = l \sqrt{\frac{x}{2C_d L(\alpha=0)}} \quad (8)$$

Using this equation (8) and the column 7 from Table 1, a value for α may be determined as well.

The optimum ARMA order found for the simulated noises was (4,3). The analysis provides the results in Table 3, where the last column is the void fraction derived from equation (8).

α	f_d	f_1	C_1/C_d	c	α_a
0.	33.86	66.02	0.554	1452	-0.025
0.05	34.67	62.33	0.642	1380	0.040
0.10	35.60	59.23	0.739	1320	0.099
0.15	36.57	56.48	0.853	1261	0.148
0.20	37.70	54.01	0.963	1200	0.191

Table 3 - Results for the ARMA analysis.

6. CONCLUDING REMARKS.

On-line pressure noise analysis may be used for detecting changes in the sensor and sensing line system. Air bubbles affect the line physical characteristics, mainly its capacitance, leading to an indetermination in the response time. Autoregressive analysis of noise may help in detecting and quantifying bubbles appearance.

The proposed modelization for a Validyne type pressure sensor, together with the AR and ARMA analysis of the stationary noise from a capacitive sensor, may be used for controlling the presence of bubbles in the sensing line, through the surveillance of both the sensor and line peaks in the PSD of the noise or the sensing line capacitance.

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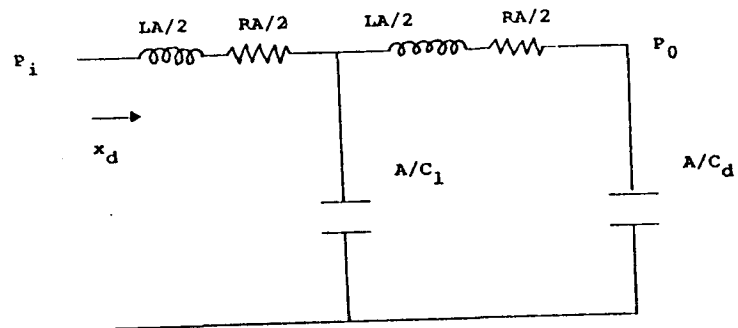


Figura 1 - Equivalent Electric Circuit.

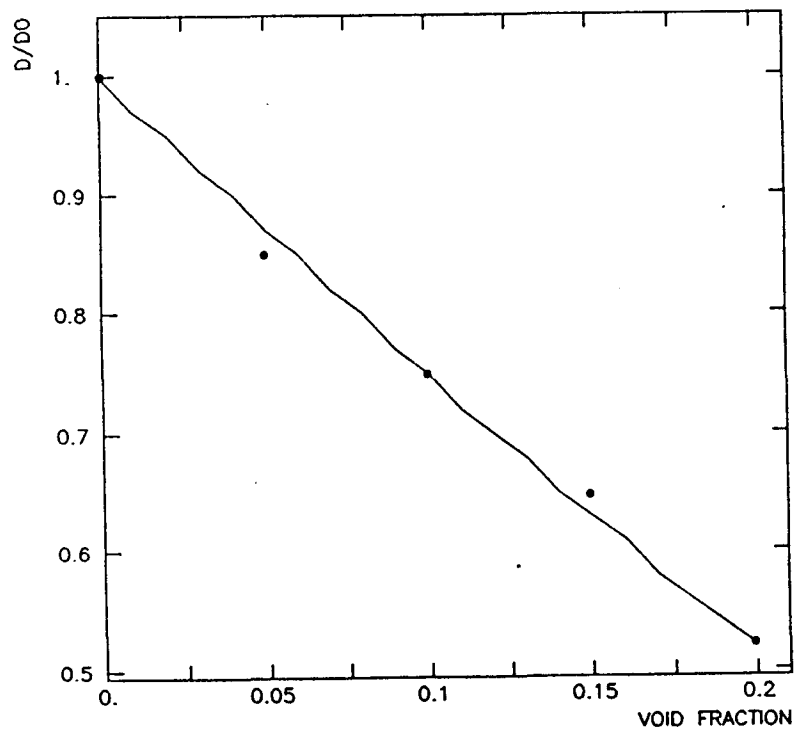
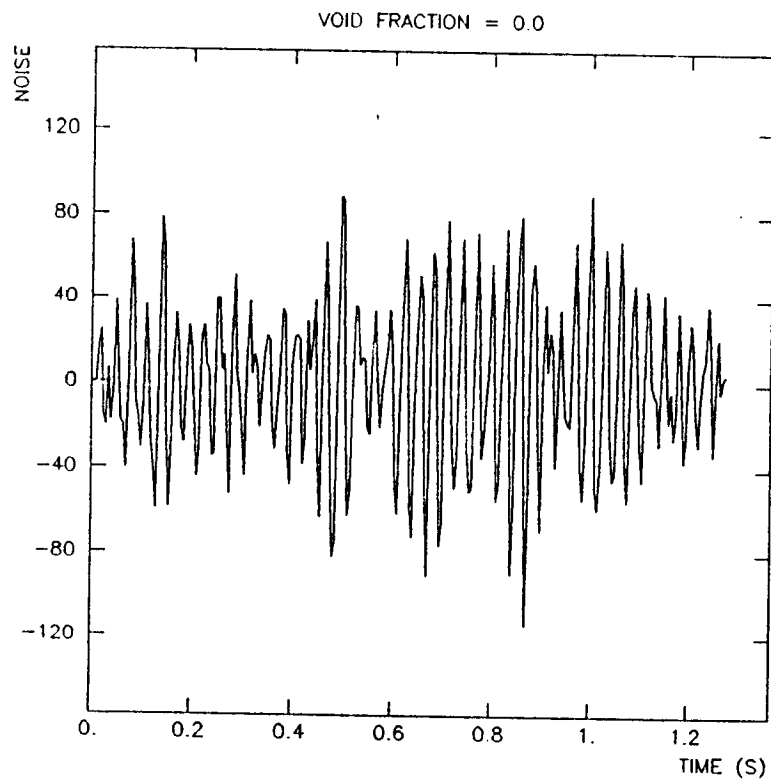
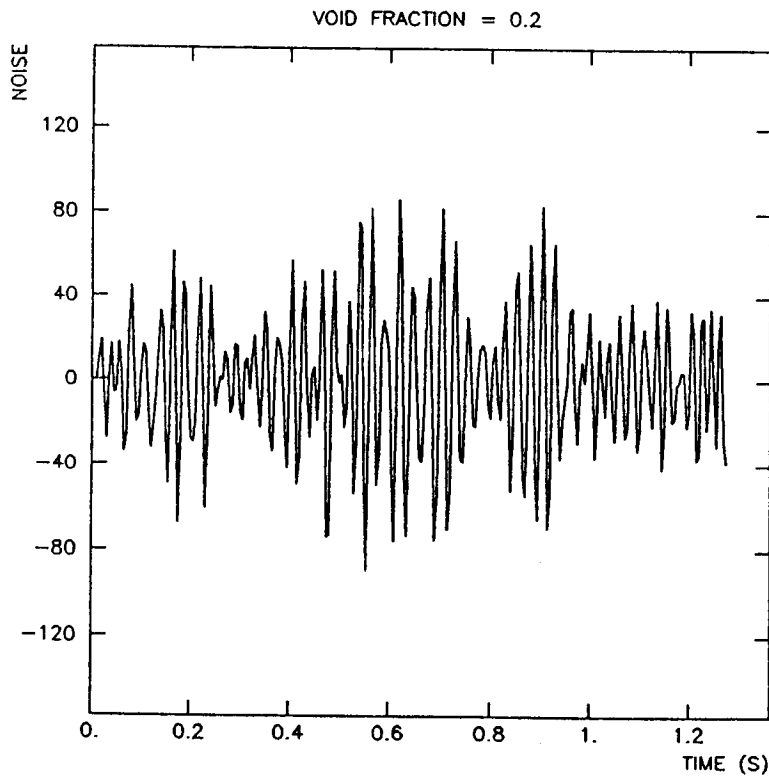


Figure 2 - Normalized peaks distance as a function of Alfa.
(Line = Theoretical dots = From ar noise analysis).



Figures 3 and 4 - Generated noises por Alfa = 0 (up) and 0.2 (down).



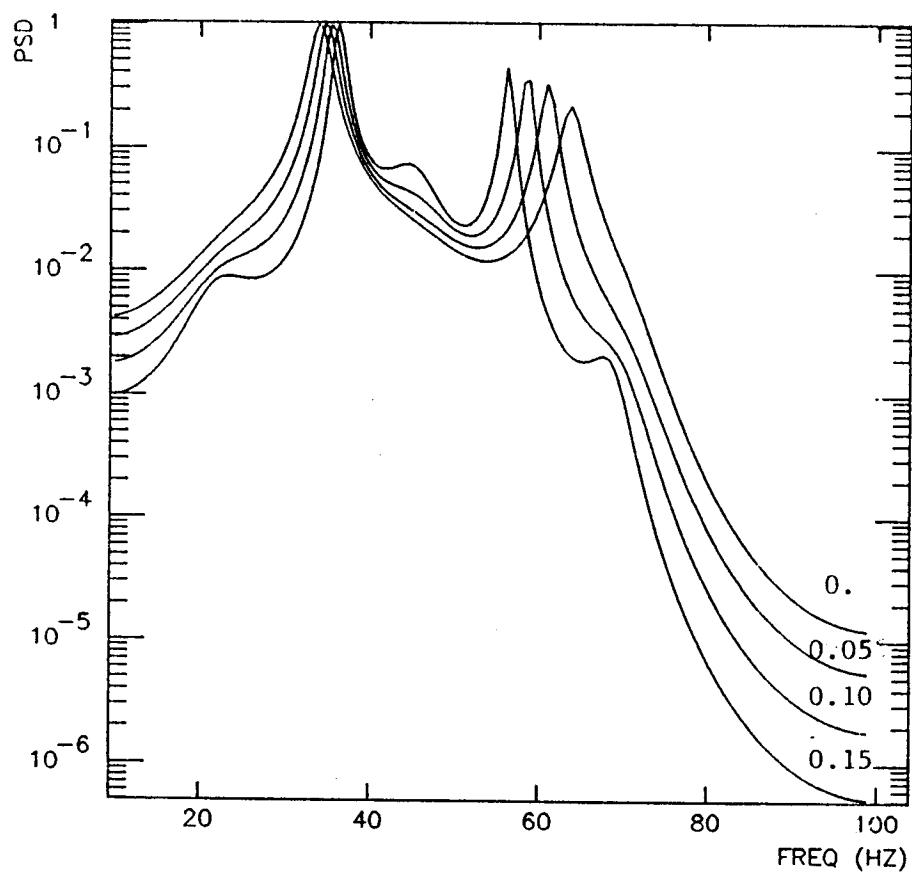


Figure 5 - Power spectral density plots for different void fractions.

CONCEPTIONS AND APPLICATIONS OF DIFFERENT METHODS FOR THE ON-LINE IDENTIFICATION OF SENSOR AND PROCESS FAULTS IN REAL TIME *

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ABSTRACT

Fault detection in power plants or other technical facilities by monitoring the time behavior of measurement signals can be performed by different methods. The selection of an appropriate method depends on the faults' characteristics. This paper describes a three level conception for the on-line identification of faults in real time. Since at each level a specific technique is used, the distinction between sensor and process faults is possible. While the methods of the first level are well established, a computer program concerning the second level has been derived by GRS. This program is designed for the detection of abrupt changes in measurement signals and is called IFDI-module (IFDI: Instrumental Fault Detection and Identification). It was tested on-line on the LOBI-MOD2 facility in the Euratom Research Center in Ispra, Italy. In respect to the third level a new technique for the detection of small drifts in physical conservation quantities is presented. Aspects of combining these techniques, of their application and their hardware implementation are discussed.

INTRODUCTION

The aim of initiating the project described in this paper four years ago at GRS was the test of existing methods of signal validation and their improvement or development of new techniques if needed respectively. The background of the project was the fact that signal validation had been recognized more and more as a necessary safeguard between plant sensors and computer based information systems for the interpretation and condensation of the huge amount of sensor data. The output of these information systems depends strongly on the accuracy of the incoming primary data: Faulty primary data will lead to faulty output conclusions which may never be detected. The aim of signal validation is therefore the detection of changes in the signal's magnitude or behavior, which do not originate from the normal dynamics of the plant.

But there is a catch: Such changes can be caused by two reasons: First, the sensor or the electronics which belongs to it has failed, hereafter called a *sensor fault*, or second, the component where the sensor is located is in an abnormal state, hereafter named as *process fault*. The distinction between

* Research sponsored by the F.R.G. Ministerium für Forschung und Technologie under contract No. RS 711A

the two types of faults cannot be performed by the fault identification algorithms alone; additional knowledge about the component considered is needed. An example will clarify the situation: a measurement signal which represents the level of a vessel can change because of a (eg. temperature) drift in the measuring device or as a consequence of a small leak in this tank. Therefore it will not be possible to design a system which validates measurement signals and ignores abnormal plant behavior.

Two consequences follow from this fact: First, as much information as possible has to be generated with the help of different algorithms of fault detection to facilitate a diagnosis. Second, other techniques than algorithmical have to be applied to include additional knowledge concerning the structure and the dynamic behavior of the system to be monitored. This paper reports activities and results obtained related to the first point. The problem of fault diagnosis using AI-techniques is at the moment being researched and developed in the GRS.

A THREE LEVEL CONCEPTION FOR FAULT DETECTION

To avoid the distinction between sensor and process faults, which is not possible without additional knowledge as discussed above, it is more appropriate from the algorithmical point of view to consider the fault's time constant. Therefore in the subsequent paper faults in measurement signals will be classified as abrupt changes or slow varying drifts. Depending on the time constant different principles must be used for fault detection and identification.

An on-line system for fault detection in signals which are scanned with a fixed rate (of about 1 s for analogous signals in German nuclear power plants) has to decide very rapidly on the correctness of the data to prevent a time delay in the diagnosis. Thus the main demand on on-line fault detection is to work in real time. Therefore special algorithms are required as well as hardware which is suited for fast processing. First the algorithmical aspect will be discussed.

For the reliable detection of faults during steady state and dynamic plant operation conditions as much information as possible is needed. This information can be gained from different levels of knowledge, the *signal level*, the *process level* and the *system level*. To obtain information from the signal level, it is appropriate to use methods which evaluate the hardware redundant signals. The second level is hereafter called process level, where a process is defined as an object in which variables of different kinds interact and produce observable signals, like vessels or heat exchangers. GRS has derived a program using different modified techniques of analytical redundancy to monitor this level. The third level takes a whole system into account, where a system consists of several processes, i.e. the primary or the secondary loop of a PWR. In this case other techniques should be applied, one new method using Petri nets has been derived by the GRS.

THE SIGNAL LEVEL

The signal level is the area of hardware redundant measurement signals. Two or more signals representing the same physical quantity are compared to each other and small deviations between the signals can be easily determined. The algorithms belonging to this signal level are appropriate to the identification of faults of any time constant and do not need additional procedural knowledge. They are well established and need not be discussed in detail. By checking the hardware redundancies only sensor faults can be identified. Keeping this fact in mind the subsequent diagnosis of the faults' origin can be simplified.

The same techniques can be used for monitoring signals which are related by non temporal models, like temperature and pressure in a saturated steam. Non temporal models describe the relationship between dependent and independent variables with algebraic or transcendental equations but not by

differential equations. With the help of the non temporal model one quantity can be transformed into the other and, as the result, two signals representing the same physical quantity can be compared. Unlike the case of hardware redundant signals the cause of a fault can be an outage of a sensor or abnormal plant behavior, eg. the steam is no longer in a saturated state.

From this it can be concluded, that as soon as procedural knowledge is used for the monitoring of measurement signals, a clear distinction between sensor and process faults is no longer possible: The measurement signal or the procedural knowledge, describing the normal state of the plant, can be wrong. This conclusion holds also for the methods of the second and third level.

THE PROCESS LEVEL AND THE IFDI-MODULE

In the process level signals representing different physical quantities are processed which belong to the same component (i.e. a vessel or a steam generator). The relationship between these signals is described in an analytical way by a physical model and in this way an *analytical redundancy* is generated. Several methods of the modern control theory are available to interpret the physical model. They are well suited for detecting abrupt changes in measurement signals. For signal validation in the process level a computer program, called IFDI-module, has been developed at the GRS [1].

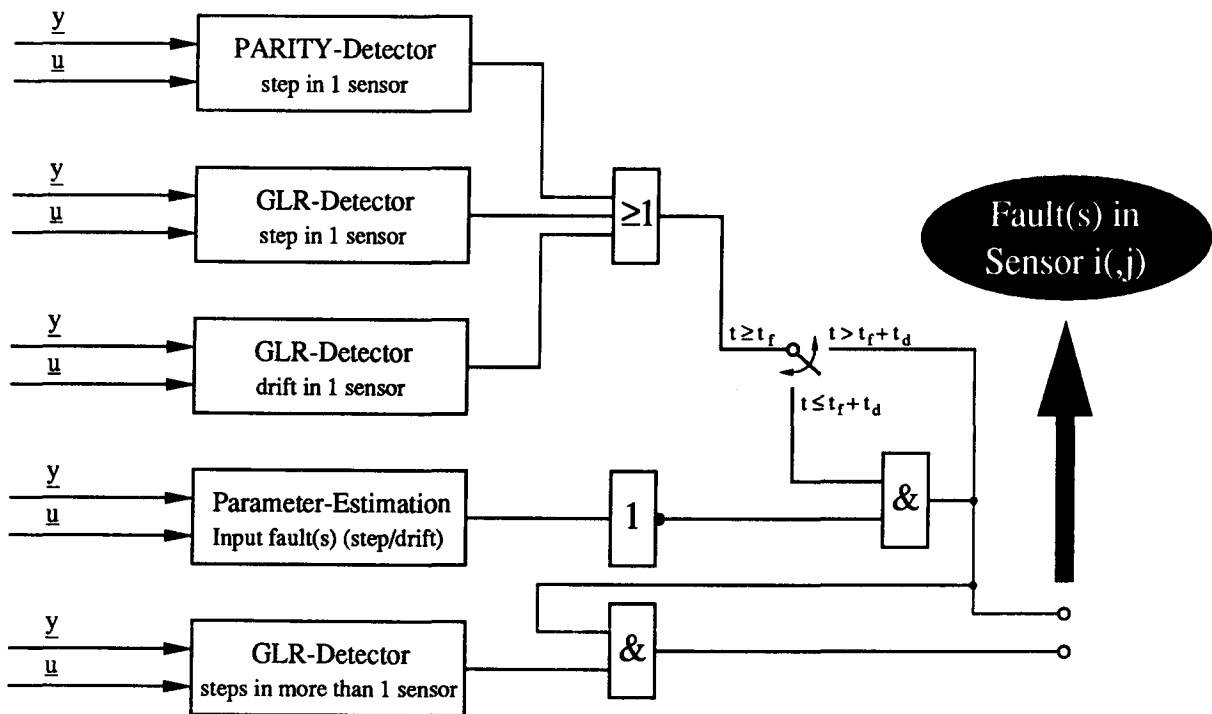


Fig. 1: The IFDI-module, a program for the on-line detection of abrupt changes in measurement signals

The IFDI module, shown in Fig. 1, is based on different methods of analytical redundancy. On the left side of Fig. 1, each of the five boxes represent a special fault detection algorithm. Three basic techniques are used, the (temporal) Parity Space algorithm, the Generalized Likelihood Ratio (GLR) method and a Least Squares Parameter Estimation technique. All these algorithms had to be modified

with respect to an on-line, real time application in the F.R.G. plants. Details of the modifications as well as the algorithm's basic properties need not be discussed in the subsequent paper, they can be found in [2].

The five boxes in Fig. 1 are named detectors. A detector is defined hereafter as a software unit which transforms the whole actual input (marked as a vector $\underline{u}$) and output ($\underline{y}$) information into a logical signal. But $\underline{u}$ means the input vector of the state space model which generates the analytical redundancy, not the input of the module. Vector $\underline{y}$, the measurement or output vector of the model, represents these quantities which can be validated by the methods discussed. The logical signal laying on the detector's outlet should be 'false' in the nofail case and should take the state 'true' if an error has occurred. The scanning rate of the detector's input and output signals is identical, so that the logical output message of the IFDI module will be actualized with the same frequency.

The task of the first three detectors in Fig. 1 is the detection of single sensor faults in the $\underline{y}$ -signals. To increase the sensitivity of the whole IFDI-module the outputs of these detectors are coupled by an OR-gain and thus an alarm can be given if one of these detectors identifies a fault. Assuming that a single sensor fault is detected at the time t_f by at least one of these detectors the output of the OR-gain will be 'true' and after t_d time steps at the time $t = t_f + t_d$ the IFDI-module will sound an alarm. The reason for the time delay is the following: A fault in one input signal (one component of $\underline{u}$) can falsify one or more theoretically generated output quantities of the model. Thus one of the first three detectors can indicate a fault, because there is now a difference between the measured and the calculated output values. This means, that a separate detection of faulty input signals is needed. This is realized in the fourth detector and such a fail alarm can be avoided. This input fault detector is based on a modified parameter estimation technique and its time behavior is different from the behavior of the other detectors. Thus a time delay of t_d time steps is at the input error detector's disposal to test if an input fault has occurred. In this case the outlet of the NOR-gain will become 'false' and no alarm can be given at the module's outlet. In the nofail case the fourth detector's output will remain 'false', the inverted signal will stay at 'true'. As a consequence the output of the AND-gain becomes 'true' and an error message can be given. In the case of simultaneous multiple sensor errors the fifth detector will sound an alarm too. The AND-gain at its outlet can help to reduce the false alarm rate. At time $t > t_f + t_d$ the switch by-passes the input failure detector because of some properties of the modified parameter estimation algorithm. These details can be found in [2]. Thus the IFDI module is able to detect failures of different form (steps and drifts) as well as failures of different type (single output and multiple output errors, single input faults). The logical network increases the sensitivity and reduces the fail alarm rate.

The application of the IFDI module to a special process must be realized in two steps; in a so-called precomputing step the failure sensitive functions (residuals) of the detection algorithms are generated with the help of the linear process model (process adaptation). Using a testing transient of the plant considered the alarm thresholds are focused in a learning, selfadapting way (plant adaptation). When the precomputing has been performed, the real time computing program, that is the IFDI-module, must be compiled and linked. It can then be used for the subsequent (timely unlimited) sensor signal surveillance.

The main advantage of the IFDI module is its process independent formulation. This general formulation makes it appropriate to all processes which can be described by linear or linearized models. Linear state space models can be derived for all processes which transport or transform mass or energy quantities because these quantities must vary in a continuous manner. Therefore the restriction on linear models is not a very limitative one for power plant applications. A real drawback of the IFDI-module is its increased complexity. To make its application easier an interactive CAE-tool (CAE: Computer Aided Engineering) has been derived to adapt the IFDI module to the process and the plant under consideration. The CAE-tool has to perform the following functions:

a) In an interactive part of the program the user can specify the component and its describing linear state space model. The derivation of this model has to be completed before applying the tool, the matrices of the model, this is the state transition matrix and the time discretized input and measurement matrices, must exist. Besides the model a testing transient is needed.

b) In a second step the dynamic behavior of the testing transient will be investigated by the tool. Very dynamic parts of the transients will be used for defining the alarm thresholds of the detectors.

c) In the precomputing of the first detector, the Parity equations are derived with the help of the state space model, the algorithm can be found in [3]. If their number increases the dimension M of the model's output vector y , a subset of M equations is selected by the tool. Three criterions are important for defining the subset, these are sensitivity, robustness and a long as possible memory span. Details can be found in [4].

d) The precomputing of the second, third and fifth detector can be performed together, because all of them use the Generalized Likelihood Ratio (GLR) technique [5]. This method evaluates the innovation of a linear Kalman filter. The first step is the design of the filter which is quite easy if the covariance matrices of the sensor and the process noise are known in advance. But in our case these quantities are unknown which complicates the computations very much. There is a lack of applicable algorithms in the literature and because of this a technique has been derived which adapts the Kalman filter to the testing transient using a trial and error principle. The definition of alarm thresholds ends the design of the GLR-detectors

e) The precomputing of the fourth detector, this was the input fault detector, can be done very quickly. The algorithm is a modification of the least squares parameter estimation technique described in [3].

f) After the adaptation of all five detectors to the process considered the (Fortran)-code of the IFDI-module will be automatically generated by the CAE-tool.

Step b) to f) will be performed automatically by the computer and in this way the CAE tool aims at the fact that the user does not have to know anything about modern control theory, analytical redundancy techniques and statistical evaluation methods. The advantage of the code generation function lies in the fact, that the code has an unambiguous and invariable structure. Thus it has become possible to analyze and optimize it with the help of software qualification tools. Thus the code of the IFDI-module will have constant quality also in the case of future applications of the CAE-tool.

ON-LINE TEST OF THE IFDI-MODULE

In the past the IFDI-module has been tested only off-line on a computer by simulating faults in the transient used. The performance of the module has been investigated as well as its sensitivity. On 22. November 1990 a first on-line test was realized on the LOBI-MOD 2 facility in the Euratom Research Centre Ispra, Italy. An on-line test was attempted for different reasons. If the software is tested off-line the program which processes the incoming data and simulates the errors will be on the same computer as the IFDI-module. In the case of an on-line test the configuration is quite different. The data as well as the faults are generated by the process and the sensors respectively while the module runs on a computer. Therefore all problems related to the interface between process and computer cannot be investigated during an off-line test. This also holds true for the difficulties arising from the sensor noise and the hardware at the interface. Moreover the real time property can easily be demonstrated during an on-line test.

The LOBI-MOD 2 facility is a non-nuclear two loop, high pressure system for the simulation of loss of cooling accidents and other transients. It is a scaled model of a primary and secondary cooling system of a F.R.G. 1300 MW_e pressurized water reactor. The primary system consists of two loops, the intact loop representing three undisturbed loops of the reference plant and the broken loop, for the simulation of breaks. This terminology is also retained during non loss of cooling accidents.

As a testing example the steam generator of the intact loop was selected. First of all a state space model of this process was derived and verified with the help of LOBI-MOD 2 transients of former experiments. The non-linear differential equations, their linearization and their verification can be found in [4]. The adaptation of the IFDI-module to the LOBI-MOD 2 Intact Loop Steam Generator (ILSG) was performed with the CAE-tool for precomputing (see the last paragraph). The IFDI-module was implemented on an IBM compatible personal computer AT-386 with a coprocessor. Additionally the personal computer was provided with a special hardware card for the coupling of the measurement devices of the LOBI-MOD 2 facility and the computer. Fig 2 shows the interface between the PC and the measuring devices, to prevent a feedback the coupling was arranged using isolation amplifiers. At the BNC - DB adapter sensor faults were simulated as described below.

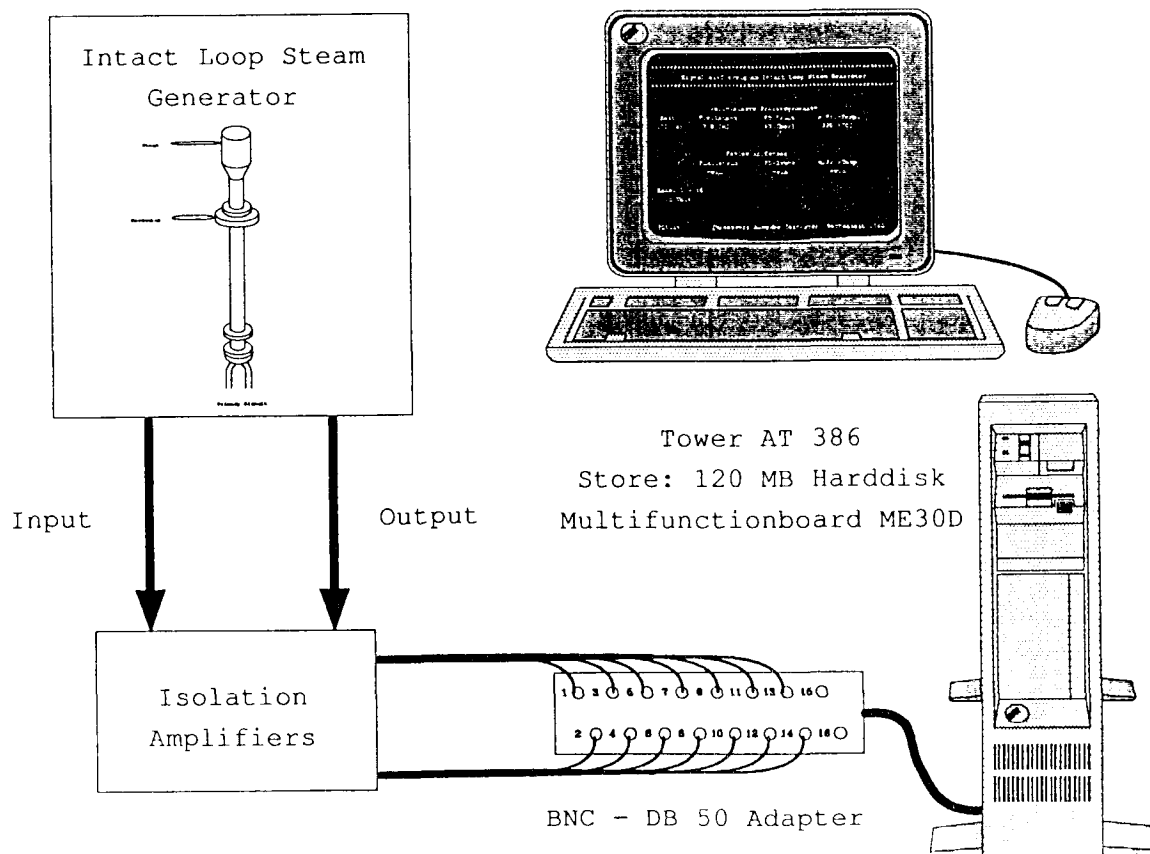


Fig.2: The interface between the LOBI-MOD 2 facility and the IFDI-module running on a personal computer

Tabel 1 lists the 14 measurement signals needed for the on-line test of the IFDI-module on the ILSG. Signals No. 8 to No. 13 are proportional to the six input signals of the ILSG state space models. Signal No.1 is the second and signal No. 14 the third output signal of the process which should be validated. The differential pressures No. 2 to No. 7 are necessary for the calculation of the first model's output value, the downcomer level.

No.	LOBI-Code	Channel	SI-Unit	Meaning
1	PA97S	5044	[MPa]	absolute pressure, secondary loop, level S
2	PD93FB10	5058	[MPa]	differential pressure, level F to B
3	PD93JF11	5057	[MPa]	differential pressure, level J to F
4	PD93LJ11	5056	[MPa]	differential pressure, level L to J
5	PD93NL11	5055	[MPa]	differential pressure, level N to L
6	PD97RN11	5065	[MPa]	differential pressure, level R to N
7	PD97RS11	5066	[MPa]	differential pressure, level R to S
8	QF14V	5033	[m/s]	fluid velocity, primary loop, pump inlet
9	QM57AFH	5028	[kg/s]	fluid mass flow, auxilary feedwater injection
10	QV63V	5036	[m ³ /s]	volumetric flow, feed line
11	QV65HVB	5040	[m ³ /s]	volumetric flow, secondary loop, ILSG exit
12	TF63H000	4176	[°C]	fluid temperature, sec. loop, ILSG inlet
13	TF12V270	4113	[°C]	fluid temperature, primary loop, ILSG inlet
14	TF92A	4260	[°C]	fluid temperature, primary loop, ILSG outlet

Tab. 1: The 14 measurement signals used for the on-line signal validation test of the IFDI-module on the intact loop steam generator of the LOBI-MOD 2 facility

The 14 analogous measurement signals, all in the range of 0 and 10 V, were connected to 14 isolation amplifiers. Behind the following adapter they were brought to a highspeed, multifunction PC-board, which made them time discrete and converted them into 12 bit integer values with a sampling rate of 200 kHz. Because of the noise in the signals, caused by the isolation amplifiers and the connecting cables, a mean value of 30 subsequent values was calculated for each measurement value.

The computer program for the on-line test took these 14 time discrete measurement values each second and converted them back to voltages. Subsequently the calibration and conversion of the 14 measurement signals into the nine values needed by the ILSG state space model were performed. After the call of the IFDI-module the results were stored on the harddisc and the program went into a waiting queue till the next full second. The calculation time needed by the program from receiving

the time discrete values till entering the waiting queue is about 200 ms. This includes the indication of the results on the screen. Without indication the calculation is only about 120 ms.

During heating up the LOBI-MOD 2 facility to nominal conditions and the subsequent BT 15 / BT 16 experiment sensor faults were simulated by falsifying the measurement signals with the help of electrical resistances which were arranged in parallel at the BNC - DB 50 adapter (see Fig. 2). The BT 15 / BT 16 experiment has been a transient representing a loss of main feedwater with delayed auxiliary feedwater injection and operating main cooling pumps (BT 15) and main cooling pumps out of operation respectively (BT 16).

26 sensor faults of different kinds were simulated:

- * single steps in the model's output values
- * synchronous steps in two output values
- * single steps in one model's input quantity
- * synchronous steps in one input and one output signal.

The IFDI-module has been designed to sound an alarm in the case of faults in the output signals, but an alarm caused by an erroneous input signal should be suppressed. The module detected and identified these faults in the expected way. Thus the on-line test has demonstrated the capability of the IFDI-module to identify sudden changes of different height in real time which are not caused by the system's dynamics. A detailed discussion of the results can be found in [6].

As a conclusion it can be said that methods of analytical redundancy are appropriate for the application in the process level. In contrast to the algorithms of hardware redundancy they compare signals which represent different physical quantities, like the downcomer level, the live steam pressure and the steam generator's outlet temperature in the previous example. To enable this comparison procedural knowledge is needed in the form of a linear state space model. The effort to derive such a model can be considerable. As mentioned above a unique diagnosis of a fault's origin, this means the distinction between a sensor and a process fault, is not possible in general due to the use of procedural knowledge.

Another property of the algorithms of analytical redundancy is their limited time memory with respect to faults. If the algorithm cannot detect a failure within this memory span, the failure will be undetectable. From this it follows that the identification of faults with a low time constant (slow varying drifts) is in principle impossible. To smooth out this disadvantage other methods must be used. These are techniques of the system level as will be shown in the next section.

THE SYSTEM LEVEL

Very slow varying failures can be identified by monitoring bigger parts of the plant consisting of several components. A new method of fault detection in this system level has been developed by the GRS, [7], which models the system under consideration as a Place/Transition (pt) Net. Pt nets, a subclass of Petri Nets, are bipartite graphs consisting of two types of elements, the places and the transitions. They have been introduced to describe the transport of a quantity, such as mass, information or a sort of goods. To remain in a system independent formulation, the transported quantity will be called a token or, if more than one unit is transported, tokens. Places are the passive elements of the net, they store tokens, while transitions transport tokens from one place to another. In [7] it has been shown, that thermo-hydraulic systems can be modeled as pt-nets, Fig. 3 presents a secondary cooling loop of a pressurized water reactor as an example. Table 2 explains the meaning of the different places in Fig. 3.

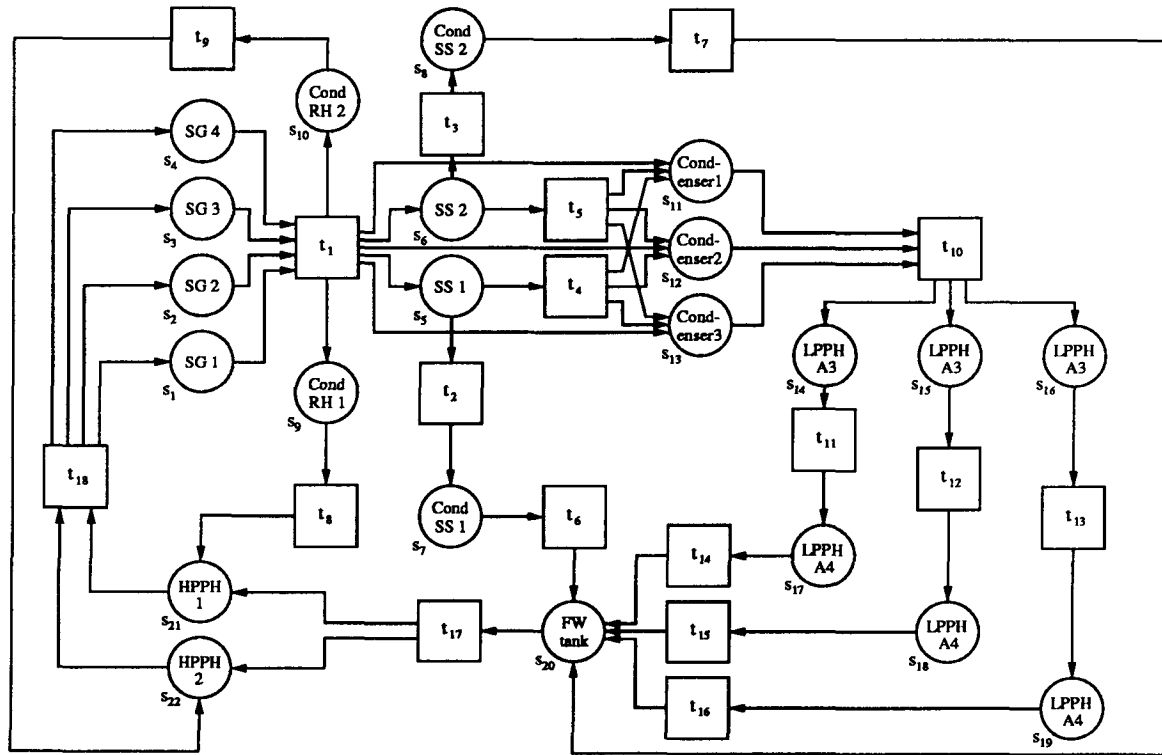


Fig. 3: The secondary cooling loop of a pressurized water reactor modelled as a mass token place / transition net

Place	Name of the Component	Place	Name of the Component
$s_1 - s_4$	steam generator 1 to 4	$s_{14} - s_{16}$	low pressure preheater A3, 1 to 3
$s_5 - s_6$	steam separator 1, 2	$s_{17} - s_{19}$	low pressure preheater A4, 1 to 3
$s_7 - s_8$	condensate vessel of steam separator 1, 2	s_{20}	feedwater tank
$s_9 - s_{10}$	condensate vessel reheater 1, 2	$s_{21} - s_{22}$	high pressure preheater 1, 2
$s_{11} - s_{13}$	condensate collecting container, condenser 1 to 3		

Table 2: Meaning of the places in Fig. 3

The algorithm for the detection of a fault, which varies very slow in time using this method is quite easy. At each time step the actual token content per place has to be calculated with the help of the temperature, level and flow measurement value. The sum of all token numbers has to be compared each scanning time point with the initial value. The difference of both quantities, low pass filtered, is an indicator for faults of low and very low time constants. In [7] the theoretical background and an example is given.

The methods of the signal level need procedural knowledge in the form of state space models. These are processed inside the validation algorithms. The algorithm of this method of fault detection based on Petri nets is simple in contrast to the former ones and much less computation time is needed. On the other hand much more knowledge is needed, that is a more in depth knowledge about the behavior of the whole system. Moreover the modelling of a system as a Petri net is not unique and thus some experience is required. Because the fault detection criterion is a conservation principle, the application is limited to physical conservation quantities. Moreover sufficient instrumentation must be provided in the system for the calculation of the token content per place. Due to the summation of the token numbers no diagnosis of the fault's origin can be given.

But besides these drawbacks, the method has two advantages which can not be provided by any other technique. Since the whole system is considered the method enables the detection of faults with very low time constants for all operational conditions of the plant. Moreover, a prognosis of the system's future behavior becomes possible because of the system's property of being an initial value problem.

Now the three levels have been discussed. This was the signal level, where the relationship between signals is monitored, the process level, where single components are considered and the system level, where the whole system is taken into account. The properties of the techniques which belong to each level have been shown and from this can be concluded that their combination will offer different advantages. These are:

- * sensitivity with respect to faults of different type
- * higher degree of information about a fault
- * help for more reliable diagnosis of the fault's origin

NEXT STEPS

Techniques belonging to the different levels have been tested separately and their performance has been verified. Methods of the signal level have been already applied in U.S. nuclear power plants with good results, while the IFDI-module has been tested on-line as described above. The Petri Net based technique for fault detection in the system level has been investigated off-line using plant data from a magnetic tape.

The combination of the different techniques can be performed in a modular software structure. Each couple of hardware redundant signals will be supervised by a separate module called HFDI-module (HFDI: Hardware redundancies' Fault Detection and Identification), each component by one IFDI-module. Additionally the Petri net method monitors signals of the whole system. All these modules will work independently after they have received their actual set of measurement signals. Thus all the modules can work in parallel. And if the structure of a problem is parallel, it is appropriate that the computer hardware for the solution of this problem is parallel too. Depending on their need of computation time a number of HFDI- or IFDI-modules can run subsequently on one processor, the next couple of modules on the next processor and so on. The partition of the software on several processors of a transputer system enables fault detection of a larger scaled system in real time. When all signals have been processed and each module has come to a decision about the quality of these signals, a diagnosis for the whole system must be generated.

A diagnosis unit which works subsequent to the transputer system has to gather the output of all the modules. The single messages have to be interpreted and from this a general view of the whole system's state must be obtained. The knowledge about the properties of the three level's fault detection techniques can assist in getting a reliable diagnosis of the fault's origin.

A first application of the three level conception combined with an AI-based diagnosis unit called *LYDIA* (earLY sensor and component fault detection and *DIAG*nosis) to a power plant secondary side

is in preparation. Instead of a living plant the GRS simulator ATLAS will be used for the generation of the measurement data. Normal and abnormal operation conditions will be simulated and about 200 - 300 measurement signals of the secondary side will be considered. The performance of *LYDIA* will be tested processing these data while sensor and process faults are simulated in addition.

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AN INNOVATIONS-BASED METHOD FOR DC-SIGNAL FAILURE DETECTION: APPLICATION TO NPP

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ABSTRACT

An innovations-based method for failure detection in dc-signals is described. The detection system receives the data from the sensors as input and forms the innovations sequence for learning period by means of Kalman filtering methodology with two basically desirable features. Namely due to adaptive feature of the method relatively low frequency noise of the sensory data for learning is easily handled, compared to blockwise processing method, on one hand, and accurate parameters' estimation with relevant statistical information on the other. The estimation is performed by defining each prediction error filter parameters as states and minimum variance estimation of each state is carried out simultaneously, the filtering process of the data being optimal. Hence, the one-step-ahead prediction filter coefficients being optimally identified, the innovation sequence is obtained as the output of the filter and the uncorrelated data sequence thus obtained are subjected to a statistical test, specifically the cumulative sum for dc-anomaly detection as the test is particularly suitable for jump or pulse type anomalies in those signals subject to dc-level change. The method particularly possesses the features of having accurate statistical signal signatures as well as model parameters' estimation obtained during the learning period, with the result that it provides the essential data required for the appropriate design of the cumulative sum test complying with the theoretical considerations.

To test the effectiveness of the method High Flux Reactor (HFR) signals were used including superimposed external jump and pulse type of anomalies for fault detection. The method has, in particular, been developed to be used for the signals of Borssele NPP on a continuous bases for monitoring purposes and proved to be perfectly expedient for the intended goals.

THE USE OF RADIATION DETECTION NOISE FOR SIGNAL
VALIDATION AND SENSOR DEGRADATION MONITORING

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ABSTRACT

Research has shown that the use of radiation detection noise can be a useful tool in analyzing the response time of radiation detectors used in nuclear power plant safety channels as well as identifying degraded performance of these sensors. The use of on-line sensor surveillance methods, such as radiation detection noise, is of importance to the nuclear power industry because it can provide an immediate indication of sensor performance. The authors introduce a comprehensive analytic model of radiation detection noise propagation through an ion-chamber type radiation sensor, including the sensing line. A signal validation method is introduced that monitors the sensor performance based on dynamic as well as static performance measures. The method compares measured signals with base line data as well as analytical predictions. This paper presents data taken in two United States Pressurized Water Reactors of different designs as well as analytical predictions.

INTRODUCTION

The use of radiation detection noise has been shown, by the authors and others (1-6) to be useful in determining changes in response time and other static and dynamic parameters in ion-chamber type radiation sensors, including uncompensated ion-chambers, compensated ion-chambers, fissions chambers and proportional counters. The sensitivity of these techniques to sensor degradations has been shown to be good (4-6), however, the lack of a complete analytical model that can analyze and predict changes in the response due to known degradations has in the past limited this technique. If known modes of sensor or sensing line degradations can be modeled from experimental data from the laboratory, or other plants, or analytically by use of a complete analytical model then the output can be used to validate sensor information and monitor sensor degradations. The original theoretical model (1-3) has been

expanded and will be discussed. This paper will also include results that demonstrate how a method can be used to develop performance indicators for nuclear power plant nuclear instrumentation channels that are sensitive to sensor degradation and are very stable with respect to differences in reactor power level and detector installation.

THEORY

The theoretical model used in demonstrating the feasibility of using detection noise has been shown to be valid for laboratory and plant conditions (3). In the following equation the sensor output power spectral density (PSD) is given as a function of the transfer function of the sensor H_d , the transfer function of the sensing line, in our case a transmission line H_T , the measurement instrumentation transfer function H_m , the reactor transfer function H_R , the noise equivalent neutron source G_{ss} , the electromagnetic pickup noise G_{em} , radiation detection noise G_{dd} and measurement noise G_{mm} , such as shot noise:

$$\begin{aligned}
 G_{yy}(\omega) = & G_{ss}(\omega) H_R(\omega) H_d(\omega) H_T(\omega) H_m(\omega) \\
 & + G_{dd}(\omega) H_d(\omega) H_T(\omega) H_m(\omega) + G_{em}(\omega) H_d(\omega) H_T(\omega) H_m(\omega) \\
 & + G_{mm}(\omega) H_m(\omega) .
 \end{aligned} \tag{1}$$

The noise equivalent neutron source G_{ss} is taken as "white" and the transfer function of the sensor, sensing line and measurement instrumentation are close to unity for low frequency, therefore the first term in equation (1) is dependent on the reactor transfer function, which is well known. In the second and third terms of equation (1) the input terms, the radiation detection noise and the electromagnetic pickup noise, are determined analytically. In the case of the electromagnetic pickup noise, a 60 Hz source with harmonics is used. In the case of the radiation detection noise source a Monte Carlo calculation is done to determine the rate of neutron interactions with the detector and the statistical properties of the noise source. (The source is nearly "white".) The transfer functions of the transmission line and the measurement instrumentation are combined. The combined system is a model with a distributed parameter model of a signal cable with a current source as the input boundary condition and a high impedance termination as the output boundary condition. The equation used is:

$$R(x)C(x) \frac{dV_m(t)}{dt} + V_m(t) = R(x)I(t) , \quad (2)$$

where $I(t)$ is the dynamic current produced in the detector given by:

$$I(t) = \frac{2\pi el [V(t) - V_m(t)]}{d [\ln(b/a)]^2} \left[\sum_{i=1}^3 \int_a^b \mu_i \frac{n_i(r, t)}{r} dr \right] . \quad (3)$$

In equations 2 and 3 $V(t)$ and $V_m(t)$ are the voltages applied to the detector and seen by the measurement instrumentation respectively. R and C are properties of the transmission line, x is the distance along the transmission line and l , d , a , b and μ_i are properties of the detector, that can be changed to simulate a degradation. The $n_i(r, t)$ terms are the distributions of ions that are electrons in the detector sensing area. These are given by:

$$\begin{aligned} \frac{\partial n_1}{\partial t} = & D_1 \frac{1}{r} \frac{\partial}{\partial r} \left(r \frac{\partial n_1}{\partial r} \right) - \frac{\mu_1 V(t)}{d \ln(b/a)} \frac{1}{r} \frac{\partial n_1}{\partial r} \\ & - v n_1 - \alpha n_1 n_2 + g_{dd}(r, t) \end{aligned} \quad (4)$$

$$\begin{aligned} \frac{\partial n_2}{\partial t} = & D_2 \frac{1}{r} \frac{\partial}{\partial r} \left(r \frac{\partial n_2}{\partial r} \right) + \frac{\mu_2 V(t)}{d \ln(b/a)} \frac{1}{r} \frac{\partial n_2}{\partial r} \\ & - \alpha n_1 n_2 - \tilde{\alpha} n_1 n_2 + g_{dd}(r, t) \end{aligned} \quad (5)$$

$$\begin{aligned} \frac{\partial n_3}{\partial t} = & D_3 \frac{1}{r} \frac{\partial}{\partial r} \left(r \frac{\partial n_3}{\partial r} \right) - \frac{\mu_3 V(t)}{d \ln(b/a)} \frac{1}{r} \frac{\partial n_3}{\partial r} \\ & + v n_1 - \tilde{\alpha} n_2 n_3 \end{aligned} \quad (6)$$

where D_{1-3} , μ_{1-3} , d , b , a , α , $\tilde{\alpha}$ and v are properties of the detector and $n_1(r, t)$ represents the electron concentration, $n_2(r, t)$ the positive ion concentration and $n_3(r, t)$ negative ion concentration, within the detector (8).

Equations 4-6 are the time domain representation of the detector transfer function H_d . Equations 2 and 3 represent the time domain form of the combined transmission line and measurement instrumentation $H_T H_m$. Since these equations are non-linear, and the more the detector becomes degraded, the more non-linear the

equations becomes, the calculation is carried out in the time domain and then converted to the frequency domain at the end for comparison with measured PSDs. The calculation proceeds as follows: first the radiation detection noise source $g_{dd}(r,t)$ is determined by a Monte Carlo calculation. Then this stochastic term is inputted into equations 4-6 to determine the electron and ion concentrations. The concentrations are integrated in equation 2 to determine the stochastic current and inputted to equation 3 to determine the output $V_m(t)$, which is equal to $g_{yy}(t)$, the time domain output. This is how the second term in equation 1 is found. The third term is found by inputting a deterministic 60 Hz signal into equation 2 and 3 and proceeding as before. The fourth term in equation 1 is found by experiment and added in after the other calculations are done.

RESULTS AND ANALYSES

Measurements have been done at a small research reactor (the Ohio State Research Reactor) and two United States Large Pressurized Water Reactors (PWR) of different designs. The PWR's were a Westinghouse two loop plant and a Babcock & Wilcox (B&W) plant. The data and analyses presented here were taken at the plants and then analyzed off-line at a later date. However, this need not be the case, as the theoretical model calculations can be done off-line and then loaded into a computer for comparison with on-line data in near real time. Four performance measures are used in this analysis. They are all a function of signal power over set frequencies as suggested by Jacquot, et. al. (5). These frequencies were chosen based on the theoretical model predictions. In this case the regions are first, low frequency (from 2.5 Hz to 32 Hz), to cover the first term in equation 1, this will show changes in the reactor state. Region two is the flat region of the detector transfer function from term 2 of equation 1 (from 32 Hz to 200 Hz). This is similar to the indicator used in the French work, see references 5 and 6. Region three includes 60 Hz and harmonics and the frequencies bands around them, to show changes in the third term in equation 1, electromagnetic pickup. This term has been shown to increase dramatically in some cable degradations. And the fourth region is at the cable resonance frequency (from 5700 Hz to 10200 Hz). Cable resonance, such as seen in pressure transducers (9), can occur in high output independence cable like this system, so this region is included.

The method of signal validation that is proposed is as follows. First, the parameters given above are found, among other factors, such as dc current. Next, the parameters are compared to baseline data and each other to determine if the signal is valid both statically and dynamically. In this way, if a signal will not follow a transient, because its response time is degraded, it can be declared non-valid before the static difference is seen. Lastly, the parameters from the non-valid sensor can be compared to a library of experimental and theoretical failures, to send to a diagnostic model of possible faults. One advantage of a method such as this is that it is very sensitive to common cause faults

because not only are the signals compared with each other, but also with baseline data.

Figure 1 (b) shows the PSD of the theoretical model of the first term of equation 1 (Figure 1 (a), data from a base line detector, is included for comparison). Figure 2 shows the PSDs of the theoretical model of the second term with and without the cable resonance. Figure 3 shows the PSD of the third term in equation 1. Figure 4 shows the PSD of the sum of the theoretical model terms and the data from the detector from the Westinghouse PWR, which was modeled. Figures 5 through 8 show the PSDs of the theoretical model predictions and the plant data, for four degradations. Figure 5 shows an increase in cable capacitance, typical of cable neutron aging. Figure 6 shows an improper installation of the detector.

Figure 7 shows a short in the cable due to moisture, and Figure 8 a reduction in detector bias, representing a short or failure of the detector high voltage cable. The theoretical model does a good job of modeling the capacitance change and the detector bias change. It does not predict as well in the other case because less is known about the mechanisms involved in those cases and more assumptions are needed in the model. However, all the cases are sensitive to changes in the frequency parameters.

Figures 9 and 10 are included to show the stability of the parameters. The radiation detection noise is dependent only on the neutron flux and the general detector configuration, therefore the output should be linear in neutron flux for similar detectors. This is what we see in Figures 9 and 10. Figure 9 shows the PSDs of one detector at two different reactor power levels and Figure 10 the PSDs of two similar detectors at two different plants of two different designs. The different detectors shown a linear response over the entire frequency span with respect to neutron flux.

SUMMARY AND CONCLUSIONS

Experimental and theoretical research has been completed which demonstrates that a method of signal validation and sensor degradation monitoring can be implemented in operating commercial nuclear power plants based on radiation detection noise analysis. Data recorded in this work has shown that this method is sensitive to sensor degradations of many types and is not sensitive to power changes in the operating range of the detector, or installation changes. The surveillance parameters provide sufficient diagnostic information to make some determination of possible faults and recommendations for preventive replacements and repairs.

This method, along with other off-line methods (1, 4-6) including measurement of saturation curves, modulation of high voltage bias supply and time and domain reflectometry have been and continue to be used for surveillance of nuclear power plant instrument channels. In conclusion we plan to continue work with this method for uses in signal validation as well.

ACKNOWLEDGMENTS

The authors wish to acknowledge Joseph W. Talnagi, Gregory S. Rowe, Alireza Behbahani and Tunc Aldemir for their assistance in the experimental and theoretical portions of this work. We also wish to acknowledge the U.S. Nuclear Regulatory Commission, Westinghouse Electric Corporation and Reuter-Stokes Corporation for their support of portions of this work.

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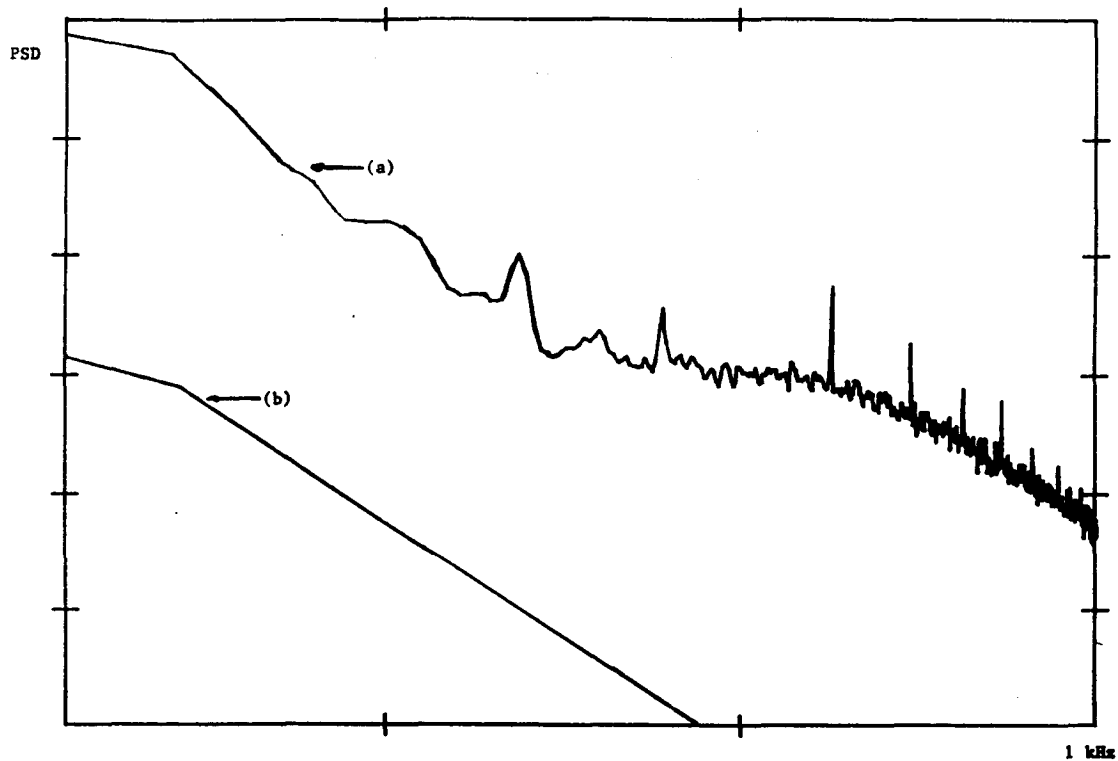


Figure 1, PSD of the top section of a Westinghouse UIC (a) and the PSD of the first term of equation one.

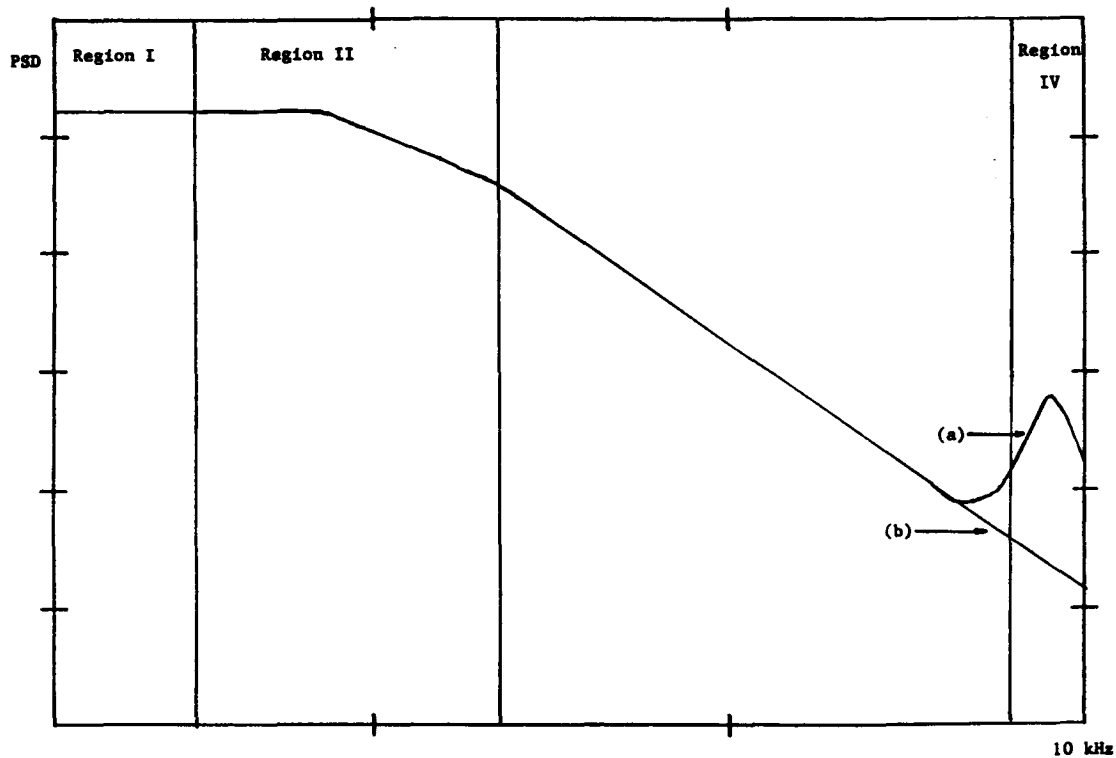


Figure 2, PSD of the second term of equation one, with (a) and without cable resonance. Note frequency regions.

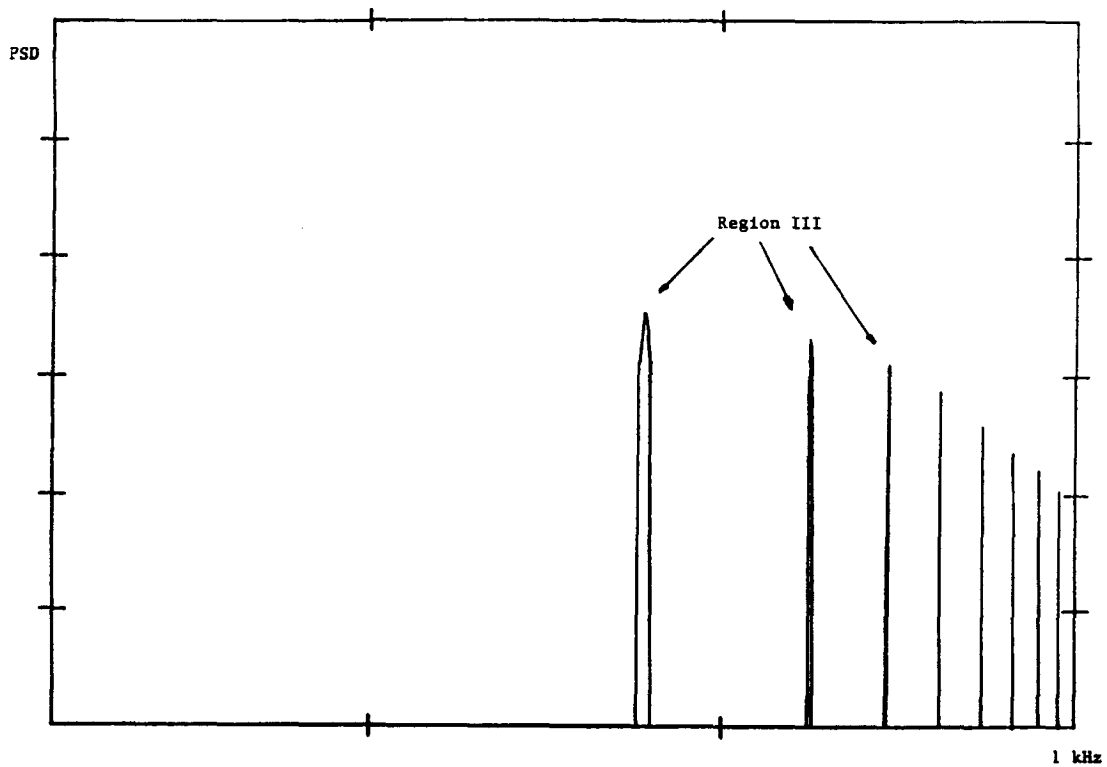


Figure 3, PSD of the third term of equation one.

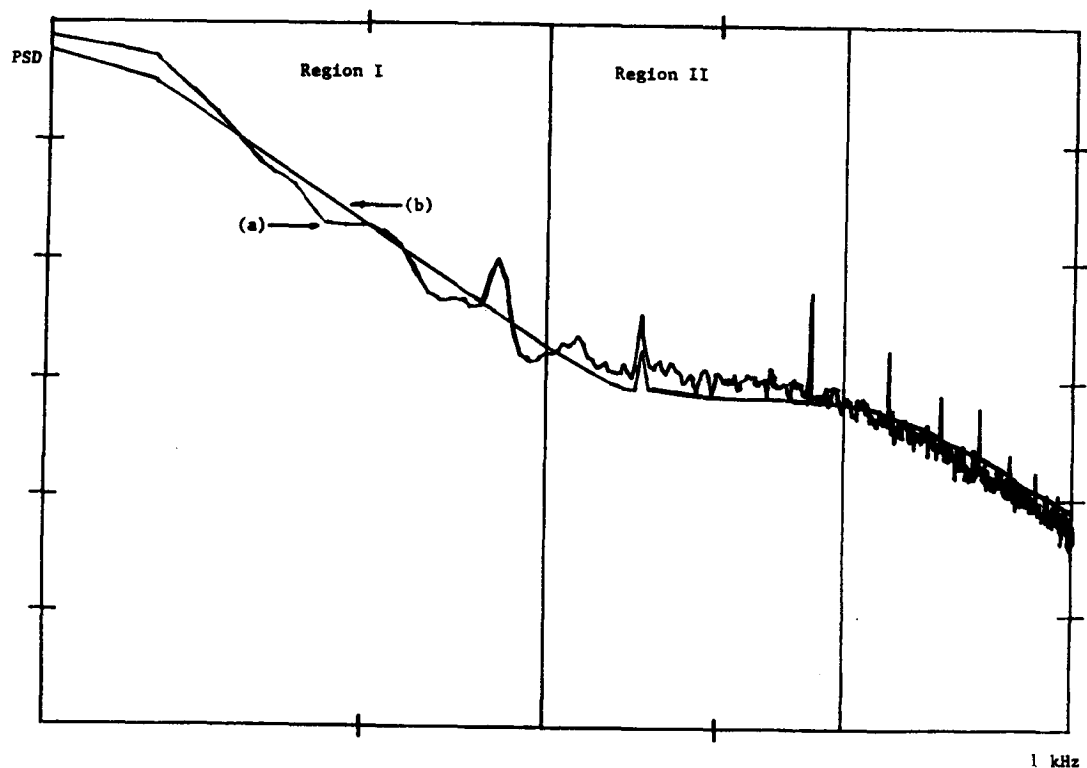


Figure 4, Comparison of the base line PSD of the Westinghouse UIC (a) with the theoretical prediction of the PSD (b).

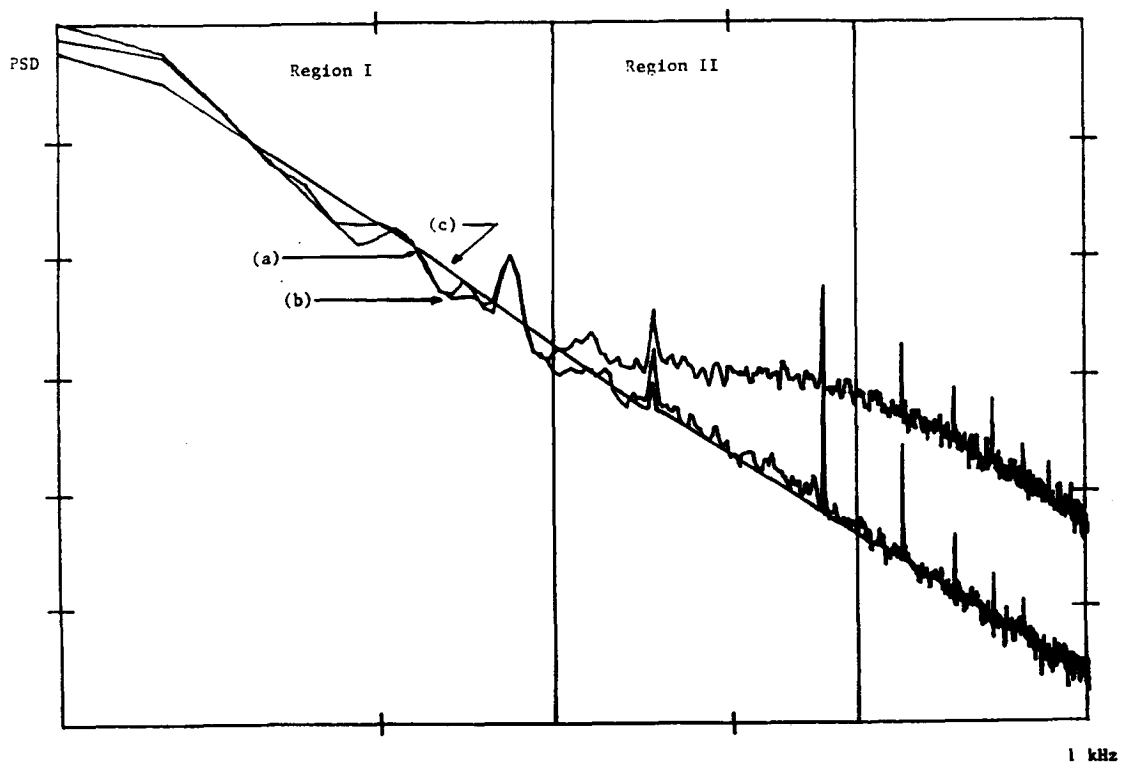


Figure 5, Comparison of the base line PSD of the Westinghouse UIC (a) with the UIC and a change in capacitance (b), and with the theoretical prediction (c).

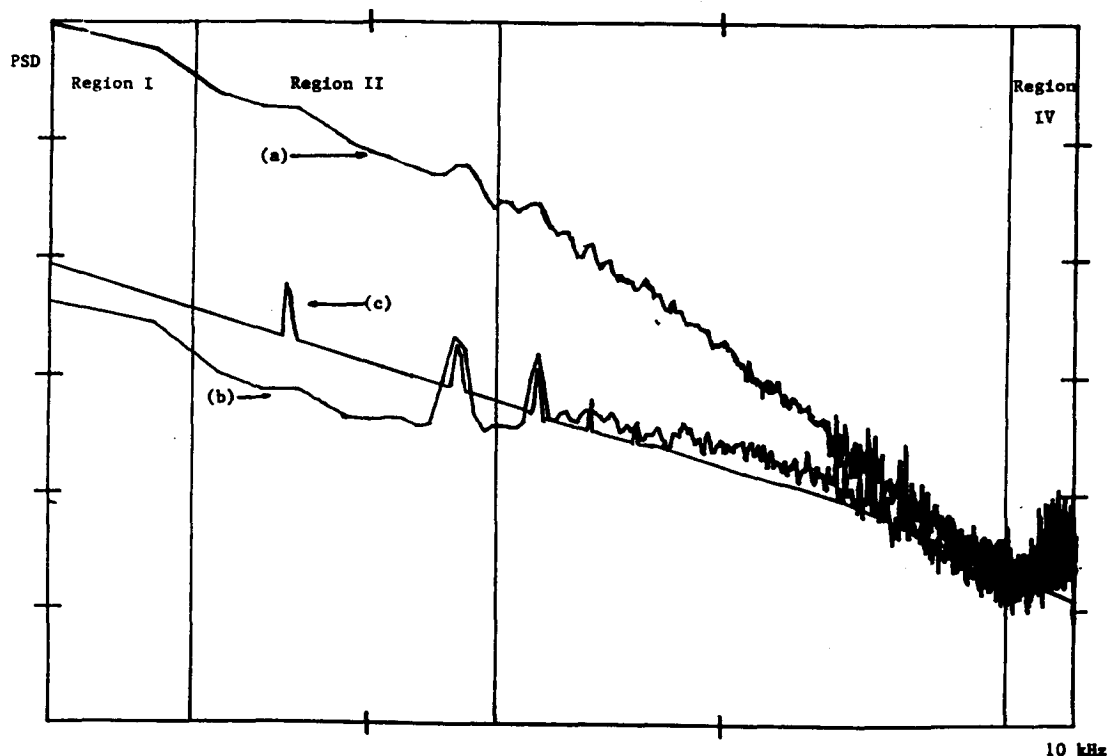


Figure 6, Comparison of the base line PSD of the Westinghouse UIC (a) with the PSD of the UIC improperly installed (b) and with the theoretical prediction (c).

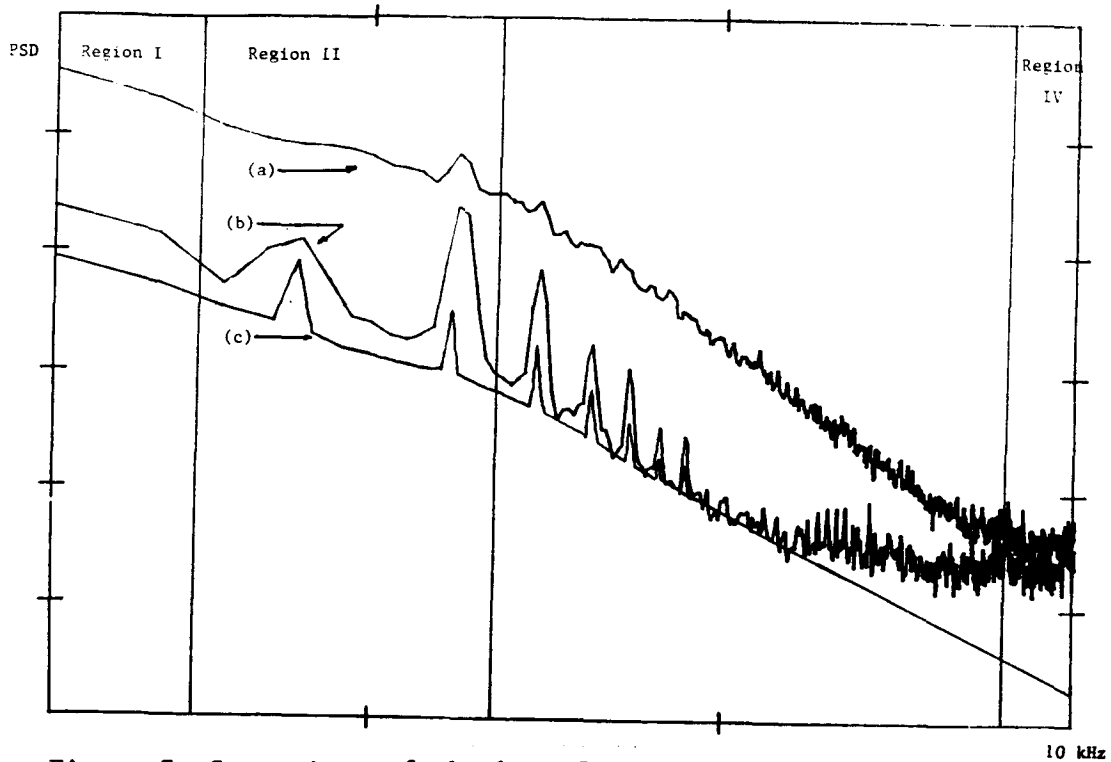


Figure 7, Comparison of the base line PSD of the Westinghouse UIC (a) with the PSD of the UIC with a moisture defect (b) and with the theoretical predication (c).

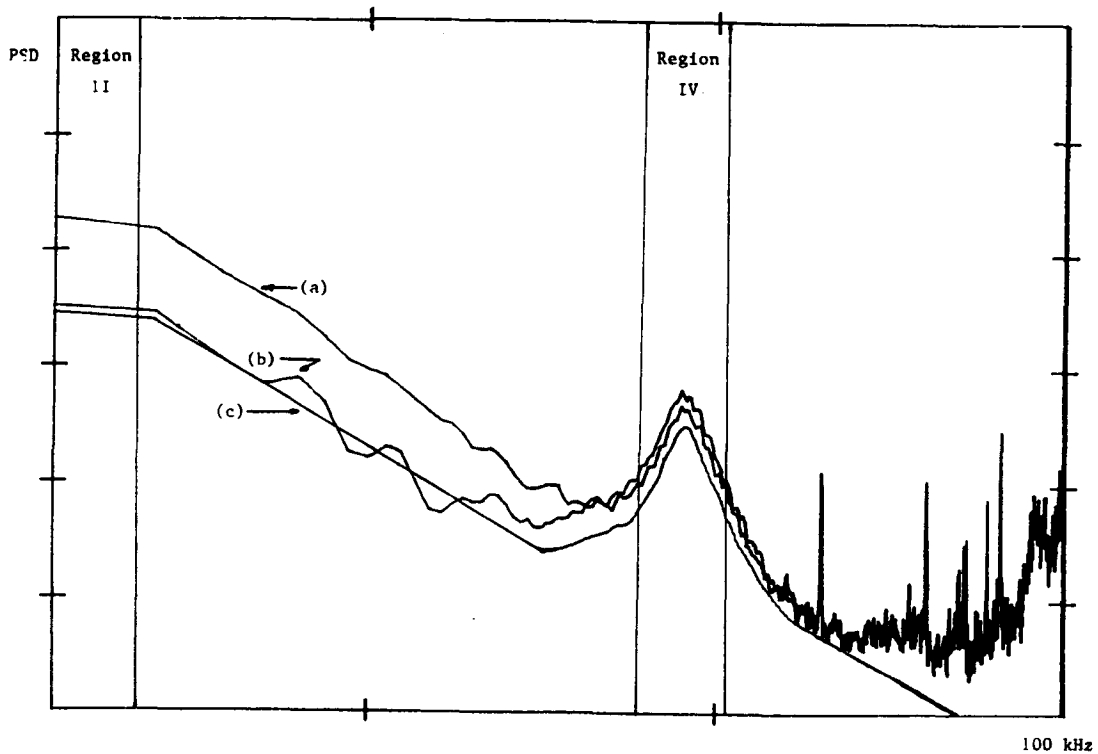


Figure 8, Comparison of the base line PSD of the Babcock and Wilcox UIC (a) with the PSD of the UIC with reduced bias voltages (b) and with the theoretical predication (c).

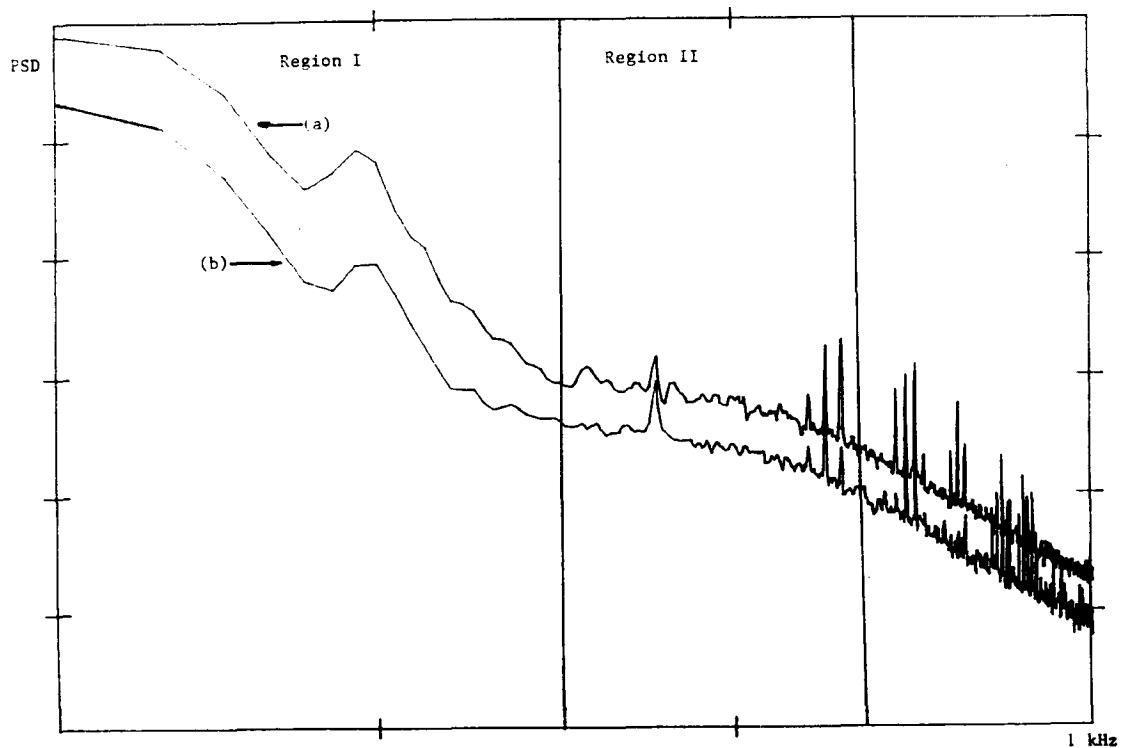


Figure 9, Comparison of the base line PSD of the Babcock and Wilcox UIC with the reactor at 83 percent power (a) and 40 percent power (b).

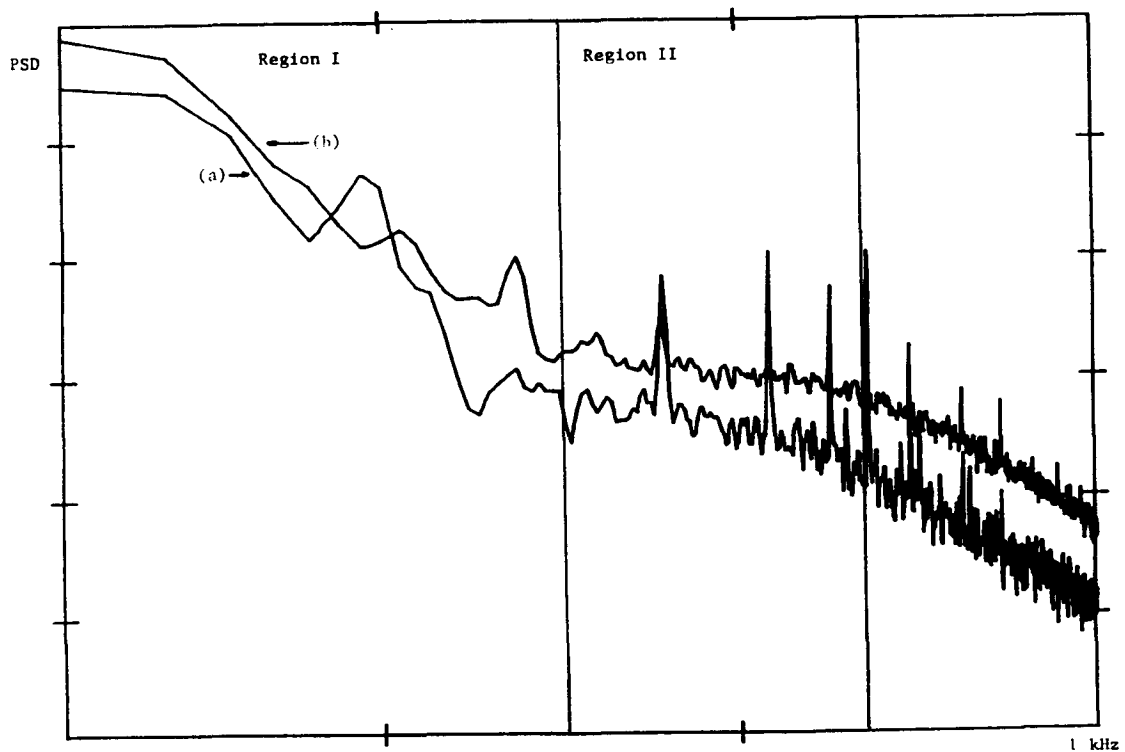


Figure 10, Comparison of the base line PSD of the Babcock and Wilcox UIC (a) with the Westinghouse UIC (b).

SENSOR HEALTH MONITORING OF THE ENTIRE SENSING LOOP IN THE SAFETY SYSTEMS OF NUCLEAR POWER STATIONS

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ABSTRACT

Plant technical specifications and NRC regulatory guides require testing of instrument loops to detect degradation and failure. Industry efforts have focused on specific manual testing to detect individual failure modes such as increased response time and calibration drift. Recent work performed by EPRI and by others using instrument loop data, failure modes and effects analyses (FMEAs), and experience with utility on-line sensor health monitoring programs has established that instrument loop cross comparison techniques can provide equivalent indication of instrument loop accuracy. This methodology provides more frequent instrument loop health indication than manual testing and reduces the requirement for manual testing.

INTRODUCTION

Surveillance and testing requirements for instrumentation in nuclear power plants were developed to assure that the process sensing loops perform as described in the plant safety analyses. The instrument loops covered by these requirements include those in the reactor protection system, the engineered safeguard functions, and containment isolation system. When the surveillance and testing requirements were defined, the actual failure modes for the instrument loops were not known. In order to account for potential failures, a conservative approach was taken requiring response time testing, loop functional tests and calibrations. The required tests are generally intrusive and have led to a number of plant scrams and Licensee Event Reports (LERs). Furthermore, it has been determined that these tests are not capable of detecting certain instrument loop failures.

This paper reviews the current testing requirements in light of new information. This new information was obtained by examining past instrument problems, performing failure modes and effects analysis (FMEAs) and by gaining experience from on-line sensor health monitoring programs. These programs monitor the

entire process sensing loop in a non-intrusive manner and decrease the need for frequent manual testing. A significant benefit of the sensor health approach is that this monitoring uses a non-intrusive means of interrogating sensor signals to determine the overall health of the sensor loop independent of the degradation mode.

Sensor health monitoring will have additional paybacks in reducing the number of instruments that require calibration and increasing the time between needed calibrations. This monitoring program will permit longer fuel cycles without requiring shutdowns during the fuel cycle to recalibrate instrumentation. More accurate sensor information can reduce instrument uncertainties which can provide increased plant operating margins. This methodology can also be used to eliminate certain manual testing such as response time testing of pressure sensors since work performed by EPRI and others indicate that these tests contain redundant information about the sensor's health.

CURRENT TEST REQUIREMENTS AND PROCEDURES

The testing is expected to detect all failure modes in a timely manner. These surveillance and testing requirements include: daily channel checks which are a cross comparison of like sensing channels to determine drift or other indications of sensing loop degradation; monthly or quarterly loop functional checks which monitor the electronics of the the sensing loop up to the final actuation device; calibrations performed each outage to compare the accuracy of the sensor to a benchmark standard; and response time measurements of the sensing loops. Nuclear power plant sensing loop surveillance and testing requirements are specified by industry standards such as IEEE 338, ISA 67.06 and NRC standards such as RG 1.118. Each of these standards provides for elimination of a specified testing requirement if other means can be shown to provide the same information.

The design of safety systems in nuclear plants includes redundancy, per IEEE 279, to allow a plant to have inoperable safety loops and still meet the required system reliability. Loops may be inoperable either due to identified failures or due to testing requirements. This design allows the sensing loop to be tested with the plant on-line. The testing is generally intrusive and is performed by lifting leads, by placing the instrument channel in the tripped condition, or by inputting a step or ramp signal and recording the response. This intrusive testing has led to numerous scrams and/or safety system actuations.

REVIEW OF PAST PROBLEMS

Informal review of NPRDS and LER data by the authors identified several scrams and safety system actuations caused by manual testing errors.

An EPRI survey of nuclear plant I&C managers (1) revealed the following were the highest concerns among I&C activities:

1. Documents and Drawings.
 - Inconsistencies among various types of documents including procedures, manuals, drawings, databases, etc. and between these and the plant as-built equipment.
 - Inadequate or erroneous information in documents, inadequate document control, lack of good retrievability and time lags in updating documents.
2. Equipment Testability.
 - Absence of needed test jacks, switches, etc.
 - Hard to test easily, properly, or risk-free because of built-in "traps".
3. Frequency of Testing.
 - Wear-out by excessive testing.
 - Unnecessary operations.
4. System Procedure Content.
 - Steps, precautions, prerequisites, necessary conservatisms, needed guidance and other contexts inadequate or erroneous.
 - Requirements from other documents not properly implemented.
 - Inadequate verification, validation and review before release.
 - Inadequate vendor information.
 - Not fully anticipating operating features or conditions.

All of these concerns are related to performing sensing loop surveillance and testing. Decreases in the number of intrusive testing procedures would ease these problems and should reduce the number of LERs.

SENSOR HEALTH MONITORING WORK

The methodology for sensor health monitoring is based on guidance given in IEEE 338. This methodology includes the determination of failure modes and detection of these failures by analyzing plant process signals. The methodology is a combination of theoretical work and evaluation of plant data. The theoretical basis utilizes FMEAs, analytical and hardware redundancy, and signal validation methods. The plant data is used to confirm the failure modes and to validate the non-intrusive test methods.

FMEAs are performed to determine potential sensor failure modes and consequently, assure that existing testing would detect these failures. ORNL (2) performed FMEAs for the three most common pressure sensor measurement types: strain gauge, capacitance, and force balance. The ORNL study did not examine electronics, relays, etc.

The EPRI response time testing program (3) evaluated extensive plant data and performed independent FMEAs on pressure transmitters and switches from six different sensor vendors to determine if all failure modes effecting response time would be detectable by other means such as sensor drift. The plant data included over 4200 individual response time data points from 39 plants. Reference 4 identified the response time testing techniques in current use; ie; hydraulic step and

ramp testing and electronic white noise testing. The plant response time testing data did not identify any response time failures or response time degradation trends.

EPRI performed FMEAs on sensors from Rosemount, Barton, Foxboro, Statham, SOR, and Tobar (Veratrak). The FMEAs verified much of the previous ORNL work. That is, all previously identified failure modes, including changes in response time would be detectable by sensor output drift. However, the FMEAs also identified one new failure mode that was not easily detectable by the existing required testing; slow loss of sensor fill fluid (oil loss). Comprehensive industry studies (5-9) determined that trending sensor drift to a more precise level could also detect oil loss. This would involve trending drift to $\sim 0.5\%$ drift accuracy rather than $\sim 2\%$. Moreover, it was demonstrated that response time degradation could be detected from the same sensor drift trending that would detect all important sensor degradation modes including oil loss. If this drift trending accuracy is approximately at the sensitivity of the sensor, it effectively becomes an on-line calibration check and provides a basis for an instrument calibration reduction program.

In order to eliminate response time testing the rest of the loop, it would be necessary to perform a similar study to that of the sensors. This would include performing FMEAs on each of the individual components in the loop such as electronics, relays, etc.

The EPRI Instrument Calibration Reduction Program (ICRP) (10) uses calibration of one redundant channel and channel cross-comparisons to the other redundant channels to infer calibration. Northeast Utilities' Millstone II plant served as a host site for the development and initial testing of the ICRP. The testing to date has demonstrated that use of hardware redundancy is a viable means of signal validation, determining instrument loop drift, and verification of calibration. A program of similar intent has been employed at Southern California Edison (11).

At Millstone II, two types of data are collected: daily steady-state data and transient data that cover the operating range of the instrument. Daily steady-state monitoring of the instrument loop provides on-line fault detection and alarming. This steady-state data is logged and the average of the validated signals is used as the "truth" to determine the instrument loop drift of each instrument. Figure 1 shows the steady state data for one parameter set.

Transient data is collected during plant transients, such as a cooldown, over the operating range of each of the instruments. The transient data from each instrument channel or sensor is compared to one instrument chosen as the reference and calibrated. This calibrated instrument loop is used as the "truth" to which each of the other channels is compared. If that instrument or channel is demonstrated as being in calibration, and the other instruments or channels (including the associated 95% confidence interval) do not deviate from this reference by more than the manufacturers' specified accuracy over the range of the transient, then the other redundant instruments can be inferred as calibrated. The

initial tests of the method show the transient data signal estimates as indicated by the diamonds in figure 2 have an accuracy of <1 psia over the measured range of 900 psia or about 0.1% with a 95% confidence interval as indicated by the triangles and boxes. The comparison to standard calibration methods as shown in figure 3 indicates the methods are of comparable accuracy.

The utility has estimated that if the methodology were applied to 55 instruments at Millstone II the number of calibrations could be reduced to 16. This would result in a savings of 250 man-hours/outage of I&C technician time.

Another sensor trending program was installed at Millstone III to monitor Rosemount transmitters (which utilize capacitance as the measurement method) for sensing cell oil loss. This program has detected transmitter degradation in Veratrak transmitters (which utilize a strain gauge as the measurement method). This program confirms the reference 3 conclusions that sensor drift is an indication of transmitter degradation for any of the pressure transmitter types investigated.

The current approach to extend calibration intervals for pressure sensors is to use on-line cross calibration techniques. This is the same methodology recommended for calibration of Resistance Temperature Detectors (RTDs) channels in PWRs (12). Therefore, the possibility of extending calibration intervals using cross calibration techniques for pressure sensors would also be applicable to RTDs.

Several industry initiatives are in progress dealing with instrument performance monitoring. ISA S67.06 (reference 4) is in the revision process with a scope change from response time testing to instrument channel performance monitoring. This standard will provide utilities an alternative to existing Technical Specification required testing which could reduce the amount of manual testing. The Boiling Water Reactor Owners Group (BWROG) is in the process of preparing a technical specification amendment to eliminate specific response time testing requirements. An EPRI-utility instrument channel performance monitoring group is in the formation process.

CONCLUSIONS/RECOMMENDATIONS

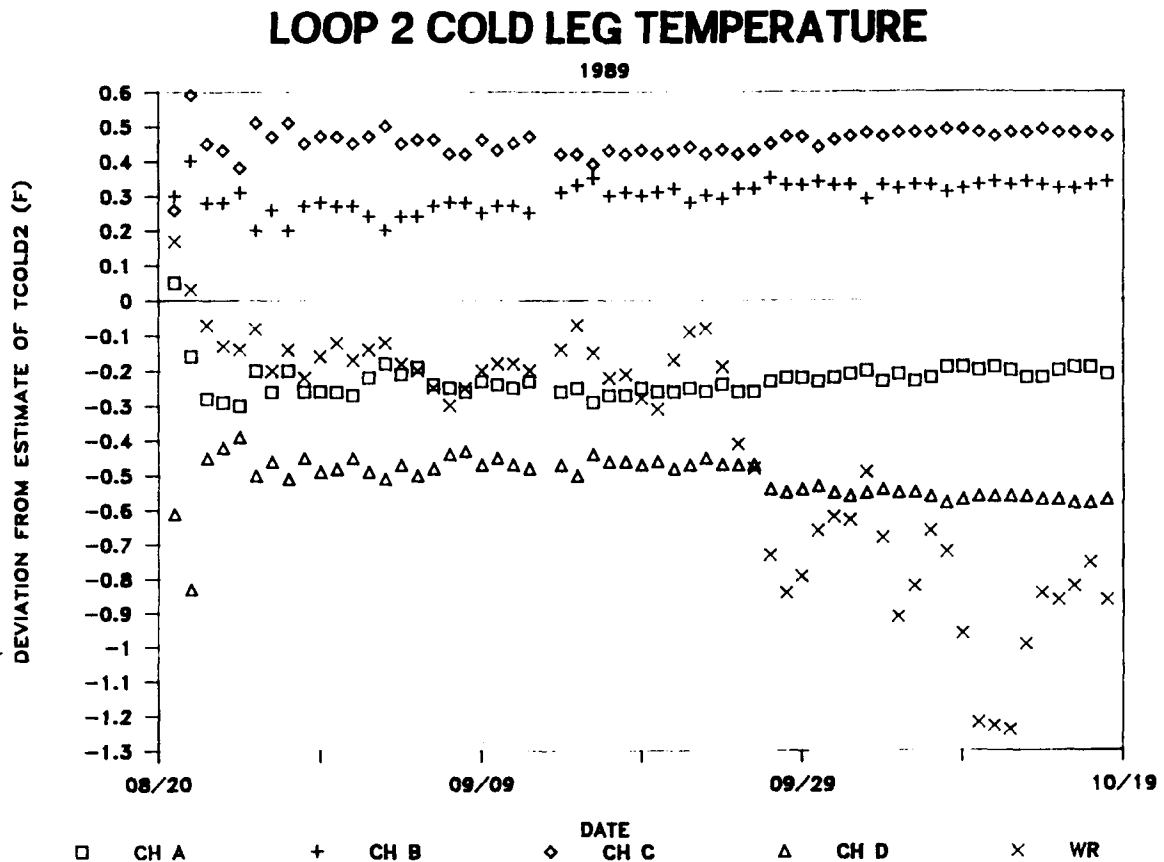
The basic requirements of a sensor health monitoring system are becoming clear. The system would monitor and perform cross channel checks, determine drift over the the instrument's calibrated range, and verify functionality of the electronics.

In order to stabilize plant operations and maintenance (O&M) costs, it is essential that industry take advantage of testing and analyses efforts to reduce the amount of manual testing of instrument loops. This should be accomplished by working with the standards organizations (eg, ISA and IEEE) to modify existing standards or develop new standards. Technical specification amendment changes to incorporate these techniques should be pursued on an owners group or overall industry basis.

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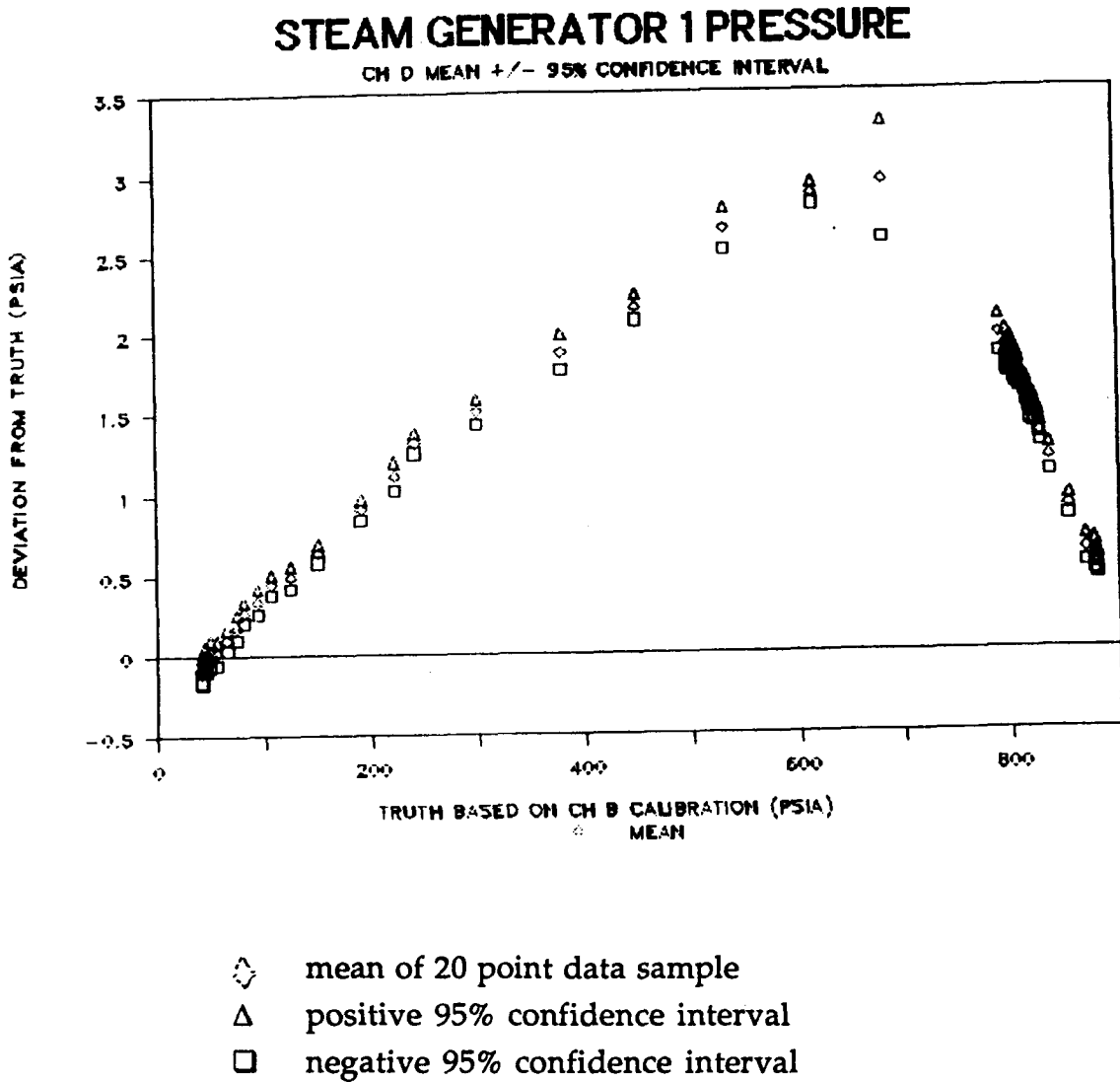
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Figure 1: Daily Steady State Data for Drift Monitoring



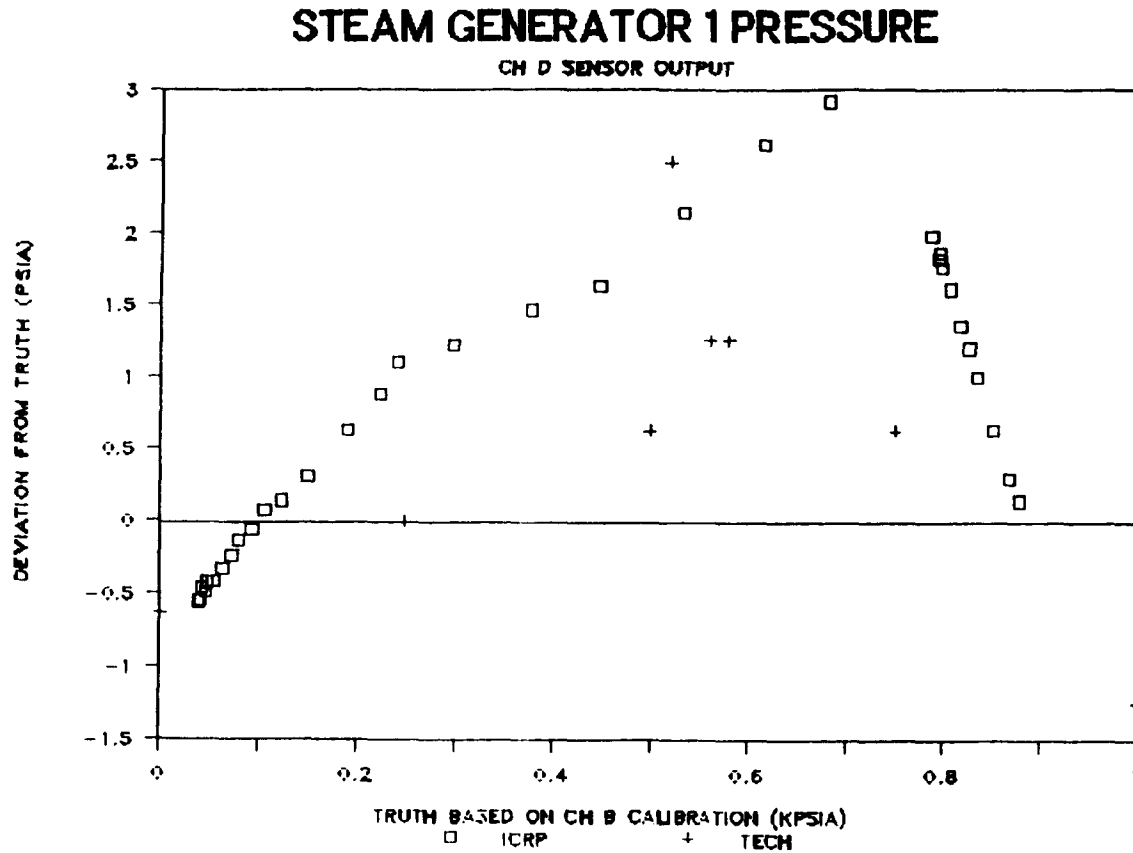
This steady-state data is logged and the average of the validated signals is used as the estimate or "truth" (the zero horizontal axis). This estimate is the basis in order to determine the individual instrument loop drift.

Figure 2: Transient Data Accuracy Over Instrument Range Collected During Plant Cooldown



The transient data for each channel (or sensor) is compared to the one instrument channel (or sensor) chosen as the reference and calibrated by the technician. This calibrated channel is used as the "truth" (the zero horizontal axis) against which each other channel is compared.

Figure 3: Comparison of ICRP and Technician Calibration Accuracy Over Instrument's Range



- ICRP Estimate of Channel Calibration compared to the channel chosen as the reference and calibrated (the "truth" shown as the horizontal zero axis)
- "+" Technician's calibration data from actual field compared to the channel chosen as the reference and calibrated (the "truth" shown as the horizontal zero axis).

EXPERIENCE WITH ON-LINE MEASUREMENT OF RESPONSE TIME OF PRESSURE SENSING SYSTEMS IN PWRs

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ABSTRACT

Noise analysis has been successfully validated and is now routinely used for measurement of response time of pressure transmitters and associated sensing lines in nuclear power plants. This paper presents the experience to date with the use of noise analysis in pressurized water reactors (PWRs) in the United States.

1. INTRODUCTION

Measurement of response times of safety-related pressure, level, and flow transmitters is mandatory in most nuclear power plants in the United States. Prior to 1987, most of these measurements were made by injecting a pressure test signal to the transmitter, and measuring its delay with respect to a high-speed reference transmitter. Since this method requires physical access to each transmitter and is tedious to perform, the authors embarked on validation of noise analysis to replace the conventional method. The validation involved laboratory testing of fifty nuclear-grade pressure transmitters. Each transmitter was tested with the conventional method and with noise analysis. This showed that noise analysis is successful in providing comparable response time results to that of the conventional method.⁽¹⁾

The laboratory noise tests were performed in a test loop made of copper tubes designed to produce pressure noise from the flow of water in the loop. The laboratory tests were followed by experimental measurements in four PWRs. The in-plant tests further confirmed the validity and practicality of noise analysis for the intended measurements.⁽²⁾ This work has been the first systematic attempt in experimental validation of noise analysis for response time measurements on pressure transmitters in nuclear power plants.

Since 1987 when the validation of noise analysis was completed, fifteen U.S. PWRs have switched from the conventional technique to the noise analysis technique. The experience from these plants is that the test is simple to implement, sufficiently accurate, and causes no disturbance to plant operation. The test of a typical set of transmitters in a nuclear plant can be completed in one or two days compared with two or three weeks that it takes to perform the

tests with the conventional method. According to utilities using the noise analysis technique, the main advantage of this technique is the capability that it provides for performing the tests on-line rather than at cold shutdown. This saves outage time and labor and results in significant cost savings in addition to reducing radiation exposure to the test personnel. Another advantage of noise analysis from a utility standpoint is that its results include the effects of sensing line delays. This relieves the utilities from having to test the sensing lines separately.

2. CHARACTERISTICS OF PRESSURE SENSING SYSTEMS IN PWRs

Figure 1 illustrates a typical pressure sensing system in a PWR. The transmitter, being an absolute or differential pressure transmitter, and the associated sensing lines are located in the field (sometimes inside the containment), and the power supply and the signal conditioning equipment are located in the control room or cable spreading room. The response time of interest consists of two components: 1) the time delay for the pressure signal to reach from the process to the transmitter through the sensing lines, and 2) the response time of the transmitter itself. With noise analysis, the overall response time including both components is measured in a single test.

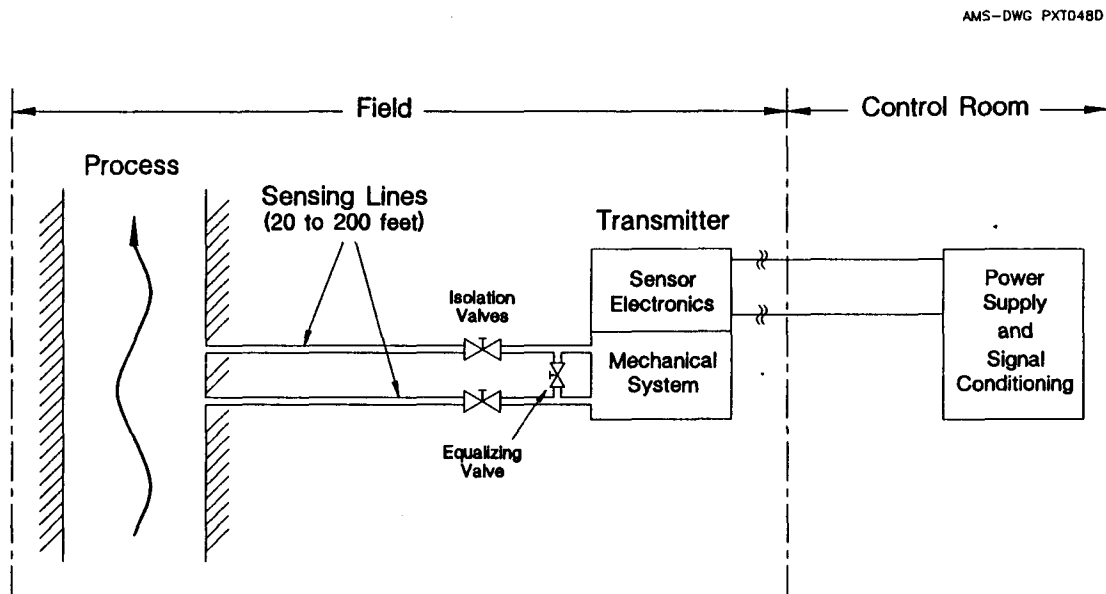


Figure 1. Illustration of a Pressure Sensing Channel in a PWR.

Pressure transmitters are different in the way that they sense the applied pressure. Some transmitters have an elastic element such as a diaphragm or bellows that must physically move to indicate the pressure, and some transmitters have sensing elements that do not move or move very little. In the latter, the response time due to the sensing line is basically equal to the speed of sound times the length of the sensing line. This amounts to a negligible time delay considering the length of sensing lines that are usually less than 500 feet. However, for transmitters whose sensing element has to move to indicate the applied pressure, such as Barton and Rosemount transmitters that are used extensively in PWRs, the delay in the sensing line is a significant part of the response time of the pressure sensing system. In these transmitters, the overall response time of the pressure sensing system is affected by the length of the sensing line, and any blockage or void that can restrict the flow of water in the sensing line or dampen the pressure signal.

Using a typical length for a PWR sensing line and a Barton transmitter as the model, the contribution of the sensing line has been estimated to be as much as 0.2 seconds provided that the line is clear of obstructions and does not have any voids. The average allowable sensor/sensing line response time in PWRs is about 0.5 seconds. That is, about 40 percent of the allowable response time may be consumed by the sensing line alone. Considering an average value of about 0.2 seconds for the response time of the transmitter's mechanical and electronics systems, a small margin is then left for the degradation of the sensing lines or the transmitter. Therefore, it is important to make periodic on-line measurement of response times of the complete pressure sensing system to ensure that the safe limits are not exceeded due to aging and other effects.

3. IMPLEMENTATION OF NOISE ANALYSIS

The implementation of noise analysis for testing of pressure sensing systems in nuclear power plants is very simple. The test is performed when the plant is at normal operating conditions. The test does not interfere with plant operation and can be performed on several transmitters at a time.

The noise data may be analyzed in frequency domain using a Fourier transform algorithm or in time domain using the autoregressive (AR) method. With either technique, the power spectral density (PSD) of the noise signal should be first examined. The shape of the power spectral density (PSD) of pressure noise signals depends on the type of transmitter being tested, the type of plant and its operating conditions, and the transmitter service being pressure, level, or flow. Although the shape of PSDs are different in different plants, a few common features are routinely found. For example, the PSDs of pressurizer pressure and pressurizer level transmitters in most PWRs tested to date have a resonance at approximately 0.5 to 0.7 Hz. This is true even in some European reactors for which PSD data are found in literature.⁽³⁾ This resonance is related to the coolant flow in and out of the pressurizer through the surge line. Figure 2 shows

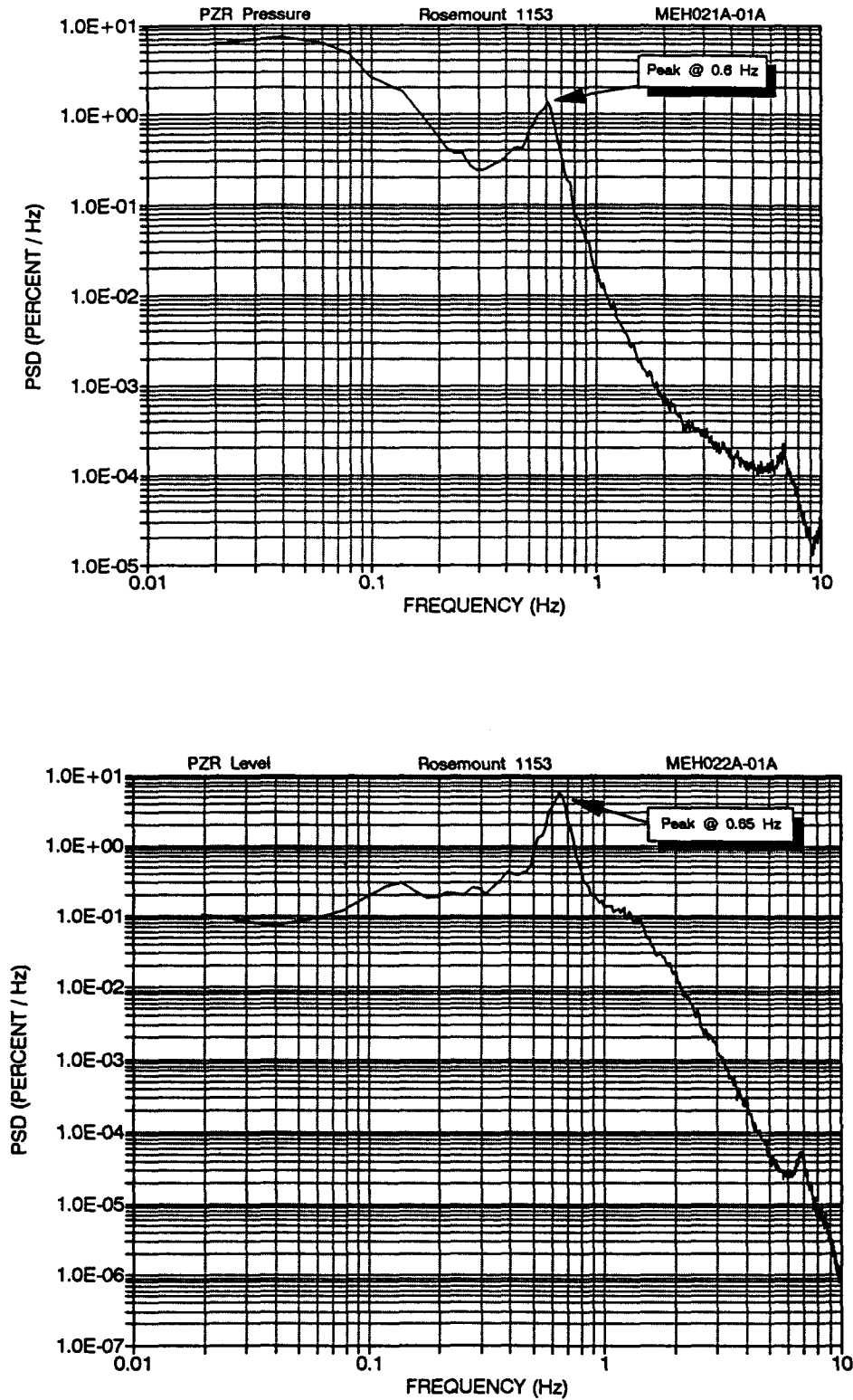


Figure 2. Typical PSDs for a Pressurizer Pressure (top) and a Pressurizer Level (bottom) Transmitter.

typical PSDs for a pressurizer pressure and a pressurizer level signal in two different PWRs. Proceeding to show more typical PSDs, we have Figure 3 which shows typical PSDs for a reactor coolant flow and a steam generator level signal. To demonstrate the repeatability of noise analysis results we have Figure 4 which shows the PSDs of a steam generator level transmitter tested twice in a PWR with approximately two years in between the tests.

The variety that exists in PSDs of different transmitters in PWRs complicates the effort to automate the analysis of the noise data to obtain the response time of a pressure sensing system. However, the experience that is being accumulated in PWRs is paving the way for development of an expert system to perform automated data acquisition and data analysis. The next generation of reactors are expected to have such an expert system as a permanent plant instrument to perform continuous on-line measurements of sensor response time.

4. MEASUREMENT OF SENSING LINE EFFECTS WITH NOISE ANALYSIS

Blockages and voids in sensing lines should show up on the noise PSD as resonances. However, until more in-plant experience is accumulated, it is not always easy to distinguish between different sensing line effects on the PSDs. What is important, however, is the fact that sensing line delays are included in the noise analysis results. This has been proven through laboratory measurements conducted with various nuclear-grade pressure transmitters. Sample results of such laboratory experiments for a Barton transmitter are discussed below in which snubbers and long sensing lines were used to simulate blockages and demonstrate the delays due to the length of the sensing line (Figure 5).

Table 1 shows sample results of the study of sensing line delays. In this experiment, the response time of the pressure sensing system in the laboratory was measured by applying a ramp signal at the input to the sensing line and measuring the delay of the transmitter/sensing line system with respect to two high-speed reference transmitters installed at the beginning and the end of the sensing line. Note that the results of the direct tests clearly show the effects of the sensing line length and the simulated blockages on the overall system response times. The direct measurements were followed by noise tests in the laboratory under the same test conditions and test arrangements as the direct tests. As shown in Table 1, the noise analysis results compare well with that of the direct measurements indicating that the results of noise analysis include the sensing line effects. The corresponding PSDs are shown in Figure 6.

Rosemount transmitters are also sensitive to the length and any blockages in the sensing lines. Figure 7 shows two PSDs for a Rosemount transmitter, one with short and clear sensing lines and one with 100 feet of sensing line and a snubber on the line to simulate a major blockage as was done for the Barton transmitter tests discussed above. A comparison of PSDs in Figures 6 and 7 shows that the response of the Rosemount system is less affected by the sensing lines than that of the Barton system.

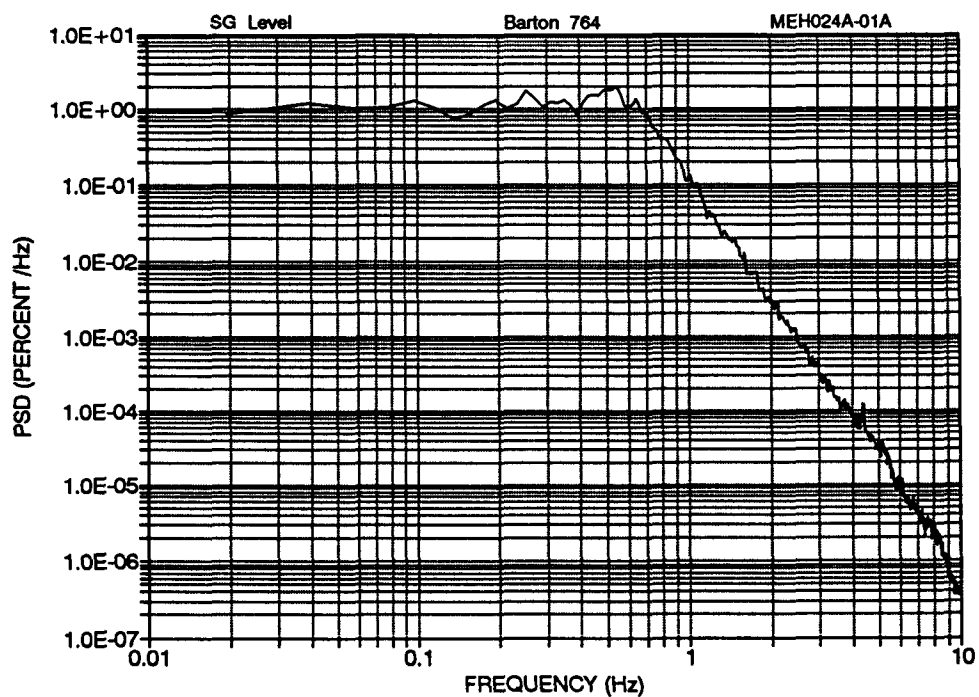
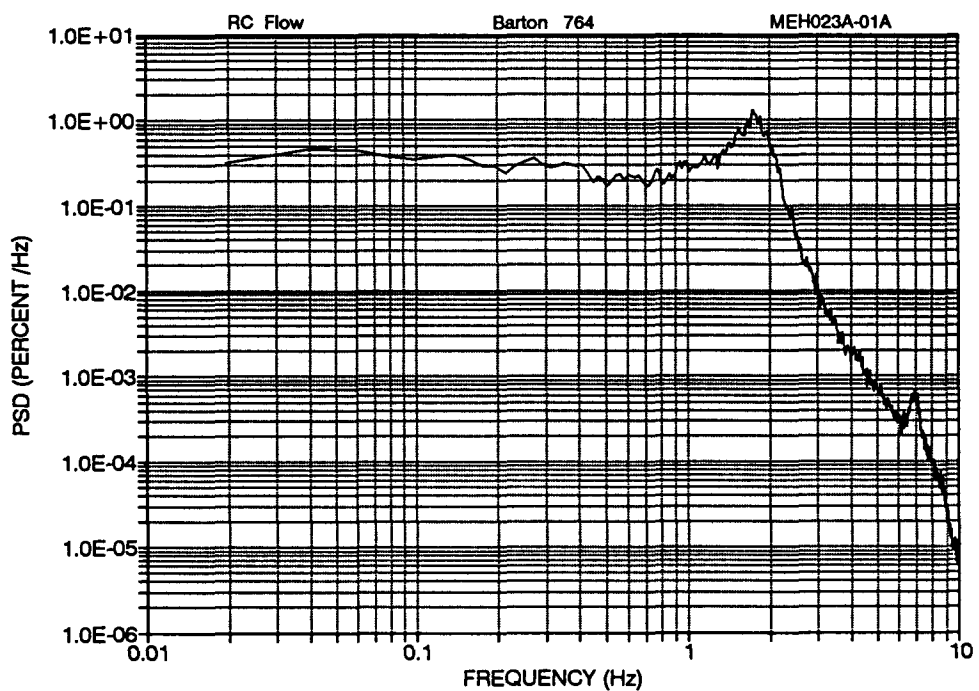


Figure 3. Typical PSDs for a Flow (top) and a Level (bottom) Signal in a PWR.

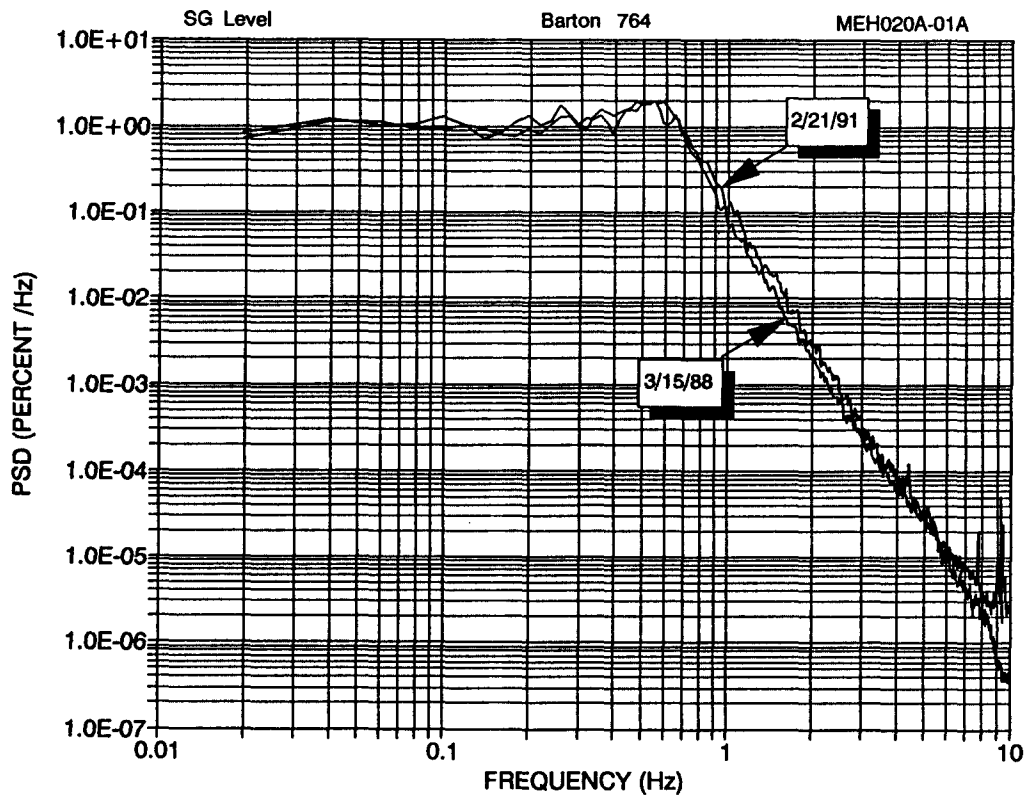


Figure 4. PSDs of a Steam Generator Level Transmitter
Showing Repeatability of Noise Analysis Results.

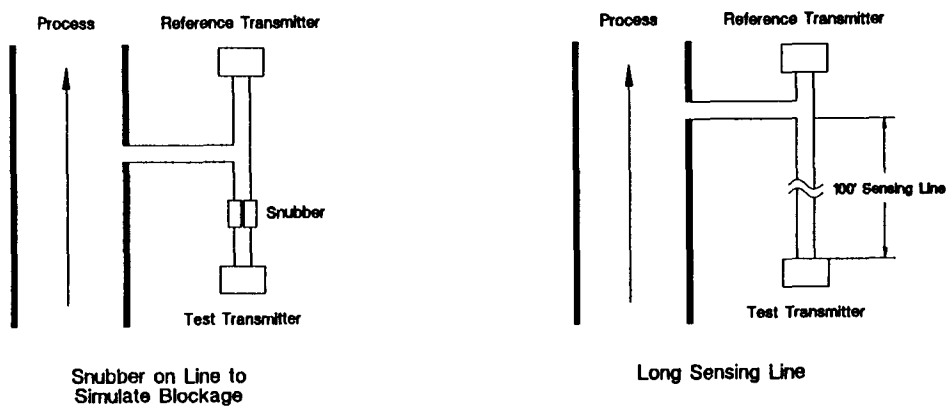


Figure 5. Laboratory Test Setup for Sensing Line Studies.

TABLE 1

Sensing Line Test Results for a
Barton Model 764 Transmitter

<u>Transmitter Tested</u>	<u>Response Time (sec)</u>	
	<u>Direct</u>	<u>Noise</u>
Reference Alone	0.00	0.00
Reference & 100 ft.	0.01	0.00
Reference & Snubber	0.34	0.27
Barton Alone	0.12	0.17
Barton & 100 ft.	0.27	0.28
Barton & Snubber	3.00	2.94

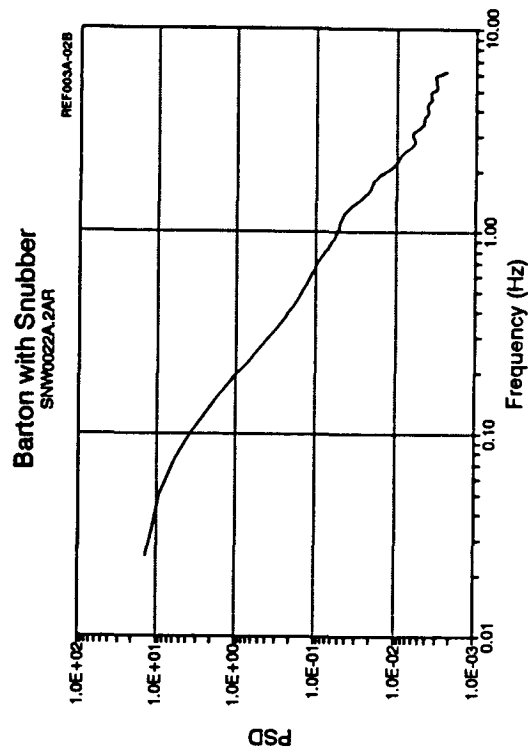
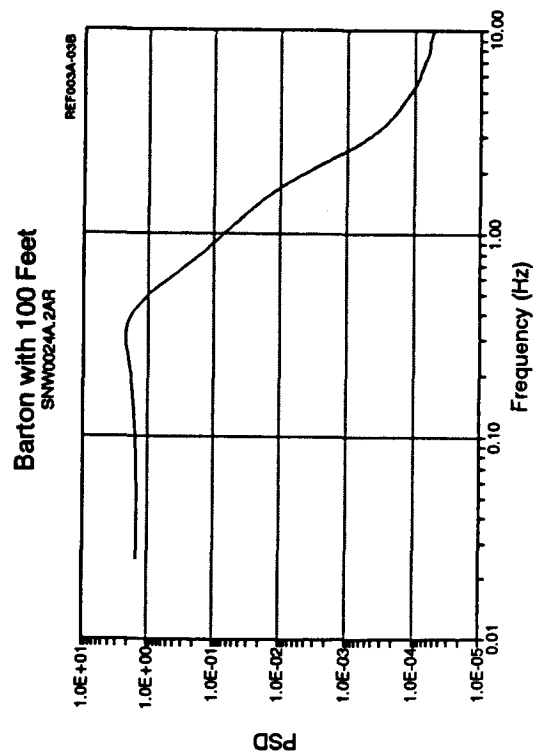
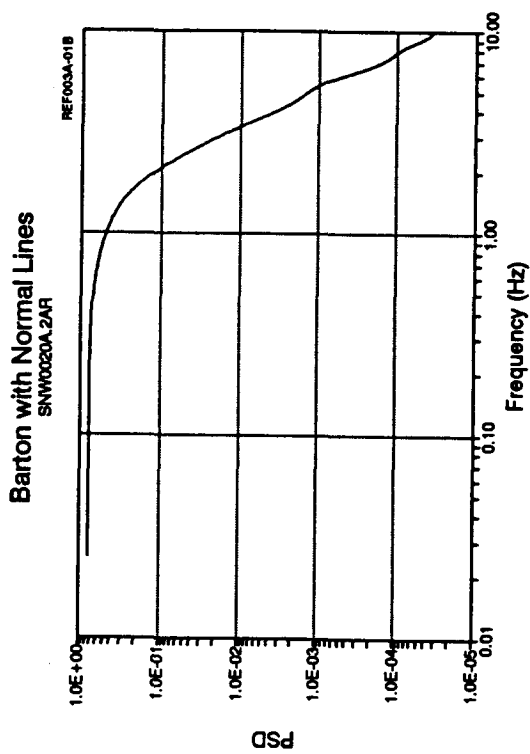


Figure 6. PSDs of Barton Transmitter With and Without Long Sensing Lines and Snubbers.

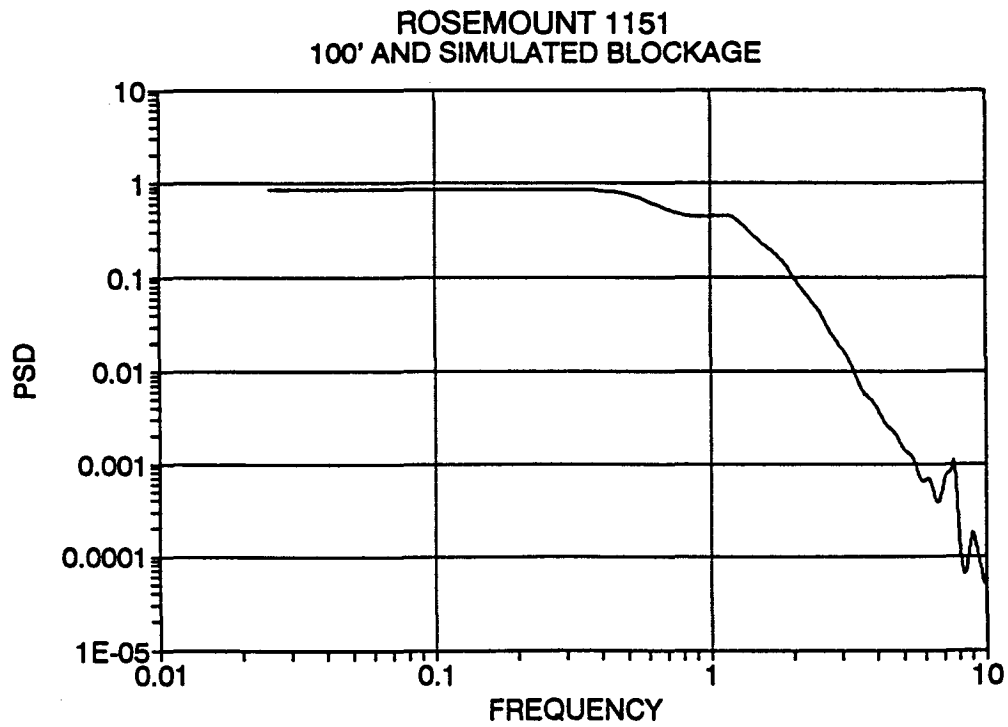
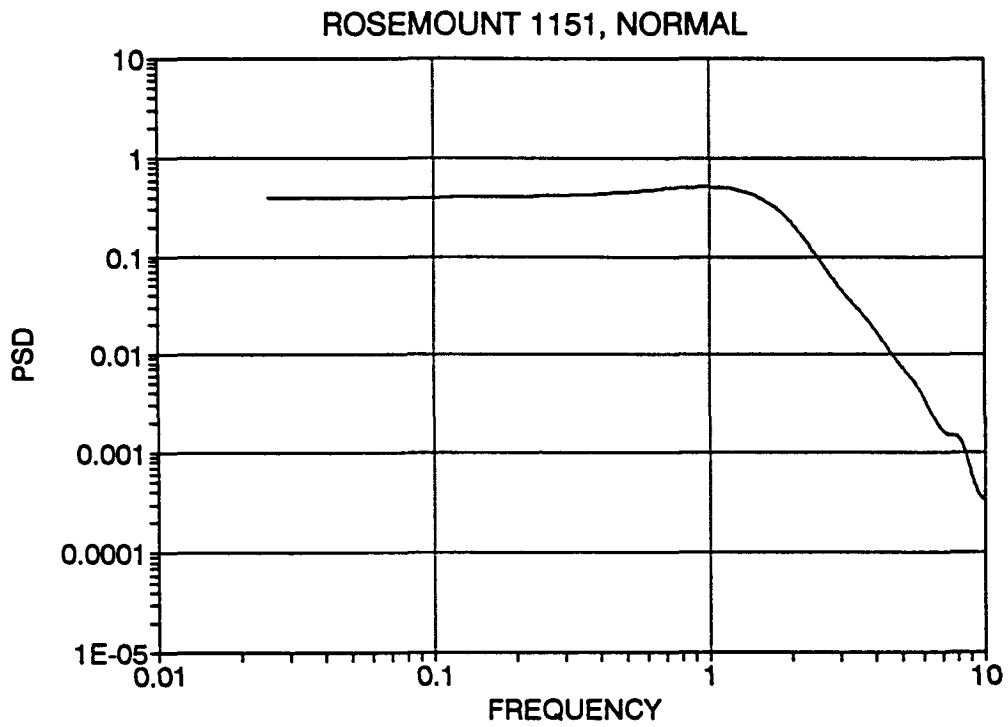


Figure 7. PSDs of a Rosemount Transmitter With and Without Long Sensing Lines and Simulated Blockages.

5. EFFECT OF SENSOR NONLINEARITY

In almost all test methods, sensor nonlinearities can complicate the data analysis, interfere with the accuracy of the test results, or restrict the validity of the test to certain conditions. Pressure transmitters are designed to have predominantly linear behavior to facilitate operation, calibration, and response time measurements. In validating the noise analysis technique for response time measurements of nuclear plant pressure transmitters reported in earlier publications,⁽²⁾ we have provided data on linearity characteristics of nuclear grade pressure transmitters. Basically, all transmitters used for nuclear safety-related applications are normally linear. The only major nonlinearities experienced to date in nuclear plant pressure transmitters are those of Rosemount transmitters that have lost fill fluid. The linearity question is often important for the transmitters that normally operate at a significantly higher or lower pressure than the trip setpoint pressure around which the response time of interest is measured. For these transmitters, an examination of the amplitude probability density (APD) of the noise data can reveal a gross nonlinearity. Figure 8 shows two APDs for a linear transmitter and an apparently nonlinear transmitter tested with noise analysis in an operating PWR. The APD for the nonlinear case is that of a Rosemount transmitter that was found to have lost fill fluid. It is clear that the APD can show the nonlinearity. Therefore, as a part of data qualification effort in noise analysis, the APD of the noise signal from plant transmitters are routinely examined for nonlinearity before the data is analyzed.

6. CONCLUSIONS

Noise analysis is an effective method for measurement of response time of pressure transmitters and associated sensing lines in nuclear power plants. The use of the method in PWRs have shown that the test is simple to implement and causes no disturbance to plant operation.

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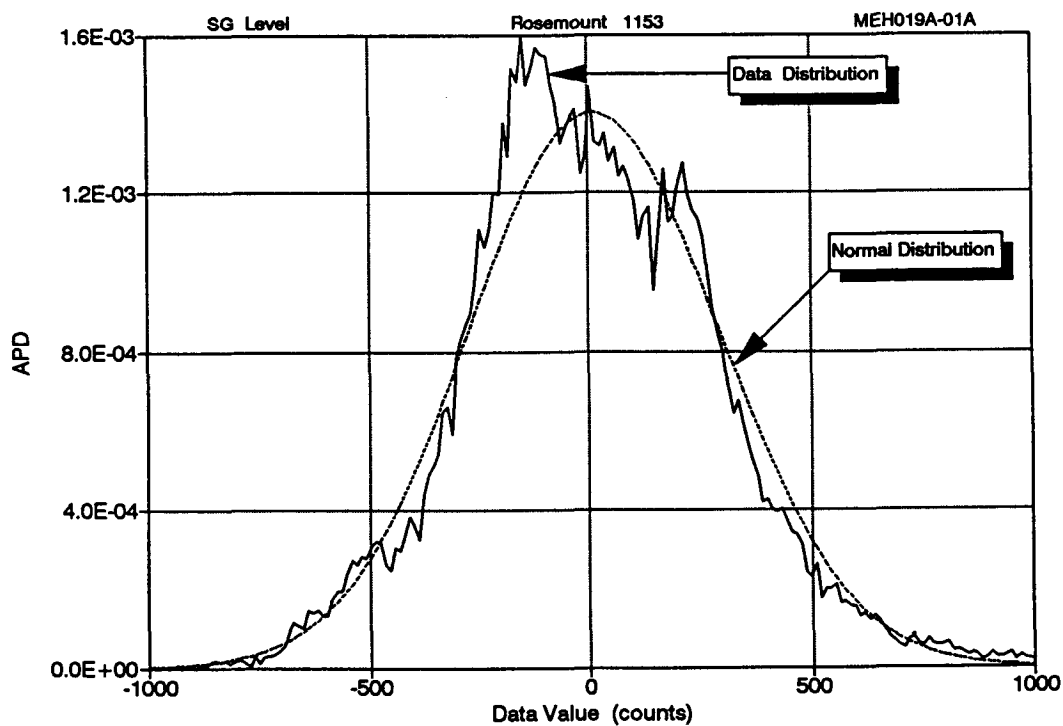
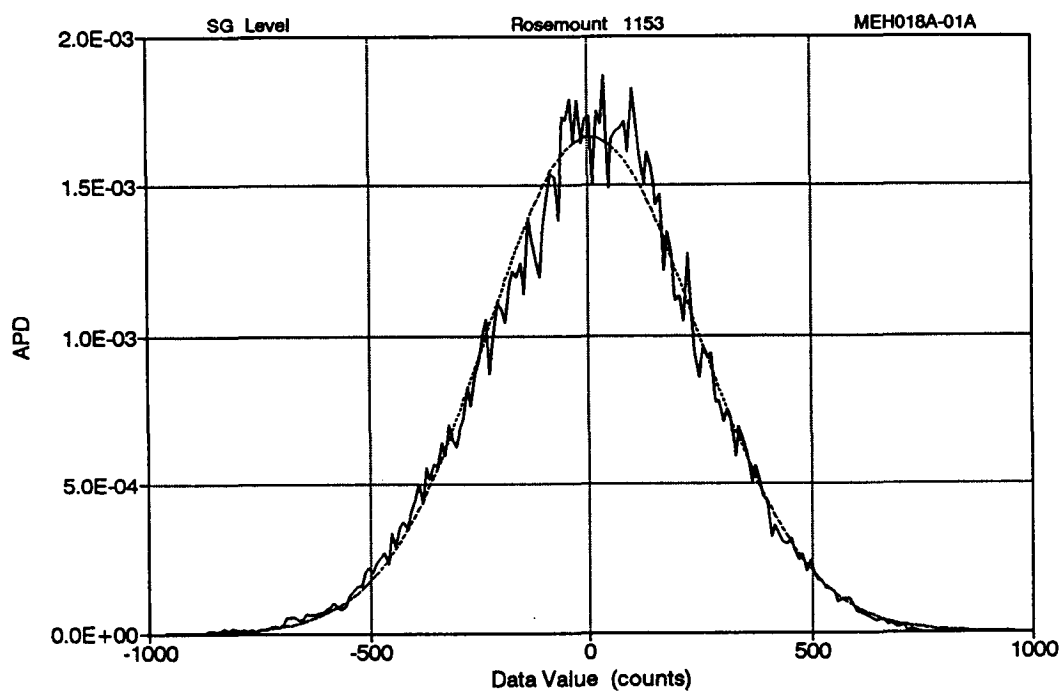


Figure 8. APDs of a Linear (top) and a Nonlinear (bottom) Pressure Transmitter.

**EPRI PROGRAM TO JUSTIFY RESPONSE
TIME TESTING REQUIREMENTS FOR
PRESSURE SENSORS**

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ABSTRACT

Response time testing requirements were imposed on pressure and differential pressure sensors as a conservative approach. This purpose of this project has been to identify the need for response time testing using the bases identified in IEEE Standard 338. A combination of plant data analyses and failure modes and effects analyses (FMEAs) was performed. Eighteen currently qualified sensor models were utilized. The results of the analyses indicate that there are only two failure modes that affect response time and not sensor output concurrently. For these failure modes, appropriate testing techniques were identified.

BACKGROUND

Safety system RTT requirements were established by IEEE Standard 338-1975, "Criteria for the Periodic Testing of Class IE Power and Protection Systems" (1). This standard established guidelines for periodic testing to verify that loop response times of installed nuclear safety-related equipment were within

the limits assumed by the design basis plant transient and accident analyses. All passive and active components in an instrument loop, including sensors, were required to be tested. Individual components could be tested in groups or separately to determine the overall loop response time. IEEE Standard 388-1975 requirements were adopted by NRC Regulatory Guide 1.118 "Periodic Testing of Electric Power and Protection Systems" Revision 1 issued in 1977 (2); IEEE Standard 338-1977, "Criteria for the Periodic Testing of Nuclear Power Generating Station Safety Systems" (3) was adopted by NRC Regulatory Guide 1.118 Revision 2 issued in June, 1978 (4). Additional guidance is provided in Instrument Society of America Standard ISA S67.06, "Response Time Testing of Nuclear Safety-Related Instrument Channels in Nuclear Power Plants", August 29, 1986 (5).

Utilities recently began assessing the RTT requirements for pressure sensors. Experience and data from a significant number of plants indicated, while RTT was both resource and exposure (ALARA) intensive, an insignificant number of pressure sensor failures had been detected through this type of testing. Various reviews of industry failure data showed most, if not all, pressure sensor failures were detected through calibration (typically performed prior to RTT), channel checks, and surveillance testing. The industry concluded from these reviews and related industry reports that:

- RTT provided potentially little benefit in the identification of failed sensors;
- RTT appeared redundant to other periodic tests;
- Response time failures, by themselves, seemed unlikely; and
- Verification of response time compliance to safety analyses could be met without RTT.

EPRI PROGRAM

EPRI established a program to evaluate the need for RTT of pressure, differential pressure, level, and flow transmitters and switches. The primary purpose of the investigation was to determine if deleting RTT could be justified per IEEE Standard 338 for specific pressure and differential pressure transmitters and switches.

IEEE Standard 338 defines a basis for eliminating RTT. Section 6.3.4 states: "...response time testing of all safety related equipment, per se, is not required if, in lieu of response time testing, the response time of the safety system equipment is verified by functional testing, calibration check, or other tests, or both."

The primary objectives of this project were to:

- evaluate existing RTT methodology using plant data;
- utilize FMEA methodology to determine if any response time degradation modes exist that would not be detected by periodic (non-RTT) methods; and
- provide RTT methods for sensors that exhibited response time degradation modes not detected by periodic methods.

This approach would not impact existing plant safety analyses and would be equally applicable to pressurized water reactors (PWRs) and boiling water reactors (BWRs).

DATA COLLECTION AND EVALUATION

The response time investigation was divided into separate data gathering and assessment activities. The first activity involved collecting and evaluating actual RTT data from utilities currently subject to RTT requirements. The second activity involved performing FMEAs on the major components of each pressure sensor type currently used by the nuclear industry in safety-related applications.

Thirty nine nuclear power plants supplied over 4200 RTT measurements representing over 2100 different pressure transmitters and switches. Three types of testing methods were found to be represented: ramp and step testing using a hydraulic test rig, and white noise analysis using an electronic test rig. Along with the test data, information regarding sensor type, sensor use, instrument range, trip setpoint, allowable response time, test method, and type of test rig were also provided. The plant data covered transmitters manufactured by ten different vendors. The vendors included Barton, Foxboro, Fischer & Porter, Tobar (Veritrak), GE, Barksdale, Static-O-Ring, ASCO, Magnetrol, and Rosemount. With the exception of Statham, all vendors supplying safety-related pressure sensors to the nuclear industry were represented by the plant data.

FMEAs were performed on the 18 sensor-types listed in Table 1. Based on the data collected from the industry for this investigation, these 18 sensor-types represent the majority of pressure sensor instrumentation currently installed or expected to be installed in safety-related systems in U.S. plants. These sensor-types also are representative of the various sensor designs (e.g., bourdon tube, force balance, capacitance, and strain gauge).

TABLE 1 SENSOR TYPES INCLUDED IN FMEAs

- Barton 288 Differential Pressure Indicating Switch
- Barton 763 Gauge Electronic Pressure Transmitter
- Barton 764 Differential Pressure Electronic Transmitter
- Foxboro N-E11DM Differential Pressure Transmitter
- Foxboro N-E13DM Differential Pressure Transmitter
- Foxboro N-E13DH Differential Pressure Transmitter
- Foxboro N-E11GH Gauge Pressure Transmitter
- Foxboro N-E11GM Gauge Pressure Transmitter
- Tobar 32PA1 Absolute Pressure Transmitter
- Tobar 32PG1 Gauge Pressure Transmitter
- Tobar 32DP1 Differential Pressure Transmitter
- Rosemount Differential Pressure Transmitter Models 1151, 1152, 1153, 1154
- Rosemount Pressure Transmitter Models 1151, 1152, 1153, 1154
- Statham PD 3200 Differential Pressure Transmitter
- Statham PG 3000 Pressure Transmitter
- SOR Differential Pressure Switch
- SOR Pressure Switch

No response time failures were found in the over 4200 measurements. Six measurements, each from a different sensor, exceeded the allowable response time provided on the plant data sheets, but were not actual response time failures. Discussions with personnel at the respective plants indicated the allowable times in the test procedures were set below technical specification requirements as a conservative measure. The response time measurements were compared to like sensors by plant personnel and found to be only slightly higher. As a result of this comparison and the fact that the response times were below technical specification limits, the sensors were declared acceptable.

There have been over 100 confirmed failures of Rosemount transmitters involving loss of fill fluid that significantly degrade response time. However, none of these failures were identified by RTT.

RTT RESULTS

The FMEAs indicate that RTT is redundant to other periodic testing for all cases but slow loss of fill fluid where the fill fluid is the working fluid and variable damping potentiometer misadjustment. For loss of fill fluid, drift trending will provide the necessary verification for the assumptions in the plant safety analyses. Using fixed rather than variable damping or

procedurally assuring that variable damping is properly set will alleviate the other response time degradation concern. The conclusions drawn from the RTT investigation follow.

- Based on the 4200 measurements, RTT has not identified any sensors that have failed response time requirements using hydraulic or electronic white noise analysis techniques. However, calibrations and other tests have detected transmitters with excessive response times.
- The limited number of test points per transmitter and the variances in RTT measurements due to type of test method and differences in test performance minimized the usefulness of the data for predicting failure trends.
- Sensor-specific response time of new sensors may not be known; pressure sensor vendors provide a nominal response time but do not provide sensor-specific RTT values to the utilities.
- Hydraulic step and ramp RTT methods, as currently performed around the sensor setpoint, may not detect a fill fluid failure mode prior to exceeding response time limits.
- Electronic white noise analysis RTT will not detect response time degradation due to loss of fill fluid failure prior to exceeding response time limits.
- The FMEAs identified two failure modes having the potential to affect response time without concurrently affecting sensor output: slow sensor fill fluid leak during pressurized operation and variable damping potentiometer misadjustment; The FMEAs also identified two manufacturing/handling defects having the potential to affect response time: low sensor fill fluid from the manufacturing process; and crimped capillaries from the manufacturing process or improper handling by the manufacturer or in the field during maintenance or plant modifications.
- Sensor failure modes associated with all Barton transmitters, models 763 and 764, and switch, model 288/289, Tobar (Veritrak), models 32PA1, 32PD1, 32PG1, SOR switches, and Foxboro (Weed), models N-E11GH, N-E11DM, N-E11GM do not affect sensor response time without significantly affecting calibration and/or sensor response. Correlations to specify the amount of sensor output versus response time degradation should be developed for Tobar transmitters.

- For Rosemount, Satham, and Foxboro E13 models, loss of fill fluid may significantly degrade sensor response time before impacting sensor output in a detectable manner using existing testing methods (e.g., hydraulic RTT, electronic white noise analysis RTT, channel checks, surveillance testing, calibration).
- Rosemount has developed correlations between drift and response time degradation that can be used by the industry to identify loss of fill-fluid prior to degrading response time. Periodic drift monitoring can be used as a method of detecting loss of fill fluid before response time is affected for Rosemount transmitters using the criteria in the Rosemount Technical Bulletins.
- At the present time, hydraulic RTT is the most effect method for response time testing Satham transmitters even though it may not identify a slow loss of fill fluid in the early stages. Drift criteria should be developed for the Satham transmitters for detecting potential loss of fill fluid.
- The power interrupt test is a viable method of RTT for force balance transmitters.
- Variable damping potentiometer misadjustment can affect response time without affecting sensor output.
- Hydraulic ramp and step, and electronic white noise analysis RTT methods can detect variable damping misadjustment (increased response time).

RECOMMENDATIONS

A summary of recommendations for modifying the current RTT program for pressure, level, and flow sensors is outlined. These recommendations are based on improving sensor failure detection, minimizing the potential for human error resulting in LERs, reducing personnel exposure, and reducing potential impact on plant down time. Utilities, Owners Groups or NUMARC can utilize this report as a technical basis for eliminating RTT requirements from Technical Specifications.

- Perform a hydraulic RTT prior to installation of a new transmitter/switch or following refurbishment of the transmitter/switch (e.g., sensor cell or variable damping components) to determine an initial sensor-specific response time value; the power interrupt test is an alternate method to use on force balance transmitters.

- Delete periodic sensor RTT requirements except for transmitters utilizing variable damping. If the utility can assure that variable damping is at its required setting and not subsequently changed, there is no need to RTT. If RTT is necessary for transmitters with variable damping, RTT using hydraulic or electronic methods.
- Perform periodic drift monitoring on all Rosemount pressure and differential pressure transmitters, models 1151, 1152, 1153 and 1154; guidance on drift monitoring can be found in EPRI NP-7121 (6) and Rosemount Technical Bulletins (7-10); drift monitoring intervals should be based on utility response to NRC Bulletin No. 90-01 (11).
- Utilities having Satham pressure and differential pressure transmitters, models PD3200 and PG3000 should continue to perform hydraulic RTT until a drift criteria can be developed relating sensor drift to response time degradation.
- Perform power interrupt tests on all Foxboro (Weed) force balance transmitters, models N-E13DA and N-E13DM, at an interval to be determined by the utility.

CURRENT STATUS

The BWR Owners Group Subcommittee on RTT met with the NRC in January 1991 and has committed to submit a technical specification amendment to eliminate RTT during the fourth quarter of 1991 based, in part, on the EPRI report (12). ISA is currently in the ballot stage in revising the scope and purpose of ISA S67.06 also based on the EPRI work.

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Fault Detection via Sequential Probability Ratio Test of Multivariate Autoregressive Modeling-Based Residual Time Series

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Summary

A statistical hypothesis test for detecting faults in noise signals has been developed and tested with nuclear power plant data. The developed technique can be regarded as a signal processing unit which generates time series highly sensitive to changes in the process dynamics. First the simultaneously measured process noise signals are transformed into residual time series, then the latter are further transformed into sequential probability ratio time series. The twofold transformation of the measured noise signals results in time functions which can be used to detect changes in the characteristics of the measured process with a predefined confidence level. The occurrence of sudden, short changes, such as spikes and jumps, are also detected and their onset and duration are determined. Description of the method and some results of analysing nuclear power plant data are given in the paper.

1. Introduction

The objective of the study reported here is to develop an automated procedure for searching for anomalies in process noise signals. The first part of the procedure is the learning period under which the characteristics of the measured process in the normal state is learned by establishing a multivariate autoregressive (MAR) model for the given set of process noise signals. This model serves as a reference model of the measured stationary process. The second part is the comparison period under which the residual times series of a new (candidate) measurement to be tested are calculated as the difference between the series of one-step predictions of the previously established MAR model and the candidate time series of the same signal set actually measured in the comparison period. The third part of the procedure is the decision period under which the sequential probability ratio test (SPRT) of the residual time series is performed. The goal of applying the SPRT algorithm to the residual time series is to decide if the measured noise signals originate from the

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normal state of the process, which was identified in the learning period, or from some other states, regarded as abnormal.

The novelty of the technique is the integration of two known techniques, namely, the calculation of the MAR-based residual time series and the sequential probability ratio test. The mathematical details of the combined MAR-SPRT method are discussed in section 3 through 6. Some of the results obtained through the application of the method to process noise signals measured at the Paks NPP (VVER-400 PWR) in Hungary are discussed in section 7. The analyzed signals were recorded from the reactor noise measuring system, which is permanently installed at all the four identical reactor units of the Paks NPP, and processes the inherent fluctuating components of process signals (noise) from the standard instrumentation of reactor core and primary loops. Noise signals of ex-core and in-core neutron detectors, core-exit thermocouples, reactor inlet/outlet pressure and pressurizer pressure transducers are regularly modelled by MAR and analyzed in different combinations and frequency ranges. Their MAR-based residual time series are processed by the SPRT program for the purpose of detecting faulty signals.

2. Fitting Multivariate Autoregressive Models to Measured Time Series

The multivariate autoregressive model fitted in the learning period represents the dynamic coupling between the components of the measured reference time series vector $\mathbf{X}(t_i)$, $i = 1, \dots, K$. In case of M measured signals the stationary time series vector $\mathbf{X}(t_i)$ has M components. The form of the linear model is defined as follow

$$\mathbf{X}(t_i) = \sum_{n=1}^N \mathbf{A}(n) \mathbf{X}(t_i - n\Delta t) + \mathbf{V}(t_i), \quad (1)$$

where N is the model order, Δt is the sampling time, and $\mathbf{V}(t_i)$ is a white noise vector with M components, which are not necessarily independent, that is, their Σ covariance matrix is not necessarily diagonal. The measured time series vector $\mathbf{X}(t_i)$, $i = 1, \dots, K$ is supposed to have stationary statistics with zero mean value.

The unknown $(M \times M)$ parameter matrices, $\mathbf{A}(n)$ and Σ are determined by the Yule-Walker matrix equations derived from Eqn. (1)

$$\mathbf{C}(k) = \sum_{n=1}^N \mathbf{A}(n) \mathbf{C}(k - n), \quad k = 1, 2, \dots, N \quad (2)$$

$$\mathbf{C}(0) = \sum_{n=1}^N \mathbf{A}(n) \mathbf{C}(-n) + \Sigma, \quad (3)$$

where the $\mathbf{C}(k)$ correlation matrices of the measured time series vector $\mathbf{X}(t_i)$ are given by the biased estimator of correlation

$$\mathbf{C}(k) = \frac{1}{K} \sum_{i=1}^{K-k} \mathbf{X}(t_{i+k}) \mathbf{X}(t_i)^T, \quad k = 1, 2, \dots, N < K \quad (4)$$

The Yule-Walker equations are solved for the MAR parameter matrices Σ and $A(n)$, $n = 1, \dots, N$ recursively with respect to increasing model order [1]. The fitted MAR model is equivalent with the measured physical process to the extent of the first N correlation matrices. Once the MAR model is fitted it can be used for generating statistical descriptors of process dynamics. By analyzing the statistical frequency dependent functions derived from the MAR model (e.g. auto power spectral density functions of signals and those of their inherent components, global and partial coherence functions, global and partial noise source contribution ratio functions, etc.) we can perform the cause-and-effect analysis of the measured process signals. Also, the main noise generating and propagating mechanisms can be identified in the process.

3. Global Spectral Functions Derived from the MAR Model

Auto and cross power spectral density functions (APSD and CPSD) are contained in the frequency dependent spectral matrix $S(f)$ calculated from the MAR parameter matrices

$$S(f) = H(f)^{-1} \Sigma H^*(f)^{-1} \Delta t, \quad (5)$$

where

$$H(f) = I - \sum_{n=1}^N A(n) \exp(-i2\pi f n \Delta t) \quad (6)$$

is an $(M \times M)$ complex transfer matrix derived from the MAR parameter matrices. The APSD functions are contained in the diagonal elements of the $S(f)$ spectral matrix, while the CPSD functions are in its off-diagonal elements. The global coherence function of signal i and j

$$COH_{ij}(f) = \frac{|S_{ij}(f)|^2}{S_{ii}(f) S_{jj}(f)} \quad (7)$$

describes the frequency dependent coupling effects via all possible signal paths connecting the two signals. The corresponding phase function is

$$PHASE_{ij}(f) = \arctg \left\{ \frac{Im[S_{ij}(f)]}{Re[S_{ij}(f)]} \right\}. \quad (8)$$

The global noise source contribution ratio function to signal i from signal j is defined as the contribution from the noise source of signal j , σ_{jj} , to the APSD function of signal i through all possible signal transmission paths

$$NSCR_{ij}(f) = \frac{|\{H(f)^{-1}\}_{ij}|^2 \sigma_{jj}}{S_{ii}(f)} \Delta t, \quad (9)$$

where σ_{jj} is the j -th diagonal element of the noise covariance matrix Σ in Eq. (3). The self-contribution ratio function of signal i is defined as the contribution from its own noise source to its APSD function through all possible signal transmission paths

$$NSCR_{ii}(f) = \frac{|\{H(f)^{-1}\}_{ii}|^2 \sigma_{ii}}{S_{ii}(f)} \Delta t. \quad (10)$$

4. MAR-based Process-Decomposition in the Frequency Domain

Based on the identified MAR model the analyzed process represented by the measured signal set can be decomposed into intersignal direct transfer functions and driving noise sources or inherent components of individual signals. In order to derive the formulae for the transfer functions and the driving noise sources, the defining equation (1) of MAR modeling was rearranged into the following form [2]

$$\mathbf{X}(f) = \mathbf{G}(f) \mathbf{X}(f) + \mathbf{N}(f), \quad (11)$$

where the elements of the $(M \times M)$ transfer matrix $\mathbf{G}(f)$ giving the frequency dependent direct transfer to signal i from signal j are expressed by the elements of MAR parameter matrices

$$G_{ij}(f) = -\frac{H_{ij}(f)}{H_{ii}(f)}, \quad G_{ii}(f) = 0. \quad (12)$$

The first term on the r.h.s of Eq. (11) denotes the intersignal coupling through direct transfer functions, while vector $\mathbf{N}(f)$ with M components represents the inherent components of the signals. The spectral matrix of the inherent components is also expressed by the elements of the MAR parameter matrices

$$Q_{ij}(f) = \langle \mathbf{N}_i(f) \mathbf{N}_j^*(f) \rangle = \frac{\sigma_{ij}}{H_{ii}(f) H_{jj}^*(f)}. \quad (13)$$

By using the derived $\mathbf{G}(f)$ and $\mathbf{Q}(f)$ matrix functions, the APSD function of any signal can be expressed as the sum of contribution from the signal's own inherent component and contributions from the inherent components of other signals through the corresponding direct signal transfer functions. For signal i the self-contribution is $Q_{ii}(f)$, while the contribution from the inherent component of signal j is $|G_{ij}|^2 Q_{jj} + 2 \operatorname{Re}[G_{ij} Q_{ij}^*]$. In a fictitious partial system which would include only signal i and j , the partial APSD of signal i would be given by the sum of the two contributions:

$$PAPSD_i(f) = Q_{ii} + |G_{ij}|^2 Q_{jj} + 2 \operatorname{Re}[G_{ij} Q_{ij}^*]. \quad (14)$$

In the real multi-signal system the APSD of signal i is expressed as a sum of its inherent APSD and the effect of the inherent components of all other signals contributing through the corresponding $G_{ij}(f)$ transfer functions

$$APSD_i(f) = Q_{ii} + \sum_{j=1}^M |G_{ij}|^2 Q_{jj} + 2 \operatorname{Re}[G_{ij} Q_{ij}^*], \quad (15)$$

which is equivalent with the i th diagonal element of spectral matrix $\mathbf{S}(f)$ in Eq. (5). Similarly, the partial CPSD function of signal i and j in a partial, two-signal system is expressed as

$$PCPSD_{ij}(f) = Q_{ij} + G_{ij} Q_{jj} + G_{ji}^* Q_{ii} + G_{ij} G_{ji}^* Q_{ij}. \quad (16)$$

The first and the last term on the r.h.s are due to the correlation between the driving noise sources of signals i and j . If the MAR model happens to give independent white noise components in Eq. (1), that is, $\sigma_{ij} = 0$ for any (i, j) signal pair in Eq. (3), then the coupling between the two signals in their CPSD function is represented by only their direct signal transfer functions (the second and third terms on the r.h.s of Eq. 16). In that case the system transfer functions are properly identified, that is, the $G_{ij}(f)$ transfer functions given by MAR model are identical with the real physical transfer functions between the measured signals. However, the independency of driving noise sources in the MAR model required for system identifiability is not guaranteed in Eq. (1). Previous experience showed that the required independency in the MAR model can be achieved by experimenting with various signal combinations, model orders and sampling frequencies.

The partial spectral functions of signals i and j , such as partial APSD and partial CPSD functions defined in Eqs. (14) and (16), characterize a fictitious two-signal system which is derived from the original MAR model by excluding the effect of the other signals and their noise sources. Similarly, the partial coherence and phase functions can be defined as

$$PCOH_{ij}(f) = \frac{|PCPSD_{ij}(f)|^2}{PAPSD_i(f) PAPSD_j(f)} \quad (17)$$

and

$$PPHASE_{ij}(f) = \arctg \left\{ \frac{Im[PCPSD_{ij}(f)]}{Re[PCPSD_{ij}(f)]} \right\}. \quad (18)$$

By following the definition of the global noise source contribution ratio functions in Eqs. (9) and (10), their partial counterparts are defined as

$$PNSCR_{ij}(f) = \frac{|G_{ij}(f)|^2 Q_{jj}(f)}{PAPSD_i(f)} \quad (19)$$

and the partial self-contribution ratio function

$$PNSCR_{ii}(f) = \frac{Q_{ii}(f)}{PAPSD_i(f)}. \quad (20)$$

The ratio function of contribution resulting from the correlation of the inherent components of signals i and j is

$$\frac{2 Re[G_{ij} Q_{ij}^*]}{PAPSD_i(f)}. \quad (21)$$

5. Calculating Residual Time Series of Candidate Measurements

In order to decide if a new measurement of the same signal set, called the candidate time series, contains errors we applied the sequential probability ratio test to the the MAR-based residual time series of the new measured signals. We assumed that the analyzed

process is in its normal, error-free state during the *learning period*. The reference time series vector measured in the learning period is denoted by

$$\mathbf{X}_R(t_i), \quad i = 1, \dots, K. \quad (22)$$

The MAR model fitted to the above time series represents the normal dynamics of the stationary process in the form of model parameter matrices

$$\Sigma_R, \quad \mathbf{A}_R(n), \quad n = 1, \dots, N. \quad (23)$$

Our goal is to decide if a new measurement of the same signal set (the candidate time series vector)

$$\mathbf{X}_C(t_i), \quad i = 1, \dots, K \quad (24)$$

measured during the *application period* is normal too, that is, similar to the reference time series in statistical sense. If errors are detected their onset and duration are to be determined too. To this end, first the time series vector of one-step predictions of the candidate time series $\mathbf{X}_C(t_i)$, $i = 1, \dots, K$ is generated by the reference MAR model

$$\hat{\mathbf{X}}_{C,R}(t_i) = \sum_{n=1}^N \mathbf{A}_R(n) \mathbf{X}_C(t_i - n\Delta t), \quad (25)$$

that is, based on the N consecutive measured values of the candidate time series, the values of the $(N + 1)$ th sample at time instant t_i can be predicted. At the same time, the actual measured values at time instant t_i are also known. The residual vector at time instant t_i is defined as the difference between the predicted and the measured values:

$$\mathbf{V}_{C,R}(t_i) = \hat{\mathbf{X}}_{C,R}(t_i) - \mathbf{X}_C(t_i). \quad (26)$$

Since the prediction is based on the reference MAR model, the predicted values represent the process response to the N number of measured samples as input under the assumption that the process is in its normal state. By shifting the N measured samples serving as input for predicting the $(N + 1)$ th sample, a time series of residual vectors can be generated. If the reference and candidate time series are similar in statistical sense, then the $\mathbf{V}_{C,R}(t_i)$ residual time series vector is white and its covariance matrix is identical with or close to the Σ_R covariance matrix of the reference MAR model. If the candidate time series is different from the reference one, then the $\mathbf{V}_{C,R}(t_i)$ residual time series vector is colored and the variance of its components is bigger than the corresponding diagonal elements of the Σ_R covariance matrix of the reference MAR model. The statistical properties of the calculated residual time series vector can be described by its auto- and cross-correlation functions and spectral functions. These functions are generated by averaging blocks of data, that is, they characterize the time series as a stationary process. However, if temporary anomalies, such as spikes, jumps occurred in the measured candidate time series, its residual time series would not be stationary, thus no time averaged based correlation or spectral functions can

be calculated. In this case the residual time series is processed sample by sample by the sequential probability ratio test.

6. Sequential Probability Ratio Test of MAR-based Residual Time Series

The sequential probability ratio test developed by Wald [3] is an optimal way for testing a hypothesis against an alternate one. The SPRT is performed for each signal independently. Let $(v_1, v_2, v_3, \dots, v_n)$ denote the successive samples of the residual time series of signal x . The basis for the SPRT is the recursive calculation of the logarithm of the likelihood ratio (LLR) function of the normal mode and an alternate degraded mode based on n samples

$$\lambda_n = \ln \frac{p_n(v_1, v_2, v_3, \dots, v_n | H_1)}{p_n(v_1, v_2, v_3, \dots, v_n | H_0)}, \quad (27)$$

where $p_n(v_1, v_2, v_3, \dots, v_n | H_1)$ is the n -dimensional probability density function of stochastic series V , assuming that the process is degraded (hypothesis H_1 : the variance of the residual time series is $\sigma_1 > \sigma_0$), and $p_n(v_1, v_2, v_3, \dots, v_n | H_0)$ is the n -dimensional probability density function of stochastic series V , assuming that the process is normal (hypothesis H_0 : the variance of the residual time series is σ_0). Since the $(v_1, v_2, v_3, \dots, v_n)$ residual time series is white or close to white, the above formula becomes additive and the LLR function is computed recursively with respect to successive time samples

$$\lambda_n = \lambda_{n-1} + \ln \frac{p_1(v_n | H_1)}{p_1(v_n | H_0)}, \quad (28)$$

where $p_1(v_n | H_1)$ and $p_1(v_n | H_0)$ are the one-dimensional probability density functions. Further simplification can be introduced if the "normal" and "degraded" hypotheses are represented by Gaussian distributions with zero mean and variance σ_0 and σ_1 , respectively

$$\lambda_n = \lambda_{n-1} + \frac{\sigma_1^2 - \sigma_0^2}{2\sigma_1^2\sigma_0^2} v_n^2 + \ln \frac{\sigma_0}{\sigma_1}. \quad (29)$$

The LLR function having value λ_n at sampling time t_n can be regarded as a time series characterizing the status of the given measured signal. The LLR time series is compared against two boundaries A and B ($A < 0 < B$) derived from the confidence levels predefined by the user

$$A = \ln \frac{\beta}{1 - \alpha} \leq \lambda_n \leq B = \ln \frac{1 - \beta}{\alpha}, \quad (30)$$

where α is the allowable false alarm rate and β is the allowable missed alarm rate. If the process is in normal state, then the LLR time series decreases and finally reaches the lower boundary ($A < 0$). Then the signal is declared to be normal under the given α , β false alarm and missed alarm probabilities. The LLR value is then reset to zero and the test continues. If the process is degraded the LLR time series increases and reaches the

upper boundary ($B > 0$). Then the signal is declared to be degraded under the given α , β false alarm and missed alarm probabilities. The LLR value is reset to zero and the test continues. No decision can be made if the LLR value is between the two boundaries. In this case the test proceeds to the next time sample and the LLR value is updated. The SPRT is an optimal procedure in the sense that a minimum number of samples is required to make a decision based on specified missed and false alarm probabilities.

7. Application of the Method to Power Plant Data

In this section some results of applying the combined MAR-SPRT method to noise signals measured at the Paks NPP are discussed. The signal analysis performed routinely includes noise signals from ex-core and in-core neutron detectors, core-exit thermocouples, reactor inlet/outlet pressure and pressurizer pressure transducers. The signals are modelled and analyzed regularly in different combinations and frequency ranges. Their MAR-based residual time series are processed by the SPRT program under various predefined missed and false alarm probabilities for searching for faulty signals. In the example to be discussed the following signals from the Paks NPP were analyzed

- x_1 = ex-core ionization chamber, J1
- x_2 = reactor inlet pressure transducer, RI
- x_3 = pressurizer differential pressure transducer, PP
- x_4 = pressurizer inlet pressure transducer, PI
- x_5 = in-core self-powered neutron detector, N4, medium in SPND string 04-37
- x_6 = in-core self-powered neutron detector, N7, uppermost in SPND string 04-37

Sampling frequency: $f_s = 50$ Hz, $\Delta t = 20$ msec

Filter frequencies: $f_{LP} = 0.01$ Hz, $f_{HP} = 20$ Hz

Number of samples per signal: $K = 30 \times 1024$

7.1. MAR Analysis in the Frequency Domain

First the MAR analysis of the reference measurement of the above six signals were performed, which constituted the learning period. The analyzed time series was considered to be error-free measured during the normal operation of the reactor. In the given case the MAR-model order was selected $N = 25$. Some of the frequency domain results obtained by MAR-modeling the above signal set are discussed in this section. Note that it is not necessary to generate the frequency domain signatures if one is interested only in the SPRT analysis of the MAR-based residual time series for fault detection. However, by analyzing the frequency domain results given by the reference MAR model may help in understanding the basic causal effects and identifying the frequency ranges of signal couplings among the reference signals measured during the learning period. What follows is just a brief example of the large number of analyzed cases. In Fig. 1 the APSD function of the ex-core neutron noise signals J1 (upper curve) and the APSD function of its inherent noise component (lower curve) are plotted together. The difference between the signal APSD and the inherent APSD below 1.5 Hz and around the 8.5 Hz peak frequency clearly shows

the contribution of other signals to the ex-core neutron noise signal at those frequencies. The source of the 8.5 Hz peak can be found in Fig. 2, which shows the APSD of reactor inlet pressure noise RI and the APSD of its inherent signal component. There are three distinct resonances in the pressure noise APSD. The strong peak in the pressure signal APSD at 0.6 Hz dominates the measured signal. The lack of this peak in the inherent APSD indicates that a resonance in a third signal affects the reactor inlet pressure noise. The second and third peaks at 8.5 Hz and 21 Hz are inherent to the reactor inlet pressure noise, at least in the group of the above six signals selected.

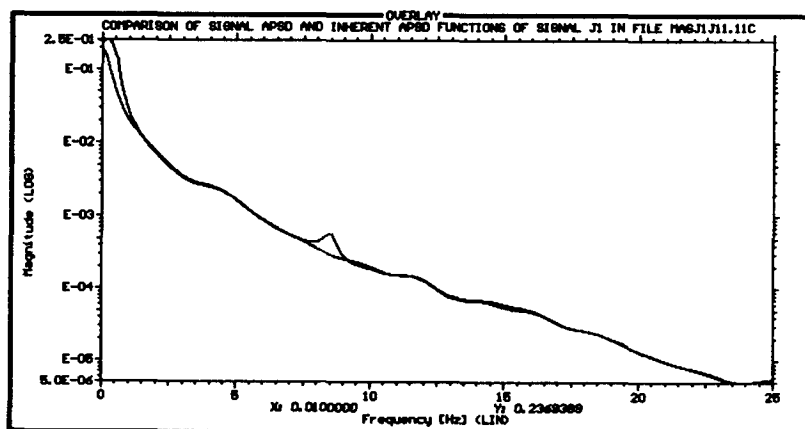


Figure 1. Signal APSD and inherent APSD functions of excore neutron noise signal J1

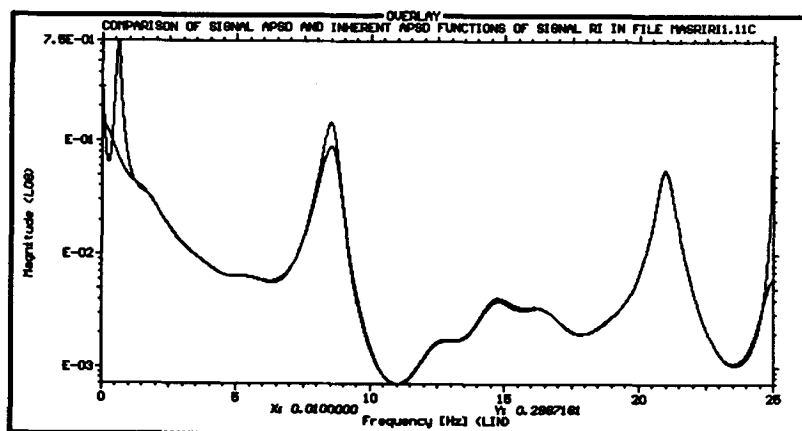


Figure 2. Signal APSD and inherent APSD of reactor inlet pressure noise signal RI

It is interesting to note, that while the 8.5 Hz resonance shows up in the excore neutron noise J1, the pressure peak at 21 Hz does not affect signal J1. This observation is confirmed by comparing the global and partial coherence functions of the excore neutron noise and the reactor inlet pressure noise signals in Fig. 3. Their global coherence is relatively high at 0.6 Hz, while their partial coherence is zero at that frequency. This shows that the two signals are not directly coupled at that frequency, rather through a third signal. Further study showed that the pressurizer pressure signal drives both excore neutron and the reactor inlet pressure noise signals at 0.6 Hz causing high global and negligible low partial (direct) coherences between the signals. Similar conclusions have been reached earlier based on

physical models by Pór et al [4]. In case of the 21 Hz peak both the global and the partial coherence is zero indicating the complete lack of signal coupling at that frequency. In Fig. 4 the global and the partial noise source contribution ratio functions from the reactor inlet pressure signal to the excore neutron signal are almost identical and have very low values except at 8.5 Hz. This indicates that the only frequency range in which signal RI directly affects signal J1 is around 8.5 Hz. Neither global nor partial (direct) signal contributions exist at other frequencies. The global and partial noise source contribution ratio functions from signal J1 to signal RI are practically zero over the whole analyzed frequency range confirming that the excore neutron signal does not affect the reactor inlet pressure signal.

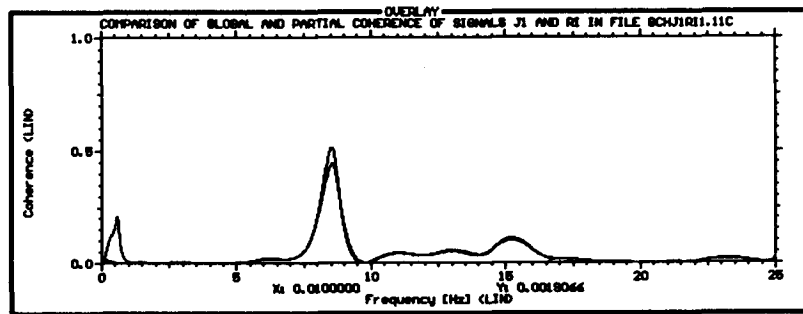


Figure 3. Global and partial coherence functions of excore neutron noise signal J1 and reactor inlet pressure noise signal RI

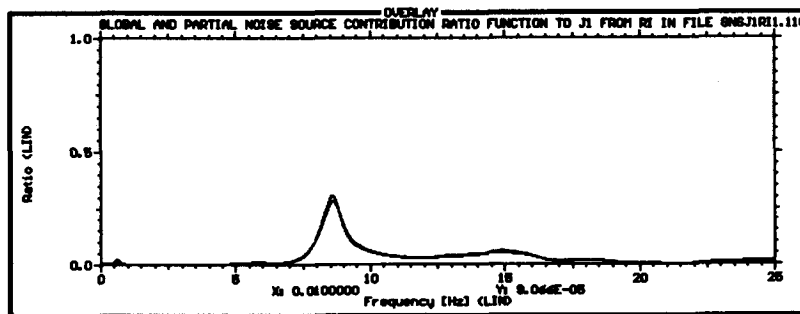


Figure 4. Global and partial noise source contribution ratio functions from the reactor inlet pressure noise signal RI to excore neutron noise signal J1

In Figure 5 the APSD function of noise signal from the uppermost incore SPND, N7 in string 04-37 (upper curve) and the APSD function of its inherent noise component (lower curve) are plotted together. As in the case of excore neutron noise in Fig. 1, the difference between the signal APSD and its inherent APSD indicates the contributions of other signals to the incore neutron noise signal below 1.5 Hz and around 8.5 Hz. The other two peaks at 14.5 Hz and 24.5 Hz are inherent parts of the signal since the two curves

are almost identical at those frequencies. The comparison of signal APSD and inherent APSD functions shows similar features in Fig. 6 for a medium incore SPND, N4 in the same detector string, with the following two exceptions: in the low frequency range the APSD magnitude of signal N4 is smaller than that of signal N7, and the resonance at 24.5 Hz is not inherently part of the incore signal N4.

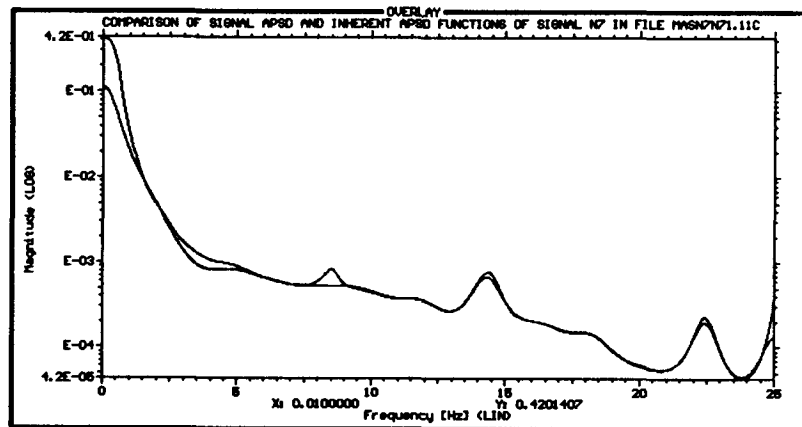


Figure 5. Signal APSD and inherent APSD functions of incore neutron noise signal N7

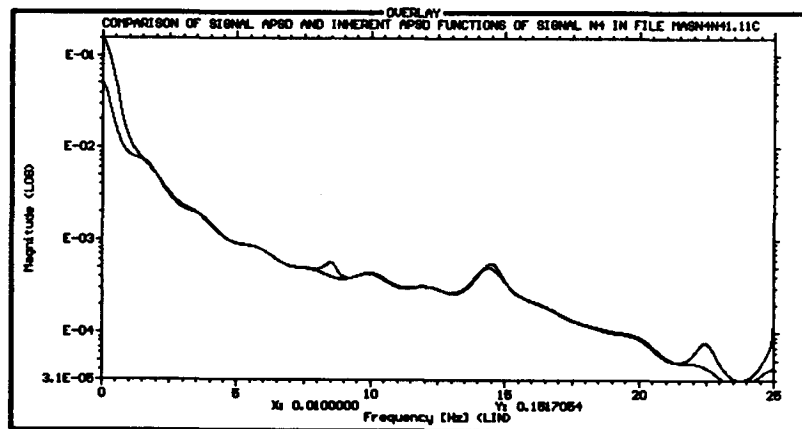


Figure 6. Signal APSD and inherent APSD functions of incore neutron noise signal N4

The coherence and phase functions of neutron signals from the same axially located SPND string, N4 and N7 are shown in Fig. 7. In the 0-5 Hz frequency range typical signatures of axially propagating coolant density fluctuations can be seen: the sink in the coherence function and the linear phase behavior. These features are typical at full power operation of Paks units and their behavior has been studied and published earlier by Glöckler et al [5]. Another interesting observation is the presence of the peak at 8.5 Hz in the global coherence function of signals N4 and N7, and its complete lack in their partial (direct) coherence function. As we saw, this peak showed up in the APSD functions of excore neutron signal J1, and incore neutron signals N4 and N7 too, but it was not inherently part of these signals, rather an effect from the reactor inlet pressure signal. The zero partial (direct) coherence at 8.5 Hz indicates that the two incore neutron signals are not directly coupled at that frequency. The reason why their global coherence is still relatively high is

that both incore signals are driven by the reactor inlet pressure signal at that frequency.

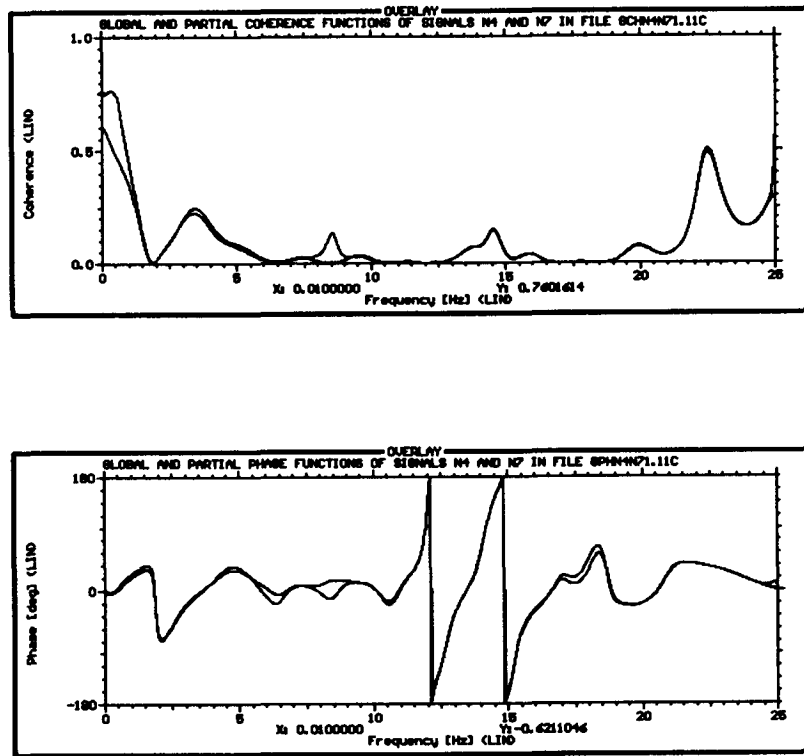


Figure 7. Global and partial coherence functions (upper figure) and phase functions (lower figure) of incore neutron noise signals N4 and N7

7.2. SPRT Analysis of MAR-based Residual Time Series

In the present study the time series analyzed in the previous section served as a reference measurement for fault detection in repeated measurements, and the MAR model based on this measurement represent the normal dynamics of the selected group of signals. Signal recording of the same set of signals was repeated at Paks NPP with the same measurement parameters as listed on page 8. The purpose of applying the SPRT to the MAR-based residual time series of this new measurement is to detect possible anomalies in it. In the following two examples of strong and weak temporary faults detected in the candidate measurement are discussed. Figure 8 shows a short section (512 samples) of the candidate time series of four measured signals with a strong spike in the pressurizer pressure noise signal. The corresponding section of the MAR-based residual time series is shown in Fig. 9. For all the four signals the residual time series have relatively low amplitude compared to the measured time series, except for the spike in the second signal. The corresponding SPRT time series are shown in Fig. 10. The allowable probabilities for both the false and the missed alarms were set to 0.1% ($\alpha = \beta = 0.001$). The ratio of variances of the Gaussian distributions representing the predefined abnormal and normal categories (σ_1/σ_0)

in Eq. (29) is 1.5. A signal is declared to be normal (or degraded) at a time instant if its SPRT function reached the lower (or the upper) boundary, then the test is continued after resetting the value of SPRT to zero.

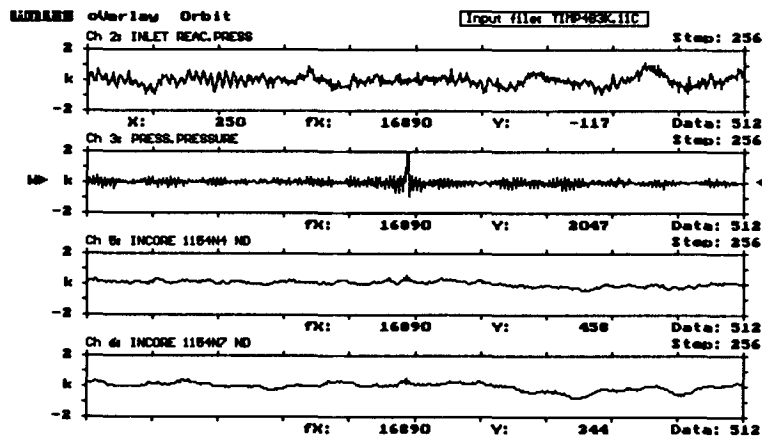


Figure 8. A section of measured signals with a strong fault in the second signal

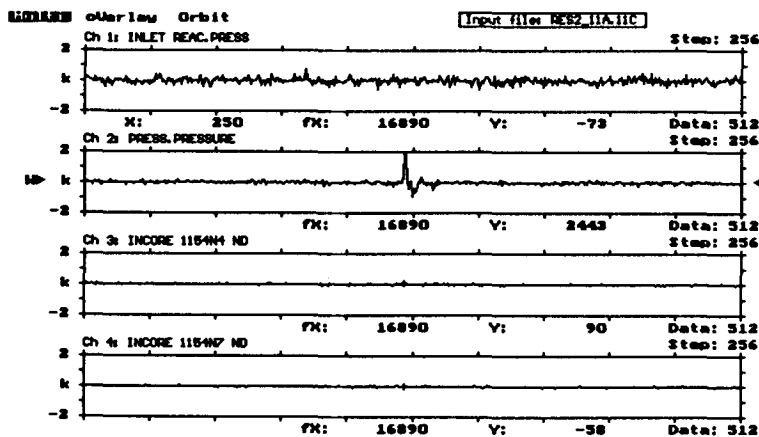


Figure 9. The corresponding section of residual time series of measured signals

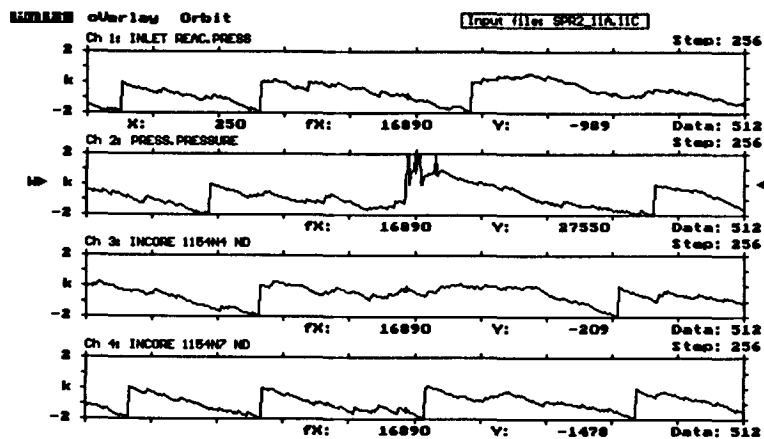


Figure 10. The corresponding section of SPRT time series of four measured signals indicating the presence of a fault in the pressurizer pressure signal

Several candidate measurements were scanned for signal anomaly by the MAR-SPRT method. In some of the large number of cases we analyzed there were anomalies whose presence was not so obvious as in the previously discussed case, especially if a relatively small nonstationarity developed gradually. It might be more difficult to detect them visually in the measured time series or in the residual time series. Such a case is shown in Figs. 11 through 13. The three figures show another section of the measured candidate time series and the calculated residual and SPRT time series of the same signal set discussed above. The SPRT in Fig. 13 detected a weak anomaly in the reactor inlet pressure signal, although the anomaly cannot be recognized in the measured time series or in the corresponding residual time series.

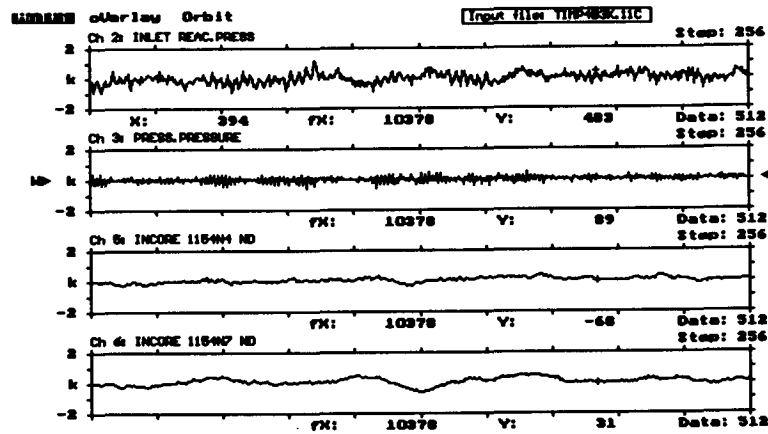


Figure 11. A different section of the same measured time series

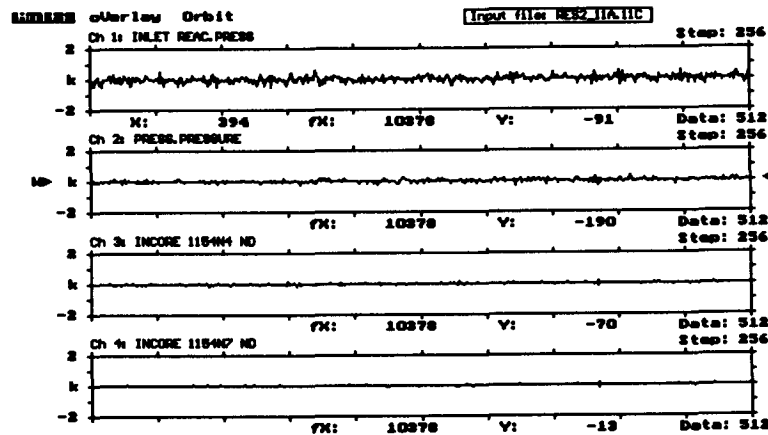


Figure 12. The corresponding section of residual time series of the four measured signals

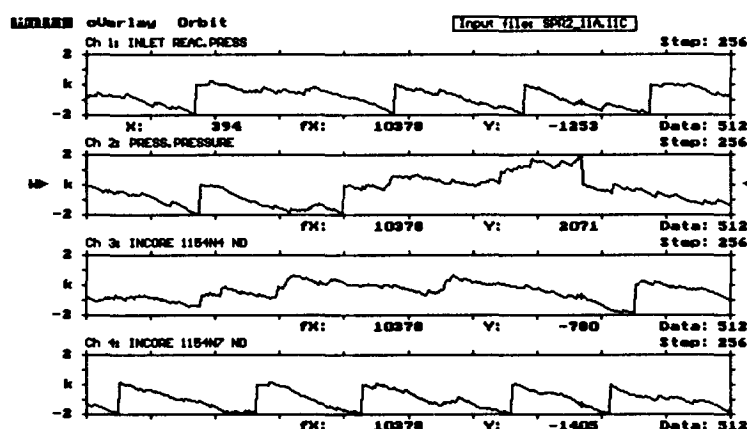


Figure 13. The corresponding section of SPRT time series of four measured signals indicating the presence of a weak fault in the pressurizer pressure signal

Further analysis of Paks and benchmark noise data [6] showed, that in addition to the short temporary signal faults, the MAR-SPRT method can detect gradual incipient failures developing over a longer period of time [7].

8. Conclusions

The SPRT analysis of MAR-based residual time series is capable of detecting nonstationarities in measured noise signals; both temporary short anomalies in the measured signals and longer slow changes in the dynamics of the measured process. This must be preceded by a substantial learning period in which the set of signals, the sampling frequency and the MAR model order must be properly chosen by experimentation. The described procedure is part of a multi-module software system developed at the Applied Reactor Physics Department of CRIP for noise-based process diagnostics and fault detection in NPPs. The PC-based system is being installed at the Kalinin VVER-1000 MW NPP.

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71.01
PCI TRANSIENT RECORDER MONITORING MACHINE VIBRATIONS ON NUCLEAR
POWERED ICE BREAKERS

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Summary

The turbo-generators on nuclear powered ice breakers are fitted with a vibration measuring system. The PC supported system, with the help of a transient recorder from the PCI (Personal Computer Instruments) family, enables early detection of changes in the running behaviour and likely machine damage. The frequency analysis (FFT) is considered when assessing the machine condition.

The vibration monitoring system receives the Fast Fourier Transformations (FFT), the PCI transient recorder results and the results of the vibration measurements.

Other possible applications of PC measuring instruments are presented.

1. Introduction

Siemens received the order to deliver turbine control technology and generators for two Finnish built nuclear powered ice breakers. Together with a turbine vibration measuring system, a system was supplied for continuous monitoring of the condition of the steam turbo-generators on both ships. These enable the early detection of changes in the running behaviour and likely machine damage. This means that probable repairs can be planned for and that unforeseen damage can generally be limited. The turbine vibration measuring system consists of a personal computer (PC) with process adaptor PA20 and a fast transient recorder. The transient recorder, which belongs to the PCI family (Personal Computer Instruments), is for acquiring and processing the binary and analogue output signals from the vibration and expansion measuring equipment of the ice breaker. Apart from three transient recorders (B3140: 8 bit, 2 MHz; B3141: 8 bit, 10 MHz; B3143: 12 bit, 1 MHz) there are ten further PCI units available: A/D Converter, Multimeter, Digital In-Out, Digital Oscilloscope, Function-Pulse Generator, Voltage-Current Calibrator, Universal Counter, Scanner, DC Power Supply and FFT Analyzer.

2. PCI Transient Recorder monitoring machine vibration of ice breaker

2.1 Objective - monitoring steam turbo-generators in ice breakers

The nuclear powered ice breaker "Taymyr" and her sister ship "Vaigatsch" are the first Russian ice breakers to be built in Finland and fitted with Siemens' control and monitoring technology. The use of atomic energy for ice breakers operating in the Arctic Polar Sea can bring many advantages. For example, fossil powered ice breakers of this magnitude, would find it virtually impossible to guarantee safe passage in remote areas.

Another important design feature of "Taymyr" and "Vaigatsch" is that of draught, or the depth of water required to float the ships.

As these ships only require 8 m draught, it is possible to navigate and clear the ice from the shallow Siberian currents. The "Taymyr" is designed so that even in extremely low temperatures of around -50°C , layers of up to 2 m thick ice can be broken. This helps the extremely difficult conditions under which ice breakers in the Polar Sea must be capable of working.

The ships' technical installations, to meet the above requirements, were accomplished by using extensive engineering expertise and correspondingly robust constructions.

The steam delivered by the pressurized water reactor and steam generator supplies two main turbines which respectively drive a turbo-generator.

2.2 The PC supported machine monitoring installation

Observing current activity and assessing the past ("life history") enables a deduction to be made regarding current and future failure probabilities of machines or machine parts. Diagnosing machines with rotating or moving parts rely predominantly on vibration measurement because the machines cause characteristic amplitudes and frequencies with moving spring-mass systems. By observing vibration values in respect of frequency and amplitude (also trends and variations) the correct function and allowable dynamic load can be forecast. Errors can be discovered earlier so that appropriate counter measures can be introduced before any great damage occurs.

The PC supported machine monitoring installation serves the purpose of operations monitor and early warning of damage for machines with moving parts. It operates online. The vibration measurement and analysis is an important means of foreseeing likely damage and can, thereby, help avoid consequential damage. The machine monitoring installation records, in cycles, output signals from the measuring transducer and, if necessary, of important parameters such as numbers of revolutions and power. Both the parameters (total vibrations) and the time functions (instantaneous values of vibrations for determining frequency spectrums) of the vibrations are undertaken (Diagram 1).

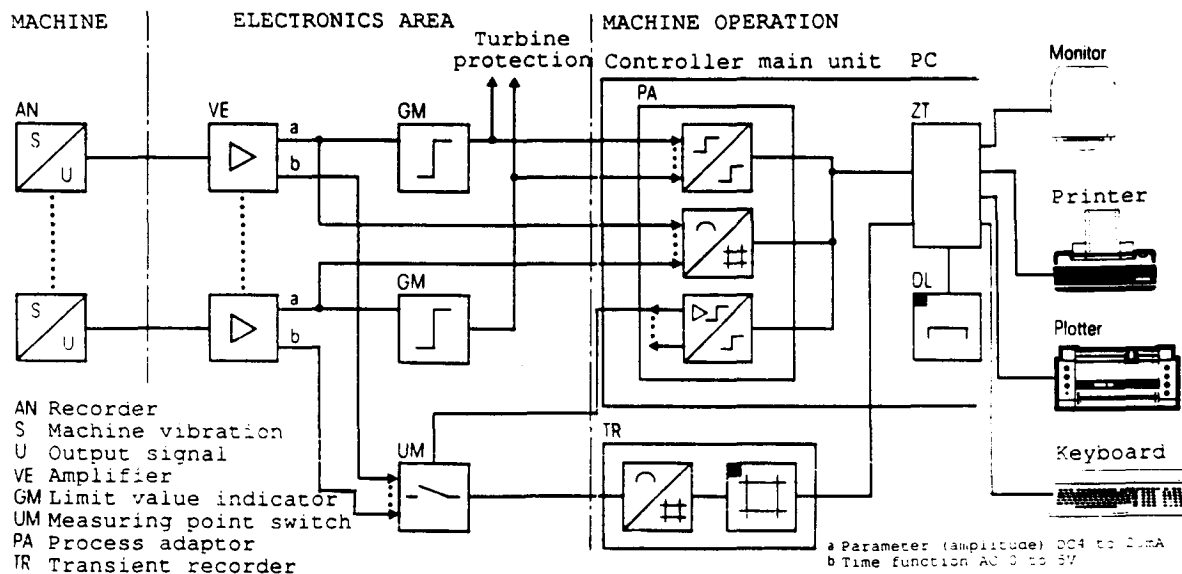


Diagram 1: The vibration measuring system facilitates the operation monitoring and early warning of damage for rotational machines

Determining parameter mean value

A smoothed mean value is computed, via the PC, from the digitized cyclic measured values. The algorithm corresponds with to one of a first order low-pass filter.

The digitizing follows with a resolution of 0.4 % (8 bit), the mean value determination with 16 figure decimal point numbers and the output normalised in three figure decimal numbers.

Absolute value parameter monitoring

The parameter mean values are monitored via the PC against those set by the user within the measuring ranges and for every channel freely selectable limit values.

There are two limit values definable on being exceeded (maximum value monitoring with preliminary and main alarms) and two limit values on being under achieved (minimum value monitoring with preliminary and main alarms). Unwanted limit values can be blocked.

The parameter monitoring is undertaken every 5 s (system cycle).

Trend determination and monitoring of parameters

The PC determines, for every channel in 18 min to 3 h cycles, the probable time TTA (time to alarm) until the respective absolute alarm limit values (main alarm of maximum value monitoring) are reached. The calculation, as shown in Diagram 3, follows via the given ratio between current mean value $\bar{x}$, the saved mean value x_{ref} , absolute alarm limit x_{al} and the co-ordinated times ΔT and TTA.

$$TTA = \frac{x_{al} - \bar{x}}{\bar{x} - x_{ref}}$$

TTA	=	probable time to main alarm
x_{al}	=	maximum value monitoring main alarm
$\bar{x}$	=	determined mean value of current measured value
x_{ref}	=	at ΔT timed saved determined mean value
ΔT	=	reference time for trend determination (constant)

The measuring range for TTA amounts to, respectively, ten times the reference time ΔT , with 1 to 10 days selectable. An allowance should be made in assessing the time TTA as damage does not, in practise, develop along a straight line when looked at in graphical terms.

The determined times TTA are given as output in the status protocol. A limit value monitoring of the trend, for every parameter channel, is undertaken when there is an under achieving of a freely selected, and for all channels common, valid time up to the alarm (TTA_{al}):

Once configured, up to 16 or 32 parameter channels and up to 7 or 14 time function channels can be monitored.

The machine monitoring installation monitors all parameters against two fixed, selectable limit values (parameter absolute alarm); limit value violations are signaled and the measured values from the appropriate measurement point are given as output.

The frequency spectrums are determined from vibration time functions (Diagram 2). Up to three frequency bands are selectable within the frequency spectrum, of which maximum vibration amplitudes are monitored if two fixed, band selectable limit values (absolute alarm of the frequency bands) are exceeded.

As regards mean values, the estimated times up to absolute alarm values are determined by the parameters, and the frequency bands via the current trends. A trend alarm is given as output by under achieving of a selectable, fixed time limit.

The measured and determined values are given as output via monitor, printer and plotter to provide information as to the machinery condition. The output can be selected in the form of signal sequential logging from status protocols or from frequency spectrum plots.

Long-term storage of measured and determined values automatically follows on to floppy disk. The parameters selected for measuring by the user, are retained in the parameter set-up.

Operation is menu guided with the main sections being parametising, monitoring run and output. The monitoring run is started automatically.

Parameter recording

The output signals of the measuring transducer (Diagram 1), which correspond to the parameters (e.g. effective value of the swing, number of rotations, power), are sampled in cycles via the process adaptor PA20 and digitized (8 bit ADU). Channels DC 0 to 10 V or DC 0 to 20 and 4 to 40 mA are allowable as signal range. The graphs can be linear or spread with two different gradients (input 0 to 50 to 100 % = output 0 to 80 to 100 %).

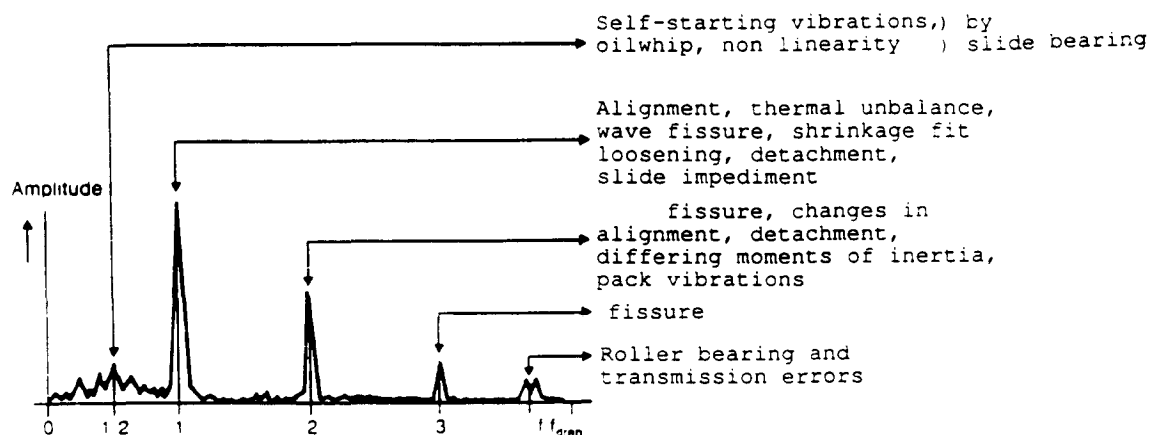


Diagram 2: Turbo-generator disturbance causes partial vibrations which, by discrete frequencies, lead to new changes in the vibration amplitude.

$$A = 1 \text{ for } TTA(t) - TTA_{al} < 0$$

A = alarm status
 $TTA(t)$ = reference time up to main alarm
 TTA_{al} = trend alarm level

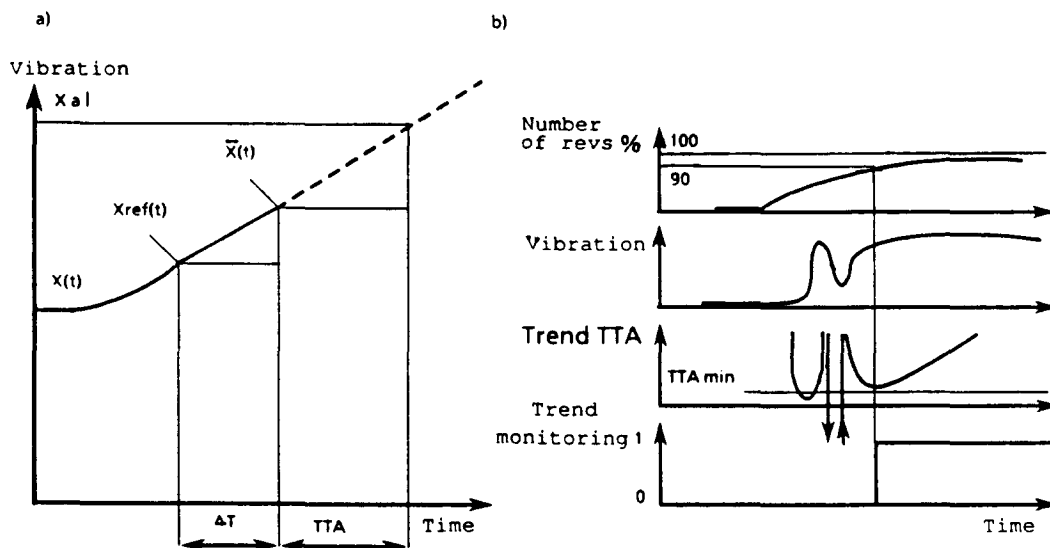


Diagram 3: Trend determination and release of trend monitoring
 a) estimated time to alarm
 b) blocking/releasing trend monitoring (e.g. run-up)

The message follows in the same manner as by absolute value monitoring.

As machine vibration is greatly dependent on the number of revolutions, the output signal of the rev-counter measuring transducer should be recorded via the process adaptor. It can then be used for releasing the trend determination and monitoring (e.g. as from 90 % of the nominated number of revolutions).

Recording of time functions

The time dependent and vibration proportional output voltages (time functions) of the connected measuring transducer (Diagram 1) are routed via the measuring point change-over switch on the input of the transient recorder B3143. The measuring point change-over switch relays are switched on, in cycles, by the PC via the binary outputs of the process adaptor PA20.

The transient recorder displays an input time function as groups of faster and regular sequences of digitized momentary values which correspond to a timed section (time window) of the time function.

A between time storage of the digitized time function is undertaken and the measured values are transferred to the transient recorder via the IEC bus. The transient recorder functions are controlled by the PC.

Frequency spectrum determination

The system controller uses a Fast Fourier Transformation (FFT) to determine (from transient recorder transferred time functions) the amplitude spectrums of individual time functions of vibration signals.

Frequency band monitoring to absolute values and trend

The user can select, per time function channel, up to three arbitrary frequency bands within the total analysing frequency range. The line spectrum with maximum amplitude is determined from every frequency band.

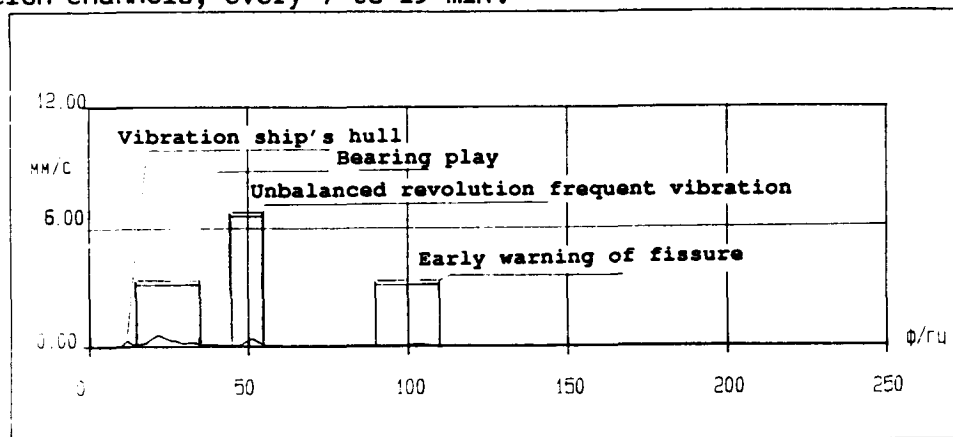
$$F_{\max} = \text{Max}(F(m_a \omega_0) \text{ to } F(m_b \omega_0)) \quad F_{\max} = \text{max. amplitude in the frequency band a to b}$$

The resolution limits and tolerances of the total spectrum analysis measuring and calculation section (including plotter) are stipulated via the specification of applied FFT sub-routines.

The frequency range (upper limit 100 Hz to 25,000 Hz) and the required resolution in the frequency axis (1 % and 2 % of the selected upper frequency limits) are selectable by the user and are valid overall for all executed spectrum analyses. The amplitude resolution amounts to 0,2% of the measuring range.

For absolute value monitoring of the spectral band, the mean values of the maximum amplitudes from two respective frequency analyses are formed in the frequency bands and tested against a freely selected limit value being exceeded (maximum value monitoring) on any time function channel and spectral band.

The windows which can be formed via the band limits and limit values are blended into the frequency analysis diagram (Diagram 4). The absolute value monitoring follows in cycles according to the number of the time function channels, every 7 to 15 min.



НАЗВАНИЕ ТОЧКИ ИЗМЕРЕНИЯ: ТУ1 ПОДШ1 ВИ-КО ДИАПАЗОН ЧАСТОТЫ: 10 - 250 ГЦ

НОМЕР ТОЧКИ ИЗМЕРЕНИЯ : 2

ДИАПАЗОНИЗ. : 0 - 50.0 мм/с

Diagram 4: Frequency analysis diagram, example Russian output

The output of the maximum amplitudes in the frequency bands, the message and reaction follows in the same manner as for the parameter absolute value monitoring.

The trend calculation and monitoring of the maximum amplitudes in the frequency bands are undertaken in the same manner as for the parameter monitoring; it is valid for the same measuring ranges TTA , reference time ΔT and limit values TTA_{al} .

The trend monitoring is undertaken every $1/3$ h to 3 h, depending on the measuring range. The output of the trend values, the messages and reactions are in the same manner as for parameter absolute value monitoring.

There are German and Russian (in Cyrillic type) versions of the software program.

2.3 The PCI Transient Recorder as interface between the analogue and digital world

The transient recorder B3143 possesses two independent input channels with which analogue signals can be quickly scanned (A/D converter 12 bit/1 MHz). It is possible, via a trigger switch, to display transient and periodic current signals. The input voltage is digitized and stored in a 16 kByte semiconductor memory of which the contents can be read-out and evaluated as often as required.

Within the scope of PC supported machine monitoring, the transient recorder serves to acquire and digitize the time functions of the vibrations which are subsequently analysed in the PC.

The transient recorder can generally be employed for

- recording of single processes
- long sequence recordings
- solving of monitoring tasks
- fast measured value recording and later detailed analysis

The working manner of the transient recorder is displayed in the block diagram (Diagram 5).

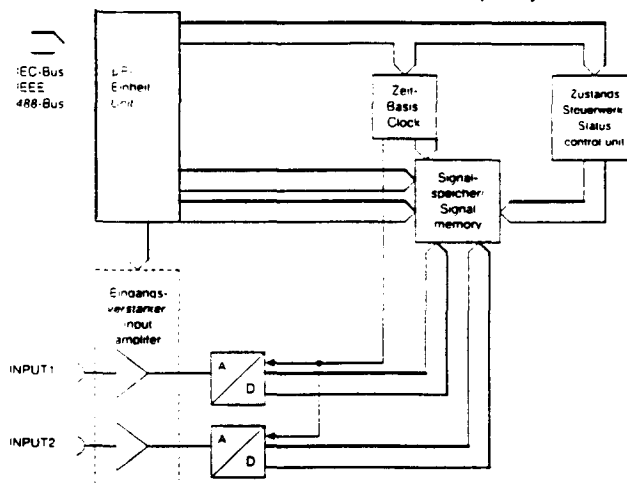


Diagram 5: PCI transient recorder block diagram

A microprocessor unit (CPU) which is capable of being remotely controlled via an IEC or TTY interface, undertakes the essential adjustment and analysis functions. The CPU enables the input amplifier, the time base and the address counter to be parametrised, and the status control task to be programmed. The input signal reaches the A/D converter, via the switchable input amplifier, where it is digitized and written in the signal memory. The microprocessor unit reads out the data from the signal memory after the recording has taken place and undertakes, if necessary, a data reduction. The results are available for further processing and can be read out via the interface.

3. Outlook - further applications

PC measuring set-ups (with IEC bus) are employed, amongst other applications, in wide ranging areas of production and quality control for function testing, incoming goods inspections and in laboratories for various applications such as prototype testing, simulation or reliability testing. In these areas of operation PC measurement instruments offer clear cost advantages in contrast to the already IEC bus measuring set-ups.

The later developed PCI FFT analyser is particularly suitable for machine monitoring because the Fourier Transformation is undertaken directly in the instrument via a signal processor. This application is to be the subject of a later publication.

A DIAGNOSTIC SYSTEM FOR TRANSIENT MONITORING AND ON-LINE FATIGUE USAGE FACTORS EVALUATION OF PRIMARY CIRCUIT COMPONENTS OF THE 1000 MW NUCLEAR POWER UNIT IN TEMELÍN

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ABSTRACT

A diagnostic system for transient monitoring and on-line fatigue usage factors evaluation of primary circuit components has been developed for the 1000 MW nuclear power units in Temelín in accordance with experience gained from analogical diagnostic systems applied at the 440 MW nuclear power units in Dukovany and Jaslovské Bohunice. Channels for pressure measurement in the primary and secondary circuits, for vibrations measurement of inner structures in steam generators and pressurizer and of connected pipes, for local temperatures measurement and for water electrical conductivity measurement inside the steam generators as well as technological parameters (media temperatures, flows etc.) via a busway are continuously included into the system.

Architecture of the diagnostic system as well as individual channels included are described in the paper. Exposed component parts are listed to which the on-line fatigue usage factors evaluation concerned.

The aims of the diagnostic system for the 1000 MW units in Temelín are:

- collection and storage of real operation loads due to pressures, temperatures and media chemical influence
- comparison of real and designed load histories
- optimization of unit service instructions
- evaluation of the components fatigue lifetime
- data collection for unit designed lifetime prolongation.

Some examples of temperature transients and fatigue usage factors development gained from diagnostic systems used at a few Czechoslovak WWER 440 units are given in conclusion.

1. AIMS OF THE SYSTEM

The diagnostic system for transients monitoring and on-line fatigue usage evaluation of components for the 1st 1000 MW unit of the nuclear power plant Temelin has been carried out as MAFES version 1 ETE (Material Fatigue Evaluation System). Its primary aim is to secure proved safety and reliability of the WWER 1000 unit operation from the point of view of components fatigue stresses and to record all loads of components measured during the unit operation systematically that is one of important sources of actual technical information for decision making on the unit life time prolongation over the designed one in the future.

The primary aim has been achieved by:

On-line record, classification and analysis of measured local and global loads of component exposed parts during the unit operation.

Computation of stress intensity from measured loads at critical points of component exposed parts in real time and their classification, analysis and storage.

Evaluation of fatigue usage factors from stress intensity ranges and material S-N curves using Palgrem-Miners hypothesis of linear fatigue cumulation and their analysis and storage.

Further aims are included in the formulation of the primary aim of the version 1 ETE of the system MAFES, namely:

- To formulate innovations in unit regulations from monitored loads and growth of fatigue usage factors which lead to minimalization of component fatigue loadings.
- To improve actual information for plant personnel instruction with reference to the history and number of unit checking operations carried out contributing most to the fatigue usage of components.
- In accordance with the actual loads passed to lay-out inspection and maintenance of the component exposed parts.
- Diagnosis of the technical state of the steam generator feed water system and control valves and evaluation of state of loops heat-up system, steam generator secondary water and thermal insulations at unit starting.

Signals of standard instrumentation sensors (pressures insides the components, temperatures of media, flow rates etc.) and signals of sensors installed at component exposed parts additionally to the unit standard instrumentation (thermocouples at outer surfaces, accelerometers, sensors for water electrical conductivity) have been used in system MAFES version 1 ETE to achieve the aims formulated above.

2. REALIZATION OF THE SYSTEM MAFES VERSION 1 ETE [7,8]

The system MAFES version 1 ETE is subdivided into the following groups:

- thermocouples at outer surface of component exposed parts,
- bus transmission of signals of the standard instrumentation sensors, especially pressures and temperatures of media,
- accelerometers with preamplifiers and auxiliary circuit installed at some components,
- sensors for steam generators secondary water electrical conductivity measurement with preamplifiers and auxiliary circuits,
- cablings with switchpoints,
- unit for system control and signal evaluation (PC computer with peripheral equipment, amplifiers, filters, A/D convertors and auxiliary test circuits),
- software for a staffless system continual operation which enables to fulfil the aims formulated for the system MAFES earlier.

Therefore, in hardware comes the system MAFES, version 1 ETE, from measuring channels of temperatures, vibrations and water electrical conductivity and bus transmission of inner pressure in pressurizer (PR) and at the secondary side of the steam generators (SG), from feed water temperature, primary water temperature, water flow rates etc. The thermocouples and accelerometers are fixed at exposed parts of the SG, PR, primary piping (PP), surge line between the PR and PP, reactor vessel and some control valves.

3. INFORMATION FLOW IN THE SYSTEM MAFES AND ITS SOFTWARE [9]

A simplified block diagram of information flow in system MAFES is given in Fig.1. The input data for the system are the characteristics of components. Exposed parts of components have been specified in compliance with results of stress analysis performed in design standard documentation and with results of measurement analysis at WWER units being in operation [1 to 6]. By critical points of component parts points have been denoted with maximal expected ranges of stress intensities.

A temperature problem has to be solved for each exposed part by finite element method (FEM) to define a relation and corresponding inverse relation between temperature boundary condition and temperature at the points of thermocouples. A solution of the elasticity problem leads to the relation between the temperature and pressure boundary condition and stress in critical points. The choice of problem model and steps of freedom of the temperature problem is very important for a technical satisfactory solution of the relations mentioned.

A very good knowledge of processes and their characteristics acting inside the component exposed parts during all regimes of unit starting and operation is unavoidable.

The system MAFES takes the measured data in given time intervals. The data have been tested by system software first.

Transient monitoring and evaluation of components fatigue usage have been performed by programs DIANA and DIAPOST. The program DIANA serves to measurement and storage of measured data during unit operation. It computes temperatures at the inner surface, stresses in critical points and fatigue usage factors of component parts likewise. The results are scanned on the display as time functions. The program enables to follow the influence of unit check operations performed by the staff on the component fatigue life degradation in a comfortable dialogue regime. The actual courses of data can be compared with those registered in the past, too.

The program DIAPOST is analogical functionally to the program DIANA but in contradistinction to DIANA it only reads stored data. The program enables repeatable analysis of measured and stored data using alternative relations for results computation.

4. SOME EXAMPLES OF THE SYSTEM MAFES OUTPUTS

Some versions of the system MAFES have been long-term tested at WVER 440 units at Dukovany and Jaslovské Bohunice. Illustrations of the system MAFES outputs on its computer display are given in Fig.2,3 and 4.

In Fig.2 the system user follows a course of the local temperature at the outer surface of the SG feed water nozzle in one time interval of WVER 440 unit starting.

Fig.3 shows the changes in levels of the stress intensity and a step by step increase of the fatigue usage factor in a critical point of the feed water nozzle in the same time interval as illustrated in Fig.2.

A typical response of temperatures of the upper part of the PR vessel and surge nozzle local surface to the chemical regime modification during unit starting is given in Fig.4.

A mixing of the water volume by a higher water injection rate has been performed with the aim to equalize the boric acid concentration in the pressurizer. Each cutting of electrical heaters leads to pressure decrease in the pressurizer, flow of colder water from the primary circuit through the surge nozzle that causes its cooling down. The local surface temperature of the nozzle has been decreased with a velocity down to $0,13 \text{ K.s}^{-1}$ from 310°C to 270°C . A subsequent switching on of electric heater group effects on surge nozzle heat up by warmer water flowing out of the PR, that manifests itself by an increase of its local surface temperature from 270°C to 310°C with a momental heating velocity of $0,33 \text{ K.s}^{-1}$ in the studied example.

The outputs of the system MAFES are actualized continuously in automatic regime. It is possible to demonstrate on display in conformable dialogue regime on pressure, local temperature,

stress intensity courses and on increase of fatigue usage factors as they are influenced by personnel actions in control room and by the stage and technical limits of the unit control system.

All outputs of the system MAFES are continuously stored on buffer disc of the PC computer.

5. CONCLUSIONS

The diagnostic system MAFES, version 1 ETE has been designed for the 1st unit of the 1000 MW nuclear power plant at Temelín for monitoring and storage of actual operational pressure, temperature, vibrational and chemical loadings and for on-line evaluation of fatigue life degradation of primary circuit components.

The system comes in hardware from of measuring channels of temperatures, vibration and electrical conductivity of secondary water in SGs and of bus transmission of signals of the standard instrumentation sensors (pressures in the primary and secondary circuits, feed water temperatures etc.). PC computer is used for control and evaluation.

The system software guarantees a long term staffless service of the system MAFES. Actual component loadings have been measured and stored, stress intensities as well as trends of fatigue usage factors in critical points of primary circuit components have been computed and stored during the operation of WWER 1000 unit. It is possible to evaluate the consequences of personnel actions performed in control room and the influence of the technical stage and limits of unit control equipment on the degree of loadings and the fatigue life degradation of the exposed parts of steam generators, pressurizer, primary pipings and reactor in comfortable dialogue regime.

The system MAFES designed for the 1st unit of Temelín proves the degree of unit safety and reliability from the viewpoint of fatigue stresses of primary circuit components and stores systematically actual in unit operation measured loadings of components for the purpose of future decision of their life-time prolongation over the designed value.

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Fig.1: Information flow in the diagnostic system MAFES, version 1 ETE for transient monitoring and on-line estimation of component fatigue usage and its outputs

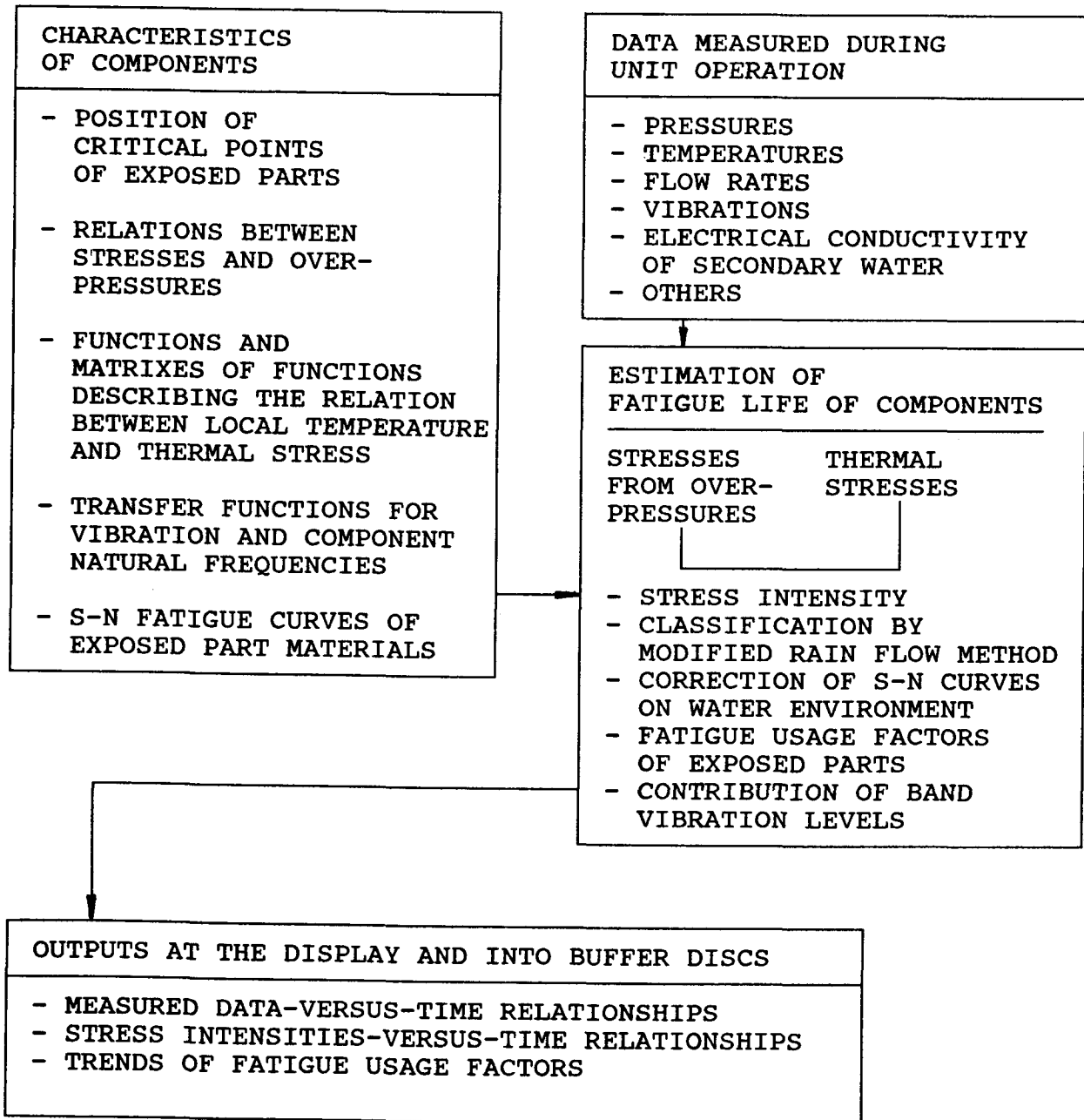


Fig.2: Local temperature at an outer surface of the SG feed water nozzle in one period of WWER 440 unit starting - an example of system MAFES output at the PC display

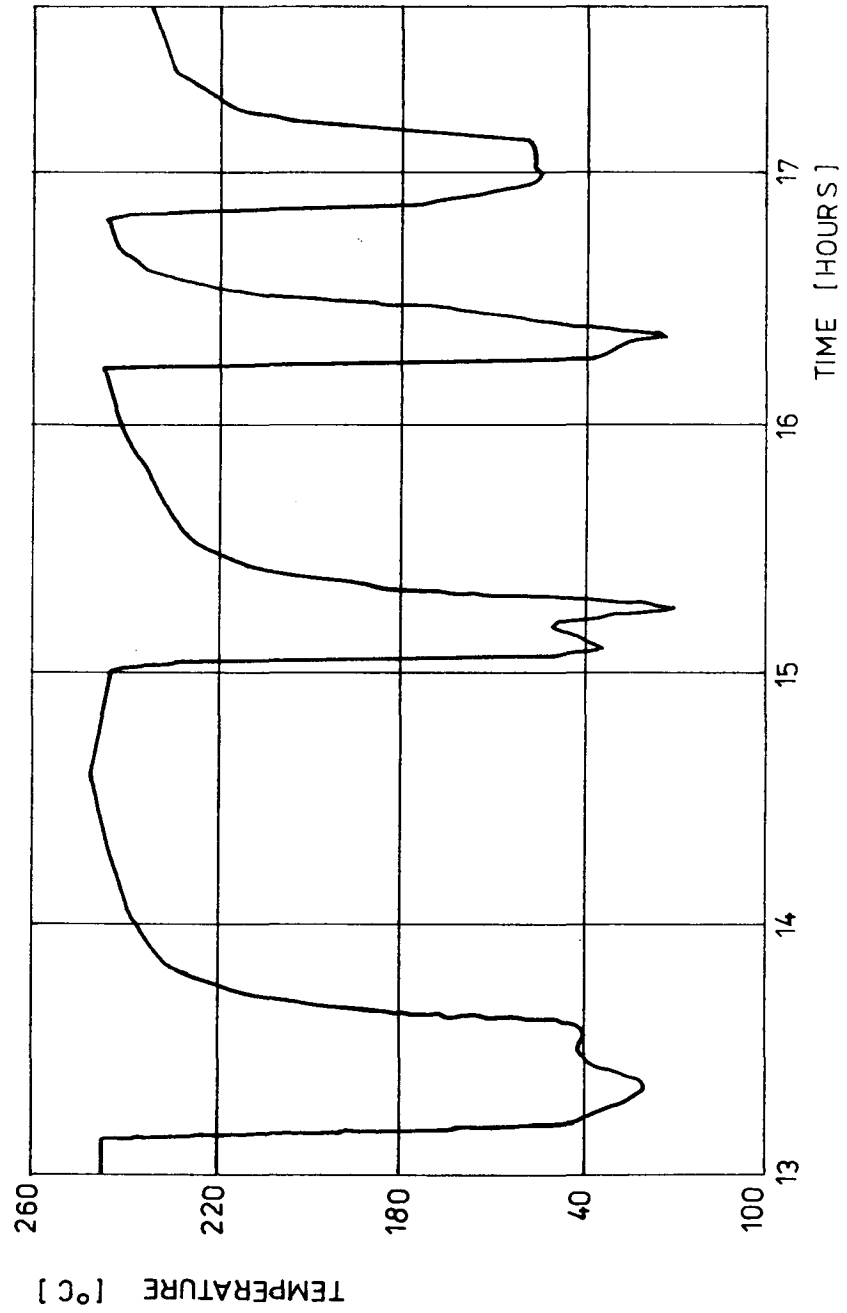


Fig.3: Stress intensity course and increase of fatigue usage factor D_u in the critical point of feed water nozzle in one period of WWER 440 unit starting - an example of system MAFES output at the PC display

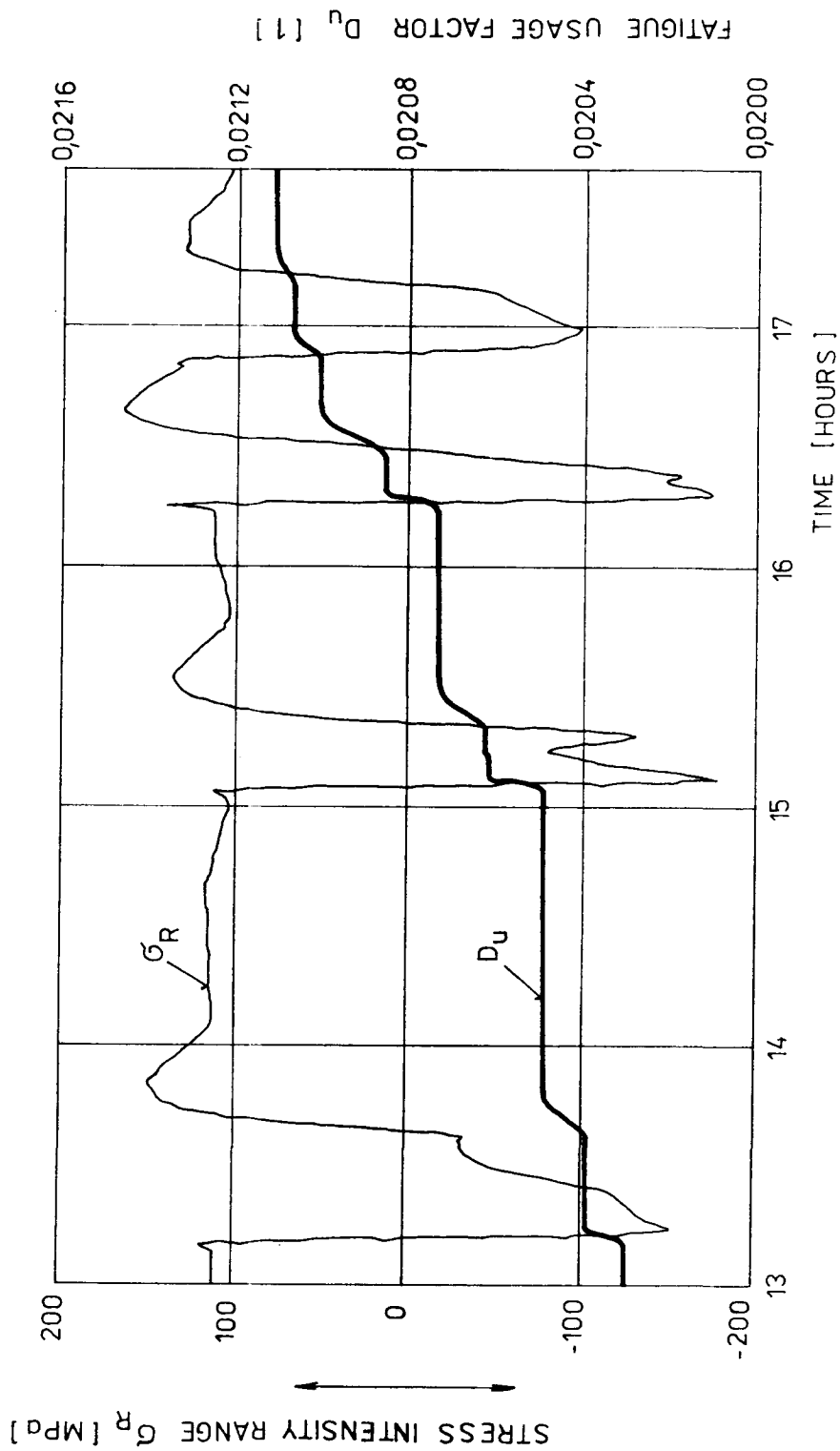
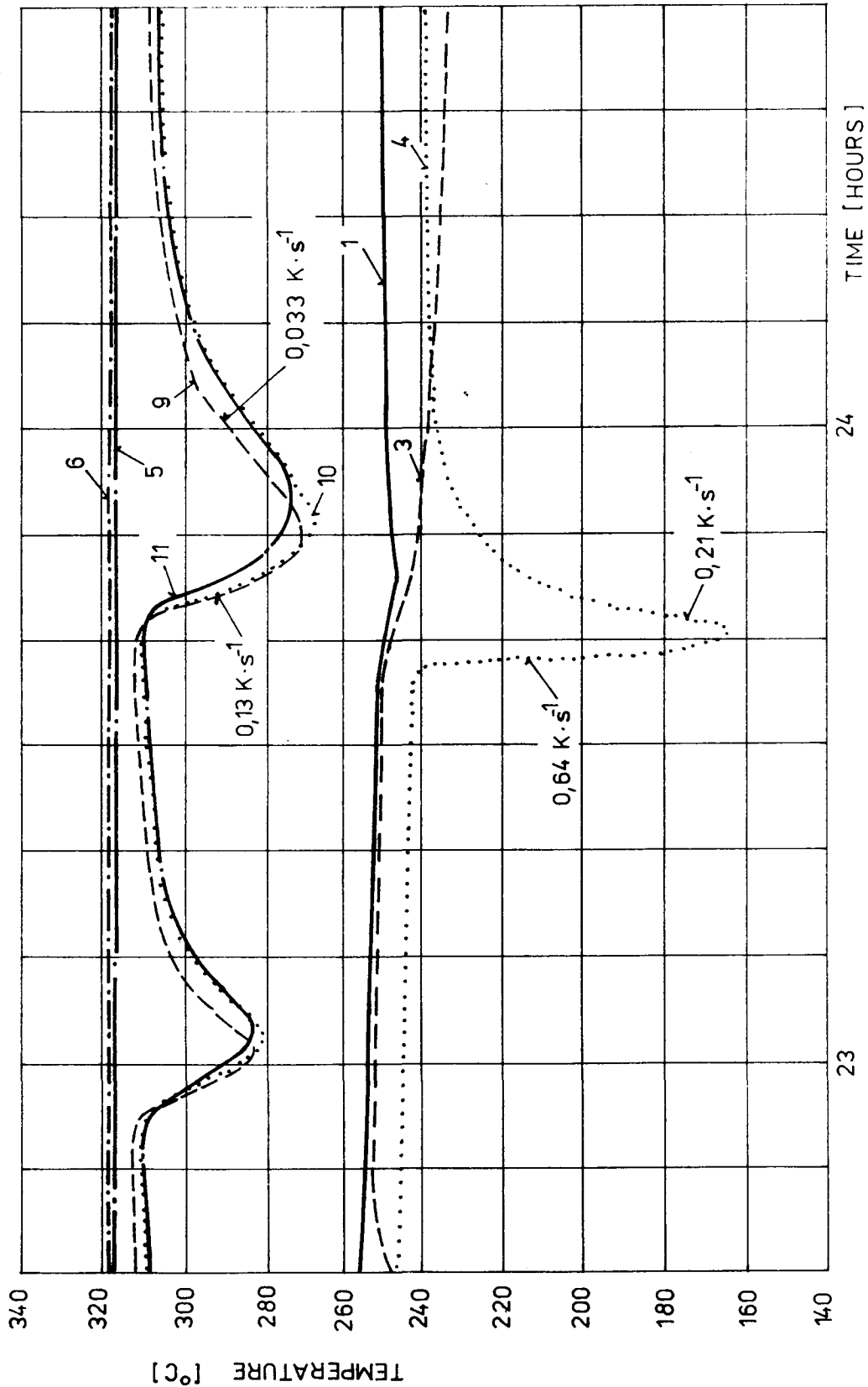


Fig.4: Typical temperature changes at the surge nozzle of the pressurizer (9,10,11) and on the pressurizer vessel upper part (5,6) and steam generator vessel (1,3) and its feed water nozzle (4) during modifications of chemical regime in the pressurizer - an example of system MAFES output at the PC display



AUTOMATED SYSTEM FOR MOTOR-OPERATED VALVE DIAGNOSTICS

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ABSTRACT

The application of new condition monitoring and diagnostics techniques is often limited by the fact that they appear very complicated and confusing to maintenance personnel, and therefore their utilization requires a considerable amount of training. However, new innovations in information processing such as expert systems and hypertext can help to solve this problem. This paper describes a software system that can be used to automate Motor-Operated Valve (MOV) testing. It uses expert system techniques to interpret test results automatically, to evaluate valve condition, and also to recommend corrective actions if they are needed. The system has a hypertext-based user-interface that is used to deliver supporting information to testing personnel.

INTRODUCTION

In nuclear power plants reliable operation of Motor-Operated Valves (MOV) is essential to assure the proper performance of safety and control systems. Plant availability is also greatly impacted by problems associated with MOV operation. It has been estimated [1] that in nuclear plants valve-related problems cost U.S. utilities \$100 million per year in loss of plant availability, and up to 30 % of the industry's annual maintenance budget.

In order to avoid unscheduled outages or unnecessary MOV maintenance during scheduled outages, predictive MOV maintenance must be performed. Predictive approach to maintenance requires that degrading mechanical and electrical behavior of MOVs can be detected at an early stage, and that the time to failure can be predicted.

Because present testing practices are not very useful in predictive MOV maintenance, extensive research and development efforts are being pursued to improve valve monitoring and diagnostics methods [2]. For MOVs the most promising new surveillance approach is valve signature analysis. This is a computer-aided testing method for measurement, management, and analysis of MOV operation related time waveforms such as motor current and valve stem thrust. Waveforms are then interpreted manually by a diagnostic expert.

An effective application of valve signature analysis requires considerable experience. Signatures are quite complicated and the various features in them must be carefully detected and analyzed. Testing personnel must also know the structure and operation of the motor operator, its possible abnormalities, and their relationships to valve signatures. In order to get signature analysis in wider and more cost-effective use in utility industry, tools that automate the various phases of MOV testing must be introduced.

We have developed a software system which can be used as an upgrade of the existing signature analysis systems, and which increases significantly the automation level in MOV testing. Our system analyzes motor current signatures that are measured when the valve is stroked. It extracts diagnostic parameters automatically from current signatures. Parameters are interpreted using a rule-based expert system, which diagnoses potential MOV problems and recommends corrective actions. The system is intended to be an intelligent job-aid for maintenance technicians who perform MOV testing. The software runs on industry standard computer hardware, and can be interfaced either with commercial signature analysis systems or with special data acquisition equipment.

MOTOR-OPERATED VALVES

Operating Principles

Motor-operated valves are used extensively in nuclear power plants in safety related and control systems. MOVs are often employed when factors such as large line size, high pressure, temperature, flow rate, or inaccessible location dictate that other types of valve operators are not adequate.

The basic construction and operation principles of all MOV types are similar, Figure 1. They consist of two main parts: the motor operator, which includes the motor and gear train, and the valve itself. The motor turns the worm gear through a gear train. The worm gear is engaged with the stem nut, which raises or lowers the threaded valve stem. This causes the valve to open or to close.

Two parts of the operator, called the limit switch and torque switch, control the stroking of the valve. Limit switch stops the motor at the end of the close-open stroke. It is directly geared to the worm shaft. The limit switch counts the rotations of the worm shaft, and shuts the motor off when a preset number of worm shaft rotations is reached.

Torque switch protects the motor from damage during valve closing and in a case of an obstruction. When the worm gear can no longer turn, the worm slides along its shaft. In doing so, the worm compresses the spring pack. This axial movement causes the shaft of the torque switch to rotate. When a preset angular position of the torque switch is reached, the motor is stopped. The calibration of the torque switch can be difficult, and it has been the focus of much MOV research recently conducted.

Anomalies in MOVs

MOVs are subject to loads and stresses from the control systems and power systems that serve them, as well as from the fluid systems in which they operate. MOVs may be subjected to partial damage or degradation that will allow operation for normal or no-load situations, but may cause failure at design basis demands. The critical problem is that MOVs have been experiencing high failure rates when called upon to operate against pressure or flow.

The basic failure modes of MOVs have been identified to be failure to stroke, plugging, and internal and external leakage [4]. The root causes of MOV failures have been addressed in many studies. It has been concluded that the most important causes of MOV failures are failed or improperly adjusted torque and limit switches.

DIAGNOSTIC TECHNIQUES FOR MOTOR-OPERATED VALVE SURVEILLANCE

Traditional methods for MOV testing include, for example full stroke exercise with stroke time measurement and seat leakage measurement. These tests can be used to verify the present valve operability, but they are not

effective in detecting degradation or predicting future degradation [2]. Therefore, new diagnostic techniques must be used for predictive maintenance of MOVs.

A very promising approach to MOV surveillance is valve signature analysis. Several valve parameters, such as valve stem thrust, motor current, and switch activations are measured using a computer during valve stroke. The signatures (parameter versus time) are displayed and a diagnostic expert makes the evaluation based on several features present in the signatures. These features can be trended over time and used for MOV maintenance planning.

Motor Current Signature Analysis

A variation of general signature analysis is a technique called Motor Current Signature Analysis (MCSA), which was developed by Oak Ridge National Laboratory [5]. MCSA can be used in connection with full scale signature analysis. Because MCSA monitoring is nonintrusive and can be performed rapidly using portable inexpensive equipment, it is very suitable for condition monitoring of MOVs. Then the more labor-intensive full-scale signature analysis can mainly be used for establishing baseline parameters and for trouble-shooting.

MCSA measures motor current using a special signal conditioning equipment and analyzes both time waveforms and frequency content of the signatures [5]. Hypothetical time-domain motor current signatures during both stroke directions are shown in Figure 2. There are several features of motor current signatures that are useful in MOV diagnostics. Some of the diagnostic features that can be obtained from the signatures are shown in Figure 2 and listed in Tables 1 and 2.

Table 1. Time-domain diagnostic features for open-close stroke

<u>Number</u>	<u>Feature</u>	<u>Descriptors</u>
1	Stroke time	(1) Value
2	Running current	(1) Average value
3	Seating margin	(1) Value
4	Seating time	(1) Value

Table 2. Time-domain diagnostic features for close-open stroke

<u>Number</u>	<u>Feature</u>	<u>Descriptors</u>
1	Stroke time	(1) Value
2	Running current	(1) Average value
3	Hammerblow	(1) Time of occurrence (2) Height
4	Unseating	(1) Time of occurrence (2) Height of the corresponding peak

Diagnosis based on valve signatures consists of the following steps: (1) identification of the basic signature primitives such as the prominent motor inrush peak at the very beginning of the stroke, and the peak at the end of the stroke corresponding to valve seating, (2) calculation of the diagnostic features listed in Tables 1 and 2 based on these primitives, and (3) comparison of features to reference values and evaluation of MOV condition. There are also some more general signature characteristics such as overall shape and noisiness of the signature, which must be considered in diagnosis.

The capability of MCSA to detect MOV abnormalities was evaluated by ORNL using extensive laboratory tests. The tests utilized MOVs with simulated degradations. It was concluded that among others the following abnormalities can be detected by MCSA: stem nut and worm gear tooth wear, degraded motor operator and valve stem lubrication, obstruction in the valve seat area, and improper operator switch settings.

AN AUTOMATED SYSTEM FOR MOV DIAGNOSTICS

Overview

The system developed in our work is a tool that can be used to automate valve testing. At present it can be used for analysis of motor current signatures, but the methodology is equally applicable to analysis of valve stem thrust and switch signatures.

The system is intended to be used either with a MCSA system or with a full scale signature analysis system. It serves as an intelligent support system or job aid for the maintenance technician. The design goals of the system are the following:

- Automation of the valve signature characterization using pattern recognition with expert system techniques.
- Automated evaluation of the MOV condition using expert system techniques.
- Demonstration of the use of hypertext for information delivery in maintenance support systems.

A schematic of the automated diagnostic system is presented in Figure 3. The system performs the previously described diagnostic steps automatically. Pre-processing module reads in time-domain valve signatures and identifies the basic signature primitives. Feature extraction module associates the primitives with known events during valve stroke and calculates the actual diagnostic parameters. The extracted parameters are sent to the diagnostic module which diagnoses potential MOV problems and recommends corrective actions.

Implementation of the System

The system runs on IBM PC and compatible computers. It needs a graphic display and a printer in order to print test reports. A suitable configuration is a 286- or 386-processor based portable computer, which is connected to data acquisition hardware. At present the system reads time-domain valve signatures, which are in ASCII file format.

The system was developed using a commercial expert system shell KnowledgePro from Knowledge Garden Inc. KnowledgePro has relatively good tools for developing backward chaining rule-based systems and for designing menu-driven, hypertext-based user-interfaces. Simple calculations can also be performed with Knowledge Pro, but it is not suitable for extensive numerical computation. Therefore the pre-processing module was written using a conventional programming language.

We have demonstrated the use of hypertext in providing supporting textual and graphic information about MOV operation to testing personnel. Figure 4 shows an explanation screen of the system where the terms 'torque switch' and 'limit switch' have been defined as hypertext buttons. The user may ask for more

information about the limit switch by activating the corresponding button, and the system opens a window giving the definition of the limit switch. There are some other related topics that can be accessed using the hypertext buttons in the definition window.

The main benefit of using hypertext in this application is the ease of developing a system that is attractive to various user classes. An expert technician needs only a check list of various phases of MOV testing. However, a novice needs complete and highly illustrated instructions. Hypertext is very suitable for this kind of selective information delivery. Information that is important to certain user classes can be hidden behind hypertext buttons, where it is easily accessible, but out of the way for those who do not need it.

Pre-Processing of MOV Signatures

The basic assumption in our signal pre-processing approach is that each MOV signature can be described by a linear combination of basic primitives, which are peaks, steps, and ramps. Figure 5 shows typical MOV motor current signatures. It is clear that they can be described with peak and step primitives. Certain abnormalities such as a bent valve stem may cause increase or decrease of motor current during the stroke. Therefore the system also looks for ramp-like behavior in the signature.

The task of the pre-processing module is to automatically extract these primitives from the measured valve signatures. Its block diagram is presented in Figure 6. It consists of two alternative peak detection algorithms and of a nonlinear filter system for step and ramp detection. The operation of the pre-processing module is described in detail in [6]. This kind of signal decomposer with a simple peak detector consisting of a median filter and an amplitude threshold was originally presented by Love and Simaan [7]. Our primary peak detection algorithm is based on the work of Marshall [8].

The output of the pre-processing module is a list of the detected primitives and their properties. The parameters used to describe the primitives are illustrated in Figure 7.

Feature Extraction

Identification of stroke events

Some of the primitives that the feature extraction module receives from the pre-processing module correspond to normal, anticipated events during the valve stroke, such as motor inrush peak or valve unseating peak. Others may correspond to abnormalities and some are purely noise. The main task of the feature extraction module is to separate the primitives corresponding to normal stroke events and the primitives that can not be explained at this point.

Feature extraction is controlled by a rule set that contains knowledge about the normal appearance of valve signatures. Also certain reference values of the valve under study are used in feature extraction. References are obtained when the MOV is known to be operating acceptably, and they include, for example average running current. Simplified rule for finding the inrush peak written in English is

*if the object type is peak
 and the start amplitude of the object is about zero
 and the end amplitude of the object is near reference running current
 then the primitive is the inrush peak.*

Similar rules are used for other anticipated stroke events.

After the feature extraction module has evaluated all of the primitives it checks whether all anticipated events are identified. It is possible that the pre-processing module fails to find an event because of a very noisy signature. On the other hand some motor-operator anomalies result in certain missing events. For example, if the valve does not seat at the end of the open-close stroke, the signature does not contain the seating peak.

In order to check if a certain event is missing because of problems with the operation of the pre-processing module or because of some real MOV abnormalities, the system asks the user if this event is visible in the signature, and if it can be characterized with the parameters defined in Figure 7.

Calculation of Diagnostic Features

After all primitives have been either identified or declared undiagnosed, the feature extraction module calculates the diagnostic parameters of Tables 1 and 2 and transfers them to the diagnostic module. The user can evaluate the results of the feature extraction using three displays. These include separate displays for normal events of the stroke (Figure 8), for diagnostic parameters with their reference values and tolerances (Figure 9), and for undiagnosed events. If diagnostic features are outside the tolerances, corresponding values are highlighted.

Diagnostic Module

The diagnostic module determines the MOV condition based on the results of feature extraction. The diagnostic rule set contains knowledge about some common MOV anomalies and detecting them in motor current signatures. It looks for three types of abnormalities in its input data:

- (1) One or several of the stroke events are missing.
- (2) There are unexpected events in the signature that can not be declared as noise.
- (3) One or several of the diagnostic features are not within their tolerances.

It is possible that more than one of these abnormality types are present. During diagnostic reasoning the user may be consulted to provide additional data. Results of the diagnostic reasoning are presented in a summary display, Figure 10. When a particular problem is selected for further analysis the user can ask for an explanation as to why the system reached this conclusion, check back the data which was the basis for a particular conclusion, or get recommendations for corrective actions or further testing of the MOV.

CONCLUDING REMARKS

So far the system has been tested using motor current measurements that were obtained in laboratory conditions. These measurements are almost noise-free, and the performance of signature pre-processing algorithms is very reliable. In the next phase the system will be subjected to extensive field testing in order to evaluate the robustness of the algorithms. The other goal of the field testing is to improve the rule sets that control feature extraction and diagnostic reasoning.

At present the system uses only a few of the diagnostic features that can be extracted from a motor current signature. Especially the use of motor current frequency spectra, would provide additional information for diagnosis of many anomaly situations. Similarly it is easy to upgrade the system to analyze also stem thrust and switch signatures.

One exciting way to develop the system further is to extend the hypertext features of the user-interface. It is possible to include animations explaining the operating principles of MOVs, still video images of MOV components with textual comments and explanations, and motion video sequences illustrating various MOV testing and maintenance procedures.

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ACKNOWLEDGEMENTS

The research and development is supported in part by a grant from Gilbert/Commonwealth, Inc. and United Services Engineering Corporation. The research by the first author is sponsored by the Finnish Utility Imatran Voima Oy. The study reported in this paper is part of the activities of the Preventive Maintenance Engineering Laboratory at The University of Tennessee.

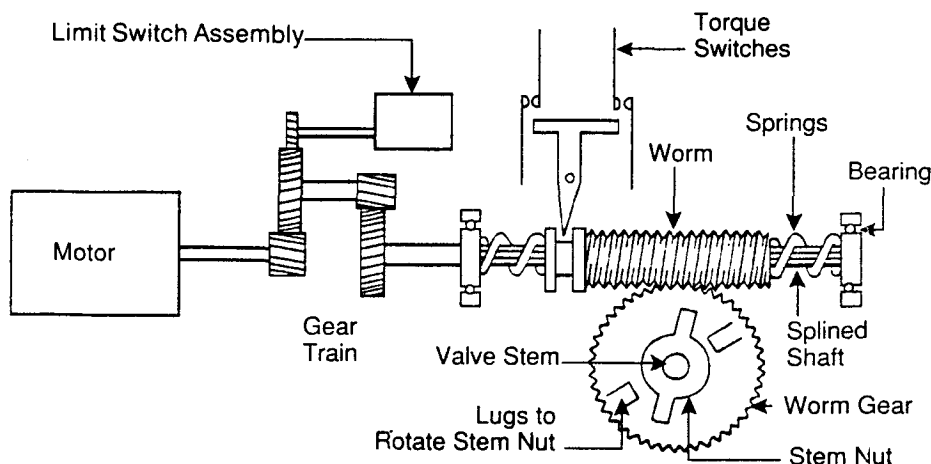


Figure 1. Functional diagram of a motor operator.
(From Ref. 3)

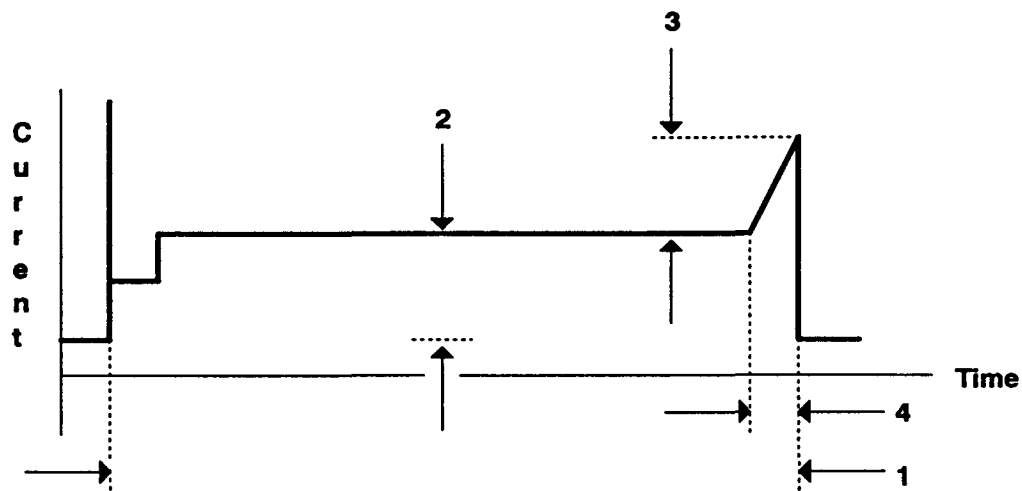


Figure 2a. Diagnostics features of an open-to-close stroke.

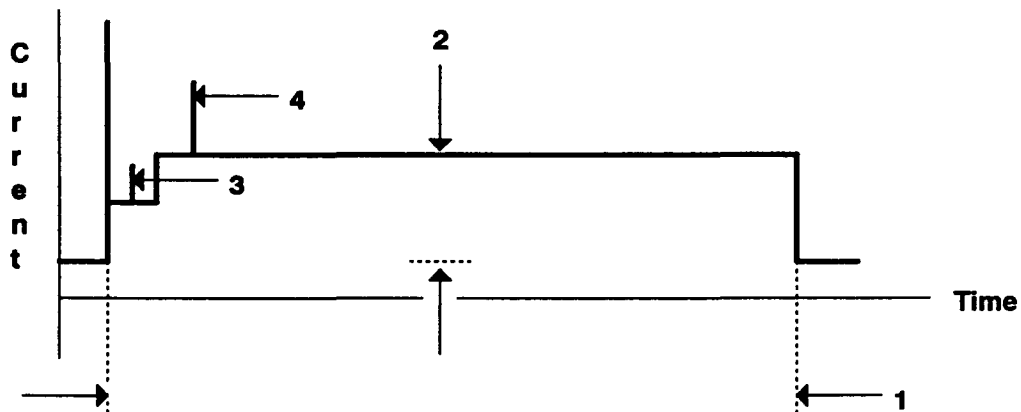


Figure 2b. Diagnostics features of a close-to-open stroke.

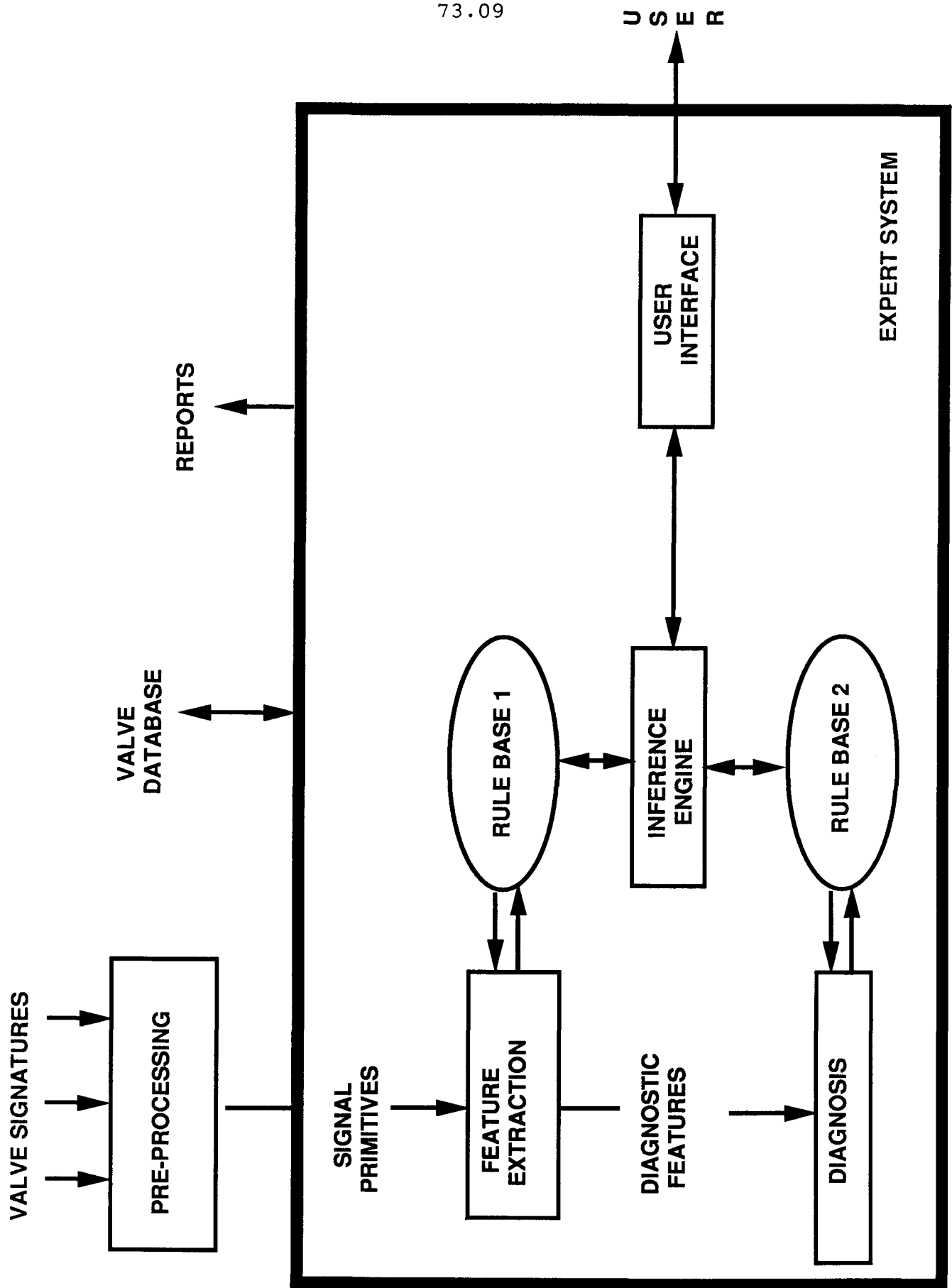


Figure 3. A schematic diagram of the automated MOV diagnostic system.

Explanation

The seating peak in the end of the stroke could not be found. Normally, when the valve gate contacts the valve seat, the load of the motor increases and it starts to draw more current. The current increases until the **torque switch** stops the motor. However, in the present case no current increase could be found, so it is probable that the close **limit switch** stopped the motor.

Limit switch

Limit switch counts the rotations of the worm shaft and stops the motor when a preset number of worm shaft rotations is reached.

Related topics: **trouble-shooting**, **Procedure of setting**, **Drawings**, **hiring diagrams**

F1 Help
Space Cont.

F3 Select
F4 View

F5 Evaluate
F6 Display KB

F7 Edit
F8 DOS

Pg 1 of 1
F10 Quit

Figure 4. Hypertext-based user interface. Information can be accessed by activating highlighted hypertext buttons.

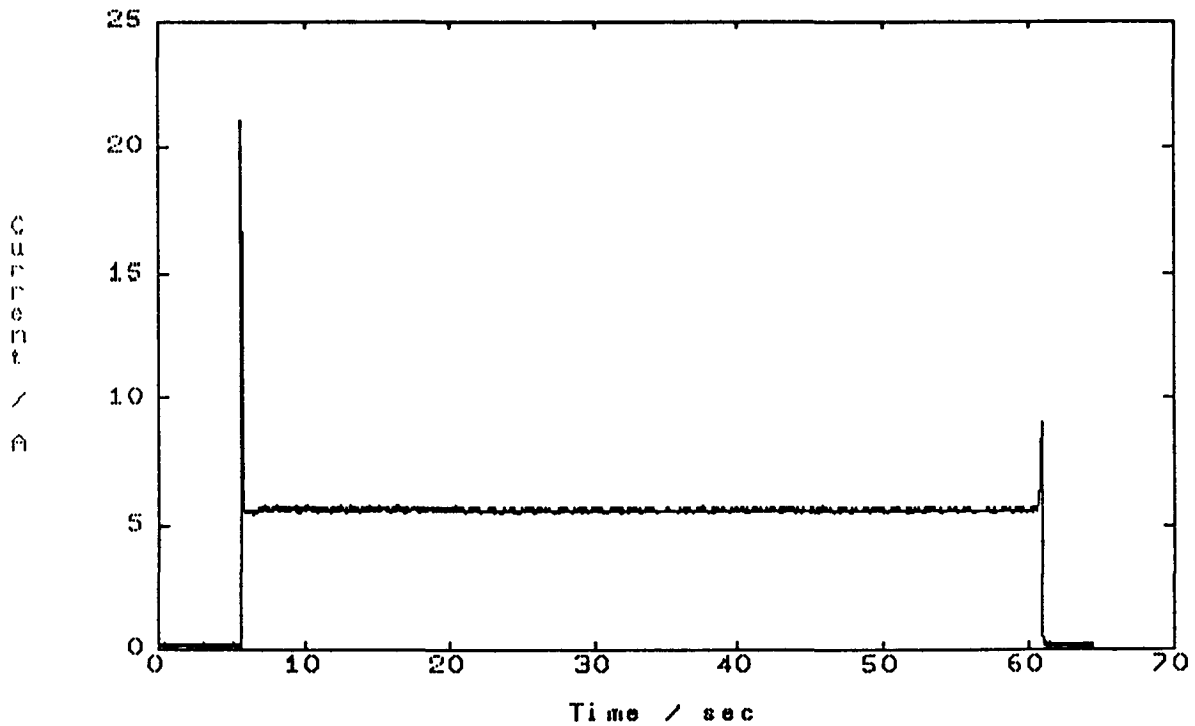


Figure 5a. MOV motor current signature during an open-to-close stroke.

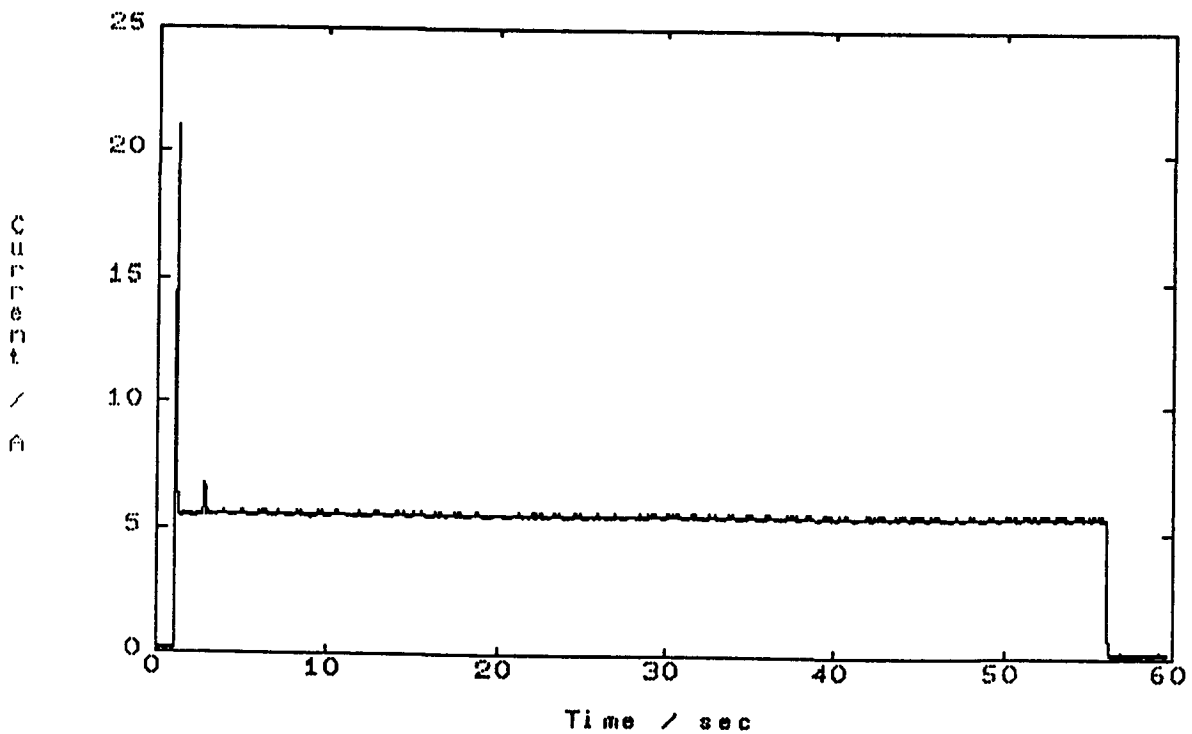


Figure 5b. MOV motor current signature during a close-to-open stroke.

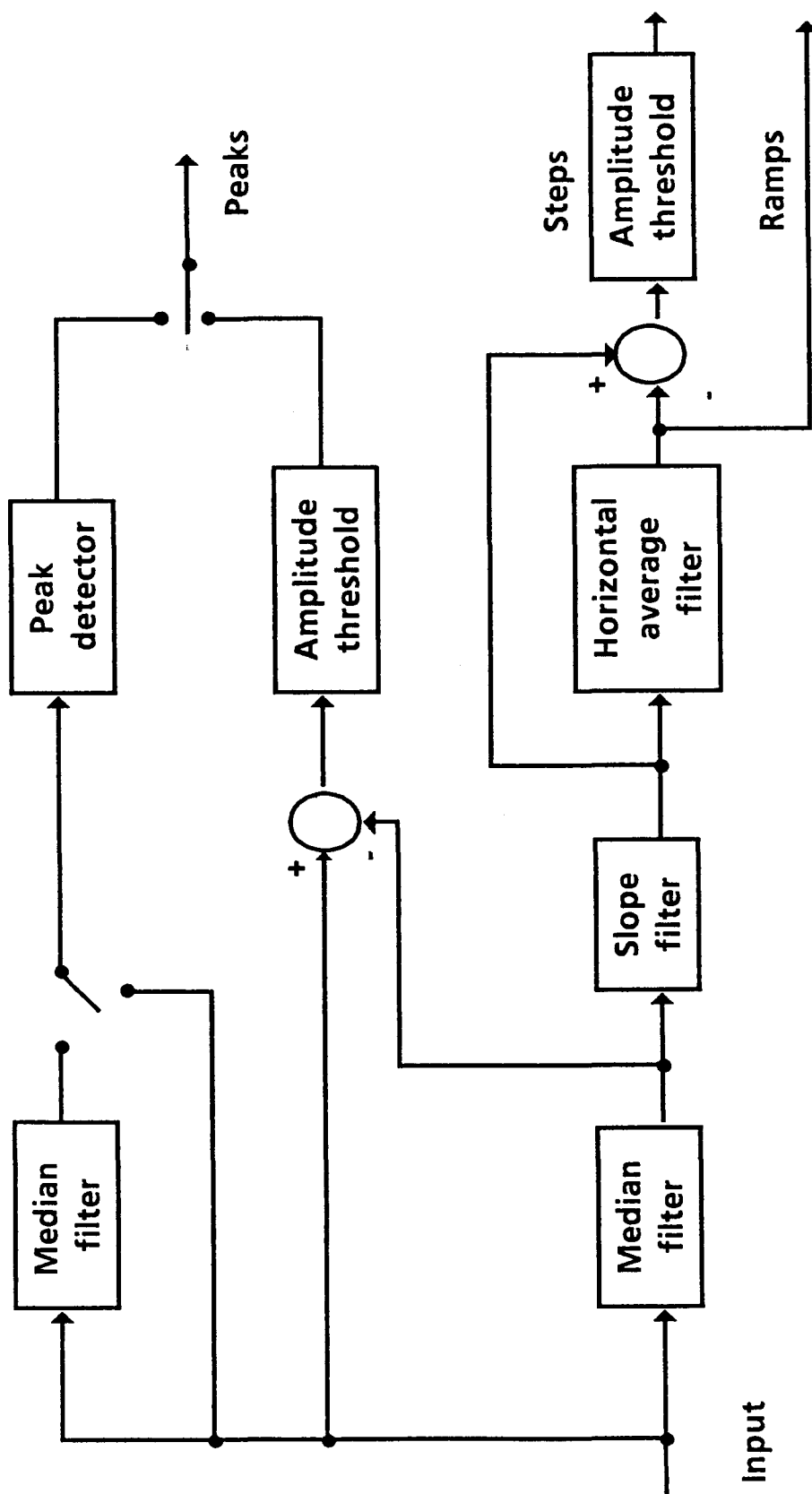


Figure 6. The functional block diagram of the pre-processing module.

ACOUSTIC MONITORING OF U-TUBE STEAM GENERATORS

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ABSTRACT

The surveillance of impacts of loosened or detached parts within the primary circuit of light water reactors as a measure for early failure detection and avoidance of consequent failures is well established in Germany. In the last years acoustic monitoring has become increasingly important also for steam generators. GRS has been involved in several cases for analysis and identification of impact events. Using our recently developed portable computer based measurement system RAMSES, burst data can be transferred to GRS analysis centre providing access to our central burst pattern data base and advanced signal interpretation software. Identification of steam generator tube bundles could be achieved by correlating burst sequence frequencies to measured vibrational eigenfrequencies. The paper describes the results of acoustic monitoring investigations and operating experience in U-tube steam generators.

INTRODUCTION

In spite of stringent quality control measures taken during design, construction, commissioning and operation, failures and degradations of components may not be excluded at the reactor primary circuit. Acoustic monitoring based on loose part monitoring systems (LPMS), which are installed in all German NPPs, is capable to detect unexpected component failures at an early stage /1-5/ and hence to reduce the high costs of unplanned shut-down of NPP's.

Assessing the mechanical integrity of steam generators by acoustic monitoring has become an important issue in the last few years. GRS experience with clarification of impact events at U-tube steam generators showed in several cases, that the advantage of acoustic monitoring measures reaches from the assessment of components status over the optimization of repair measures and reduction of doses for the repair personnel up to accompanying precaution measures according to requirements of licensing authorities. Current analysis activities concentrate on investigations of failure induced impacts with a plant independent trending. Basic work has been sponsored by the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, BMU, which is highly acknowledged.

PROBLEM-ORIENTED STEAM GENERATOR ACOUSTIC MONITORING

In the German RSK-Guidelines /8/ the use of adequate measures to detect and localize loosened or detached parts within the pressure retaining boundary is required. LPMS have now been developed to a satisfactory status /7/. Fig. 1 shows the sensor positions of a 1300 MWe PWR and response signals to test impacts at four loops.

Impacts of a loosened part are characterized by an invariate position and an often low-energy amplitude; they may deliver a typical precursor-function before a final rupture. In the last years impact events have been detected which were caused not only by foreign bodies within the steam generator inlet plenum (primary side) or the feedwater ring (secondary side), but also by other components such as spacer grids, tube bundles, etc.

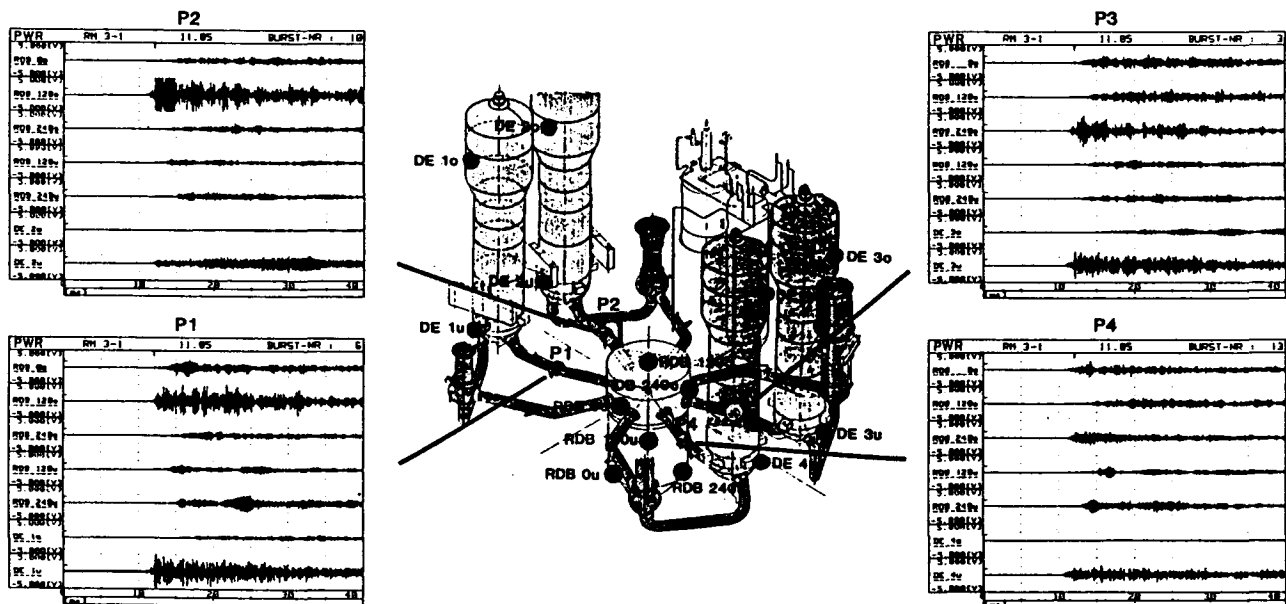


Fig. 1: Burst pattern of test impacts at PWR primary circuit

INTEGRITY OF TUBE BUNDLES

The steam generators used in nuclear power plants are large shell and tube heat exchangers which transfer the core heat to secondary coolant to raise steam. Next reactor vessel, they are the largest components in a nuclear steam-supply system. The integrity of steam generators which keep the physical separation between active primary coolant and inactive secondary feed water is of great importance. U-tube steam generators of 1300 MWe NPPs consist of more than 4000 U-tubes. Since a single tube leak will lead to a plant shut-down, there is motivation for measures to get high reliability in steam generators.

On the one hand it is realized by SG routine inspections, periodical in-service eddy current testing and conventional control measures. On the other hand the occurrence of a tube leakage will be noticed by the reactor protection system instrumentation. The incident of Japanese Mihama plant on February 9, 1991 caused by a tube leak with a subsequent forty minutes plant operation shows that methods which can give indications at an early stage for an ongoing tube failure and which contribute to maintenance of steam generator tube and component integrity will reach additional importance.

SG SENSOR CONCEPT

Acoustic monitoring as a very sensitive method for detecting unnormal stressing resulting from mechanical impacts or contacts can provide this information in advance of real failures. U-tube steam generators in German PWRs have as a minimum two sensors, one at the entrance to the primary inlet plenum, and the other at the feedwater line (see fig. 1). These sensors are specifically used for a global surveillance of the steam generator with respect to primary or secondary side detached parts.

Meanwhile in several plants for diagnosis purposes additional sensors have been installed at SG vessel, positioned for example at the U-tube bend area or above the tube sheet in order to overcome specific sound propagation conditions (shielding effect of tube sheet, complicated wave paths) and major spatial distances. Typically these sensors are integrated in the monitoring system in a different way: One additional sensor per steam generator is equipped with a full alarm circuitry (generally active), whereas the other sensors are used only as passive diagnosis channels. Signals of extended SG sensor configuration are shown in the next section.

SG TEST IMPACTS AND VIBRATIONAL EIGENFREQUENCIES

Analysis of test impact signals which are performed during plant shut-down enables not only a hardware test of the monitoring system but provides also important references by the measured signal patterns. In a 1300 MWe NPP tube bundles in the four steam generators have been fixed with a specific comb construction. After installation of two additional sensors at the SG wall near the U-bend area at each SG an acoustic monitoring surveillance program was carried through; for one SG investigations of tube bundle vibrations were performed with an additional SG internal accelerometer instrumentation. During plant shut-down test impacts have been performed within the steam generator to the comb construction of the tube bundles by an aluminium rod; the impact signals have been measured. Figure 2 shows the observed signal pattern with a time span of 40 ms (amplitudes are differently scaled for obvious reasons). The acoustic transit time from tube bundle sensor RB 240 to the sensors DE 312 and DE 132 (outside of the vessel) is nearly 3 ms. Known wave paths and propagation velocities [2,3] show that the acoustic propagation from tube bundle area is dominated in this case by the a_0 plate wave mode. These reference signals are stored in GRS burst data base D 9002.

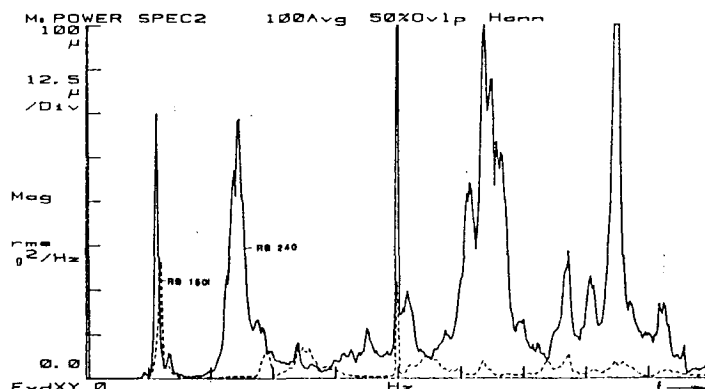
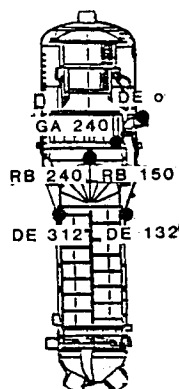
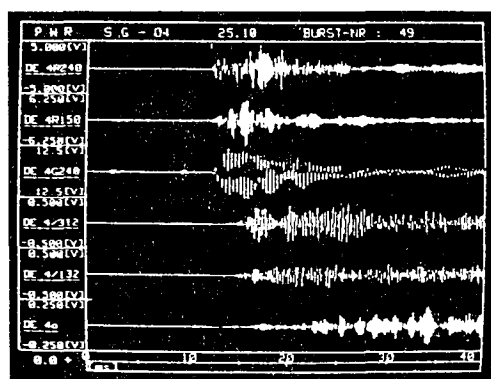


Fig. 2: SG burst pattern of a test impact on tube bundle bend area

Fig. 3: APSD of tube bundle vibrations

Vibrational measurements have been carried out on a SG under full power operation using accelerometers installed at tube bundle area. The analysis of these signals showed dominating resonance frequencies of steam generator components. Figure 3 shows the APSD of tube bundle sensors RB 240 and RB 150. Frequency peaks can be attributed to eigenfrequencies of the tube bundles and to pendular vibration of the steam generator as known from the vibration surveillance of the primary circuit. Even though the amplitudes are very small (less than 0.3 mm), the knowledge of these frequencies may be very important for the interpretation of SG impacts. A frequency change could be noticed at the beginning of the fuel cycle, which could be explained as a settling down behaviour. After the first 14 days no additional frequency shifts have been observed.

REMOTE SG DIAGNOSIS SUPPORT BY GRS RAMSES SYSTEM

For unexplained steam generator acoustic signals, a detailed burst data registration and interpretation of the involved measurement channels over a certain period is required. Sporadic impact events of low frequency (i.e. 1 per hour) can occur. Analog LPMS give primarily only a very rough localisation by indicating the responsible measuring channels (for example steam generator No. X or Y, top or bottom) for the following analysis and evaluation. Burst data preferably in digitized form and signal plots with a complete representation of burst flanks should be available; but only the next situated sensors to the roughly localized impact position are relevant in the most cases. Their short-term clarification is strongly requested both for an early failure detection as well as for practical reasons (maintaining the surveillance function of the measurement channel, reducing the expense for alarm confirmation etc.).

Based on practical experience a concept for diagnosis support by a Remote Acoustic Monitoring and Signal Evaluation System (RAMSES) has recently been developed. It is based on a computer communication between the GRS laboratory burst analysis system MEDEA /3/ and a portable digital system consisting of four fast transient recorder storage modules. It can be set up short-dated and in a temporary way at the plant. Especially the analog LPMS technique, which is used in earlier German plants, can be supplemented in an effective manner. Two identical transfer programs are activated, as data transfer takes place by modems via the telephone line. At the start of data communication an automatic synchronized connection between both computers is established with password protection and consequent hand-shake data transfer. The data transfer rate is 2.400 baud, full duplex, block size is variable. Figure 4 shows the hardware configuration of the remote acoustic monitoring and signal evaluation system RAMSES.

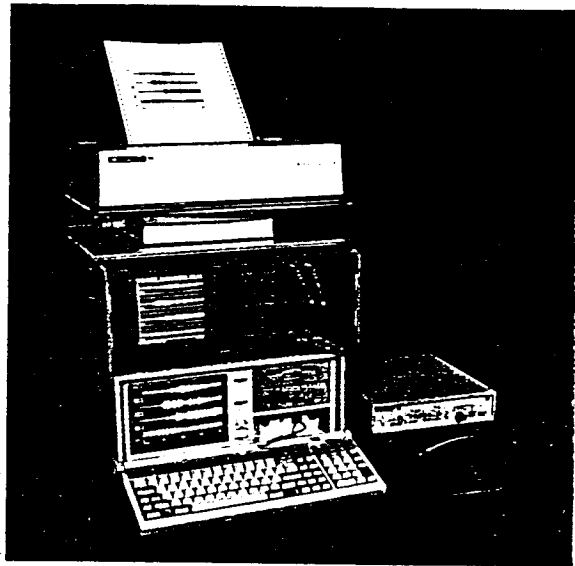


Fig. 4: Hardware configuration of RAMSES system

RAMSES contains software packages for remote controlled setting of the transient storage modules via the telephone net, for transfer of the data to the onsite computer after event detection, for a storage of the data on hard disk onsite, for plotting the data on graphic screen and printer and for data transfer of qualified signal patterns to the GRS analysis centre. The following data are available onsite:

- event number, date, time and amplitude of each registered event,
- list of all qualified events,
- four-channel-plot of all events

Specific evaluation functions can automatically be implemented by the use of file transfer between host and onsite station. Data coupling to GRS analysis centre gives access to additional digital analysis functions. Experiences with RAMSES system are very positive, first results have been documented in /4/.

ADVANCED DIGITAL SG ANALYSIS METHODS

INTERVAL TIME ANALYSIS

Interval time analysis of burst sequences has been proved to be a valuable tool for evaluation of the basic impact process. By use of modern digital systems with minimum time gap between subsequent bursts - MEDEA system /3/ in block mode option has a time gap of less than 5 msec - an identification of position-fixed impacting parts can be reached.

Impacts of loosened parts should result in burst sequences, whose time intervals are inverses of fundamental or harmonics of vibrational eigenfrequencies of the concerned component (e.g. tube bundle). Impact rates up to 90 Hz have been observed, an example (fig. 14) is given in a later section.

IMPROVED SG LOCALIZATION PROCEDURES

Basic requirement for an improved SG localization procedure is a qualified interpretation of failure indicating burst signals. Verification of SG localization algorithms has been performed by using test impacts with known impact positions; the individual burst transit times have been determined interactively at the computer display. SG plate wave velocities - which are dependent on wall thickness and frequency - have been calculated from the governing differential equations /3/. Fig. 5, 6 show the results of s_0 , a_0 , a_1 -mode for SG upper cylinder part and SG shroud (wall thickness 84 mm resp. 18 mm) in frequency range 0 - 25 kHz.

The localization result has been evaluated as a graph on the screen using source location algorithms based on hyperbolic intersection, circle intersection and direct location, which have been discussed earlier /3/. Structural inhomogenities have been considered by using conformal mapping of the structure.

The results show for steam generator components a reliable and sufficiently accurate localization of the position, where the structure-borne sound waves are fed into the steam generator vessel wall and deliver according to our experience an enhancement of the reliability of SG burst interpretation.

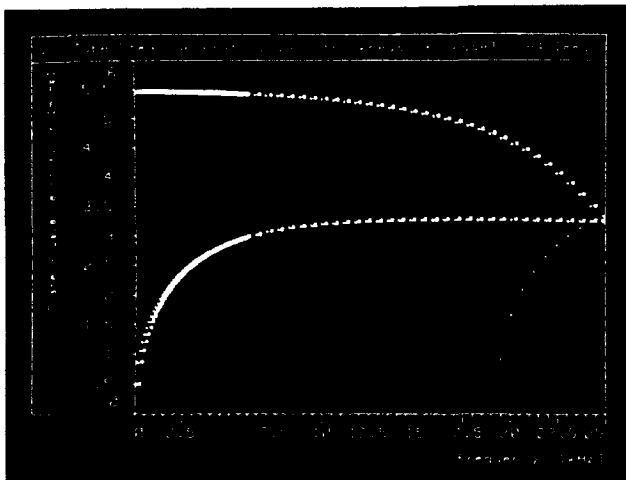


Fig. 5: Plate wave velocities of SG upper cylinder vessel

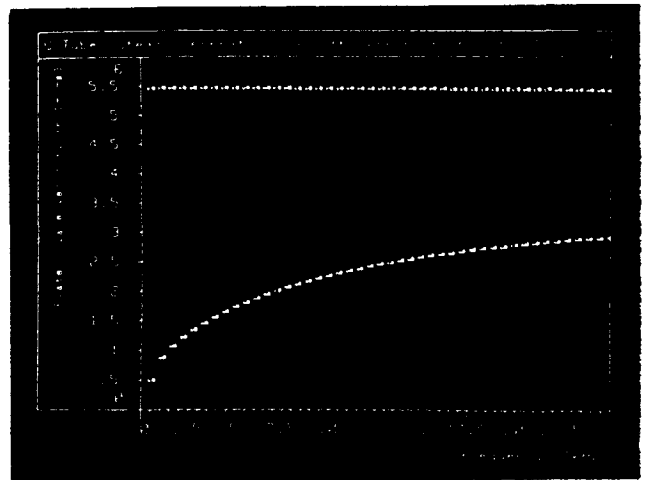


Fig. 6: Plate wave velocities of SG shroud

HERTZ THEORY IMPACTOR MASS ESTIMATION

Basic methods for impactor mass estimation have been published in /2/. In an EPRI research program /9/ additional methods are discussed. Meanwhile Hertz theory has proven as an important and valuable tool for estimating the mass of an impactor. Figure 7 shows the basic equations for an impact of a sphere to a massive plate. In the last few years in several cases mass estimation could reliably help for evaluating the significance for safety of impacts. An example of a successful mass estimation is given in fig. 18.

contact time	$t_c = \pi k_h m^4 V_o^{-2} R^{-2}$	$k_h = ((15/16)((1-\mu_1^2)/E_1 + (1-\mu_2^2)/E_2))^{-1/4}$
max. approach	$D_{max} = k_h (m V_o^2)^4 R^{-2}$	m: mass of impactor
max. acceleration	$A_{max} = k_h^{-1} m^{-4} V_o^{1/2} R^2$	R: radius of impactor
max. force	$F_{max} = k_h^{-1} (m V_o^2)^6 R^2$	V_o : impact velocity of impactor

Fig. 7: Hertz theory governing equations (impact sphere/plate)

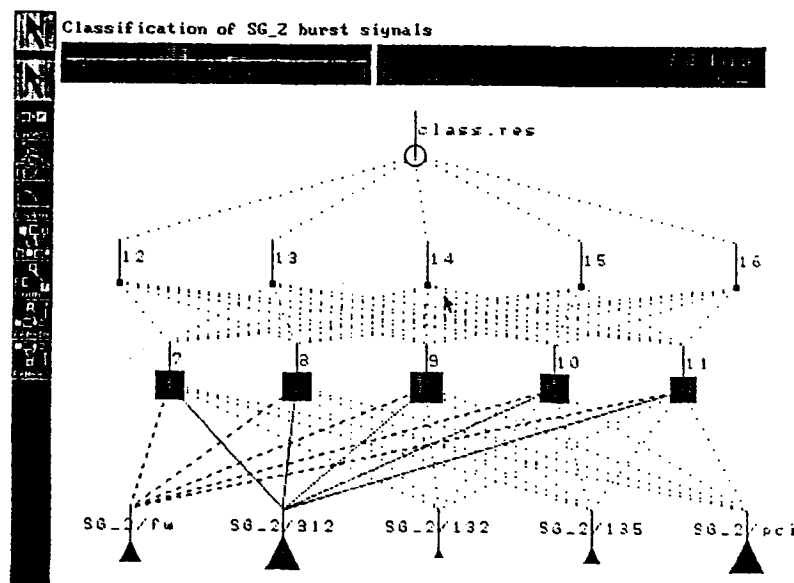


Fig. 8: Neural network for SG burst type classification

BURST CLASSIFICATION BY NEURAL NETWORKS

The use of neural networks will add new features to SG acoustic monitoring and early failure detection. As part of pattern recognition the classification of burst signals with non-linear classifiers can be used for advanced signal analysis (type classification, localization, mass estimation). Figure 8 shows a trained neural network with five inputs corresponding to five steam generator sensors, two hidden layers and one classification output. It has been trained for identification of specific burst parameters as rise time, relative amplitudes and pulse duration, which are available in GRS database D 9002. Preliminary results show a good characterization potential for different types of burst signals.

SG OPERATING EXPERIENCES WITH IMPACT INDUCED ACOUSTIC SIGNALS

Additional to routine in-service inspections of steam generators during plant revision and in order to assure steam generator integrity also during plant operation, acoustic monitoring is increasingly used as a supplement measure for prevention of or provision against failures. An early detection enables dedicated trending and limitation of impact events. GRS has been involved intensively to the collection and analysis of signals (long-term behaviour, plant influences, fault diagnosis). With the following SG operating experiences with impact induced acoustic signals the capability of acoustic monitoring of steam generators shall be demonstrated.

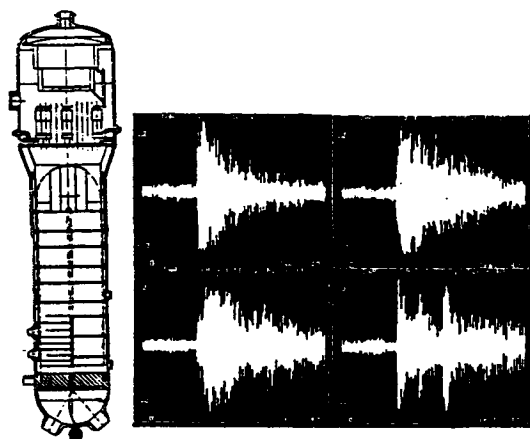


Fig. 9: Impact signals of a loose part

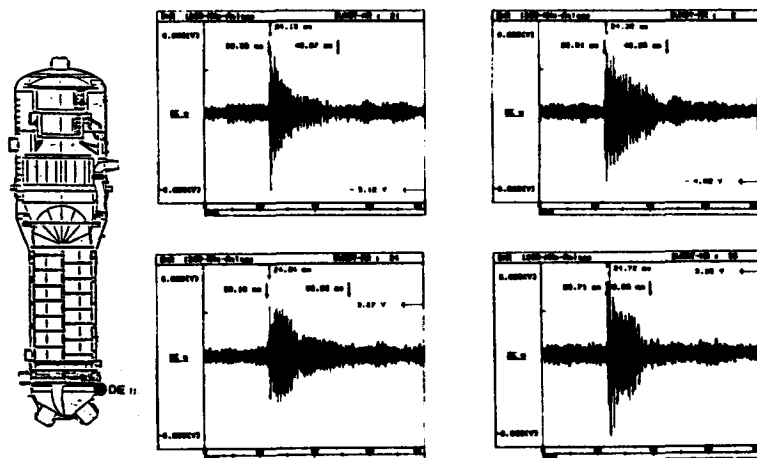


Fig. 10: Characteristic values of impact signals

SG INLET PLENUM IMPACTS

Detection and identification of detached parts in natural collection rooms like the inlet plenum of steam generator is a primary task of acoustic monitoring. Already very small impacting loose parts result in bursts at the sensor of the steam generator inlet plenum, which are very well detectable against the normal background. According to the knowledge of the author in the 14 operating PWR's in Germany only few major impact occurrences per year are noticed; the mass region of the impactors is typically from 10 grams to 200 grams, various loose parts within the inlet plenum have been observed.

Impacts of detached parts in the inlet plenum of U-tube SG are characterized by the fact, that relevant burst signals are detectable only by the sensor at SG inlet plenum due to the strong acoustic attenuation effect of the tube sheet. Therefore the different and specific shape of burst signals together with their sequence measured only by one sensor has to be used for identification of the detached part. Figure 9 shows impact signals of a sensor at primary coolant inlet caused by impacts of a pin (mass 197 g), which was detached from upper core support plate and has been transported with the coolant from the reactor vessel to the inlet plenum. The analysis delivers very sharp signal rise; the ratios of burst signal amplitude to that of background noise reach values up to 12:1.

Burst sequences, rise times and additional signal parameters have been calculated for a burst ensemble of 200 bursts and have been compared with distributions of impacts of other detached parts. Fig. 10 shows characteristic values (burst start time, duration and amplitude) of impacts, which have algorithmically been determined. Various burst forms can be classified in accordance with different impact positions within the inlet plenum. By use of adequate parameter correlation a fast identification of the impacting part can be achieved.

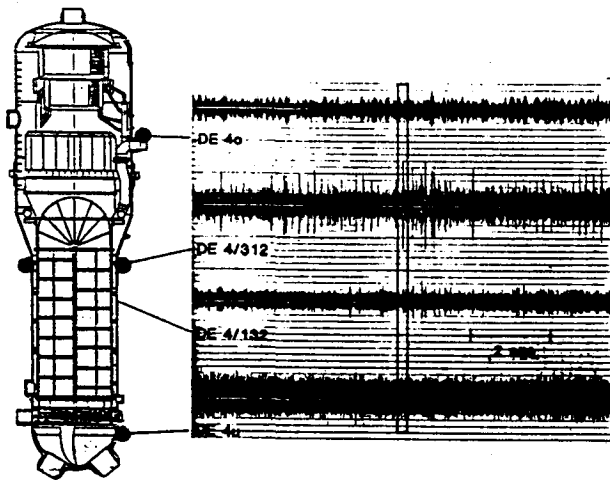


Fig. 11: record of tube bundle impact signals

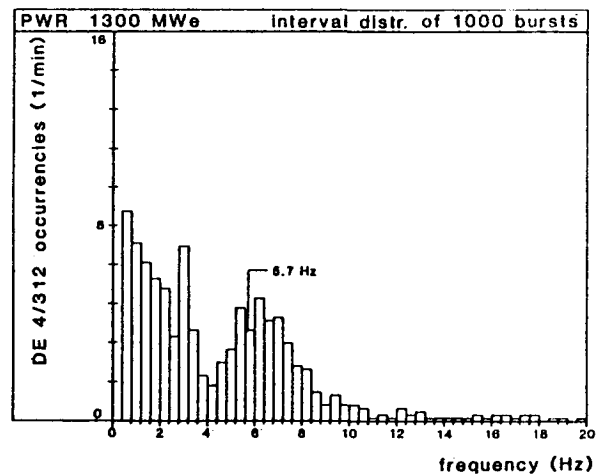


Fig. 12: Frequency distribution of burst time internals

TUBE BUNDLE IMPACTS

In the steam generator of a 1300 MWe plant impacts have been detected suddenly during plant operation. Figure 11 shows a strip chart record of four bandpass filtered signals. Only from sensor DE 4/312 characteristic burst signals could be observed with high sequence rate; amplitude ratios are up to 6:1. The analysis results yielded metallic impacts originating from one fixed position. Interval time analysis of figure 12 showed a distribution of the measured burst sequences with a characteristic shape and a dominant peak at 5.7 Hz. This frequency could well be correlated to measured vibrations of steam generator tube bundle. The agreement between both measured peaks at 5.7 Hz confirmed the participation of tube bundle of the steam generator to the impacts. This finding was supported by the fact that the impacts were subjected to operating conditions of secondary side (feedwater flow, unsymmetric fluid load). By appropriate operating measures the impacts could be avoided in the subsequent operation.

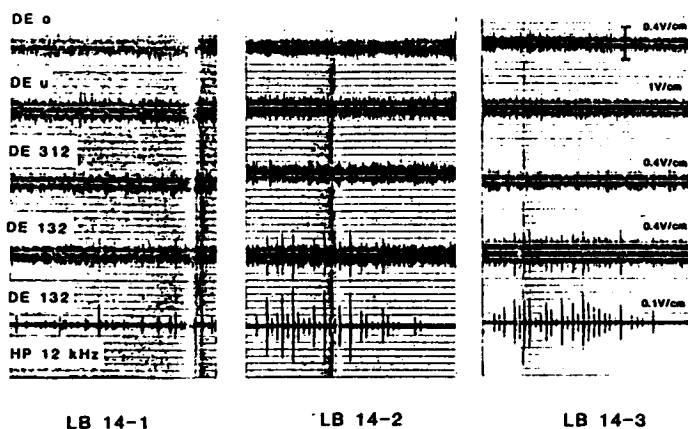


Fig. 13: record of spacer grid contacts

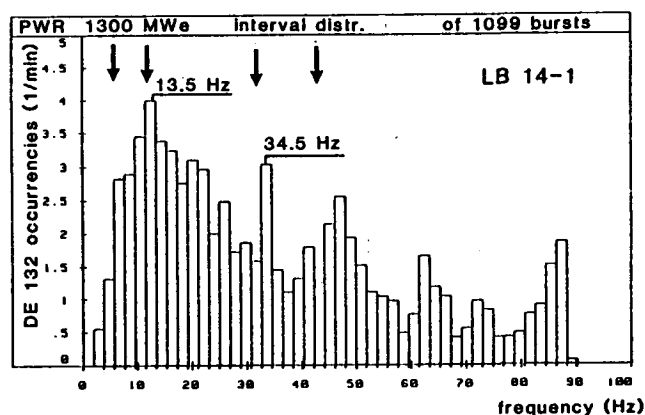


Fig. 14: Frequency distribution of burst time intervals

SPACER GRID CONTACTS

In an upper steam generator sensor burst signals of high frequency content have been detected. A profile of signals of three measurements in the fuel cycle is given in fig. 13. In a strip chart record burst sequences of constant periodicity and varying amplitudes could be noticed. The frequency spectrum of an intense burst signal showed a dominant frequency of 18.5 kHz (a sensor crystal resonance frequency). In figure 14 the distribution of burst sequences of more than 1000 bursts is presented. Very dominant peaks at 13.5 Hz and 34.5 Hz are obvious.

Analysis of signals showed that metallic impacts of detached parts could be excluded; the high signal frequency could well be correlated with very short contact times, caused by the presence of crack relaxation. As the measurement system answers in resonance only very low energy events are concerned. Constant burst form and analysis of rise times showed a location within the steam generator of more than 1.5 m and less than 4 m. The burst interval distribution in fig. 14 shows that the dominant frequencies coincide very well with eigenfrequencies of tube bundles which have been measured before. An inspection in the next revision was recommended.

Finding of the inspection was a small crack of a weld of a spacer grid with a wave path of 3.9 m to the sensor, which was in good agreement with the prediction.

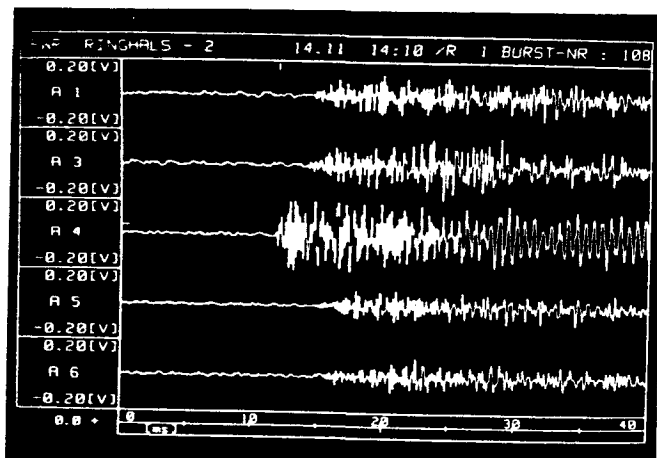


Fig. 15: Signal pattern of feedwater ring impacts

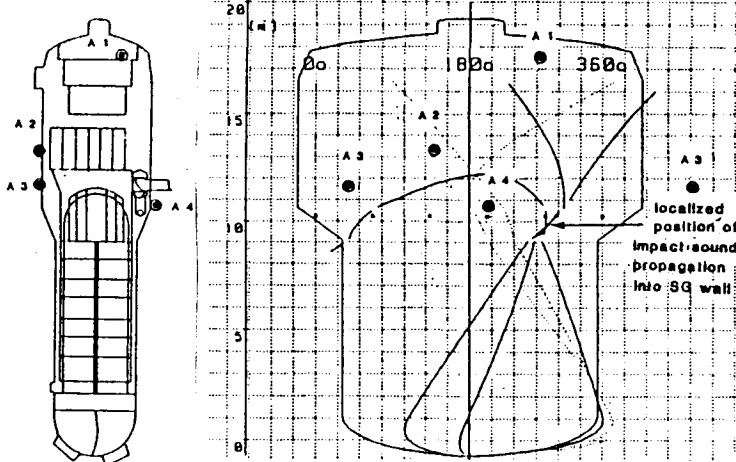


Fig. 16: Localization graphs of Ringhals impacts

RINGHALS FEEDWATER RING IMPACTS

In the Swedish NPP Ringhals-2, a 4-loop 900 MWe Westinghouse PWR, new steam generators have been installed by Siemens/KWU. Unexplained acoustic indications occurred in one steam generator at higher power levels. The Swedish licensing authority made its approval for full power operation dependent on a complete and reliable diagnosis of these acoustic events. The signals have been stored on magnetic tape and analyzed in GRS laboratory /6/. The following diagnosis result was gained and presented to the Swedish authority: fluid induced position-invariant metallic impacts of a loose part with mass of 100-250 g within or at the feedwater ring at the angle position 260° - 280° . Figure 15 shows a burst pattern of measured impact signals. The position of the upper sensors in a schematic vertical projection of the steam generator is given in the left part of fig. 16. The localization graphs, drawn in the steam generator development are presented in the right part of fig. 16. They have been determined from burst arrival times using a localization program developed by GRS. Intersection of the localization graphs yields the position where the sound enters the vessel wall, in this case at one of six supports of the feedwater ring (see fig. 16).

Mass estimation has been performed using Hertz theory [2,3]. Figure 17 shows a power spectral density of an intense impact signal, from which an impact contact time of about $120 \mu\text{s}$ has been determined.

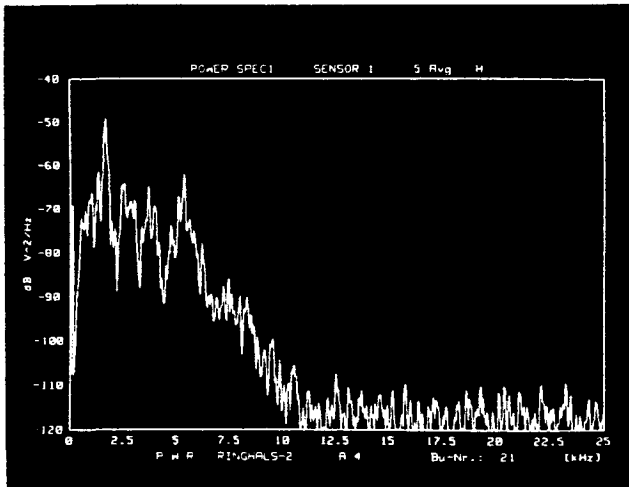


Fig. 17: Burst power spectral density of feedwater ring impact signal

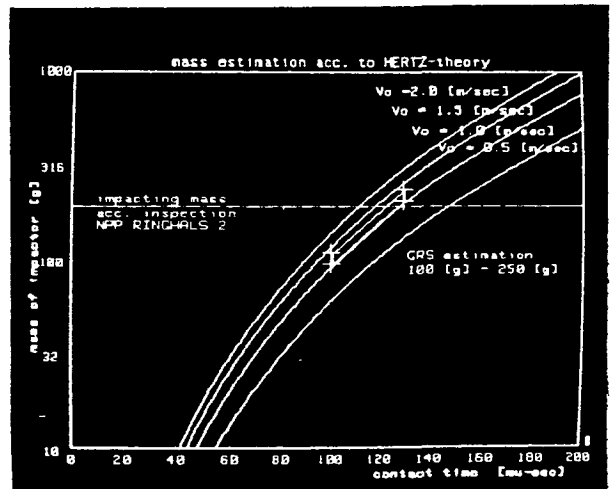


Fig. 18: Mass estimation of Ringhals impacts

The authority accepted the GRS diagnosis, a surveillance program was established to monitor the steam generator until the end of the fuel cycle. The meanwhile realized inspection of the feedwater ring proved the GRS diagnosis in full degree: Localization and mass estimation have been confirmed by observed parts of a device for inert gas provision during pipe welding (essentially metal disks) fixed by a wire, which have been found exactly within the identified region of the feedwater ring. Fig. 18 shows the comparison of estimated (based on Hertz theory calculation) and observed mass of impactor.

CONCLUSIONS

Experiences in the last few years proved that problem-oriented SG acoustic monitoring in Germany has contributed to enhanced U-tube SG safety. Basic requirement for a reliable SG diagnosis in the actual case is the availability of a knowledge base for interpretation and evaluation of failure indicating burst signals. Further SG acoustic monitoring developments will concentrate on improved diagnosis assessment by use of signal data bases and advanced digital analysis methods.

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DISCOVERY AND CHARACTERIZATION OF LOOSE PART ACTIVITY AT MAINE YANKEE ATOMIC POWER STATION

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ABSTRACT

Loose part activity was detected at Maine Yankee Atomic Power Station by installed instrumentation and the utilization of a statistical methodology to trend loose part monitoring system instrument behavior. This was followed by comprehensive measurements on-site using temporary and permanent instrumentation which characterized the location, energy, and mass of the loose part.

INTRODUCTION

The detection of loose parts, or impacts in a nuclear power plant is typically performed by monitoring the signals from permanently installed accelerometers mounted near potential collection sites for loose parts. A typical nuclear facility will consist of 12-16 channels around the primary loop. Normal operation of these systems consists of continuously monitoring the conditioned sensor output and alert (or alarm) when signal levels exceed a certain threshold value. Generally a tape recorder is a part of the monitoring system and is automatically activated when an alarm is generated. The recorded signals are then further analyzed for validation of impacting and characterization.

Maine Yankee has in place a comprehensive Loose Parts Monitoring (LPM) surveillance program which utilizes LPM detection and alarm system equipment and long-term LPM trend analysis surveillance. The detection equipment monitors three sensors (accelerometers) on the top of the Reactor Vessel (RV), two sensors mounted on instrument guide tubes at the bottom of the RV and a sensor for each steam generator. The charge output of these sensors are converted to a voltage, amplified and

routed into conditioning equipment calibrated to produce alerts and alarms in the control room when metal-metal impacts are detected. Maine Yankee also utilizes recently developed Modified Amplitude Probability Density (MAPD) analysis (1,2) to trend the behavior of their loose part channels. The MAPD is constructed from a normal APD by plotting the Log (base 10) of the amplitude probability versus the signal amplitude squared and normalized by the standard deviation. For true Gaussian noise the result is a straight line having a slope of ~ -0.22 . If there is signal contribution from another source (i.e., impacting or electrical noise) the slope departs from this value.

LOOSE PART DETECTION

The primary indication of a loose part was observed by the trend of the MAPD slope parameter and an increasing amount of alerts in the control room from the installed equipment. Figure 1 shows the trend of the MAPD slope parameter for a 10 month period beginning in April of 1989. The sudden increase observed in September 1989 clearly indicates a change in the monitored signal. This, coupled with an increasing number alerts and metallic impacts heard through audio monitoring lead to the conclusion that there was a loose part in the vicinity of the reactor vessel. From tape recorded data, the calculation of time delays between the response of permanently installed sensors led to the conclusion that impacting was coming from the vicinity of Steam Generator 1 and that on-site measurements should be done to more closely characterize the impacts.

ON-SITE MEASUREMENTS

The equipment used for on-site analysis consisted of:

- Two-channel transient capture device with printer
- A 0.91 kilogram (2 lb) mass impacting device¹ calibrated to 6.8×10^6 ergs (0.5 ft-lbf).
- Four channels of instrumentation, each channel being comprised of the following:
 - Magnetic Mount
 - Accelerometer (Endevco)
 - TEC Model 504A charge converter
 - TEC Model 932 signal conditioning module
 - TEC Model 1432 impact detector
- Rack and required power supplies and cables
- An 8-channel strip chart recorder.

1 CE Model E-LPMS-482-001, available from ABB (formerly Combustion Engineering).

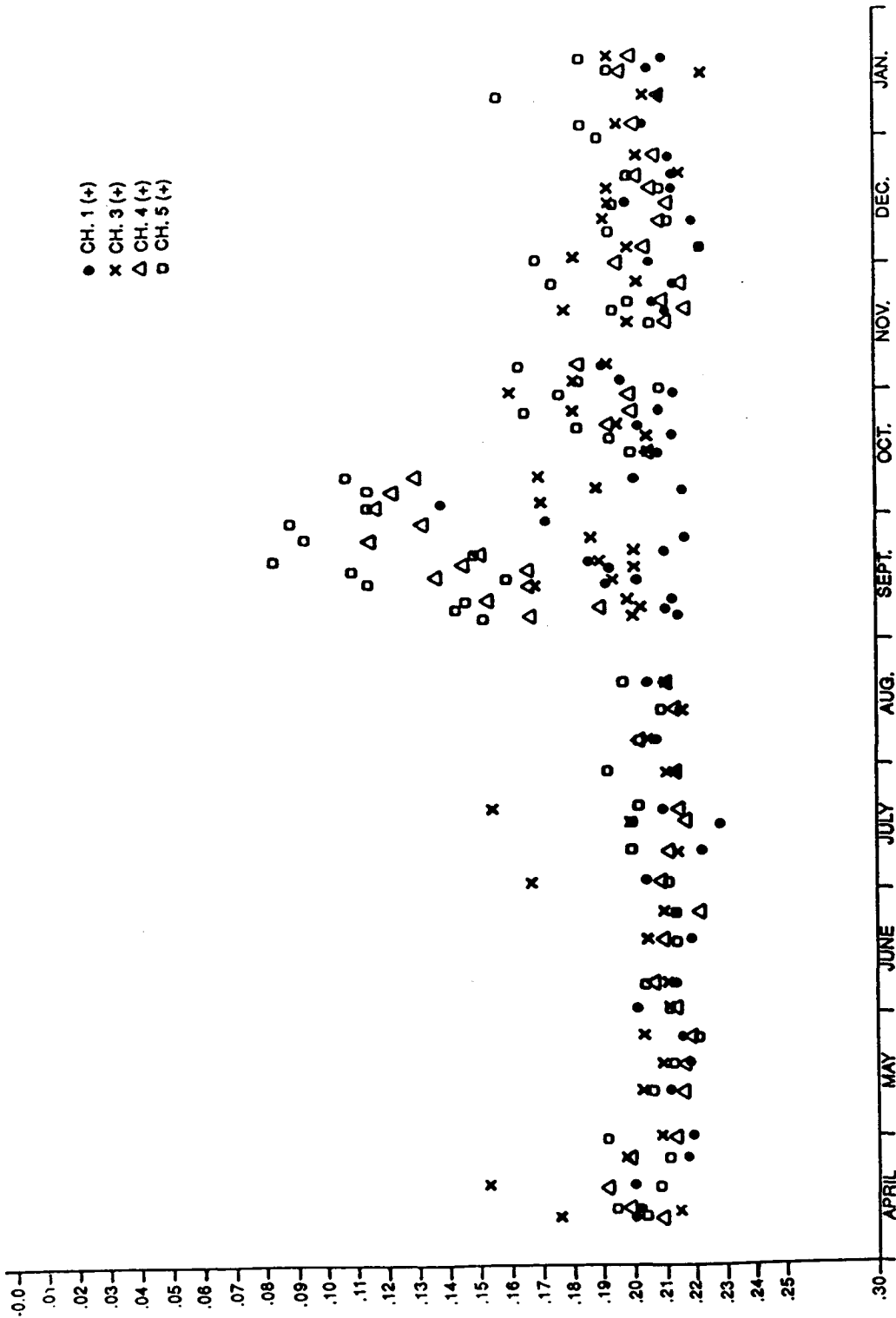


Figure 1. Trend of MAPD Slopes, April 1989 to January 1990.

This instrumentation was temporarily located at four positions around Steam Generator 1 as shown in Figure 2:

1. A sensor (Channel 1) on the blowdown line near the permanently installed sensor.
2. A sensor (Channel 2) mounted directly on the manway at the inlet side to the steam generator.
3. A sensor (Channel 3) on the vent line exiting the generator slightly above the tube sheet.
4. A sensor (Channel 4) on the opposite side of the steam generator on the same blowdown line.

An initial data set was acquired by recording signals accessible in the control room. These are the same as those mentioned in the introduction. This recording consisted of three runs of four channels each so that all five sensors on the reactor vessel and each sensor from the three steam generators were recorded. For the remaining data sets using the temporary equipment, the signal from the sensor for Steam Generator #1 was kept common.

Impacts using the precalibrated impactor (6.8×10^6 ergs) were introduced downstream of Channel 4 on the blowdown line. A second set of impacts was introduced on another line exiting the generator which was closer to Channels 1 and 3 at the point of entry to steam generator.

Following the analysis of the results of these impacts (see below) a second data set was obtained. The location of the four sensors for this data set was the same as those for the first data set with the exception that Channel 4 was moved to the upper valve body of the motor operated isolation gate valve. The isolation valve is located approximately 3.3 meters (11 feet) upstream of the steam generator in the primary hot line. The impacts for the second data set were introduced directly on the manway within 5-10 cm (2-4 inches) of the sensor for Channel 2.

RESULTS AND OBSERVATIONS OF MEASUREMENTS

From the initially recorded data it was confirmed that the most active channel was Steam Generator No. 1 (SG#1). When impacts were obvious on Reactor Vessel channels 1, 4 and 5 in the general time frame of a larger event occurring on SG#1, they were all lagging. This is shown in Figure 3 which contains a portion of a trace from the output of the TEC Model 1432 detector modules for data recorded on 9/20/89. Some events on SG#1 were not accompanied by obvious responses on the reactor vessel sensors. This implied that the events occurring in the vicinity of SG#1 were not large. There was no activity seen on Steam Generators 2 and 3.

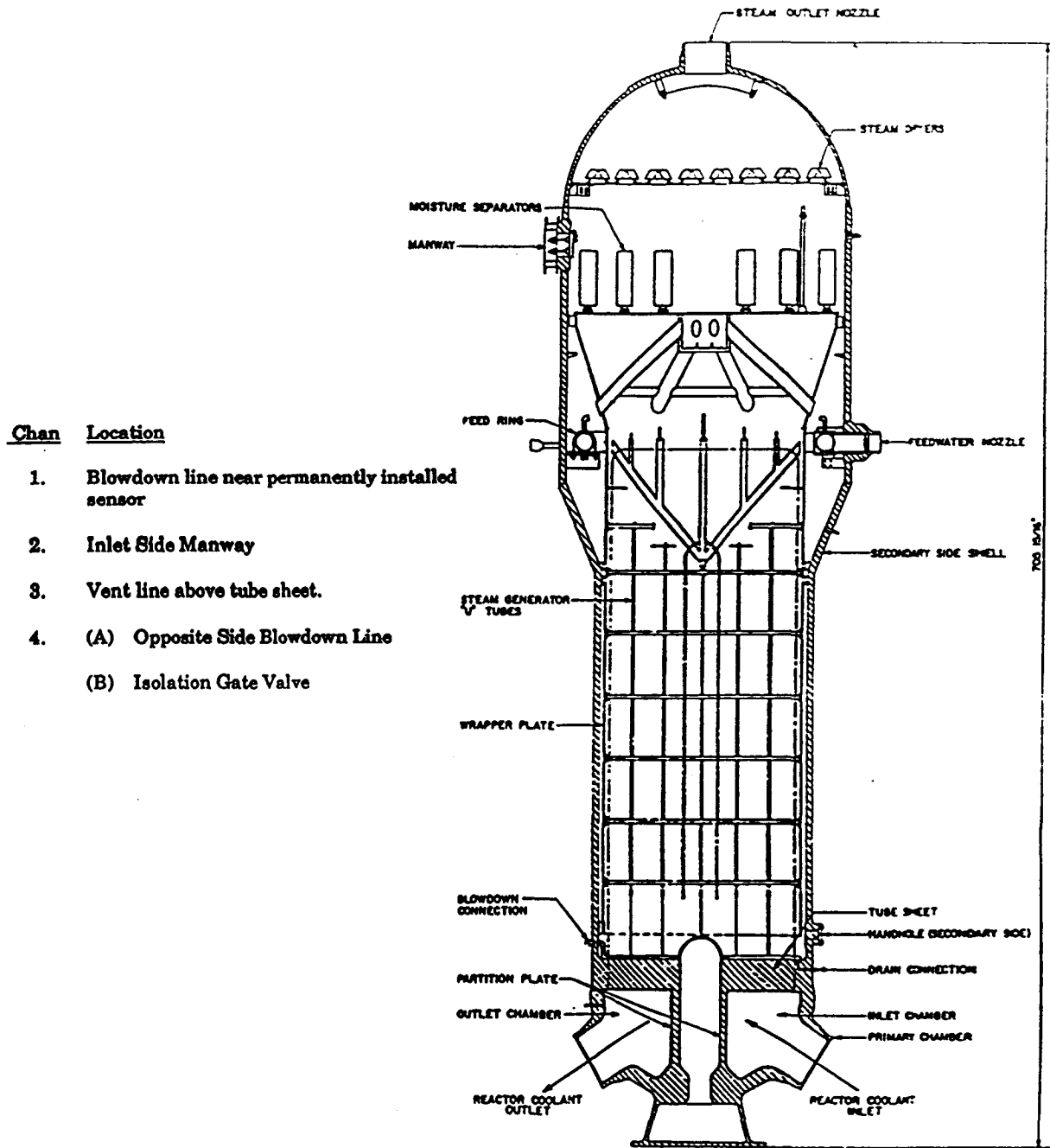


Figure 2. Location of Temporary Loose Part Monitoring Sensors.

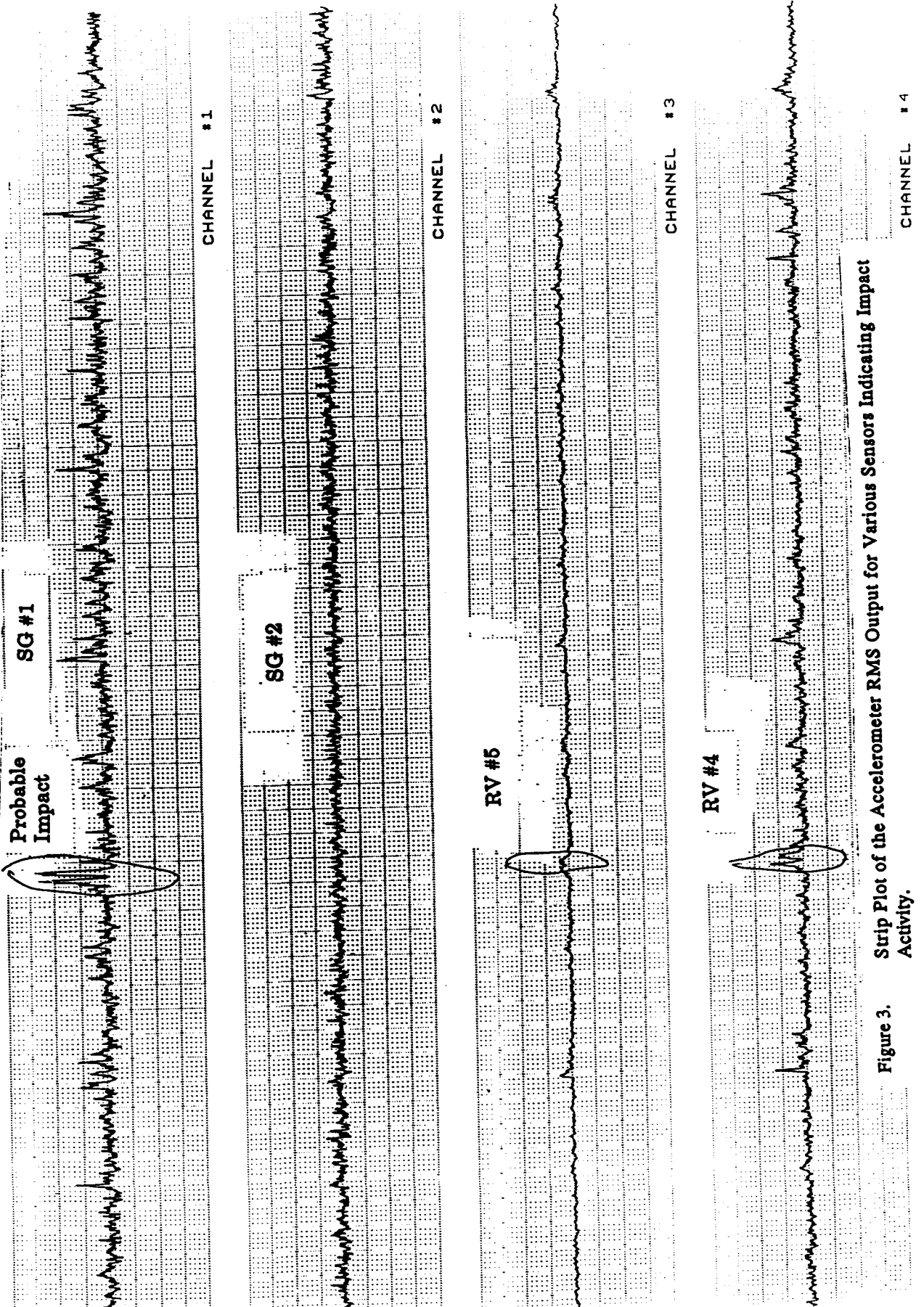


Figure 3.

Strip Plot of the Accelerometer RMS Output for Various Sensors Indicating Impact Activity.

Data Set #1 (In-containment Recording on 9/20/89).

Signals measured on the four temporary channels while the first set of deliberate impacts were executed indicated that the impacts were strongest on Channel 4 since it was closest to the impact location. The next strongest impact indication was on Channel 1 followed by Channel 3. The deliberate impacts were not obvious on Channel 2 (sensor mounted on manway), hence no meaningful data was obtained to permit definitive statements relative to the energy within the normal impacting signature. From this data, it was concluded that impacts should be made directly on the steam generator if at all possible. It was also obvious that the impact signature on Channel 1 from the calibrated impacting device was significantly greater than that from the unknown impacting i.e., the impacts observed at power (referred to as "normal" impacts henceforth). Further observations of normal impacts indicated that the sensors near the inlet side of the steam generator were the most active and Channel 4 (the exit side of the steam generator) was the least active. From this, it was concluded that it was improbable that the impacting was occurring up in the steam generator. If the impacting was high in the steam generator, Channel 4 would most probably have the same activity as Channel 1. The most probable place for the impacting was reasoned to be toward the inlet side (either in or outside) the steam generator.

An individual transient capture event from Data Set #1 of a normal impact is presented in Figure 4. The important observation from this event was that the sensor on the manway (Channel #2) was responding at a higher frequency than that seen by the sensor mounted on the blowdown line (3300 Hz versus 2200 Hz). Thus the sensor on the blowdown line was being dominated by the resonance frequency of the blowdown line and was of little value in providing information relative to the mass of the impacting component. Assuming that the 3300 Hz signature for the manway sensor is characteristic of the impacting, then it is representative of a nominal 2 Kg (4.4 lb.) mass rather than a larger 3-4 Kg (6.6-8.8 lb) mass (3) which the 2200 Hz would suggest.²

Data Set #2 (In-containment Recording on 9/21/89). For the second data set within containment, the impacts from the impactor were introduced on the manway within a few inches of the sensor comprising Channel 3. The signature of the impacting was captured in the control room using the LPM computer for the SG#1 and RV#1 channels. The important observations made from this data were:

1. The 6.8×10^6 erg (0.5 ft-lbf) impact by the 0.91 Kg (2 lb) mass on the steam generator manway was clearly discernible on the SG#1 sensor. It was significantly larger (about a factor of 3) than the impacting signature that was occurring at power.

2 The use of frequency for mass determination is meaningful only for a free loose part. If the part is fixed (hinged), then it could very well be more massive.

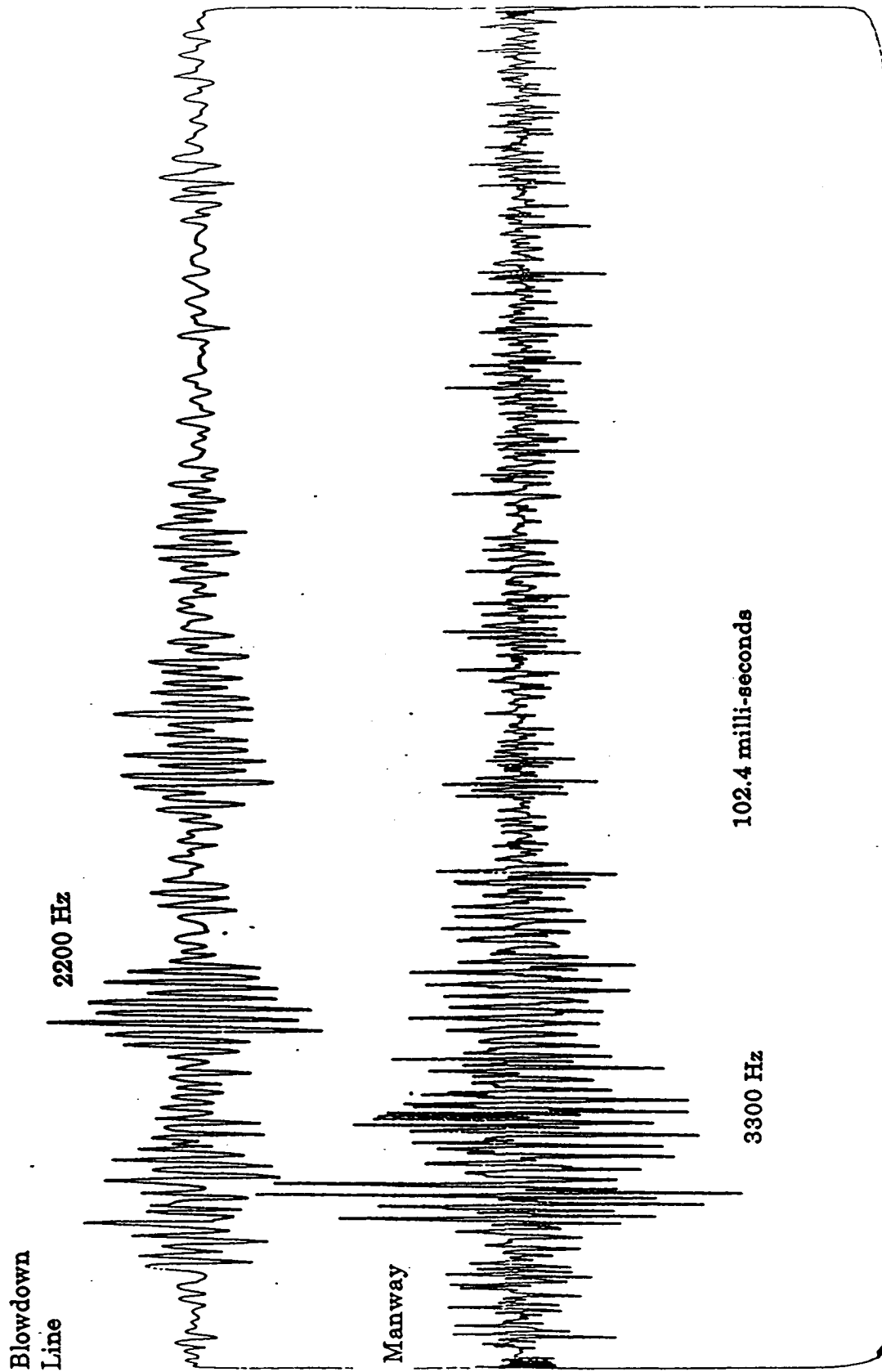


Figure 4. Strip Plot of the Accelerometer Output from Sensors on the Blowdown Line and Manway.

2. Normal impact signatures were believed to be present in the reactor vessel #1 channel channel at a very low level and they were lagging the Steam Generator sensor by about 4 milliseconds.
3. The signal level of normal impacts detected by the sensor mounted on the valve was much larger than any other channel and this signal always led any activity seen on any other channel.

From these observations, it was concluded that the energy within the impacting object was low, i.e. no greater than 6.8×10^6 ergs (0.5 ft-lbf) and the impacting must have been occurring within or around the valve.

Finally it was observed from the PSDs of active and quiescent signals that the frequency generated by the impacts at the valve (i.e. 3300 Hz) was also seen by reactor vessel sensors. Figure 5 shows the ratio of active and quiet PSDs for the SG#1 sensor. Peaks are dominant at 2200 Hz, the pipe resonance, and at 3300 Hz, the impact characteristic frequency. Figure 6 shows the same ratio for the Reactor Vessel Sensor No. 5 (located at the bottom of the vessel). The impact characteristic frequency is clearly seen at 3300 Hz.

ANALYSIS

From the data presented, the following conclusions were drawn:

1. The impacting was occurring within or around the gate valve located approximately 3.3 meters (11 feet) in the hot leg upstream of steam generator number 1.
2. The impacting object was in the vicinity of 2 Kg (4.4 pounds) if it was loose³
3. The energy introduced into the structure was small for each impact. Based on the impacts induced with the impactor, the unknown impact signature was less than 6.8×10^6 ergs (0.5 ft-lbf) This amount of energy was not expected to introduce any damage.

Following these analyses, the recommendation was made to trend impact energy using the MAPD slope parameter and to trend the rate of impacts by monitoring alert outputs of the impact detectors. Followup activities revealed that when the gate valve was moved, the impacting would change. Thus the valve was positioned such that impacting was minimal. This reduction in impacting was clearly indicated in the MAPD slope trend.

3 This observation is based on the frequency within the impact signature. If the object is "hinged", the mass may be greater, i.e., the authors are not aware of any data correlating mass to frequency for this situation. Experience suggests it could be a larger object.

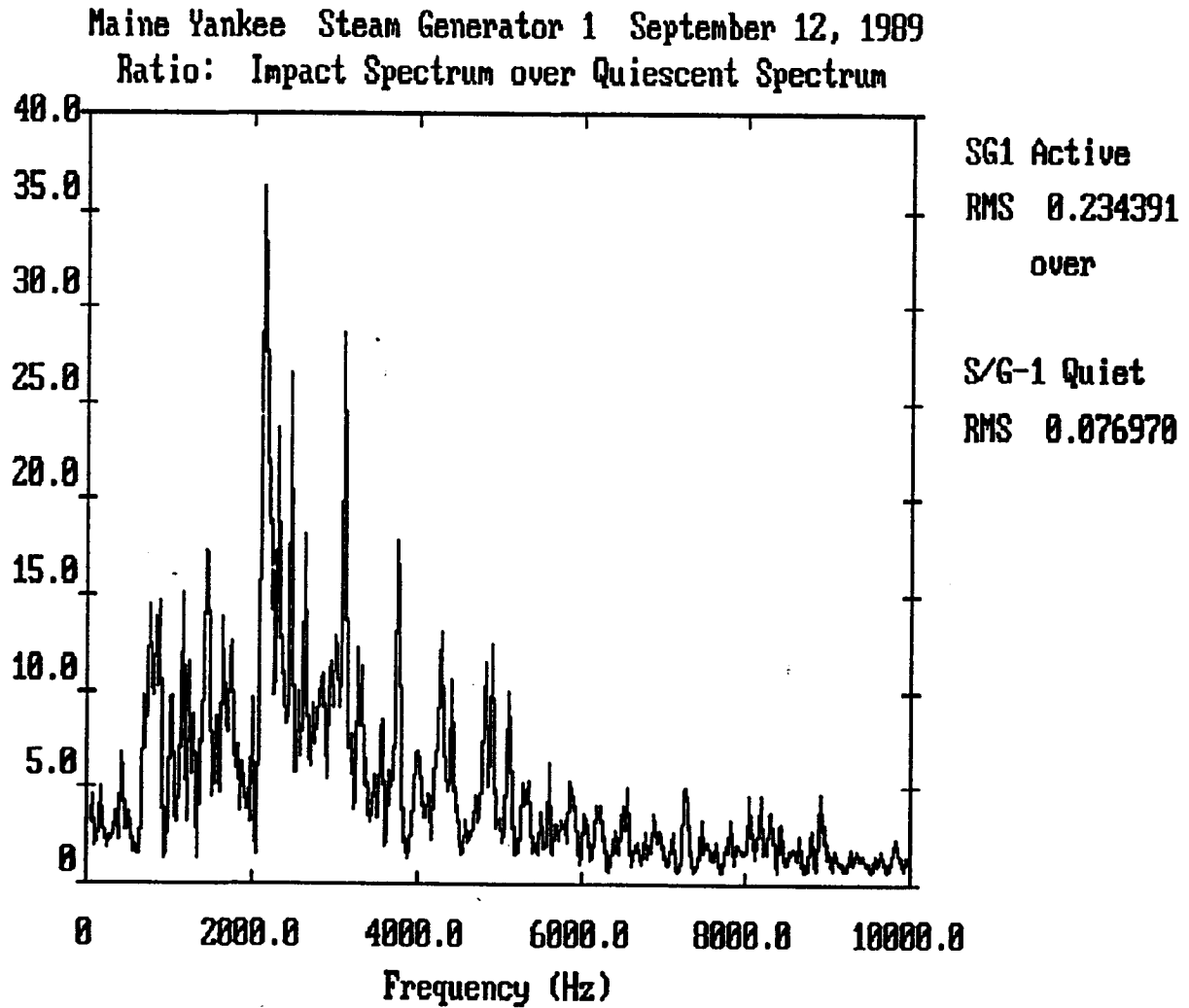


Figure 5. Ratio of PSDs from Steam Generator 1 Taken when the Sensor was Active and Quiet.

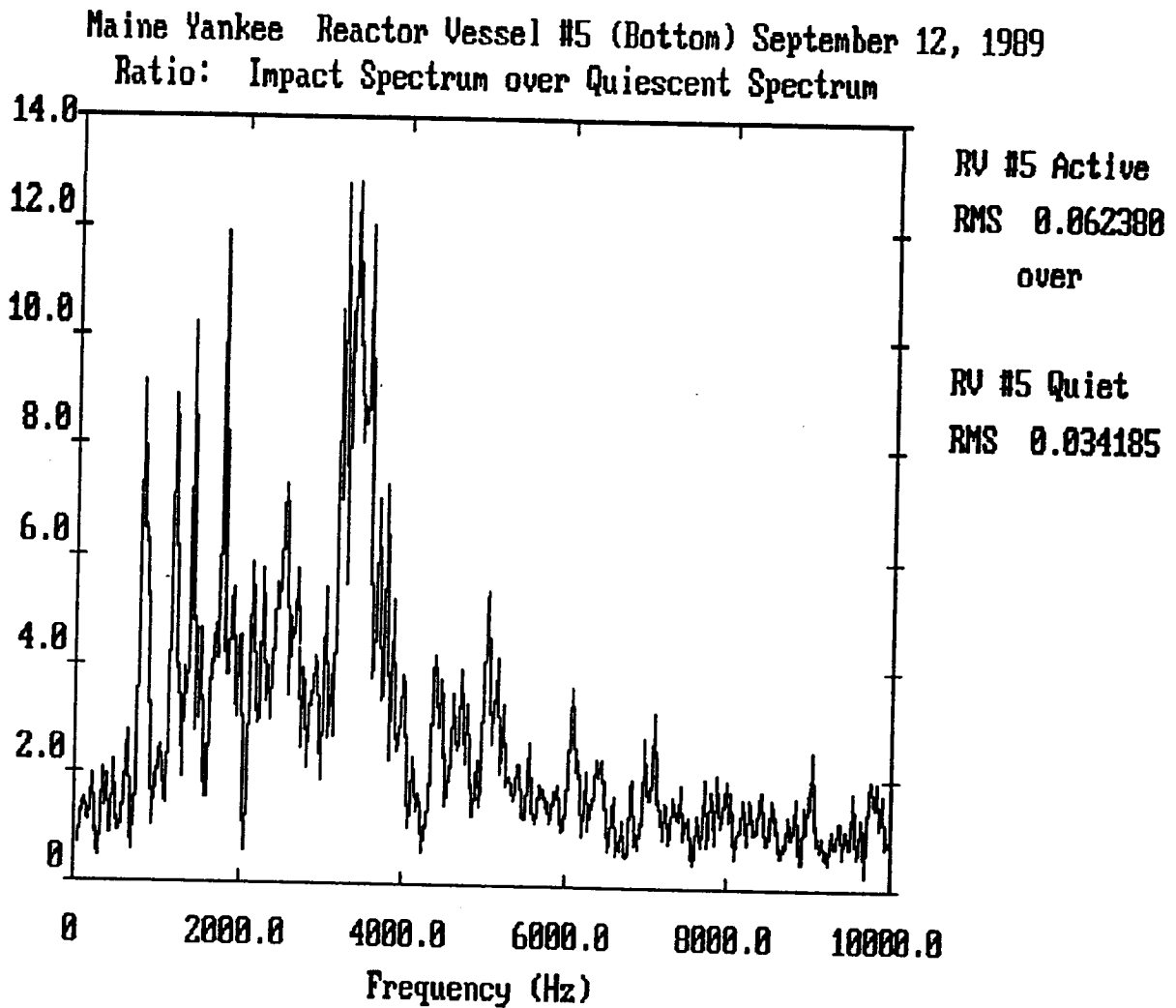


Figure 6. Ratio of PSDs from the Reactor Vessel Bottom Taken when the Sensor was Active and Quiet.

CONCLUSIONS AND RECOMMENDATIONS

From this experience we conclude the following:

- The trend of the MAPD slope clearly indicated impacting and the lack of impacting. This is a valuable tool for tracking the behavior of impact detecting systems.
- The systematic measurements performed on-site provided an excellent characterization of the impacts, i.e.,
 1. The impacts occurred within or around the Isolation Gate Valve,
 2. The weight of the object was estimated to be ~2 Kg (4.4 lbs).
 3. The impact energy was small, less than 6.8×10^6 ergs (0.5 ft-lbf).

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Design Considerations of Digital Based Loose Parts Monitoring Systems

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ABSTRACT

Experience with the design and operation of two generations of digital loose parts monitoring systems (LPMS) over the last 5 years has led to a reconsideration of the hardware and software architecture for current digital LPMS. The early versions of the digital LPMS were far superior to their analog predecessors but were severely limited in their burst storage capability and lacked the capability of performing analysis functions while still maintaining the loose parts monitoring function. Hardware and software architectural considerations a third generation digital LPMS which incorporates dual independent microprocessors to rectify the limitations of the earlier digital LPMS designs are discussed. This third generation digital LPMS meets or exceeds the requirements for a USA LPMS enumerated in Part 12 of the ASME/ANSI Operations and Maintenance Standard.

BACKGROUND

The introduction of microprocessor-based instruments in the early 1980s led to the development of a critical instrument for loose parts monitoring: the digital oscilloscope. The digital oscilloscope permitted the acoustical bursts to be captured and analyzed in considerable detail, hence fostering the understanding of the theory underlying loose parts detection and diagnostics. The digital oscilloscope also revealed the severe complexity and major data storage and manipulation requirements when using digitized waveforms. Hundreds of kilobytes of memory are required to capture just one burst, not including other requirements. The advent of lower cost high density disk drives and the continuing cost decline of large RAMS have only recently made it possible to develop affordable digital hardware with adequate storage capacity.

With lower cost hardware solutions available, the largest impediment to the proliferation of digital LPMS is currently the software development. The capture of multiple channels of burst data is only one of the first steps in the complex software controlled chain of events required for a

reliable LPMS. In particular, it is essential that a digital LPMS be capable of capturing a string of consecutive bursts in rapid succession while other data storage and data manipulations are being performed by the system. Post burst capture software requirements for a digital LPMS should include some modest statistical capability coupled with advanced off-line analysis capabilities and burst data bases. As a last requirement, all the LPMS acquired data should be available for access through a Local Area Network (LAN) or through a modem.

HARDWARE and SOFTWARE CONSIDERATIONS

The data acquisition, data storage, and data manipulation requirements are indeed formidable for a digital LPMS when one considers that each of the 22 channels should be digitized with 12 bit resolution and at a rate between 50 or 100KHz for a duration (window) of between 50 or 100 msec. The earlier digital systems were essentially modified transient recorders optimized for speed with the event detection (alarm) function performed by analog circuits associated with each channel. The capture of the first burst was the main consideration of these early digital systems and the capture of the subsequent bursts were hampered by long "dead time" of the system while down-loading the dynamic memory to a more permanent storage. Furthermore, all event detection and capture functions in these early digital systems were essentially halted when data analysis or data access functions had to be performed.

Figure 1 depicts the overall structure of a modern dual microprocessor based LPMS. The system depicted incorporates the typical layout of a LPMS: piezoelectric accelerometers (1) to detect the structure borne metal-to-metal impact signals followed by the signal conditioner (3), the analog to digital converter (4), the transient recorder (7), and the system microprocessor (8). Additionally, the traditional audio monitor (6) is depicted as well as an analog tape recorder (5) and enhanced filter (11) optional capabilities. Interfacing with the plant is performed through the control unit (10). This paper will concentrate on discussing the design considerations of the transient recorder (7) and the system microprocessor (8).

One of the most critical hardware/software design reconsideration was to separate the detection and capture function from the long term storage and analysis functions. Each of these two functions are currently performed by a 80386 microprocessor controlled subsystem. Each of the two 80386 microprocessors communicate with each other for status information and data access. In this way the event detection and interim data storage functions are unencumbered by the data base, data analysis, and data access functions. New bursts can be detected and captured by the LPMS whilst the analyst can continue to diagnose and evaluate the effects of the event. Additionally, this division of functions between microprocessors allows considerable increase in processing speed since each of the microprocessor's software can be optimized for the dedicated function.

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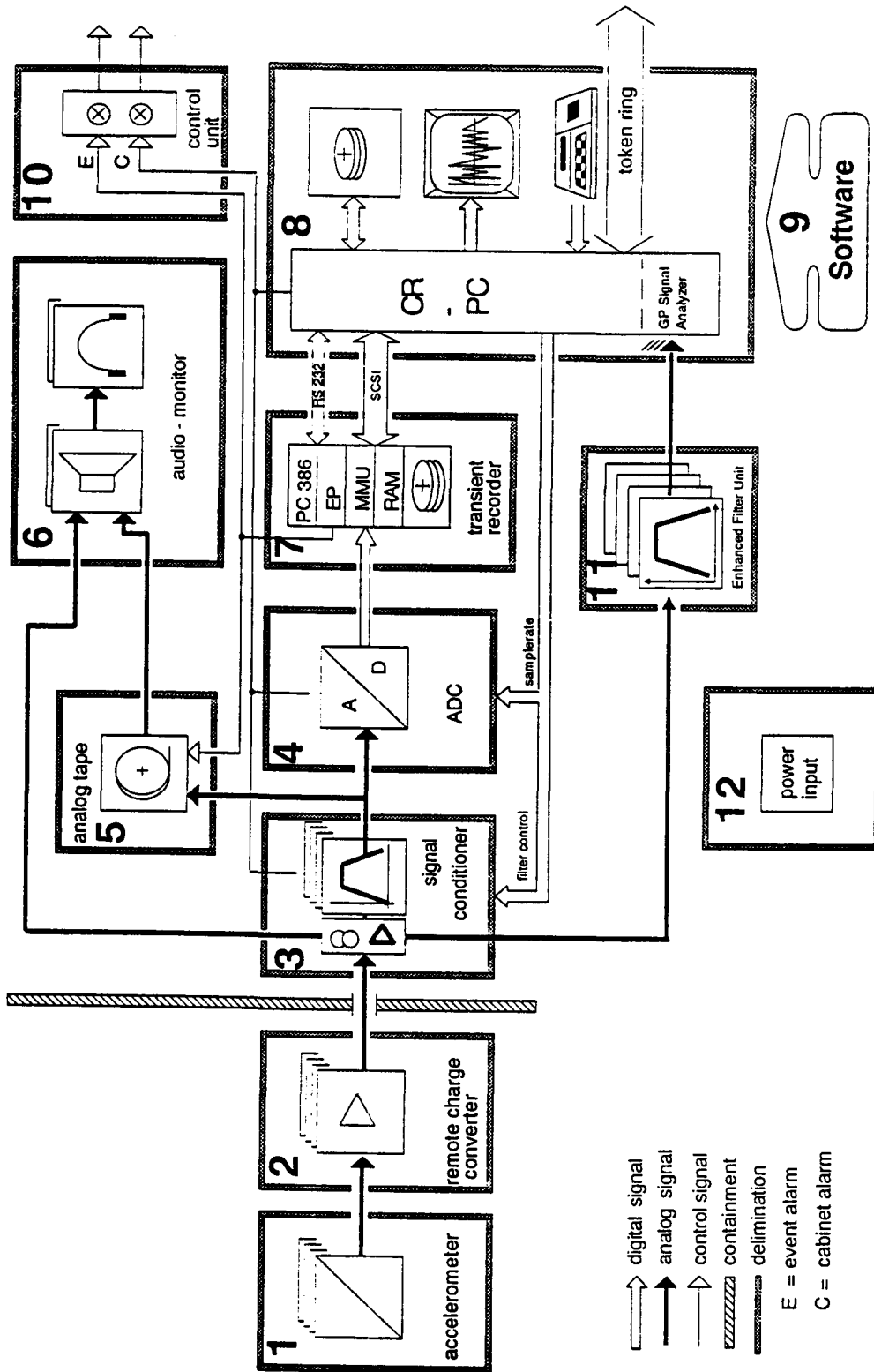


Figure 1: Overall System Structure of a Dual Microprocessor Based LPMS

The capability of capturing consecutive bursts was an early design requirement. A segmented, multiple layered, dynamic memory scheme was developed which, when coupled with quick down-loading of segments of the dynamic memory to a dedicated hard disk drive, was sufficiently fast that multiple burst capture by the transient recorder is currently limited by the physical phenomena being monitored. Optimized software was developed to reliably detect events indicative of metal-to-metal impacts and to perform the memory management functions. The software for reliably detecting a burst indicative of metal to metal impact has evolved considerably from the triggering software of transient recorders. Given that the digitized data is adequately band-limited by high roll-off filters in the 1 to 15KHz range, the entire data capture decision relies on the comparison of a moving short term RMS average with either a fixed threshold or a relative threshold. The use of a short term RMS average for triggering instead of the instantaneous value essentially eliminates the triggering on non-acoustical spikes caused by electrical noises or other forms of interferences. The short term RMS is first compared to a fixed high-level set-point for detection of major events. The short term RMS can also be compared to a fixed low-level set-point for detection of failed channel. After these comparisons a long term RMS is obtained from the short term RMS and compared to the current short term RMS value. Burst capture is initiated when the current short term RMS value exceeds the long term RMS by a user selectable value. In order to preclude capturing bursts of inconsequential events, the variable threshold level is not permitted to go below a user selectable value.

Upon the detection of an event, the data segment of interest is "frozen" on the RAM with the user selectable pre-trigger times and window lengths. The new data continues to be temporarily stored in other segments of the RAM and available for capture. The "frozen" RAM data is then downloaded to a high speed SCSI hard drive for interim storage and the RAM segment made available for further data capture. This segmented, multi-layered approach when coupled to the down-loading to a hard-disk is fast enough to present a serious problem for fast digital LPMS: the expenditure of data storage in storing the uninteresting "tail ends" of high energy acoustical bursts. This problem was solved with the design requirement that the event detection function for a new burst would not be enabled until the short term RMS value for all channels is below both the respective fixed and floating threshold values for a user selectable time span. This software logic also ensures that only windows with a clear "first burst" are captured.

In order to eliminate the LPMS analyst having to choose between either analysis of an event or capture the next event (burst), the system design incorporates a second 80386 microprocessor - the system microprocessor. The system microprocessor effectively permits the operator to perform advanced burst analysis functions without compromising the essential monitoring function. Additionally, the system microprocessor manages all system default settings, the burst data base, and remote (LAN or modem) communications. The system microprocessor is essentially "dormant" under most operational conditions. Upon the detection of an event the transient recorder microprocessor signals the system microprocessor that an event has occurred. The system

microprocessor then monitors the SCSI line for activity and when the transient recorder hard drive stops loading data from the transient recorder RAM, the system microprocessor commands the system hard drive to acquire the data stored in the transient recorder hard drive. Once the data stored in the transient recorder hard drive is transmitted to the system hard drive the data on transient recorder hard drive can be overwritten, hence the transient recorder hard drive is ready for data acquisition of a new sequence of burst activities.

The system microprocessor is equipped with a number of peripherals such as a large color CRT operated under VGA and a keyboard with a built-in track-ball. Additionally, the LPMS are equipped with some form of data transmitting capability: LAN (Ethernet or Token Ring) or modem. The data transmitting capability enables the LPMS to be accessed remotely by analysts for data evaluation and data trending. Currently the nuclear plants in the USA are implementing some form of LAN which greatly enhances the data transmittal speed. Use of data transmittal greatly enhances the effectiveness of a LPMS. The utility analyst can access the LPMS data base for historical storage, detailed trending, and detailed off-line analysis. Additionally, the remote access allows critical event data to be expeditiously provided to off-site analysts for data interpretation.

Besides the hardware considerations, one critical design requirement for the dual-microprocessor LPMS was to incorporate a user friendly interface. The software of the transient recorder is transparent to the user and should only be accessible by a trained LPMS engineer. The system microprocessor software, however, should allow a user with minimal training to obtain sufficient information to judge the severity of an event. To this extent, the system microprocessor software operates under "Windows 3.0", enabling the user to select a variety of displays and functions from pull-down menus. Naturally, for the more experienced LPMS engineer, the system provides enhanced detailed analysis functions such as inverse FFTs and digital filtering.

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