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FAULT DETECTION IN BOILING WATER REACTORS BY NOISE ANALYSIS

PAPER TO BE PRESENTED AT
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1 INTRODUCTION

Surveillance systems for industrial processes based on fault detection have been discussed during the last years. For nuclear power plants both simple hard wired voters and more sophisticated software based systems, related to reactor noise surveillance and disturbance analysis methods have been proposed.

In an abnormal operating condition it is important to perform an early, reliable fault detection and diagnosis in order to prevent further degradation by the propagation of a developing failure.

Alarm annunciation and control panel indicators have been the traditional means in control room design of alerting the operator in abnormal situations. In a complex system like a nuclear power plant the operator should interpret and integrate a large amount of information, supplied by the instrumentation system. He should also relate this to the operating procedures and use his own skill to diagnose the cause of the abnormality and determine the best recovery action. The trend in process automation has put the operator in a new situation. Instead of taking an active part in the control process he has more turned to a supervisory role. Due to the complex structure of modern control systems this may lead to severe problems during abnormal operation and emergency conditons.

On-line surveillance systems currently in use and under development are therefore designed to aid the operator. These advanced surveillance systems do not only display primary information from sensors. They also perform extensive data-processing and analysis.

This paper describes the principles and main ideas of a research project. A system is beeing developed to detect abnormal operation, defined by noise pattern changes in a nuclear reactor. It supports the operator with a diagnostic capability related to the cause and effects of different failures.

The reactor noise process and applicable methods for reactor noise surveillance are described in Section 2. In Section 3 process fault detection using various methods are presented. In Section 4 a suitable on-line parameter identification method is described. In Section 5 the use of expert system for diagnosis is discussed and in Section 6 the design principles and structure, as well as implementation aspects of a small test system are described.

2 REACTOR NOISE SURVEILLANCE

The noise process

Power reactor noise have been investigated for more than ten years. Extensive analysis work have been devoted to the description of the different noise sources, their physical origin and interaction. The dynamics of a nuclear plant (BWR) can be described as a multivariable system with noise sources and feedbacks c.f. Fig 1.

A change in a noise source or a transfer function will thus be reflected in more than one process variable. Surveillance of reactor noise normally means identification of the different sources and determination of the properties of the inherent transfer functions. The measures usually used are power density spectra, coherence, correlation functions, partial coherence, signal to noise ratio etc. Some typical noise records from abnormal operation are shown in Fig 2 and Fig 3.

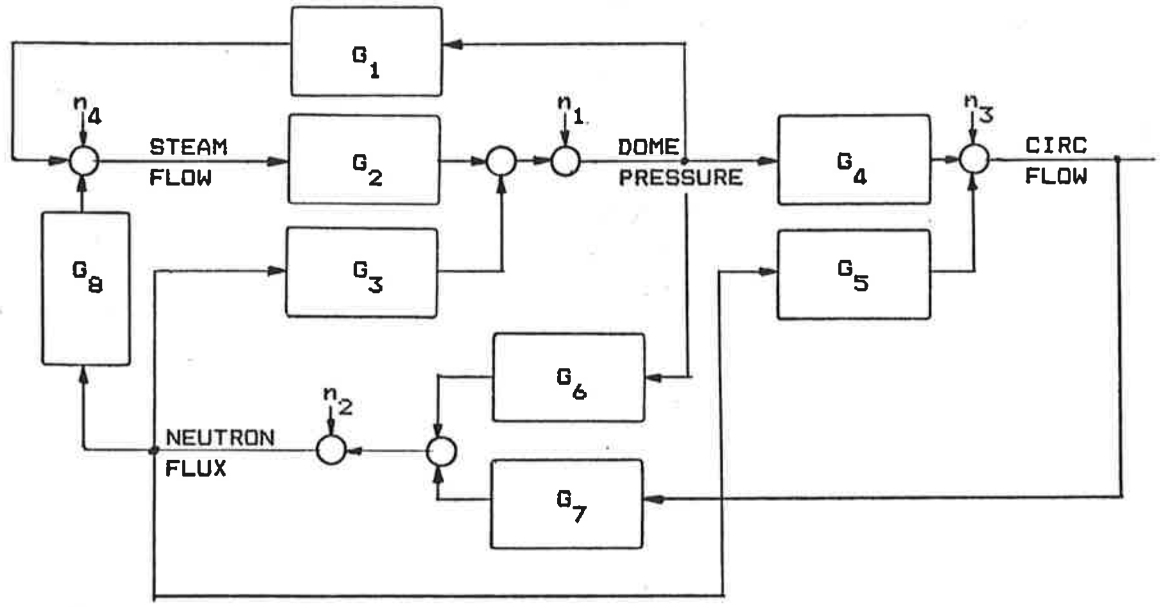

Fig 1 Simplified linear dynamical structure of a BWR plant

Surveillance systems

Surveillance systems based on reactor noise monitoring are now on the verge of being applied on-line. One technique used in this form of automation is pattern recognition, which is based on the possibility of recognizing a sample pattern as belonging to normal or abnormal reference categories. Identification of system states and estimation of relevant parameters could be another possibility to detect abnormal operation or a trend of moving out of a safe range. Deterministic models are sometimes not sufficient to describe the phenomena, because of the complexity of the interactions. Statistical pattern recognition methods and identification techniques have therefore been used in some adaptive learning systems in order to detect malfunctions in early stages[1].

The use of signal analysis methods, addressing the stochastic fluctuations (noise) on the process variables has shown a high potential for both malfunction detection and failure diagnosis[2].

Sensitive systems have been developed, which are able to detect and monitor the beginning of system failures based on FFT analysis and statistical test procedures. Surveillance based on stability monitoring of inherent dynamics in BWR plants have also been suggested[3].

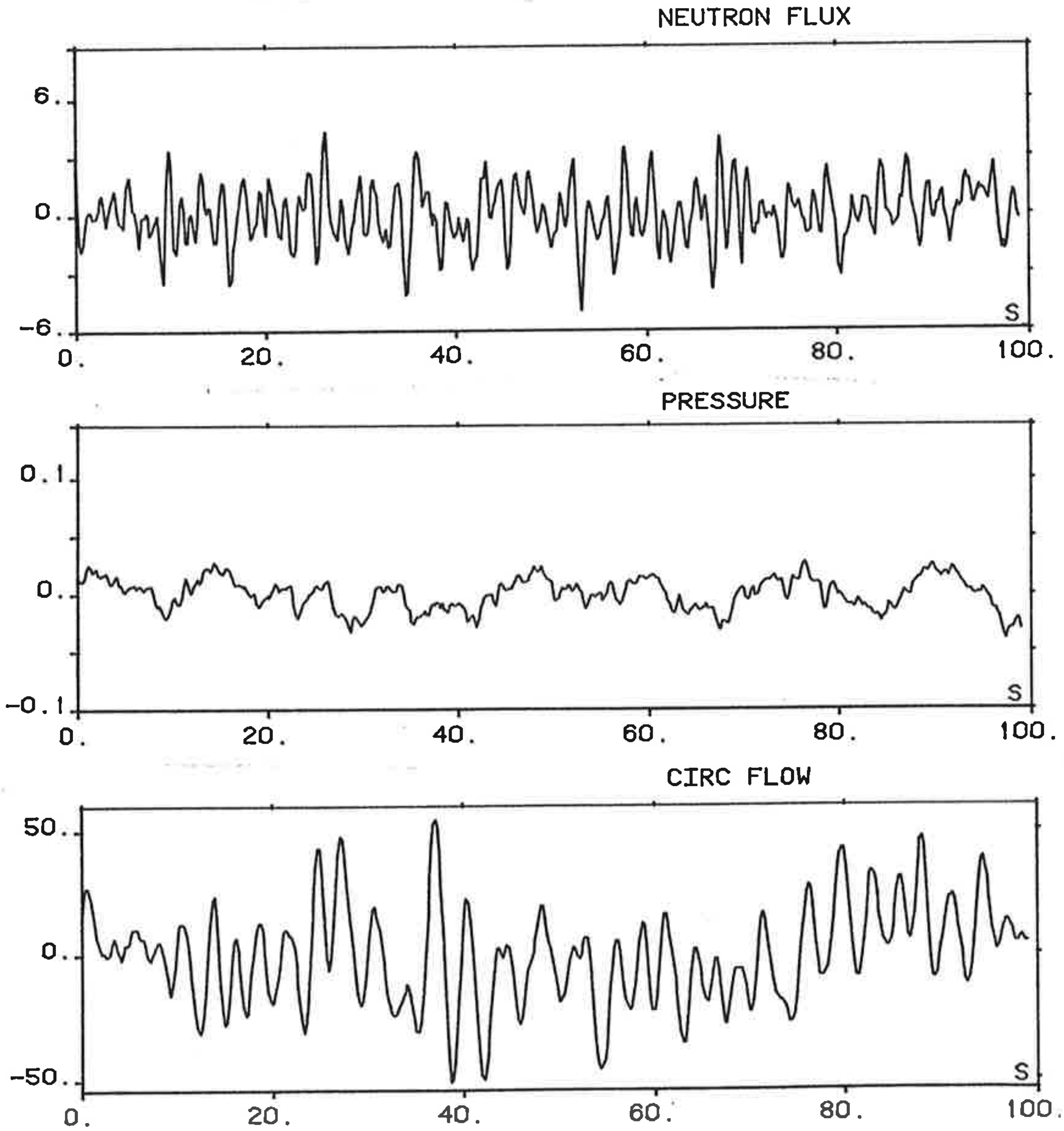

Fig 2 Noise records from an abnormal operating condition

In Fig 2, the noise records from an abnormal condition, characterized by an amplitude increase of higher noise frequencies was shown, which probably corresponds to an anomaly in the steam generation process (e.g. bypass boiling). In Fig 3, the noise records from another abnormal condition are given. In this case the amplitude of the lower frequencies are increased, which was identified as a small leakage in the turbine reheater system.

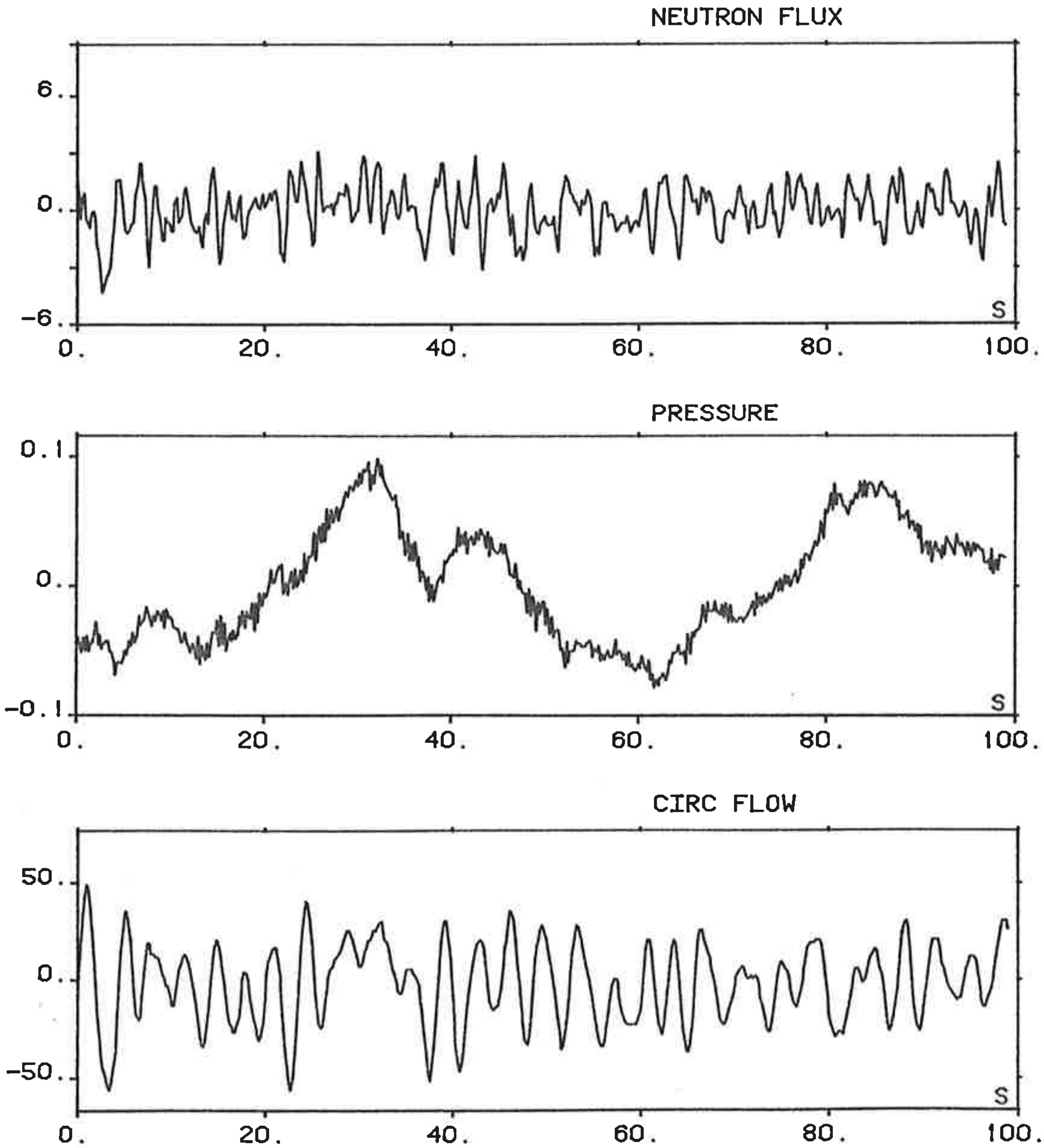

Fig 3 Noise records in the case of turbine reheater leakage.

3. FAULT DETECTION METHODS

Many methods have been proposed for detection of faults in dynamic systems[4,5]. Conventional schemes normally use hard-wired logic to detect system failures and voting systems to improve safety and availability. This form of detection assumes normally a "catastrophic failure", like a sensor hard-over-failure or a measured process variable out of operating range.

However, a small change of the stochastic information, superimposed on the signal mean value, may also imply a failure.

Many fault detection systems are based on the following requirements:

1. The time when the fault occur is not known apriori.
2. The structure of the fault is not known apriori.

To detect when a failure occurs and to diagnose its structure, tracking algorithms have been used together different decision rules. Most fault detection schemes applied so far in reactor noise surveillance systems have used statistical tests to decide if a newly obtained sample pattern belongs to a normal or abnormal category.

Various criteria and discriminants have also been proposed[6]. A squared n-dimensional distance of deviations, nomalized by their individual standard deviations σ_J is commonly used:

$$D_I = \sum_{J=1}^{n} \left[\frac{\text{Descriptor - Nominal value}}{\sigma_J} \right]^2 \qquad (1)$$

The descriptors have normally been chosen from significant parts of power density spectra. The use of signal spectra to determine abnormality are exemplified in Fig 4, which shows the power density spectra of the dome pressure and in Fig 5 the neutron flux density for the abnormal cases discussed in section 2.

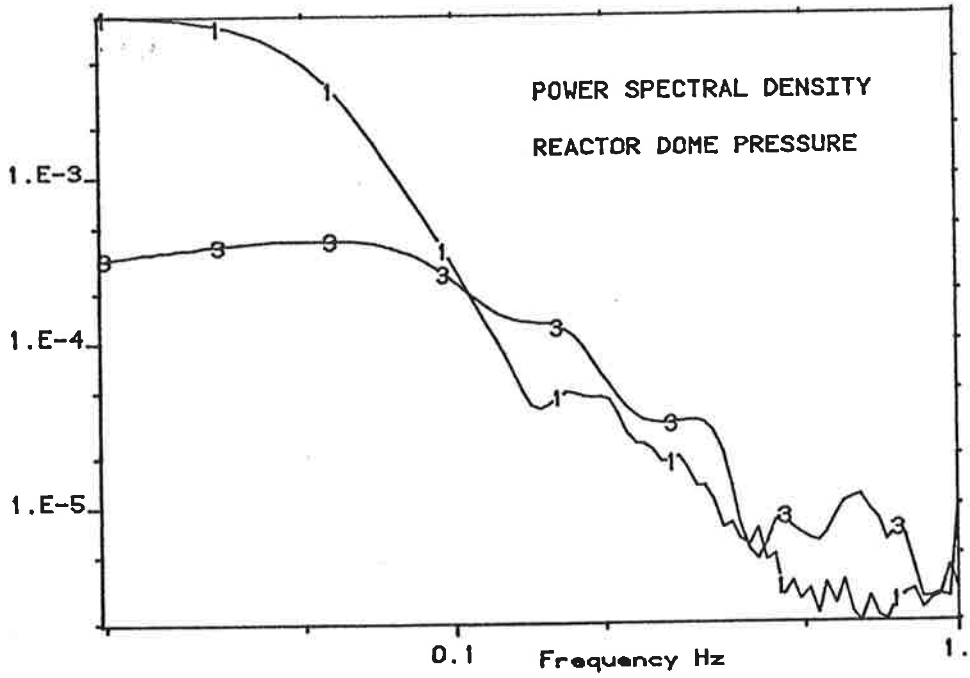

Fig 4 Spectrum of Dome Pressure in case of abnormal operation

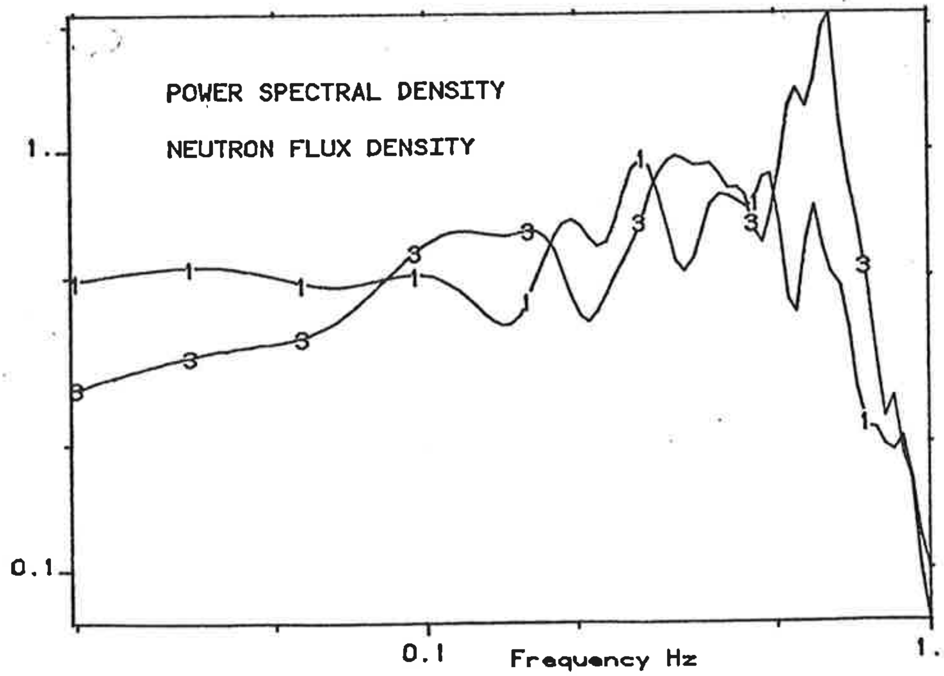

Fig 5 Spectrum of Neutron Flux in case of abnormal operation

In "Signature Analysis" systems for rotating machinery, signal time-averaging techniques and envelop detection, have shown to be effective for reducing random noise and characterizing abnormal patterns[7]. In other systems related to mechanical fault diagnosis[8], classification of signals in terms of autocorrelation functions have been utilized. In an engine-vibration fault diagnosis system, an unknown signal is e.g. classified by comparing the norms of its signal projections on a choosen subset of eigenfunctions. These eigenfunctions are either preselected or learned from normal and abnormal conditions.

Another powerful class of detection schemes is based on statistical tests on the innovation sequence from Kalman filters[4,9]. A fundamental property of the Kalman filter, is that for a linear system the innovation sequence will be a zero-mean, white noise process with a given precomputable covariance.

One failure detection method successfully applied to the Kalman filter innovations is known as the Generalized Likelihood Ratio method (GLR). This method uses a probablistic measure to perform multiple hyphotesis tests, connected to various postulated failure modes.

The use of normalized innovations have also been suggested[9]. For this sequence the test limits can be generated directly, based on the desired confidence limits (false alarm rate).

When there is a small number of failure modes, the GLR method can be implemented as a bank of detectors running in parallel. Good results have been achived both in flight control systems[10], in nuclear systems[11] and for arrythmia detection of ECG data[12].

Only a few approaches have been reported concerning fault detection methods based on time-series analysis, related to parameter identification of AR, ARMA or ARMAX structures.

One example is a fault detection and life prediction study of a cutting machine[13], where a number of performance indicies have been compared and evaluated. These were, quadric distance of AR parameter difference, variance of the residuals, and other measures related to e.g information content (Kullback meeasures etc.).

Adaptive fault detection

Most fault detection methods assumes that the driving noise has a constant variance and are normally based on static parameters. However, another fault detection method which allows the noise variance to change with time has been suggested recently[14]. This method uses the innovations $\Delta\Theta(t)$, of the parameter estimates and is thus suitable for application in adaptive on-line fault detection systems. By exponential filtering of the parameter innovations and forming a quantity s(t), given by:

$$v(t) = \gamma_1 \ v(t-1) + \Delta\hat{\Theta}(t) \tag{2}$$

$$s(t) = \text{sign} \ (\ \Delta\hat{\Theta}(t)^T \ v(t-1)) \tag{3}$$

a fault detection scheme can be based on the statistics in s(t).

In normal operation, when the parameter estimates are fluctuating close to their true values, s(t) has approximately a symmetric Bernoullian distribution, with mass 0.5 each at -1 and +1. Summing up the latest values of s(t),(for computational simplicity by exponential filtering), the stochastic test variable r(t) is defined by:

$$r(t) = \gamma_2 \ r(t-1) + (1 - \gamma_2) \ s(t) \tag{4}$$

When the parameter estimates are close to the true ones, r(t) has a mean close to zero. When a fault has occured, a positive mean is expected. The parameter γ_2 determines how many s(t) that will be taken under consideration and controls the detector sensitivity. For values of γ_2 close to 1, the variable r(t) will be approximately Gaussian with a variance:

$$\sigma^2 = \frac{1 - \gamma_2}{1 + \gamma_2} \tag{5}$$

It is possible to specify how frequently false alarms are allowed to occur. If it is acceptable to get a false alarm every n:th sample, a fault detection should be given every time r(t) is greater than a threshold r_0, defined by:

$$P(r(t) \geq r_0) = \frac{1}{\sqrt{2\pi}\,\sigma} \int_{r_0}^{\infty} \exp\left(-\frac{x^2}{2\sigma^2}\right) dx = \frac{1}{n} \tag{6}$$

The relations between the false alarm rate (1/n), detection treshold (r_0), and filter constant γ_2 are given in Fig 6.

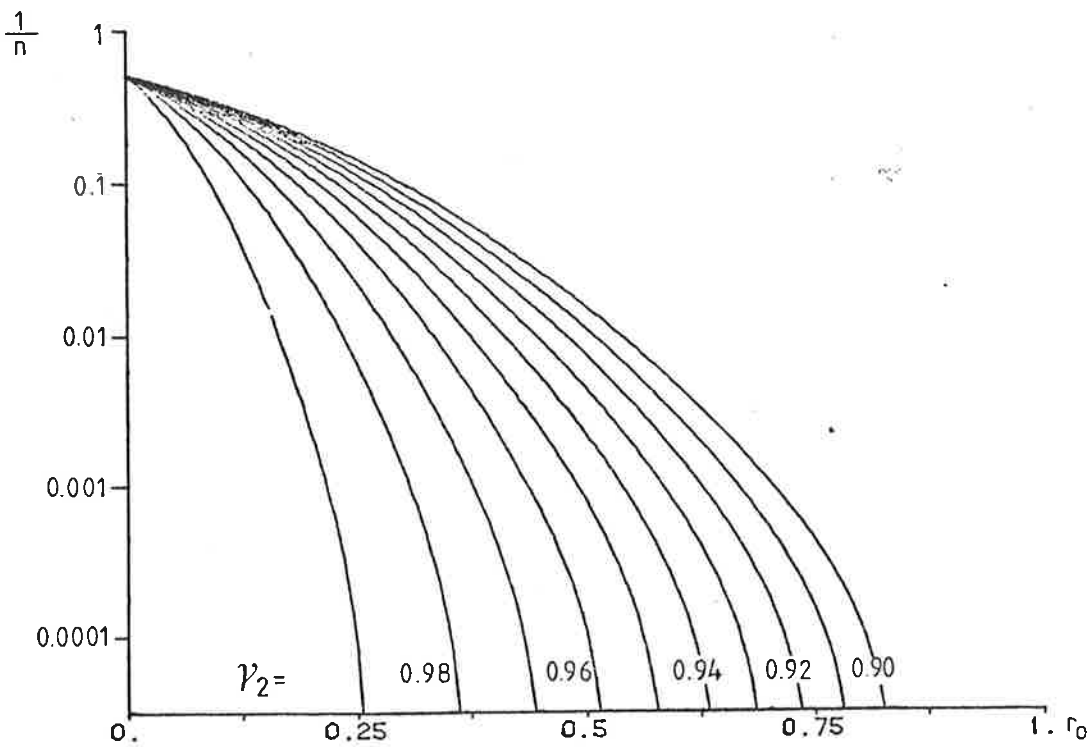

Fig 6 Parameter relations

A detection of a fault indicates that the parameter estimates are bad. The parameter estimation algorithm must be modified to handle this information properly to improve the convergence to the new parameter values. One way to do this is to increase the norm of $P(t)$, which can be achived in two ways: One is to decrease the forgetting factor λ, which has the effect that $P(t)$ is scaled with almost maintained eigenvectors and the growth of $P(t)$ is nearly exponential. The second method is to add a constant times the unity matrix to $P(t)$, in which case $P(t)$ grows instantaneously.

One way of chosing the scale factor $\beta(t)$, can be by studying the eigenvalue of $[\, I - P(t)\varphi(t)\varphi(t)^T]$ which differs from 1. This eigenvalue also determines the parameter increment.

The eigenvalue ν_0 is then:

$$\nu_0 = \frac{\lambda}{\lambda + \varphi(t)^T P(t-1)\ \varphi(t)} \tag{7}$$

Suppose now that a eigenvalue $\nu(t)$ is wanted when a fault occur. $\beta(t)$ could then be chosen as:

$$\beta(t) = \frac{1}{\varphi(t)^T\ \varphi(t)} \ (\ \nu_0(t) - \nu(t)\ ) \tag{8}$$

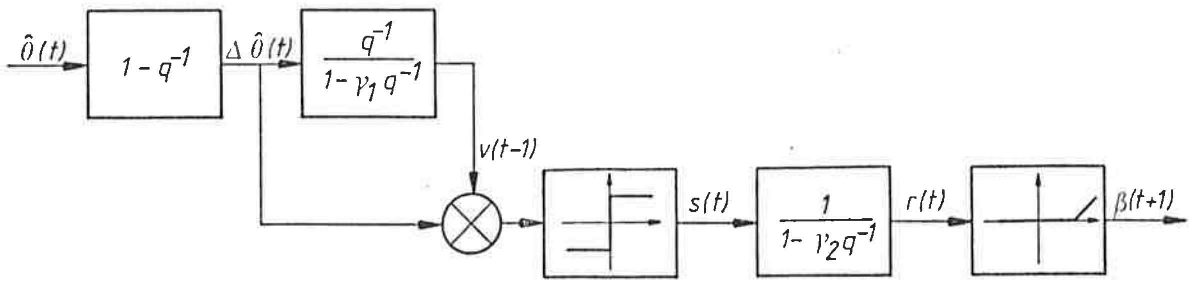

Fig 7 General structure of the detector

4 PARAMETER ESTIMATION METHODS

The application of parametric identification techniques implies that a model is fitted to measured input-output data. In the Single Input Single Output (SISO) case a typcical model structure can be:

$$A(q^{-1})\ y(t) = B(q^{-1})\ u(t) + C(q^{-1})\ e(t) \tag{8}$$

where e(t) is supposed to be white noise and A,B,C are polynomial functions in the shift operator. This model can now is generalized to other forms[15], and represented as:

$$(1 + A)\ y(t) = \left\{\frac{B}{1 + F}\right\} u(t-T_d) + \left\{\frac{1 + C}{1 + D}\right\} e(t) \tag{9}$$

or:

$$y(t) = \frac{B}{A}\ u(t-T_d) + \frac{C}{D}\ e(t) \tag{10}$$

Identification according to these general structures covers a broad class of methods in real-time identification.

A recursive algorithm

A suitable recursive algorithm for the given structure (10) can be found by e.g introducing the variables z(t) and v(t) defined as the filtered values of u and ε. By forming a measurement vector $\varphi(t)$, composed of the old values of y,z,u,v and ε, and a parameter vector $\Theta(t)$, the system representation (10) can now be reformulated in a much simpler form:

$$y(t) = \Theta^T \cdot \varphi(t) + \varepsilon(t) \tag{11}$$

Identification of the parameters $\Theta(t)$ can be made through many approaches. Off-line procedures use blocked data, and when C and $D \neq 0$ the parameter determination normally involves a non-linear minimization algorithm.

However, recursive (on-line) processing using every new sample for parameter updating have some advantages. Especially in memory saving, but also in making the computational scheme simple.

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The parameters, covariances, residual and forgetting factor updates are given by the following recursive procedures:

$$\theta(t+1)=\theta(t) + P(t+1)\cdot\varphi(t+1)\cdot\varepsilon(t+1) \tag{12}$$

$$P(t+1) = \left[P(t) - \frac{P(t)\cdot\varphi^{T}(t+1)\cdot\varphi(t+1)\cdot P(t)}{\lambda(t+1)+\varphi^{T}(t+1)\cdot P(t)\cdot\varphi(t+1)}\right] / \lambda(t+1) + \beta(t)\, I \tag{13}$$

$$\varepsilon(t+1) = y(t+1) - \theta^{T}(t)\cdot\varphi(t+1) \tag{14}$$

$$\lambda(t+1) = \lambda_0\cdot\lambda(t) - (1 - \lambda_0) \tag{15}$$

The introduction of the forgetting-factor λ, allows the system to be slowly timevarying, $\beta(t)$ is a non-negative scalar and I the unity matrix. The effect of a positive $\beta(t)$ is that the $P(t)$ matrix obtains a greater norm than otherwise and parameter updating is made in a direction closer to $\varphi(t)$. The problem of choosing $\beta(t)$ recursively was discussed in section 3.

Model structure

The identification problem also includes determination of the model order of the actual polynomials A,B,C.D,F. There are many methods to do this[16]. Polynomial tests, tests for residual independence, tests for normality, statistical F-tests, Akaike tests etc.

A previous case study[17], concerning on-line identification and surveillance of a Boiling Water Reactor Pump Servo System showed the importance of selecting proper model structures for identification. In this project, model structures will be chosen prior to the implementation of the identification schemes. However, it is assumed that the system dynamic characteristics do not change so drastically in the abnormal cases that the selected model structures no longer are valid or useful.

Example

Consider the inherent transfer function of a Boiling Water Reactor, concerning the pressure-flux stability. When a system operates under abnormal conditions, the exitation of the different modes normally increases. This can e.g. be reflected by a better "identifiability" of the process dynamics. An example of identification in an abnormal operating condition is given below. In Fig 8 the input/output data are shown, and in Fig 9 the parameters from on-line estimation are given. The model structure was A,B,C,D (c.f. eqation (10)), the model order 2 and the forgetting factor $\lambda=0.975$.

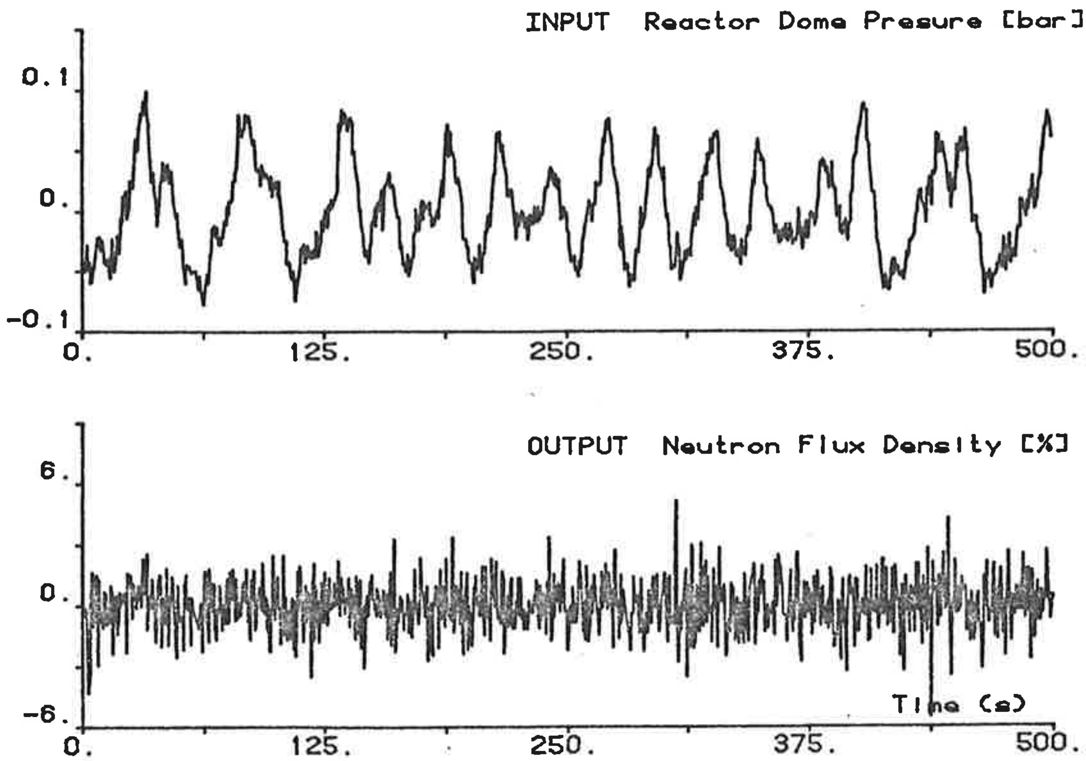

Fig 8 Input and Output data from abnormal condition.

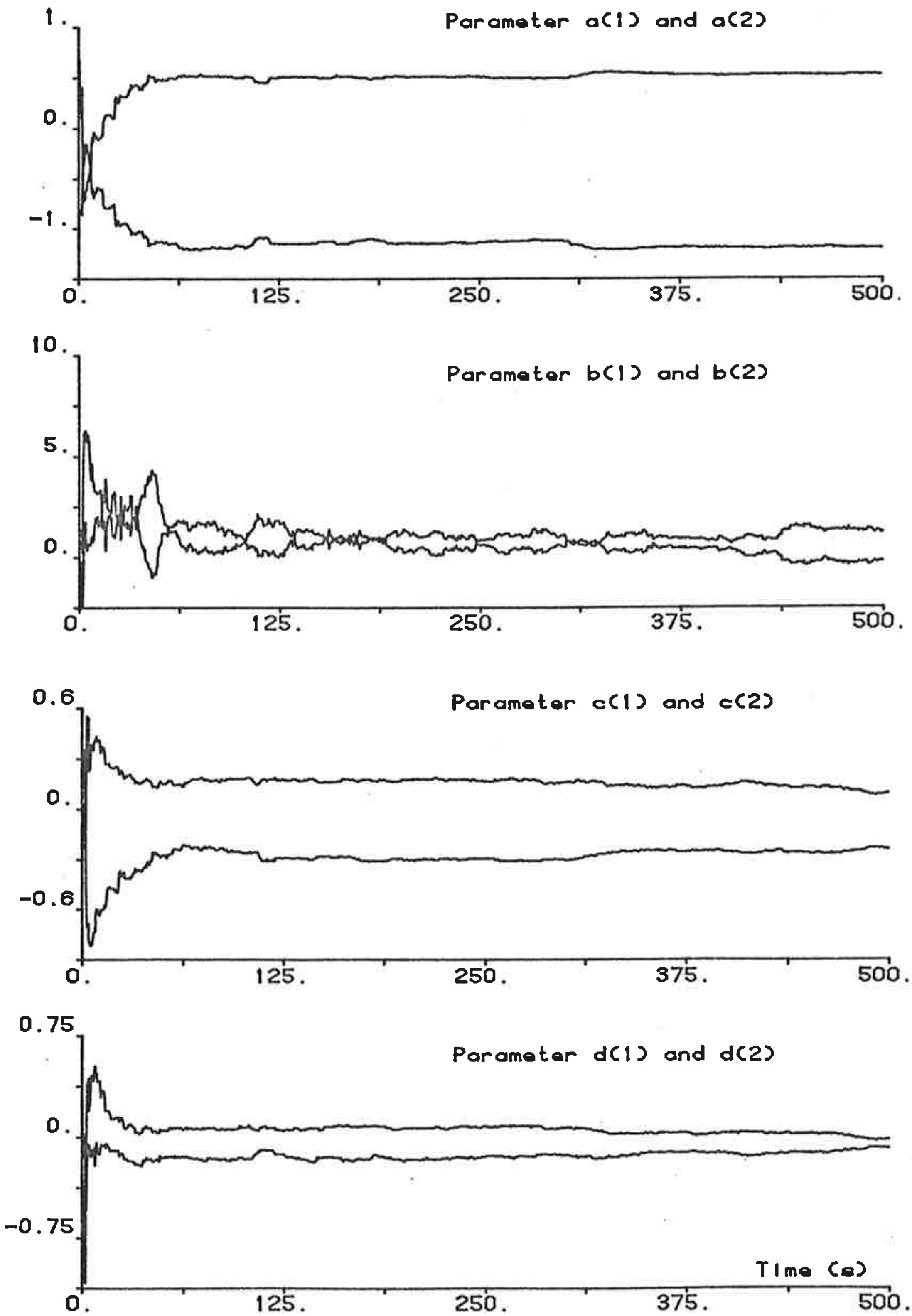

Fig 9 On-line parameter estimation of model Pressure - Flux

5 EXPERT SYSTEMS FOR DIAGNOSIS

Detection of abnormal operation is a simple form of diagnosis. Due to the complicated interactions, expert judgment is necessary to localize the origin of a fault indicated by a change in the noise pattern of a nuclear reactor. The problem of diagnosis is thus one of classifying an object or cause based on uncertain information. Diagnosis can be posed as a statistical problem. This requires the estimation of a multivariable probability function, from vast amounts of data.

Development of knowledge-based expert systems have progressed during the last years. In these systems the expert knowledge, concerning a well-defined and bounded domain are formed into a rule-base, normally called the production system. The rules have the general form of: if-then-else patterns, normally combined with a probability measure. Complex hypothesis structures can then be formed using a number of rules. The task of a knowledge-based expert system is to perform a search in the rule-base in order to decide the most probable event (cause).

The diagnosis of a change in the noise pattern can be guided by specific knowledge obtained from system identification and by the structure of the dynamic process. One idea in this project is to formulate a number of specific rules, concerning the dynamical behaviour of different subsystems, normal and abnormal characteristics and criteria to separate different effects and causes.

One way to perform the identification work is to use some existing CAD-packages for simulation, identification and model analysis. (SIMNON, IDPAC, RECID and MODPAC). Since they include a MACRO facility, a number of tailored procedures for specific identification and parameter estimations can easily be generated.

In Fig 10 a possible tree-structure for BWR noise diagnostics is described. The first separation level has here been chosen to decide from which system part a disturbance origins. However, by the multivariable nature of the process, this separation is a complicated task. The judgements involved in this step must thus be related to the knowledge in multivariable system identification. The measures of partial coherency, noise power contribution etc. may be applicable.

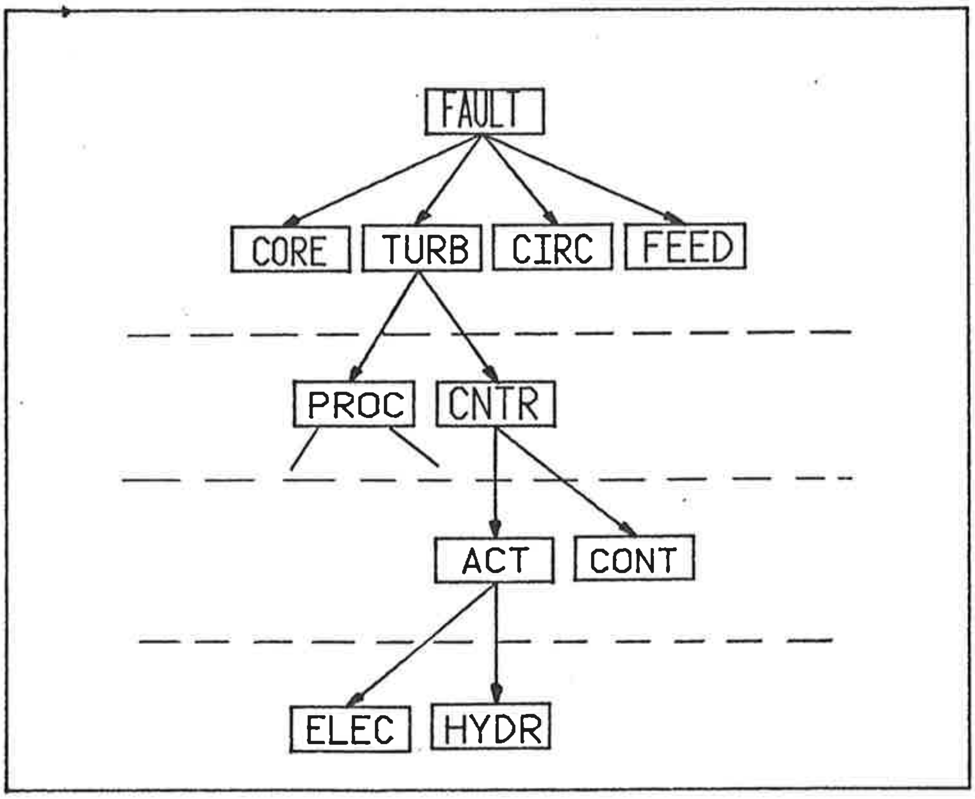

Fig 10 Diagnostic tree for BWR noise analysis

The idea is to apply the identification macros and connect them with a rule based expert system in order to recognize faults and predict system behaviour. Example of rules for diagnosing a pressure sensor failure are:

RULE 201: IF parameter distance of Sensor A is greater than a limit ε AND parameter distance of the redundant Sensor B is lower than a limit δ THEN Sensor_A deviation WITH PROBABILITY pb1(...)

RULE 202: IF (Residual variance for Sensor A model / Normal residual variance) is greater than a limit ϑ THEN Sensor__A__Noise__Level__Change WITH PROBABILITY pb2(...)

RULE 203: IF (Transfer Function C/A differs from normal) THEN Noise_Characteristic__Change WITH PROBABILITY pb3(...)

6 A TEST SYSTEM

A surveillance system with failure diagnostic capability is currently under development. It is based on the following requirements:

1. Early detection of abnormal behaviour.
2. Failure diagnosing capability.
3. Prediction of failure propagation and estimation of consequencies.

However, it should be mentioned, that this test system will not be considered as a final concept, but merely as a prototype for investigation of the ideas presented above.

Structure

The problem of detection and diagnosis can be seen as two separate, but interconnected tasks. Generally, one can say that simple detection mechanisms normally requires more diagnostic power and vice versa.

The test system in this project will be directed towards a simple, adaptive detector, implemented in a small micro computer APPLE II, while the diagosis part, which requires more computing power, will be located in a VAX 11/750.

The overall approach can be summarized:

By using an on-line parameter identification algorithm and adaptive fault detection method, a noise pattern change can be monitored and detected. When a change has occured, a first level diagnosis can be started, addressing the task of identifying the primary system of concern. Based on the fault detection, identifications and perhaps operator support, a symptom/cause data base is formed and transferred to the diagosis system.

The general structure is given in Fig 11.

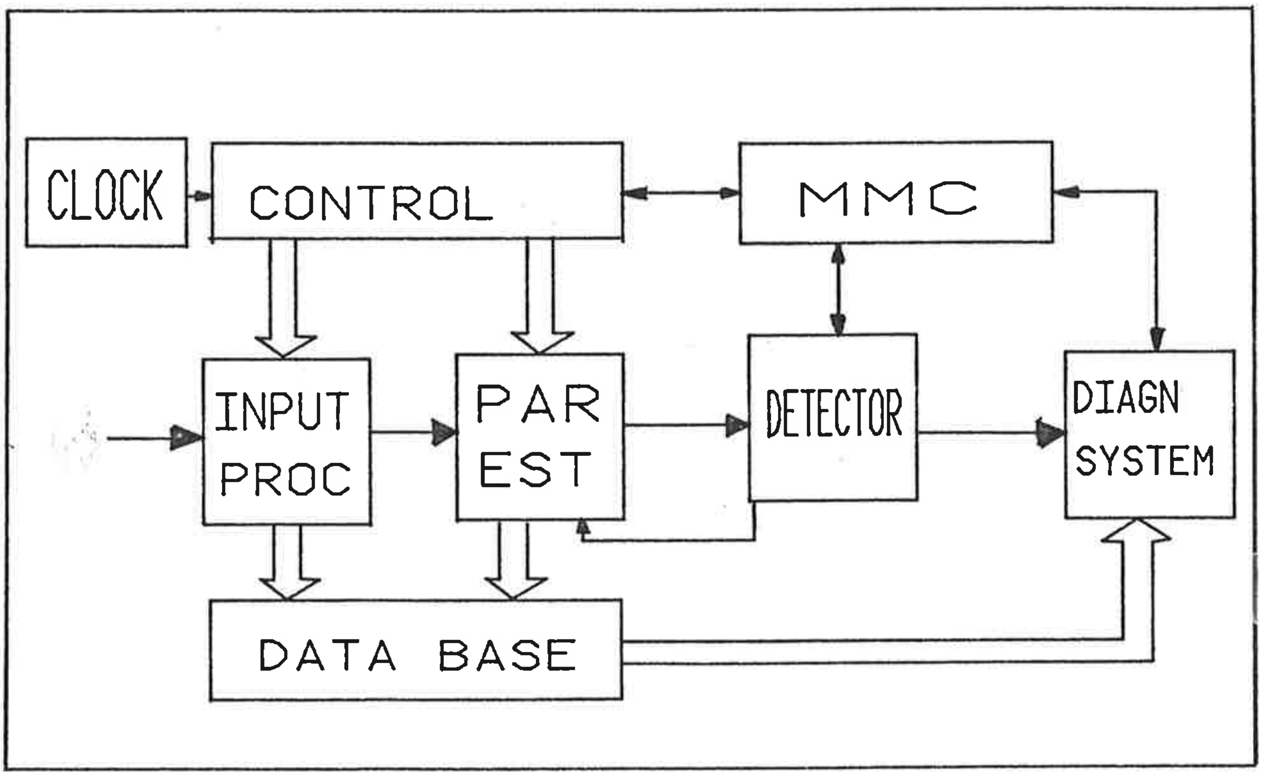

Fig 11 General system structure

Implementation

The detector part of the system is currently under implementation. The hardware selected for this test system is an APPLE II computer, supported with a 5 Mb disc, 16 channel A/D converter and a Real Time Clock. The signals are properly isolated from the process using a special Band Pass filter (0.005 - 3.0 Hz). The sampling rate is 10 Hz.

USCD Pascal have been chosen for development of the detector software, However, the software for the diagnosis system is not yet frozen. Probably LISP will be used for Man Machine Communication, while the standard identification, simulation and model analysis packages are designed in FORTRAN 77.

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