WORKING MATERIAL

DIAGNOSTIC SYSTEMS
IN
NUCLEAR POWER PLANTS

*Proceedings of a Technical Committee' Meeting
Organized by
the International Atomic Energy Agency
in Co-operation with
Turkish Atomic Energy Authority*

*22-24 June 1998
Istanbul, Turkey*

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FOREWORD

The nuclear power industry has a quite long tradition for on-line diagnostic of mechanical components because of the restricted accessibility to vital mechanical components and the safety issues involved should these components fail. Therefore considerable efforts were put in developing diagnostic systems which are able to detect arising mechanical problems at an early stage. A great deal of attention is being paid to avoid any abnormal events which may occur during the operation of equipment, systems and components of nuclear power plants. The early diagnosis of deviations from normal conditions is considered to be a main way to ensure the avoidance of abnormal events. Computers are increasingly being exploited to provide higher level information on process behavior, such as: early indication of the deviation of the process from normal conditions; rapid identification of the root cause of any disturbance; prediction of the evolution of a disturbance; operator aid through computerized help. Many or the systems are classified as process diagnostic systems related to plant operability although they do have an impact on safety. The integration of these systems into the main control room and the assessment of their impact on operator performance and control room practice remains a significant challenge.

Following the recommendation of several Member States to strengthen the Agency's activity in this field, two divisions of IAEA the Division of Nuclear Power and the Division of Nuclear Installation Safety jointly established in 1995 the International Task Force on Nuclear Power Plant Diagnostics. The terms of reference and scope of the task force cover both technological developments and safety/licensing aspect of diagnostics. In 1995, a Technical Committee Meeting on "Advances in Safety Related Diagnostics and Early Failure Detection Systems" was organized in Vienna with emphasis on safety and licensing issues. In 1996, a Specialists Meeting on "Monitoring and Diagnosis Systems to Improve Nuclear Power Plants Reliability and Safety" was held in the United Kingdom, which placed emphasis on technical development of diagnostic systems. The third meeting, a Technical Committee Meeting on "Nuclear Power Plant Diagnostics - Safety Aspects and Licensing" was held in 1997 in Portoroz, Slovenia with the purpose to review developed systems and methods in diagnostics in the scope of their impact and importance to the safety of nuclear power plants.

This report contains papers presented at the Technical Committee Meeting on Diagnostic Systems in Nuclear Power Plants, which was held in Istanbul, Turkey from 22 to 24 June 1998. This Meeting was the fourth and the final one in the row of meetings organized in the framework of the International Task Force.

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IAEA Technical Committee Meeting on
Diagnostic Systems in Nuclear Power Plants

Istanbul, Turkey
22-24 June 1998

PROGRAMME

<u>**Monday, June 22**</u>

8:30 - 9:00   Registration, *registration desk in the Bosphorus Hall, President Hotell Istanbul.*

9:00 - 9:30   **Opening Session**

Welcoming Remarks - *Emin Özbas, Acting Head, Turkish Atomic Energy Authority.*
Welcoming Remarks - *Vladimir Neboyan, IAEA.*
Overview of IAEA Specialists Meeting - *Gül Göktepe, Technical Coordinator.*

9:30 - 10:30   **Session 1: Experience with monitoring and diagnosis systems in NPP (1)**
Chairperson: Ozer Ciftcioglu, Turkey

1.1   General review of diagnostic systems in EDF's PWR units. *R.Chevalier, France.*

1.2   Diagnostic systems developed in NPRI for NPPs. *G.Okša, P.Kuchárek, Slovak Republic.*

10:30 - 11:00   *Coffee Break and Registration*

11:00 - 12:30   **Session 1: (Continuation)**

1.3   Performance demonstration experience for reactor pressure vessel shell ultrasonic testing systems. *V. Zado, Croatia.*

1.4   Diagnostic system for process control at NPP Dukovany load follow. *J.Rubek, I.Petružela, Czech Republic.*

12:30 - 14:00   *Lunch Break*

14:00 - 15:00   **Session 2: Experience with monitoring and diagnosis systems in NPP (2)**
Chairperson: Imre Pázsit, Sweden

2.1   Surveillance and fault diagnosis for power plants in the Netherlands: operational experience. *E.Türkcan, Ö.Ciftcioglu, T.H.J.J.van der Hagen, Netherlands, Turkey.*

2.2   Diagnostics of phase state of the coolant in PWR by temperature noises. *M.Levadnyi, Belarus.*

15:00 - 15:30   *Coffee Break*

15:30 - 17:00   **Session 2: (Continuation)**

2.3   Experiences with digital acoustic monitoring system for PWRs and BWRs. *B.J.Olma, Germany.*

2.4   Localisation of a channel instability in a BWR via neutron noise methods. *I.Pázsit, J.K-H.Karlsson, Sweden.*

2.5   Experience of diagnostic system application in research reactors. *A.T.Mikulski, Poland.*

17:00   *Free time (Social programme will be announced at the meeting)*

Tuesday, June 23

9:00 - 11:00   **Session 3: Development trends and advanced technologies (1)** *Chairperson: Erdinc Turkcan, Netherlands*

3.1   Development trends of diagnostic systems for nuclear power plants. *U.Kunze, U.Pohl, Germany.*

3.2   Soft computing for fault diagnosis in power plants. *Ö.Ciftcioglu, E.Türkcan, Tukey, Netherlands.*

3.3   Some aspects of diagnostic systems perspective. *D.Korošec, Slovenia.*

3.4   Power oscillation and stability in water cooled reactors. *G.Por, G.Kis, Hungary.*

11:00 - 11:30   *Coffee Break*

11:30 - 12:30   **Session 3: (Continuation)**

3.5   Applications of wavelet transforms for power plant signal analysis. *S.Seker, E.Türkcan, B.R.Upadhyaya, A.S.Erbay, Turkey, Netherlands, USA.*

3.6   Implementing artificial neural networks in nuclear power plants diagnostic systems: issues and challenges. *Z.Boger, Israel.*

12:30 - 14:00   *Lunch break*

14:00 - 16:00   **Pannel Discussion** *Chairperson: Gabor POR, Hungary*

Needs, planning, licensing, introducing and maintaining diagnostic systems for nuclear power plant.

Wednesday, June 24

9:00 - 11:00   **Session 4: Development trends and advanced technologies (2)**
Chairperson: Tanzer Türker, Turkey

4.1   A PC-based signal validation system for nuclear power plants. *A.S.Erbay, B.R.Upadhyaya, S.Seker, USA, Turkey.*

4.2   Further development of NPP surveillance and diagnostics by use of intelligent technologies. *D.Wach, Y.Ding, Germany.*

4.3   Field-based systems and advanced diagnostics. *E.Eryurek, USA.*

4.4   Analysis of the monitoring system for the spallation neutron source SINQ. *E.Badreddin, Switzerland.*

11:00 - 11:30   *Coffee Break*

11:30 - 12:30   **Session 5: General discussion, conclusions and recommendations**
Chairperson: Werner Bastl, Germany

12:30   End of the Technical Committee Meeting

TABLE OF CONTENTS

SESSION 1:

EXPERIENCE WITH MONITORING AND DIAGNOSIS SYSTEMS IN NPP (1)

GENERAL REVIEW OF DIAGNOSTIC SYSTEMS IN EDF PWR UNITS

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Abstract

Since the beginning of the French nuclear program, Electricité De France (EDF) has looked for ways to improve the availability and safety of its nuclear units. Therefore, monitoring systems on turbogenerators, reactor coolant pumps, primary circuits and core internal structures were designed by the Research and Development Division and implemented with technologies available during the 1970's. However, mainly because of difficulties for data interpretation by plant personnel, EDF subsequently decided to design and develop different tools to help plant operators to process a diagnosis:

- a new generation of the Monitoring and Diagnostic System called PSAD,
- expert systems for diagnosis on reactor coolant pumps (RCP) « DIAPO » and turbogenerator units (TG) « DIVA »,
- diagnostic guides written for most equipment pending the installation of new monitoring and diagnosis systems.

The first version of PSAD, installed in five units, performs on-line monitoring of the turbogenerator shaft line, steam inlet valves, the reactor coolant pumps and the generator stator. The second version not yet implemented, will include Loose Part Detection (LPD) and Core Internal Structure Monitoring (CISM). The level of diagnosis achieved by PSAD depends on the component monitored. The TG and RCP monitoring functions of PSAD compute high level diagnosis descriptors such as natural frequencies and long term trends but do not elaborate a diagnosis automatically. However, a diagnostic assistance window is available on-line, whenever a warning message is displayed, whether for immediate or later action. The window presents a diagnostic approach whose purpose is to find the causes of the symptoms observed. This diagnosis approach is automated in the DIVA and DIAPO expert systems. Numerous potential faults can be identified for both systems thanks to a hierarchy of abnormal situations. The user interactively answers questions when information is needed to progress in the diagnosis. The resulting diagnosis is a list of various faults with a corresponding degree of confidence. For Internal Structures Monitoring and Loose Part Detection in the primary circuit, PSAD can perform a complete diagnosis. Signals from accelerometers are used to identify the specific vibration modes of the internal structures. Any evolution of these frequencies is detected and a message is triggered corresponding to a specific fault. LPD uses the rate of coincident impacts detected in the signal from the different sensors to diagnose a loose part. Finally, for most equipment, diagnostic guides, including diagnosis procedure and forms describing the faults, have been offered to plant operators.

INTRODUCTION

Since the beginning of the French nuclear program, Electricité De France (EDF) has looked for ways to improve the availability and safety of its nuclear units. Therefore, on-line monitoring systems were designed by the Research and Development Division and implemented with technologies available during the 1970's.

The most important on-line monitoring systems concern: monitoring of core internal structure, loose part detection, turbogenerators, steam valves and reactor coolants pumps. All these systems are installed on all PWR units.

The data processing modules which were designed for these systems have proven their efficiency regarding incipient failure detection. The data collected and processed with this equipment were found to be very valuable for diagnostic purposes.

However several limitations to the existing systems have been identified:

- difficult data interpretation by plant personnel,
- time consuming tasks in routine operation and maintenance of monitoring equipment,
- difficulty to transmit data between the plant personnel and centralised experts.

EDF thus decided to design and develop different tools to help plants operators to process a diagnosis :

- a new generation of Monitoring and Diagnostic System called PSAD ("Poste de Surveillance et d'Aide au Diagnostic" in French), integrating all this experience feedback through state-of-the-art data acquisition and processing equipment,
- expert systems for diagnosis on the reactor coolant pumps (RCP) « DIAPO » and turbogenerator units (TG) « DIVA »,
- diagnostic guides written for most equipment pending the installation of the new monitoring and diagnosis systems.

GENERAL PRESENTATION OF MONITORING AND DIAGNOSTIC SYSTEM CALLED PSAD

The major features introduced by PSAD are:

- early, on-line detection of operating faults,
- computation of significant complementary data in real time for an efficient diagnosis,
- assistance for the maintenance staff through diagnosis with the use of expert systems,
- a homogenous user interface for all of the monitoring functions
- the ability to transfer any data to the EDF national analysis centre for further diagnosis by experts.

PSAD is designed with a flexible hardware and software architecture in order to be open to new monitoring functions in the future.

The first version of PSAD performs on-line monitoring of the turbogenerator shaft line, steam inlet valves, reactor coolant pumps and the generator rotor.

Hardware and software design

The hardware architecture is divided into four levels:

- at the machinery level (turbogenerator, reactor coolant pumps, vessel, primary circuit, ...): several real-time Monitoring Units,

- at the nuclear unit level: the Diagnosis Workstation,
- at the site level: a plant Analysis Workstation,
- at the national level (wherever corporate expert teams are located): Remote Workstations.

The plant-wide components communicate through local area networks and remote sites are connected by specialised communications lines.
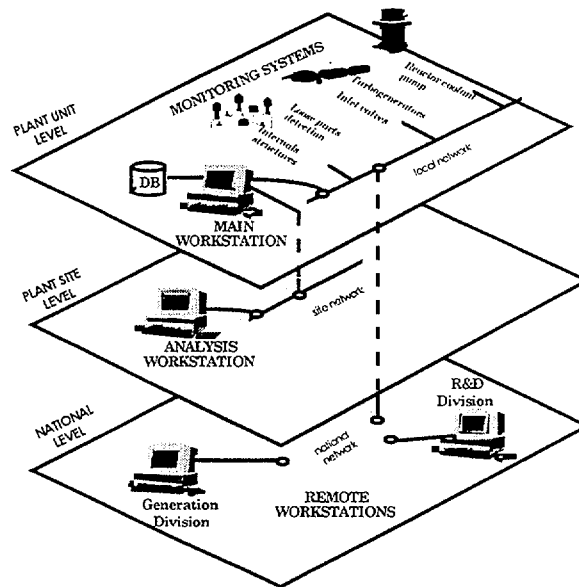
Figure 1: The PSAD overall hardware architecture.

On-Line Monitoring Units

The on-line monitoring units are located close to the monitored equipment in the plant and provide continuous acquisition of raw data and real-time processing of physical measurements. Each of them is dedicated to one or more machines, depending on the monitoring instrumentation: one monitoring unit can receive up to 150 sensors.

The PSAD system uses the concept of descriptors which represent a significant facet or characteristic for monitoring a machine.

The raw data make up the **Level 1 Descriptors**, acquired through specialised electronic or data processing boards. They include the values related to immediate machine operation: spectrum analysis, harmonic orders, RMS and peak-to-peak values, A/D conversion for static signals (temperature, pressure, flow,...), position and movements of valves, etc....

More specific data are computed by user-specified real-time algorithms using combinations of level 1 descriptors. These data, called **Level 2 Descriptors**, provide an additional significant description of the process which is not directly available from the sensors, for example rated power.

Level 1 & 2 descriptors are stored locally and monitored to determine if changes occur in the immediate condition of a machine, in which case warnings are generated automatically.

Data reduction mechanisms are then applied to all data so that only significant information is transmitted to the Diagnosis Workstation for storage in the data base.

The Diagnosis Workstation

There is one Main Workstation for each nuclear unit which provides the main user interface for a PSAD system. Its screen display informs operator teams of malfunctions on the monitored components: warnings are displayed in different colours depending on their seriousness.

The Diagnosis Workstation also computes more information, called **Level 3 Descriptors**, based on the history of level 1 & 2 descriptors provided by the different monitoring units. They are used to track long term evolution of a vibration for example (identification of critical speeds and natural frequencies, determination of the sensitivity to operating parameters). This information gives a complete characterisation of the machine's operation under normal and abnormal conditions.

All the descriptor values are stored in a high capacity relational data base resident on the Diagnosis Workstation. Historical data covering the entire machine lifetime are permanently available on disk, allowing immediate on-line access. Fully automatic backup to tape drives prevents any loss of data and guarantees minimal unavailability.

The Site Analysis Workstation

The Analysis Workstation is a central access point to the data stored on the different Diagnosis Workstations of a plant site.

All the graphical and diagnostic functionality of a Diagnostic Workstation is duplicated to provide parallel assistance with a diagnosis. All data is obtained directly from the PSAD systems being studied through remote queries of their databases.

The maintenance analysts can thus perform behaviour comparisons and data correlation between the monitored components of different nuclear units.

Remote Workstations

They are typically located at the headquarters of the Generation and Research & Development Divisions and are used by national experts or equipment specialists either to perform general studies of component behaviours or to confirm and complete a pre-diagnosis initiated on site.

DIAGNOSIS OF TURBOGENERATORS AND REACTOR COOLANT PUMPS BY PSAD

Using sophisticated graphic display software and diagnostic functions , the operators and experts are able to diagnose the following equipment :

- the turbogenerator shaft line; up to 40 typical faults can be detected: unbalances (mechanical, thermal and rubbing), misalignment (bearings and supporting structures), lubrication defects (oil-whip), rotor faults (cracks, blade loss), coupling faults ...

- steam inlet valves; faults such as tightness defects, sticking, seat-body separation, stem break can be identified.

- the generator; up to 10 typical faults can be detected such as ventilation problems, rubbing, short-circuits, rod defects ...

- the reactor coolant pumps; up to 50 typical faults can be detected on the shaft and seals: bearings and motor like unbalances (mechanical, thermal and rubbing), misalignment (bearings and supporting structures), rotor faults (cracks, windings), damaged or sticking seals ...

Diagnostic functions

The operators and experts consult all of these historical data using sophisticated graphic display software and diagnostic functions including:

- quick and simple selection of the descriptors through explicit diagrams of the monitored components (see Figure 2 below); sets of descriptors to be graphed constitute a diagnostic context used to study a specific defect and can be saved and recalled by the various users,
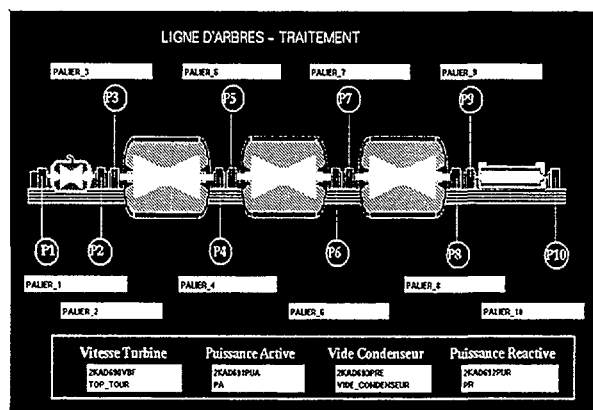
Figure 2 : Turbogenerator diagram for descriptor selection.

- a complete set of tools for graphing data: trends, Bode plots, Nyquist plots, spectra, Waterfall plots, bar charts, etc...
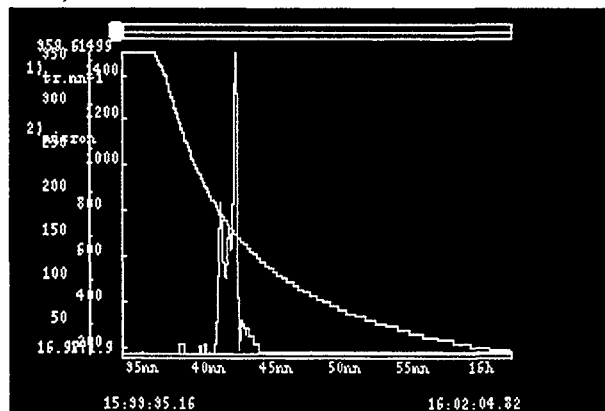
Figure 3 : Example of vibration plots.

- identification of critical speeds: at the end of each run-down (or run-up), a modal identification algorithm determines critical speeds, modal damping and modal participation from measurements acquired in the frequency windows selected for each descriptor (e.g. bearing sensor 1, amplitude and phase of the 2nd order harmonic); a warning message will

be triggered if these parameters evolve beyond a predefined threshold during subsequent speed-transition phases,

- identification of resonance frequencies: while operating under rated conditions, the spectrum analysis of a rotating machine vibration signal makes it possible to highlight both the response to harmonic excitations and modal responses to wide band excitations (fluid, steam, etc.),
- statistical analysis tools: besides monitoring the usual signal levels under nominal conditions, PSAD implements supervision based on a statistical analysis; its purpose is to define statistical reference states for the behaviour of machines and to be able to diagnose mechanical deterioration by following any changes over time,
- determine the sensitivity to operating parameters: at a given operating speed, the PSAD system computes the vibration sensitivity of the machine to variations of an operating parameter such as the power or output voltage of a generator; this sensitivity vector is stored and a warning message is generated if its value progresses beyond configured thresholds,
- compute a deviation vector: the average vibration vector (1st and 2nd harmonics) of the vibration magnitude is computed continuously and compared with a reference value; several types of messages can be generated, depending on the extent or the persistence of any difference between the two,
- measure valve stroke times during openings and closures: through periodic maintenance tests, PSAD can detect any variations due to abnormal rubbing.

Diagnostic Assistance

In addition to the functionality described above, a new Diagnostic Assistance function has recently been added to this system.
Whenever a warning message is displayed, whether for immediate or later action, a diagnostic assistance window is available on-line. The purpose of this assistance is to:

- explain and clarify the meaning of the message
- help guide the operator through the data analysis steps needed to find the malfunction(s) which caused the warning message.

The first step of a diagnosis is to recognise the possible malfunctions which may have caused the observed symptoms, then to verify these hypotheses. The diagnosis window guides the operator in finding the information which will support or refute each hypothesis.

For example, if the warning message is « step increase of RMS vibration in turbine bearing X », the diagnostic assistance will suggest to look for the time of the step event, any coinciding change in certain harmonics, and any correlation with operating parameters. Depending on the results of these searches, the tool could suggest such malfunctions as a loose coupling or the loss of a turbine blade. The final confirmation of a diagnosis is made by comparing the phenomenon to typical malfunction references or observations from previous malfunctions.

The diagnostic assistance is not an automatic tool, but when dealing with catalogued malfunctions, it leads the operator efficiently from a warning message to an optimal diagnosis.

DIAGNOSIS OF NEW FUNCTIONS IN PSAD

Diagnostic of Loose Part Detection (LPD)

The primary cooling system in nuclear power plants includes a great number of components which are subject to repeated stress. Certain parts can break off and be carried away with circulating coolant until they reach and remain in a specific area called the "trapping zone". Such objects may weigh several hundred grams and can cause major damage incurring costly repairs.

While such incidents are rare, an automatic monitoring system must be able to detect loose parts and alert plant operators when necessary. Loose part detection is based on the observation of acoustic waves produced by these objects as they hit the walls of the primary cooling system:

- when a loose part hits the structure of the extended primary cooling system, the waves produced by the impact are propagated throughout the structure. The appearance of coinciding transients (called a coincidence) in the signal from the different sensors of a given zone characterises a mechanical impact.
- as loose parts are trapped, they hit the structure in a repetitive manner. The rate of coincident impacts is therefore characteristic of a loose part.
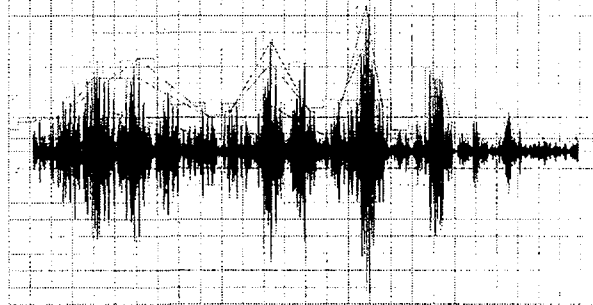
Figure 2: Loose part impact characterisation.

The objective of the LPD function is to trigger an alarm only for loose parts (using noise filtering to avoid false alarms), while alerting operators of any doubtful cases.

Elaborated signal processing has been developed and automatic detection and characterisation of events are performed by a monitoring unit while automatic statistical analysis, localisation and graphical analysis of a loose part event, confirmed or suspected, are performed on the PSAD Diagnosis Workstation.

Core Internal Structure Monitoring (CISM)

Vibration analysis of the core internal structures monitors the good mechanical behaviour of the hold-down spring, the attachments of the thermal shield on the core barrel, and the fuel rod assemblies. The potential incidents include loss of functions, rupture of flexures and deformation, or even rupture of fuel rod assembly spring sets and centring pins.

The CISM functionality must be able to discriminate between true vibration events and normal changes in vibration amplitude, indicating the transition from one normal state to another normal state. These different states correspond to different types of contact between

internals and the vessel. In addition, CISM must be able to ignore the general increase of the monitoring signal level due to fuel burn up as well as help diagnose any malfunctions not yet observed.

Monitoring is based on spectrum analysis of two types of signals, each from a distinct set of sensors:

- ex-core neutron chambers on which the incident neutron flux varies with the thickness of the water layer between the core barrel and the reactor vessel,
- accelerometers which detect forced vibration of internals on the reactor vessel.

Slow mechanical behaviour changes imply an increase of vibration levels and decrease of frequencies. The periodic analysis of the vibration of the structures enables detection of such changes. Furthermore, continuous monitoring of vibration levels enables the detection of unusual signal variations, pointing out the beginning of some kind of degradation. This involves monitoring RMS values in frequency bands centred around known phenomena to detect any values which exceed predefined thresholds.
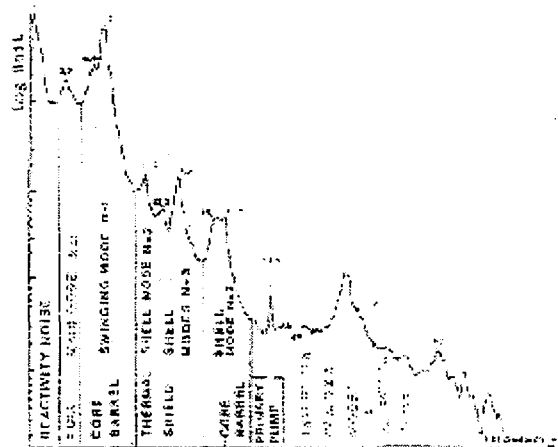
Figure 3: Main modes detected in a neutron noise signature (reactors with cylindrical thermal shields)

The PSAD diagnosis workstation automatically monitors two kinds of core internal structure behaviour:

- detection of abnormally low frequencies and diagnosis of current vibration behaviour
- detection of frequency decrease and adjustment for the evolution in the vibration behaviour since the beginning of the current fuel cycle.

DIVA : EXPERT SYSTEM FOR DIAGNOSIS OF THE TURBO GENERATOR SET

To complete the Diagnostic Assistance function available in PSAD, EDF undertook in the mid-Eighties to develop an expert system for aid in diagnosis of turbogenerator sets: the DIVA system. The software has been industrialised.

DIVA: the diagnosis model

The objective of the DIVA diagnostic approach is to find the causes of symptoms observed. DIVA draws on the fact that, when a fault occurs, the observations correspond to abnormal situations which are familiar to experts. These situations are ordered from the most general to the most specific, to allow for progressive, efficient identification. In general, when a situation is sufficiently specific, its cause is a specific fault which can then be diagnosed and characterised. The user responds interactively to questions which enable DIVA to recognise or reject typical situations it "knows". Finally, DIVA proposes a diagnosis which consists in the various faults known to be compatible with the situations recognised, together with the corresponding degrees of confidence. These degrees express the conformity between the typical fault manifestations and the symptoms actually observed. The fault identification can refined by additional information as to its location, its possible cause, possible corrective measures, etc.

DIVA: the knowledge base

Implementation of the diagnostic process depends on a knowledge base containing a full set of pertinent expert knowledge. The present base allows for identification of 35 faults. It integrates a description of 90 situations, corresponding to possible equipment state at the time of incidents occurring at nominal speed, during run-up and run-down. The symptoms relate to some 150 parameters. The mechanism of recognition used 2,000 rules. This knowledge base has been extensively tested, validated and refined by experts. It will continue to evolve independently of the information system, as new operation feedback is collected. The prototype of DIVA has been developed in co-operation with GEC-Alsthom. The industrial version has been installed on a nuclear power plant in 1995. Current studies include possibilities of remote activation in order to centralise maintenance of the knowledge base.

DIAPO: EXPERT SYSTEM FOR DIAGNOSIS OF THE REACTOR COOLANT PUMP SET

Similarly to what had been done with turbogenerators, EDF decided to develop an expert system for aid in diagnosis of reactor coolant pumps sets (RCP): the DIAPO system. A full-scope prototype of the software has been developed with RCP manufacturer Jeumont-Industrie. An industrial product will be derived from this prototype by the end of 1998.

DIAPO: the diagnostic technique

The objective of DIAPO diagnostic approach is to find the causes of observed symptoms. To do this, DIAPO exploits several models of RCP failures. Each model covers a facet of diagnosis: identification of a faulty part, primary cause of a malfunction, category of problem... Some one hundred potential RCP faults can be identified thanks to a hierarchy of abnormal situations, a set of cause-to-effect relationships linking the origins of dysfunction to their manifestations and a physical description of the RCP set associated with knowledge of where failures are located.

The user responds interactively to questions which help DIAPO to progress in its diagnosis. For the set of observations which have been made, the final diagnostic result is a combination of the explanations provided by the different models.

This fault identification can be refined by additional information as to seriousness, possible corrective measures, etc.

DIAPO: the knowledge base

Implementation of this diagnostic process requires a full set of pertinent expert knowledge. Thus the causal description of RCP dysfunction, for example, required the building of a graph of some one thousand relations. This knowledge base has now been tested, validated and refined by experts. It will continue to evolve as new feedback is collected.

DIAGNOSTIC GUIDES

The PSAD system is operational in EDF for the monitoring of turbogenerators and reactor coolant pumps on five units. However, the main components (TGS, RCP and primary circuit) of the nuclear power plants operated by EDF are monitored continuously by systems dating from 1970. These systems insure the detection of faults but do not provide enough assistance for diagnosis.

Therefore, to assist users of power plants and notably in wait for the generalisation of PSAD, diagnosis guides have been written for the monitoring of TGS and RCP. Concerning the Core Internal Structure Monitoring and Loose Part Detection, the diagnosis of faults is carried out by the Research and Development Division. Nevertheless, specific guides have been written for the experts. Most of the main auxiliary rotating machinery is monitored periodically using a data collector. A specific project was carried out and its goal was to produce diagnostic guides.

The principles of all these guides are very similar. They describe the method of diagnosis and list necessary information. They contain the following information:

- forms of evocation gathering the different types of machine behaviour by symptoms,
- catalogue of monitoring and diagnostic methods,
- forms of faults detailing each listed defect and giving actual examples of these faults,
- the diagnosis procedure (symptoms/faults) that can be limited to a table of evocation, which gives a synthesis of most probable defects.

EXPERTISE ORGANISATION IN EDF

All the diagnostic tools described in this document are dedicated to plant operators, who perform the first analysis. To assist them in performing complex diagnoses, teams of diagnostic experts for major components have been formed at EDF for many years. The decision has been taken to structure theses teams in a diagnostic expertise network :

- operating services, whose goal is to help plant operators to prepare maintenance, for example determining machine behaviour,
- maintenance and development of knowledge, for example producing expert system and guides,
- animation and co-ordination of the expertise network.

The project started in 1998. The purpose is to optimise efficiency in services rendered to the plants.

CONCLUSION

The optimisation of maintenance notably by the use of condition-based maintenance, constitutes an important step in the reduction of maintenance costs at EDF. Condition-based maintenance requires not only knowledge of the state of the equipment with the help of monitoring systems but also the anticipation of its evolution. Diagnosis of the condition of equipment constitutes an mandatory preliminary for prognosis. The PSAD system has been designed to help operators to optimise maintenance of the monitored equipment. The detection aspect is achieved for all the monitored equipment. The part of played in diagnosis by PSAD depends on the equipment. Thus, when the number of faults is limited (Loose Part Detection) or when the relationships symptoms/faults are simple (Core Internal Structure), the operation of diagnosis is performed with the use of algorithmic software inside PSAD. For monitoring functions such as TGS, RCP and generator monitoring, it has been necessary to develop expert systems based on artificial intelligence mechanisms, because of the great number of faults and the complexity of the diagnosis process. Feedback in the use of diagnosis tools shows difficulties to valorise these products. They demand an important implication and competence from users who often prefer as far as vital equipment is concerned, to insure the diagnosis with the help of manufacturers or EDF experts.

REFERENCES

Monitoring and Aid to Diagnosis of French PWR A.JOUSSELIN, A. TRENTY, J.C. BENAS, Y. RENAULT, J.L. BUSQUET, B. MOUHAMED, SMORN VII Conference, 1995.

Monitoring of Large Rotating Machines at EDF R. CHEVALIER, G.P. OSWALD, J. MOREL IFTOMM, UDINE, 1993.

Building and maintaining a Large Knowledge-Based System from a 'Knowledge Level' Perspective: the DIVA experiment J.M. DAVID, J.P. KRIVINE, B. RICARD In « Second Generation Expert Systems », edited by J.M. David, J.P. Krivine et R. Simmons Springer Verlag, 1993.

DIAPO, a case study in applying advanced AI techniques to the diagnosis of a complex system M. PORCHERON, B. RICARD, J.L. BUSQUET, P. PARENT 11th European Conference on Artificial Intelligence (ECAI'94)

General review of on-line monitoring techniques used in EDF's NPPs GERMAIN Jean-Luc IAEA Specialists Meeting on « Nuclear Power Plant Condition Monitoring and Maintenance » 2 to 5 june 1998. Lyon France

DIAGNOSTIC SYSTEMS DEVELOPED IN NPPRI (VUJE) TRNAVA Inc. FOR NNP's.

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Abstract

Since foundation of Nuclear Power Plant Research Institute (NPPRI) in 1977, the department of diagnostics has been dealt with problems related to the theoretical, practical and organisatory questions of operational diagnostics connected with PWR type nuclear components. This department acts directly in locality of NPP Jaslovské Bohunice, but there are performances for all NPP in Slovak or Czech Republic (Dukovany, Mochovce, and Temelín). Besides direct services and achievements for NPP there exist advisory, experts and research activities for the government and supervising authorities, too.

In 1985, NPPRI began systematically construct and verify technical means for operational diagnostics of main circulating pumps (MCP) with good results, based on own rich practical experiences and contacts with organisations abroad. In recent years NPPRI as one of recognised qualified and authorised institutions in Slovak Republic has begun to develop a new generation of diagnostic systems for NPP on high technical level but with lower procuring costs in comparison with western countries products.

This contribution deals with four following types of diagnostic systems which were not only developed but also delivered and installed on Slovak and Czech nuclear units:

- Loose part monitoring system (LPMS)
- Humidity monitoring system (HUMON)
- Reactor coolant pumps monitoring system (RCPMS)
- Primary circuit vibration monitoring system (VMS)

Main features of new generation from middle of 1990´s of these systems are described in this paper and operational experiences with them too.

1. INTRODUTION

The operational diagnostics in the primary circuit of nuclear power plant is very important for the issues of nuclear safety and technical reliability. NPPRI (VUJE) Trnava, Inc. produces and installs various technical means including the stationary diagnostic systems which are operating in all NPPs in Czech and Slovak Republic (Jaslovske Bohunice, Dukovany and – in preparation – Mochovce and Temelin). Technical diagnostics in our institute has its own history of more than 20 years now and we have started with installations of our own diagnostic systems about 10 years ago. Our production includes the loose part monitoring system, main circulating pump monitoring system, system for the monitoring of vibrations of primary loops and humidity monitoring system.

The first generation of these systems developed at the end of 1980's was based on then first personal computers together with simple (i.e., „one user and one task") operating systems like DOS. We have developed the charge preamplifiers and special electronics for the signal

conditioning and processing and have used the commercially available sensors like accelerometers, displacement sensors, humidity probes, etc. Putting it together into one diagnostic system meant to develop the controlling software on the „low end" (i.e., programmes for digital signal processors, digital antialiasing, highpass and lowpass filters, programmes for data transmission, etc.), and the user software for data manipulation and evaluation.

After installation of first diagnostic systems we have gained precious experience and obtained a lot of feedback information from diagnostic personnel in the NPPs. This process led at first to the hardware and software improvements of already installed systems. Eventually, it was clear to us that a new version of diagnostic systems would be necessary which includes all the improvements of the old version and is based on a new philosophy of data acquisition, processing and evaluation.

In this paper the new version of diagnostic systems are illustrated which are produced in NPPRI (VUJE) Trnava, Inc. from the middle of 1990's. Each system is described in detail and then the common hardware and software features of both systems are described. The existence of common features regardless to the physical background, individual for each system, means the modularity and versatility of technical solution as well as the shorter production intervals.

2. LOOSE PART MONITORING SYSTEM (LPMS)

Impact of loose parts on the walls of nuclear power equipment of reactor coolant systems in nuclear power plants provides a serious hazard of damaging this equipment. Therefore a need arises to monitor continuously natural collection locations in reactor coolant systems for occurrence of loose parts. LPMS is designed for continual loose parts monitoring.

System for diagnostics of loose parts in reactor coolant system power plant, built on modern technical hardware of „high tech" type, is one of the result of research and development activities in NPPRI. Purpose of system implementation is :

- identification of loose parts (system is capable to detect a loose part with kinetic energy of 0.1J at distance 1m from nearest sensor)
- loose part localisation
- mass estimation

2.1 Hardware and software

The system is built on modular structure of hardware and software. Possible configurations include 32 measuring channels as a maximum and the implemented multi-task operating system enables simultaneous processing of a number tasks which assures continuous monitoring function of system. System consists of :
- measuring chains (accelerometers with freq. range from 1kHz to (10-25)kHz)
- force transducers
- impulse hammers with specified and programmable settings of impulse energy
- module of digital signal processors
    - max. 32 parallel channels
    - isolation amplifiers (ampl. factor 1-100)
    - A/D converters (16bits resolution, sampling freq. max 100kHz)
    - antialiasing filters
    - digital lowpass and highpass filtering (programmable, 96dB/oct)
    - environment temperature of primary electronic up to 65°C (up to 105°C)
- evaluation and storage part (based on PC)

- modules for control of non-standard equipment (impulse hammers, generator of calibrated signal, autodiagnostics of measuring circuits)
- audio module for visual display and acoustic monitoring of measuring signals
- 2 channel oscilloscope

2.2 Working regime
- initialisation and setting of system
- calibration of system during operation
- continual monitoring
- detailed analysis of impulse events
- print-out of alarm protocols following the detection of impulse event

3. HUMIDITY MONITORING SYSTÉM (HUMON)

The HUidity MONitoring system is designated to monitor continuously the humidity in the confinement (hermetical compartments) of nuclear power plants. Purpose of system implementation is to fulfil the LBB criterion (Leak Before Break). For NPP BOHUNICE 3 and 4 it means to detect leak 4l/min in 1 hour.

3.1 Hardware and software
System consists of the following main parts :
- measurement and control part of the system
  - sensors
  - analogous-digital transmitter with 32 inputs,
  - processor for data pre-processing
  - pneumatic suction module
  - set of tubes is used
  - pneumatic valves
  - source of dry air
- central evaluation module based on PC
- software.

In the realisation for V-2 Bohunice, the measurement and control part of the system is situated in the conditionally accessible part of the confinement (reactor coolant pump platform). The pneumatic part of the system with a suck-off module, the set of fans and the generator of air with the defined humidity are situated there as well. The air is sucked from the selected parts of the confinement by means of a suction module and tubes and its humidity is then measured by means of sensors of absolute humidity situated in the measurement chambers.

3.2 Working regime and preparatory works
- anemometric air flow measurement in the steam generator (SG) compartment,
- calibration of the sensors of absolute humidity,
- determination of the dependence of the flow rate in the particular sampling lines on the negative pressure generated by the suction-off module,
- verification of the system sensitivity by simulating a leak in selected points of the SG compartment
- continual monitoring based on comparison with reference values
- detailed analysis and special testing such as signal analysis procedures, trend evaluation,

archived results management, statistic computation etc. are possible to perform under operator control

- print-out of alarm protocols following the detection of impulse event

4. REACTOR COOLANT PUMPS MONITORING SYSTEM (RCPMS)

Large emphasis has been given to the diagnostics of rotational machines on basis of measuring vibrations and ultrasonic emission with orientation mainly on reactor coolant pumps. This system, built on the same modern technical hardware of „high tech" type as LPMS hardware, is one of the result of research and development activities in NPPRI.

System is designed for permanent monitoring of the status of all RCPs on the basis of measurement of mechanical vibrations in both acoustic and ultrasonic frequency ranges, as well as for the performance of measurements in interactive mode. Classification of the monitored object, based on comparison of actual parameters with limiting values of specified reference states, provides a part of diagnostic tests carried out automatically.

System is of a modular structure of both hardware and software so that it can be used also for the monitoring of mechanical status of other large rotating machines.

4.1 Hardware and software

The system is built on modular structure of hardware and software. Possible configurations include 84 measuring channels as a maximum and the implemented multi-task operating system enables simultaneous processing of a number tasks which assures continuous monitoring function of system. System consists of :

- measuring chains
  - accelerometers
  - ultrasonic sensors
  - optional sensors for shaft vibrations and tachometers
- module of digital signal processors
  - max. 84 channels (36 direct and others multiplexed 12x4)
  - isolation amplifiers (ampl. factor 1-100)
  - A/D converters (16bits resolution, sampling freq. max 100kHz)
  - antialiasing filters
  - digital lowpass and highpass filtering (programmable, 96dB/oct)
- evaluation and storage part (based on PC)
- modules for control of non-standard equipment (generator of calibrated signal, autodiagnostics of measuring circuits)
- audio module for visual display and acoustics monitoring of measuring signals
- 2 channel oscilloscope

4.2 Working regime and software modules

- service with special software
- configuration of system (including generation of limiting values)
- continual monitoring based on comparison with reference measurements in defined periods
- detailed analysis and special testing such as signal analysis procedures, trend evaluation, archived results management, statistic computation etc. are possible to perform under operator control
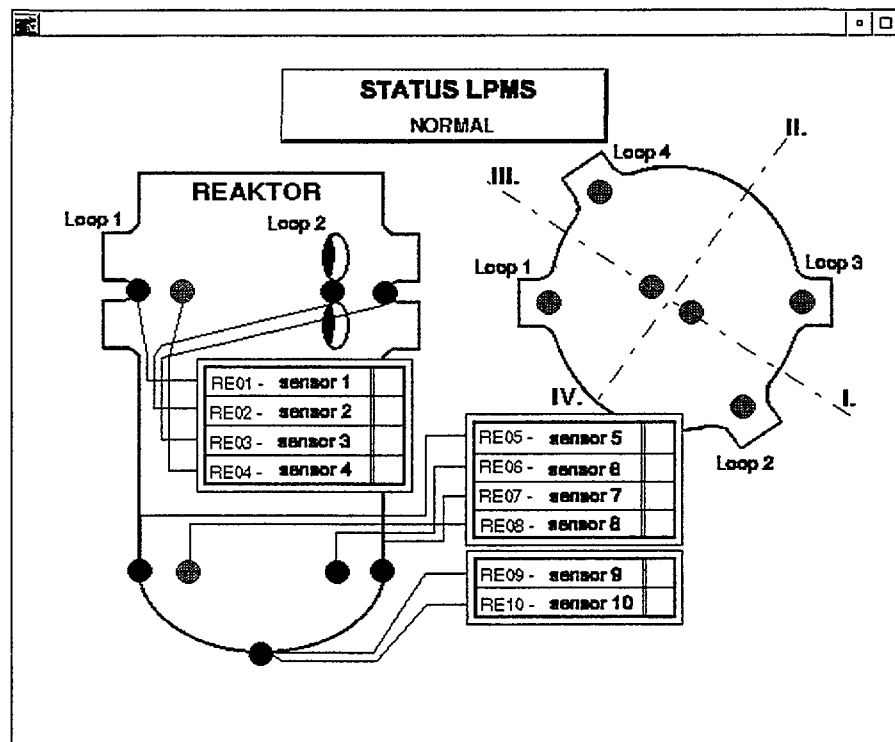- print-out of protocols

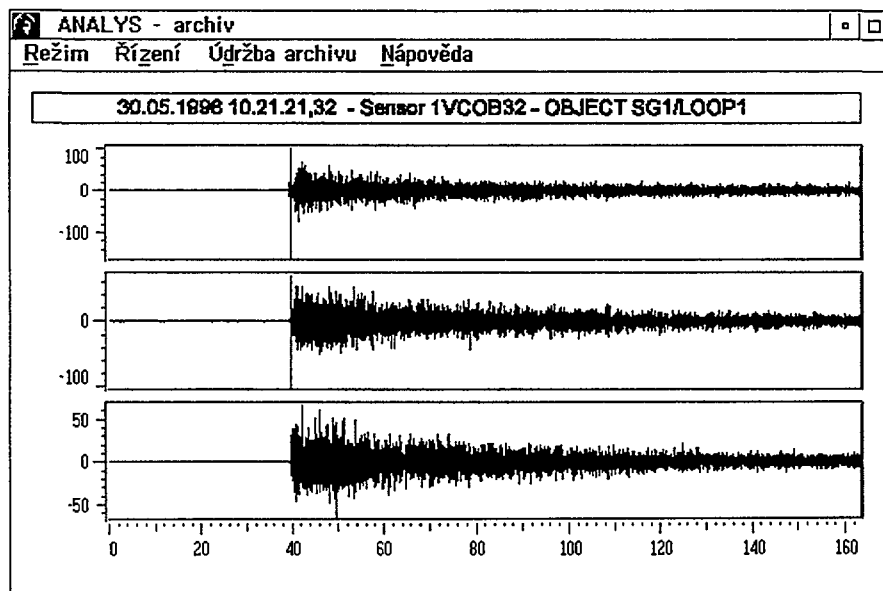**Fig. 1** LPMS - proposal of sensor loacation on reactor vesel.

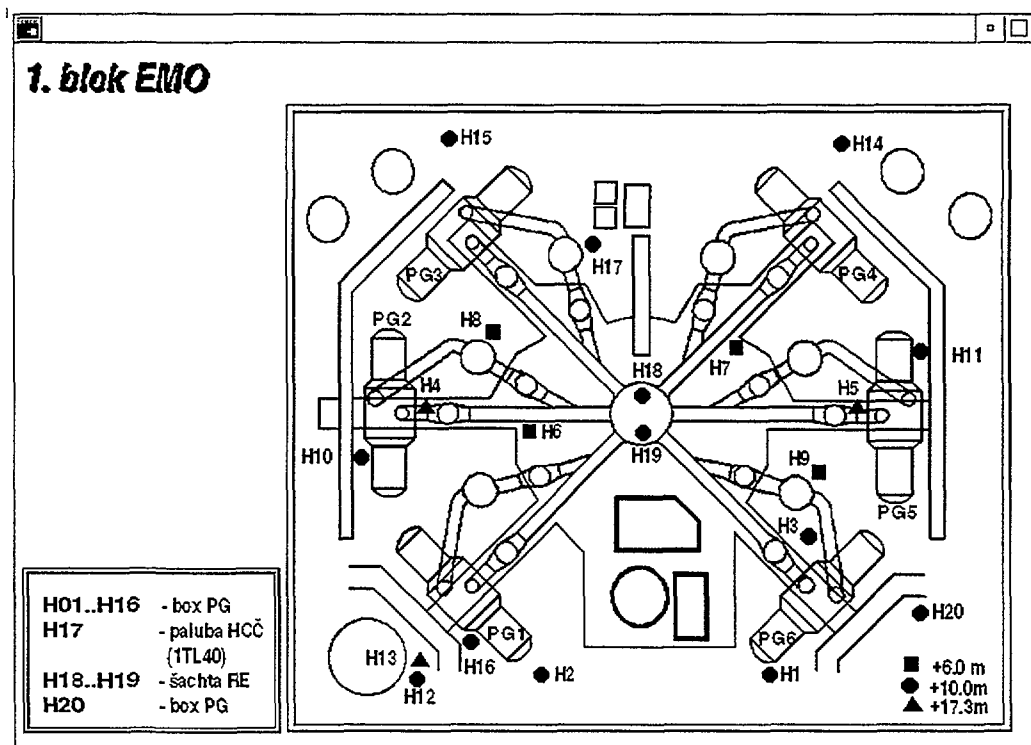**Fig. 2** Burst from loose part in time domain.

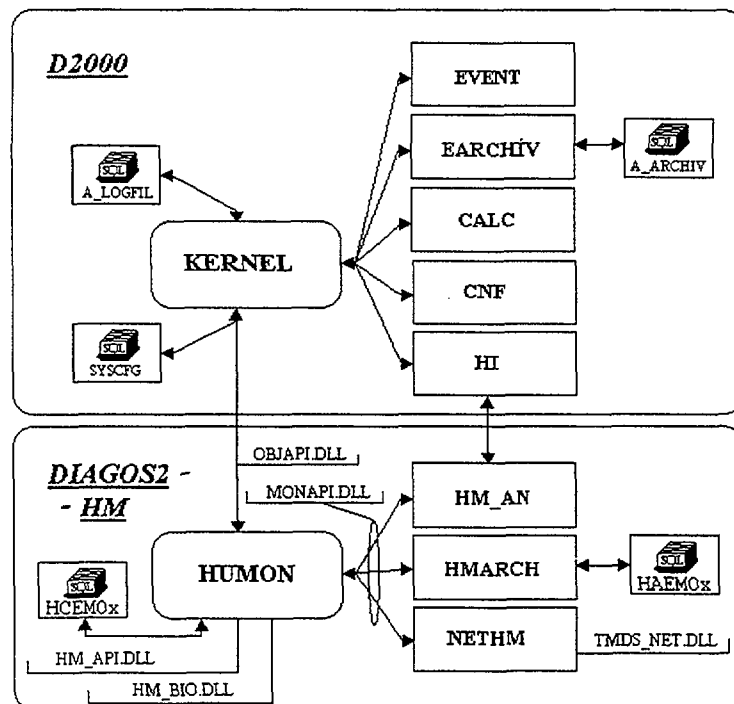**Fig. 3** HUMON - proposal of sensor location

Fig. 4 HUMON - structure of software modules.

5. PRIMARY CIRCUIT VIBRATION MONITORING SYSTEM (VMS)

System is designed for periodic or repetitive realisation of diagnostic vibration tests, mainly in low-frequency range (up to 100Hz). Measured or monitored objects are components of PWR coolant loops. Subject of attention is their vibration behaviour and their own modal properties. Main task is to detect and prevent an extensive dynamic load with high cyclic fatigue and changes or failures in placing of main loop components. System is capable to cooperate with the diagnostic system for reactor diagnostics and noise analysis. The system is based on :

- hardware of high-tech type
- performed theoretical calculations
- experimental works
- long term experience with vibration diagnostics

5.1 Measuring chains.
- relative vibrations
- absolute vibrations (accelerometers)
- pressure fluctuations of coolant
- neutron noise
- outputs from other diagnostic or measuring system channels

5.2 Hardware and software
Hardware and software is based on RCPMS with some special modules for the vibration monitoring of coolant loops and whole primary circuit :
- computation of FFT and cross-spectra simultaneously with sampling
- module for the extraction of operation shapes of vibration
- module for the animation of vibration modes
- multichannel spectral analysis

5.3 Working regime
- realisation of detailed diagnostic tests under operator control several times during campaign is supposed
- data collection for experimental modal analysis or operation shapes
- automatic data collection for steady-state and for transient regimes in NPP

6. COMMON FEATURES OF SYSTEMS PRODUCED BY VUJE TRNAVA INC.

Delivery of diagnostic systems includes :
- delivery of complete technical documentation
- preparation of projects for installation
- preparation of programmes for pre-operational tests
- personal support of pre-operational testing
- training of personnel
- technical and scientific support after warranty period

Hardware features :
- Permanent possibility for calibration of measurement chains
- Internal source of dry air (HUIMON)
- Internal generator of calibrated signal (LPMS, RCPMS, VMS)
- Special tools (impulse hammer for LPMS)

Signal pre-processing unit
- 16 data bit A/D converters
- digital anti-aliasing filters with 96dB/oct
- parallel processing of 32 input channels on max. sampling frequency 100kHz
- programmable input gains in the range from 1 to 100

Special processor for real-time processing :
- max. 32 input channels sampled in parallel
- real-time Fourier analysis with programmable data windows and full spectrum matrix
- tresholding of input signals on RMS value
- up to 64 multiplexed channels

Software features :
- data evaluation on industrial PC
- multitasking operating system (OS/2, WIN NT)
- graphical windows-oriented user interface
- SQL-type database (GUPTA, SYBASE)
- standard network support
- software protection
- off-line analysis of archived data during the measurement

Qualification of diagnostic systems
- Seismic qualification
- Electromagnetic compatibility
- Enviromental withstanding

6.1 SYSTEMS INSTALLED OR UNDER PREPARATION

	LPMS	HUMON	RCPMS	VMS
Bohunice 1	1992	-	1992	-
Bohunice 2	1992	-	1992	-
Bohunice 3	1994	1996	1994	1994
Bohunice 4	1994	1996	1994	1994
Dukovany 1	1998 *	-	-	-
Dukovany 2	1998 *	-	-	-
Dukovany 3	1998 *	-	-	-
Dukovany 4	1998 *	-	-	-
Mochovce 1	-	1998	1998	-
Mochovce 2	-	1998 *	1998 *	-
Temelin 1	1995 **	-	-	-
Temelin 2	1996 **	-	-	-

(*)   under preparation
(**)   shipped

7. PRACTICAL EXPERIENCES

Feedback information and experience with our first diagnostic systems showed some important results :

System of users.

It is very important to divide users into at least three groups. This division is made through access rights for the operation or modification of user software. Plus our systems are blocked against the non-authorised action by means of the hardware key. This feature divided users into basic groups :

Operator - basic level for diagnostic personnel in NPP. This level is dedicated for basic tasks - printing, collection and sorting information. No important changes are allowed for this basic level.

System operator - advanced level, which enables to control system (start and stop measurement, sensor calibration, setting display and print parameters...)

Administrator - level for advanced personnel in NPP. This level enables the design and implementation of own screens and the extensive re-definition of parameters of monitoring system. This level enables to connect special software tools and watch internal software variables.

Alarms.

It is very important to reduce false alarms in systems. Too many false alarms have influence on trust in system. There are two alarm levels defined in our diagnostic and monitoring systems.

Warning level - is used to increase attention. Here is time for determination of phenomena, which have caused a problem. In many cases personnel is able to distinguish false alarm arising and prevent its occurrence.

Alarm level - is used for alarm indication of system.

Network connection

All systems now are ready to work in network environment. Today software version works with mechanism of "named pipes" from "peer-to-peer" service. This mechanism is supported in OS/2 WARP and Windows NT (Windows 95 partly) operating systems. In network environment some software must run on data acquisition computer and others everywhere on network (LAN).

Data acquisition computer - software modules responsible for data acquisition and data acquisition configuration, service and maintenance modules. Archive process with primary data.

Data display computer - software modules for data presentation, local archivation, printing, etc.

8. SUMMARY

Despite the various physical processes that are specific for each task in the NPP primary circuit, the new generation of diagnostic systems, produced in NPPRI (VUJE) Trnava, Inc., has some common features, which include:

- the orientation on the newest digital technology in data acquisition, conditioning and pre-processing by means of digital signal processors and sophisticated logical arrays;
- the principle of modularity both in hardware as well as in the software development;
- the orientation in software development on the multi-tasking environment (Windows NT, OS/2 operating systems) that is crucial in some applications (e.g., loose part monitoring)

where the measurement must be continuous regardless on the other operations performed by the operator;

- the network support which is the standard requirement nowadays.

We hope that this approach will enable us in the future to be very flexible in the design of new diagnostic tools and systems which will be needed in NPPs.

PERFORMANCE DEMONSTRATION EXPERIENCE FOR REACTOR PRESSURE VESSEL SHELL ULTRASONIC TESTING

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Abstract

The most ultrasonic testing techniques used by many vendors for pressurized water reactor (PWR) examinations were based on American Society of Mechanical Engineers "Boiler and Pressurized Vessel Code" (ASME B&PV Code) Sections XI and V. The Addenda of ASME B&PV Code Section XI, Edition 1989 introduced Appendix VIII - "Performance Demonstration for Ultrasonic Examination Systems". In an effort to increase confidence in performance of ultrasonic testing of the operating nuclear power plants in United States, the ultrasonic testing performance demonstration examination of reactor vessel welds is performed in accordance with Performance Demonstration Initiative (PDI) program which is based on ASME Code Section XI, Appendix VIII requirements. This article provides information regarding extensive qualification preparation works performed prior EPRI guided performance demonstration exam of reactor vessel shell welds accomplished in January 1997 for the scope of Appendix VIII, Supplements IV and VI. Additionally, an overview of the procedures based on requirements of ASME Code Section XI and V in comparison to procedure prepared for Appendix VIII examination is given and discussed. The samples of ultrasonic signals obtained from artificial flaws implanted in vessel material are presented and results of ultrasonic testing are compared to actual flaw sizes.

Introduction

The most ultrasonic testing (UT) techniques used by many vendors for Pressurized Water Reactor (PWR) examinations were based on the **American Society of Mechanical Engineers (ASME) Boiler and Pressure Vessel Code, Sections XI and V**. The ASME Code editions up to and including edition 1986 specified the following requirements for Ultrasonic Testing (UT):

> ➤ personnel qualifications, experience, visual acuity and ability to differentiate colors used in the method
> ➤ system calibration: calibration block, instrument performances, transducer's refracted angles (0, 45, 60 deg.)
> ➤ examination performance (4 directions if applicable)
> ➤ recording criteria (amplitude based)
> ➤ flaw sizing (amplitude based)
> ➤ flaw analysis criteria (acceptance standards)

In order to improve safety of the components by improving the UT technique's detection capabilities, the UT requirements have been modified by obligations of United States Nuclear Regulatory Commission **Regulatory Guide (RG) 1.150** Revision 1 issued in 1982.

The RG 1.150 introduced new, additional prerequisites to the ASME Code requirements:

> more conservative flaw sizing in the inner 25% of the vessel wall volume (amplitude based)
> scanning for near surface flaws (application of additional search units)

The 1989 Addenda of the ASME Section XI introduced Appendix VIII, "Performance Demonstration for Ultrasonic Examination Systems" in an effort to increase confidence in the performance of UT of the operating nuclear power plants. By the ASME Code, Appendix VIII the reactor vessel shell performance demonstration qualification is divided in two supplements: Supplement 4 which deals with inner 25% of the vessel wall, and Supplement 6 which deals with vessel wall thickness from 25% to full thickness of the component.
This appendix provides the requirements for satisfying of the following:
> qualification of personnel, equipment and examination procedures through the use of flawed test specimens and blind tests in order to demonstrate capability of flaw detection and sizing
> the acceptable false call rate
> tolerance of flaw under-sizing and over-sizing

Qualification Preparation Works

During the year 1992, the first Inetec-WesDyne (subsidiary of Westinghouse) works regarding the organization of the Appendix VIII qualification has been undertaken. Beside all other necessary activities to be performed, the qualification strategy has been directed to:
> determination of the equipment to be used
> developing of the examination procedure
The criteria of defining equipment to be used for qualification have been based on the following facts:
> acquired experience in RPV examinations
> quality of acquisition system regarding the data quality obtained
> system reliability
> proposed scanning speed (6 inch / sec. – 150 mm/sec)
> instrument possibilities to minimize noise level (data averaging)
> possibility of automated flaw detection and sizing
Beside challenging flaw detection and sizing criteria, the examination procedure introduced the following goals:
> minimizing the time needed for system calibration regardless of :
  □ RPV material chemical composition
  □ RPV material heat treatment
  □ RPV wall thickness
> minimizing "on vessel" time
> simple and fast failed component substitution
> application of automated flaw sizing

Determination of the Equipment to be Used for Appendix VIII Qualification

The equipment used for RPV examinations at that time has been evaluated for conformance with established requirements. It has been found that:

> ➢ no major equipment changes are needed to be performed for qualification purposes
> ➢ the number of cable connectors and cable length have to be changed due to later possibility of pulser/receiver board set up on the scanner in close proximity to transducer
> ➢ minor acquisition software changes need to be performed in order to speed up the system characterization

The above prerequisites have been easy to perform. The fast Fourier transformation included up to that time in the analysis software has been added to an acquisition part of the software so the system characterization is provided by a "click" of the button.

The Procedure Development

The procedure development process was much more complicated:

> ➢ while older procedures simply incorporates ASME Code examination rules and in accordance to them prescribe examination requirements, procedure to be prepared for Appendix VIII examinations does not have any prescribed guidance or directions.
> ➢ for Appendix VIII examinations ASME Code gives only the requirements regarding system tolerance and tolerance of obtained results.
> ➢ severe detection and sizing criteria required special attention and considerations during preparation of the procedure. The most parts of the procedure needed to be verified and experimentally proven. For that reason, procedure development process has been performed on a special way: the most steps written in the procedure have been verified by practical trials. Examples of artificial flaw and real crack tip diffracted signal measurements with and their actual dimensions are presented on figure 1 and figure 2.

After an extensive research and experimental works have been performed, the final version of the procedure has been produced. Generally, procedure define:

> ➢ type of material and minimal diameter of the vessel for which procedure is applicable
> ➢ applicable thickness range
> ➢ scanning requirements
> ➢ side from which examination has to be performed
> ➢ couplant
> ➢ essential equipment together with required instrument performance documentation and replacement equipment (system characterization - transducers, pulser/receivers, cables)
> ➢ requirements for personnel (level of previous qualification regarding to SNT-TC-1A and ASME Code Section XI)
> ➢ examination sensitivity adjustment
> ➢ examination requirements - determination of the essential variables: sampling frequency, Peak Detect and Hold (PDH), system delay, buffer length, A-scan data averaging, Pulse Repetition Frequency (PRF), increment value, scanning speed, pulser and receiver settings, channel triggering sequence, criteria for accepting of acquired data, etc.
> ➢ analysis requirements:

> ❑ verifying of the sensitivity level,
> ❑ resolution of flaw signals and non relevant signals such as geometry reflections, beam redirected signals, mode converted signals,
> ❑ criteria for flaw length measurements (for each type of transducer),
> ❑ criteria for flaw through-wall size measurements (tip diffraction),
> ❑ recording requirements: data file name, software revision, weld ID, flaw length, through-wall extent of the flaw, flaw ligament, name and signature of examiner

➢ examination records:
> ❑ examination procedure,
> ❑ system characterization,
> ❑ sensitivity calibration,
> ❑ identification of examined areas and area restricted from examination due to the access limitations
> ❑ indications recorded,
> ❑ personnel certifications,
> ❑ dates and times of examination,
> ❑ reference block drawing,
> ❑ equipment identification and performance documentation

Conclusion

Based on knowledge acquired during preparation of qualification, successful Appendix VIII qualification exam passed in January 1997 and in comparison with experience acquired during extensive examinations of the reactor pressure vessels by use of ASME Code based procedures, the following issues may be noted:

➢ the ASME Code based procedures, which includes requirements of RG 1.150 would not be capable of passing the qualification test. This may be explained as follows:
> ❑ sensitivity of the ASME based procedures may be assumed as adequate
> ❑ the detection part of qualification might be passed only if skilled analyst would perform data analysis
> ❑ ASME Code amplitude based sizing criteria have shown inconsistent measurements (in some cases flaws are undersized and in other cases flaws are oversized)

➢ automated flaw sizing (length and through-wall) did not show acceptable results for qualification

➢ increasing of a scanning speed to more than 6 inch per second does not influence the quality of ultrasonic data

➢ identification of TIP DIFFRACTED signals provide enough precise measuring technique for flaw length and through-wall sizing for both, Supplement 4 and Supplement 6 examinations

➢ system qualified in accordance with Appendix VIII provides application of less conservative approach to analytical flaw evaluation

Technical Committee Meeting on "Diagnostic Systems in Nuclear Power Plants"
June 22 – 24, 1998
Istambul, TURKEY

Figure 1. EDM notch response, tip diffraction measurement and
actual through-wall dimension

Technical Committee Meeting on "Diagnostic Systems in Nuclear Power Plants"
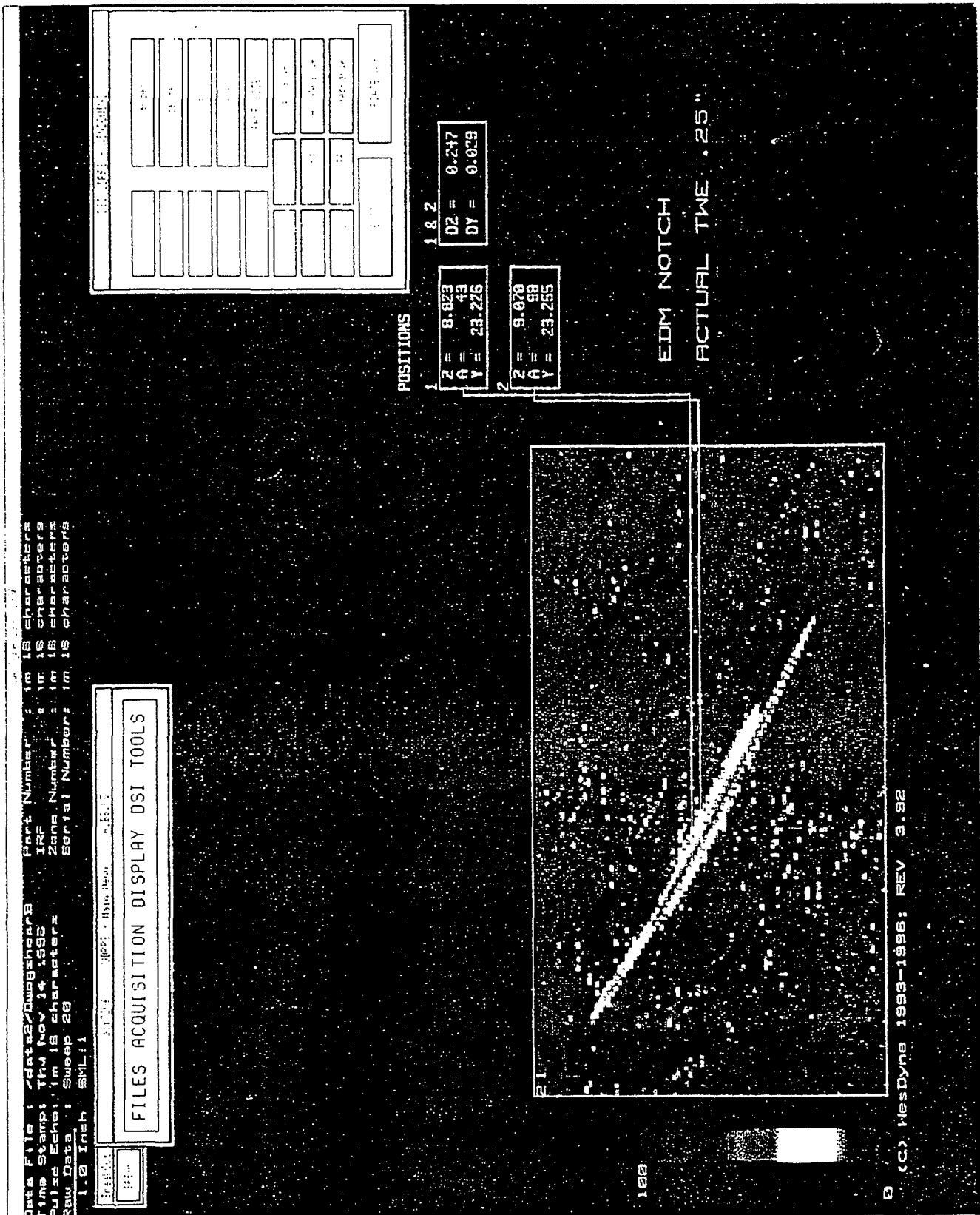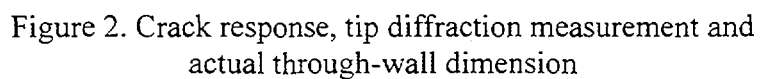June 22 – 24, 1998
Istambul, TURKEY

Figure 2. Crack response, tip diffraction measurement and
actual through-wall dimension

XA9949672

DIAGNOSTIC SYSTEM FOR PROCESS CONTROL AT NPP DUKOVANY LOAD FOLLOW

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Abstract

The NPP Dukovany is being operated in the frequency control since 1996. In last year a project for the plant load follow has been developed. One part of the project is to install a diagnostic system for process control. At present the main control loops of the plant control system are regular tested after unit refuelling only. The functionality and control system parameter adjusting is tested by certificated procedures. This state is unsuitable in view of the plan load follow operation. The relevant operational modes are based on minimisation of influence on plant component life time and on achievement of planned unit parameters. Therefore it is necessary to provide testing of main control system parts in shorter time period. Mainly at time when the unit is really in load follow operation. The paper describes the diagnostic system for process control which will be at NPP Dukovany implemented. The principal of the system will be evaluation of real and expected changes of technological variables. The system utilises thermohydraulical relation among main technological variables and relation among controlled and manipulated variables. Outputs of the system will be used to operational staff support at the plant operation. It enables:

- determination of control system state
- estimation and check of future control system state
- early indication of the deviation of process from normal conditions
- check of efficiency of operational staff intervention into plant control

The system gives the plant operator new information for the plant process control. Simultaneously the coupling of new system outputs on existing signalisation is solved.

1. INTRODUCTION

The NPP Dukovany is being operated in (primary) frequency control since 1996. Modification enabling the plant operation at extreme frequency deviations were implemented in 1996-1997. In last time the successful tests were performed which verified the developed solution which makes possible operation of NPP Dukovany units in secondary frequency control (power changes in range 100-90% P_{nom}) and in tertiary control (power changes in 100-50% P_{nom} weekendly in limited number of cycles per year).

The developed solution is a result of evaluation of load follow operation on the plant live time, on extent of necessary plant system modifications (I&C especially), on plant safety and on plant economy. The tests performed on the second unit confirmed the expected minimal influence of load follow operation on the plant system life time. On basis of this work a project was developed which defines modification in plant technological and in I&C systems and improvement in plant information and diagnostic system.

2. PRESENT STATE

The primary frequency control is operated within the range ±2,5% P_{nom} at average power level 97-97,5% P_{nom} at frequency deviation ±87,5% mHz. The change of turbine power is performed within time of 30 s after frequency change.

Introduction of primary frequency control meant implementation of following modifications in plant systems:

1) reactor and turbine power control (control of reactor power is provided by the self-power control)

2) completitions of operational procedures and of plant information system

3) development of computerised operator support (enabling easy malfunction distinguish)

4) development of procedures for automatic documentation elaboration (for the State Office for Nuclear Safety etc.)

The system of secondary frequency control in Czech electric network at present does not include NPP Dukovany because project of the NPP does not involve this control. The plant has no link with central controller (located in central dispatching) which performs evaluation of the power system balance.

The NPP Dukovany is operating in load diagram of constant steam pressure (at the whole unit power range). As far influence of load follow operation on primary circuit components life time this diagram is not suitable.

The reactor power control is performed by the sixth control roads group which has relatively stronght influence on reactivity. This makes not easy effective reactor power control.

Also the turbine has rather small reserve in control valves position which limits the achievable turbine power increase.

The tertiary power control can be at present provided at NPP Dukovany manually with minimal diagnostics with unpleasant influence into unit economy (accuracy of boron concentration changes etc.). The load diagram of constant steam pressure used in plant operation excludes operation in tertiary control in power range 100÷(75-50)% P_{nom} without boron concentration changes.

In accordance with the project the NPP Dukovany could not be operated at extreme deviated frequency. Measures enabling this operation were in the plant implemented in last years (1996-97).

3. ASSUMED POWER RANGES FOR FREQUENCY AND POWER CONTROL

Power range for primary and secondary control (without limitation number of power cycle)

Type of control	Control range of the NPP	
	P_{min}	P_{max}
primary control ±2,5% P_{max}	99	101,5%
secondary control	90	100%
primary and secondary control ±2,5%	94	99%

Power range for tertiary control

Power range	limiting boundaries
100-75% P_{nom}	without boron concentration change
100-(75-50)% P_{nom}	with partial boron concentration change at decreases power level

      The tertiary power control operation is assumed for the weekend power control in very limited number of cycles only which enables the Technical specifications.

      Simultaneous unit operation in secondary control, secondary and primary control and in tertiary control in not acceptable.

      Operation in secondary and tertiary control is planned so that the present length of fuel cycle will be not changed.

4. ASSUMED HARDWARE MODIFICATIONS IN UNIT SYSTEMS NECESSARY FOR FREQUENCY AND POWER CONTROL

      The following unit system modifications with be performed:

− establishment of new load diagram (increased steam pressure at decreased reactor power)

− development of criteria (or limits) for implementation of the unit into load follow operation

− modifications in I&C instrumentation
  - turbine power and turbine by pass controller
  - reactor power controller
  - reactor power limitation controller
  - new steam flow measurement (behind the steam generator and ahead of turbine)

− implementation of new modules in I&C
  - organiser of secondary control (assures the link between the terminal installed in the central control dispatching and the turbogenerator, establishes boundary conditions for the plant operation in load follow

- block adjusting the steam pressure flow set point (for the turbine and reactor controller)

- modifications of the plant technological system enabling
  - adjusting and check of new modules after refuelling before the start up
  - running check of new modules after refuelling
  - statistic evaluation of technological variables changes at load follow operation
  - evaluation of load follow on selected component degradation
  - elaboration of records documenting new operational mode for the regulatory body

- modification of diagnostic system
  - diagnostics of material degradation (described in chapter No. 5)
  - diagnostics of correct control system function (described in chapter No. 6)

- development of modifications in operational and project documentation

5. DIAGNOSIS OF TECHNOLOGICAL COMPONENT LIFE TIME AT UNIT LOAD FOLLOW OPERATION

Introduction of NPP Dukovany in to load follow means the increase of transients with rather strong change of reactor and turbine power. This contributes to:

a) increase of number of controller actions (influence on reliability)

b) increase of failures of control road and control valves

c) decrease of life time by low frequency fatigue

d) increase of transient which could lead to the Technical Specification violation

e) increase of probability of incidents

To reduce the negative influence of load follow operation on technological systems, the unit load diagram of unconstant steam pressure will be applied. The load diagram will be characterised as follows:

- the steam pressure increase with decreasing power will be done with respect of transients (the steam generator safety valves will be not readjusted)

- the decrease of thermic turbine efficiency will be compensated by the steam pressure increase

- the inlet coolant temperature to the reactor will be in the power range 100-50% P_{nom} almost constant

- lower compensation of reactivity at power changes will be achieved (decrease of control rod position movements)

- decrease of primary circuits controllers inputs into process

The following diagnostics which aims to reduce the negative influence of load follow (see items a, b, c, d) will be implement at the NPP Dukovany:

5.1. On-line registration (filling) operational modes connected with primary, secondary and tertiary control and with „island operation"

The present way of registration of operational modes is performed from point of view:

a) check of the Technical specifications at plant operation

b) documentation development and additional analysis of transients

It is planned to extend this way to:

a) on-line SW - processing of selected analogy technological variables

b) calculation of unmesurable variables (boundaries and limits of the plant regarding to the load follow)

c) estimation of selected values of variables and substitution of wrong values based on informational redundancy

5.2 Monitoring of selected types of failures and material degradation of plant components

The material degradation monitoring of main plant components is at present performed by manual registrating of unit transients number and by its comparing with allowed numbers. Computation of material degradation is then performed consequently.

Main task of monitoring of load follow operational conditions is to distinguish individual unit states and transients from load follow transients (primary, secondary and tertiary control).

The following technological equipments will be monitored:

− reactor vessel (surfice of the vessel in axial direction, cold and hot part throat of the vessel)

− primary circuit (inlets and outlets of the primary circuits)

− steam generator (feed water inlet throat, bottom part of steam generator vessel)

Measured values will be stored and off-line evaluated by diagnostic system DIALIFE. This system is at present under development in Czech republic (Institute for Applied Mechanics, Brno). This system provides temperature and tension analyses and from achieved results makes assessment of technological components degradation.

The system will be completed in phase of load follow project implementation by following functions:

– data estimation. It will assure, that for the component material degradation only estimated data (checked to be correct) will be used. The method based on mutual physical links between individual values will be applied

– correct operational modes classification. It will provide classification of transients to be able distiquish and select transients caused by usual failures, by manual control and transients caused by unit operation in primary, secondary or tertiary control

– automatic reports development for the documentation (for ownerof the plant, for the regulatory body)

Structure of DIALIFE implementation into the diagnostic system is displayed on Fig. 1. The three abovementioned functiones remove influence of plant personnel on results of the evaluation and enable automation of the work. The estimation of data measured by 800 temperature sensors and operational modes classification will be performed by unamtignous defined rules. Data processing will be also more convenient.

6. DIAGNOSTIC OF MAIN CONTROL LOOPS CORRECT FUNCTION

6.1 Requirements to diagnostics of main control loops

Implementation of control loops control results from following requirements:

– quality of frequency and unit power control must be done so that electrical power grid requirements are achieved

– the unit transients must be done so that following requirements are fulfilled
  • real material degradation of main technological component corresponds to the project analyses
  • real boron concentration change at power transients corresponds to the project calculation
  • short term increase of the reactor power over nominal power is achieved by combination of road control and self power control without unexpected switch of the reactor controller in to other operational modes

The check of the control system which can fulfil these requirements will be of two kinds:

– check of the system at shut down unit conditions (unit is not operating), i.e. check of signals and their transmition, adjusting of important values of the control system. This check will assure achievement of important assumptions for corret function of the control system at real plant transients

– check at operating unit, i.e. check that real changes of technological variables and movements of actuators are as expected by project analyses.

The check of control system at operating unit is performed at changing unit condition (change of unit dynamics at burn up process, influence of small mulfunctions, ageing of control system components, etc.).

6.2 Diagnostics at not operating unit conditions

The diagnostics will concern to:

- unit operation at secondary control, simultaneous secondary and primary control and tertiary control

- unit operation at extreme frequency deviations (unit transient into „island operation", operation in the „island" and connection of the unit to the restored power network.

The check will be performed at refuelling and before unit start up. The tests of systems, procedures of their implementation, methods of evaluation are prepared to be developed.

As an example, importance of this kind of diagnostics confirms an analysis of turbine switch tests performed at unit No. 2 in 1996 and in 1997. At these tests the turbine power time behaviour was the same but the turbine speed exceed was different. According to the turbine manufacture it was caused by degradation of turbine back clap valve.

6.3 Diagnostics at operating unit conditions

From requirements to I&C system modification related to the unit load follow operation the following control system equipment will be checked

- block of steam pressure setting (new block which creates the steam pressure deviation according to the new implemented load diagram for individual controllers

- turbine controller. The controller assess fulfilment of requirements to the power unit changes

- pressurise pressure water level controller. The role of the controller is very important because it can minimise temperature changes in bottom part of the component and minimise the material degradation

- primary pressure controllers. The controllers can minimise primary pressure deviations and influence the pressurise pressure degradation

- water niveau control in the steam generator. The controller must assure stable operating conditions for the steam generator at the unit power control

- reactor power control. Reactor power control will be performed by combination of road control and by self-power control

- secondary unit control organiser. The block will calculate the boundary conditions for secondary, primary and secondary and for tertiary control

6.4 Method of diagnostics of the control system correct function

The method of the diagnostics of selected controllers or modules will be based on comparing of expected state of technological variables with real (measured) state. The expected state of technological variable will be stated by calculation (mathematical simulation, etc.).
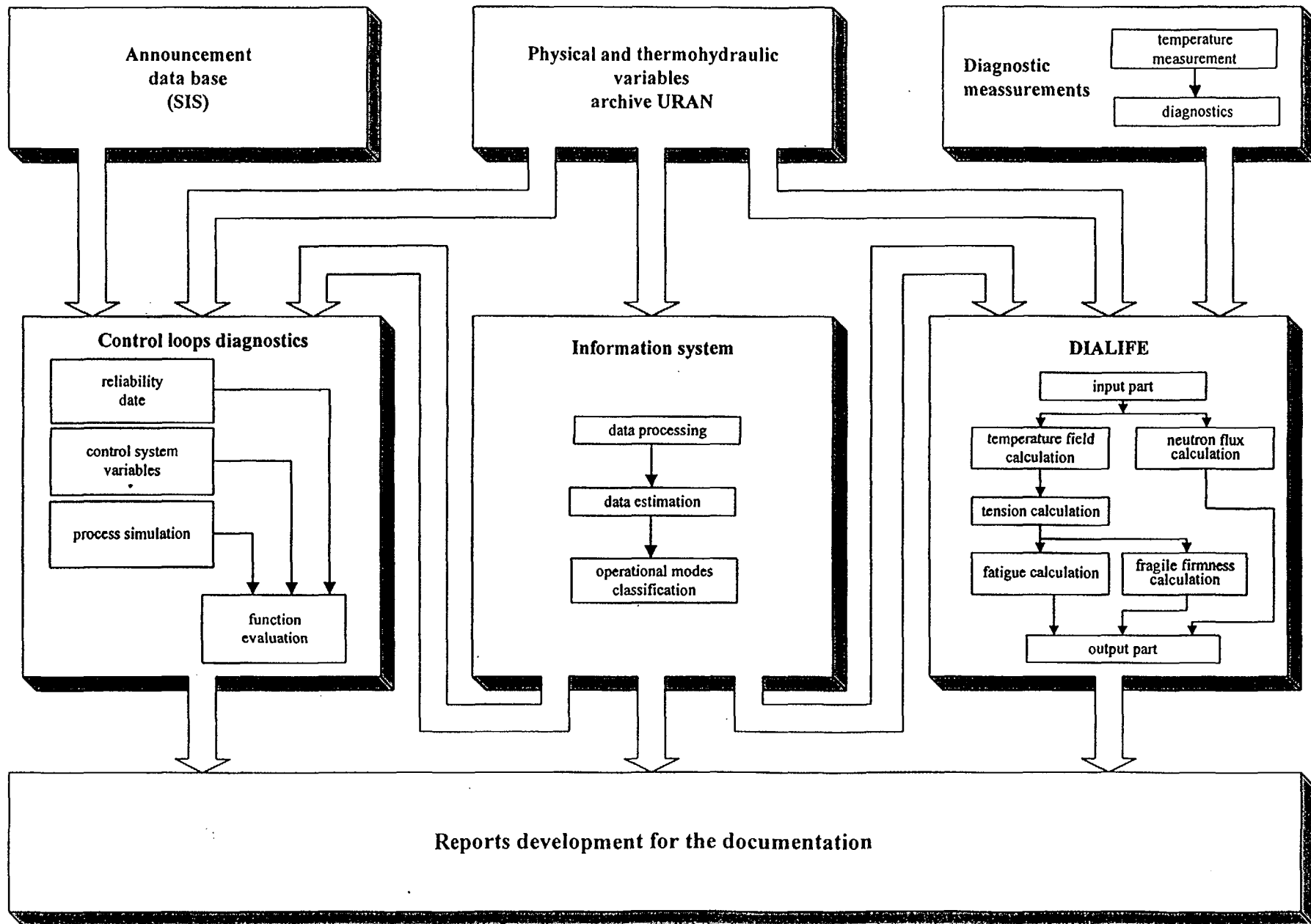
The input signals for the diagnostic system will be taken from technological information system after their estimation on quality.

Structure of the control loops diagnostic is displayed on Fig. 1.

7. CONCLUSION

The establishment of NPP Dukovany units in frequency and power control leads to new requirements on increase of the plant diagnosis level, i.e. introduction of new functions and outputs which the present system does not fulfil. Further there are new demands on higher quality and correctness of diagnostic system outputs (information) for the operator support. Simultaneously it is required an objective evaluation of the load follow operation on plant systems (degradation, life time etc.).

Fig 1 Structure of proposed NPP Dukovany Diagnostic system

Announcement
data base
(SIS)

Physical and thermohydraulic
variables
archive URAN

Diagnostic
meassurements

temperature
measurement

diagnostics

Control loops diagnostics

reliability
date

control system
variables

process simulation

function
evaluation

Information system

data processing

data estimation

operational modes
classification

DIALIFE

input part

temperature field
calculation

neutron flux
calculation

tension calculation

fatigue calculation

fragile firmness
calculation

output part

Reports development for the documentation

SESSION 2:

EXPERIENCE WITH MONITORING AND DIAGNOSIS SYSTEMS IN NPP (2)

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

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Abstract

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

1. INTRODUCTION

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

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

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

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

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

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

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

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

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

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

2.1 BORSSELE PRIMARY SYSTEM INTEGRITY AND SENSOR TESTING MEASUREMENTS

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

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

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

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

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

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

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

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

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

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

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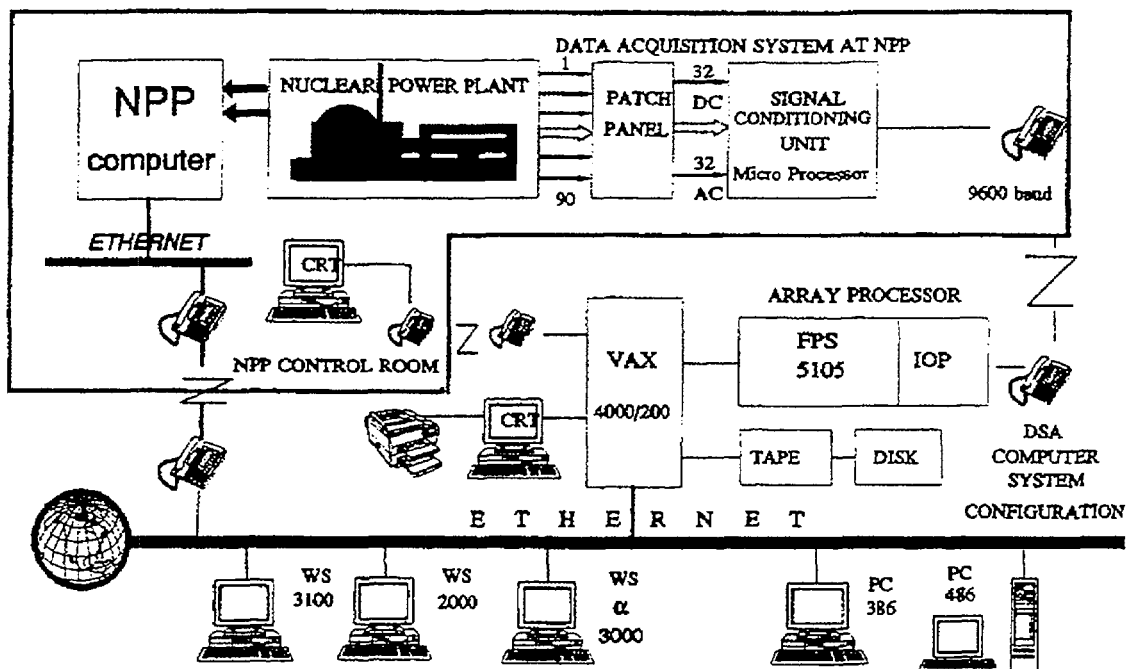

Fig.1: *Real-time NPP (Borssele) monitoring overview..*

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

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

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

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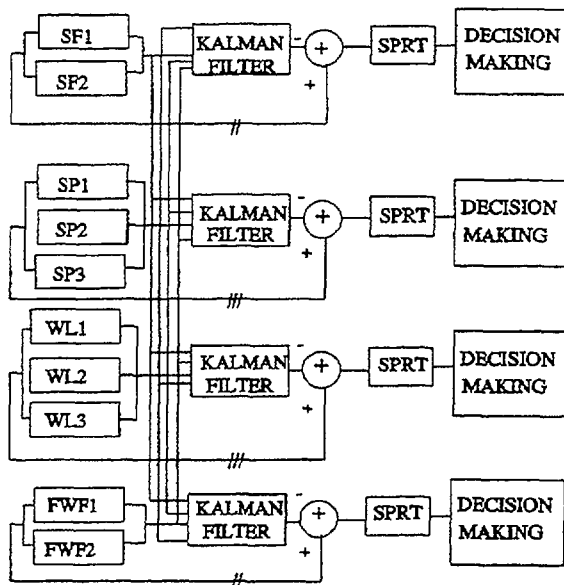

Fig.2: *Block scheme of the sensor failure detection for steam generator sensors [12].*

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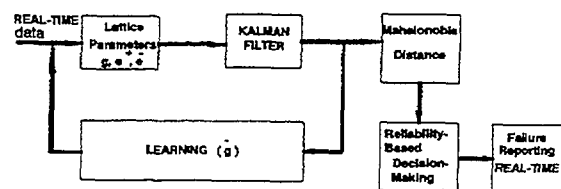
model parameters are assessed for Borssele NPP and the sensor failure detection method for dynamic system presented for steam generator water level, pressure, feed water flow and pressurizer pressure, water level [11,12] and incore signals [13]. Failure detection is based on monitoring of the residuals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

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

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

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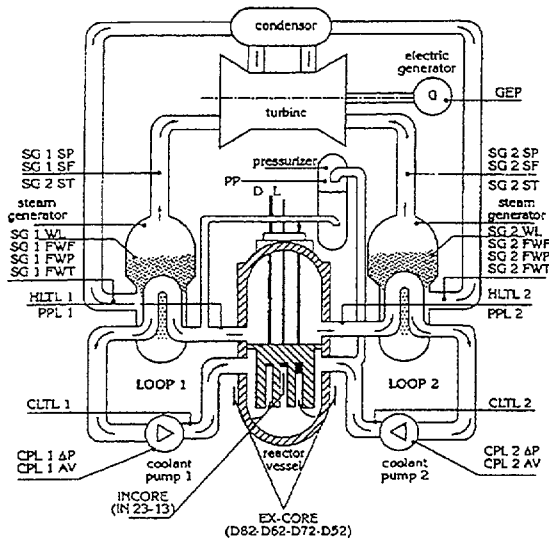

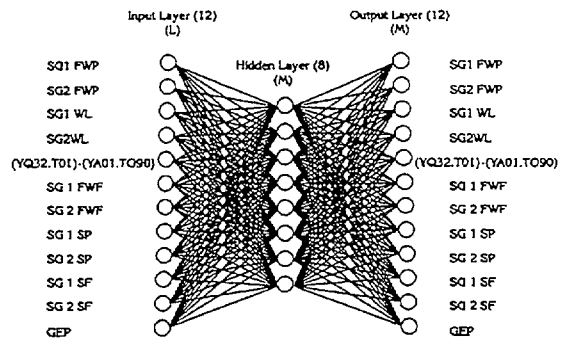Fig.4: *Schematics of the Borssele NPP and measured signals.*

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

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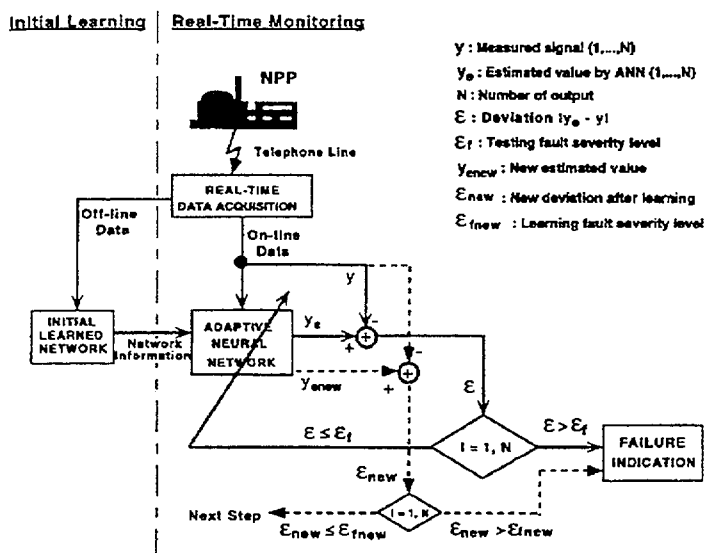

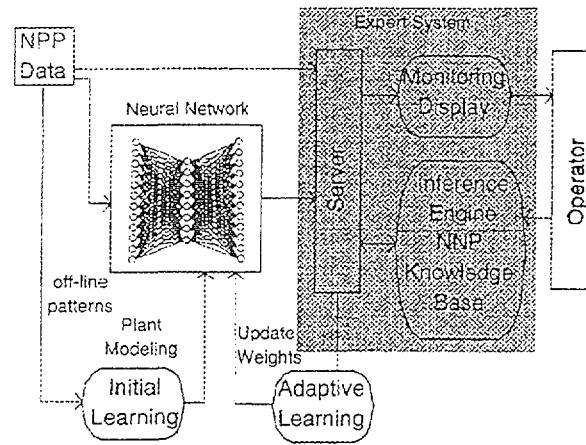Fig.6: *Block diagram of adaptive neural network.*

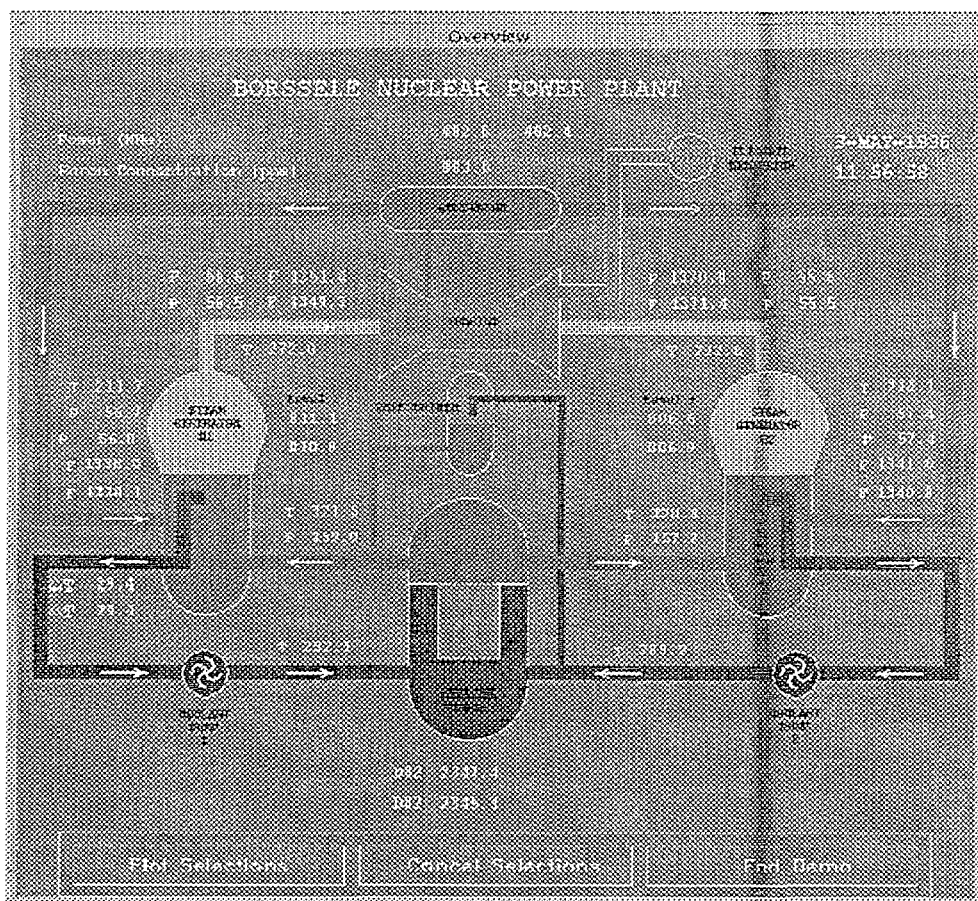Fig.7: *Diagram of Hybrid AI Systems [24].*

Fig.8: *Monitoring display by real-time neural network; Measured and NN estimated (light) values.*
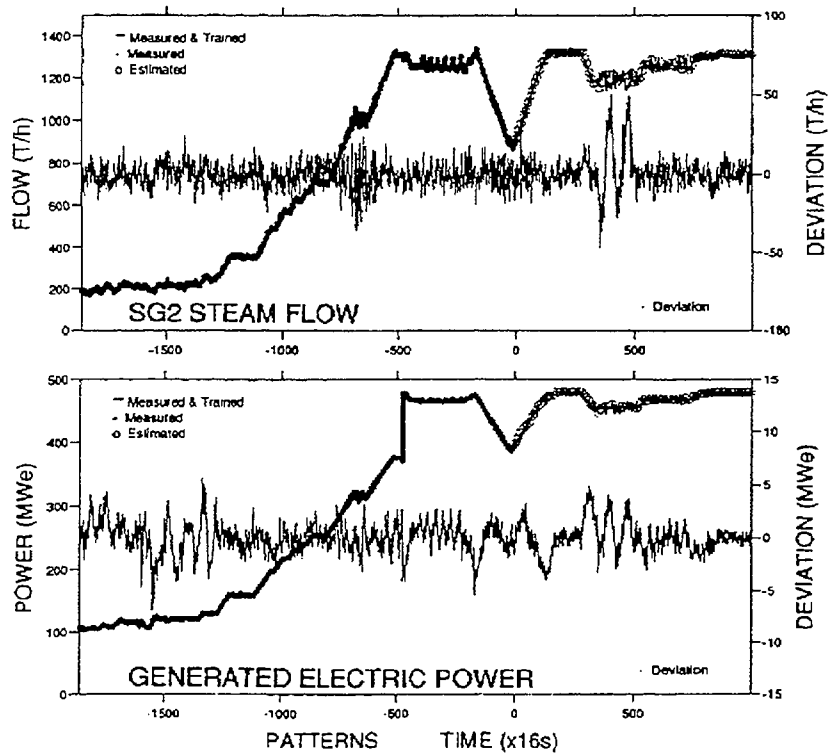
Fig.9: Monitored steam flow and generated electric power by
neural network. The network was trained using the data
presented before time equal zero. [25].
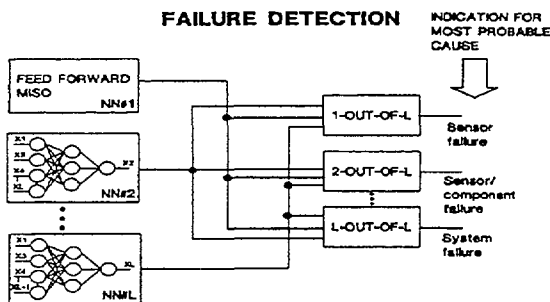
Fig.10: The MISO structure and failure
detection structure [26].

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

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

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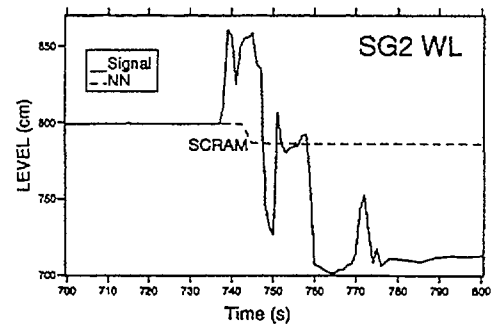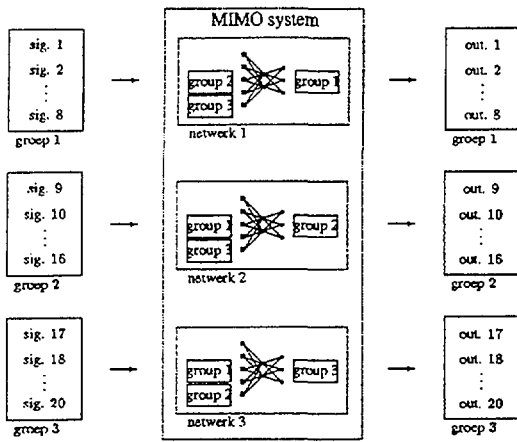

Fig.12:*Scheme of MIMO for monitoring a system with 20 sensors in 3 groups. The first and second groups 8 sensors (in SG1 and SG2) and the third group has 4 sensors (reactor core) [29].*
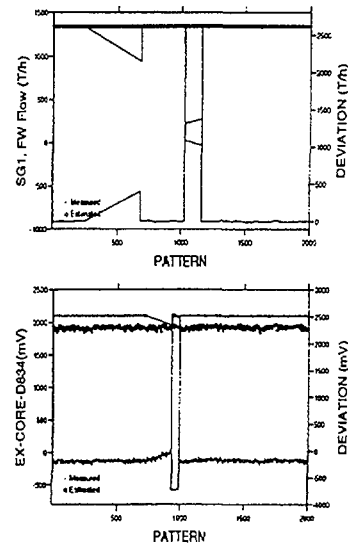

Fig.13:*Results of test with MIMO system with 20 signals in group 3 and 8 neuron in the second layer. Two different failures identified SG1, FW Flow signal(above) with two failures and ex-core neutron detector sensor signal (below) [29].*

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

2.3 HARDWARE/SOFTWARE SYSTEMS FOR SIGNAL PROCESSING AND PROCESS MONITORING

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

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

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

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

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

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

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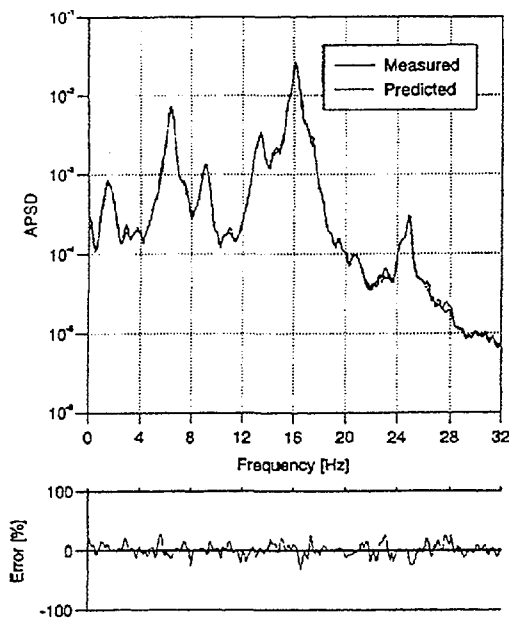
Fig.14:*Real-time neural network monitoring for spectral pattern recognition for primary pressure signals with error indication [35].*
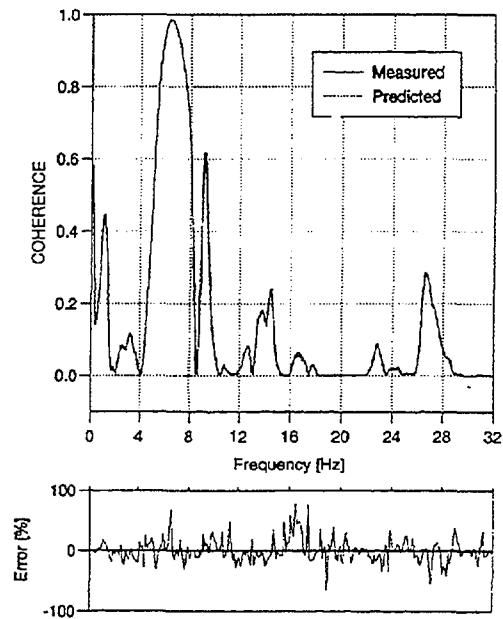
Fig.15:*Real-time neural network monitoring for coherence between primary pressure signal 1 and 2 with the error indication between measured and predicted signals.*

3. DODEWAARD NUCLER POWER PLANT MONITORING AND DIAGNOSTICS

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

3.1. BOILING WATER REACTOR NOISE AND STABILITY MEASUREMENTS

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

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

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

3.2. DEVELOPMENT OF ANOMALY DETECTION TECHNIQUES

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

The performance of an anomaly-detection method has been studied by three detection parameters, namely: the false alarm probability (FAP), the alarm failure probability (AFP) and average time to alarm (ATA). These rates can be determined from the probabilities. The important difference between the SPRT and the former methods is that a decision about the state of the signal is not taken every time step of the signal. Moreover, the number of time steps between two decisions is not constant. For optimization of the anomaly detection method, the false alarm rate (FAR) should be as low as possible and the average time to alarm (ATA) as short as possible. Study showed that the SPRT method gives the fastest response to a change in standard deviation of the residual noise for given false alarm rate (FAR).
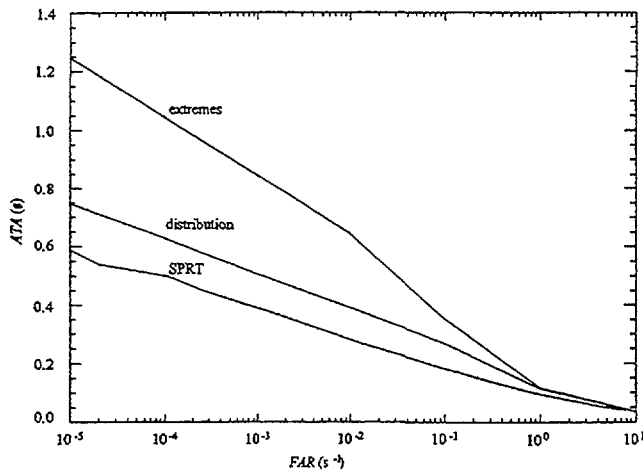
Fig.16: Comparison of the average time to alarm (ATA) for the three anomaly detection methods as a function of the false alarm rate (FAR) ($f_c = 100$ Hz; anomaly: 50% increase in standard deviation) [44].

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

Fig.17:*Autocorrelation function (ACF) of the output signal of a second-order system fed with white noise (upper graph) and the Dodewaard neutron noise (graph below)* [44].

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

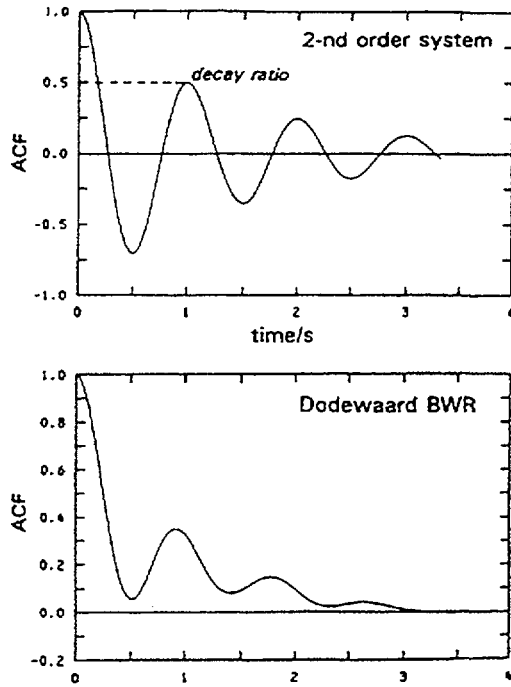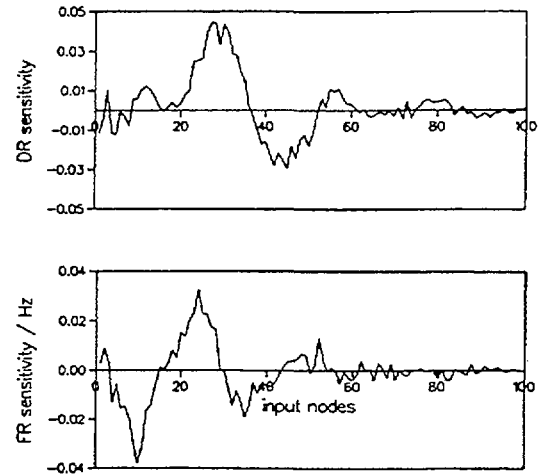In the neural network topology auto associative network with three layers was used. In the first layer the ACF of 60 time lags as a number of input node 60 is filled, in the hidden layer 30 nodes are used and at the output layer DR and resonance frequency are estimated. Study of the sensitivity analysis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

4. CONCLUSIONS

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

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

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

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

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

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

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

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

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

References:

[1]   DEN BOER J,., Plant Lifetime Management and Extenuation, Proceedings of PLIM & PLEX'95, Nice, France, Nuclear Engineering International and French and the American Nuclear Society, ISBN 0-617—0079-6, (1995).

[2]   TÜRKCAN E., DRAGT J.B., Borssele PWR Noise Measurements, Analysis and Interpretation, (SMORN-II) Progress in Nuclear Energy, Vol. 1, Nr. 2-4, pp. 293-306, (1977).

[3]   TÜRKCAN E., Review of Borssele PWR Noise Experiments, Analysis and Interpretation, (SMORN-III) Progress in Nuclear Energy, Vol. 9, pp.437-452, Arnhem (1982).

[4]   TÜRKCAN E., OGUMA, R. Improved Noise Analysis Methods for on-line determination of incore instrumentation and power reactor parameters, Proc. of a Specialists' Meeting on In-Core Instrumentation and Reactor Assessment, Frederikstad Norway 10-13 Oct. 1983, OECD, (1984).

[5]   OGUMA, R., TÜRKCAN E., Applications of an Improved Multivariable Noise Analysis Method to Investigation of PWR Noise: Signal Transmission Path Analysis. (SMORN-IV), Progress in Nuclear Energy, Vol.15, pp. 863-873, (1985).

[6]   TÜRKCAN, ECN Petten's On-Line Monitoring of NPP via Noise Analysis, Nuclear Europe, No. 6/'86, p.39.

[7]   TÜRKCAN E., QUADVLIET W.H..J., PEETERS T.T.J.M., VERHOEF J.P., Operational Experiences on the Borssele NPP Computer Based Surveillance ad Diagnostic System On-Line, (SMORN-VI), A Symposium on Nuclear Reactor Surveillance and Diagnostics, May 19-24, 1991, Gatlinburg, TN, USA. p. 3, (1991).

[8]   CIFTCIOGLU Ö., TÜRKCAN E., Sequential Decision Reliability Concept and Failure Rate Assessment: Application to Nuclear Power Plant Surveillance Instrumentation, IAEA Specialists' Meeting on Analysis and Experience in Control and Instrumentation as a Decision Tool, 16-19 October 1990, The Netherlands.

[9]   CIFTCIOGLU Ö., TÜRKCAN E., Failure detection By Adaptive Lattice Modelling Using Kalman Filtering Methodology: Application to NPP, (SMORN-VI), A Symposium on Nuclear Reactor Surveillance and Diagnostics, May 19-24, 1991, Gatlinburg, TN, USA. p.30, (1991).

[10]   PEETERS T.T.J.M., CIFTCIOGLU Ö., TÜRKCAN E., An Innovation-Based Method for DC Signal Failure Detection: Application to NPP, (SMORN-VI), A Symposium on Nuclear Reactor Surveillance and Diagnostics, May 19-24, 1991, Gatlinburg,TN, USA. p. 65 (1991).

[11]   TÜRKCAN E., CIFTCIOGLU Ö., Sensor Failure Detection in Dynamic Systems by Kalman Filtering Methodology, Dynamics and Control in Nuclear Power Stations, BNES, (Ed) M.H. Butterford, pp. 131-140, (1991).

[12]   CIFTCIOGLU Ö., TÜRKCAN E., Real-Time Sensor Failure Detection By Dynamical Modeling of a PWR Plant, 8th Power Plant Dynamics, Control and Testing Symposium, May 27-29, Knoxville, TN, USA, p.34 (1992).

[13]   CIFTCIOGLU Ö., TÜRKCAN E., Studies on Signal Analysis and Sensor Surveillance for In-Core Signals in NPP, In-Core Instrumentation and Reactor Core Assessment, Pittsburgh, Oct. 1-4, pp.131-143, (1991).

[14]   CIFTCIOGLU Ö., TÜRKCAN E., SEKER S., Failure Detection Studies by Layered Neural Network, ECN-RX—91-044, The Netherlands, (June 1991).

[15]   ERYÜREK E., TÜRKCAN E., Neural Networks for Sensor Validation and Plant-wide Monitoring, Nuclear Europe Worldscan No.1-2, Jan./Feb. 1992, pp. 72-74.

[16]   ERYÜREK E., UPADHYAYA B.R., CIFTCIOGLU Ö., TÜRKCAN E., Neural Networks for Operational Transients Recognition an Diagnostics in Nuclear power plants, 8th Power Plant Dynamics, Control and Testing Symposium, May 27-29, Knoxville, TN, USA, p. 58 (1992).

[17]   TÜRKCAN E., CIFTCIOGLU Ö., ERYÜREK E., UPADHYAYA B.R., On-Line Plant Monitoring Wide Band Operation Monitoring Using Neural Networks, 8th Power Plant Dynamics, Control and Testing Symposium, May 27-29, Knoxville, TN, USA,, p. 54 (1992).

[18]   CIFTCIOGLU Ö., TÜRKCAN E., Enhancement of Verification and Validation for Nuclear Reactors Through Artificial Intelligence, IAEA-TECDOC-762, Proceedings of a Specialists Meeting held in Moscow, Russian Federation, 17-21 May 1993, pp. 271-279.

[19]   NABESHIMA K., TÜRKCAN E., CIFTCIOGLU Ö., ICANN'93, S. Gielen and B. Kappen (eds.), Springer Verlag, (1993), pp 863-866.

[20]   TÜRKCAN E., CIFTCIOGLU Ö., NABESHIMA K., Neural Networks for Real-Time NPP Monitoring, Nuclear Europe Worldscan No. 11/12, p. 31 (1993).

[21]   TÜRKCAN E., CIFTCIOGLU Ö., On-Line Surveillance System for Borssele NPP Monitoring and Diagnostics, PLEX-93, Zurich, 29 Nov-1 Dec., pp.408-420, (1993).

[22]   CIFTCIOGLU Ö., TÜRKCAN E., Neural Network Training By Parameter Optimization Approach, ICANN'93, S. Gielen and B. Kappen (eds.), Springer Verlag, (1993), pp.871.

[23]   CIFTCIOGLU Ö., TÜRKCAN E., Adaptive Training of Feed Forward Neural Networks By Kalman Filtering, ECN Report ECN-CX--95-001, (1995).

[24]   NABESHIMA K., SUZUKI K., TÜRKCAN E., Real-Time NPP Monitoring with Hybrid Artificial Intelligence System, Proceedings of 9th Power Plant Dynamics, Control and Testing Symposium, May 24-26,1995, pp. 51, Knoxville, TN, USA, (1995).

[25]   NABESHIMA K., SUZUDO T., SUZUKI K., TÜRKCAN E., Real-Time Power Plant Monitoring with Neural Network, Journal of Nuclear Science and Technology, Vol. 35, No. 2, pp.93~100, (February 1998).

[26]   CIFTCIOGLU Ö., TÜRKCAN E., Data Fusion and sensor Management for Nuclear Power Plant Safety, IAEA 621-SP-384.41, Proceedings Of The Specialists' Meeting Jointly Organized By The IAEA and Nuclear Electric Ltd. And Held in Gloucester, UK, 14-17 May 1996.

[27]   TÜRKCAN E., VERHOEF J.P., CIFTCIOGLU Ö., New Technologies In Nuclear Power Plant Monitoring and Diagnosis, IAEA 621-SP-384.41, Proceedings Of The Specialists' Meeting Jointly Organized By The IAEA and Nuclear Electric Ltd. And Held in Gloucester, UK, 14-17 May 1996.

[28]   SUZUDO T., TÜRKCAN E., VERHOEF J.P., Monitoring and Analysis of Nuclear Power Plant Signals Based on Nonlinear Dynamical Methodology, Journal of Nuclear Science and Technology, Vol. 34, No. 3, p. 340-247 (March 1997).

[29]   TÜRKCAN E., VERSTEEGH J.G.E., Neural Network Training By Extended Kalman Filtering for Detection of Signal/Systems Failures (MISO/MIMO Systems). MARCON 98, Maintenance And Reliability Conference Proceedings, May 12-14, 1998, p. 66.

[30]   CIFTCIOGLU Ö., TÜRKCAN E., A Potential Approach for Plant Monitoring: Wavelet Technology, Proceedings of 9th Power Plant Dynamics, Control and Testing Symposium, May 24-26,1995, p. 82, Knoxville, TN, USA, (1995).

[31]   TÜRKCAN E., CIFTCIOGLU Ö., Multi-Resolution Pattern Analysis For Neural Network Training, (SMORN-VII), Nuclear Energy Agency OECD, Vol.1, pp. 278-285, (1995).

[32]   CIFTCIOGLU Ö., TÜRKCAN E., Decay Ratio Studies in BWR and PWR using Wavelet Studies, OECD/NEANSC, INCORE 96, Oct. 14-17, (1996), Mito, Japan.

[33]   CIFTCIOGLU Ö., TÜRKCAN E., Multi Resolution Signal Estimation Using Neural Networks, Stichting Neurale Netwerken Conference 1997, Amsterdam, The Netherlands. Editors B. Kappen, Stan Gielen, Progress in Neural Processing :8, World Scientific, pp. 169-174, (1997)..

[34]   TÜRKCAN E., VAN DER HAGEN, T.H.J.J., Plans to Participate in the IAEA Coordinated Research Programme: Evaluation of High Temperature Gas Cooled Reactor Performance, IMORN-27, Proceedings of the informal Meeting on Reactor Noise, Nov.18-20, Valencia, Spain (1997).

[35]   TÜRKCAN E., Real-Time Spectral Pattern Recognition Using Neural Network For Condition Monitoring, MARCON 98, Maintenance And Reliability Conference Proceedings, May 12-14, 1998, p. 56.

[36]   VAN DE VEER, J.H.C., Noise analysis of the Dodewaard Boiling Water Reactor: Characteristics and Time History, Progress in Nuclear Energy, Vol. 9, pp607-618 (1982).

[37]   KLEISS, E.B.J. and VAN DAM H., Incore Power Feedback Effects Deduced from Neutron Noise Measurement, Annals of Nuclear Energy, pp.205-214, (1981).

[38]   KLEISS, E.B.J. and VAN DAM H, A Twin Self-Powered Neutron Detector for Steam Velocity, Nuclear Technology Vol. 53, pp31-37, (1981).

[39]   KLEISS, E.B.J. and OOSTERKAMP W.J. and NISSEN W.H.M., Experience with incore neutron detectors for BWR coolant velocity measurements, Progress in Nuclear Energy, Vol. 15, pp. 735-743, (1983).

[40]   VAN DER HAGEN, T.H.J.J., Nuclear Technology, Vol. 83, pp. 171-181, (1988).

[41]   VAN DER HAGEN, VAN DAM H., HOOGENBOOM J.E, NISSEN W.H.M. and VAN DER VOET, Stability Monitoring of a Boiling Water Reactor, Proc. Int. Conf. Physics of Reactors, Marseilles, France, April 23-27, (1990).

[42]   STEKELENBURG A, J, C., VAN DER HAGEN, T.H.J.J., Experience with Application of Noise Analysis Based Measurement Techniques to the Dodewaard Natural Cooled BWR, (SMORN-VII) Proceedings of Nuclear Energy Agency, OECD, Vol.1, pp. 474-482, (1995).

[43]   VAN DER HAGEN, T.H.J.J., PAZSIT I., THOMSON O., MELKERSON B., Methods for the Determination of the In-Phase and Out-Of-Phase Stability Characteristics of a Boiling Water Reactor, Nuclear Technology, Vol.107, pp. 193-214, (aug. 1994).

[44]   VAN DER HAGEN, T.H.J.J., HOOGENBOOM, J.E., SCHOONWELLE H., VAN DAM, H, Developments in Anomaly Detection and Stability Monitoring at IRI, Delft, 9th Power Plant Dynamics, Control & Testing Symposium Proceedings, p. 36, Knoxville, TN, USA, May 24-26, (1995).

[45]   VAN DER HAGEN T.H.J.J., Artificial Neural Networks Versus Conventional Methods for Boiling Water Reactor Stability Monitoring, Nuclear Technology Vol.109, pp. 286-305 (1995).

[46]   SCHOONWELLE H., VAN DER HAGEN, T.H.J.J., HOOGENBOOM J.E., Practical and Theoretical Aspects of the Sequential Probability Ratio Test for Anomaly Detection, (SMORN-VII) Proceedings of Nuclear Energy Agency, OECD, Vol.1, pp. 231-239, (1995).

DIAGNOSTICS OF A PHASE STATE OF THE COOLANT IN PWR BY TEMPERATURE NOISES

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Abstract

The diagnostics of a phase state of the coolant under the normal operation of the reactor and at the pressure drop in it has been developed. The diagnostics is based on the registration and the analysis of temperature noises of the coolant. It ensures the control for appearing of a steam-gas mixture and for the level of the coolant in the reactor. At present the diagnostics system is being tested at NPP «Kozloduy» in Bulgaria.

1. INTRODUCTION

Diagnostics and control are fundamental tasks when ensuring NPP safety. Early detection and warning of damages, prevention of emergencies is the more effective way in principle for ensuring safety, efficiency and their increasing under the conditions of operating plant. The results of the analysis having been carried out on the existing diagnostics methods of appearing and development of steam-gas volume in the power reactor vessel have shown the absence of control mode for appearing of steam-gas volume at pressure drop of the coolant in the reactor plant. For the purpose of increasing NPP safety at the specified accidental situation the method of early diagnostics of appearing steam-gas volume in the reactor at pressure drop in it has been developed. The method consists of measuring an integral spectral density of noise capacity of the coolant's temperatures in a frequency band of 0.05-1 Hz by the height above the active core, as well as of determining their coherence function and estimating the coolant's state above the active core by variation of these values [1].

Detectors of the system are thermocouples which monitor the temperature in the reactor. The equipment of the system executes measurement of a spectral density of the rate of the coolant's temperature noise and their functions of coherence in a noise band of 0.05-1 Hz. The phase state of the coolant is determined by these values in the place of thermocouples' location, such as single phase, steam-water, steam-gaseous. The diagnostics of a steam-water phase and its evolution to a steam phase of the coolant in the reactor does not depend on its power and is carried out at the temperatures of 100-350°C. The diagnostics system allows the rate of the phase state changing of the coolant to be monitored.

2. DIAGNOSTICS SYSTEM

The diagnostics technique is based on the model where the measured temperature noise of the coolant is presented as the equation

$$\delta T = \delta k (T_s - \overline{T}_l) + (1 - \overline{k}) \delta T_l$$

where:

δT – temperature noise of the coolant, T_s – steam temperature, $\overline{T}_l$ – average temperature of a liquid phase, $\overline{k}, \delta k$ – weight coefficient and its noise, which are proportional to steam content. At boiling of the coolant with underheating-up when $1°C < \Delta T_s < 10°C$ (ΔT_s – underheating-up

till the saturation temperature), the weight coefficient $\bar{k} \ll 1$. As it is seen from the equation, this results in increasing the temperature noise in comparison with the temperature noise of its liquid phase, at which $\bar{k} = 0$, $\delta k = 0$. At approaching the average temperature of the liquid phase of the coolant $\bar{T}_l$ to the saturation temperature T_s the portion of the weight coefficient $\bar{k}$ decreases because of the difference of $T_s - \bar{T}_l$, and the temperature noise of the coolant decreases. The tendency of decreasing the temperature noise is observed at boiling of the coolant in the whole volume, because the second term of the equation decreases as the weight coefficient grows. Under the saturation state the temperature noise of the coolant is minimum. It is seen, that the change of the coolant's phase state only is the basis of the diagnostics technique for its state.

Apparatus means of the system include:

standard thermocouples T located above the active core in different height, two as minimum, one thermocouple is located at the output of T core, and the second thermocouple – under the T cover;

weak-noising amplifier with filters of frequencies > 1 Hz;

computer of low level with microprocessor units of accumulation, information treatment and control for outer devices;

computer of upper level of PC AT-586 type (Pentium).

The amplifier and the computer of low level must be located to thermocouples as close as possible.

Each amplifier is connected via galvanic isolation which excludes the influence of the system on functioning of standard measuring channels, as well as via the capacity < 2 mkf for filtration of a direct component of T signal.

For the control of the system's serviceability either the devices actuating standard signals to the inlet of the amplifiers can be envisaged, or the control of serviceability is ensured by program means.

3. DETERMINATION ALGORITHM OF PHASE STATE OF THE COOLANT

Analogous alternating signals of thermocoupls T1 and T2 coming after amplifiers are transformed by the computer of low level into a digital form which is a temporal sequence of signals through constant intervals of time Δ. A digital statistical analysis of temporal sequences of T1 and T2 signals is carried out.

Autocorrelation and crosscorrelation functions φ_{11}, φ_{22}, φ_{12} of T1 and T2 signals are calculated.

Auto- and cross-spectral densities of capacity Φ_{11}, Φ_{22}, Φ_{12} are calculated.

Coherence function of two thermocouples γ_{12} is calculated.

Integral autospectral density of T1 and T2 capacity is calculated: $S_{11} = \int_{0.05}^{1} \varphi_{11}(f)df$;

$$S_{22} = \int_{0.05}^{1} \varphi_{22}(f)df$$

The value of the integral autospectral density of capacity of each thermocoupls T is compared with its value having been measured before: $\dfrac{S_{11}(t)}{S_{11}(t_0)}$; $\dfrac{S_{22}(t)}{S_{22}(t_0)}$

The value of coherence function of two T is compared with its value having been measured before: $\dfrac{\gamma_{12}(t)}{\gamma_{12}(t_0)}$

At values of $\dfrac{S_{11}(t)}{S_{11}(t_0)} < 10$, $\dfrac{S_{22}(t)}{S_{22}(t_0)} < 10$, $\dfrac{\gamma_{12}(t)}{\gamma_{12}(t_0)} \geq 0,4$ the coolant is a single-phase.

At values of $\dfrac{S_{11}(t)}{S_{11}(t_0)} < 10$, $\dfrac{S_{22}(t)}{S_{22}(t_0)} \geq 10$, $\dfrac{\gamma_{12}(t)}{\gamma_{12}(t_0)} < 0,3$ steam-gas mixture is under the cover

At values of $\dfrac{S_{11}(t)}{S_{11}(t_0)} \geq 10$ steam-gas mixture is above the core.

At values of $\dfrac{S_{22}(t)}{S_{22}(t_0)} \leq 100$, $\dfrac{\gamma_{12}(t)}{\gamma_{12}(t_0)} = 0$ steam-gas mixture is under the cover

At values of $\dfrac{S_{11}(t)}{S_{11}(t_0)} \leq 100$ steam-gas-mixture is above the core.

Computation algorithms of correlation functions, spectral densities and correlation are standard as well as the programs of their computations [2].

Specifications of computer of low level are determined by a pass band of analogous signals by the amplifier and the accuracy of comparative spectral analysis.

Under the maximum error of 40% and the pass band of 0.05-1 Hz DAT must ensure:

quantum velocity (sample of the data) of 2 c^{-1};

duration of measuring of T=20 c;

number of samples of N=40;

low frequency of the signal – 0.05 Hz;

maximum number of delays m=4;

temporal increment Δ=0.5 c;

frequency increment Δf= 0.25 Hz.

REFERENCES

[1] Levadnyi V., et al., Patent Russia №96115951 (1996).

[2] Kim T.R., et al., SMORN-VII, Rep. 1.2, Avignon, France (1995)

EXPERIENCE WITH DIGITAL ACOUSTIC MONITORING SYSTEMS FOR PWR'S AND BWR'S

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Abstract

Substantial progress could be reached both in system technics and in application of digital acoustic monitoring systems for assessing mechanical integrity of reactor primary systems. For the surveillance of PWR's and BWR's during power operation of the plants, acoustic signals of Loose Parts Monitoring System sensors are continuously monitored for signal bursts associated with metallic impacts. ISTec/GRS experience with its digital systems MEDEA and RAMSES has shown that acoustic signature analysis is very successful for detecting component failures at an early stage. Methods for trending and classification of digital burst signals are shown, experience with their practical use will be presented.

1. Introduction

Assessing the mechanical integrity of reactor primary systems during power operation of the plants is performed by acoustic monitoring using loose parts monitoring systems (LPMS). These systems are designed to detect, locate and evaluate detached or loosened parts and foreign objects in the reactor coolant system. Efforts to advance the safety of nuclear power plants (NPP) using modern computer technology have led to powerful new solutions for more automated fault diagnosis systems. LPMS are capable to detect component failures at an early stage /1-3/. In the German RSK-guidelines /4/ the use of adequate measures is required in order

- to detect free and captive loose parts within the pressure retaining boundary and
- to localise loose parts as well as possible.

LPMS are installed in all nuclear power plants in Germany. LPMS have to be seen as information systems whose indications give the plant personnel enough time for adequate counter-measures. The observation of acoustical alterations or exceeding an alert level does not mean a critical situation. Therefore, technical requirements which are needed for safety relevant measurement channels must not be fulfilled in this case. On the other hand, the demand for an effective LPMS is obvious with respect to the avoidance of damage. Both the recognition of developing failures and the possibility to evaluate these failures during plant operation in spite of inaccessibility of the components are especially desirable for safety reasons. This is illustrated by the fact that the LPMS system software of both leading German system manufacturers Siemens (for KÜS'95 /5/) and AZT (for KAP 90 /6/) is quality assured and certified.

The task of acoustic monitoring of the reactor primary system is to monitor continuously the acoustic signals and to give an indication in the case of burst events. Acoustic burst occurrences are generated by the energy delivery from impacts of detached or loosened parts hitting the inner surface of the pressure retaining boundary of reactor coolant or reactor internals. Piezoelectric accelerometers working in the acoustic frequency range and resistant to temperature and radiation have been found to be very effective for their detection.
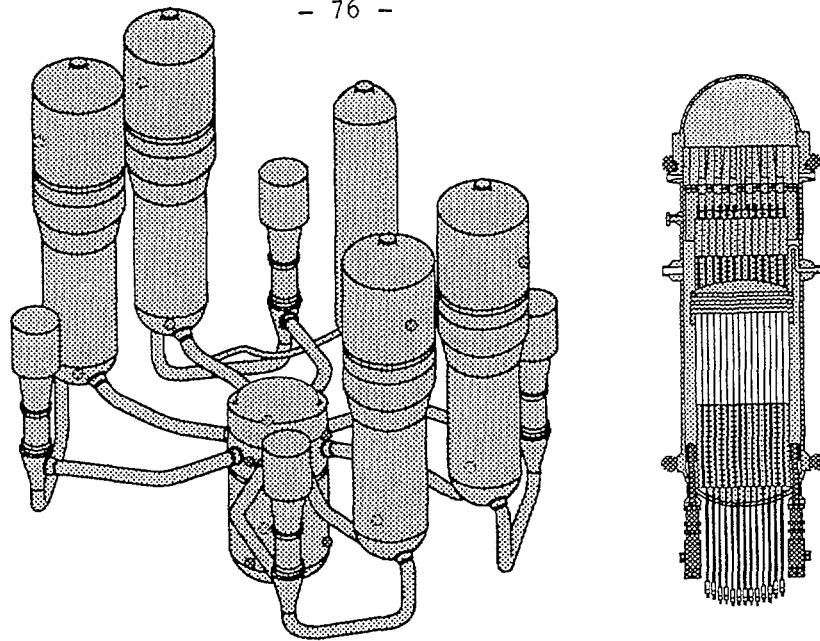
Fig. 1: Sensor positions of loose parts monitoring systems for PWR and BWR

Fig. 1 shows - marked with small circles - sensor positions of LPMS for a 1300 MW PWR and a BWR. The sensors are mounted as near as possible to the surface of the monitored structure and are positioned in different levels at areas which are natural collection rooms for loose parts (lower plenum of reactor vessel or steam generator) or which have a good detection capability for impacts of internals (upper part of reactor vessel and steam generator). The number of sensors as well as their type of adaption (magnet-adapted, screw-adapted, mixed adapted) differ from plant to plant. In a 4 loop PWR at least 14 sensors are recommended. In reality the systems are of different technical level depending on their period of construction. Fig 2 shows the number of sensors, their type of adaption and the technics of installed LPMS in German LWRs. Digital LPMS essentially comprise a data acquisition unit, which consists of a transient recorder with up to 32 channels, a high-end PC with appropriate periphery and software for the control of data flow, data storage and analysis. By the new digital LPMS acoustic signals of new quality and enhanced information supply are now available, in recent years more and more utilities have replaced old analog systems with modern digital systems.

NPP	number	magnet-adapted	screw-adapted	mixed adapted	analog technics	analog with digital evaluation	digital technics PC based
		LPMS sensors			LPMS technics		
Obrigheim	12	●	●		●	●	
Stade	17		●	●	●	●	
Neckarwestheim 1	13			●			●
Biblis A	16	●				●	
Biblis B	14	●		●			●
Unterweser	14	●					●
Grafenrheinfeld	20	●	●				●
Philippsburg 2	16		●		●	●	
Grohnde	16				●	●	
Mülheim-Kärlich	12		●			●	
Brokdorf	14	●					●
Isar 2	16		●				●
Emsland	16		●		●	●	
Neckarwestheim 2	16		●				●
Brunsbüttel	8		●				●
Isar 1	10	●					●
Philippsburg 1	10	●			●	●	
Krümmel	8		●				●
Gundremmingen B	12		●				●
Gundremmingen C	12		●				●

Fig. 2 LPMS sensors and system technics in German LWR's

2. Acoustic signal analysis systems

LPMS have been developed now to a satisfactory status. The systems work on-line and monitor the reactor coolant system with fixed and floating alert levels in order to detect detached, loosened or foreign parts. Current investigations concentrate on the improvement of on-line diagnosis methods and trending of components status.

Basic requirement for acoustic monitoring of active and passive components within the primary system of Light Water Reactors (LWRs) is the qualified analysis and detailed burst data interpretation of acoustic signals. A fast digital off-line burst processing system (MEDEA-system) has been realised in the ISTec laboratory. Its major components are a 16 channels transient recorder, a UNIX- workstation, fast data storage facilities, interactive analysis software and a burst data base (fig. 3).
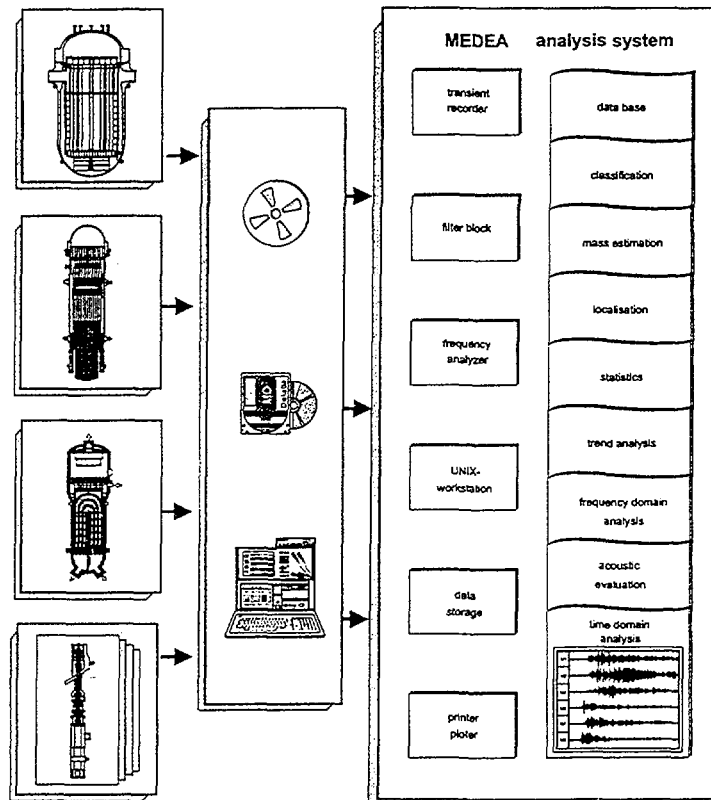

Fig. 3: MEDEA-system for off-line acoustic analysis

Plant measurement data reach ISTec laboratory by FM recordings, MO-discs or the RAMSES system (fig. 4). The Remote Acoustic Monitoring and Signal Evaluation System (RAMSES) has been developed by ISTec for on-site digital signal recording and diagnosis support to the plant. Meanwhile two RAMSES systems have been established. The most advanced is PC-based and consists of six transient recorder storage modules, a graphic display and a modem. Software packages have been implemented needed for the storage of the data to the on-site computer after event detection, the remote controlled settings of the transient storage modules via the telephone line, the data transfer of qualified signal patterns to the ISTec laboratory as well as the online diagnostic information on site.
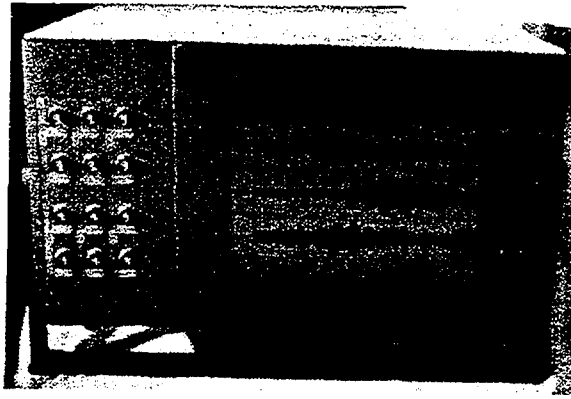
Fig. 4: RAMSES system for on-site measurements

3. Burst Signal Analysis

By the increasing use of digital LPMS in Germany, signal patterns of alert indications are stored more and more in digital form. In the following, some recent developments realised for burst signal analysis and evaluation are presented. Burst data sets are regularly copied on site for archive purposes, but also flexible discs or MOs are used for transfer of the data to separate analysis computers. Additionally to MEDEA analyses of FM recordings, ISTec has analysed digital data sets of nine different plants. Fig. 5 shows an overview of recent analyses, the rectangles mark the covered registration time and the number of analysed signal patterns.
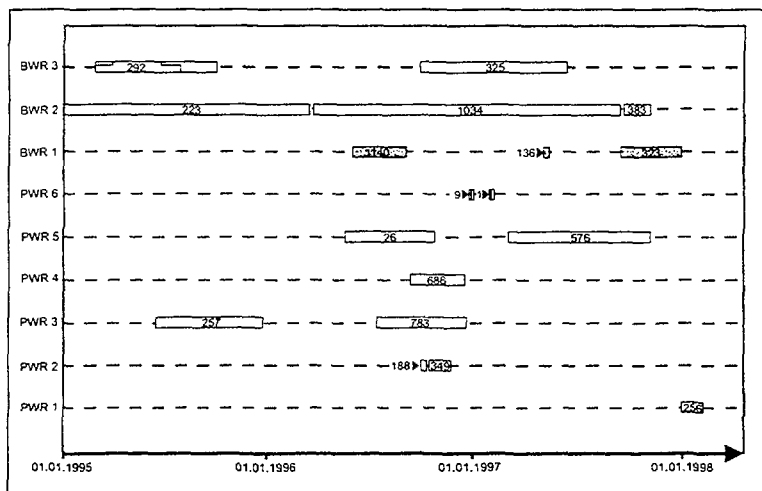

Fig. 5: Digital LPMS data sets, analysed by ISTec

The comparison of actual burst signals with reference signals is important for acoustic analyses. Due to the stochastic character of acoustic signals a direct comparison of time signals would not be reliable. In order to find adequate reference patterns, the calculation of signal parameters is necessary. The comparison is then performed on the basis of predetermined characteristic values, which can be calculated by NNCT analysis software, which is part of the MEDEA system of ISTec.

The data set formats are different for different system manufacturers, ISTec has got the knowledge of the specific data formats. For the NNCT analysis software, a data access is possible for MEDEA and RAMSES data of ISTec, for KAP 90 data of AZT, for KÜS'95 data of Siemens and famos data of imc (see fig. 6). By use of specific C input filter routines

analyses of data of the different signal formats of the different manufacturers are possible in a common way. For a more automated way of burst data handling and data processing the ODBC driver is used for the data storage in a data base. These functions are integrated in the NNCT analysis software of the MEDEA system.
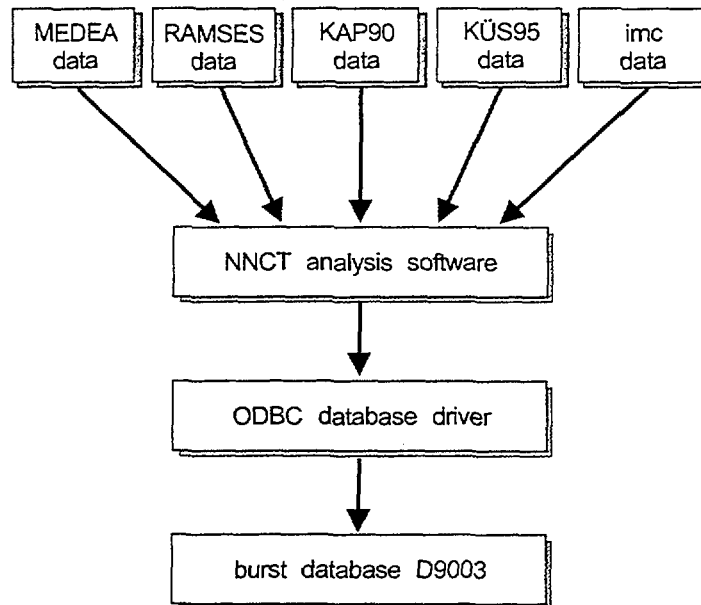

Fig. 6: Signal analyses and data storage of digital LPMS data

Acoustic signatures from measurements and analyses of 14 German LWRs with more than 11000 bursts are available. In a burst pattern data base they are characterised by the event type, measurement and signal parameters. The new burst data base D 9003 has been realised as an ACCESS data base under Windows 95. The structure is as follows. Data administration of the measurement campaigns is concentrated in a leading HEADER data set. It contains information about plant, fuel element cycles, name of the measurement, number of channels, number of bursts and measurement configuration. The results of signal analyses are stored in a RESULT data set, which is stored separately for each different plant. The RESULT data set contains signal parameters, classification values, process data, alarm type, signal amplitudes, location results and diagnosis. Fig. 7 shows the structure of the burst data base D 9003.
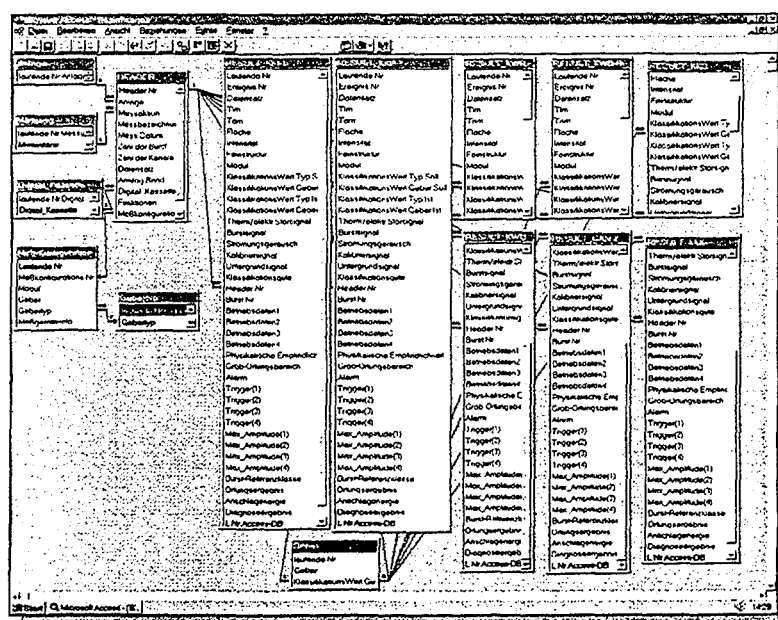

Fig. 7: Structure of database D 9003

The detailed and reliable evaluation of acoustic events requires extensive know-how and analysis efforts. Analyses are performed on the basis of short term samples. Operationally induced signal patterns have to be identified and circled out. Plant independent registration and analysis of operational experience, which has been gained on site, provide status information for components assessment. Basic significance for the interpretation of acoustic signal patterns has the evaluation of test impacts. By permanently installed automatic pulse hammers of the LPMS KÜS'95 at the four loops of PWR's, test impacts of known impact energy can be performed during plant operation, the acoustic response of the LPMS sensors is registered and can be used as a reference. Fig. 8 shows the signal pattern of a test impact performed on the hot leg of loop 2 of a 1300 MWe PWR. The pattern is presented as a 15-channel display of KÜS'95 data by use of NNCT software of ISTec.
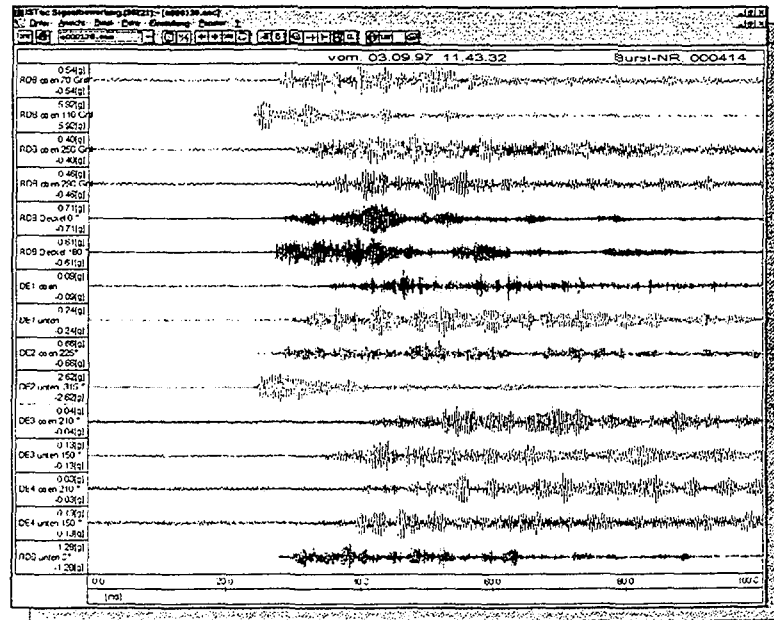

Fig. 8: Signal pattern of a test impact with an automatic impulse hammer

The important question for the origin of the sound source of a measured acoustic event can be answered by using localisation methods which are available by digital LPMS. Triangulation by means of hyperbola intersection is the standard method for localisation. For a three sensor combination the solution of hyperbola equations result in two intersection points which can be shown on a development of the structure. Is a fourth signal pattern available, a decision and identification of the intersection point can numerically be given. For cylindrical surfaces like the reactor vessel, a new direct localisation algorithm on the basis of measured path time differences has been implemented in the MEDEA analysis software. In fig. 9 a 3 channel signal pattern of a test impact on cold leg of loop 4 of a PWR, whose LPMS data were of famos data type, is shown. In the right part of fig. 9 known hyperbola graphs are shown on a development of the reactor vessel. Low variations of burst propagation speed determine the five hyperbolas. Additionally, the result of the direct localisation algorithm for the same burst pattern is shown by circles. The position of the circles is identical with the intersection of the hyperbolas and shows the correctness of the algorithm.
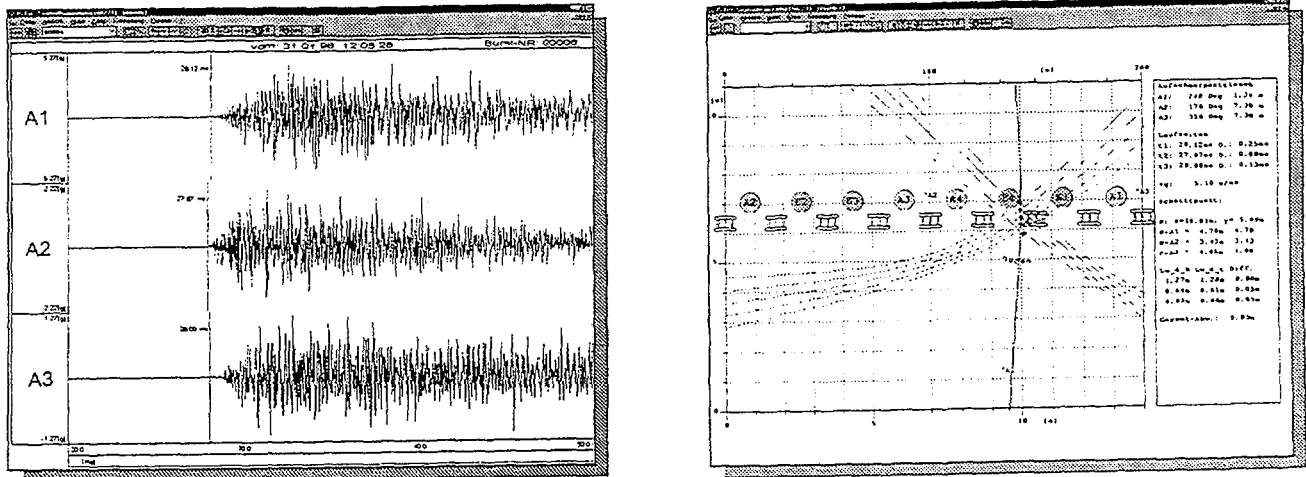
Fig. 9: Hyperbola and direct source location of a test impact

LPMS contain an alarm processing unit with absolute and variable (floating) thresholds. Due to the high sensitivity of acoustic monitoring, the detection potential for impact occurrences is comparatively high. Low energetic and minor relevant events are indicated and could be seen as precursors of real failures. They are of great value as status indicators, if they can be used for safety assessment of primary system components. On the other hand, too frequent unnecessary alarms can reduce the confidence to this monitoring technique and should be avoided by appropriate evaluation and additional measures. In order to reduce false alarms, specific zone localisation areas have been calculated for primary system of PWR's (KWU type, 1300 MWe) and BWR's (KWU type, 900 MWe), based on newly developed direct location algorithm. Table 1 shows the time differences between sensors of different measurement planes as a result for the localisation area lower plenum, calculated for symmetrical So plate waves.

TABLE 1: Calculated time differences for zone localisation area lower plenum (So plate waves)

Time difference [ms] between sensors of different measurement planes, localisation area lower plenum	BWR reactor vessel top	PWR reactor vessel top	PWR steam generator top
BWR reactor vessel down	2.8 - 3.5	-	-
PWR reactor vessel down	-	2.8 - 4.2	-
PWR steam generator down	-	1.8-2.4	2.2-2.6

Recently, ISTec has developed two software modules as add-ons for acoustic evaluation and classification of LPMS signatures. By means of the acoustic module with its signal supplement technics, an optimised audio replay of digitally stored LPMS burst signal is available, which is very convenient for practical signal evaluation /7,8/. An automated LPMS burst type classification is established by the classification module /9,10/. The classification module uses a trained neural net with 5 input nodes, two hidden layers with 5 nodes each and two output nodes. Five burstform-sensitive parameters are calculated automatically: local maximum time, global maximum time, normalised area, intensity ratio and fine structure. The output value determines the class value, which is separated in five pre-defined type classes: electrical/thermal disturbance signal, burst signal, flow induced noise, calibration signal and

background. The classification module has been tested with acoustic signatures of different German NPPs and is trained ready to use. Test results and practical experience show a more than 90 % correct classification rate. Fig. 10 shows the user dialogue for multiple burst type classification.
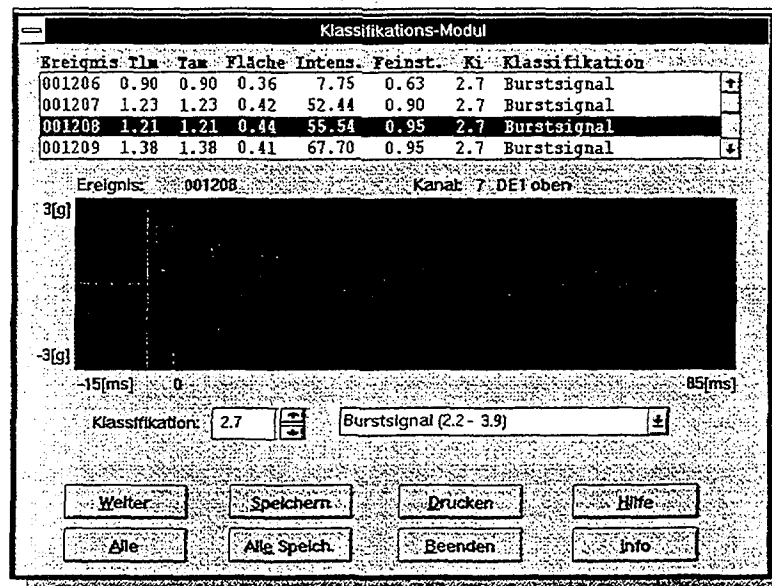

Fig. 10: User dialogue for multiple burst type classification

4. Experience with Acoustic Status Evaluation of Primary System Components

Interpreted case studies and well known reference patterns are the basis for the evaluation of extraordinary acoustic signatures. With a large number of occurrences ISTec/GRS has been involved for analysis and for clarification of the problem by means of acoustic analysis. The advantage of its use has become obvious in numerous cases. Their spectrum reaches from

- status assessment of the primary system and its components over
- support and optimisation of repair measures with reduction of radiation dosage to personnel up to
- flanking and accompanying measures for worst case considerations for plant operation.

The common idea of safety assessment of reactor primary system by acoustic analysis is to use acoustic signatures for an integral component status assessment. Surveillance task is always a prevention of failures or a specific precaution against damage.

Emphasis of current activities on acoustic monitoring of the primary system of BWR's and PWR's is put on the enhancement of the knowledge base for the interpretation of acoustic signatures.

A 10-channel burst signal pattern of a BWR reactor vessel, which was automatically registered and stored from LPMS after having exceeded the alert level as one of three burst occurrences, is shown in the middle part of fig. 11. The signals are displayed with overall 5-g-scaling of a NNCT display of KAP 90 data. Preceding signal parts are observed at the sensors in the area of steam line sensors M1 to M3, the rise flanks are comparably flat.

With the use of the newly developed classification module of ISTec, which is also applicable to KAP 90 data, acoustic signatures can be classified with the help of a knowledge base and can be evaluated with respect to their signal type. In the upper right part of fig. 11 the calculated burst parameters of the signal M 3, which was the trigger signal, are shown. The determined signal values are 2.59 msec for the 'local' and 'global' maximum time, 0.33 for

the 'normalised area', 4.76 for the 'intensity ratio' and 0.41 for 'fine structure'. The classification value of the burst signal, determined by a trained neural net, results in 3.7. This value lies within the class of 2.2 - 3.9, which characterises real burst occurrences.

For determination of the associated cause, trend analyses of operational data, which have been measured by a turbine monitoring system, have been applied. In the lower part of fig. 11 the trend of operational data plant power (output and reactive), steam temperature and steam pressure are shown in the period of 10:00-20:00 hours of the measurement day, the time of the three burst occurrences are marked with arrows. In this period the plant power has been reduced for a test of the turbine control valve. Additional detailed analyses showed that the time of the occurrences of the burst events were well correlated with tests of individual turbine check valves. As the determined origin fits well to the signal forms and rise times of the burst signals this position is confirmed. The events can be characterised as operationally induced and externally coupled from the region of turbine control valves. Acoustic monitoring of the reactor vessel gave no indication for impacts of detached or loosened parts.
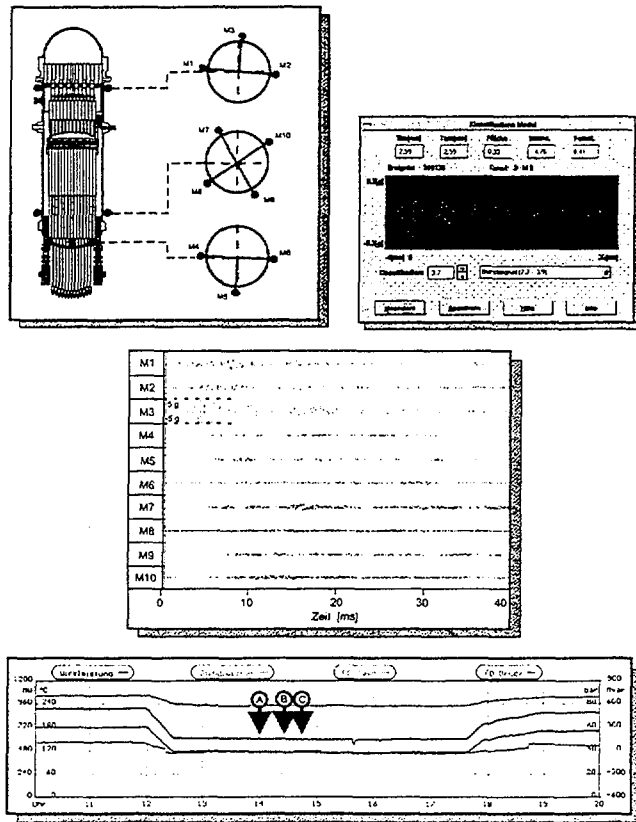

Fig. 11: Operationally induced burst signals in the sequence of a test of turbine control valve.

The experience with signal indications, if they can be supported by additional plant process parameters like pump speed, flow and pressure, which are available in addition to the burst

data in the digital LPMS KAP90, is also positive. The NNCT module of ISTec provides a trend display of burst signals together with selected process signals of KAP90 data. Fig. 12 shows for one fuel element cycle a trend display of bursts together with the speed of the internal axial pumps of a 900 MWe BWR. In the lower part of fig. 12 the burst amplitudes are displayed as a function of time, the occurrence of a burst event is marked by a circle. In the upper part of fig. 12 the corresponding variable pump speed is shown. Fig. 12 confirms that there is an appreciable accumulation of operationally induced burst occurrences during transient phases of plant operation.
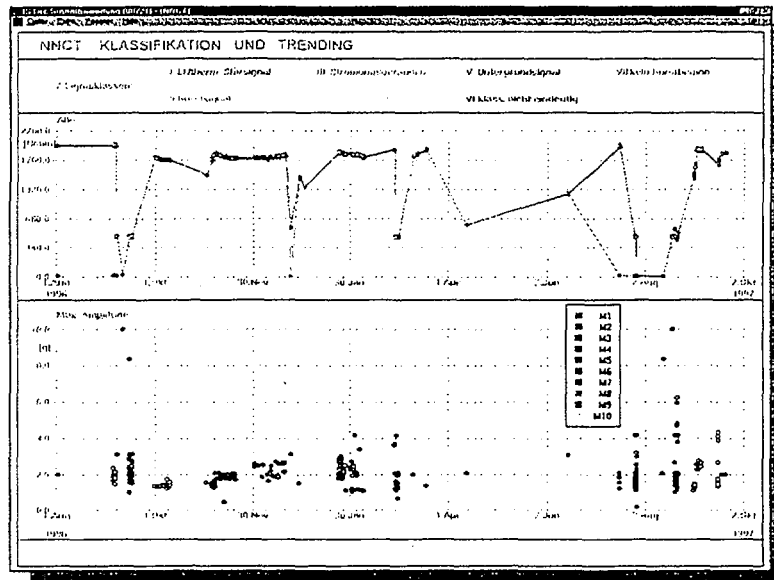

Fig. 12: Trending of digital KAP 90 data together with speed of internal axial pumps

In a PWR plant with a digital LPMS KÜS'95 256 stored signals have been analysed, which have been registered within the frame of a month. The alert indications of four sensors of reactor vessel have been analysed with NNCT module of ISTec, different signal types could be identified by the classification module of ISTec. In the lower part of fig. 13 the amplitude trend of the alert indications is shown. The upper part of fig. 13 presents the data of burst classification. It results in 122 occurrences of impacts, 4 fluid type signals and 7 electrical/thermal disturbance signals. The comparison of this trend with trends of formerly measured and analysed burst signals showed that these bursts coincide with uncritical bursts, which are already known from former fuel cycles and which occur after plant transients or after start-up phase for a limited time of about two weeks. This result has been assessed by the fact, that the transients in the burst frequency occurrence are timely correlated with operational transients of the plant.

5. Conclusions

Successful applications of acoustic status evaluation of primary system components have been described. More than the mere detection of loose parts, acoustic signal analysis has high potential for safety assessment of the primary system and its components with respect to their mechanical integrity. The high cost of unplanned shut-down of the plant can be reduced and the safety of nuclear power stations can be improved by applying such methods. Basic requirement for a reliable diagnosis is the availability of a knowledge basis for the interpretation and evaluation of acoustic signatures. Ongoing work is dedicated to further

enhancement of diagnosis tools so that more automated fault diagnosis systems will be available in the near future.
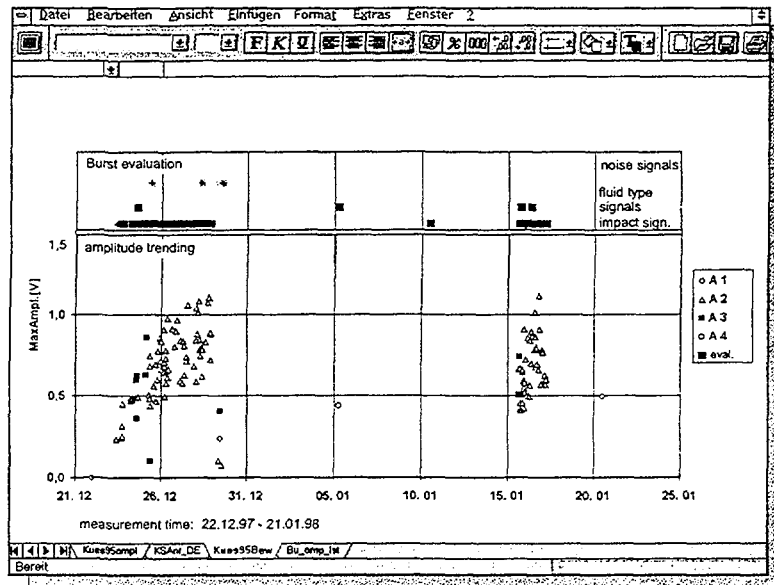

Fig. 13: Use of classification module for evaluation of acoustic events

6. References

[1] B. J. Olma, "Acoustic Monitoring of U-tube Steam Generators", proceedings of SMORN VI Symposium, Gatlinburg, USA,19.-24.5.1991, Vol. 2, pp. 74.01 - 74.13

[2] B. J. Olma, Y. Ding, R. Enders, "Operational Experiences with Automated Acoustic Burst Classification by Neural Networks", proceedings of the 7th Symposium On Nuclear Reactor Surveillance And Diagnostics (SMORN VII), Avignon, France, June 1995

[3] B. J. Olma, "Potential of Acoustic Monitoring for Safety Assessment of Primary System", IAEA Technical Committee Meeting on "Nuclear Power Plant Diagnostics - Safety Aspects and Licensing", Portorosz, Slovenia, June 23-26, 1997

[4] RSK-Guidelines for Pressurised Water Reactors, 3.Edition, October 1981

[5] B. Bechtold, W. Knoblach, U. Kunze, "The New Loose Part Monitoring System KÜS 95", proceedings of the 7th Symposium On Nuclear Reactor Surveillance And Diagnostics (SMORN VII), Avignon, France, June 1995

[6] L.Cleemann, F. Elfinger, "Loose Parts Monitoring System", proceedings of the 7th Symposium On Nuclear Reactor Surveillance And Diagnostics (SMORN VII), Avignon, France, June 1995

[7] B. J. Olma, "Audio replay of acoustic burst signals for digital loose parts monitoring systems", Kerntechnik, November 1995, Vol. 60/5-6

[8] European Patent 0 740 153

[9] B. Olma, D. Wach, "On-line classification of acoustic burst signals by a neural network - application to loose parts monitoring in nuclear power plants", 3rd IEEE Conference on Control Applications, August 24-26, 1994, Glasgow, Scotland

[10] Y. Ding, D. Wach "A fuzzy diagnosis system for automatic classification of acoustic burst events in nuclear power plants", Pre-prints of the IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes - Safeprocess '97, August 26-28, 1997, Kingston Upon Hull, United Kingdom

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LOCALISATION OF A CHANNEL INSTABILITY
IN A BWR VIA NEUTRON NOISE METHODS

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Abstract

A special type of instability occurred in the Swedish BWR Forsmark 1 in 1996. In contrast to the better known global or regional (out-of-phase) instabilities, the decay ratio appeared to be very high in one half of the core and quite low in the other half. A more detailed analysis showed that the most likely reason for the observed behaviour is a local perturbation of thermohydraulic character, e.g. a density wave oscillation (DWO), induced by the incorrect positioning of a fuel assembly (an "unseated" assembly). In such a case it is of large importance to determine the position of the unseated assembly already during operation such that it can be easily found during reloading.

The subject of this paper is to report on development and application of methods by which the position of such a local perturbation can be determined. Two different methods that support and complement each other were used. First a visualisation technique was elaborated which expedites a very good qualitative comprehension of the situation and which can be useful for the operators. It also gives an important basis for the application of the localisation algorithm. Second, a quantitative (algorithmic) localisation method, suited for this type of perturbation, was elaborated. This latter takes noise spectra from selected detectors as input and yields the perturbation position as output. The method was tested on simulated data, and then applied to the Forsmark measurements. The location of the disturbance, found by the algorithm, is in accordance with independent judgements for the case, and close to a position where an unseated assembly was found during refuelling.

1. INTRODUCTION

A special type of instability occurred in the Swedish BWR Forsmark 1 in 1996. This event has been described and analysed in several reports previously (Refs. [1] and [2]). We will only briefly summarize the findings that led to the present study.

The phenomenon was discovered as a half-core instability phenomenon in the start-up measurements after refuelling in 1996. To investigate the phenomenon, measurements were made with several in-core detectors in early 1997 in a position of the power-flow map where the instability was fully developed. It was found that in one half of the core the decay ratios, as well as the noise rms values, were much higher than in the other half. Some results from the most characteristic measurement, referred to as measurement M2 in the continuation, are shown in Figs 1 and 2 below as an illustration.

Further analysis of the measurements (Refs [1]- [3]) made it likely that the reason for the behaviour shown in these figures is a localised perturbation, such as a density wave oscillation in one or a few fuel assemblies. In such a case, the position of the instability is of large
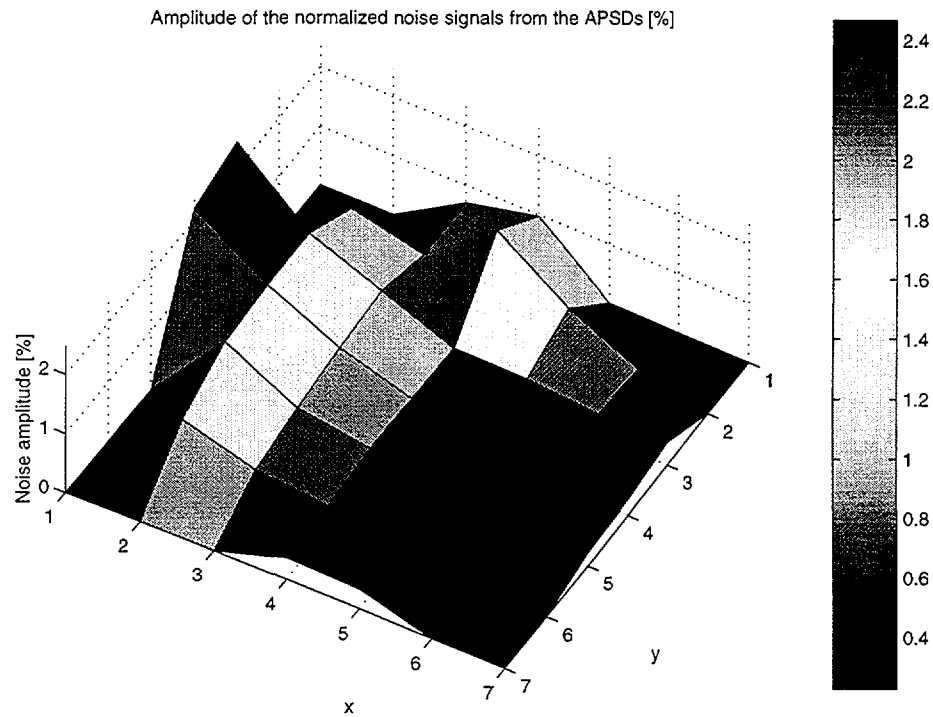
Fig. 1. *Distribution of the noise amplitudes in a horizontal cross section of the core in measurement M2 in Forsmark-1*
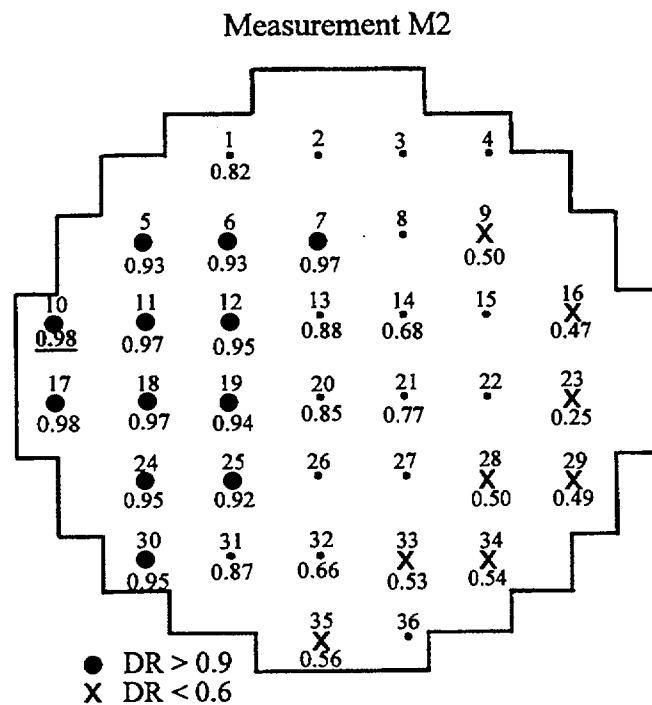
Fig. 2. *Distribution of the decay ratios (DR) of the various LPRMs in measurement M2 in Forsmark-1 (from Ref. [2]). Upper line: LPRM number. Lower: DR*

diagnostic interest, because an inspection of the fuel assembly or assemblies in which the instability occurred may reveal the reason of its appearance. One hypothesis is that the instability arose due to an improper "seating" of the assembly. Without having a qualified guess about the approximate position of the instability, it is practically not possible to find a reason because there is no possibility to check every fuel assembly, due to time constraints.

Hence, it is of large importance to determine the position of the unseated assembly already during operation such that it can be easily found during reloading.

Local perturbations can be localised from neutron noise measurements. One possibility is to use the noise contribution ratio or signal transmission path analysis methods (Refs. [2] and [3]). In these methods a multivariate analysis of several LPRM signals is used and one of them is pointed out as the driving force for the other detector signals. The position of the perturbation is then assumed to lie either at the position of the LPRM or in its neighbourhood.

There exists however another method by which the location of the perturbation can be determined. One can utilize the fact that any localised perturbation induces a space-dependent neutron noise. The noise amplitude and the phase decay with increasing distance from the source, thus the space dependence carries information on the position of the source. By modelling the noise source in some functional form, and calculating the reactor physical dynamic transfer function of the core, the induced neutron noise can be expressed via formulas, either analytical or numerical, in which the position of the perturbation is included as an argument. By the use of such relationships or formulas, a method of localisation can be elaborated, by which the position of the perturbation can be found from the measured neutron noise and the calculated transfer function of the system. Such a strategy was used in the past for the localisation of an excessively vibrating control rod in a VVER-type pressurized water reactor (Refs. [4] and [5]). The purpose of the present investigation was to elaborate and test a similar method for the channel instability, which formally corresponds to the case of an absorber of variable strength.

The advantage of such a method is that it uses reactor physics knowledge on the spatial attenuation of the neutron noise from a source. Due to this fact, the spatial resolution of the localisation procedure is high; it can in principle point out any position in the core, and not only the discrete detector positions. In practice, of course, the accuracy of the method can be low for various reasons that will be discussed later on. The important point at this stage is that there is no principal limitation involved in the spatial resolution of the method.

A localisation method, suited for this type of perturbation, was elaborated. The method was tested on simulated data, and then applied to the Forsmark measurements. The location of the disturbance, found by the algorithm, is in accordance with independent judgements for the case, and close to a position where an unseated assembly was found during refuelling.

2. VISUALISATON OF THE NOISE AS AN OPERATOR AID AND AS A QUALITATIVE INVESTIGATION OF THE NOISE SOURCE

An algorithmic method for locating a localised perturbation is based on an expression for the induced neutron noise. In this expression a functional form of the noise source is used. There exist different types of localised perturbations. One of them is the so-called "reactor oscillator" (Ref. [6]) which is conceptually equal to a localised absorber of variable strength. The second type is represented by the lateral vibrations of an absorber rod. These noise sources have different representations, and also the spatial structure of the neutron noise induced by a vibrating absorber and an absorber of variable strength is rather different. This means that for each different perturbation type one has to use a different algorithm. There exists an algorithm for the vibrating rod, but not for the absorber with variable strength.

Intuitively, it is expected that a channel instability is equivalent to a reactor oscillator, i.e. an absorber of variable strength. For its localisation a new algorithm needs to be elaborated. This will be reported in Section 3. However, before this assumption is actually

used, one must assure that the assumption on the type of the noise source is correct. This is only possible by an investigation of the spatial structure of the noise, i.e. the LPRM detector signals.

The need for this investigation led us to a method which has a significant diagnostic value itself, even if it only yields qualitative information. This method consists of a visualisation of the joint space-time behaviour of the noise in the core directly in the time domain. An animation or motion picture of the space- and time-dependent neutron noise was constructed using computer codes written as scripts in the package MATLAB. In Fig. 3 a sequence, showing one cycle of the instability oscillation in measurement M" in Forsmark, is shown from this movie.
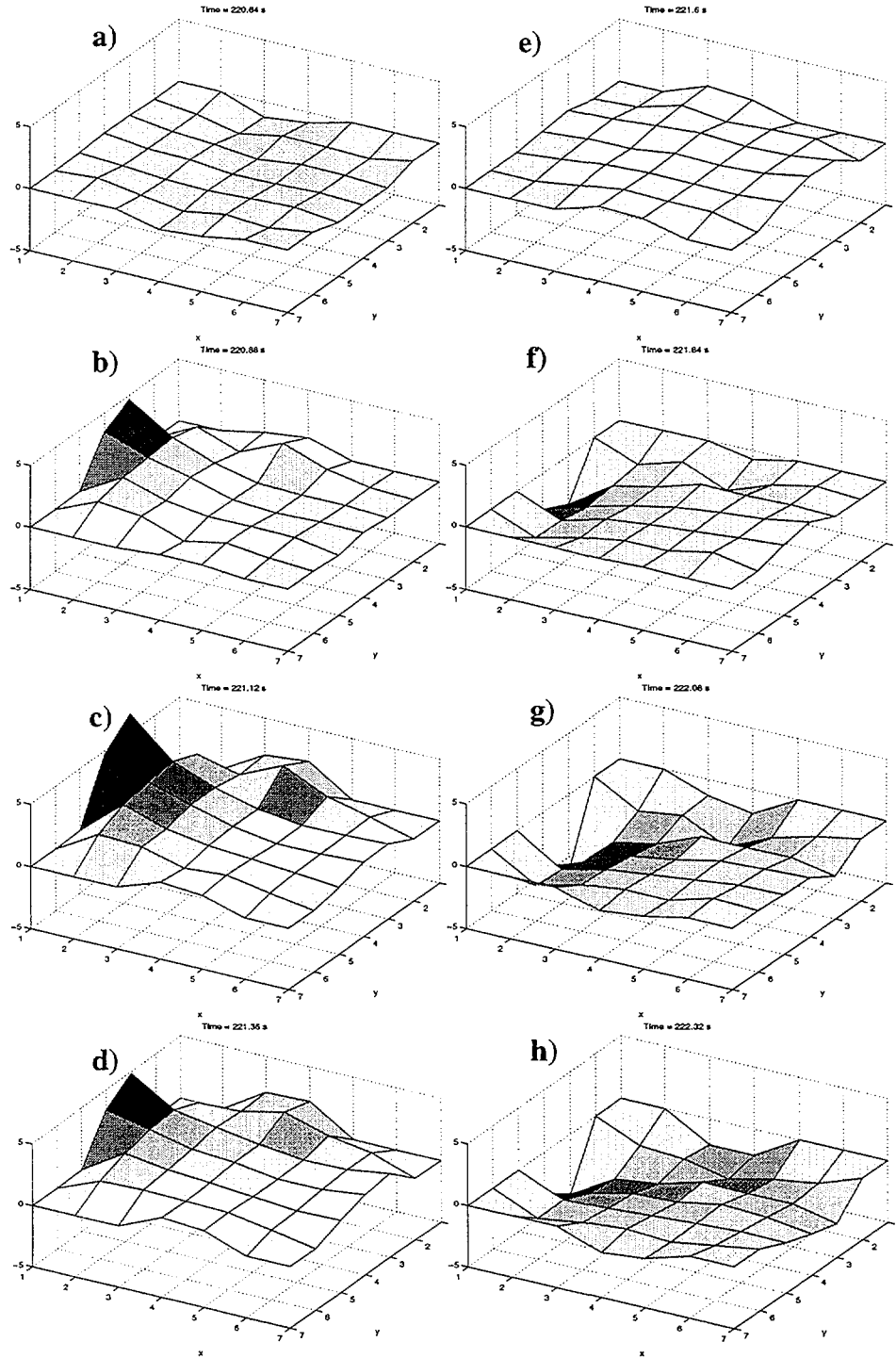

Fig. 3. The figure shows the amplitude of the flux in the x-y plane for a single cycle.

The advantages of this method are as follows:

- it shows raw signals, in contrast to processed ones such as power spectra, thus they can be interpreted without expert signal processing knowledge and used by people with reactor physics or operating experience;

- since it contains only minimal signal processing, it can be used on-line;

- it can be used to confirm the existence of a few, spatially separated noise sources, which is a pre-requisite for using the algorithmic localisation method;

- finally, it gives information on the selection of the detectors for the algorithmic method.

An analysis of a few minutes of the display yields the following conclusions on the perturbation in the concrete case of the Forsmark measurements M2:

- the spatial peaks in the noise field are all generated by an absorber of variable strength rather than by a perturbation corresponding to lateral vibrations. (This latter could be the case for instance if two adjacent channels oscillated in opposite phase);

- there is one primary spatial peak (i.e. localised perturbation) and one secondary peak of smaller amplitude than the primary. Further, there are also perturbations at other positions that appear and vanish in a non-stationary way;

- the oscillations are not stationary in time, not even for the two principal peaks. However, for these latter, one may assume approximate stationarity such that spectral analysis methods can be applied;

- the principal individual perturbations (spatial peaks) are quite well separated in space.

Based on the above, it was assumed that the perturbation consists of a single oscillation of the variable strength absorber type. The spatial separation between any two perturbations appearing concurrently was large enough (larger than the attenuation length of the noise, see later) such that two different perturbations that occur simultaneously can be localised separately, by using a suitably selected set of detectors in the Forsmark measurement.

3. THE ALGORITHMIC LOCALISATION METHOD

The starting point is an expression of the noise in the frequency domain as a convolution of the transfer function (Green's function) of the unperturbed system, and the noise source (Ref. [7]):

$$\delta\phi\,(r,\omega) \;=\; \int G\,(r,r',\omega)\,S\,(r',\omega)\,dr' \tag{1}$$

Here, $G\,(r,r',\omega)$ is the transfer function, discussed later, and $S\,(r',\omega)$ is the noise source, or perturbation, that induces the noise. It consists of the fluctuations of the macroscopic cross sections which appear in the time-dependent diffusion equations.

A noise source of variable strength at a fixed position r_p can be represented functionally as

$$S\,(r',\omega) \;=\; \gamma(\omega)\,\delta\,(r'-r_p) \tag{2}$$

In reality, the noise source is not a δ-function, rather it has a finite volume. This fact can be easily accounted for, and will not be discussed here. Applying (2) in (1), the noise, as measured by a detector at position r_i, is given as

$$\delta\phi\,(r_i, \omega) \;=\; \gamma(\omega)\,G\,(r_i, r_p, \omega) \tag{3}$$

In this expression, $\delta\phi\,(r_i, \omega)$ is known from measurement, and $G\,(r_i, r_p, \omega)$ can be calculated as a function of its arguments. However, $\gamma(\omega)$ and r_p are noise source properties, and they are not known in a practical case. Since the main interest lies in the determination of the source position (localisation), we will use the notation r as the argument for the position of the source in the algorithm. Thus, we have succeeded in the localisation procedure when we obtain $r = r_p$.

To this order we consider an expression for the ratio of two detector signals, which will be given as

$$\frac{\delta\phi\,(r_i, \omega)}{\delta\phi\,(r_j, \omega)} \;=\; \frac{G\,(r_i, r, \omega)}{G\,(r_j, r, \omega)} \tag{4}$$

In this expression, the source strength $\gamma(\omega)$ is eliminated. The l.h.s. is known from measurement, and the unknown perturbation position r can in principle be obtained as the value (more precisely, one of the values) which, when substituted into (4), satisfies the equation. Using only one pair of detectors, in general there will be a whole line on the 2-D plane, in which the search for r is made, each point of which satisfies (4). Such a line was called a "localisation curve" in Ref. [4]. One needs at least one more detector to obtain one or two more localisation curves, such that the intersection of such lines gives the true perturbation position. Besides, in practice one uses power spectra instead of Fourier-transforms of the signals.

Thus the method goes as follows. Having access to n detectors, one can select $n\,(n-1)\,/2$ pairs and corresponding ratios of the type (4). Then, for pair r_i and r_j, one defines the quantities

$$\delta_{ij}\,(r) \;=\; \frac{APSD_i}{APSD_j} - \left|\frac{G\,(r_i, r, \omega)}{G\,(r_j, r, \omega)}\right|^2 \tag{5}$$

and

$$\delta_{ijkl}\,(r) \;=\; \frac{CPSD_{ij}}{CPSD_{kl}} - \frac{G^*\,(r_i, r, \omega)\,G\,(r_j, r, \omega)}{G^*\,(r_k, r, \omega)\,G\,(r_l, r, \omega)}; \qquad i \neq j,\, k \neq l \tag{6}$$

where, in general, $\delta_{ijkl}\,(r)$ is complex. Clearly, theoretically $\delta_{ij}\,(r)$ and $\delta_{ijkl}\,(r)$ are zero in an ideal case if $r = r_p$. This would be the case if no background noise, no measurement error existed etc. In practice however all these exist, thus in general (5) and (6) will deviate from zero for all r values. It can however be expected that the deviation from zero will be minimum for the true rod position. Thus, we define an optimization function as

$$g\,(r) \;=\; \sum_{\substack{i,j,k,l \\ i \neq j;\, k \neq l}} \left|\delta_{ijkl}\,(r)\right|^2 + \sum_{i,j} \delta_{ij}^2\,(r) \tag{7}$$

The position of the perturbation is then given as the value $r = r_p$ for which g is minimum:

$$\min g\,(r) \;\Rightarrow\; r = r_p \tag{8}$$

The localisation method, as described above, can be extended to localize several concurrent noise sources. However, the complexity of the method increases somewhat and the amount of computational effort needed increases significantly. However, as long as the noise sources are not over-lapping each other substantially, the multiple source method does not necessarily improve the localisation but it does still increase the complexity. Because of the above reasons, we have only applied and tested the single source method by using a suitably selected set of detectors for the few individual perturbations.

The calculation of the transfer function will not be described in detail here, we refer to references [7] and [8]. We have used one-group diffusion theory, one group of delayed neutrons and a bare, homogeneous cylindrical reactor in 2-dimensional $r - \phi$ geometry. This model is essentially the same as the one used in the study and application of the method of localising a vibrating control rod (Ref. [4]). The transfer function in this model is given as

$$
G(r, r_p, \omega) = \frac{1}{4} [Y_0 (B|r - r_p|) -
$$

$$
- \sum_{n=0}^{\infty} \frac{(2 - \delta_{n,0}) Y_n (BR) J_n (Br_p)}{J_n (BR)} J_n (Br) \cos (n (\alpha - \alpha_p))] \tag{9}
$$

This transfer function was used both in the simulation tests and in the concrete application with Forsmark data.

4. TEST OF THE ALGORITHM WITH SIMULATED DATA

To get some hands-on experience with the algorithm, and to get some estimate of its performance, it was first tested in simulation tests. These tests were conceptually similar to those performed in the study of the algorithm for the localisation of a vibrating control rod. The starting point is the selection of the position of the source, r_p, and a few detector positions r_i, $i = 1, 2, 3$. To simplify the simulations, we have selected the minimum possible number of detectors, which is three. Then the induced noise at these detector positions is calculated by (3), after which the calculated noise values were used in the localisation algorithm (5) and (7). The minimisation procedure was performed in the whole 2-D plane, yielding an absolute minimum. Since the perturbation position is known in advance in these tests, the correctness of the result, and thus the performance of the algorithm, can be judged.

The significance of the test is motivated among others also by the fact that expression in (7) may have several minima, and there is no prior proof of the hypothesis that the perturbation position yields the absolute minimum. Especially in the case of "disturbed" or "not clean" detector signals, such a proof may not exist at all since the deviations between the assumption of the model and reality are not known in exact quantitative terms. Thus the only way of finding the answers to such questions is to perform numerical simulations with both "clean" and "contaminated" signals (the contamination is also simulated). Another goal of the test is to check the sensitivity of the algorithm to disturbing effects such as background noise, statistical measurement error etc. Even if the existence of these does not lead to the occurrence of a global minimum at a position completely different from that of the true perturbation position, it will lead to deteriorated accuracy of the method. The simulation of the perturbed signals is achieved by adding a random number of a few percent to each calculated detector signal before performing the localisation step (7).

A layout of the selected source position and detector positions is seen in Fig. 4. The absolute value and phase of the induced neutron noise are shown in Fig. 5 over the whole cross-section of the core, i.e. not only in the three detector positions (which are indicated in Fig. 4) that will be used in the localisation algorithm. It is seen how the amplitude of the noise decreases and the phase delay increases with increasing distance from the source. From the quantitative results an attenuation length, i.e. a distance within which most of the noise amplitude change takes place, can be extracted. This attenuation length is about half of the radius of the core. The space-dependence also agrees qualitatively with the one seen in Fig. 3. The magnitude of the attenuation length is also in agreement with the fact that the oscillations are felt in about one half of the core.
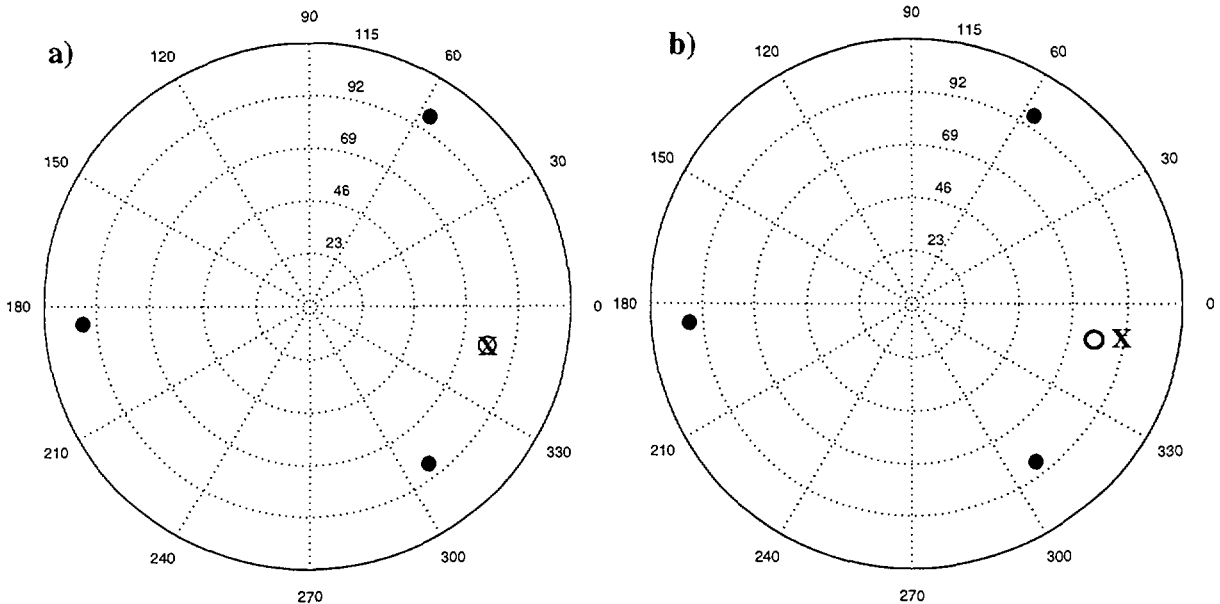

Fig. 4. The localised source position is marked by 'X'. The detectors used in the localisation are indicated by '●' and the actual source position by 'O'. In Fig. 4b the localisation algorithm was disturbed by the addition of extraneous random noise to the detector signals.

Expression (7) whose absolute minimum is to give the source position, is shown in Fig. 6. It is seen that it has a relatively simple structure, with only one minimum which is very well discernible, and it also coincides with the source position. This is reassuring, although the smoothness of the function $g(r)$ depends partly on the use of a homogeneous reactor model. In an inhomogeneous reactor model it may not be as simple; this question will be investigated in the future.

The results of the algorithm for one case are shown in a different way in Fig. 4, where a direct estimation on the precision can be visually made. The figure shows the results of the algorithm both for the case when pure (unperturbed) signals were used in the localisation step (Fig. 4a), and the case when perturbed signals were used (Fig. 4b). In the latter case a random number with a variance of 5% of the mean value of each signal was added to all three detector signals. It is seen that in the latter case the precision of the algorithm deteriorates, as expected. For perturbations of this magnitude, the deterioration is not large.

5. APPLICATION OF THE METHOD TO FORSMARK DATA

The layout of the core, with all detectors available in the measurement, is shown in Fig. 7. The number of detectors is much larger than the required minimum of 3 detectors, which was used in the simulation tests. Actually, it was not practical to use all detectors at a
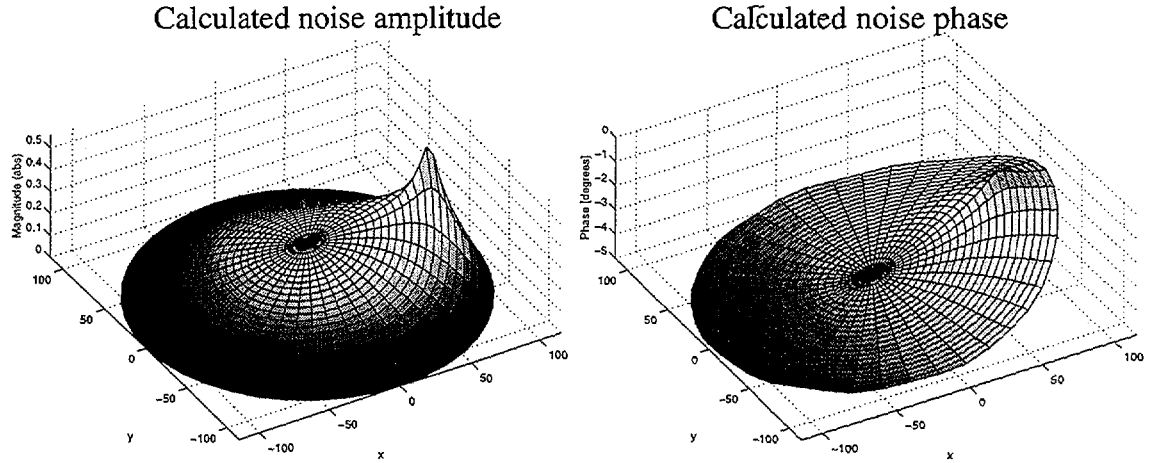
Calculated noise amplitude   Calculated noise phase

Fig. 5. The spatial distribution of the calculated noise amplitude and its phase
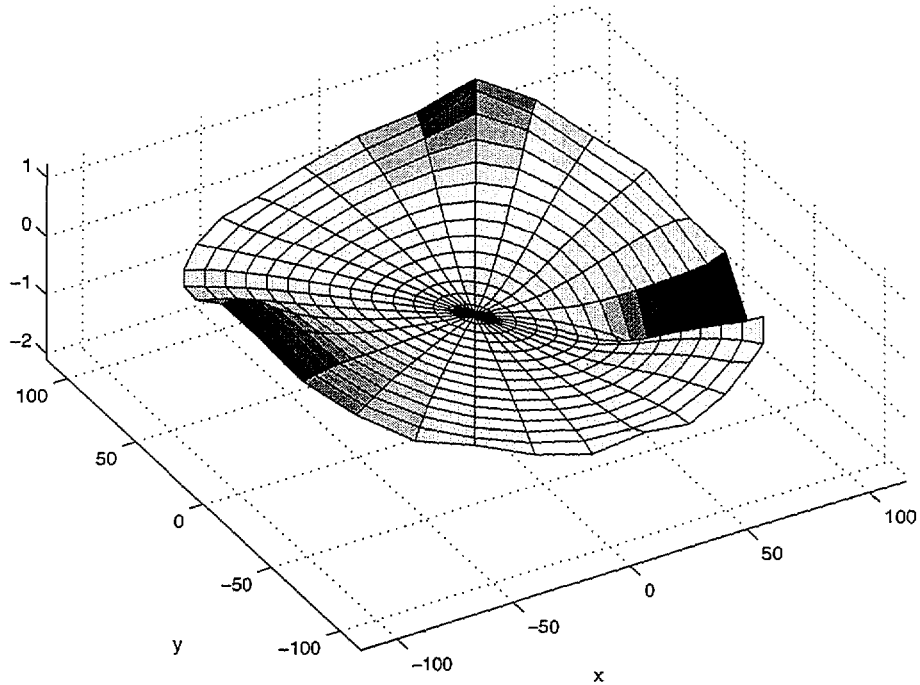
Fig. 6. The minimization surface in logarithmic scale.

time in a localisation run, only a limited set. There are two reasons why a limited set of detectors is more efficient than using all of them. First, as both the measurement "movie" (Fig. 3) and the simulated results (Fig. 5) show, the amplitude of the noise diminishes relatively fast away from the source, with a relaxation length smaller than the core radius. Since the background noise (i.e. noise from sources other than the instability) can be expected to be a smooth function of core position, e.g. follow the space dependence of the static flux, the relative weight of the useful noise is low in the signal of detectors that are far away from the source. Thus, the localisation is more accurate if only detectors from the same half or quadrant of the core are used where the source position is situated. The second reason for why using detectors around the suspected source position is effective is that the present algorithm is based on the assumption of one single source being active at a time. The measurement movie, on the other hand, makes it likely that at least one or two noise sources are acting, even if not stationarily, only in a sporadic manner. Fortunately, these potential sources are all separated from each other by a distance comparable with or larger than the noise attenuation length. By selecting groups of detectors around each potential source, the effect of other

sources is minimised and the various source positions can be determined separately by applying the single-source algorithm individually. It is this strategy that has been used in the present work.

Selecting a group of detectors is of course a somewhat subjective moment. Since the result of the localisation depends on the detectors used in the localisation algorithm, the selection of a set of detectors introduces an element of arbitrariness into the procedure. This kind of influencing the outcome of the results is justified by the fact that the conditions in a practical case do not exactly correspond to the idealised conditions assumed in the algorithm. The selection of a "most suitable" set of detectors is made in order to minimize the consequences of this deviation between practice and theory, and is performed by using reactor physics expertise.

We have tried to locate two noise sources, primarily the principal one close to LPRM 10, and a secondary one close to LPRM 7 (for the poistions of the different LPRMs, see Fig. 2). The results of the first case, concerning the primary source, are shown in Fig. 7. The figure
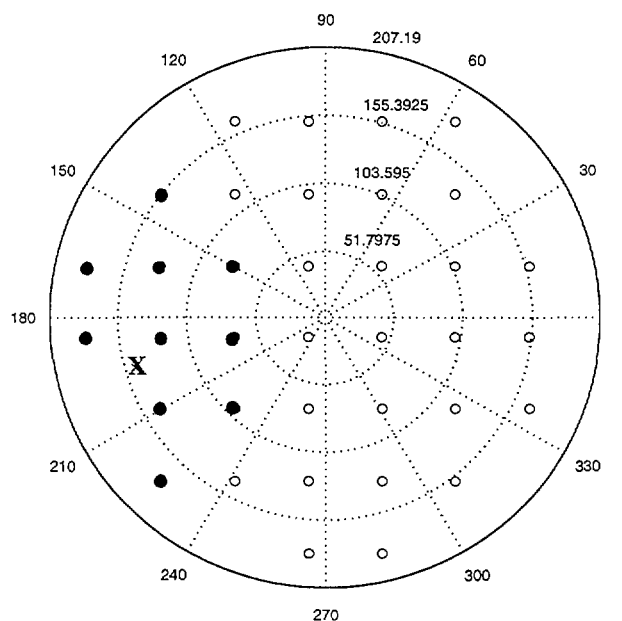
Fig. 7. The position of the source (X) as obtained by the locali-sation method using the detectors (●).

also shows the detectors that were selected in this localisation procedure. The result of the localisation is also shown in Fig. 8, where it is seen that the identified position is neighbouring to a position (18,3) where an unseated fuel assembly was found after revision 1997.

Varying the number and position of the detectors used in the procedure will naturally affect the result of localisation. This was also investigated by choosing various detector sets. As long as detectors are taken mostly from the west half of the core, the variation of the result is quite moderate. Choosing detectors from the other half of the core will lead to significantly different results. This is in accordance with the previous reasoning on the selection of the most suitable set of detectors above. At any rate, the result shown in Figs. 7 and 8 is the one that appears to be most plausible.

Results of the localisation of the secondary source, including the position of the detectors used is shown in Fig. 9. This position too corresponds quite well to the local oscillations seen in the movie. Hence it is also demonstrated that the two noise sources could
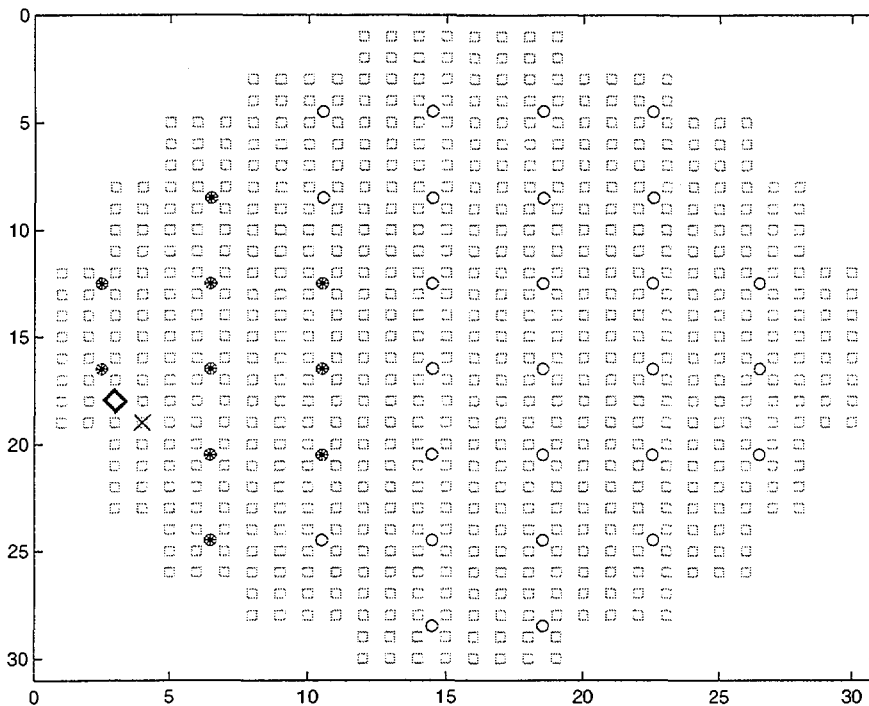
Fig. 8. The position of the source as obtained by the localisation method and the position of the unseated fuel element is indicated by a cross (x) and a diamond character (◇), respectively.
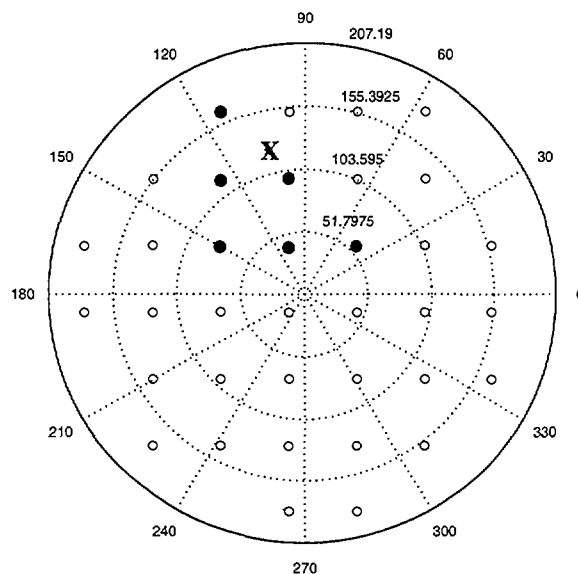
Fig. 9. The position of the secondary source as obtained by the indicated detectors (●) in the localisation method.

be identified separately by the use of suitably selected detector sets, and by applying the single source localisation algorithm.

6. CONCLUSIONS AND FUTURE WORK

The main purpose of this study was to test the applicability of the localisation technique in a practical case, using the Forsmark measurements. Such an algorithm has not been used and tested before. The study, both in simulations and with measured data, showed that the algorithm works satisfactorily. It was demonstrated that the resolution of the method is higher than the distance between the detectors in the core. It was also seen that two or three sources

can be localised individually if they are separated sufficiently well in space, with applying the single source localisation algorithm by using suitable selected sets of detectors.

One weakness of the method in its present form is the very simple core model used in the calculation of the transfer function. Besides of using one-group theory, the most important restriction is the use of a homogeneous bare reactor model. Core inhomogeneities, reflector, and most important, control rod patterns cannot be taken into account in the present model. The most important task in the further development of the method is to extend it to two energy groups, include a reflector, and take into account the inhomogeneous core structure. This will require fully numeric methods, and perhaps parallel computing techniques due to the large complexity of the calculational task.

ACKNOWLEDGEMENTS

REFERENCES

[1] LANSÅKER, P., Forsmark internal report FT-Rapport 97/485 (In Swedish) (1997)

[2] OGUMA, R., Swedish Nuclear Power Inspectorate (SKI) Report 97:42 (1997)

[3] SÖDERLUND, M., Forsmark internal report FT-Rapport 97/295 (In Swedish) (1997)

[4] PÁZSIT, I. and GLÖCKLER, O., *Nucl. Sci. Engng.* Vol. **88**, pp. 77-87 (1984)

[5] PÁZSIT, I. and GLÖCKLER, O., *Nucl. Sci. Engng.* Vol. **99**, pp. 313-328 (1988)

[6] BELL, G. I. and GLASSTONE, S., *Nuclear Reactor Theory*, Van Nostrand Reinhold Company, New York (1970)

[7] PÁZSIT, I. and GARIS, N. S., Swedish Nuclear Power Inspectorate (SKI) Report 95:14 (In Swedish) (1995)

[8] KARLSSON, J. K-H. and PÁZSIT, I. Study of the possibility of localising a channel instability in Forsmark-1, SKI report, to be published (1998)

SESSION 3:

DEVELOPMENT TRENDS AND ADVANCED TECHNOLOGIES
(1)

DEVELOPMENT TRENDS FOR DIAGNOSTIC SYSTEMS IN NUCLEAR POWER PLANTS

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1 ABSTRACT

Monitoring systems used in nuclear power plants have made remarkable progress over the past four or five years. Development has followed the trends and changes in philosophy for the purpose of monitoring systems in nuclear power plants: They are no longer expected to fulfill only safety tasks, the plant personnel require information on which to base condition-oriented maintenance.

A new generation of monitoring and diagnostic systems has been developed by Siemens recently. This new generation, called Series '95, is PC-based. An overview is given for the KÜS '95 loose parts diagnostic system, the SÜS '95 vibration monitoring system, the FLÜS leak detection system and the SIPLUG valve diagnostics system.

The objectives behind the development of these new systems are both safety-related and economic.

The new systems improve the reliability and quality of monitoring techniques and incorporate better detection and diagnostic capabilities. Progress has also been made in automation of the systems so as to reduce routine work, give higher sensitivity for the monitoring task and reduce the scope of maintenance.

2 CHANGES IN OBJECTIVES OF MONITORING AND DIAGNOSTIC SYSTEMS

Monitoring systems used in nuclear power plants have made remarkable progress over the past four or five years. Development has followed the trends and changes in philosophy for the purpose of monitoring systems in nuclear power plants: They are no longer expected to fulfill only safety tasks, the plant personnel require information on which to base condition-oriented maintenance.

The experience gained from backfitting a large number of monitoring systems with digital recording and diagnostic units during the last three years can be summarized as follows:

- Costs for system implementation, system operation and maintenance must be weighed against the benefits of reducing potential risks of damage through monitoring and other benefits from the operation of the diagnostic systems, and should yield positive results.

- Monitoring and diagnostic systems should be standard I&C equipment. The costs for their operation and servicing must be of the same order as those for other I&C systems.

- Monitoring and diagnostic systems should provide information about the behavior of the plant to allow condition-oriented maintenance of plant components and to prevent unplanned outages due to failures.

A new generation of monitoring and diagnostic systems has been developed by Siemens recently. This new generation, called Series '95, is PC-based.

The objectives behind the development of these new systems are both safety-related and economic. They include:

- Early detection of faults, and hence minimization of damage,

- Enhancement of trouble-shooting features,

- Prevention of sequential damage,

- Reduction of periodic inspection costs and radiation exposure and

- Compliance with licensing requirements.

The new systems improve the reliability and quality of monitoring techniques and incorporate better detection and diagnostic capabilities. Progress has also been made in automation of the systems so as to reduce routine work, give higher sensitivity for the monitoring task and reduce the scope of maintenance.

3 FROM LOOSE PARTS MONITORING TO DIAGNOSTICS

For more than 20 years now, nuclear power plants in the U.S., Germany and other western countries have been required to install and operate loose parts monitoring systems. In 1990 IEC 988 "Acoustic monitoring systems for loose parts detection - Characteristics, design criteria and operational procedures" was elaborated and published. Despite this, loose parts monitoring is not a standard requirement for nuclear plants worldwide.

Reasons for this could be as follows:

- The first loose parts monitoring systems suffered from low sensitivity and a high rate of false alarms,

- Loose parts occur very seldom and most of them can be avoided if reactor coolant system maintenance is carefully performed (the experience of the last two years would not appear to corroborate this statement),

- Loose parts monitoring systems involve additional expense (implementation, operation and servicing).

Recent developments in loose parts monitoring systems have improved the capabilities of these systems, allowing the risk of damage to primary circuit components as a result of loose parts to be reduced significantly. Operation and servicing of the system is almost fully automated in order to reduce the related time and expense.
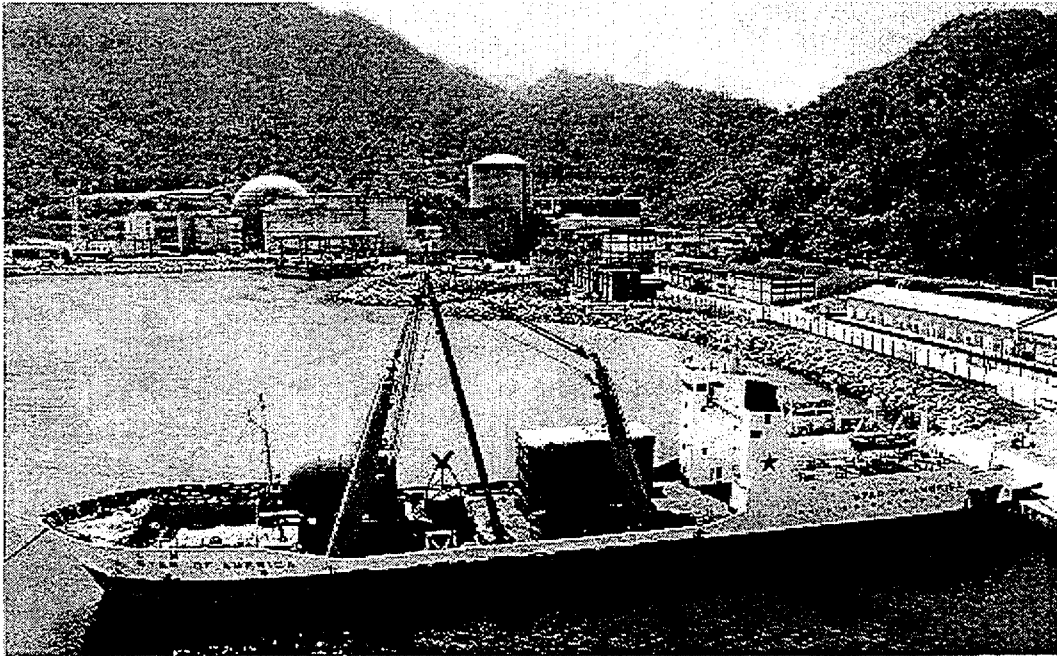
Figure 1 Angra 2 (Brazil) is one of more than ten plants equipped with the KÜS '95 loose parts monitoring system

The new Siemens KÜS '95 loose parts diagnostic system for the detection and location of structure-borne noise evaluates noises made by loose parts in an analysis and a diagnostic phase. The main benefit of the system is its ability to determine whether or not structure-borne noises detected coincide with previously recorded reference events. These reference events are used as the basis for subsequent diagnosis. In addition, they also give the system the ability to decide if the noise in question originates from a loose part or is just a normal operational event, such as is often the case. A normal event is filed as a 'Known Event', thereby avoiding unnecessary evaluations.

If the event is relevant or unknown, however, a KÜS system alarm is triggered. The operator can then either assign the event to one of the known classes of reference events in an off-line evaluation process, or can define the event as a new reference class and perform a corresponding diagnosis. The system incorporates all the analysis tools required for this process.

The system performs:

- Reliable detection of loose parts and minimization of data and spurious alarms through diagnostic capabilities for burst classification,

- Determination of the point of impact: The system measures the signal transit time difference. This makes use of the fact that when a loose part impacts with the wall of the reactor coolant system, a burst is produced which propagates at the speed of sound, thus reaching the structure-borne noise sensors at different times. The point of impact is determined on the basis of the geometry of the reactor coolant system, the speed of sound and the transit time differences for the individual signals produced by the same impact event. At the 1995 international benchmark test organized from the Nuclear Energy Agency of the OECD, KÜS '95 was able to locate the points of impact to within just a few centimeters. The results are displayed with the aid of a 3D view of the reactor coolant system and can easily understood (this view is similar to the sketch in Figure 2).

- Estimation of the mass of the loose part: The structure-borne noise signals also contain information on the mass of the impacting object. The underlying physical principle is explained by Hertz's law, which states that the time during which two bodies remain in contact following an impact is a function of their masses and velocities. During the above benchmark test, KÜS was able to determine the mass of 6 different bodies in the range between 50g and 15kg to within approximately 30 percent, an accuracy which is perfectly adequate for practical applications.

- Automatic in-service inspection of whole system: A basic principle of system design is that control is exercised over instrument chains and algorithms in order to produce physically identical variables during in-service inspection and calibration; i.e. for loose parts monitoring a remote impact hammer produces impact events on the nuclear power plant components. The system features complex self-monitoring functions which range from pure hardware monitoring (power failure) to complex functional monitoring (watchdog functions) which also cover the software. All data relating to system component malfunctions are visually annunciated on an alarm unit. Such malfunctions are also recorded by the system and logged.

4 COMPLETE VIBRATION MONITORING THROUGH TO THE RESULTS REPORT

Damage to reactor coolant system components in nuclear power plants as a result of mechanical vibrations is very rare. When an event of this type occurs, the result to date has normally been an extended outage with costly repairs. Vibration monitoring systems make it possible to detect changes in the vibration behavior of reactor coolant system components, reactor pressure vessel internals and reactor coolant pumps in pressurized water reactor plants at an early stage. Implementation and operation of vibration monitoring systems is required in nuclear safety standards (e.g. in KTA 3201.4, KTA 3204 and DIN 25475/2 for Germany).

A change in the vibration behavior of a component is one of the most sensitive indicators for changes in its mechanical condition, e.g.

- Relaxation of tensioning for flow baffle mounting bolts

- Reduction in the stiffness of core barrel holddown springs

- Damage to journal bearings in a reactor coolant pump or

- Shaft cracking in a reactor coolant pump.

An extensive knowledge base is available on the correlation between the vibration behavior of reactor coolant system components and their associated mechanical condition for Siemens plants. This is due to the fact that baseline vibration measurements are taken during commissioning in Siemens plants, supplemented by many years of feedback of experience from operation of vibration monitoring systems at Siemens and other vendor plants. This knowledge was not implemented in the vibration monitoring system previously, so that vibration measurements were time-consuming.

```
Influenced Component  :  L1SL, RCP
Vibration             :  T, h
Signal(s)             :  R1R
Function              :  APSD
Parameter             :  Freq. [Hz]
Trend-No.             :  F38
Reference value       :  20.8
Actual value          :  21.1
Normalized value      :  21.1
Lower threshold       :  -0.3
Upper threshold       :   0.3
Deviation             :   0.4
Indication            :   >
```
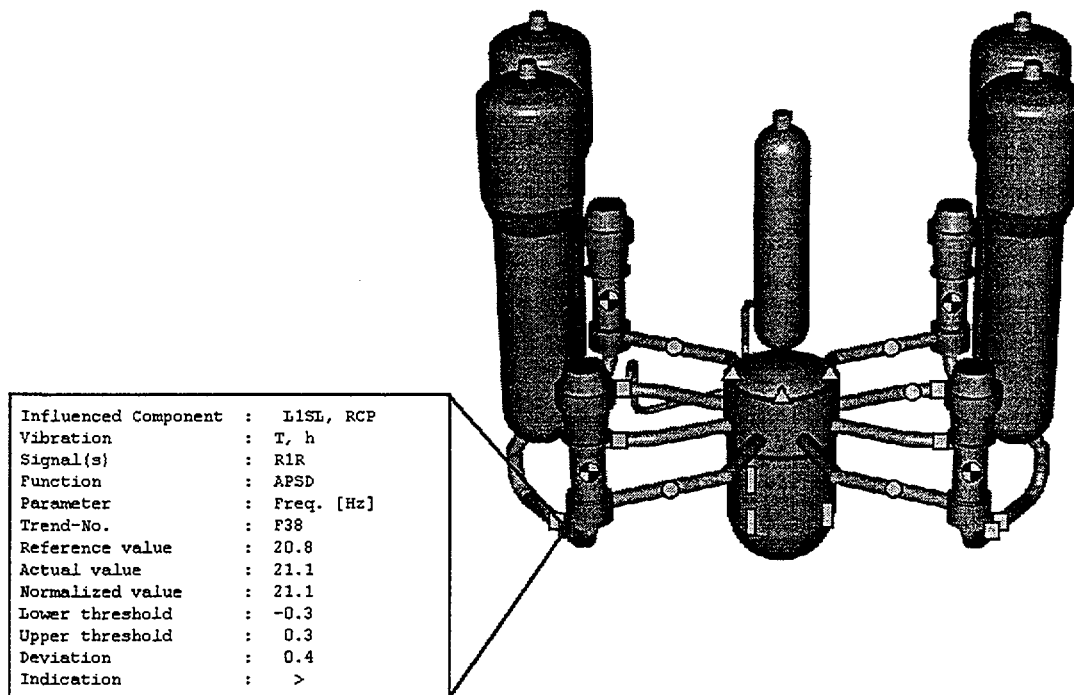
Figure 2 SÜS '95 displays the location of an affected reactor coolant component

The new SÜS '95 vibration monitoring system now performs these necessary and routine tasks without operator intervention. It performs the complete measurement procedure automatically at preselected time intervals, the procedure ranging from calibration of the instrumentation chains, analysis of the signals and monitoring of preset limits to evaluation of the measured data, any documentation of the results required and updating of the vibration measurement database to include the most recent data. If desired, the system can generate a standard report in Word for Windows format, this presenting the results of monitoring in the form of plain text, tables and diagrams. In the event of deviations, the affected reactor coolant system component and the abnormal vibration waveform are specified and indicated on a view of the reactor coolant system (Figure 2). The advantages of the SÜS '95 system are a drastic reduction in necessary resources, well-founded analysis of the mechanical state of components and visualization of results of the analysis.

5 SAFETY THROUGH DIFFERENT PRICIPLES FOR DETECTION AND LOCATING REACTOR COOLANT SYSTEM LEAKS

Analysis of events at nuclear power plants shows that it is impossible to completely rule out leaks at flange connections, valves, isolation valves, etc. Fluid escaping from external leaks can sometimes result in considerable system contamination. Plant safety considerations also make it essential to avoid even internal leaks (such as from safety valves to the pressurizer relief tank), with the result that suitable leakage monitoring systems must be provided.

These risks can be minimized with leakage monitoring systems. Early detection of leaks from cracks in line with the leak-before-break criterion is an appropriate method of preventing a reactor coolant line rupture. According to this criterion, once a through-wall crack has developed, a considerable period of time under stress will elapse before the crack reaches a critical length resulting in a pipe rupture. It should be emphasized that although such off-normal conditions involving "leaks-before-breaks" are extremely unlikely to occur, the plant

should nevertheless be monitored for such conditions on the basis of the general safety considerations outlined above.

In terms of plant availability, on the other hand, leakage monitoring systems are important for detecting the considerably more realistic cases of leaks which occur during operation or start-up. Prompt identification and localization of these leaks can limit consequential damage and reduce possible outage times.

Discussion has started again recently, especially in Europe, on improvements to leak detection and on monitoring requirements. One approach of a new quality in the field of leak monitoring is the use of different monitoring principles in parallel.

FLÜS	ALÜS	LDS
Leak Detection with Permeable Tube	**Acoustic Leakage Monitoring**	**Global Surveillance**
■ Surveillance of long insulated pipes or piping system carrying water or steam	■ Structure-borne noise ■ Prompt detection and localization of internal and external leaks	■ Atmospheric humidity ■ Condensed water at air cooler ■ Sump level

Safety through Diversity and Redundancy

Figure 3 Reliable leak detection through different physical principles

This explains the reasons behind Siemens' development of three different systems for the detection and localization of reactor coolant system leaks in PWRs (Figure 3). These systems are as follows:

- "FLÜS", a moisture leak detection system,

- "ALÜS", an acoustic leak monitoring system and

- "LDS", leak detection system with humidity measurement equipment.

These three systems operate according to completely different physical principles (diffusion of water molecules, acoustic emission and humidity in the containment) and complement one another in terms of their application. The systems are based on the same design concept as PC-based instrumentation systems with modern user software and follow the same standardized strategy in terms of alarm philosophy, self-monitoring and user reliability.
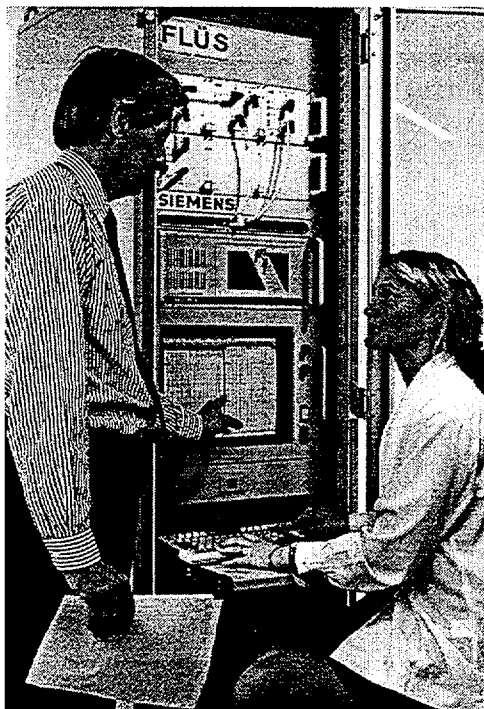
Figure 4 FLÜS leak detection system with extremely high sensitivity of better than 1 kg/h

An innovative and interesting solution is implemented in the FLÜS system (Figure 4): Humidity is detected in the vicinity of a leak by means of a temperature and radiation-resistant metallic tube filled with dry air and positioned either inside the thermal insulation (local monitoring of components) or inside the equipment compartment (global monitoring). The sensor tube has diffusion points (Figure 5) through which ambient humidity can pass. At predetermined time intervals, the air column from the tube is drawn through a moisture sensor. The system measures the moisture content of the air as a function of time and the speed of the air column. Using these data, it determines the leakage rate as well as the leak location. In parallel with this action, the air in the tube is replaced by dry air for the next diffusion interval. The system can detect extremely small leaks with leakage rates as low as 1 kg/h by the end of 15 minutes at the latest, an outstanding sensitivity.

Figure 5 FLÜS sensor tube with diffusion element through which ambient humidity can pass

The end of the air column sampled in each measurement is selectively marked by a defined amount of moisture (test leak). This defines the reference values for transit time and moisture content and is also used for self-monitoring of the entire system.
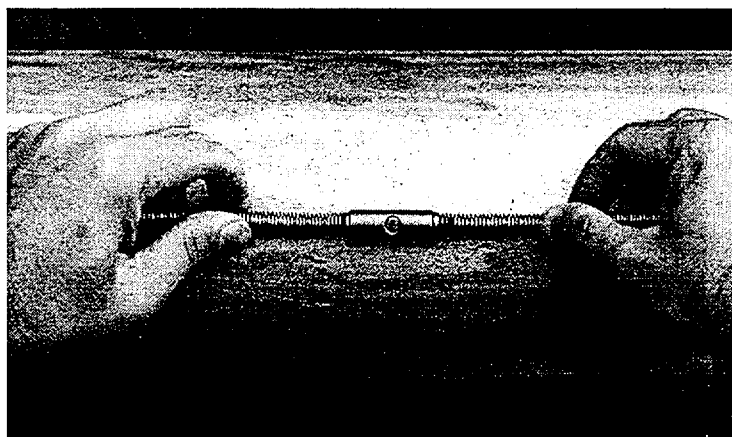
Although FLÜS is a very new system, two such systems have been already implemented, at Obrigheim (Germany) and Ringhals 1 (Sweden).

As already mentioned, leakage detection in a nuclear power plant should be based on a combination of the ALÜS, and FLÜS and LDS systems. FLÜS is used to monitor the reactor coolant pressure boundary for leaks to the outside, LDS for global monitoring of equipment and operating compartment humidity, while ALÜS provides redundancy and serves above all to monitor critical valves for internal leaks.

6 VALVE DIAGNOSTICS DURING POWER OPERATION

Almost 90 percent of the mechanical components in a power plant comprise valves. The ability to function and readiness to function for valves has a decisive impact on the availability and reliability of the industrial systems of which the valves form a part.

Recent developments led to a valve performance concept that comprises an analytical section that must be performed once and includes:

- The model for function describing the required positioning forces and torques for actuation and considers the relevant parameters with tolerances

- The model for stress analysis covering the load-carrying capacity of valve components and

- Design evaluation covering the limits and weak points for the parameters relevant for function

Verification of ability to function is followed by periodic testing to verify readiness to function. These tests assure early detection of faults over the entire service life of the valve and allow timely performance of maintenance and repair measures to avoid problems. The approach used for monitoring performance of a valve and its associated electric actuator comprises the measurement of active power for the actuator. This parameter allows fast evaluation via the motor control center(MCC) and diagnostic measurements in the event of out-of-tolerance situations. (Beside active power measurement, detailed measurements at the location of the valve are also used to check the parameters for the mechanical equipment.)

To allow the required periodic testing of valve actuators to be performed during normal plant operation, Siemens developed the mobile microprocessor-controlled data logger SIPLUG for recording active power.

All the components are housed in a standard, compact plug-in module of the type found in power plants. SIPLUG remains in the standby mode until the valve is actuated and is then activated automatically. It then measures the current, voltage and control parameters, calculates active power and stores the values in its internal memory. The memory is sufficient for a recording time of approximately 400 s, which means that multiple valve actuation can be easily recorded.

At periodic intervals, SIPLUG is hooked up to a PC which reads and evaluates the stored data.

SIPLUG valve diagnostics thus allows changes in the condition of a valve and its actuator system (including the controls) to be reported during power operation. The measurements are performed under operating conditions and from the motor control center, so there is no additional valve testing, no radiation exposure and reduced cost. The unit can be easily installed on MCCs from a wide range of different manufacturers.
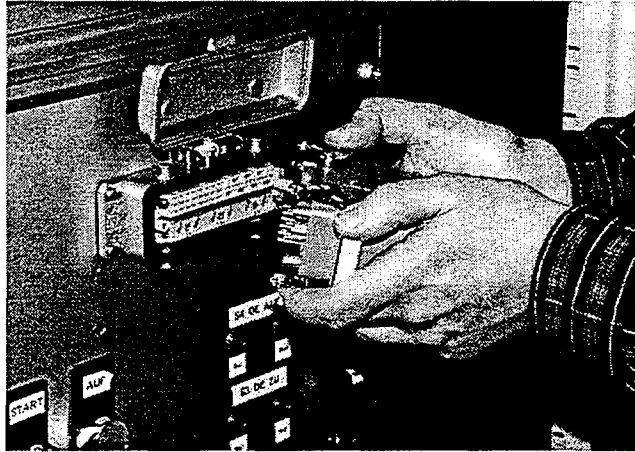
Figure 6 SIPLUG is connected with valve actuator control unit in the MCC

7 BENEFITS FROM EXPERIENCE

Siemens, as a manufacturer of power plant components, already has more than 20 years of experience with monitoring systems applied in Siemens and other vendor plants. The new developments exploit this extensive experience which has been integrated into the evaluation procedures of the systems.

Development trends are toward diagnostic systems for reactor coolant system component monitoring that are no longer restricted to use by specialists. They bring the systems closer to standard I&C and offer valuable information about plant component behavior, particularly with a view to introducing modern maintenance strategies.

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SOFT COMPUTING FOR FAULT DIAGNOSIS IN POWER PLANTS

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Abstract

Considering the advancements in the AI technology, there arises a new concept known as *soft computing*. It can be defined as the processing of uncertain information with the AI methods, that refers to explicitly the methods using neural networks, fuzzy logic and evolutionary algorithms. In this respect, soft computing is a new dimension in information processing technology where linguistic information can also be processed in contrast with the classical stochastic and deterministic treatments of data. On one hand it can process uncertain/incomplete information and on the other hand it can deal with non-linearity of large-scale systems where uncertainty is particularly relevant with respect to linguistic information and incompleteness is related to fault tolerance in fault diagnosis. In this perspective, the potential role of soft computing in power plant operation is presented.

1. INTRODUCTION

Parallel to rapid advancements of modern technologies, there emerged a new concept articulated as *complexity*, which is beyond its traditional use. This is partly phenomenological since the concept is generic enough to use in different situations but it is still context dependent and needs to be defined in each case. From the nuclear power plant (NPP) viewpoint the complexity may be understood as multiple interacting processes in a large-scale industrial process environment. In this context, complexity suggests vast amount of data acquisition to be processed during the operation especially referring to three major executions: monitoring, control, diagnostic. Here the problem is the appropriate processing of the data obtained in such a way that the redundancies in processing are avoided and correlations among data are identified to cope with the real-time or other limitations. In this perspective, it is not difficult to realise that the conventional data processing methods may not be efficient enough even though they may be effective enough. This basic conjecture is quite illustrative to indicate why artificial intelligence (AI) technologies should be integrated to NPP environment. Such integration can take various forms like AI-based monitoring, control, diagnostic, maintenance, operator decision support system (ODSS) and so forth.

In the present context, AI is to establish systems that show intelligent behaviour and perform complex data analysis tasks with a level of competence that might even supersede the level of the domain human experts. The characteristic feature of AI is its heuristic nature where the term heuristic refers to knowledge that is used to control the reasoning leading to correct or satisfactory solution.

Two of the major pioneering/preliminary approaches to AI are the *symbol manipulating approach* and *connectionist approach*. Symbol manipulating approach gave birth to expert systems. Connectionist approach is due to neuronal structure in the brain where the complexity is due to the number of the simple operations so that intelligence appears as an illusion as result of cumulating of large numbers of simple connected phenomena. Artificial neural networks (ANN) are the most familiar structure of the connectionist approaches. In the last decade there is a rapid development in the AI technology as well as its utilisation in nuclear industry, in particular power plant monitoring, control and fault diagnosis. The two approaches above for AI have rapidly developed to advanced stages establishing their associated technologies. At the same time they were joined by other AI-based paradigms which have also established their associated technologies before long.

The subject matter of this work is *soft computing* which is processing of uncertain information with the AI methods, that refers to explicitly the methods using **neural networks, fuzzy logic** and **genetic/evolutionary algorithms**. In this respect, soft computing is a new dimension in information processing technology where linguistic information can also be processed in contrast with the classical stochastic and deterministic treatments of data. Referring to this in the context of diagnostic systems in NPPs, the organisation of the paper is as follows. Section two describes the major components of the AI, in perspective. Section three describes an emerging AI technology as a synergistic combination of the existing AI technologies described in the preceding section from the view point of NPP operation. This is followed by the conclusions.

2. PARADIGMS OF ARTIFICIAL INTELLIGENCE AND DIAGNOSTIC SYSTEMS

Artificial intelligence is concerned with the development of systems that emulate the intelligent behaviour of human and further can perform complex tasks. The associated soft computing related paradigms are briefly presented in perspective from the view point of their merits in NPP monitoring and diagnostics.

2.1. Knowledge based expert systems.

Presumably, the first substantial AI attempt was made by means of knowledge-based systems (KBS). KBS provides a convenient way for encoding and storing human knowledge. If this knowledge is from a human expert, then the system is termed as expert system. Such systems supposedly perform on the level of human expert, autonomous reasoning tasks such as diagnosis, decision making. The current status of expert systems is briefly described below.

A first generation expert system is a shallow expert system that consists of knowledge processing unit and a heuristic knowledge base. An expert shell contains no a priory knowledge. It has to be filled with domain knowledge prior to its use. Domain knowledge is captured in production rules. The production rule paradigm is a model for human reasoning. It captures an expert's experience and casual reasoning strategy. It is a representation paradigm where knowledge can be captured in the form of rules. The rules consist of compiled associations of facts and phenomena with solutions and actions. The knowledge base containing these rules is a large set of recompiled chunks of deep knowledge ready to use rather than a collection of shallow knowledge in the form of if-then rules.

In the first-generation expert systems, two fundamental forms of reasoning process is involved. These are forward chaining and backward chaining. Both strategies work on production rules, but complementary. Forward chaining works from antecedent to conclusion, while backward chaining works from conclusion to antecedent. There are several ways for the improvements to increase search speed, performance. However first generation expert systems contain shallow knowledge. Expert systems based on purely shallow knowledge cannot give satisfactory explanations about their behaviour and show abrupt degradation at the edge of their knowledge domain, since no compiled knowledge about cases that never have occurred before is available. Moreover, since knowledge elicitation depends on subjective human experts addressing only a limited number of cases, the expert system's knowledge domain is incomplete and possibly inconsistent of format and meaning. The disadvantages and limitations of first generation expert systems are summarised below [1]:

Incoherent sequences of questions; redundant questions; historical information on a case is not maintained, requiring the user to enter it again for each consultation on that case; inflexible user interface where information is required to be entered in very specific terminology's and formats, otherwise information is ignored; User is nor allowed to revoke an answer or to pursue the effects of an alternative answer; explanations do not cover al the explanation needs of the user; Performance degrades dramatically when dealing with rare case; Inability to recognise that a problem case is at the periphery or outside of its area of expertise; Difficult to modify the system's knowledge. Consistency checks are not facilitated; Inability of the system to evolve on the basis of its experiences in problem solving.

The causes of disadvantages and limitations above are explained as follows:
Shortcomings of reasoning knowledge that it is not complete; the generic tasks and strategies are implicit; shortcomings of domain-factual knowledge due to its structure which is not compatible to the way human experts model their knowledge.

The causes all originate from the differences and incompatibilities between human and expert systems knowledge representation and processing. Referring to the shortcomings of the first generation expert systems, the second-generation solutions are briefly as follows. In second generation expert systems, knowledge is derived from the first principles introducing generality. However this does not imply that the resulting model precisely describe the physical model because the first principles are not detailed enough for the complexity of the real world.

Designing a second-generation expert system with the objective to overcome a specific first generation limitation without solving this limitation in the context of others is prone generating local, non-robust solutions. For sound improvements in second generation expert systems, the limitations in the first generation counterpart must be well understood. Hence, the architecture should then be designed from the perspective of the root causes and not of their effects. Then, the architecture will provide a global and thus effective solution. Integrating first and second generation expert systems should make it possible to use heuristic knowledge to decide when to carry reasoning back and forth from heuristics to first principles. This is important when experience fails or is lacking or when the domain model is incomplete. Efficiency and the ability to reason progressively ensure that model-based reasoning is performed in time. This is very important for critical situations where response time should be small to avoid imminent accidents. A progressive reasoning mechanism generates a preliminary answer using only a very small knowledge base. While time is available, gradually larger knowledge bases are accessed to refine this answer step by step. After some time, the current inference takes the precedence.

In spite of inherent limitations, expert systems can be quite effective and efficient diagnostic tool in plant diagnostic applications. However in their safety related applications care should be exercised. Some guidelines for such cases are summarised below [2].

- The expert system should be based on the best possible risk analysis;
- The quality of the risk analysis should be checked, especially for completeness;
- Advice rules should be expressed in terms of possibility rather than probability;
- The system should be robust, so that in cases of doubt safe advice is given;
- For each advice rule, the range of possible contexts in which the rule may be applied should be evaluated;
- The system should be designed to provide support to the operator, rather than safety actions, so that the need for safety actions can be avoided.

2.2. Neural Networks

Neural network is a data processing system consisting of a number of simple, highly interconnected processing elements in an input/output architecture. A neural network is a distributed information processor where structural information can be stored and can be made available for use in later reference. It resembles the brain functions because the network through a learning process acquires knowledge and the information/knowledge stored is distributed in the form of connection weights of the network structure. A feed-forward neural network is generally structured with a set of a prescribed number of elementary processing units arranged in several layers. The very first layer that is, input layer, external information is coupled to the network. Each subsequent layer receives the information provided by the immediate lower level and sends the processed information directly to the upper layer. The output layer delivers the final processed information for use in the intended application. There are many variants of feed-forward structure, as well as many other variants of the neural network structures.

Neural networks found rapid and vast interest in plant operation especially in monitoring, diagnostic and control due to their potential for fault detection and non-linear characteristics. For monitoring and diagnostics, perhaps the most important generic structures are first self organising networks due to their classification ability used for large data classification and reduction before processing [2-4] and second feed-forward structure in auto-associative form [5-10] due to its special features. The architecture of autoassociative network is shown in Fig.1. The measurements from the plant sensors are applied to the input of the network. The input measurement vector is non-linear mapped to bottleneck layer. Subsequently, the mapped information is non-linear de-mapped to the output layer of the network. The bottleneck layer (hidden layer) plays important role in the effectiveness of the network. It has a dimension, i.e., number of nodes smaller than that at the input or output. It prevents a simple one-to-one mapping as result of training and the least-square training criterion assures that the internal representation developed by the network contains the maximum information it can accumulate with the existing structure.

The non-linear mapping and de-mapping provides that, in such multivariate plant monitoring, the network can be much more sensitive to process changes, and may help to highlight incipient problems (early fault detection) before they become obvious yielding serious problems.
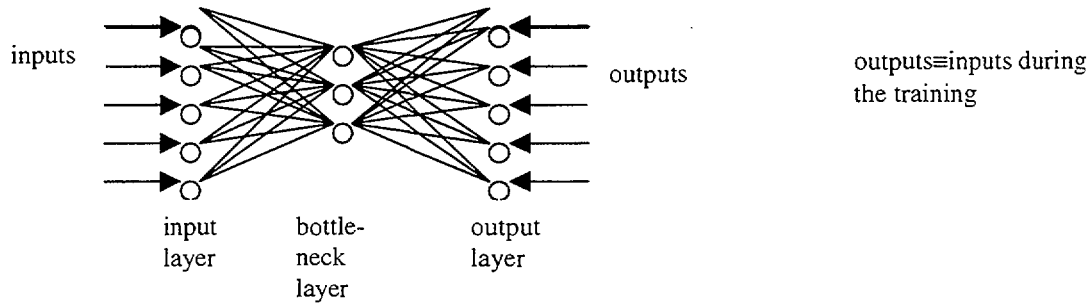
Figure 1 . Architecture of the auto-associative network

One more important feature of autoassociative network is that it plays the role of noise filtering. This can be seen as follows. Presently, we assume inputs to the network are plant measurement vectors. The training set is formed by the collection of these vectors, each of which belong to different times and plant conditions in the operation. The variations within the set of measurement vectors consist of operational changes, process disturbances and the associated control system responses together with process and measurement noises. Since as the result of training the correlation between the process signals (measurement vector components) are established, the uncorrelated variations are excluded, i.e. filtered out. The process noise is correlated since the measurements are coming from the same process. However, measurement noises are uncorrelated and their effects are eliminated that it results in improved training yielding improved estimation of the measurement vector at the output. The positive effect of the noise filtering can be observed also by introducing additive white noise on the process signals in the measurement vector before training. Enhanced training performance due to noise filtering phenomenon of auto-associative network with plant signals is reported in the literature [11] and it is termed as *robust training* [10].

Due to their non-linear characteristics, neural networks are also used for preliminarily non-linear control of diverse applications as a part of neural network research. Today, firm foundations of system identification and control of dynamical systems using neural networks is established [12,13]. For power plants, improved safety demands require new control laws to perform novel control functions with novel supervision and plant control concepts [14]. In general, when the uncertainties in a process environment are 'large', the common feedback controllers may not be satisfactory enough. Adaptive controllers may be the solution by adapting the system dynamics parameters in the model. However, in a plant environment there are cases where one need to significantly increase the operating range. This requires dealing effectively with significant uncertainties of the complex dynamic system in addition to increasing the validity range of the control methods. Alternatively, this requires coping with significant unmodeled and unanticipated changes in the plant, in the environment and in the control objectives. This is the issue of non-linear and intelligent control where neural networks play important role.

2.3. Fuzzy Logic

Fuzzy logic conventionally is a generic name including the fuzzy set theory, fuzzy logic itself and the associated technology. Fuzzy set theory was introduced through Zadeh [15]. With fuzzy sets, a numerical value is classified into one or more linguistic labels. These labels may be

discrete as well as continuous and they are coined as membership functions that represent the numerical strength of linguistic labels for the domain of classification. Since the membership functions can overlap, this results in multi-value representation of the knowledge. An input value intersects with one or more membership functions of the input classification and therefore it is attached to several linguistic labels.

A fuzzy set A on the universe X is a set defined by a membership function μ_A representing a mapping

$$\mu_A : X \rightarrow \{0,1\}$$

where the value $\mu_A(x)$ for the fuzzy set A is called the membership value of $x \in X$. The membership value can be interpreted as the degree of x belonging to the fuzzy set A. A typical membership function might be as shown in Fig.2.

Before entering a fuzzy system, the information at hand is fuzzified. This is done by an input classification, matching the input value against a chosen set of linguistic labels. These labels partly overlap as shown in Fig.1, so that a numerical value can be classified into more than one label, each with an associated member value. Inference is carried out with evaluating fuzzy production rules where the propagation of the fuzziness is linear with respect to arithmetic operations. Logical combinations are performed in a systematic way with certain rules known as norms. The extension of the intersection and union of two classical sets to the intersection and union of two fuzzy sets is not uniquely defined. However, intersection and union operations for fuzzy sets should have the counterpart intersection and union of classical sets.
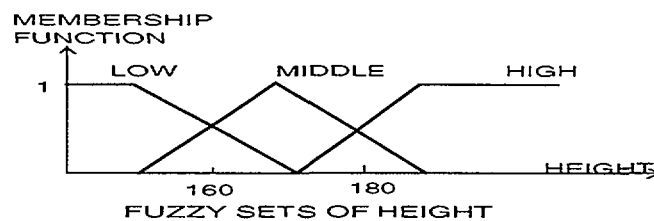
Figure 2: Representation of fuzzy sets of heights

Zadeh · proposed to use the following definitions

$$\mu_{A \cup B} = \min(\mu_A(x), \mu_B(x))$$
$$\mu_{A \cap B} = \max(\mu_A(x), \mu_B(x))$$

If we restrict $\mu_A(x)$ and $\mu_B(x)$ to values $\{0,1\}$, then these operators reduce to the intersection and union as defined for classical sets. Since one linguistic value can be attached to several numerical values in the context it is considered, more than one rule might be triggered producing several answers. This multiple answer can be combined to reach an optimal decision or a decision region. This is illustrated in Fig.3.

RULE: IF X1=S and X2=M then Y=L

Figure 3: Fuzzy inference

Among the industrial applications fuzzy logic control become very popular in the last decade. However, referring to conventional fixed feedback and/or adaptive control in a power plant environment for fault diagnosis and safety, such exercises is not to conceive. In this respect the followings are useful to remember [16]:
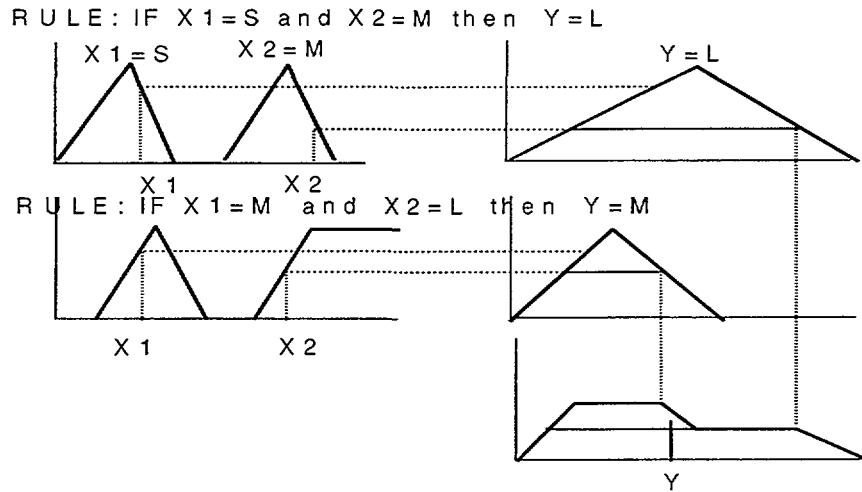
Fuzzy controller should not be used when

- conventional control theory yields a satisfactory result;
- an easily solvable and adequate mathematical model already exists;
- the control problem is not solvable/system is not controllable.

However, in complex, dynamical systems to meet the demand of intelligent decision-makings for various purposes fuzzy logic may play important role. Among such decision-making needs, fault diagnosis and intelligent/autonomous control takes important place where intelligent decision making is required to generate appropriate control actions. Fuzzy logic functionality is enhanced by fuzzy neural systems and they are subject matter of soft computing.

2.4. Genetic/Evolutionary Algorithms

Genetic algorithms (GA) [17] are stochastic search techniques having inspiration from the natural selection and genetics. They can be used in different ways and can play the key role in intelligent systems, as they can easily be corporate in such systems. Presumably, they are mostly articulated as powerful optimisation algorithms the criterion of which is termed as *fitness/evaluation function*. The linguistic quantities can also be integrated into the optimisation scheme, as is the case in fuzzy logic. GA type optimisation algorithm is conceptually flexible so that it is also used in applications where the conventional optimisation algorithms may be prevalent such as neural network training problems. In this particular example the motivation may be to avoid the risk of hanging on the local minima during the training. Another significant application example might be the optimal membership function determination or fuzzy IF-THEN rules identification in fuzzy-logic-based intelligent systems.

3. SOFT COMPUTING

Soft computing (SC) deals with the processing of uncertain information with AI methods. As the concept of uncertainty is different than the classical analytical paradigm, the treatment of

the uncertainty itself is subject to uncertainties, such as membership function determination, for instance. Even this simple example indicates that the soft computing as an innovative approach to constructing computationally intelligent systems, is not an easy task. It is an emerging approach to computing having the reasoning of human as a counterpart in decision-makings.

In the preceding section the tools of SC are presented. From the industrial application point of view, neural network technology and fuzzy logic technology and other AI technologies are in the course of fusion forming a counterpart technology known as SC technology. From the nuclear industry viewpoint, SC technology is quite appealing due to following reasons:

- Handling of the non-linearity and approximate dynamic system model provisions and other provisions of a large scale system is relatively easy;
- Intelligent decision makings are produced where due to the complexity of the power plant the necessity of such decisions inevitably exist;
- Expert knowledge base systems can be formed and they may be effective in plant's diagnostic use over the first and second generation expert systems;
- Relatively easy to device as goal-oriented dedicated systems;
- Provide new methods, methodologies and the associated paradigms which are essential for cross validations;
- Individual deficiencies of AI tools are eliminated by joint involvement in the application.

The power of soft computing can be attributed to the following features:
- SC is a sub-domain of a well-established area in Electrical Engineering known as **Non-linear System Identification**
- Neural and fuzzy systems have ample common working area where both methods can individually be applied with the associated trade-offs;
- The tools of SC are closely related and co-operative though, seemingly this co-operative feature is not apparent;
- SC technology is already established. Powerful commercial software and hardware is available.

Referring to the first item above, the system identification and soft computing methods with their relevance are shown together in Fig.4.
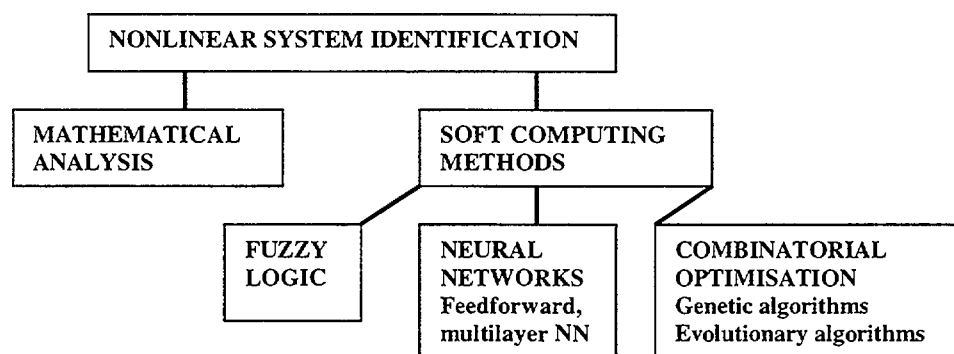

Figure 4. Nonlinear system identification methods and some associated paradigms

It is possible to consider the non-linear system identification in a unified form so that mathematical analysis methods and the soft computing methods can be investigated in a single

framework [18]. In this case the problem becomes a multivariate function approximation of the form

$$f(x)= \sum_{i=1}^{k} w_i \, \Phi_i \, (x) \qquad\qquad (1)$$

i.e., weighted sum of basis function, where $\Phi_i(x)$ is the base function; w_i is the weight factor. The base functions can be selected as the soft computing application requires. In case base functions are selected to be Gaussian functions, the neural network counterpart of the equation becomes radial basis function (RBF) networks. The NN topology of the RBF network is shown in Fig.5.
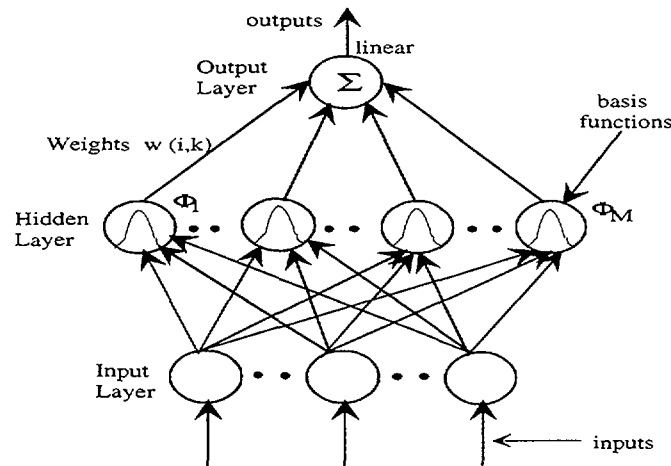

Figure 5. Radial-basis function network topology

It is interesting to note that, the RBF structure in Fig.5, is the same structure of a fuzzy logic where Gaussian functions play the role of Gaussian membership functions [19]. Such a counterpart network representation of fuzzy logic is termed as fuzzy logic network. Inputs and outputs of the network correspond to appropriately determined input and output fuzzy vectors respectively. In such a scheme, the training of the NN would result in the accurate assessment of the fuzzy membership functions in fuzzy logic.

Further different selection of the base functions in Eq.1, gives further different associated interpretations to the equation. In the context of SC, following interpretations are far reaching:

- The base functions are sigmoids. Then the corresponding NN structure becomes feedforward multi-layer perceptron (MLP) network;

- The base functions are wavelet functions. Then function approximation becomes multiresolution wavelet decomposition of the function which exibits a number of interesting properties [20] and they find powerful applications in plant operation and monitoring [21-22];

- The base functions are wavelet functions. Then the corresponding NN structure becomes wavenet networks (WN) [23]. Since wavelet functions exibit special properties, the network also possesses special features in SC. One interesting property can be exercised by means of orthogonal wavelets so that orthogonal membership functions in fuzzy logic are obtained for special SC applications.

The unification of SC methods through Eq.1 is schematically shown in Fig.6.
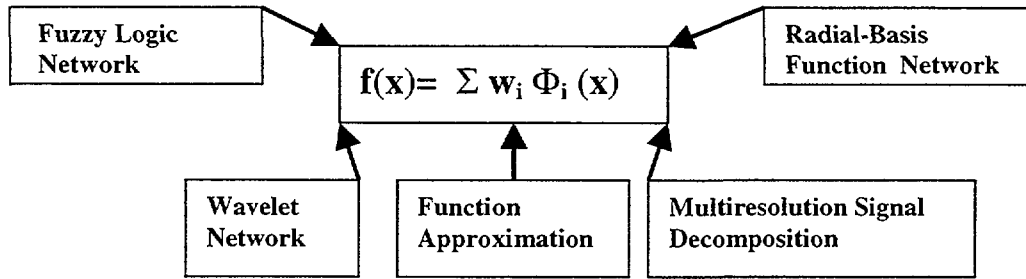
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┌─────────────────┐        ┌───────────────────────┐      ┌──────────────────────┐
│ Fuzzy Logic     │        │                       │      │ Radial-Basis         │
│ Network         │───────▶│  f(x)= Σ wᵢ Φᵢ (x)    │◀─────│ Function  Network    │
└─────────────────┘        │                       │      └──────────────────────┘
                           └───────────────────────┘
                               ▲       ▲       ▲
                               │       │       │
          ┌─────────────┐  ┌──────────────┐  ┌────────────────────────┐
          │ Wavelet     │  │ Function     │  │ Multiresolution Signal │
          │ Network     │  │ Approximation│  │ Decomposition          │
          └─────────────┘  └──────────────┘  └────────────────────────┘
```

Figure 6. Unification of soft computing methods

From the power plant operation viewpoint, most soft computing implementations can be viewed as intelligent applications using a knowledge base, as they supposedly possess domain expert knowledge. In the network representation of fuzzy logic as counterpart of RBF networks, each node at the hidden layer (Fig.5) corresponds associated fuzzy IF-THEN rule.

Soft computing technology play important role in nuclear power plant operation [24- 29].

As an alternative to the network representation of fuzzy logic as knowledge base, another fuzzy logic approach is fuzzy associative memory (FAM) [30] which has the interpretation as fuzzy computation with matrices that they are referred to as FAM matrices. The fuzzy input vector in fuzzy logic network above, is used to form a product with associated FAM matrix so that the output is a fuzzy vector of a multivalued logic. Here, each FAM matrix corresponds to a fuzzy IF-THEN rule, as before.

4. CONCLUSIONS

Neural, fuzzy and other intelligent technologies are joining on a common place known as soft computing. Soft computing technology has important applications in power plants since the support of intelligent technologies in man-machine interfaced complex integrated systems is desirable to meet the general demand of high information processing capacity, required in such systems. This is basically due to the complexity where many interactions within the system take place so that conventional decision-making procedures or plant control schemes need to be supported by intelligent means. Soft computing is an emerging intelligent approach with the associated technology especially addressed for industrial applications. The theoretical foundations of the approach is rather sound. Presently, it is plausible to talk about grey rather than black box, due to the recent advancements in the NN research. The unified representation of soft computing is a milestone as this representation clearly points out the mathematical foundations of soft computing and its relevance to other mathematical methods and the associated disciplines. In this respect, SC will continue to benefit substantially from other disciplines and apparently the progress on soft computing will keep on its rapid pace.

From the diagnostic systems viewpoint in power plants, as an alternative, soft computing is a new approach for the followings tasks:
• Intelligent monitoring;
• Intelligent control;

- Expert system control;
- Intelligent decision support.

REFERENCES

[1] CIFTCIOGLU, Ö. and E. TÜRKCAN, Supervisory monitoring system in nuclear power plants, IAEA Technical Committee Meeting on Nuclear Power Plant Diagnostics-Safety Aspects and Licensing, Portoroz, Slovenia 23-25 June1997

[2] HOLLNAGEL, E. (Ed.), The Reliability of Expert Systems, Ellis Horwood Limited Publishers, Chichester, 1989

[3] NABESHIMA et al., Neural network with an expert system for real-time NPP Monitoring, SMORN VII, 7th Symposium on Nuclear Surveillance and Diagnostics, Avignon, France, 19-23 June 1995

[4] FANTONI F.P. and MAZZOLA A., Transient and steady state signal validation in nuclear power plants using autoassociative neural networks and pattern recognition, ibid, p.423

[5] CIFTCIOGLU Ö. and E. TÜRKCAN, On-line plant-wide monitoring using neural networks 8th Power Plant Dynamics, Control and Testing Symposium, May 27-29, Knoxville, Tennessee, USA,1992

[6] UHRIG R.E., Potential use of neural networks in nuclear power plants, ibid., p.56.01

[7] NABESHIMA K. et al, Real-time nuclear power plant monitoring with adaptively trained neural network, ICANN'93: International Conference on Artificial Neural Networks, 13-16 September 1993, Amsterdam, The Netherlands

[8] NABESHIMA K. et al., Development of nuclear power plant monitoring system with neural network using on-line PWR plant simulator, IAEA Specialists'meeting on monitoring and diagnosis systems to improve NPP reliability and safety, 14-17 May 1996, Gloucester, U.K.

[9] UPADHYAYA B.R. and ERYUREK E., Application of Neural Networks for sensor validation and plant monitoring, Nuclear Technology, Vol.97, p.170, February 1992

[10] WREST, D.J., et al. Instrument surveillance and calibration verification through plant wide monitoring using autoassociative neural networks, Proc. IAEA Monitoring and Diagnosis Systems to Improve NPP Reliability and Safety, 14-17 May 1996, Gloucester, UK

[11] CIFTCIOGLU Ö. and E. TÜRKCAN, Neural network benchmark on condition monitoring in nuclear power plants, Vol.1 Analysis Results', OECD NEA-NSC-DOC(96) 29, August 1996

[12] WARWICK K. and IRWIN G.W. (Eds.), Neural Networks for Control and Systems, IEE, London, 1992

[13] Narendra K.S. and Parthasarathy, Identification and control of dynamical systems using neural networks, IEEE Transactions on Neural Networks, Vol.1, No.1, March 1990

[14] CIFTCIOGLU Ö. and Türkcan E., Supervisory monitoring and control in power plants, International Nuclear Congress ENC'98, October 25-28, 1998, Nice, FRANCE

[15] L.A. Zadeh, Fuzzy sets. *Information and Control* 8, pp.338-353, 1965

[16] REZNIK L., Fuzzy Controllers, Newness Publ. Co., Boston, 1997

[17] Goldberg D.E., Genetic Algorithms in Search, Optimisation, and Machine Learning, Addison Wesley Publ. Co., Reading, Massachutsetts, 1989

[18] CIFTCIOGLU Ö., Artifical Neural Networks and Control, lecture notes (unpublished), TU Delft, The Netherlands, 1998

[19] Jang J.-S.R. and Sun C.-T, Functional equivalence between radial basis function networks and fuzzy inference systems, IEEE Trans. on Neural networks, Vol.4, No.1, p.156, Jan.1993

[20] DAUBECHIES I., Ten Lectures on Wavelets, S.I.A.M., 1992

[21] CIFTCIOGLU Ö. and TÜRKCAN E., Decay ratio studies in BWR and PWR using wavelet,

INCORE96', Specialists' Meeting on In-Core Instrumentation and Reactor Core
Assessment, 14-17 October 1996, Mito-Shi, Japan.

[22] CIFTCIOGLU Ö. and TÜRKCAN E., Transient detection by wavelet transform in plant
monitoring, A Symposium on Nuclear Reactor Surveillance and Diagnostics (SMORN
VII), 19-23 June 1995, Avignon, France

[23] ZHANG Q. and BENVENISTE A., Wavelet Networks, IEEE Trans. on Neural Networks,
3 (6), pp.889-898, 1992

[24] IKONOMOPOULOS A. et al., Integration of neural networks with fuzzy reasoning for
measuring operational parameters in a nuclear reactor, Nuclear Technology, Vol.104,
October 1993.

[25] FANTONI P. F., Fuzzy models applied to full range signal validation in nuclear power
plants, Proc. NPIC & HMIT'96, The 1996 ANS Int. Top. Meeting on Nuclear Plant
Instrumentation, Control, and Human-Machine Interface Technologies, May 6-9, 1996, the
Pennsylvania State University, USA, 1996

[26] HINES J.W et al., Signal validation using an adaptive neural fuzzy inference system,
Nuclear Technology Vol.119, p.181, Aug.1997

[27] ERBAY A.S. and UPADHYAYA B.R, A personal computer-based on-line signal
validation system for nuclear power plants, Nuclear Technology, Vol.119, p.63, July 1997

[28] DZWINEL W. and PEPYOLYSHEV N.YU., Pattern recognition, neural networks, genetic
algorithms and high performance computing in nuclear reactor diagnostics, results and
perspectives, SMORN VII, 7[th] Symposium on Nuclear Surveillance and Diagnostics, p.302,
Avignon, France, 19-23 June 1995

[29] KOZMA R. et al., Predictive acquisition of knowledge by a hybrid nuclear power plant
monitoring system, Proc. 9[th] Power Plant Dynamics, Control & Testing Symposium,
p.59.01, May 24-26,1995, Knoxville, Tennessee

[30] KOSKO B., Neural Networks and Fuzzy Systems, Prentice Hall, Englewood Cliffs, NJ
07632, 1992.

SOME ASPECTS OF DIAGNOSTIC SYSTEMS PERSPECTIVE

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Abstract

The integrity and safety of all nuclear power plant systems and components is guaranteed by the high requirements to quality assurance during all phases of design, fabrication, construction and operation. Many of the countries operating nuclear facilities, introduced advanced, sophisticated diagnostic systems for continuous monitoring safety important process parameters. The licensee should perform an assessment of the existing diagnostic systems, often supplied by the original design, their reliability and the need for the introduction of the additional monitoring/diagnostic systems. The operating experience should be taken into account and the assessment of the further needs. On this field has to be made on the results of PSA studies. In addition to the cost benefit analysis the evaluation of the new diagnostic systems in the light of nuclear safety should be also made. Experience, gained from the utilities, which have already installed this kind of the equipment should be very useful. Introducing new diagnostic systems will require often a safety assessment of the necessary modifications. Licensing process should be based on the existing nuclear legislation with certain additional requirements.

1. PERFORMANCE AND RELIABILITY OF SAFETY EQUIPMENT

The nuclear power plant components and systems have high requirements for the quality and reliability during the operation. To fulfill the requirements of the existing regulation, codes and standards it is necessary to have actually on line data about the condition of the safety most important components [1].

Monitoring of the safety important process parameters is very important in the last few years. The world wide practice shows that introducing some of the monitoring and diagnostic systems has very good results. Licensee avoids specific situations, that can lead to transients or damage of safety important equipment.

Some of the countries with nuclear power plants have already installed advanced, sophisticate systems to follow the behavior of key parameters, affecting reliability of safety important equipment. The direct consequence of using such systems is improvement of the performance indicators.

The years of experience gained in the operation and application of the monitoring systems help to the further development of this systems and new methods of evaluation.

Monitoring and diagnostic systems therefore should be treated as an effective tool to maintain the performance and reliability of the nuclear power plant at the high level.

The aging phenomena becomes more and more present in the majority of the nuclear power plants. The general vision in the nuclear world is nuclear power plant life extension. The data, obtained from monitoring systems could be of great value in such decision making process and cost benefit studies.

2. THE NEED FOR INTRODUCTION OF MONITORING SYSTEMS

It is common that nuclear power plants western type have some of the monitoring systems built in by the original design. The operating personnel have to have a variety of physical parameters on-line to be able safe operate the nuclear power plant.

The operational events, like transients, scrams, failures etc. leads the owner of the nuclear power plants to the fact, that existing monitoring systems are not sufficient to prevent the system or equipment against failure.

The good experience with monitoring systems at some nuclear power plants should help the management of the power plant, which do not have them yet, to make the decision introducing them.

The essential features of the diagnostic system are:

- detection
- localization
- analysis

The need for introduction of such systems should be based on these features. The detailed analysis of operational events should lead the licensee to allocate the potentional systems/components, which are suitable to be monitored with additional system.

The producers of monitoring systems have generally two basic strategies, designing them [2]:

- monitoring and recording of influences on the system during typical plant process and over its total service life with determination of the collective loads for typical operation
- recording the primary and secondary parameters which characterize system performance and which change significantly when an anomaly occurs

In accordance with this approach, the measurement locations, measurement chain and the method of data verification and evaluation should be done.

3. THE ASSESSMENT OF MONITORING/ DIAGNOSTIC SYSTEMS

The reliability assessment of monitoring systems is necessary due to the reason that licensee needs the reliable system with high confidence level. The false alarms, uncertainty and unreliable signals could lead to the wrong decisions.

Appropriate selection of the systems and methods of the signal evaluation is very important. It is expected, that new introduced monitoring system will be tested and selected on the all available data from the manufacturer and some users, if they exist.

The specific criteria should take into account the compatibility of new obtained signals with the existing monitoring systems signals, built in system by the design.

The overall assessment of monitoring system should be done on the basis of [3]:

- monitoring system type
- measurement transducer selection

- measurement parameter selection
- measurement location
- time interval between measurements
- spectrum interpretation and fault diagnosis
- trend analysis
- computer software/hardware requirements

4. MONITORING SYSTEMS IN THE LIGHT OF LICENSING PROCESS

Safety evaluation of the diagnostic system is necessary. It allows licensees to change the design, revise the procedures or conduct tests or experiments without prior regulatory authority approval in the case there no unreviewed safety question exist. But often happened, that new installed system introduce safety important question, not yet reviewed. Regulatory authority approval is necessary in such case to implement the activity.
The nuclear power plants have to use existing national or international guidelines to perform adequate safety evaluation.
Among others, the licensee have to answer on questions, contained in safety evaluation process guidance [4], like:

- may the proposed activity increase the probability of occurrence of an accident evaluated previously in the Safety Analysis Report (SAR)

- may the proposed activity increase the consequences of an accident evaluated previously in the SAR

- may the proposed activity increase the probability of occurrence of a malfunction of equipment important to safety evaluated previously in the SAR

- may the proposed activity increase the probability of the consequence of a malfunction of equipment important to safety evaluated previously in the SAR

- may the proposed activity create the possibility of an accident of a different type than any evaluated previously in SAR

- may the proposed activity create the possibility of a malfunction of equipment important to safety of a different type than any evaluated previously in the SAR

- does the proposed activity reduce the margin of safety as defined in the basis of technical specification

In fact, a change, that involves an unreviewed safety question may be a safety improvement by significantly reducing the risk on one area at the expense of a slight increase in risk in another area.
The responsibility lies with the utility to assure that changes are safe.

5. FURTHER PERSPECTIVE OF THE DIAGNOSTIC SYSTEMS

The introduction of monitoring system into nuclear power plant system is at the present time the need very strongly present in nuclear countries. The new approach in the maintenance activities (on-line maintenance, the effectiveness of the maintenance) and the requests of the nuclear regulatory authorities on the field of reliable operation are the bases for introduction of monitoring systems.

The nuclear events databases are very good sources to allocate the potential systems and components to be monitored. New developed methods in measurement systems and their computerized support are more developed than in the past years. A data acquisition system is needed for the collection of all required data, their conditioning, trending and storage.

Probabilistic safety analysis allocate the most safety significant systems and their components. Using the data of these analysis there is a possibility to select most vital locations at the systems and their components to be monitored.

The operational, maintenance and engineering personnel at the nuclear power plants is problem solving oriented and the monitoring systems with diagnosis capabilities are the tools for improving nuclear safety.

Diagnostic systems can be seen as a particular category of the operator support system. The use of diagnostic systems can play important role in preventing accident conditions and can play very important role in nuclear power plant condition monitoring programs and tracking of the aging effects during the plant life cycle.

6. REFERENCES

[1]   Use of Diagnostic Systems to Monitor Performance and Reliability of Safety Equipment, IAEA TCM, Oct. 1993, Vienna

[2]   V.Streicher, Dr. U.Kunze: Ageing Phenomena and Diagnostics for PWR Type reactors, IAEA TC on Ageing Phenomena, Dec. 1996, Karlsruhe

[3]   Shock and Vibration Handbook, Fourth Ed., C.M. Harris, McGraw-Hill, 1995

[4]   Guidelines for 10 CFR 50.59 Safety Evaluation, NSAC 125, June 1989

POWER OSCILLATION AND STABILITY IN WATER COOLED REACTORS

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Abstract

Periodic oscillation in measured temperature fluctuation was observed near to surface of a heated rod in certain heat transfer range. The frequency of the peak found in power spectral density of temperature fluctuation and period estimated from the cross correlation function for two axially placed thermocouples change linearly with linear energy (or surface heat) production. It was concluded that a resonance of such surface (inlet) temperature oscillation with the pole of the reactor transfer function can be responsible for power oscillation in BWR and PWR, thus instability is not solely due to reactor transfer function.

1. INTRODUCTION

It is well known that power oscillation can occur in boiling water reactors (BWR) during initial start up at certain power level and flow regime. Such observation is as old as the history of this type: first it was presented in Geneve conference in 1958 [1,2]. From the very beginning this power oscillation was explained by feedback effects in boiling water reactors. It has been shown that due to feedback effects the reactor transfer function of these reactor may have poles, which leads to instability, thus power tends to oscillate. Damping factor was also characterized by this model. This model served always as a basis for stability estimation. Decay ratio (DR) estimated using this model has been generally accepted and today is widely used in BWR operation.

Gialdi et al.[3] presented operational experience of power oscillation in BWR, measuring neutron oscillation by incore neutron detectors. It was shown, that the magnitude of those oscillations is different for different fuel assemblies (coolant channels) and even their phase can be different. The exact nature of those oscillation needed some explanation different from point kinetic approach [4,5]. Detailed investigation on In-Phase and Out-of-Phase power oscillation were carried out in Sweden [6], where the magnitude of autocorrelation function was found to be also different in different fuel assemblies. To explain the situation global and local DR were introduced. Power oscillation was also noticed in pressurized water reactors (PWR) much later, and it was also proposed [6] to estimate a so called modified decay ratio (mDR) to handle the problem similarly to BWR. The fact that the physical mechanism of formation of neutron oscillation has not been totally understood became clear also from the excellent survey of Hagen et al.[7] on two types of instability in natural circulation BWR with potentially different mechanism.

While we believe that both point kinetic [1,2,4] and the extended one dimensional approximation [5] describe correctly the transfer function of the reactor, which have really those feedback effects we also think that one aspects of this phenomena has been neglected until now. Power oscillation is a consequence, it is a measurable outlet signal from the reactor system. Since the outlet it is a multiplication of the reactor transfer function to the inlet

fluctuation. Until now there was very little evidence and discussion on the nature of the inlet (temperature and/or density) fluctuation. It was assumed that inlet fluctuation have white (or pink) character and the reactor transfer function is solely responsible for the power oscillation. Oscillation of the power was measured by excore neutron detectors [1,2,4,6,7], sometimes by incore neutron detectors [3,5] and also using top-of core thermocouples. Since those measurements carries information only on power (neutron flux) oscillation, it is not obvious that solely the transfer function, i.e. feedbacks in reactor kinetics are responsible for singularities (for peaks in frequency domain). It is equally possible that the inlet fluctuation has also oscillating character. We shall examine this possibility and we are going to show that that there exist a chaotic oscillation at certain condition on heated and cooled surfaces.

2. EXPERIMENTS

Experiments were carried out with the aim to test new thermocouples suited for incore temperature measurements in research reactors. Since the final aim was to measure transport effect in the water we made an out of pile experiment to test the performance of new thermocouples without radiation effects. An electrically heated rod was placed in a small water tank. We managed to put our thermocouples as near as possible to the heated surface(within 1 mm distance from the surface, but never in touch). The distance between axially placed thermocouple was 8 mm (see Figs.1. and 3.).
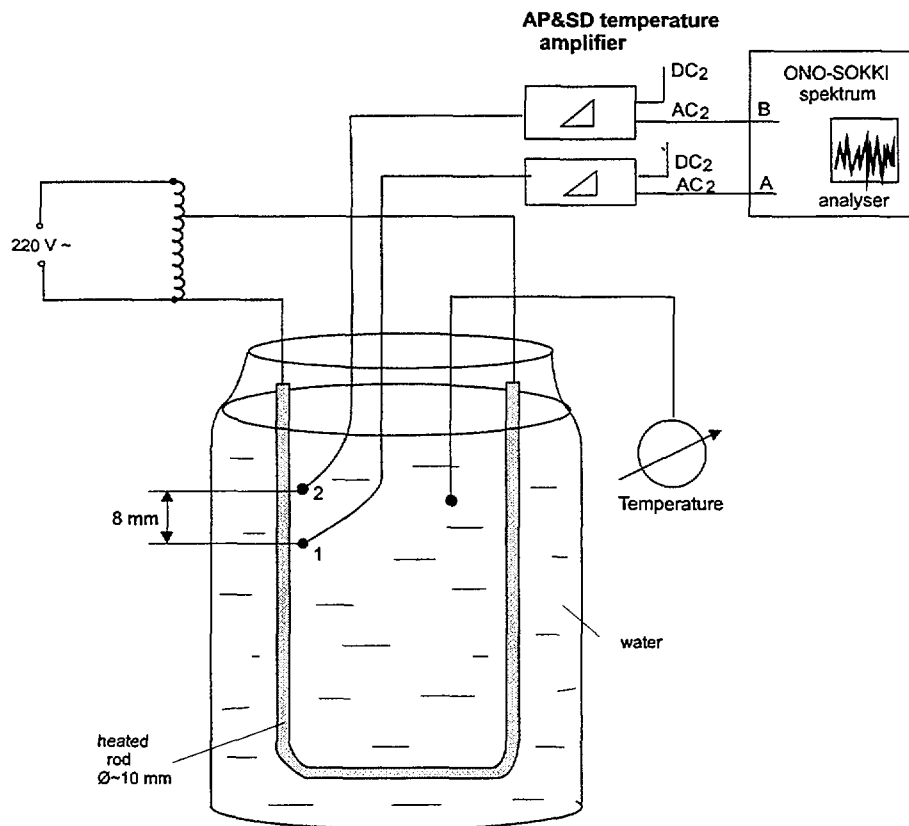

Fig.1. Experimental arrangement

We used a thermocouple amplifiers (AP&SD Ltd.) which enabled us to measure both the temperature as well as the fluctuation of the temperature. Fluctuation as low as 0.01 degree Centigrade were clearly distingushable in the time plot of temperature fluctuation (Fig.2).

Signals were sampled but we also used spectrum analyzer (ONO-SOKKI) for on-line measurement. In this short announcement we rely mainly on results measured by spectrum analyzer. Autopower spectral densities (APSD), phase and coherence were estimated for the two detector signals. Also cross correlation function (CCF) was calculated for different heating rate. A changeable transformer allow us to change the input voltage, thus the electrical power heat-up rate of the heated rod.

3.   RESULTS

To our surprise we could observe periodic oscillation in time signals beginning from a certain heating rate to a maximum of that rate (cf. Fig.2.). Below the given heating region and above that oscillation disappeared. Naturally we tested all our equipment about the origin of that oscillation. But we were convinced even more with video pictures taken about the surface of the heated rod (see one picture of that video on Fig.3.)
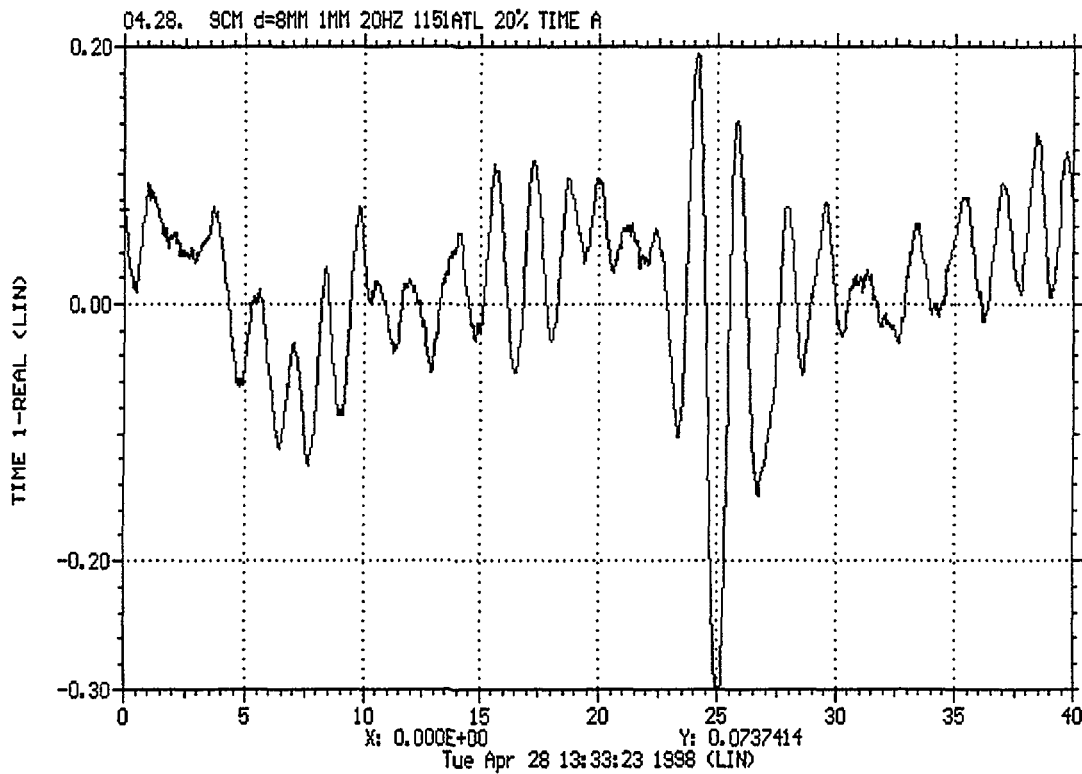

Fig.2. Time signals recorded from thermocouples

On video record one can clearly see the water streaming upward in the vicinity of the surface (within 2 mm distance from the surface). The laminar stream became turbulent at certain heating rate. Turbulence were clearly visible in the form of helical turbulence disattaching from the heated surface. It was even more interesting that they were more or less equidistant when traveling with the water. This helical forms passing the thermocouples gave oscillation character of the temperature signal. We believe it is rather simple to repeat this experiment anywhere.
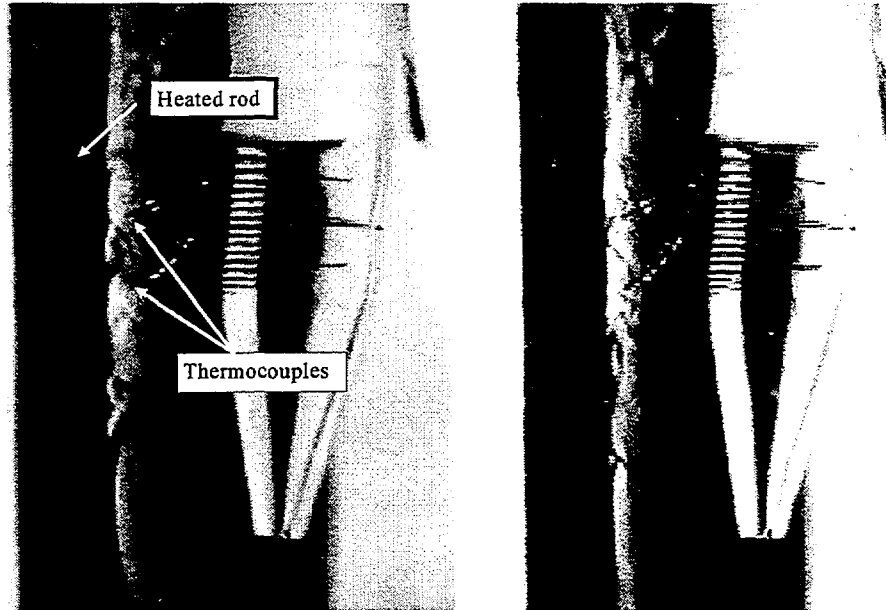
Fig.3. Picture taken from video shot clearly shows helical formation near to heated surface. They travel with the water.

Now if the signal itself has oscillating character, then it is obvious that it must have a resonance frequency in APSD (see Fig.4).
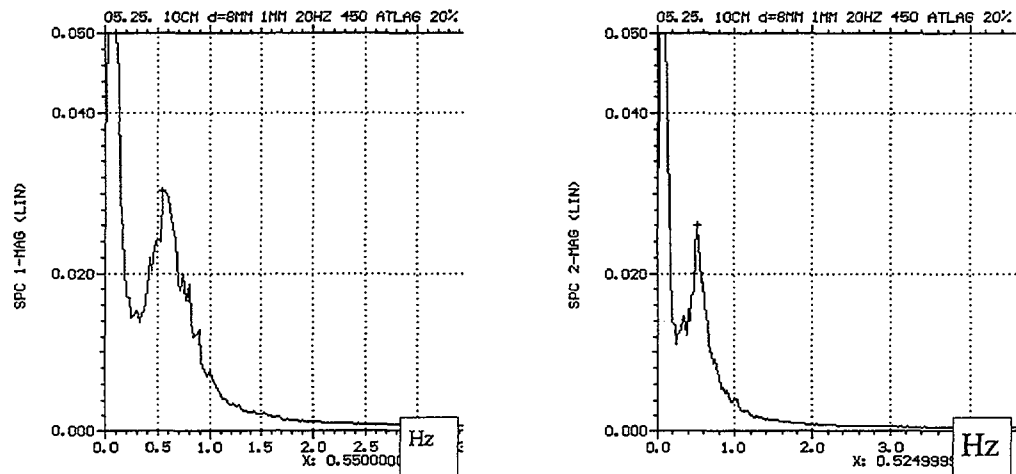

Fig.4. APSD of temperature oscillation with clear oscillation peak

At the same time there were coherence and well defined phase between axially placed thermocouple signals. The linear character of the phase dependence on frequency is well known from the theory of propagating disturbance. Any time delay in two correlated signals will express itself in linear phase dependence on frequency. From the slope of this linear phase function one can define the time delay, and knowing the distance between the sensors the velocity of the water stream can be estimated. It is clear from Fig.5. that the slope of the phase depends on heating rate. Table 1. shows the estimated parameters.
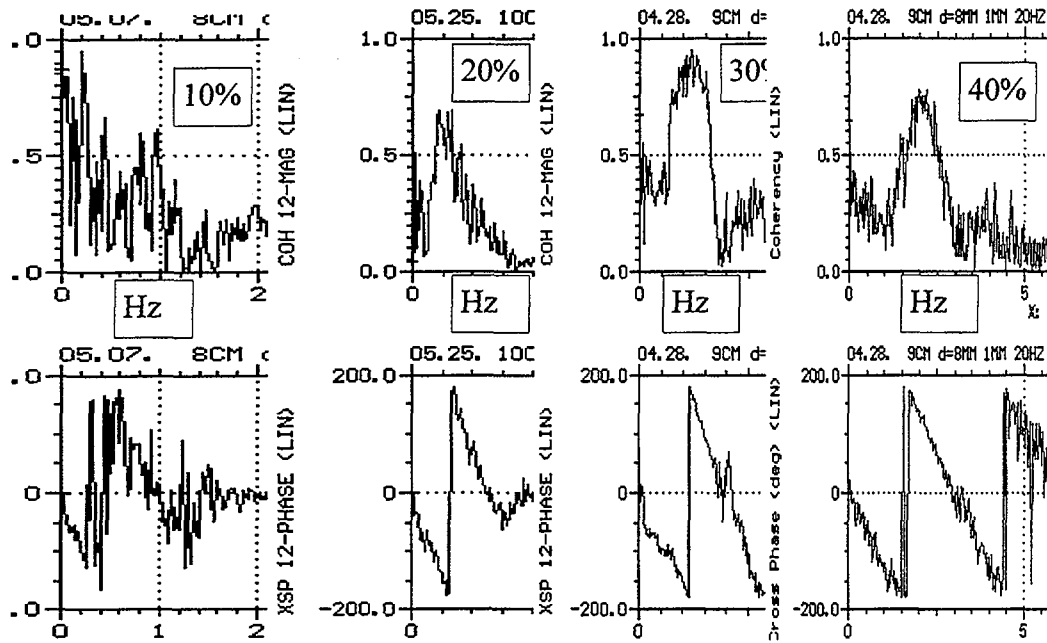
Fig.5. Coherence and phase between axially placed thermocouples at different heating rate

TABLE I. DEPENDENCE OF THE ESTIMATED EIGENFREQUENCIES FROM THE ENERGY SUPPLY OR LINEAR /SURFACE HEAT PRODUCTION

Power in % /Watts	Linear power [W/cm] /Surface power [W/cm2]	CCF maximum [sec]	Frequency from CCF [mHz]	Frequency from Coherency [mHz]	Velocity from CCF [cm/s]
10/ 27.6	0.55 / 2.19	1.2323	231	220	0.649
20/ 80	1.6 / 6.36	0.8102	617	650	0.988
30/ 184.9	3.7 / 14.71	0.4392	1108	1175	1.821
40/ 352.8	7.1 / 28.07	0.3026	2049	2175	2.644
50/ 558	11.2 / 44.4	0.3026	1829	1850	2.644
60/ 845	16.9 / 67.24	0.2562	512	440	3.122

It is also well known that CCF can be also used for time delay estimation. The deviation of the maximum of CCF characterizes the time delay in the signal. Since our signal carries not only stochastic character but it contains also periodic component CCF will also show periodic character as it can be seen on Fig.6.

First of all from the period of CCF one can draw conclusion on the average period of the oscillation of the time signal. This period should be reciprocal to the estimated eigenfrequency of the oscillation from APSD. Comparison and good agreement with the theory can be well seen in Table I. The change of period follows linearly the change of heating power.
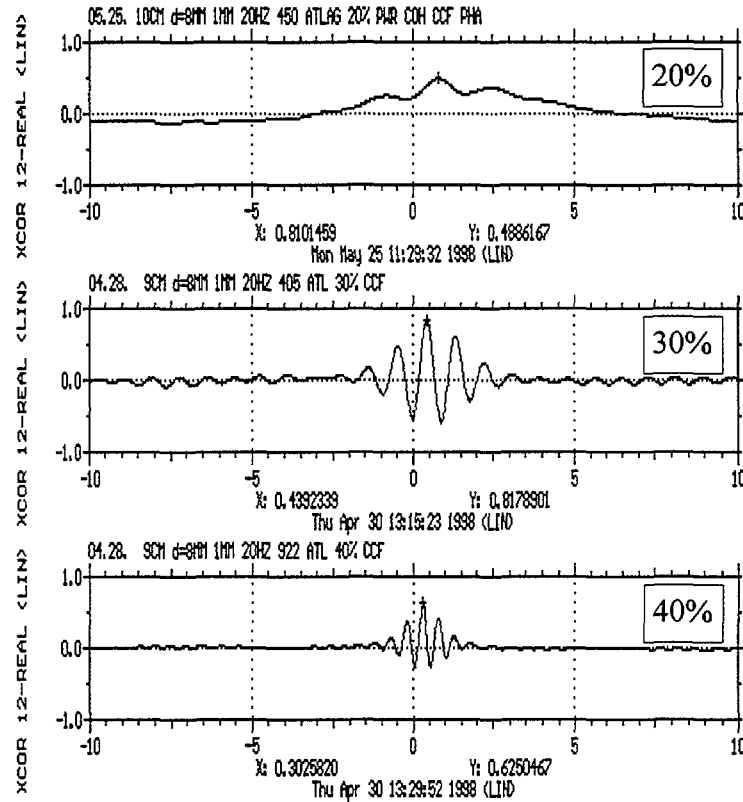
Fig.6. CCF for different heating rates. Observe the different oscillation periods and time delays

4. DISCUSSION

It was observed, that at relatively high power production rate instabilities are formatted on the surface of an electrically heated rod. This shows that at linear heat production larger than 0.5 W/cm (or surface power generation larger than 2.5 W/cm^2) the heat transfer becomes nonlinear and helical forms of turbulence were generated at rather simple circumstances, which lead to oscillation of the temperature field. This new observation is very important for any boiling, heating or cooling process since oscillation of the heat (temperature) near to surface changes the character of the heat removal from the surface of the heated rod. At heat generation larger than 10 W/cm (or 50 W/cm^2) another regime of heat transfer took place, which also had eigenfrequency, but it had stochastic character.

We believe that this is the original cause of the power oscillation in water cooled reactors which has been observed more than 30 years now. In fact investigation of such problems initiated this research as well. We found analyzing our experiment that the oscillation had an eigenfrequency, which linearly depends on the heating power in certain heating range (see Fig.7.). In fact this linearity was observed until (quasi)periodic oscillation took place. When the periodic character was disappearing linearity dropped though there was still a peak in the APSD, - nonperiodic but stochastic nature.

It is well known that the transfer function of the reactor has pole with a frequency of about 1 Hz as well. During the start up of a BWR the heating rate is growing, consequently temperature oscillation might be formatted on the surface of heated fuel rods similarly like in our experiment. The eigenfrequency of such oscillation shifts toward the higher frequencies when the heating rate is growing. Since there is an instability of the transfer function of the reactor system itself at the same frequency region, changing the eigenfrequency of the

oscillation with the growing heating one will get resonance of the two function at certain heating condition. This explains the magnitude of this oscillation and also why it is disappearing with further growth of the heating or velocities of the coolant [7].
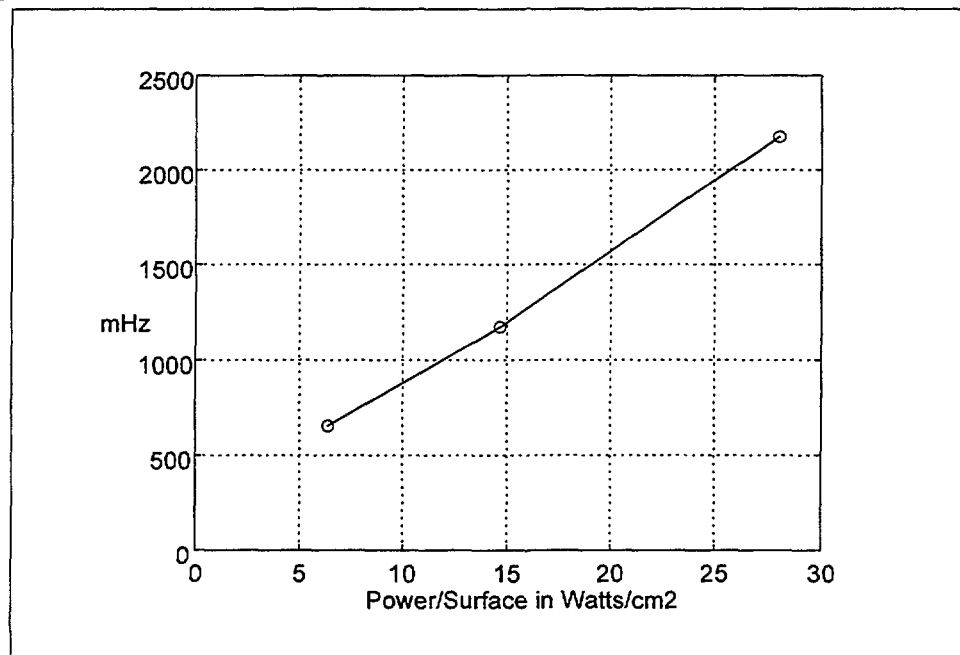

Fig. 7. Dependence of the oscillation frequency on the power of the heating of the rod

The concept of estimating DR widely used today to characterize the instability of BWRs [5] and PWRs[6]. All DR estimation techniques make use from the assumption of white character of inlet fluctuation (inlet in the sense that it is the inlet for reactor transfer function). It is also clear from our experiment that not solely the DR of the reactor transfer function is responsible for power oscillation. Consequently estimation of DR based on such model will overestimate the value of DR thus overestimate the instability of the reactor. Similar conclusion was made in [7].

It is also clear from our experiment why we get sometime power oscillation in case of PWR [5], where nobody has proved until now that the reactor transfer function can have poles. It is connected to the new technology of fuel fabrication, which allows a heat transfer to the cladding so rapidly, that similar oscillation of the temperature field at the surface of fuel pins can take place in PWR as well.

Finally we have to understand, that the reactor core has a strong coupling via neutronic processes. Therefore if we have a temperature fluctuation in one spot it may have effect on temperature fluctuation in another spot. They are connected either in phase (total power oscillation) or in antiphase. This is quite natural if generating noise (temperature oscillation) falls exactly in resonance with the transfer function of the reactor. Here we must understand also, that the period of power oscillation driven by reactivity feedbacks are connected to the coolant transport (time) via the total core, which have a very similar value. Hence the practical method of correction of such problems: one has to avoid (or at least to leave) such resonance situation as fast as possible, either heating further fast (which might be not very easy), or changing the velocity of the coolant.

ACKNOWLEDGMENTS

REFERENCES

[1] Snyder T. and J. Thie, Physics of Boiling Water Reactors, Proc. of the 2nd UN Int. Conf. on Peaceful Uses of Atomic Energy, Geneva, Sept., 1958, paper 2402.

[2] Thie J., Theoretical Reactor Statics and Kinetics of Boiling Water Reactors, Proc. of the 2nd UN Int. Conf. on Peaceful Uses of Atomic Energy, Geneva, Sept., 1958, paper 638.

[3] Gialdi E., Grifoni S., C. Parmeggiani and Tricoli C: Core Stability in Operating BWR: Operational Experience, Progress in Nucl. Energy, Vol. 15., pp. 447-459, (1985)

[4] March-Leuba J., Blakeman E.D.: A Mechanism for Out-of-Phase Instabilities in Boiling Water Reactors, Nucl. Sci. Eng. vol.107, pp.173-179, (1991)

[5] Y.M. Farawila, D.W. Pruitt, D. Kreuter: Analysis of BWR Out-of-Phase Instabilities in the Frequency Domain, Trans. Am. Nucl. Soc. vol.66., p 571 (1992)

[5] Van der Hagen T.H.J.J., I. Pazsit, O. Thomson, Methods for the Determination of the In-Phase and Out-of-Phase Stability Characteristics of Boiling Water Reactor, Nuclear Technology, vol. 107, P.193, (1994)

[6] G. Por and J. Runkel: A Study on Applicability of Decay Ratio Estimation in a Pressurized Water Reactor, Nucl. Sci. Eng. vol.116, pp.205-212, (1994)

[7] T.H.J.J. Hagen, D.D.R van Bragt, F.J. van der Kaa, J. Karuza, D. Lillian, W.H.M. Nissen, A.J.C. Stekelenburg and J.A.A. Wouters: Exploring the Doodeward Type-I and Type-II Stability; from Start-up to Shut-down, from Stable to Unstable, Ann. Nucl. Energy vol. 24, pp. 659-669 (1997)

APPLICATIONS OF WAVELET TRANSFORMS FOR NUCLEAR POWER PLANT SIGNAL ANALYSIS

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Abstract

The safety of Nuclear Power Plants (NPPs) may be enhanced by the timely processing of information derived from multiple process signals from NPPs. The most widely used technique in signal analysis applications is the Fourier transform in the frequency domain to generate power spectral densities (PSD). However, the Fourier transform is global in nature and will obscure any non-stationary signal feature. Lately, a powerful technique called the *Wavelet Transform*, has been developed. This transform uses certain basis functions for representing the data in an effective manner, with capability for sub-band analysis and providing time-frequency localization as needed. This paper presents a brief overview of wavelets applied to the nuclear industry for signal processing and plant monitoring. The basic theory of *Wavelets* is also summarized. In order to illustrate the application of wavelet transforms data were acquired from the operating nuclear power plant Borssele in the Netherlands. The experimental data consist of various signals in the power plant and are selected from a stationary power operation. Their frequency characteristics and the mutual relations were investigated using MATLAB signal processing and wavelet toolbox for computing their PSDs and coherence functions by multi-resolution analysis. The results indicate that the sub-band PSD matches with the original signal PSD and enhances the estimation of coherence functions. The *Wavelet* analysis demonstrates the feasibility of application to stationary signals to provide better estimates in the frequency band of interest as compared to the classical FFT approach.

1. INTRODUCTION

A nuclear power plant is a complex system and the various types of sensor signals, depending on the physics of the process, detection ability of the sensors and under the continuously varying operational conditions, carry valuable information on the safety of the system. The analysis of these signals in time and frequency domains, during the last four decades, has been used for the safe operation of NPPs. The traditionally used signal analysis tool is the Fourier transform, which by producing power spectral densities (PSDs), allows time dependent signals to be studied in the frequency domain. However, the Fourier transform is global in nature, and is ill-suited for studying non-stationary signals and their frequency components. In such cases several short-time Fourier transforms (STFT) or windowed Fourier transforms are used with limited capability. During the past two decades another powerful tool, called *Wavelet Transform*, has been applied to various signal analysis problems and is especially more efficient than the Fourier analysis whenever a signal shows non-stationary behavior or discontinuities. Wavelet analysis can assist in the extraction of imbedded information in process signals.

This paper gives a brief theory of Wavelet Transforms multi-resolution analysis (MRA) [1,2], and describes the applications reported in the literature.

In this work, we applied wavelet analysis to various signals of a pressurized water reactor, plant measured during a stationary power operation. We selected three different sensor signals which a characterize the physical process involved. In this respect, we wanted to show how to use the MRA and compare it with standard PSD calculations. The application involved coherence analysis in both cases. Operating nuclear power plant signals measured from different sensors in the primary loop of the plant were used to demonstrate the ability of the Wavelet analysis. Three different types of sensor signals and their mutual effects were observed to identify the physical characteristics of the system at stationary power operation. The results of the MRA analysis and comparison with the standard FFT method, calculated PSD and coherence functions for various signals, together with their conclusions, are given.

2. REVIEW OF WAVELET APPLICATIONS IN NPP SIGNAL ANALSIS

Nuclear power plants, consist of large components with different physical behavior of these components. The analysis of NPP signals is mainly based on frequency domain analysis using Fourier transforms but in case of transients and discontinuities in the signal, Fourier Transforms do not yield proper results because of averaging over the entire time domain. Short-time Fourier transforms (STFT) using Gabor [3] and other window functions do not yield elegant solutions and are limited by various inadequacies. The wavelet transforms (WT), developed in 1980 by Grossman and Morlet [4] used in quantum physics, later explored by Stephane Mallat [5] and Ingrid Daubechies [6], work by constructing a set of wavelet orthonormal basis functions, have become the cornerstone of wavelet applications in signal processing.

Applications in nuclear engineering have been very recent. Perez *et.al.*[7a] indicated the usability of the wavelets in case of noise corrupted signals. Later Mattingly and Perez [7b] extended the study with Gabor and continuous wavelet transforms for application to simulated nonstationary process data. They showed that Gabor and continuous wavelet analysis appear

to be superior to conventional Fourier methods for detecting nonstationary features in acquired process signals.

Otaduy and Georgovich [8] made a comparison between original and wavelet spectra for the experimental data obtained from fuel/coolant interaction experiment. They determined that wavelet based results were effective in the identification of regional effects.

Ciftcioglu and Türkcan [9] demonstrated and simultaneous processing of signals obtained by the wavelet transform by using neural networks in auto-associative mode. In this work main coolant pump vibration signals were decomposed by MRA and their PSD estimates were reconstructed by neural networks. In a later study [10], time-frequency representation of steam flow and generated electric power signals during transients, were used to demonstrate the enhanced time information for fast transients as well as increased decomposed signal power for slow transients. In the same series of studies [11] sub-band variances were calculated to show the changes in the noise power during different operational transient ranges. In another study, Türkcan and Ciftcioglu [12] showed that WT can be a very useful tool in pattern analysis for the purpose of effective neural network training. The application can also be carried out locally rather than over the total data so that, probable problematic regions of data in neural network training can be effectively treated with a focused attention. The wavelet transforms play the role of zoom-in and zoom-out process on the data without any restriction on the zooming power in principle, except the practical consideration of block length used in the wavelet transformation. Another interesting application is given [13] for wavelet-based decay ratio estimation for monitoring of stability in BWRs and PWRs.

Suzudo et.al. have investigated power-law spectra in the temperature signals of the secondary loop in the Borssele NPP [14], where small deviations from linearity are not noticeable in the PSD. Antonopoulos-Domis and Tambouratzits proposed [15] system identification during a transient using discrete WT for denoising and signal reconstruction, followed by classical spectral analysis. Ciftcioglu and Türkcan [16] showed neural networks can be used for fast multiresolution random signal decomposition for noise analysis, in particular for signal monitoring purposes in real-time.

Racz and Pazsit proposed to use wavelet analysis as a tool for detecting detector tube impacting [17]. They proved by modeling the impacting between the fuel box and the detector using Haar transformation for transient detection. In their investigations they used the Swedish BWR Barseback-1 LPRM signals where the impacting occurred during detector string vibrations.

Another very recent application of wavelet transform is given by Hooper and Upadhyaya et al [18] for removing unwanted noise incorporated in the eddy current measurements. The method works first by transforming the data to the frequency domain using discrete WT. The wavelet transform separates the signal into seven separate frequency ranges and the signal below the threshold limit is removed. The WT of eddy current signals of tube wall degradation caused by stress-corrosion cracking, pitting and intergranular attack were used to isolate steam generator tubing defects. Another application to rotating machinery degradation trending was reported by Seker, Upadhyaya et al [19]. It may be that the wavelet transform has become well-known as a useful tool in various signal processing applications in nuclear industry and it can be incorporated in the fast algorithms to compute compact representations of functions and data sets.

3. BRIEF THEORY OF WAVELET TRANSFORMS AND MULTI-RESOLUTION ANALYSIS

Joseph Fourier discovered that he could superpose sines and cosines to approximate functions. The wavelets, first mentioned by Haar in 1909, had compact support which means it vanishes outside of the finite interval, but Haar wavelets are not continuously differentiable. Later David Marr used wavelets with an effective algorithm for numerical image processing (early 1980) by an earlier discovered function that can vary in scale and can conserve energy when computing the functional energy. In between 1960 and 1980, mathematicians such as Grossman and Morlet [4] defined wavelets in the context of quantum physics. In 1985 Stephane Mallat [5] gave a lift to digital signal processing by discovering pyramidal algorithms, and orthonormal wavelet bases. Meyer [20] constructed the first nontrivial wavelets; his wavelets are continuously differentiable but without having compact support. Later Daubechies [2, 6, 20] used Mallat's work to construct a set of wavelet orthonormal basis functions that are the cornerstone of wavelet applications today.

3.1. Continuous Wavelet Transform (CWT)

The class of functions that present the wavelet transform are those that are square integrable on the real line. This class is denoted as $L^2(R)$.

$$f(x) \in L^2(R) \qquad \Rightarrow \qquad \int_{-\infty}^{+\infty} |f(x)|^2 \, dx < \infty \tag{1}$$

The set of functions that are generated in the wavelet analysis are obtained by dilating (scaling) and translating (time shifting) a single prototype function, which is called the mother wavelet. The wavelet function $\psi(x) \in L^2(R)$ has two characteristic parameters, called dilation (a) and translation (b), which vary continuously. A set of wavelet basis function $\psi_{a,b}(x)$ may be given as

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}} \psi(\frac{x-b}{a}) \qquad a, b \in R \, ; a \neq 0 \tag{2}$$

Here, the translation parameter, "b", controls the position of the wavelet in time. The "narrow" wavelet can access high frequency information, while the more dilated wavelet can access low frequency information. This means that the parameter "a" varies for different frequencies. The continuous wavelet transform is defined by

$$W_{a,b}(f) = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{+\infty} f(x) \psi_{a,b}(x) \, dx \, . \tag{3}$$

The wavelet coefficients are given as the inner product of the function being transformed with each basis function.

3.2. Discrete Wavelet Transforms (DWT)

Daubechies invented one of the most elegant families of wavelets. They are called compactly supported orthonormal wavelets, which are used in discrete wavelet transform (DWT). In this approach, the scaling function is used to compute the ψ. The scaling function $\phi(x)$ and the corresponding wavelet $\psi(x)$ are defined by

$$\phi(x) = \sum_{k=0}^{N-1} c_k \, \phi(2x - k) \tag{4}$$

$$\psi(x) = \sum_{k=0}^{N-1} (-1)^k \, c_k \, \phi(2x + k - N + 1) \tag{5}$$

where N is an even number of wavelet coefficients c_k, $k= 0$ to N-1. The discrete presentation of an orthonormal compactly supported wavelet basis of $L^2(R)$ is formed by dilation and translation of signal function $\psi(x)$, called the wavelet function. Assuming that the dilation parameters "a" and "b" take only discrete values.

$a = a_0^{\ j}$, $b = k b_0 a_0^{\ j}$. Where $k, j \in Z$, $a_0 > 1$, and $b_0 > 0$. The wavelet function may be rewritten as

$$\psi_{j,k}(x) = a_0^{-j/2} \, \psi(a_0^{-j} x - k b_0) \tag{6}$$

and, the discrete wavelet transform (DWT) is defined as

$$DWT(f) = <f, \psi_{j,k}> = \int_{-\infty}^{+\infty} f(x) \, a_0^{-j/2} \, \psi(a_0^{-j} x - k b_0) \, dx \tag{7}$$

The dilations and translations are chosen based on power of two, so called dyadic scales and positions, which make the analysis efficient and accurate. In this case, the frequency axis is partitioned into bands by using the power of two for the scale parameter "a". Considering samples at the dyadic values, one may get $b_0 = 1$ and $a_0 = 2$, and then the discrete wavelet transform becomes

$$DWT(f) = <f, \psi_{j,k}> = \int_{-\infty}^{+\infty} f(x) \, \{ 2^{-j/2} \, \psi(2^{-j} x - k) \} \, dx \tag{8}$$

Here, $\psi_{j,k}(x)$ is defined as

$$\psi_{j,k}(x) = 2^{-j/2} \psi(2^{-j} x - k), \qquad j, k \in Z \tag{9}$$

The wavelet prototype functions defined by this last DWT equation were created by Daubechies.

3.3. Multi-resolution Analysis (MRA)

Mallat introduced an efficient algorithm to perform the DWT known as the Multi-resolution Analysis (MRA). It is well known in the signal processing area as the two-channel sub-band coder. The MRA of L^2 (R) consists of successive approximations of the space V_j of L^2 (R). There exist a scaling function $\phi(x) \in V_0$ such that

$$\phi_{j,k}(x) = 2^{-j/2}\phi(2^{-j}x - k); \quad j,k \in Z \tag{10}$$

For the scaling function $\phi(x) \in V_0 \subset V_1$, there is a sequence $\{h_k\}$,

$$\phi(x) = 2\sum_k h_k\ \phi(2x - k). \tag{11}$$

This equation is known as two-scale difference equation. Furthermore, let us define W_j as a complementary space of V_j in V_{j+1}, such that $V_{j+1} = V_j \oplus W_j$ and $\overset{+\infty}{\underset{j=-\infty}{\oplus}} W_j = L^2(R)$. Since the $\psi(x)$ is a wavelet and it is also an element of V_0, a sequence $\{g_k\}$ exists such that

$$\psi(x) = 2\sum_k g_k\ \phi(2x - k) \tag{12}$$

It is concluded that the multiscale representation of a signal $f(x)$ may be achieved in different scales of the frequency domain by means of an orthogonal family of functions $\phi(x)$. Now, let us show how to compute the function in V_j. The projection of the signal $f(x) \in V_0$ on V_j defined by $P_v f^i(x)$ is given by

$$P_v f^i(x) = \sum_k c_{j,k}\ \phi_{j,k}(x) \tag{13}$$

Here, $c_{j,k} = <f, \phi_{j,k}(x)>$. Similarly, the projection of the function $f(x)$ on the subspace W_j is also defined by

$$P_w f^j(x) = \sum_k d_{j,k}\ \psi_{j,k}(x) \tag{14}$$

where $d_{j,k} = <f, \psi_{j,k}(x)>$. Because of $V_j = V_{j-1} \oplus W_{j-1}$, the original function $f(x) \in V_0$ can be rewritten as

$$f(x) = \sum_k c_{j,k}\ \phi_{j,k}(x) + \sum_j^{J-1}\sum_k d_{j,k}\ \psi_{j,k}(x) \qquad J > j_0 \tag{15}$$

The coefficients $c_{j,k}$ and $d_{j,k}$ are given by

$$c_{j-1,k} = \sqrt{2}\sum_i h_{i-2k}\ c_{j,k} \tag{16}$$

and

$$d_{j,k} = \sqrt{2}\sum_j g_{j-2k}\ c_{j,k}. \tag{17}$$

The multiresolution representation is linked to Finite Impulse Response (FIR) filters. The scaling function ϕ and the wavelet ψ are obtained using the filter theory and consequently also the coefficients are defined by these last two equations. If at $x=t/2$, $F\{\phi(x)\}$ is considered and

$$\Phi(\omega) = H\left(\frac{\omega}{2}\right)\Phi\left(\frac{\omega}{2}\right) \tag{18}$$

As $\phi(0) \neq 0$, $H(0)=1$, this means that $H(\omega)$ is a low-pass filter. According to this result $\phi(t)$ is computed by the low-pass filter $H(\omega)$. The mother wavelet $\psi(t)$ is computed by defining the function $G(\omega)$ so that $H(\omega)G^*(\omega) + H(\omega+\pi)G^*(\omega+\pi) = 0$. Here, $H(\omega)$ and $G(\omega)$ are quadrature mirror filters for MRA solution.

$$G(\omega) = -\exp(-j\omega)H^*(\omega+\pi) \tag{19}$$

Substituting $H(0)=1$ and $H(\pi)=0$, it yields $G(0)=0$ and $G(\pi)=1$, respectively. This means that $G(\omega)$ is a high pass filter. As a result, the MRA is a kind of two-channel sub-band coder used in the high-pass and low-pass filters, from which the original signal can be reconstructed.

4. APPLICATION TO NUCLEAR POWER PLANT

The signal processing of the Borssele nuclear power plant was started during the first core cycle in 1974 and regular measurements were carried out since then. The purpose of these measurements [22] was to estimate core physics parameters, testing of sensors and the enhancement of the measuring techniques and instrumentation. Since 1981, these measurements were carried out by an on-line system. Several advanced techniques were developed for signal processing, including AI-techniques and they were used for the real-time monitoring of the plant on a continuous basis.

Borssele nuclear power plant is owned and operated by EPZ in the Netherlands and was built by KWU-Siemens of Germany. Borssele power plant is a PWR with two-coolant loops, two steam generators and two main coolant pumps. The nominal power is 480 MWe. In this investigation experimental data from the database of Borssele NPP is used for illustration of the *Wavelet* application. The experimental data were acquired during the on-line monitoring of primary system integrity and core support barrel motions. In these experiments, noise signals of the four ex-core neutron detectors, two primary coolant pressure signals and one vibration transducer signal of the main coolant loop-1 were used. Noise data were sampled at 64 samples/second and represent stationary reactor operation at nominal reactor power. Figure 1 shows the primary loop and the detector locations.
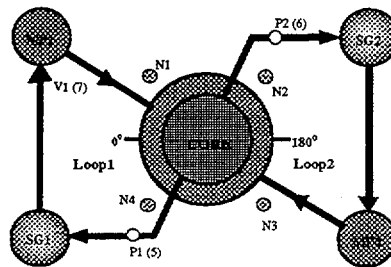

Figure 1. Borssele reactor primary system and sensor locations.

Analysis of the data was carried out by MATLAB-Wavelet toolbox. First, Power Spectral Density (PSD) and coherence functions between the signals were calculated. The signals were then divided into three levels in terms of sub-bands, which are defined as *approximations* and *details*. Initially, the wavelet analysis requires the selection of an optimal wavelet. This can be determined by Shannon's entropy function as an energy function. In this manner, Daubechies' mother wavelet ('db20'), that is defined in the MATLAB-wavelet toolbox, was used for the multi-resolution analysis of the signals. We considered the multi-resolution analysis (MRA) in four sub-bands in terms of the three *details* and one *approximation*. These sub-bands cover entire frequency range of interest, namely, (0-4 Hz), (4-8 Hz), (8-16 Hz) and (16-32 Hz). Where, the (0-4) Hz frequency band shows third approximation (a3) and the other sub-bands also indicate the frequency bands in the third detail (d3), second detail (d2) and first detail (d1), respectively. Figures 2, 3 and 4 show measured signals (actual signal 320 s.) and sub-band divided signals for ex-core neutron detector (N1), pressure sensor (P1) and vibration sensor (V1) in loop-1, respectively. Note that the main signal y can be reconstructed by y = a3 + d3 + d2 + d1 for each time point.
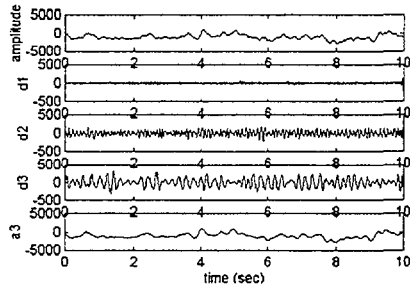

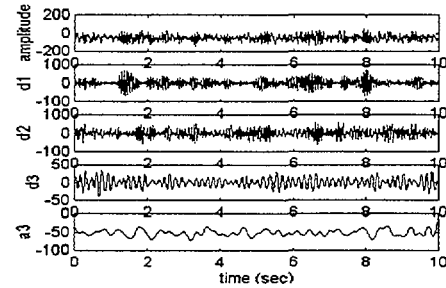Figure 2. Signal and sub-bands of neutron signal N1.

Figure 3. Signal and sub-bands of Primary pressure signal P1.
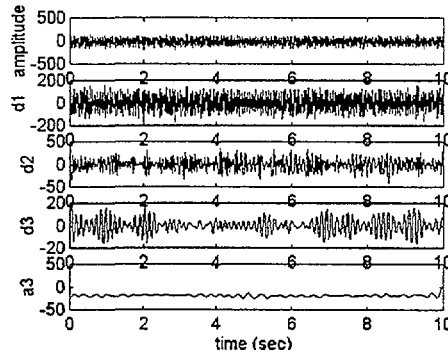

Figure 4. Signal and sub-bands of pump vibration signal V1.

The lower frequency (in Figure 2) is the main power of the N signals that can be seen by a3 as well as in the PSD in Figure 5. The d1 higher frequency details indicate very small amplitude and nearly no contribution to actual signal but it has a physical meaning. In pressure signals contribution of d1 and d2 are nearly same. PSD of P1 as seen in Figure 6 explains this. In the V1 signal highest amplitude is in d1, which can be compared Figure 7. Clear oscillatory behavior indicates that the frequency around 25 Hz is not a stationary one and caused by rotational speed of the main coolant pump.

Figures 5, 6 and 7 show the PSD functions of signals N1, P1 and V1, respectively in *solid* lines. The reconstructed PSD functions from the sub-band signals are also shown in the

figures in *dashed* lines. The construction of PSDs is carried out using the sub-band signals of *approximation* a3 (0-4 Hz), and the *detailed* d3 (4-8 Hz), d2 (8-16 Hz), and d1 (16-32 Hz) portions of the calculated PSDs. The comparison shows an excellent matching of the spectra calculated using the MATLAB-Wavelet toolbox [23] for all the three-selected detector signals.
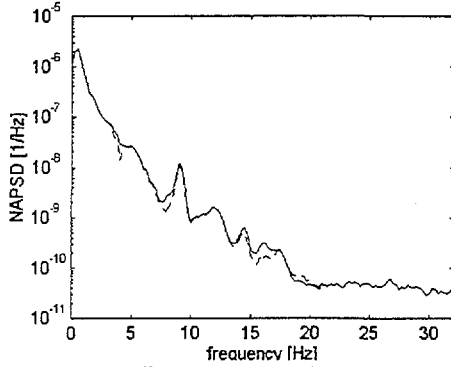

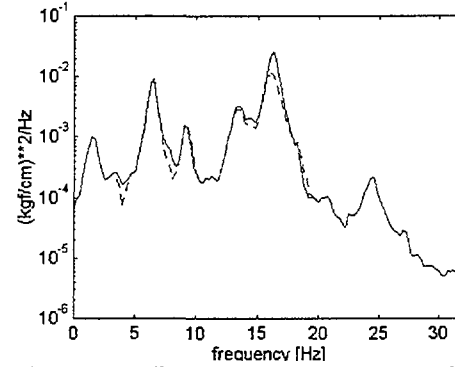Figure 5. Power spectral density of N1.
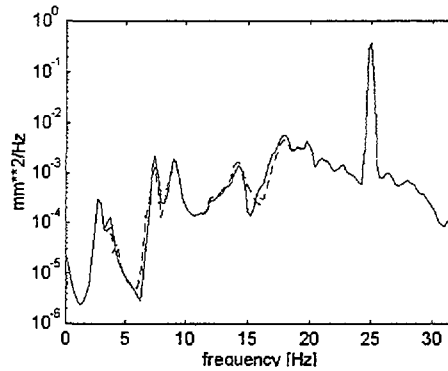
Figure 6. Power spectral density of P1.

Figure 7. Power spectral density of V1.

Selected sensor combinations was used for on-line monitoring of the primary system. Signals of the 4 ex-core neutron detectors are used to detect core barrel motion (CBM) using spectral decomposition technique, where pressure signals of both coolant loops are the driving forces for the core barrel motion and other effects and the pump vibration signal gives information about the main coolant pump behavior. All seven sensor signals and their mutual effects give information about the primary system integrity and its safe operation. Several peaks were observed in the PSD functions and contain information about the physical behavior of the system. Their mutual interactions are observed by coherence and phase information that are also calculated on-line. Spectral decomposition of the four ex-core neutron detectors gives information about the CBM amplitude (about $10\mu m$), directions of the movement and the reactivity effect at 9.2 Hz induced by differential pressure in the primary system. The spectral peaks at 5-7 Hz caused by fuel vibration, 9.2 Hz is a reactivity effect, around 11.7 Hz the core barrel beam mode vibration. The 14.9 Hz and 17.5 Hz peaks are caused by reactor pressure vessel vibration. After about 20 Hz, the spectrum is flat, and yields information about the detector efficiency of the IC ex-core neutron detector by known mean current. The fluctuations in the coolant pressure are the main source of all effects seen in the PSD of the pressure signals. Both PSDs of the P1 and P2 pressure sensors indicate 6.5 Hz caused by fluid resonance (standing wave effect) and the 9.2 Hz is due to differential pressure created in the core. The signals are in-phase and the amplitude of the peak depends on the boron concentration. The peak at 13.6 Hz is due to the standing wave of the coolant outlet pipe and

18.2 Hz and 19.5 Hz are caused by the resonance of the Barton cells (pressure sensors). The 24.5 Hz peak is caused by forced vertical vibration of the reactor pressure vessel-core barrel (RPV–CB) due to main coolant pump (MCP) unbalanced forces [24]. As it is observed, several effects interact with each other. One has to understand these effects and must monitor continuously to detect timely occurrence of events. In case of multi-resolution analysis it is possible to devise the MRA sub-bands for each desired frequency and monitor its amplitude and time. In some cases, due to the bad S/N characteristics of the signal it is difficult to see the coherence between the signals. One of the objectives of this study is to see how the coherence function behaves with sub-band (MRA) analysis and to determine any enhancement of the coherence information. For the same sub-band division, we have calculated the coherence between different signals and afterwards reconstructed them by concatenating. The integral sub-band coherence is also compared with the total signal coherence. Figures 8 through 15 show the various combinations of coherence functions. Here, N3 and N4 are ex-core neutron detectors in loop-1 and loop-2, respectively. P2 is also a pressure sensor in loop-2.
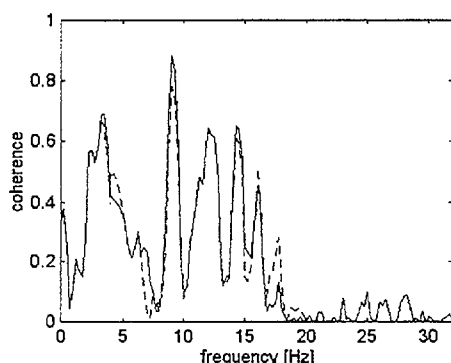
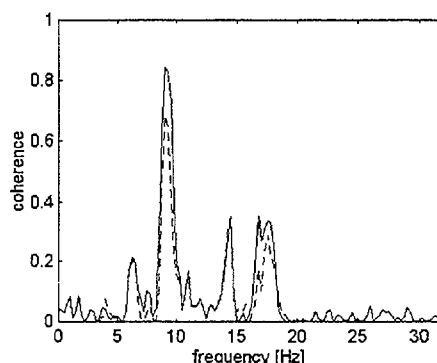Figure 8. Comparison of coherence N1-N3.
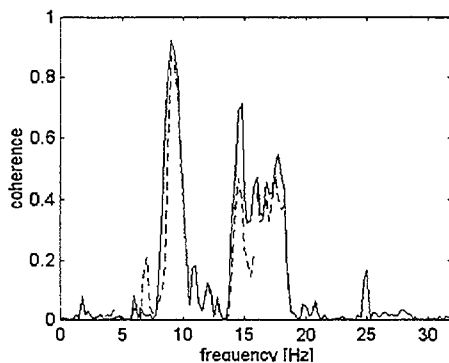
Figure 9. Comparison of coherence N3-P1.
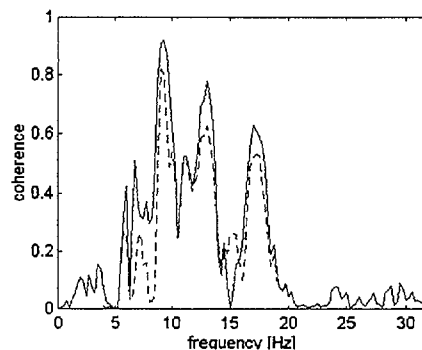
Figure 10. Comparison of coherence N3-V1.
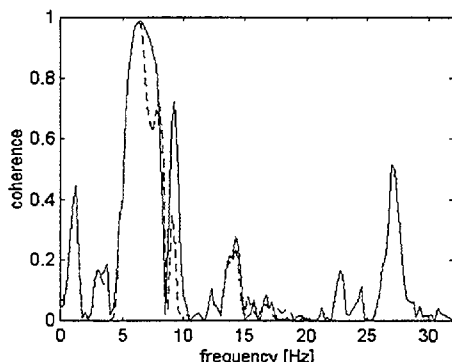
Figure 11.Comparison of coherence P1-V1.
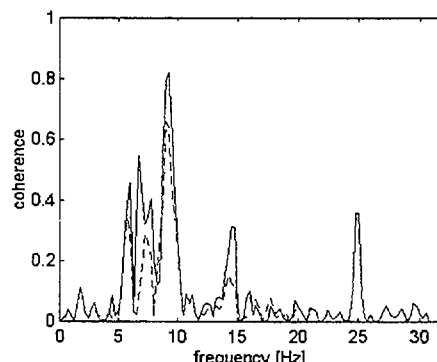
Figure 12. Comparison of coherence P1-P2.

Figure 13. Comparison of coherence P2-V1
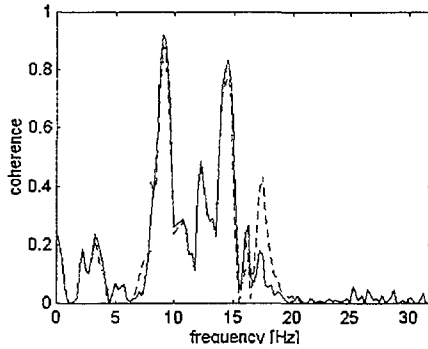
Figure 14. Comparison of coherence N1-N4.
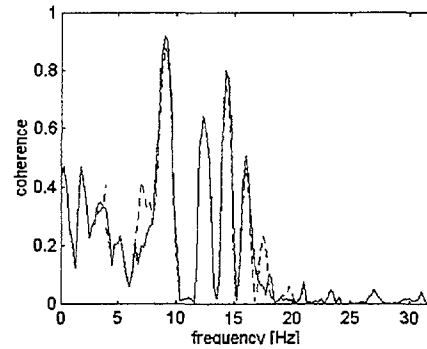
Figure 15.Comparison of coherence N3-N4.

The coherence function indicates the relation between the signals. Even the correlation between the neutron detectors (Figures 8, 14 and 15) are not the same due to their position around the core barrel. Various coherence functions indicate some small changes on the peak amplitude and frequency. Reconstruction on the coherence function is also successful. One major advantage of wavelets is time localization of signals. As Figures 16-a and 16-b indicate, the signals used in this study are stationary signals for which the spectral information does not change with time. Joint time-frequency spectra of pressure signal (P1) and its second detail (d2) sub-band using short time Fourier transform (STFT) technique are shown as follows.
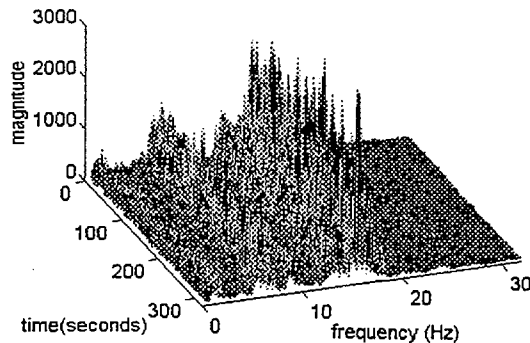
Figure 16-a. STFT of the pressure signal (P1).
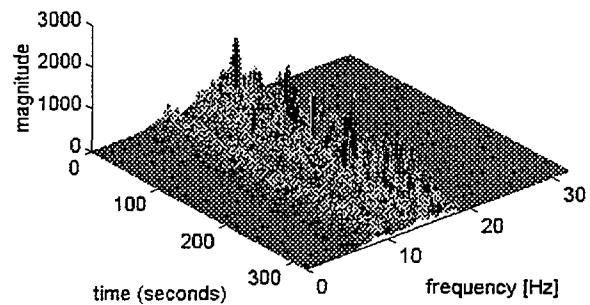
Figure 16-b. STFT for the d2 sub-band of P1.

5. CONCLUSIONS

The sub-band analysis of signals, using wavelet transforms, was applied to stationary noise data from an operating nuclear power plant. The multi-resolution technique was applied to neutron detector, primary pressure and pump vibration signals. An excellent matching between signal power spectra, using Fourier transform and wavelet multi-resolution analysis (MRA) was observed in all cases. The pairwise coherence analysis showed some enhancement using the sub-band MRA analysis. Thus, the reconstruction of the PSD and coherence functions is successfully applied. The use of wavelet transform sub-band analysis provides a minimum distortion of the signals, and allows the monitoring of frequency regions more effectively than the classical Fourier transforms.

6. ACKNOWLEDGEMENTS

REFERENCES

[1] MALLAT, S., *A Theory for Multiresolution Signal Decomposition the Wavelet Representation*, IEEE Trans. Pattern Anal. And Machine Intelligence, 31.pp 679-693, (1989).

[2] DAUBECHIES, I., *The Wavelet Transform, Time-Frequency Localization and Signal Analysis*, IEEE Trans. On Information Theory, Vol. 36, no.5,September, (1990).

[3] GABOR, D., *Theory of Communications, J.IEEE*, 93 ,3, p 429 (1946).

[4] GROSSMAN, A., MORLET, J., *Mathematics and Physics, 2, L.* Streit, Ed., World Scientific Publishing, Singapore.

[5] MALLAT,S.,*IEEE Trans. Acoustics, Speech, Signal Process.*,37,12,p2091, (1981).

[6] DAUBECHIES,I., *Commun. Pure Appl. Math.,* 41, 909 , (1989).

[7a] PEREZ, R. B., et.al., *Wavelets and the Generation of Time-Dependent Power Spectral Densities*, paper 62.01, 8th POWER PLANT DYNAMICS, CONTROL and TESTING SYMPOSIUM, May 27-29, 1992, Knoxville, Tennessee, USA.

[7b] MARTINGLY, J. K., PEREZ, R. B., *Numerical Implementation of Gabor and Continuos Wavelet Analyses* , paper 79.01, 9th POWER PLANT DYNAMICS CONTROL and TESTING SYMPOSIUM, May 24-26, (1995), Knoxville, TN, USA.

[8] OTADUY, P. J., GEORGEWICH, V., *Component identification of Nonstationary Signals Using Wavelets*, ANS Annual Meeting, TANSAO'68,part-A, p197-199,(1993).

[9] CIFTCIOGLU, O., TÜRKCAN, E., *Wavelets Understands Neural Networks*, ECN-RX— 94-031, (1994).

[10] CIFTCIOGLU, O., TÜRKCAN, E., *A Potential Approach for Plant Monitoring: Wavelet Technology.* 9th POWER PLANT DYNAMICS, CONTROL and TESTING SYMPOSIUM, May 24-26, (1995), Knoxville, Tennessee, USA, paper 82.01.

[11] CIFTCIOGLU, O., TÜRKCAN, E., *Transient Detection by Wavelet Transform in Plant Monitoring*, SMORN VII: Symposium on Nuclear Reactor Surveillance and Diagnostics. Proceedings, Avignon, France, 9-23 June 1995. Vol. 1, pp. 185-193. Also in, Netherlands Energy Research Foundation, ECN Report, ECN-RX—95-024, (1995).

[12] TÜRKCAN, E., CIFTCIOGLU, O., *Multiresolution Pattern Analysis for Neural Network Training*, SMORN VII: Symposium on Nuclear Reactor Surveillance and Diagnostics. Proceedings, Avignon, France, (19-23 June 1995). Vol.1, pp.278-285. Netherlands Energy Research Foundation, ECN Report, ECN-RX—95-023, 1995.

[13] CIFTCIOGLU, O., TÜRKCAN, E., *Decay Ratio Studies in BWR and PWR using Wavelet Studies*, OECD/NEANSC, INCORE 96, October 14-17, (1996), Mito, Japan.

[14] SUZUDO, T., VERHOEF, J. P., TÜRKCAN, E., *Power-Law Spectra Found in Plant Signal of the Borssele NPP: An Analysis Using Wavelet*, Netherlands Energy Research Foundation, ECN Report, ECN-R--6-011 (1996).

[15] ANTONOPOULOS-DOMIS, M., TAMBOURATSIZ, T., *System Identification During a Transient Wavelet Multiresolution Analysis Followed by Spectral Techniques*, IMORN'27, November 18-20, (1997) Valencia, Spain. Edited by CIEMAT & Universidad Politecnica De Valencia (Spain).

[16] CIFTCIOGLU, O., TÜRKCAN, E., *Studies For Wavelet Transform By Neural Networks,* , IMORN'27, November 18-20, (1997) Valencia, Spain. Edited by CIEMAT & Universidad Politecnica De Valencia (Spain).

[17] RACZ A., PAZSIT, I., *Diagnostics of Detector Tube Impacting with Wavelet Techniques,* Annals of Nuclear Energy Vol.25, Nr.6, December 1997, pp.387-400.

[18] HOOPER, W., UPADHYAYA, B.R., HENRY, G., BEHRAVESH and BENSON, J. M., *Advances in Diagnosis of Steam Generator Tubing Using Eddy Current Data Analysis,* Maintenance and Reliability Conference MARCON'98, May 12-14, (1998), Vol. 1, pp. 27.01-27.14, Knoxville, TN, May 1998.

[19] SEKER S., UPADHYAYA, B.R., ERBAY, A.S., McCLANAHAN, J. P., and DaSILVA, A. A., *Rotating Machinery Monitoring and Degradation Trending Using Wavelet Transforms,* Proc. MARCON' 98, Vol.1, pp. 23.01-23.11, Knoxville, TN, May 12-14, (1998).

[20] MEYER, Y., ONDELETTES, Function Splines, et Analyses Graduees, Univ. of Torino, (1986).

[21] DAUBECHIES, I., *IEEE Trans. Information Theory, 38, 2, (Mar. 1992).*

[22] TÜRKCAN, E., et.al., *Operational Experiences On the Borssele Nuclear Power Plant Using Computer Based Surveillance and Diagnostic System On-line,* SMORN-VI, Gatlinburg, Tennessee, USA 1991, Also in: Netherlands Energy Research Foundation, ECN Report, ECN-RX—91-057, (1991).

[23] *WAVELET Toolbox for use with MATLAB,* The Math Works, (March 1996).

[24] TÜRKCAN E., Borssele Reactor Data Benchmark Test, (Eds.) BERNARD P., and NAGEL P., NEACP-L-282. Report of the SMORN-IV, Physical Benchmark (1985).

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IMPLEMENTING ARTIFICIAL NEURAL NETWORKS IN NUCLEAR POWER PLANTS DIAGNOSTIC SYSTEMS: ISSUES AND CHALLENGES

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Abstract

A recent review of artificial intelligence applications in nuclear power plants (NPP) diagnostics and fault detection finds that mostly expert systems (ES) and artificial neural networks (ANN) techniques were researched and proposed, but the number of actual implementations in NPP diagnostics systems is very small. It lists the perceived obstacles to the ANN-based system acceptance and implementation. This paper analyses this list. Some of ANN limitations relate to "quantitative" difficulties of designing and training large-scale ANNs. The availability of an efficient large-scale ANN training algorithm may alleviate most of these concerns. Other perceived drawbacks refer to the "qualitative" aspects of ANN acceptance - how and when can we rely on the quality of the advice given by the ANN model. Several techniques are available that help to brighten the "black box" image of the ANN. Analysis of the trained ANN can identify the significant inputs. Calculation of the Causal Indices may reveal the magnitude and sign of the influence of each input on each output. Both these techniques increase the confidence of the users when they conform to known knowledge, or point to plausible relationships. Analysis of the behavior of the neurons in the hidden layer can identify false ANN classification when presented with noisy or corrupt data. Auto-associative NN can identify faulty sensors or data. Two examples of the ANN capabilities as possible diagnostic tools are given, using NPP data, one classifying internal reactor disturbances by neutron noise spectra analysis, the other identifying the faults causes of several transients. To use these techniques the ANN developers need large amount of training data of as many transients as possible. Such data is routinely generated in NPP simulators during the periodic qualification of NPP operators. The IAEA can help by encouraging the saving and distributing the transient data to developers of ANN diagnostic system, to serve as benchmarks in Verification and Validation tests, and as "Confidence Building Measures" of the ANN diagnostics and fault detection potential.

Introduction

Artificial neural networks (ANN) modeling techniques were suggested as viable solutions to diagnostic and fault identification issues in nuclear power plants (NPP) as early as 1988 [1]. Professor Uhrig published the first results in transient identification in NPP in 1989, [2], and remained active since then in this area. The International Atomic Energy Agency (IAEA) has reviewed the feasibility of expert systems (ES) and ANN applications

in NPP safety systems in some of it's Expert Group meetings since 1988, and several papers were presented on possible ANN-based systems. [3-11]. A recent IAEA meeting on NPP instrumentation and control systems recognized their potential usefulness and recommended their development and implementation [12]. However, reviewing the recent publications in this area shows that the number of actual implementations in NPP is very small. Most of the published papers are still from the academic community, universities and national research institutes, with only occasional co-operation with electrical utility personnel, the ultimate users.

A recent review of artificial intelligence (AI) applications in NPP diagnostics and fault detection by Reifman [13] finds that mostly ES and ANN techniques were researched and proposed. It reviews and classifies 95 publications (of which 33 were ANN-based), and presents most of the issues that are involved in the AI-based applications in the nuclear power industry. It covers mainly work published in American technical journals and conferences up to 1995, thus some relevant European or recent work were not included.

This paper lists new ANN-based NPP diagnostics developments and some earlier papers not reviewed by Reifman. It then discusses the possible obstacles to the ANN-based system acceptance and implementation listed in [13]. It describes the challenges facing system developers, and suggests some solutions. Examples of the ANN capabilities as possible diagnostic tools are given, as well as description of some techniques to increase the ANN modeling robustness and reliability.

Recent ANN diagnostics implementations review

A search of the INIS data base up to the end of 1996 has revealed about 300 hundred papers concerning the use of ANN-based systems in NPPs. Additional papers were published in the technical literature in 1997-8. Of course not all of them deal with diagnostics, as several papers deals with off-line NPP-related issues such as fuel reload optimization, power and heat distribution in the fuel elements, fault detection in fuel elements or steam header welds. Most of the new papers that describe actual implementations in NPPs come from the Republic of Korea and Japan, long active in this area. Some of the ANN related papers from these countries, which were not included in reference 10, and new papers are listed as references, [14-41]. An encouraging feature in these papers is the affiliation of some of the authors with large industrial companies or electrical utilities, and not only with universities or research institutes, as in the USA and Europe. It indicates readiness to consider ANN-based diagnostics in real NPP implementation.

Frequently asked questions in ANN modeling

The theory and practice of ANN modeling are described in many books and journal articles, and it is assumed that there is no need to repeat it in this paper. After enumerating the ANN applications, Reifman cites in his review the limitations and drawbacks of the ANN technology: (The numbers in parenthesis are mine, to facilitate

later reference) [ref. 13, pp. 80-81].

" (1) The training process is time consuming and needs large amount of training data, the quality of which strongly affects the success of the approach.

(2) Neural networks are also difficult to train when many categories of transients are to be identified.

(3) As the number of variables m in the problems increases, the complexity increases faster than a polynomial of order m.

(4) Difficulties in differentiating some transient that exhibit similar behavior in almost all the process variables have also been reported.

(5) Scale up is more difficult in expert systems and involves extending the input and output nodes, reconstructing the ANN architecture and re-training the entire system from scratch.

(6) When new transient data are made available, incremental learning does not seem to be possible with most types of ANNs.

(7) Unlike expert systems, ANN lacks explanation facilities and cannot explain the decision path of the underlying knowledge base.

(8) The advantage of the ANN to generalize from trained examples and perform inferences when the input data are beyond the scope their knowledge (in other words, the ability of ANNs to always provide an answer) has negative consequences. For example, a feed forward network might incorrectly give a classification answer with high confidence for a new type of transient on which it has never been trained.

(9) The necessity to anticipate all possible transient scenarios and use them for training is another limitation of the use of ANNs as transient classification tools".

Later in his review Reifman deals with specific issues of process diagnostic advisory systems, and describes the different AI approaches and possible solutions to these issues, [Ref. 13, pp. 87-92]:
" a. Multiple-Component faults
 b. Limited instrumentation
 c. Transient dynamics
 d. Propagation of disturbances
 e. Corrupted signal observation
 f. Verification and validation
 g. Portability
 h. Scalability".

As will be shown in the following sections, advanced ANN training and analysis techniques may solve some of these issues. What challenges do the NPP diagnostics system designers face when they try to implement these techniques are discussed in the final section.

ANN training issues

The ANN limitations (1-5) in the preceding list relate to the known difficulties of

designing and training large ANNs. The availability of efficient large-scale ANN training algorithm may alleviate most of these concerns. Guterman developed a Principal Component Analysis - Conjugate Gradient (PCA-CG) algorithm which calculates from the training data a non-heuristic estimate of the number of processing elements, "neurons" are needed in the hidden layer, and starts the training with non-random connection weights. It was shown to reduce by a factor of 30-50 the number of epochs needed for training several benchmark models. [42]. This algorithm was incorporated in a commercial software in 1992 [43]. Several applications of this algorithm to large-scale modeling of industrial plants [44-46], instrumentation spectra analysis [47-50], and quantitative structure - activity relationship (QSAR) [51] were published since 1992, establishing the practical feasibility of training ANNs with hundreds of inputs and outputs on a PC machine. The constant increase in the available computing power and speed should make the use of this algorithm even more suitable to the large scale modeling necessary for solving the NPP diagnostics system training issues.

The incremental training (issue no. 6) is more complex. Adding it to the original data and retraining may incorporate data of new operating regions, with no change in the basic system model. The are ways to generate appropriate representative "old" data, if the original training data is no longer available [52]. In their recent work, Nabeshima and co-workers [41] show that the ANN can learn the different behavior of an NPP in different phases of the fuel burnup, by re-training on-line with a database containing progressively more recent data than older data.

The missing explanation facility (issue no. 7) can be found in the various knowledge extraction techniques. One of them, the Causal Index (CI) method [53], is easily implemented by analysis of the trained ANN. It provides an indication of the magnitude and sign of the global relationship between each input and output. If the global relationship is not detailed enough, some of the input values may be replaced by fuzzy membership function values. Thus three or five times the number of inputs would be used, depending on the desired granularity. The CI would be then calculated from the larger trained ANN, thus getting different CI values of the low, medium and high ranges of the inputs.

Another method is the extraction of logical rules from the analysis of the trained ANN [54]. If combined with the identification of the more relevant inputs, it can provide explanation of much of the ANN prediction and classification results. It then may be the basis of backward-chaining expert system, checking for the existence of the conditions necessary for the specific transient, to verify the ANN prediction. Hybrid ANN, AI and modeling combinations are reported to increase the system acceptance and the confidence in its robustness [55].

This leads us to the next issue, the ability of the ANN to admit it's ignorance and not mislead the operator with false identification of events not in the training data. As reported in [13], there are ANN architectures that give an estimate of the confidence in it's predictions and thus say "I do not know". If the hybrid explanation facility mentioned

in the previous section is employed, the danger of "false positives" is reduced. Good classification ANN has a typical "binary" pattern of the outputs of the neurons in the hidden layer. If the pattern is unusual, it helps detecting some of the doubtful identifications, [54].

The number of possible faults and transients is of course very large, and there is the problem of accumulating enough training data (issue 10). The incremental training facility gives the possibility to continuously upgrade the diagnostic ANN, ensuring, at least, that a new transient or event that occurred in some NPP will be recognized in the future in other NPPs. The nuclear power industry is unique in possessing elaborate simulators, used to train NPP operators to identify and correct any simulated faults and transients. As these simulators are in use every day, with operator teams from different NPP, there is a possibility of collecting a large number of training data of the NPP response to simulated, known, faults or multiple faults in every phase of the NPP operation range.

Specific diagnostic issues

Some of the specific diagnostic issues were already covered in the preceding section. Issue b, the limited instrumentation, is amenable to ANN modeling, using the "virtual instrument" concept. Such an "instrument" measurement can be learned off line from laboratory data, calculated variable from thermodynamic tables, material or energy balances [45]. When necessary, the ANN predicted value of this variable might be monitored.

Issue e, corrupted signal observation, may be dealt with by the auto-associative neural network architecture, in which all inputs are also presented to the ANN output. Any deviation between the real and predicted instrument reading can be investigated and when necessary, the predicted value would be considered the correct one [20]. It was shown [21] that even simultaneous two-sensor failure can be detected.

Issue f, verification and validation, has dogged the development of any AI application in NPP. In ES, all rules have to be thoroughly checked out. The situation in the ANN is better, if the database generation and training are carried out as recommended in the previous sections. A recent paper addresses this issue, and the conclusion is that "... given the present maturity of the technology, acceptable safety cases might be formulated in the area of operator advisory systems designed to reduce accident frequencies. .... Nevertheless, AI-based systems should be treated with caution - further research is required into suitable designs and safety demonstration techniques." [56].

The two last issues, Portability and Scalability, are much more easily dealt with when ANN are used, compared with ES systems. The actual size of the ANN is minimal, just the connection weight matrix and the input/output scaling values. Thus there are no software compatibility issues. The computing platform requirements are also trivial, as most of the computational effort is off-line during the training phase, so modest speed

and storage memory are needed for the on-line monitoring.

Examples of the advanced ANN application to NPP data

In my earlier presentations, the advanced ANN application examples were demonstrated using industrial plant data, [44,57]. Two examples of the ANN capabilities are shown now using real and simulated NPP data.

The first example classifies abnormal reactor internal state using neutron noise spectra analysis, measured in the NIOBE boiling facility at the HOR research reactor in the Netherlands, [52]. In the ANN training, an initial 128-64-3 structure was used, with automatic pruning by a "forgetting" constant. The final ANN structure was 14-5-3, and causal knowledge was extracted by analysis of the surviving connection weights [58]. As the required number of data presentations (epochs) was in the order of tens of thousands, a super-computer was needed to achieve a reasonable training time.

Using 1050 examples of spectra of the same data, provided by Kozma and his co-workers, the CG-PCA algorithm trained a 128-3-3 ANN to classify the three reactor states. Several hundreds of epochs were needed on a PC machine from 26 training examples of neutron noise auto power spectral density of each state. Seven re-trainings after the progressive elimination of the less relevant inputs yielded a 7-3-3 ANN, still capable of perfect classification of the training data. The ANN then classified the rest of the data. Some of the classification results were ambiguous, identifying a class with uncertainty (output value less than 0.7, or two outputs with values higher than 0.7). The results of both ANN classifications are shown in Table 1.

ANN	Full					Reduced			
	out1	out2	out3	#cases		out1	out2	out3	#cases
Class1	1	0	0	502		1	0	0	495
Class2	0	1	0	111		0	1	0	160
Class3	0	0	1	377		0	0	1	349
sum				990					1004
Doubtful									
	0	0	0	9		0	0	0	14
	1	1	0	45		1	1	0	9
	0	1	1	1		0	1	1	3
	1	0	1	5		1	0	1	20
sum				60					46

Table 1: Classification of the reactor core state by the ANN outputs

To improve the correct classification rate, the "binary" patterns of the outputs of the neurons in the hidden layer were analyzed, by examining the connection weights from the (supposedly) binary hidden neurons to the output neurons (Table 1). As there are three hidden neurons in the trained ANNs, up to eight possible binary patterns are possible.

Multiplying each pattern by the connection weight vector, (at the lower part of the table) and summing the results with the bias value, the predicted outputs are compared. (Table 2).

ANN	Full					Reduced			
Pattern	hid1	hid2	hid3	#cases		hid1	hid2	hid3	#cases
Class1	0	1	0	438		0	1	0	502
Class1	1	1	0	67					
Class2	0	0	1	100		0	0	0	153
Class2	1	1	1	20					
Class3	0	0	0	379		1	1	1	357
Class3	1	0	0	9					
sum				1013					1012
Doubtful									
	0	1	1	25		0	1	1	25
	1	0	1	12		1	0	1	3
						1	1	0	10
sum				37					38
Connection weights between the hidden and output layers									
	h1	h2	h3	bias		h1	h2	h3	bias
o1	-0.1384	4.4681	-0.1108	-2.2001		0.5021	4.5133	-5.0241	-2.2141
o2	-0.0403	-0.1306	4.4321	-2.1723		-6.0077	-4.4748	6.0529	2.2207
o3	0.1529	-4.3768	-4.3434	2.182		5.523	-0.0373	-1.0446	-2.204

Table 2: Classification of the reactor core state by the ANN hidden neurons' outputs

It may be seen that some of the patterns are unique, some are ambiguous, and new subclasses are identified. Eliminating the less relevant inputs decreased the doubtful classification rate from 6.2% to 4.8%. The use of the hidden neuron pattern decreases the doubtful classification rate even more, to 3.8%.

The second application example is the identification of a NPP component fault by analysis of the resulting transient data. Reifman and Vitela obtained the dynamic response data of 20 instruments to three simulated faults, 10, 25, 40 seconds after the fault occurrence. They trained a 20-20-3 ANN, and showed that the conjugate-gradient error minimization was much more efficient than the back-propagation methods usually used for training [59]. The same data was made available to me for comparison, and a 20-4-3 ANN was trained from the data at 40 seconds. The verification was made using the earlier data, 10, 25 seconds after the fault. In 71 cases out of the 72 verification cases the faults were classified correctly. The one wrong classification was declared to be doubtful, as the hidden layer neurons' output pattern was unique. Two progressive retraining with the more relevant inputs gave the minimal list of nine instruments necessary for the correct classification. The causal indices were calculated for the two ANNs (Table 3).

ANN	Full			Reduced		
Component	Feedwater	Feed flow	Turbine CV	Feedwater	Feed flow	Turbine CV
Fault	pump trip	tx fail hi	fail close	pump trip	tx fail hi	fail close
Plant parameter						
Quench tank pressure	-1	-1	2			
Hot &cold leg A dtemp	0	1	0			
Hot &cold leg B dtemp	2	3	-5	15	-5	-10
Pressurizer pressure	-7	8	-1			
Pressurizer water level	1	-5	5			
Pressurizer level	0	6	-7			
Reactor power %	3	5	-8			
Steam gen. A water level	-4	-4	9	5	-12	7
Steam gen. B water level	0	-10	11	4	-12	8
Steam gen. A exit pres.	-1	-5	5	3	-11	8
Steam gen. B exit pres.	-1	-5	5			
HP turbine throttle. pres.	0	-6	5	2	-10	8
HP turbine exhaust pres.	3	-1	-1			
Feedwater loop A CV dp	-22	25	-4	-25	29	-4
Feedwater loop B CV dp	-30	32	-2	-32	36	-3
Feedwater loop A inlet P	-18	13	4	-17	7	10
Feedwater loop B inlet P	-18	11	6	-17	7	10
Letdown water flow	3	-4	1			
Makeup water flow	-7	11	-4			

Table 3: Causal Indices relating the instrumentation readings to the faults

It may be seen that the CI in the reduced ANN are much more distinct than those in the full ANN. This effect may be used in verification of an initial classification by the full ANN, and can be used in an explanation facility. It may be seen the thermo-hydraulic causal relationships are correct. For example, when the feed water flow transmitter fails high, the control system decrease the water flow rate to "correct" the flow, which would then decrease the water level in the steam generators. Conversely, a turbine CV closure will increase the water level in the steam generators, as no steam leaves them.

Discussion and conclusions

Reviewing the recent publications, it seems that the ANN as a tool for NPP fault diagnostics is moving from the academic research phase to the practical demonstration phase. The reported NPP applications are encouraging, in overcoming some of the issues of real-time data handling, reactor core behavior change following the fuel burnup, and operator interface. Most important is the possible gain in operator confidence and acceptance of the ANN. Also encouraging is the possible acceptance of the ANN by the regulators, realizing the potential safety improvement of early operator fault identification.

In my opinion, some of the seemingly negative aspects of the ANN modeling can be overcome using the advanced techniques demonstrated by the two examples. It was shown that large ANN could be efficiently trained for quick identification of faults, with adequate confidence in the results.

The most pressing need now is for the generation of large database of simulated transients, to be used in developing realistic, large-scale ANN NPP fault diagnostic systems. Once developed, these systems could be tested in daily operation, with the results proving or disproving the underlying concepts. In parallel, hybrid verification and explanation techniques would be integrated in the diagnostic system.

The IAEA could help in this task by encouraging the owners of the NPP to collect, and share, the simulated transient data generated during the training of the operating personnel in identifying and overcoming possible faults.

References

[1] Yiftah, S., (1988). Neural Networks - Potential application in the nuclear industry: Preliminary comments and reflections. *"Use of Expert Systems in Nuclear Safety"*, International Atomic Energy Agency, IAEA-TECDOC-542, pp. 177-182.

[2] Uhrig, R. E. and Guo, Z., (1989). Use of neural networks to identify transient operating conditions in nuclear plants, *Proceedings of SPIE Conference on Applications in Artificial Intelligence,* Orlando, March 1989.

[4] Boger, Z., (1988). Expert systems in nuclear power plants - how soon can they be implemented? *"Use of Expert Systems in Nuclear Safety"*, International Atomic Energy Agency, IAEA-TECDOC-542, pp. 165-176.

[5] Boger, Z., (1989). Survey of INIS database concerning expert systems in nuclear power plants. *"Use of Expert Systems in Nuclear Safety"*, International Atomic Energy Agency, IAEA-TECDOC-542, pp. 97-98, 245-344.

[6] Boger, Z., (1991). Possible roles of neural networks in developing expert systems in the nuclear industry. *"Expert Systems in the Nuclear Industry"*, International Atomic Energy Agency, IAEA-TECDOC-660, pp. 147-161.

[7] Boger, Z., (1992). The role of neural networks in nuclear power plant safety systems. *"The Potential of Knowledge Based Systems in Nuclear Installations"*, International Atomic Energy Agency, IAEA-TECDOC-700, pp. 63-75. Also as Israeli Atomic Energy Commission technical report NRCN (TN) - 145, Dec. 1993.

[8] Boger, Z., (1993). The status of artificial neural networks applications in the nuclear industry. *"Current Practices and Future Trends in Expert System Developments in Use in the Nuclear Industry"*. International Atomic Energy Agency, IAEA-TECDOC-769, pp. 33-46.

[9] Keter, A. and Boger, Z., (1994). Application of artificial neural networks in estimation of probable accident causes in nuclear power plants. *"Current practices and future trends in expert system developments in use in the nuclear industry."* International Atomic Energy Agency, IAEA-TECDOC-769, pp. 103-112.

[10] Stritar, A. and Laskover, M., (1994). Application of neural networks in nuclear safety analysis. *"Current practices and future trends in expert system developments in use in the nuclear industry."* International Atomic Energy Agency, IAEA-TECDOC-769, International

Atomic Energy Agency, pp. 47-54.

[11] Elias, E., Wacholder, M. and Tramer, M., (1994). Nuclear power plant diagnostics using artificial neural networks. *"Current practices and future trends in expert system developments in use in the nuclear industry."* IAEA-TECDOC-769, International Atomic Energy Agency, pp. 137-144.

[12] International Working Group on NPP Control and Instrumentation (1997). Conclusions and Recommendations. *"Advanced Control Systems to Improve Nuclear Power Plant Reliability and Efficiency"*, International Atomic Energy Agency, IAEA-TECDOC-952, pp. 98-99.

[13] Reifman, J., (1977). Survey of artificial intelligence methods for detection and identification of component faults in nuclear power plants. *Nuclear Technology*, (July 1997), v. 119, pp. 76-97,.

[14] Horiguchi, M., Fukawa, N. and Nishimura, K., (1991). Development of nuclear power plant diagnosis technique using neural networks. *Toshiba-Rebyu*, (Dec 1991), v. 46(12). pp. 939-942.

[15] Chang, S. H. and Cheon, S. W., (1992). Research on artificial neural network applications for nuclear power plants. *Proceedings of Post ANP'92 conference seminar on human cognitive and cooperative activities in advanced technological systems*, Kyoto, Nov 1992, pp. 107-118.

[16] Cheon, S. W., Chang, S. H., Chung, H. Y. and; Zeung, N. B., (1993). Application of neural networks to multiple alarm processing and diagnosis in nuclear power plants. *IEEE Transactions on Nuclear Science*, (Feb 1993), v. 40(1), pp. 11-20.

[17] Kim, W. J., Chang, S. H. and Lee, B. H., (1993). Application of neural networks to signal prediction in nuclear power plant. *IEEE Transactions on Nuclear Science*, (Oct 1993), v. 40(5), pp. 1337-1341.

[18] Ohga, Y. and Seki, H., (1993). Abnormal event identification in nuclear power plants using a neural network and knowledge processing. *Nuclear-Technology*, (Feb 1993), v. 101(2). p. 159-167.

[19] Miyake, M., Arita, S., Oga, Y. and Kamio, T., (1993). Alarm handling method and its application to nuclear power plants. *Hitachi-Hyoron*, (Feb 1993), v. 75(2), pp. 29-32.

[20] Turkcan, E. and Ciftcioglu, O., (1993). Enhancement of verification and validation for nuclear reactors through artificial intelligence. *"Operator support systems in nuclear power reactors"*, International Atomic Energy Agency, IAEA-TECDOC-762, pp. 271-279.

[21] Turkcan, E. and Ciftcioglu, O., (1993). On-line operator support system integrated with monitoring and diagnostic system. *"Operator support systems in nuclear power reactors"*, International Atomic Energy Agency, IAEA-TECDOC-762, pp. 61-70.

[22] Kozma, R., Sato, S., Sakuma, M., Kitamura, M. and Sugiyama, T., (1994). Generalization of knowledge acquired by a reactor core monitoring system based on a neuro-fuzzy algorithm. IMORN-25: Informal meeting on reactor noise, Raleigh, NC, USA, June 1994. *Progress in Nuclear Energy*, (1995), v. 29(3-4). p. 203-214.

[23] Chung, H. Y., Bien, Z., Park, J. H. and Seon, P.H., (1994). Incipient multiple fault diagnosis in real time with applications to large-scale systems. *IEEE Transactions on Nuclear Science*, (Aug 1994), v. 41(4Pt2), pp. 1692-1703.

[24] Nabeshima, K., Kozma, R. and Turkcan, E., (1993). Analysis of the response time of an on-line boiling monitoring system in research reactors with MTR-type fuel. *Proceedings of the 16th International meeting on reduced enrichment for research and test reactors*, Oarai, Ibaraki, Japan, Oct 1993, pp. 266-273. (JAERI-M--94-042).

[25] Nabeshima, K., Turkcan, E. and Ciftcioglu, O., (1994). Nuclear power plant monitoring using real-time learning neural network. *Proceedings of the AIR'94 specialists' meeting on application of artificial intelligence and robotics to nuclear plants*, Tokai, Ibaraki, Japan, May 1994, pp. 313-322. (INIS-JP-027).

[26] Furukawa, H., Kuchimura, K., Kitamura, M. and Washio, T., (1995). Information diversification for intelligent diagnosis of nuclear plants. *Nippon Genshiryoku Gakkai Shi.*, (Aug

1995), v. 37(8). p. 729-739.

[27] Kozma, R., Sato, S., Sakuma, M., Kitamura, M. and Sugiyama, T., (1995). Generalization of knowledge acquired by a reactor core monitoring system based on a neuro-fuzzy algorithm. *Progress in Nuclear Energy*, v. 29(3/4), pp. 203-214.

[28] Washio, T., Sakuma, M., Furukawa, H. and Kitamura, M., (1995). Criteria of diversity evaluation for intelligent diagnosis of nuclear power plants. *Nippon Genshiryoku Gakkai Shi.*, (Dec 1995), v. 37(12). p. 1128-1136.

[29] Seung, H. S. and Lee, U. C., (1995). Application of an artificial neural network to reactor core analysis. *Transactions of the American Nuclear Society*, Philadelphia, Jun 1995, v. 72, pp. 347-348. (CONF-950601)

[30] Kang, H. G. and Seong, P. H., (1995). A real-time monitoring system of core support barrel vibration using FEM data and self-organizing neural networks. *Nuclear Engineering and Design*, v. 58(1), (Sep 1995), pp. 19-29.

[31] Kee, C. K., Soon, J. S., Won, M. P., Jae, C. P. and Chang, S. H., (1995). A stochastic approach to accident identification in nuclear power plants. *Proceedings of the Specialists' Meeting on Instrumentation and Equipment for Monitoring and Controlling NPP Post-Accident Situations*. Dimitrovgrad, Russian Federation, Sep 1995, pp. 59-70. (IAEA IWG NPPCI-95/12).

[32] Nabeshima, K., Suzuki, K., Shinohara, Y. and Turkcan, E., (1995). Nuclear power plant monitoring method by neural network and its application to actual nuclear reactor. JAERI Research Report 95-076.

[33] Arita, S., Ohga, Y., Yoshida, Y., Yudate, T. and Aoki, Y., (1995). Development of a method of selecting important alarms for nuclear power plants. *Journal of Nuclear Science and Technology*, (Dec 1995), v. 32(12). p. 1218-1229.

[33] Kozma, R. and Nabeshima, K., (1995). Studies on the detection of incipient coolant boiling in nuclear reactors using artificial neural networks. Annals of Nuclear Energy, (July 1995), v. 22(7). p. 483-496.

[34] Thompson, A. C., Weller, P. R. and Summers, R., (1996). Use of neural networks in a system transient code. *Proceedings of the ASME/JSME Fluid Engineering and Laser Anemometry Conference*, pp. 169-173.

[35] Fantoni, P. F. and Mazzola, A., (1996). Multiple-failure signal validation in nuclear power plants using artificial neural networks. *Nuclear Technology*, v. 113, (March 1996), pp.368-374.

[36] Ohga, Y., Arita, S., Fukuzaki, T., Tanikawa, N., Takano, Y., Shiratori, S. and Wada, T., (1996). Evaluation tests of event identification method using neural network at Kashiwazaki Kariva nuclear power station unit no. 4. *Journal of Nuclear Science and Technology*, v. 33(5), (May 1996), pp. 439-447.

[37] Ishihara, Y., Kasai, M., Kambara, M., Mitsuda, H., Kurata, T. and Shirosaki, H., (1996). Study of a transient identification system using a neural network for a PWR plant. *Proceedings of the ASME/JSME International Conference on Nuclear Engineering*, ICONE-4, v. 1(B), pp. 1045-1051.

[38] Furukawa, H., Ueda, T. and Kitamura, M., (1996). Systematic method for rational definition of plant diagnostic systems by self-organizing neural networks. *Neurocomputing*, v. 13(2-4), (Oct. 1996), pp. 171-183.

[39] Mao, H., (1997). Artificial neural network method for alarm of loose parts in nuclear power stations. *China Mechanical Engineering*, v. 8(2), (Apr. 1997), pp. 41-43.

[40] Hines, J. W., Uhrig, R. E., Black C. and Xu, Xiau, (1997). Evaluation of instrument calibration monitoring using artificial neural networks. *Proceedings of the American Nuclear Society Annual Meeting*, Albuquerque, Nov. 1997, pp.112-113.

[41] Nabeshima, K., Suzudo, T., Suzuki, K and Turkcan, E., (1998). Real-time nuclear power monitoring with neural network. *Journal of Nuclear Science and Technology*, v. 35(2), (Feb. 1998), pp. 93-100.

[42] Guterman, H., (1994). Application of principal component analysis to the design of neural networks. *Neural, Parallel & Scientific Computing*, v. 2, pp. 43-54.

[43] TURBO - NEURON is a product of NEXSYS - Expert Neural Networks Ltd., TEMED Science Based Industrial Park, DN Arava, 86800, Israel.

[44] Boger, Z., (1992). Application of neural networks to water and wastewater treatment plant operation. *Instrument Society of America Transactions*, (1992), v. 31(1), pp. 25-33.

[45] Boger, Z., Guterman H. and Segal, T., (1996). Application of large scale artificial neural networks for modeling the response of a naphtha stabilizer distillation train. *Proceedings the American Institute of Chemical Engineers Annual Meeting*, Chicago 1996. (Available on the Internet, http://www.che.wisc.edu/aiche/1996/10b-abstracts/24.html).

[46] Boger, Z., (1997). Experience in industrial plant model development using large-scale artificial neural networks. *Information Sciences - Applications*, v. 101(3:4), 1997, pp. 203-215.

[47] Boger, Z. and Karpas Z., (1994). Use of neural networks for quantitative ion mobility spectrometric measurements. *Journal of Chemical Information and Computer Science*, v. 34, 1994, pp. 576-580.

[48] Boger Z. and Karpas Z., (1994). Application of neural networks for interpretation of ion mobility and X-ray fluorescence spectra. *Analytica Chimica Acta*, v. 292, 1994, pp. 243-251.

[49] Talaie, A., Boger, Z., Romagnoli, J. A., Adelejou, S. B. and Yuan, Y.J., (1996). Data acquisition, signal processing and modeling : A study of conducting polypyrrole formate biosensor. Part 1: Batch experiment. *Synthetic Metals*, v. 83, 1996, pp. 21-26.

[50] Boger, Z., Ratton, L., Kunt, T. A., Mc Avoy, T. J., Cavicchi, R. E. and Semancik, S., (1997). Robust classification of "Artificial Nose" sensor data by artificial neural networks. *Proceedings of the International Federation for Automatic Control, ADCHEM '97*, Banff, Canada, 1997.

[51] Boger, Z., (1996). Enhanced capabilities of artificial neural networks for predicting molecular activity. *Proceedings of the Third Electronic Computational Chemistry Conference*, Nov. 1996. (Available on the Internet, http://hackberry.chem.niu.edu/ECCC3/papers/paper66/paper66.html).

[52] Frean, M. and Robins, A., (1977). Catastrophic forgetting: a review and an analysis of the pseudo-rehearsal solution. Report AIM-36-97-2, Artificial Intelligence Laboratory, Computer and Information Science, University of Otago, Dunedin, New Zealand.

[53] Baba, I. Enbutu, I. and Yoda, M., (1990). Explicit representation of knowledge acquired from plant historical data using neural network, *Proceedings of the International. Joint Conference on Neural Networks*. San Diego, 1990, v. 3, pp. 155-160.

[54] Boger, Z., (1997). Knowledge extraction from artificial neural networks models. *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, SMC'97*, Orlando, Florida, Oct. 1997, pp. 3030-3035.

[55] Hines, J. W., Miller, D. W. and Hajek, B. K., (1996). A hybrid approach for detecting and isolating faults in nuclear power plant interacting systems. *Nuclear Technology*, v. 115, (Sept. 1996), pp. 342-358.

[56] Wainwright, N., (1995). A regulator's viewpoint on the use of AI in the nuclear industry. *Nuclear Energy*, v. 34(2), (April 1995), pp. 93-97.

[57] Boger, Z., (1993). Large scale neural networks - possible applications in nuclear power plants. *Proceedings of the ANS Topical Meeting on Nuclear Plant Instrumentation, Control and Man-Machine Interface Technologies*, Oak Ridge, Tennessee, Apr. 1993, pp. 624-631. Summary in IAEC Research Laboratories annual report 1993, IA-1521, pp. 199-200.

[58] Kozma, R., Van Dam, H., and Hoogenboom, J. E., (1992). Identification of flow patterns by neutron noise analysis. *Nuclear Technology*, v. 100, pp. 97-104.

[59] Reifman, J. and Vitela, J. E., (1994). Accelerating learning of neural networks with conjugate gradients for nuclear power applications. *Nuclear Technology*, v. 106, (May 1994), pp. 225-241.

SESSION 4:

DEVELOPMENT TRENDS AND ADVANCED TECHNOLOGIES
(2)

A PC-BASED SIGNAL VALIDATION SYSTEM
FOR NUCLEAR POWER PLANTS

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Abstract

In order to achieve the desired operating configuration in any process, the system conditions must be measured accurately. Examples of measurements are temperature, pressure, flow, level, motor current, vibration, etc. However, in order to operate within desired limits, it is important to know the reliability of plant measurements. Signal validation (SV) deals with this issue, and is defined as the detection, isolation and characterization of faulty signals. Also referred to as fault detection, signal validation checks inconsistencies among redundant measurements and estimates their expected values using other measurements and system models. The benefits of SV are both economic and safety related. Catastrophic signal failure can result in plant shutdown and lost revenue. Pre-catastrophic failure detection would therefore minimize plant downtime and increase plant availability. The control action taken depends primarily upon the information provided by the plant instruments. Thus, increased plant productivity and increased reliability of operator actions, would result from the implementation of such a system. The purpose of this study is to investigate some of the existing signal validation methods by incremental improvements and to develop new modules. Each of the SV modules performs a specific task. The architecture consists of four modules, an information base and a system executive integrated with a graphical user interface (GUI). All the modules are used for validation during both steady-state and transient operating conditions. The entire system was developed in the PC-framework under Microsoft Windows™. Some improvements were made in the structure of static data-driven models by incorporating one and two-step regression. Kalman filtering is based on the use of a physical model of plant components and was implemented for a steam generator system in a nuclear power plant. This is applicable to both steady-state and transient operations. The system executive performs several tasks: sequencing of module operation, requisition of additional data, evaluating SV information from the various modules, and displaying instrument or system status to the operator. The decision-making within the system executive was developed using a robust fuzzy logic approach. The computer display was performed by GUI objects compatible with Microsoft Windows.

INTRODUCTION

In order to achieve the desired operating configuration in any process, the system conditions must be measured accurately. Examples of measurements are temperature, pressure, flow, level, motor current, vibration, etc. However, in order to operate within desired limits, it is important to know the reliability of plant measurements. Signal validation (SV) deals with this issue, and is defined as the detection, isolation and characterization of faulty signals. Also referred to as fault detection, signal validation checks inconsistencies among redundant measurements and estimates their expected values using other measurements and system models.

The benefits of SV are both economic and safety related. Catastrophic signal failure can result in plant shutdown and lost revenue. Pre-catastrophic failure detection would therefore minimize plant downtime and increase plant availability. The control action taken depends primarily upon the information provided by the plant instruments. Thus, increased plant productivity and increased reliability of operator actions, would result from the implementation of such a system.

The purpose of this study is to investigate some of the existing signal validation methods by incremental improvements and to develop new modules. Each of the SV modules performs a specific task. The architecture consists of four modules, an information base and a system executive integrated with a graphical user interface (GUI). The following four modules were integrated in the new PC-based system (See Fig. 1).

- Generalized Consistency Checking (GCC) and Sequential Probability Ratio Test (SPRT),
- Process Empirical Modeling (PEM),
- Artificial Neural Network (ANN) prediction, and
- Kalman Filtering Technique (KFT).

All the modules are used for validation during both steady-state and transient operating conditions. The entire system was developed in the PC-framework under Microsoft Windows™. Some improvements were made in the structure of static data-driven models by incorporating one and two-step regression. Kalman filtering is based on the use of a physical model of plant components and was implemented for a steam generator system in a nuclear power plant. This is applicable to both steady-state and transient operations.

The system executive performs several tasks: sequencing of module operation, requisition of additional data, evaluating SV information from the various modules, and displaying instrument or system status to the operator. The decision-making within the system executive was developed using a robust fuzzy logic approach. The computer display was performed by GUI objects compatible with Microsoft Windows™.

SIGNAL VALIDATION MODULES

The primary advantage of using different SV algorithms is to compensate for prediction errors during transient operating conditions, in which some SV modules may not give good estimations of the measured variables. Another potential benefit is to have software redundancy, so that false alarms may be reduced. These modules operate in parallel and the system architecture is flexible for adding or removing an SV module. Operational data from two pressurized water reactors (PWRs) were used to develop these modules.

Generalized Consistency Checking (GCC) and
Sequential Probability Ratio Test (SPRT)

The GCC and SPRT techniques were developed previously at The University of Tennessee and applied to a signal validation system.[1,2,3] GCC is a method for the systematic cross comparison of signals from redundant sensors measuring the same process variable. The algorithm provides information about measurement inconsistencies at each sampling instant. After excluding the signals with maximum inconsistency indices, the best estimate at any time is computed as a weighted average of the remaining signals. The procedure is then repeated for subsequent sampling instants. The algorithm does not make comparisons between sets of measurements at different times. Any two redundant measurements are defined to be inconsistent if the difference between their values is greater than a specified threshold value. This threshold value depends on the selected signal pair and is based on sensor tolerances and technical specifications. The inconsistency indices of the individual measurements and the best estimate for the given process variable are determined as functions of sampling time instants.

The SPRT has the ability to check and record sensor degradation. The SPRT makes decisions on the basis of cumulative information provided by the measurement history. Unlike the GCC method, the SPRT does not make inter-signal comparison or consistency checking among the signals. The SPRT is an optimal decision-making (DM) procedure and requires a minimum number of samples from a sensor to make decisions based on specified missed- and false-alarm probabilities. These quantities provide a measure of confidence for the decision. The SPRT is applied to the difference between the sensor output and the estimated value of the process variable. The estimate is obtained from the GCC algorithm. The SPRT uses recursive calculations of the logarithm of the likelihood ratio (LLR) function representing the degradation information of a sensor based on samples.

The SPRT is performed for bias and noise degradations after the GCC analysis of the module is completed. The two algorithms are combined as one module and produce several outputs that are used in DM:

- Estimate of the process variable,
- LLR for each signal,
- Inconsistency index for each signal, and
- Indication if the signal is excluded from calculations.

Figures 2 and 3 show results of this SV algorithm using operational data from a four-loop PWR power plant. The LLR value of -10 in Fig. 3 indicated that sensors 1 and 2 were normal while the +20 value of LLR indicated possible anomaly in sensor 3.

Process Empirical Modeling (PEM)

The PEM module was developed and used previously at The University of Tennessee for signal validation applications.[1,2,3] The PEM establishes multiple-input single-output (MISO) models. The measured sensor output is then compared against a predicted output based on the PEM. The module provides an independent estimation of a process variable. Monitoring sensor degradation or drift by on-line monitoring of the sensor output is possible using the estimates of the PEM module.

The PEM creates an optimal nonlinear MISO model from a given data set. This data set has a similar function as the training data set used in artificial neural networks. The form of the data-driven predictive model is

$$y = c_0 + \sum_{i=1}^{m} c_i \Phi_i(\underline{x})$$ (1)

where

y = estimate of the process variable at time instant t,

$\underline{x}$ = vector of input signals at time instant t,

m = number of terms in the model,

Φ_i = nonlinear function of input signals, and

c_i = constant coefficient.

This equation can also be interpreted in the following form:

$$y = f(\underline{x}(t))$$ (2)

As a new contribution of this research, the static model given in Equation (2) is extended also for dynamic systems in which system variables can change significantly over time. A system may be modeled with a first order or a second order differential equation in the form:

$$\frac{dy}{dt} = f(\underline{x})$$ (3)

or

$$\frac{dy}{dt} = f\left(\frac{d\underline{x}}{dt}, \underline{x}\right)$$ (4)

or

$$y = f\left(\frac{d\underline{x}}{dt}, \underline{x}\right)$$ (5)

Using finite-difference numerical technique, the first derivative is approximated as

$$\frac{dy}{dt} = \frac{y(t) - y(t-1)}{\Delta t}$$ (6)

where t denotes the discrete sampling time and Δt denotes the sampling time interval. Then Equation (3) may be converted from continuous time domain to discrete time domain as:

$$y(t) = f(\underline{x}(t), y(t-1))$$ (7)

Equations (4) becomes

$$y(t) = f(\underline{x}(t), \underline{x}(t-1), \underline{y}(t-1))$$ (8)

and Equation (5) becomes

$$y(t) = f(\underline{x}(t), \underline{x}(t-1))$$ (9)

Both forms of discrete representations (Equations (7) and (9)) were incorporated in the PEM module. The previous values of input and output vectors are treated as an additional input to the regular PEM model given in Equation (1). Thus, the algorithm remains the same for all forms of the model equation.

PEM was performed for two variables: steam generator wide range water level and steam generator pressure. Table I shows the functional forms of the PEM module for these two different data sets with the following input signals.

$x(1)$ = steam generator feedwater flow rate,

$x(2)$ = steam generator wide-range water level at previous time instant,

$x(3)$ = reactor coolant system (RCS) flow rate,

$x(4)$ = steam generator steam flow rate,

$x(5)$ = steam generator steam pressure at previous time instant,

$x(6)$ = hot leg temperature, and

$x(7)$ = cold leg temperature.

The models were created using 100 training patterns, which were sampled at regular intervals over the entire data interval. The PEM models were incorporated into the PC-based signal validation system. As seen in Table I, dynamic models improved the accuracy of the estimated variable. However, in some type of sensors, a static model is accurate enough to predict the estimated state variable.

Artificial Neural Networks (ANNs)

ANNs are parallel computational models for mapping one set of data with another set. In this study, an SV module was developed using a hetero-associative backpropagation ANN. During ANN modeling, two types of models were taken into consideration: One incorporating Equation (2) and the other incorporating Equations (7) and (9). The hyperbolic tangent was chosen as the transfer function for the processing element. Figure 4 shows a backpropagation ANN for dynamic systems such as transient and semi-transient behaviors in Nuclear Power Plants.

The ANN module was developed with NeuralWare's NeuralWorks software with a fast-backpropagation algorithm.[4] The software produced a C subroutine which was incorporated into the PC-based signal validation system as an SV module. Results obtained from this SV module were similar in behavior to those obtained from PEM, provided that both the algorithms were executed with the same training data. Table II shows the signals used to estimate the steam generator wide-range water level and steam generator pressure.

Kalman Filtering Technique (KFT)

The Kalman filtering technique (KFT) is an optimal state estimation algorithm for general stochastic systems.[5] It requires the knowledge of a dynamic system model and is applicable to both stationary and nonstationary processes. The KFT has been studied and developed thoroughly in several areas.

The Kalman filter can be thought of as an optimal estimator that produces three types of outputs,[6] given a noisy measurement sequence and the associated models (Fig. 5). It can be thought of as a state estimator or a reconstructor, that is, it reconstructs estimates of the state $x(t)$ from noisy measurements $y(t)$. In this respect, it is almost an implicit solution of equations: since the state is not available directly, the models used can be considered as the means to implicitly extract $x(t)$ from $y(t)$. Second, the Kalman estimator may be thought of as a measurement filter. It accepts a noisy measurement sequence $y(t)$, and produces a filtered measurement sequence $\hat{y}(t|t)$ as the output. Finally, the estimator serves as a whitening filter that accepts noisy correlated measurements $y(t)$ and produces uncorrelated or white random process $e(t)$, called the innovations sequence. The notation $(t|t-1)$ denotes an estimation for time instant t with measurements given up to time $t-1$.

A process may be modeled by a set of stochastic linear vector difference equations in the state-space form as

$$x(t) = Ax(t-1) + Bw(t-1) \qquad (10)$$

where x is the state vector with Gaussian noise sequence $\{w\}$ and noise covariance Q. The corresponding measurement model is given by

$$y(t) = Cx(t) + v(t) \qquad (11)$$

where y is the measurement vector with Gaussian noise sequence $\{v\}$ and noise covariance R. Coefficient matrices A, B and C are determined using the parameters of the physical model. The equations that describe the state estimation are called the Kalman filter equations. The optimal filtered estimate $\hat{x}(t|t)$ is then computed recursively as[6]

$$\hat{x}(t|t) = \hat{x}(t|t-1) + G(t)e(t) \qquad (12)$$

where

$\hat{x}(t|t-1) = A\hat{x}(t-1|t-1)$ = one-step state prediction,

$G(t)$ = Kalman gain, and

$e(t) = y(t) - C\hat{x}(t|t-1)$ = innovation sequence, information gained from a subsequent measurement.

The recursive algorithm of the KFT is illustrated in Fig. 6. The recursive algorithm is initiated with $P(0|0) = P(0)$, which is the initial error covariance matrix of the initial state estimation $\hat{x}(0|0)$. The algorithm is executed for each measurement sample, and a filtered estimate is calculated.

Extension to State Estimation of Nonlinear Systems

The primary assumption made, in the development of the Kalman filter equations was that the system to be modeled should be linear. However, most of the real-world modeling includes nonlinear equations, so that a modification to the standard Kalman filtering algorithm is needed. For example the U-tube steam generator (UTSG) model of a PWR is described by nonlinear equations and is used in this study for the application of KFT.

The modification to the standard Kalman filter begins by modeling the system using nonlinear difference equations in the state-space form as

$$x(t) = f(x(t-1)) + w(t-1) \tag{13}$$

and the corresponding measurement model

$$y(t) = h(x(t)) + v(t) \tag{14}$$

where

$x(t) =$ state vector with Gaussian noise sequence $\{w\}$ and noise variance Q,

$y(t) =$ measurement vector with Gaussian noise sequence $\{v\}$ and noise variance R, and

$f(x(t))$, $h(x(t)) =$ nonlinear functions of the state vector.

The optimal filter estimate is calculated using the following equations

$$\hat{x}(t|t) = \hat{x}(t|t-1) + G(t)e(t) \tag{15}$$

$$\hat{x}(t|t-1) = f(\hat{x}(t-1|t-1)) \tag{16}$$

In the extended Kalman filter, the Kalman gain $G(t)$ has partial differentiations of the nonlinear functions of the state vector. The overall algorithmic procedure for the extended Kalman filter in calculating the optimal estimates is similar to the one given in Fig. 6.

The PC-based signal validation system has a KFT module which is based on the extended Kalman filter, and uses a nonlinear model of the UTSG. This model was previously developed at The University of Tennessee for a four-loop PWR.[7] The model consists of 19 state variables for the steam generator and 4 state variables for the controller, for a total of 23 state variables. The measurement vector includes

- steam generator wide-range water level,
- steam generator pressure,
- steam generator main feedwater flow,
- steam generator steam flow,
- reactor coolant system (RCS) flow,
- hot leg temperature, and
- cold leg temperature.

The UTSG model equations were discretized in the form of Equation (16). The discretized model equations were used in calculating the state estimates and their partial differentials were used in calculating the Kalman gain. The results obtained from this technique indicate that the estimations from the KFT module were very close to the actual *good* measurements. The use of measurements provides high accuracy in estimating these variables.

SIGNAL VALIDATION SYSTEM INTEGRATION

The system executive controls input-output among various devices and the programs. One important task of the system executive is to receive live data from an operational nuclear power plant. This is accomplished by using a local area network (LAN) and gathering information from a data acquisition computer. Figure 7 shows the schematic of acquiring live data for the PC-based signal validation program, whereas Fig. 1 shows a general overview of the integration of the individual SV modules

Fuzzy Logic Decision Making

The decision-making (DM) algorithm consists of three steps:
1. Construction of fuzzy sets from primary events. These are errors between measurements and SV module estimations or other indices such as inconsistency indices from general consistency checking.
2. Propagation of fuzzy sets through the fault-tree (fuzzy OR gate).[8]
3. Comparison of the resultant fuzzy set with prototype fuzzy sets (*very bad, bad, medium, good* or *very good*) using dissemble index calculations.

In the first step, the SV modules produce an estimate. The absolute difference between the estimated and measured value is used to construct a fuzzy set in the truthness domain. For another module, like the GCC module, the inconsistency index may be used to construct this fuzzy set. A graphical representation of converting from crisp error to fuzzy truthness is given in Fig. 8a. Suppose the difference between the measured and estimated steam generator pressure is 30 psi. From Fig. 8a, this yields with 70% belief, the sensor is faulty (If the error is more than 40 psi, it is definite that the sensor is faulty). The truth 0.7 is then taken as the basis for the maximum of the membership function and a triangular membership function in the *Truth* domain *[0,1]* is constructed as shown in Fig. 8b. Here *Truth* is an indication of the truthness of the sensor being faulty. The relationship between the confidence and the error is different for each state variable and for each module. If the signal validation module produces estimates closer to the measurements, then the relationship between the error and confidence will be on a much tighter scale (e.g. 30 psi will mark a 100% confidence, rather than 30 psi marking 70% confidence of the sensor being faulty).

In the second step, every primary event (in this study the error between the measured and estimated state) of the fault-tree is considered as fuzzy and a membership function, $\mu_{PE}(x) \to [0,1]$, describing the degree of membership to a particular set, is constructed. The AND, OR, and NOT gates composing the fault-tree are treated linguistically, and their dyadic operation on the fuzzy sets constituting the primary events is computed through the extension principle.[9] For example, the OR gate is modeled using the extension principle as:

$$\mu_{R_1 \cup R_2}(x, y) = \max_{x \cup y}\left(\min\left(\mu_{R_1}(x), \mu_{R_2}(y)\right)\right) \tag{17}$$

where $\cup$ denotes the maximum of two crisp values. The fault-tree, used in DM for the PC-based SV system, is shown in Fig. 9.

In the final step of DM, the outcome of the logical operations is a new fuzzy set defined in the range *[0,1]*. The top event is also considered as a fuzzy variable that takes five fuzzy values, namely, *safe, no fault, fault warning, fault, severe fault*. This value can also be interpreted as a sensor quality index such as *very good, good, medium, bad* and *very bad*. The five fuzzy values are algebraically depicted in the range *[0,1]* with five membership functions that compose a library of prototypes. Generally, the result of the logical operations on the membership functions defining the primary events will be somewhat different from the prototype membership functions defining the linguistic values of the top event. The prototype library is shown in Fig. 10.

In order to draw a conclusion concerning the type of top event, the distance between the computed membership function and the prototype membership functions is calculated. This distance is also referred to as the dissemblence index and the minimum dissemblence index value is used to define the output of the fault-tree as *safe, no fault, fault warning, fault* or *severe fault*. An overall schematic of the DM is given in Fig. 11.

Graphical User Interface

Another important task of the system executive is to display processed and measured data to the user. This task is accomplished in a user-friendly environment in which the user is able to navigate through the information space easily. Hypertext links and Microsoft Windows™ standards enable the design of graphical user interface (GUI) objects. These GUI objects are designed with virtual reality techniques so that the user can recognize them by relating them with every-day objects. Navigation through this

information space is managed by point-and-click operations of the mouse interface of a standard PC. This simplifies the use of key sequences to accomplish a certain action.

The GUI of the PC-based signal validation system has different ways of displaying information. Instant measurements are displayed in digital and analog forms. The analog displays, as shown in Fig. 12, are simulated using graphical objects. However, digital presentations of the measurements are always important for plant engineering systems. Also, an historical trend plot of the measured and estimated values is of importance, to conclude a final decision about the system. The graphical plots are created with Visual Basic's extended custom control objects. Navigating to these plots are established by hypertext buttons, located at the border of each corresponding information window.

The results of the DM module are also displayed by means of modern techniques. If the sampling time is in the order of a minute or less, it may be difficult for the user to read out the final outcome of the fuzzy logic fault-tree in terms of linguistic values, such as *safe, no fault, fault warning, fault* and *severe fault*. Instead, icon representations of such values are used as shown in Fig. 12. The icon "smiley" is used to indicate the final outcome of the DM module.

The information displayed in the windows shown in Fig. 12 are instantaneous displays of measured values, results of SV module estimates and fuzzy logic based DM results. An historical plot can be obtained by pressing the plot button on the bottom of each instantaneous display window. In addition, an historical plot of the quality index is also shown as a function of time. The quality index has the following meaning.

0 = safe,

1 = no fault,

2 = fault warning,

3 = fault,

4 = severe fault.

An example of historical plot of the SV modules are shown in Fig. 13. Note that since steam generator wide range water level measurements consist of only one sensor channel, GCC algorithm is not applied for this measurement. If the measurement has more than one sensor channel, then the plot window incorporates buttons for each related sensor at the bottom of each historical trend plot window. The user may click these buttons to view the related information.

The system executive also provides some hypertext buttons, which provide links to product information and on-line help. The on-line help was developed with Microsoft Word and compiled with Microsoft Help Compiler.

CONCLUSIONS

In general, the results obtained from the studies have shown the feasibility of implementing a PC-based signal validation system for nuclear power plants. The UTSG in a nuclear power plant was the focus of study in this research. Steam generator water level and steam generator pressure signals from a UTSG were used to illustrate the performance of the four signal validation modules.

The PC-based signal validation system was tested using off-line data obtained from two PWR's. The sampling interval for PWR-1 data was 15 minutes, whereas the sampling interval for PWR-2 data was 30 seconds. It was noticed in this study, that the sampling time of data is important to obtain an accurate model for the PEM and ANN modules. For example, if fluctuating water levels are measured at very short sampling intervals, the model to be fit to the data may confuse the training phase of constructing these models. Therefore, longer sampling time intervals are more suitable for steam generator water level (e.g. in the order of minutes).

While, the incorporation of the GCC module in the PC-based signal validation system was straightforward, the development of the PEM and ANN modules required several variations in input signal selection. Static models were found to be sufficient to validate the steam generator pressure. The steam generator wide-range water level signal was modeled successfully with dynamic structures such as incorporating past measurements of the input variables. The use of such models is very common in the ANN literature, whereas the same technique was applied to the PEM module for the first time to construct a model of the steam generator wide range water level.

Another important observation that was made during this study was the similarity between ANNs and PEM: for the same number and type of training patterns (100 training patterns over the entire transient and steady-state operating conditions) both models behaved similarly in predicting the signals to be validated.

Since the KFT requires an analytical model of the system to be validated, previously developed models of the UTSG were used.[7] This model performed very well when used in conjunction with measurements from another similar plant in the KFT calculations. The measurement of several signals is crucial in obtaining a good KFT estimate. Since the KFT module and the UTSG model make several assumptions, the state estimation has some error, compared with the state measurement. Excellent results can be obtained by including state measurements in correcting the KFT estimate.

The use of SPRT in fault detection can be made sensitive to small changes in signal levels by the proper choice of false-alarm and missed-alarm probabilities. Thus the incipient changes in instrument calibration can be detected with as low as 0.5% changes in the signal levels.

The fault-tree methodology provided a useful tool in developing a procedure for sensor status determination. To reach a final conclusion, a fuzzy logic was used for fault-tree computations. The results were displayed in a user-friendly manner by means of icons, so that the results of the DM could be recognized easily, even at short sampling time intervals and at a high screen information update rate.

As the DM plots indicate, deviations were detected in the steam generator wide range level for some time instants. These might have occurred due to the level fluctuations inside the UTSG during process transients. The DM algorithm of the system executive detected very few anomalies (in spikes) in the steam generator pressure sensors.

The development of the signal validation system in the Microsoft Windows™ environment enabled the use of effective GUIs. Since this is a common operating system, this validation technology can be easily ported to compatible PCs in nuclear power plants.

ACKNOWLEDGMENTS

REFERENCES

1. B. R. Upadhyaya, T. W. Kerlin, K. E. holbert, O. Glocker, V. M. Morgenstern, and Z. Frey, "Signal Validation in Nuclear Power Plants," Annual Report prepared for the U.S. Department of Energy by The University of Tennessee, DOE/NE/37959-24 (September 1988).

2. K. E. Holbert, "Comprehensive Signal Validation for Nuclear Power Plants," Ph.D. Dissertation, The University of Tennessee, nuclear Engineering (August 1989).

3. B. R. Upadhyaya, T. W. Kerlin, K. E. holbert, O. Glocker, V. M. Morgenstern, Z. Frey and J. Olvera, "Development and Testing of an Integrated Signal Validation System for Nuclear Power Plants," Volume 1, 2, 3, Research report prepared for the U.S. Department of Energy, DOE/NE/37959 34, 35, 36 (September 1989).

4. NeuralWare, "Neural Computing," Technical Publications Group, NeuralWare Inc. (1993).

5. R. E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," Journal of Basic Engineering, Volume 82 (1960).

6. R. G. Brown, "Introduction to Random Signals and Applied Kalman Filtering," John Wiley, New York (1992).

7. E. Eryürek, "A Parallel, Fault-Tolerant control and Diagnostics System for Nuclear Power Plants," Ph.D. Dissertation, The University of Tennessee, Nuclear Engineering (1994).

8. A. S. Erbay and A. Ikonomopoulos, "A Fuzzy Logic Methodology for Fault-Tree Analysis in Critical Safety Systems," Transactions of the American Nuclear Society, Volume 68, Part A, pp. 134 -135, San Diego California (June 1993).

9. D. Dubois and H. Prade, "Fuzzy Sets and Systems: Theory and Applications," Academic Press, Boston, Massachusetts (1980).
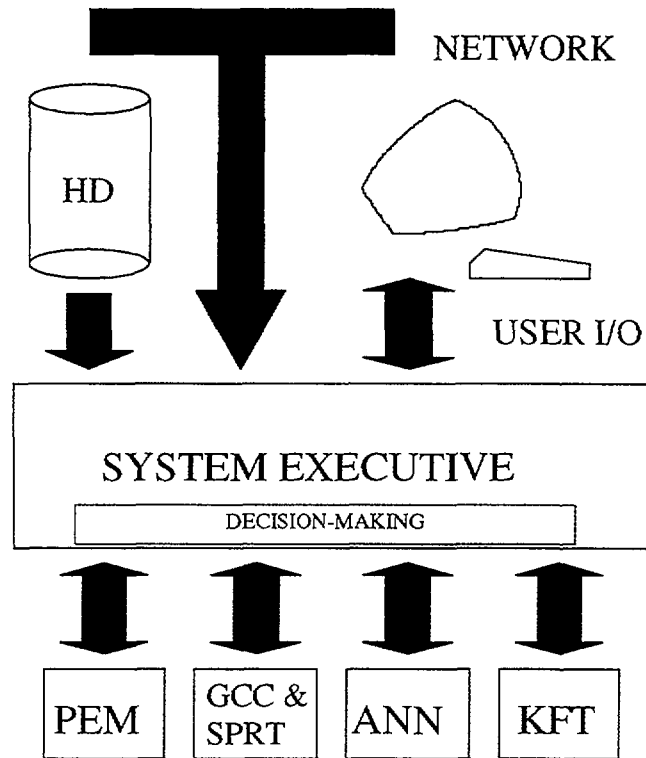
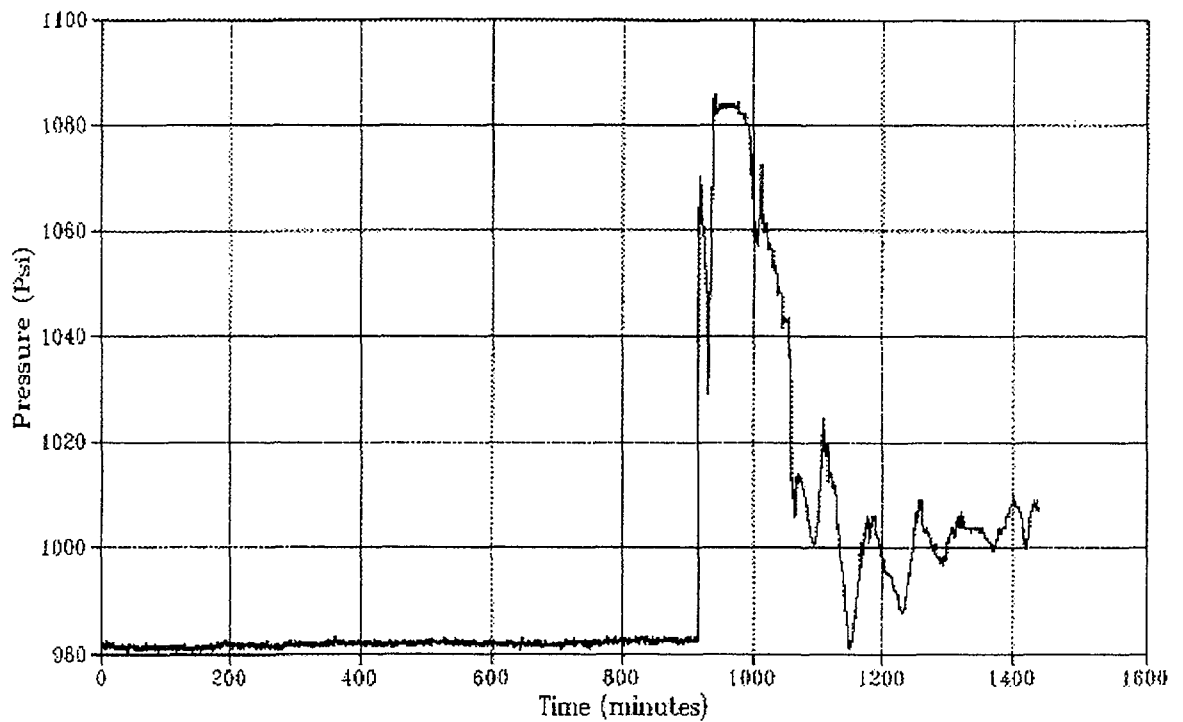**Figure 1:** Integration of SV modules with system executive.
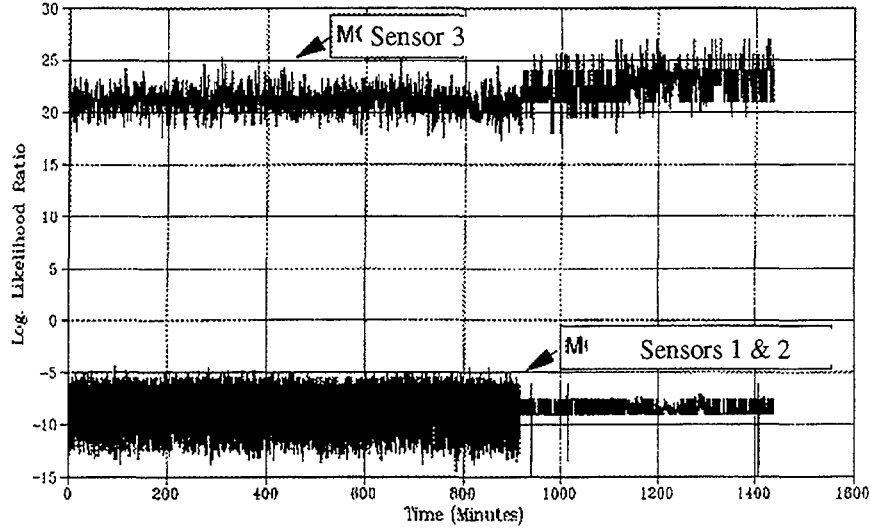

Figure 2: GCC estimate of the steam generator pressure.

Figure 3: LLR computed by SPRT of the steam generator pressure.

Table I: Process empirical models.

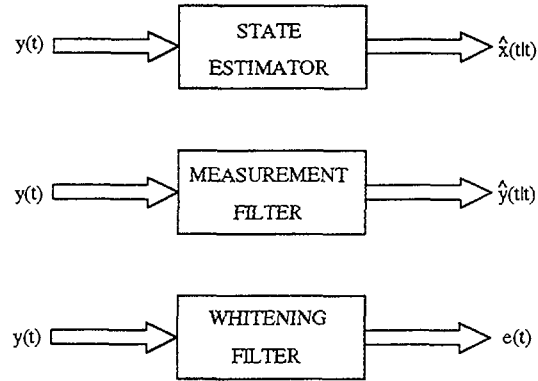| Modeled State Variable	Model	Constants	Modeling Error
Steam Generator Water Level	$c_1x(3)^2 + c_2x(7) + c_3x(7)^2 + c_4x(6) + c_5x(6)^2 + c_6$ *(Static model)*	$c_1 = -0.003$ $c_2 = 59.869$ $c_3 = -0.054$ $c_4 = -16.315$ $c_5 = 0.014$ $c_6 = -1176.855$	4.13%
Steam Generator Pressure	$c_1x(7) + c_2x(4) + c_3x(6) + c_4x(1) + c_5$ *(Static model)*	$c_1 = 8.311$ $c_2 = -13.888$ $c_3 = 0.121$ $c_4 = -0.016$ $c_5 = -3633.133$	0.31%
Steam Generator Water Level	$c_1x(2) + c_2x(7) + c_3x(6) + c_4x(1) + c_5x(4) + c_6$ *(Dynamic model)*	$c_1 = 0.993$ $c_2 = -.040$ $c_3 = 0.041$ $c_4 = 0.001$ $c_5 = -2.266$ $c_6 = .331$	0.47%
Steam Generator Pressure	$c_1x(5) + c_2x(7) + c_3x(6) + c_4x(1) + c_5x(4) + c_6$ *(Dynamic model)*	$c_1 = 1.019$ $c_2 = 0.190$ $c_3 = -0.368$ $c_4 = 0.003$ $c_5 = 4.348$ $c_6 = 78.404$	0.09%

$$\bar{y}(t)$$

OUTPUT LAYER

HIDDEN LAYER

INPUT LAYER

x(t-1) x(t)   y(t-1)

Figure 4: Backpropagation ANN for dynamic systems.

Table II: Inputs used in ANN modeling.

Estimated Variable	Steam Generator Main Feedwater Flow	RCS Flow	Steam Generator Steam Flow	Hot Leg Temperature	Cold Leg Temperature	Steam Generator Water Level	Steam Generator Pressure
Steam Generator Water Level or Pressure (Static Modeling)	t	t	t	t	t	N/A	N/A
Steam Generator Water Level (Dynamic Modeling)	t	t	t	t	t	t-1	N/A
Steam Generator Pressure for (Dynamic Modeling)	t	t	t	t	t	N/A	t-1
Steam Generator Water Level or Pressure (Dynamic Modeling)	t, t-1	t, t-1	t, t-1	t, t-1	t, t-1	N/A	N/A

Figure 5: Various representations of the Kalman filter estimator.
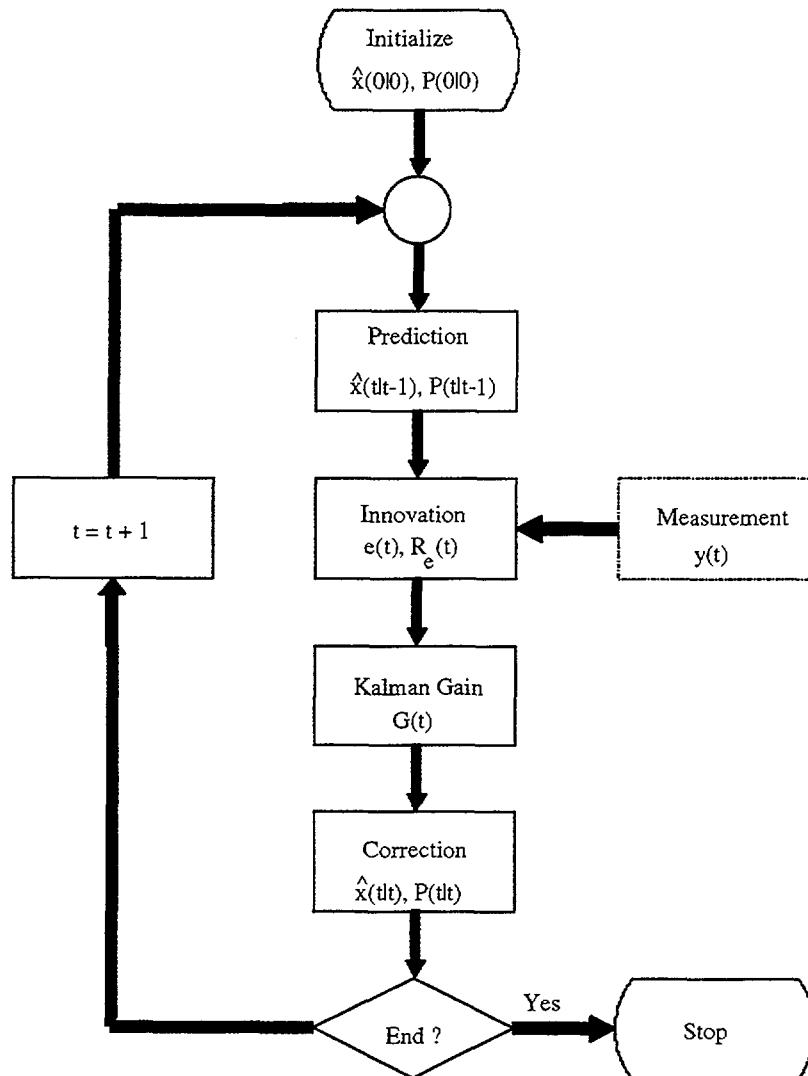
Figure 6: Kalman filter calculations.
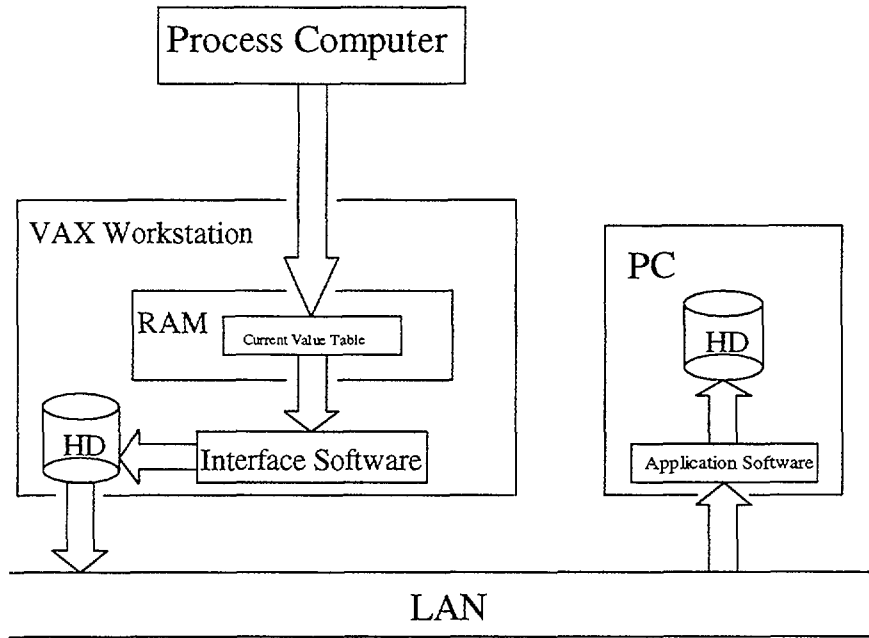
Figure 7: Information flow from process computer to the PC-based signal validation system.
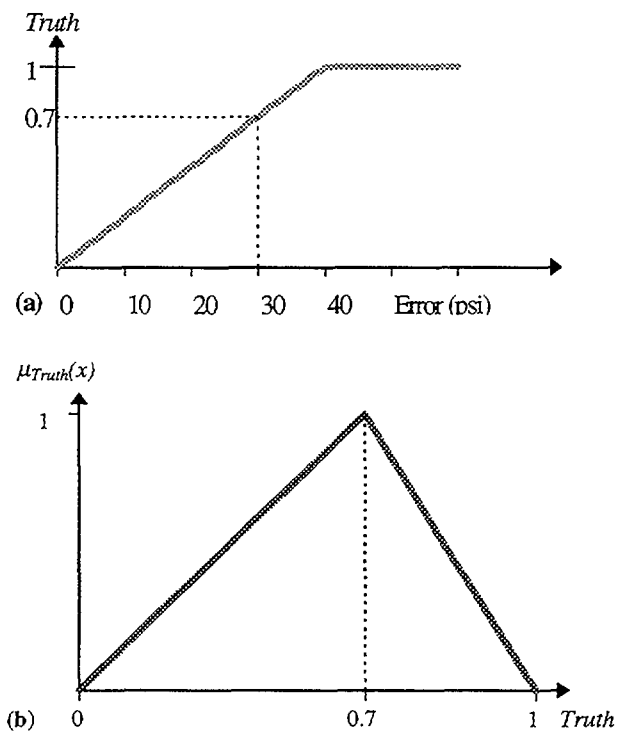
Figure 8: Construction of fuzzy sets from crisp errors between measurements and estimates.
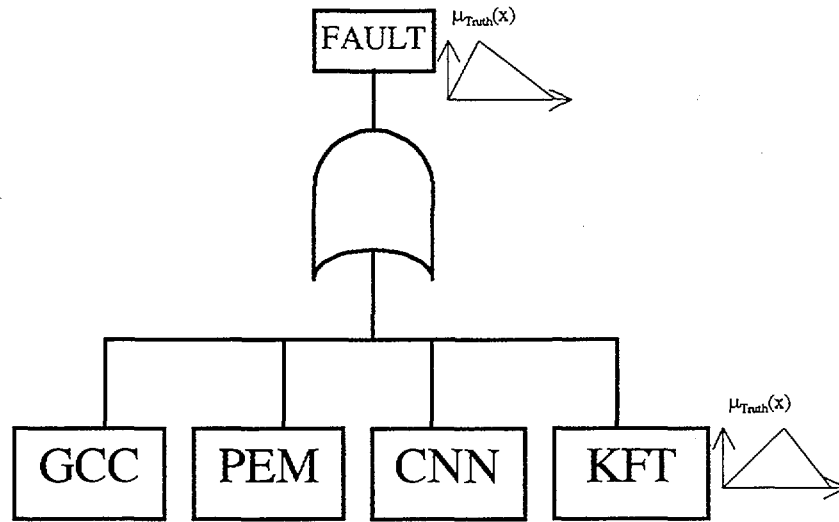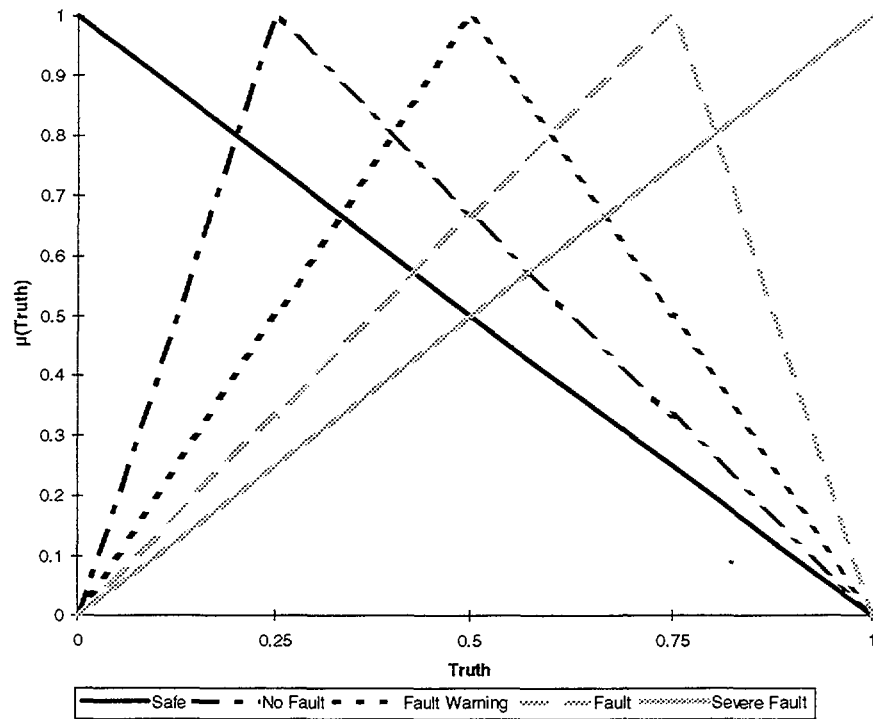
Figure 9: Fault-tree leading to sensor fault.

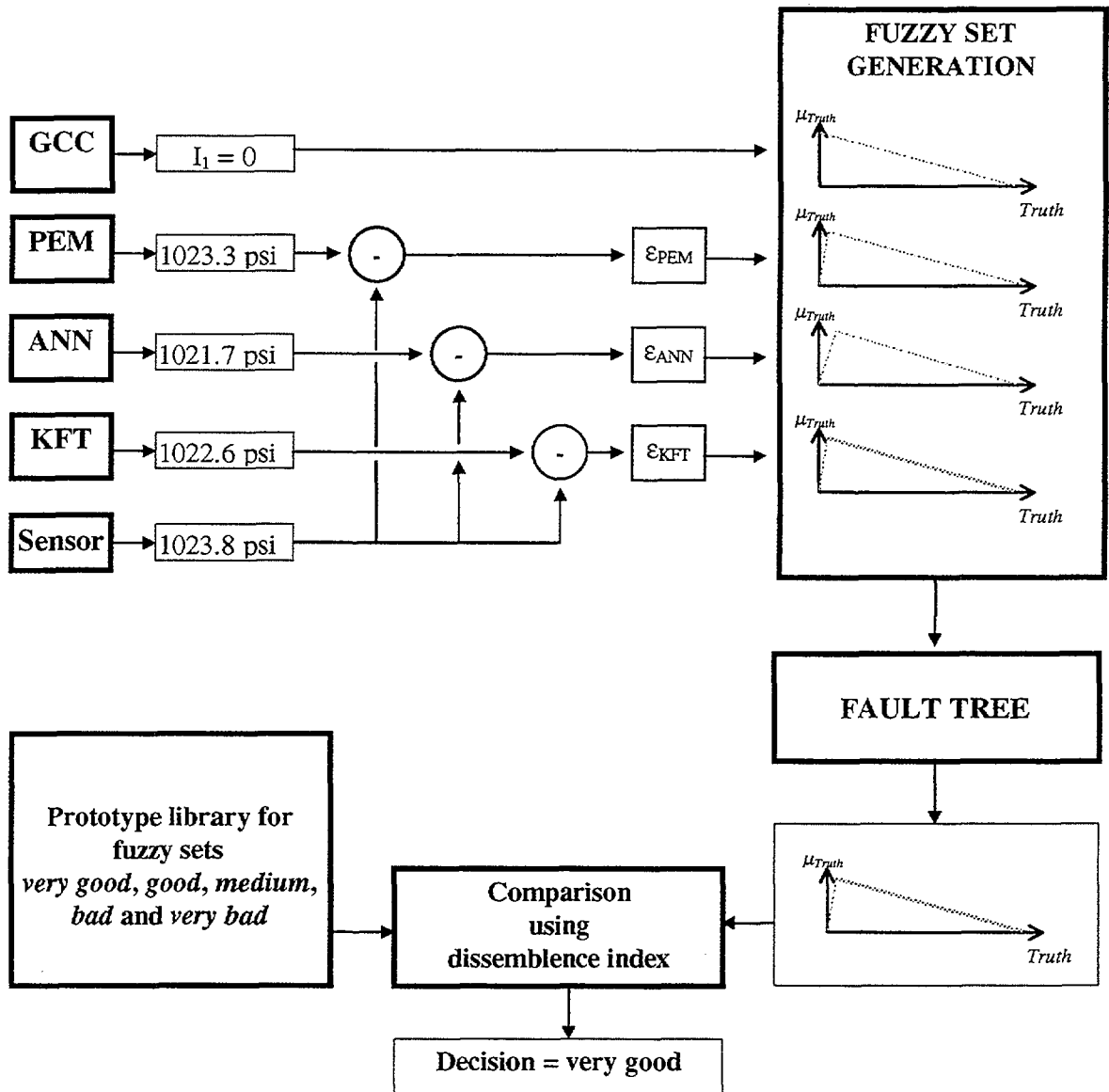

Figure 10: Library of prototype fuzzy sets.

Figure 11: An example of making a decision for pressure sensor status using fault-tree methodology.
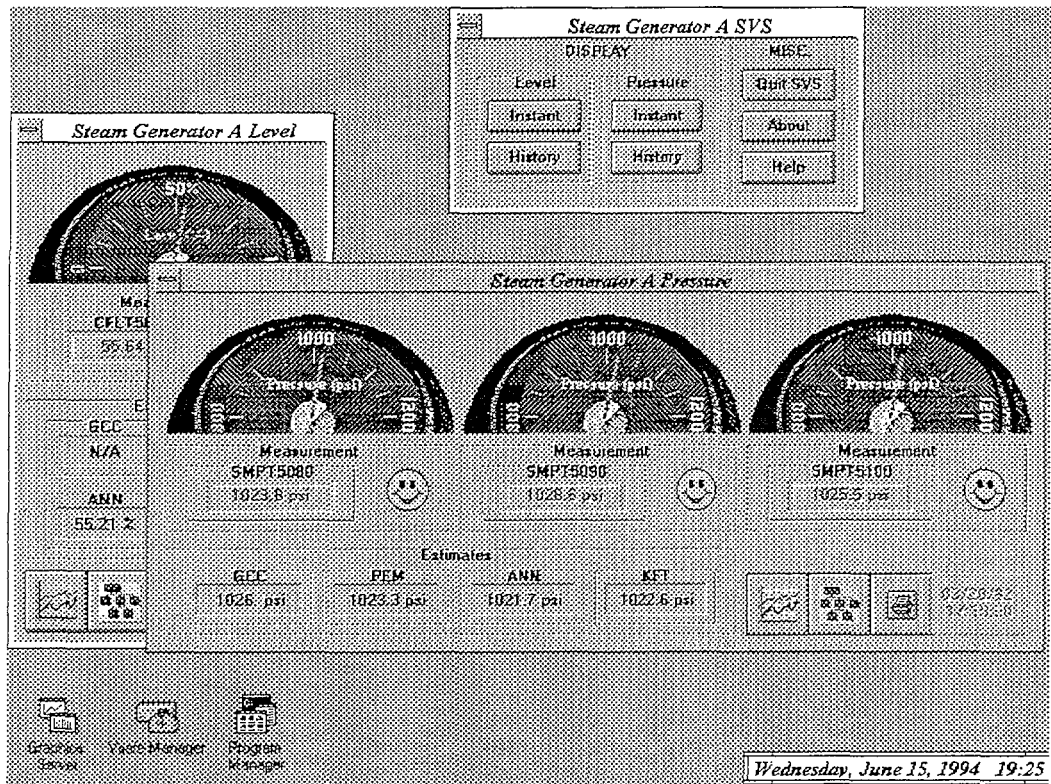
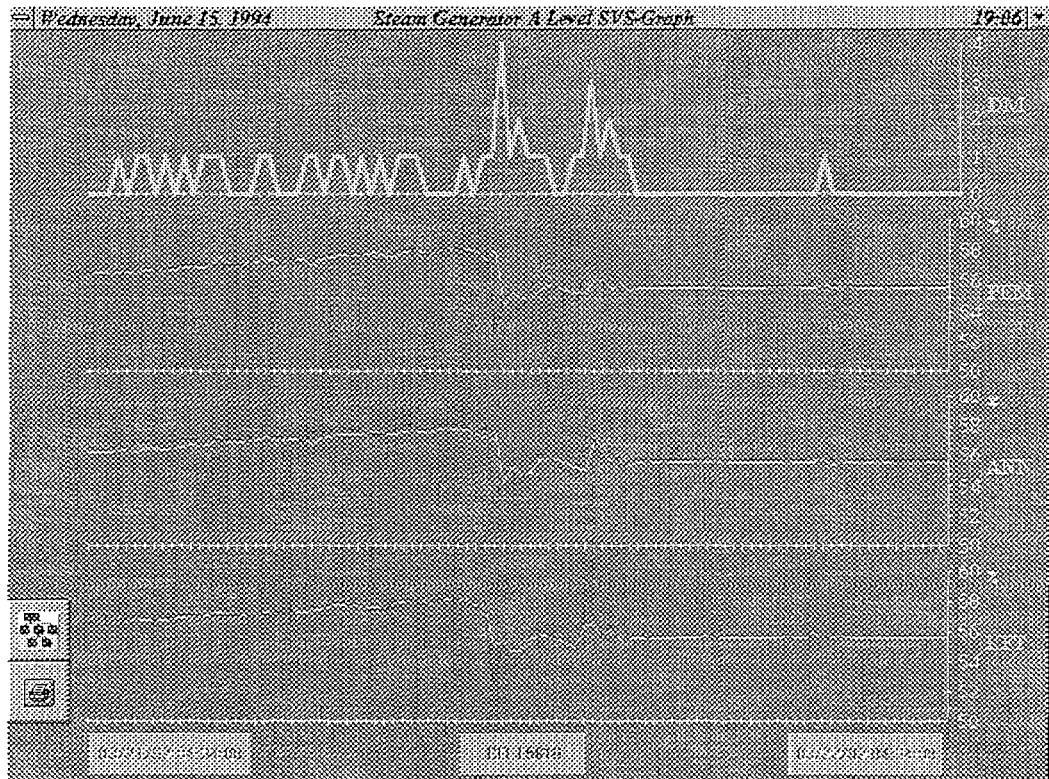**Figure 12:** Initial GUI of the PC-based signal validation system.

Figure 13: Information window displaying the historical trend of steam generator wide range water level and SV module estimates and DM results.

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FURTHER DEVELOPMENT OF NPP SURVEILLANCE AND DIAGNOSTIC SYSTEMS BY USE OF INTELLIGENT TECHNOLOGIES

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Abstract

Recent development work at ISTec/GRS has been directed to more automation of surveillance techniques by utilization of the technological progress and existing tools. Neural nets, fuzzy techniques and rule-based methods were investigated for application in feature classification and automized identification of anomalies. First applications were aimed at classification of useful patterns and suppression of non-relevant signal components in order to avoid false alarms (e.g. in acoustic monitoring) and at signal validation under normal and disturbed plant conditions. Other on-going projects are aimed at the application of the successful methods to other surveillance tasks such as on-line assessment of sensor behaviour and ageing phenomena of instrumentation. The paper gives an insight in the intelligent analysis techniques and highlights their potential use for other surveillance tasks in nuclear power plants.

INTRODUCTION

On-line component and process monitoring as well as incipient fault detection systems have been developed and applied successfully during the last two and a half decades /BOS93/, /WAC95/. Useful on-line information on component conditions, degradations, or other anomalies is provided to the operator in a way that at any time during operation the actual status can be assessed and – if there are first indications or incipient anomalies - contermeasures can be planned carefully in due time without stress. As an additional layer in the defense-in-depth concept diagnostic systems play an important role for improving the safety and availability of NPPs.

The measurement and analysis principles of the systems dealt in sequel are based on signature analysis of dynamic signals, on feature selection, and - for the time being - on assessment of deviations/trends of features (or feature sets/feature vectors) by human experts using model knowledge and/or long-term operational experiences. The extensive implementation of the human experts in the diagnostic process – as usual up to now – is rather time-consuming and costly. Therefore, in future work emphasis should be placed on the reduction of costs created by human evolvement where reasonably possible. Basic investigations how to substitute the human assessment at least partly and to promote from feature monitoring/trending systems to real diagnostic systems have been performed by ISTec within the last years.

The progress in computer technology in particular with respect to performance and cost/benefits and the availability of new developments in computer science providing software tools for intelligent signal analyses are excellent prerequisites for further developments and applications towards more advanced on-line systems with automized reasoning and diagnostic capabilities.

Recent development work at ISTec/GRS has been directed to improve existing surveillance techniques by utilization of the technological progress and existing tools. Neural nets, fuzzy techniques and rule-based methods were investigated with respect to their potential for application in feature classification and automized identification of anomalies. First goals were aimed at classification of useful patterns and suppression of non-relevant signal components in order to avoid false alarms (e. g. in acoustic monitoring) and at signal validation under normal and disturbed plant conditions. Other on-going projects are aimed at the application of the successful methods to non-mechanical surveillance tasks such as on-line assessment of sensor behavior and aging phenomena of instrumentation. The paper gives an insight in the intelligent analysis techniques and highlights their potential use for other surveillance tasks in nuclear power plants.

1. AUTOMIZED DIAGNOSIS BASED ON NEURAL NETS

Advanced burst signal processing in loose parts monitoring (LPM) has been a first application towards more automized diagnosis. Classification module has been developed by our institute and applied for the Siemens LPMS KÜS'95 /BEC 95/. The motivation of this development was enforced by the fact, that more and more German utilities are replacing their old analogue systems by a new generation of digital LPMS. With the help of modern hardware and software technologies new possibilities are available for digital data acquisition, storage, userfriendly interfaces and implementation of improved false alarm reduction strategies.

The classification module is based on an multi-layer feed forward artificial neural network with five input nodes (x1 to x5), two hidden layers with five nodes each, and two output nodes (y1 and y2), Figure 1a.
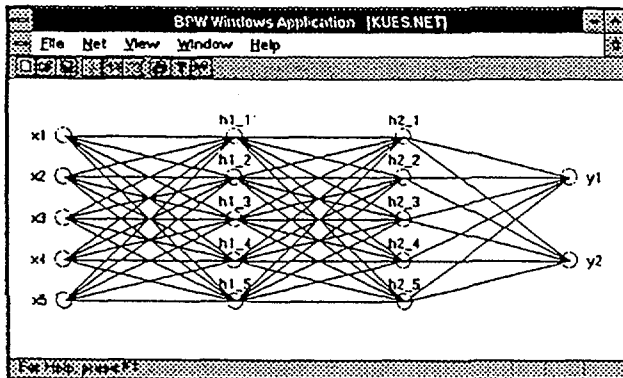

Fig. 1a: Structure of the neural network

Five parameters which characterize the burst form adequately, are determined automatically: the local maximum time (=Tlm), the global maximum time (=Tam), the normalized area (=Fläche), the intensity ration (=Intens) and the fine structure (=Feinst.) /OS 87/. They are used as inputs of the neural network and the output values y1 determines the class value. y2 is a sensor identification value. Each event is classified as one of the five possible classes (or an unknown class): electrical/thermal disturbance signal, burst signal, flow induced noise, calibration signal and background signal. The software has a single event user interface and a user dialogue for the classification of burst ensembles. The later is demonstrated in figure 1b.
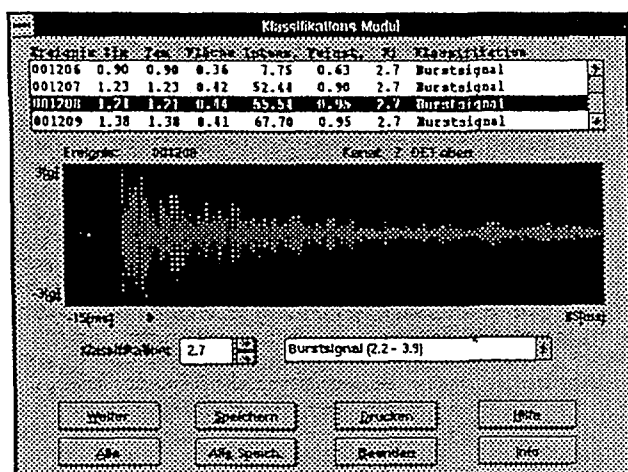

Fig. 1b: User dialogue for the burst ensemble classification

The list above the signal graphs contains: the event number, five calculated feature values, the class value and class type in full text. Below the signal graph are: the edit button for the class a value of the selected acoustic event, other control buttons for save, list printing, etc.

In this way the digitally stored signal patterns can be classified into the pre-defined classes automatically. Test results in the ISTec acoustic Lab using digital or tape-recorded plant signals achieved a correct classification rate of ca. 90 %. The supervisor in the plant can extend the user training set and retrain the network for adaption of the diagnostic capability to special signal paths in his plant without any change of the software.

The classification module and another acoustic module are programmed as MS-Windows 3.1 dynamic link library (DLL) add-ons and already installed in German PWR and a Russian plant of VVER-1000-type /DIN 96/.

Other research activities at ISTec are dealing with the fuzzy logic application in LPMS /DW 97/ and the combination of both technologies which leads to a neuro-fuzzy classification systems /DIN 98/.

2. AUTOMIZED DIAGNOSIS BASED ON FUZZY LOGIC

The theory of fuzzy sets and fuzzy logic /ZAD 65/, /ZAD 75/ are widely used in the automatic decision making /ZIM 87/, fuzzy control /PRE 92/ and also – more and more – in fuzzy diagnosis systems /FRA 94/, /ISE 95/.

Fig. 2 shows the basic concept of a fuzzy logic based classification/diagnosis system with the main steps: fuzzification, rule inference and defuzzification. Its structure is comparable to the fuzzy control systems (in special cases where fuzzy diagnosis results are desired the defuzzification step can even be omitted). Mathematically the classification/diagnosis process can be described as a mapping of a feature vector into a class/fault vector.

2.1 Definition of Fuzzy variables

For designing of a fuzzy logic based system the five signal parameters (Tlmax, Tgmax, Area, Intens. and FeinStr.) can be used as fuzzy input variables directly and the system output is a fuzzy class value. The class value has to make four possible linguistic values according to the four possible class types. Each input variable was assigned with three possible linguistic values "small", "medium" and "big" at the beginning (can be increased to very big, very small, etc. , if necessary). Figure 3 shows an example for a feature value x.
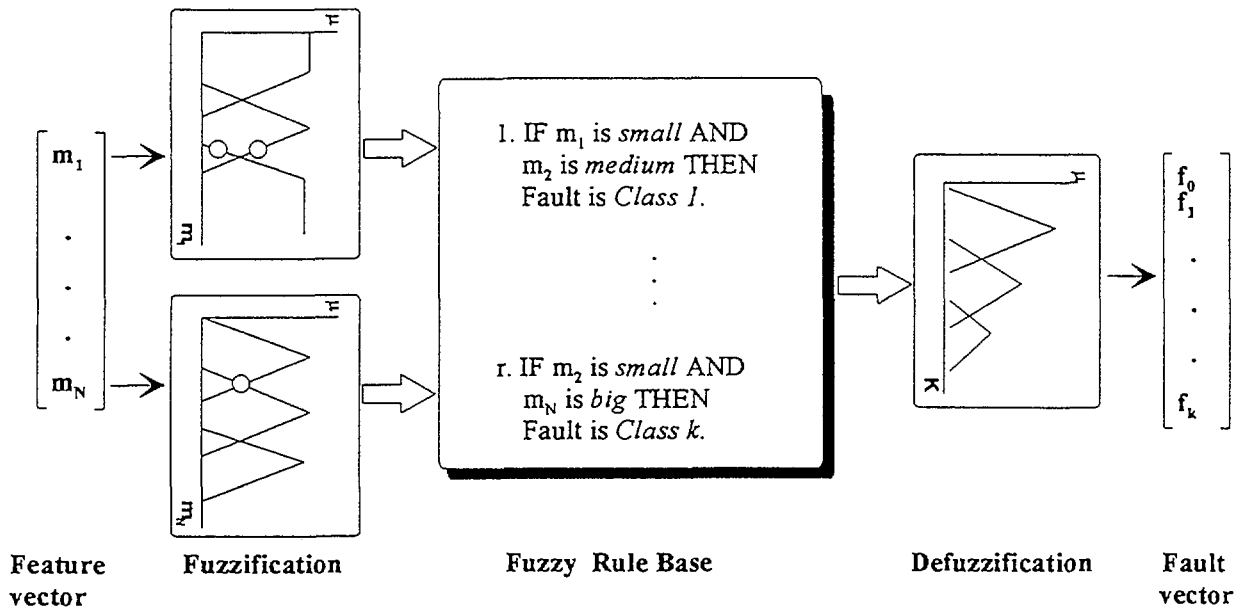
Feature vector   Fuzzification   Fuzzy Rule Base   Defuzzification   Fault vector

Fig. 2. Basic concept of a fuzzy diagnosis system

Fig. 3. Fuzzification of a feature value x

Fig. 4. Max-Min- and Max-Prod-Inference (Preuß, 1992)

2.2 The Fuzzy Inference

From the two inference methods well-known in the literature (Fig. 4) the Max-Prod-Method is used. It keeps the shape of the membership functions and is easier to be implemented.

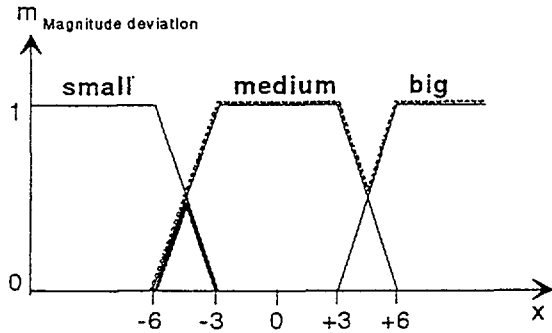## 3. SYSTEM OPTIMISATION BASED ON - STATISTICAL ANALYSIS
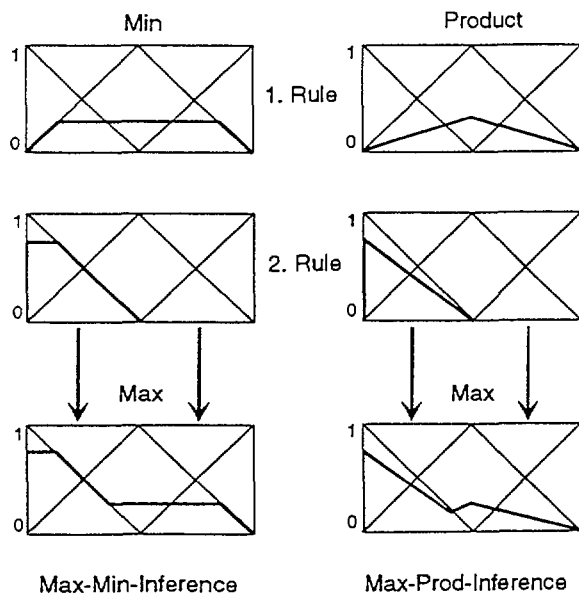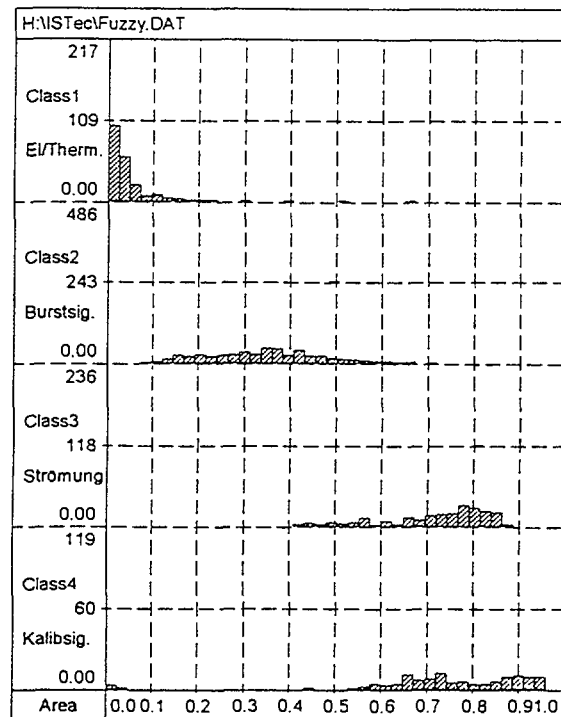

Fig. 5. Histogram of the parameter "Area"

3.1 Generation of Membership Functions and the Fuzzy Rule Base

The membership functions are generated and optimised after intensive statistical data analysis (1058 data records of four known classes classified by human experts are used). The well-known statistical histograms were used to get the shape of membership functions. Fig. 5 gives an example of the distribution of the fuzzy variable "Area" according to different classes (the x axis is normalised). Other graphical representations of the data set like the distributions of different parameters versus one special class are also helpful. Based on these analysis results the fuzzy rule base can be generated (Table 1) and the membership functions optimised interactively for achieving the best diagnosis results (Fig. 6).

Table 1 The generated rule matrix

Features/ Class	El./Therm. Signal	Burst Signal	Ström. Signal	Kalib Signal
TLmax	very small	small	big	
TGmax				small
Area	small	medium	big	very big
Intens.			small	
FeinStr.	small	medium		small or big

3.2 The Operator-Mix

Because the signal transfer path of the acoustic signals are rather complex in the nuclear power plants and the signal/noise ratio is sometimes low, the calculated feature values are uncertain. The described fuzzy system achieved a correct reclassification rate of ca. 91.7% using the 1058 data set. A neural network solution (trained with the same data set) with a reclassification rate of 95.3% is only a little bit better. Table 2 shows the judgement matrix of the reclassification results of the fuzzy system. The diagonal elements are correct classifications and the $c0$ class represent possible rejections (no classification).

Table 2 Judgement Matrix

	c1	c2	c3	c4	c0
c1	87%	12.4%	0.5%	0.0%	0.0%
c2	0.8%	98%	0.6%	0.4%	0.0%
c3	0.0%	18.6%	81%	0.0%	0.0%
c4	5.9%	0.0%	0.0%	94%	0.0%

For safety related applications like the nuclear power plant it could be desirable to achieve 100% for the critical class $c2$ (= no missing alarm). This requirement couldn't be achieved by tuning membership functions using the rule base in table 1.
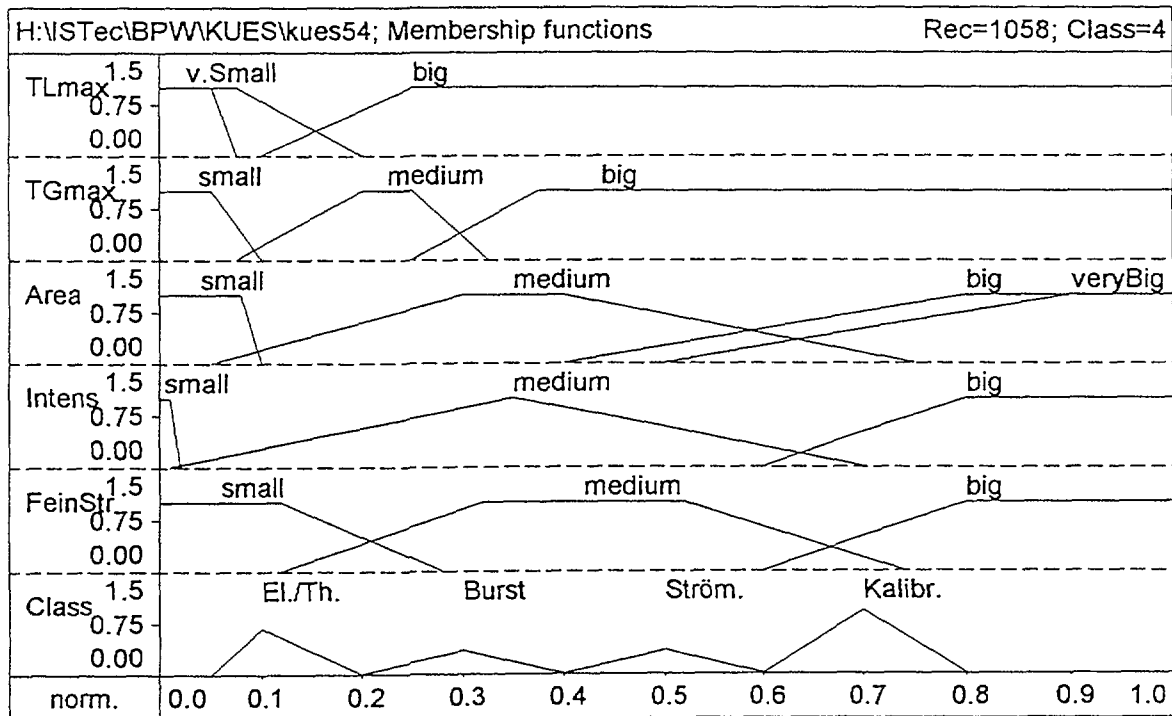

Fig. 6. Optimised membership functions

Better results became possible by the mixed use of the AND-operators. For the non critical classes (c1, c3 and c4) the normal Min-operator is used for the logical AND-Operation:

$$m(A \text{ and } B) = \min(m_a, m_b) \quad (1)$$

Whereas for the critical class c2 the Average-operator is used instead:

$$m(A \text{ and } B) = (m_a + m_b) / 2 \quad (2)$$

Formula (2) is comparable with the fuzzy distance measure. It takes the averaged fullfilment of different fuzzy variables and has no so strong excluding property as the Min-operator. It could be expected that the c2 class patterns are easier to pass the classifier. Table 3 shows the new results.

Table 3 Judgement matrix using mixed AND-operators

	c1	c2	c3	c4	c0
c1	82%	17.1%	0.5%	0.0%	0.0%
c2	0.0%	100%	0.0%	0.0%	0.0%
c3	0.0%	33.5%	66%	0.4%	0.0%
c4	0.0%	9.2%	0.0%	88%	2.5%

The total performance goes down to 87.5% which can be interpreted as the costs for getting 100% correct classification for class 2 (no missing alarm).

4. AUTOMIZED DIAGNOSIS WITH KNOWLEDGE-BASED SYSTEMS

Since nearly three decades of method development and application of surveillance and diagnostic techniques in nuclear power plants ISTec (formerly GRS and LRA of Technical University Munich) has collected comprehensive operational experiences and built up databanks for signatures and long-term trends in the different diagnosis domains. All analysis results gained from two third of the German NPPs are available including such before the time when the automated data acquisition with the condition monitoring system COMOS was established (i. e. before 1987). The databanks and the teams of experts for the particular diagnosis domains form an excellent platform for the ISTec Diagnosis Center in Garching.

Besides reliable and short-term support to the plant operator and maintenance personal for interpretation of observed signature deviations (in vibration) or burst patterns (in acoustics), an important objective of the Center is the collection of knowledge and maintaining it for future applications or further system/method developments. Therefore, with the collected data material and

operational experiences a broad basis and best prerequisites are given for further improvement by introducing rule-based methods, systems with learning capabilities, or knowledge-based systems.

In a first step a knowledge-based diagnosis system has been developed for primary circuit components /BD 93/. Hereby an industry expert shell was used used together with the comprehensive knowledge of the vibration signature databank as well as calculations with a structure model by which parameter sensitivity studies and fault simulations were performed.

In an other project the basic structure of a knowledge-based fault diagnosis system for rotating machineries system was developed for monitoring the condition of an emergency and residual heat removal pump during monthly repetitive tests of this stand-by safety system /SDW 92/. The results were encouraging and showed that for more-dimensional feature vectors an automized reasoning for the identification of the causes of anomalies is not only beneficial, but also feasible with reasonable effort.

An interesting application is assumed in the field of signal validation especially for cases when redundany or analytical diversity (on-line model calculation) is not possible, but self-validation from the sensor signal itself is needed. Since knowledge about characteristic feature behavior caused by incipient failures in measuring channels is available and also knowledge about the dependency of these features on time, an approach with a rule-based diagnostic systems is supposed to be feasible and can solve problems raising up during accident situations in NPPs. A comparison and evaluation of existing concepts and national approaches has been performed recently within an common European project /WAD 95/, /WEU 96/. Also methods based on neural net application have been investigated in this project.

5. CONCLUCIONS

Several intelligent technologies have been investigated with respect to their potential, feasibility of realization, and benefits in operational use for different tasks in on-line surveillance and diagnostics of safety relevant components. Neural nets, fuzzy techniques, and knowledge-based systems as well as combinations of these techniques were applied to actual diagnostic tasks.

A fuzzy logic based classification/diagnosis system for automatic classification of acoustic burst events of the loose parts monitoring system (LPMS) in nuclear power plants has been developed. The performance is comparable to a neural network solution. The advantages of the fuzzy system are on the one side a better understanding of the diagnosis results and on the other side demonstrated by the ability to achieve 100% correct classifica-

tion for the critical class which is difficult to be guaranteed by the neural network solution.

A further progress can be achieved by the combination of both methods /DIN 97/. The expected high reduction rate of false alarms will be proved in future practical use and make the LPMS-system and also other comparable information systems e.g. the vibration monitoring system /BOS 93/ more reliable so that the plant operator will get more precise information about the plant conditions. Also the combination of these methods with a rule-based diagnosis is seen to be a way for more automation. The measurements and analysis principles shown in the paper are applicable for other surveillance tasks based on feature classification such as leak monitoring, aging detection and signal validation.

6. REFERENCES

/BD 93/   Bauernfeind V., Y. Ding (1993): Decision tree based knowledge acquisition and failure diagnosis using a PWR loop vibration model, SMIRT '93, Stuttgart, Germany

/BOS 93/   Bauernfeind, V., B.J. Olma, R. Sunder and D. Wach (1993): Development of diagnostic methods for on-line condition monitoring of primary system components. *Kerntechnik* **58 No. 2**, Carl Hanser Verlag, Munich.

/BKK 95/   Bechtold, B., Knoblach, W. and Kunze, U. (1995): The New Loose Parts Monitoring System KÜS'95. *Proceedings of the 7th Symposium on Nuclear Reactor Surveillance and Diagnostics (SMORN VII)*, Avignion/France.

/CE 95/   Cleemann, L. and F.X. Elfinger (1995): Loose Parts Monitoring System. *Proceedings of the 7th Symposium on Nuclear Reactor Surveillance and Diagnostics (SMORN VII)*. France.

/DIN 96/   Ding, Y. (1996). Advanced Software Tools for Digital Loose Part Monitoring Systems. *Proc. of IAEA-Specialists' Meeting on Monitoring and Diagnosis to Improve Nuclear Power Plant Reliability and Safety*, Barnwood, U.K.

/DW 97/ Y. Ding, D. Wach (1997): A fuzzy diagnosis system for automatic classification of acoustic burst events in nuclear power plants. IFAC Symposium Safeprocess '97, Kingston Upon Hall/U. K.

/DIN 97/   Ding, Y.: Fehlerfrüherkennung und –diagnose in Kernkraftwerken mit Hilfe eines Neuro-Fuzzy-Ansatzes. Dissertation Technical University Munich, Herbert Utz Verlag München, IBSN-3-89675-297-9, Dez. 1997

/FRA 94/   Frank, P.M. (1994): Diagnoseverfahren in der Automatisierungstechnik. *Automatisierungstechnik* 42/2. R. Oldenbourg Verlag.

/ISE 95/   Isermann, R. (1995): Fault Detection and Diagnosis - Methods and Applications. *2nd International Symposium on Acoustical and Vibratory Surveillance Methods and Diagnostic Techniques*, Senlis/France.

/OS 87/   Olma, B.J., Schütz, B. (1987): Advanced Burst Processing Methods in Loose Parts Monitoring. *Proceedings of the 5th Symposium on Nuclear Reactor Surveillance and Diagnostics (SMORN V,*. Munich/Germany.

/OW 91/   Olma, B. J., D. Wach (1991): Acoustic, Noise and Vibration Monitoring - Useful Methods in Condition Monitoring and On-line Degradation Diagnosis. *IAEA Technical Committee Meeting on "Utilization of Condition Monitoring and Degradation Systems to Improve Nuclear Safety"*, Vienna/Austria.

/OW 94/   Olma, B. J., D. Wach (1994): On-line classification of acoustic burst signals by a neural network - application to loose parts monitoring in nuclear power plants, *3. IEEE-Conference on Control Applications*, Glasgow/UK.

/ODE 95/   Olma, B. J., Ding, Y., Enders, R. (1995): Operational Experiences with Automated Acoustic Burst Classification by Neural Networks. Proceedings of the 7[th] Symposium on Nuclear Reactor Surveillance and Diagnostics (SMORN VII), Avignion, France

/PRE 92/   Preuß, Hans-Peter (1992): Fuzzy Control - heuristische Regelung mittels unscharfer Logik. *atp - Automatisierungstechnische Praxis* 34/4+5, R. Oldenbourg Verlag.

/SDW 92/   Saedtler, E., Y. Ding, D. Wach (1992): Improved diagnosis techniques for rotating machinery with the aid of knowledge-based methods. 8[th] Int. IMEKO Symposium on Technical Diagnostics, Dresden, Germany

/TC 95/   Türkcan E., Ö. Cigtcioglu (1995): Neural Network Benchmark for SMORN-VII. Proceedings of the 7[th] Symposium on Nuclear Reactor Surveillance and Diagnostics (SMORN VII), Avignion, France

/WAC 95/   Wach, D. (1995): Surveillance and Diagnostics in NNPs – Progress Made, Operational Needs and Perspective for Future Development, 7[th] Symposium on Nuclear Surveillance and Diagnostics SMORN VII, Avignion, France

/WAD 95/   Wach D. (Ed.): State of the art report on instrumentation and signal validation in accident situations Vol. 1 and Vol. 2 (Appendices) RCA-AMS project EU Contract No. FI35-CT93-001, ISTec-A-133, November 1995

/WEU 96/   Reinforced Concerted Action on Reactor Safety, Project 8, Accident Management Support, Final Progress Report, EU 17126 EN (1996)

/ZAD 65/   Zadeh, Lofti A.(1965): Fuzzy Sets. *Information and Control* 8, pp. 338-353.

/ZAD 75/   Zadeh, Lofti A. (1975): Fuzzy Logic and Approximate Reasoning. *Synthese* 30, pp. 407-428.

/ZIM 87/   Zimmermann, H.-J. (1987): Fuzzy Sets, Decision Making, and Expert Systems. Kluwer Academic Publishers.

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FIELD-BASED SYSTEMS AND ADVANCED DIAGNOSTICS

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Abstract

Detection and characterization of anomalies in an industrial plant provide improved plant availability and plant efficiency thus yielding increased economic efficiency. Traditionally, detection of process anomalies is done at a high-level control system through various signal validation methods. These signal validation techniques rely on data from transmitters, which measure related process variables. Correlating these signals and deducing anomalies often is a very time consuming and a difficult task. Delays in detecting these anomalies can be costly during plant operation. Conventional centralized approaches also suffer from their dependence on detailed mathematical models of the processes. Smart field devices have the advantage of providing the necessary information directly to the control system as anomalies develop during operation of the processes enabling operators to take necessary steps to either prevent an unnecessary shut down before the problem becomes serious or schedule maintenance on the problematic loop. Fisher-Rosemount's PlantWeb™ architecture addresses *"Enhanced Measurement, Advanced Diagnostics* and *Control in the Field."* PlantWeb™ builds open process management systems by networking intelligent field devices, scalable control and systems platforms, and integrated modular software. A description of PlantWeb™ and how it improves various process conditions and reduces operating cost of a plant as well as a high level description of *"Enhanced Measurement, Advanced Diagnostics* and *Control in the Field,"* will be provided in this paper. PlantWeb™ is the trademark for Fisher-Rosemount's new field-based architecture that uses emerging technologies to utilize the power of intelligent field devices and deliver critical process and equipment information to improve plant performance.

1. Introduction

Increasing economic efficiency is the most important task of various engineering groups and managers of industrial plants. Plant engineers have increased process efficiency through implementing optimum process control systems and providing assistance to operators through monitoring and system condition analyzers. However, increase in economic efficiency will be limited by simply focusing on advanced control schemes. Improvements in plant availability will have larger impact in increasing the economic efficiency of an operating plant. Improving the component availability can be achieved through early detection of anomalies, providing condition-based real-time maintenance. Figure 1 gives a schematic representation of these complementary approaches. They are complementary because having the best control scheme will be limited in the event of a catastrophic critical plant component failure.

Figure 2 displays the traditional role of signal validation modules and where signal validation schemes are applied. It is easy to determine the inefficiency of applying validatory schemes at that high level when we consider the signal linearization, damping, and communication delays that mask the true readings of sensors. Even though readings are accurate by the time they reach this high level sensor validation systems, the critical information hidden in the raw data has been lost.
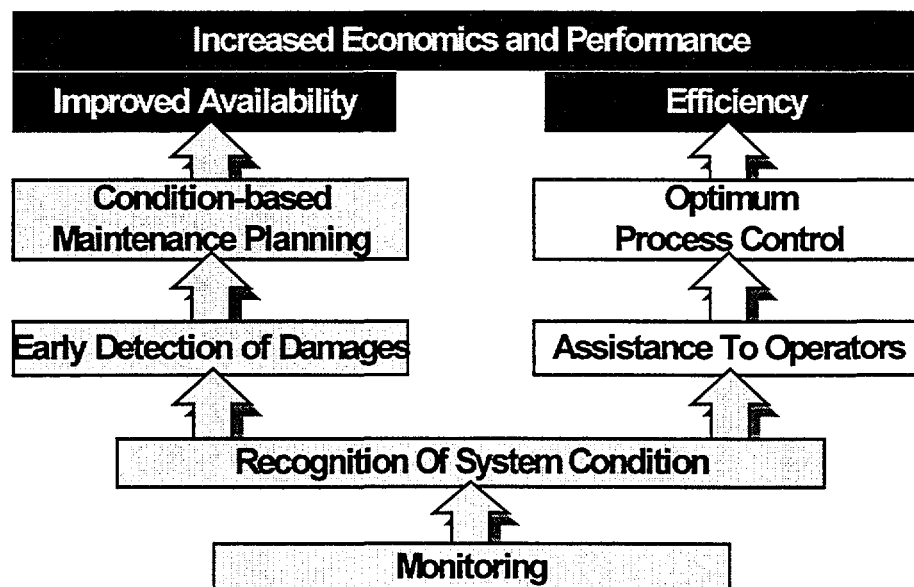

Figure 1. Advanced diagnostics improves plant availability and efficiency.

Both of these approaches depend on recognition of system condition and therefore directly depend on the quality of observed signals. There has been an extensive amount of work in the area of signal validation. However, most of the previous work in this field concentrates on cases where there is either hardware or analytical redundancy. For instance, if there are three or more

sensors measuring the same process variable, one can implement a consistency checking or majority voting type of algorithm as a signal validation method to detect signal anomalies. In addition, model based techniques [1, 2, 3, 4, 5] are heavily used when different types of measurements are available for the same process or the same system. Most of these techniques are based on the modeling of the normal behavior of a sensor by autoregression time series and then monitoring its behavior [1, 4]. These various techniques for signal validation have been integrated with high-level control systems and their data acquisition systems to provide the assistance that the plant operators need during operation.
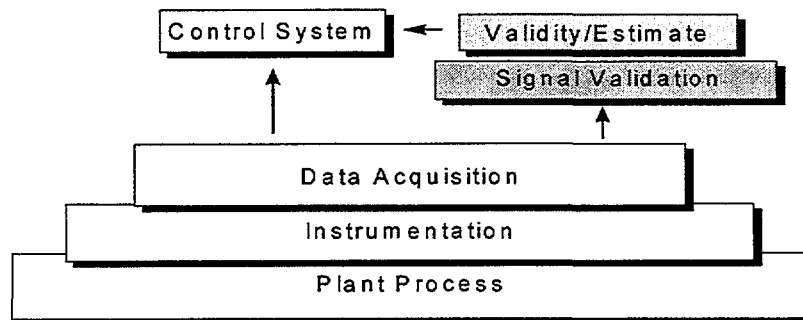

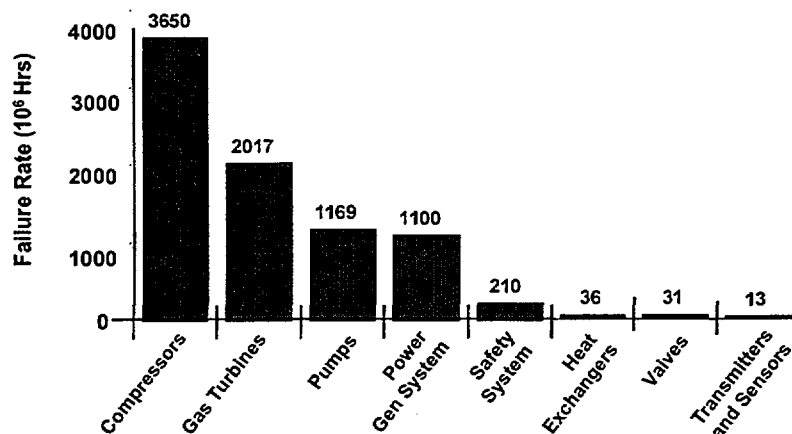Figure 2. Traditional role of signal validation in plant instrumentation.

Figure 3. OREDA Failure analysis data demonstrates that rotating equipment are the least reliable devices in an operating plant compared to transmitters and sensors.

2. Asset Management Begins With Field-Based Data

Understanding the failure rate of various pieces of equipment is key to a predictive maintenance program. Industry data (see Figure 3) has shown that the least reliable instruments are typically rotating equipment, with transmitters being the most reliable.

Various industry data have indicated that transmitters and sensors are the first candidates for inspection in the event of an anomaly. 1997 HPI maintenance spending data indicates that nearly 20% of the maintenance budget is spent on inspecting transmitters (Figure 4) which are the least likely candidates for the detected anomaly. Elimination of these unnecessary inspections can have a major impact on maintenance costs. Knowing that the instrument is healthy is therefore equally as important as if it has failed [6].

Maintenance log data of a large chemical plant have also shown that nearly 65% of the time these inspections indicated that transmitters were healthy, thus leading to waste of resources which increases the operational cost of a plant.

A typical service call for a process instrument can cost $300 per call, which can quickly exceed the purchase cost of the instrument. Figure 5 shows the results of a large chemical company's field maintenance logs. 35% of the trips made to the field were routine checks, where no problems were found. Another 28% of the field trips were reactions to a problem, but not found in the transmitter. A total of 63% of the trips to the transmitter would have been unnecessary if the health of the transmitter had been known [6].
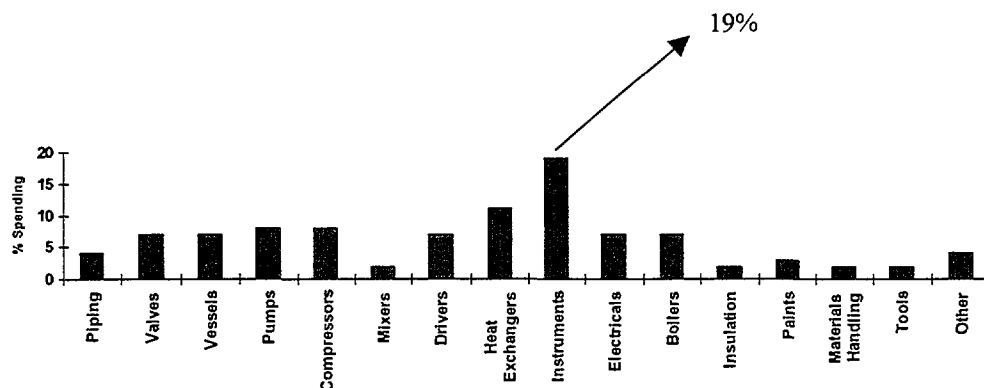
Source: HPI Market Data 1997

Figure 4. Hydrocarbon Petroleum Industry data indicates that nearly 20% of maintenance budget is spent on instruments.

3. Plantwide Asset Management and Integrated Diagnostics Technologies

Advancements in communication and software technologies are now enabling the integration of islands of automation for asset management system to provide a plant wide view for the operator.

As we see in Figure 6, advancements in communication and electronics technology have fostered many of the automation improvements in the process control industry. The advent of the DCS and smart instruments in the 70's and 80's have provided the foundation for automated process control that is pervasive in today's industry. The usage of process control has been attributed as having reduced the operating cost of process industry plants by 5 to 9%.
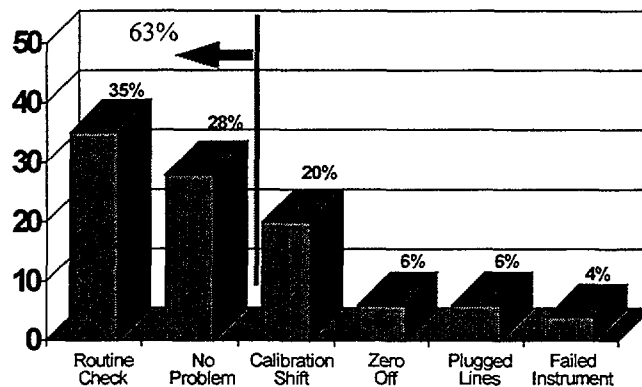

Figure 5. Large chemical company's maintenance logs indicates that 63% of trips made to a transmitter was not necessary.

The advances in communications and software have now given birth to a new generation system most often referred to as the "field-based system". Field-based system is founded on the ability to network field devices, i.e. sensors, valves, smart motors etc. with controls and asset management systems to provide for an integrated information system that can be used for control and automated maintenance [7].

The shift to field centered architecture is underway and is being led by open field device communication protocols such as HART® and Foundation Fieldbus. More than 4,000,000 HART® based instruments and valves are installed in the worldwide process control industry and can be used as the platform for diagnostics information needed for a plant-wide maintenance strategy [6].
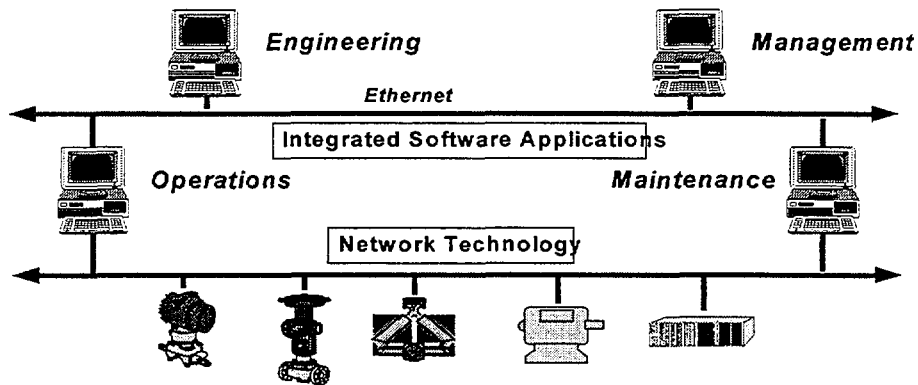
Figure 6. Field-based architecture integrates asset management with intelligent devices.

4. The Transmitter Role Changes to Data Server

The role of the field device, especially the digital transmitter, changes dramatically in the transition to the field-based architecture. Formerly, the transmitter has provided a single piece of information to the process controller, the process variable. However, in the age of the networked transmitters, the role of the transmitters changes to that of a data server.

In a Fieldbus and HART® based network, the transmitter is now able to provide diagnostics
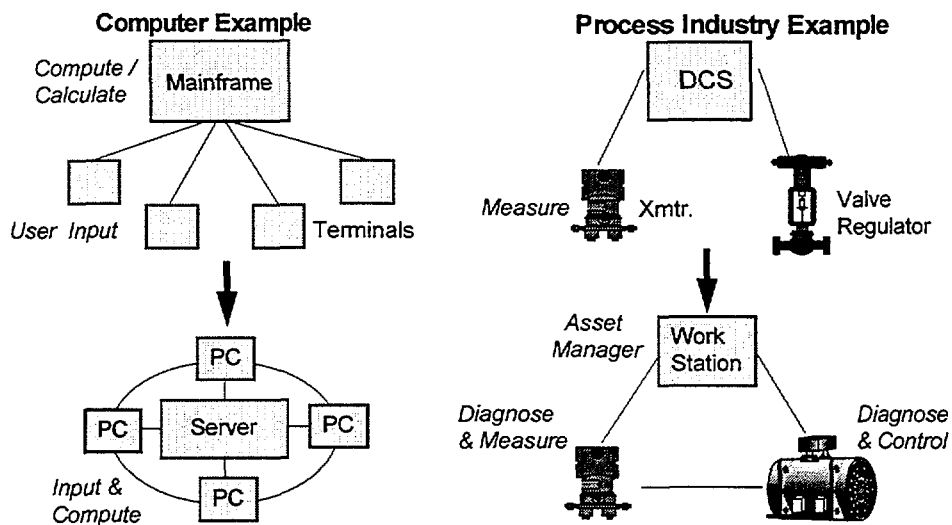

Figure 7. Transmitter's role changes to data server in field-based architecture.

information on the health of the sensor, the health of the process and even on the health of other pieces of equipment connected to the process, e.g. the valve, the compressor etc.

The ability to provide a standard set of diagnostics from networked field devices is the foundation of an integrated Plant Asset Management System. An integrated AMS system

provides the capability of advanced maintenance scheduling based on measured and predicted needs thus increased plant uptime and reduced maintenance cost.

5. Smart Field Devices Improve Availability

Today's smart field devices consist of two essential parts: A sensor module and an electronics module. As silicon technology advances, the tasks that can be accomplished within the electronics module expand significantly. Microcomputers within an electronics module are responsible for tasks such as sensor linearization, damping, communication and diagnostics. Since transmitters are devices that contact processes and provide measurements on these processes, performing anomaly detection, whether they are related to the measurement device or process itself, can be another task for transmitters, thus making them more intelligent field devices that are aware of the changes in their environment.

Advanced diagnostics approaches address: *fault detection, fault isolation and root cause analysis.* Early detection of anomalies, either process related or device related, is key to improving plant availability. A common methodology for fault detection throughout field devices, i.e. transmitters, valves, motors would improve the diagnostics capability and possibility of early anomaly detection. Once an anomaly is detected, the next step will be isolating this anomaly and relating it to a most probable device as the originator of the anomaly, i.e. valves, motors, pumps or transmitters. Isolation of the faulty device will provide a diagnostics system to perform more advanced diagnostics on devices to determine the root cause of the problem. Determining the root cause of the problem will enable plant engineers and technical personnel to arrange necessary changes to prevent similar problems from occurring in the future.

While sensors have long been recognized for their value in providing a measure of the process variable for closed loop control, the value of a sensor for condition monitoring of the plant equipment and process is a relatively new phenomenon.

Condition monitoring systems have become prevalent for the monitoring of high cost equipment such as rotary machines, e.g. compressors and turbines. Many companies report paybacks of only a few months for strategically placed vibration-monitoring systems.

However, until recently, condition based maintenance systems have been "stand alone systems" that have existed as "island of automation" (see Figure 8) without the ability to be coordinated with other pieces of equipment and data to provide for a plant-wide view. It has not been possible to provide the ability to manage the entire plant asset to achieve maximum plant uptime at the lowest possible maintenance cost.

6. Asset Management Solutions and Process Control

Asset management can be defined as maintaining product equipment properly to deliver maximum performance and service life at minimal cost. Three major aspects of an asset management solution system can be described as:

- Smart field devices: Information gathering and information dissemination about their operational status as well as the process.
- Communication protocol: An open communication protocol which is capable of transmitting information from field devices and control systems, regardless of the manufacturer, to the designated areas.
- On-line Software: Dedicated software system that provides necessary tools to analyze and display information coming from various field devices to help the operators or maintenance personnel.
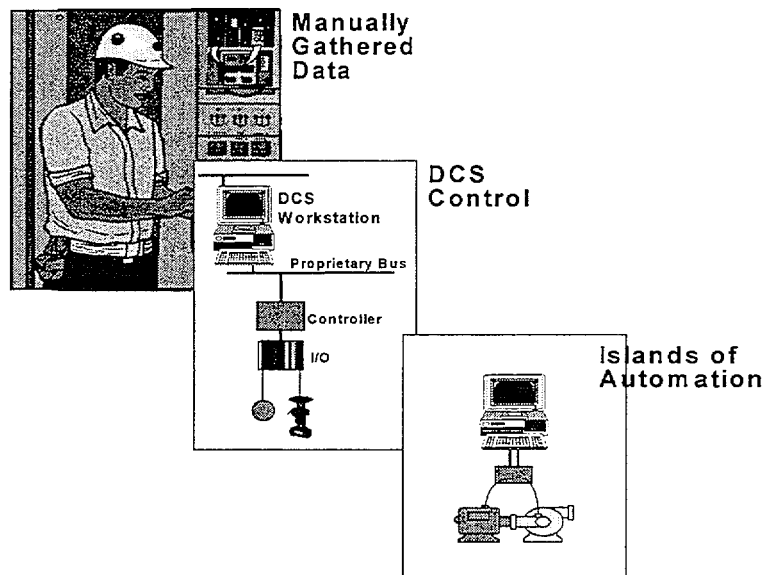
Figure 8. Today's condition monitoring systems are islands of automation and are not integrated.

Today, Fisher-Rosemount offers a large family of intelligent field devices with digital open communication systems such as HART® and Fieldbus for pressure, temperature, flow, and level measurements [7]. Some of the enhanced measurement capabilities of these intelligent field devices include multivariable measurement in a single transmitter, field-based controller, dual-element RTDs, and radar level measurement as part of PlantWeb™ (Figure 9). Rosemount's 3095MV model offers three independent process variable measurement, differential pressure, absolute pressure and temperature as well as level calculation and flow rate calculation. Similarly, Rosemount's 3095C is a field-based control and measurement device for level applications where PID controller and an auto-tuner for the PID reside within the same transmitter. 3244MV is a multivariable temperature transmitter which two independent temperature measurements can be obtained for ΔT control with a dual element RTD for "hot backup" in the event of a sensor failure and a drift detection capability for dual element RTDs [7].

Fisher-Rosemount has shown its dedication to open communication systems more than a decade ago by donating its digital communication system HART® to the industry which, later became process automation standard with hundreds of manufacturers offering products that support HART®. Similarly, Fisher-Rosemount is the leading manufacturer in measurement and control devices that support Fieldbus.

Fisher-Rosemount's Asset Management Solutions (AMS) product is the leading PC-based software for providing on-line diagnostics for equipment and process monitoring. Integration of AMS and intelligent field devices will help reduce process variations, improve availability and efficiency of process plants. AMS provides calibration, valve diagnostics, transmitter diagnostics, audit trail, on-line configuration systems and many other assets related information [7].
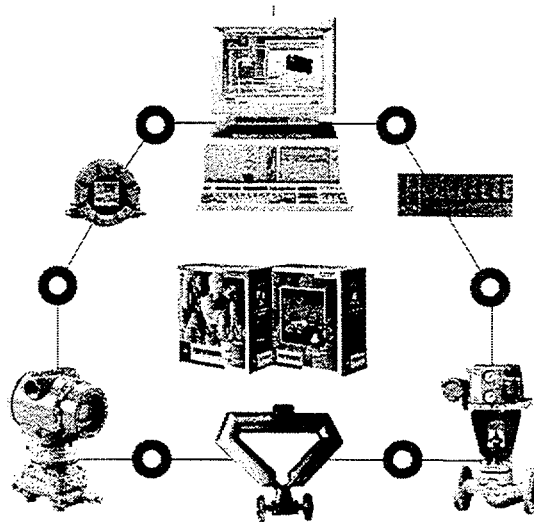

Figure 9. PlantWeb™ field-based architecture provides open process management solutions by networking intelligent field devices, scalable platforms and software.

7. Conclusion

A field-based architecture and its application to diagnostics, asset management is discussed in this paper. Importance of intelligent devices for anomaly detection, open networking for information and system analysis, and on-line software system for monitoring and diagnostics have been outlined. Improving economic efficiency and plant performance may be achieved through "Enhanced Measurement, Advanced Diagnostics and Control in the Field. Although each of these components are equally important and effective, integration of these concepts will provide the highest desired performance and economical impact.

Bibliography

1. B. R. Upadhyaya et al, "Performance Monitoring and Control Design of Nuclear Power Plants," Final Report, UTNE/TVA/92-09, September 1994.

2. R. Upadhyaya and T. W. Kerlin, "Estimation of Response Time Characteristics of Platinum Resistance Thermometers by Noise Analysis Technique," ISA Transactions, Vol. 17, No 4, pp. 21-38, 1978.

3. N. Clark and W. Setzer, "Sensor Fault Detection in a System with Random Disturbances," IEEE Transactions on Aerospace and Electronics System, Vol. 16, No 4, pp. 468-473, 1980.

4. P. Henry and D. W. Clarke, "The Self-Validating Sensor: Rationale, Definition and Examples," Report No: QUEL 1978/93, University of Oxford, Department of Engineering Science, 1993.

5. S. K. Yung and D. W. Clarke, "Local Sensor Validation," Measurement and Control, Vol. 22, pp. 132-141, June 1989.

6. Gary Lenz, ". Electronic Flow Measurement (EFM) Diagnostics Can Reduce Gas Industry O&M Costs Through Improved Asset Management," ISA'96, Chicago, October 1997.

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ANALYSIS OF THE MONITORING SYSTEM FOR THE SPALLATION NEUTRON SOURCE "SINQ"

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Abstract: Petri Net models (PN) and Fault-Tree Analysis (FTA) are employed for the purpose of reliability analysis of the spallation neutron source SINQ. The monitoring and shut-down system (SDS) structure is investigated using a Petri-Net model. The reliability data are processed using a Fault-Tree model of the dominant part. Finally, suggestions for the improvement of system availability are made.

Keywords: monitoring, Petri networks, neuron source, fault tree, reliability

1. INTRODUCTION

1.1 Brief functional description

Paul Scherrer Institute-Villigen-Switzerland, has built one of the largest spallation neutron sources (SINQ) for research purposes. For the following description please refer to Fig. 1. The proton beam from a low energy source is accelerated to approx. 600MeV by means of a ring-cyclotron. The beam current is approx. 1.5 mA. Different kinds of sensors monitor the vacuum, magnet current, beam profile and ionisation along the transportation path. A number of fast (and slower) acting shutter are activated by the beam shut down system. The main shut-down actuator, however, is the kicker-magnet assembly placed directly after the low energetic source. Finally, the proton beam hits a Zircaloy target in a tank of D_2O for cooling and neutron moderation. The target window is also cooled by another D_2O jacket.

1.2 Problem statement

The shut-down of SINQ is formulated as a Two-Time-Scale (TTS) problem as follows (see Fig.2):
a) Fast-Time Scale (FTS): Events which lead to a shut-down for a period of ≤ 1 month (e.g. short-term vacuum and/or cooling failure).
b) Slow-Time Scale (STS): Events which lead to a shut-down of >1 month (e.g. D_2O-contamination of the proton beam transport line or target defects.
Based on the time-scale classification made above, we consider the STS only. Further, we shall concentrate on the D_2O-contamination of the proton beam transport keeping target defect events out of the scope of this analysis.
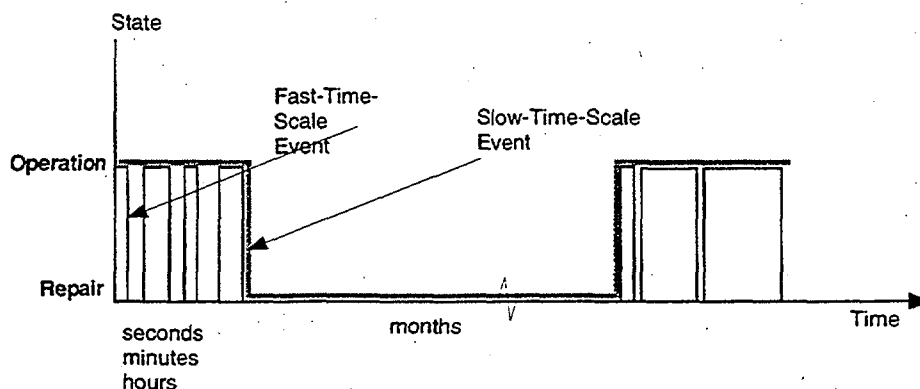

Fig. 2 Two-time scale events

VERTIKALSCHNITT

Feststofftarget SINO

GS1
GS2
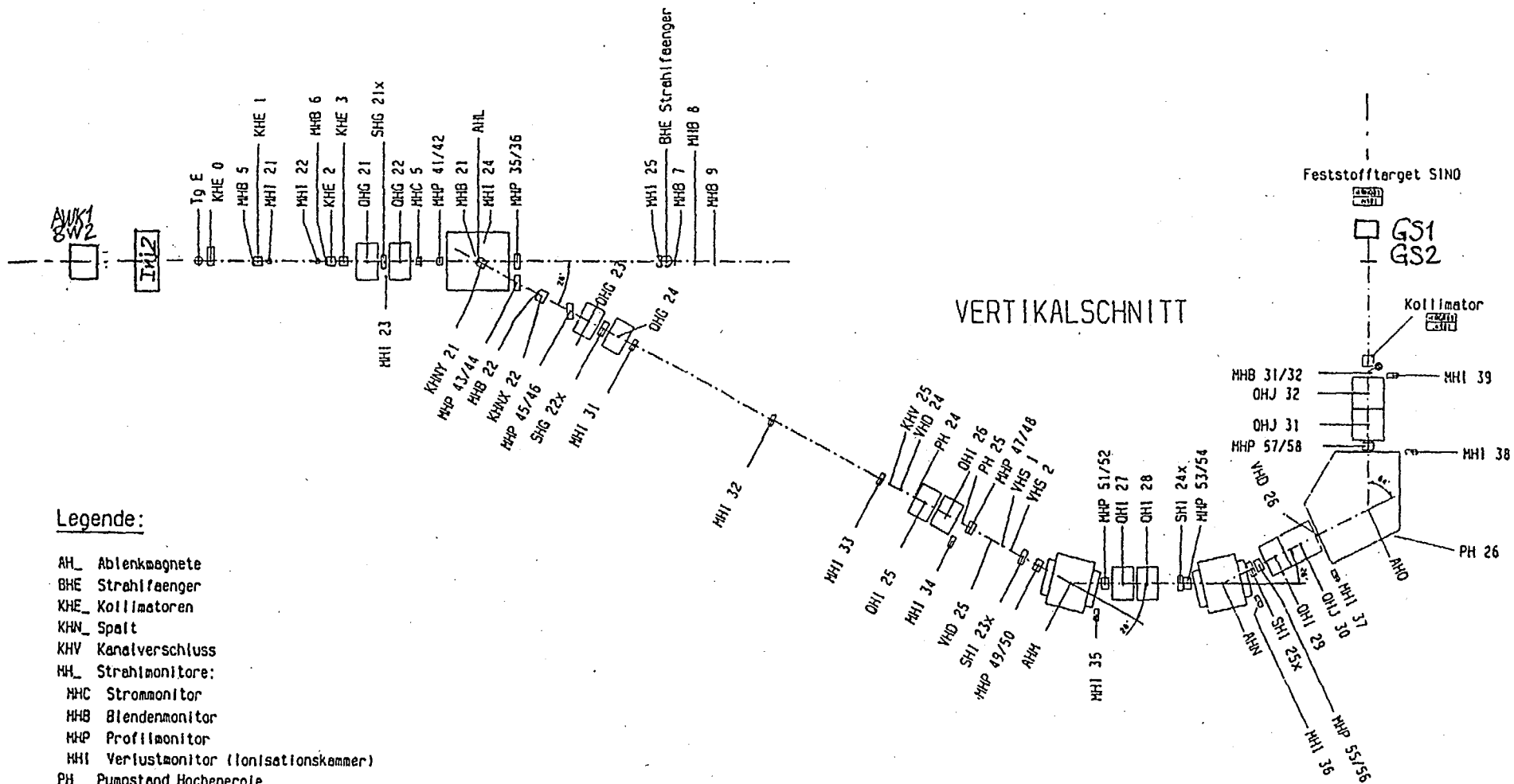
Kollimator

Legende:

AH_   Ablenkmagnete
BHE   Strahlfaenger
KHE_ Kollimatoren
KHN_ Spalt
KHV   Kanalverschluss
HH_   Strahlmonitore:
  HHC   Strommonitor
  HHB   Blendenmonitor
  HHP   Profilmonitor
  HHI   Verlustmonitor (Ionisationskammer)
PH   Pumpstand Hochenergie
OH_   Quadrupole
SH_   Steuermagnete
TgE   Target E
VHS   Schnellschluss-Schieber
VHD   Durchgangsventil Hochenergie

Fig. 1

2. SOLUTION APPROACH

In this study, we shall also adopt the following general procedure :
a) definition of the system under investigation
b) investigation of the monitoring system through a discrete-event model (Petri Net)
c) qualitative analysis based on the PN-model to suggest improvements
d) quantitative analysis by means of a Boolean model (FTA)

The system under investigation consists of:
• Injector: only as far as the shut-down mechanism is concerned
• Accelerator: only as far as its interlock is concerned.
• Proton beam transport line.
• Target-window: only as far as leakage is concerned
• Electronics and power supplies of the SDS

Based on the documents [1] and [2], a sensor-actuator "Book-keeping" has been made for the purpose of determining the most important pairs involved in the SDS.

2.1.1 Sensors

1) Vacuum pressure sensors GS1&GS2 (redundant)
2) Vacuum pressure sensors GH25&GH26 (redundant)
3) Cooling medium pressure sensors "Eckhardt"
4) Cooling medium temperature sensors PT-100
5) Magnet current-monitors MHC
6) Tritium-monitors
7) Beam monitors (Ionisation MHI and Profile MHP)

2.1.2 Actuators

1) Kicker-magnet (AWK1&BW2): Deflection magnet AWK1 will react in < 1 msec, (700µsec after loss of vacuum the deflection current in the magnet is 90% of its nominal value) when triggered by GS1&GS2.
2) Vacuum shutters VHS1&VHS2: These are fast shutters (< 25 msec, directly triggered by GS1&GS2). They will not withstand the proton-beam but for a short-time (burns-through) and are only partially tight. Therefore, they interrupt both vacuum and proton-transport process only for a limited period of time (~500 msec for a moving-shutter; 36 msec for a stationary shutter).
3) Vacuum shutters VHD25&VHD26: These shutters are slower than VHS1&VHS2 (<200 msec until completely closed) and can interrupt the vacuum and proton-beam transport processes for a longer time period (~ 1.0 sec).
4) Accelerator-Interlock

3. CASCADE STRUCTURE

The cascade structure is a proven structure for building controllers and monitors. It has demonstrated its robustness through many industrial application. A typical cascade structure is shown in Fig.3. It consists of several **nested** monitoring loops each involving a sensor-actuator pair.
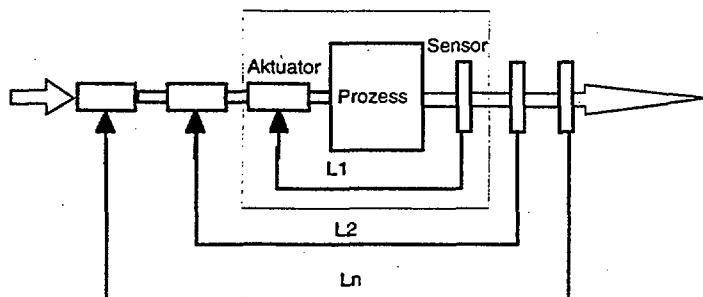

Fig.3 Cascade structure

3.1 Basic Properties of the Cascade Structure

3.1.1 Time-delay

The time-delay within a single loop is simply the sum of all individual delays of the process, the sensor and the actuator. For the i-th loop in general, the overall time delay can be computed recursively as:

$$\tau_{i+1} = \tau_i + \tau_{s_{i+1}} + \tau_{a_{i+1}} \quad , \quad i = 1,2,3,\cdots$$

where the suffices s and a stands for sensor and actuator respectively.
Therefore, sensors and actuators employed in the outer loops can be chosen slower than those employed in the inner loops.

3.1.2 Reliability and failure probability

- Since a loop (not the whole system) fails if either of its sensor or actuator fails, then the failure probability is an **OR**-conjunction of the sensor-actuator pair involved,

$$p_{as} = p_a + p_s - p_a \cdot p_s$$

In other words, a sensor-actuator pair represents two blocks in **series** with the reliabilities R_s and R_a respectively. Then the reliability of the loop can be written as,

$$R_{as} = R_a \cdot R_s$$

- For the nested loops, on the other-hand, an **AND**-conjunction applies since the system fails only if all its loops fail. Under the assumption of independent loop-failure, the overall failure probability can be written as,

$$P_n = P_{n-1} \cdot P_{n-2} \cdots P_2 \cdot P_1$$

In terms of reliability, one can think of the loops as **parallel** blocks. The overall reliability function for 1 out of 2 can be written as,

$$R = R_1 + R_2 - R_1 \cdot R_2$$

In general, the Reliability-function for n-loops can be written as,

$$R = 1 - \prod_{i=1}^{n}(1 - R_i)$$

This means that the reliability increases with the increase of the number of loops.

4. PETRI-NET MODELLING

Since the monitoring action takes place in a discrete-event state space, finite-state machines and Petri Nets (PN) are suitable for modelling the SDS. Useful readings on the principles and applications of Petri networks are found in [9], [10]. When ever possible, the processes are modelled using the synchronous-graph class of PN to avoid non-determinism and conflicts.
The PN-model serves several purposes:
a) understanding of the monitoring process (only then, a PN-model can be built) and analysis of the monitoring structure.
b) simulation of the logical discrete-event monitoring behaviour of the SINQ shut-down system (SDS).
c) examination of the monitoring reaction to specific failures (Scenario-generation). This one of the major advantages of using parameteric models.
d) determination of the dominant components and monitoring loops which reduces the effort in a subsequent quantitative analysis (FTA).

In the following, the operational space (in contrast to the failure space in FTA) will be modelled. The PN-model will be built for Type 1 and 2 failure only, i.e., the fast and slow shut-down systems (Schnelles-Abschalt-System SAS and Langsames-Abschalt-System LAS). The PN-model for the overall SINQ monitoring process is shown in Fig.4. The shaded blocks are by themselves processes (subnets).

4.1 Structure Analysis

Based on the investigation of PN-model for SINQ-SDS, the following is investigated:
1) Examination of the cascade structure: The monitoring loops are listed hereafter in an inside-to-outside order.
   - 1st-loop for the vacuum process: GS→VHS (+AWK1) : fast ($\approx$ 25 msec)
   - 2nd-loop for the vacuum process: GS→VHD (BW2); slower ($\approx$ 200 msec)
   - 3rd-loop for vacuum process: GH→VHD; slower ($\approx$ 2 sec)
   - 4th-loop for the cooling process: PT100→VHD(+AWK1/BW2); slowest ($\approx$ 90 sec)
   - 5th-loop for vacuum process: GS→AWK1; **fastest** ($\approx$ 1 msec)

We **conclude** that the cascade structure does **not strictly** hold. Although loops 1-4 follow a cascade scheme, the fastest actuator (AWK1) is always activated. The **outer-most** fifth loop is the **fastest** which violates the cascade structure design rules.
In other words, since the fastest loop is the outer-most, all other inner loops do not contribute to the prevention of contamination of the proton-beam transport line.
2) There is no overall loop for the system output (Neutrons):
   This is to point-out that the monitoring is based on secondary processes and not on the main one which is the Neutron production process itself.
3) The proton-beam transport process is monitored using the MHx monitors as sensors and the accelerator interlock as an actuator.
4) The fastest monitoring loop is implemented for the vacuum process. This means that the action will follow **after** a leakage has occurred.
5) The monitoring of the cooling process is approximately three orders of magnitude slower than that of the vacuum process.
6) Importance Analysis:
   a) vacuum-pressure monitors GS1&GS2 build a **dominant** node in the monitoring topology, they are redundant but not diverse and are of the same type.
   b) fast shutters VHS1&VHS2 are mounted are of the same type and not fail-safe.
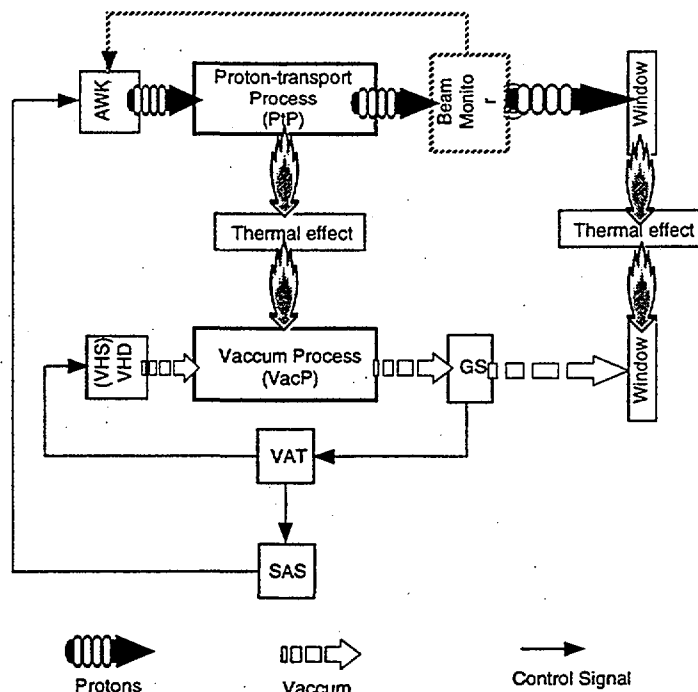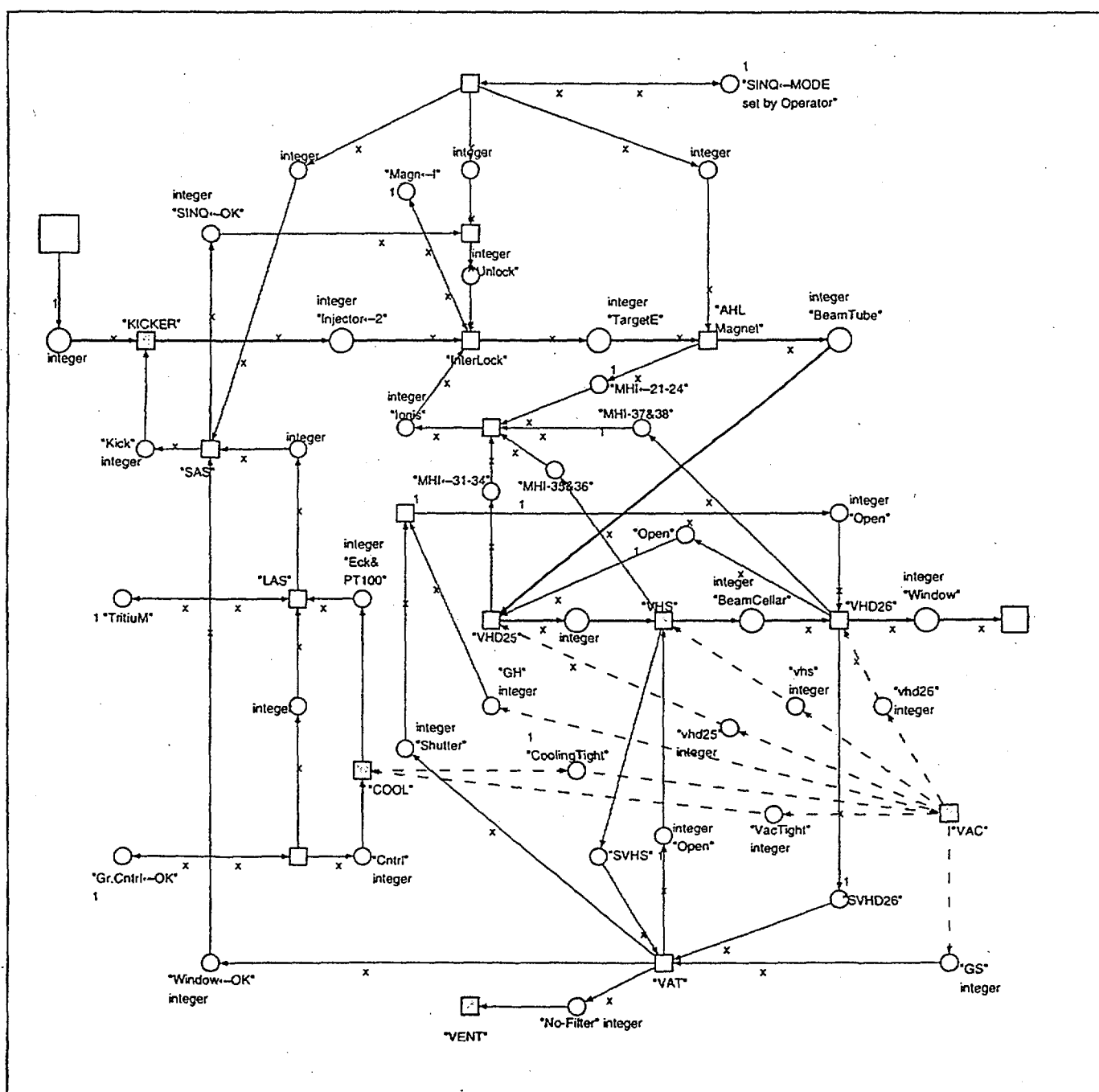   c) the individual connections from GS1,GS2 to VHS1,VHS2 are not redundant.

Fig.5 Enhanced monitoring structure

SINQ-Shut-down system

Fig. 4

ASystem-PP

4.2 Enhancement Suggestions

As a result of the system analysis using PN-models, we to monitor the proton-beam transport process itself as a part of the SINQ-SDS (not only the accelerator interlock). This can be done using additional (or the current) beam monitors (MHx) triggering the Kicker-magnet (AWK1). This provision brings-along two **benefits** (refer to Fig. 5):
a) adds a monitoring loop which acts **before** a damage to the target-window occurs
b) adds diversity to the fast monitoring loop of the vacuum process (GS→AWK1)

5. FAULT TREE ANALYSIS

For a (serious) D_2O contamination to occur, two things must happen simultaneously:
a) the window must be damaged either due to some mechanical effects or fatigue and/or overheating through a collapsed proton beam and b) the SINQ-SDS must fail.
The two events a) and b) are represented by the two blocks of the Fault-Tree in Fig. 6.

Assuming a χ^2-distribution for the failure, then the *upper bound* for the failure rate can be computed as [8]:

$$\lambda_o = \frac{\chi^2\left[v,(1+\gamma)/2\right]}{2\sum\limits_{i=1}^{n}\tau_i}$$

where $v = 2^{m+1}$ is the degree of freedom with m the number of failures, γ is the confidence level, τ_i is the duration of operation of the i-th unit, and n is the number of units.
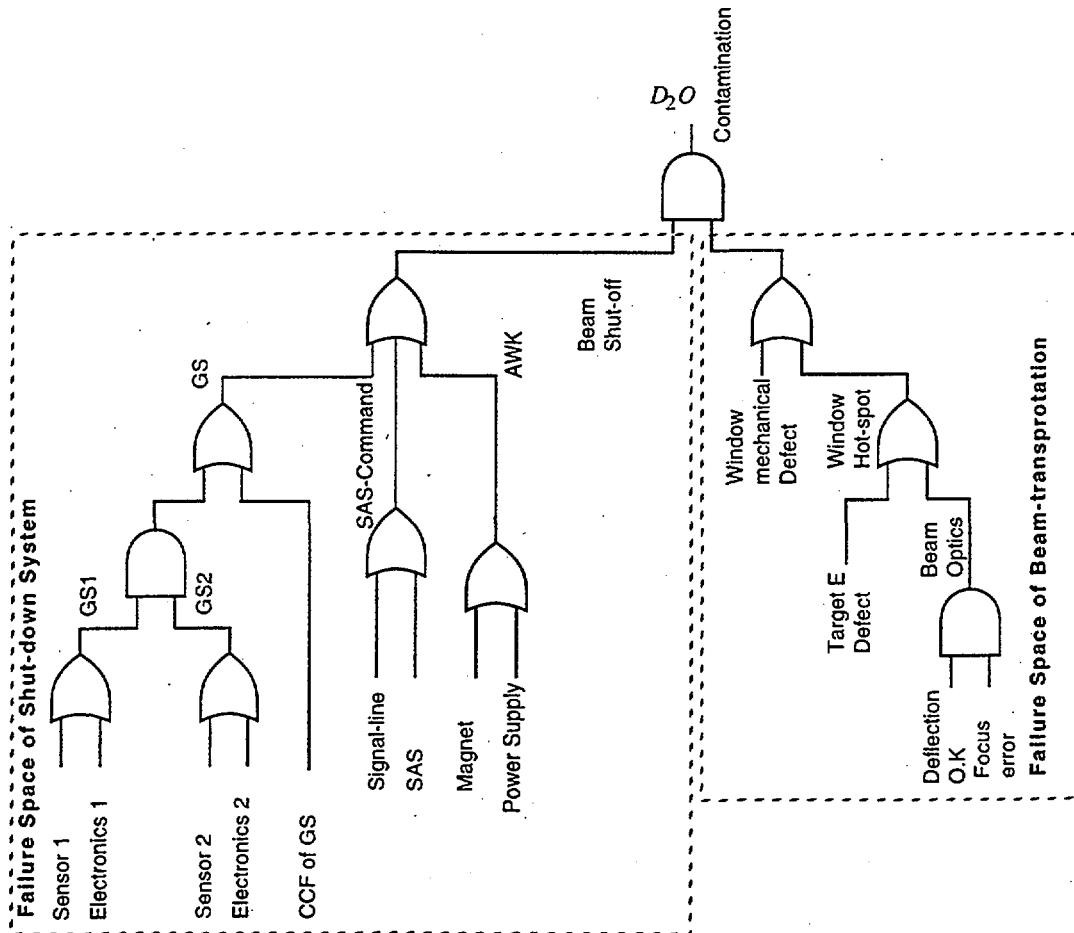We assume a confidence level of 0.95.

Fig.6. Fault-Tree with D_2O contamination as a Top-Event

To use the failure rates obtained from the above formula in the fault tree, the failure probabilities within a time period are to be computed. Assuming a *constant failure* rate, i.e., exponential distribution, the probability that a failure occurs within the time t given that the component is functional at $t=0$ is equal to, $P(\text{failure in time } t) = 1 - e^{\lambda t} \approx \lambda t$

For t = one hour (and 6000 hours per year), the **overall failure probability** of the **shut-down system** is computed as: $P_{sds} = 60.3 \cdot 10^{-6}$ per demand

6. CONCLUSIONS AND FINAL REMARKS

In the reliability analysis of SINQ, Petri-net models have been employed to investigate the monitoring structure and to run simulation for the fault propagation. Reduced fault tree models are then employed in the final evaluation of the failure probability.

On the basis of the previous analysis, our conclusions can be summarised as follows:

1) There is essentially a single dominant loop in the SDS, namely GS1&GS2→AWK1. This loop monitors the vacuum process and, therefore, reacts only after leakage had already occurred.

2) The fast sensors and shutters (GS1&2, VHS1&2) involved in this loop are built to meet the principle of redundancy but not diversity.

3) The overall failure probability of the SDS is $P_{sds} = 60.3 \cdot 10^{-6}$ per demand

4) Enhancement to the monitoring system can be made by monitoring the proton beam transportation process.

REFERENCES

[1]   Perret, Ch., "Sicherheitsbericht zur Spallations-Neutronenquelle SINQ am Paul Scherrer Institut (PSI)", Doku. Nr. 814/PC38-1011.A

[2]   Heidenreich, G., "Abschaltzeit p-Strahl bei Schliessenden Ventilen VHS1, VHS2", Doku. Nr. 818/HG13-301.-, 8-Feb-93

[3]   Braun, R., "Anschluss des Speisegerätes AHL an das Abschaltsystem", Doku.Nr. 837/BR81-301

[4]   The Spallation Neutron Source SINQ, PSI, Oct. 1994

[5]   Braun, R., "Konzept für SINQ-Abschaltsystem", Doku.Nr. 837/BR81-401

[6]   Braun, R., "Vorführung Schnelles Abschaltsystem am 22.5.1996", Doku.Nr. 837/BR81-601

[7]   SystemSpecs 2.1 Reference Manual, IvyTeam, July 1994

[8]   Zuverlässigkeitskenngrössenermittlung im Kernkraftwerk Biblis - Abschlussberciht- Band2, 1984

[9]   Baumgarten, B., Petri-Netze, Grundlagen und Anwendumgen, BI Wissenschaftsverlag, 1990.

[10]   Jensen, K., Rozenberg, G., High-level Petri-Nets, Theory and Applications, Springer Verlag, 1991.

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