Article

Application of artificial neural networks for the development of a signal monitoring system

Shahla Keyvan, Ajaya Durg and Jyothi Nagaraj

Nuclear Engineering Department
University of Missouri-Rolla
Rolla, MO 65409–0170

Abstract: *A prototype of a Signal Monitoring System (SMS) utilizing artificial neural networks is developed in this work. The prototype system is unique in: 1) its utilization of state-of-the-art technology in pattern recognition such as the Adaptive Resonance Theory family of neural networks, and 2) the integration of neural network results of pattern recognition and fault identification databases.*

The system is developed in an X-windows environment that offers an excellent Graphical User Interface (GUI). Motif software is used to build the GUI. The system is user-friendly, menu-driven, and allows the user to select signals and paradigms of interest. The system provides the status or condition of the signals tested as either normal or faulty. In the case of faulty status, SMS, through an integrated database, identifies the fault and indicates the progress of the fault relative to the normal condition as well as relative to the previous tests.

Nuclear reactor signals from an Experimental Breeder Reactor are analyzed to closely represent actual reactor operational data. The signals are both measured signals collected by a Data Acquisition System as well as simulated signals.

Keywords: pattern recognition, Signal Monitoring System, artificial neural networks, ART2-A network, Cascade Correlation Network

1. Introduction

Safe and efficient operation of a nuclear plant demands careful monitoring of the operating conditions. Plantwide monitoring is useful in providing information about the condition of safety related components. Monitoring involves analysis of the associated signals of a component, often the output of sensors and meters. Proper analysis of these signals gives valuable information on the status of the component.

Various noise analysis and system identification techniques utilize signals in the form of time series data to unscramble the useful information in the data (Sakuma *et al,* 1995; Runkel *et al*, 1995). Simplifying assumptions about the structure of a signal are made in order to reduce the computation required to achieve accurate classification. For applications where such assumptions are valid, these techniques perform well. However, if the signals are not simply distributed or are highly correlated, these techniques become inadequate. The recent developments in learning algorithms of neural networks, on the other hand, have provided potential alternatives to traditional pattern recognition techniques. The inherent complexity and nonlinearity in a nuclear reactor, and the strong correlation existing among reactor signals, require a new approach with far less restrictive assumptions about the structure of the input patterns than the traditional pattern recognition techniques. Neural networks offer a flexible, general-purpose approach to building the complex, highly nonlinear models that are required for a complex system such as a nuclear power plant. Neural networks have the potential to provide significant advantages over alternative techniques for plant applications as diverse as modeling, control, diagnostics and monitoring. The unique features of neural networks are their ability to model arbitrarily complex multidimensional functions, their learning abilities, their fine grained parallel architecture, and their inherent robustness to noise. Once developed, the models can be used for various purposes (Kumar & Guez, 1991; Glockler *et al,* 1995).

Noise analysis techniques provide a tool for pattern recognition and monitoring purposes in nuclear reactor systems (Trapp *et al*, 1995; Por *et al*, 1995). One such method has been developed and applied to the signals from the Experimental Breeder Reactor (EBR-II) nuclear plant for degradation monitoring of the reactor pump shaft. It requires prior identification of the dynamics associated with the specific degradation of the reactor pump shaft (Keyvan, 1988). Neural networks, on the other hand, do not require *a priori* fault-related parameter identification. What makes neural computing different from traditional computing and expert systems is that unlike traditional expert systems where knowledge is made explicit in the form of rules, neural networks generate their own rules by learning from being shown examples. It is this characteristic of artificial neural networks that makes them attractive for monitoring purposes in nuclear reactor diagnostic applications (Dzwinel & Pepyolyshev 1995). Neural networks have been considered and evaluated for application in nuclear plants for fault diagnostics; reactor control; sensor validation; plant status monitoring; design of nuclear fuel cycle reload; and vibration analysis (Guo & Uhrig, 1992; Bartlett & Uhrig, 1992).

This paper demonstrates a prototype Signal Monitoring System (SMS) which incorporates artificial neural networks for pattern recognition and integrates the results with a database for fault identification. The SMS system is developed in an X-windows environment that offers an excellent Graphical User Interface (GUI). Motif software is used to build the GUI. The system has the capability of integrating between selected neural network paradigms, a fault identification database, and a fault trend analysis module.

Figure 1 shows the schematic diagram of the system. The following are the main features of the SMS:

- The system distinguishes between normal and faulty sensor signals.
- In the case of a faulty signal, the system identifies the fault and provides a measure of the degree of severity of the identified problem (fault trend).
- An option is provided to change the neural network configuration parameters and train the network again.
- The system is sufficiently user-friendly and requires minimal technical knowledge about neural networks.

As mentioned above, the system has many unique characteristics and is sufficiently user-friendly that it can be used by neural networks experts as well as a user with hardly any knowledge about neural networks. In addition, no data analysis or prior knowledge is required on the part of the user. This makes it a very useful computer-based aid to a nuclear reactor operator for monitoring purpose.

2. Signal description

The pump power signals from the EBR-II nuclear reactor are used as input to the SMS. Also, four simulated signal

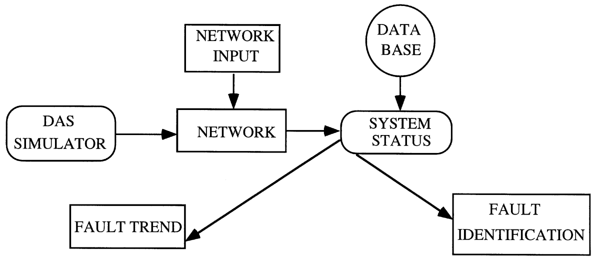


Figure 1: *Schematic of the Signal Monitoring System*

data are generated representing a simulated rapid degradation of the EBR-II pump shaft and are used to test the feasibility and sensitivity of the SMS performance.

The signals utilized in SMS are divided in two groups, the actual measured signal and the simulated signals. The measured signal is the pump power signal from pump number 1 of the EBR-II nuclear reactor which was collected on 29th January 1991. Figure 2 shows the plot of this signal data for a fifty-second time period. This measured (collected) signal is used to simulate and generate faulty signals representing four levels of shaft degradation. Each degradation level is created by slightly changing the degradation dynamic (eigenvalue) in the original collected pump signal as shown in Table 1 (Keyvan, 1988). Figures 3 through 6 show the plot of pump power data for cases 1 through 4 simulations respectively.

3. Neural network description

Neural networks are information processing systems motivated by the goals of reproducing the cognitive processes and organizational models of neurobiological systems. By virtue of their computational structure, neural networks feature attractive characteristics such as graceful degradation, robustness with fragmented and noisy data, parallel distributed processing, generalization to patterns outside of the training set, nonlinear modeling capabilities, and learning.

A neural network is the most appropriate technique for application in environments where robust, fault-tolerant pattern recognition is necessary in a real-time mode and in which incoming data may be distorted or noisy.

The specific characteristics of a neural network depend on the paradigm utilized. The paradigm is determined by the architecture and the neurodynamics employed. The architecture defines the arrangement of the neurons (also called processing elements) and their interconnections (see Fig. 7). The neurodynamics specifies how the inputs to the neurons are going to be combined together (i.e. short term memory), what type of functions or relationships are going to be used to develop the output, and how the adaptive coefficients (i.e. long term memory) are going to be modified.

The learning mechanism which handles modifications to the adaptive coefficients can be classified under supervised, unsupervised, and reinforcement learning. Supervised learning takes place when the network is trained using pairs of inputs and desired outputs. A training set is used to train the neural network when using a supervised learning algorithm such as Backpropagation. The model is then validated using new data or data that was not part of the training set. In unsupervised learning, the network is able to self-organize the categories. Reinforcement learning adds feedback to unsupervised learning to evaluate the pattern classification process.

The spectrum of different paradigms is quite extensive.

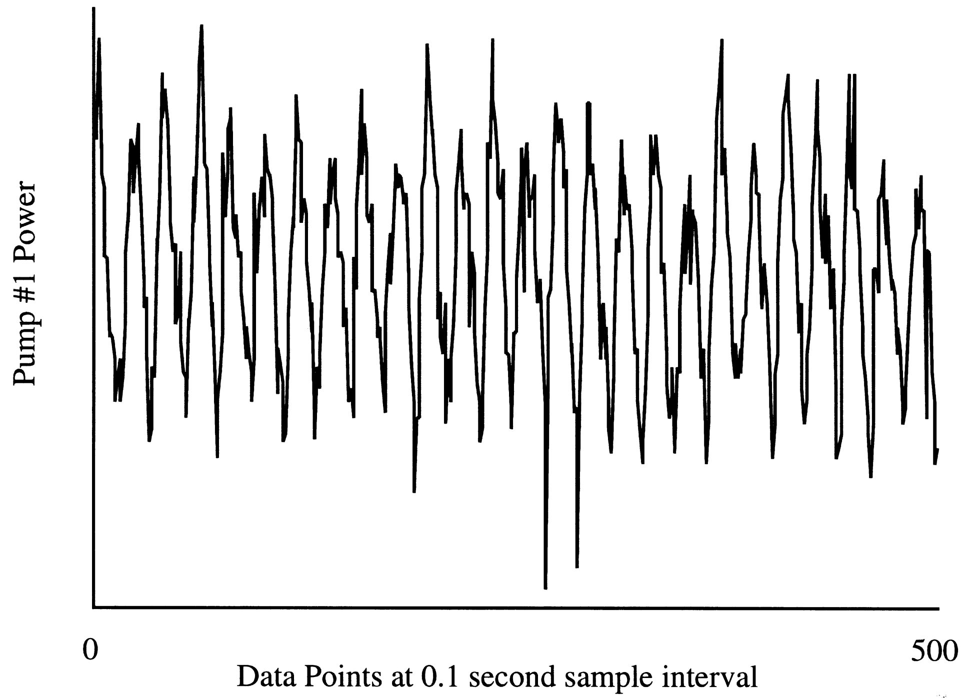


Figure 2: *Plot of Pump #1 Measured Power Signal (collected on 29th January 1991)*

Table 1: *Simulated dynamics representing four degradation levels*

SIMULATED CASE	*EIGENVALUE*
periodicity = 12	0.866 ± 0.50 i
Case 1 (degradation level 1)	0.79 ± 0.43 i
Case 2 (degradation level 2)	0.82 ± 0.45 i
Case 3 (degradation level 3)	0.74 ± 0.48 i
Case 4 (degradation level 4)	0.86 ± 0.50 i

For example, the network architectures range from simplistic one-layer to the hierarchical networks. In addition, there are a large number of algorithms that can be used to modify the adaptive coefficients. The various paradigms have their limitations and strengths, hence one must identify the suitable application areas to which they lend themselves.

Adaptive Resonance Theory (ART) represents a family of neural networks that organize and categorize arbitrary sequences of input patterns in real-time. A class of these networks, called ART 1, is unsupervised and can be used only for binary patterns. ART 2, which is also an unsupervised class, responds to both binary and analog patterns (Carpenter & Grossberg, 1987, 1988). The class ART 3 features an advanced reinforcement feedback mechanism which can alter the classification sensitivity (Carpenter & Grossberg 1990). The class "fuzzy" ART is similar in architecture to ART 1; however, fuzzy operators are added in order to handle analog patterns without losing the advantages of ART 1 architecture (Carpenter, Grossberg & Rosen 1991a). The class ARTMAP ("predictive" ART) is built upon the basic ART designs, while incorporating supervision in the learning process (Carpenter, Grossberg & Reynolds, 1991). Fuzzy ARTMAP has the capability of handling nonstationary stochastic signals and supervised learning (Carpenter, Grossberg, Markuzon, Reynolds & Rosen, 1992). ART 2-A ("algorithmic" ART) is a special case of ART 2 which emphasizes the intermediate and fast learning rates, hence accelerating the learning process by about three orders of magnitude (Carpenter, Grossberg & Rosen, 1991b).

3.1 Neural networks installed in SMS

ART 2 and ART 2-A of the ART family of neural networks and Cascade Correlation network are currently installed in the SMS menu as appropriate networks to choose from. These neural networks are selected based on a comprehensive examination and evaluation of various artificial neural networks for application to the nuclear reactor signals. The evaluation included ART 2, ART 2-A, Fuzzy Adaptive Resonance Theory (Fuzzy ART), and Fuzzy ARTMAP paradigms of the ART family, as well as, Backpropagation, Cascade Correlation, and Restricted Coulomb Energy (RCE) networks. Several simulators were built. The relative speed of all networks was also examined (Keyvan, Durg & Rabelo 1993a, 1993b; Keyvan, Rabelo & Malkani, 1992; Keyvan & Rabelo, 1992; Keyvan & Durg, 1992; Keyvan & Rabelo, 1991).

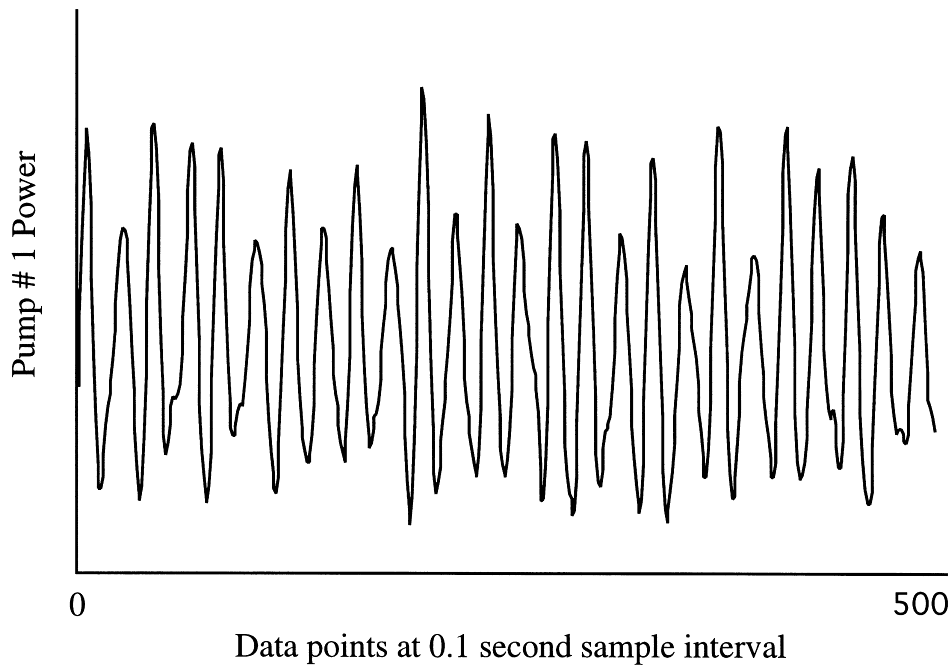


Figure 3: *Simulated Degradation Level 1*

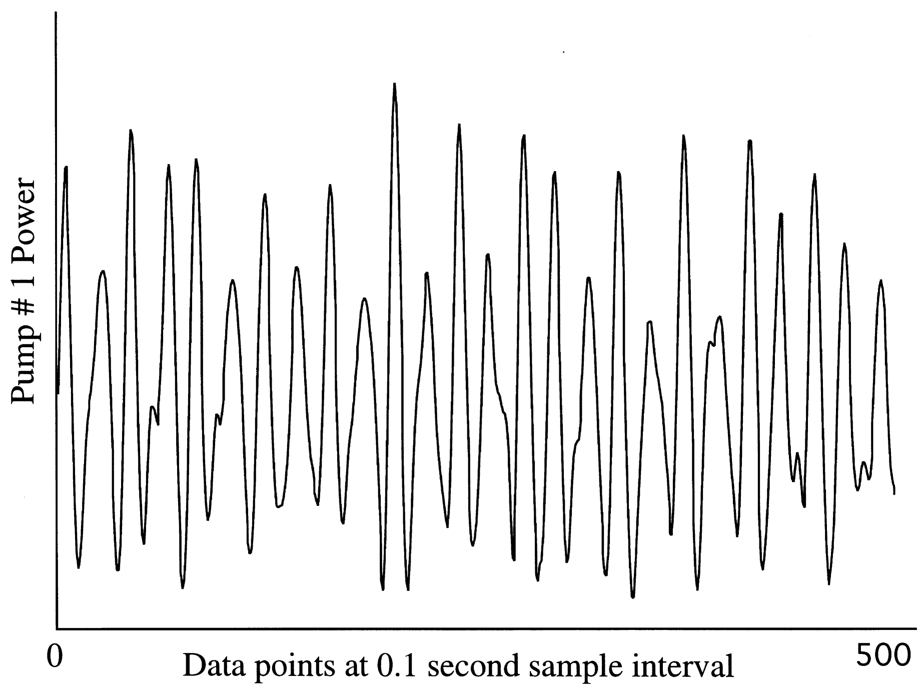


Figure 4: *Simulated Degradation Level 2*

3.2 ART 2/ART 2-A (Algorithmic ART)

The ART 2 network architecture utilized in SMS is shown in Fig. 7.

ART 2-A is a special case of ART 2 designed for large-scale pattern recognition tasks. Its algorithmic-type nature lends itself to rapid prototyping in hardware and software.

ART 2-A has three fields: F_0, F_1, and F_2 (Fig. 8). The output of the F_1 field which is also the output of the F_0 field is the vector I defined by:

$$I = \text{normal}\ (f(\text{normal}(I^0)))$$

where I^0 is the input vector of dimensionality M, and normal is an operator defined by:

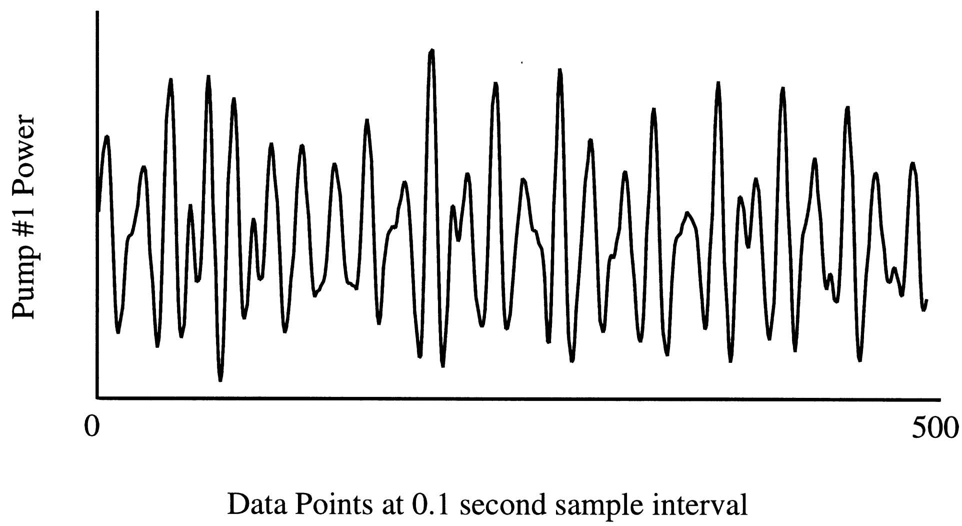


Figure 5: *Simulated Degradation Level 3*

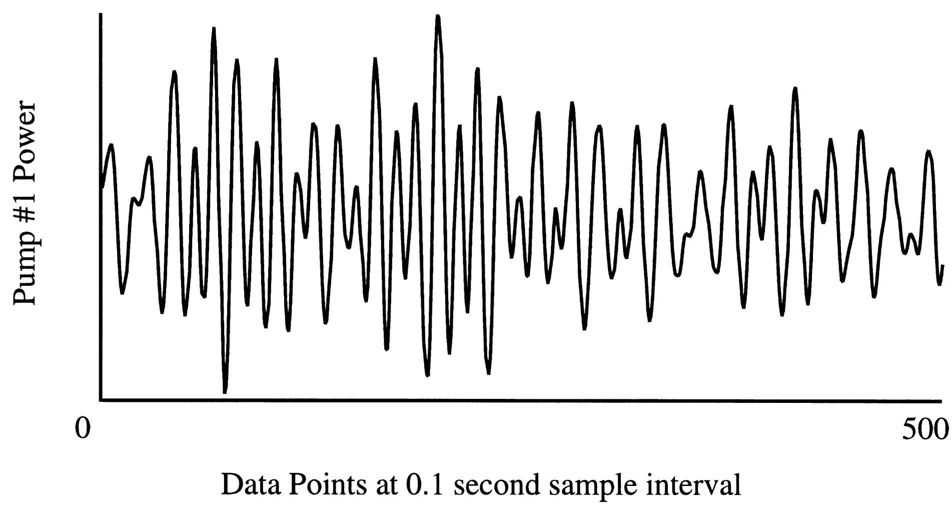


Figure 6: *Simulated Degradation Level 4*

$$\text{normal}(x) = x/\|x\|$$

and f( ) is a piecewise linear function:

$$f(x) = \begin{cases} 0 \text{ if } 0 \leq x < \theta \\ x \text{ if } x \geq \theta, \quad 0 < \theta \leq (M)^{-1/2} \end{cases}$$

The Long Term memory (LTM) vector in ART 2-A is scaled, and it could be interpreted as the LTM vector of ART 2 divided by $\frac{1}{(1-d)}$ (Fig. 7). As in ART 2, the F_2 node ART 2-A makes a choice if the J^{th} node becomes maximally active. In addition, the F_2 Short Term Memory (STM) activation represents the degree of match of the vector I and the scaled Long Term Memory (LTM) vector.

LTM adjustments are performed in a single iteration and are reduced to algebraic equations for fast and intermediate learning (which may need more trials to achieve stable categories) as follows:

$$z_j = \begin{cases} 1 & \text{if J is uncommitted} \\ \text{normal } (\beta \text{ normal } (\psi) + (1-\beta)\, z_J) & \text{if J is committed} \end{cases}$$

where,

$$\psi_i = \begin{cases} I_i \text{ if } z_{Ji} > \theta \\ 0 \text{ otherwise} \end{cases}$$

and $0 \leq ß \leq 1$ (e.g. $ß = 1$ for fast learning).

Due to the utilization of algebraic equations and simplistic arithmetic procedures which involve less iterations, ART 2-A is typically three orders of magnitude faster than ART 2.

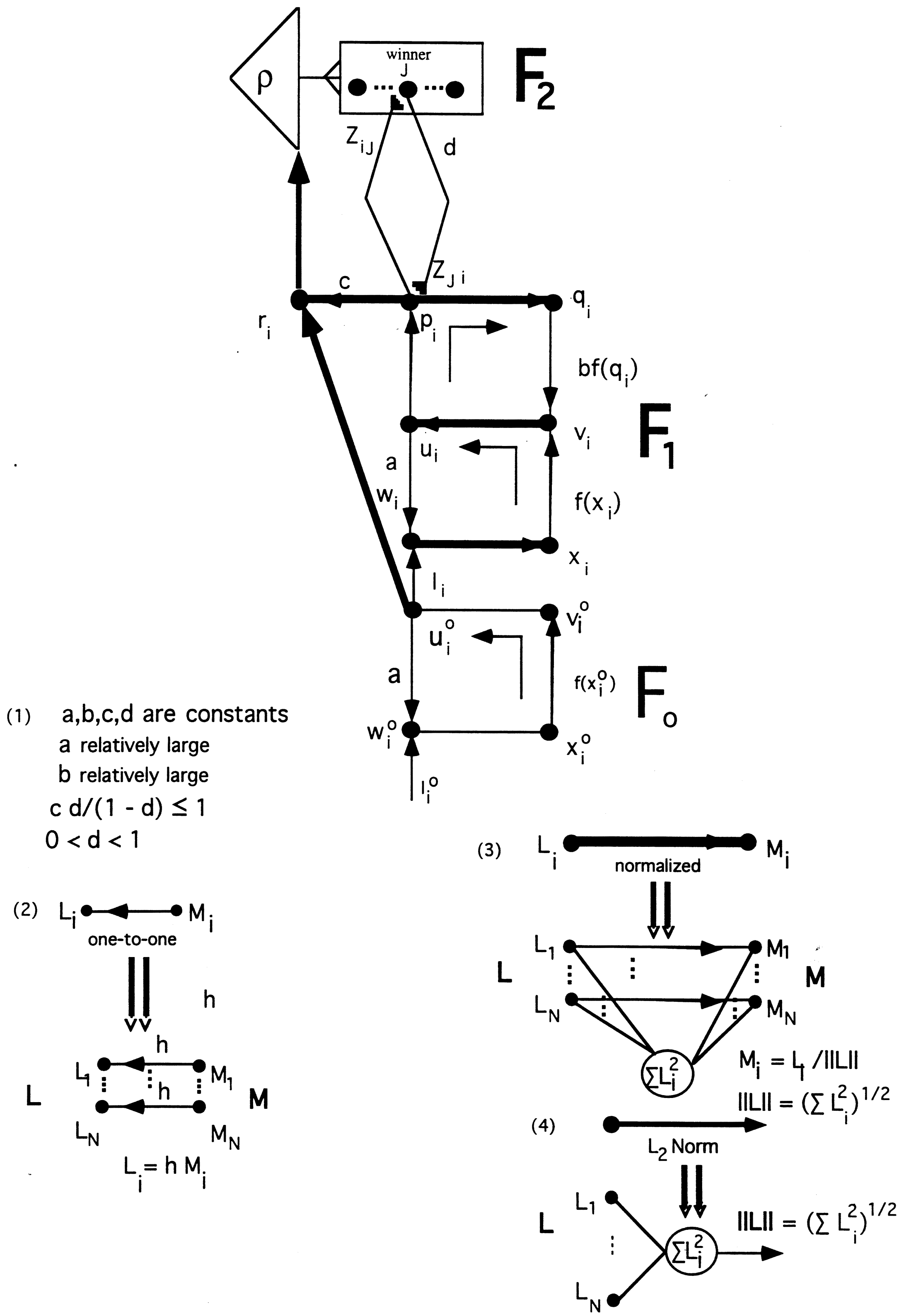
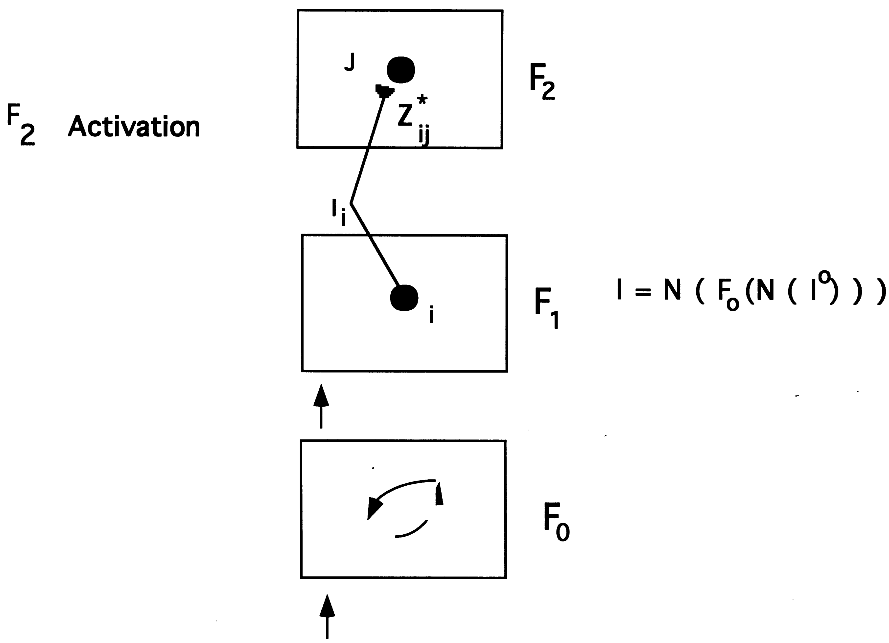


Figure 7: *ART 2 Network Architecture (from Carpenter & Grossberg, 1987)*



Learning

$$Z_J = \begin{cases} I \ \text{if } J \text{ is uncommitted} \\ \text{normal}(ß \ \text{normal}(\psi)+(1-ß_J)Z) \ \text{if} \\ J \ \text{is committed} \end{cases}$$

where

$$\psi_i = \begin{cases} I_i \ \text{if } Z_{Ji} > \theta \\ 0 \quad \text{otherwise} \end{cases}$$

and $0 \leq ß \leq 1$ **(e.g. ß = 1 for fast learning).**

Figure 8: *ART 2-A Network Architecture*

3.3 Cascade Correlation paradigm

Cascade Correlation, a supervised learning algorithm, is an improvement over the popular Backpropagation algorithm. The main disadvantage of the Backpropagation algorithm is that it learns slowly. One of the reasons for this slow learning is the moving target problem (Fahlman & Lebiere, 1990). Briefly stated, the problem is that each unit in the interior of the network is trying to evolve into a feature detector that will contribute in some way to the network's overall performance, but its task is greatly complicated by the fact that all the other units are also changing at the same time. The error signal propagated back to a unit defines the problem that the unit is trying to solve, but this problem changes constantly. Instead of a situation in which each unit moves quickly and directly to assume some useful role, we see a complex dance among all the units that takes a long time to settle down.

The Cascade Correlation algorithm overcomes this problem by allowing only one hidden unit to evolve at any given time. This allows the network to learn faster. The network architecture is termed as cascade architecture, since hidden units are added (cascaded) to the network one at a time until the network yields the desired performance. For each new hidden unit, an attempt is made to maximize the magnitude of the correlation between the output of the new unit and the residual error signal. Hence the paradigm is termed Cascade Correlation.

The cascade architecture begins with some input and one or more output units (as required by the problem), but with no hidden units. Hidden units are added to the network one by one. There is a connection from every input unit to every output and hidden unit, and a connection from every hidden unit to every output unit. The hidden units' input weights are frozen at the time the unit is added to the network, and only the output connections are trained repeatedly. At the hidden and output units, the incoming signals are summed and the sum is passed through an activation function to produce the output signals at the hidden and output units respectively. Figure 9 shows the network architecture for Cascade Correlation.

4. Signal Monitoring System description

SMS consists of the following main modules:

- Network
- Parameters
- File
- System Status

Network: The network module provides access to various neural network paradigms that can be used for pattern identification. Both supervised and unsupervised paradigms are considered. The following paradigms are currently installed in the system :

(a) Unsupervised networks:
- ART 2
- ART 2-A

(b) Supervised networks :
- Cascade Correlation

Parameters: Network parameters are needed to configure the neural network. This module allows modification of the network parameters. When a network is selected, the default values of the parameters are loaded. These values can be modified and permanently saved to a file for future use if desired. The changes to the parameter values can be accomplished by direct modification, which can be adopted when the user has some prior understanding of the network parameters. The network parameters can be modified by editing the default values displayed in the "Parameters" window. A "Help" facility is also provided at this point which gives basic information about the parameters.

File: This module keeps track of all the input data files to be applied to the neural network ("Data" submodule) and the files for network parameters ("parameters" submodule). The required input signal data file to be applied to the neural network can be chosen from the "Data" submenu under the file menu. The desired data file is chosen to run the neural network for fault identification. The default file setup is that containing normal signal data.

System Status: This module provides the actual diagnostic information about the nuclear reactor components. As mentioned earlier, SMS was built to monitor the signals in the pump shaft of a nuclear reactor and identify faults therein. A neural network memory and fault identification database were established to identify the simulated degradation in the pump shaft.

The diagnostic information is obtained by clicking on the "System Status" button. Once the "System Status" is selected, the selected signal data from the "Data" submenu is applied as input to the selected neural network. The neural network runs in the background and classifies the given input signal using the already established memory into one of these categories : normal, case 1, case 2, case 3, case 4, or unknown signal. If the signal is identified as normal, a status report is displayed as shown in Figure 10; otherwise, a faulty status report is displayed as shown in Figure 11. In case of the faulty status report, the normal signal is also shown for comparison. A description of the fault can be obtained by selecting the "Describe Fault" button shown in Figure 11. The fault description corresponding to the current faulty signal is gathered from the existing fault data base and displayed at this point (Fig. 12). The faults are

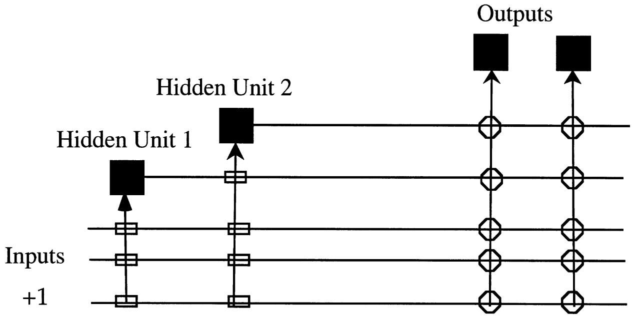


Figure 9: *Cascade Correlation network architecture*

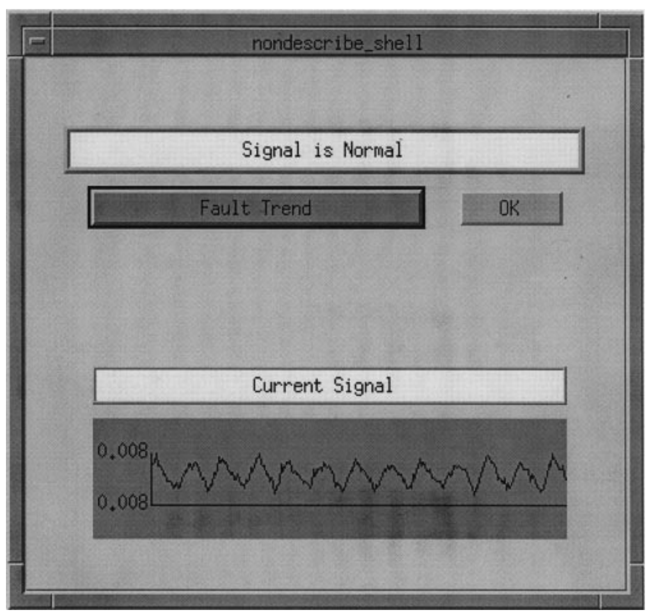


Figure 10: *Output from SMS for a Normal Signal*

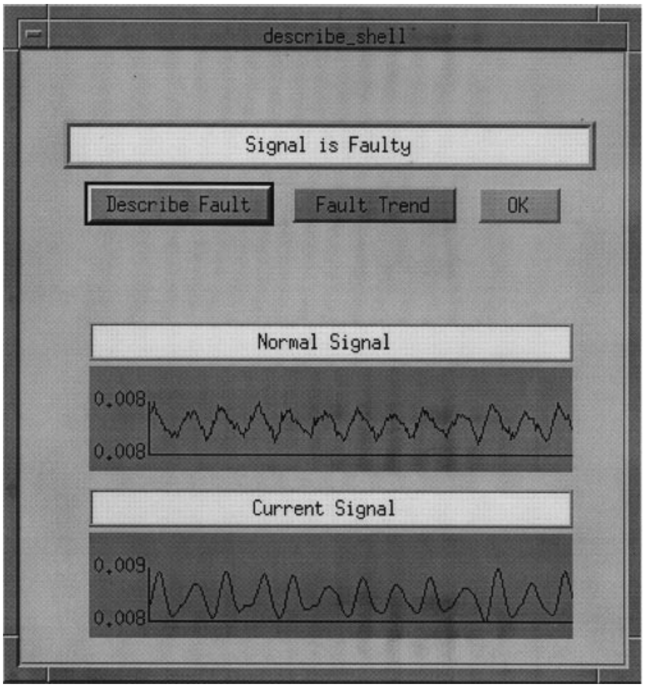


Figure 11: *Output from SMS for a Faulty Signal*

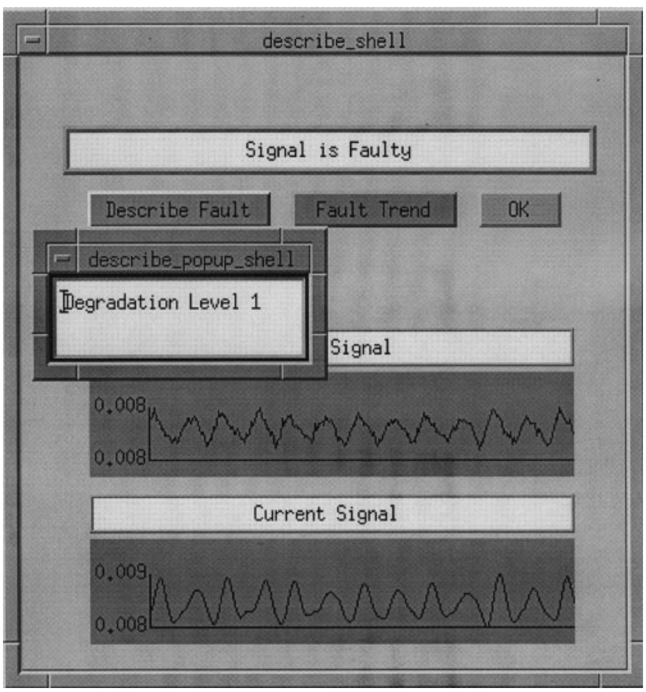


Figure 12: *Description of the Faulty Signal*

described as "Degradation level 1", "Degradation level 2", etc. The "Fault Trend" button (Fig. 12) is selected to view a plot showing the relative degradations. The fault trend indicates a measure of degradation level. It also maintains a history of degradation of the faults by putting the current time stamp (minutes: seconds) below the trend index, thus capturing the progress of the faults over a period of time

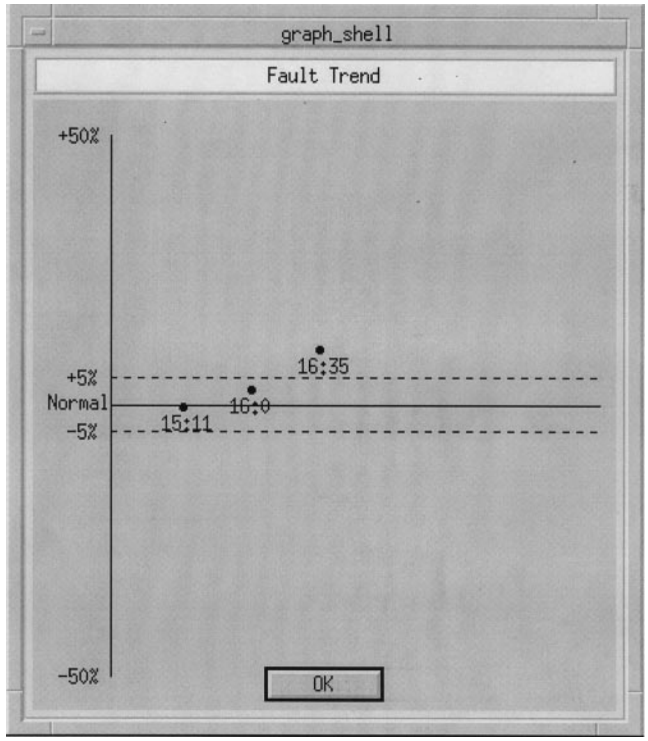


Figure 13: *Fault Trend for Normal and Faulty Signal*

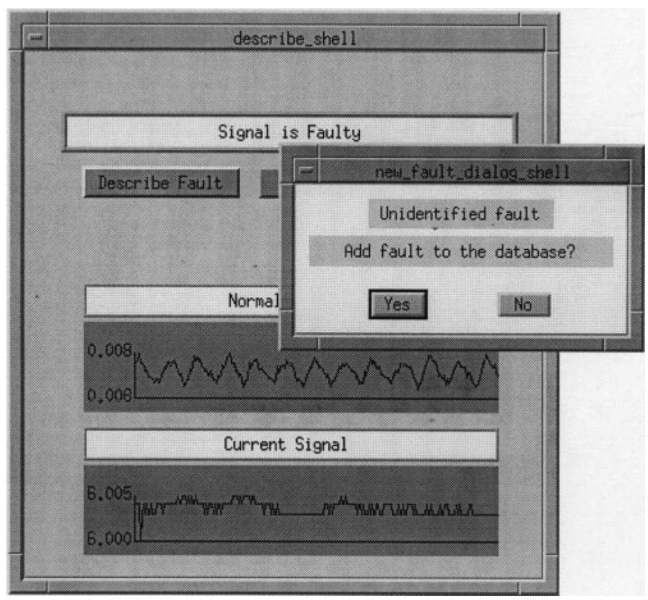


Figure 14: *The Output of SMS for an Unidentified Faulty Signal*

(Fig. 13). When a new fault different from the ones currently registered in the database is encountered, the SMS output will be "unidentified fault", as shown in Figure 14.

5. Conclusions

This paper has addressed the need for advancing state-of-the-art diagnostic techniques for the purpose of monitoring signals from nuclear reactor components. The prototype SMS system demonstrates the feasibility of identifying faulty signals and providing a history trend of the tests performed using artificial neural networks. In addition, verification of the performance of the system is not a hypothetical one, rather a very practical one. This is due to the simulation strategy which changes only one parameter related to the shaft degradation and preserves all other dynamics including the noise in the original signal.

The SMS performance shows the feasibility of developing a diagnostic system using supervised neural networks as well as unsupervised ART paradigms. Figures 10 through 14 show the actual computer screen of the SMS system output displaying proper pattern recognition and other capabilities. Although the system utilizes signals from a nuclear plant, it can be easily modified for other industry applications using an appropriate database.

Acknowledgements

This work was supported by:

(1) National Science Foundation under reference number ECS-9111145, and

(2) a grant from University of Missouri Research Board.

The authors wish to acknowledge:

Argonne National Laboratory, Argonne West, EBR-II Division for providing the data. Dr Luis C. Rabelo (Ohio University) for his contribution in writing the original code on the ART networks. Mr Scott R. Crowder (Carnegie Mellon University) for his contribution in writing the original code on the Cascade Correlation network.

References

Bartlett, E.B. and R.E. Uhrig (1992) Nuclear Power Plant status diagnostics using an Artificial Neural Network, *Nuclear Technology*, **97**, 272–281.

Carpenter, G.A. and S. Grossberg (1987) ART 2: Self-Organization of Stable Category Recognition Codes for Analog Input Patterns, *Applied Optics*, **26**, 4919–4930.

Carpenter, G.A. and S. Grossberg (1988) The ART of Adaptive Pattern Recognition by a Self-Organizing Neural Network. *Computer*, 77–88.

Carpenter, G.A. and S. Grossberg (1990) ART 3: Hierarchical Search Using Chemical Transmitters in Self-Organizing Pattern Recognition Architectures, *Neural Networks*, **3**, 129–152.

Carpenter, G.A., S. Grossberg, N. Markuzon, J. Reynolds and D. Rosen (1992) FUZZY ARTMAP: An Adaptive Resonance Architecture for incremental learning of analog map. *Proceedings of IJCNN*, **3**, 309–314.

Carpenter, G.A., S. Grossberg and J. Reynolds (1991) ARTMAP: Supervised Real-Time Learning and Classification of Nonstationary Data by a Self-Organizing Neural Network, in G. Carpenter and S. Grossberg (eds.), *Pattern Recognition By Self-Organizing Neural Networks*, Cambridge, Massachusetts: MIT Press.

Carpenter, G.A., S. Grossberg and D. Rosen (1991a) Fuzzy ART: Fast stable learning and categorization of analog patterns by an adaptive resonance system, *CAS/CNS-TR-91–015*.

Carpenter, G.A., S. Grossberg and Rosen, D. (1991b) ART 2-A: An Adaptive Resonance Algorithm for Rapid Category Learning and Recognition. IEEE *Transactions on Neural Networks* (II) 151–156.

Dzwinel, W. and Y.N. Pepyolyshev (1995) Pattern Recognition, Neural Networks, Genetic Algorithms and High Performance Computing in Nuclear reactor diagnostics, *SMORN VII, 7th Symposium on Nuclear Reactor Surveillance and Diagnostics*, **1**, p. 4.5.

Fahlman S.E. and C. Lebiere (1990) The Cascade Correlation Learning Architecture. CMU-CS-90-100, School of Computer Science, Carnegie Mellon University.

Glockler, O., I. Paszit and N.S. Gans (1995) Neural Network Techniques for Control Rod Localization, *SMORN VII, 7th Symposium on Nuclear Reactor Surveillance and Diagnostics*, **1**, p. 4.10.

Guo, Z. and R.E. Uhrig (1992) Use of Artificial Neural Networks to Analyze Nuclear Power Plant Performance, *Nuclear Technology*, **99**, 36–42.

Keyvan, S. (1988) Degradation Monitoring of Pump Components in a Nuclear Power Plant, Presented at the ANS/ENS Topical Meeting on nuclear power plant life extension, Snowbird, Utah.

Keyvan, S. and A. Durg (1992) Pump Shaft Condition Monitoring via Artificial Neural Networks. *Proceedings of the 5th Predictive Maintenance Conference*, sponsored by EPRI, Knoxville, TN.

Keyvan, S., A. Durg and L.C. Rabelo (1993a) Application of Artificial Neural Networks for Development of Diagnostic Monitoring System in Nuclear Plants, *Proceedings of ANS Topical Meeting on Nuclear Plant Instrumentation, Control and Man-Machine Interface Technologies*, **1**, 515–522.

Keyvan, S., A. Durg and L.C. Rabelo (1993b) Evaluation of the Performance of Various Artificial Neural Networks on the Signal Fault Diagnosis in Nuclear Reactor Systems. *Proceedings of the International Joint Conference on Neural Networks* (IJCNN) , **3**, 1719–1723.

Keyvan, S. and L.C. Rabelo (1991) Intelligent Engineering Systems Through Artificial Neural Networks, in C.H. Dagli, S.R.T. Kumara and Y.C. Shin (eds), *Nuclear Reactor Pump Diagnostics via Noise analysis/Artificial Neural Networks*. New York: ASME Press, 651–656.

Keyvan, S. and L.C. Rabelo (1992) Sensor Signal Analysis by Neural Networks for Surveillance in Nuclear Reactors. *IEEE, Transactions on Nuclear Science*, **39**(2), 292–298.

Keyvan, S., L.C. Rabelo and A. Malkani (1992) Nuclear Reactor Condition Monitoring by Adaptive Resonance Theory. *Proceedings of the International Joint Conference on Neural Networks* (IJCNN), **3**, 321–328.

Kumar, S.S. and A. Guez (1991) Art Based Adaptive Pole Placement for Neurocontrollers, *Neural Networks*, **4**, 319–335.

Por, G., P. Kantor and I. Sokotov (1995) Experience with a Reactor Noise Diagnostics System for VVER-1000 Mwe Type Russian Reactors, *SMORN VII, 7th Symposium on Nuclear Reactor Surveillance and Diagnostics*, **1**, p. 1.6.

Rumelhart, D.E., G.E. Hinton and R.J. Williams (1986) Learning Internal Representations by error propagation. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, MIT Press.

Runkel, J., E. Laggiard, D. Stegemann, J. Fiedler, P. Heideman, H.P. Mies, R. Oed, F.P. Weiss and F. Altstadt (1995)

Application of Noise Analysis in two BWR units of NPP Gundremmingen, *SMORN VII, 7th Symposium on Nuclear Reactor Surveillance and Diagnostics*, **1**, p. 1.5.
SAKUMA, M., R. KOZMA, M. KITAMURA, H. SCHOONEWELLE and J.E. HOOGENBOOM (1995) Boiling Anomaly Detection by various Signal Characterization Methods, *SMORN VII, 7th Symposium on Nuclear Reactor Surveillance and Diagnostics*, **1**, p. 3.9.
TRAPP, J.P., R. BERGER, A. LEBRUN, C. LHUILLIER, M. PORTIER, M. DICRESCENZO, J.L. PERRIN and L. MARTIN (1995) Evolution of FBR Surveillance using a Noise Analysis and an online Signal Processing, *SMORN VII, 7th Symposium on Nuclear Reactor Surveillance and Diagnostics*, **1**, p. 1.10.

The authors

Shahla Keyvan

Dr Shahla Keyvan (BS, Engineering — Nuclear emphasis, Electrical minor), University of Washington in Seattle, 1974; MS & NE, Nuclear Engineering, Massachusetts Institute of Technology, 1978; PhD Nuclear Engineering, University of California, Berkeley, 1983) is Associate Professor and Director of the graduate program in the Nuclear Engineering Department at the University of Missouri-Rolla (UMR). Prior to joining UMR in 1990, she worked in industry for seven years. Her research interests are in the areas of Artificial Intelligence (AI) applied to nuclear and Fossil Power Plants; machine vision, image processing and AI for inspection and quality control.

Jyothi Nagaraj

Ms Jyothi Nagaraj received a BS degree in Electrical Engineering from UVCE, Bangalore, India. She received two MS degrees, one in Electrical Engineering and the other in Computer Science from the University of Missouri-Rolla (UMR). She is currently working as an Information Systems Specialist with EMC Corporation, Hopkinton, MA.

Ajaya Durg

Mr Ajaya Durg is currently a senior engineer at Intel corporation in Santa Clara, California. He received his master's degree from the University of Missouri-Rolla, (1993) and a bachelor's degree from Osmania University, India (1989). He has worked in various fields including the application of Neural Networks to Nuclear Engineering, development of performance analysis tools for Pentium class microprocessors and image processing. He is currently developing innovative image processing algorithms for digital video processing.