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Shahla Keyvan
Missouri University of Science and Technology

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Sensor Signal Analysis by Neural Networks for Surveillance in Nuclear Reactors

Shahla Keyvan and Luis C. Rabelo

Abstract—**The application of neural networks as a tool for reactor diagnostics is examined here. Reactor pump signals utilized in a wear-out monitoring system developed for early detection of the degradation of a pump shaft [17] are analyzed as a semi-benchmark test to study the feasibility of neural networks for monitoring and surveillance in nuclear reactors. The Adaptive Resonance Theory (ART 2 and ART 2-A) paradigm of neural networks is applied in this study. The signals are collected signals as well as generated signals simulating the wear progress. The wear-out monitoring system applies noise analysis techniques, and is capable of distinguishing these signals apart and providing a measure of the progress of the degradation. This paper presents the results of the analysis of these data, and provides an evaluation on the performance of ART 2-A and ART 2 for reactor signal analysis. The selection of ART 2 is due to its desired design principles such as unsupervised learning, stability-plasticity, search-direct access, and the match-reset tradeoffs. ART 2-A is selected for its speed. Two simulators are built. One is ART 2, and the other ART 2-A. The result is a success for both paradigms, and the study shows that ART 2-A is not only able to learn and distinguish the patterns from each other, its learning speed is also extremely fast despite the high-dimensional input spaces.**

Introduction

Nuclear reactors are designed with a certain anticipated useful life. As the plants approach their design life, plans must be devised to extend their operating life as long as economically viable. Needless to say, the adequate surveillance and monitoring of reactor components are of utmost importance from a safety point of view, especially in the case of an aging plant. In order to assure safe operation, nuclear power plants are designed and built incorporating a large number of sensors of various kinds to monitor reactor parameters at all time. Examples of these parameters (signals) are: coolant flow, temperature, pressure, neutron flux, reactor power, pump speed, pump pressure, etc. Signals from sensors carry valuable information in their fluctuating part which can be utilized for the surveillance and monitoring of reactor components. It is this application of the reactor instrumentation and sensor signals which is the subject of this paper.

The objective of this research work is to evaluate the application of unsupervised neural networks (NN's) in the analysis of sensor signals for reactor surveillance and monitoring. Signals utilized in a wear-out monitoring system developed for detection and surveillance of the pump shaft degradation of the EBR-II nuclear reactor are used here. The pump shaft degradation was simulated to show the feasibility of the monitoring system [17]. The system utilizes information available in operation data in the form of fluctuations, and provides indications of changes in equipment performance through time-series analysis of collected signals. The pump shaft degradation is due to material (sodium and sodium oxide) buildup on the shaft in the running clearance between the shaft and the lower labyrinth.

The diagnosis is based on the monitoring of the performance and the impact of an equipment/component on the operation environment through the analysis of associated signals from the reactor sensors. The wear-out monitoring system which uses noise analysis and regression modeling is capable of recognizing the progress of degradation. The recognition is achieved using parameters called "wear measure parameters" which were developed for the system to distinguish each simulated signal, as well as for indicating relative degradation furtherance. The wear-out monitoring system is based on noise analysis and utilizes the dynamic data system (DDS) approach of autoregressive moving average (ARMA) regression modeling. The mathematical representation of the model for a univariate system is

$$\begin{aligned}(1 - a_1 Z^{-1} - a_2 Z^{-2} - \cdots - a_n Z^{-n}) Y(k) \\ = (b_1 Z^{-1} - b_2 Z^{-2} - \cdots - b_{n-1} Z^{-(n-1)}) R(k)\end{aligned}$$

where

$Y(k)$	discrete signal data
$R(k)$	white noise residual
a, b	autoregressive moving average parameters
k	index of time interval
$Z^{-1}Y(k)$	$Y(k-1)$.

The autoregressive and moving average parameters are then decomposed into pairs of complex discrete roots (eigenvalues), i.e., for a second-order dynamic,

$$r_{1,2} = \alpha \pm \beta i$$

where

$$a_1 = r_1 + r_2, \; a_2 = -r_1 r_2.$$

Similarly,

$$r_{1,2}^* = \alpha^* \pm \beta^* i$$

where

$$b_1 = r_1^* + r_2^*, \; b_2 = -r_1^* r_2^*.$$

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S. Keyvan is with the Department of Nuclear Engineering, University of Missouri—Rolla, Rolla, MO 65401.

L. C. Rabelo is with the Department of Industrial and Systems Engineering, Ohio University, Athens, OH 45701.

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The pattern recognition and the measure of wear progress in the monitoring system are achieved by introducing new parameters (representing an index of wear progress) which are based on the increase of the impact of the wear-related dynamic on the signal fluctuation as degradation progresses. A detailed description of the system is given in [17].

The time involved in the learning process of the neural networks is of concern when applying high-dimensional input spaces for reactor diagnostics. Hence, the ART 2-A paradigm is selected for its high speed in learning, and its performance is compared with ART 2. The pump sensor signals utilized in the wear-out monitoring system which applies noise analysis techniques are used here as a semi-benchmark testing against the performance of the monitoring system.

The main objective here is to test the selected neural network paradigms ART 2-A and ART 2 for the capability of detecting and recognizing different levels of degradations separately. In addition, the goal is to achieve this objective without any pre/post signal processing or analysis.

Signal Description

The signals utilized in this study are divided into two groups, the actual measured signal and the simulated signals. The measured signal is the pump power data from pump number 1 of the EBR-II nuclear reactor which are collected from sensors by the plant data acquisition system. Fig. 1 shows the original plot of these signal data for a 50 s time period. The first 25 s from this measured signal are used to provide two sets of patterns, with 500 data points representing the normal pump power signal in this study.

Four simulations are performed to generate signals representing four levels of pump shaft degradation. In each level, the wear dynamic eigenvalue present in the measured or collected signal is replaced by a characteristic root of the same frequency, but a smaller damping factor; all other dynamics including noise in the original collected signal are untouched and remain the same. Table I shows the eigenvalues corresponding to each simulated datum [17]. Again, the first 25 s of these simulated signals are used in our study to provide two sets of patterns of 500 data points for each simulation. Fig. 2 shows the two sets of data corresponding to the measured pump power signal. Figs. 3–6 show the simulated sets of data. The measured signals of Fig. 2 are referred to as pattern N. The signals of Figs. 3–6 are referred to as patterns A, B, C, D, respectively. Thus, file *NDABC* contains the five sets of data of patterns N, D, A, B, and C, respectively.

Neural Networks

NN's 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, NN's feature attractive characteristics such as graceful degradation, robust recall with fragmented and noisy data, parallel distributed processing, generalization to patterns outside of the training set, nonlinear modeling capabilities, and learning.

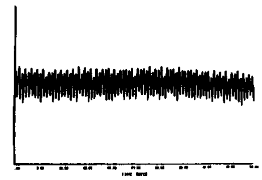
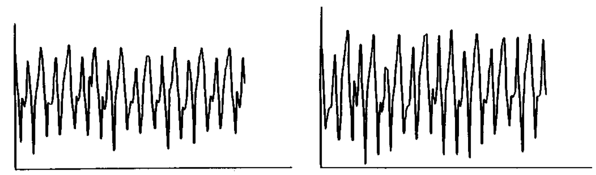
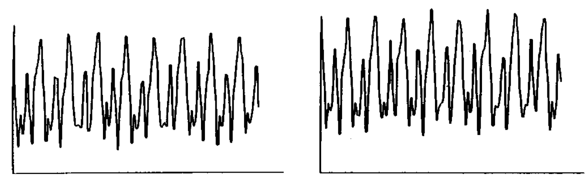


Fig. 1. Measured pump power signal.



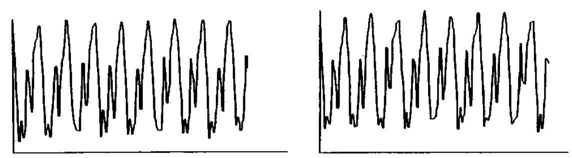
(a) (b)

Fig. 2. Normal pump power data (pattern N). (a) First set of data. (b) Second set of data.



(a) (b)

Fig. 3. Simulated pump power data (pattern A). (a) First set of data. (b) Second set of data.



(a) (b)

Fig. 4. Simulated pump power data (pattern B). (a) First set of data. (b) Second set of data.

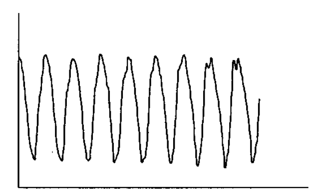
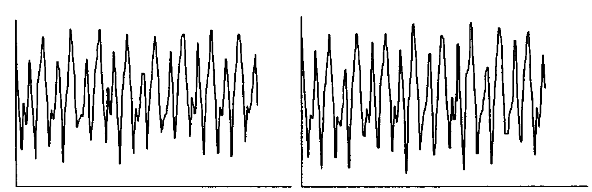


Fig. 5. First set of data of simulated pump power data (pattern C).



(a) (b)

Fig. 6. Simulated pump power data (pattern D). (a) First set of data. (b) Second set of data.

TABLE I
SIMULATED DYNAMICS

Simulated Level	Eigenvalue
1 (pattern *D*)	$0.79 \pm 0.43\ i$
2 (pattern *A*)	$0.82 \pm 0.45\ i$
3 (pattern *B*)	$0.84 \pm 0.48\ i$
4 (pattern *C*)	$0.86 \pm 0.50\ i$

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 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 function or relationship is 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 input and desired outputs. 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. For example, the network architectures range from simplistic perceptrons [18] to the hierarchical neocognitron [10]. In addition, there is a large number of algorithms for the modification of the adaptive coefficients. The various paradigms developed have their limitations and strengths; hence, one must identify the suitable application areas for which they lend themselves.

ART 2

ART represents a family of NN's which self-organize categories in response to arbitrary sequences of input patterns in real time for pattern recognition [6]. A class of these networks called ART 1 [3], which is unsupervised, can be used only for binary patterns. ART 2 [4], [5], which is also an unsupervised class, responds to both binary and analog patterns. The class ART 3 [7] features an advanced reinforcement feedback mechanism which can alter the classification sensitivity or directly engage the search mechanism. The class "fuzzy" ART [9] 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. The class ARTMAP ("predictive" ART) [8] is built upon the basic ART designs, while incorporating supervision in the learning process. ART 2-A ("algorithmic" ART) [2] is a special case of ART 2 which emphasizes the intermediate and fast learning rates, hence accelerating the learning process by three orders of magnitude.

Design Principles: ART 2 networks must utilize several combinations of mechanisms to satisfy multiple design principles such as the stability-plasticity tradeoff, search-direct access tradeoff, match-reset tradeoff, and biological plausibility [4], [6].

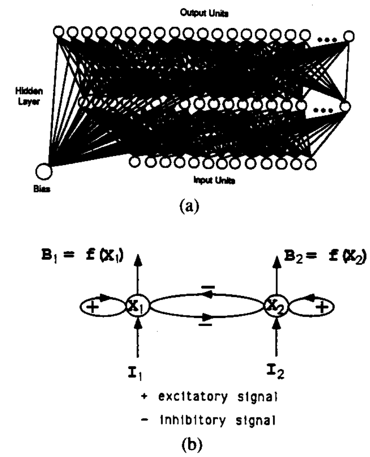


Fig. 7. Neural networks samples. (a) Backpropagation network with a hidden layer [19]. (b) Shunting network [1], [13].

The stability-plasticity tradeoff requires that the architectural mechanisms must prevent established codes from being removed or continuously recoded. However, established codes must be plastic over the learning process.

The search-direct access tradeoff calls for a direct access to an established category by the corresponding input pattern that has become familiar to the network. Search should only occur with unfamiliar input patterns.

The match-reset tradeoff emphasizes that the network should be able to react to small differences between an input pattern and an established category. However, if a specific category is chosen, reset is inhibited during the learning process, even when a new category is being established.

Biological plausibility requires differential equations and locality [20]. The neurons in ART obey differential equations based on nonlinear equations describing the membrane conductances, membrane permeability changes, and nerve behavior based on membrane potentials [16]. Locality implies that the transmission of information is only possible among components which are in physical contact.

Topology and Neurodynamics: The principal architectural elements of an ART 2 network are the attentional and orienting subsystems.

Attentional Subsystem: The attentional subsystem is composed of long-term memory and short-term memory elements.

Short-Term Memory (STM): $F1$, the input representation field, and $F2$, the category representation field, are the two STM main components ($F1$ and $F2$ are both shunting networks [1], [7], [13]).

$F1$ is composed of three layers, with STM activation equations as (see Fig. 8) [4]

$$p_i = u_i + \Sigma g(y_j)$$
$$q_i = p_i / \| p \|$$
$$v_i = f(x_i) + bf(q_i)$$
$$u_i = v_i / \| v \|$$
$$w_i = I_i + au_i$$
$$x_i = w_i / \| w \|$$

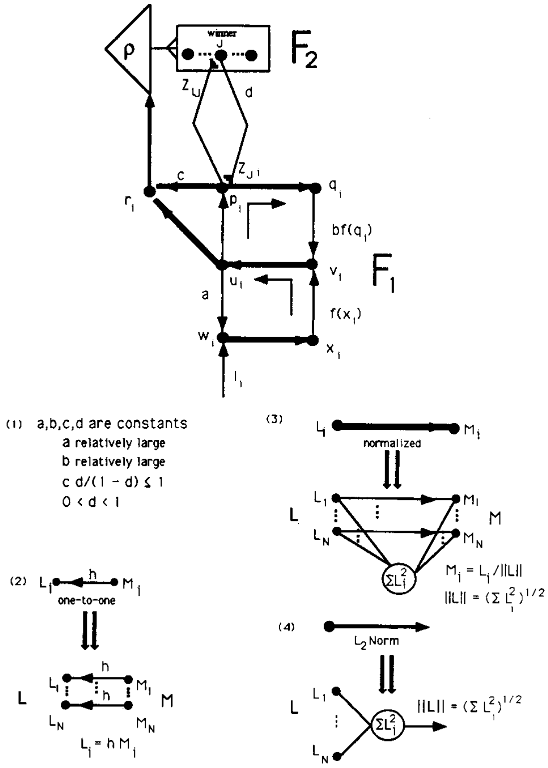


Fig. 8. Typical ART 2 architecture [2], [4].

where a, b, c, and d are constants, y_j is the STM activation of the jth $F2$ node, $\| \ \|$ is the L_2 norm, and $f()$ is an internal signal function. The normalization mechanism, among other tasks, keeps $F1$ from saturation in spite of the constant presence of the input pattern during the learning process. The internal signal function $f()$ is critical in noise suppression and contrast enhancement (in this research, a piecewise linear function was utilized; see Fig. 9) [4], [12], [15]. The $F1$ design provides internal feedback and a correlation between normalized bottom-up and top-down signals to allow stability and matching sensitivity.

The $F2$ field, by means of competitive interactions of the $F2$ nodes, chooses the one (i.e., winner) which responds maximally to the vector p as p is applied to the bottom-up adaptive filter (see Fig. 8). The $F2$ field also suppresses $F2$ nodes (i.e., reset) as guided by the orienting subsystem. Consequently, the signals of the $F2$ nodes are assigned based on the $F2$ nodes' STM activation according to

$$g(y_j) = \begin{cases} d & \text{if the } j\text{th } F2 \text{ node is the winner } (J) \\ & \quad \text{based on } \max\left(\Sigma p_i z_{ij}\right) \text{ and it has} \\ & \quad \text{not been reset in this trial} \\ 0 & \text{otherwise.} \end{cases}$$

Long-Term Memory (LTM): LTM is made up of two components, the bottom-up adaptive coefficient (z_{ij}) and the top-down adaptive coefficient (z_{ji}), where learning (LTM changes) and therefore category structuring occurs (see Fig. 8).

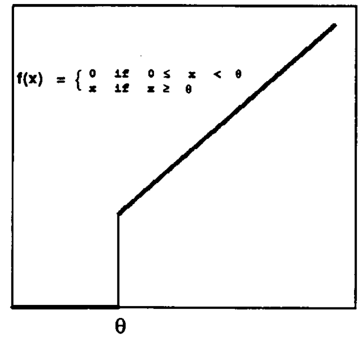


Fig. 9. Piecewise linear function.

For bottom-up adaptive coefficients, the following learning equation (steepest descent) is utilized [1], [4], [12], [14]:

$$dz_{iJ}/dt = \left[p_i - z_{iJ}\right]d.$$

That is, the weight vector $(z_{1J}, \cdots, z_{NJ})$ keeps track of the incoming signal vector p and the Jth node in $F2$ is identified as the winner with its respective output d. In addition, vector p,[1] when the $F2$ field is active and a winner has been selected (J), is expressed by

$$p_i = u_i + d z_{iJ}.$$

Therefore,

$$dz_{iJ}/dt = d(1-d)\left[u_i/(1-d) - z_{iJ}\right].$$

For top-down adaptive coefficients, the following equation (steepest descent) is utilized [1], [4], [11]:

$$dz_{Ji}/dt = \left[p_i - z_{Ji}\right]d.$$

That is, the weight vector keeps track of the $F1$ activity vector p and d is the output of the winner node. Substituting for p_i in the same fashion as in the bottom-up situation will result in

$$dz_{Ji}/dt = d(1-d)\left[u_i/(1-d) - z_{Ji}\right].$$

Two kinds of learning could be distinguished in ART 2: slow and fast. In slow learning, the short "rendezvous" between an input pattern and the network during a trial does not allow sufficient LTM changes for the adaptive coefficients to reach their asymptotic values. On the other hand, in fast learning, the "rendezvous" is long enough that the adaptive coefficients can "approach new equilibrium values on every trial" as follows:

Adjust **LTM** → Adjust **STM** → Adjust **LTM** → ⋯ → **LTM** Equilibrium.

Orienting Subsystem: The orienting subsystem helps to direct the search for categories. When the orienting subsystem is activated, vector u $(u_1, \cdots, u_N)$, containing the bottom-up processed input, and vector p, containing the top-down expectation, are utilized to calculate the degree of match (vector r):

$$r_i = (u_i + cp_i)/(\|u\| + \|cp\|).$$

[1] $P_i = u_i$ if $f2$ is inactive.

If vectors $\boldsymbol{u}$ and $\boldsymbol{p}$ are similar, then $\|\boldsymbol{r}\|$ will be close to one (e.g., a value of one being a perfect match). Thus, the reset rule for the orienting subsystem is as follows.

IF $\|\boldsymbol{r}\| < \rho$ (ρ is the match sensitivity parameter or vigilance factor)

THEN reset the winning $F2$ node (preventing it from competing again during this trial).

IF FAST LEARNING

THEN select an uncommitted node and resonate[2]

ELSE resonate.[2]

ART 2-A ("Algorithmic" ART)

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

ART 2-A has three fields: $F0$, $F1$, and $F2$. The output of the $F1$ field, which is also the output of the $F0$ field, is the vector $\boldsymbol{I}$ defined by

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

where $\boldsymbol{I}^0$ is the input vector of dimensionality M, normal is an operator defined by

$$\textbf{normal}\ (x) = x / \|x\|,$$

and $f()$ is a piecewise linear function (see Fig. 9) with $0 < \theta \le (M)^{1/2}$.

The LTM vector in ART 2-A is scaled, and it could be interpreted as the LTM vector of ART 2 divided by $1/(1-d)$. As in ART 2, the $F2$ node ART 2-A makes a choice if the Jth node becomes maximally active. In addition, the $F2$ STM activation represents the degree of match of the vector $\boldsymbol{I}$ and the scaled LTM vector. It can be shown that ρ^* (vigilance parameter of ART 2-A) is related to the ρ of ART 2.

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:

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

where

$$\psi_i = \begin{cases} \boldsymbol{I}_i & \text{if } z_{Ji} > \theta \\ \boldsymbol{0} & \text{otherwise} \end{cases}$$

and $0 \le \beta \le 1$ (e.g., $\beta = 1$ for fast learning).

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

Analysis of Results

To evaluate the performance of the ART networks for learning and differentiating patterns N, A, B, C, and D, several tests are performed using both ART 2 and ART 2-A networks. The first test was to apply the six sets of data of 500 dimensionality each in the order of "*NAB*" as one input file. The result of this test is given in Table II. The ART 2-A network is capable of distinguishing these patterns from each other, as well as ART 2. As shown in Table II, the first two sets belonging to pattern N are assigned to category O, the two sets of pattern A are in category 1, and category 2 is assigned to the two sets of pattern B. The duration (on average) of one of these fast learning trials in ART 2-A is on the order of hundreds of milliseconds using a simulator built with the C programming language for a Macintosh IIfx running under A/UX. The fast learning sessions required only one presentation of the input data set to provide stable results. However, a second presentation was allowed. LTM traces at the end of the second presentation are plotted in Fig. 11 for test 1.

The next test was to check the effect of mixing the order of presentation of the patterns. Hence, the new file "*NBA*" was created by interchanging the order of presentation of file A with file B. As shown in Table II, the ART 2-A network (as well as ART 2) performance in distinguishing the patterns from each other is invariant to the order of presentation of the patterns in our study. It must be mentioned that in presenting the file *NBA*, the network did not use any of the LTM results of file *NAB*; hence, the categories 0, 1, and 2 of file *NBA* are independent of the categories 0, 1, and 2 of the file *NAB* trial. Next, a new file is examined called file "*NBNA*" which is created by repeating file N after present-

[2] Adjust top-down and bottom-up adaptive coefficients.

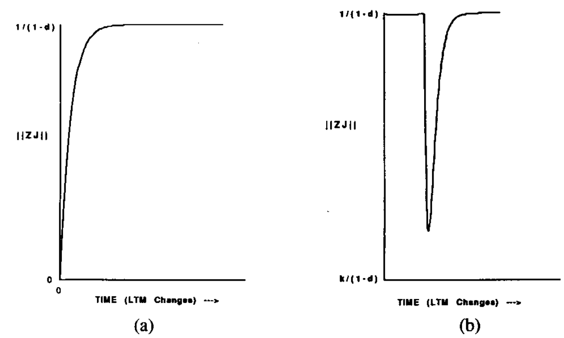


Fig. 10. Fast learning trial (set 1 of pattern N data). (a) Uncommitted node. (b) Committed node.

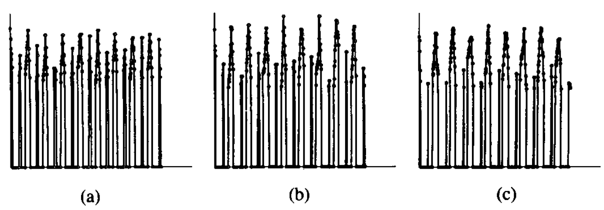


Fig. 11. LTM of categories corresponding to Test 1. (a) Pattern N. (b) Pattern A. (c) Pattern B.

TABLE II
Result of Testing Pattern Order Presentation in ART 2-A

Test	File	Category	Vigilance
1	*NAB*	001122	Medium
2	*NBA*	001122	Medium
3	*NBNA*	00110022	Medium

TABLE III
IMPACT OF VIGILANCE PARAMETER ON PATTERN CLASSIFICATION IN ART 2-A

Test	File	Category	Vigilance
4	*NBNA*	00110022	Medium
5	*NBNA*	01230145	High
6	*NAB*	012345	High
7	*NAB*	000000	Low

ing file *B*. The result shows that neither network (ART 2-A or ART 2) is disturbed by the new pattern *N* being repeated, and appropriate categories are established as given in Table II.

The vigilance parameter (ρ) sets the criterion for matching by controlling the activation of the orienting subsystem. Under the exact same conditions, lower vigilance leads to coarser categories and higher vigilance to finer categories. Table III shows the result of the impact of the vigilance parameter on the sensitivity of the pattern matching of the ART 2-A network. A high vigilance resulted in six categories, one for each set of input data. A low vigilance, on the other hand, assigned all of the patterns into one category, and a proper medium vigilance resulted in appropriate pattern recognition.

To closely follow the improvement of recognition as the vigilance factor increases from a low to a high value in ART 2-A, an input file consisting of the first 500 data sets of each and every pattern *N* through *D* is created. As described in the signal description section, pattern *D* corresponds to the first level of degradation, and patterns *A*, *B*, and *C* to the second, third, and fourth levels, respectively. The result of this test is given in Table IV. As vigilance is increased, the first pattern distinguished is the fourth-level degradation *C*, then third-level *B*, and finally, patterns *D* and *A* together (*D* and *A* are more closely related than *D* and *N*) before all patterns are distinguished from each other at increased vigilance.

The next run, shown in Table V, was for evaluating the performance of ART 2-A in recognizing the learned patterns. Two files *NAB* and *NBNA* were created by adding random noise, as well as fragmenting the first 25 s of data sets for patterns *N*, *A*, and *B*. These files were used as input to an ART 2-A simulator which uses the learned LTM's and bypasses the learning process. The result, as shown in Table V, again indicates the fine performance of this network in the recognition of learned categories.

All of the tests were performed using fast learning trials. Fig. 10 illustrates one of these trials for both a committed and an uncommitted node for ART 2. For an uncommitted node, $\|Z_J\|$ goes from a small value (in this plot, the initial values are obtained from z_{Ji}) to $1/(1-d)$. For a committed node which has accepted a new pattern, $\|Z_J\|$ starts from $1/(1-d)$ at the beginning with decreasing behavior, and asymptotically goes to $1/(1-d)$ at the end. This behavior indicates that previous encoded features of relatively low importance and not present in the current input pattern are being suppressed, and features which are significant to the category and the input pattern are reinforced. On the other hand, ART 2-A fast learning, which uses algebraic equa-

TABLE IV
RESULT OF ART 2-A PERFORMANCE IN RECOGNIZING PATTERNS OF FILE *NDABC*

Category	Vigilance
00000	Very low
00001	Low
00012	Relatively low
01123	Low to medium
01234	Medium/high

TABLE V
RESULT OF ART 2-A PATTERN RECOGNITION TEST OF LEARNED PATTERNS

File	Category	Vigilance
NAB	001122	0.0
NBNA	00110022	0.0

tions, converges in a single iteration. This accelerated process does not preclude ART 2-A from the development of stable categories, typically in one presentation (see Fig. 11).

CONCLUSION

This study is by no means a comparison between ART 2-A and ART 2; rather, it is a feasibility study for the application of self-organizing networks to nuclear reactor sensor signals for the purpose of monitoring reactor components. The result of this work shows that, indeed, the ART networks are capable of pattern recognition and detection of fault and abnormality in a reactor sensor signal.

In conclusion, the fast training characteristic of ART 2-A is necessary for real-time learning, and is essential for our problem due to high-dimensional input patterns. An unsupervised network is desirable in order to avoid relying on a teacher based on theoretical or laboratory results on equipment qualification tests which do not represent the exact condition and true harsh environment existing in a nuclear reactor. Reactor surveillance requires systems capable of broadening their horizon to evolve and cope with new information/situations. ART networks provide an example of such a mechanism (as a difference from other techniques such as knowledge-based systems).

Our final implementation calls for a combination of unsupervised/supervised hierarchy. The first level of this hierarchy should have real-time learning, degradation detection capabilities, and ability in qualitative classification. The second level of the hierarchy is composed of several specialized supervised elements yielding a quantitative measure of the wear. This quantitative measure will be based on our previous studies on wear measure parameters (17) using ARMA as a teacher! Finally, the third level, based on an established database, will forecast the progress of the wear. In addition, this design supports effective human–machine interfaces by providing a starting point and direction in fault diagnosis through the hierarchy of the various levels of sensitivity for recognition and classification. Therefore, the feasibility study in this paper encompasses the kind of tasks required for the first level.

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