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NUCLEAR POWER PLANT DIAGNOSTICS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In this work, the nuclear power plant operating status recognition issue is investigated using artificial neural networks (ANNs). The objective is to train an ANN to classify nuclear power plant accident conditions and to assess the potential of future work in the area of plant diagnostics with ANNs. To this end, an ANN was trained to recognize normal operating conditions as well as potentially unsafe conditions based on nuclear power plant training simulator generated accident scenarios. These scenarios include; hot and cold leg loss of coolant, control rod ejection, loss of offsite power, main steam line break, main feedwater line break and steam generator tube leak accidents. Findings show that ANNs can be used to diagnose and classify nuclear power plant conditions with good results.

INTRODUCTION

Nuclear electric power generating stations require careful monitoring. Corrective actions must be applied whenever a potentially unsafe plant condition occurs or is anticipated. The diagnoses of these conditions must therefore be quick and accurate. The objective of the nuclear power plant diagnostic advisor described herein is to provide plant condition diagnoses in sufficient time to allow plant operators to confirm and perform corrective actions. The effort required for this objective becomes more difficult when degraded monitoring systems give noisy, incomplete or intermittent data. Moreover, many of the potentially unsafe conditions which need to be recognized have never actually occurred and therefore cannot be fully anticipated. These unsafe scenarios which have not been anticipated or simulated beforehand must be recognized as such.

Steps toward the exploitation of the generalization characteristics of neural networks with respect to the difficulties discussed above would be a significant contribution to nuclear plant safety and was therefore investigated. This paper describes the results of an inquiry into the application of ANNs to nuclear power plant fault diagnoses for nuclear power plants.

NETWORK AND NODAL ARCHITECTURES

The ANNs used here incorporate layered continuous perceptrons and a self-optimizing stochastic learning algorithm[1]. A brief review of this algorithm is given below.

A mapping, M_{I+1} which may be continuous or discrete, such that

$$M_{I+1}(X_{1,n}) = X_{I+1,n} \tag{1}$$

is modeled by a network of layered nodes as shown in Figure 1, where

$$X_{1,n} = (x_{1,1,n}, x_{1,2,n}, \ldots, x_{1,J(1),n})^T \tag{2}$$

is the input vector and

$$X_{I+1,n} = (x_{I+1,1,n}, x_{I+1,2,n}, \ldots, x_{I+1,J(I+1),n})^T \tag{3}$$

is the output vector, which corresponds to the output of the I'th layer of active (hidden or output) nodes, and J(1) and J(I+1) are the dimensions of the input and output vectors respectively. Note that the input nodes are inactive in that their input is equal to their output. Also, note that n is the training set exemplar (input-output pattern) number. Each active node has the following generalized input-output relation,

$$x_{i,j,n} = k1_{i,j} \cdot \{ (1/\pi) \cdot \arctan(g1_{i,j} \cdot \sum_{k=1}^{K} w_{i,j,k} \cdot x_{i-1,k,n} + b1_{i,j}) + 1/2 \}. \tag{4}$$

The trainable parameter sets are $\{b1_{i,j}\}$, $\{g1_{i,j}\}$, $\{k1_{i,j}\}$ and $\{w_{i,j,k}\}$. The artificial neurons used here are more general than those used in the backpropagation paradigm[2] in that the nodal bias $\{b1_{i,j}\}$, gain $\{g1_{i,j}\}$, activation constant $\{k1_{i,j}\}$ as well as the usual interconnection weights $\{w_{i,j,k}\}$ are trainable. Not only do these nodes have more trainable parameters, but they also use the arctangent rather than the usual sigmoid function.

The error cost function, over which the trainable parameter sets are optimized, has the form,

$$c(W) = (\sum_{n=1}^{N} \cdot \sum_{j=1}^{J(I+1)} (\Omega_{I+1,j,n} - x_{I+1,j,n})^2 / NJ(I+1))^{1/2} \tag{5}$$

Where N is the number of training exemplars in the training set, $\{\Omega_1, \Omega_{I+1}\}$. Note that $\{\Omega_1\}$ is a subset of all possible inputs $\{X_1\}$, and $\{\Omega_{I+1}\}$ is a subset of all correct or desired outputs $\{XD_{I+1}\}$ associated with $\{X_1\}$. The challenge is to reconstruct or approximate the desired mapping Z_{I+1}, such that,

$$XD_{I+1} = Z_{I+1}(X_1), \tag{6}$$

from $\{\Omega_1, \Omega_{I+1}\}$. There are, however, many solutions M_{I+1}, which satisfy the training set

$$\Omega_{I+1} = M_{I+1}(\Omega_1), \tag{7}$$

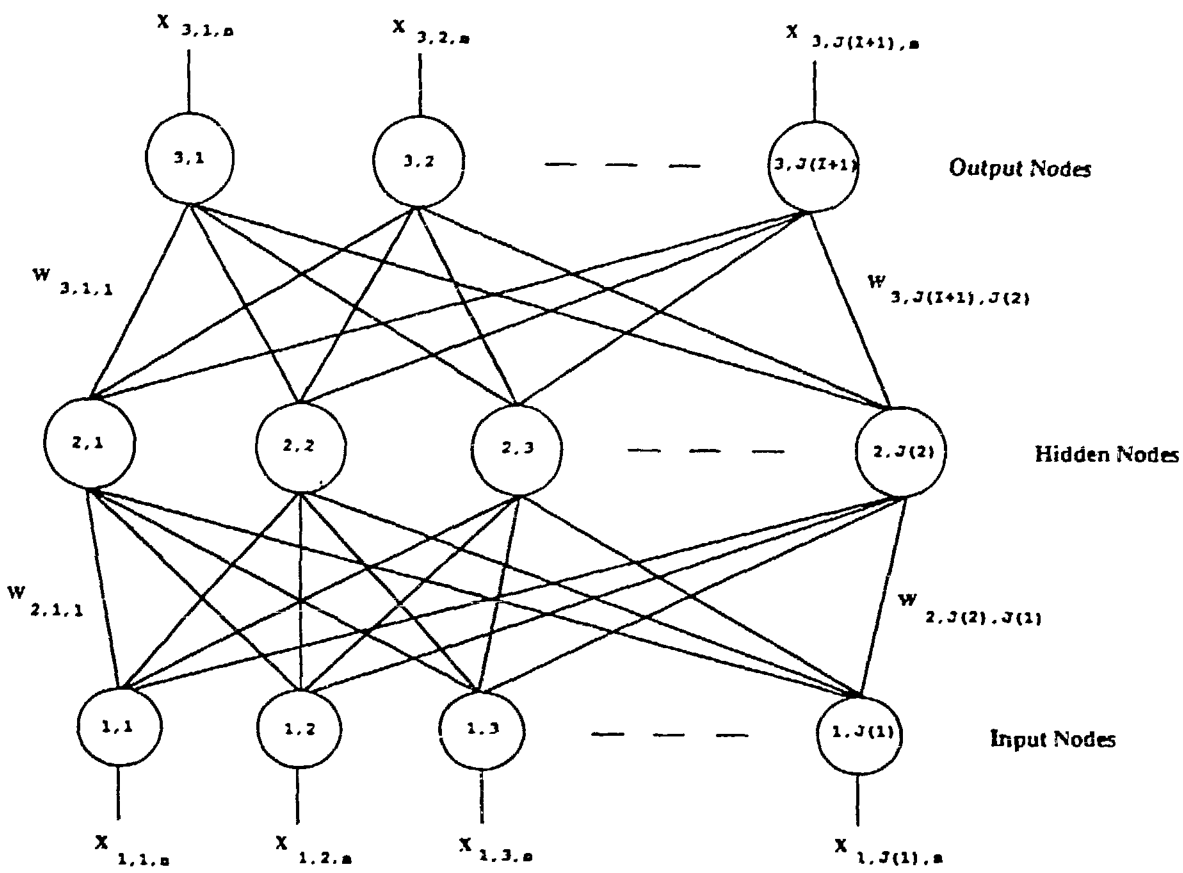

Figure 1. An Example network showing input, hidden and output nodes, as well as the indexing notation for the nodes, activations and weights. Note that I = 2 in this example.

none of which are necessarily the desired solution

$$\Omega_{l+1} = Z_{l+1}(\Omega_l). \tag{8}$$

An outline of the training method is given in Figure 2. The key to the nodal optimization is step 4, where the challenge is to determine the best way to adapt the selection criteria so that the result is an increased probability of a successful selection at future times. Once the optimization problem is posed in integral form, the stochastic evaluation of integrals procedure[3] is used towards its solution. The theory of Monte Carlo importance function biasing [4] then provides the optimal probability density function from which to select future estimates of the changes in the parameters being optimized.

The key to the dynamic node architecture (DNA) approach is steps 7 and 8. This can be seen if it is realized that the network training procedure should seek to minimize both c(W) and the number of nodes[5,6,7]. The DNA approach can be achieved as follows. Start the network with only a few nodes. Since the network is most likely too small to learn the desired mapping, add nodes until the network learns the training set to the desired accuracy. Once this is achieved eliminate a node which has near-zero nodal importance and retrain if necessary.

1. Make two initial random parameter set guesses and evaluate c(W) for each;
2. Store the best parameter set, discard the parameter set with the largest c(W);
3. Make a small random change to each member of a parameter set and evaluate the cost function at this new time step, $c^{t+1}(W)$. if $c^{t+1}(W) < c^t(W)$ continue to 4, if not, go to 2;
4. change the parameter selection criteria based on information gained during step 3;
5. Apply the same, successful, parameter changes again. If $c^{t+1}(W) < c^t(W)$ go to 5, repeat a fixed number of times, if not, go to step 2 or 6;
6. Apply the algorithm, 1 through 5, in turn to each adaptable parameter set, $\{b1_{i,j}\}$, $\{g1_{i,j}\}$, $\{k1_{i,j}\}$, and $\{w_{i,j,k}\}$;
7. If the network learning is slow, expand the network architecture by adding a node to the most important layer;
8. If the total cost is acceptable, such that $c^t(W) < \varepsilon$ for some desired ε, then reduce the network size by deleting the least important node;
9. If the network structure oscillates about a fixed architecture stop, otherwise go to 2.

Figure 2. An outline of the network training paradigm

METHOD OF SOLUTION

As a first step toward the realization of the objectives stated in the introduction of thi paper, the following approach was taken: An artificial neural network was taught to recognize seven accident scenarios plus the normal full power steady state operating condition using plant training simulator data from the Watts Bar Nuclear Power Station[8,9]. The accidents analyzed and their 3-bit training codes are given in Table 1. The variables used for network input are presented in Table 2. The data set for each scenario contains 27 plant process variables at intervals of 1/2 second for at least 250 seconds. Within each data set the accident condition is preceded by a period of normal full power operation. The challenge is to use the artificial neural network described above to recognize and distinguish each of the eight plant conditions based on the given data. Approximately 350 single time steps of data were used to train all eight of the conditions analyzed. The data time points were chosen in an iterative fashion. The first step was to train the network to distinguish the steady state shutdown conditions which occur after each accident scenario. Then the network is recalled on each scenario for the entire start to finish time period. Data is added to the training set for each scenario where the network was in error and the ANN was retrained to improve its performance.

TABLE I

Desired Network Output Layer Activation, Time of Start of Transient and Reactor SCRAM Time for Each of the Trained Scenarios.

Plant Condition	Desired Output Node Activation 1	2	3	Transient Start Time(sec)	Reactor SCRAM Time(sec)
Total Loss of Offsite Power	1	1	1	20.58	29.58
Main Feedwater Line Break	1	1	0	32.92	48.42
Main Steam Line Break	1	0	1	46.83	57.83
Control Rod Ejection	1	0	0	30.08	74.08
Hot Leg Loss of Coolant	0	1	1	15.58	19.58
Cold Leg Loss of Coolant	0	1	0	14.58	19.08
Steam Generator Tube Leak	0	0	1	31.58	411.08
Normal Operation	0	0	0	-	-

TABLE II
Plant Variables Used as Input to the Diagnostic Network

Variable Number	Description
1	Control rod shutdown bank position
2	Nuclear power level
3	Plant megawatt output
4	Volume control tank level
5	Reactor building equipment drain level
6	Containment pressure
7	Flux axial offset
8	Steam generator steam flow
9	Steam generator main steam pressure
10	Steam generator feed water inlet flow
11	Steam generator feed water pressure
12	Steam generator auxiliary feed water flow
13	Steam generator water level
14	Pressurizer water level
15	Pressurizer pressure
16	Pressurizer surge line temperature
17	Reactor coolant system loop spray temperature
18	Reactor coolant system hot-leg pressure
19	Reactor coolant system cold-leg temperature
20	Reactor coolant system hot-leg temperature
21	Reactor coolant system average temperature
22	Reactor coolant system loop coolant flow
23	Reactor coolant system loop delta temperature
24	Steam generator building liquid sample monitor
25	Containment liquid effluent radiation monitor
26	Containment building lower compartment radiation monitor
27	Containment building upper compartment radiation monitor

RESULTS

Figures 3 and 4 show typical results. Three lines on these figures show the activations of each output node of the network. The fourth line on each graph has binary values and shows the correct, or desired, output for each active node. This line, and the associated start of transient time, can be identified by the right angle bend near the upper lefthand corner of the graph. Note also that the reactor automatic SCRAM times are indicated on each graph by an "x" on the time axis. No operator action is assumed during the scenarios. Table 3 summarizes the results for all seven of the accident conditions analyzed. The 2% noise cases include pseudo-Gaussian noise with a standard deviation of 2% of the actual variable value added to all of the network inputs.

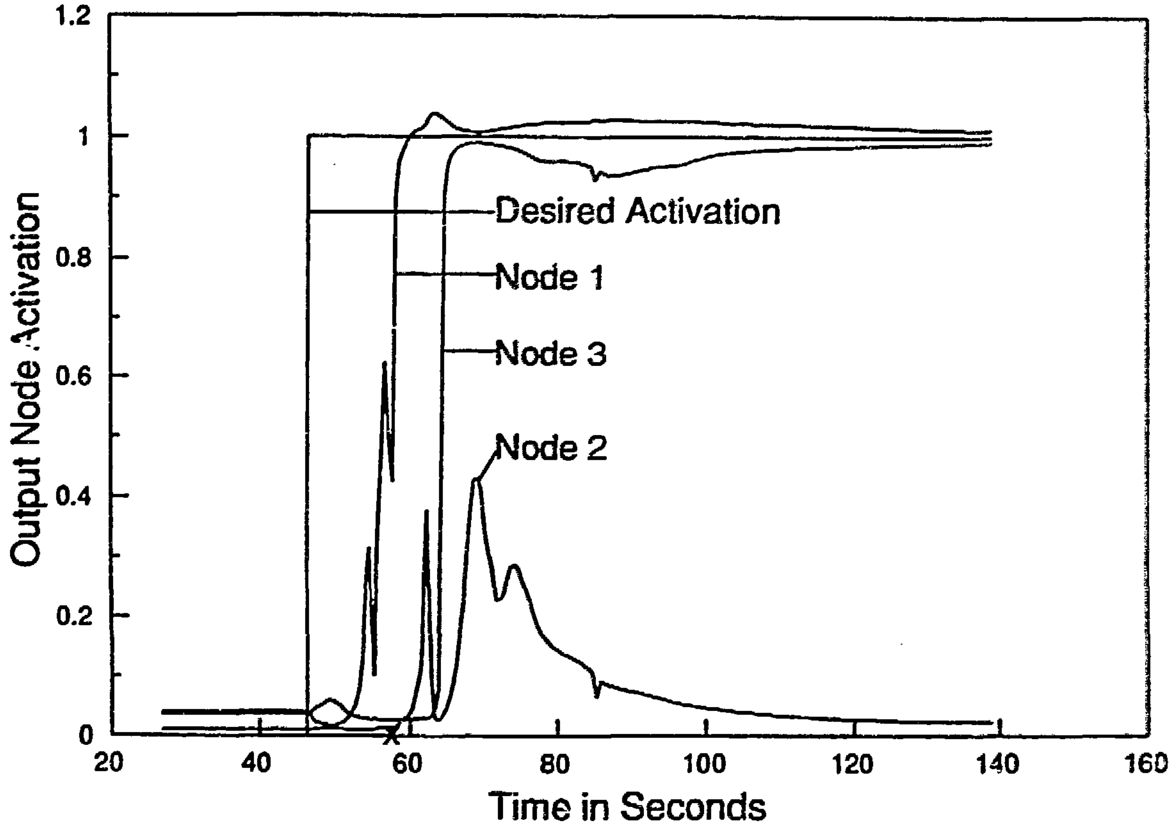

Figure 3. Activation of the network output layer as a function of time in response to the main steam line break accident scenario. The desired response is (1,0,1). No noise is added.

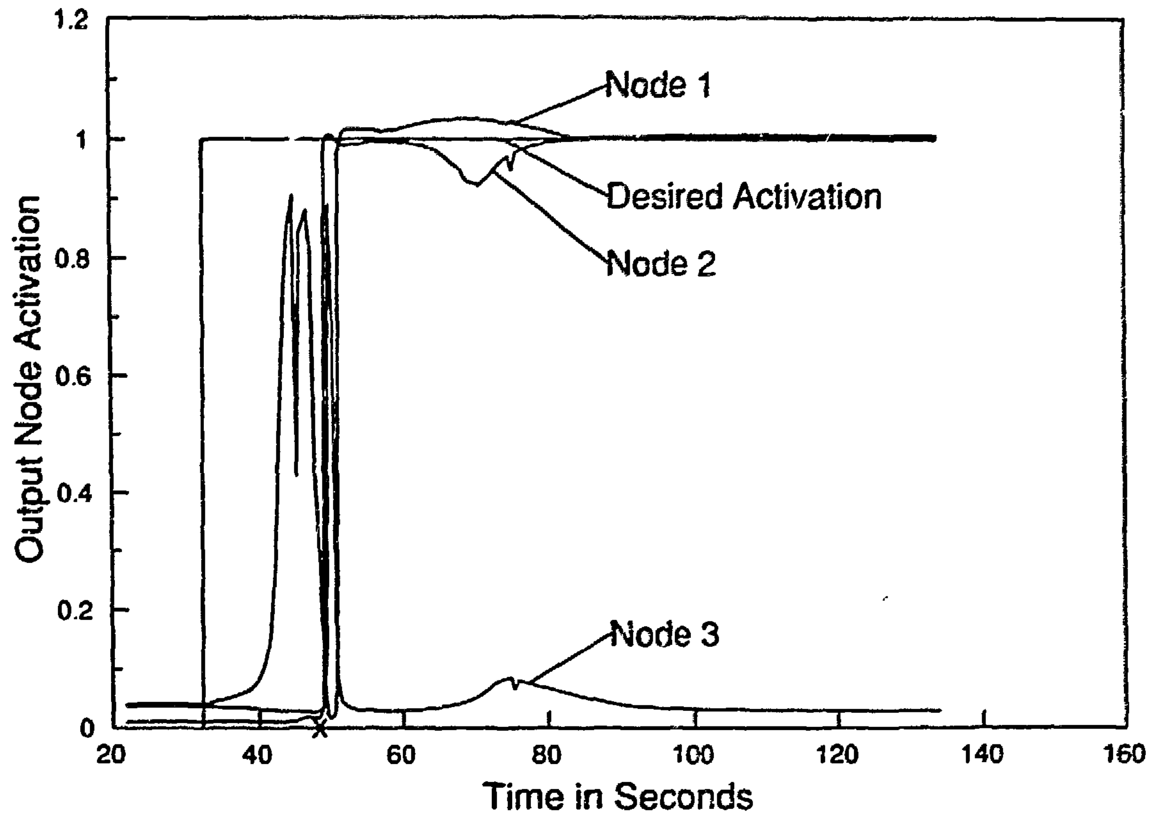

Figure 4. Activation of the network output layer as a function of time in response to the main feedwater line break accident scenario. The desired response is (1,1,0). No noise is added.

TABLE III
Time From Start of Accident to Transient Recognition and Reactor SCRAM for Each of the Trained Scenarios.

Plant Condition	Time to Diagnose Transient (sec)		Time to Reactor SCRAM (sec)
	No-Noise	2% Noise	
Total Loss of Offsite Power	6.5	5.5	9.0
Main Feedwater Line Break	18.5	62.0	15.5
Main Steam Line Break	29.0	66.0	11.0
Control Rod Ejection	20.0	19.0	44.0
Hot Leg Loss of Coolant Accident	29.0	47.5	4.0
Cold Leg Loss of Coolant Accident	19.5	37.5	4.5
Steam Generator Tube Leak	86.0	113.0	379.5

CONCLUSIONS

Artificial neural network techniques are shown to be a potentially serviceable methodology with respect to nuclear power plant accident diagnostics. The feasibility of using artificial neural network technology as a diagnostic tool for nuclear power plant safety is therefore demonstrated.

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