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Use of neural networks to identify transient operating conditions in nuclear power plants

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ABSTRACT

A technique using neural networks as a means of diagnosing specific abnormal conditions or problems in nuclear power plants is investigated and found to be feasible. The technique is based on the fact that each physical state of the plant can be represented by a unique pattern of instrument readings, which can be related to the condition of the plant. Neural networks are used to relate this pattern to the fault or problem.

1. INTRODUCTION

In the operation of a nuclear power plant, great quantities of numeric, symbolic, and quantitative information are handled by the reactor operators even during routine operation. The sheer magnitude of the number of process parameters and systems interactions poses difficulties for the operators, particularly during abnormal or emergency situations. Recovery from an upset situation depends upon the facility with which available raw data can be converted into and assimilated as meaningful knowledge. In operating a nuclear power plant, people are sometimes affected by stress and emotion that may have varying degrees of influence on their performance. Taking some of the uncertainty and guesswork out of their decisions by providing expert advice in the form of real-time diagnostics has the potential to increase plant availability, reliability, and safety by avoiding errors that lead to trips or power reductions. The emerging technology of neural networks offers a method of implementing real-time diagnostics in a nuclear power plant.

2. STATE OF THE PLANT

When a nuclear power plant is operating safely, the readings of the hundreds, or even thousands, of instruments in a typical control room form a pattern (or unique set) of readings that represent a "safe" state of the plant. When a disturbance occurs, the instrument readings form a different pattern that represents a different state that may be safe or unsafe, depending upon the nature of the disturbance. The fact that the pattern of instrument readings is different for every given condition is sufficient to provide a basis for identifying the state of the plant at any given time. It requires a rapid (real-time), efficient method of "pattern recognition" to implement a diagnostic tool based on this principle that is useful in the operation of nuclear power plants.

3. NETWORKS OF ARTIFICIAL NEURONS3.1 General characteristics

In the past few years, networks of adaptive, artificial neurons--a concept involving a non-algorithmic approach to information processing that was deemphasized a decade ago--has had a resurgence because of advances in the technology. The Japanese highlighted neural networks systems (sometimes called connectionist systems or neurocomputers) in their recently announced "Sixth Generation" computer development program. In certain applications, such as pattern recognition, neural networks have performed very well (e.g., they have been used to read both handwriting and Japanese Kanji characters--tasks that conventional computers and expert systems perform poorly). Applying this technology to diagnostics in nuclear power plants is one of the topics being investigated by the authors for the U.S. Department of Energy.¹

In its most elementary form a neural network consists of groups of nodes (sometimes called artificial neurons, processing elements, or neurides) arranged in three or more layers in which the output of each of the nodes in a given layer serves as input to each of the nodes in the next higher layer. Each of the inputs to a node is adjusted by a weighting factor or coefficient that can be varied to help adjust the output of the network to match the desired output. The node sums the weighted inputs and passes the result through a nonlinear filtering system that is characterized by an internal threshold or offset and by the type of nonlinearity used (usually a sigmoidal logic element) to nodes in the next higher layer.

Neural networks are specified by the network arrangement, the node characteristics (sometimes called its transfer function), and the learning rules that determine how the adaptive coefficients are adjusted to match the neural network model with the actual system. Since the inputs and weights (adaptive coefficients) change

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over time, the network adapts and learns. Each node is completely self-sufficient and operates independently of all other nodes. However, the operation of each node affects the behavior of the entire network since each node's output becomes the input to many other nodes.

3.2 Supervised training

One method by which a neural network learns how to process information is by being given supervised training while it runs through a series of trial-and-error exercises. In supervised training, the network is supplied with both the input and the desired output, the network output is compared with the desired output, and its coefficients are adjusted to improve performance (i.e., minimize error). The adjustment is based on the learning laws built into the network (e.g., least mean square errors). The iterative process continues until a predetermined level of performance is reached.

3.3 Features of neural networks

Neural networks may be designed so as to classify an input pattern as one of several predefined type (e.g., the various fault states of a power plant) or to create, as needed, categories or classes of system states that can be interpreted by a human operator. Such neural networks have demonstrated high performance even when presented with noisy, sparse, and incomplete data.

A second desirable feature of neural networks is their ability to respond in real-time to the changing system state descriptions provided by continuous sensor input. For complex systems involving many sensors and possible fault types (such as nuclear power plants), real-time response is a challenge to both human operators and expert systems. The inherent parallelism of neural networks makes real-time processing of data and information feasible. After neural networks have been trained to recognize the types of different sensor output patterns that give rise to different system states or faults, only one computer cycle is required to detect a specific state or condition.

Neural networks have the ability to recognize patterns, even when the information making up these patterns is noisy or incomplete. Unlike most computer programs, neural network implementations in hardware are very fault tolerant (i.e., neural network systems can operate even when some individual nodes in the network are destroyed). The reduction in system performance is about proportional to the amount of the network damaged. Thus, systems of adaptive, artificial neural networks have high promise for use in environments in which robust, fault-tolerant pattern recognition is necessary in a real-time mode, and in which the incoming data may be distorted or noisy. This makes adaptive neural networks ideally suited as a candidate for fault monitoring and diagnosis, control, and risk evaluation in nuclear power plant environments.

4. APPLICATION TO IDENTIFICATION OF STEAM GENERATOR TRANSIENTS

Identification of transients in a steam generator has been chosen to demonstrate the ability of a neural network to diagnose specific abnormal conditions in a nuclear power plant. The dynamic behavior of the steam generator is an important factor in the operation of a PWR nuclear power plant. This is because the steam generator acts as the thermal coupling between the reactor and the turbine. Also, the steam generators serve as a steam reservoir which can supply or store extra steam during sudden power demand changes or transients.

For demonstration purposes, a set of data from a simulation of an isolated U-tube steam generator (UTSG) was used as the training data for the network. The operating status of a steam generator can be represented by values such as pressure, temperature, steam flow, and feedwater flow. If these quantities are used as the training data for a neural network, they can be categorized to represent the system states by the neural network. After training, the neural network can accept signals from an actual steam generator to monitor the status of the system. A back-propagation neural network is used for training and recall (monitoring) in this example.

The simulation of the UTSG used is a linear model with 7 state variables (15 lumps and 2 input variables from the controller) developed by Ali² and Kerlin and Katz³ using the software package Matrix-X. Although such a simulation does not precisely simulate a real UTSG, the main purpose here is to verify that a back-propagation neural network can be used for identification of the transients.

4.1 Getting data from the simulator

Six step change perturbations were introduced to the system:

1. Positive and negative step changes in primary inlet temperature,
2. Positive and negative step changes in feedwater temperature, and
3. Positive and negative step changes in the valve coefficient (percentage of the full-open position).

Four state variables were chosen as the system responses to reflect the system behaviors for each perturbation:

1. primary inlet temperature,
2. primary outlet temperature,
3. downcomer water level, and
4. steam pressure.

The plots of these four quantities for the perturbations of $+5.56^{\circ}\text{C}$ ($+10^{\circ}\text{F}$) step change in primary inlet temperature, $+5.56^{\circ}\text{C}$ ($+10^{\circ}\text{F}$) in feedwater temperature, and $+10\%$ in the valve opening coefficient are shown in Fig. 1. It is readily seen that the patterns are different for the three different perturbations. The steam pressure, for example, goes up for a positive perturbation of primary inlet temperature and goes down for a positive perturbation of steam valve coefficient. Similar characteristic changes are apparent from a comparison of the behavior of the four chosen UTSG variables. Since the back-propagation network can be trained to distinguish the different input patterns, it can distinguish between the different kinds of steam generator perturbations.

The four response curves for the three positive 5.56°C (10°F) and 10% perturbations of Fig. 1 and similar response curves for three negative 5.56°C (10°F) and 10% perturbations constitute the input pattern for training the back-propagation neural network. Ten samples were taken at 10-s intervals for each of the 4 variables (a total of 40 samples) from the response curves of the 6 simulations, digitized, and used as inputs to the neural network. The desired outputs for training of the network, defined by 3-bit binary quantities representing the output states caused by the 6 perturbations, are listed in Table 1.

4.2 The Back-Propagation Neural Network

A back-propagation neural network has three or more layers in which a number of process elements (PEs) in a layer are fully connected with other PEs in the next higher layer. It employs an error-correction encoding law and supervised learning for storing pattern pairs (a_i, b_i) , where a_i is a component of the n -dimension input vector and b_i is a component of the m -dimension desired output vector.

Figure 1. Response curves from the simulation for positive 5.56°C (10°F) and 10% perturbations.

Table 1. Desired outputs used for training neural network

Output state	Corresponding perturbation
1 0 0	Positive perturbation in primary inlet temp.
0 1 0	Positive perturbation in feedwater temp.
0 0 1	Positive perturbation in valve coefficient
1 1 0	Negative perturbation in primary inlet temp.
0 1 1	Negative perturbation in feedwater temp.
1 0 1	Negative perturbation in valve coefficient

In this study, a three-layer back-propagation network is set up with 40 PEs in the input layer and 3 PEs in the output layer to match the dimensions of the training input and output vectors. The middle layer consisted of 12 PEs because it appeared to represent a reasonable compromise between ease of training and precision. The architecture of the network is shown schematically in Fig. 2.

4.3 Encoding of the data

The data for the perturbations of $\pm 5.56^{\circ}\text{C}$ ($\pm 10^{\circ}\text{F}$) in primary inlet temperature, $\pm 5.56^{\circ}\text{C}$ ($\pm 10^{\circ}\text{F}$) in feedwater water temperature, and $\pm 10\%$ in valve opening coefficient are used as six sets of training data for the network. The data were normalized to unity by dividing by the largest value before putting them into the neural network to satisfy the requirement of the input form of the neural network used.

After 1000 data training cycles (which may take from a few seconds to a few hours, depending upon the computer hardware and software), the network could distinguish the six different perturbations successfully. When the same data as for training are presented to the network, the recall results are shown in Table 2.

Responses of the UTSG for ± 5 , ± 15 , and $\pm 20\%$ and ± 2.78 , ± 8.33 , and $\pm 11.11^{\circ}\text{C}$ were then generated by the simulation model, sampled, digitized, and applied to the neural network in the same manner as before. The network also recognized all six different kinds of perturbations at the 2.8, 8.4 and 11.1 $^{\circ}\text{C}$ and 5, 15, and 20% levels even though it had been trained only with 10% perturbations. Artificial random noise with a uniform distribution and an amplitude up to $\pm 90\%$ of the input data was introduced into the trained network, and the recall results presented in Table 3 show that the network can still identify the UTSG transient correctly. Table 4 shows just how badly the input was distorted by noise having 90% of the amplitude of the input; yet, the neural network readily identified the transient.

Figure 2. Schematic diagram of the neural network.

Table 2. Comparison of network recall output with desired results after 1000 training cycles (no noise in the input data)

Desired Result			Recall result		
1	0	0	0.962	0.003	0.058
0	1	0	0.047	0.964	0.001
0	0	1	0.022	0.054	0.949
1	1	0	0.941	0.966	0.057
0	1	1	0.043	0.956	0.998
1	0	1	0.998	0.040	0.936

Table 3. Comparison of network recall output with desired results after 1000 training cycles (uniformly distributed noise--amplitude equal $\pm 90\%$ of input data amplitude)

Desired Result			Recall result		
1	0	0	0.946	0.004	0.052
0	1	0	0.060	0.958	0.002
0	0	1	0.083	0.126	0.800
1	1	0	0.941	0.970	0.060
0	1	1	0.054	0.952	0.998
1	0	1	0.998	0.050	0.946

Table 4. Distortion produced in the input primary inlet temperature signal by uniformly distributed noise having an amplitude equal to $\pm 90\%$ of the amplitude of the input signal

Time (s)	Input signal without noise	input signal with 90% noise
0.5	10.00	16.65
1.5	10.00	11.12
2.5	10.00	3.88
3.5	10.00	11.01
4.5	10.00	2.64
5.5	10.00	6.45
6.5	10.00	4.10
7.5	10.00	18.33
8.5	10.00	5.89
9.5	10.00	7.73

Although the neural network was able to diagnose the cause of the transient and whether it is a positive or negative perturbation, it could not determine the size of the perturbation. This is because the magnitude of the output of a simulation using a linear model will be proportional to the amplitude of the input perturbation. Hence, the input data to the neural network for different amplitudes of perturbations becomes the same after normalization even though the amplitude of the perturbation is changing by a factor of 4. However, it is possible to determine the amplitude of the perturbation by comparing the magnitude of the input vector prior to normalization with the output of the neural network. In an actual UTSG that exhibits nonlinear behavior (or a nonlinear simulation of a UTSG), it should be possible to identify the magnitude of the transient if the appropriate training data are available.

5. DISCUSSION OF RESULTS AND CONCLUSIONS

The back-propagation neural network used in this project demonstrated the feasibility of using neural networks to recognize transients of a UTSG. It distinguished six different kinds of perturbations introduced into the UTSG simulator. Furthermore, it gave the correct output even though the input data had very large levels of noise.

If the signals (which come from pressure sensors, thermocouples, and water level indicators, etc. located on a UTSG in a nuclear power plant) for all the possible transient and normal operation conditions were used as training input patterns, the trained network could be utilized in the control room to monitor the behavior of the steam generator in real time. Once the data are entered in the neural network, the specific abnormal condition can be identified in a single cycle (i.e., in real time). The same method may be used for other plant components such as reactor core, pressurizer, or pumps, provided a representation of the appropriate variables is available. If neural networks monitoring each of the plant components are combined, the behavior of the whole nuclear power plant could be monitored for specific abnormal conditions. Therefore, neural networks may provide a new and powerful tool for detection and identification of specific faults or conditions in a nuclear power plant.

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