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10.3 Nuclear Power Plant Fault-Diagnosis Using Artificial Neural Networks

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NUCLEAR POWER PLANT FAULT-DIAGNOSIS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Artificial neural networks (ANNs) have been applied to various fields due to their fault and noise tolerance and generalization characteristics. As an application to nuclear engineering, we apply neural networks to the early recognition of nuclear power plant operational transients. If a transient or accident occurs, the network will advise the plant operators in a timely manner. More importantly, we investigate the ability of the network to provide a measure of the confidence level in its diagnosis. In this research an ANN is trained to diagnose the status of the San Onofre Nuclear Generation Station using data obtained from the plant's training simulator [1]. Stacked generalization is then applied to predict the error in the ANN diagnosis [2]. The data used consisted of 10 scenarios that include typical design basis accidents as well as less severe transients. The results show that the trained network is capable of diagnosing all 10 instabilities as well as providing a measure of the level of confidence in its diagnoses.

INTRODUCTION

Nuclear power plant safety is important to both the public and nuclear professionals. Early transient diagnosis can give reactor operators extra time to formulate and perform corrective actions that can prevent a transient from developing into a potentially serious accident. It is most beneficial to provide both the diagnosis and a figure of merit describing the diagnosis accuracy. Estimating the uncertainties associated with the ANN diagnoses of nuclear power plant transients is a vital step towards enhancing safety since it is unproductive for operating personel to be misled by an incorrect automated diagnosis.

ANNs have many advantages over expert systems, since expert systems require explicit rules which is a time consuming process for both programming and excecuting. However, one disadvantage of ANNs has been the relative difficulty of assigning error bounds to their outputs. This disadvantage has limited the application of ANN techniques to areas where verification is not too important or where other methods can be used as independent checks on the results.

In this work a fault diagnostic adviser was developed by training a backpropagation neural network [4] to diagnose the status of the San Onofre Nuclear

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Generating Station using data obtained from the plant's training simulator [1]. The data simulate the plant's conditions through time during 10 transients scenarios. Table 1. lists these scenarios. We then apply stacked generalization to provide a measure of the level of confidence in each transient's diagnosis performed by the ANN.

The results of our research show that the ANN fault diagnostic adviser can not only correctly diagnose each scenario but most importantly it can provide error bounds on its diagnoses. The application of stacked genralization to nuclear power plant fault diagnostics is the central contribution of this paper.

STACKED GENERALIZATION

Generalization is the ability to classify a given novel input based on its relation with known stored knowledge. Mathematical algorithms that can interpolate or extrapolate the behaviour of a given set of input-output examples are called generalizers [5,6]. Accordingly ANNs are generalizers.

Resolving the uncertainties associated with ANNs generalization is a major concern for ANN researchers [7]. Stacked generalization, however, is a technique that can be used to address this concern. There are several different ways to implement stacked generalization. When applied to a single generalizer, stacked generalization can provide estimates of classification error. In this research we use a backpropagation neural network as the single generalizer to diagnose nuclear power plant instabilities. We then apply the stacked generalization technique to predict the error associated with the diagnostic adviser output. Predicting the error of the ANN adviser is accomplished by training one network to learn the relationship between the inputs and the outputs of the desired mapping (in our case the nuclear power plant fault diagnostics). and another network is trained to learn the relationship between its inputs and the classification errors of the first network. When presented with a novel input, the first network will classify the input, while the second network will predict the error in the output of the first network.

To employ stacked generalization we begin with a collection of r partitions of the learning set L. The i-th partition P_i splits the learning set L into two disjoint subsets L_{ij}, where $1 < i < r$, and $j \epsilon \{1,2\}$. In this work, we arbitrarily chose a partition set with r = m where m is the number of patterns in the training set L [8]. Therefore, for all i, L_{i2} consists of a single pattern (x,y), the corresponding L_{i1} consists of the remainder of the training set {L-(x,y)}. Wolpert [2] defines the original learning set L as the level 0 space. Any network applied directly to L in the level 0 space is then called a level 0 generalizer, and the original learning set L is called a level 0 learning set. The level 0 generalizer is then trained on the subset {L-(x,y)} and asked the question x. The level 0 generalizer's output, g and the vector (Euclidean distance) from x to its nearest neighbor in {L-(x,y)}. k are saved. Since the level 0 generalizer has not been trained with the pair (x,y), g will, in general, differ from y. Therefore; when the question is x, the ANN answer differs from the desired output y by $(g-y)$. This information along with the question x and its vector to the nearest neighbor in the learning set can be cast as input-output in a new learning set in level 1 space. The level 1 input is the pair (x,k) and the output is $|g-y|$. Choosing other partitions of L gives other such patterns. Taken together, these patterns constitute a level 1 learning set L'. This level 1 learning set contains the relationship between the set of questions {q} and the level 0 generalizer's error in guessing the outputs correspond to the set {q}. We then train a level 1 generalizer to learn this relationship from the level 1 training set. We then ask the level 0 generalizer a novel question q, and feed the pair q and the vector from q to the nearest neighbor in L, as a question to the level 1 generalizer. The output of the level 0 generalizer will be the classification (answer) of the question q, while the output of the level 1 generalizer is an estimate of the level 0 generalizer's error in classifying the question q.

METHOD

The nuclear power plant fault diagnostic adviser developed here uses a backpropagation neural network with a 33 X 22 X 10 X 4 architecture as the level 0 generalizer. Thus, the network has 33 nodes in the input layer, 22 nodes in the first hidden layer, 10 nodes in the second hidden layer, and 4 nodes in the output layer. The 33 input nodes receive as an input a single time slice snapshot of 33 of the plant variables, and the 4 output nodes are used to distinguish each of the 10 transient conditions with a distinct 4-bit binary code. The two hidden layer architecture was employed after attempting several different architectures.

Training the ANN adviser is accomplished iteratively [3,7,9]. The initial training set contained 20 patterns, two from each transient. These two patterns were: the first pattern in each scenario, corresponding to normal operating conditions at time = 1 second, and the last pattern in each scenario, corresponding to a time when the transient is well established. Training on this data was performed until a root mean square (RMS) error of .01 was obtained. The next step in the iterative training approach is to recall the network on the entire data set for each of the 10 transients. The error obtained from the recall set is then plotted against time for each transient. Usually there are several peaks in these plots where the error is very high. These peaks correspond to patterns that the ANN incorrectly classifies because they are very different from those chosen in the initial training set. These incorrectly classified patterns are then included in the training set of the network for the next training iteration. These steps are repeated until all peaks in the recall set fell below .1 RMS error. The final training set contained 113 patterns selected from all 10 scenarios.

The final training set, obtained by the procedure outlined above, is the level 0 training set, L. The level 1 training set was composed of the level 0 input x and the vector k from x to its nearest neighbor. The level 1 desired output is the difference between the level 0 actual and desired outputs. The level 1 generalizer is another backpropagation neural network with a 66 X 30 X 20 X 10 X 4 architecture. Again, this architecture was chosen after several attempts were made to find the optimal architecture.

RESULTS

Table 1 shows that the ANN fault diagnostic adviser is capable of classifying each of the 10 transients as well as providing a measure of the confidence level in its classification. The first column in Table 1. lists the 10 transients used in this research. The second column shows the transients onset times. The third column shows the time needed for the network to make a diagnosis. The fourth column shows the additional time spent between the correct diagnosis and the instant when the confidence in the classification reaches and maintains an acceptable level. The acceptable confidence level was arbitrarily taken to be a value below .1 in the estimated error of the diagnosis.

Figures 1 and 2 are one example of the 10 pairs of plots that were obtained by diagnosing and predicting the error in the diagnoses of the 10 transients. The small peaks at early times in Figure 1 indicate that the adviser has detected an instability in the plant's conditions. After few seconds, the adviser tells us that the Stuck Open Pressurizer Safety with High Pressure Injection Inhibited transient is responsible for the instability in the plant. Figure 2 however, indicates that the level of confidence is low until 63 seconds after transient onset.

Another interesting example is the Turbine Trip From 50% Power, illustrated in Figures 3 and 4. Figure 3 shows that the ANN adviser makes a correct diagnosis of this transient after only 1 seconds. Figure 4, however, shows that the predicted error on this diagnosis is above 0.1 for the entire scenario. Although the classification of this transient is correct, the network confidence in its classification is low since the estimated error is large for the entire time period. The diagnosis of the Turbine Trip From 50% Power is unreliable even though it is correct. The network is capable of diagnosing the transient because of the generalization capabilities of ANNs but it failed to assure the diagnosis. The cause of this failure is that the data for this particular transient were collected from 50% power while the rest of the data were collected from 100% power. The level of confidence in the diagnosis of this transient can be increased by training the ANN adviser with more transients from this, lower, reactor power level.

CONCLUSION

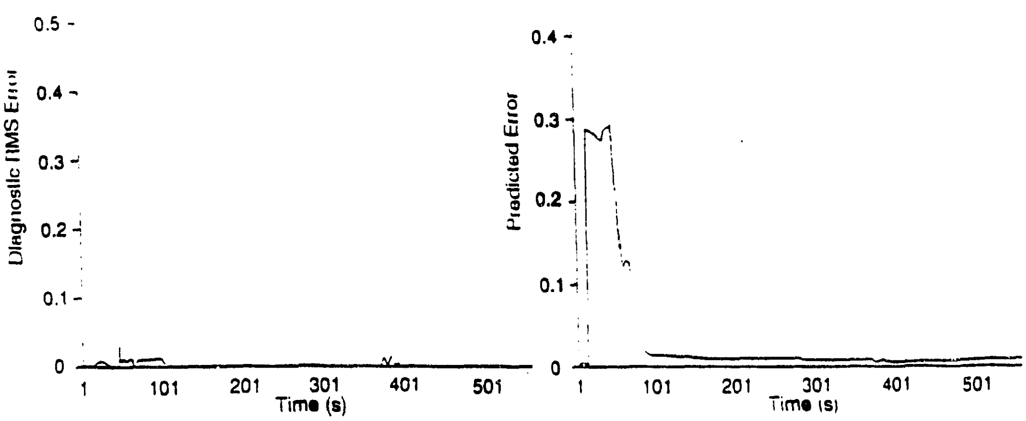
This paper has demonstrated the feasibility of using ANN technology coupled with the stacked generalization technique as a diagnostic tool for nuclear power plant transients. In this research the stacked generalization technique was used to predict the level of confidence in each diagnosis. Notice that the network, according to table 1, responds very rapidly to the changes in the plant conditions. The results of the stacked generalization agreed with what we would expect. The diagnoses of 9 of the transients was correct with a high level of confidence. While the confidence in diagnosing the Turbine Trip from 50% Power was low because of the different power level at which the transient occurred.

Future work will focus on the goal of testing a prototype ANN adviser at a nuclear power plant. This will necessitate the training and development of an integrated ANN advisor that is capable of classifying many more transients as well as providing a prediction of the errors in its results. Implementing such an adviser in a nuclear power plant will provide continuous and accurate monitoring

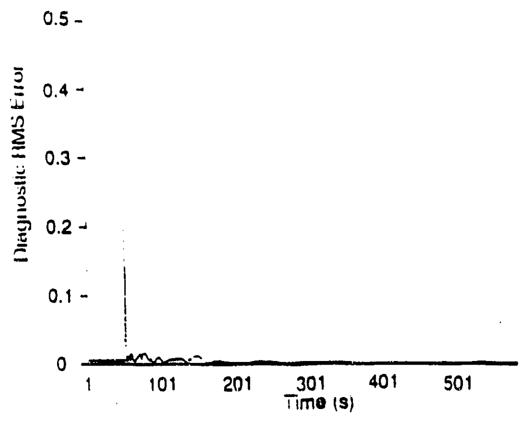
Table 1: Summary of ANN diagnostic adviser results

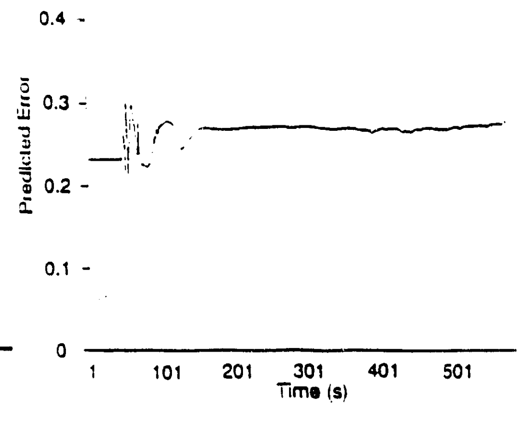
Name of transient	Transient onset time (s)	Time, after the onset, needed to diagnose the transient (s)	Additional time, after correct diagnosis, needed to assure the diagnosis (s)
1. Turbine Trip/Reactor Trip.	6	30	1
2. Loss of Main Feedwater Pumps.	47	3	0.
3. Closure of Both Main Steam Isolation Valves.	7	28	0.
4. Trip of All Reactor Coolant Pumps.	16	2	0.
5. Trip of a Single Reactor Coolant Pump.	14	62	0.
6. Turbine Trip From 50% power.	50	1	Fail to make an assured diagnosis.
7. Loss of Coolant Accident With Loss of Off-Site Power.	7	14	0.
8. Main Steam Line Break.	6	4	31
9. Stuck Open Pressurizer Safety Valve With High Pressure Injection Inhibited	15	Immediate diagnosis.	63
10.Single Turbine Governor Valve Closure.	7	16	0.

of the plant's integrity. It will also provide fast and reliable diagnosis of system instabilities and therefore will significantly enhance the safety of nuclear power plants.



Figures 1 and 2. Plots of time versus error for the level 0 generalizer (left) and time versus output for the level 1 generalizer (right) for the Stuck Open Pressurizer Safety With High Pressure Injection Inhibited transient. The predicted confidence of the level 0 generalizer's output is one minus the level 1 generalizer's output.





Figures 3 and 4. Plots of time versus error for the level 0 generalizer (left) and time versus output for the level 1 generalizer (right) for the Turbine Trip From 50% Power transient. The predicted confidence of the level 0 generalizer's output is one minus the level 1 generalizer's output.

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