Pattern Recognition Techniques for Transient Detection to Enhance Nuclear Reactors' Operational Safety

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Introduction

Nuclear power plants are highly complex systems that are operated and monitored by humans. When faced with an unplanned transient, such as a plant accident scenario, equipment failure or an external disturbance to the system, the operator has to carry out diagnostic and corrective actions. The anomalous operating conditions must be diagnosed and identified through the process' instrument readings. The sheer number of instruments can make the diagnosis process fairly difficult. The difficulty in the diagnosis process is compounded by the fact that these anomalies develop over time. Hence, depending on the severity of accident, instruments' readings might not give clear indication of an anomaly at its incipient stage. The operator's response may be too late to mitigate or minimize the negative consequences of such anomalies. The objective of this research is to develop a module based on artificial intelligence technologies that will assist the operator to identify the transients at the earliest stages of their developments. Early detection will help in minimizing or even mitigating the negative consequences of such transients. It is equally important to identify the type of transient correctly. Misidentification of transients might result in incorrect action by the operator.

Transient detection can be classified as a pattern recognition problem. When a transient occurs starting from steady state operation, instruments' readings develop a time dependent pattern. These patterns are unique with respect to the type of accident, severity of accident, and initial conditions. For example, the system's response to a Main Steam Line break will differ from its response to a loss of coolant accident. Therefore, by properly selecting the variables used by the pattern recognition system, the relevant features will be extracted from the measurements.

To tackle this problem, a number of linear and nonlinear pattern recognition techniques can be utilized. For this work, artificial neural networks will be utilized for transient identification. Their advantages are the following: adaptive learning, nonlinear generalization, faults tolerance, resistance to noisy data, and parallel processing. However, the standard pattern recognition techniques will classify any pattern to fit the closest matching pattern. However, since the neural network cannot be trained on all possible transients, it is important that it does not classify transients on which it has not been trained. Otherwise, the system will wrongly classify patterns that it does not know.

This will hinder the proper diagnosis of the problem by the operator. To overcome this problem, it was proposed by Bartal, Lin and Uhrig (1995) to use probabilistic neural networks. These networks have a parameter that will classify a pattern depending on its probability to matching a specific pattern. Hence, when a pattern has low probability of being any of the "learned" patterns, it will be classified as "Don't Know". For this work, to minimize the pitfall of false identification of transients on which the network has not been trained, a network is trained to identify each individual transient, each network has only one transient associated with it. Each network is not only trained to identify each transient, but it is also trained to reject the other transients as being that specific transient. In other words, the neural network that is trained to identify loss of coolant accidents is also trained to classify the other transients as "normal" operating condition to minimize transients' misidentification.

Prior Work on Transient Detection

The importance of transient detection and diagnosis is paramount in the nuclear power industry for the enhancement of the safe operation of reactors. For this reason, many research groups have studied the possibility of implementing on line fault diagnostic systems. A brief summary of the approaches taken by some of these groups will be summarized below. A more extensive list is provided in the reference section.

It has been demonstrated by Uhrig (1992), Bartal, et. al. (1993, 1995), and Bartlet et.al. (1991) that neural networks can be utilized for fault diagnostic in nuclear power plants. This approach has been used to detect the transient at its incipient stage. If the transient is slowly developing, this may give the operator the time to carry out corrective action prior to reactor scram. In case the transient occurs rapidly and a reactor scram takes place, then the system is still able to identify the fault to assist in reducing the time to restart the reactor. On the other hand, other systems, such as Ohga, and Seki, (1993) identify transients after the reactor scram has taken place. The purpose of the identification at this stage is for operational support. From our perspective, the identification at the incipient stage is much more useful to the operator. It also enhances the safety of reactor operation. However, the experience gained from the development of the post-scram transient diagnostic system has been valuable for the development of our system.

One major issue with use of neural networks is the uncertainty about the transient that is being identified. This problem is especially relevant when the network is exposed to a transient that it has not learned before. To overcome this problem, Ohga, and Seki (1993) have developed an expert system that compares the decision of the neural network to the actual status of the plant (including valve positions, pumps status, etc.). If the transient identified matches the patterns listed in the expert system database, the transient is confirmed. If that was not the case, then the transient identification is erroneous, and the operators do not rely on the system. The limitations of this system are that it requires a significant time to identify the transient, and the expert system database becomes very large as new configurations are added.

Cheon and Chang (1993) developed an approach that bypasses the need for an expert system. In this system, not only the state variables, such as flow rates, temperatures, and pressures, are used as inputs to the neural network, but also equipment and alarm status. Using this method, the network performs some of the work of the expert system is supposed to do. Therefore, the expected configuration of a system will also play a role in the identification of the transient. The authors found that their system is fault tolerant, in a sense that if an input signal is erroneous, or not all the data presented is proper, the system is still able to identify the transient properly. The system was also able to identify multiple transients simultaneously. This characteristic is very positive since sensors tend to be noisy and degrade with time. However, this system's performance suffers when the network is exposed to transients on which it has not been trained. This drawback is common to almost all systems because neural networks extrapolate beyond their training region poorly.

One possible method for minimizing the problem of misidentification is the use of modular networks. By using individual neural networks for each transient, the individual networks are then asked to identify if the transient to be detected fits a certain pattern without the need for the network to do extrapolation. For example, if a transient occurs, the output of each network is based on how well the pattern fits the transient it has been trained on. If the pattern fits the training data well, then the output of the network should be very close to the excepted output. On the other hand, if there is an uncertainty, then the output will not match the desired output well. Therefore, by placing very low tolerance on deviating from the expected output, only transients that could positively identified are announced and poorly defined transients would be labeled as "don't know".

Kim and Bartlet (1993) proposed the use of some mathematical techniques that will quantify the error in the network's prediction. The methods they use are based on statistical techniques

Ozaki, Suda, and Ozawa (1997) proposed a diagnosis system that is purely based on the use of expert system. The system utilizes plant alarms and configuration to diagnose a transient. This system performs identification, but not detection, after the fact that a transient has taken place. Another method proposed by Tamaoki, Sato, and Takahashi (1992) is to use sensor noise signatures to carry fault diagnostic. The limitation of such a system is that typical signatures for all abnormalities must be stored. This approach is impractical since it is impossible to obtain signatures for abnormalities for different all operating conditions. The last approach is based on the use of a model of the plant and compares the readings from the sensors to the model's prediction.

Scope of the System

The Nuclear Regulatory Commission requires that operators be able to identify about thirty-six accidents and transients. They are listed in Appendix A. We selected eight of these accident scenarios for use in this study. The selected transients are listed in Table 1.

Accident Scenarios to be Identified
MAIN FEEDWATER LINE BREAK INSIDE CONTAINMENT LEAK
MAIN FEEDWATER LINE BREAK OUTSIDE CONTAINMENT LEAK
MAIN STEAM BREAK INSIDE CONTAINMENT LEAK
MAIN STEAM BREAK OUTSIDE OF CONTAINMENT LEAK
ROD EJECTION
LOSS OF COOLANT ACCIDENT (LOCA) – HOT LEG
LOSS OF COOLANT ACCIDENT (LOCA) – COLD LEG
STEAM GENERATOR TUBE FAILURE LEAK

Table 1: List of Accidents To Be Identified using Transient Detection System

When designing a pattern recognition system, it is imperative to have data that is representative of a plant's response to all of the transients to be identified. This data was obtained from TVA's Watts Bar Nuclear Power Plant simulator. Data was collected for the eight specific accidents to be monitored. For each accident scenario, data was collected for three different levels of severity, and two power levels (100% and 50% of full power). This gave us a total of 48 transients. The sampling rate was 4 Hz., and the data was collected for a time period of steady state operation before the fault was introduced into the system. The collection process continued until a few minutes after the reactor tripped. The reading of 350 measurements were collected for all the transients.

Variables Selection

For any pattern recognition system to be successful, the pattern that it needs to identify must have distinct features that can be separable in the "feature" space. For this problem, the features are embedded in the signals that are input into the system. Therefore, it is imperative that variables that uniquely identify these transients are incorporated into the system. The variable selection process in transient detection includes identifying the signals that have the most relevant information about the specific transients. The criterion for selecting any variable is simply based on its level of response to any specific transient. For example, for the case of main steam line break, it is expected that the water level in the steam generator will change in a much more drastic manner then the change in the temperature on the primary coolant side. This is because the water level is much more related and "closer" to the event that is taking place. Therefore, all of the 350 signals that were collected for each of the transients were classified as "Significant Change", "Minor Change", and "No Change". These three categories were used in the selection process. The signals with very minor changes or no changes at all were disregarded since they did not have significant information regarding the transients. This classification of signals resulted in 65 signals that had significant and necessary information for the detection of transients. Not all of these 65 signals responded to all eight transients. Hence, the sixty-five signals were also subdivided further into eight subgroups. Each group consisted of signals that responded to each specific transient. The number of variables per group varied from eight to twenty one. Therefore, each of the transients had its own group of variables that were used for neural network training.

Transient Identification

As mentioned above, eight individual neural networks were utilized for identifying each of the eight accident scenarios. The reason for using eight networks is the added freedom in the selection of the variables. Also one large network would be difficult to train and manage. This gave us the ability to extract unique features that represent the events to be monitored. When features of events are distinguishable, then the probability of misidentification is negligible.
Each neural network was trained on data for all the simulated transients and normal conditions. It was trained to give an output of one when it is exposed to the data of a specific transient, and zero for all other transients. This guaranteed that the network has been exposed to all other transients and it will not misidentify them. The networks were trained on data representing transients at both 100% and 50% full power levels. The objective here was to allow the networks to interpolate any accident scenario that occurs at power levels other between 50% and 100% power.

The networks were able to distinguish between all the transients (Figure 1) except for the loss of coolant accidents in the hot leg and the cold leg. When the two networks were being trained on each of the transients, they were not able to reach adequate training goals. Upon reviewing the 350 signals available for each transient, it was observed that the signals were very similar. Hence, the neural networks were unable to distinguish

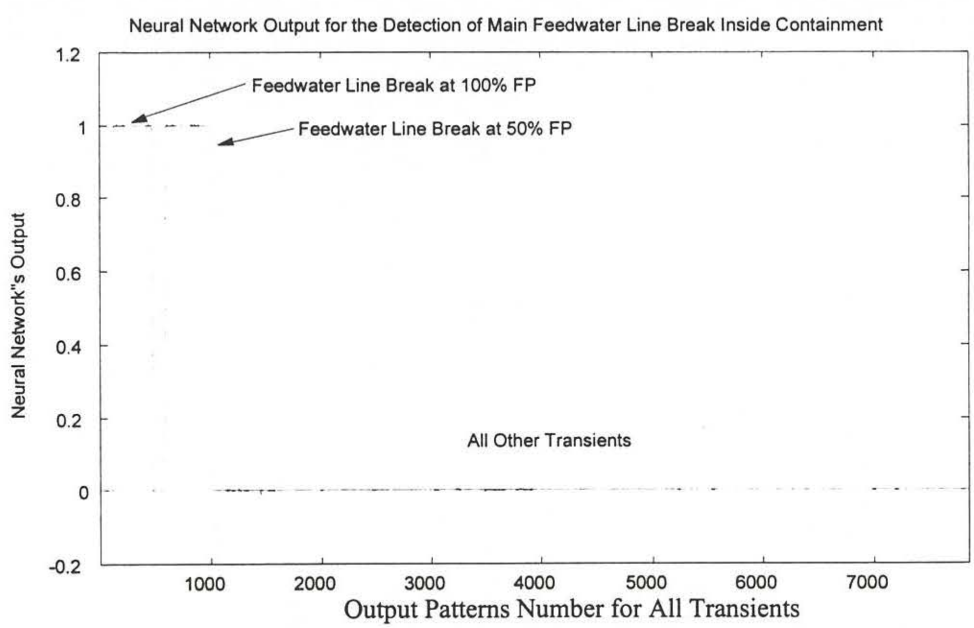

Figure 1: Neural Network Output for the Identification of Main Feedwater Line Break Inside Containment

between the two. This observation was not surprising since both events were of similar nature. Because no differentiating information was present in the collected signals, the two transients are now considered as one. The system will now identify loss of coolant accidents without reference to the fact that it is in the cold or hot leg of the primary coolant system. Figure 1 shows the output network for all the simulated transients for the network that is trained to detect main feedwater break inside containment.

Conclusion

The preliminary results are excellent. The system was able to identify six of the eight original transients robustly. The two transients that it had difficulty to distinguish in between are grouped together to be identified as loss of coolant accident without specifying the hot leg or the cold leg. By merging the two transients into one event, the system will also be able to identify them robustly as a LOCA. The system has not been tested on "unseen", or noisy data.

Future Work

There are a number of issues that still have to be investigated. The primary one has to do with the minimal severity level that this system is able to detect and how quickly. The less the severity of the accident is the less likely that the signals will develop patterns indicating accident conditions. This is due to the fact the control system will compensate small perturbations to the system. The system still has to be tested on data that it has not seen at different power levels and of different severity levels. For identifying minor transients, it might be necessary to approach the problem from a different perspective. One possibility is to look at the control system's signals because it possible to monitor changes in signals at a much lower level.

Acknowledgment

We would like to thank Ms. Kay Lovell, of TVA's Simulator Services at Watts Bar NPP, for her help and guidance, and TVA for allowing access to their simulator for data collection. We would also like to acknowledge Idaho National Engineering and Environmental Laboratory for funding this research.

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Appendix A

List of Accidents and Transients Operators are Required to Know by NRC Regulations

Feedwater system malfunctions resulting in decrease in feedwater temperature
Feedwater system malfunctions resulting in increase in feedwater flow
Steam pressure regulator malfunctions or failures resulting in increase in steam flow
Inadvertent opening of a steam generator relief or safety valve
Spectrum of steam system piping failures inside and outside of containment
Radiological consequences of main steam line failures outside of containment
Loss of external load
Turbine Trip
Loss of condenser vacuum
Steam pressure regulator failure (Closed)
Loss of non-emergency A-C power to the station auxiliaries
Loss of normal feedwater flow
Feedwater system pipe brakes inside and outside containment
Loss of forced reactor coolant flow including trip of pump and flow controller malfunctions
Reactor coolant pump rotor seizure and reactor coolant pump shaft break
Uncontrolled control rod assembly withdrawal from a subcritical or low power startup condition
Uncontrolled control rod assembly withdrawal at power
Control rod misoperation (system malfunction or operator error)
Startup of an inactive loop or recirculation loop at the incorrect temperature
Chemical and volume control system malfunction resulting in a decrease in boron concentration in the reactor coolant
Inadvertent loading and operation of a fuel assembly in an improper position
Spectrum of rod ejection accidents
Radiological consequences of a control rod ejection accident
Inadvertent operation of ECCS
Chemical and volume system malfunction that increases reactor coolant inventory
Inadvertent opening of pressurizer relief valve
Failure of small lines carrying primary coolant outside containment
Radiological consequences of steam generator tube failure
Loss-of-coolant accidents resulting from spectrum of postulated piping breaks within reactor coolant pressure boundary
Radiological consequences of a design basis loss-of-coolant accident: Containment leakage contribution
Radiological consequences of a design basis loss-of-coolant accident: leakage from engineered safety features components outside containment
Postulated radioactive releases due to liquid-containing tank failures
Radiological consequences of fuel handling accidents
Spent fuel cask drop accidents
Anticipated transients without scram (ATWS)
Radiological consequences of an ATWS event