An American Nuclear Society International Topical Meeting

CONF-950914--11

SAFETY OF OPERATING REACTORS

PROCEEDINGS

September 17-20, 1995

Hyatt Regency • Seattle (Bellevue), Washington

FG03-92ER75838

DISCLAIMER

CONF-950914--11

USE OF ARTIFICIAL INTELLIGENCE IN SEVERE ACCIDENT DIAGNOSIS FOR PWRS

Zheng Wu
University of California, Los Angeles
BOX 951597, 48-121 Eng IV Bldg
Los Angeles, CA 90095-1597
310-825-3259

David Okrent
University of California, Los Angeles
BOX 951597, 48-121 Eng IV Bldg
Los Angeles, CA 90095-1597
310-825-3259

William E. Kastenberg
University of California, Berkeley
4155 Etcheverry Hall
Berkeley, CA 94720-1730
510-643-0574

ABSTRACT

A combination approach of an expert system and neural networks is used to implement a prototype severe accident diagnostic system which would monitor the progression of the severe accident and provide necessary plant status information to assist the plant staff in accident management during the accident. The station blackout accident in a pressurized water reactor (PWR) is used as the study case. The current phase of research focus is on distinguishing different primary system failure modes and following the accident transient before and up to vessel breach.

1. INTRODUCTION

Severe accident management has been recognized as an essential element to enhance nuclear power plant safety, and a large effort has been devoted on related issues.[1,2,3] Silverman and Klopp used a neural network-based expert system for the purpose of severe accident management.[4] The system was used to predict parameters important for accident management during loss of coolant accidents (LOCA), e.g., the time available to core support plate and reactor vessel failure and time remaining until recovery actions were too late to prevent core damage. Guarro et al. have proposed an accident management advisor system (AMAS) as a decision aid for interpreting the instrument information and managing accident conditions in a nuclear power plant.[5] The modified logical flowgraph methodology was used to interpret the instrument readings to derive the plant parameters, and the plant status was determined through the Baysian Belief Network (BBN). Recently, artificial neural networks have been used for BWR ATWS transients pattern recognition.[6] Core power, vessel pressure, number of open safety relief valves, and suppression pool temperature have been chosen to define the four patterns for the training of the networks. The results show that the neural networks can successfully retrieve the patterns even with large random noise and partial loss of the input information. As indicated by the authors, this kind of error resistance might be useful in severe accident situations where the instrumentation may not be available because of the harsh environment. Neural networks have also been used in many other areas of nuclear power plants, including transient diagnostics, sensor validation, plant-wide monitoring, check valve monitoring, and vibration analysis.[7] In most of these applications, multi-layer, feed-forward backpropagation neural networks are used. A dynamic node architecture scheme for neural network training was proposed by Basu and Bartlett to optimize the neural network structure.[8] For a three layer backpropagation neural network, while the neuron number of input and output layers is usually determined by the diagnostic problem, the number of neurons for the hidden layer is added or deleted dynamically during the training until the optimal criteria are met with a certain number of hidden neurons. Neural networks with schemes other than backpropagation have also been applied to fault diagnosis. Specht's probabilistic neural networks were modified and integrated with influence diagrams for power plant monitoring and diagnostics.[9,10] Marseguerra and Zio proposed a stochastic neural network (boltzmann machine) and used it to diagnose a pipe break in a simulated auxiliary feedwater system.[11]

It is important for the personnel in charge of accident management during the accident to understand the status of the power plant and the progression trend of the accident in order to evaluate and implement effective prevention or mitigation strategies. While there are lots of efforts on diagnostic systems for accidents before core damage,[12,13,14] there is a general lack of diagnosis methodologies for severe accidents where the core would undergo severe damage and accidents might progress beyond vessel breach.

A combination approach of an expert system and neural networks is used to implement a prototype severe accident diagnostic system which would monitor the progression of the severe accident and provide necessary plant status information to assist the plant staff in accident management during the accident. The station blackout accident in a pressurized water reactor (PWR) is used as the study case. The current phase of research focus is on distinguishing different primary system failure modes and following the accident transient before and up to vessel breach. Section II is a brief discussion of the station blackout accident. Section III presents the diagnosis methodology. Section IV describes neural networks and the expert system. Section V shows the neural network training results. And finally, Section VII is the summary of the work.

II. STATION BLACKOUT ACCIDENT

One of the major type of accidents is Station Blackout, which contributes a relatively large risk to nuclear power plant operation and might progress to the stage of severe core damage or further. Station Blackout is the situation when both offsite and onsite AC power are unavailable. During these accidents, there are various primary system failure modes, including reactor coolant pump (RCP) seal failure, power operated relief valve (PORV) stuck open or safety relief valve (SRV) stuck open, temperature-induced hot leg/surge line failure (H/S Failure), temperature-induced steam generator tube rupture (ISGTR), and vessel breach (VB). At the start of the accident, there is loss of RCP seal cooling because of a loss of AC power. Large or small seal failures might develop and cause the loss of reactor coolant system (RCS) inventory. There also might be primary system inventory loss through the PORVs or SRVs cycling. With the uncovery of the core, the PORVs or SRVs would operate at a much higher temperature than the normal condition and might fail to reclose during one of the cycles. ISGTR or creep rupture of the hot leg/surge line might also happen if the system is exposed to superheated steam and hydrogen due to natural circulation over a period of time under high differential pressure. If any of these occurs, the RCS might be depressurized and the vessel might fail at intermediate or low pressure, and hence a high pressure melt injection, which may cause containment failure by direct heating, would be unlikely to happen. If none of these happens, the VB will probably occur at high pressure and direct containment heating might happen. After vessel breach, the accident will continue to progress and the containment might be endangered and fail, if it is not already failed at VB.

Preliminary analysis indicates that primary system pressure undergoes more or less distinct dynamic responses with various failure modes during station blackout.[3,15] After the initial transient period, there is a decrease of the primary system pressure because of energy transfer to the secondary system before the dryout of steam generators and possible energy loss through the primary system opening (e.g. RCP seal leaking). After the dryout of the steam generators, the primary system pressure will increase to the PORV setpoint when the PORVs start cycling. The primary system pressure will fluctuate accordingly. For the case of large RCP seal failure, the pressure drop might be so large that the pressure will no longer go up to the PORV setpoint. Depending on different primary failure modes, there might be a different primary system pressure history. In addition, there are other sensor readings which could be used to distinguish different failure modes.[16] For example, when ISGTR occurs, the pressure, temperature, and radiation level of the secondary side of the steam generator will normally increase. In summary, the combination of the primary system pressure history and other instrumentation indications could be used to diagnose various primary system failure modes during station blackout accidents.

III. METHODOLOGY

There are basically two fundamental problems for the diagnostic task, i.e., detection of a failure and identification of the failure. The detection process would uncover a possible primary system failure from abnormal sensor readings and the identification process would determine which failure actually occurs from the time series of the signals. It is important to distinguish these two steps of the diagnosis because it usually takes more data to identify what exactly happens after the detection. For example, it is rather easy and quick to tell that the reactor vessel has been breached, or the hot leg/surge line fails, from the sudden large decrease of the primary system pressure, whereas it is hard to see right away which of these two happens. For the case of PORV Stuck Open, the failure could not be detected for some sustained period of time until the sensor readings show substantial abnormality. The same situation applies to ISGTR without radiation reading of the secondary side of steam generators. Various uncertainties have to be considered during the accident progression. First, there is uncertainty regarding which failure occurs. For example, during a station blackout accident, the auxiliary feedwater system may either be in operation or fail at the initiation of the accident. After uncovery of the top of the active fuel, there might be failure of steam generator tubes, failure of the hot leg/surge line, or a stuck open power operated relief valve. Second, there is uncertainty regarding when the failure occurs. The timing of each possible failure is hard to determine. It is not possible to specify exactly when the power operated relief valve would be stuck open under abnormal operation conditions. Third, there is uncertainty regarding severity of the failure. For example, the size of the reactor coolant pump seal leak is not known and one is unable to determine this beforehand. And fourth, there is uncertainty regarding whether further failures occur. There might be multiple failures during the accident progression.

The proposed framework for the diagnosis is a combination of an expert system and artificial neural networks. The rule-based expert system is used for the basic plant overall monitoring and diagnosis. Specific neural networks will be initiated by the expert system to determine the patterns of special events during the accident progression. This severe accident diagnosis system will be used to distinguish different failures, severity of the failure and further failures based on the available instrumentation reading.

The expert system will be used to monitor the progression from the start of the accidents. The initial accident conditions and major change of plant status will be recorded and displayed. This system will also determine when the diagnostic neural networks should be initiated for failure detection and identification. The diagnostic results from neural networks will be compared, if possible, with the results from the expert system. The difference between the actual sensor reading during the accidents and the MAAP simulation will be shown in order to justify the use of neural networks and accommodate large uncertainty. MAAP simulation codes could generate the primary system pressure history and other indications, e.g., secondary side pressure and temperature, containment temperature and pressure, radiation levels. The results will also provide bounding values and timing information of the failures. Thus, MAAP run results are used to gain qualitative, semi-qualitative, and quantitative instrument reading change patterns to form the knowledge base of the expert system. Other scientific knowledge and engineering judgment will also be incorporated into the knowledge base.

The transient data from MAAP runs can be used to train the neural networks to distinguish various failure patterns. Since the timing of the failure is uncertain, the results of use of neural networks for diagnosis purposes must be treated cautiously since the neural network training highly depends on the scenarios, even though the neural networks retain some capability of resistance to signal noise. The training of the neural networks needs to be studied in view of several uncertainties, including variability in initial conditions, differences between MAAP and actual performance, changing configuration after initiation of MAAP, misleading sensor signals, etc. These and other considerations will be examined in order to use the neural networks to best advantage. These multiple sub scenario conditions suggest that for each principal scenario, it will be useful to have a few MAAP runs appropriately selected. Two groups of back propagation neural networks are designed for diagnostic purposes. One group is for detection of possible primary system failure (Detection Neural Networks) and the other is for failure identification (Identification Neural Networks). The data to be used for the training is tested progressively to maximize the best possible results. The data used for neural network training will be increased time step by time step into the accident until the test results would not be better. After the determination of that training data which is shown to be effective, the two neural networks can be constructed and tested.

IV. NEURAL NETWORKS AND EXPERT SYSTEM

The human brain accomplishes very complicated tasks by using billions of simple neurons which are interconnected. Artificial neural networks are the computer simulations of human brain function.[17,18,19] These networks have many artificial neurons, usually called processing elements. These processing elements are organized in layers and have similar functions as human neurons by adding up the weighted values of the many inputs. The input layer acts as a buffer for the input data. The output layer acts as a buffer for the output results. There might be one or more hidden layers in between. A learning process is accomplished by presenting both input data and desired output results and then obtaining the weighting coefficients among layers of processing elements by some learning algorithms. During the recall process, the trained neural network takes inputs and generates output results. Figure 1 shows the basic structure of the diagnostic neural networks. It is a three-layer, feed-forward, backpropagation neural network. The MAAP data is used to train the neural networks which are then tested against all the other scenarios. To some extent, this would guarantee the generality of the neural networks to detect and identify the faults under various conditions.

The expert system will provide the general environment for monitoring the overall plant status, determination of neural networks usage, displaying necessary information. The expert system also provides independent primary system failure diagnosis, if possible. The software used for the proposed expert system will be NEXPERT OBJECT,[20] which is a commercial software under the IBM PC window environment. IF-THEN rules are used for backward reasoning and forward reasoning. Figure 2 shows the logic flow of the diagnostic system.

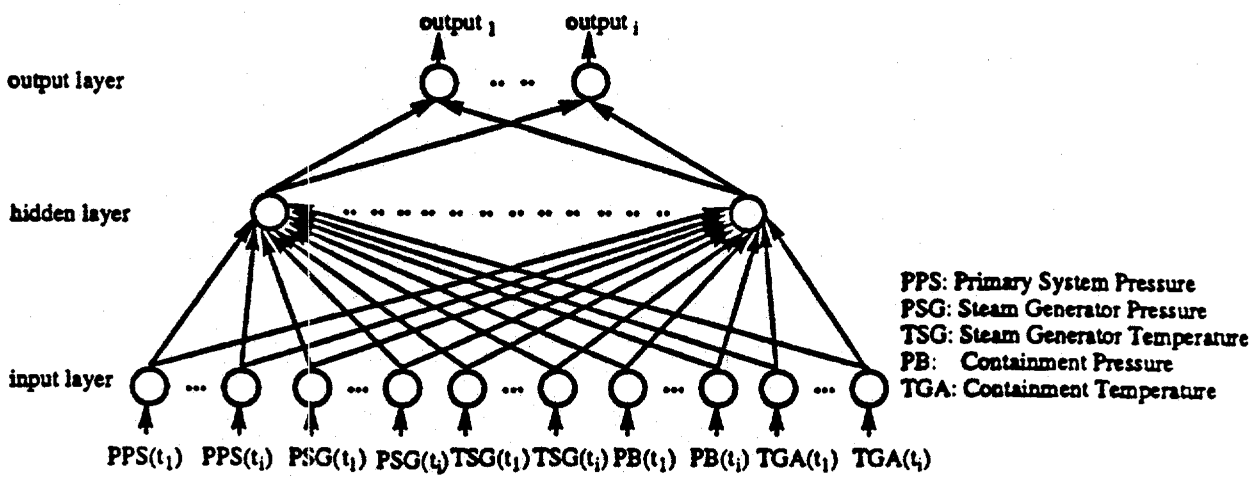

FIGURE 1 A THREE LAYER BACK PROPAGATION NEURAL NETWORK

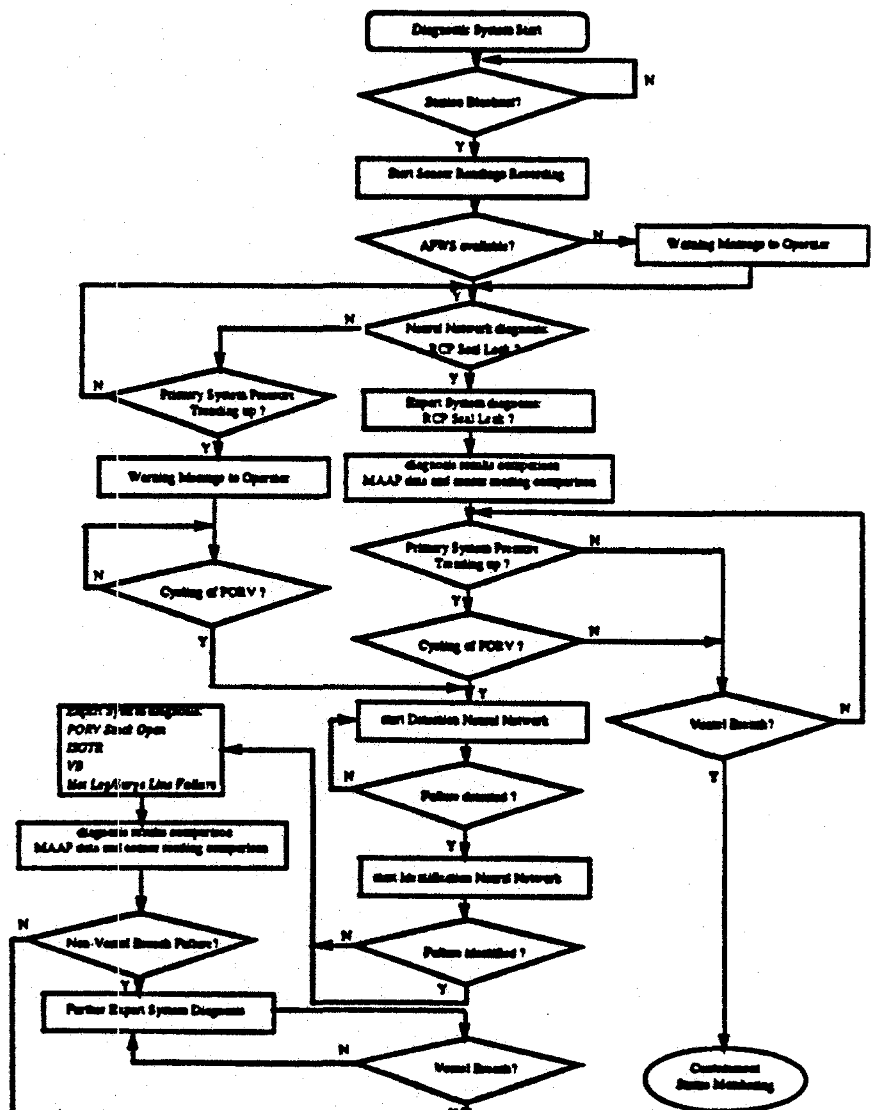

FIGURE 2 LOGIC FLOW OF THE PROTOTYPE SEVERE ACCIDENT DIAGNOSTIC SYSTEM

V. NEURAL NETWORK TRAINING

MAAP simulation runs have been conducted by Dr. Dave Dion of PG&E for thirty six (36) accident scenarios (ASs). These results were used as the first effort to formulate the methodology or ways of diagnosis of the primary system failures before vessel breach during station blackout conditions. Accident scenarios AS1, AS2a, AS2b, AS3a, AS4a are chosen to be the reference data, representing Vessel Breach, ISGTR (1 tube), ISGTR (10 tubes), Hot Line/Surge Line Failure, PORV Stuck Open cases respectively. Sensor readings of primary system pressure, steam generator pressure, steam generator temperature, containment pressure, and containment temperature were used for diagnosis.

To evaluate the data adequacy for diagnosis and to determine the data for neural network training for failure detection and identification, training data was taken from the start of the failure and the amount of data was progressive increased (every 20 second step). The input neurons are determined according to the amount of data for training. There are two output neurons with mapping scheme for training shown in table 1.

TABLE 1 MAPPING SCHEME FOR NEURAL NETWORK TRAINING FOR DATA EVALUATION

CASE NAME	Output Neuron 1 target	Output Neuron 2 target
Vessel Breach	0.1	0.1
ISGTR	0.1	0.9
Hot Leg / Surge Line Failure	0.9	0.1
PORV Stuck Open	0.9	0.9

Fourteen groups of data (3x20s, 4x20s, 5x20s, 6x20s, 7x20s, 8x20s, 9x20s, 10x20s, 13x20s, 14x20s, 15x20s, 16x20s, 17x20s, and 20x20s) from AS1 (Vessel Breach), AS2a (ISGTR), AS2b(ISGTR), AS3a(H/S Failure), AS4a(PORV Failure) were used for the training. Sensor data is normalized between 0.0 and 1.0. For the network recall process, any data less than 0.25 is treated as 0, any data above 0.75 is treated as 1.0, any data between 0.25 and 0.5 is treated as likely 0, any data between 0.5 and 0.75 is treated as likely 1. The mapping scheme used for testing is shown in table 2.

Table 3 to Table 6 show the test results. Case 1 is the AFWS initially working and no RCP Seal Failure case. Case 2 is the AFWS initially working with RCP Seal Failure case. Case 3 is the AFWS initially Non-working and no RCP Seal Failure case. Case 4 is the AFWS initially Non-working with RCP Seal Failure case.

TABLE 2 OUTPUT MAPPING SCHEME FOR TESTING FOR DATA EVALUATION

Output Neuron 1	Output Neuron 2	Mapping Case
0.0 - 0.25	0.0 - 0.25	Vessel Breach
0.25 - 0.5	0.0 - 0.25	likely Vessel Breach
0.0 - 0.25	0.25 - 0.5	likely Vessel Breach
0.25 - 0.5	0.25 - 0.5	likely Vessel Breach
0.0 - 0.25	0.75 - 1.0	ISGTR
0.25 - 0.5	0.75 - 1.0	likely ISGTR
0.0 - 0.25	0.5 - 0.75	likely ISGTR
0.25 - 0.5	0.5 - 0.75	likely ISGTR
0.75 - 1.0	0.0 - 0.25	H/S Failure
0.75 - 1.0	0.25 - 0.5	likely H/S Failure
0.5 - 0.75	0.0 - 0.25	likely H/S Failure
0.5 - 0.75	0.25 - 0.5	likely H/S Failure
0.75 - 1.0	0.75 - 1.0	PORV Failure
0.5 - 0.75	0.75 - 1.0	likely PORV Failure
0.75 - 1.0	0.5 - 0.75	likely PORV Failure
0.5 - 0.75	0.5 - 0.75	likely PORV Failure

With the increase of the data into the failure, the neural networks recall ability converges to a certain level where test results are no longer improved with more data. From the results, the converged time data for VB and H/S Failure is 3x20s. The converged time data for ISGTR and PORV Stuck Open is 15x20s.

Finally, the Detection Neural Networks and Identification Neural Network were constructed. For each of the two neural networks, there are 80 input neurons representing 15 time steps of data of 20 second each. There are three output neurons with the mapping scheme shown in table 7. The training samples included data of the no failure case. The training data for Vessel Breach and H/S Failure ranged from 3x20s to 8x20s into the failure. The training data for ISGTR and PORV Stuck Open ranged from 10x20s to 15x20s. Since the number of input neurons is fixed at 80 or 15 time steps of 20 seconds, most training data also covers a portion of the no failure case. Figure 3 and Figure 4 show the convergence of the training of the neural networks which combines the expert system and the neural networks.

TABLE 3 TEST RESULTS FOR VESSEL BREACH IDENTIFICATION

time s data	3x20	4x20	5x20	6x20	7x20	8x20	9x20	10x20	15x20	16x20	17x20	20x20
case1												
case2	++	++	++	++	++	++	++	++	++	++	++	++
case3	+	++	++	++	++	++	++	++	++	++	++	++
case4	+	++	++	++	++	++	++	++	++	++	++	++

Note: ++ positive + likely positive - likely negative -- negative (same for table 4-6)

TABLE 4 TEST RESULTS FOR HOT LEG/SURGE LINE IDENTIFICATION

time s data	3x20	4x20	5x20	6x20	7x20	8x20	9x20	10x20	15x20	16x20	17x20	20x20
case1	++	++	++	++	++	++	++	++	++	++	++	++
case2	++	++	++	++	++	++	++	++	++	++	++	++
case3	++	++	++	++	++	++	++	++	++	++	++	++
case4	++	++	++	++	++	++	++	++	++	++	++	++

TABLE 5 TEST RESULTS FOR ISGTR IDENTIFICATION

time s data	3x20	4x20	5x20	6x20	7x20	8x20	9x20	10x20	15x20	16x20	17x20	20x20
case1	++	++	++	++	++	++	++	++	++	++	++	++
case2	++	++	++	++	++	++	++	++	++	++	++	++
case3	++	+	- PORV	- PORV	- PORV	- PORV	+	+	+	+	+	+
case4	++	++	++	++	+	+	+	+	+	+	+	+

TABLE 6 TEST RESULTS FOR PORV STUCK OPEN IDENTIFICATION

time s data	3x20	4x20	5x20	6x20	7x20	8x20	9x20	10x20	15x20	16x20	17x20	20x20
case1	++	++	++	++	++	++	++	++	++	++	++	++
case2	- ISGT R	- ISGTR	- ISGR	- ISGT R	- ISGTR	+	+	+	++	++	++	++
case3	+	- ISGTR	+	+	+	+	+	+	++	++	++	++
case4	+	++	++	++	++	++	++	++	++	++	++	++

TABLE 7 MAPPING SCHEME FOR DETECTION AND IDENTIFICATION NEURAL NETWORKS TRAINING

CASE NAME	Output Neuron 1	Output Neuron 2	Output Neuron 3
No Failure	0.1	0.1	0.1
Vessel Breach	0.9	0.1	0.1
ISGTR	0.9	0.1	0.9
H/S Failure	0.9	0.9	0.1
PORV Failure	0.9	0.9	0.9

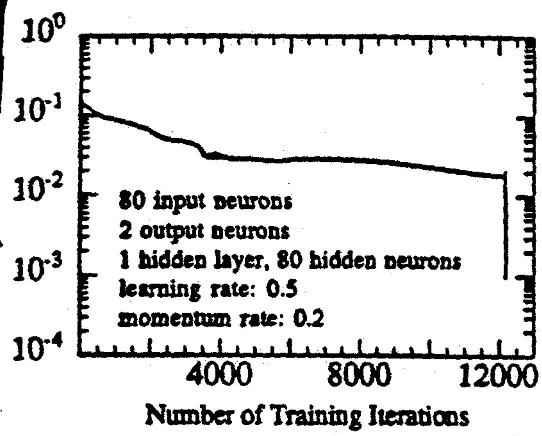

FIGURE 3 TRAINING CONVERGENCE FOR DETECTION NEURAL NETWORK

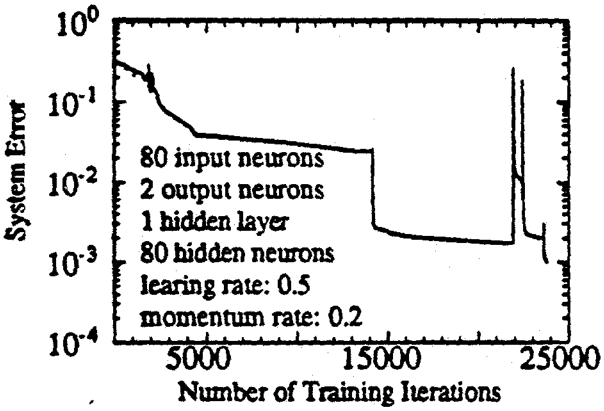

FIGURE 4 TRAINING CONVERGENCE FOR IDENTIFICATION NEURAL NETWORK

When networks were tested, VB or H/S Failure could be detected 20 seconds into the failure and identified 30 seconds into the failure. The diagnosis could be confirmed for several more time steps. The ISGTR or PORV Stuck Open could be detected 160 seconds into the failure and be identified 180 seconds into the failure. Test of no failure cases was successful. When 30% of random noise was added to the training data, the Detection Neural Network could still correctly detect various failures. Vessel Breach or H/S Failure could be correctly identified by the Identification Neural Network with 25% random noise added to the training data. PORV Stuck Open and ISGTR could be correctly identified with 10% random noise.

The Detection Neural Network and Identification Neural Network can be initiated during the cycling of the PORV, long before the start of primary system failure. Every 20 seconds, new time step data can be fed in and the oldest time step data thrown out. If the situation is classified as No Failure by the Detection Neural Network, the process would continue. If some failure is detected by the Detection Neural Network, the Identification Neural Network would be initiated to identify which failure occurred. Further data input would be used for diagnosis confirmation. The expert system would provide separate confirmation, and would advise of differences between sensor readings and the MAAP results.

VI. SUMMARY

Artificial intelligence, such as expert systems and neural networks, has been used to detect and identify primary system failures during station blackout. Among the things accomplished, the use of neural networks to evaluate data adequacy and sufficiency is a novel application of such a technique. The same technique will be used to construct neural networks for RCP Seal Failure cases. Even though we give a scale for some sort of uncertainty assessment, a more thorough uncertainty analysis would be desirable, if possible. Expert system knowledge base formation and the integration of the prototype severe accident diagnostic system are the remaining tasks.

ACKNOWLEDGMENT

The authors wish to thank Tom Leserman and Dave Dion of Pacific Gas and Electric Company for useful discussions and the MAAP results. This work is supported in part by grants from PG&E/DOE and Southern California Edison Co.

REFERENCES

[1] USNRC, *Severe Accident Risks: An Assessment for Five U.S. Nuclear Power Plant*.NUREG-1150, April, 1989

[2] Hanson, D.J. et al., *Accident Management Information Needs*. NUREG/CR-5513, April, 1990

[3] Brownson, D.A. et al., *Intentional Depressurization Accident Management Strategy for Pressurized Water reactors*. NUREG/CR-5937, April, 1993

[4] Silverman, E.B. and Klopp, G.T., " Neural Network-Based Expert System For Severe Accident management", *EPRI Proceedings*, 1990

[5] Guarro, S. et al., "A Decision Aid for Interpreting Instrument Information and managing Accident Conditions in Nuclear Power Plant ", OECD/CSNI Specialists Meeting On Instrumentation To Management Severe Accidents, Cologne, Germany, March 16-17, 1992

[6] Xing, L. and Okrent, D., "Application of Neural Networks in Accident Management", Proceedings of

PSA International Topical Meeting, Clearwater Beach, Florida, 1993

[7] Uhrig, R.E., "Potential Use of Neural Networks in Nuclear Power Plants". IEEE International Conference on Neural Networks, 1993

[8] Basu, A. and Bartlett, E. B., "Detecting Faults in a Nuclear Power Plant by using Dynamic Node Architecture Artificial Neural Networks". *Nuclear Science and Engineering*, No. 116, 313-325, 1994

[9] Marseguerra, M. and Zio, E., "Fault Diagnosis via Neural Networks: the Boltzmann Machine". *Nuclear Science and Engineering*, No. 117, 194-200, 1994

[10] Specht, D.F., "Probabilistic Neural Networks". *Neural Networks*, Vol. 3, 1990

[11] Agogino, A. et al., "Integrating Neural Networks with Influence Diagrams for Power Plant Monitoring and Diagnostics". IEEE International Conference on Neural Networks, 1993

[12] Guarro, S.B., "Diagnostic Models for Engineering Process Management: A Critical Review of Objectives, Constraints and Applicable Tools". *Reliability Engineering and System Safety*, NO.30, 1990

[13] Kim, I.S. et al., "A Model-based Approach to On-line Process Disturbance Management: The Models". *Reliability Engineering and System Safety*, NO.29, 1990

[14] Yang, J.O., Chang, S.H., "A Diagnostic Expert System for the Nuclear Power Plant Based on the Hybrid Knowledge Approach". IEEE Transactions on Nuclear Science, Vol.36, NO.6, 1989

[15] Knudson, D.L., Dobbe, C.A., *Assessment of the Potential for High Pressure Melt Ejection resulting from a Surry Station Blackout Transient*. NUREG/CR-5949, May, 1993.

[16] Oehlberg, R.N. et al., "Practical Considerations in Accident Management". Proceedings of International Meeting on safety of Thermal Reactors, Oregon, July 21-25, 1991

[17] Marvin Minsky and Seymour Papert, "Perceptrons", Cambridge, MA: MIT Press, 1969.

[18] Yoh-Han Pao, "Adaptive Pattern Recognition and Neural Networks", Copyright 1989,Addison-Wesley Publishing Company, Inc.

[19] B. Müller, J. Reinhardt, "Neural Networks, An Introduction", Copyright © Springer-Verlag Berlin Heidelberg 1990.

[20] "NEXPERT Object", Copyright 1987, by Neuron Data Inc.