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Neural Network Recognition of Nuclear Power Plant Transients :

Final Report : 4/15/92 - 4/15/95

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May 15, 1995.

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N O T I C E

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Neural Network Recognition of Nuclear Power Plant Transients:

Final Performance Report
4/16/92 - 4/15/95

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Thank you.

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NEURAL NETWORK RECOGNITION OF NUCLEAR POWER PLANT TRANSIENTS

1 Abstract

The objective of this report is to describe results obtained during the second year of funding that will lead to the development of an artificial neural network (ANN) fault - diagnostic system for the real - time classification of operational transients at nuclear power plants. The ultimate goal of this three-year project is to design, build, and test a prototype diagnostic adviser for use in the control room or technical support center at Duane Arnold Energy Center (DAEC); such a prototype could be integrated into the plant process computer or safety-parameter display system. The adviser could then warn and inform plant operators and engineers of plant component failures in a timely manner. This report describes the work accomplished in the second of three scheduled years for the project. Included herein is a summary of the second year's results as well as descriptions of each of the major topics undertaken by the researchers. Also included are reprints of the articles written under this funding as well as those that were published during the funded period.

2 Work Performed During the Period

2.1 Objective of Work

The objective of this research project is to develop an ANN fault-diagnostic system for the real-time detection and classification of nuclear power plant transients and component failures. The ultimate goal is to design, build, and test a prototype diagnostic adviser for use in the control room or technical support center at the Duane Arnold Energy Center (DAEC).

The significance of the proposed work is the potential improvement in nuclear power plant operational safety realized through the timely warning and diagnosis of abnormal plant operating conditions. Another technical significance of the research is the advancement of the theory of ANN techniques and their application to fault diagnosis as well as insights and advances in the areas of information prioritization and accident mitigation and management. These advances can be applied to both boiling - water reactors (BWRs) and pressurized-water reactors (PWRs) as well as any other industrial process where accident avoidance is paramount. Quicker accident diagnostics and the resultant improvement in mitigation efforts will be of great value to nuclear plant safety.

The general aim of this research is twofold: to investigate and to educate in the fields of nuclear engineering and artificial intelligence applications.

2.2 Summary of Results

The following is a brief list of accomplishments for the reporting period.

1. More than 60 transient scenarios have been collected at the DAEC training simulator. A list of these transients is given in Table 3.
2. Error analysis methodology that provides an estimated level of confidence in the transient diagnosis has been improved and implemented on a set of ten transient scenarios obtained from San Onofre Nuclear Generating Station. A complete description of this work is given in Sections 4.1 and 11.1.
3. An input importance analysis method has been developed (Bartlett 1993d). This approach is actually a combination of methods using information theory (Bartlett 1992b: Section 11.2, Hyvarinen 1970, Kullback 1959, Shannon 1971, Watanabe 1969) and ANN derivatives (Bartlett 1991b, Lanc 1991). The approach can help

determine the relative importance of individual plant variables for diagnosing specific sets of nuclear power plant transients.

4. Dynamic Node Architecture Learning with Backpropagation has a very high probability of being useful. This work is a re-creation of Bartlett's Ph.D. for a boiling-water reactor using backpropagation ANNs. Sections 4.3 and 11.2 describes our work in this area.
5. A broad - based adviser has been developed that is capable of diagnosing 27 distinct transients collected from DAEC simulator; actually, the adviser diagnoses a total of 43 scenarios since some of the 27 transients contain different severity conditions. Section 11.2 describes the work leading to the development of the adviser (Basu 1993b). This adviser has given us great insight into the possible design structure of the final diagnostic system, and has made the researchers capable of evolving a complicated ANN solution with verification in order to bring the final diagnostic adviser to fruition.
6. It is important in many industrial applications of ANNs to be able to determine the sensitivity of the output of an ANN to changes in the inputs. A method of obtaining useful results has been developed that uses multivariate third order polynomials to describe the behavior of the ANN around a specific operating point. These polynomials are determined by taking partial derivatives of the output in question with respect to a specific input or inputs and then reconstructing the polynomials from these derivatives. The method and results are shown in Section 11.5.

7. Educational Goals Attained

- One Masters degree completed December 1992 (K. Kim)

- Four students passed the written and oral Ph.D. qualifying exam. (A. Basu, C. Dhanwada, J. Kerr, K. Kim)
 - One Ph.D proposal defense completed September 1993 (K. Kim)
 - Three Ph.D proposal defense to be completed December 1993 (A. Basu, C. Dhanwada, J. Kerr)
8. Significant progress has been made toward the completion of the second year's goals set out in the original and continuation research proposals – see Section 3.1.

2.3 Time Devoted by Principal Investigator

The PI has devoted 25% of his time to this project. This will continue till the scheduled completion of the project.

3 Detailed Description of Research Work

3.1 Effect of Performed Work on Research Plan and Timetable

It was originally proposed to implement the approach of ANN analysis demonstrated in Bartlett 1990 and Bartlett and Uhrig 1992 to the nuclear power plant accident diagnostic problem. The tasks involved were separated into three phases that would require approximately one year each. Phases II and III were outlined in the proposed research timetable as follows. (See Bartlett 1993e for revised timetable for Year III.)

Proposed Timetable

Year II

1. Refinement of accident list
2. Refinement of input variables lists for each branch network

3. Continued collection of simulated plant transients
4. Collection of data from plant operations and incorporation of instrument noise into training data
5. Enhancement of network training techniques
6. Design of diagnostic system, including the network tree and related architectures
7. Further adaptations of stacked generalization methodologies to verify results

Year III

1. Comparison between competing designs and design of the diagnostic system
2. Final training of diagnostic system including use of parallel computer if needed
3. Testing of final diagnostic system on both simulator and actual plant data
4. Address unforeseen issues from previous phase

Significant progress toward these goals has been accomplished during the first and second funding periods. Below is a brief discussion of the milestones accomplished and their relationship to the originally proposed goals during the second funding period.

1. Refinement of accident list

After careful analysis and discussions with DAEC staff, a list of 85 distinct transient has been identified during the initial stages of this research. These scenarios include two broad categories of operational transients. In the first category are the more potentially dangerous scenarios. These are most likely to be fast acting and initiated by large component failures such as a recirculation loop rupture. The second category contains the presumably more frequent but less severe scenarios. Typical scenarios in this category include, for example, small steam leakage in a steam tunnel.

Table 1 shows the working list of accidents of interest. We have already collected a total of 63 transient scenarios (a few transients were simulated at different severity conditions) and are well on our way to defining lists for secondary component failures and accidents that exhibit similar symptoms.

2. Refinement of input variables lists for each branch network

It is possible that as many as 300 plant variables may be needed for the diagnosis of the approximately 100 accidents and transients of particular interest. However, too many variables may cause training difficulties in designing a diagnostic network system. For the refinement of input variable selection, redundant or less important variables must be chosen and removed. The determination of the exact set of variables for the desired set of accidents is necessary and can be done by assessing information contents with respect to variables of interest. For the assessment of information content for input variables, input variable importance is computed by neural networks (see Section 11.3: Bartlett 1993d, Basu 1993a). This methodology can be adapted for reduction of input variables for the prototype design of the final diagnostic system. The list of variables being used for training of the ANN diagnostic adviser can be found in Table 2.

3. Continued collection of simulated plant transients

Table 3 includes a new list of the collected scenarios. A description of each of these is included in Section 9. Notice that many of the transients have been simulated more than once. This is because either a different initial condition, a different operating power level, a different severity level, or a secondary malfunction was simulated along with the original malfunction. Some of the initial plant conditions were also simulated without any malfunctions. More simulator work is needed in order to complete the list of transients of initial interest Table 1. This work will proceed into the final year of the project.

Table 1: Transient Scenarios of Initial Interest

Number	Accident Designation	Accident Description
1	AD02	Automatic depressurization system channel fail to initiate
2	AD05	Serious automatic depressurization system actuation
3	CS02	Core spray injection line break, headers A & B
4	CS03	Core spray inadvertent initiation
5	CU01	Reactor water clean-up heat -exchanger tube leak
6	CU07	Reactor water clean-up leak in heat -exchanger room
7	CU09	Reactor water clean-up regenerative heat -exchanger tube leak
8	CU10	Reactor water clean-up coolant leakage outside the primary containment
9	ED01	Loss of offsite power
10	EG01	Main generator trip, primary lockout & backup lockout
11	FW01	Condenser hotwell level controller failure
12	FW02	Condensate pump trip
13	FW04	Condensate filter demineralizer resin injection
14	FW05	Feedwater hydrogen controller failure
16	FW06	Feedwater heater drain valve fails
15	FW07	Feedwater heater dump valve fails
17	FW08	Feedwater heater tube leak
18	FW09	Reactor feedwater pump trip
19	FW12	Feedwater regulator valve controller failure
20	FW13	Master and feedwater regulator valve controller oscillation
21	FW14	Feedwater flow transmitter failure
22	FW17	Main feedwater line break inside primary containment
23	FW18	Main feedwater line break outside primary containment
24	HP01	High-pressure core injection inadvertent initiation
25	HP05	High-pressure core injection steam supply line break (High-pressure core injection room)
26	HP08	High-pressure core injection steam supply line break (Torus room)
27	IA01	Loss of instrumentation air
28	IA02	Instrumentation air header leaks
29	ID01	Drywell leakage
30	ID04	High-pressure core injection room leakage
31	ID05	Reactor core isolation cooling room leakage
32	ID06	Southeast corner room leakage
33	ID07	Northwest corner room leakage
34	ID08	Torus room leakage
35	MC01	Main circulation water pump trip

Table 1: . . . continued

Number	Accident Designation	Accident Description
36	MC02	Main condenser tube blockage
37	MC03	Cooling tower fans trip
38	MC04	Main condenser air inleakage
39	MC07	Main condenser tube leakage
40	MC08	Cooling tower riser pipe break
41	MS02	Steam leak inside primary containment
42	MS03	Main steamline rupture inside primary containment
43	MS04	Main steamline rupture outside primary containment
44	MS06	Main steam isolation valve fails close
45	MS08	Steam leakage in steam tunnel
46	MS14	Loss of extraction steam to feedwater heater
47	MS19	Spurious group 1 isolation
48	MS21	Spurious group 2 isolation
49	MS23	Spurious group 3 isolation
50	MS25	Spurious group 4 isolation
51	MS27	Spurious group 5 isolation
52	MS29	Spurious group 6A isolation (reactor core isolation cooling)
53	MS30	Spurious group 6B isolation (high-pressure core injection)
54	MS32	Spurious group 7 isolation
55	NM11	Recirculation flow unit fails
56	RC01	Reactor core isolation cooling system failure
57	RD11	Control rod drive hydraulic pump trip
58	RD13	Loss of air pressure to control rod drive HCL's
59	RD14	SCRAM discharge volume level high
60	RH01	Residual heat removal pump trip
61	RH02	Residual heat removal heat exchanger tube leak
62	RH03	Residual heat removal pump discharge line break
63	RH05	Residual heat removal/suppression pool suction line blockage
64	RH06	Residual heat removal heat exchanger B/P valve fails
65	RP03	Spurious SCRAM with operator action
66	RP05	Reactor protection system SCRAM circuit failure (Anticipated transient without SCRAM)
67	RR05	Recirculation pump shaft seizure
68	RR06	Recirculation motor generator drive motor breaker trip
69	RR07	Recirculation motor generator field breaker trip
70	RR08	Recirculation pump high vibration
71	RR10	Recirculation pump speed feedback signal failure
72	RR11	Recirculation pump seal failure
73	RR12	Recirculation motor generator oil pump failure

Table 1: . . . continued

Number	Accident Designation	Accident Description
65	RP03	Spurious SCRAM with operator action
74	RR15	Recirculation loop rupture (design basis loss of coolant accident 100%)
75	RR16	Recirculation pump RPT breaker trip
76	RR17	Recirculation motor generator flow controller fails
77	RR18	Recirculation motor generator scoop tube oscillations
78	RR20	Narrow range level transmitter failure
79	RR30	Coolant leakage inside primary containment
80	RR32	Lo-lo-lo level switch failure
81	RX01	Fuel cladding failure
82	SL01	Standby liquid pump trip
83	TC01	Main turbine trip
84	TC02	Electro-hydraulic control failures
85	SW19	River water supply pump trip

4. Collection of data from plant operations and incorporation of instrument noise into training data

The principal investigator and ISU research team had discussed the collection of data from on-site plant operation and noise data from instrument with DAEC technical staff. The data collection will be initiated as soon as the current outage of DAEC reactor due to fuel reloading ends.

5. Enhancement of network training techniques

This goal has been addressed by the investigations of Kim, Basu, Dhanwada (see Bartlett 1992b, Sections 4.2-4.7). A diagnostic adviser has been developed that can diagnose 27 distinct transients based on the data of 43 transient scenarios collected from the DAEC training simulator (Basu 1993a,b). This adviser, which is the most broad-based effort towards the development of the final diagnostic adviser, will help lead the research towards the ultimate form and structure of the final adviser. In the final design of diagnostic system, a single network called root network was trained

Table 2: Refined List of Important Plant Variables

	Variable Desig.	Description	Min. Value	Max. Value	Variable Unit
1	A041	Local power range monitor 16-25 flux level B	0.0	125.0	% power
2	A091	Source range monitor channel B	0.0	00.0	%
3	B000	Average power range monitor A Flux level	0.0	125.0	% power
4	B012	Reactor total core flow	0.0	60.0	Mlb/hr
5	B013	Reactor core pressure-differential	0.0	30.0	psid
6	B014	Control rod drive system flow	0.0	0.025	Mlb/hr
7	B015	Reactor feedwater loop A flow	0.0	4.0	Mlb/hr
8	B016	Reactor feedwater loop B flow	0.0	4.0	Mlb/hr
9	B017	Cleanup system flow	0.0	0.07691	Mlb/hr
10	B022	Total steam flow	0.0	8.0	Mlb/hr
11	B023	Cleanup system inlet temperature	0.0	755.0	°F
12	B024	Cleanup system outlet temperature	0.0	600.0	°F
13	B026	Recirculation loop A1 drive flow	0.0	15.1	Mlb/hr
14	B028	Recirculation loop B1 drive flow	0.0	15.1	Mlb/hr
15	B030	Reactor feedwater channel A1 temperature	280.0	430.0	°F
16	B032	Reactor feedwater channel B1 temperature	280.0	430.0	°F
17	B034	Recirculation loop A1 inlet temperature	260.0	580.0	°F
18	B036	Recirculation loop B1 inlet temperature	260.0	580.0	°F
19	B038	Recirculation A wide range temperature	50.4	789.6	°F
20	B039	Recirculation B wide range temperature	50.4	789.6	°F
21	B061	Reactor coolant total jet pumps 1-8 flow B	0.0	36.7	Mlb/hr
22	B062	Reactor coolant total jet pumps 9-16 flow A	0.0	36.7	Mlb/hr
23	B063	Reactor coolant total outlet steam flow A	0.0	2.0	Mlb/hr
24	B064	Reactor coolant total outlet steam flow B	0.0	2.0	Mlb/hr
25	B065	Reactor coolant total outlet steam flow C	0.0	2.0	Mlb/hr

Table 2: . . . continued

Variable Desig.	Description	Min. Value	Max. Value	Variable Unit
26 B066	Reactor coolant total outlet steam flow D	0.0	2.0	MIb/hr
27 B079	Reactor recirculation pump A motor vibration	0.0	10.0	MILS
28 B080	Reactor recirculation pump B motor vibration	0.0	10.0	MILS
29 B083	Control rod drive cooling-water differential pressure	0.0	500.0	dpsi
30 B084	Control rod drive cooling-water differential pressure	0.0	60.0	dpsi
31 B085	Torus air temperature #1	0.0	500.0	°F
32 B086	Torus air temperature #2	0.0	500.0	°F
33 B087	Torus air temperature #3	0.0	500.0	°F
34 B088	Torus air temperature #4	0.0	500.0	°F
35 B089	Drywell temperature azimuth 0 elevation 750	0.0	500.0	°F
36 B090	Drywell temperature azimuth 245 elevation 750	0.0	500.0	°F
37 B091	Drywell temperature azimuth 90 elevation 765	0.0	500.0	°F
38 B092	Drywell temperature azimuth 270 elevation 765	0.0	500.0	°F
39 B093	Drywell temperature azimuth 270 elevation 765	0.0	500.0	°F
40 B094	Drywell temperature azimuth 180 elevation 780	0.0	500.0	°F
41 B095	Drywell temperature azimuth 270 elevation 830	0.0	500.0	°F
42 B096	Drywell temperature center elevation 750	0.0	500.0	°F
43 B098	Torus water temperature	0.0	752.0	°F
44 B099	Torus water temperature	0.0	752.0	°F
45 B103	Drywell pressure	0.0	100.0	psia
46 B104	Torus pressure	0.0	100.0	psia
47 B105	Torus water level	-10.0	10.0	inch
48 B120	Torus radiation monitor A	-1.0	100.0	%
49 B121	Torus radiation monitor B	-1.0	100.0	%
50 B122	Reactor water level	158.0	218.0	inch
51 B124	Reactor water level	158.0	218.0	inch
52 B1257	Fuel zone level indication	-153.0	218.0	inch
53 B126	Reactor water level	158.0	458.0	inch
54 B127	Reactor vessel pressure	0.0	1200.0	psig

Table 2: . . . continued

Variable Desig.	Description	Min. Value	Max. Value	Variable Unit
55 B128	Reactor vessel pressure	0.0	1200.0	psig
56 B129	Reactor vessel pressure	0.0	1500.0	psig
57 B130	Reactor vessel pressure	0.0	1500.0	psig
58 B137	Torus water level	1.5	16.0	ft
59 B138	Torus water level	1.5	16.0	ft
60 B150	Core spray A flow	-1767.8	5000.0	gpm
61 B151	Core spray B flow	-1767.8	5000.0	gpm
62 B160	Reactor core isolation cooling flow	-62.5	500.0	gpm
63 B161	High-pressure core injection flow	-437.5	3500.0	gpm
64 B162	Residual heat removal A flow	-75.0	15000.0	gpm
65 B163	Residual heat removal B flow	-75.0	150.0	gpm
66 B164	Drywell radiation monitor A	-1.0	100.0	%
67 B165	Drywell radiation monitor B	0.0	100.0	%
68 B166	Post-treat activity	0.0	100.0	%
69 B168	Pretreat activity	0.0	100.0	%
70 B171	Analyzer A O ₂ concentration	-1.25	10.0	%
71 B172	Analyzer A H ₂ concentration	-1.25	10.0	%
72 B173	Analyzer B O ₂ concentration	-1.25	10.0	%
73 B174	Analyzer B H ₂ concentration	-1.25	10.0	%
74 B180	Clean-up system flow	0.0	200.0	gpm
75 B196	Reactor water level-fuel zone A	-153.0	218.0	inch
76 B197	Reactor water level-fuel zone B	-153.0	218.0	inch
77 B247	Turbine steam bypass	0.0	500.0	°F
78 B248	Turbine steam bypass	0.0	500.0	°F
79 E000	4160 V Switch Gear bus 1A1 A-B	0.0	5.25	KV
80 F004	Condensate pump A&B discharge pressure	0.0	600.0	psig
81 F005	Low-pressure condenser circulating water inlet temperature A	0.0	200.0	°F
82 F010	High-pressure condenser circulating water outlet temperature A	0.0	200.0	°F
83 F011	Low-pressure condenser circulating water pressure differential A	0.0	10.0	dpsi
84 F015	Circulating water pump A&B discharge pressure	0.0	100.0	psig
85 F018	Cooling tower A discharge water temperature	0.0	752.0	°F
86 F019	Cooling tower B discharge water temperature	0.0	752.0	°F
87 F040	1P-1A reactor feed pump suction pressure	0.0	600.0	psig

Table 2: . . . continued

	Variable Desig.	Description	Min. Value	Max. Value	Variable Unit
88	F041	1P-1B reactor feed pump suction pressure	0.0	600.0	psig
89	F042	1P-1A reactor feed pump discharge pressure	0.0	2000.0	psig
90	F043	1P-1B reactor feed pump discharge	0.0	2000.0	psig
91	F044	Condensate total flow	0.0	8.0	Mlb/hr
92	F045	Condensate makeup flow	-10.0	100.0	Klb/H
93	F046	Condensate rejection flow	0.0	50.0	Klb/H
94	F094	Feedwater final pressure	0.0	2000.0	psig
95	G001	Generator gross watts	0.0	720.0	MWE
96	T039	Low-pressure condenser pressure	0.0	30.0	inHg
97	T040	High-pressure condenser pressure	0.0	30.0	inHg
98	F002	Condenser hotwell level	0.0	14.0	inch
99	F086	Demineralizer tank A effluent conductivity	0.0	0.2	m. mho
100	F087	Demineralizer tank A effluent conductivity	0.0	0.2	m. mho
101	F088	Demineralizer tank A effluent conductivity	0.0	0.2	m. mho
102	F089	Demineralizer tank A effluent conductivity	0.0	0.2	m. mho
103	F090	Demineralizer tank A effluent conductivity	0.0	0.2	m. mho
104	F091	Condenser demineralizer effluent conductivity	0.0	0.2	m. mho
105	AR000	North CRD module area radm			
106	CR001	Control Rod 18-03	-99.0	48.0	notch
107	CR003	Control Rod 26-03	-99.0	48.0	notch
108	CR020	Control Rod 06-15	-99.0	48.0	notch
109	CR021	Control Rod 10-15	-99.0	48.0	notch
110	CR023	Control Rod 18-15	-99.0	48.0	notch
111	B559	Steam lines rad monitor downscale	0.0	1.0	
112	B560	Steam lines rad monitor high	0.0	1.0	
113	D524	Main Steam Line high rad channel A1	0.0	1.0	
114	D525	Main Steam Line high rad channel B1	0.0	1.0	
115	D526	Main Steam Line high rad channel A2	0.0	1.0	
116	D527	Main Steam Line high rad channel B2	0.0	1.0	

to detect a normal or abnormal condition at any instance of time. The root network activates the group of diagnostic networks called category network if the root network determines that the plant is in any condition other than normal. The diagnostic network then produce the diagnostic output that classifies the abnormal condition. This approach, together with the other methodologies developed as part of this research effort, will be adapted for the final adviser design. In addition, the developed error prediction method can be applied to the final adviser design for verification of the outputs of the adviser.

6. Design of diagnostic system, including the network tree and related architectures

A broad based diagnostic adviser was designed and developed that could detect 27 distinct transients based on the data from 43 transient scenarios collected from the DAEC training simulator (Basu 1993b). In this adviser, a root network is used to determine if the plant is in a normal condition or not. If an anomaly is detected in the plant status, a classifier network identifies the particular transient in progress. This advance is based on the preliminary design of the adviser system presented in the previous performance report (Bartlett 1992b).

The final design of the adviser system followed from the earlier efforts. A small scale demonstration of this design is presented in Section 4.3. The root network has the same function as in the preliminary design, i.e. it detects an abnormality in the plant condition. Following the detection of an abnormal plant status, the particular transient is identified by a collection of small networks in the classifier level. Each of these networks is trained to identify one particular transient such that it outputs 1 for that transient and 0 for others. This design has certain distinct advantages. Firstly, this is a modular design, and each network can be trained independently and simultaneously. New transients can be incorporated into the adviser by adding a new networks in the classifier level. The existing classifier networks need to be trained

Table 3: Transient scenarios collected

Number	Transient Designation	Accident Description
1	AD05	Inadvertent initiation of automatic depressurization system
2	CU10	Reactor water clean-up coolant leakage
3	CU10	Reactor water clean-up coolant leakage with automatic group 5 isolation malfunction
4	FW02	Condensate pump trip
5	FW04	Condensate Filter demineralizer resin injection
6	FW08	Feedwater tube leak inside heaters (100% severity)
7	FW08	Feedwater tube leak inside heaters (60% severity)
8	FW08	Feedwater tube leak inside heaters (30% severity)
9	FW09	Reactor feedwater pump trip
10	FW12	Feedwater regulator valve controller failure (100% severity)
11	FW12	Feedwater regulator valve controller failure (60% severity)
12	FW17	Main feedwater line break inside primary containment (100% severity)
13	FW17	Main feedwater line break inside primary containment (60% severity)
14	FW17	Main feedwater line break inside primary containment (30% severity)
15	FW18	Main feedwater line break outside primary containment (100% severity)
16	FW18	Main feedwater line break outside primary containment (60% severity)
17	FW18	Main feedwater line break outside primary containment (30% severity)
18	HP05	High-pressure core injection steam supply line break (High pressure core injection room 100% severity)
19	HP05	High-pressure core injection steam supply line break (High pressure core injection room 60% severity)
20	HP05	High-pressure core injection steam supply line break (High pressure core injection room 30% severity)
21	HP08	High-pressure core injection steam supply line break (Torus room, 100% severity)
22	HP08	High-pressure core injection steam supply line break (Torus room, 60% severity)

Table 3: . . . continued

23	HP08	High-pressure core injection steam supply line break (Toros room, 30% severity)
24	IA01	Complete loss of instrumentation air (100% severity)
25	IA01	Complete loss of instrumentation air (60% severity)
26	MC01	Main circulation water pump trip
27	MC04	Main condenser air inleakage (100% severity)
28	MC04	Main condenser air inleakage (60% severity)
29	MC04	Main condenser air inleakage (30% severity)
30	MS02	Steam leak inside primary containment (100% single ended shear)
31	MS02	Steam leak inside primary containment (60% single ended shear)
32	MS02	Steam leak inside primary containment (30% single ended shear)
33	MS03	Main steam line rupture inside primary containment (100% double ended shear)
34	MS03	Main steam line rupture inside primary containment (60% double ended shear)
35	MS03	Main steam line rupture inside primary containment (30% double ended shear)
36	MS04	Main steam line rupture outside primary containment (100% double ended shear)
37	MS04	Main steam line rupture outside primary containment (60% double ended shear)
38	MS04	Main steam line rupture outside primary containment (30% double ended shear)
39	MS14	Loss of extraction steam to feedwater heater
40	MS19	Spurious group 1 isolation
41	MS32	Spurious group 7 isolation
42	RP03	Spurious SCRAM with operator action
43	RP05	Reactor protection system SCRAM circuit failure (ATWS)
44	RP05	Reactor protection system SCRAM circuit failure (ATWS) and alternate rod insert
45	RR05	Recirculation pump shaft seizure
46	RR10	Recirculation pump speed feedback signal failure
47	RR11	Recirculation pump seal failure

Table 3: . . . continued

Number	Accident Designation	Accident Description
48	RR15	Recirculation loop rupture (design basis Loss of coolant accident 100% severity)
49	RR15	Recirculation loop rupture (design basis Loss of coolant accident 60% severity)
50	RR15	Recirculation loop rupture (design basis Loss of coolant accident 30% severity)
51	RR30	Coolant leakage inside primary containment (100% single ended shear)
52	RR30	Coolant leakage inside primary containment (60% double ended shear)
53	RR30	Coolant leakage inside primary containment (30% double ended shear)
54	RX01	Fuel cladding failure
55	TC02	EHC hydraulic pump trip causing pump motors fails
56	TC02	Electro-hydraulic control failures
57	IC14	Spurious SCRAM at 100% power beginning of cycle
58	IC20	Spurious SCRAM at 100% power end of cycle with no operator action
59	IC20	Spurious SCRAM at 100% power end of cycle with operator action; feedater level is not controlled
60	IC20	Spurious SCRAM at 100% power end of cycle with operator action; feedater level is controlled
61	IC22	Spurious SCRAM at 25% power beginning of cycle
62	IC23	Spurious SCRAM at 75% power beginning of cycle
63	IC24	Spurious SCRAM at 100% power middle of cycle

further to output 0 for the patterns corresponding to the new transients, and the root network needs to be trained to detect the onset of the new transients. This is a much easier task than rebuilding the entire adviser system from scratch in an attempt to increase its diagnostic capability. In addition, all the component networks of the adviser need not use the same inputs. The designer is free to use only those plant variables as inputs that are required for that particular network's diagnostic task.

As a demonstration, an adviser was designed to detect four distinct transients. This required a root network and four networks in the classifier layer. Then it was decided to add two more transients to the adviser's diagnostic capability. The existing

root network was further trained to detect the onset of the two additional transients. The four existing networks in the classifier layer were trained further to output 0 for the two additional transients. Two more networks were trained to detect the two new transients and were integrated into the structure of the classifier network. The success of this approach lays the foundation for the final adviser that will be developed in the coming year.

7. Further adaptations of stacked generalization methodologies to verify results

Resolving the uncertainties associated with the output from diagnostic networks is very crucial in nuclear power plant (NPP) fault-diagnostics. Provision of a figure of merit in the form of error bound on outputs of a diagnostic network can be an integral part of verification and validation in NPP fault-diagnostics. Hence, the diagnosis incorporated with a figure of merit can be easily assayed whether the diagnosis from the network is reliable or must be discarded.

The method of how to predict the error bounds for a developed NPP fault-diagnostic adviser is elaborately described in Section 11.1. The original stacked generalization technique for error prediction faces difficulties in generating error information associated with providing error bounds when the technique is applied to enormous, complex problems, such as the 43 transient scenario problem (Section 4.1: Kim 1993a,b). These difficulties can be solved by adapting a partitioning scheme called modified bootstrap partition criterion (MBPC) developed in the research for San Onofre Nuclear Generating Station (Kim 1993a). The results show that MBPC scheme reduces the difficulties of the stacked generalization technique and make the error prediction method possible for more complicated applications without degrading the expected performance of the method. This advanced error prediction method will be applied to provide error bounds on the diagnosis obtained from a fault-diagnostic adviser for DAEC simulated data.

4 Research Proposals of Doctorate Students

This section contains the research proposals submitted and in the process of being submitted by the PI's doctorate students.

4.1 Error Bound Prediction for Nuclear Power Plant Fault Diagnostic Adviser Using Artificial Neural Networks

This proposal was submitted by Keehoon Kim to the Program of Study Committee and approved on September 2, 1993.

Research Proposal for Doctoral Dissertation

***Error Bound Prediction for Nuclear Power Plant Fault-Diagnostic
Advisor Using Artificial Neural Networks***

Keehoon Kim

**Department of Mechanical Engineering
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1993

Abstract

Resolving the uncertainties associated with solutions obtained from artificial neural networks (ANNs) is a major concern for many ANN researchers. A figure of merit for a solution provided by ANNs is important because it is an integral part of verification and validation in numerous engineering applications. An ANN solution incorporated with a figure of merit can be easily assayed whether the solution is reliable or must be discarded. Especially, providing the figure of merit for ANN solutions is very crucial when ANNs are applied to nuclear power plant (NPP) fault detection and therefore the detected diagnoses by ANNs should be verified.

In this research for the author's Ph.D. dissertation, a fault-diagnostic advisor for nuclear power plant transients that is based on ANNs will be developed. The goal of this research is to provide a figure of merit in the form of error bounds on the ANN advisor's solutions for a verification purpose in nuclear power plant fault-diagnostics. Simulated data in Duane Arnold Energy Center (DAEC) located at Palo, Iowa, will be used in developing the advisor and verifying its diagnoses by providing error bounds on them. An error prediction method further refined in this research will be implemented and justified.

I. Statement of Work

1. Objective of Proposed Work

The objective of the proposed research is to verify diagnoses obtained from a NPP fault-diagnostic advisor by providing error bounds on the diagnoses. The NPP fault-diagnostic advisor using ANNs provides its diagnosis in real time for a novel symptom or operational transient in NPPs. Corresponding to the advisor diagnosis, the error prediction method developed in the research provides an error bound on the diagnosis, and then operator or technical staff can use the error measured diagnosis in their mitigation process or for strategic or diagnostic purpose after the transient is under control.

2. Description of Research Work Proposed

2.1 Background The error prediction method to be used in the research is based on the stacked generalization technique [12]. The background and theory of the stacked generalization technique is described in detail in the paper that was submitted for publication to Nuclear Technology, the journal of American Nuclear Society (refer to Appendix C). The data used in the development of the advisor for the paper contains 10 simulated anomalies for the San Onofre Nuclear Power Generating Station (SONGS), a pressurized water reactor (PWR) power plant of 800 Mwe. The stacked generalization approach was used with two different partitioning schemes; one of them is a newly developed scheme for this research. The results of these partitioning schemes were compared. This work showed that the advisor system for SONGS is capable of recognizing all 10 anomalies while providing estimated error bounds on each of its diagnoses.

2.2 Data to be used for the proposed work For the proposed research, the author will apply the error prediction technique to more complicated, difficult fault-diagnostic problems that have never been solved for the verification purpose in nuclear engineering. Twenty-seven distinct transients simulated by DAEC simulation computer will be used for the research. Since some transients were collected at various severity conditions, the simulated transients includes a total of 43 different scenarios. For example, the transient of main feedwater line break inside primary containment was simulated at two different severities, 60 % and 30 %. These severities specify the size of the sheared portion of the feedwater line at the outlet of the check valve. These 43 transients are listed in Appendix A. Each data set for a transient was collected for ninety-seven plant variables at intervals of one second as the simulated transient proceed. The ninety seven plant variables include power level, reactor core flow, feedwater temperature, drywell temperature, torus pressure, and so on. The transient data sets are divided into two parts; one for a normal operating condition, followed by the other for an abnormal transient condition. The ninety seven plant variables are tabulated in Appendix B.

2.3 Method of solution The method of how to predict the error bounds for a developed NPP fault-diagnostic advisor is elaborately described in the submitted paper (sections III and IV). The method will be applied to solve the proposed fault-diagnostic problem of 43 different scenarios. The 43 scenarios problem definitely increase the complexity of diagnostics and verification. The original stacked generalization technique faces difficulties in generating error information

associated with providing error bounds when the technique is applied to enormous, complex problems, such as the 43 different scenario problem in this proposal (refer to section III in the submitted paper). These difficulties can be solved by adapting a partitioning scheme called modified bootstrap partition criterion (MBPC) developed in the research for SONGS. Please see sections III, IV and V in the submitted paper for its details and results. The MBPC scheme will reduce the difficulties of the stacked generalization technique and make the proposed error prediction method possible for more complicated applications without degrading the expected performance of the method.

Noises or degraded data are usually involved in many engineering applications and processes. In the NPP fault-diagnostics, noises from many sources can degrade the information provided to operators in the plant control room or the ANN advisor system for fault diagnosis. The degraded information might cause the advisor system to deviate from desired behaviors. The performance of the ANN advisor system and its error prediction, responded to the noises, are therefore an important subject. In the proposed work, artificially generated noise will be incorporated into the ANN advisor and the error prediction system. In order to justify the predicted error bounds to be irrelevant or at least relatively robust to the added noise, the responses of the ANN advisor and error prediction system to the inserted noise will be investigated.

3. Expected Results and Contribution

The error prediction method is expected to provide a figure of merit in the form of error bounds for verification of the diagnosis obtained by the ANN advisor. The ANN advisor and error prediction system will be tested on noisy data so that the system can be implemented to real NPPs even under noisy environments. The developed error prediction method can be applied to enormously complex problems with less difficulties and computational efforts. The theory and method of error prediction investigated here will be also an original contribution to artificial intelligence technology because the method can be applied to any ANN models for verification or validation.

II. Appendix A

The twenty seven transients, and forty three scenarios to be used to develop the ANN advisor and to verify its diagnoses.

No	Scenario Code	Transient Description
1	cu10	Reactor water clean-up coolant leakage
2	cu10gp5	Reactor water clean-up coolant leakage with failure of Group 5 isolation valves
3	fw04a	Condensate filter demineralization resin injection
4	fw09a	Reactor feedwater pump trip
5	fw12c0	Feedwater regulator valve controller stuck closed
6	fw12c1	Feedwater regulator valve controller stuck open
7	fw17a	Main feedwater line break inside primary containment
8	fw18a fw18a_2 fw18a_3	Main feedwater line break outside primary containment - 100% severity - 60% severity - 30% severity
9	hp05 hp05_2 hp05_3	High pressure core injection (HPCI) steam supply line break in HPCI room - 100% severity - 60% severity - 30% severity
10	hp08 hp08_2 hp08_3	High pressure core injection (HPCI) steam supply line break in torus room - 100% severity - 60% severity - 30% severity
11	ic20scr2	Spurious scram with effective operator action to avoid feedwater pump trip. Initial condition IC20: 100% power, End of Cycle (EOC)
12	ic20scrm	Spurious scram with no operator action. Initial condition IC20: 100% power, EOC.
13	ic22scrm	Spurious scram. Initial condition IC22: 25% power, Beginning of Cycle
14	ic23scrm	Spurious scram. Initial condition IC23: 75% power, Beginning of Cycle
15	ic24scrm	Spurious scram. Initial condition IC24: 100% power, Middle of Cycle (MOC)
16	ms02 ms02_2 ms02_3	Steam leak inside primary containment - 100% severity - 60% severity - 30% severity
17	ms03a ms03a_2 ms03a_3	Main steam line (MSL) rupture inside primary containment - 100% severity - 60% severity - 30% severity

Appendix A ... continued.

No	Scenario Code	Transient Description
18	ms04a ms04a_2 ms04a_3	Main steam line (MSL) rupture outside primary containment - 100% severity - 60% severity - 30% severity
19	ms19ab	Spurious group 1 isolation
20	ms32	Spurious group 7 isolation
21	rp05tc01	Reactor protection system SCRAM circuit failure (ATWS) with alternate rod injection
22	rp5actc1	Reactor protection system SCRAM circuit failure (ATWS) with failure of alternate rod injection
23	rr10	Recirculation pump speed feedback signal failure
24	rr15a rr15a_2 rr15a_3	Recirculation loop rupture (design basis Loss of Coolant Accident) - 100% severity - 60% severity - 30% severity
25	rr30 rr30_2 rr30_3	Coolant leakage inside primary containment - 100% severity - 60% severity - 30% severity
26	rx01	Fuel cladding (5%) failure
27	tc02	Electrical hydraulic control (EHC) system hydraulic pump failure

III. Appendix B

These are 97 plant variables to trend the 43 scenarios at interval of one second for five to six minutes. The 97 variables are used as inputs for the ANN advisor.

Serial Number	Variable Designation	Description	Min. Value	Max. Value	Unit
1	A041	Local power range monitor 16-25 flux level B	0.0	125.0	% power
2	A091	Source range monitor channel B	0.0	100.0	%
3	B000	Average power range monitor A Flux level	0.0	125.0	% power
4	B012	Reactor total core flow	0.0	60.0	Mlb/hr
5	B013	Reactor core pressure-differential	0.0	30.0	psid
6	B014	Control rod drive system flow	0.0	0.025	Mlb/hr
7	B015	Reactor feedwater loop A flow	0.0	4.0	Mlb/hr
8	B016	Reactor feedwater loop B flow	0.0	4.0	Mlb/hr
9	B017	Cleanup system flow	0.0	0.07691	Mlb/hr
10	B022	Total steam flow	0.0	8.0	Mlb/hr
11	B023	Cleanup system inlet temperature	0.0	755.0	Deg F
12	B024	Cleanup system outlet temperature	0.0	600.0	Deg F
13	B026	Recirculation loop A1 drive flow	0.0	15.1	Mlb/hr
14	B028	Recirculation loop B1 drive flow	0.0	15.1	Mlb/hr
15	B030	Reactor feedwater channel A1 temperature	280.0	430.0	Deg F
16	B032	Reactor feedwater channel B1 temperature	280.0	430.0	Deg F
17	B034	Recirculation loop A1 inlet temperature	260.0	580.0	Deg F
18	B036	Recirculation loop B1 inlet temperature	260.0	580.0	Deg F
19	B038	Recirculation A wide range temperature	50.4	789.6	Deg F
20	B039	Recirculation B wide range temperature	50.4	789.6	Deg F
21	B061	Reactor coolant total jet pumps 1-8 flow B	0.0	36.7	Mlb/hr
22	B062	Reactor coolant total jet pumps 9-16 flow A	0.0	36.7	Mlb/hr
23	B063	Reactor coolant total outlet steam flow A	0.0	2.0	Mlb/hr
24	B064	Reactor coolant total outlet steam flow B	0.0	2.0	Mlb/hr
25	B065	Reactor coolant total outlet steam flow C	0.0	2.0	Mlb/hr
26	B066	Reactor coolant total outlet steam flow D	0.0	2.0	Mlb/hr
27	B079	Reactor recirculation pump A motor vibration	0.0	10.0	MILS
28	B080	Reactor recirculation pump B motor vibration	0.0	10.0	MILS
29	B083	Control rod drive cooling-water differential pressure	0.0	500.0	dpsi
30	B084	Control rod drive cooling-water differential pressure	0.0	60.0	dpsi
31	B085	Torus air temperature #1	0.0	500.0	Deg F
32	B086	Torus air temperature #2	0.0	500.0	Deg F
33	B087	Torus air temperature #3	0.0	500.0	Deg F

34	B088	Torus air temperature #4	0.0	500.0	Deg F
35	B089	Drywell temperature azimuth 0 elevation 750	0.0	500.0	Deg F
36	B090	Drywell temperature azimuth 245 elevation 750	0.0	500.0	Deg F
37	B091	Drywell temperature azimuth 90 elevation 765	0.0	500.0	Deg F
38	B092	Drywell temperature azimuth 270 elevation 765	0.0	500.0	Deg F
39	B093	Drywell temperature azimuth 270 elevation 765	0.0	500.0	Deg F
40	B094	Drywell temperature azimuth 180 elevation 780	0.0	500.0	Deg F
41	B095	Drywell temperature azimuth 270 elevation 830	0.0	500.0	Deg F
42	B096	Drywell temperature center elevation 750	0.0	500.0	Deg F
43	B098	Torus water temperature	0.0	752.0	Deg F
44	B099	Torus water temperature	0.0	752.0	Deg F
45	B103	Drywell pressure	0.0	100.0	psia
46	B104	Torus pressure	0.0	100.0	psia
47	B105	Torus water level	-10.0	10.0	inch
48	B120	Torus radiation monitor A	-1.0	100.0	%
49	B121	Torus radiation monitor B	-1.0	100.0	%
50	B122	Reactor water level	158.0	218.0	inch
51	B124	Reactor water level	158.0	218.0	inch
52	B1257	Fuel zone level indication	-153.0	218.0	inch
53	B126	Reactor water level	158.0	458.0	inch
54	B127	Reactor vessel pressure	0.0	1200.0	psig
55	B128	Reactor vessel pressure	0.0	1200.0	psig
56	B129	Reactor vessel pressure	0.0	1500.0	psig
57	B130	Reactor vessel pressure	0.0	1500.0	psig
58	B137	Torus water level	1.5	16.0	ft
59	B138	Torus water level	1.5	16.0	ft
60	B150	Core spray A flow	-1767.8	5000.0	gpm
61	B151	Core spray B flow	-1767.8	5000.0	gpm
62	B160	Reactor core isolation cooling flow	-62.5	500.0	gpm
63	B161	High-pressure core injection flow	-437.5	3500.0	gpm
64	B162	Residual heat removal A flow	-75.0	15000.0	gpm
65	B163	Residual heat removal B flow	-75.0	150.0	gpm
66	B164	Drywell radiation monitor A	-1.0	100.0	%
67	B165	Drywell radiation monitor B	0.0	100.0	%
68	B166	Post-treat activity	0.0	100.0	%
69	B168	Pretreat activity	0.0	100.0	%
70	B171	Analyzer A - O ₂ concentration	-1.25	10.0	%
71	B172	Analyzer A - H ₂ concentration	-1.25	10.0	%
72	B173	Analyzer B - O ₂ concentration	-1.25	10.0	%
73	B174	Analyzer B - H ₂ concentration	-1.25	10.0	%
74	B180	Clean-up system flow	0.0	200.0	gpm
75	B196	Reactor water level-fuel zone A	-153.0	218.0	inch
76	B197	Reactor water level-fuel zone B	-153.0	218.0	inch
77	B247	Turbine steam bypass	0.0	500.0	Deg F
78	B248	Turbine steam bypass	0.0	500.0	Deg F
79	E000	4160 V switch gear bus 1A1 A-B	0.0	5.25	KV
80	F004	Condensate pump A & B discharge pressure	0.0	600.0	psig
81	F005	Low-pressure condenser circulating water inlet temperature A	0.0	200.0	Deg F
82	F010	High-pressure condenser circulating water outlet temperature A	0.0	200.0	Deg F
83	F011	Low-pressure condenser circulating water pressure differential A	0.0	10.0	dpsi
84	F015	Circulating water pump A & B discharge pressure	0.0	100.0	psig

85	F018	Cooling tower A discharge water temperature	0.0	752.0	Deg F
86	F019	Cooling tower B discharge water temperature	0.0	752.0	Deg F
87	F040	1P-1A reactor feed pump suction pressure	0.0	600.0	psig
88	F041	1P-1B reactor feed pump suction pressure	0.0	600.0	psig
89	F042	1P-1A reactor feed pump discharge pressure	0.0	2000.0	psig
90	F043	1P-1B reactor feed pump discharge pressure	0.0	2000.0	psig
91	F044	Condensate total flow	0.0	8.0	Mlb/hr
92	F045	Condensate makeup flow	-10.0	100.0	Klb/H
93	F046	Condensate rejection flow	0.0	50.0	Klb/H
94	F094	Feedwater final pressure	0.0	2000.0	psig
95	G001	Generator gross watts	0.0	720.0	MWE
96	T039	Low-pressure condenser pressure	0.0	30.0	inHg
97	T040	High-pressure condenser pressure	0.0	30.0	inHg

IV. Appendix C

This is the paper that was submitted to Nuclear Technology, the journal of American Nuclear Society for peer review and publication. The results of the research in this paper show that the error prediction method can provide the error bounds on diagnoses obtained from an ANN fault-diagnostic advisor for novel inputs.

Error Prediction for a Nuclear Power Plant Fault-Diagnostic Advisor Using Neural Networks

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Abstract

The objective of this research is to develop a fault-diagnostic advisor for nuclear power plant transients that is based on artificial neural networks. This paper describes a method that provides an error bound and therefore a figure of merit for the diagnosis provided by this advisor. The data used in the development of the advisor contains 10 simulated anomalies for the San Onofre Nuclear Power Generating Station (SONGS). The stacked generalization approach is used with two different partitioning schemes. The results of these partitioning schemes are compared. This work shows that the advisor is capable of recognizing all 10 anomalies while providing estimated error bounds on each of its diagnoses.

Key Words

Artificial neural networks, Classification, Error prediction, Fault-diagnostics, Nuclear power plant transients, Partition criteria, Stacked generalization, Verification and validation.

I. INTRODUCTION

The accidents at Three-Mile Island and Chernobyl have focused the demand for nuclear power plant (NPP) safety. This demand has propelled the development and implementation of innovative reactor designs,(1) better safety systems,(2) human factor studies,(3) and stricter safety requirements.(4) Even with these developments and implementations, it is still imprudent to assume that a NPP accident can never occur. Accidents may originate from many sources. For example, numerous dangerous accidents originate as relatively mild operational transients. When an operational transient does occur, a quick and accurate diagnosis is very important to plant safety since relatively simple procedures can usually be implemented to correct the situation. The major danger is in misdiagnosing a transient and therefore performing an inappropriate corrective procedure that can lead to an even more dangerous situation. Transients may, however, develop over a short period and may not grant the operators enough time to perform a diagnosis and take the appropriate corrective actions to avoid more serious plant conditions. A computer-aided diagnostic advisor system that can perform diagnoses quickly is therefore important to safety. These diagnoses could also be used by technical support personnel for diagnostic or strategic purposes after the transient is under control, presumably to avoid future occurrences of similar difficulties.

Conventional computer-aided, fault-diagnostic advisors have used expert systems. These advisor systems can provide accurate diagnoses but have some problem areas.(5,6) For example, an expert system may require significant computation time and resources to progress through the many decision levels required to formulate a diagnosis. These systems may also be subject to a combinatorial explosion of such decisions as the complexity of the monitoring

system increases. Additionally, the monitored input variables can be degraded by noise, which can cause expert systems to deviate from the formulated conditions at critical decision levels.

Recent work using artificial neural networks (ANNs) to surmount some of the aforementioned shortcomings with expert systems has been published by Bartlett and Uhrig (7,8) as well as Ohka and Seki.(9) One shortcoming of ANNs is that there is a general lack of theory that allows for provision of estimated errors on ANN solutions for validation and verification purposes.(5-7,10,11) Providing a figure of merit for an ANN advisor is very important to NPP safety in the event of an enigmatic diagnosis. This paper describes a method that provides an error bound and therefore a figure of merit for the diagnosis provided by an ANN NPP fault-diagnostic advisor.

The next section of this paper gives background on ANNs. Section III addresses error prediction and describes the stacked generalization scheme(12) used in this work to provide error bounds on the ANN fault-diagnostic advisor. Section IV explains the methods used and the data investigated in this paper. Results and conclusions are given in sections V and VI.

II. ARTIFICIAL NEURAL NETWORKS

II.A. Motivation

Mathematical models can be developed to characterize many physical systems. These models can be very accurate when the underlying laws are known. However, when the laws are not well understood or the system is very complex, empirical methods are employed to develop approximate mathematical models,

which can be very useful if used correctly. These empirical models can be developed automatically by using methods called generalizers(12,13) because they infer parent functions from sets of data. Many generalizers provide good results if the processes they model are well behaved. For example, statistical methods work well for data that is linear and normally distributed. Unfortunately, many systems are not so well behaved because of nonlinearities in the system being modeled. Nonlinear modeling is an arduous task and is not easily accomplished with standard techniques. Recent work has demonstrated that nonlinear modeling can be accomplished by ANNs.(14-17) The nonlinear modeling abilities of ANNs have served as the motivation for their use in this work because the NPP transient diagnostic problem is highly nonlinear.(7,8,17,18)

II.B. Introduction to Artificial Neural Networks

ANNs are computer algorithms that are motivated by biological neural systems. ANNs consist of highly interconnected processing elements called neurons or nodes that produce output signals based on a weighted sum of the input signals they receive.(19-21) Input signals can originate from other neurons or inputs while output signals either become the input signals for other neurons or the ANN output. The ANN in Figure-1 has four layers of neurons, referred to as the input layer, the first and second hidden layer, and the output layer. During training, an ANN is presented k examples in a learning or training set of known input-output patterns, $\{(x_i, y_i) \mid y_i = f(x_i); i = 1 \text{ to } k\}$, each of which consists of m inputs and n outputs. When one input pattern x_i is presented to the ANN via the input layer, it is fed through the neurons in the hidden and output layers to generate a corresponding output pattern y_i' , which is the ANN estimate of y_i . A typical neuron is represented in Figure 2. The weighted sum of the neuron's inputs is processed through a transfer function to produce an output signal. The ANN is trained by repetitious presentation of the training set and adjusting the

inter-neural connection weights so that the output signal y_i' converges to y_i . These inter-neural weights are represented by the lines connecting the neurons in Figure 1. There are many methods for obtaining convergence, but backpropagation(19-21), which is relatively simple, straightforward and very useful, is employed widely and will be used in this paper.

A backpropagation ANN that provides a function mapping can be regarded as a generalizer if several restrictions are satisfied.(12,13,22) These restrictions are as follows. Let L be a learning data set in $\mathbf{R}^m \times \mathbf{R}^n$ space where m is the dimension of the input space and n is the dimension of the output space. The first restriction requires that the order of the presentation of data to a generalizer be invariant, i.e., the learning of a generalizer is irrelevant to a specific order of the data presentation. The second restriction requires that when a generalizer is asked a question from the data set L , the generalizer must reproduce the corresponding output vector from L . The third restriction requires that the domain of a generalizer must be singlevalued. In other words, two or more outputs corresponding to a single input vector cannot be allowed. The fourth restriction refers to the least number of input-output patterns in the learning set L . In order to map the parent function, a generalizer needs at least k training pairs in the learning set, such that $k > m$ where m is equal to the dimension of the generalizer that is the number of input variables. The last restriction refers to the necessary dimensionality of the input vectors in a learning set. A generalizer is not defined when the components of all the input vectors in the learning set lie on an $m-1$ or less dimensional hyperplane even if the generalizer has enough training patterns. For example, assume that the components of all the input vectors in a learning set lie on a hyperplane whose dimension is less than that of the generalizer. Even if the fourth restriction is fulfilled ($k > m$), the learning set would not provide sufficient information to generalize the parent function of a higher dimension. Thus, a generalizer requires the components of all the input vectors in a learning set to lie on, at least, the same dimensional hyperplane as

that of the generalizer. ANNs including backpropagation are generalizers when the aforementioned restrictions are satisfied.(22)

III. ERROR PREDICTION ON A GENERALIZER

III.A. Stacked Generalization

Stacked generalization can be thought of as an extension of cross validation.(12) Cross validation is one of many methods in nonparametric statistics that have been developed to cope with difficulties associated with data that is not normally distributed.(23,24) Statistical modeling by nonparametric methods can be much more accurate and appropriate for cases that depend upon non-normal data distributions or unknown distributions, such as our fault-diagnostics data.(25) Cross validation can address the selection of the best model for a given non-normal experimental data set.(26) Thus, cross validation can be used to pick the best generalizer among many possible generalizers by developing the generalizer with a portion of the available data and testing it on the remainder of the data.(12,23,26)

Stacked generalization, unlike cross validation, can be used to improve the generalization accuracy for one or more generalizers; or when used with a single ANN generalizer, it can be used to estimate the error of a generalizer that is presented a novel input. Let $F^{(0)}$ be an ANN trained on a learning set L . Our goal is to estimate error bounds on outputs obtained by $F^{(0)}$. For a chosen partition criterion, the learning set L is partitioned into two subsets. An ANN that is called the level 0 generalizer $f^{(0)}$ and has the same architecture of the $F^{(0)}$ is trained on one partitioned subset. The performance of $f^{(0)}$ is measured by testing the generalizer on the remaining partitioned subset. Since the second subset is not

used in training $f^{(0)}$, the output of $f^{(0)}$ will, in general, deviate from the desired output. This deviation represents the error between the untrained input and the ANN's output. Another partition is chosen and the process of training and testing is repeated. The performance data that includes the untrained input, a vector from the untrained input to its nearest pattern in the first subset and the deviation, constitutes a new learning set L' called the level 1 learning set. A new ANN called the level 1 generalizer $P^{(1)}$ is trained on the level 1 learning set L' . The level 1 generalizer $P^{(1)}$ learns the relationship between the inputs and the errors of $f^{(0)}$ and then can estimate a figure of merit in the form of an error bound on outputs of the ANN $F^{(0)}$. This stacking procedure is the essence of the stacked generalization approach and is illustrated in Figure 3.

Three different partition criteria for the stacked generalization method are investigated, two of which are applied to NPP fault-diagnostics in this work. The stacking procedure is accomplished by three different partitioning criteria all of which provide a diagnostic figure of merit estimate for the NPP fault-diagnostic advisor developed in this work. They are cross validation partition criterion (CVPC), bootstrap partition criterion (BPC), and modified bootstrap partition criterion (MBPC). Each of these methods yields slightly different results and these differences are the subject of the discussion of this paper.

As a preliminary to the discussions of these methods, let us define the following concepts. Let Q be the universal set of questions ($Q = \{q, u\}$) where q is a question of interest and u is an unknown solution for the question. This situation is shown in Figure 4. The unknown solution u is provided by an ANN generalizer called $F^{(0)}$. A subset $L \subset Q$ is chosen to be a learning set used to train the generalizer. Let $L = \{(x_i, y_i) | i = 1 \text{ to } k\}$ where y_i is a known solution corresponding to x_i . The learning set L consists of k patterns of input-output vectors, $x_i \in \mathbf{R}^m$ and $y_i \in \mathbf{R}^n$. For the problem of NPP diagnostics, Q

corresponds to the set of all plant transients and normal conditions. The ANN generalizer $F^{(0)}$ corresponds to an ANN NPP fault-diagnostic advisor. Asking a novel question $q \in Q - L$ of $F^{(0)}$ is equivalent to requesting the fault-diagnostic advisor to diagnose a novel transient symptom q . A diagnosis u is then obtained from the advisor $F^{(0)}$. A figure of merit ϵ associated with u is then provided by the level 1 ANN $P^{(1)}$ such that the resultant output from the advisor system is $u \pm \epsilon$.

III.B. Error Prediction with Cross Validation Partition Criterion (CVPC)

Stacked generalization employs a set of t partitions chosen from the learning set L . To obtain a partition i , where i ranges from one to t , split L into two disjointed sets, L_{i1} and L_{i2} . The cross validation partition criterion (CVPC) (12) is defined such that t is equal to k where t is the number of partitions and k is the number of training patterns in L . For each i , L_{i2} consists of a single pair (x_i, y_i) in L , and the corresponding L_{i1} consists of the remainder of L , i.e., $L - (x_i, y_i)$. Since t is equal to k , then $\cup L_{i2} = L$ for all i , and $L_{i2} \cap L_{j2} = \emptyset$ for $i \neq j$. The space of the original learning set L , $\mathbf{R}^m \times \mathbf{R}^n$, is called the level 0 space. The level 0 generalizer $f^{(0)}$ is applied directly to the level 0 learning set L in the level 0 space. In Figures 3 and 4, a partition is shown by dividing L into two subsets, $L_{i1} = L - (x, y)$ and $L_{i2} = (x, y)$. Note that the subscript i for the input-output pattern is dropped for convenience in the figures. Given the partition, the generalizer $f^{(0)}$ is trained on the subset L_{i1} . The untrained question x in L_{i2} is then presented to $f^{(0)}$. The answer g given by $f^{(0)}$ for the novel question x will be, in general, different from the correct answer (output) y . In addition to this information, the vector x' defined as difference vector from x to its nearest neighbor in L_{i1} is computed. The nearest neighbor is obtained by using Euclidean distance. Now, when the question is x , the correct answer y differs from the answer g provided by $f^{(0)}$ by $\epsilon = |g - y|$. The error information ϵ along with x and x' defines the level 1 information space for the generalizer $F^{(0)}$. This information

is used to form a new learning set L' in the level 1 space. Hence, the new level 1 learning set L' consists of an input (x, x') and an output $|g - y|$ for each partition i . These pairs constitute the level 1 learning set L' . A level 1 generalizer $P^{(1)}$ is then trained on the level 1 learning set L' .

Next, we ask the ANN generalizer $F^{(0)}$ trained on the entirety of L a novel question $q \in Q - L$. The ANN generalizer $F^{(0)}$ provides a solution for the question. The level 1 generalizer $P^{(1)}$ trained on the level 1 learning set L' is fed the question q with the vector q' from q to its nearest neighbor in L . The output of $P^{(1)}$ then provides the figure of merit for the solution of $F^{(0)}$. The results of this procedure for SONGS data are shown in Figures 6, 8 and 10.

III.C. Error Prediction with Bootstrap Partition Criterion (BPC)

Using CVPC requires that the total number of partitions t is equal to the number of training patterns k in a given learning set. The computation time for generating the level 1 learning set increases in proportion to the number of training patterns k since the level 0 ANN $F^{(0)}$ must be trained and tested k times. When k is large, which is typical of real applications, the computation time as well as human effort can be very lengthy and impractical. The total number of partitions can be reduced by employing a method we have developed. The first method is called bootstrap partition criterion (BPC).

When applying BPC, a partitioned set L_{i2} can be chosen to have multiple elements rather than one as in CVPC. When those elements are chosen randomly from the original learning set L , we designate it as the bootstrap partition criterion (BPC) method because it is similar to the bootstrapping method in nonparametric statistics.^(12,27) In the original nonparametric bootstrapping method, the multiple elements are chosen randomly for each partition, however, this may allow some particular elements to appear several times. Without imposing proper conditions, the total number of partitions might increase due to

the repeated selection of some patterns. The repeated selection results in a situation where the total partition number t would not be significantly reduced or the desired results are not attained. The unnecessary increase in the total partitions is avoided by adapting the constraints of Xiangdong's partition set. (28) For BPC, we impose his two constraints on the partition sets with a modification as follows. First, predetermine a number of L_{i2} elements, say s . Choose at random s elements from L such that $L_{i2} = \{(x_1, y_1), (x_2, y_2), \dots, (x_s, y_s)\}$ and $L_{i1} = L - L_{i2}$. Second, require $\cup L_{i2} = L$ for all i and $L_{i2} \cap L_{j2} = \emptyset$ for $i \neq j$. As required by these conditions, a pattern in L_{i2} will appear only once in all of the partitions. When s is chosen such that $k/s \sim 10$, the total computation time will be reduced to one-tenth of that of CVPC.

III.D. Error Estimation with Modified Bootstrap Partition Criterion (MBPC)

The BPC scheme can reduce the total number of partitions t , but due to the random selection of s elements of L_{i2} , the scheme may provide varying results. In order to improve the reliability of the results for ANN NPP fault diagnostics, we propose a modified bootstrap partition criterion (MBPC) that has the advantages of BPC without the disadvantages of random selection of the elements in the partition sets. MBPC is an extension of BPC where the L_{i2} patterns are chosen systematically to model the specific problem.

For the case of NPP fault diagnostics, the ANN advisor must recognize a transient whose plant variables are dynamically changing according to plant function. In addition, the advisor needs to distinguish a particular transient from many different transients of interest. Therefore, the learning set may consist of r separate groups pertaining to the r different transients. These r groups differ from each other such that the r patterns for L_{i2} can be selected from each transient group at the same time. This selection can minimize the loss of information related to the desired error bounds by the random selection of L_{i2} in BPC. It

follows that MBPC requires two more constraints on the learning set not imposed on BPC. First, L_{i2} must be a set of r single patterns chosen from each transient group. If the number of training patterns in a specific transient group is larger than r , an additional constraint is imposed as follows. A maximum of two patterns can be selected from the particular group whose number of training patterns is larger than r . For example, assume that there are three different transients A, B and C, i.e., $r = 3$, and the transient groups A, B, and C have 2, 3, and 5 training patterns, respectively. If a total of 3 partitions ($t=3$) are chosen, the second constraint is applied to the partitions such that two patterns from C and one pattern from A and B are selected for two partitions. For the remaining partition, one pattern is selected from A, B and C. In fact, the last partition doesn't contain any pattern from A because A has only two patterns. These modifications for NPP fault diagnostics can reduce the difficulties of using BPC while maintaining the accuracy of CVPC and speed of BPC. This can be seen by the results shown in Figures 6, 8 and 10.

IV. METHOD OF SOLUTION

An ANN NPP fault-diagnostic advisor $F^{(0)}$ is developed to detect and classify various operational transients at San Onofre Nuclear Generating Station (SONGS). A figure of merit for its diagnosis is provided by a $P^{(1)}$ generalizer called the ANN error predictor. The data used for training the ANN fault-diagnostic advisor was obtained from SONGS, owned by Southern California Edison Co. and San Diego Gas & Electric Co. (29) SONGS is a pressurized water reactor (PWR) plant that provides 800 MWe. Ten transient scenarios listed in Table I are included in the data set for ANN training. The scenarios include design-basis accidents and less severe transients. Note that the

stuck open pressurizer safety valve with high pressure injection inhibited is similar to the condition that occurred at the Three-Mile Island accident in 1979. The data sets for the ten transients, each contain 33 plant variables illustrated in Table II. These variables are collected at time step intervals of one second for a period of ten minutes. Note that this time snap shot, or single time slice, of data does not include temporal information. The main advantage of the single time step approach is simplicity of training and execution.(7) Thus the ANN advisor $F^{(0)}$ can diagnose transients at the very instant the plant variables are presented because the ANN does not need to observe trends or temporal variation. In each data set, normal operation conditions are followed by transient conditions. Notice that with the exception of the turbine trip from 50% power, all of the transient scenarios start from the full-power, normal operating condition. The ten transient conditions plus the normal steady-state operating conditions with a different initial power constitute the learning set with 113 patterns for the ANN advisor $F^{(0)}$. The learning set L of 113 input-output patterns is obtained by the procedures outlined by Bartlett and Uhrig.(7) The number of the patterns in the learning set L is only about 2% out of the 6203 patterns of the entire data set Q for the ten scenarios. This learning set includes ten initial conditions due to different initial power and flux levels. The remaining 103 input-output patterns correspond to abnormal conditions of the ten transients.

The ANN advisor for SONGS is established by training $F^{(0)}$ on the learning set L. The advisor $F^{(0)}$ uses a backpropagation ANN and is trained until a training root mean square (RMS) error of 0.01 is obtained. The ANN $F^{(0)}$ has 33 input nodes each corresponding to the 33 plant variables, 22 nodes in the first hidden layer, 10 nodes in the second hidden layer, and 4 nodes in the output layer (33-22-10-4). The four output nodes are used to distinguish each of the ten transient conditions with a distinct 4-bit binary code as listed in Table I. The two-hidden-layer architecture was employed after attempting several different architectures. In this investigation, each of the three partitioning approaches

outlined in the previous section is compared. The first step toward generating a level 1 learning set L' for any of the partitioning schemes is to create t partitions of L :

- i) In the CVPC case, the partition is chosen to be $t = k = 113$. For i , where $i = 1$ to t , $L_{i2} = (x_i, y_i)$ with the conditions of $L_{m2} \cap L_{n2} = \emptyset$ for $m \neq n$ and $\cup L_{i2} = L$ for all i .
- ii) In the BPC case, the total number of partitions, t , is chosen to be 12 with $s = 10$ the predetermined element number. For i , where $i = 1$ to t , $L_{i2} = \{(x_l, y_l) | l = 1 \text{ to } s\}$ is randomly chosen with the conditions of $L_{m2} \cap L_{n2} = \emptyset$ for $m \neq n$ and $\cup L_{i2} = L$ for all i . This partition scheme is not simulated in this investigation because of the disadvantage of the scheme discussed in the preceding section.
- iii) In the MBPC case, $r = 10$ groups because L contains 10 distinct transients. For partition i , $L_{i2} = \{(x_l, y_l) | l = 1 \text{ to } r\}$ where each pattern is randomly chosen from each transient group with the conditions of $L_{m2} \cap L_{n2} = \emptyset$ for $m \neq n$ and $\cup L_{i2} = L$ for all i . In the learning set L for SONGS, four transient groups have training patterns larger than r where r is 10. Thus, total number of partitions, t is chosen to be 12, and the second constraint allows a maximum of two patterns to be selected from each of these four groups.

Another backpropagation ANN $f^{(0)}$ having the same architecture of the developed advisor $F^{(0)}$, is used as a level 0 ANN. For each partition, $f^{(0)}$ is trained on L_{i1} and then presented input patterns in L_{i2} as questions. The error ϵ of $f^{(0)}$ for a question is computed by subtracting the $f^{(0)}$ output from the desired output, as follows:

$$\epsilon_j = |g_j - y_j|, \quad j=1,2,3,4. \quad (1)$$

where g_j is a value of the j -th output node on $f^{(0)}$ and y_j is a j -th component of the

desired output y corresponding to the question x . The next step is to calculate vector x' from x to its nearest neighbor vector x_{nn} . The nearest neighbor vector x_{nn} from x is chosen in the L_{i1} such that x_{nn} has the smallest Euclidean distance (l_2 -norm) from x . The vector x' from x to its nearest neighbor x_{nn} is determined by the equation,

$$x'_i = ((x_i - x_{nn\ i}) + 1) / 2 \quad (2)$$

for the i -th component of the vector since negative values are not appropriate as an input to an ANN. Additionally, this transformation formula insures that all components are within the interval $[0,1]$ required by backpropagation ANN. For all partitions given by one of two partition criteria, a total of 113 trios of x , x' , and ϵ are acquired. Therefore, the level 1 learning set L' consists of these 113 trios. These new input-output patterns in L' are used to train a level 1 generalizer $P^{(1)}$ in order to provide error bounds on the results of the developed ANN fault-diagnostic advisor $F^{(0)}$. The ANN error predictor $P^{(1)}$ is a backpropagation ANN with a 66-30-20-10-4 architecture. Again, this architecture was chosen after several attempts to find the optimal architecture.

The ANN advisor $F^{(0)}$ is designed to categorize the untaught input conditions at the plant into a normal condition or a specific transient. This classification is the diagnosis of the level 0 $F^{(0)}$ for an unknown symptom $q \in Q - L$ in the plant operational status within generalized knowledge about the ten transients. The novel input-condition that is fed into $F^{(0)}$ and the vector from the input condition to its nearest pattern in L are presented as an input condition to $P^{(1)}$. For those level 1 input conditions, the ANN error predictor $P^{(1)}$ will predict the error bounds ϵ on the diagnoses of the ANN fault-diagnostic advisor $F^{(0)}$.

V. RESULTS OF THE RESEARCH

Figures 5 through 11 and Table III show the results of this research. Figures 5, 7, and 9 display the advisor's true diagnostic RMS error. The true diagnostic error is the actual error as compared with the true solution. The true solutions, in this case, are obtainable because the transients were simulated by the SONGS simulation computer which is assumed to be correct. The ANN error predictor $P^{(1)}$ provides an estimated error bound associated with the advisor's diagnosis as a figure of merit estimate. The estimated error bound is shown in Figures 6, 8, and 10 corresponding to each of the odd-numbered figures, respectively. The solid line in these figures represents the estimated error bound obtained by using MBPC, the dashed line by CVPC. The figures show that the predicted errors by the MBPC method are much closer to the true diagnostic errors than those by the CVPC method. Note that MBPC reduces considerably the total number of partitions, $t = 12$, compared with that of CVPC, $t=113$, for generating L' . Figure 11 shows an example of the classification resulting from the combination of the error bounds with the diagnoses of the advisor $F^{(0)}$ for turbine trip/reactor trip as seen in Figures 9 and 10. Note that when an error bound falls below 0.1, the diagnosis is considered to be acceptable. This error-combined classification at each instant of input data presentation can be provided as a final result to the operators or technical support staff at SONGS, or indeed this approach can be used at any other NPP or process plant where accident avoidance is paramount. Table III summarizes the results of the advisor $F^{(0)}$ and the error predictor $P^{(1)}$ developed by using MBPC. The third column shows the time when the advisor $F^{(0)}$ makes a diagnosis with the true diagnostic RMS error below 0.1 after transient onset. The fourth column displays the time when an error bound predicted by $P^{(1)}$ falls below 0.1 after transient onset.

The ANN advisor $F^{(0)}$ responds very quickly to the onset of the transients. However, since the plant input variables are dynamically and suddenly changing during the short transitory period after the onset of each abnormal condition, the advisor's diagnoses are inconclusive for this period. This transitory period for each transient is shown in the odd-numbered figures as well as in the third column of Table III. The advisor $F^{(0)}$ classifies the abnormal conditions with true diagnostic errors below 0.1 within 30 seconds after transient onset, and even immediately in the case of the stuck open pressurizer safety with high pressure injection inhibited. One exception is the trip of a single reactor coolant pump for which the classification takes about 62 seconds. This transient is characteristically similar to the trip of all reactor coolant pumps. It is understandable that the advisor may need more time to distinguish between these two transients. Note that the required time for diagnosing the trip of all reactor coolant pumps after the onset is only 2 seconds.

In the even numbered figures, the predicted error bounds indicate the estimated uncertainty in the $F^{(0)}$ advisor's diagnosis. For example, during the transitory period in Figure 10, in this case from 6 seconds through 37 seconds, the predicted errors are so much larger than 0.1 that the diagnosis for this period is unreliable. Hence, the classification is undetermined for this transitory period as seen in Figure 11. Since the diagnosis is undetermined, the plant personnel should not consider the output of the advisor when determining plant conditions for mitigation purposes. After the transitory period passes, the predicted error bounds are less than 0.1. The diagnosis of the advisor is then reliable and Figure 11 shows that the classification is turbine trip/reactor trip. In Table III, the predicted error of single turbine governor valve closure is below 0.1 for the entire period. But the true diagnostic error is higher than 0.1 for the transitory period of 16 seconds after the onset. This inconsistency can be eliminated by adding more data delineating the features of the transitory period. This remedy is confirmed by the fact that the training data set L used in this research contains no patterns between a period of

from 2 to 29 seconds.

Another fascinating example is the turbine trip from 50% power. In Table III, the error bounds on the diagnoses are large for 211 seconds after the onset at 50 seconds, including the normal operation period. This indicates that the diagnosis is unreliable for both the normal operation and the transient condition periods. In contrast with the predicted error bounds, the true diagnostic errors falls below 0.1 in one second after the transient onset. This discrepancy looks like an undesirable result of the method used in this research. But, in fact, it justifies the method. Notice that all the data for the other transients were collected from 100% power, except for this particular transient where the data were collected from 50% power. Consequently, from the viewpoint of generalization accuracy as measured by stacked generalization, the advisor is not able to sufficiently generalize this specific scenario of the turbine trip from 50% power from others. In other words, the confidence on the diagnoses for this transient is very low. The assuredness on the diagnoses of this transient can be increased by training the ANN advisor with more transients from this lower reactor power level. This additional training will increase the generalization accuracy for this transient as well as others at this lower power level.

As seen in the odd-numbered figures, the true diagnostic RMS error is conventionally used as a measure of a recall performance. The recall performance is typically utilized to check the generalization accuracy within a single transient. Hence, the generalization accuracy of the ANN diagnoses within a single specific transient is obtained by checking the recall performance. However, this generalization accuracy within a single transient cannot provide the generalization accuracy for the unique transient scenario being compared with other transient scenarios. For example, the error prediction result indicates that the transient of the turbine trip from 50% power needs additional training data in order to be generalized from the other transients. Hence, the generalization accuracy for a

transient scenario with respect to other transient scenarios can only be obtained by applying the error prediction method investigated in this work.

VI. CONCLUSIONS

The objective of this work is to demonstrate a verification technique that provides a figure of merit for the diagnosis of an ANN fault-diagnostic advisor for NPPs. To this end, an ANN advisor is successfully developed to detect and classify ten transient scenarios and ten normal conditions in a PWR nuclear power plant. The error prediction is accomplished by applying the stacked generalization technique to the ANN advisor for providing a figure of merit for the advisor. The results demonstrate the feasibility of the error prediction method for the validation of NPP status diagnostics. The results of the proposed MBPC method show a considerable reduction in computation time and effort without any reduction in the accuracy of the predicted error. Additionally, our error prediction approach can tell us the generalization accuracy for each individual transient scenario as compared with all the other scenarios. The error prediction technique developed in this investigation can also be utilized in all ANN applications.

Fundamentally, the error prediction used in this work uses the nonparametric statistical information in a learning set. Accordingly, each example in a learning set is closely related to generalization accuracy, i.e., the more appropriate the selection of the examples in the training set, the better the generalization. Hence, we suggest that stacked generalization be applied as a more suitable method for the selection of examples for the learning set in future work. In addition, further refinement of the stacked generalization technique will be needed because the dimension of input vectors is doubled in the level 1 space.

Level 1 ANN training time therefore increases considerably when the number of plant input variables is large, which is common in fault-diagnostic problems. Furthermore, the correlations of the generalization accuracy of a level 1 generalizer to its training accuracy should be investigated.

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Table I

List of Ten Accident Scenarios with Transient Onset Time and Desired ANN Output Layer Activation

No.	Scenario	Transient onset time (sec.)	Desired output node activation			
			1	2	3	4
	Normal Operation	(before transient onset)	0	0	0	0
1.	Turbine Trip/Reactor Trip	6	1	0	0	0
2.	Loss of Main Feedwater Pumps	47	0	1	0	0
3.	Closure of Both Main Steam Isolation Valves	7	0	0	1	0
4.	Trip of All Reactor Coolant Pumps	16	0	0	0	1
5.	Trip of A Single Reactor Coolant Pump	14	1	1	0	0
6.	Turbine Trip From 50% Power	50	1	0	1	0
7.	Loss of Coolant Accident (LOCA) With Loss of Off-Site Power	7	1	0	0	1
8.	Main Steam Line Break	6	0	1	1	0
9.	Stuck Open Pressurizer Safety with High Pressure Injection Inhibited	15	0	1	0	1
10.	Single Turbine Governor Valve Closure	7	0	0	1	1

Table II

Plant Variables Used as Input to the ANN Fault-Diagnostic Adviser F⁽⁰⁾

-
1. Power (flux)
 2. Average Temperature (Deg F)
 3. Hot Leg 1 Temperature (Deg F)
 4. Cold Leg 1A Temperature (Deg F)
 5. Cold Leg 1B Temperature (Deg F)
 6. Hot Leg 2 Temperature (Deg F)
 7. Cold Leg 2A Temperature (Deg F)
 8. Cold Leg 2B Temperature (Deg F)
 9. Pressurizer Pressure (psia)
 10. Pressurizer Level (%)
 11. Pressurizer Temperature (Deg F)
 12. Steam Generator 88 Narrow Range Level (%)
 13. Steam Generator 88 Water Level (%)
 14. Steam Generator 88 Feed Water Flow (gpm)
 15. Steam Generator 88 Feed Water Flow (Lb/sec)
 16. Steam Generator 88 Steam Flow (Lb/sec)
 17. Steam Generator 88 Pressure (psi)
 18. Steam Generator 89 Narrow Range Level (%)
 19. Steam Generator 89 Water Level (%)
 20. Steam Generator 89 Feed Water Flow (gpm)
 21. Steam Generator 89 Feed Water Flow (Lb/sec)
 22. Steam Generator 89 Steam Flow (Lb/sec)
 23. Steam Generator 89 Pressure (psi)
 24. Containment Pressure (psig)
 25. Containment Temperature (Deg F)
 26. Pressurizer Relief Steam Flow
 27. Pressurizer Relief Liquid Flow
 28. Core Inlet Flow
 29. Saturation Margin
 30. Surge Line Temperature (Deg F)
 31. Source Range Counts (cps)
 32. Reactor Vessel Head Level
 33. Reactor Vessel Plenum Level
-

Table III

Summary of the Results of the ANN Adviser $F^{(0)}$ and the Error Predictor $P^{(1)}$

Scenario	Transient onset time (sec.)	Time after transient onset for the true diagnostic error to fall below 0.1^a (sec.)	Time after transient onset for the error bound predicted by $P^{(1)}$ to fall below 0.1^a (sec.)
1. Turbine Trip/Reactor Trip	6	30	32
2. Loss of Main Feedwater Pumps	47	3	36
3. Closure of Both Main Steam Isolation Valves	7	28	21
4. Trip of All Reactor Coolant Pumps	16	2	20
5. Trip of a Single Reactor Coolant Pump	14	62	31
6. Turbine Trip From 50% Power	50	1	211
7. Loss of Coolant Accident (LOCA) with Loss of Off-Site Power	7	14	4
8. Main Steam Line Break	6	4	20
9. Stuck Open Pressurizer Safety with High Pressure Injection Inhibited	15	0	46
10. Single Turbine Governor Valve Closure	7	16	0

^a The value is arbitrarily assigned for an illumination purpose.

Figure Captions

Figure 1.

A feedforward neural network with four-layer architecture.

Figure 2.

Forward activation in neuron O_{pi} in a neural network. θ_i is a bias for the neuron.

Figure 3.

Illustration of the stacked generalization procedure. The level 0 generalizer $f^{(0)}$ is used in generating the level 1 learning set L' for a given partition. The level 1 generalizer $P^{(1)}$ provides a figure of merit in the form of an error bound for an output obtained by $F^{(0)}$ for the untrained question q .

Figure 4.

Illustration of a set of question and its unknown answer Q and a set of learning examples L with a partition given by cross validation partition criterion (CVPC).

Figure 5.

True diagnostic error (RMS) of $F^{(0)}$ diagnosis compared with the true solution in the case of closure of both main steam isolation valves.

Figure 6.

Estimated error bounds provided by the error predictor $P^{(1)}$ for two different partitioning schemes on the advisor $F^{(0)}$ diagnosis. Solid line represents the estimated error bounds by using modified bootstrap partition criterion (MBPC); dashed line by using cross validation partition criterion (CVPC).

Figure 7.

True diagnostic error (RMS) of $F^{(0)}$ diagnosis compared with the true solution in the case of trip of a single reactor coolant pump.

Figure 8.

Estimated error bounds provided by the error predictor $P^{(1)}$ for two different partitioning schemes on the ANN advisor $F^{(0)}$ diagnosis. Solid line represents the estimated error bounds by using modified bootstrap partition criterion (MBPC); dashed line by using cross validation partition criterion (CVPC).

Figure 9.

True diagnostic error (RMS) of $F^{(0)}$ diagnosis compared with the true solution in the case of turbine trip/reactor trip.

Figure 10.

Estimated error bounds provided by the error predictor $P^{(1)}$ for two different partitioning schemes on the ANN advisor $F^{(0)}$ diagnosis. Solid line represents the estimated error bounds by using modified bootstrap partition criterion (MBPC); dashed line by using cross validation partition criterion (CVPC).

Figure 11.

Classification of the advisor diagnosis combined with the predicted error bound for the turbine trip/reactor trip. This classification will be provided plant personnel as a final result of the ANN fault-diagnostic advisor system, as an transient proceeds in a NPP.

FIGURE 2

Title: Error prediction for a nuclear power plant fault-diagnostic
 advisor using neural networks
 Keehoon Kim & Eric B. Bartlett

FIGURE 3

Title: Error prediction for a nuclear power plant fault-diagnostic
advisor using neural networks
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FIGURE 4

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FIGURE 5

Title: Error prediction for a nuclear power plant fault-diagnostic
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FIGURE 6

Title: Error prediction for a nuclear power plant fault-diagnostic
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FIGURE 7
Title: Error prediction for a nuclear power plant fault-diagnostic
advisor using neural networks
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FIGURE 8

Title: Error prediction for a nuclear power plant fault-diagnostic
advisor using neural networks
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FIGURE 10

Title: Error prediction for a nuclear power plant fault-diagnostic
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FIGURE 11

Title: Error prediction for a nuclear power plant fault-diagnostic
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4.2 Medical Image Reconstruction via a Statistically Tailored Neural Network Simulated on a Massively Parallel Computer

This proposal was submitted by John Kerr to the Program of Study Committee and will be defended on November 12, 1993.

**Medical image reconstruction via a statistically
tailored neural network simulated on a
massively parallel computer**

by

John Patrick Kerr

A Ph.D. Proposal Submitted to the
Program of Study Committee for Review
and Determination of Ph.D. Candidate Status

OBJECTIVE

The objective of the proposed research is to determine if a backpropagation neural network with statistically tailored activation functions simulated on a massively parallel machine has the capacity to improve the speed, the quality, and consequently, the clinical value of single photon emission computed tomography (SPECT) image reconstruction.

BACKGROUND

Single Photon Emission Computed Tomography (SPECT)

SPECT is a radiopharmaceutical medical imaging technique that provides three-dimensional distribution mapping of a radionuclide after its administration to a patient [1,2]. The radionuclide emits gamma photons as it decays and is scanned with a gamma ray scintillation camera after it localizes in the target area of the body [3,4]. The planar gamma camera images taken 180° about the patient, provide all the information necessary to produce cross-sectional images of the radionuclide distribution in the target organ. When reconstructed, the three-dimensional image array provides information on pathologic processes and physiological functioning in the target organ. SPECT imaging is primarily used for identifying organ lesions and evaluating metabolic processes. Reconstruction is typically achieved via a filtered backprojection algorithm [5,6]. Although this method provides useful information, it does have several limitations that create a high percentage of statistical uncertainty in the reconstructed images. A neural network could be trained to compensate for the sources of the uncertainty, and produce higher quality and diagnostically more valuable reconstructed images.

The sources of uncertainty in the reconstructed image include radiation attenuation, scatter effects, motion artifacts, and finite resolution artifacts [7,8]. Useful compensation techniques for these image quality degradation effects are highly dependent on the source organ. Correction methods for the physical photon transport effects in SPECT imaging of the brain are valuable because of the location and approximately uniform shielding of the brain. The general circular shape of the head allows the gamma camera to rotate in close proximity to the brain and thus, SPECT imaging is relatively quick and of higher resolution than the imaging of other organs. The head can also be readily stabilized which greatly reduces motion

artifacts. In addition, the skull is roughly uniform and so linear models of the attenuation effects are often used to improve the quality of the reconstructed brain images [9,10].

Likewise, cardiovascular SPECT is a valuable imaging technique in that it provides detailed information of the cardiac wall motion and function without superimposed adjacent structures, such as occurs with planar blood-pool imaging [11]. Thallium-201 SPECT imaging which is commonly used for cardiovascular SPECT, provides the clinician with the ability to visualize the heart with respect to its wall and valve boundaries again, without foreground or background interference. Cardiovascular SPECT is limited by decreased resolution due to increased distance between the gamma camera collimator and the heart, large non uniform attenuation due to the thorax, and the amount of patient discomfort associated with the time required for imaging. Attempts to model the thorax to compensate for attenuation have been very unsuccessful and typically, no attenuation compensation is used with cardiovascular SPECT [12]. Likewise, motion artifacts are inherent in imaging the heart. Neither the heart nor the thoracic cavity can be stabilized during imaging. Gated cardiovascular SPECT in which photon detection's are only counted during the end diastolic or end systolic period of the heart cycle, have been tried but the large increase in the time required to get adequate photon counts makes it a somewhat impractical technique [11,13].

Artificial Neural Networks

Artificial neural networks (ANNs) have been shown to provide solutions to problems that conventional computer architecture's cannot solve readily, or at all. Examples of areas in which ANNs have shown promise are speech and pattern recognition [14], control systems [15], and image enhancement [16]. The architecture of a feed-forward neural network is modeled after the neural structure in the cerebral cortex of the brain. Much as people are a product of experience and learning by example, so to is the knowledge possessed by a neural network based on what it is taught, or trained to know. Backpropagation is a popular, often implemented training algorithm [17,18]. In this algorithm, a known set of training data is fed through the network and the error, which is the calculated difference between the expected output and the actual output, is fed back through the network. Interconnection weight values which represent the collective knowledge of the network, are then adjusted with respect to the back-propagated error to minimize the error in the outputs. Thoroughly training a network often requires presenting the entire training set thousands or even hundreds of thousands of times. As the size of the problem being addressed by the neural network grows, the ability of the ANN to be trained in a reasonable amount of time becomes the limiting factor in its use, particular when the network is implemented on a serial (single processor) computer.

The architecture of a multi-layer neural network has a natural parallel structure. The processing elements (PEs), or neurons, in each layer of the network receive inputs simultaneously from the previous layer and process individual outputs independent of each other. Consequently, implementing an ANN on a traditional single processor, or von Neumann computer, takes a considerable amounts of time to process the same instructions for each PE, one at a time. The time saved training an ANN implemented on a parallel computer may provide the improved training time necessary to apply neural networks to more complex

problems that require large architecture's. Medical image reconstruction, in particular SPECT imaging, is a good example of a larger problem.

A backpropagation neural network was simulated on the MasPar MP-1 single instruction multiple data (SIMD). The neural network was trained to produce reconstructions of sections of 8 x 8 SPECT brain images, given the planar gamma ray scans of the target area of the brain [19]. The neural networks ability to learn the relationship between the object, in this case brain sections, and its projections, or ray-sums, showed that a larger neural network could be developed to generate full SPECT image reconstructions from completely novel planar images, and thus, potentially be utilized clinically for SPECT image reconstruction.

Likewise, comparisons between the execution speed of the neural network on a serial machine versus a parallel machine (MP-1), showed that networks containing a 160 to 180 nodes could be trained four times faster on the parallel machine. When these results are extrapolated to neural network architectures that would be needed for full SPECT image reconstruction, which would require 8,000 to 12,000 nodes, it can be seen that such a neural network simulated on the parallel machine could execute at two to three orders of magnitude faster than on a serial machine. This kind of processing power would make very larger neural networks practical to implement and train. Therefore, it has been shown that full SPECT image reconstruction via a neural network is feasible and also trainable in a reasonable amount of time. A more in-depth background description of SPECT imaging, ANNs, and parallel computing can be found in [20].

PROFESSIONAL BIOGRAPHY

I received a bachelor of science degree in computer engineering from Iowa State University in the fall of 1986. Subsequently, I moved to St. Louis where I worked for the McDonnell Aircraft Company (McAir) as a avionics systems engineer for the F/A-18 Hornet aircraft. While at McAir I was the lead engineer on three avionics systems: the data storage set which used 256kb EEPROMs to record in-flight events and aircraft status; the digital map set which recalled digitized color maps stored on a 360 MB optical disk, based on the aircraft's location; and the multipurpose display indicator which is the primary cockpit display and has four symbol generators that allow it to drive four independent displays. After a year of pontificating and the cancellation of a major aircraft, I decided to return to Iowa State in the spring of 1991 to pursue graduate work in biomedical engineering.

In August of 1992 I received a masters of engineering in biomedical engineering. My thesis research, entitled " The parallel implementation of a backpropagation neural network and its applicability of SPECT image reconstruction," demonstrated the ability of a standard backpropagation neural network implemented on a massively parallel computer , to learn the planar-to-tomogram relationship to 8 x 8 sections of SPECT images. Based on that knowledge, the trained ANNs were able to accurately reconstruct novel 8 x 8 images [20]. Essentially, the masters research was a small-scale feasibility study for the research proposed herein.

METHODS AND PRELIMINARY RESULTS

A description of the research methods and preliminary results of a ANN with statistically tailored activation functions to learn the planar-to-tomogram relationship of full 64 x 64 cardiovascular SPECT images, and generalize that knowledge to accurately produce novel reconstruction is given in the following paper: "A statistically tailored neural network approach to tomographic imaging on a massively parallel computer."

A statistically tailored neural network approach to tomographic image reconstruction on a massively parallel computer

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ABSTRACT

An artificial neural network (ANN) trained on quality medical tomographic images produced by an iterative technique, such as a Monte Carlo method, or trained on phantom data may be able to learn the planar data-to-tomographic image relationship with very high precision. As a result, a properly trained ANN can produce comparably accurate, novel image reconstructions but without the high computational cost inherent in the Monte Carlo technique. We have previously shown that a standard backpropagation neural network can be trained to reconstruct sections of single photon emission computed tomography (SPECT) images based on the planar image projections as inputs. In this study, we present a method of selecting activation functions for a backpropagation ANN that is readily trainable for full SPECT image reconstruction. The activation functions used for this work are based on the estimated probability density functions (p.d.f.s) of the ANN training set data. The statistically tailored ANN and the standard sigmoidal backpropagation ANN methods are compared both in terms of their trainability and generalization ability for SPECT. We demonstrate that a neural network that uses statistically tailored activation functions can learn the functional relationship between the planar images and the tomograms fast and accurately. The results presented also demonstrate that a statistically tailored ANN can reconstruct novel tomographic images of a quality comparable to that of the images used to train the network (less than 0.94% RMS difference). In addition, the ANNs used for this work are simulated on the MasPar MP-2, a single-instruction multiple-data (SIMD), massively parallel computer. By taking advantage of the natural parallel structure of the ANN, very large networks (over 10,000 nodes) can be trained on the MP-2 in a very reasonable amount of time. Ultimately, an adequately trained ANN should be able to properly compensate for physical photon transport effects, background noise, and artifacts while reconstructing the tomographic image.

Keywords: artificial neural network, backpropagation, probability density function, single photon emission computed tomography (SPECT), massively parallel computing.

I. INTRODUCTION

Emission computed tomography (ECT) utilizes the emitted radiation of a nuclear medical radiopharmaceutical to produce a series of transverse sections of the radionuclide distribution.¹ The transverse image slices are reconstructed from a series of noninvasive, two-dimensional planar views taken about the target area of a patient.² Filtered backprojection algorithms encompass a wide range of analytic and algebraic reconstruction techniques,²⁻⁴ and are predominantly used in clinical single photon emission computed tomography (SPECT) image reconstruction.^{5,6} These techniques are typically used in clinical environments primarily because of their ability to handle incomplete and noisy data, and to generate reconstructions in a relatively short period of time.^{2,7} Despite their wide acceptance, the quality of filtered backprojection reconstructions is often degraded by artifacts, attenuation, and scatter effects.⁸⁻¹¹ Iterative algorithms, such as Monte Carlo methods that model the photon transport of the radionuclide distribution,¹²⁻¹⁵ are very adept at accurately compensating for attenuation and scatter effects in the reconstructed images. However, iterative methods as well as compensatory techniques used in conjunction with filtered backprojection typically have high computational costs.^{16,17} In this paper, we demonstrate that an artificial neural network (ANN) trained on filtered backprojection reconstructions, with two-dimensional Butterworth prefiltering, can reconstruct novel images equivalent to those produced by the filtered backprojection algorithm. Ultimately we hope to show that an ANN trained on the highly accurate, iteratively reconstructed Monte Carlo images can learn the planar data-to-tomographic image relationship and consequently produce novel reconstructions with an accuracy comparable to Monte Carlo methods in a fraction of the time the Monte Carlo methods take.

The backpropagation ANNs, that we will use are often referred to as mapping neural networks because of their ability to learn difficult functions or functional relationships that are otherwise hard to evaluate.¹⁸ ANNs have been shown to be useful in SPECT and PET image diagnostics,^{19,20} image filtering,²¹ electrical impedance tomography,²² and a variety of other medical applications.²³⁻²⁶ The advantages of ECT image reconstruction with an ANN are two-fold: first, a trained ANN can generate a reconstructed image slice from the planar projections almost instantaneously, even on simple serial computers; second, quality reconstructions of novel images can be obtained using an ANN training set composed of high-quality reconstructions, such as produced with a Monte Carlo method. The purpose of this work is to demonstrate that a backpropagation ANN with statistically tailored activation functions can produce high-speed SPECT image reconstructions with statistical error content comparable to that found in the images used to train the neural network.

For ECT, the time required for ANN image reconstruction will be very short. Once the ANN is trained for image reconstruction, novel planar data need only be fed forward through the network to generate the reconstructed image at the outputs of the ANN as shown in Fig. 1. On the other hand, backpropagation training of a neural network is a rather inefficient descending-hill search algorithm.^{27,28} The inefficiency in training an ANN stems from the thousands or often several of thousands of iterations that the training set data must be presented to the network before it sufficiently learns the input-output relationship. Consequently, while a trained ANN can perform image reconstructions quickly and simply, the one-time training process itself can be very time consuming and may be impractical when very large architectures are used. As an example, it would be impractical to train the approximately 10,000 node ANN needed for 64 x 64 SPECT image reconstruction on a serial computer because the computational processes of each node in the network have to be executed individually. The processing time of the ANN can be greatly improved by taking advantage of the natural parallel structure of the multilayer ANN architecture.

The parallel nature of the neural network can be exploited by implementing the ANN on a parallel machine. The MasPar MP-2 is a single-instruction multiple-data (SIMD), massively parallel system that is composed of a 64 x 64 interconnected mesh of processing elements (PEs). Each PE consists of a 32-bit processor, local memory, and I/O circuitry. The functions of nodes in each layer of an ANN distributed on the MP-2 can be executed simultaneously by dedicating a PE to execute the processes of one node in each layer of the network. This greatly improves the time in which an iteration of the ANN training set, or training epoch, can be performed. As a result larger architectures which may increase execution rates on a serial machine by two- or three-orders of magnitude only cause small increases in the execution rate of the parallel machine network implementation.

In previous work we and others have shown that image reconstruction with a back-propagation ANN is feasible,^{29,30} and that better generalization and faster training could be achieved with a uniformly distributed, three-phase activation function versus a standard sigmoidal activation function.³¹ In the latter work, we speculated that the optimal activation function for ANN image reconstruction might be related to the probability density function (p.d.f.) of the ANN training data. We propose and empirically test this hypothesis by comparing the ability of identical ANN architectures to generate 64 x 64 reconstructions of SPECT images using standard sigmoidal activation functions, and statistically tailored activation functions. We contend that the statistically tailored activation functions, in conjunction with the backpropagation training algorithm, will prove to be the superior transfer functions for the network nodes both in terms of the ANN's ability to learn the reconstruction function from the training set images and to generalize its knowledge for novel image reconstruction. A comparison of the speed of execution of a parallel ANN implementation versus a serial ANN implementation will also be made to demonstrate the necessity of parallel ANN training for SPECT image reconstruction.

II. BACKGROUND: BACKPROPAGATION NEURAL NETWORK

A. Forward Propagation

The three-layer, fully-interconnected ANN architecture used for image reconstruction consists of 4,096 input nodes to handle the sixty-four 64-quadrant planar data, 4,096 output nodes to produce each 64 x 64 slice reconstruction, and a user-selectable number of hidden layer nodes, as seen in Fig. 1. The input layer performs no operation on the data but rather distributes the data via interconnections to all nodes in the middle, or hidden, layer. Each value sent across an interconnection is weighted. The weights associated with the interconnections are the parameters adjusted during training and consequently represent the knowledge possessed by the ANN. Each node in the hidden layer and output layer sum the values received from interconnections and then on the basis of that value generate an output via an activation function $f(I)$.

$$f(I) = \text{the node output value} \quad (1)$$

where

$$I = \sum_j x_{i,j} w_{i,j}$$

$$x_{i,j} = \text{the output of the } j\text{th node in the previous layer } i$$

$$w_{i,j} = \text{the weight associated with the interconnection from the } j\text{th node in the previous layer } i$$

A sigmoidal activation function similar to the one shown in Fig. 2 and defined in Eq. (2) is typically used with a backpropagation ANN.³²

$$f(I) = m_{i,j} [(1/\pi) \arctan(g_{i,j} I + f_{i,j}) + 1/2] \quad (2)$$

where

$$m_{i,j} = \text{the output constant to adjust the slope of the function}$$

$$g_{i,j} = \text{the gain adjustment of the summed input value}$$

$$f_{i,j} = \text{the output bias which shifts the zero point of the function}$$

The ANN training set from which the ANN learns the input-output function must adequately represent the mapping domain of the functional relation.³³ This means that the training set data must closely approximate the probability density function (p.d.f.) of the output space. The training data are normalized into a 0.1 to 0.9 range since the activation functions are asymptotically limited between 0 and 1. Normalization of the data allows the network to train to values at the extremes of the output range without having to drive the network outputs into saturation. During training, the output of the standard sigmoidal activation function tends to be driven toward one of the two plateaus (0 or 1). As a result, backpropagation neural

networks are predominantly used as classifiers to categorize each input vector into the appropriate complex decision region.³²

B. Error backpropagation

The ANN training set is made up of (X_i, Y_i) data pairs in which Y_i is the known functional output associated with the input vector X_i . In the course of a training iteration, the output produced by an input vector that has been forward-propagated through the network is subtracted from the expected output vector. This output difference is back-propagated through the network to make interconnection weight adjustments thus, minimizing the network error.³³ The basic concept of backpropagation learning states that the interconnection weight values can be adjusted to minimize the error in the outputs because the error surface is differentiable, $\partial F(w)/\partial w$. By chain rule expansion the change in the networks error $F(w)$ with respect to the input I can be determined σ_i , as shown in Eqs. (3) and (4).

$$\partial F(w)/\partial w = \partial F(w)/\partial I * \partial I/\partial w \quad (3)$$

$$\sigma_i = \partial F(w)/\partial I = \partial F(w)/\partial w * \partial w/\partial I \quad (4)$$

A good in-depth description of this derivation can be found in Hecht-Nielsen³³.

For our application, the output vector is the reconstructed image associated with the planar view inputs. The error in the reconstruction is calculated for each node in the output layer as shown in Fig. 3. The backpropagation training algorithm adjusts the interconnection weight values between layers according to the delta rule.^{27,28,33}

$$w_{i,j} \text{ new} = w_{i,j} \text{ old} + \eta \sigma_i x_i + \alpha (w_{i,j} \text{ old} - w_{i,j} \text{ previous}) \quad (5)$$

where

$$\begin{aligned} w_{i,j} \text{ old} &= \text{the present weight value of the interconnection} \\ &\quad \text{from the } j\text{th hidden node to the } i\text{th output node} \\ w_{i,j} \text{ previous} &= \text{the interconnection weight value prior to being} \\ &\quad \text{adjusted to } w_{i,j} \text{ old} \end{aligned}$$

To adjust the weight values of the interconnections between the hidden layer and the output layer, we define σ_i in Eq. (5) as the error difference in the i th node $(d_i - y_i)$ multiplied by the associated value of the activation function derivative.

$$\sigma_i = f'(y_i) (d_i - y_i) \quad (6)$$

where, for the sigmoidal activation function shown in Eq. (2),

$$f(y_i) = d[\arctan(y_i)]/dy_i = 1 / (1 + y_i^2)$$

Old interconnection weights are adjusted so as to minimize the error between the expected output d_i and the actual output y_i in Eq (5). The error value is multiplied by a learning rate η that governs the magnitude of each adjustment and by the last input across that interconnection x_i which factors the weight adjustment values according to the magnitude of the last input vector. The momentum term α provides an impetus to the weight adjustment in order to take into account the direction in which the weight was adjusted in the previous training iteration. The momentum term helps the training network avoid small local minima.^{28,32}

The derivative of the arctangent sigmoidal activation function $f'(y_i)$ shown in Fig. 4, is also used by the network during training to add stability to the network and to prevent too much emphasis in error adjustments being placed on large weight values.^{27,28} The bell-shape of the derivative creates a high degree of activity in nodes whose outputs are in the center of the output range. Again, this shows why the backpropagation ANN is adept at classification. As all the outputs approach 0 or 1, the activity in weight adjustments, as factored by $f'(y_i)$, is reduced and the stability of the network is increased.

The weight values associated with the interconnections from the input layer to the hidden layer do not have the advantage of knowing the expected outputs of the hidden layer nodes. Consequently, these weight values must be adjusted according to a different value of σ_i in the generalized delta rule.^{27,28}

$$\sigma_i = f'(x_i) * \sum_{k=0}^K (d_k - y_k) * w_{i,k} \quad (7)$$

where

$$w_{i,k} = \text{the interconnection weight from the } i\text{th hidden node to the } k\text{th output node}$$

Instead of using the difference between the expected and actual value of the associated output node, the error associated with a hidden node is the error in the entire output vector weighted with respect to the interconnection weights from that particular hidden node ($\sum [d_k - y_k]$). Again, the input-to-hidden layer interconnection weight adjustments are a function of the derivative of the hidden layer node activation function, $f'(x_i)$.

C. RMS Error

For this study, the measured error in the networks capacity to accurately recall training set data is calculated as the RMS error, C.

$$C = \{ [1/(N * J)] * [\sum_{n=1}^N \sum_{j=1}^J (D_{n,j} - Y_{n,j})^2] \}^{1/2} \quad (8)$$

where

J	=	the number of nodes in the output layer
N	=	the number of patterns in the training set
D _{n,j}	=	the expected output of the jth output layer node for the nth training set pattern
Y _{n,j}	=	the actual output of the jth output layer node for the nth training set pattern

The error represents the mean RMS error in the ANN's ability to reconstruct the training set images. The RMS error of the training set data typically gives a good estimation of the RMS error that will be seen when the ANN generates outputs on the basis of novel inputs, provided of course, that the training set is representative of the application domain.³³

III. MATHEMATICAL METHODS

The backpropagation ANN consists of three, and occasionally more, layers of nodes. The importance of a three-layer network versus a one- or two-layer network is demonstrated by Kolmogorov's mapping neural network existence theorem, as derived by Hecht-Nielsen.³³ The theorem states that a three-layer network of n input nodes, $2n+1$ hidden nodes, and m output nodes can exactly represent the input-output mapping, even when the data is discontinuous.³³ Although proving an ANN solution exists, the Kolmogorov theorem gives no insight as to whether smaller hidden-layer networks can also represent the functional mapping, nor does it suggest optimal or even good transfer functions for the network.

Associated with the functional mapping to be learned by each backpropagation ANN is a w -dimensional error surface, $F(w)$, where w is the number of interconnections in the architecture.^{28,33} The backpropagation algorithm performs a gradient-descent search of the error surface and is prone to becoming stuck in local minima or stuck on plateaus where the gradient is small, as seen in Fig. 5. As a result, a global minima or an acceptably low local minima of $F(w)$ might never be found. The ability to find a global minima is highly dependant on where on the error surface training begins. Since no features of the error surface are known, a random set of interconnection weight values w are initially chosen. When an ANN trains to a minima there is no way of knowing whether the network has reached a local minima, a global minima, or a large, low-gradient plateau. Often, if the minimum error the ANN is trained to is not acceptable for the intended application, a new set of initial weight values is selected and training restarted.

As mentioned in the previous section, the nodes in a standard backpropagation ANN utilize a sigmoidal activation function. We also noted that the backpropagation neural network is very adept as a classifier when using a sigmoidal activation function and its derivative. During training the bell-shaped derivative, as used in the delta rule and generalized delta rule in Eqs. (6) and (7), produces large changes in the interconnection weights associated with outputs around 0.5. As the output of a node approaches either 0 or 1, the changes in the interconnection weights to that node become smaller; and the network becomes more stable. Unfortunately, when training outputs that are continuous in the normalized 0.1 to 0.9 output range, the network tends to become unstable and oscillate about the expected output values. This is particularly true for outputs near 0.5. However, since we hope the training set data is a good representation of the mapping to be learned, the probability density function (p.d.f.) of the data should provide good estimates of the input range p.d.f. and the output domain p.d.f.

The key characteristic of a good output layer activation function is one that will allow easy training across the continuous range of values and increase the stability to the network as it learns. We contend that an activation function equal to the integral of the inverse estimated p.d.f. for each output node, as in Eq. (9), should provide a better training response by the network.

$$y_i = \int [z(x_i)] dx_i \quad (9)$$

where

$$z(x_i) = \text{the estimated inverse p.d.f. for the } i\text{th output node based on the distribution of the nodes training set data values}$$

For the demonstration of SPECT image reconstruction in this paper, a common activation function is used for all output nodes.

$$\begin{aligned} y &= \int \{ 1.2/[1 + 36(I + 2.93706)^2] + 0.4/[1 + 169(I + 2.25918)^2] \\ &\quad + 1.5/[1 + 1.21(I + 1.43482)^2] \} dx \\ &= \{ 1.2[(1/\pi) \arctan[6(I + 2.93706)] + 0.5] \\ &\quad + 0.4[(1/\pi) \arctan[13(I + 2.25918)] + 0.5] \\ &\quad + 1.5[(1/\pi) \arctan[1.1(I + 1.43482)] + 0.5] \} / 3.1 \end{aligned} \quad (10)$$

Ideally, each output node activation function is derived from the estimated p.d.f. obtained from the training set data for each node. The single activation function used here is based on the estimated p.d.f. of all pixel values of the output node in the ANN training set (see Fig. 6). We determined this an acceptable approximation of the output layer activation functions, since the intent of the application in this paper is to show the attainable improvements in ANN performance with a statistically tailored activation function versus a standard sigmoidal activation function. Also, if the performance of a common activation function is good enough

for the application at hand, we will save the time to derive activation functions for all 4,096 output nodes.

A graph of Eq. (10) and the three arctangent functions that comprise the output layer activation function are shown in Fig. 7. This figure shows that the integral of the inverse p.d.f. provides a greater range of inputs to the most expected output values according to the estimated p.d.f. This means that the most frequently occurring output values are far more accessible in the activation function than the more rarely occurring values. Consequently, the ANN can train to the most common output range and once there it can readily distinguish between the most frequently encountered output values. The theory behind this selection of output layer activation functions is also supported by the effect on training of the activation function derivative, or the inverse p.d.f., in the delta rule. As the network trains, the majority of values converge to the expected value range of the activation function, driven by large values of the derivative function. As the common values reach the expected output range, the activity of the derivative functions in the adjustment of weight values declines and the network stabilizes. The reduced activity in weight adjustments also allows the network, during additional training, to distinguish between output values without experiencing large oscillations, as often seen with a standard sigmoidal function and derivative.

On the other hand, an activation function derived from integrating the estimated p.d.f. of the training set input vectors is best suited for the hidden layer.

$$\begin{aligned}
 y &= \int \{1/[1 + 196(I + 3.077)^2] + 0.38/[1 + 33.64(I + 2.587)^2] \\
 &\quad + 0.58/[1 + 2.89(I + 1.760)^2]\} dx \\
 &= \{0.55[(1/\pi) \arctan[14(I + 3.077)] + 0.5] \\
 &\quad + 0.38[(1/\pi) \arctan[5.8(I + 2.620)] + 0.5] \\
 &\quad + (1/\pi) \arctan[1.7(I + 1.760)] + 0.5\}/1.96
 \end{aligned} \tag{11}$$

Each node of the hidden layer receives a weighted sum of all elements in the input vector. Accordingly, the input vector whose sum falls in the mostly densely distributed part of the p.d.f. as shown in Fig. 8, will occupy a larger portion of the output range than a less frequently encountered vector sum, (see Fig. 9). By delivering a broad range of values from the dense areas of the input sum p.d.f. to the output layer, the output nodes have a better capacity to distinguish between closely distributed outputs, and thus should provide a better ANN model for training and generalizing.

Each of the statistically tailored activation functions are composed of the sum of three sigmoidal functions. The combination of three functions proved sufficient to approximate the cumulative distribution functions (c.d.f.s) of the SPECT training set data used in this study. Exact fits to the training set c.d.f.s are not necessary since they themselves are approximations of the actual c.d.f.s. We also expect that any discrepancies in activation function approximations will be compensated for through ANN training. We have used sigmoidal

functions in order to retain the training advantages of using the S-shaped sigmoidal, nonlinear elements, which have been shown to provide superior generalization capabilities to linear and polynomial functions.^{27,33} In addition, we maintain a link to organic cerebral neurons that show a natural sigmoidal relationship between the input wave density to a neuron and the output pulse density of a neuron.³⁴

We have already discussed the properties of the sigmoidal function and its derivative, shown in Figs. 2 and 4 and Eqs. (2) and (6). The derivative of the sigmoidal function enables large weight changes when the output value of the associated nodes is in the middle of the 0 to 1 output range and only small weight adjustments near the asymptotes. Consequently, the sigmoidal activation function and derivative are well suited for training problems for which the expected output values are binary. Since each output node in the SPECT reconstruction ANN must be readily trainable across a continuous range of outputs, the standard sigmoidal ANNs are not expected to perform as well as the ANNs with statistically tailored activation functions.

Likewise, we have described how a standard backpropagation ANN with a sigmoidal activation function is adept as a classifier network. It also provides a good argument for using the statistically-based activation functions we have proposed here. As can be seen from Fig. 4, the sigmoidal function derivative is essentially the inverse distribution of the expected outputs for a classifier network, since only values of 1 and 0 are typically desired from the network. For the hidden layer nodes, the sigmoidal derivative approximates a Gaussian distribution. Since each node in the hidden layer receives a weighted sum of all the inputs, this is probably a good estimate of the input data distribution, particularly for problems where the inputs, like the classifier output, are binary.

IV. PARALLEL SIMULATION OF A MULTILAYER NEURAL NETWORK

Massively parallel processing uses the processing power of a large number of interconnected processors to increase the computational throughput of executable computer code. Distributing a large computational problem across hundreds and often thousands of processors or processing elements (PEs) often produces significant improvement in performance versus a single processor, or Von Neumann type, architecture.³⁵⁻³⁷ A parallel architecture in which the same code is executed simultaneously by an interconnected array of processors with data local to each processor is referred to as a single-instruction multiple-data (SIMD) machine.³⁸ The parallel structure of a multilayer neural network makes it an excellent candidate for simulation on an SIMD architecture, and in fact there are many examples of ANNs simulated on this type of parallel computer.³⁹⁻⁴³

The parallelism of an ANN is associated with the layers of the network, since each node in a layer performs identical calculations on data that is independent of every other node in that layer. For our work the MasPar MP-2, an SIMD massively parallel computer, is used to

simulate the ANNs. The MP-2 consists of a 64×64 interconnected array of PEs. Each PE is composed of a 32-bit processor, 64 KB of local memory, and a high-speed I/O interface. All serial instructions are executed by a control processor, which also decodes and broadcasts each parallel instruction to the PE array. A block diagram of the MP-2 and a PE are shown in Fig. 10. The eight directional intercommunication pathways provide direct, high-speed links between PEs that lie in one of the eight directions from one another. PEs that need to exchange data but do not directionally line up in the array must use the control processor to communicate. The parallel code will be ineffective if many PEs are communicating via the control processor. Therefore, improvement in the data processing rate of the MP-2 versus a serial machine, is directly dependent on the amount of parallelism in the task to be coded, how readily it can be distributed amongst the 8,196 processors, and how well the high-speed intercommunication links in the PE array can be utilized.

The large ANN architectures used for image reconstruction are distributed on the MP-2 as shown in Fig. 11. The ANNs are simulated on the PE array so as to best take advantage of the natural parallel structure of the neural networks and to utilize the high-speed communication pathways. Since the image reconstruction ANN requires 4,096 input nodes and 4,096 output nodes, the ANN is distributed on the PE array so that each PE simulates the functions of a node from both the input layer and the output layer. Additionally, a number of PEs must also simulate nodes in the hidden layer. The maximum size ANN architecture that can be simulated with this parallel implementation format is a $4,096 \times 4,096 \times 4,096$ node network. The 4K Byte local memories associated with each PE allows the interconnection weights to be represented with single-precision, floating-point variables. Using large variables, such as 4-Byte variables, to handle weight values allows the ANN the capacity to fine-tune the recall accuracy of the ANN and achieve very small RMS errors.¹⁸

The transfer of data from layer to layer in the network is handled by using north, south, east, and west communication pathways. As opposed to linking PEs through the control processor, these direct pathways are all high-speed PE-to-PE communication links. Thus, the network throughput is kept high by not having to use the control processor to handle the forward and backpropagation of data through the network. For this ANN simulation method, the control processor is only required to distribute the input data on the PE array and to calculate the RMS error after each training epoch.

V. RESULTS

A. SPECT Training Set Data

Cardiovascular SPECT images were used to train the neural networks and to test the trained ANN's ability to reconstruct novel 64×64 images. The planar view images were each two-dimensionally filtered using a Butterworth filter with a critical frequency of 0.5 cycles/cm and

a power factor of 15. The transverse image slices were then reconstructed using conventional filtered backprojection.

The ANN training set consisted of every other slice of a 16-slice cardiac SPECT image, and the sixty-four planar views of each image slice. The SPECT images not used in the training set were subsequently used to determine each trained ANN's ability to accurately reconstruct the novel tomograms from the associated planar data. The novel reconstructions can then be compared to those attained from the Butterworth filtered backprojection algorithm, to determine if the quality of the ANN reconstructions is directly associated to the quality of the training set images.

B. Activation Function Evaluation

Four architectures with randomly selected hidden layer sizes were constructed to evaluate the training and generalization capabilities of the statistically tailored activation function ANNs versus the standard sigmoidal activation function ANNs. Each architecture, using the two activation function types, were trained for 2,000 iterations on the eight SPECT image training set. The minimum RMS errors attained by each network are listed in Table I. In each case the statistically tailored ANNs trained to a much lower RMS error than their counterpart standard sigmoidal ANNs. An RMS error versus training epoch comparison of the statistically tailored ANN and the standard sigmoidal ANN with $4,096 \times 484 \times 4,096$ architectures is shown in Fig. 12. As was the case with all architectures, the standard sigmoidal ANN initially trains quickly and then plateaus, where as the statistically tailored ANN trains slightly slower in the first few hundred iterations, but then continues past the standard sigmoidal plateau, eventually plateauing at an RMS error of approximately 0.009.

A more critical measure of the ANN's reconstruction capabilities is in the trained ANN's ability to accurately reconstruct novel images. The best RMS errors achieved by each trained ANN on the eight SPECT images not used to train the networks are listed in Table II. Here again the statistically tailored ANNs significantly outperformed the standard sigmoidal ANNs. For the $4,096 \times 484 \times 4,096$ architecture, the statistically tailored ANN reconstructed the novel images with less than 0.94% error from the expected Butterworth-filtered backprojection reconstructions. No standard sigmoidal ANN could reconstruct the novel images with less than 1.4% error. A comparison of the generalization ability of a statistically tailored ANN and standard sigmoidal ANN during training is shown in Fig. 13. In both instances the generalization ability of the networks initially follows the RMS error of the training set. However, after reaching the minimum RMS error the generalization ability of the standard sigmoidal network declines with additional training because the network begins to memorize the training set and thus recalls training set reconstructions when presented with novel planar data inputs. For the statistically tailored ANN, however, the generalization ability of the ANN continues to improve, even after it appears to begin memorizing.

A novel image reconstruction by both a statistically tailored ANN and a standard sigmoidal ANN are shown, along with filtered backprojection reconstructions, in Fig. 14. This visual comparison of the ANN reconstructions clearly shows the greater accuracy of the statistically tailored ANN compared with that of the standard sigmoidal ANN or the filtered backprojection reconstruction without Butterworth filtering.

C. Parallel ANN Execution Efficiency

The four ANN architectures used in this study were also evaluated in terms of parallel code versus serial code execution rates. The MasPar Parallel Language (MPL) is a C language derivative with parallel commands added. We wrote the parallel code used for this work by modifying an ANN code we wrote entirely in C. The required times to train each architecture with the serial code and the parallel code are listed in Table III. The serial times had to be extrapolated from smaller architectures, since the DEC 5000/133 workstation used to execute the serial ANN code did not have the memory capacity to handle all the interconnection weights of the reconstruction networks. As shown in Fig. 15, the parallel code execution rate increases at a very small linear slope with increasing hidden layer size. Conversely, the serial code execution rate increases with a large exponential slope with increasing hidden layer size. The parallel code execution rates range from 40 to 100 times faster than the theoretical serial code execution rates. For larger hidden layer architectures, the parallel code execution rate approaches three-orders of magnitude improvement over the serial code.

VI. DISCUSSION

The results of Tables I and II demonstrate that the statistically tailored neural network clearly out-performs the standard sigmoidal ANN. Although the RMS error differences between the two network types appear small, these numbers can be deceptive. The difference between the image reconstructed with 0.9% error and the image reconstructed with 1.4% error, in Fig. 14, is significant. As seen in Fig. 16, the statistically tailored ANN novel image reconstruction is a very accurate representation of the expected image, and not merely a reproduction of a training set image. On the other hand, the standard sigmoidal ANN reconstruction of the same novel image in Fig. 17, is far less representative of the expected image, and possesses many of the features of a training set image. Even though the two reconstructions of the same novel image differ by less than 1% RMS, that 1% is significant since the cardiac portion of the 64 x 64 image, is small. As a result, the statistically tailored ANN is able to generalize its knowledge attained during training to more accurately produce high-quality reconstructions.

The statistically tailored neural networks proved to be a superior backpropagation ANN method for SPECT image reconstruction when compared with the standard sigmoidal backpropagation ANNs. Each statistically tailored ANN trained to a significantly lower RMS

error than the same architecture standard sigmoidal ANN. In addition, all four statistically tailored ANNs achieved RMS errors lower than the best standard sigmoidal ANN. Furthermore, the standard sigmoidal ANNs tended to reach a plateau at the minimum RMS error in approximately 1,000 training epochs, while the statistically tailored ANNs, which also reach a plateau at approximately 1,000 training iterations continued to improve slowly over the next 1,000 iterations, as seen in Fig. 12.

Likewise, the statistically tailored ANNs showed excellent generalization capabilities. Again, the statistically tailored ANNs reconstructed the novel image set to much lower RMS errors than the standard sigmoidal ANNs with the same architecture. One surprising, and potentially invaluable, characteristic of the statistically tailored ANNs is seen in Fig. 13. The figure shows that the standard sigmoidal ANN reaches a minimum generalization RMS error in 1,100 training epochs, and then gradually gets worse with additional training. This is a common and usually expected characteristic of the backpropagation ANN.³² However, the statistically tailored ANN, after appearing to lose its generalization ability at 1,500 training epochs as shown in Fig. 12, quickly recovers and by the two-thousandth training epoch the novel images set RMS error and the training set RMS error are practically identical. Perhaps the loss in generalization was a consequence of the training set RMS error dropping to a lower plateau at the 1,500 training epoch mark. Note however, that for the two training set RMS error plateaus in the 1,000 to 2,000 training epoch range, the generalization RMS error improves with additional training. If this is indeed a characteristic of the statistically tailored neural network, then overtraining of a network cannot occur. Thus, the generalization RMS error need not be continuously monitored during training.

Of the four ANN architectures trained, one network was able to reconstruct the novel image set with less than 1% RMS error, and one network reconstructed the novel image set right at 1% RMS error. As was demonstrated by Fig. 14, a reconstruction with 0.9% RMS error is an accurate and valuable image, but with 1.4% RMS error, the same image may not accurately represent the expected image. Even with the statistically tailored ANN there is no assurance that the selected hidden layer size for an ANN is trainable to an RMS error below 1%. Undoubtedly, the optimal ANN architecture for reconstructing every slice of a completely novel SPECT scan will differ from the best architecture presented here. However, a dynamic node architecture (DNA) method has been developed⁴⁴ and applied practically⁴⁵ that guarantees finding the optimal architecture for a given training set. Whether a DNA neural network for image reconstruction can be trained in a reasonable amount of time on a parallel computer is yet to be determined.

It came as no surprise that the parallel computer ANN execution rates were upwards of three orders of magnitude better than the serial computer ANN. But execution rate information was included to show the natural parallelism of neural networks and to show the necessity of using a parallel machine to train an ANN for SPECT image reconstruction. Each parallel ANN required less than three hours of computer time to train for 2,000 iterations on the eight image training set. It is likely that the training set required to train an ANN to reconstruct

every slice of an entirely novel SPECT scan will be considerably larger; our results show, however, that ANN training for image reconstruction can be achieved in a reasonable amount of time.

VII. CONCLUDING REMARKS

In Sec. I we speculated that a properly trained neural network could produce novel image reconstructions of a quality comparable to that of the images used to train the network. The results we have presented have verified that hypothesis. In Fig. 16, a filtered backprojection reconstruction of the novel image, without the two-dimensional Butterworth filtering of the planar data, was included to reinforce our hypothesis. Since the network was trained on images with prefiltering, the network essentially learned to perform the Butterworth prefiltering of the planar data and reconstruct a tomogram on the basis of that data. Likewise, an ANN trained on reconstructions produced via a Monte Carlo method, can produce novel images of Monte Carlo quality, and in a fraction of the time.

Two potential limitations of this reconstruction method are in the orientation of the planar data and the ultimate size of the ANN training set. The first limitation involves determining how well the neural network can handle planar data that does not begin a scan at the same relative location to the patient. If this is in fact a problem the ANN cannot handle, the data may be normalized prior to ANN reconstruction to alleviate the neural networks problem. The second potential limitation deals with the scope of the ANN's generalized knowledge. For example, can a network trained exclusively on normal cardiac SPECT images accurately reconstruct abnormal images? If the training set must have an example of every possible cardiac anomaly in order to produce accurate reconstructions across the entire range of possible images, the training set will be impractically large. However, the results presented here show that an example of every slice of a full SPECT image is not needed in the training set for the ANN to accurately reconstruct novel slices. Likewise, an ANN may be able to reconstruct abnormal images even though it has been exclusively trained on normal images.

Improvements to the RMS error results could have been obtained in several ways, such as reducing the 64×64 inputs and outputs to the actual 64 pixel diameter circular gamma camera field-of-view. But our goal was to show that a statistically tailored backpropagation neural network could accurately produce novel SPECT image reconstructions, and this was achieved without the aforementioned improvements.

It is worth noting that an ANN trained for SPECT reconstruction can also be used to compress the images for storage. The output of the hidden layer, which is much smaller than the reconstructed image, can be stored to reduce the amount of computer disk space required to handle the image. The hidden layer outputs can subsequently be recalled and passed through the ANN's output layer to retrieve the reconstructed image. For the $4,096 \times 484 \times$

4,096 architecture used here, a better than 8-to-1 compression of each reconstruction is attained at the hidden layer.

Future work will strive to overcome the aforementioned potential limitations of ANN image reconstruction, and to determine if a neural network can correct for scatter and attenuation effects in its reconstructions. The nonlinear nature of neural networks may enable them to compensate accurately for nonlinear sources of error, such as attenuation. Ultimately, the speed and trainability of neural networks for image reconstruction may prove them to be valuable tools for clinical applications.

VIII. ACKNOWLEDGMENTS

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List of Figures

Figure No.

1. Basic block diagram of the three-layer ANN architecture used for SPECT image reconstruction. The 4,096 inputs correspond to the sixty-four 64-quadrant planar views taken 180° about the target area. The 4,096 outputs represent the 64 x 64 reconstruction region. The hidden layer is of user-selectable size.
2. Sigmoidal activation function used with standard backpropagation ANNs. Activation functions are used by the hidden layer and output layer nodes. The ANN training set data is typically normalized between 0.1 and 0.9 so that outputs near 0 and 1 can be attained by the network without having to drive the output nodes into saturation.
3. During each training iteration the difference between the expected output and the actual output of the ANN is back-propagated through the network. The weights of the two layers of interconnections are then adjusted according to the delta rule and generalized delta rule to reduce the network error. After repeated training iterations the ANN will begin to learn the functional relationship between the input vectors and output vectors.
4. Derivative of the standard sigmoidal activation function. In the delta rule the derivative of the sigmoid function factors the interconnection weight adjustments. For nodes with outputs near 0 and 1, the associated interconnection weight adjustments are small.
5. An example error surface, $f(w)$, with respect to all the ANN's interconnection weights is shown. Local minima and plateaus may appear as global minima during training. There is typically no way of determining if a global minima has been reached, since the error surface is in w -dimension space.
6. Three arctangent derivatives were used to fit the inverse statistical distribution of the ANN training set output data. The planar input data distribution was normalized between -3.077 and 3.077 so as to correspond to the 0.1 to 0.9 range of the standard sigmoidal activation function. This was done so that an accurate comparison between the statistically tailored and standard sigmoidal activation functions could be made.

7. The statistically tailored output layer activation function is shown as the sum of the three arctangents attained by integrating the inverse output data distribution functions.
8. Three arctangent derivatives were used to fit the statistical distribution of the ANN training set input data. The planar input data distribution was normalized between -3.077 and 3.077 so as to correspond to the 0.1 to 0.9 range of the standard sigmoidal activation function.
9. The statistically tailored hidden layer activation function is shown as the sum of the three arctangents attained by integrating the input data distribution functions.
10. The MasPar MP-2 is composed of a 64×64 array of processing elements (PEs). Each PE consists of a 32-bit processor, 64 KBytes of memory, and input/output circuitry. All parallel commands are decoded and distributed to the PE array by a serial control processor.
11. The PE array is made up of 4096 processors. The $4,096 \times N \times 4,096$ ANN architectures were mapped onto the PE array so that each PE handles the processes of one node from each layer of the neural network. The hidden layers used were much smaller than the input and output layers, so not all PEs handle the processes of a hidden layer node.
12. The RMS error in recalling the training set reconstructions for the $4,096 \times 484 \times 4,096$ architecture is shown with respect to training epoch for both the statistically tailored ANN and the standard sigmoidal ANN. As was the case with the other three architectures trained, the statistically tailored ANN reached a lower RMS error than the standard sigmoidal ANN. The statistically tailored ANN also continued to reduce its RMS error throughout the 2,000 training iterations. The standard sigmoidal ANN reached its minimum RMS error after approximately 1,000 iterations and did not improve over the last 1,000 training epochs.
13. The RMS error in recalling the training set reconstructions and novel set reconstructions for the $4,096 \times 484 \times 4,096$ architecture is shown versus training epoch for both the statistically tailored ANN and standard sigmoidal ANN. The good generalization ability of the statistically tailored ANN is demonstrated by the training set and novel set RMS errors being approximately the same. The generalization ability of the standard sigmoidal ANN is best after about 1,000 training epochs, and gradually declines with additional training.

14. Each of the reconstructions are based on the same planar data. The top left image was reconstructed the same as all the images in the ANN training set, via filtered backprojection with 2-D Butterworth prefiltering. The top right image is the statistically tailored $4,096 \times 484 \times 4,096$ ANN reconstruction. The bottom left image is the standard sigmoidal $4,096 \times 484 \times 4,096$ ANN reconstruction. The bottom left image was produced via filtered backprojection without the 2-D Butterworth prefiltering. The statistically tailored ANN reconstruction closely matches the expected image, top left.
15. A comparison of the extrapolated DEC 5000/133 ANN training times and the MasPar MP-2 ANN training times are shown. The ANNs consisted of $4096 \times N \times 4096$ architectures, with the hidden layer size N being the variable. Not surprisingly the MP-2 times are minimally affected by increased hidden layer size, while the DEC 5000/133 times increase dramatically.
16. The top left image is the seventh slice of a 16-slice cardiac SPECT voxel and was a image in the ANN training set. The top right image is the statistically tailored $4,096 \times 484 \times 4,096$ ANN reconstruction. The bottom left image is the filtered backprojection with 2-D Butterworth prefiltering reconstruction of the eighth slice. The bottom right image is the ninth slice of a 16-slice cardiac SPECT voxel and was a image in the ANN training set. The statistically tailored ANN reconstruction closely matches the expected image, bottom left, and is not merely a reproduction of the closest training set image.
17. The top left image is the seventh slice of a 16-slice cardiac SPECT voxel and was a image in the ANN training set. The top right image is the standard sigmoidal $4,096 \times 484 \times 4,096$ ANN reconstruction. The bottom left image is the filtered backprojection with 2-D Butterworth prefiltering reconstruction of the eighth slice. The bottom right image is the ninth slice of a 16-slice cardiac SPECT voxel and was a image in the ANN training set. The standard sigmoidal ANN reconstruction has more of the seventh slices features than the desired eighth slices features. This ANN has not fully learned the input-output relationship and is recalling a training set image rather than producing the novel image.

4096 Outputs - 64 x 64 SPECT Image

4096 Inputs - Planar Data

MasPar MP-2 64x64 PE Array

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Table No.

- I. Minimum RMS errors attained in 2,000 training epochs for the four architectures and the two activation function types. For each architecture the neural network utilizing statistically tailored activation functions trained to a lower RMS error than any of the ANNs utilizing the standard sigmoidal activation function. The hidden layer size for each architecture was arbitrarily chosen.
- II. Minimum average RMS error attained by each ANN architecture reconstructing the eight novel images. Each statistically tailored ANN was able to reconstruct the eight novel images with less error than the same architecture standard sigmoidal ANN. Upon visual inspection, only the statistically tailored ANNs with 484 and 625 hidden nodes produced images that accurately represented the features of the novel images.
- III. Parallel ANN and serial ANN execution rates for the four ANNs used to compare activation functions. The MP-2's execution rate increases at a slow linear rate with increasing hidden layer size. The DEC 5000/133 execution rate increases at an exponential rate with increasing hidden layer size. At 1,000 hidden nodes the parallel machine trains the ANN 100 times faster than the serial computer. The serial rates were extrapolated from smaller architectures because the DEC 5000/133 workstation did not have adequate core memory to handle the $4,096 \times N \times 4,096$ architectures.

Table I : Minimum RMS errors attained in 2000 training epochs

ANN Architecture	Activation Function Type	Minimum RMS Error
4096 x 324 x 4096	Statistically Tailored	0.010529
	Standard Sigmoidal	0.020116
4096 x 484 x 4096	Statistically Tailored	0.008703
	Standard Sigmoidal	0.012740
4096 x 625 x 4096	Statistically Tailored	0.009309
	Standard Sigmoidal	0.018772
4096 x 961 x 4096	Statistically Tailored	0.011972
	Standard Sigmoidal	0.020333

Table II : Minimum average RMS error in eight novel image reconstructions

ANN Architecture	Activation Function Type	Minimum RMS Error
4096 x 324 x 4096	Statistically Tailored	0.011389
	Standard Sigmoidal	0.020454
4096 x 484 x 4096	Statistically Tailored	0.008619
	Standard Sigmoidal	0.013911
4096 x 625 x 4094	Statistically Tailored	0.010022
	Standard Sigmoidal	0.016678
4096 x 961 4096	Statistically Tailored	0.014676
	Standard Sigmoidal	0.023611

Table III : Parallel ANN and serial ANN execution rates

Execution rates in seconds to perform 100 training epochs of the eight image SPECT training set.		
ANN Architecture	MasPar MP-2 Execution Rate	Dec 5000/133 Execution Rate
4,096 x 324 x 4,096	439	17.920
4,096 x 484 x 4,096	469	23.680
4,096 x 625 x 4,096	495	31.360
4,096 x 961 x 4,096	552	50,560

FUTURE WORK

The preliminary work demonstrates that ANN reconstruction is faster than conventional filtered backprojection techniques [3,12,13], and significantly faster than Monte Carlo methods [21,22,23]. Likewise, it has been shown that the quality of ANN SPECT image reconstruction is dependent on the quality of the images used to train the ANN. Based on the results presented here, neural network reconstruction of full novel SPECT images is achievable.

The next step to this end will be to determine if statistically tailored activation functions are the best ANN functions for SPECT. This can be achieved by comparing the trainability and generalization ability of statistically tailored activation functions with other activation functions that have been shown to be well suited for backpropagation learning [24,25].

Once the best activation functions for ANN SPECT are chosen it will then be necessary to determine if an ANN can be trained on multiple cardiovascular SPECT images and then accurately reconstruct all slices of an entirely novel cardiovascular SPECT image. Potential difficulties with reconstructing an entirely novel SPECT image are related to the orientation of the tomograms to be constructed and the field-of-view of the planar data. In the preliminary work it was known that the novel images were oriented identically to the ANN training set images because all the images used were taken from one full SPECT scan. Although the full SPECT scans used to train the ANN will be closely aligned with the novel SPECT scan the planar data may have to be normalized so the reconstructions have a common center of gravity.

Subsequently, once a trained ANN can accurately reconstruct every slice of a novel SPECT image, it will important to determine if an ANN trained with normal SPECT images can accurately reconstruct abnormal SPECT images. This work is dependent on the availability of the abnormal data. However, it is important step in determining the amount of data that will ultimately be required to adequately train an ANN for SPECT reconstruction in a clinical environment. If it is determined that an example of every cardiovascular abnormality and every possible location of its occurrence is required in the ANN training then the probability of the proposed method ever reaching clinical test phase is small. This is because such a training set size would be impractical for good ANN training, and improbable to produce.

The final analysis of the ANN will be to determine how well an ANN trained on brain SPECT images can reproduce an entirely novel SPECT brain image, an abnormal brain SPECT image, and a cardiovascular SPECT image. This is again dependent on the availability of the SPECT data. Since SPECT imaging of the brain is of higher resolution than

cardiovascular SPECT it will be useful to ascertain if results can be attained similar to those achieved on the cardiovascular data. Additionally, it will be important to the issue of ANN training set size to learn if an ANN trained on brain images can reconstruct cardiovascular images. An ANN trained on brain SPECT may be able to reconstruct cardiovascular images accurately since the brain reconstruction requires almost the entire 64-pixel in diameter reconstruction field. If so, an ANN trained for SPECT would not require an all encompassing training set, and perhaps an ANN trained on a statistically randomized training set could learn to reconstruct any type of SPECT image.

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4.3 Detecting Faults in a Nuclear Power Plant Using Dynamic Node Architecture Artificial Neural Networks

This is a draft of the proposal to be submitted by Anujit Basu to the Program of Study Committee and will be defended towards the end of November, 1993.

Research Proposal for Doctoral Dissertation

*Detecting Faults in a Nuclear Power Plant Using
Dynamic Node Architecture Artificial Neural Networks*

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1993

1 Introduction

The safe operation of a nuclear reactor in a power plant is of utmost importance to the nuclear engineering community and quite vital to creating a more positive attitude towards nuclear energy among the rest of the society. The author has previously demonstrated the use of Artificial Neural Networks (ANNs) to increase the operational safety of nuclear reactors by being the basis of a fault diagnostic system in a power plant cite thesis, APC paper, Appendix A. The results of the latest efforts can be seen in Appendix A. The scaling of this approach to develop a full-fledged diagnostic advisor provides a substantial challenge, and it is this problem that the author proposes to solve.

2 Background Information

2.1 Current Procedures in Nuclear Power Plants

Currently, power plants employ automatic safety systems that allow the plant to operate within a predefined operating range. These systems verify that the plant variables conforms to preassigned safety limits. If the plant enters an abnormal condition, the safety systems either trigger an automatic shutdown (safety trip) of the reactor or notify the operators through alarms or indicators. The sequence of events leading to the plant shutdown are analyzed later by technical support teams located both on and off site. Use of an ANN-based plant diagnostic advisor will be helpful in better understanding these events both in real time and during an event evaluation after the plant is safely shut down.

Response to an abnormal condition at the nuclear power plants are currently based on procedures, which deal with the symptoms of the plant. The operators are trained to react to a developing situation based on these sets of procedures. Developed by extensive offsite analysis, these procedures aim to shut the plant down with minimal risk of damage to the plant and the surroundings. The root cause does not effect the procedural response.

2.2 Expert System Based Diagnostics

Nuclear power plant status diagnostics can also be performed by expert systems. These expert systems usually rely on elaborate fault-tree type analysis to evaluate the current plant status. Further discussion on expert system based diagnostics, and comparisons with ANN based diagnostics can be found in Appendix A.

2.3 Neural Networks

Neural networks are a fast-emerging branch of the science of artificial intelligence. Hecht-Nielsen [15] defines a neural network as a "parallel, distributed information processing structure consisting of processing elements interconnected together with unidirectional signal channels called connections." The dense interconnection of these simple processing elements or nodes provides the ANN models with their characteristic properties. Lippmann [20] describes the ANN process as a simultaneous exploration of competing hypotheses utilizing massively parallel networks composed of individual processing elements connected by variable weights. This is opposed to a von Neumann computer that performs a program of sequential instructions. The layered feed-forward ANN, as shown in Fig. 1 (Appendix A), was used in this work. This model consists of nodes arranged in layers, with the nodes of any layer being connected to the nodes in an adjacent layer through variable weights. A node takes its input from every node of the layer below it, and feeds its output to every node of the layer above it. There are no connections between nodes of the same layer. In such networks, the first layer is the input layer where the nodes are inactive, their outputs being equal to their inputs. The last layer is the output layer. The layers in between consist of "hidden" nodes, so called because they are isolated from the outside environment. The design of a network architecture is rather arbitrary; only the number of nodes in the input and output layers are fixed by the problem at hand. The simplest node, shown in Fig. 2 (Appendix A), sums weighted inputs and passes the result through a squashing function, sometimes also called the transfer function. The output signal of a node can be of any mathematical type desired [8] but is usually nonlinier and analog and is governed by the transfer

function. In this work, the transfer function was a sigmoid of the form

$$f(x) = \frac{1}{1 + e^x} \quad (1)$$

where x is the weighted sum of the outputs of the nodes in the previous layer, and $f(x)$ is the output. The behavior of this function can be seen in Fig. 3 (Appendix A).

The publication of the backpropagation technique by Rumelhart *et al.* [24] has been the most influential development in the field of neural networks in the past decade. They suggested a learning procedure that involved the presentation of a set of input-output patterns. The ANN uses the input vector to produce an output vector which is then compared with the expected or desired output vector to calculate the error for all the active nodes. The weights are changed using the delta and the generalized delta rules [15, 24, 9] such that the errors decrease during the next iteration. The error in the output nodes is easily calculated as the difference between the actual output and the desired output. The delta rule calculates the change in weights for the output layer. It is not possible to calculate the error in the hidden nodes in this way as their correct or expected outputs are not known. An error is assigned to each hidden node by backpropagating the error of the output nodes to the hidden nodes using the very same weights that were used to propagate the error to the output nodes in the first place [9]. The generalized delta rule, which is the delta rule modified for the hidden nodes, is used to change the weights in the hidden layers.

Dynamic Node Architectures

The problem addressed in the proposed research is very complex in its scope, and effective generalization is important for the best results. Good generalization requires that the network(s) have the optimum size to solve a problem. But this optimum size is not known a priori. The derivative DNA scheme developed by Bartlett and Basu [4] progresses in a systematic method to arrive at the appropriate architecture for any particular problem by adding and deleting nodes as required and using a quantitative measure of the importance of each hidden node. A description of this method can be found in Appendix A.

3 Statement of Proposed Work

3.1 Objectives

The author's previous work has relied primarily on one network to perform the diagnostics. In the later works, a hierarchy of two networks was used, but the job of classifying all the transients was still done by one network. This approach will be incapable of dealing with a large number of transients and input variables. The objective of the proposed work is to develop a fault diagnostic system with a certain degree of modularity built into it. The author proposes to develop a system that can be expanded to increase its capability as desired. The present design, like the one shown in Appendix A, is handicapped in this respect. Any effort to increase the scope of the advisor system would require the new system to be rebuilt from scratch.

3.2 Description of the Proposed Advisor

The proposed design of the advisor is presented in Figure 1. The root network will be responsible for detecting the onset of any transient. It will output 0 for normal condition, and 1 for any abnormal condition. When the root network detects an abnormality, the second layer of networks will try and identify the transient in progress. Each of the networks in this layer are trained to identify one particular transient. Thus, the network that corresponds to the ongoing transient will output 1 and the others will output 0. When the outputs of the networks stabilize, the diagnosis will be complete.

3.3 Advantages of the Proposed Advisor

The proposed design of the advisor has many advantages. The first is its modularity. Suppose the diagnostic ability of the trained advisor is to be increased by one more transient. Then, the root network can be trained further to recognize the onset of this transient. In addition, all the existing networks in the event identification layer need to be trained to output 0 for the input patterns corresponding this transient. This can be done starting with the existing networks. Also, a whole new network needs to be trained to output 0 for all the previous transients and 1 for

Figure 1: The design of the proposed advisor

the new transient. This is a much easier task compared to designing a new adviser from scratch. Also, a single ANN based classifier would not be able to accommodate an increase in transient scenarios as the number of distinct binary codes it can handle is limited by the number of output nodes in the network. The proposed advisor will be free of this constrain.

Each network in the classifier layer is trained to identify only one transient. So, it will be possible to develop a scheme for the network to select the variables it needs for the purpose. It is reasonable that not all the 97 variables used in previous work will be needed by each network. The author proposes to extend the DNA scheme to the input layer so that each network can select the input variables appropriate for its task.

Another advantage of the proposed adviser is the number of individual networks. Since the workload is distributed among the networks, none of them will be very large. So, training

each of them will be faster, and since the networks are independent of each other, they can be trained simultaneously on different machines. This will be very convenient given the widespread availability of powerful workstations.

3.4 Preliminary Investigations

This section describes a preliminary adviser developed based on the proposed design. This adviser was initially designed to recognize four transients. Therefore, the trained adviser consisted of a root network, and four ANNs capable of detecting the individual transients. After this adviser was developed, it was decided to add two more transients to the diagnostic capability of the adviser. The root network was trained further to recognize the onset of this transient. The four networks in the classifier layer were trained further to output 0 for these two new transients. Two new networks were trained to recognize these two new transients. These new networks now become part of the classifier layer. The performance result of this adviser can be seen in Table 1.

Table 1: The performance of the root network and the six networks in the classifier layer.

Trans. Num.	Scenario Code	Class. Net.	Scram Time (sec)	Root Diag. (sec)	Classification Time (in Seconds)						
					net1	net2	net3	net4	net5	net6	overall
1	rr15a	net1	1	0	2	6	8	2	6	2	8
2	fw17a	net2	1	0	10	3	1	6	8	7	10
3	ms14-6	net3	n/s	6	6	14	6	9	12	11	14
4	hp05	net4	n/s	12	12	6	23	28	22	18	28
5	fw02a	net5	499	6	16	12	22	18	9	22	22
6	ms03a	net6	2	0	3	7	10	1	3	14	14

n/s = no safety trip

3.5 Conclusions from Preliminary Investigations

The results in Table 1 shows that the final adviser was able to detect and identify all transients in less than 30 seconds. Each transient is identified by one network and the diagnosis is complete when the other networks output 0. This adviser was initially designed and developed to detect four transients. The diagnostic capacity of the adviser was subsequently increased to detect six

transients. This could be performed without discarding the previous adviser, but by using it as the basis for the bigger adviser. This shows the viability of the proposed design for the adviser that the authour envisions.

Each network in this work used all the 97 plant data as input for training. A dynamic input selection scheme can substantially reduce training time for the development of the adviser. it is hoped that the overall diagnostic performance of the adviser will increase with each network using only those variables required for its diagnostic task.

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Appendix A

The following is a copy of the paper titled "Detecting Faults in a Nuclear Power Plant Using Dynamic Node Architecture Artificial Neural Networks" submitted to *Nuclear Science and Engineering* for peer review and publication.

Detecting Faults in a Nuclear Power Plant Using Dynamic

Node Architecture Artificial Neural Networks

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Detecting Faults in a Nuclear Power Plant Using Dynamic Node Architecture Artificial Neural Networks

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Abstract

This paper describes an artificial neural network- (ANN-) based diagnostic adviser capable of identifying the operating status of a nuclear power plant. A dynamic node architecture (DNA) scheme is used to optimize the architectures of the two backpropagation ANNs which embody the adviser. The first or root network is used to determine whether the plant is in a normal operating condition or not. If the plant is not in a normal condition, the second, or classifier network is used to recognize the particular off-normal condition or transient taking place. These networks are developed using simulated plant behavior during both normal and abnormal conditions. Data from the nuclear generating station training simulator at Iowa Electric Light and Power Company's Duane Arnold Energy Center (DAEC) is used in this work. The adviser is effective at diagnosing 27 distinct transients based on 43 scenarios simulated at various severities which contain up to 3% noise.

1 Introduction

The safe operation of nuclear power reactors is very important to the nuclear engineering community and vital to creating a more positive attitude towards nuclear energy. This paper explains how artificial neural networks (ANNs) can be used to increase the operational safety of nuclear reactors by being the basis of a fault diagnostic system for a nuclear power plant. Faults in the various systems and components of nuclear power plants cause distinct behavioral transients. These transients can be identified and the particular faults that cause them detected. It is hoped that neurocomputing, as the science of neural networks is sometimes called, will provide an important contribution towards the recognition and classification of operational transients at nuclear power plants and thereby improve their safety.

The feasibility of using ANNs for a fault diagnostic adviser has been demonstrated in earlier work [1]. The present work describes the evolution of this earlier research and develops and enhances the previously used approaches for boiling water reactors (BWRs) as opposed to pressurized water reactors (PWRs). The present work also demonstrates the usefulness of ANN techniques for diagnosing many more transients over a wider range of severities. The diagnostic task investigated here requires the detection of 27 transients at a BWR using 97 plant variables as inputs as opposed to 7 transients and 27 variables in the earlier investigation. Not only does the increase in the number of variables and transients make the adviser more applicable but it is also significant because an increase in the number of input and output variables in an ANN application increases the difficulty of obtaining a solution very rapidly. This is due to the non-polynomial-time completeness of neural network learning [2]. Therefore, as the number of variables n in the problem increases, the complexity increases faster than a polynomial of order n [3]. This makes larger problems very difficult to solve using ANNs. A hierarchical approach is introduced in this work that segregates the diagnostic problem into small component parts to circumvent the aforementioned learning difficulties. The training complexity is reduced by using a modular hierarchy of two ANNs which distributes the burden of the diagnosis. The single network as used in the previous work had considerable difficulty solving the present diagnostic

problem due to its larger scale. This hierarchical approach has many advantages as the number of transients and variables is increased. For example, the individual component networks in this hierarchy are trained independently and simultaneously. Moreover, all the ANNs in the hierarchy do not need to use the same input variables. The system developer is then free to use only those variables needed for each ANN in the hierarchy to complete its particular task. [add a concluding sentence here.]

The ANNs used in this work utilize the backpropagation learning algorithm in contrast to the stochastic learning algorithm used in the previous work. Backpropagation is a much more widely understood and accepted paradigm. A dynamic node architecture (DNA) scheme was developed for backpropagation networks that eliminates the need for preset architectures, thus eliminating another difficulty associated with ANN applications [11]. The successful implementation of the DNA scheme in a backpropagation network enabled the development of the relatively large networks without recourse to guesswork inherent with the usual architecture preselection.

Power plants currently employ automatic safety systems that allow the plant to operate within a predefined operating range. These systems verify that plant variables conform to preassigned safety limits. If a plant variable exits from its safety range, safety systems either trigger an automatic reactor shutdown (safety trip) or notify the operators of the violation through alarms or indicators. Corrective actions performed by the operators following such events are based on procedures, which address symptoms. The operators are trained to react to each symptom by following procedures. Developed by extensive offsite analysis, these procedures are designed to put the plant in a safe condition with minimal risk or damage to the environment. The root cause of a transient does not effect the procedural response. After the plant is in a safe condition, the sequence of events leading to a plant shutdown or alarm are analyzed by technical review teams comprising of operators and shift and plant engineers [4].

The operators in a nuclear power plant are expected to monitor a large number and variety of plant parameters. These parameters, or variables, are relayed to the operator in the control room by instrumentation located in the various systems that comprise the plant. It is conceivable that the operators can commit mistakes during the stressful situation following an abnormal event.

The responsibility on the operator can be overwhelming. In such situations, a diagnosis by the ANN-based plant diagnostic adviser could reassure the operators about the adequacy of their procedural actions. The adviser's diagnosis could also provide clues to the operator about certain symptoms that might have been overlooked or are likely to develop in the near future. The adviser would be able to diagnose many transients in enough time to warn the operators of an impending automatic safety trip. The operators can then, in accordance with procedures, carry out a manual reactor trip that would be safer and easier on the plant components as compared to a fast automatic shutdown.

Later during a technical review, a time record of the instantaneous response of the ANN adviser could be a valuable tool in understanding the evolution of the abnormal event. The quick diagnosis of a transient by the ANN adviser could help the reviewers evaluate the appropriateness of the emergency operating procedures. The adequacy of operator actions can also be evaluated in this light.

Nuclear power plant diagnostics can also be performed by expert systems. Such diagnostic systems usually rely on elaborate decision trees to evaluate the current plant status [5, 6, 7]. The most notable effort in this regard is the Reactor Safety Assessment System (RSAS) developed jointly by the Idaho National Engineering Laboratory, the University of Maryland, and the U. S. Nuclear Regulatory Commission [5, 8]. Expert systems such as RSAS require knowledge to be specifically enumerated and incorporated into their knowledge base about every aspect of the system that is analyzed. This knowledge can be stored as numerous if-then logic statements that assist the expert system in performing a fault-tree type analysis [9, 10]. For nuclear power plants, this enumeration process for an exhaustive root cause analysis can require large amounts of personnel time. Every conceivable scenario should be analyzed to assure that as many transients as possible can be differentiated. The temporal behavior of all important variables is also required. All of this information must be manually incorporated into the expert system in a precise and methodical way. On the other hand, ANNs do not need an explicit knowledge base. The designer need only have a working model of the plant and a knowledge that certain sensors are important indicators of the health of the plant. Most nuclear power plants have such a working model

in the form of a training simulator. ANNs learn their responses from sets of training data and then generalize this information to the actual operating plant. A training set is a collection of input-output patterns that are used by the network to infer the functional relationship between their inputs and outputs. Generalization in this context is the ability to "quantitatively estimate certain characteristics or features of a phenomenon never before encountered on the basis of similarities with things previously known" [11].

Most of the possible transients at nuclear power plants have never actually occurred and data for such scenarios are obtained through computer simulation. The noise and fault tolerant capabilities of neural networks are advantageous in developing an adviser based on such simulated data. These data are generated on a computer and do not contain any noise. But the adviser is expected to perform under real plant conditions where the input data can be expected to be corrupted by some noise. The generalization capability of ANNs enables them to correctly classify patterns containing such noise. Fault tolerance of the neural networks is advantageous when there is failure of plant instrumentation. In such situations, an expert system might fail catastrophically if certain decisions in its analysis are based on such failed inputs. On the other hand, the ANN adviser could perform relatively accurately, disregarding the particular sensor fault. This fault tolerance capability of ANNs is due to their distributed memory in the form of the weights. As the number of failed sensors increase, the performance of the ANN adviser will gradually deteriorate. Moreover, a neural network-based adviser system can produce its output in finer time steps compared to an elaborate expert system and therefore can provide better clues during event evaluations.

The following section gives a brief introduction to ANNs. This section also introduces the difficulty of deciding network architectures and the solution using our DNA scheme. Section 3 gives a description of the design and development of the nuclear power plant fault diagnostic adviser. Section 4 presents the performance results of the adviser with both pure simulator data and data corrupted by 3% Gaussian noise. Section 5 contains concluding remarks.

2 Neural Networks

Neural networks are a fast-emerging branch of the science of artificial intelligence. Hecht-Nielsen [14] defines a neural network as a "parallel, distributed information processing structure consisting of processing elements interconnected together with unidirectional signal channels called connections." The dense interconnection of these simple processing elements or nodes provides the ANN models with their characteristic properties. Lippmann [16] describes the ANN process as a simultaneous exploration of competing hypotheses utilizing massively parallel networks composed of individual processing elements connected by variable weights. This is opposed to a von Neumann computer that performs a program of sequential instructions. The layered feed-forward ANN, as shown in Figure 1, was used in this work. This model consists of nodes arranged in layers, with the nodes of any layer being connected to the nodes in an adjacent layer through variable weights. A node takes its input from every node of the layer below it, and feeds its output to every node of the layer above it. There are no connections between nodes of the same layer. In such networks, the first layer is the input layer where the nodes are inactive, their outputs being equal to their inputs. The last layer is the output layer. The layers in between consist of "hidden" nodes, so called because they are isolated from the outside environment. The design of a network architecture is rather arbitrary; only the number of nodes in the input and output layers are fixed by the problem at hand. The simplest node, shown in Figure 2, sums weighted inputs and passes the result through a squashing function, sometimes also called the transfer function. The output signal of a node can be of any mathematical type desired [15] but is usually nonlinier and analog and is governed by the transfer function. In this work, the transfer function was a sigmoid of the form

$$f(x) = \frac{1}{1 + e^x} \quad (1)$$

where x is the weighted sum of the outputs of the nodes in the previous layer, and $f(x)$ is the output. The behavior of this function can be seen in Figure 3.

The publication of the backpropagation technique by Rumelhart *et al.* [17] has been the most influential development in the field of neural networks in the past decade. They suggested a

learning procedure that involved the presentation of a set of input-output patterns. The ANN uses the input vector to produce an output vector which is then compared with the expected or desired output vector to calculate the error for all the active nodes. The weights are changed using the delta and the generalized delta rules [14, 17, 18] such that the errors decrease during the next iteration. The error in the output nodes is easily calculated as the difference between the actual output and the desired output. The delta rule calculates the change in weights for the output layer. It is not possible to calculate the error in the hidden nodes in this way as their correct or expected outputs are not known. An error is assigned to each hidden node by backpropagating the error of the output nodes to the hidden nodes using the very same weights that were used to propagate the error to the output nodes in the first place [18]. The generalized delta rule, which is the delta rule modified for the hidden nodes, is used to change the weights in the hidden layers.

Most backpropagation networks, including those used in this work, are layered and feed-forward; they always consist of at least three layers of nodes. The number of inputs and outputs are fixed by the problem at hand. The only choice of network architecture is the number of hidden nodes. This choice needs to be exercised carefully. If the hidden layer is too large, it will encourage the network to memorize the input patterns rather than generalize the input into features [14, 18]. The large number of nodes and weights give the network more ways to distinguish features causing the specifics being learned rather than the generalities. This reduces the network's ability to correctly classify novel patterns after training is complete. On the other hand, a hidden layer that is too small will drastically increase the number of iterations and thus the computer time required to train the network. In the extreme case, the network might be untrainable to perform the required task [18]. There are no hard and fast rules for determining the optimum architecture; most rules in use at this time are empirical in nature and are derived by heuristic methods [19, 20, 21].

The present work develops an ANN based diagnostic adviser for a nuclear power plant. This adviser uses 97 plant variables as inputs. The output is a combination of five binaries. As the design of the adviser progresses, the network needs to be trained a number of times with different

numbers of patterns in the training set. If a search for the appropriate architecture is attempted before each training phase, the problem would assume mammoth proportions involving significant amounts of guesswork. It is therefore imperative to develop a systematic method that will derive optimum, or near optimum, architectures for a given problem. The DNA scheme described below is one such method.

Dynamic Node Architectures

Other researchers have attempted to develop various dynamic architecture schemes but have left some facets of the problem unanswered. For example, one approach prunes unnecessary weights from a fully connected and trained network [22, 23, 24]. This results in a sparsely connected network devoid of redundant weights. This approach wastes computer time by training unnecessary nodes and weights in large networks. Moreover, some amount of guesswork is still involved in deciding the initial network size which needs to be more than the optimum architecture. [This is not an easy task for very complex problems involving large numbers of inputs.] Another approach [25, 26, 27] starts with small networks and builds them up until the network can successfully learn the training set. Most of these algorithms stop when the training set is first learned. But it is known that learning a functional relationship requires more nodes than recalling the same function [11]. Work by Hirose *et al.* [26] addresses this issue by eliminating the last added node after the network can successfully learn the training set. The process of deleting nodes continues until the smallest network is found that can learn the problem. This process assumes that the last added node should be eliminated first. But Hirose *et al.* have no definite way to verify this assertion.

The derivative DNA scheme developed by Bartlett and Basu [11] progresses in a systematic method to arrive at the appropriate architecture for any particular problem by adding and deleting nodes as required and using a quantitative measure of the importance of each hidden node. Training is initiated with one hidden node that is unable to arrive at a good solution. As training progresses, the network soon reaches a learning plateau where it cannot reduce its error below a certain value during a number of successive iterations. A node is then added to the hidden

layer. The weights connecting this new node are assigned very small random values so that the addition of this node does not disrupt the network performance. Training is resumed and the network soon reaches another plateau when another node is added. This process is continued until the network reaches a satisfactory level of performance. At this stage, not all of the hidden nodes may be necessary to solve the mapping. Therefore, the hidden node with the least importance is removed from the network. The resultant network might require further training, depending on the deleted node's importance to the ANN function. Upon continued training, the smaller network might be able to learn the mapping. Then the next node with the least importance is deleted. This process is continued until the network is too small to learn the problem. Now nodes are added until the problem is relearned. The process of deleting and adding nodes is continued until the algorithm starts oscillating about some relative minimum architecture. Note that the architecture given by this scheme may not be the minimum architecture but is very close to it. The architecture given by the DNA scheme is influenced by the selection of various parameters like the learning rate, and the number of iterations spent on a learning plateau before a node is added.

Importance of a Node

The importance of a node can be defined in many ways. The skeletonization method [28, 29] measures the change in the error of the network output with the deletion of each node and assigns a greater importance to the node whose deletion causes a greater change. But if a hidden node is biasing the output of the network, i.e., it has a near constant output over the training set, this method will determine that this node is very important even though it is unimportant to the dynamics of the network. Another importance measure [30] is based on the values of the weights leading to and from the node and is binary in nature. Our importance measure, on the other hand, assumes that if changes in the output of a hidden node are more detrimental in deciding the output of the network than a similar change in the output of another hidden node, then the former node is more important to the dynamic functioning of the network than the latter node. In this case, the importance of the j th hidden node with respect to the k th output node

is defined as [11]

$$I_{(x_j|x_k)} = E\left[\left|\frac{\delta x_{k,n}}{\delta x_{j,n}}\right|\right] * dx_j^{max} \quad (2)$$

where $E[...]$ is the expectation over the entire training set and dx_j^{max} is the maximum change in the output of the j th hidden layer node over the entire training set. The above equation gives the partial importance of the j th hidden node with respect to the k th output node. If the network consists of more than one hidden layer, the partial importance of any of these hidden nodes with respect to any output node can be found out by using the chain rule. The total importance of the j th hidden node is the sum of the partial importances of that node with respect to all the output nodes. Mathematically,

$$I_{(x_j)} = \sum_{k=1}^{kmax} I_{(x_j|x_k)} \quad (3)$$

where $kmax$ is the number of output layer nodes. The importance of a layer can be similarly defined as the sum of the importances of the nodes in that layer.

DNA Training: An Example

A typical network learning problem is the exclusive-nor problem. The training data for this example is shown in Table 1. The working of the DNA algorithm is illustrated by solving this problem. The starting architecture is $2 \times 1 \times 1$, i.e., two input, one hidden, and one output nodes. The training target was an RMS error of 0.01. Table 2 shows the training history for this problem. It is known that one node cannot solve this problem, but two can. The DNA scheme adds a second node when the network is unable to reduce its error during many iterations. This architecture reaches a plateau above the target RMS error, and a third node is added. This $2 \times 3 \times 1$ architecture also is unable to learn the problem before a plateau is reached, and a fourth node is added. The $2 \times 4 \times 1$ architecture is successful in learning the problem. Now, the node with the least importance is deleted. This leaves the network with three hidden nodes and is now able to reach the target RMS error. Another node is deleted and upon further training, the $2 \times 2 \times 1$ network is also able to learn the problem to the desired level of accuracy. The further elimination of a node renders the network with only one hidden node. This is not sufficient to

learn the problem and a node is added. This process is continued and the algorithm oscillates around the optimum architecture of $2 \times 2 \times 1$. This oscillation can be clearly seen from Table 2.

Computer simulations were carried out to compare the performance of DNA-generated networks and networks trained by conventional fixed node architecture (FNA) schemes. For the exclusive-nor problem, the DNA algorithm gave a minimum network of size $2 \times 2 \times 1$. Two more networks with 5 and 10 hidden nodes are trained to the same level of accuracy on the exclusive-nor problem by using an FNA scheme. Then all three networks were used to recall on data corrupted by 5% uniform noise. The results in Table 3 show that the DNA architecture network outperformed the larger networks in the noisy situation. This indicates better generalization due to lesser number of nodes and weights.

3 Designing the Nuclear Power Plant Adviser

This section describes the development of an ANN-based diagnostic adviser capable of detecting and classifying a large variety of transients at a nuclear power plant. ANNs that can recognize a diverse range of transients need to draw information from many plant variables. The choice of accidents and variables is therefore very important. Two documents were consulted for the purpose: the *Updated Final Safety Analysis Report* [31] and the *Malfunction Cause and Effects Report* [32], both pertaining to the Duane Arnold Energy Center (DAEC). These documents describe many power plant transients. Discussions between personnel at DAEC and fellow researchers at Iowa State University (ISU) [33] resulted in a preliminary list of transients to be simulated on the operator training simulator and plant variables to be monitored [13]. Twenty seven of these transients were selected for this work. Some of these transients can occur at varying severities. For the adviser to detect a transient irrespective of its intensity, some transients were simulated at different severities. We therefore trained the adviser to recognize 27 distinct transients by using data from the simulation of 43 scenarios.

Data Collection and Processing

The raw data were obtained from the DAEC operators' training simulator. This data consisted of the numerical values of 97 plant variables at intervals of one second. The data also included a Yes/No binary switch that indicated the onset of the transient. The variables were selected from the complete list of 2,369 variables available on the simulator. These 97 variables, listed in Table 4, were judged to be sufficient for an operator to diagnose the transients being investigated [33] and were selected as the inputs for the proposed adviser. These variables covered a wide variety of plant instrumentation such as pressures and temperatures in the various systems of the plant, radiation monitors, and flow meters. Raw data obtained from DAEC were reformatted and normalized in the range [0,1] as required by backpropagation neural networks. Normalization was based on the maximum and minimum possible values of the variables.

The Structure of the Adviser

In earlier approaches [1, 12, 34] we trained one network to output a particular binary for the normal operating conditions, and different binaries for each of the transients investigated. This burdens one network with too much work. In the current work we have a collection of two networks in the adviser. One is a root network to recognize if the plant is in a normal condition or not, and the second is a classifier network used to identify the particular transient. The values of the 97 chosen variables, at any single instant of time, are assumed to contain enough information to diagnose the plant status. This approach of using time-slice data without any temporal information was used in previous work [1, 12]. As will be seen later, this information proved to be adequate to solve the problem. Therefore, both networks have 97 input nodes. The root network has only one output node, which gives an output of 0 if the plant is in a normal condition and 1 otherwise. The classifier network needs to be able to distinguish between 27 different transients, and thus needs to output as many different binaries. This task can be done with five binary outputs, and consequently, this network has five output nodes. A listing of the transients investigated can be found in Table 5, and the output binaries assigned to them can be found in Table 6.

Training the Adviser

The training data for both the networks were chosen in an iterative manner. For the first trial of the root network, one pattern at the beginning and one at the end of each of the 43 simulations were taken to form the training set. The initial training set therefore contained 86 patterns. Training was initiated with one hidden node. The target RMS error was 0.10. As the training progressed, the DNA scheme added more nodes and gave a final architecture with five hidden nodes. The network was used to recall all the patterns over the entire length of the 43 simulations. The network, as expected, did not do a very good job of classifying all the patterns. The patterns with the worst recall errors were added to the training set and the network from the previous trial was trained further. This process was continued until the network could detect the onset of all the transients within a reasonable amount of time.

A similar approach was used to train the classifier network. In this case, the normal operating conditions were not used because this network would be called upon to classify only those patterns that the root network had decided were abnormal. So the first training attempt had only 43 patterns in it, one from the end of each simulation.

This network training problem is slightly different from the conventional problems solved using neural networks. In most cases, a training set is given and is used to train a network. The recall set is not known beforehand, and the trained network is used to recall on unseen patterns. But in our case, the recall set is known from the simulations. We try to define the training set, through the various trials, so that it is a fairly accurate representation of the recall set. Consequently, good generalization is extremely important to keep the number of patterns in the training set to a minimum as well as to make the adviser fault and noise tolerant.

The final architecture of the root network was $97 \times 9 \times 1$ and the classifier network was $97 \times 26 \times 5$. The advantages of the DNA algorithm can be appreciated here. Suppose a conventional fixed architecture scheme was used to solve this problem. In that case for the first trial, we need to guess at a few architectures, train all of them, and choose the architecture with the best performance for later trials. But the training set changes, in fact increases, with each trial. Consequently, there is no guarantee that the best architecture for a given trial will also be good

enough for the following trials. Thus a fixed node architecture scheme would have been extremely inconvenient for developing the nuclear power plant status diagnostic adviser discussed in this paper.

4 Results

A total of 43 different scenarios representing 27 distinct transients were used for this study. The fault diagnostic adviser was trained on pure simulator data, and its performance was tested on both pure data and data corrupted by 3% Gaussian noise. The noisy data was computer generated to add noise with a Gaussian distribution and a 3% standard deviation of the pure data. Table 6 gives a summary of the diagnostic performance of the adviser. The adviser was a combination of two different networks. The root network was used to detect an abnormal status, and subsequently the classifier network was used to identify the particular transient in progress.

The root network was able to detect all the transients irrespective of noise within 40 seconds. A look at Table 6 will show that a vast majority of these were actually within 20 seconds. The root network needed only 192 patterns to be trained to this level of performance, which is less than 2.5% of the total of 7,854 patterns. Similarly, the classifier network was able to identify all the transients within 2 minutes of the initiating events. This network required 464 patterns, which is less than 6% of the total number of patterns.

The results can be best understood by looking at certain examples from Table 6. Transient scenario "fw12c1" (transient number 6), assigned the output binary code 10110, is the failure of the feedwater regulator valve controller which leaves the valve stuck open. This caused the plant to undergo a safety trip 90 seconds after the initiating event. The root network was able to detect an abnormality in the plant status immediately after the initiation event. This ability was not hampered even when noise was added to the data. The classifier network diagnosed the transient after 104 seconds since its advent. Under noisy condition, successful diagnosis was achieved at 109 seconds.

From Table 6 it can be seen that some of the transients caused almost immediate safety trips

of the reactor. In such cases, the adviser will not be able to prevent the safety trip. For example let us look at transient "ms04a" (transient number 18). This transient is caused by the rupture of the main steam line outside the primary containment. We had three scenarios for this transient corresponding to 100% (ms04a), 60% (ms04a_2), and 30% (mso4a_3) severity of the rupture. All these transients were assigned the same binary output code 10011 as the adviser should be able to classify them as the same transient. The plant underwent a safety trip within two seconds of the initiating event in all the three cases. The root network was able to detect an anomaly in the plant status almost immediately. But the short time before the safety trip will not give the operators a chance to take any action. During such rapid transients, the operators follow the procedures laid out in the plant Emergency Operation Procedures. This will take some time to go into effect [33]. As the plant goes through the shutting down process, the classifier network diagnoses the transient at around 70 seconds since the initiating event. This diagnosis can be a valuable tool for the shift technical adviser to evaluate the condition of the plant. Later, the adviser can provide valuable clues during technical reviews of the transient.

There are many transients that do not cause a safety trip over a prolonged period of time. An example is transient "rx01" (transient number 26). This transient is caused by a 5% failure of the fuel cladding, resulting in radioactive contamination of the coolant cycle. The root network detects an abnormality at 11 seconds since the initiating event, and the classifier network diagnoses the transient at the 18 second mark. During this time the operators will be undertaking any tasks mandated by the plant operating procedures. A definite diagnosis by the adviser in such a situation would help the shift technical adviser in proper assessment of the situation and judge the validity of the procedures being performed. The procedures are quite extensive, but it is conceivable that the plant enters a situation not foreseen in the procedures. If the shift technical adviser feels that information provided by the diagnostic adviser conflicts with the procedures being carried out, he can authorize shutting down the plant.

5 Conclusions

The first conclusion from this work is the viability of using neural networks to detect a very wide variety of operational transients at a boiling water reactor (BWR) nuclear power plant. An ANN-based adviser was successfully trained to detect and classify 27 distinct transients and the four normal conditions. The adviser performed well even when the data was corrupted by noise, and so was fairly noise tolerant. The adviser used two neural networks functioning in a hierarchical manner. Further evolution in the direction of the hierarchical approach could produce advisers capable of drawing information from more plant instrumentation and diagnosing a wider range of transients.

A DNA scheme based on a derivative importance function was developed to arrive at a relative optimum network architecture for any problem. It eliminated the guesswork associated with pre-set architectures used in conventional neural network training schemes. The use of DNA allowed the speedy development of the adviser by eliminating a large amount of guesswork that would otherwise have been required to determine appropriate architectures. Use of a fixed architecture scheme would have been a major hurdle because the training set increased as the development of the adviser progressed.

Practical acceptance of this technology would depend on the ability to incorporate some modularity in the design of the system, making it possible to increase the scope of the adviser beginning with the existing system, and not from scratch. It is conceivable that not all of the 97 variables are needed to identify each transient. A simplification of the system design incorporating a number of small ANNs will make it possible to identify the important variables for the task of transient identification.

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Figure 1: A three-layered feed-forward backpropagation neural network.

Figure 2: A simple node detailed.

Figure 3: The sigmoid transfer function.

Table 1: Exclusive-nor training data

Pattern	Input1	Input2	Output
1	0.0	0.0	1.0
2	0.0	1.0	0.0
3	1.0	0.0	0.0
4	1.0	1.0	1.0

Table 2: Dynamic node architecture training history for the exclusive-nor problem

Architecture				Architecture				Architecture			
In	Hid	Out	RMS Error	In	Hid	Out	RMS Error	In	Hid	Out	RMS Error
2	1	1	0.50122	2	3	1	0.01793	2	4	1	0.02828
2	1	1	0.38725	2	4	1	0.01929	2	4	1	0.00997
2	2	1	0.39071	2	4	1	0.00993	2	3	1	0.02877
2	2	1	0.11059	2	3	1	0.02243	2	3	1	0.00982
2	3	1	0.11902	2	3	1	0.00972	2	2	1	0.06837
2	3	1	0.03376	2	2	1	0.04227	2	2	1	0.00999
2	4	1	0.04133	2	2	1	0.00999	2	1	1	0.49962
2	4	1	0.00997	2	1	1	0.49979	2	1	1	0.49224
2	3	1	0.02521	2	1	1	0.49286	2	2	1	0.42182
2	3	1	0.00981	2	2	1	0.32188	2	2	1	0.14522
2	2	1	0.06242	2	2	1	0.06229	2	3	1	0.18256
2	2	1	0.02109	2	3	1	0.06681	2	3	1	0.01644
2	3	1	0.03027	2	3	1	0.01483	2	4	1	0.02388

Table 3: Comparative recall performance of neural networks derived by DNA and FNA schemes

Architecture	Scheme	Training RMS error	Recall RMS error
2x 2x1	DNA	9.9956E-03	0.00999
2x 5x1	FNA	9.9278E-03	0.01831
2x10x1	FNA	9.7582E-03	0.01983

Table 4: Plant Variables Used to Train the ANN Adviser.

Serial Number	Variable Designation	Description	Min. Value	Max. Value	Variable Unit
1	A041	Local power range monitor 16-25 flux level B	0.0	125.0	% power
2	A091	Source range monitor channel B	0.0	100.0	%
3	B000	Average power range monitor A Flux level	0.0	125.0	% power
4	B012	Reactor total core flow	0.0	60.0	Mlb/hr
5	B013	Reactor core pressure-differential	0.0	30.0	psid
6	B014	Control rod drive system flow	0.0	0.025	Mlb/hr
7	B015	Reactor feedwater loop A flow	0.0	4.0	Mlb/hr
8	B016	Reactor feedwater loop B flow	0.0	4.0	Mlb/hr
9	B017	Cleanup system flow	0.0	0.07691	Mlb/hr
10	B022	Total steam flow	0.0	8.0	Mlb/hr
11	B023	Cleanup system inlet temperature	0.0	755.0	°F
12	B024	Cleanup system outlet temperature	0.0	600.0	°F
13	B026	Recirculation loop A1 drive flow	0.0	15.1	Mlb/hr
14	B028	Recirculation loop B1 drive flow	0.0	15.1	Mlb/hr
15	B030	Reactor feedwater channel A1 temperature	280.0	430.0	°F
16	B032	Reactor feedwater channel B1 temperature	280.0	430.0	°F
17	B034	Recirculation loop A1 inlet temperature	260.0	580.0	°F
18	B036	Recirculation loop B1 inlet temperature	260.0	580.0	°F
19	B038	Recirculation A wide range temperature	50.4	789.6	°F
20	B039	Recirculation B wide range temperature	50.4	789.6	°F
21	B061	Reactor coolant total jet pumps 1-8 flow B	0.0	36.7	Mlb/hr
22	B062	Reactor coolant total jet pumps 9-16 flow A	0.0	36.7	Mlb/hr
23	B063	Reactor coolant total outlet steam flow A	0.0	2.0	Mlb/hr
24	B064	Reactor coolant total outlet steam flow B	0.0	2.0	Mlb/hr
25	B065	Reactor coolant total outlet steam flow C	0.0	2.0	Mlb/hr

Table 4: . . . continued

Serial Number	Variable Designation	Description	Min. Value	Max. Value	Variable Unit
26	B066	Reactor coolant total outlet steam flow D	0.0	2.0	Mlb/hr
27	B079	Reactor recirculation pump A motor vibration	0.0	10.0	MILS
28	B080	Reactor recirculation pump B motor vibration	0.0	10.0	MILS
29	B083	Control rod drive cooling-water differential pressure	0.0	500.0	dpsi
30	B084	Control rod drive cooling-water differential pressure	0.0	60.0	dpsi
31	B085	Torus air temperature #1	0.0	500.0	°F
32	B086	Torus air temperature #2	0.0	500.0	°F
33	B087	Torus air temperature #3	0.0	500.0	°F
34	B088	Torus air temperature #4	0.0	500.0	°F
35	B089	Drywell temperature azimuth 0 elevation 750	0.0	500.0	°F
36	B090	Drywell temperature azimuth 245 elevation 750	0.0	500.0	°F
37	B091	Drywell temperature azimuth 90 elevation 765	0.0	500.0	°F
38	B092	Drywell temperature azimuth 270 elevation 765	0.0	500.0	°F
39	B093	Drywell temperature azimuth 270 elevation 765	0.0	500.0	°F
40	B094	Drywell temperature azimuth 180 elevation 780	0.0	500.0	°F
41	B095	Drywell temperature azimuth 270 elevation 830	0.0	500.0	°F
42	B096	Drywell temperature center elevation 750	0.0	500.0	°F
43	B098	Torus water temperature	0.0	752.0	°F
44	B099	Torus water temperature	0.0	752.0	°F
45	B103	Drywell pressure	0.0	100.0	psia
46	B104	Torus pressure	0.0	100.0	psia
47	B105	Torus water level	-10.0	10.0	in.
48	B120	Torus radiation monitor A	-1.0	100.0	%
49	B121	Torus radiation monitor B	-1.0	100.0	%
50	B122	Reactor water level	158.0	218.0	in.
51	B124	Reactor water level	158.0	218.0	in.
52	B1257	Fuel zone level indication	-153.0	218.0	in.
53	B126	Reactor water level	158.0	458.0	in.
54	B127	Reactor vessel pressure	0.0	1200.0	psig

Table 4: . . . continued

Serial Number	Variable Designation	Description	Min. Value	Max. Value	Variable Unit
55	B128	Reactor vessel pressure	0.0	1200.0	psig
56	B129	Reactor vessel pressure	0.0	1500.0	psig
57	B130	Reactor vessel pressure	0.0	1500.0	psig
58	B137	Torus water level	1.5	16.0	ft
59	B138	Torus water level	1.5	16.0	ft
60	B150	Core spray A flow	-1767.8	5000.0	gpm
61	B151	Core spray B flow	-1767.8	5000.0	gpm
62	B160	Reactor core isolation cooling flow	-62.5	500.0	gpm
63	B161	High-pressure core injection flow	-437.5	3500.0	gpm
64	B162	Residual heat removal A flow	-75.0	15000.0	gpm
65	B163	Residual heat removal B flow	-75.0	150.0	gpm
66	B164	Drywell radiation monitor A	-1.0	100.0	%
67	B165	Drywell radiation monitor B	0.0	100.0	%
68	B166	Post-treat activity	0.0	100.0	%
69	B168	Pretreat activity	0.0	100.0	%
70	B171	Analyzer A — O ₂ concentration	-1.25	10.0	%
71	B172	Analyzer A — H ₂ concentration	-1.25	10.0	%
72	B173	Analyzer B — O ₂ concentration	-1.25	10.0	%
73	B174	Analyzer B — H ₂ concentration	-1.25	10.0	%
74	B180	Clean-up system flow	0.0	200.0	gpm
75	B196	Reactor water level-fuel zone A	-153.0	218.0	in.
76	B197	Reactor water level-fuel zone B	-153.0	218.0	in.
77	B247	Turbine steam bypass	0.0	500.0	°F
78	B248	Turbine steam bypass	0.0	500.0	°F
79	E000	4160 V switch gear bus 1A1 A-B	0.0	5.25	KV
80	F004	Condensate pump A&B discharge pressure	0.0	600.0	psig
81	F005	Low-pressure condenser circulating water inlet temperature A	0.0	200.0	°F
82	F010	High-pressure condenser circulating water outlet temperature A	0.0	200.0	°F
83	F011	Low-pressure condenser circulating water pressure differential A	0.0	10.0	dpsi
84	F015	Circulating water pump A&B discharge pressure	0.0	100.0	psig
85	F018	Cooling tower A discharge water temperature	0.0	752.0	°F
86	F019	Cooling tower B discharge water temperature	0.0	752.0	°F
87	F040	1P-1A reactor feed pump suction pressure	0.0	600.0	psig

Table 4: . . . continued

Serial Number	Variable Designation	Description	Min. Value	Max. Value	Variable Unit
88	F041	1P-1B reactor feed pump suction pressure	0.0	600.0	psig
89	F042	1P-1A reactor feed pump discharge pressure	0.0	2000.0	psig
90	F043	1P-1B reactor feed pump discharge	0.0	2000.0	psig
91	F044	Condensate total flow	0.0	8.0	Mlb/hr
92	F045	Condensate makeup flow	-10.0	100.0	Klb/H
93	F046	Condensate rejection flow	0.0	50.0	Klb/H
94	F094	Feedwater final pressure	0.0	2000.0	psig
95	G001	Generator gross watts	0.0	720.0	MWE
96	T039	Low-pressure condenser pressure	0.0	30.0	in.-Hg
97	T040	High-pressure condenser pressure	0.0	30.0	in.-Hg

Table 5: The twenty-seven transients, and the forty-three scenarios used to design the adviser.

No.	Scenario	Description
1	cul0	Reactor water clean-up coolant leakage
2	cul0gp5	Reactor water clean-up coolant leakage with failure of Group 5 isolation valves.
3	fw04a	Condensate filter demineralizer resin injection
4	fw09a	Reactor feedwater pump trip
5	fw12c0	Feedwater regulator valve controller stuck closed
6	fw12c1	Feedwater regulator valve controller stuck open
7	fw17a	Main feedwater line break inside primary containment
8	fw18a fw18a_2 fw18a_3	Main feedwater line break outside primary containment - 100% severity - 60% severity - 30% severity
9	hp05 hp05_2 hp05_3	High-pressure core injection (HPCI) steam supply line break in HPCI room - 100% severity - 60% severity - 30% severity
10	hp08 hp08_2 hp08_3	High-pressure core injection steam supply line break in torus room - 100% severity - 60% severity - 30% severity
11	ic20scr2	Spurious scram with effective operator action to avoid feedwater pump trip. Initial condition IC20 : 100% power, End of Cycle
12	ic20scrm	Spurious scram with no operator action. Initial condition IC20 : 100% power, End of Cycle.
13	ic22scra	Spurious scram. Initial condition IC22: 25% power, Beginning of Cycle
14	ic23scrm	Spurious scram. Initial condition IC23 : 75% power, Beginning of Cycle
15	ic24scrm	Spurious scram. Initial condition IC24 : 100% power, Middle of Cycle
16	ms02 ms02_2 ms02_3	Steam leak inside primary containment - 100% severity - 60% severity - 30% severity
17	ms03a ms03a_2 ms03a_3	Main steam line rupture inside primary containment - 100% severity - 60% severity - 30% severity
18	ms04a ms04a_2 ms04a_3	Main steam line rupture outside primary containment - 100% severity - 60% severity - 30% severity
19	ms19ab	Spurious group 1 isolation
20	ms32	Spurious group 7 isolation

Table 5: ...continued...

No.	Scenario	Description
21	rp05tc01	Reactor protection system SCRAM circuit failure (ATWS) with alternate rod injection
22	rp5actc1	Reactor protection system SCRAM circuit failure (ATWS) with failure of alternate rod injection
23	rr10	Recirculation pump speed feedback signal failure
24	rr15a rr15a_2 rr15a_3	Recirculation loop rupture (design basis Loss of Coolant Accident) - 100% severity - 60% severity - 30% severity
25	rr30 rr30_2 rr30_3	Coolant leakage inside primary containment - 100% severity - 60% severity - 30% severity
26	rx01	Fuel cladding (5%) failure
27	tc02	Electrical hydraulic control (EHC) system hydraulic pump failure

Table 6: The output binaries, time to safety trip, detection time (by the root network) and the classification time (by the classifier network) for each scenario. The diagnosis and classification times are since the initiation of the transient. Forty-three scenarios representing twenty-seven transients were used to design the adviser. The performance results are for both pure and noisy data.

Transient Number	Scenario Code	Output Binaries	Safety Trip Time (sec)	Root Diagnosis Time (sec)		Classification Time (sec)	
				Pure	Noise	Pure	Noise
1	cu10	1 1 0 0 0	n/s	5	5	62	62
2	cu10gp5	1 1 0 0 1	44	0	0	104	112
3	fw04a	1 1 1 0 1	n/s	25	27	40	52
4	fw09a	1 1 1 0 0	n/s	17	16	53	55
5	fw12c0	0 1 1 0 0	10	7	7	38	41
6	fw12c1	1 0 1 0 0	90	0	0	104	109
7	fw17a	0 1 0 0 1	1	0	1	74	86
8	fw18a	1 0 0 0 1	8	5	5	57	55
	fw18a.2		24	8	12	58	62
	fw18a.3		n/s	26	33	93	101
9	hp05	0 1 1 0 1	n/s	14	14	67	63
	hp05.2		n/s	22	18	2	18
	hp05.3		n/s	30	32	2	18
10	hp08	1 0 1 0 1	n/s	14	15	71	77
	hp08.2		n/s	34	32	96	108
	hp08.3		n/s	38	34	115	112
11	ic20scr2	0 0 1 0 0	1	2	5	93	93
12	ic20scrm	0 1 0 0 0	1	2	2	116	118
13	ic22scra	1 0 0 0 0	1	9	12	49	51
14	ic23scrm	0 0 0 0 0	1	2	2	81	75
15	ic24scrm	1 0 0 1 0	1	10	8	64	62
16	ms02	0 1 1 1 1	3	4	4	46	46
	ms02.2		3	4	4	56	59
	ms02.3		4	5	5	61	60
17	ms03a	1 0 1 1 1	2	0	0	85	101
	ms03a.2		1	0	0	38	38
	ms03a.3		2	2	2	71	73
18	ms04a	1 0 0 1 1	2	0	1	69	68
	ms04a.2		2	0	1	68	68
	ms04a.3		2	0	3	69	68
19	ms19ab	1 0 1 1 0	17	20	26	76	91
20	ms32	0 0 0 1 1	98	9	12	105	112
21	rp05tc01	0 0 1 0 1	20	5	5	63	62
22	rp5actcl	0 0 1 1 0	n/s	5	5	54	66
23	rr10	0 1 0 1 0	n/s	17	26	66	71

Table 6: ...continued...

Transient Number	Scenario Code	Output Binaries	Safety Trip Time (sec)	Root Diagnosis Time (sec)		Classification Time (sec)	
				Pure	Noise	Pure	Noise
24	rr15a	1 1 0 1 0	1	0	2	23	26
	rr15a_2		1	0	2	81	78
	rr15a_3		1	2	2	21	31
25	rr30	1 1 0 1 1	18	7	9	101	96
	rr30_2		30	21	24	83	88
	rr30_3		59	29	27	112	109
26	rx01	1 1 1 1 0	n/s	11	18	18	23
27	tc02	0 0 1 1 1	5	6	5	70	83

n/s = no safety trip

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7 Glossary of Terms

Accidents: A severe instability in nuclear power plant conditions that might include injury of the personnel, damage of hardware or a release of radioactive materials.

Activation or transfer function: Usually a nonlinear function used in nodes in ANNs that perform computations. The input to the function is the weighted sum of all nodes' inputs. The network passes the output of the function to other nodes or to the outside environment as an output of the network. Examples of these functions are the sigmoidal, the hard limiter, the identity function.

Artificial neural network (ANN): A computing system made up of simple, highly interconnected processing elements which process information.

Artificial neural network architecture: The number of layers and nodes, and the way these nodes are interconnected via weights.

Convergence of weights: The modification of weights during training in order to find a final stable set of values that will give the desired outputs. Backpropagation training algorithm employs this type of convergence.

Generalization: The ability of the network to classify a given novel input based on its relation with known stored knowledge.

Generalizer: A mathematical algorithm that can infer a parent function from given examples (training set). An ANN is one example of a generalizer.

Hidden layer: A set of hidden nodes.

Hidden nodes: Computational elements that do not directly receive data, or send data to, the ANNs external environment.

Input nodes: Elements that receive information from the external environment. Typically they perform no computations.

Learning (training or teaching the network): A mathematical rule for adjusting the interneuron connection weights in order to optimize the ANN performance.

Mapping by a network: Finding the set(s) of weights that will relate a set of inputs with a set of desired outputs.

Nodes (processing or computational elements): The computational elements that make up an ANN. In their typical form they sum their weighted inputs and pass the result through a nonlinearity function.

Output nodes: Computational elements that are capable of sending signals to the network's external environment.

Recall set: A set of patterns which the trained network is used to classify.

RMS error: The root mean square of the differences of the actual and the desired outputs of the network.

Similar transients: Transients at nuclear power plants that cause groups of the measuring instruments to show similar responses for different instabilities.

Stacked generalization: A technique that can predict the error in the output of a single generalizer.

Supervised learning: Learning that uses information available outside the network to make adjustments in weights, number of times the data is presented, and when to terminate the learning process.

Training algorithm: A mathematical rule for adjusting the interneuron

connection weights in order to optimize the ANN performance by providing convergence of weights.

Training patterns: A set the values of the networks inputs and their associated outputs.

Training set: A set of input patterns and their corresponding outputs.

Transient: A severe deviation from the normal operating conditions of nuclear power plants.

Unsupervised learning or self organization: A process that relies only on information available in the input patterns to modify the parameters of the network. Unlike the supervised learning, the outputs in the unsupervised learning scheme are not supplied to the network.

Weights: The interconnections between the nodes of the network. Weights can be real, integers, and complex numbers.

8 ISU/DAEC Plant Trip Log Book

This section is a copy of the daily records of the trips made by the project members to the Duane Arnold Energy Center.

ISU/DAEC PLANT TRIP
LOG BOOK

Date : April 1991 In Attendance:
Depart ISU : 1. Don Vest from DAEC
Arrive DAEC :
Depart DAEC :
Arrive ISU :

ACCOMPLISHMENTS :

Discussions were held between Don Vest from DAEC and students and faculty of the nuclear engineering program. Topics covered were plant process variables, and transient selection. The discussions lasted for about two and a half hours.

Present at the meeting were (from ISU):

Dr. E.B. Bartlett
Dr. R.A. Danofsky
John Adams
Anujit Basu
Serhat Alten
Terry Lanc
Keehoon Kim

The list of plant variables and the list of operational transients were reviewed. A tentative selection was made of the important variables and transients. A brief outline was presented about the capabilities and restrictions of the operator training simulator at the DAEC training facility.

ISU/DAEC PLANT TRIP
LOG BOOK

Date : May 11, 1991

Depart ISU : 11:00 AM

Arrive DAEC : 1:30 AM

Depart DAEC : 6:00 PM

Arrive ISU : 9:00 PM

In Attendance:

1. Dr. R.A.Danofsky (ISU)

2. Dr. E.B.Bartlett (ISU)

3. Serhat Alten (ISU)

4. Terry Lanc (ISU)

5. Don Vest (DAEC)

ACCOMPLISHMENTS :

Discussions were held with Don Vest and plant personnel. Topics covered included logistics and data collection strategies. A tour of the training facility and the simulator was also carried out.

This trip was mainly intended to establish contact with the personnel at the DAEC operator training center.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: June 03, 1991	In Attendance:
Depart ISU	: 2:30 PM	1. Dr.E.B.Bartlett (ISU)
Arrive DAEC	: 4:30 PM	2. Anujit Basu (ISU)
Depart DAEC	: 11:00 PM	3. Taher Aljundi (ISU)
Arrive ISU	: 1:00 AM, Jun 4	4. Keehoon Kim (ISU)
		5. Don Vest (DAEC)
		6. Craig Hunt (DAEC)

ACCOMPLISHMENTS :

Discussions were held with Don Vest and Craig Hunt of DAEC on plant process variables to be monitored during simulation for transients of general interest. A list of 83 variables were chosen and put in a control file for trending during simulation.

Transient Simulated : RR15A

Recirculation loop 'A' rupture

(Design-basis LOCA, 100% double ended shear - loop A)

Length of simulation : 5 minutes

File Name : RR15A.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: July 20, 1991	In Attendance:
Depart ISU	: 7:30 AM	1. Dr. E. B. Bartlett (ISU)
Arrive DAEC	: 10:45 AM	2. Terry Lanc (ISU)
Depart DAEC	: 7:00 PM	3. Anujit Basu (ISU)
Arrive ISU	: 9:00 PM	4. Keehoon Kim (ISU)
		5. Taher Aljundi (ISU)
		6. John Kerr (ISU)
		7. Don Vest (DAEC)
		8. Craig Hunt (DAEC)

ACCOMPLISHMENTS :

Further discussions were held with Don Vest and Craig Hunt on plant process variables to be monitored for transients of general interest. The 83 variables list from the previous trip was expanded to 97 variables. Two variables from the previous list, which were judged to be unimportant, were dropped. The new list also contained a boolean transient true-false switch which indicated the onset of the transient.

Transients Simulated : MS14 and FW17

MS14 : Loss of feedwater heating to both feedwater heaters 6A and 6B.

This transient is caused due to loss of extraction steam.

Initial condition is IC24, 100% power, Middle of Fuel Cycle (MOC).

Run Time : 5 min 46 sec including 17 sec of normal data

File name : MS14_6.DAT

FW17 : Main feedwater line break inside primary containment. 100% break in feedwater line 'A'.

Initial condition is IC24, 100% power, MOC.

Run Time : 5 min 16 sec including 11 sec of normal data

File name : FW17A.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: August 31, 1991	In Attendance:
Depart ISU	: 7:15 AM	1. Dr.E.B.Bartlett (ISU)
Arrive DAEC	: 10:30 AM	2. Anujit Basu (ISU)
Depart DAEC	: 4:30 PM	3. Terry Lanc (ISU)
Arrive ISU	: 6:30 PM	4. Don Vest (DAEC)
		5. Craig Hunt (DAEC)

ACCOMPLISHMENTS :

Discussions were continued with Don Vest and Craig Hunt as to transients to be simulated and variables to be monitored. The 97 variables list was expanded to 98 variables; in the process some old variables were dropped and some new ones added.

Transients Simulated : MC01 and FW02

MC01 : Main circulation water pump 'A' trip.
Initial condition IC24, 100%power, MOC.
Run Time : 9 min 46 sec including 6 sec of normal data.

File name : MC01A.DAT

FW02 : Condensate pump 'A' trip.
Initial condition IC24, 100% power, MOC.
Run time : 12 min 44 sec including 6 sec of normal data.

File name : FW02A.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: September 14, 1991	In Attendance:	
Depart ISU	: 7:15 AM	1. Dr.E.B.Bartlett	(ISU)
Arrive DAEC	: 10:15 AM	2. Anujit Basu	(ISU)
Depart DAEC	: 4:15 PM	3. Chalapathy Dhanwada	(ISU)
Arrive ISU	: 6:15 PM	4. Terry Lanc	(ISU)
		5. Don Vest	(DAEC)

ACCOMPLISHMENTS :

Discussions were held with Don Vest on ATWS and variables being monitored. In view of the particular transients to be simulated this day, two more booleans were added, making 100 variables. The software on the simulator at the DAEC facility currently has the capability to trend only 100 variables during a simulation.

Transients Simulated : RPO5

The first transient simulated was the main turbine trip together with failure to scram and failure of alternate rod injection (ARI). No operator action was involved. Initial condition was IC24, 100% power, MOC. The actual plant, as well as the simulator, would have automatically scrambled after the initiation of this transient failing which, ARI would initiate, safely shutting down the reactor. The two booleans introduced were the used to suppress both of these safety features by holding their values at 0.0.

File name : RP5ACTC1.DAT

The second transient simulated was also the main turbine trip together with failure to scram. But in this case ARI does occur. No operator action was involved. Initial condition was IC24, 100% power, MOC. The ARI resulted in a slow scram. As the ARI did not need to be over-ridden at this time, the corresponding boolean was removed, and so only 99 variables were used in this simulation.

File name : RPO5TC01.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date : September 28, 1991

Depart ISU : 7:00 AM

Arrive DAEC : 10:00 AM

Depart DAEC : 3:00 PM

Arrive ISU : 5:00 PM

In Attendance:

1. Anujit Basu (ISU)

2. Terry Lanc (ISU)

3. Don Vest (DAEC)

ACCOMPLISHMENTS :

Discussions were held with Don Vest on various initial conditions. The proposed adviser will be able to detect both normal and abnormal conditions. So it is important to collect data concerning various normal conditions too. It was decided to simulate all the standard initial conditions available on the simulator, and to follow each simulation by a spurious scram.

An attempt was made to simulate a condition, but the system was inoperative. No data was obtained on this trip.

Photographs were taken for publicity of the project. An instructional tour of the simulator complex was undertaken.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: October 12, 1991	In Attendance:	
Depart ISU	: 7:00 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 9:45 AM	2. Chalapathy Dhanwada	(ISU)
Depart DAEC	: 5:00 PM	3. Taher Aljundi	(ISU)
Arrive ISU	: 7:00 PM	4. Don Vest	(DAEC)

ACCOMPLISHMENTS :

Two initial conditions were simulated with spurious scram.

IC22 : This is 25% Power, Beginning of Cycle (BOC)
98 variables trended.

File name : IC22SCRA.DAT

IC14 : This is 100% Power, Beginning of Cycle (BOC)
98 variables trended.

File name : IC14SCRA.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: October 26, 1991	In Attendance:	
Depart ISU	: 7:00 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 10:00 AM	2. Chalapathy Dhanwada	(ISU)
Depart DAEC	: 4:00 PM	3. Keehoon Kim	(ISU)
Arrive ISU	: 6:00 PM	4. Don Vest	(DAEC)

ACCOMPLISHMENTS :

Further initial conditions with spurious scrams were simulated.

IC23 : This is 75% Power, Beginning of Cycle (BOC)
98 variables trended.

File name : IC23SCRA.DAT

IC20 : This is 100% Power, End of Cycle (EOC)
98 variables trended.

File name : IC20SCRA.DAT

IC24 : This is 100% Power, Middle of Cycle (MOC)
98 variables trended.

File name : IC24SCRA.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: November 16, 1991	In Attendance:	
Depart ISU	: 7:05 AM	1. Dr.E.B.Bartlett	(ISU)
Arrive DAEC	: 10:00 AM	2. Anujit Basu	(ISU)
Depart DAEC	: 5:30 PM	3. Chalapathy Dhanwada	(ISU)
Arrive ISU	: 7:30 PM	4. Terry Lanc	(ISU)
		5. Don Vest	(DAEC)

ACCOMPLISHMENTS :

Transients Simulated : HP05 and HP08

HP05 : High Pressure Coolant Injection (HPCI) steam line break in HPCI room. 100% severity. Initial condition IC20, 100% power, EOC.

File name : IC20HP05.DAT

HP08 : HPCI steam line break in Torus room. 100% severity. Initial condition IC20, 100% power, EOC.

File name : IC20HP08.DAT

Discussions were held with Don Vest about anticipated operator action. All previous accidents did not have any operator action. But during a prolonged transient in a real plant, the operator will be taking preventive and/or corrective action. The proposed adviser should be able to recognize the transient in spite of such interventions by the operators. For this reason, it was decided to simulate some transients with operator action.

Transients Simulated : RP03

RP03 : Spurious scram with operator action. Initial condition IC20, 100% power, EOC. The operators were not able to successfully control the Reactor Pressure Vessel (RPV) levels which led to the trip of feed pumps.

File name : IC20SCR1.DAT

RP03 : Spurious scram with operator action. Initial condition

IC20, 100% power, EOC. This time the operators were able to successfully control the RPV levels to prevent trip of feed pumps.

File name : IC20SCR2.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: December 14, 1991	In Attendance:	
Depart ISU	: 7:05 AM	1. Dr.E.B.Bartlett	(ISU)
Arrive DAEC	: 10:10 AM	2. Anujit Basu	(ISU)
Depart DAEC	: 5:20 AM	3. Terry Lanc	(ISU)
Arrive ISU	: 7:30 AM	4. Taher Aljundi	(ISU)
		5. Chalapathy Dhanwada	(ISU)
		6. Don Vest	(DAEC)
		7. Dan Berchenbriter	(DAEC)

ACCOMPLISHMENTS :

Discussions were held with Don Vest and Dan Berchenbriter on agenda for the next several months.

Transients Simulated : CU10

CU10 : Loss of reactor clean-up water (coolant). Accident is caused by reactor water clean-up line break outside primary containment. Initial condition IC24, 100% power, MOC. Decay heat is normal. No operator action is involved. Initially, the reactor water level goes down and valve on the reactor water clean-up line closes. There is a high differential temperature, and group 5 isolation occurs. The reactor water level drops to 180 inches and then rises back to 190 inches. The plant recovers. Reactor building high radiation alarm sounds. Accident recovery duration is approximately 2 minutes and 30 seconds.

File Name : CU10.DAT

Talked about schedule. The next trip was planned on Jan. 18, 1992.

Went on a trip through the plant. Visited the reactor building, the turbine building, the spent fuel storage pool area and the control room. The plant was being prepared for a refueling outage.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: December 15, 1991	In Attendance:	
Depart ISU	: ---	1. Don Vest	(DAEC)
Arrive DAEC	: ---	2. Dan Berchenbriter	(DAEC)
Depart DAEC	: ---		
Arrive ISU	: ---		

ACCOMPLISHMENTS :

The previous accident, loss of reactor clean-up water (CU10), was repeated. This time, failure of group 5 isolation valves was added to the scenario. This work was performed without an ISU crew present, and the data was sent over.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: January 18, 1992	In Attendance:	
Depart ISU	: 7:00 AM	1. Taher Aljundi	(ISU)
Arrive DAEC	: 9:45 AM	2. Terry Lanc	(ISU)
Depart DAEC	: 4:20 PM	3. Chalapathy Dhanwada	(ISU)
Arrive ISU	: 6:30 PM	4. Dan Berchenbriter	(DAEC)
		5. Craig Hunt	(DAEC)

ACCOMPLISHMENTS :

Discussions were held about the transients to be simulated. The trend file was modified a bit and now contained 100 variables.

Transients Simulated : FW18 and MS19

FW18 : Main feedwater line A break outside primary containment in the ground floor of turbine building. Thick 360 crack on 16" line, single-ended shear break. Two phase flow limits loss. There is loss of pressure in the common line behind the feedwater pumps. This cause the feedwater pumps to trip.

File Name : FW18A.DAT

MS19 : Group 1 isolation caused by failure of relays. The valves fail closed on both legs A & B. Leg A alone would have resulted in only an alarm sounding. Reactor vessel level drops. Relief valve allows vessel to blow down to torus.

File Name : MS19.DAT

RR30 : This transient was simulated but data was not collected due to hardware problems. See log from the next trip for a description of the transient.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: February 1, 1992	In Attendance:	
Depart ISU	: 6:55 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 9:15 AM	2. Chalapathy Dhanwada	(ISU)
Depart DAEC	: 3:45 PM	3. Rodney Schuler	(ISU)
Arrive ISU	: 5:45 PM	4. Taher Aljundi	(ISU)
		5. Dan Birchenbriter	(DAEC)
		6. Craig Hunt	(DAEC)

ACCOMPLISHMENTS :

Transients Simulated : RR30, MS03, MS04, and FW09

RR30 : Coolant leakage inside primary containment. The simulation was a 100% double ended shear in a 2" diameter pipe. This transient is caused by weld failure in the reactor vessel bottom drain pipe. Initial condition IC24, 100% power, MOC.

File Name : RR30.DAT

MS03 : Main steam line (MSL) rupture inside primary containment. Steam line A was selected for the simulation. The break was of 100% severity, i.e. a double-ended shear in the 20" diameter steam line. This transient is caused by piping failure or flow restriction at the high pressure instrument tap that feed control room monitor steam flow instrumentation. Initial condition IC24, 100% power MOC.

File Name : MS03A.DAT

MS04 : This transient is the same as MS03 except that it is caused by piping failure at main steam common header. This results in a rupture outside the primary containment at the tube inlet header.

File Name : MS04A.DAT

FW09 : Reactor feedwater pump trip. The simulation was a trip of pump A. This transient is caused by a spurious trip signal. Initial condition IC24, 100% power, MOC. This malfunction causes the selected main feedwater pump to trip in standby

due to a spurious trip signal. The pump motor breaker will trip open and annunciation will activate. The pump pressure and flow will decrease and the recirculation valve, if open, will close.

File Name : FW19A.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: February 15, 1992	In Attendance:
Depart ISU	: 7:00 AM	1. Anujit Basu (ISU)
Arrive DAEC	: 10:00 AM	2. Taher Aljundi (ISU)
Depart DAEC	: 2:30 PM	3. Dan Berchenbriter (DAEC)
Arrive ISU	: 4:30 PM	4. Craig Hunt (DAEC)

ACCOMPLISHMENTS :

Transients Simulated : MS02, FW12, and MS32

MS02 : Steam leak inside primary containment. This transient is caused by main steam leak at RCIC line elbow. Initial condition IC24, 100% power, MOC. Main steam flow will increase and reactor pressure will decrease. High drywell pressure at 2 PSIG will trip the reactor.

File Name : MS02A.DAT

FW12 : Feedwater regulator valve controller failure. This transient is caused by the failure of the controller of the feedwater regulator valve, causing the valve to be stuck at a particular position. Two simulations were carried out, one for the valve stuck fully open and the other for the valve stuck fully closed. Both simulations had initial conditions IC24, 100% power, MOC.

(a) High : This is the scenario when the valve is stuck open all the way.

File Name : FW12H.DAT

(b) Low : This is the scenario when the valve is stuck in the fully closed position.

File Name : FW12L.DAT

MS32 : Spurious group 7 isolation. Short circuit causes relay CR4841 to trip close. Closure will cause the drywell to energize. This causes the group 7 isolation valve to trip close. Closure will cause the drywell to

loose cooling; drywell temperature and pressure will increase. At 2 PSIG drywell pressure, the reactor will scram, Emergency Core Cooling System (ECCS) will be initiated and group 2,3,4, and 5 isolation will be initiated. Initial condition IC24, 100% power, MOC.

File Name : MS32.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: February 29, 1992	In Attendance:	
Depart ISU	: 7:00 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 9:20 AM	2. Taher Aljundi	(ISU)
Depart DAEC	: 2:05 PM	3. Dan Berchenbriter	(DAEC)
Arrive ISU	: 4:15 PM	4. Craig Hunt	(DAEC)

ACCOMPLISHMENTS :

Transients Simulated : RX01, RR10, TC02, and FW04

RX01 : Fuel cladding failure. Simulation was for 100% severity which was 30% fuel clad damage. As the damage increases, the amount of activity in the reactor recirculation loop and the main steam system will increase. This activity will propagate throughout the plant and the radiation monitoring system will indicate the same. At 100% severity, the main steam line radiation monitors will cause main steam isolation and reactor scram at set point. Initial condition IC24, 100% power, MOC.

File Name : RX01.DAT

RR10 : Recirculation pump speed feedback signal failure. For the simulation, 100% of the feedback signal to pump A was lost. This caused fluctuations in the steam flow and power generated. Initial condition IC24, 100% power, MOC.

File Name : RR10A.DAT

TC02 : Emergency Hydraulic Cooling (EHC) system hydraulic pump trip. Both pumps A & B were made to trip in the simulation. The EHC pumps fail and trip on overload. Turbine trip follows as the EHC system pressure reaches 1300 PSIG. Initial condition IC24, 100% power, MOC.

File Name : TC02.DAT

FW04 : Condensate filter demin resin injection. At 100% severity, this malfunction causes a 5% resin release. The resin

release is caused from the demineralizer filter. The malfunction results in resin buildup in the reactor vessel. Manifests in increased radiation levels. Initial condition IC24, 100% power, MOC.

File Name.: FW04A.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: March 14, 1992	In Attendance:	
Depart ISU	: 7:10 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 9:40 AM	2. Taher Aljundi	(ISU)
Depart DAEC	: 2:20 PM	3. Rodney Schuler	(ISU)
Arrive ISU	: 4:30 PM	4. Chalapathy Dhanwada	(ISU)
		5. Dan Berchenbriter	(DAEC)

ACCOMPLISHMENTS :

Talked to Dan Berchenbriter about present variables being monitored and addition to that list in the near future. Also talked about "similar" accidents. Reviewed goals and progress to date.

The simulator was down for upgradation. Took an educational tour of the plant. The plant was down for a refueling outage at the time.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: March 28, 1992	In Attendance:	
Depart ISU	: 7:15 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 9:50 AM	2. Taher Aljundi	(ISU)
Depart DAEC	: 2:00 PM	3. Dan Berchenbriter	(DAEC)
Arrive ISU	: 4:00 PM	4. Craig Hunt	(DAEC)

ACCOMPLISHMENTS :

On this trip, some of the earlier transients were repeated at different severities. This is because the adviser would be expected to recognize a transient irrespective of it's severity. It is expected that if severities of 100%, 60% and 30% are used to train the adviser, it will be able to generalize the transient over the entire range of severities.

Transients Simulated : RR15 and FW17

RR15 : For a description of this transient, see entry dated June 3, 1991.

- (a) The transient at 100% severity is repeated as the variables being monitored had changed since the last time this transient had been simulated.

File Name : RR15A_1.DAT

- (b) The transient was simulated at 60% severity.

File Name : RR15A_2.DAT

- (c) The transient was simulated at 30% severity.

File Name : RR15A_3.DAT

FW17 : For a description of this transient, see entry dated July 20, 1991.

(a) The transient was simulated at 60% severity.

File Name : FW17A_2.DAT

(b) The transient was simulated at 30% severity.

File Name : FW17A_3.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: April 25, 1992	In Attendance:	
Depart ISU	: 7:20 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 10:10 AM	2. Taher Aljundi	(ISU)
Depart DAEC	: 2:15 PM	3. Chalapathy Dhanwada	(ISU)
Arrive ISU	: 4:15 PM	4. Dan Berchenbriter	(DAEC)
		5. Craig Hunt	(DAEC)

ACCOMPLISHMENTS :

Further simulation were carried out for previously simulated transients but at different severities.

Transients Simulated : HP05 and HP08

HP05 : For a description of this transient, see entry dated November 16, 1991. Initial condition IC20, 100% power, EOC.

(a) The transient was simulated at 60% severity.

File Name : HP05_2.DAT

(b) The transient was simulated at 30% severity.

File Name : HP05_3.DAT

HP08 : For a description of this transient, see entry dated November 16, 1991. Initial condition IC20, 100% power, EOC.

(a) The transient was simulated at 60% severity.

File Name : HP08_2.DAT

(b) The transient was simulated at 30% severity.

File Name : HP08_3.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: June 20, 1992	In Attendance:	
Depart ISU	: 7:18 AM	1. Taher Aljundi	(ISU)
Arrive DAEC	: 10:06 AM	2. Chalapathy Dhanwada	(ISU)
Depart DAEC	: 2:15 PM	3. Craig Hunt	(DAEC)
Arrive ISU	: 4:15 PM		

ACCOMPLISHMENTS :

Further simulation were carried out for previously simulated transients but at different severities.

Transients Simulated : FW18, MS03 and RR30

FW18 : For a description of this transient, see entry dated January 18, 1992. Initial condition IC24, 100% power, MOC.

(a) The transient was simulated at 60% severity.

File Name : FW18A_2.DAT

(b) The transient was simulated at 30% severity.

File Name : FW18A_3.DAT

MS03 : For a description of this transient, see entry dated February 1, 1992. Initial condition IC24, 100% power, MOC.

(a) The transient was simulated at 60% severity.

File Name : MS03A_2.DAT

(b) The transient was simulated at 30% severity.

File Name : MS03A_3.DAT

RR30 : For a description of this transient, see entry dated
February 1, 1992. Initial condition IC24, 100% power,
MOC.

(a) The transient was simulated at 60% severity.

File Name : RR30_2.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: July 18, 1992	In Attendance:
Depart ISU	: 7:00 AM	1. Anujit Basu (ISU)
Arrive DAEC	: 10:05 AM	2. Chalapathy Dhanwada (ISU)
Depart DAEC	: 2:10 PM	3. Craig Hunt (DAEC)
Arrive ISU	: 4:10 PM	

ACCOMPLISHMENTS :

Discussions were held with Craig Hunt about steady states, system noise, errors in the data over the first few seconds of simulation, etc.

- > Steady state variations are due to computations based on physics, and is not a random or computer generated noise.
- > The only simulated noise is on the meter readouts.
- > Boiling noise is not built into the system and so is not simulated.

Further simulation were carried out for previously simulated transients but at different severities.

Transients Simulated : RR30, MS02 and MS04.

RR30 : For a description of this transient, see entry dated February 1, 1992. Initial condition IC24, 100% power, MOC.

- (a) The transient was simulated at 30% severity.
File Name : RR30_3.DAT

MS02 : For a description of this transient, see entry dated February 15, 1992. Initial condition IC24, 100% power, MOC.

- (a) The transient was simulated at 60% severity.
File Name : MS02_2.DAT
- (b) The transient was simulated at 30% severity.
File Name : MS02_3.DAT

MS04 : For a description of this transient, see entry dated February 1, 1992. Initial condition IC24, 100% power, MOC.

- (a) The transient was simulated at 60% severity.
File Name : MS04A_2.DAT

(b) The transient was simulated at 30% severity.
File Name : MS04A_3.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: October 16, 1992	In Attendance:
Depart ISU	: 10:10 AM	1. Dr. Eric Bartlett (ISU)
Arrive DAEC	: 1:15 PM	2. Dr. Richard Danofsky (ISU)
Depart DAEC	: 4:00 PM	3. Dr. Dan Bullen (ISU)
Arrive ISU	: 6:10 PM	4. John Adams (ISU)
		5. Anujit Basu (ISU)
		6. Eric Daugherty (ISU)
		7. Chalapathy Dhanwada (ISU)
		8. John Hawkinson (ISU)
		9. Keeshoon Kim (ISU)
		and many Iowa Electric personnel.

ACCOMPLISHMENTS :

This trip was mainly an effort to update the executives and plant personnel about the advances being made on this project. This was important as Iowa Electric Light and Power company is donating substantially to the project by way of simulator time and simulator personnel overtime.

The main agenda of the trip was a presentation by Anujit Basu. This presentation was an account of Basu's Master's thesis. Anujit Basu finished his Master's in August 1992, and is supported by the DOE grant.

The attendees were also introduced to other projects being investigated by faculty and graduate students in the Nuclear Engineering program at Iowa State University.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: October 23, 1992	In Attendance:	
Depart ISU	: 7:00 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 10:05 AM	2. Chalapathy Dhanwada	(ISU)
Depart DAEC	: 2:10 PM	3. Craig Hunt	(DAEC)
Arrive ISU	: 4:10 PM		

ACCOMPLISHMENTS :

Discussions with Craig Hunt about the work to be done over the next few trips. Also discussed about the distinct transients that caused almost identical effects in the various plant parameters, and how neural networks can identify and differentiate these transients.

Transients Simulated : RX01 and FW04.

RX01 : For a description of this transient, see entry dated February 29, 1992. Initial condition IC24, 100% power, MOC.

(a) The transient was simulated at 60% severity.

File Name : RX01_2.DAT

(b) The transient was simulated at 30% severity.

File Name : RX01_3.DAT

Note: The wait time in the batch file C.ISUBAT was changed to 120 frames (about 10 sec). This gives us a little more normal operating time at the beginning of each simulation.

FW04 : For a description of this transient, see entry dated February 29, 1992. Initial condition IC24, 100% power, MOC.

(a) The transient was simulated at 60% severity.

File Name : FW04_2.DAT

(b) The transient was simulated at 30% severity.

File Name : FW04_3.DAT

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: November 14, 1992	In Attendance:	
Depart ISU	: 7:02 AM	1. Anujit Basu	(ISU)
Arrive DAEC	: 10:01 AM	2. Chalapathy Dhanwada	(ISU)
Depart DAEC	: 2:25 PM	3. Craig Hunt	(DAEC)
Arrive ISU	: 4:30 PM		

ACCOMPLISHMENTS :

Some selected 'PROTECTED INITIAL CONDITIONS' were simulated during this visit. In the simulations listed below, no malfunction was inserted. Data represents simulated steady state reactor operation. For a description of the ICs, see 'Iowa Electric Light and Power Company, Simulator Operating Instructions, Simulator operation, No. 3.2, Rev. 1, Attachment 9.1, pp. 9-17'.

- 1) IC14: Full power operations (ANSI parameters). Moderator temp = saturated conditions, reactor pressure = power dependent, reactor power level = 100% power, reactivity = critical, xenon condition = 100% equilibrium, core life = beginning of life. This IC is set up to meet the ANSI criteria for 100% power.
Datafile: IC14.dat
- 2) IC20: Full power operations/Max. decay heat (EOL). Moderator temp = saturated conditions, reactor pressure = power dependent, reactor power level = 100% power, reactivity = critical, xenon condition = 100% equilibrium, core life = end of life. This IC is similar to IC15 except it has 20% more decay heat than normal.
Datafile: IC20.dat
- 3) IC22: 25% power (ANSI parameters). Moderator temp = saturated conditions, reactor pressure = power dependent, reactor power level = 25% power, reactivity = critical, xenon condition = 25% equilibrium, core life = beginning of life. This IC is set up to meet the ANSI criteria for 25% power.
Datafile: IC22.dat
- 4) IC23: 75% power (ANSI) parameters). This IC is similar to IC-22, except at 75% power.
Datafile: IC23.dat
- 5) IC24: Full power operations (Middle of life). This IC is similar to IC-14, except the core is at middle of life.

Datafile: IC24.dat

Discussions with Craig Hunt resulted in a list of transients similar in nature which are difficult to diagnose. Also variables that might be helpful in telling these transients apart (from ANN point of view) were investigated. These transients will be simulated during the next few trips.

ISU/DAEC PLANT TRIP
LOG BOOK

Date : December 12, 1992 In Attendance:
Depart ISU : 7:20 AM 1. Anujit Basu (ISU)
Arrive DAEC : 9:35 AM 2. Craig Hunt (DAEC)
Depart DAEC :
Arrive ISU :

ACCOMPLISHMENTS :

Discussed about plant variables useful for diagnosing similar transients. A new trend variable list, C.ISUTWO, was written which include these new variables. These are:

S#	Variable	Description	Min	Max	Unit
---	-----	-----	---	---	----
1)	YCAFO02	Cond hotwell level	0.0	14.0	INCH
2)	YCAFO86	Demin tank A effluent cdtv	0.0	0.2	MMHO
3)	YCAFO87	Demin tank A effluent cdtv	0.0	0.2	MMHO
4)	YCAFO88	Demin tank A effluent cdtv	0.0	0.2	MMHO
5)	YCAFO89	Demin tank A effluent cdtv	0.0	0.2	MMHO
6)	YCAFO90	Demin tank A effluent cdtv	0.0	0.2	MMHO
7)	YCAFO91	Cond demin effluent cdtv	0.0	0.2	MMHO
8)	YCAR000	North CRD module area radm			
9)	YCACR001	CR 18-03	-99.0	48.0	NOTCH
10)	YCACR003	CCR 26-03	-99.0	48.0	NOTCH
11)	YCACR020	CR 06-15	-99.0	48.0	NOTCH
12)	YCACR021	CR 10-15	-99.0	48.0	NOTCH
13)	YCACR023	CR 18-15	-99.0	48.0	NOTCH
14)	YCDB559	Steam lines radm DNSC	0.0	1.0	
15)	YCDB560	Steam lines rad high	0.0	1.0	
16)	YCDD524	MSL high rad channel A1	0.0	1.0	
17)	YCDD525	MSL high rad channel B1	0.0	1.0	
18)	YCDD526	MSL high rad channel A2	0.0	1.0	
19)	YCDD527	MSL high rad channel B2	0.0	1.0	

Abbreviations used:

cond- condenser
cdtv- conductivity
cr(d)- control rod (drive)
demin- demineralizer
rad(m)- radiation (monitor)

MSL- main steam line

DNSC- Downscale

MMHO- milli mho

The minimum and maximum limits given above are the limits on the instrument used to measure/display the variable.

The simulator is undergoing maintenance servicing. No new scenarios were simulated.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: Jan 9, 1993	In Attendance:
Depart ISU	: 7:25 AM	1. Chalapathy Dhanwada (ISU)
Arrive DAEC	: 9:50 AM	2. Anujit Basu (ISU)
Depart DAEC	:	3. Craig Hunt (DAEC)
Arrive ISU	:	

ACCOMPLISHMENTS :

Two transient scenarios, fw17a and ms14-6 simulated on July 20, 1991, did not include all the 97 variables from C.ISUONE. (C.ISUONE was expanded to 97 variables on the subsequent trip.) Hence, these two scenarios were repeated today using C.ISUONE so that they will have the same number of trend variables as the rest of the datafiles.

- 1) FW17A: Main feedwater line break inside primary containment. 100% break in feedwater line. IC24, 100% power, MOC.
Datafile: fw17a.dat
- 2) MS14-6: Loss of feedwater heating to both feedwater heaters 6A and 6B due to loss of extraction steam. This transient does not have a severity associated with it.
IC24, 100% power, MOC.
Datafile: ms14-6.dat

NOTE: These two new datafiles replace the older datafiles of same name.

Due changed plant conditions, two transient scenarios simulated earlier no longer represent the true plant conditions during the transient. Hence these two scenarios were resimulated. These new datafiles replace the older version in the databank maintained on Project Vincent (ISU).

- 1) RX01: Fuel failure at 100% severity corresponding to 30% fuel failure. IC24, 100% power, MOC.
Datafiles:
rx01.dat. Replaces previous version dated Feb 29, 92.
rx01.da2. This is for the second trend file C.ISUTWO.

- 2) FW04: Resin injection from condensate demineralizer. 100% severity corresponding to 5% release. IC24, 100% power, MOC. Datafile: fw04a.dat. Replaces previous version dated Feb 29, 92.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: May 1, 1993	In Attendance:	
Depart ISU	: 7:01 AM	1. Chalapathy Dhanwada	(ISU)
Arrive DAEC	: 10:13 AM	2. Anujit Basu	(ISU)
Depart DAEC	: 2:10 PM	3. Craig Hunt	(DAEC)
Arrive ISU	: 4:15 PM		

ACCOMPLISHMENTS :

Simulations

FW04A: Resin injection from condensate demineralizer. 100% severity corresponding to 5% release. IC24, 100% power, MOC.

Datafile:

fw04a.da2. This data is for the second trend file C.ISUTWO. Data for the first trend file C.ISUONE was obtained in the last visit.

A new transient scenario FW08 was simulated. Data was obtained for the first trend file, C.ISUONE.

FW08: Feewater heater tube leak in heater 6A. Generic, variable. 0-100% = 0-4" diameter, 100% power, tube failure (equivalent to rupture of about 30 tubes). Malfunction causes a tube failure in the selected feewater heater at a rate specified by the severity.

Datafiles:

fw08-6.dat: 100% severity.
fw08-6_2.dat: 60% severity.
fw08-6_2.dat: 30% severity.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: May 15, 1993	In Attendance:	
Depart ISU	: 7:50 AM	1. Chalapathy Dhanwada	(ISU)
Arrive DAEC	: 10:17 AM	2. Eric Daugherty	(ISU)
Depart DAEC	:	3. Craig Hunt	(DAEC)
Arrive ISU	:		

ACCOMPLISHMENTS :

Simulations

FW08: Feedwater heater tube leak in heater 6A. IC24, 100% power, Middle of cycle. The following three scenarios were simulated for the second trend file, C.ISUTW0.

Datafiles:

fw08-6.da2: 100% severity
fw08-6_2.da2: 60% severity
fw08-6_3.da2: 30% severity

FW02: Condensate pump A trip. No loss of power. Associated FW pump trips automatically. Reactor trips on low level. Turbine trips on reverse power. IC24, 100% power, middle of cycle. The runback of recirculation pumps delays reactor scram. This simulation is for the second trend file, C.ISUTW0.
Datafile: fw02a.da2

FW09: Reactor feedwater pump A trip due to spurious trip signal. IC24, 100% power, middle of cycle. This simulation is for the second trend file, C.ISUTW0.
Datafile: fw09a.da2

Discussions

Discussed problems encountered diagnosing transients
fw02a.dat, mc01.dat. Most important variables for these two transients are:

FW02A: FW004, FW044, FW040, FW041
MC01: F011, F015

Discussed the standard deviations and correlation coefficients of the first 97 plant variables (C.ISUONE). These statistics were obtained from data representing fifty scenarios. Generally, variables exhibiting near 0 (1) correlation agree with correlation expected from physical reasoning.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: June 12, 1993	In Attendance:	
Depart ISU	: 7:45 AM	1. Chalapathy Dhanwada (ISU)	
Arrive DAEC	: 10:30 AM	2. Craig Hunt (DAEC)	
Depart DAEC	:		
Arrive ISU	:		

ACCOMPLISHMENTS :

Discussions

Variable naming convention:

Example: YCAA041

YC => The variable is a PPC variable

A => 'Analog' (D => 'Digital')

A041 => Variable ID

Simulations

ALL following simulations were performed using the second trend file, C.ISUTW0.

FW12: Master feedwater controller failure. Fails both feedwater regulator valves. IC24, 100% power, middle of cycle.

Datafiles:

fw12c0.da2: Feedwater regulator valves fail fully closed (0%).

fw12c1.da2: Feedwater regulator valves fail fully opened (100%).

FW17: Main feedwater line 'A' break inside primary containment.

IC24, 100% power, middle of cycle.

Datafiles:

fw17a.da2: 100% single ended shear.

fw17a_2.da2: 60% single ended shear.

fw17a_3.da2: 30% single ended shear.

FW18: Main feedwater line break outside primary containment.

Ground floor of turbine building. Thick crack 360 degrees,

16 inch line, single ended shear. IC24, 100% power, middle

of cycle. Two phase flow limits loss. Loss of pressure behind feedwater pumps to line in common. Pumps trip.

Datafiles:

fw18a.da2: 100% break.

fw18a_2.da2: 60% break.

fw18a_3.da2: 30% break.

NOTE: C. Hunt requested a copy of our DoE report.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: June 26, 1993	In Attendance:	
Depart ISU	: 8.35 AM	1. Scott Wendt	(ISU)
Arrive DAEC	: 10:35 AM	2. Chalapathy Dhanwada	(ISU)
Depart DAEC	: 1:35 PM	3. Craig Hunt	(DAEC)
Arrive ISU	: 4:00 PM		

ACCOMPLISHMENTS :

A copy of the recent DoE report was given to C. Hunt. Simulations were delayed due to problems encountered with PROCOMM. Apparently, default PROCOMM settings were modified by a previous user. This made it impossible for us to download data from GOULD. The settings had to be restored before the data could be downloaded.

Simulations

The following simulations are for the second trend file C.ISUTWO.

HP05: Accident is high pressure coolant injection (HPCI) steam line break in HPCI room. IC26, 100% power, end of cycle. Decay heat is 10% of full power. No operator action. Note: Initial conditions IC26 is old IC20.

Datafiles:

hp05.da2: 100% break.
hp05_2.da2: 60% break.
hp05_3.da2: 30% break.

IC26: Simulation of initial conditions IC26. No malfunction inserted. This is same as old IC20 except that it has 20% more decay heat than normal. Moderator temperature = saturated conditions, reactor pressure = power dependent, reactor power level = 100% power, reactivity = critical, xenon condition = 100% equilibrium, core life = end of life.

Datafile:

ic26.da2

Discussions

Discussed about the data on reactor scrams. (cf. letter to Dr. E.B. Bartlett from Leo Beltracci about "Analysis and evaluation of Operational Data, 1990 Annual Report".)

1. Only some of the scram conditions in the report can be simulated.
2. Craig Hunt requested meeting with Dr. Bartlett to discuss about future transients to simulate.
3. Future visits: July 10 & 24; Aug 7.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: June 24, 1993	In Attendance:	
Depart ISU	: 7:35 AM	1. Chalapathy Dhanwada	(ISU)
Arrive DAEC	: 9:55 AM	2. Anujit Basu	(ISU)
Depart DAEC	: 1:58 PM	3. Scott Wendt	(ISU)
Arrive ISU	: 4:45 PM	4. Craig Hunt	(DAEC)

ACCOMPLISHMENTS :

Discussions

Discussed about similar transients and possible scenarios for future simulations.

MC01 & MC04: Similar

CU07 & CU10: Similar

IA02 & AD02: These malfunctions result in only very mild transients in plant conditions.

Some possible future simulations: AD05, IA01, LD??, MC04, RD13, RR05, RR11.

Simulations

AD05: Automatic depressurization system (ADS) spurious initiation. IC24, 100% power, middle of cycle.

Datafile:

ad05.dat

IA01: Complete loss of instrument air (IA01). IC24, 100% power, middle of cycle.

Datafiles:

ia01.dat: 100% severity. Scram occurred at 7:02, but collection was stopped at 4:27. Discard the last 6 to 10 seconds data in this datafile. This last bit of simulation may not be OK because we had some problems with computer memory overflow. Hence, use up to the first 4 min and 15 sec of this data as only that part represents the true plant conditions.

ia01_2.dat: 60% severity. This datafile is OK till the end of simulation.

NOTE: Data at 30% severity for this scenario was not collected

as it was observed that the transient becomes very mild.

MC04: Main condenser air inleakage. IC24, 100% power, middle of cycle. This scenario is similar to MC01. But, unlike MC01, this malfunction does have severities associated with it.

Datafiles:

mc04a.dat: 100% severity.

mc04a_2.dat: 60% severity.

ISU/DAEC PLANT TRIP
LOG BOOK

Date	: Sept 11, 1993	In Attendance:	
Depart ISU	: 7:45 AM	1. Chalapathy Dhanwada	(ISU)
Arrive DAEC	: 10:02 AM	2. Anujit Basu	(ISU)
Depart DAEC	: 2:15 PM	3. Craig Hunt	(DAEC)
Arrive ISU	:		

ACCOMPLISHMENTS :

Discussions

Disussed about the possibility of acquiring actual plant operating data. We were informed that the data is on tape archives stored at the plant. This data can be easily obtained -- requested for a copy. Tape archive at DAEC uses Gould 1600-6250 bits per inch, VAX format, 1/2 inch catridge. TA70 drive. Beginning of cycle data corresponds to cold clean reactor -- this data does not exist. Longest sampling interval is 15 seconds. Most data available is for 100% power.

Simulations

MC04: Main condenser air inleakage. IC24, 100% power, middle of cycle. This scenario is similar to MC01. But, unlike MC01, this malfunction does have severities associated with it.

Datafile:

mc04a_3.dat: 30% severity.

RD13: Loss of air pressure to control rod drive hydraulic control units (HCUs). IC24, 100% power, middle of cycle. No scram occurred for simulation of this scenario at 30% severity.

Datafiles:

rd13.dat: 100% severity
rd13_2.dat: 60% severity
rd13_3.dat: 30% severity

RR05: Recirculation pump shaft seizure. Malfunction variable is a boolean (no severities). IC24, 100% power, middle of cycle.

Datafile:

rr05.dat

RR11: Recirculation pump seal failure. Two seals on each of the two recirculation pumps A & B. Simulation was performed with failure of both seals on pump A. Failure of a single seal does not lead to a scram (transient) as the second seal is by design a backup against failure of the first. YP:MRR11B is not included in the trend file -- this boolean goes true at the same time as YP:MRR11A which is included in the trend file. IC24, 100% power, middle of cycle.

Datafile:

rr11a.dat

9 Description of Transient Scenarios

A brief description of the several transient scenarios simulated by the ISU team at the DAEC simulator is given in this section. The following is the list of all transient scenarios described:

AD05	CU10	FW02	FW04
FW08	FW09	FW12	FW17
FW18	HP05	HP08	IA01
MC01	MC04	MS02	MS03
MS04	MS14	MS19	MS32
RD13	RP05	RR05	RR10
RR11	RR15	RR30	RX01
TC02			

Some selected Protected Initial Conditions described are:

IC14	IC20	IC22	IC23
IC24	IC26		

Datafiles

For each scenario simulated, the initial conditions used are noted. Data for a total of 97 plant variables of initial interest (from trend control file C.ISUONE) were collected for several scenarios. These data files have extension ".dat" on them. Other files have extension ".da2" on them. The trend control file for these files is C.ISUTWO which has an additional 19 plant variables of initial interest.

MALFUNCTION AD05

Spurious automatic depressurization system (ADS) actuation

A. Logic A

B. Logic B

Generic. Logic Failure. 100% power.

This malfunction will cause the selected ADS channel to actuate spuriously from a channel logic failure. The effected valves will not respond to any other actuation signals, open or close, auto, or manual.

The failed valves will cause the steam flow to increase and the reactor pressure will decrease. The reactor vessel water level will decrease, causing reactor scram on low level at 170". The suppression pool parameters will respond to the increased temperature, pressure and level will react to the steam regulating valve (SRV) discharge. The emergency core cooling system (ECCS) will activate automatically and provide the system with cooling as the plant condition degrades.

The rate of depressurization and level decrease will be consistent with the mass and energy balances on the vessel.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

ad05.dat: Transient is inadvertant initiation of ADS (AD05A). IC24, 100% power, middle of cycle. This is for the first trend file.

MALFUNCTION CU10

Coolant leakage outside the primary containment. Severity is variable: 0 - 100% = 0 - 4" diameter pipe (single-ended shear). Reactor Water Cleanup System (RWCS) expansion joint failure at 100% power.

This malfunction will cause a leak to occur at the cleanup system inlet expansion joint. The leak rate will be determined by the specified severity.

A low-severity leak will cause the ambient temperature to increase and will actuate the leak detection system isolation and annunciation at setpoint. As severity increases the leak detection system will be actuated by area temp/temp differentials. Prior to isolation, a brief decrease in pressure and flow will indicate mass loss on the inlet to the RWCS pumps. The pump discharge pressure will decrease proportional to leak severity and the cleanup system return temperature will decrease. When the reactor water cleanup system leak detection system activates, motor valves (MO-2700, 2701, 2740) will close, and the RWCU pumps will trip. The motor valve position indicating lights will indicate the valves are closed, and the RWCU pump motor breaker will indicate the breaker is open. The RWCU leak will cause the system pressure to decrease to atmospheric pressure. The system flow will decrease resulting in appropriate annunciation. The cleanup holding pumps will start automatically from the system low flow. System temperature will slowly decay to ambient, and the heat load on Reactor Building Closed Coolant Water (RBCCW) will decrease rapidly.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

cul0.dat: Accident is reactor water cleanup line break outside primary containment 100% break. IC24, 100% power, Middle of Cycle (MOC). Malfunction is YP:MCU10 at 100%. Decay heat is normal. No operator action.

cul0gp5.dat: Accident is reactor water cleanup line break outside primary containment 100% break. IC24, 100% power, Middle of Cycle (MOC). Malfunction is YP:MCU10 at 100%. Decay heat is normal. No operator action. Automatic group 5 isolation is overridden. Valves M02700, 2701, 2740 do not close feedwater pumps run out trip on delayed overload.

MALFUNCTION FW02

Malfunction is condensate pump trip.

A) Pump A B) Pump B

Generic, breaker overcurrent device (50) failure, 100% power.

This malfunction will cause the selected main condensate pump breaker to trip from a faulty overcurrent device (50). The condensate pump breaker will indicate open, motor current will decrease, and annunciation from the trip will occur.

When the condensate pump motor breaker trips, the pump will stop, and pump discharge pressure and flow will decrease. The corresponding reactor feedwater pump will trip and the recirculation system will run back low water level of 186" to 45% speed. Condensate header pressure will decrease, and flow will increase as the remaining condensate pump capacity is exceeded.

If both condensate pumps are tripped, the reactor feedwater pumps will trip. The recirculation pumps will start to run back at 186" Reactor Pressure Vessel (RPV) water level to 45% speed.

The reactor will scram when level reaches 170".

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

fw02a.dat: Accident is trip of condensate pump A. No loss of power. When a condensate pump trips, the associated feedwater pump trips automatically. Reactor trips on low level. The turbine then trips on reverse power. IC24, 100% power, Middle of Cycle (MOC). Malfunction is YP:MFW02(A) the runback of recirculation pumps delays the reactor scram.

MALFUNCTION FW04

Malfunction is condensate filter demineralization resin injection.

- A) Filter A B) Filter B
- C) Filter C D) Filter D
- E) Filter E

Generic, variable, 1 - 100% = 1 - 5% resin release, resin retention element failure, 100% power.

This malfunction will cause the release of resin from the selected demineralizer filter to the severity selected. Any release of resin into the condensate system will cause a buildup in the reactor vessel. Irradiation and carryover into the main steam system will cause the radiation monitoring system to respond to increased radiation levels and annunciation. High temperature and radiation cause a large increase in reactor vessel conductivity and a decrease in water pH.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

fw04a.dat: Condensate filter demin resin injection causes increase in vessel conductivity and steam line radiation IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION FW08

Feedwater heater tube leak.

A) Heater 1A B) Heater 1B C) Heater 2A D) Heater 2B
E) Heater 3A F) Heater 3B G) Heater 4A H) Heater 4B

Generic, variable. 0 - 100% = 0 - 4" diameter (equivalent to rupture of approx 30 tubes) tube failure 100% power.

This malfunction will cause a tube failure in the selected feedwater heater at a rate specified by the severity.

As the leak severity increases for the selected feedwater heater, water from the condensate system, for heaters #1 - #5, and water from the feedpump discharge, for heaters #6 will be induced into the shell side of the heater. The addition of mass will cause the mass within the heater to increase and the level control system will respond and modulate the drain and dump valves open. The cascading effect of the excess mass will impact the downline low pressure feedwater heaters and the level control systems.

A maximum severity or multiple leaks in the #6 heater could cause insufficient feedwater flow to the reactor vessel and result in a reactor scram on low water level. A maximum severity or multiple leaks in the #1 - #5 heaters could result in a low suction pressure trip of the reactor feedpumps. A less severe leak will result in decreased feedwater heating and decrease in condenser vacuum.

If the heater inleakage exceeds the normal drain and dump capacity the level will increase and actuate the high and hi-hi level annunciators. The level could backup into the turbine resulting in a turbine trip from high vibration, reactor scram and recirculation RPT breakers to open. The hi and hi-hi level alarms are bypassed if HS1393 in bypass and there is a turbine trip or a reactor scram.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

Feedwater tube leak inside heaters 6A & 6B. IC24, 100% power, middle of cycle.

The following three simulations are for the first trend file:

fw08-6.dat: 100% severity corresponding to 30 tubes breaking
fw08-6_2.dat: 60% severity corresponding to 18 tubes breaking
fw08-6_3.dat: 30% severity corresponding to 9 tubes breaking

The following three simulations are for the second trend file:

fw08-6.da2: 100% severity corresponding to 30 tubes breaking
fw08-6_2.da2: 60% severity corresponding to 18 tubes breaking
fw08-6_3.da2: 30% severity corresponding to 9 tubes breaking

MALFUNCTION FW09

Malfunction is reactor feedwater pump trip.

A) Pump A B) Pump B

Generic, spurious trip signal, 100% power.

This malfunction will cause the selected main feedwater pump to trip instantly from a spurious trip signal. The pump motor breaker will trip open and annunciation will activate. The pump pressure and flow will decrease and the recirculation valve will close, if open.

The main feedwater pump trip will cause a partial loss of feedwater to the reactor, the level will decrease, and speed is runback to 45% at the recirculation pump. Reactor and turbine power are reduced accordingly. The feedwater control valves will modulate and maintain reactor water level in the control band at the reduced power level. The plant will stabilize at a new lower power. It is possible for low water level scram because of too high a power level or load line.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

fw09a.dat: Accident is reactor feedwater pump 'A' trip. IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION FW12

Feedwater regulator valve controller (FWRV) failure (auto).

A) FWRV A B) FWRV B C) Master controller

Generic, variable. 0 - 100% = 0 - 100% of valve position. Auto output signal failure. 100% power.

This malfunction will cause the selected feedwater regulator valve controller output to fail to the specified severity. The output will cause the regulator valve to modulate normally to the new position independent of the automatic control input signal. Placing the affected controller in the manual control mode will allow operator control.

If the regulator valve position is decreased, the flow provided will decrease, if the uneffected feedwater regulator valve capacity permits, it will open and compensate for the failed valve control. If the failed valve closes or closes sufficiently to decrease the total system capacity the reactor water level will decrease. A reactor scram may result.

If the output signal on the effected controller drops below 6 milliamps. The feedwater control valve lockout relay will actuate. An amber alarm light and annunciation will respond.

If the regulator valve position is increased, the flow provided will increase and the uneffected feedwater regulator valve will close to compensate for the failed control valve. The plant will remain stable in this condition. As flow is increased for either reactor feedwater pump to a value exceeding the design capacity, the motor current developed may exceed the overcurrent rating and the unit will trip on overcurrent.

The master controller failure will cause the feedwater regulator valve controllers in auto to respond in unison, the overall effect will be similar to the above failures. Excessive flow will increase reactor water level and decreased flow will lower reactor water level. A reactor high water level of 211" will result in a trip of both feedwater pumps and the main turbine.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

Master feedwater controller failure. Fails both feedwater regulator valves. 100% power, IC24, middle of cycle. The following two simulations are for the first trend file:

fw12c0.dat: Feedwater regulator valves fail fully closed

fw12c1.dat: Feedwater regulator valves fail fully opened

The following two simulations are for the second trend file:

fw12c0.da2: Feedwater regulator valves fail fully closed
fw12c1.da2: Feedwater regulator valves fail fully opened

MALFUNCTION FW17

Malfunction is main feedwater line break inside primary containment.

A. Feed line A

B. Feed line B

Generic, variable, 0-100% = 0-16" diameter double-ended shear weld failure on outlet of check valve, 100% power. This malfunction will cause the selected feed line inside the primary containment to shear at the outlet of the check valve to the size specified by severity. This malfunction is unisolable from the reactor vessel through the selected feedwater line.

At 100% severity, the rupture will cause a rapid depressurization of the reactor vessel and feedwater line. The reactor water level will initially increase resulting in a high-level trip of the main turbine, reactor feed pumps, High Pressure Coolant Injection (HPCI) and Reactor Core Isolation Cooling (RCIC). Low-Pressure Coolant Injection (LPCI) and Core Spray (CS) will initiate on the resulting containment pressure of 2 psig and inject into the reactor vessel when reactor pressure decreases below the shutoff head of the pumps. (Inject valves for LPCI and CS will not open until reactor pressure decreases below 400 PSIG).

Drywell pressure and temperature will increase rapidly, and at 2 PSI group isolations 2,3,4,8,9 and reactor scram will occur. Suppression pool temperature and level will increase in response to the rupture severity. The reactor water level will decrease rapidly actuating reactor trip, and turbine reactor water low, low-low, low-low-low isolation signals for groups 1,2,3,4,5,7,8, seal purge.

The core spray, HPCI and LPCI systems will actuate and begin to flood the reactor with water. The unisolated rupture will continue to cause mass loss from the reactor to the drywell and suppression pool. HPCI and RCIC will receive initiation signals on lo-lo reactor water level. If the reactor pressure is greater than 100 PSIG, these systems will initiate.

Depending on which feedwater line is broken, HPCI or RCIC will inject to the reactor vessel. ('A' feedwater line break, RCIC injects to vessel, portion of HPCI bay inject and rest through break, and the opposite is true of 'B' feedwater line breaks).

The reactor will cooldown in response to the Emergency Core Cooling System (ECCS), and the event will eventually stabilize. Reactor pressure and drywell pressure will equalize on large break in very short period of time.

This malfunction is unrecoverable, and the simulator will have to be reinitialized for malfunction removal.

Datafiles:

fwl7a_2.dat: Accident is main feed water line break. 60% single-ended shear loop A IC24, 100% power, MOC.

fwl7a_3.dat: Accident is main feed water line break. 30% single-ended shear - loop A IC24, 100% power, MOC.

MALFUNCTION FW18

Malfunction is main feedwater line break outside primary containment.

A. Feed line A

B. Feed line B

Generic, variable, 0-100% = 0-16" diameter double-ended shear weld failure on outlet of feed reg valve 100% power. This malfunction will cause the selected feed line outside the primary containment to shear at the outlet of the feedwater regulator valve to the size specified by severity.

At 100% severity, the rupture will cause the feedwater header pressure to decrease rapidly to less than reactor pressure. Header flow will increase rapidly to maximum, and the feedwater pumps capacity will be exceeded and trip on low suction pressure of 250 PSIG. Initially the feedwater regulator valves will modulate open from steam/feedwater mismatch, then open when the decreasing reactor water level overrides control.

A reactor scram will occur when reactor water level decreases from lack of feedwater, the low water level causes High Pressure Coolant Injection (HPCI), and Reactor Core Isolation Cooling (RCIC) actuation and begin to flood the reactor with water and eventually recover the level. Group isolations will occur at the respective setpoints.

The reactor will cool down in response to the Emergency Core Coolant System (ECCS), and the event will eventually stabilize. This malfunction is unrecoverable, and the simulator will have to be reinitialized for malfunction removal.

Datafiles:

fwl8a.dat: Accident is main feedwater line break outside primary containment 100% break.

MALFUNCTION HP05

Malfunction is High Pressure Coolant Injection (HPCI) steam supply line break (HPCI room). Variable, exponential. 0J-J100% = 0J-J10" diameter single-ended shear weld failure on HPCI steam supply line any, HPCI in operation. This malfunction will cause the HPCI turbine steam supply line to break at the drain pot inlet. The break size will be specified by severity.

A low severity steam line break will cause the HPCI turbine speed to decrease. The turbine speed controller will cause the throttle valve to open and return the speed to setpoint.

As severity increases, the steam flow will increase and the turbine speed/pumping capacity will decrease. The emergency area cooler will detect a high differential temperature, high room temperature or high steam flow (300%) caused by the steam line break and actuate an auto-isolation signal, closing the steam isolation valves MO-2238, MO-2239, torus suction valves close, and tripping the turbine. The room fire suppression system may activate at high severities.

The HPCI turbine steam inlet valve HV-2201 will close, the turbine speed will decrease, and exhaust pressure will go to minimum. The HPCI pump discharge pressure and flow will decrease as pump capacity is lost. Reactor water level will not increase from the HPCI system. Without a manual reset the turbine will not attempt a restart at 119.5".

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

hp05.2.dat: Accident is High Pressure Coolant Injection (HPCI) steam line break in HPCI room. 60% single-ended shear IC20, 100% power, End of Cycle (EOC).

hp05.3.dat: Accident is High Pressure Coolant Injection (HPCI) steam line break in HPCI room. 30% single-ended shear IC20, 100% power, End of Cycle (EOC).

MALFUNCTION HP08

Malfunction is High Pressure Coolant Injection (HPCI) steam supply line break (torus room), variable, 0-100% = 0-10" diameter single-ended shear, weld failure on HPCI supply line at M0-2298 any, HPCI in operation. This malfunction will cause the HPCI turbine steam supply line to break in the torus room at the outlet of M0-2298. The break size will be specified by severity. A low-severity steam line break will cause the HPCI turbine speed to decrease, and the turbine speed controller will cause the throttle valve to open and return the speed to setpoint. HPCI isolation can result if the torus area temperature increases to the high setpoint or has a high D/T for greater than 15 minutes.

As severity increases, the steam flow will increase, and the turbine speed/pumping capacity will decrease. The excessive steam flow will cause a high steam line D/P isolation signal to be generated, closing the steam isolation valves MO-2238, MO-2239, torus suction valves close and tripping the turbine.

The HPCI turbine steam inlet valve MO-2202 will close, the turbine speed will decrease, and exhaust pressure will go to minimum. The HPCI pump discharge pressure and flow will decrease as pump capacity is lost. Reactor water level will not increase from the HPCI system. Without a manual reset the turbine will not attempt a restart at 119.5".

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

hp08.2.dat: Accident is High Pressure Coolant Injection (HPCI) steam line break in torus room. 60% single-ended shear IC20, 100% power, End of Cycle (EOC).

hp08.3.dat: Accident is High Pressure Coolant Injection (HPCI) steam line break in torus room. 30% single-ended shear IC20, 100% power, End of Cycle (EOC).

MALFUNCTION IA01

Loss of instrument air

Variable 0 - 100% = 0 - 200% of capacity (CFM). 100% capacity = 3000 CFM. Air receiver leak 100% power

This malfunction will cause the instrument air system to leak from the air receiver at a rate specified by severity.

At severities less than 100% the pressure will decrease to the auto start setpoint of the standby compressors which will start and recharge the system.

At severities greater than 100% the system pressure will decrease with all three compressors running, severity will determine the rate of decrease. The following automatic functions will occur at setpoint:

1. 87 PSIG - service air low press ann.
2. 82 PSIG - CV3032 isolates service air hdr.
3. 85 PSIG - inst air dryer disch press low ann.
4. 80 PSIG - CV3034, CV3035, CV3039 isolate appropriate I.A. hdrs
5. 60 PSIG - breathing air low press ann.

Each isolated air header pressure will decrease dependent on header air usage and individual components will go to their fail position or mode.

The plant is expected to trip and will stabilize in a post shutdown condition.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

ia01.dat: Transient is complete loss of instrumentation air (IA01). 100% severity. IC24, 100% power, MOC. This is for the first trend file.

ia01_2.dat: Transient is complete loss of instrumentation air (IA01). 60% severity. IC24, 100% power, MOC. This is for the first trend file.

MALFUNCTION MC01

Malfunction is main circulating water pump trip.

A. Pump A, LP4A

B. Pump B, LP4B

Generic, upper motor bearing failure, 100% power. This malfunction will cause the selected main circulating water-pump motor upper bearing to fail, resulting in a motor breaker trip on overcurrent.

The circulating water-pump upper motor bearing will fail causing the motor speed or current to fluctuate. After approximately one minute the motor bearing will seize and cause a very high current to be drawn by the motor, and the supply breaker will trip on overcurrent. As the circulating water pump discharges pressure, flow will decrease, and the pump discharge valve will close. The cooling tower basin level will increase slightly then return to normal as the system mass rebalances.

With a circulating water pump tripped the circulating water temperatures will increase across the condensers. Condenser vacuum will decrease, and annunciation and a turbine trip will result, causing a reactor scram and Reactor Pump Trip (RPT). The plant protection system will respond appropriately to the turbine trip, and the plant will stabilize in a post trip condition with Electro-hydraulic Control (EHC) maintaining reactor pressure with the bypass valves.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

mc01a.dat: Accident is main circulation water pump "a" trip. No loss of power IC24, 100% power, Middle of Cycle (MOC). Malfunction is YP:MMC01(A).

MALFUNCTION MC04

Main condenser air inleakage.

A) High pressure condenser B) Low pressure condenser

Generic, variable. 0 - 100% = 0 - 1000 SCFM at 29" Hg. Condenser boot seal failure. 100% power.

This malfunction will cause the selected condenser to have air inleakage at a CFM rate specified by severity.

At low severities the air ejector system will compensate for the air inleakage, however as severity is increased the selected condenser will lead a total vacuum decrease by both condensers. As the condenser pressure decreases the following functions occur:

- 1) 5.0" HgAbs - Condenser low vacuum annunciation
- 2) 5.0" HgAbs - Turbine 1B/1C low vacuum annunciation
- 3) 7.5" HgAbs - Turbine trip actuates
- 4) 19" HgAbs - Group 1 isolation signal
- 5) 22" HgAbs - Bypass valves are closed

The offgas system will be affected by this malfunction. The pressure and flow will increase and as severity increases, the loop seals will isolate on high pressure. The flow will alarm. The recombiner temperatures will decrease depending on the malfunction. Offgas should stabilize after a short period of time.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

Main condenser air inleakage. IC24, 100% power, middle of cycle.

mc04a.dat: 100% severity

mc04a.2.dat: 60% severity

mc04a.3.dat: 30% severity

MALFUNCTION MS02

Steam leak inside the primary containment. Variable 0 - 100% = 0 - 4" diameter single ended shear. Caused by RCIC steam line weld failure at elbow instrument tap (unisolable). 100% power. This malfunction will cause a main steam leak at RCIC line elbow instrument tap at a rate specified by severity. Very small severities will cause local heating inside the drywell, a very slight pressure increase, and an increase in leakage to the drywell floor drain system.

The main steam flow will increase and rx pressure will decrease. The turbine Electro-Hydraulic Control (EHC) system will detect the pressure decrease and respond to maintain pressure. With the decreased steam flow the feed flow will decrease causing the reactor vessel water level to decrease until the level dominates and stabilizes the level.

The drywell pressure and temp will respond quickly to the leak and the high drywell pressure trip at 2 psig. The HPCI, LPCI, CS and DG's will start, group 2, 3, 4, 5 isolations will activate. If the rx pressure decreases to 850 psig, group 1 isolation will occur and isolate the turbine bypass system. The rx will continue to blow down and the rx pressure and level will decrease consistent with the severity. Reactor pressure and temperature will decrease rapidly. The torus level and temperature will increase in response to the rupture.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

ms02_2.dat: RCIC line break inside primary containment. The simulation was a 60% single ended shear in a 4" dia pipe. Initial condition is IC24, 100% power, Middle of Cycle (MOC). 60% severity.

ms02_3.dat: RCIC line break inside primary containment. The simulation was a 30% single ended shear in a 4" dia pipe. Initial condition is IC24, 100% power, Middle of Cycle (MOC). 30% severity.

MALFUNCTION MS03

Malfunction is Main Steam Line (MSL) rupture inside primary containment.

- A. Steam line A
- B. Steam line B
- C. Steam line C
- D. Steam line D

Generic, variable, 0- 100% = 0 - 20" diameter double-ended shear piping on flow restricter at the high pressure instrument tap that feed CRM steam flow instrumentation, 100% power. This malfunction will cause the selected main steam line to rupture at the flow restricter inlet at a rate specified by severity.

At very low severities, local drywell temperatures will increase. Drywell pressure increase will be small. The drywell floor drain sump will fill up faster, and the drywell cooling system will indicate temperature increases. At lower severities, the main steam flow will increase, measured flow will decrease, and reactor pressure will decrease. The turbine bypass and control valves will modulate close, if open, in an attempt to increase steam pressure.

The feedwater control system will increase feedflow to control the increased demand. The hotwell level control system will begin to makeup from the condensate storage tank to maintain the hotwell level in the normal control band, compensating for the system mass loss. The drywell temperature/pressure will increase at an appropriate level consistent with severity.

At higher severities, the excessive main steam pressure decrease will cause the main turbine control valves to close, attempting to maintain steam pressure. Whenever the steam line pressure decreases to 850 PSIG, the main steam isolation signal and group I isolation will activate and the Main Steam isolation Valve (MSIV) will close, the reactor will scram, and the turbine bypass system will isolate. The reactor will continue to blow down, and the reactor pressure and level will decrease consistent with the severity. The drywell temperature/pressure increase will cause the ECCS to activate at 2 PSIG, and group isolation II, III & IV will occur. Reactor pressure and temperature will decrease rapidly.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

ms03a.dat: Accident is main steam line header double ended shear, 100%. (20" line). IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION MS04

Malfunction is Main Steam Line (MSL) rupture outside primary containment.

- A. Steam line A
- B. Steam line B
- C. Steam line C
- D. Steam line D

Generic, variable, 0 - 100% = 0 - 20" diameter double-ended shear, piping failure at ms common header, 100% power. This malfunction will cause the selected main steam line to rupture outside the containment at the turbine inlet header at a rate specified by severity. At lower severities, the main steam flow will increase, and reactor pressure will decrease. The turbine bypass and control valves will modulate close, if open, in an attempt to increase steam pressure to control the increased demand. The hotwell level control system will begin to makeup from the condensate storage tank to maintain the hotwell level in the normal control band, compensating for the system mass loss. A Primary Containment Isolation System (PCIS) group I isolation is possible on steam line high temp (200 DEG F), and probability increases with severity.

At 100% severity, the PCIS group I isolation will be initiated on steam line low-pressure (850 PSIG in the run mode) with the steam line flow (140%) as a backup. The reactor will scram on MSIV closure. Because of the rapid steaming rate, the reactor water level will rapidly increase causing the main turbine and both reactor feed pumps, HPCI and RCIC, to trip. As the MSIVs close, steam flow through the break will cease, voids will collapse, and reactor water level will stabilize at some new lower level. Emergency Core Cooling System (ECCS) will respond to maintain adequate core cooling. The pressure rise in the turbine building will cause the blowout panels to function, releasing the steam cloud to the environment.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

ms04a.dat: Accident is main steam line header double ended shear, 100%. (20" line). Outside primary containment. IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION MS14

Loss of extraction steam to feedwater heater

- A) Heater 1A B) Heater 2A C) Heater 3A D) Heater 4A
E) Heater 5A F) Heater 6A G) Heater 1B H) Heater 2B
I) Heater 3B J) Heater 4B K) Heater 5B L) Heater 6B

Generic, extraction line restriction, 100% power.

This malfunction will cause the selected feedwater heater to lose extraction steam.

The loss of extraction steam will cause the selected heater level to decrease and the associated heat gain across the heater will be lost. The resultant decrease in feedwater temperature will cause a power increase for the resultant load. The extent of power increase will be based on the heater selected, and/or the number of heaters selected. Worst case would produce a reactor scram on high flux. Less severe failures will produce possible long term effects for fuel failure considerations and administrative requirements.

The reduced drain flow to the next heater in the drain line will cause its level to decrease and the heater level controller will modulate to compensate and maintain the setpoint level. The reduced flow will cause a cascading effect for the remaining heaters down line. Once the mass transient is over, the drain heaters individual level control system will compensate for the loss of extraction steam and stabilize transient condition.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

ms14-6.dat: Loss of feedwater heating to both feedwater heaters 6A & 6B. IC24, 100% power, middle of cycle. No associated severity.

MALFUNCTION MS19

Malfunction is spurious group I isolation.

A. Logic 'A'

B. Logic 'B'

Generic, relay failure, 100% power. This malfunction will cause the selected group I isolation relay to fail and cause the isolation signal to be generated.

The failure of logic 'A' will cause the group I isolation annunciator to actuate without valve response.

The failure of logic 'B' will cause the group I isolation annunciator to actuate without valve response.

The failure of both logic 'A' and 'B' will cause the below listed inboard/outboard isolation valves to trip closed. The valve positions will be displayed at the hand-switches and IC03. The valves are listed below:

M0-4423	M0-4424	CV-4639	CV-4640	CV-4412	CV-4415
CV-4418	CV-4420	CV-4413	CV-4416	CV-4419	CV-4421

The closing of the Main Steam Isolation Valve (MSIV) inboard or outboard will result in a reactor scram, turbine trip, and plant shutdown. Reactor high pressure will activate the Low Low Set (LLS), and reactor pressure will be controlled at about 900 to 1020 PSIG.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

msl9ab.dat: Accident is feedwater relay failures A and B logic causing a group I isolation. IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION MS32

Spurious group 7 isolation. Discrete. Short circuit causes relay CR4841 to energize. 100% power.

This malfunction will cause the selected group 7 isolation relay to fail and cause the isolation signal to be generated.

The failure of relay CR4841 will cause the group 7 isolation valves to trip closed. The valve positions will be displayed at the handswitches and 1C03. The isolation valves are listed below:

MO4841A MO4841B

MO4841A/B closure will cause the respective recirculation pumps to loose cooling, overheat and fail.

CV5718A CV5718B CV5704A CV5704B

CV5718A/B and CV5704A/B closure will cause the drywell to loose cooling, drywell temperature and pressure will increase. At 2 PSIG the reactor will scram, emergency core cooling system (ECCS) will be initiated and PCIS group 2,3,4, and 5 isolations will be initiated.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

ms32.dat: Spurious group 7 isolation. Isolates well water cooling to the drywell.
IC24, 100% power, middle of cycle.

MALFUNCTION RD13

Loss of air pressure to control rod drive (CRD) hydraulic control units (HCUs).

Variable 0 - 100% = 0 - 1.5" diameter pipe break. Air header piping failure. 100% power.

This malfunction will cause the loss of air pressure to the CRD HCU'S at a rate consistant with the piping failure specified by severity.

Loss of air pressure will cause the flow control valves to fail closed eliminating the supply from the CRD pumps to the drive, exhaust and cooling water headers. The scram discharge volume will be isolated when CV'S 1867A/B and 1859A/B fail closed. Manipulation of the rod control system will not be available, however the charging header will remain pressurized. The drive/exhaust valves, CV1849,1850 are fail open valves. If they loose air pressure the charging header pressure will insert the control rods.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

rd13.dat: Transient is loss of air to HCU (RD13). 100% severity. IC24, 100% power, MOC. This is for the first trend file.

rd13.2.dat: Transient is loss of air to HCU (RD13). 60% severity. IC24, 100% power, MOC. This is for the first trend file.

rd13.3.dat: Transient is loss of air to HCU (RD13). 30% severity. IC24, 100% power, MOC. This is for the first trend file.

MALFUNCTION RP05

Malfunction RPS scram circuit failure (ATWS).

- A. Auto-scram failure
- B. Manual-scram failure
- C. ARI failure
- D. RPS fuse removal failure
- E. All individual rod-scram switches fail
- F. Hydraulic lock-scram discharge volume

Discrete, RPS scram circuit internal short circuit in wiring (A,B,C,D,E) scram discharge volume blockage (F), 100% power. This malfunction will cause the selected RPS scram circuit to fail to cause a reactor scram when actuated.

(A,B,C,D,E) selection of the hydraulic lock malfunction will reduce the scram discharge volume to simulate flow blockage.

If the auto-scram is selected for failure, the plant will respond to the effects of the condition that generated the scram signal. The annunciators and indications will respond to auto-scram inputs as they are generated. However, the plant will remain operating until a protection feature or injection of sodium pentaborate causes the plant to shutdown. The reactor has the manual-scram capability functional, and the operator can utilize this mode as desired.

With an active auto-scram, the plant will scram as required by logic whenever the appropriate condition exists.

A failure of ARI to cause a scram will also cause a failure of the RPT breakers to trip on lo-lo reactor water level, high reactor pressure, or manual initiation of ARI.

The effects of the manual-scram feature failures would be the response failure of the function to respond when activated manually.

RPS fuse removal failure simulates a failure of the RPS fuse removal to work.

Failure of the rod-scram switches simulates a failure of all 89 scram switches to work.

The hydraulic lock malfunction reduces the volume and will allow the rods to partially insert, with each scram signal/reset applied.

Insertion of all (6) generic failures will result in a "ATWS" condition.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

rp05tc01.dat: Accident is trip of main turbine together with failure to scram (ATWS). No operator action. IC24, 100% power, Middle of Cycle (MOC). Malfunction is YP:MTC01 (turbine trip) followed by YP:MRP05(A) (failure to automatically scram). Scram will be delayed and slow. Scram is from alternate rod

insert (ARI). Recirculation pumps also trip on ARI. ARI is triggered at 119" vessel level or 1140 PSIG vessel pressure. Recirculation pump trips at turbine control valves fast closure or stop valves less than 90% open.

rp5actcl.dat: Accident is trip of main turbine together with failure to scram (ATWS), and Alternate Rod Insert (ARI). No operator action. IC24, 100% power, Middle of Cycle (MOC). Malfunction is YP:MTC01 (turbine trip) followed by YP:MRP05(A) (failure to automatically scram) and YP:MRP05(C) (failure of ARI). Recirculation pump trips on turbine control valves fast closure or stop valves less than 90% open.

MALFUNCTION RR05

Recirculation pump shaft seizure

A) Pump A

B) Pump B

Generic. Internal pump failure. 100% power.

This malfunction will cause the selected recirculation pump to seize mechanically and cause locked rotor current to develop for the motor.

The selected recirculation pump internal total failure will be preceded by about 30 seconds of erratic speed, flow, current and excessive vibration as the failure develops into a totally seized pump. The recirculation M-G supplying power to the failing recirculation pump will have excessive generator current, which will result in a motor-generator lockout relay trip. The lockout actuation will trip open the generator field breaker, interrupting power generation for the seized recirculation pump motor.

The recirculation pump trip will reduce the loop flow to minimum, core total flow and discharge pressure will decrease. With less core discharge pressure, the unaffected loop flow will increase slightly. Because the recirculation system total flow and pressure decrease, increased core voiding will reduce core power and cause a rapid increase in reactor vessel level. As reactor power decreases, the turbine generator power will decrease, the plant will stabilize at reduced power and vessel level will return to normal.

Malfunction removal will restore the effected components to normal. Operator action may be required to restore the plant to normal.

Datafiles:

rr05.dat: Recirculation pump shaft seizure. IC24, 100% power, middle of cycle.

MALFUNCTION RR10

Malfunction recirculation pump speed feedback signal failure.

A. Pump A

B. Pump B

Generic, variable, 0 - 100% = 0 - 100% of feedback signal, speed control circuit failure, 50% power. This malfunction will cause the selected recirculation pump speed-control feedback circuit to fail to the specified severity. The pump speed indicator will fail to the specified severity. With the tachogenerator signal failing below the speed demand/manual pot position signal, the recirculation pump actual speed will increase, and the scoop tube will increase to maximum or auto lock if auto-lock conditions are met. With the tachogenerator signal failing above the speed demand/manual pot position signal, the recirculation actual speed will decrease to minimum.

The resulting effect on the plant will be the increase in power for an increased recirculation flow and a decrease in power for a decreased recirculation flow. Turbine generator power and control valve positions will respond as appropriate. Annunciator response to flow limits and control failures will actuate at setpoint.

Reactor water level will respond to the opposite of the recirculation speed initially until feedflow and steam flow can get matched at the proper water level.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

rrl0.dat: Accident is recirculation pump speed feedback signal failure caused by speed circuit control failure IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION RR11

Recirculation pump seal failure

- A. Pump A #1 lower seal
- B. Pump A #2 upper seal
- C. Pump B #1 lower seal
- D. Pump B #2 upper seal

Generic, variable 0 - 100% = 0 - 1.1 GPM (NOTE: For FLR of #1 and #2 seal, 100% = 60 GPM total) worn seal 100% power.

This malfunction will cause the selected recirculation pump seal to become worn and fail to a level specified by severity.

Failure of a single seal will cause the seal leakoff to go to the amount specified by severity. The seal leak detection system will indicate high flow and actuate the annunciator. The leak flow will flow to the rad waste system *via* the existing lineup.

Failure of #1 seal will give indication of increasing pressure of #2 seal cavity pressure. If pressure exceeds 500 PSIG, then the failure is #1 seal. The increased severity will cause a seal staging hi/lo flow ann. When flow is 0.9 GPM.

Failure of #2 seal will give indication of increasing pressure of #2 seal cavity pressure. If pressure is less than 500 PSIG, then the failure is #2 seal. The increased severity will cause an outer seal leak hi flow ann. When flow is 0.1 GPM.

Failure of both seals will result in substantially higher leak flows to the rad waste system. Mini-purge makeup system flow will contribute 4 GPM maximum, the balance being madeup from leakage past the seals. At maximum D/P and seal failures the flow is expected to be 60 GPM worst case. This will cause drywell pressure to increase above 2 PSIG resulting in reactor scram and various isolations.

Datafiles:

rr11a.dat: Transient is failure of both shaft seals on 'A' recirculation pump (RR11). 100% severity. IC24, 100% power, MOC. This is for the first trend file.

MALFUNCTION RR15

Malfunction is recirculation loop rupture (design basis Loss of Coolant Accident (LOCA) at 100%).

A. Loop A

B. Loop B

Generic, variable, 0 - 100% = 0 - 22" diameter double-ended shear piping failure at recirc pump suction, 100% power. This malfunction will cause the selected recirculation loop, inside the primary containment, to shear at the recirculation pump suction to the size specified by severity.

At 100% severity, the rupture will cause the recirculation loop and reactor pressure to decrease rapidly. The affected loop recirculation pump will cavitate and flow will be lost. Reactor water level will decrease rapidly as the reactor blows down through the rupture into the containment. The reactor water level decrease will actuate reactor scram, and reactor water level low, low-low, low-low-low isolation signals for groups 1, 2, 3, 4, 5, 7, 8, seal purge. The Core Spray (CS), High-Pressure Coolant Injection (HPCI), Low-Pressure Coolant Injection (LPCI), DG, and ADS systems will actuate and begin to flood the reactor with water. The RR pump discharge valves will close on the non-broken loop on the LPCI loop select signal. Reactor feed pumps will trip on overcurrent.

At 100% severity, the HPCI and RCIC will receive initiation signals. However, the reactor pressure will decrease so fast that they will trip and isolate on low pressure before they will have any noticeable effect. Drywell pressure and temperature will increase rapidly and at 2 PSI group isolations 2,3,4,8,9 will occur. Suppression pool temperature and level will increase in response to the rupture severity. The reactor will cooldown in response to the Emergency Core Coolant System (ECCS), and the event will eventually stabilize.

This malfunction is unrecoverable, and the simulator will have to be reinitialized for malfunction removal.

Datafiles:

rrl5a_2.dat: Accident is recirculation loop rupture. 60% double-ended shear - loop a IC24, 100% power, Middle of Cycle (MOC).

rrl5a_3.dat: Accident is recirculation loop rupture. 30% double-ended shear - loop a IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION RR30

Malfunction is coolant leakage inside primary containment. Variable (exponential), 0 - 100% = 0 - J2" diameter pipe (double-ended shear) reactor vessel bottom drain weld failure, 100% power. This malfunction will cause reactor coolant to leak from the reactor vessel bottom drain failed weld at a rate specified by severity. As severity increases the mass loss from the reactor will easily be made up for by the hotwell level control system. In fact, at 100% severity the effects on reactor level/hotwell level will be very small. The most effective display of mass loss will be at hot standby.

At 100% severity, drywell pressure, temperature, and activity will increase. At 2 PSI, group isolations 2,3,4,5,8 will occur. Suppression pool temperature and level will increase in response to the rupture severity. The reactor scram will result from the 2 PSIG drywell pressure, and a turbine trip will result from reserve power.

The shutdown plant will cooldown in response to the Emergency Core Cooling (ECC) and will stabilize. The longterm effect of the leak will be the transfer of the Condensate Storage Tanks (CST) mass to the suppression pool via the leak in the reactor vessel.

At small severities where the drywell pressure remains below 2 PSIG, the floor drain equipment system will see a high leak (in excess of the 5 GPM tech spec limit). The drywell cooler heat load will increase as seen on the cooler temperatures on IC25.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

rr30.dat: Accident is reactor bottom head drain 100% single-ended shear (2" line). IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION RX01

Malfunction is fuel cladding failure. Variable, exponential, 0 -100% = 0 - 30% fuel clad damage, fuel cladding degradation. 100% power. This malfunction will cause the fuel cladding to fail to a value specified by severity.

As the fuel failure increases, the amount of activity in the reactor recirculation and main steam system will increase. This activity will propagate throughout the plant and the radiation monitoring system will detect, indicate, and alarm as the activity increases. At low severities, offgas post-treat radiation monitors will cause offgas to isolate (without a group isolation) resulting in a loss of condenser vacuum, main turbine trips, and reactor scram. As the severity increases, the main steam line radiation monitors will cause main steam line isolation and reactor scram at setpoint. As the normal power dependent background radiation levels decrease, the additional radiation levels will be more evident on area and process monitors. At high severities the before mentioned will occur faster with more dramatic increases. Various system trips and isolations will occur, protecting the environment from excessive discharges.

The sequence of the fuel failure indication will be as follows:

1. Offgas pretreat and post-treat radiation monitors increase
2. Offgas stack release will start to increase
3. Offgas system isolates on post-treat hi-hi radiation level
4. Main steam line radiation monitors respond:
 - a. MSL high radiation alarm
 - b. Group I isolation
 - c. Reactor scram
5. Drywell monitors increase
6. Torus radiation monitors increase from relief valve discharge or HPCI and/or RCIC exhaust.
7. Reactor building area radiation increases from Emergency Core Cooling System (ECCS) system operation. (HPCI, RCIC, LPCI, CS).

NOTE: Malfunction severity will cause some of the above items to be "passed over" or will result in a delayed response.

Datafile:

rx01.dat: Accident is 30% fuel clad failure. Causes high radiation alarm to go off IC24, 100% power, Middle of Cycle (MOC).

MALFUNCTION TC02

Malfunction is EHC hydraulic pump trip.

A. Pump A

B. Pump B

Generic, motor failure, 100% power. This malfunction will cause the selected EHC pump motor to fail and trip on overload. The starter will open, and an annunciator will actuate.

The unaffected EHC pump will start when the low pressure annunciator actuates at 1300 PSIG EHC system pressure.

If the unaffected EHC pump is unavailable or both EHC pumps are failed, the turbine will trip at 1100 PSIG EHC system pressure. When the turbine trip is initiated, the turbine stop valves, control valves, and combined intermediate valves will rapidly close. The reactor/main steam pressure increases rapidly activating the turbine bypass system. The turbine bypass system will modulate as necessary to control the steam pressure by dumping steam to the main condenser. A reactor scram will occur as a result of the turbine trip. Recirculation pumps will trip when the RPT breakers open from a turbine trip.

4KV bus close-circuit transfer is initiated. The main generator 286/B lockout relay will actuate from the anti-motoring trip protection. The main generator output breakers 352-H and/or 352-I will trip open and lockout. The generator exciter field breaker will open. Generator indication of current, voltage, megawatts, megavars, etc. will decrease to zero. Appropriate annunciators for generator trip will actuate.

The plant will stabilize in a post shutdown condition.

Malfunction removal will restore the affected components to normal. Operator action may be required to restore the plant to normal.

Datafile:

tc02.dat: Accident is EHC hydraulic pump trip causes pump motors to fail and trip on overload. IC24, 100% power, Middle of Cycle (MOC).

SOME SELECTED INITIAL CONDITIONS (IC) DESCRIPTIONS

IC-14 FULL POWER OPERATIONS (ANSI PARAMETERS)

- A) Moderator temperature = saturated conditions
- B) Reactor pressure = power dependent
- C) Reactor power level = 100% power
- D) Reactivity = critical
- E) Xenon condition = 100% equilibrium
- F) Core life = beginning of life

This IC is set up to meet the ANSI criteria for 100% power.

IC-20 FULL POWER OPERATION/MAX DECAY HEAT (EOL)

- A) Moderator temperature = saturated conditions
- B) Reactor pressure = power dependent
- C) Reactor power level = 100% power
- D) Reactivity = critical
- E) Xenon condition = 100% equilibrium
- F) Core life = end of life

This IC is similar to IC-15 except it has 20% more decay heat than normal.

Note: Effective Jan 27, 1993, some changes in IC-nomenclature were made.

The above initial conditions - the older "IC-20" - is now "IC-26" except that it has 20% more decay heat than normal (see below). The new initial conditions "IC-20" is similar to IC-14 except that all cooling tower fans are on.

IC-22 25% POWER (ANSI PARAMETERS)

- A) Moderator temperature = saturated conditions
- B) Reactor pressure = power dependent
- C) Reactor power level = 25% power
- D) Reactivity = critical
- E) Xenon condition = equilibrium for 25% power
- F) Core life = beginning of life

This IC is set up to meet the ANSI criteria for 25% power.

IC-23 75% POWER (ANSI PARAMETERS)

This IC is similar to IC-22, except at 75% power.

IC-24 FULL POWER OPERATIONS (MOL)

This IC is similar to IC-14, except the core is at middle of life (MOL).

IC-26 100% POWER (EOL)

This IC is similar to IC-20 (i.e., the older version given above), except that it has 20% more decay heat than normal.

Datafiles:

ic14scra.dat: Accident is spurious scram. No operator action. IC14, 100% power, BOC. Malfunction is YP:MRP03.

ic20scr1.dat: Accident is spurious scram with operator action. IC20, 100% power, EOC. Malfunction is YP:MRP03. Decay heat is 10% of full power. Operator action is according to integrated plant operating instruction (IPOI) NO. 5 - reactor scram. Actions include: mode switch to shutdown position, feedwater level controller to 175 inches, use reactor water cleanup to maintain RPV level, trip 'A' feed and condensate pumps, manually control feed regulator valves, insert all Source Range Monitor (SRM) and Intermediate Range Monitor (IRM) detectors. Level was not adequately controlled, and both feed pumps and turbine tripped on high RPV level (212 inches).

ic20scr2.dat: Accident is spurious scram with operator action. IC20, 100% power, EOC. Malfunction is YP:MRP03. Decay heat is 10% of full power. Operator action is according to Integrated Plant Operating Instruction (IPOI) NO. 5 - reactor scram. Actions include: mode switch to shutdown position, feedwater level controller to 175 inches, use reactor water cleanup to maintain RPV level, trip 'A' feed and condensate pumps, manually control feed regulator valves, insert all SRM and IRM detectors. Level was manually controlled to prevent the trip of feed pumps and turbine.

ic20scrm.dat: Accident is spurious scram. No operator action. IC20, 100% power, EOC. Malfunction is YP:MRP03.

ic22scrm.dat: Accident is spurious scram. No operator action. IC22, 25% power, BOC. Malfunction is YP:MRP03.

ic23scrm.dat: Accident is spurious scram. No operator action. IC23, 75% power, BOC. Malfunction is YP:MRP03.

ic24scrm.dat: Accident is spurious scram. No operator action. IC24, 100% power, MOC. Malfunction is YP:MRP03.

10 Articles Published During the Project Period

This section contains the journal papers, abstracts, and conference papers that were published or accepted for publication during the current funding.

*These papers have been removed for separate
cycling. At*

11 Articles Submitted During the Period

This section contains the papers submitted for review and publication to various journals.

Papers have been removed for separate cybing. At