ARTIFICIAL NEURAL NETWORKS BASED DIAGNOSTIC SYSTEM FOR IDENTIFYING LOCA SCENARIOS IN NUCLEAR POWER PLANTS

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ABSTRACT

Nuclear power plant experiences a number of transients during its operations. These transients may be due to equipment failure, malfunctioning of process support systems etc. In such a situation, the plant may result in an abnormal state which is undesired. In case of such an undesired plant condition, the operator has to carry out diagnostic and corrective actions. The operator’s response may be too late to mitigate or minimize the negative consequences due to short time and lack of expert knowledge. When an event occurs starting from the steady state operation, instruments’ readings develop a time dependent pattern and these patterns are unique with respect to the type of an event. Therefore, by properly selecting the plant process parameters, the transients can be distinguished. This paper presents a methodology for identification of loss of coolant accident (LOCA) scenarios in 220MWe Indian pressurised heavy water reactors (PHWRs). This is an operator support system based artificial neural networks (ANNs) that continuously monitors the plant conditions and identifies a LOCA scenario quickly based on the reactor process parameter values, and assists the operator to initiate corrective actions during abnormal operations of the plant. Large break LOCA in reactor inlet or outlet header and with or without the availability of emergency core cooling system (ECCS) has been considered and the break scenarios ranging from 20% to 200% of the header break have been analysed. The input data for process parameters has been generated through various analyses for reactor core, primary heat transport system and containment system using RELAP5 and CONTRAN codes for training ANNs. In order to validate the trained ANN model several unseen LOCA scenarios have been generated from the codes and directly predicted from the ANN model. The predicted results from the model are satisfactory. In order to see the feasibility of implementing in the plant for online diagnosis, this entire system has been set up on a distributed network and has been demonstrated successfully. Whenever an event is identified, this system will display the type of the event, time at which the event has occurred, relevant process parameters and their values at the time of initiation of the event and necessary operator actions.

INTRODUCTION

Nuclear power plants are highly complex systems that are operated and monitored by human operators. When faced with an unplanned transient, such as a plant accident scenario, equipment failure or an external disturbance to the system, the operator has to carry out the diagnostic and corrective actions based on the process instrument readings. Depending upon the severity of an accident, instruments’ readings might not give a clear indication of an anomaly at its incipient stage. Therefore, it necessitates developing an intelligent system that will assist the operator to identify such transients at the earliest stages of their developments. The objective of the plant diagnostic system in any potentially unsafe scenario is to give the plant operators appropriate inputs to formulate, confirm, initiate and perform the corrective actions [1]. Analysis of an event involves determination of the consequence of a specified event such as loss of coolant accident (LOCA) in terms of fuel temperature, storage tank level, containment temperature and pressure and releases, if any. Diagnosis is the identification of the event from the instrumented signals. For this purpose a methodology has been developed which consists of database of the above mentioned process parameters. An artificial neural network based diagnostic system has been developed to diagnose the initiating events (IEs) of a typical Indian PHWR from the process parameters available in the computerised operator information system (COIS). To train the network a large database of these parameters has been generated. The break scenarios have been modeled with a single neural network consisting of 37 input, 3 output and 2 layers of hidden neurons. Among the list of many process parameters available in the COIS [2], 35 parameters such as south inlet header pressure, south outlet header pressure, D_2O storage tank level, pump room pressure, reactor power, etc. are found to be significant for LOCA identification and have been selected for diagnosis. The time-dependent transient data pertaining to the reactor core and the primary heat transport has been generated using RELAP5 [3] thermal hydraulic code. The training and testing of neural networks were carried out using BIKAS neural networks simulator [4]. The results obtained from the study are satisfactory and will be helpful in the accident management of NPPs.

METHODOLOGY

Event description

Initiation of break at inlet header leads to a sudden depressurisation of the primary heat transport (PHT) system. The initial depressurisation rate is found to be high due to initial high blowdown rate. Within a few milliseconds the pressure falls to the saturation pressure level causing the coolant to flash. The formation of void causes the break discharge rate to be reduced leading to reduction in depressurisation rate. As the break leads to core voiding, the power increases suddenly due to positive coolant void coefficient of the reactor. The peak reactor power is different in different LOCA scenarios. The maximum peak power rises to 1.93 times the initial power in case of 200% break. After the reactor scram, power starts coming down and follow the decay power curve. The variation of quality in different sizes of break is all most similar. In broken path the fluctuation of quality is very high since this pass is directly connected to broken header. ECCS starts the injection when the pressure in any one of the headers reaches 55 kg/cm^2 (g). The time of injection and rate of ECCS coolant enters into the channel depends upon the size of the break. Several trip signals will be activated namely high log rate, low PHT pressure, high neutron power, low PHT coolant flow and high reactor building pressure one after the other in a short period of time. Sequence of actuation of trip signals is largely dependent upon the break size and location. In general, for large breaks on reactor inlet header (RIH) side, high log rate signal is the first signal followed by high neutron power, while for breaks on reactor outlet header (ROH) side, low pressure signal is usually the first signal followed by high log rate. In general, it is observed that, larger the break larger the blowdown energy discharge and more depressurisation. Hence, early injection of ECCS is possible [5].

Database generation

Analysis has been carried out for the following cases of LOCA: (i) Reactor Inlet Header Break with ECCS available (RIHECCS) (ii) Reactor Outlet Header Break with ECCS available (ROHECCS) (iii) Reactor Inlet Header Break without ECCS (RIHNoECCS) (iv) Outlet Header Break without ECCS (ROHNoECCS). Various break sizes ranging from 20% to 200% have been considered in each case mentioned above. In each case, it has been assumed that the reactor has tripped on the first trip signal. The inverse calculation of identifying the event from the symptoms is based on a large ensemble of such signals generated by the following analyses. The flow of information among the system codes to generate the database is shown in Figure 1. In the first stage, the core thermal-hydraulic response of the plant under an accident is computed, followed by computation of fission products (FPs) release from the reactor core. This release is based on the fuel temperature transients computed in the first stage and the steady state FP inventory present in the core. In the third stage, FP transport in the primary heat transport system and its release into the containment is computed with the core thermal-hydraulic parameters and FP release parameters computed in stage one and two respectively. In the next stage, containment thermal hydraulic behaviour, FP retention by different containment engineered safety features (ESFs) and deposition are evaluated [5].

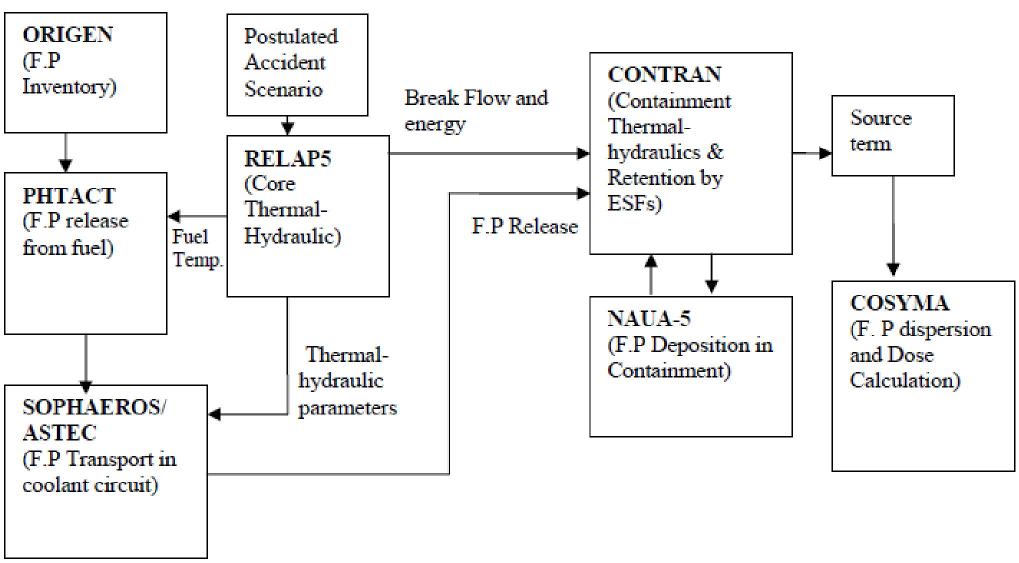

Fig. 1: Integration of various computational tools for database generation and consequence analysis

To study the system behaviour under large break LOCA condition, a wide range of break sizes is considered. A spectrum of break sizes have been analysed for core and containment. Following are some of the typical process parameters' profiles generated from RELAP5 simulation for a 200% break in RIH with ECCS case. For example, Figure 2 shows the header pressure in the broken and unbroken pass and Figure 3 shows the D_2O inventory in the PHT system.

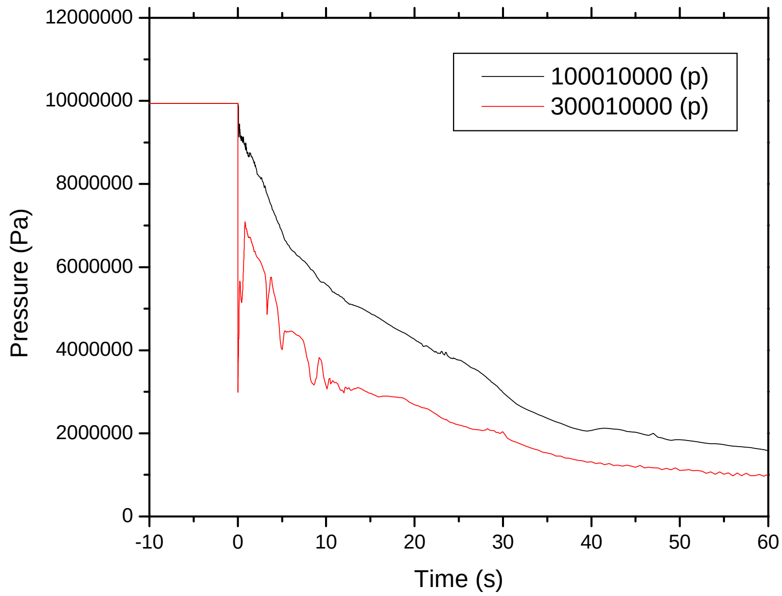

Fig. 2: RIH pressure

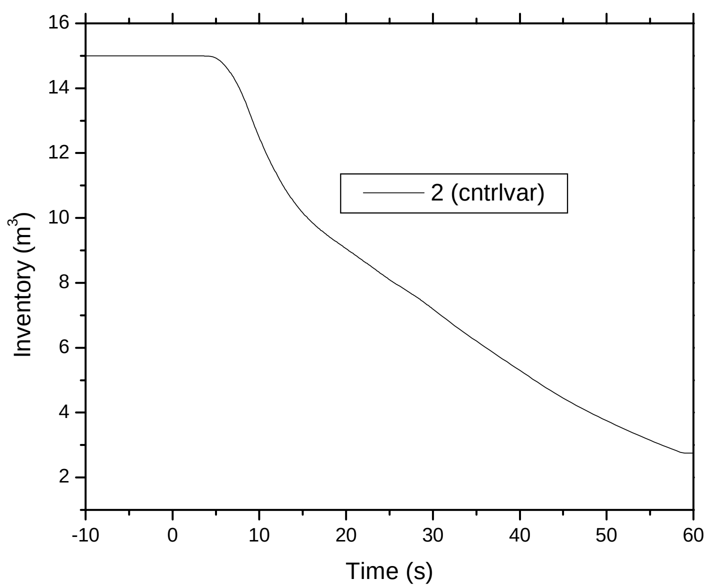

Fig. 3: D_2O inventory in PHT system

Neural networks

An artificial neural network based diagnostic system has been developed with the transient data mentioned above for various postulated accident scenarios of LOCA. ANN is an information processing paradigm that is inspired by the way the biological nervous systems, such as the brain, process information [6]. It is a system modeled based on human brain. ANNs, like humans, learn by examples. It is an attempt to simulate, within specialized hardware or sophisticated software, the multiple layers of neurons [7]. Each neuron is linked to a few of its neighbours with varying coefficients of connectivity that represent the strengths of these connections. Learning is accomplished by adjusting these strengths to cause the overall network to output appropriate results [8]. A general characteristic of a neural network is the ability that quickly recognizes the various conditions or states of a complex system once it has been suitably trained [9]. The functional block diagram of ANN based diagnostic system known as symptom based diagnostic system (SBDS) is shown in Figure 4.

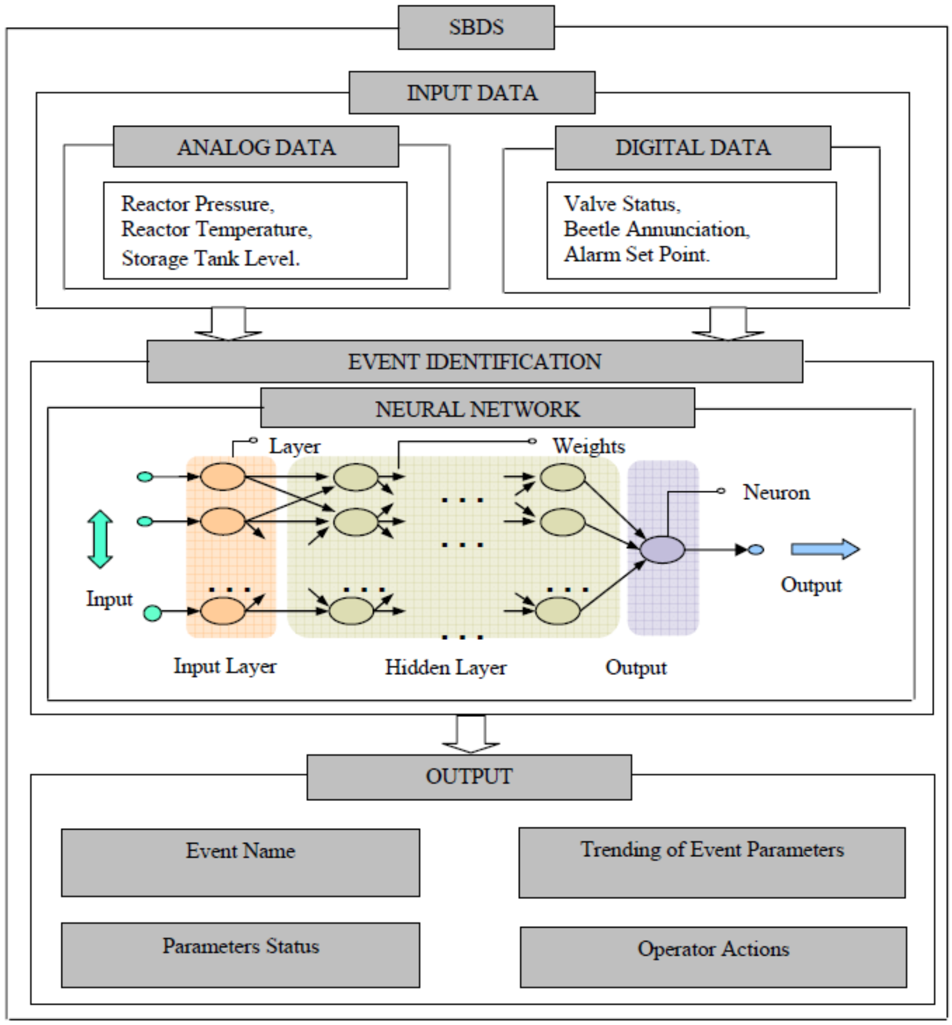

Fig. 4: Functional block diagram of SBDS

It mainly consists of three stages of processing, namely, the input, output and the event identification stage. In the input stage, the data is taken from the COIS and processed into training and testing files. This data is used for training and testing the neural networks in the event identification stage. In the event identification stage, neural network processes the data through a bank of artificial neuron layers and arrives at an optimum solution by adjusting the synaptic weights. Finally, the diagnostic results obtained in the event identification stage are displayed in the output stage, which is an operator screen. In the output stage, following information is displayed: the plant status, i.e., the plant normal or any transient has occurred, parameters and their current process values, trend of the important process parameters and operator actions whenever an event is detected. In the prediction mode, from the transients recorded on the operator information system, the system predicts the information on LOCA (location and size of break) and status of availability of ECCS. Hence the occurrence of an event such as LOCA can be detected by continuously monitoring the reactor process parameters such as PHT storage tank level, pressure and temperature, steam generator level, containment pressure and temperature, etc. The events are modelled based on the relevant reactor process parameters' time dependent data as available on the COIS. A large amount of time dependent data has been generated in order to train and test the neural networks for the selected scenarios so that these scenarios can be identified during reactor operations. The important process parameters identified from the COIS of a typical Indian

PHWRs for the LOCA is shown in Table 1. Only the measurable parameters, which are listed in COIS have been selected for this analysis.

Table 1: List of process parameters for LOCA

Sl. No.	Parameter Description	Process Range
1	South inlet header (CL) pressure CH-G	0 - 120 kg/sq. cm g
2	PHT pressure in south hot header CH-D	55 - 105 kg/sq. cm g
3	North inlet header (CR) pressure CH - G	0 - 120 kg/sq. cm g
4	PHT pressure in north hot header CH-D	55 - 105 kg/sq. cm g
5	ΔP across header HR & CL CH - G	- 75 - 75 cmWC
6	ΔP across header HL & CR CH - G	- 75 - 75 cmWC
7	D_2O storage tank level CH - E	0 - 4 M
8	SG1 inlet temperature	0 - 320 Deg. C
9	SG1 outlet temperature	0 - 320 Deg. C
10	SG2 inlet temperature	0 - 320 Deg. C
11	SG2 outlet temperature	0 - 320 Deg. C
12	SG3 inlet temperature	0 - 320 Deg. C
13	SG3 outlet temperature	0 - 320 Deg. C
14	SG4 inlet temperature	0 - 320 Deg. C
15	SG4 outlet temperature	0 - 320 Deg. C
16	Diff temperature across SG1 CH - E	0 - 55 Deg. C
17	Diff temperature across SG2 CH - E	0 - 55 Deg. C
18	Diff temperature across SG3 CH - A/D	0 - 55 Deg. C
19	Diff temperature across SG4 CH - A/D	0 - 55 Deg. C
20	Steam flow from BO1	0 - 375000 kg/Hr
21	Steam flow from BO2	0 - 375000 kg/Hr
22	Steam flow from BO3	0 - 375000 kg/Hr
23	Steam flow from BO4	0 - 375000 kg/Hr
24	Selected channel N - 13 inlet temp	0 - 300 Deg. C
25	Selected channel N - 13 outlet temp	0 - 300 Deg. C
26	Selected channel H - 18 inlet temp	0 - 300 Deg. C
27	Selected channel H - 18 outlet temp	0 - 300 Deg. C
28	Channel flow south N - 13 CH - D	0 - 51100 kg/Hr
29	Channel flow south H - 18 CH - E	0 - 45200 kg/Hr
30	RB pump room pressure (WR)	0.1 - 5 kg/sq. cm g
31	PHT pump room air temperature	0 - 100 Deg. C
32	D_2O level in 3335 - TK1 CH - G	0 - 168 cm
33	H_2O level in 3335 - TK3A & 3B CH - G	0 - 3852 mmWC
34	PSS linear N CH - D	0 - 150 %FP
35	PSS log rate CH - D	- 20 - 20 %/sec
36	PHT pump room air temperature	High (Digital)
37	PSS log rate CH - D	Trip (Digital)

In order to illustrate the developed methodology, large break LOCA in RIH with ECCS is selected. The break sizes considered for this event are 20%, 60%, 75%, 100%, 120%, 160% and 200% of double ended break in RIH. In addition to these break cases, normal operating condition of the reactor is simulated. A 60 seconds transient duration is considered under the assumption that this time duration is sufficient to identify a large break LOCA scenario [5]. To accomplish this task, a neural network consisting of 37 input neurons and 3 output neurons has been selected. A 3-neuron output pattern represents as follows: the first parameter of the output represents the size of the break (percent of cross-sectional area of RIH), second parameter representing the location of the break (i.e., 0 for RIH and 1 for ROH) and the last parameter representing the status of ECCS (i.e., 0 for without the availability of ECCS and 1 for with the availability of ECCS). Table 2 shows the representation of output neurons for 20% break case. A similar representation is followed for remaining break scenarios. The total number of break scenarios is 32 and they are derived as follows; the break sizes are 20%, 40%, 60%, 75%, 100%, 120%, 160% and 200%, each one being in RIH and ROH, and again with and without ECCS thus leading to a total of 32 large break LOCA scenarios. In addition, the normal reactor state is also modelled in the same network.

Table 2: Output representation

Output pattern	Description
20.0, 0.0, 0.0	20% break in RIH with ECCS
20.0, 0.0, 1.0	20% break in RIH without ECCS
20.0, 1.0, 0.0	20% break in ROH with ECCS
20.0, 1.0, 1.0	20% break in ROH without ECCS

As discussed earlier, the transient data was generated using RELAP5 and other thermal-hydraulic codes. The number of hidden layers and neurons in each layer were selected based on the following study [11]. First order resilient back propagation with batch mode of training was used. Unipolar sigmoid activation function and sum squared error function were used. The network consisting of 37 input neurons, 3 output neurons, 26 neurons in first and 19 neurons in second hidden layers. The number of neurons in the hidden layers was selected by carrying out a parametric study and choosing the configuration with the minimum error [11]. Training of ANN was carried out on a typical Pentium IV processor with 1.5GHz and 512MB of RAM. The total CPU time the simulator took was approximately 24Hrs to converge to a minimum error of 1.42E-02 in about 76000 epochs.

RESULTS AND DISCUSSION

Table 3 shows the testing results obtained from neural network model. The value of each of the second and third parameters of the output can be either 0 or 1. However, in a floating point arithmetic calculation with the ANN they can assume values other than 0 or 1. For these parameters, calculated values less than 0.5 are regarded as 0 and those above 0.5 are regarded as 1. For example, in Table-3, the calculated values of (122.64, 1.0031, -0.0608) in the third case under 120% break will be regarded as (122.64, 1.0, 0) which is very close to the desired output.

Table 3: Testing results of ANN

Break size (%)	Desired output			Calculated output			RMS error (%)
0	0.0	0.0	0.0	0.2322	-0.0033	-0.1249	0.1523
20	20.0	0.0	0.0	20.95	-0.00497	0.3597	2.34
	20.0	0.0	1.0	19.90	0.0025	0.6459	2.365
	20.0	1.0	0.0	17.21	1.0022	0.0759	3.087
	20.0	1.0	1.0	22.289	0.997	0.995	3.002
60	60.0	0.0	0.0	61.68	-0.00012	0.148	2.912
	60.0	0.0	1.0	59.73	-0.00077	0.8665	3.358
	60.0	1.0	0.0	59.276	0.998	0.0038	2.712
	60.0	1.0	1.0	56.70	0.999	0.983	3.105
100	100.0	0.0	0.0	103.37	0.0012	0.1397	3.64
	100.0	0.0	1.0	104.23	-0.0032	0.8558	4.107
	100.0	1.0	0.0	101.37	1.0028	-0.0589	2.907
	100.0	1.0	1.0	101.086	1.00	1.0275	3.974
120	120.0	0.0	0.0	120.17	0.0016	0.1134	3.56
	120.0	0.0	1.0	119.39	-0.00048	0.8451	4.422
	120.0	1.0	0.0	122.64	1.0031	-0.0608	2.971
	120.0	1.0	1.0	122.208	0.997	1.043	4.258
200	200.0	0.0	0.0	197.98	0.00033	0.00212	4.856
	200.0	0.0	1.0	193.49	-0.00066	0.97	4.84
	200.0	1.0	0.0	194.87	0.998	-0.0512	5.733
	200.0	1.0	1.0	194.015	1.00	1.059	5.438

Few case studies were carried out with the transients of some selected event scenarios which were not used for training and testing of the ANN. Table 4 shows the predicted results for these scenarios.

Table 4: Predicted results from a trained network

Break area (%)	Desired output			Predicted output		
40	40.0	0.0	0.0	38.29	0.017	0.15
	40.0	1.0	0.0	38.75	0.99	0.8008
	40.0	1.0	1.0	36.84	0.998	0.878
50	50.0	0.0	0.0	49.27	0.129	0.044
75	75	0.0	0.0	79.85	0.00215	0.169
	75	0.0	1.0	77.016	-0.0042	0.862
	75	1.0	0.0	74.014	0.995	-0.064
	75	1.0	1.0	71.58	0.995	0.985
160	160.0	0.0	0.0	158.66	-0.00014	0.040
	160.0	0.0	1.0	158.006	0.00216	0.7765
	160.0	1.0	0.0	163.6	1.003	-0.027
	160.0	1.0	1.0	164.38	0.996	1.047

Figure 5 shows the plot of desired verses calculated breaks obtained from a trained network. It can be seen from Figure 5 that the predicted breaks are in good agreement.

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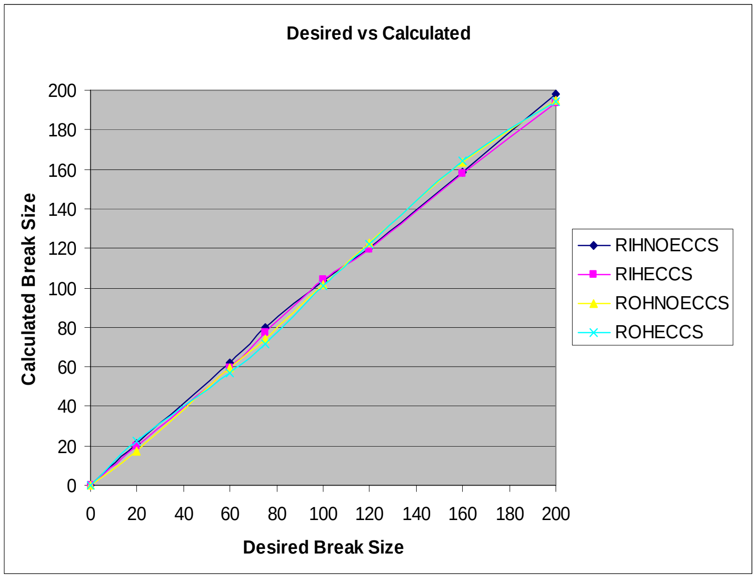

Fig. 5: Desired verses calculated breaks

Figure 6 shows a typical snapshot for the identified transient along with the important process parameters and their current process values. The reactor status, type of LOCA scenario is displayed at the top of the screen. The detected break size, location and availability of ECCS are displayed at the bottom of the screen. Operator actions, whenever an event is identified, will be displayed on the operator screen for the identified transient. The most relevant parameters are highlighted when they cross certain set limits.

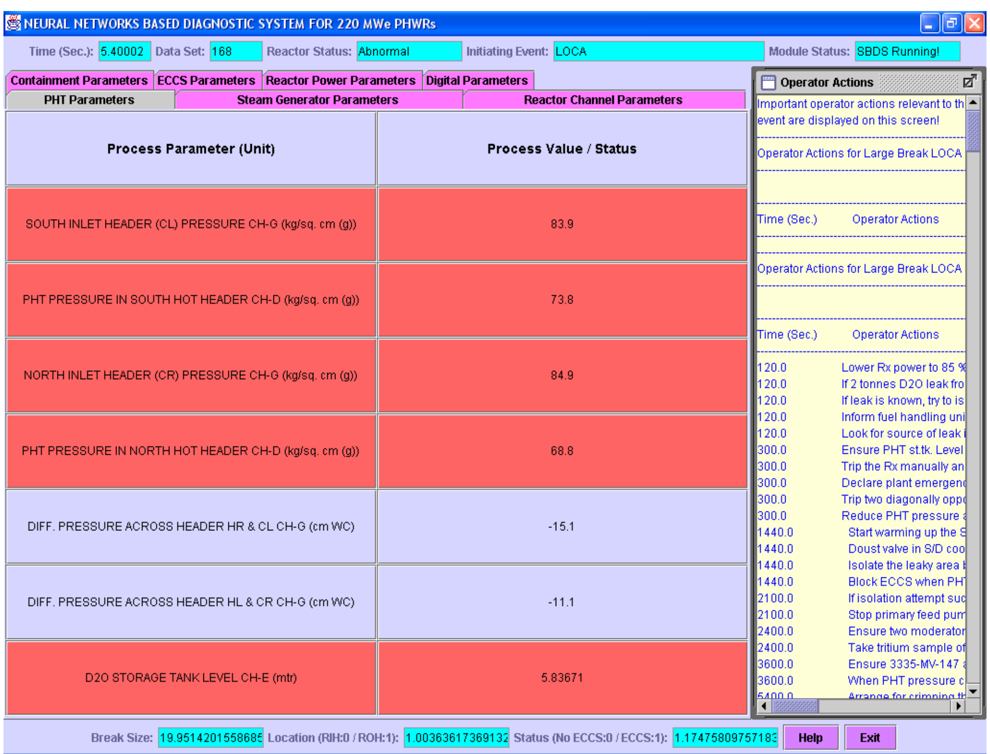

Fig. 9: Window showing the identified scenario and relevant process parameters

CONCLUSIONS

In this study, several scenarios of large break LOCA with and without the availability of ECCS have been modeled using artificial neural networks. The LOCA in RIH with ECCS, RIH without ECCS, and ROH with and without ECCS scenarios have been analyzed. The break sizes ranging from 20% to 200% in reactor headers are considered. A few break sizes were predicted without being trained earlier. The errors in the test results obtained from ANN are quite small. The error in prediction in ranges with sparse data for training is somewhat higher. However, this can be corrected by training with a larger data set. The proposed system would be useful in accident management.

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