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Proposed Neural Network Approach for Monitoring Plant Status in Korean Next Generation Reactors

P.V. Varde, Hur Seop, D.Y. Lee, B.S. Moon, and J.B. Han

Korea Atomic Energy Research Institute

P.O. Box 105, Taeduk Science Town, Daejeon 305-600, Korea

Email:Varde_pv@yahoo.com

Fax:+82-42-868-8916

Abstract

This paper reports the development work carried out in respect of a proposed application of Neural Network approach for the Korean Next generation Reactor (KNGR) now referred as APR-1400. The emphasis is on establishing the methodology and the approach to be adopted towards realizing this application in the next generation reactors. Keeping in view the advantages and limitation of Artificial Neural Network Approach, the role of ANN has been limited to plant status or to be more precise plant transient monitoring. The simulation work carried out so far and the results obtained shows that artificial neural network approach caters to the requirements of plant status monitoring and qualifies to be incorporated as a part of proposed operator support systems of the referenced nuclear power plant.

Key Words : Artificial Neural Network, Next Generation Nuclear Plants, Plant Status Monitoring, Reactor Operations, Transient Simulation.

1. Introduction

The application of artificial neural network (ANN) or more commonly referred as the Neural Network (NN) to the operation of nuclear power plants has become a favorite subject for the researcher world over. This is due to the advantages offered by this approach for the problems, which, earlier seemed intricate in nature and could have been difficult to solve using mathematical methods or heuristic logics. It is evident from the available literature that neural networks are increasingly being applied to nuclear power plant operations [1]. Various applications of NN in nuclear power plant include, plant wide monitoring, measurement of operational parameters, signal validation, diagnosis of normal conditions, modeling plant thermodynamics, to increase efficiency, fuel loading pattern optimization, reactivity surveillance, classification and prediction of critical heat flux, etc.. Although the available literature in the area of application of NN approach to NPP operations shows that this approach is being efficiently used to solve many problems, however, the degree of success, in terms of real-time application of this method and the limitations it poses are not clearly reported. This is due to the fact that the information involved in this approach is complex and less understood. For instance, there is no well defined rule for incorporating the number of nodes in the hidden layer. There are some literature which observes that the number of nodes in the hidden layer should be around three times the number of nodes in the input layer [2]. However, this observation could, at the best, be considered applicable to the specific problem under study and could not be used as a guiding generalized factor in designing the neural network. Similarly, it is argued that the input values should be normalized between 0.1 and 0.9 instead of 0 and 1. This is done to the ensure linear scaling of input values and alleviate saturation problem associated problem with the sigmoidal function. However, the availability of fast processing speed using the advanced computers hardly poses any problem if the input variables are assigned the values between 0 and 1 including '0' and '1'. This argument has been demonstrated in this paper. Then there is this issue of 'how much' training could be considered enough to make the neural network to be called as robust. An attempt has been made to discuss the issues mentioned above in the succeeding sections in this paper. If the selected patterns are assumed to be representative of the actual plant scenario than the developmental work presented in this paper and the earlier work done by the author [3] qualifies to be a benchmark simulation exercise on plant status monitoring for nuclear power plants.

The section 2, discusses the basic concept associated with the ANN modeling for plant status monitoring. Section 3 presents the modeling procedure adopted for plant status monitoring and architecture of the network. The methodology used for training of the network has been discussed in section 4. The results of the simulations, including the recall tests performed have been presented in section 5 and finally the conclusions of this study are given in section 6.

2. ANN Model

The earlier work carried out on transient identification [3] and the subsequent survey of literature on similar problems has amply demonstrated that the application of feed forward multilayer ANN comprising of one input layer, one hidden layer and one output layer forms effective architecture for reactor status monitoring type of problems. The input nodes which receive the signals from the plant are connected through the hidden nodes to the output nodes, which finally gives the ANN output. The input layer consists of a set of variables (x_1, x_2, x_3, ...x_n) and the output layer consists of set of activation values (o_1, o_2, o_3, ...o_n). If the target output is to predict only one variable as a function of the variables x_i's, then the output is a single variable o. The relationship between these associations can be represented as follows[4]:

$$o = C_o + \sum_{i=1}^{n} C_i \phi_i (x_1, x_2, x_3, ..., x_n) \quad (1)$$

where, Φ are nonlinear polynomial functions. Instead of modeling an explicit functional form the ANN relates o_i with x_i using a network of connection weights between pairs of nodes of adjacent layers. The node in the ANN sums the product of the products of the input and connection weights from the nodes of the previous layer and then limits it by a nonlinear threshold function. The weighed sum of the inputs for the j^{th} node in a layer k is given by

$$net_j = \sum_i w_{ij}^k x_i^{(k-1)} + b_j^{(k)} \quad (2)$$

where $w_{ij}^{(k)}$ is the connection weight between the i^{th} node in the k-1 layer and j^{th} node in the k layer, $x_i^{(k-1)}$ is the output from the i^{th} node in the *k-1* layer, and $b_j^{(k)}$ is the bias associated with the j^{th} node of layer k and it produces the effect similar to adjusting the threshold function of the processing node.

For calculating the output of a node, the weighed sum of the inputs available from equation (2) is processed using an activation threshold function. There are many functions available for this purpose. However, depending on the nature of problem these functions are applied in the ANN. The sigmoid function is widely used as an activation function. For this problem the sigmoid function can be represented as follows:

$$x_j^{(k)} = \frac{1}{1 + \exp(-net_j^{(k)})} \quad (3)$$

Apart from Sigmoid function two more activation functions were used for the problem under study. These functions are 'Tansigmoid' and a linear function called 'Pureline'[5]. The use of these functions in the design of this network has been discussed in the succeeding section of this paper.

3. Plant Status Monitoring and ANN Architecture

The underlining principle used for the reactor status monitoring is that each reactor state can be associated using a 'unique pattern' of the plant symptoms. These symptoms include the reactor pre-trip, trip and analogue instrument readings of various plant parameters available in the control room of the plant. Whenever, a plant transient occurs the affected input signals coming to the control room of the plant changes its state and form a pattern which can be used as an indicator of the stabilized state of the plant.

Accordingly, the signals required for identifying various reactor states were identified. Table 1 gives the list of the signals available in the plant control room of KNGR. It may be noted that the value of various parameters are indicated in the table can be considered as the typical values used for this simulation and need not be assumed as the final value used for implementation in the design of Instrument & Control System of the plant.

Table 1 Reactor Trip Parameters

Parameter (Unit)	Nominal Full Power	Trip Setting
Variable Overpower (%)	100	125
Hi Log-rate (%)	0	6
Hi LPD (kw/ft)	< 14	20
Lo DNBR	1.79	> 1.2
Hi Pressurize Pr. (psia)	2250	2425
Lo Pressurize Pr. (psia)	2250	1750
Lo SG Water level (%)	82	45
Lo SG Pr. (psia)	1070	870
Hi Cont. Pr. (psia)	0 - 5	14*
Hi SG Water level (%)	82	94
Lo Reactor Coolant flow (%)	80	*60

Legends : Hi: High, DNBR: Departure from Nucleate Boiling Ratio; LPD: Local Power Density; SG: Steam Generator; Pr.: Pressure. * Assumed value

Table 2: Input vector / pattern parameters

No.	Code	Symptom description
1	PT-1	SG 1 low pressure
2	PT-2	SG 2 low pressure
3	PT-3	Containment pressure high
4	PT-4	SG 1 Low level
5	PT-5	SG 2 Low level
6	PT-6	SG 1 differential pressure low
7	PT-7	SG 2 differential pressure low
8	PT-8	SG 1 level high

9	PT-9	SG 2 level high
10	PT-10	Pressurizer pressure low
11	PT-11	Pressurizer pressure high
12	PT-12	Log rate high
13	PT-13	DNBR low
14	PT-14	Local Power Density high
15	PT-15	Variable over power
16	PT-16	Containment pressure v. high
17	T-17	SG 1 low pressure
18	T-18	SG 2 low pressure
19	T-19	Containment pressure high
20	T-20	SG 1 Low level
21	T-21	SG 2 Low level
22	T-22	SG 1 differential pressure low
23	T-23	SG 2 differential pressure low
24	T-24	SG 1 level high
25	T-25	SG 2 level high
26	T-26	Pressurizer pressure low
27	T-27	Pressurizer pressure high
28	T-28	Log rate high
29	T-29	DNBR low
30	T-30	Local Power Density high
31	T-31	Variable over power
32	T-32	Containment pressure v. high
33	R-33	SG 1 low pressure
34	R-34	SG 2 low pressure
35	R-35	Containment pressure high
36	R-36	SG 1 Low level
37	R-37	SG 2 Low level
38	R-38	SG 1 differential pressure low
39	R-39	SG 2 differential pressure low
40	R-40	SG 1 level high
41	R-41	SG 2 level high
42	R-42	Pressurizer pressure low
43	R-43	Pressurizer pressure high
44	R-44	Log rate high
45	R-45	DNBR low
46	R-46	Local Power Density high
47	R-47	Variable over power
48	R-48	Containment pressure v. high

Legends: PT: Pre-trip, T: Trip, R: Instrument Readings

Using these parameter trip settings and the instrument range (which was assumed in this experiment as the data on precise range of instrument is not available at this stage) for the corresponding parameter the values were normalized between zero and 1. Say for instance the range of the instrument used for monitoring the pressurizer pressure is 0 to 3000 psia, then the value of trip setting of 1700 becomes 0.7 as the normalized value of the above parameter. These normalized values were used in assigning the value of instrument reading for pattern formulation.

The parameter listed in the above table was used to generate the pattern. One pattern composed of 13 each reactor pre-trips, trips and analog readings. It may be noted that the digital reactor protection systems in KNGRs have been designed using four redundant channel and follows 2/4 coincidence logic for enhanced safety reliability and availability. However, this study being demonstration exercise we have used inputs from Channel A only. The reason for the same is that in the real-time ANN model of the plant the 2-out-of-four processing will be done by a model called preprocessor module. In this module apart from the 2/4 processing, the normalization of the analog parameter will also be performed. Once the processing of the input data is over the data will be supplied to the ANN. In retrospect, the

same ANN configuration may be utilized for the future real-time application in KNGRs. Table 2 shows the list of input symptoms that forms a skeleton of one vector / pattern for ANN.

Actually, the design manual and the associated matrix table lists 24 reactor states to be identified using the above symptoms.

Table 3: Nomenclature of the reactor states

Transient No.	Transient Description
TR-1	Reactor Operation Normal
TR-2	Feedwater Temp. decrease
TR-3	Feedwater flow increase
TR-4	ISOGADV
TR-5	Turbine trip
TR-6	Loss of condenser vacuum
TR-7	Loss of feedwater flow
TR-8	Loss of RC flow / 1 RCP seizer
TR-9	RCP shaft break
TR-10	Uncontrolled CEA withdrawal at low power
TR-11	Inadvertent de-boration
TR-12	CEA ejection
TR-13	LOCA

Legend: ISOGADV: Inadvertent operation of steam generator atmospheric dump valve, CEA: Control Element Assembly, LOCA Loss of coolant accident.

Table 4: Input pattern for ANN training

Transient No. → Symptoms ↓	TR-1	TR-2	TR-3	TR-4	TR-5	TR-6	TR-7	TR-8	TR-9	TR-10	TR-11	TR-12	TR-13
PT-1	0	1	0	1	0	0	0	0	0	0	0	0	0
PT-2	0	1	0	1	0	0	0	0	0	0	0	0	0
PT-3	0	0	0	0	0	0	0	0	0	0	0	0	0
PT-4	0	0	0	0	0	0	1	0	0	0	0	0	0
PT-5	0	0	0	0	0	0	1	0	0	0	0	0	0
PT-6	0	0	0	0	0	0	0	0	1	0	0	0	0
PT-7	0	0	0	0	0	0	0	0	1	0	0	0	0
PT-8	0	0	0	0	0	1	0	0	0	0	0	0	0
PT-9	0	0	1	0	0	1	0	0	0	0	0	0	0
PT-10	0	0	1	0	0	0	0	0	0	0	0	0	1
PT-11	0	0	0	0	1	0	1	0	0	1	1	0	0
PT-12	0	0	0	0	0	0	0	0	0	0	1	0	0
PT-13	0	0	1	1	0	0	0	1	0	1	1	0	1
PT-14	0	0	1	0	0	0	0	0	0	1	1	0	0
PT-15	0	0	0	0	0	0	0	0	0	0	1	1	0
PT-16	0	0	0	0	0	0	0	0	0	0	0	0	0
T-17	0	1	0	1	0	0	0	0	0	0	0	0	0
T-18	0	1	0	1	0	0	0	0	0	0	0	0	0
T-19	0	0	0	0	0	0	0	0	0	0	0	0	0
T-20	0	0	0	0	0	0	1	0	0	0	0	0	0
T-21	0	0	0	0	0	0	1	0	0	0	0	0	0
T-22	0	0	0	0	0	0	0	0	1	0	0	0	0
T-23	0	0	0	0	0	0	0	0	1	0	0	0	0
T-24	0	0	1	0	0	1	0	0	0	0	0	0	0
T-25	0	0	1	0	0	1	0	0	0	0	0	0	0
T-26	0	0	0	0	0	0	0	0	0	0	0	0	1
T-27	0	0	0	0	1	0	1	0	0	1	1	0	0
T-28	0	0	0	0	0	0	0	0	0	0	1	0	0
T-29	0	0	0	1	0	0	0	1	0	1	1	0	1
T-30	0	0	1	0	0	0	0	0	0	1	1	0	0
T-31	0	0	0	0	0	0	0	0	0	0	1	1	0
T-32	0	0	0	0	0	0	0	0	0	0	0	0	0
R-33	.7	.6	.7	.6	.7	.7	.7	.7	.7	.7	.7	.7	.7
R-34	.7	.6	.7	.6	.7	.7	.7	.7	.7	.7	.7	.7	.7
R-35	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12	.12
R-36	.82	.82	.82	.82	.82	.82	.45	.82	.82	.82	.82	.82	.82
R-37	.82	.82	.82	.82	.82	.82	.45	.82	.82	.82	.82	.82	.82
R-38	.7	.7	.7	.7	.7	.7	.7	.7	.4	.7	.7	.7	.7
R-39	.7	.7	.7	.7	.7	.7	.7	.7	.4	.7	.7	.7	.7
R-40	.82	.82	.94	.82	.82	.94	.82	.82	.82	.82	.82	.82	.82
R-41	.82	.82	.94	.82	.82	.94	.82	.82	.82	.82	.82	.82	.82
R-42	.75	.75	.75	.75	.75	.75	.75	.75	.75	.75	.75	.75	.57
R-43	.75	.75	.75	.75	.8	.8	.8	.75	.75	.8	.8	.75	.75
R-44	0	0	0	0	0	0	0	0	0	0	.3	0	0
R-45	.9	.9	.6	.6	.9	.9	.9	.6	.9	.6	.6	.9	.6
R-46	.3	.3	.42	.3	.3	.3	.3	.3	.3	.42	.42	.3	.3
R-47	.5	.5	.5	.5	.5	.5	.5	.5	.5	.5	.62	.62	.5
R-48	.13	.13	.13	.13	.13	.13	.13	.13	.13	.13	.13	.13	.13

However, for ANN training only 13 reactor states have used as for the remaining 9 reactor states the designers are either yet to finalize the extra parameters or the analog instrument readings such that these transients also form a unique patterns to enable its identification. The list of the 13 reactor states for which the ANN was trained has been shown in Table 3.

Though the plant is at advanced stage, there were some areas where the required information was not enough to finalize the ANN modeling requirements. Hence, some assumptions were made. It was ensured that these assumptions in no way compromised the capability of the future real-time ANN. These assumptions were as follows:

a) While formulating the patterns it was assumed that all the trip parameters will have corresponding pre-trips and for each trip parameter there will be analog instrumentation available in control room of the reactor.

b) Pre-trip setting was assumed to be 10% lower /higher than the corresponding trip setting.

c) During the normalization process it was observed that some parameters instead of having fixed nominal value, vary between a range of values. For such parameter the mean value of the indicated range was considered as the value of the node for normal operation.

d) Only Channel A parameters and trips considered for this study. It was assumed that the pre-processor module will handle 2-out-of-4 logic and normalization of the trips / variables. This has helped to reduce the size of the ANN. One could expect ANN to be more robust with pre-processor module installed.

Considering the above the final matrix table was prepared for 13 reactor conditions. Table 4 shows the patterns / vector formulated for ANN training.

For identifying these transients various options were worked out. The selection of the option had a bearing on the design of the neural network. The two modes which

Table 5: Reactor transient identification matrix

TR-1	1	0	0	0	0	0	0	0	0	0	0	0	0
TR-2	0	1	0	0	0	0	0	0	0	0	0	0	0
TR-3	0	0	1	0	0	0	0	0	0	0	0	0	0
TR-4	0	0	0	1	0	0	0	0	0	0	0	0	0
TR-5	0	0	0	0	1	0	0	0	0	0	0	0	0
TR-6	0	0	0	0	0	1	0	0	0	0	0	0	0
TR-7	0	0	0	0	0	0	1	0	0	0	0	0	0
TR-8	0	0	0	0	0	0	0	1	0	0	0	0	0
TR-9	0	0	0	0	0	0	0	0	1	0	0	0	0
TR-10	0	0	0	0	0	0	0	0	0	1	0	0	0
TR-11	0	0	0	0	0	0	0	0	0	0	1	0	0
TR-12	0	0	0	0	0	0	0	0	0	0	0	1	0
TR-13	0	0	0	0	0	0	0	0	0	0	0	0	1

were found to suit the requirements of transient identification was a) Identify the transients by their respective numbers and b) Use a 13×13 matrix for identifying these transients. Both the options were studied while designing the network. Only one node was required at the output layer if the transients were to be identified using its respective number. However, the results were found to be not very encouraging with this mode. No definite reason could be attributed for non-convergence of the error when option 1 was used. However, the use of 13×13 matrix was found to be working well. This choice necessitated to have network with 13 nodes at the output layer. Accordingly, a 13×13 matrix was used for ANN training with '1' placed diagonally in the matrix making a unique array of for each transient as shown in Table 5. A multilayer feed forward network architecture was selected with three layers: one each for input layer, hidden layer and output layer. Based on the requirements of reactor status monitoring it had 49 (48 nodes for plant signal and 1 bias node) nodes in the input layer and arbitrarily ~ 80 nodes in the hidden layer and 13 nodes in the output layer. Fig. 1 shows the ANN model implemented for plant status monitoring.

4. Network Training

The Backpropagataion network (BPN) algorithm was considered appropriate for implementation of training scheme for the network. Initial assignment of the weights was random in the range +0.1 to -0.1. The BPN algorithm attempts to minimize the overall mean square error (MSE) between the desired and the actual output for all the output nodes over all the input patterns by iteratively adjusting the weights. The training was carried out in batch mode in using the Neural Network Toolbox in MATLAB environment. The objective here was to select the network parameters, the training rate, momentum coefficient and number of nodes in the hidden layer such that it allows the convergence of the network to achieve a target MSE value of 1E-5. This required a parametric study to be performed using the above said parameters and the network does not get stuck in the local minima. Apart from this the other and rather secondary objective was to arrive at a network configuration such that the convergence of MSE is achieved in optimum number o epochs. As part of parametric study, repeated trials were made with the activation functions, viz, 'sigmoid', 'tansigmoid' and the linear function 'pureline', in the three layers of the network. These functions are available in the MATLAB library.

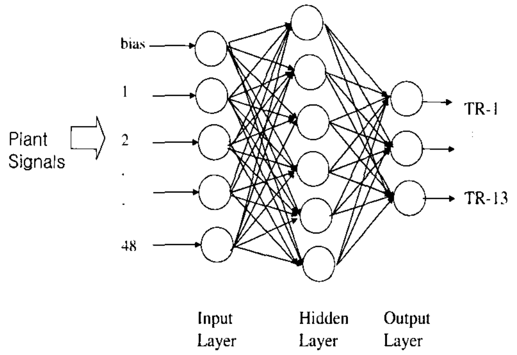

Fig. 1: ANN Architecture for reactor status Monitoring

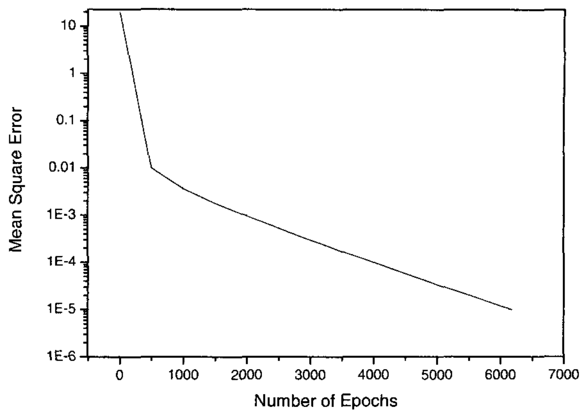

Fig. 2: Convergence of error during training of Network

Table 6 Final parameter of Network

Parameter description	Value
Number of layer	3
Number of nodes in input layer	49
Number of node in hidden layer	100
Number of nodes in output layer	13
Training rate	0.2
Number of epoch required for training	6248
CPU Time required for training (min)	12
Error target	1e-5
Activation function - input layer	Sigmoid
Activation function – hidden layer	tansig
Activation function – output layer	pureline

It may be noted that successful convergence could be achieved only after arriving with the configuration as shown in Table 6, i.e. sigmoid, tansig and pureline transfer function in the input, hidden and output layer, respectively. The convergence of MSE during the training of the network could be achieved in 6248 iterations or epochs as shown in Fig. 2.

5. Testing of Network by Simulating near real-time scenarios

Having completed training of the network successfully, the next phase was to perform the recall tests on the network to demonstrate the feasibility of ANN methodology for the target application.

The testing of the network was carried out by simulating the plant conditions based on the monitoring and diagnostic requirements of the plant as follows:

5.1 Learned patterns

The first requirements which comes from the plant is that the network should be capable of identifying all the pre-defined scenarios for which the Emergency Operating Procedure exists. To cater to this requirements the recall tests were performed on the trained network. Table 7 shows the result of the this test. By having a look at the values, which are ~ 1.0 (while the other values are ~ 0.0), on the diagonal elements of the matrix, one can be sure that network has capability to identify the scenarios with required accuracy.

5.2 Unlearned patterns

These patterns were based on the real-time operational experience of the plants. The objective was to check the network behavior for i) situation which the network had not encountered earlier and b) the anticipated plant conditions for which network behavior is expected to be on the well defined lines. Accordingly, four simulation tests were performed as follows:

5.2.1 Sensor failed data

This test was performed using 3rd transient namely 'feedwater flow increase'. To simulate the sensor failure data the 29th node was modified by changing the original value of from 1 to 0. The result of the simulation test as shown in Table 8, demonstrates that the ANN was able to identify the transient number 3 in spite of the fact the information was incomplete.

5.2.2 Noisy data

Often it has been seen during reactor operations that noisy data makes it difficult for the operator to arrive at certain conclusions. The background signal suppresses the original signal or the background noise makes the signal to register for

Table 7: Recall test results with learned patterns

Reactor Transient	Recall vectors												
TR-1	0.9905	0.0045	0.0012	-0.0052	0.0054	-0.0002	-0.0009	0.0064	0.0003	-0.0023	0.0002	0.0016	-0.0019
TR-2	0.0151	0.9950	-0.0005	0.0067	-0.0060	-0.0008	0.0011	-0.0109	-0.0017	0.0024	-0.0005	-0.0019	0.0022
TR-3	-0.0040	-0.0013	0.9991	-0.0003	0.0019	0.0007	-0.0006	0.0027	0.0008	-0.0001	0.0002	0.0015	-0.0005
TR-4	0.0034	0.0022	0.0000	0.9983	-0.0045	-0.0002	0.0004	0.0031	-0.0008	-0.0006	0.0009	-0.0021	-0.0000
TR-5	0.0105	-0.0018	-0.0007	0.0028	0.9946	-0.0000	0.0008	- 0.0055	-0.0009	0.0017	0.0003	-0.0034	0.0014
TR-6	0.0045	-0.0018	-0.0002	0.0022	-0.0020	0.9996	0.0003	-0.0041	0.0001	0.0013	0.0001	-0.0005	0.0004
TR-7	-0.0032	0.0010	-0.0004	-0.0025	0.0012	0.0001	0.9998	-0.0042	0.0004	-0.0007	0.0005	0.0009	-0.0013
TR-8	-0.0025	0.0001	-0.0009	-0.0013	0.0019	0.0007	-0.0003	1.0030	0.0004	-0.0004	0.0002	-0.0006	-0.0001
TR-9	-0.0004	0.0006	-0.0001	-0.0005	0.0013	-0.0003	0.0001	0.0017	1.0000	-0.0006	0.0002	-0.0009	-0.0011
TR-10	-0.0078	0.0021	0.0005	-0.0031	0.0035	0.0005	-0.0009	0.0061	0.0009	0.9982	0.0000	0.0011	-0.0011
TR-11	-0.0087	0.0029	0.0007	-0.0032	0.0039	0.0000	-0.0007	0.0056	0.0004	-0.0005	0.9990	0.0019	-0.0013
TR-12	0.0090	-0.0048	-0.0002	0.0060	-0.0042	-0.0005	0.0007	-0.0085	-0.0010	0.0018	0.0005	0.9998	0.0016
TR-13	0.0053	-0.0029	-0.0014	0.0026	-0.0037	-0.0000	0.0008	-0.0024	-0.0001	0.0007	0.0001	-0.0003	1.0012

Table 8: Recall tests with unlearned patterns

Unlearned Pattern		Results of recall tests												
1 Sensor failure data		0.4208	0.0037	1.0681	0.0007	0.4414	-0.1605	-0.0640	-0.0142	0.1786	0.1467	0.2295	-0.2446	-0.0139
2 Data with noise		-0.0660	-0.0735	-0.0365	-0.0183	0.0205	0.1748	1.0673	0.0526	-0.0311	-0.0101	-0.0790	-0.0748	-0.0724
3. Calibration error (on unsafe side)		-0.2941	0.3420	-0.2678	0.7218	0.2567	0.6042	1.5249	-0.1631	-0.2706	0.3564	0.0095	-0.2391	-0.2438
4. Presence of single trip before the transient started	a)	-0.7859	-0.3746	0.1511	0.3841	0.0197	0.1578	-0.2967	-0.1488	-0.0532	0.7130	-0.1591	0.1024	0.6108
	b)	0.9727	0.0109	-0.7113	0.3306	0.1454	-0.0157	0.1873	-0.3526	0.2770	-0.0626	0.1202	-0.0069	0.9176

the condition when there is no activation. This may happen due to voltage pick-up or superimposition of other transient noise on the original signal. The pattern no 7 on 'loss of feedwater flow' was selected for this simulation. This condition was simulated by a) reducing the strength of the original signal. To achieve this the value of node 1 was modified from 0 to 0.1 (representative of voltage pickup) and the value of nodes 10, 19 and 20 were changed from 1 to 0.9 (to reflect reduction of signal strength due to background noise). As could be observed from the results given in Table 7, the network could successfully handle this situation and in spite of noisy data the transient 7 could be identified.

5.2.3 Calibration Error (on unsafe side)

This is a problem associated with process instrumentation or any analog type of systems. This condition results when the calibration of root instrumentation goes wrong or due to some drift problem the instrument reads more (for safe decreasing trend) and due to which the reading shown on the instrument is more than the actual reading. This causes the associated trip system to be ineffective. This test was performed using transient number 7. To simulate this condition the value of nodes 20 (SG 1 level low) a trip was modified from 1 to 0 and the value of node 36 (analog reading of SG 1 level) was changed from 0.45 to 0.55. In all the value of two nodes were changed in the original vector representing transient 7. The result shows that the value of 7^{th} node is 1.5249. A close look at the results for this transient shows that value of node no 7 stands out compared to other nodes. Hence, it can be concluded that this transient could be identified successfully by the network.

5.2.4 Presence of single trip before the transient sets in

The trips and alarm checks are performed in the control room by manually generating the trip in single channel. Now in case the transient occurs during the time when one trip parameter channel was remaining registered, this could be deviation from what the network has been trained. This condition was created by changing the value of node number 15 (variable overpower trip) from 0 to 1 in transient vector 4 on IOSGADV (Inadvertent Operation of Steam Generator Atmospheric Dump Valve). The natural language meaning of this change is that when this transient occurred that time the overpower trip was already 'in' in control room. It may be noted that the network failed to identify this scenario. To further investigate this problem this test was repeated on transient number 1. Here the node 1 was modified from 0 to 1. But the results were fuzzy. Though the transient number 1 was identified with reasonable accuracy, the transient no. 13 which represents LOCA condition was also identified though with less intensity than transient 1. However, the results are not acceptable. It may be noted that this type of scenario will not be encountered by the ANN as in real life the network will be fed after 2-out-of 4 processing in the pre-processor. Hence, this trip will get filtered out and what the network will see is the actual transient as it was modeled during the training.

6. Conclusions

An approach for modeling the plant transient and its identification using a three layer neural network has been proposed for the Korean Next Generation Plants. The recall tests performed demonstrate the feasibility of using this approach as part of operator support system for nuclear power plant. The testing carried out also brings out the limitation of this methodology. However, as discussed in the previous section these limitations do not, in any way, make this approach restrictive for its applications to plant operations. It can always be argued that more rigorous testing will go a long way in making network more robust. It is expected that as more data and information are available, the modeling of the transient would be more accurate which in turn enable training of the network more effective.

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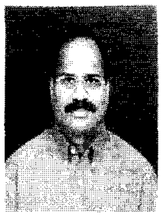


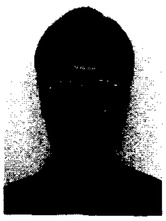
P.V. Varde

P.V. Varde received B.E. (Mech.) from the APS University, Rewa (India) in 1983 and Ph.D.(Engg.) from Indian Institute of Technology, Bombay, (India) in 1996. He is working with Bhabha Atomic Research Centre, Mumbai since 1983. He received best paper award in the International Conference on Quality Reliability & Controls held in the year 2001. His area of specialization includes Probabilistic Safety Assessment of Nuclear Research Reactor and Power Plants, Design of Expert Systems and Nuclear Plant Operation and Safety. He is presently working as RCA-Postdoctoral Fellow at Korea Atomic Energy Research Institute.

Address for correspondence:
Dr. P.V. Varde
Dhruva Complex, BARC,
Mumbai (India) – 400 085
Email : varde_pv@yahoo.com,
Phone : 91-22-2559 4689

Hur Seop

Hur Seop completed B.S. in the year 1988 and MS (physics) in the year 1990 from Sogang University of Korea. He joined Korea Atomic Research Institute in the year 1990 and presently he is working as a Senior Researcher here. His area of interests includes Signal processing, development of instrumentation sensors.



D.Y. Lee

He received the B.A. and M.S. degree in electrical engineering from Kyung-Pook National University, Korea, in 1984 and 1987, respectively. He is under the Ph.D. course in electrical engineering of Choong-Nam National University, Korea. He joined the Instrumentation and Control Department of Korea Atomic Energy Research Institute in 1987. His current research interests concern the reliability assessment of the instrumentation and control system, and the development of the operator support system in nuclear power plant.

B.S. Moon

B.S. Moon completed Ph.D. in Mathematics from University of Illinois, 1974. From 1974 – 1978 he worked with Sargent & Lundy Engineers (Chicago). Since 1978 he is working with Korea Atomic Energy Research Institute. His area of research interest are Fuzzy systems, Neural Networks. Phone : 042-868-2980,
Fax : 042-868-8916,
Email : bsmoon@kaeri.re.kr

J.B. Han

He completed B.S. from Yonsei University and M.S. in Electronics Engineering from Chungnam University in the year 1980 and 1996, respectively. From 1980 to 1996 he worked as Manager, Instrumentation & Control at Korea Atomic Energy Research Institute. In 1997 he took over as Director, Instrument & Control Division at Korea Electric Power Company. Presently he is the Director of the Instrumentation & Control / Human Factor Division at Korea Atomic Energy Research Institute