On-line Training of Neural Network for Monitoring Plant Transients

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Abstract

The work described in this paper deals with the proposed application of an Artificial Neural Network Model for the Advanced Pressurized Water Reactor APR-1400 transient identification. The approach adopted for testing the network take note of the expectation which should be fulfilled by a network for real-time application, like testing with data in on-line mode and use of actual or real-life patterns for training. The recall test performed demonstrates that use of neural network for transient identification is indeed an attractive preposition.

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

1. Introduction

Artificial Neural Networks (ANN) are finding wide acceptability in solving real life problem in all walks of life including nuclear power plants [1]. The recent developments in computer technology and improved understanding of neural network models have made all this possible. However, when it comes to real-time application the need of more and more data in time and spatial domain are required to simulate real-time scenario during the training of artificial neural network model to make the network more robust. Many application have been observed to have failed for the want of real-time simulating environment.

This paper reports the simulation work carried out for on-line application of an artificial neural network. The approach adopted comprised of i) Data collection from in the real-time mode from the plant, ii) Development of a simulator to facilitate plant transient, iii) Simulate the transient on one Server machine and iv) train / test the neural network on other client machine. This approach has been found to be very effective in training and subsequent testing of the network. The results obtained shows that this approach facilitate simulation of real-time scenario and hence reduces room for surprises for the subsequent implementation of the transient identification system in the control room of the plant. The emphasis is on establishing the methodology and the approach to be adopted towards realizing this application. 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 [2]. 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 APR-1400.

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, 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. Similarly, it is argued that the input

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values should be normalized between 0.1 and 0.9 instead of 0 and 1. 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'. In this paper an attempt has been made to touch upon these issues

The section 2, discusses the basic concept associated with the ANN modeling for plant status monitoring. Section 3 presents the procedure adopted for plant status monitoring. The methodology used for training of the network has been discussed in section 4. The simulation modeling 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 neural network model selected keeping in view the requirements of transient identification is shown in Fig. 1. There are 49 nodes to process the signal coming from the plant in the input layer and 13 nodes to identify 13 transients. The number of nodes in the hidden nodes have been selected after carrying out a parametric study such that efficient convergence is achieved.

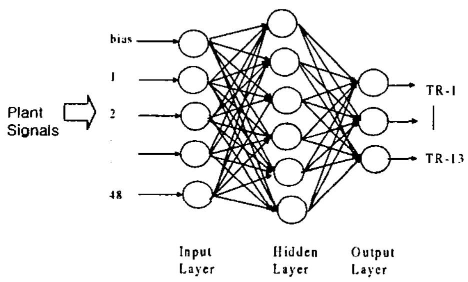

Fig. 1 ANN model for transient identification

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 jth node in a layer k is given by

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

where $w_{ij}^{(k)}$ is the connection weight between the ith node in the k-1 layer and jth 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 jth 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 (1) 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:

$$x_j^{(k)} = \frac{1}{1+\exp(-net_j^{(k)})} \qquad (2)$$

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'[3]. The use of these functions in the design of this network has been discussed in the succeeding section of this paper.

3. Plant Transient Monitoring

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.

Table 1: Nomenclature of the reactor states

Tran. 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.

The list of the 13 reactor states for which the ANN was trained has been shown in Table 1. Considering the above the final matrix table was prepared for 13 reactor conditions and the patterns / vector formulated for ANN training.

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 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.

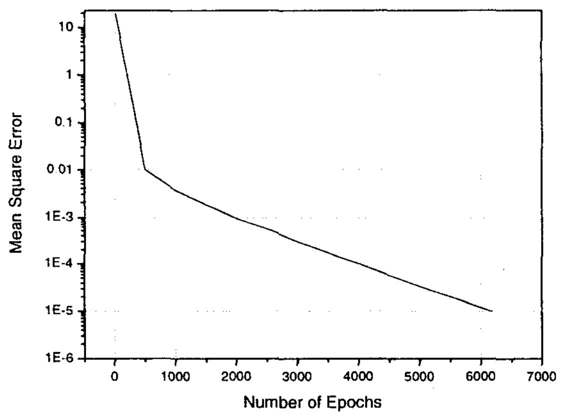

Fig. 2: Convergence of error during training of Network

Table 2: 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 2, 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. Network Simulation tests

The tests were carried out using a simulator specially developed for simulating plant transient scenario in time and spatial domain. The network was trained using patterns comprising of stabilized values varying between 0 and 1 at the end of the transient at each node in the input layer. Here, it could be argued that all the signals in a pattern were registering at a fixed time. But in actual scenario during a transient the signals keep coming for a finite duration and we get the stabilized pattern (for which the network was trained) only at the end of the transient. To bridge this gape the signals in a pattern were fired in time domain as it happens during an actual transient. Please see fig. 3 for better understanding of the process of simulation. Please note that only part of pattern (only 15 nodes out of 49 has been shown due to space limitation). On right side part of the pattern used for training has been shown. The plant signals registers in time domain, for instance the 12^{th} signal from the pattern registers first at the onset of the transient again the signal 2 registers during second epoch in time and at the end of

the transient all signals as given in the trained patterns registers. The variation of mean square error with time has been shown in figure 4 for this transient. As could be seen the transient could be identified with an error value of $\sim 10^{-5}$.

Signal sampling → epochs / Plant sensor signals	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Pattern used for training
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	.7	0	0	0	0	0	0	0	0	0	0	0	.8
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

T= 0.0 (Transient start) Time → (Transient end) T=t

Fig. 3: Depiction of real-time scenario for transient identification

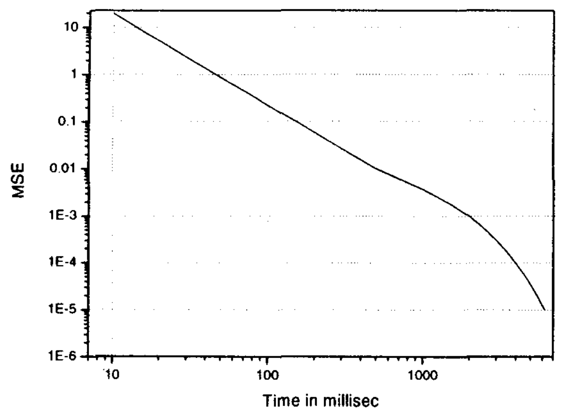

Fig 4: convergence of error with time during transient simulation

Other aspects of the real-time scenario that the network apart from learned patterns may encounter unlearned patterns. These simulations were carried out 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 these requirements the recall tests were performed on the trained network. As expected the network could identify all the transients with the MSE ~ 10^{-5}. Hence, it could be claimed that the network does a perfect job for the scenario for which it was trained.

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, 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 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). 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 7th 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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