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Neural Network Model for an Event Detection System in Prototype Fast Breeder Reactor

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***Abstract:** System failures are identified and quantified by modeling artificial intelligent systems using the required process parameters that cause the failure. In this paper, an artificial neural network (ANN) model has been implemented for detection of various events in Prototype Fast Breeder Reactor (PFBR). Using the conventional, in-house developed thermal-hydraulics model of PFBR operator training simulator, input data has been generated to train the ANN model for various events associated with PFBR subsystems. The subsystems considered here are Primary Sodium Circuit and Neutronics system of PFBR. Operators have to take immediate actions in order to tackle the unsought occurrence of events due to mechanical and electrical failures, thereby ensuring the safe operations of the power plant. In those scenarios, neural network serves as a useful tool in identifying the events at the early stage of their occurrence. The artificial neural network (ANN) models developed here are able to identify the events quickly as compared to the conventional methods. Various learning algorithms based on back propagation network has been successfully applied to the neural network model and the network has been fine tuned towards detecting the events accurately. The resilient back propagation algorithm shows better results compared to other variants.*

***Index Terms:** Nuclear Power Plant, Event Detection, Prototype Fast Breeder Reactor, Neural Network, Back Propagation Network.*

I. INTRODUCTION

Nuclear power plants are highly complex, safety critical systems being operated by human operators in which safe and reliable operation is of prime importance. In nuclear reactor thousands of alarm generate within seconds of time if any parameter crosses its threshold limit leading to any abnormal situations. The operators might get perplexed by seeing a lot of alarms, hence may fail to act immediately in order to mitigate the negative consequences of such events [1]. Hence the operators need to take proper and timely action in order to avoid plant accidents in case of any upset in plant systems. The problem can be solved by using artificial intelligence techniques and neural network is one of the advanced techniques widely used for detecting transient dynamics and monitoring and diagnosing the plant characteristics. A brief study of neural network applications in transient diagnosis is given by Uhrig et al. [1] for enhancing the operational safety. For reactor operation and fault diagnosis, an operator support system and knowledge based system has been developed by Varde et al. [2]. Neural network and wavelet transform is being used for fault diagnosis and classification by Kamal H. et al. [3]. Recurrent neural network is trained for identification of anomalous events in a Pressurized Water Reactor 900 Megawatt Nuclear Power Plant (NPP) by Davide Roverso [4]. A dynamic neural network aggregation model is developed for transient detection, classification and prediction in NPP by Kun Mo et al. [5]. For identification of accident scenario in nuclear research reactor a diagnostic system based on neural network and expert system is being used by Santosh et al. [6]. Probabilistic ANN is modeled for identification of unlabelled transient in NPP by Mark J. E. et al. [7]. Fault detection and diagnosis has been carried out by Sorsa et al [8]. A symptom based diagnostic system for nuclear power plant is developed using artificial neural network by Santosh et al. [9]. ANN based system identification and control of nuclear power plant has been performed by Parlos et al. [10].

The event identification in a NPP can be detected by two approaches, model based and data driven approach. The model based approach incorporates physical models which detect the fault by checking the consistency between the observed behavior and the predicted behavior through the model [11]. A data driven model uses operational data in normal and transient conditions for fault diagnosis and detection [12]. It has the ability to model non-linear systems without using the physical expressions that exist among their variables and without understanding intricacies of the system characteristics [13]. The main objective of this paper is to develop an Event Detection System (EDS) for identifying various events in fast breeder reactor subsystems at the earliest time of occurrence. The EDS is based on data driven, single neural network model that helps the operator in detecting the events much faster and accurate as compared to the conventional thermo hydraulics methods. A whole set of data ranging from normal state of operation to transient states has been obtained with the help of thermal hydraulics simulation code. The conventional model used here is DYANA-P (dynamic analysis-P) method that is based on rigorous thermo hydraulics calculations. The data used as input to train the model has already been validated and recorded in event analysis report of Prototype Fast Breeder Reactor. Standard back propagation learning algorithm and its variants have been applied and tested to arrive at the best suited algorithm.

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II. A BRIEF DESCRIPTION OF PROTOTYPE FAST BREEDER REACTOR

Prototype Fast Breeder Reactor (PFBR) is a 500 MWe (Megawatt Electrical), Plutonium and Uranium mixed oxide (PuO_2 and UO_2) fuel, sodium cooled, pool type reactor. PFBR simulator is a full scope replica type simulator which covers the entire plant. The heat transport system of PFBR consists of Primary Sodium Circuit, Secondary Sodium Circuit and Steam Water System. The Primary Sodium Circuit, considered in this event analysis study, is contained inside the main vessel of the reactor. It consists of two primary sodium pumps and four Intermediate Heat Exchangers (IHX). Neutronics model is an important subsystem of PFBR simulator which simulates the neutron flux monitoring system of the actual reactor.

III. DESCRIPTION OF EVENTS

Events are the unsought occurrence of plant conditions which affect the safe operation of plant. The event associated with Neutronics System is Control and Safety Rod (CSR) withdrawal. The events associated with Primary Sodium Circuit are Primary Pipe Rupture, Primary Sodium Pump Trip and Primary Pump Seizure.

In case of the one Control And Safety Rod (CSR) withdrawal event, the positive reactivity is added continuously to the system which in turn will result in SCRAM (Safety Control Rod Accelerated Movement) i.e., dropping of rods to shutdown the reactor. It has been simulated by considering that one CSR moves upward from its initial location at a speed of 2 mm/s. The reactivity insertion rate during this transient has been calculated based on the speed of movement of CSR and reactivity worth data of CSR corresponding to its position inside the core at that instant. Because of the insertion of external reactivity, reactor power increases and corresponding coolant temperature also increases. When the reactivity crosses the trip threshold of +10 pcm at 3.47 s SCRAM is initiated. Apart from reactivity (ρ) the other effective SCRAM parameters available during this event are high linear power (Lin P), central subassembly outlet temperature (θ_{CSAM}), increase in central subassembly temperature rise ($\Delta\theta_{CSA}$), power to flow ratio (P/Q) Among the various parameters, ρ and θ_{CSAM} are the first SCRAM parameters that trigger reactor to SCRAM independently by SDS 1 and SDS 2 respectively.

In case of primary pipe rupture event, primary sodium flow by-passes the core back to the cold pool through the break and the core flow decreases rapidly. It can be seen that the core flow goes to as low as 30 % at about 0.6 s before stabilizing at 32 %. The rapid reduction in the flow through the core results in the sodium and core temperatures to rise. Four parameters viz. P/Q, θ_{CSAM}, ρ and $\Delta\theta_{CSAM}$ parameters are available as effective SCRAM parameters during the event. The evolution of process values of flow and temperature related SCRAM parameters for both the events are shown in figure 1.

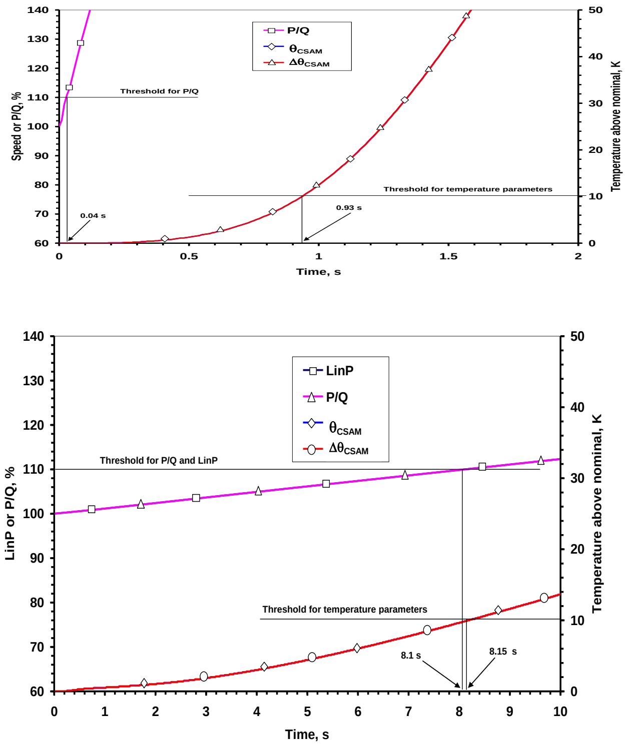
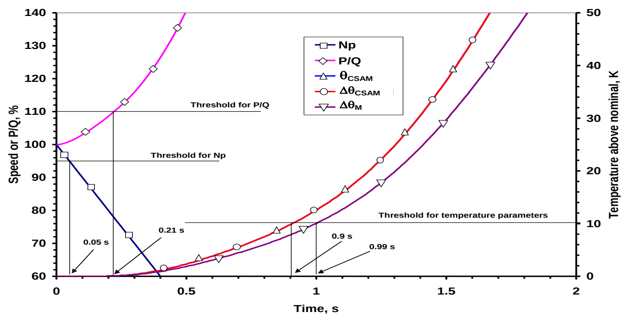


Fig. 1 Evolution of process values of temperature and power related SCRAM parameter during (a) Primary pipe rupture and (b) one CSR withdrawal

When one Primary Sodium Pump (PSP) trip occurs, the speed of the tripped PSP flow reduces gradually against inertia to 50% in 2.6s and to 0% in 9.4s. Due to parallel operation of two PSPs the operating PSP flow increases to 126% in order to balance the core flow. The total core flow reduces to 61% in 10s. Hence the power to flow ratio (P/Q) increases and then the central subassembly outlet temperature (θ_{CSA}) increases which leads to increase in central subassembly temperature rise ($\Delta\theta_{CSA}$) and mean core temperature rise ($\Delta\theta_M$). Out of a set of SCRAM parameters five effective SCRAM parameters viz. Np (Pump speed), P/Q, θ_{CSA}, $\Delta\theta_{CSA}$ and $\Delta\theta_M$ are used for protection of this event. Figure 2 depicts the evolution of process values for SCRAM parameters for PSP trip and seizure event [14].



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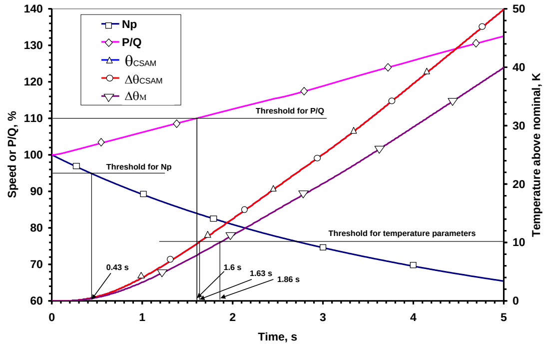

Fig. 2 Evolution of process values of temperature and power related SCRAM parameter during (a) PSP trip and (b) PSP seizure

When a PSP Seizure occurs there is a ramp reduction of the speed of one pump to zero in one second. The second pump is considered to be continuing to operate at full speed. The operating PSP flow increases to 125% and the core flow reduces to 37% in 1.7s. With decrease in flow in such a fast rate the sodium temperature increases very rapidly. Out of several number of SCRAM parameters six effective parameters viz. N_P, P/Q, θ_{CSAM}, ⍰ ρ (reactivity), $\Delta\theta_{CSAM}$, and θ_M parameters are available during the event.

IV. NEURAL NETWORK MODELING

The event identification can be classified as pattern recognition problem. An event follows a time dependent pattern and each pattern is unique for a particular type of event. ANN is one of the non linear pattern recognition techniques that can be used for transient identification [1]. ANNs are massively parallel and interconnected adaptive networks of simple processing elements called neurons which are intended to abstract and model some characteristic and functionality of human brain. Connection links are associated with weights which are multiplied with the neuron inputs. The activation function is then applied to the net sum (weight multiplied with input) to get outputs [15]. The ANNs are well known for their properties like generalization, fault tolerance, robustness, function approximation, regression, pattern classification, optimization and many more [16].

A neural network can be viewed as weighted directed graphs in which neurons can be connected in either feed forward or feedback networks. In feed forward network, the architecture has no loops, whereas in feedback network loops occur because of feedback connections. In a three layer feed forward perceptron, the network is consisting of input layer, hidden layer and output layer. The signals are fed to the input layer and then it passes to the output layer through hidden layer.

V. DATA COLLECTION AND TRAINING ALGORITHMS

The event related input data has been generated from in-house developed thermal hydraulics code and validated as per the event analysis reports of PFBR. The input dataset containing 172 samples has been chosen in such a way that it covers the entire range of operations from steady state to transient conditions. The significant parameters namely reactivity (ρ), linear power (Lin P), central subassembly outlet temperature (θ_{CSAM}), increase in central subassembly temperature rise ($\Delta\theta$CSA), mean core temperature rise ($\Delta\theta$M), power to flow ratio (P/Q), pump speed (Np) are used to represent input nodes to the neural network. The nominal and threshold limits of parameter values associated with the events are shown in table 1. The neural network designed for EDS is feed forward network with multilayer perceptron architecture. The network has seven input nodes in input layer, four output nodes in output layer and one hidden layer in which hidden nodes can be varied.

Table1: Nominal and Threshold values for SCRAM parameters

SCRAM parameters	Nominal Value	Threshold
P/Q	1.1	0.99
Np	590 rpm	-5% of nominal value
θ_{CSAM}	853 K	+10K of nominal value
$\Delta\theta_{CSAM}$	423K	+10K of nominal value
$\Delta\theta_M$	433K	+10K of nominal value
Reactivity	1.2 pcm	10 pcm
Lin P	1250 MWt	+10% of nominal value

The four output nodes in the ANN designate four different events namely PSP trip, CSR withdrawal, PSP seizure and primary pipe rupture respectively. The figure 3 depicts the three layer neural network architecture used for identifying the four events.

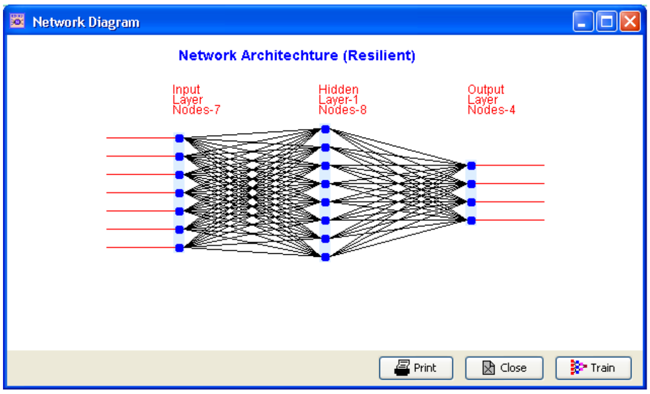

Fig. 3 Architecture of Neural Network

BIKAS (Bhabha Atomic Research Centre – Indian Institute of Technology Kanpur-Artificial Neural Networks – Simulator) is a general purpose neural network simulator written in JAVA. BIKAS has been used for training the network with various back propagation learning algorithms with different weight optimization schemes. The datasets are normalized using the simulator in order to scale down the entire range of data into 0.1-0.9 before training. Different weight optimization algorithms namely Standard Back Propagation, Back Propagation with momentum in pattern mode, Back Propagation with momentum in batch mode, Quick propagation and Resilient back propagation have been applied and results are analyzed. A brief explanation of each of the algorithms is given below.

A. Standard Back Propagation (Bp) Algorithm with Pattern Mode

In standard back propagation algorithm, the inputs are applied to the input layer of the network. The random weights are then applied to the connection links between input layer and hidden layer neurons. The weights are in turn multiplied with the inputs and the summed up result is then applied with an activation function to calculate the output for hidden layer. The activation function used here is sigmoid activation which can be represented by equation 1. Sigmoid activation function is preferred as with sigmoid units, a small change in weight produces a change in output which is the main criteria of back propagation algorithm.

$$\left[\frac{1}{1+\exp(-x)}\right] \quad (1)$$

Where x is the summed up result of the weight multiplied with inputs. The outputs of the output layer are also calculated similarly. The weight update is performed by back propagating the mean square error which is represented in equation 2.

$$\text{Mean Square Error} = \frac{1}{TSN} * \sum_{t=1}^{TSN} \sum_{k=1}^{NON} \left(\left(d_{out}\right)_{kt} - O_{kt}\right)^2 \quad (2)$$

Where TSN represents the number of training samples, NON represents the number of output nodes, $dout$ and O represents desired and actual outputs.

In standard back propagation algorithm with pattern mode the weights are updated after each input pattern is applied [18].

B. BP Algorithm with Momentum and Pattern Mode

In case of back propagation algorithm with pattern mode and momentum, the momentum factor is used in order to improve the local minima problem. This method takes the error estimate from the result in presenting just the current pattern. It introduces noise into the learning process and it is known that an accurate calculation of the error gradient is possible only when all training patterns have been presented. The momentum term also avoids the oscillations of the error curve. After various trials and fine tuning, the momentum value found here is 0.8.

C. BP Algorithm with Momentum and Batch Mode

Back propagation algorithm with momentum and batch mode learning explains that the weight update is done after the entire training set is applied to the input layer. It takes the total training error over all the patterns into account. The momentum speeds up convergence of training a feed-forward neural network.

D. Quick Propagation Algorithm

The quick propagation algorithm requires the computation of the second order derivatives of the error function. It assumes the error to be locally quadratic and attempts to jump in one step from the current position directly in to the minimum of the parabola. The weight update formula is represented in equation 3.

$$\Delta w(t) = \frac{s(t)}{s(t-1)-s(t)} \Delta w(t-1) \quad (3)$$

Where $s(t)$ and $s(t-1)$ are the current and previous values of the error gradient vector $\partial E/\partial w$, $\Delta w(t)$ is the weight change and $\Delta w(t-1)$ is weight change in previous step.

E. Resilient Back Propagation Algorithm

The resilient back propagation algorithm the direction of each weight update is based on the sign of the partial derivative of $\partial E/\partial w_{ij}$. A step size Δ_{ij} i.e., the update amount of weight w_{ij}, is adapted for each weight individually. The main difference to other techniques is that the step sizes are independent of the absolute value of the partial derivatives. The weight formula is shown is equation 4 and 5[17].

$$\Delta_{ij}(t) = \begin{cases} \eta + * \Delta_{ij}(t-1) & if \ \frac{\partial E}{\partial w_{ij}}(t) * \frac{\partial E}{\partial w_{ij}}(t-1) > 0 \\ \eta - * \Delta_{ij}(t-1) & if \ \frac{\partial E}{\partial w_{ij}}(t) * \frac{\partial E}{\partial w_{ij}}(t-1) < 0 \\ \Delta_{ij}(t-1) & otherwise \end{cases} \quad (4)$$

Where Δi_j represents the new update value that solely determines the weight-update.

$\partial E/\partial w_{ij}(t)$, $\partial E/\partial w_{ij}(t-1)$ are partial derivative of error for current and previous steps. Once the update value for each weight is adapted, the weight update can be represented as follows.

$$\Delta w_{ij}(t) = \begin{cases} -\Delta_{ij}(t) & if \ \frac{\partial E}{\partial w_{ij}}(t) > 0 \\ +\Delta_{ij}(t) & if \ \frac{\partial E}{\partial w_{ij}}(t) < 0 \\ 0 & else \end{cases} \quad (5)$$

Where $\Delta w_{ij}(t)$ determines the change in weight parameter.

In case of resilient back propagation algorithm the partial derivative is not used directly for weight optimization. It only indicates the direction of weight update. η^{+} represents the learning rate increment factor and η^{-} represents the learning rate decrement factor and the value of two learning rate factors are 1.2 and 0.5 respectively, found experimentally from previous literatures. The initial weight update value is represented as Δ_0 and the lower and upper bounds are represented as Δ_{max} and $\Delta_{min.}$ The value of Δ_0 is 0.07, Δ_{max} is 50 and Δ_{min} is 0.001[17].

VI. DATA COLLECTION AND TRAINING ALGORITHMS

Out of 172 datasets in input dataset, 152 datasets have been chosen for training and testing. 20 distinct datasets which are not included in the training set are used for prediction. The performance goal error value is set in the order of 1.0 E-04 as beyond this there is no much variation in the mean square value. The learning rate factor used in weight optimization formula is standardized based on the experience gained from our earlier ANN simulation work and set as 0.7. The figure 4 depicts the graph between mean square error and number of hidden nodes. The optimal number of hidden nodes is found to be 8 after carrying out trials with various hidden nodes starting from 5 to 12 for 1000 epochs [18]. After optimizing the key parameters, the network is trained with different variants of back propagation algorithms to find out the suitable model which produces optimal results.

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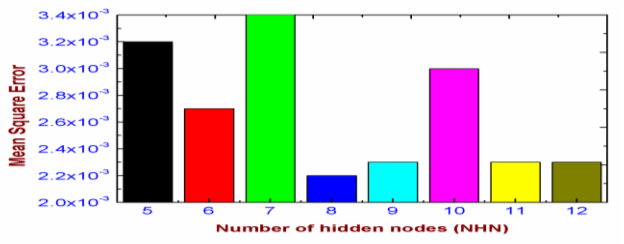

Fig. 4 Trial results for different number of hidden nodes (1000 iterations)

The figure 5 depicts the graph for standard back propagation algorithm with pattern mode learning. The error value starts with 0.0057. After ten thousand iterations the error reduces up to 7.47 E-04.It took 30 minutes to run BIKAS simulator program for ten thousand iterations in (2.66 GHz Intel Core 2 Duo processor).

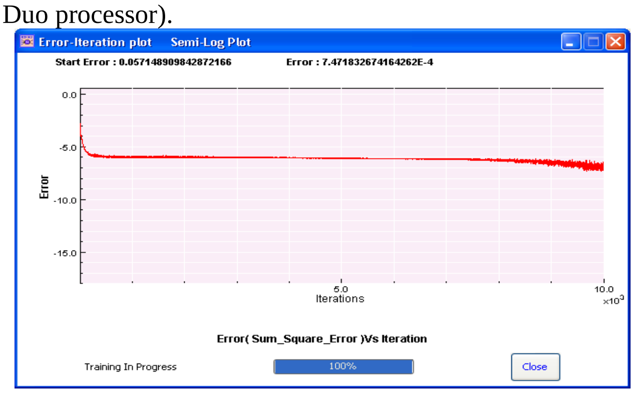

Fig. 5 Error vs. Epoch curve for Standard BP algorithm (pattern mode)

The figure 6 indicates the back propagation algorithm with pattern mode learning and momentum parameter. The performance goal error value starts with 0.057. It shows that the mean square error reduces to 9.14 E-04 after ten thousand iterations.

Fig. 6 Error vs. Epoch curve for Standard BP algorithm (pattern mode with momentum)

The figure 7 shows the standard BP algorithm with batch mode learning with momentum parameter. The performance goal error value starts with 0.060 and after ten thousand iterations the error factor reduces to 0.0059.

Fig. 7 Error vs. Epoch curve for Standard BP algorithm (batch mode with momentum)

The figure 8 shows the graph for quick propagation algorithm. The performance goal error value starts with 0.070 and after ten thousand iterations the error factor reduces to 4.86 E-04.

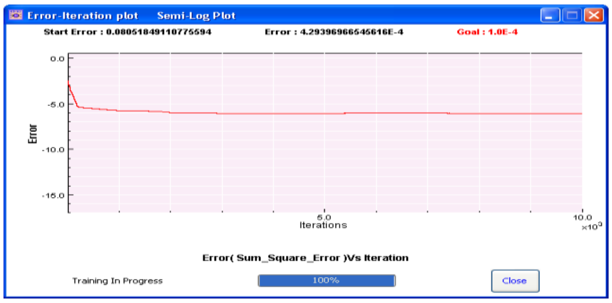

Fig. 8 Error vs. Epoch curve for Quick Propagation algorithm

The figure 9 depicts the mean square error versus epoch's graph of resilient back propagation algorithm. The performance goal error value starts with 0.080. For ten thousand iterations the mean square error reduces 4.29 E-04.

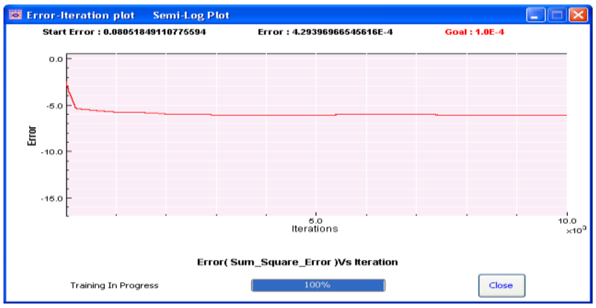

Fig. 9 Error vs. Epoch curve for Resilient Algorithm

VII. RESULTS AND DISCUSSION

Multilayer feed forward ANN model has been implemented and trained with BP algorithm and its variants to identify events related to PFBR subsystems. The best performing algorithm has been found out during the training process. From the figure 10 shown below, it can be seen that the resilient back propagation algorithm is showing faster convergence and yields satisfactory results. The graph also shows that the back propagation algorithm with batch mode and momentum parameter is not able to converge to the required performance goal error even after ten thousand epochs. After training, testing has been carried out for resilient back propagation model with 25 test cases within the range of input data set. The testing results are shown in figure 11. It shows the neural network results are almost matching with the desired outputs and the resilient back propagation algorithm gives the least mean square error.

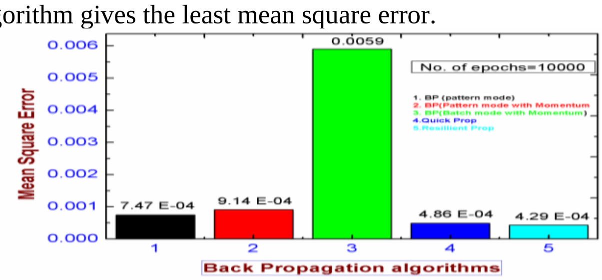

Fig10 Mean square error for five different algorithms for 10000 epoch

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Table I The desired and actual output test results of 25 samples

Actual Outputs				Desired Outputs			
1	2	3	4	5	6	7	8
1.0585	-0.103	-0.0136	-0.1036	1	0	0	0
0.9827	0.0784	0.0503	-0.0401	1	0	0	0
0.9735	0.0169	0.0091	0.0665	1	0	0	0
0.9961	0.0012	-0.0055	-0.0091	1	0	0	0
0.9901	-5.95E-04	-0.001	-0.0157	1	0	0	0
0.9901	-0.002	-6.82E-05	-0.0186	1	0	0	0
-0.0094	1.0179	-0.1249	0.0155	0	1	0	0
-0.0224	1.0414	-0.1249	0.017	0	1	0	0
-0.022	1.0549	-0.1249	0.015	0	1	0	0
-0.0149	1.0631	-0.1249	0.0124	0	1	0	0
-0.1048	-0.1247	1.1235	-0.0924	0	0	1	0
-0.1171	-0.1247	1.1239	-0.1103	0	0	1	0
-0.1209	-0.1246	1.1243	-0.1169	0	0	1	0
-0.1225	-0.123	1.1229	-0.116	0	0	1	0
-0.1147	-0.1199	1.1173	-0.1145	0	0	1	0
0.0014	-0.0119	0.9544	0.044	0	0	1	0
0.0017	-0.011	0.9733	0.0257	0	0	1	0
0.0027	-0.0098	0.9877	0.011	0	0	1	0
0.0098	-0.0072	0.9863	0.0082	0	0	1	0
-0.1249	0.0106	-0.118	1.1214	0	0	0	1
0.0169	0.0111	0.0363	0.9837	0	0	0	1
0.0184	0.0062	0.0345	0.9757	0	0	0	1
0.0196	0.0026	0.0235	0.9789	0	0	0	1
0.02	-0.0013	0.0134	0.9819	0	0	0	1
0.0198	-0.0058	0.0043	0.9845	0	0	0	1

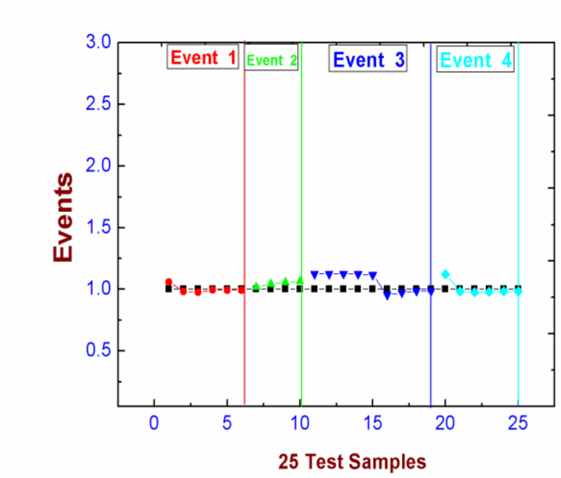

Fig. 11 Neural Network results for testing samples showing simulator and neural network output

During validation phase after testing, twenty distinct samples which are not used in training set are applied to the resilient back propagation model for prediction. The prediction results shown in figure 12 are in excellent agreement with the validated results of conventional model. It shows that the occurrence of events can be identified with negligible error using the neural network model.

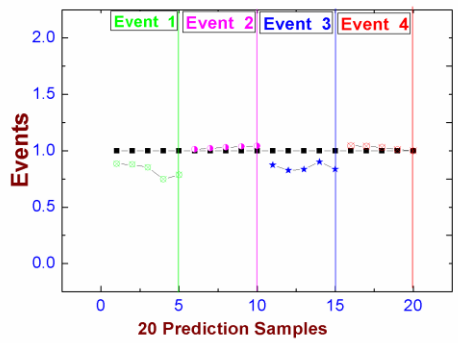

Fig. 12 Prediction results for various events showing simulator and neural network outputs

IX. CONCLUSION

The neural network model has been developed for identification of events in Primary Sodium Circuit and Neutronics Subsystem of PFBR. Multilayer perceptron architecture has been used with various back propagation learning algorithms. Different weight optimization algorithms namely standard BP, BP with momentum in pattern mode, BP with momentum in batch mode, Quick propagation and Resilient BP have been applied successfully for training the model and the results are analyzed to determine the best suited learning algorithm. In comparison with the conventional methods, the ANN methodologies are found to be fast in achieving the results.

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Based on the above case studies, it can also be concluded that the quick propagation and resilient back propagation algorithms give least error margins. Out of the two, resilient back propagation algorithm gives better estimation and faster convergence for this case of event detection. The results show that the neural network model can be applied to the plant operations as an event detection system to help the operators in identifying anomalies and taking timely decisions.

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