USING NEURAL NETWOK IN FAULT DIAGNOSIS of NUCLEAR POWER REACTORS

A. ABO-SHOSHA[§], F. A. MOHAMED[§], M. ELBARDINY*, N. EL-RABAIE*, A. MONTASSER*

[§] Atomic Energy Authority (AEA), Cairo, Egypt.

*** Automatic Control Dept. Faculty of Electronic Eng., Menoufia Uni., Egypt.**

Abstract: In this paper, artificial neural networks (ANNs) are used in fault diagnosis of a nuclear power reactor (NPR). The Multilayer Neural Networks (MNNs) are used as a fault detection system, and this type of networks are learned using error back propagation training algorithm (EBPTA). The neural fault diagnosis system (NFDS) is used to identify reactor cooling pump (RCP) faults. To speed up the learning process, the momentum method has been used to enhance the performance of the NFDS. Based on the presented case of study NFDS can recognize the cause of alarms well, and simply identify the faults.

Keywords

Neural Network, Fault Diagnosis, Nuclear Power Plants.

I- INTRODUCTION

ANNs have received much attention in both the research community and the media in recent years. ANNs have been shown to elegantly and powerfully realize solutions to problems in pattern recognition, associative Memory, and data base retrieval. ANNs exhibit a surprising number of the biological network characteristics. The main characteristic is the ability of the network for learning. ANNs have been applied to many areas; Expert systems building [1], Optical Character Recognition (OCR) [2], text to speech conversion [3], image or data analysis and compression [4], control system design [5], and other applications. The incorporation of the ANN into the diagnostic domain may yield great benefits in terms of speed, robustness, and knowledge acquisition. Also, these are capable of operating with a noisy, incomplete, and possibly erroneous input data. Especially among various advantages, the general mapping capability of pattern recognition improves the diagnostic performance of the NFDS. Several application studies of the ANNs on NPR have been carried out. Uhrig et al. studies the performance of the NPR by using ANNs [6]. Roh et al. have proposed the applicability of thermal power prediction by ANNs [7]. Se Woo Cheon et al. have studied multiple alarms and diagnosis system of NPR [8] using different AI based techniques. In this paper, the feasibility study of the ANNs application on the diagnosis of multiple alarms in NPRs has been introduced. When a plant disturbance occurs, sensors outputs or instruments may trigger firing of alarms and form a different alarm pattern that represents a different fault. The diagnosis of faults is approached from a pattern matching perspective in that an input pattern is constructed from multiple alarm symptoms and that symptom pattern is matched to an appropriate output pattern that corresponds to the fault occurred. The EBPTA algorithm [9] is used to train multiple alarm patterns. This algorithm is a systematic method for training MNNs and has been widely applied to many areas. Alarms related to the RCP system will be chosen as a diagnostic domain. The implemented NFDS layout contains an input layer, which consists of 12 alarm input nodes, a hidden layer, which consists of 7 nodes, and an output layer, which consists of 9-class fault identification nodes. In section (II), the idea of system fault diagnosis will be clarified. In section (III), the MNNs performance study will be presented. In section (IV), results of the NFDS learning is presented. Finally in section (V) the conclusion is drawn.

II- Alarming and Fault Diagnosis

NPRs fig. (1), are large in scale and complex, so the information from local fields is excessive, and therefore plant operators cannot properly process it. When a plant malfunction occurs, there are data influxes, so the cause of the malfunction cannot be easily and promptly identified.

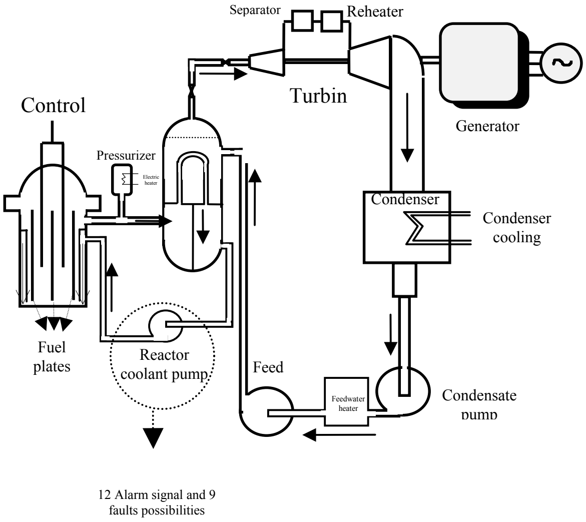

Figure 1. Reactor Cooling Pump Fault Diagnosis

A typical NPR may have around 2,000 alarms in the main control room in addition to the display of analog data. During plant transients, mode changes and component trips, hundreds of alarms may be activated in a short time. Hence, to increase the plant safety, the operator support systems such as ANNs assisted alarming and diagnosis systems become more important. The significant aggravating factor of the Three Mile Island (TMI) accident in 1979 was the large number of fired alarms. In one simulated Loss-Of-Coolant Accident (LOCA), 500 lights, went on or off within the first minute, and 800 in the second. As plant's transducers are breaded all over system parts, the measurement signals flows toward local or central control panel.

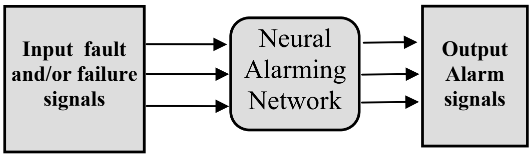

Figure 2. Neural Alarm Processing Network

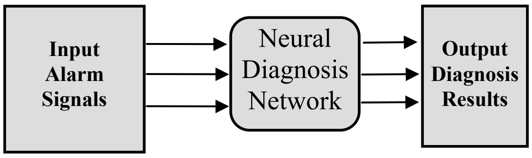

Figure 3. Neural Fault Diagnoses Network

If any one of the system's parts has a fault or failure, transducers transfer a fault or failure signal to the Neural alarming network which is considered as an alarm signal generator. This process is called Alarm processing stage as shown in fig.(2). The objectives of the neural based alarm processing system are; to reduce the number of alarms presented, to recognize alarms so that they could be grouped in relation to a single cause, to order the alarms within a group, and to display suitable alarm messages. Alarming signals and messages are transferred to neural diagnosis Network to analyze alarm signal and to identify a primary causal alarm, and can diagnose possible failure modes and failed systems. This process is called diagnosis stage as shown in fig.(3).

III - The MNNs performance analysis

Adapted perceptron units are arranged in layers, and so this model is naturally enough termed the multilayer perceptron. The basic details are shown in fig.(4). The MNNs model has three layers; an input layer, an output layer, and a layer in between, not connected directly to the input or the output, and so hidden layer. Each unit in the hidden layer and the output layer is like a perceptron unit. These units in the input layer serve to distribute the values they receive to the next layer, and so do not perform a weighted sum or threshold. We now have a network that should be able to be learned to recognize more complex things; let us examine the learning rule in more details.

The basic processing function of every node in the MNN is the sigmoidal fuction, which has the ollowing form:

$$O = \frac{1}{1+e^{-\lambda\, net}} \quad \text{whereas } \lambda > 0$$

λ is called steepness constant. The net function is the summation of weights multiplied by the corresponding inputs. The net fuction can be expressed by the following form: $net = \sum_{1}^{n} W_i X_i$

The learning rule parameters of MNN has three layers; input, hidden, and output are shown as follow:

Step 8: The training cycle is completed. For $E < E_{\max}$ terminate the training session. Output weights *W,V* and *E.*

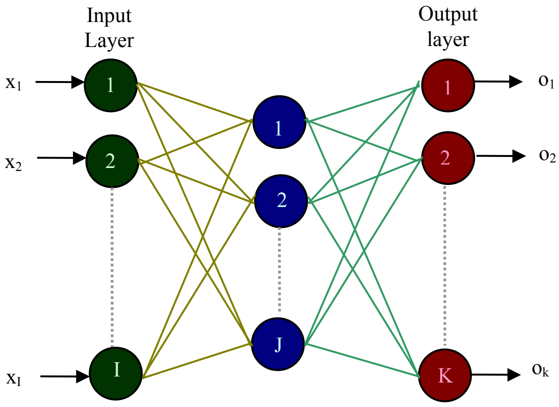

Figure 4. Multi-Layer Neural Network

I	number of inputs nodes		
J	number of hiddens nodes		
K	number of outputs nodes		
η	the learning speed constant		
h	hidden layer outputs	*w*	output weights
RMS	Root Mean Square of error	*O*	outputs
v	hidden layer weights	*d*	the desired
P	number of patterns	*X*	inputs

The EBPTA [4] has the following sequence steps:

Step 1: $\eta > 0,\ E_{\max}$ chosen.

Weights *W* and *V* are initialized at a small random values, W is (*KxJ*) and *V* is (*JxI*).

Step 2: Training step starts here. Input is presented and the layer's output is computed.

$h_j = f(v_j^t x), \ for\ j = 1,2,3,\ldots,J$, and

$o_k = f(w_k^t h), \ for\ k = 1,2,3,\ldots\ldots\ldots,K$

Step 3 : Error Value is computed:

$E \leftarrow \frac{1}{2}(d_k - o_k)^k + E$

Step 4: Error signal vectors Δ_o and Δ_y of both output and hidden layer are computed.

Vector Δ_o is (*Kx1*) and Δ_y is (*Jx1*).

The error signal term of output layer is

$$\Delta_{ok} = 0.5(d_k - o_k)(1 - o_k^2),\ for\ k = 1,2,\ldots,K$$

The error signal term of the hidden layer is

$$\Delta_{yj} = (1 - h_j)\sum_{k=1}^{K}\Delta_{ok}W_{kj}, \quad for\ j = 1,2,\ldots,J$$

Step 5: Output layer weights will be adjusted as:

$w_{kj} \leftarrow w_{kj} + \eta\Delta_{ok}h_j,$

$for\ k = 1,2,\ldots\ldots,K\ and \quad j = 1,2,\ldots\ldots,J$

Step 6: Hidden layer weights will be adjusted as:

$v_{ji} \leftarrow v_{ji} + \eta\Delta_{yj}x_i,$

$for\ j = 1,2,\ldots.,J\ \ and \quad i = 1,2,\ldots\ldots,I$

Step 7: If p < P then p ← p+1, and go to step 2; otherwise, go to step 8.

If $E > E_{\max}$, then $E \leftarrow 0,\ p \leftarrow 1,$ and initiate the new training cycle by going to step 2.

The preceding algorithm can be enhanced if we add the momentum term to the weight change in every learning step so, the weights change will have the following form: $W(t+1) = \Delta W(t) + \alpha(w(t) - w(t-1))$ Δ.w(t) is the weight change due to EBPTA and $\alpha(w(t) - w(t-1))$ is the momentum term and α is the momentum constant.

IV - Results of the NFDS training

The design of the NFDS is shown in fig. (5.a, 5.b). The overall NPR has tight alarming and fault diagnosis system. This system has multi-level alarm and fault diagnosis system. Every part of the Plant has its own diagnosis system. The overall Plant has a global alarming and fault diagnosis system, which links all individual subsystems. As the control system of the plant can be tested by ANNs to define the fault if found, also all parts of the plant can be tested by a pattern recognition ANNs techniques. One of the most important parts of the NPR is the RCP, shown in fig. (1). This part of Reactor has 12 alarming signal (a1, a2, a3, ...a12) and the possibility of faults are 9 (c1, c2, c3, ...c9) (these data belong to Kori-2 NPR). The design of the ANNs used is shown in fig. (5.a, 5.b) whereas it consists of 12 input nodes, 7 hidden nodes, 9 output nodes. The parameters of the NFDS learning are shown in table (1). The definition of the faults and their corresponding alarms are shown in table (2.a, 2.b). The I/O patterns that used in the NFDS learning are shown in table (3.a, 3.b). The output of the NFDS after training of the 9 faults outputs compared with the reference patterns is shown in fig. (6.a) also the output of the hidden layer is shown in fig. (6.b). NFDS training process errors (RMS error & patterns error) are shown in fig. (7.a, 7.b).

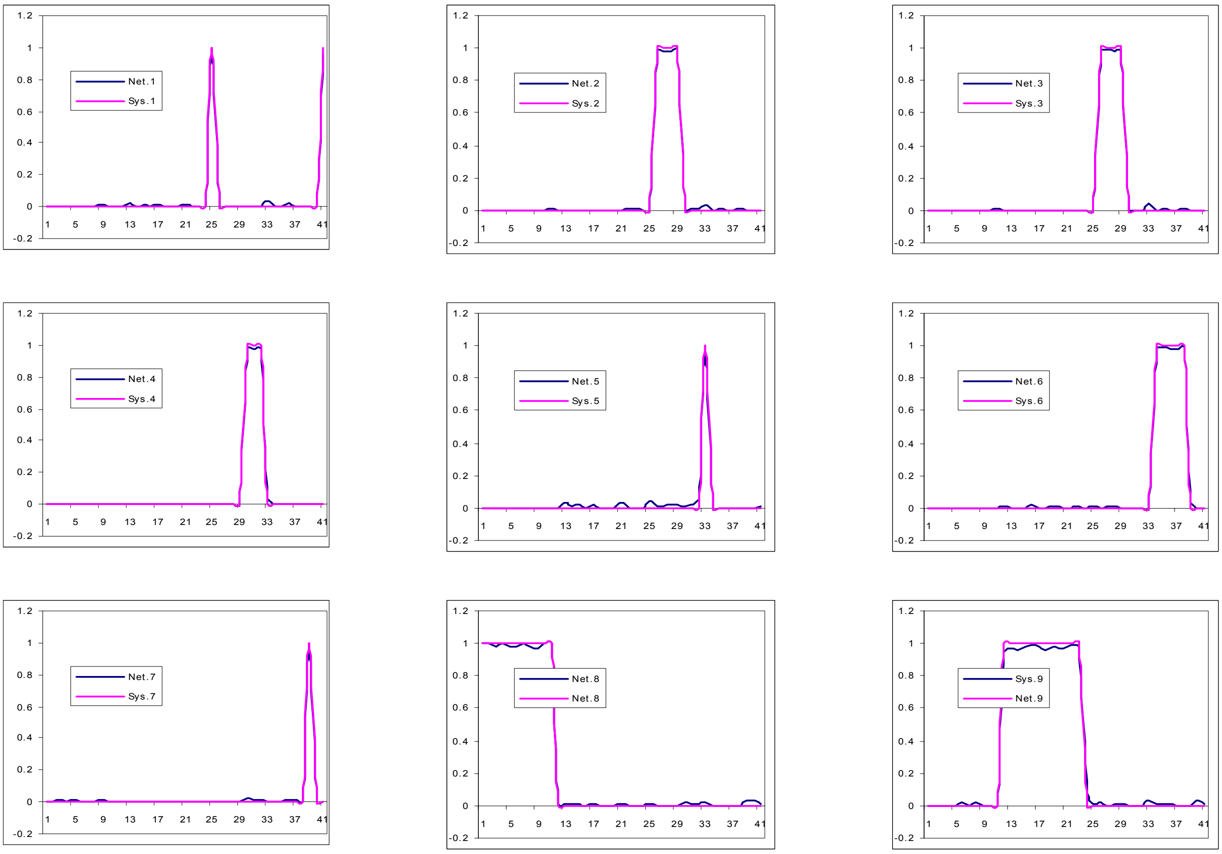

Figure 6. Results of the NFDS. NFDS outcomes (Net1 – Net9) and the real data pattern represented by signals Sys1 – Sys9 are presented.

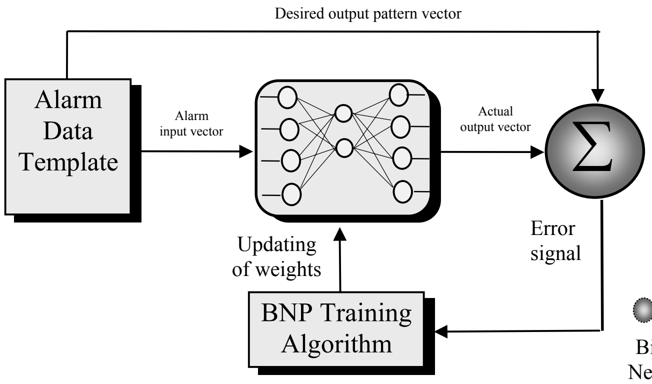

Figure (5.a) The NFDS learning diagram

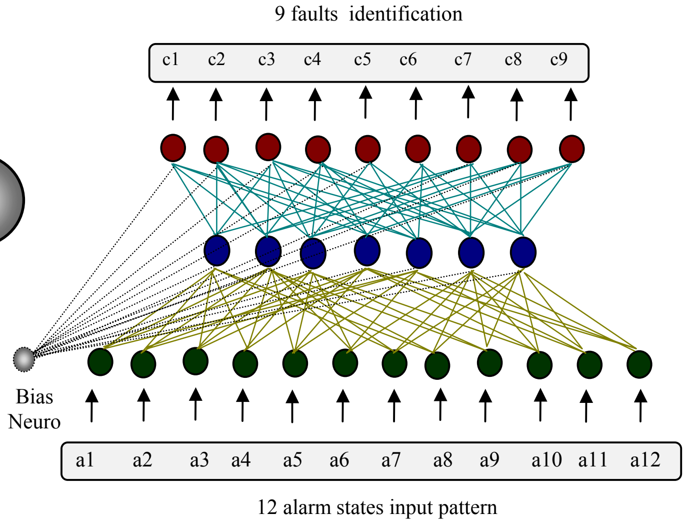

Figure (5.b) Structure of the implemented Neural Network

Parameters of Network Learning	**Parameter value**
Learning speed constant (η)	1
Momentum term constant α	0.5
Activation function constant λ	1
Number of layers	3
Size of input layer (I)	12
Size of hidden layer (J)	7
Size of output layer (K)	9
Total number of weights	163
Number of training iterations	9370
Good patterns percent %	100%
Target error	0.01
Number of patterns	41

Table (1) MNNs learning parameters

Alarm signal	Description
a1	Seal injection filter differential pressure high
a2	Charging pump flow low
a3	Seal injection flow low
a4	No. 1 Seal differential pressure low
a5	No. 1 Seal leak off flow low
a6	Standpipe level low
a7	Standpipe level high
a8	No. 1 Seal leak off flow high
a9	Thermal barrier flow low
a10	Thermal barrier temperature high
a11	Bearing flow low
a12	Bearing temperature high

Table (2.a) Alarming signals definition

Fault signal	Description
c1	Seal injection filter blockage
c2	Charging pump failure
c3	Seal injection water high temperature
c4	Reactor coolant system pressure less than 400 psig
c5	No. 1 Seal damaged
c6	Volume control tank back pressure high
c7	No. 2 Seal failure
c8	Insufficient component cooling water flow to RCP
c9	Motor Bearing damaged

Table (2.b) Fault signals definition

For every Training pattern, hidden layer nodes have their own outputs which are used as inputs to the output layer nodes fig. (6.b). As the learning process is continuing, the RMS error decreases until the allowed error is achieved fig. (7.a), then the training stops. After network training, every pattern of data has its own error value, which is called pattern error fig. (7.b). As the EBPTA is running, weights of the NFDS are changing till the allowed error RMS reaches its recommended value learning, then learning stops. The final values of the NFDS weights Table (4.a, 4.b) after learning process are considered as parameters of the NFDS so, by using these weights we can obtain the diagnosis of any fault can be caused by any alarms pattern.

From presented results we can notice that the smooth decrement of RMS error fig.(7.a) indicates that the learning process is successful and parameters shown in table(1) have the right. The maximum value of patterns error is 0.01 as it shown in fig.(7.b) this gives an indication for the high precession of the trained NFDS. The outputs comparison of both reference training patterns and the output of the NFDS shows that they are typical, see fig. (6.a), so the network is well trained and it can easily detect any possible system faults.

I/J	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	I_{12}	Bias
J_1	0.772224	-2.575770	-2.968279	-1.527949	-2.701183	-2.891085	3.458638	0.554643	3.992241	4.800466	-0.117097	-3.645547	-1.046137
J_2	-3.510940	4.248124	4.836761	-0.211267	0.565614	-1.964359	1.669075	3.618754	3.356682	-0.541792	10.555010	-5.796823	-1.056916
J_3	3.604107	0.779662	-5.110226	3.426324	0.078442	-1.214220	3.001766	2.690068	2.670565	0.363516	3.732952	3.982546	-0.478989
J_4	-4.111095	4.355207	4.961661	-2.294521	-0.060033	0.503069	-5.630965	4.093045	-2.840454	1.933527	-5.181878	10.23510	-1.522178
J_5	-3.140531	-1.263471	-0.721704	0.722002	0.055449	0.534959	2.786481	0.560736	2.389881	2.080778	-2.597786	3.408858	3.315486
J_6	-6.001679	1.695633	-4.827979	-4.917046	-0.178021	-0.266681	3.283131	2.155575	3.720587	-2.497535	0.197679	-1.330115	1.075096
J_7	-1.797588	-2.647076	-2.229811	2.628608	3.397908	-1.556637	-0.949784	1.913303	-2.685196	-2.308124	0.047333	0.648037	-0.933387

Table (4.a) Values of weights connecting input (I) layer and hihhen (J) layer

J/K	J_1	J_2	J_3	J_4	J_5	J_6	J_7	Bias
K_1	-5.372857	3.007073	-1.261026	3.153662	-1.565332	8.808074	1.219400	-8.683843
K_2	-0.411021	3.999145	-9.782379	2.436713	1.921711	-4.159352	0.887077	-2.673245
K_3	-1.397202	3.521675	-10.083530	1.083925	0.507167	-4.232245	0.412539	0.102973
K_4	-2.064060	-5.710126	-0.041468	-9.963771	5.207565	-6.491211	2.831223	-1.663526
K_5	-1.728810	-4.453911	-5.278646	-2.274853	2.374379	3.025831	-1.878296	0.029978
K_6	3.864617	-0.036708	0.277635	-6.922861	0.849211	7.200072	-0.799805	-7.202872
K_7	7.578858	-5.210524	-4.937312	0.836119	0.014531	-2.271354	-2.792292	-0.953751
K_8	0.087371	4.704370	1.566721	-11.301430	-6.604207	-4.744246	-2.719789	0.586710
K_9	-1.658034	-10.150310	2.958169	9.843201	-9.823715	-0.041349	1.219673	1.766101

Table (4.b) Values of weights connecting hidden (J) layer and output (k) layer

V - Conclusion

In this paper, the feasibility study of the NFDS using the EBPTA paradigm is presented. The Neural Network Approach has more powerful advantages (e.g., Short knowledge acquisition time, low development cost, fast running time, robustness to noisy alarm signals, and general mapping capabilities) over the conventional alarm processing methods. Results show that once the network has been fully trained with various alarm patterns, it can identify with a good accuracy the faults well. Although untrained or incomplete/sensor-failed alarm patterns are given, the network can diagnose a fault properly. In addition, multiple faults can be easily diagnosed using a given alarm pattern. The network also has the capability of identifying the time-varying fault behavior. In conclusion, the neural network approach is almost appropriate for pattern recognition problems in environments where plant actual data are abundant and noisy. Moreover, the neural network based systems can run very fast if hardware implementations are becoming available. This makes the systems, specially well suited for real-time applications such as alarm processing and fault diagnosis in NPR.

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