FAULT DETECTION AND DIAGNOSIS OF POWER CONVERTERS USING ARTIFICIAL NEURAL NETWORKS

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Abstract: Fault detection and diagnosis in real-time are areas of research interest in knowledge-based expert systems. Rule-based and model-based approaches have been successfully applied to some domains, but are too slow to be effectively applied in a real-time environment. This paper explores the suitability of using artificial neural networks for fault detection and diagnosis of power converter systems. The paper describes a neural network design and simulation environment for real-time fault diagnosis of thyristor converters used in HVDC power transmission systems.

Key words: Fault detection and diagnosis, neural network, converter.

1 INTRODUCTION

An important application of artificial intelligence (AI) is the diagnosis of faults of mechanisms and systems in general. Traditional approaches to the problem of diagnosis is to construct a heuristic, rule-based system which embodies a portion of the compiled experience of a human expert. These systems perform diagnosis by mapping fault symptoms to generated hypothesis to arrive at diagnostic conclusions. Second generation expert systems, also termed as model-based reasoning perform diagnosis based on the structure and behaviour of the physical system. Model-based expert systems apply a qualitative model of numerical simulation of the problem domain in the diagnostic process. These systems reason on the basis of physical principles and therefore are capable of performing diagnosis for a wide range of inputs. Application of fault-based and model-based qualitative reasoning for power system fault diagnosis discussed by the authors in [9] provides an comparative and integrated approach of integrated diagnostic system for efficient problem solving. The search process involved in second generation systems is exhaustive and hence time consuming. Also simulation of models are usually too slow to be effectively applied in a real-time environment. Knowledge acquisition is a problem shared by both rule and model-based expert systems. Rule-based systems must often be tediously hand encoded and are not suitable for representing non-causal knowledge.

Artificial neural networks (ANN) are found to be suitable for the above requirements. Artificial neural networks are massively parallel interconnected networks of simple adaptive elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as the biological counterparts[1, 2, 3]. Neural networks find wide applications in parallel distributed processing and in real-time environments. Neural networks have considerable advantages over expert systems in terms of knowledge acquisition, addition of new knowledge, performance and speed[4]. Recently interest in the application of associative memories and neural networks to problems encountered in diagnostic expert systems development has increased. Neural networks appear to offer features which coincide well with the requirements of pattern-based diagnosis. An important feature of fault diagnosis using neural networks is that they can interpolate among the training to give an appropriate response for cases described by neighboring or noisy input data. This paper gives in brief the design and simulation of an neural network for real-time fault diagnosis of thyristors converters used in HVDC power transmission systems. In this paper fault diagnosis is conceptualized as the association of patterns of input data representing the behaviour of the physical system to one or more fault conditions. The fault diagnostic system consisting of a two-level neural network was trained using data from the digital simulation of a two-terminal dc system. The network model detects the severity and duration of the fault. The top-level network is trained with 14 input representations, six associated with converter faults and eight with external faults. The four lower level networks are associated with each classifier are designed to categorize input patterns according to fault severity and duration. Nine input patterns, consisting of combinations of three level severity levels and three durations are used to train the lower level networks. Twenty four different faults were considered and the network was able to detect, classify and diagnose the type, duration and severity of the fault. The performance of the neural network for fault detection and diagnosis under the presence of external noise and was found to be satisfactory.

2 NEURAL NETWORKS FOR FAULT DETECTION AND DIAGNOSIS

Neural networks is one of the fastest growing areas of artificial intelligence. Neural networks as inherently parallel machines and as a result, they can solve problems much faster that a serial digital computer. In addition, many neural networks have the ability to learn nonlinear relationships. Instead of programming these nets, they are presented with a series of examples from which the governing relationships are learned. Neural networks are massively parallel interconnections of simple adaptive elements. Figure 1 shows the topology of the neural network employed in the current research. The basic unit of a neural network is a processing element or a node. Each processing element usually has one or more inputs and a single output. These processing elements are most elegantly described by a simple function providing a mapping from n-dimensional space (inputs) to one dimensional space (output).

Real-time diagnosis of faults occurring in complex systems is an active area of research in the field of knowledge-based expert systems. Real-time environments present many challenges which must be effectively and

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.ficiently addressed by expert system designer. A real-time diagnostic system must be capable of performing an accurate diagnosis quickly enough for effective remedial action to be taken. Recently there has been growing interest in the application of associative memories and neural networks to problems encountered in expert systems. Most of the earlier works deal with the application of assoictaive memories and neural networks to pattern recognition and mapping[4, 5].

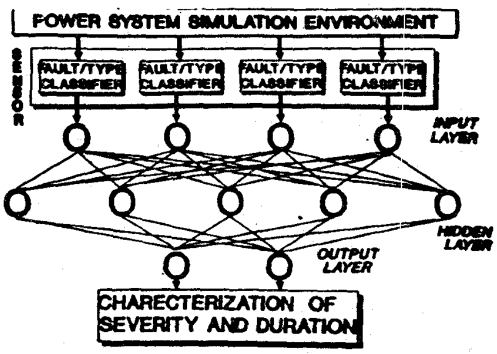

Figure 1 Neural network topology.

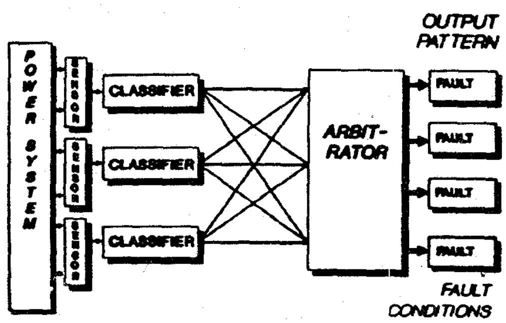

Figure 2. Pattern-based diagnosis.

The behaviour of a physical system is often described in terms of the temporal behaviour of various physical parameters relating to the system. Figure 2 shows the basic principle of the diagnostic process conceptualized as mapping of patterns of sensor data to a pattern associated with a fault condition. Each sensor is associated with a classifying system, which determines the fault condition indicated by the sensor. A real number between 0 and 1 is output by each classifier for each possible fault condition. The output of each classifier then is input to an arbitrator which determines the output of the diagnostic system. The arbitrator combines the outputs of the classifiers and outputs a pattern of real numbers corresponding to the output of the system as a whole. The arbitrator may simply average the outputs of the sensors, or it may apply appropriate domain knowledge from the expert system and assign some sensors more weight than others. The calculation of the output of the neural network involves only two matrix multiplications and two applications of the activation functions. the use of neural networks require very little computational overhead and allows diagnosis to be accomplished in real-time[5]. The algorithm for training the neural networks is written in FORTRAN as the neural networks involve mostly mathematical calculations, rather than symbolic manipulations.

3 LEARNING.

Artificial neural networks learn patterns of activations and hence, learning can be equated to determining the proper values of the connection strengths that allow all the nodes to achieve the correct state of activation for a given pattern of inputs. Once the pattern of activation is established, the resulting outputs let the network classify an input pattern. The adaptive nature of the neural network allows the weights to be learned by experience, thus producing a self-organizing system. Much of the recent interest in neural networks can be attributed to new and more effective learning heuristics. A robust learning heuristic for multi-layered feed forward neural network called the Generalized delta rule (GDR) or back propagation learning rule has been recently proposed by Rummelhart[4, 12, 13]. The back propagation training algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of a three layer feed forward neural network and the desired output. It uses a gradient search technique to minimize a cost function equal to the mean square difference between the desired and the actual net outputs. The desired output of all the nodes is low (0.1) unless the node corresponding to the class the current input is from in which case it is high (0.9). The neural network is trained by initially selecting small random weights and internal thresholds and then presenting all training data repeatedly. Weights are adjusted after every trail using information specifying the appropriate desired fault condition. The back propagation algorithm propagates error terms to adapt weights from nodes in the output layer to nodes in the hidden and input layer. This algorithm has been modified to the requirements of fault analysis in power converters and applied in the research effort.

3.1 Back Propagation Algorithm:

Let M, N and P be the number of nodes in the input, hidden and output layer respectively. Let X(I), Y(J), Z(K), I=1,M; J=1,N; K=1,P, be the pattern vectors at the input, hidden and output layers respectively. B(J), and D(K)are bias of offset vectors in the hidden and output layers respectively. V(I,J) and W(J,K) are the connection weights in the input to hidden layer and hidden to output layer.

The computation of output of the input layer is given by (Input to hidden layer)

$$Y_{2J} = 1/(1+\exp(-(Y_{1J})))$$

where $Y_{1J} = [E(V_{IJ} * X_I) - B_I]$

Output of the hidden layer:

$$Y_{3K} = [E(W_{JK} * Y_{2J}) - D_K]$$

Computed Output:

$$Y_K = 1/(1+\exp(-(Y_{3K})))$$

<u>Adapting weights</u>

Error term in output layer:

$$D_{1K} = Y_K*(1 - Y_K) * (Y_K - D_K)$$

Error term in hidden layer:

$$D_{2J} = Y_{2J}*(1 - Y_{2J}) * \{E(W_{JK} * D_{1K})\}$$

Adapting weights without momentum function:

$$V_{IJ} = V_{IJ} + u*D_{2J}*Y_{2J}$$

$$W_{JK} = W_{JK} + u*D_{1K}*Z_K$$

Adapting weights with momentum function:

$$V_{IJ}(t+1) = V_{IJ}(t) + u*D_{2J}*Y_{2J} + a*[V_{IJ}(t) - V_{IJ}(t-1)]$$

$$W_{JK}(t+1) = W_{JK}(t) + u*D_{1K}*Z_K + a*[W_{JK}(t) - W_{JK}(t-1)]$$

4 AN INTRODUCTION TO THE PROBLEM OF FAULT DIAGNOSIS OF POWER CONVERTERS

Thyristor power converters are widely used in high voltage direct current (HVDC) power transmission systems. Power converters usually constitute a six pulse Graetz bridge circuit or a twelve pulse converter. Power transmission through direct current constitutes an important and integrated part of AC system. Fault detection and diagnosis of HVDC systems is an essential aspect of study for the reliable operation of the integrated power system. The task of detection and diagnosis of faults on converters are usually performed with the help of microprocessors which monitor continuously the performance of the converter under different operating conditions. A new approach to fault detection and diagnosis of hvdc systems has been proposed by the authors where the conduction patterns of the thyristors of the converter are used for the development of a Fault Diagnostic Expert System (FDES) for fault detection and diagnosis of HVDC systems [6, 7, 8]. The patterns of voltage-zone periods and pulse-zone periods are also used for diagnosing the fault. A typical bridge conduction pattern consisting of patterns of conducting thyristors, voltage-zone periods and pulse-zone periods is given in figure 3.

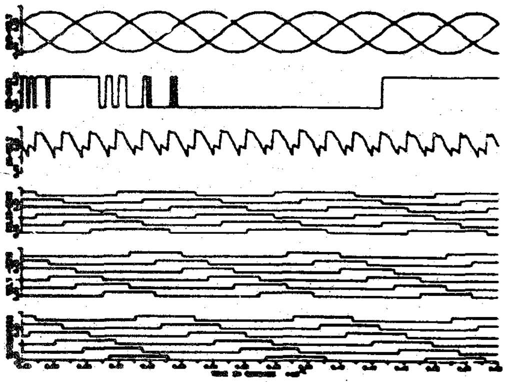

Figure 3. Typical bridge conduction pattern of converter.

5 NEURAL NETWORK DESIGN

A two layer neural network consisting of 24 input nodes, 10 hidden nodes and 6 output nodes are used. Out of the 24 input nodes, six nodes each are allocated for the thyristor conduction pattern, voltage-zone periods and pulse-zone periods. The remaining 6 nodes are allocated as follows; two for direct voltage and direct current, three for the ac system bus voltage and the last one for the time instant of sampling. The nodes in the hidden layer were varied from 10 to 25 for every input pattern and the performance of the network in determining the optimum hidden nodes was carried out. It was found that twelve nodes in the hidden layer gave the most optimum and satisfactory performance in terms of fault detection, discrimination and diagnosis. The output layer consists of six nodes corresponding to the different fault conditions on the converter. Six major faults on the converter are considered. An input pattern corresponding to a particular fault condition is fed to the neural network and the desired output pattern corresponding to the fault condition is impressed at the output. The neural network is trained using the back propagation algorithm till the error in the weights between successive iterations is less than a specified minimum value. The neural network is trained off-line for twelve different types of faults and used on-line. Table 1 shows the training set for normal and abnormal operation of the converter. When an unknown output pattern corresponding to the fault condition is given at the output layer of the neural network, the diagnostic system classifies the type duration and severity of the fault. The neural network is trained with the help of the data obtained through the digital simulation of a two terminal dc-system. The neural network designed is able to determine the severity and duration of the fault. The structure of the prototype diagnostic system is given in figure 4. Sensor data is input to the neural network which has been trained to recognize the difference between the behaviour exhibited by converter faults and faults external to the converter. Once a gross identification of the fault has been made, the sensor data is passed to lower-level neural networks which have been trained to recognize the severity and duration of the fault. Each classifier has five associated neural networks, one to determine the type of the fault and four to determine the severity and duration of converter and external faults. The top level neural networks have two output nodes. One output node is activated if a converter fault is detected, while the other is activated if external faults are detected. The output activations are real numbers between 0 and 1. This output format allows a network to indicate that an input behavioral pattern exhibits features common to both fault scenarios. Lower level networks have four output nodes, each of which identifies either one of the four severity levels or one of four durations. Data from the four sensors are input into the four top level neural networks, each of which independently attempts to identify the fault condition. If a network recognizes an input pattern as characteristic of a converter fault, the node associated with converter faults will be highly activated. Corresponding output activations from each top level network are averaged to yield the overall top-level response to the input patterns. The result is a characterization of the fault as either a converter fault or external fault. The diagnostic system now attempts to determine the severity and duration of the fault. This is accomplished by applying the same simulation data which was used for the top-level fault identification to the lower level neural networks. Each sensor will input information into two neural networks, one which determines the fault severity and one which determines the duration.

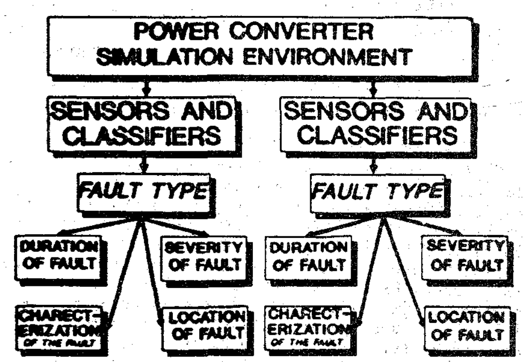

Figure 4. Structure of a prototype diagnostic system.

5.1 Behavioral representation

To train and use neural networks, behavioral data must be presented to the inputs of the networks. Two methods of representing behavioral data have been considered in this paper. In the first method, simulation data is presented to the input layer of the neural network as a vector of continuous real variables. Each node in the input layer corresponds to a point in time since a fault was detected. The activation of each input node is the magnitude of a parameter at each point of time. Therefore, each input node represents a sample of the data at different times. In the prototype plementation, 20 input nodes were used, spanning a 2.0 second interval. As a result the adjacent input nodes contain data 0.1 seconds apart. Ten nodes were utilized in the hidden layer. In the second method, parameter behaviour is represented in a binary form. The waveform describing the temporal behaviour of the converter is represented as a field of 0's and 1's corresponding to the off and on states of the thyristors of the converter. The field is represented as a single binary vector which is presented to the input of the neural network. Twenty time intervals and twenty magnitude intervals are encoded. As a result, the neural network for this representation requires 400 input nodes. Five hidden nodes were utilized in this implementation.

5.2 Training the neural network

The fault diagnostic system was trained using data from the digital simulation of a two terminal dc system. The training process used for a top-level network is shown. The network has two output nodes, each of which is associated with either a converter fault or an external fault. During training, a behavioral pattern representing a fault condition is applied to the input level, while a 1, indicating the full activation is applied to the corresponding output node. The generalized back-propagation algorithm is then invoked to adjust the connection weights to be consistent with the imposed input and output patterns. At this point the network has been trained to recognize a single representation of a converter fault. The training process is now repeated with a representation of the external (dc-line) fault presented to the input nodes, and an activation of 1 imposed on the corresponding output node. The connection weights are readjusted to accommodate the new input. During the process, the ability of the network to recognize the first input will be degraded. The network must in effect be repeatedly retrained on the two scenarios until the system of weights converges to steady state value.

Table 1.Training set for learning in neural network

TRAINING SET FOR THE NORMAL AND ABNORMAL OPERATION OF THE CONVERTER

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
	TH 1	TH 2	TH 3	TH 4	TH 5	TH 6	PZ 1	PZ 2	PZ 3	PZ 4	PZ 5	PZ 6	VZ 1	VZ 2	VZ 3	VZ 4	VZ 5	VZ 6	DC V1	DC I1	AC V1	AC V2	AC V3
I. NORMAL OPERATION																									
1	1	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	0	1	1	1	-1	-1	-1		
2	1	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1	-1	-1	0		
3	1	1	0	0	0	1	1	1	0	0	0	1	1	[illegible]	0	0	0	1	1	1	-1	-1	-1		
4	1	1	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	-1	0	-1		
5	1	1	1	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0	1	1	-1	-1	-1		
6	0	1	1	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	1	1	0	-1	-1		
7	0	1	1	1	0	0	0	1	1	0	0	0	0	0	1	1	0	0	1	1	-1	-1	-1		
8	0	0	1	1	0	0	0	0	1	1	1	0	0	0	1	1	1	0	1	1	-1	-1	0		
9	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	1	1	1	1	1	-1	-1	-1		
10	0	0	0	1	1	0	0	0	0	1	1	1	0	0	0	0	1	1	1	1	-1	0	-1		
11	0	0	0	1	1	1	0	0	0	1	1	1	1	0	0	0	1	1	1	1	-1	-1	-1		
12	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1	1	0	-1	-1		
II. ABNORMAL OPERATION																									
1	1	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	0	1	1	1	-1	-1	-1		
2	0	0	0	0	1	1	0	1	0	0	1	1	1	1	0	0	0	1	1	1	0	-1	-1		
3	0	1	0	0	1	1	0	1	0	0	0	1	1	1	0	0	0	0	1	1	0	-1	-1		
4	0	1	0	0	1	1	0	1	0	0	0	0	1	1	1	0	0	0	1	1	0	0	-1		
5	0	1	0	0	1	0	0	1	0	0	0	0	0	1	1	0	0	0	1	1	0	0	-1		
6	0	1	0	0	1	0	0	1	0	1	0	0	0	1	1	1	0	0	1	1	0	0	-1		
7	0	1	0	1	1	0	0	1	0	1	0	0	0	0	1	1	0	0	1	1	-1	0	-1		
8	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	1	1	0	1	1	-1	0	-1		
9	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	1	1	0	1	1	-1	-1	-1		
10	0	0	0	1	1	0	0	0	0	1	1	1	0	0	0	1	1	1	1	1	-1	0	-1		
11	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1	1	1	-1	-1	-1		
12	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1	1	0	-1	-1		

A training set of more than one input pattern is to be associated with a particular output. For instance six different converter faults are associated with the output assigned to identify them. Similarly eight external fault patterns are associated with the output node signifying the identification of an external fault. As a result, each top-level network is trained with 14 input representations, six associated with converter faults and eight associated with external faults. The four lower-level networks associated with each classifier are designed to categorize input patterns according to fault severity and duration. Nine input patterns, consisting of combinations of three severity levels and three durations, are used to train the lower-level networks. Each lower-level has three outputs, corresponding to the different levels of severity or duration, depending on how the network is trained. The severity classifiers are taught that all faults of the same severity are to be classified together, regardless of the fault duration. The networks designed to classify fault durations are taught that all faults of the same duration are to be classified together regardless of the severity of the fault. The same input patterns are used to train each network (how the training patterns are grouped determines the function of the network). Training represents the most computationally intensive aspect of the development of a neural network-based diagnostic system. The time required to training a network can vary widely, depending on the number of nodes in a network and the number of training sets used. However, the similarity of input representations in the training set has the most significant effect on training times. If two input representations are nearly equivalent, but are required to activate different output nodes, the training times can be excessive. In the fault diagnostic system described in this paper, the neural network is trained for 800 to 1000 presentations of input and output patterns. The top-level network which contained a large number of similar patterns which were required to activate different output nodes, required over 2000 presentations of data for convergence of the weights to be achieved.

5.3 Results of Power converter diagnosis

This paper (testing and evaluation of the power converter diagnostic system) has focused on the ability of the system to correctly diagnose fault conditions of varying degrees of severity and duration. Input patterns representing either a converter fault or external fault patterns were presented to the inputs of the top-level networks. The system was evaluated on the basis of 1) whether the top-level networks correctly identified the fault condition, and 2) whether the lower-level networks correctly identified the severity and duration of the fault. Severity and duration combinations were chosen which were not in the training sets of the neural networks. All real-time environments exhibit some level of noise from instrumentation. The effects of noise on the response of the diagnostic system were assessed by randomly perturbing the inputs to the neural networks. The diagnostic systems utilizing either the first or second methods of input data representation (continuous-variable or binary input, respectively) successfully differentiated between a converter fault and an external fault. The different input patterns and output fault conditions derived theoretically for normal and abnormal fault conditions used to train the neural network is given in table 1. An important advantage of the neural network based diagnosis is its performance in real-time environments and under the influence of noisy or varied input data, thus exhibiting resilience.

6 Conclusions.

Application of artificial neural networks for fault detection and diagnosis of thyristor power converter used in HVDC power transmission is described in this paper. Suitability of the neural network for pattern-based diagnosis is justified with the help of a case study. Neural networks are most suitable for diagnosis under real-time environments. Also neural networks are suitable in situations where acquisition and representation of knowledge are the bottlenecks in developing expert systems. To achieve better performance of the diagnostic system, two neural networks one for detecting the fault and the other for diagnosing the fault, are to be employed. The first network is to be trained for different time instants of the thyristors conduction patterns, hence detecting the instant of occurrence of the fault corresponding to the abnormal behaviour of the converter. The second network is to be trained for different durations of the patterns of conducting thyristors, voltage zone periods and pulse zone periods. The two networks are to interact with the

.sed expert system and provide a efficient .ach to real time fault detection and diagnosis.

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