International Journal of Electrical and Power Engineering 5 (4): 181-185, 2011
ISSN: 1990-7958

Three Phase Fault Diagnosis Based on RBF Neural Network Optimized By PSO Algorithm

[1]M. Sivakumar and [2]R.M.S. Parvathi
[1]Anna University, Tamil Nadu, India
[2]Sengunthar College of Engineering, Tamil Nadu, India

Abstract: The present study proposes a fault diagnosis methodology of three phase inverter circuit base on Radial Basis Function (RBF) artificial neural network trained by Particle Swarm Optimization (PSO) algorithm. Using the appropriate stimulus signal, fault features are extracted from efficient points in frequency response of the circuit directly and then a fault dictionary is created by collecting signatures of different fault conditions. Trained by the examples contained in the fault dictionary, the RBF neural network optimized by PSO has been demonstrated to provide robust diagnosis to the difficult problem of soft faults in three phase inverter circuits. The experimental result shows that the proposed technique is succeeded in diagnosing and locating faults effectively.

Key words: Three phase inverter circuit, fault diagnosis, PSO, RBF neural network, stimulus signal, India

INTRODUCTION

Due to the development of modern electronic technology, automatic fault diagnosis of three phase inverter circuits has become an increasingly important issue. The diagnosis using artificial intelligence is one of the hot areas on circuit fault diagnosis. Expect systems, fuzzy theory, neural networks have been gradually applied to fault diagnosis of three phase circuits. In this century as the important research orientation, evolutionary computation theory is studied to use in the fault diagnosis more frequently.

Three phase inverter circuit fault is divided into two categories; one for hard faults (also known as catastrophic faults), refers to short circuit open failure component failure usually caused by structural changes in the circuit and those for the soft fault (also known as parameter failure) that element beyond the parameter of offset allowable tolerance range, the circuit soft errors occur normally only caused by abnormal or deterioration of system performance. And therefore, hard-fault detection and diagnosis is easier than the soft fault. The methods which can diagnosis soft fault diagnosis of hardware failure can also be general. A hard-fault can be seen as a special case of soft faults, so we only study of hard faults in this research. With the technology development of artificial neural networks, it is widely applied to modeling and identification of non-linear system. One of the most popular neural network models is the Radial Basics Function (RBF) neural network. RBF neural network has a simple topology, learning rate of the learning process fast and transparent and so on. However, the traditional RBF neural network learning strategies have great shortcomings; they can only find the optimal solution in the local space to determine the parameters of the network structure. At present, it is difficult to obtain optimum values of the network structure parameters in theory. Particle Swarm Optimization (PSO) algorithm is a new evolutionary algorithm developed in recent years. PSO algorithm developed in recent years. PSO algorithm belongs to a kind of evolutionary algorithm and similar to generic algorithm, starting from a random solution by iteration to find the optimal solution; it is through the fitness to evaluate the solution quality. But it is much simpler than the rules of genetic algorithm. It can be used to solve a wide array of different optimization problems such as neural network training (Engelbrecht and Ismail, 1999; Van den Bergh, 1999; Van den Bergh and Engelbrecht, 2000; Eberhart and Hu, 1999). In this study, a PSO-RBF neural network is proposed in order to implement three phase circuit fault diagnosis in which RBF neural network is trained by the PSO algorithm. Simulation results for the identification of three phase inverter circuit fault diagnosis show the effectiveness of the proposed method.

THE REDIAL BASIS FUNCTION NETWORK BASED ON PARTICLE SWARM OPTIMIZATION LEARNING ALGORITHM

RBF network is consists of three layers, its structure is shown in Fig. 1. The 1st layer is the input layer formed by the signal source node, the 2nd layer is hidden layer and the 3rd layer is output layer. Weights among the

Corresponding Author: M. Sivakumar, Gnanamani College of Technology, Namakkal, Tamil Nadu, India

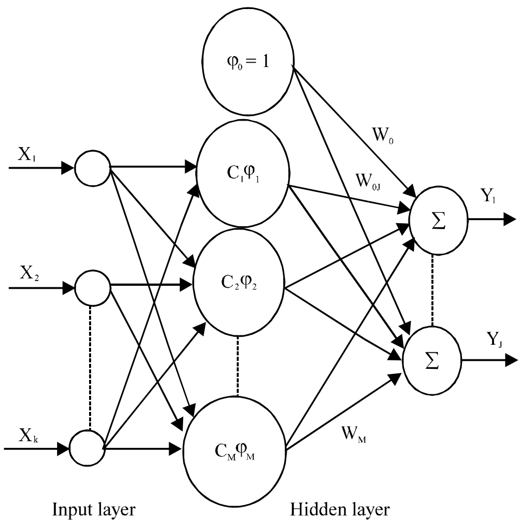

Fig. 1: The basic architecture of RBF neural network

hidden layer and output layer expressed with w_{ij} ($i = 1, 2, \ldots, I$, $j = 1, 2, \ldots, J$). The basic function of the network is φ (X_k, C_i) where C_i are the center vector of the ith node, Output layer set the threshold as φ_0 which has weights W_{0j}. Such a network can be represented by the following parametric model:

$$y_{j(X)} = W_{0j} + \sum_{i=1}^{M} W_{ij\varphi}(X_k, C_i),\ j = 1, 2, \ldots, J \tag{1}$$

If the basis function of the network is a Gaussian function then:

$$\Phi(X_k, C_i) = \exp\left[\frac{-\|X_k - C_i\|^2}{2\sigma_i^2}\right] \tag{2}$$

Then, we define error function as:

$$E = \frac{1}{2}\sum_{i=1}^{M}(y_d - y_i)^2 \tag{3}$$

The y_d is a desired output vector. The dilation and translation parameters are randomly initialized at beginning and will be optimized by PSO algorithm.

Particle swarm optimization: The Particle Swarm Optimization (PSO) is a population based optimization method first proposed by Kennedy and Eberhart (1995). Particle swarms explore the search space through a population of particles which adapt by returning to previously successful regions. Each individual trajectory in the search space adjusted by dynamically changing the velocity of each particle, according to its own flying experience and the flight experience of the other particles. The position of particle i in the N-dimensional search space can be represented by $X_i = (X_{i1}, X_{i2}, \ldots, X_{id})$ and also the velocity is expressed by $V_i = (V_{i1}, V_{i2}, \ldots, V_{id})$. According to the best fitness value determined by a user-defined fitness function each particle knows its best value so far (pbest) and its position and the best value so far in the group (gbest) among pbest. Then, the new velocities and the positions of the particles for next fitness evaluation are calculated using the following two equations:

$$\begin{aligned} v_{td}^{k+1} &= \omega \times v_{id}^{k} + c_1 \times \text{rand}(.) \times (v_{id} - x_{id}^{k}) + \\ & c_2 \times \text{rand}(.) \times (p_{gd} - x_{id}^{k}) x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \end{aligned} \tag{4}$$

Where:

c_1 and c_2	=	Constants known as acceleration coefficients
rand (.)	=	Two separately generated uniformly distributed random numbers in the range [0, 1]
x_{ik}	=	The current position of particle I at iteration k
pbest I	=	The pbest of particle I
gbest	=	The gbest of the group
ω	=	Inertia weight

Equation 5 shows how ω is calculated:

$$\omega\ (t) = (0.9) - (t/\text{max. number}) \times 0.5 \tag{5}$$

Using Eq. 5, a certain velocity which gradually gets close to pbest and gbest can be calculated.

Training RBF neural networks with PSO: The PSO for neural network optimization has two main aspects; first, for the network training to optimize the network connection weights between layers; the second is to optimize the network topology. The Particle Swarm Optimization algorithm (PSO) is designed to optimize the centers, the widths and the weights of RBF Network in this context. The identification steps of PSO to optimize RBF network are presented as follows:

- **Step 1**: Collecting the training samples
- **Step 2**: Construct and initialize RBF topological structure
- **Step 3**: Initialize particle swarm population size and the maximum iteration number; initialize pbest and gbest
- **Step 4:** For each particle, evaluate its fitness degree according to the fitness function. Update its P_{id} and P_{gd}

- **Step 5:** Adjust the velocity and position
- **Step 6:** Repeat step 4 and 6, until it reaches the computing requirements
- **Step 7:** Global optimal particle experienced by groups in the best position is mapped to the structure of the network parameters. RBF optimal structure is gained according to optimal output result
- **Step 8:** Input the test samples to verify whether the system is able to meet the required functionality

PSO-RBF NEURAL NETWORK FOR DIAGNOSIS FAULTS

There are two categories of three phase inverter circuit fault diagnosis: Simulation Before Test (SBT) and Simulation After Test (SAT). Among these, simulation before test automated fault detection methods (Catelani and Fort, 2002) seem to have some advantages when the topology of the Circuit Under Test (CUT) is complex. SBT approach builds some forms of a data dictionary through simulation and use pattern recognition concept to identify and locate faults. The fault dictionary is a table responding the mapping from the fault list into a list of faculty responses. In that way, the diagnostic process becomes a search through the fault dictionary. Neural networks being universal approximates are the best way both to capture the mapping and to search through the dictionary, thereby to perform diagnosis (Wang *et al.*, 2008). The RBF neural network is a typical local approximation neural network which has fast convergence and can achieve the global optimal solution. It is better than BP neural network in the approximation capability, sorting capability and learning speed. In order to improve RBF real-time performance, PSO is employed to train and optimize RBF structure online. Then, PSO-RBF neural network for diagnosing three phase inverter circuit faults is formed. Three phase inverter circuit fault diagnosis system based on PSO-RBF neural network mainly consists of two process: learning (training) process, diagnostic (test) process. Flow chart of the three phase circuit fault diagnosis based on PSO-RBF neural network is shown in Fig. 2. The design of a diagnosis SBT-based approach for a Circuit under Test (CUT) is an articulated process that requires the following:

- Input stimuli section, the identification of the most appropriate test stimuli able to excite the CUT so that the faculty-induced effect propagates to an observable node. Three phase inverter circuit test stimuli signal is usually the work of signal or other input signals such as DC signals, square wave signals, pulse signal, multi-frequency sinusoidal signals, piecewise linear function of signals, step signals, etc.

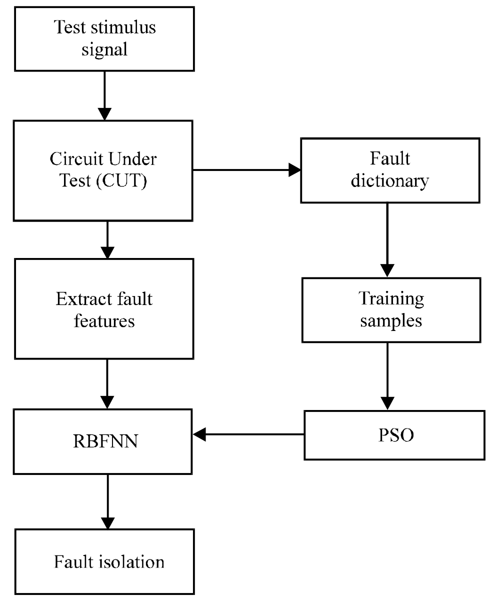

Fig. 2: PSO-RBF neural network fault diagnosis

- Identification of the most observable test nodes in the CUT
- The fault set of three phase inverter circuit fault include two categories; one for hard faults (also known as catastrophic faults), refers to short-circuit open failure component failure, usually cased by structural changes in the circuit and those for the soft fault (also known as parameter failure) that element beyond the parameters of offset allowable tolerance range
- Extraction of a set of features from the signals measured at the test nodes. The selected features must be able to highlight faults of three phase inverter circuit
- Construction of a fault dictionary in fault conditions are simulated by applying a predefined input stimuli set to the circuit inputs, the circuit responses, represented the CUT signature for the simulated fault condition; signatures are subsequently collected in a fault dictionary
- The establishment and training of PSO-RBF neural networks. By using PSO learning algorithm, the initial training parameters of the RBF ANN can be determined
- In fault diagnosis apply PSO-RBF neural network to fault diagnosis of the CUT for the fault features. Compare the measured CUT response with all the signatures contained in the fault dictionary. By summing the fault classes for every element and every faults tolerance range, the faults diagnosing and location can be achieved quickly and from the maximum number fault classes of the tolerance range

NVERTER FUULT MODELING AND SIMULATION

Figure 3 shows the system of inverter and mainly make up of rectifier, inverter and load circuit. Three phase H-bridge inverter circuit as an example is analyzed in this study three phase inverter open circuit failure include power tube short circuit, open circuit and trigger pulse lost faults. There are five faults types; no-power tube failure, single tube failure, two power failures in the same bridge arm, two power failure in the same half bridge arm, cross tube power failure and 22 kinds of failures in all. Fault code is S1S2S3S4S5, S1S2S3 represents fault type, S6 represents the components failure of the same bridge arm and the value of S6 can be determined by simple logic. Neural network topology structure is composed of input layer, hidden layer and output layer. Input layer is the three low frequency energy value, the input layer neuron number is 3.

The output layer neuron number is 5. Main parameters of PSO are; C1 = C2 = 2, Cd = 0.35, Δ = 2.5. Simulation model of inverter circuit is established in Matlab 7.0. Neural obtains from wavelet transform of the fault signals. Neural network of PSO-BP begin to training. Test sample is diagnosed in the network of training good. Table 1 shows the actual output. The data shows that faults code of actual output after rounding is the same as settings in faults diagnosis system. The same neural network is trained by using the standard of BP algorithm and builds the same map in contrast to the PSO-BP algorithm. The convergence curve is shown in Fig. 3

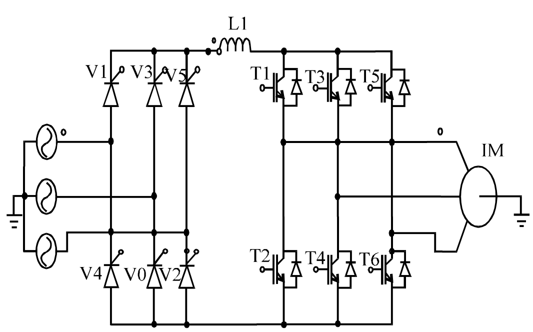

Fig. 3: Three phase inverter fault diagnosis circuit

which indicates PSO-BP algorithm error is 0.028 at 2500 times. BP algorithm error is 0.059 at 5000 times. PSO-BP hybrid algorithm is superior to BP algorithm for the same structure of the network and the same sample set. PSO-BP algorithm can be used in power and electronic circuits fault diagnosis for the advantages of quick optimization, high accuracy and short training time.

EXPERIMENTAL SETUP AND SIMULATED OUTPUT

The experimental setup is represented in Fig. 4. A three phase wyes-connected cascade multilevel inverter using 100 V, 70 a IGBTs as the switching devices was used to produce the output voltage signals. The Opal RT-lab system is utilized to generate gate drive signals and interfaces with the gate drive board. The switching angles

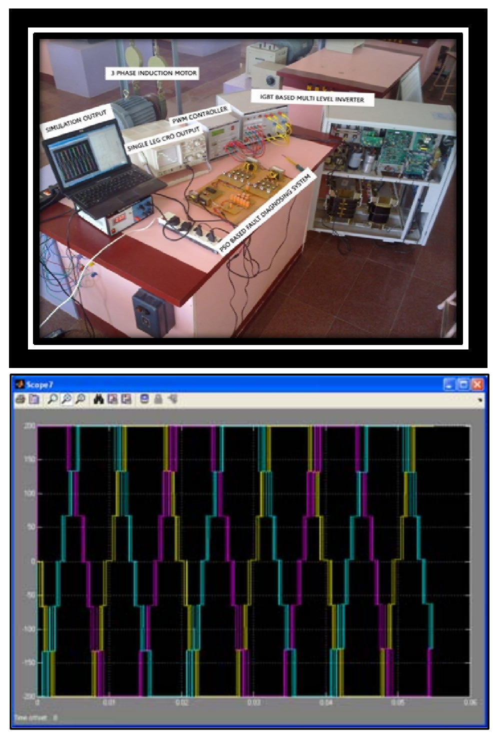

Fig. 4: Experimental setup and simulated output

Table 1: Experimental data

Simultaneous switching devices	Switch data coding S1	S2	S3	S3	S4	S5	Fault code	Diagnosis
Correct	0.0034	0.0004	0	0.0067	0.0030	0	000000	Correct
T2 (IGBT)	0	0.8999	0.0060	0.0010	1	0	001011	Correct
TIT2 (Two IGBT of upper and lower leg)	0.0004	0.8989	0.0063	0.0065	0.9778	0.0008	010110	Correct
TIT5 (Two IGBT of the same half-bridge)	0.0008	1	0.9870	0.9675	1	0.0045	011100	Correct
T2T3 (Two cross IGBT)	1	0.0006	0.0001	0.0140	0.9768	0.8976	100001	Correct

are calculated by using simlink based on sinusoidal PWM. A separated individual 12 V dc power supply is supplied to each H-bridge inverter in both simulation and experiment. Fault occurrence is created by physically removing the switch in the desired position. A DL 1540c is used to measure output voltage signals shown in Fig. 4 as ASCII files. The measured signals are set to N = 10032; sampling frequency is 200 kHz. The voltage spectrum is calculated and transferred to the neural network fault classification system.

CONCLUSION

A fault diagnosis system in a multi-level inverter using PSO and neural networks has been proposed. The proposed networks perform very well with both simulation and experimental testing data set. It should be noted that the test sets are not the same as the training sets. The test set should be data that the networks have not ever seen before. The classification performance is very good >90%. Obviously, the results show that the PSO conveys lower dimensional input space and reduces the time necessary to train a neural network. Also, the reduced noise may improve the mapping performance which leads to the total classification performance. PSO-NN has a better overall classification performance by about 6% points.

ACKNOWLEDGEMENT

This research described in this study was supported by the Research and Development Cell, Gnanamani College of Technology, Namakkal, Tamil Nadu, India. Reference code: GCT2010EER.

REFERENCES

Catelani, M. and A. Fort, 2002. Soft fault detection and isolation in analog circuits: Some results and a comparison between a fuzzy approach and radial basis function network. IEEE Trans. Instrumentation Measurement, 51: 196-202.

Eberhart, R.C. and X. Hu, 1999. Human tremor analysis using particle swarm optimization. Proceeding of the Congress on Evolutionary Computation, July 6-9, Washington, DC, USA., pp: 1927-1930.

Engelbrecht, A.P. and A. Ismail, 1999. Training product unit neural networks. Stability and Control. Theor. Appl., 2: 59-74.

Kennedy, J. and R. Eberhart, 1995. Particle swarm optimization. Proc. IEEE Int. Conf. Neural Networks, 4: 1942-1948.

Van den Bergh, F., 1999. Particle swarm weight initialization in multi-layer perceptiron artificial neural networks. Development and Practice of Artificial Intelligence Techniques, pp: 41-45.

Van den Bergh, F. and A.P. Engelbrecht, 2000. Cooperative learning in neural networks using particle swarm optimizers. S. Afr. Comput. J., 26: 84-90.

Wang, C., Y. Xie and G. Chen, 2008. Fault diagnosis based on radial basis function neural network in analog circuits. Int. Conf. Commun. Circuits Syst., 2: 1183-1185.