CHAPTER 8

FAULT DIAGNOSIS USING SOFT COMPUTING TECHNIQUES

8.1 FAULT DIAGNOSIS RESULTS OF DWT-ANN APPROACH

In continuation of the above work, to automate the process of fault diagnosis of multilevel inverters, Artificial Neural Network (ANN) was used. In the present work, ANN has been applied to the problem of identifying the faulty switch in the multilevel inverter. Among the various ANN architectures available in the literature, the multilayer feed forward network with back propagation learning algorithm has been used because of its simple approach and good generalization capability. The details of the optimized neural network used in the present study are shown in Table 8.1.

Table 8.1 Specifications of DWT-Artificial Neural Network

No. of Inputs	11
No. of Neurons in Hidden Layer	20
No. of Neurons in Output Layer	9
Learning Rate (η)	0.1
No. of Iterations	2800
No. of Training Sets	204
No. of Test Input Sets	150
Convergence Criteria	0.01

Artificial neural networks are highly parallel, adaptive learning system that can learn a task by generalizing from case studies of the tasks (Frederic & Pham 2013). In this work, the 9 values of energy content at different level of decomposition obtained from DWT MRA technique and two voltage ratios (Vrms/Vdc and Vrms/Vav) of the output voltage signal at different fault conditions are given as an input to the neural network. The 9 output neurons were used to classify the fault as no fault, S1A fault, S2A fault, S3A fault, S4A fault, S1B fault, S2B fault, S3B fault and S4B fault. Table 8.2 shows the ANN training pattern used for different switch faults of multilevel inverter. In the training pattern, each neuron is assigned for a particular fault and then trained for a binary value of 1 or 0 as shown in the table.

Table 8.2 Training pattern of DWT- ANN method

Nature of Fault	Position of Neuron	Training Pattern
No fault	1	[1 0 0 0 0 0 0 0 0]
S1A fault	2	[0 1 0 0 0 0 0 0 0]
S1B fault	3	[0 0 1 0 0 0 0 0 0]
S2A fault	4	[0 0 0 1 0 0 0 0 0]
S2B fault	5	[0 0 0 0 1 0 0 0 0]
S3A fault	6	[0 0 0 0 0 1 0 0 0]
S3B fault	7	[0 0 0 0 0 0 1 0 0]
S4A fault	8	[0 0 0 0 0 0 0 1 0]
S4B fault	9	[0 0 0 0 0 0 0 0 1]

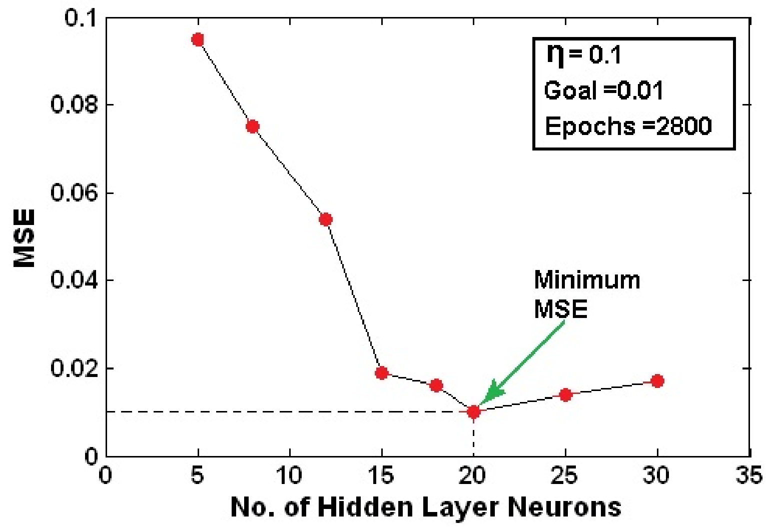


Figure 8.1 Evaluation of the mean square error of the neural network at different no. of hidden layer neurons

The important factors influencing the performance of the neural network are the number of processing elements in the hidden layer and the number of iterations.

- Figure 8.1 shows the mean square error values obtained with the different number of hidden layer neurons.
- It clearly indicates that the mean square error value obtained with 20 hidden layer neurons is the minimum.
- As the number of hidden layer neurons increases above 20, the neural network takes more time to learn and to reach the convergence criteria.
- To obtain an optimum value for the number of iterations, the mean square error value of the network has been evaluated by maintaining the learning rate to be 0.1 with 20 hidden layer neurons.

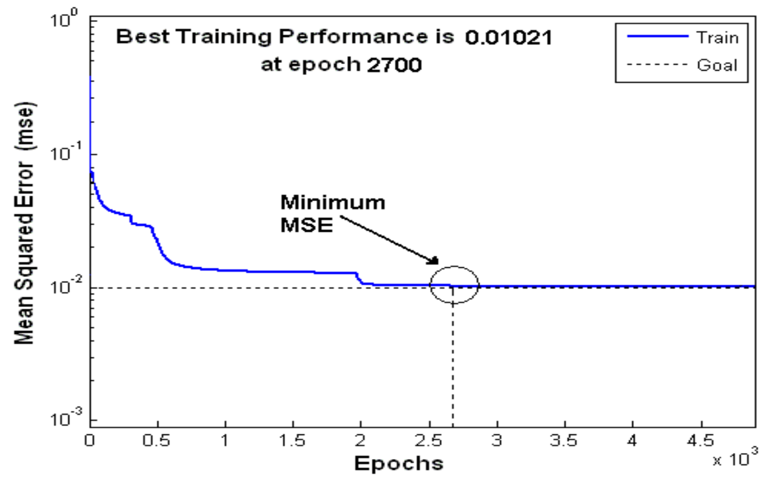


Figure 8.2 Variations in the MSE of the ANN during training with respect to increase in no. of iterations

- Figure 8.2 shows the performance of the network for different iteration numbers.
- It is observed that during training process the present network reaches the convergence criteria near 2800 iterations.
- It indicates that 2800 iterations are sufficient for the successful training of the optimized neural network.
- Therefore, in this work, the performance of the back propagation neural network has been studied with 20 hidden layer neurons maintaining the value of the learning rate to be 0.1 and the number of iterations to be 2800.

The neural network identification rates have been studied with 204 training sets consisting of each fault conditions at modulation index values ranging from 0.8 to 0.95. Then 150 additional data were used for the identification testing purpose at different modulation index ranging from 0.8 to 0.95.

- Table 8.3 shows the identification rates of neural network at different no. of hidden layer neurons.
- Initially, the neural network is tested with the input data corresponding to the trained modulation index ranging from 0.8 to 0.95 and the network is able to identify 100% accurately all fault cases.
- Then the neural network is also tested with input data corresponding to modulation index ranging from 0.8 to 0.95.
- It is observed that the performance of the neural network is better for 20 hidden layer neurons when compared with other cases and the overall identification rate for all fault cases is 97 % in this case and the neural network is able to identify the fault efficiently almost for all fault cases.

Table 8.3 Identification rates of DWT-ANN approach

Nature of Fault	**Identification rate (%) at different no. of hidden layer neurons**		
	15	**20**	**25**
No fault	100	100	100
S1A fault	97	100	98
S1B fault	93	96	94
S2A fault	92	97	96
S2B fault	91	97	97
S3A fault	95	99	94
S3B fault	91	96	93
S4A fault	93	95	94
S4B fault	94	96	95

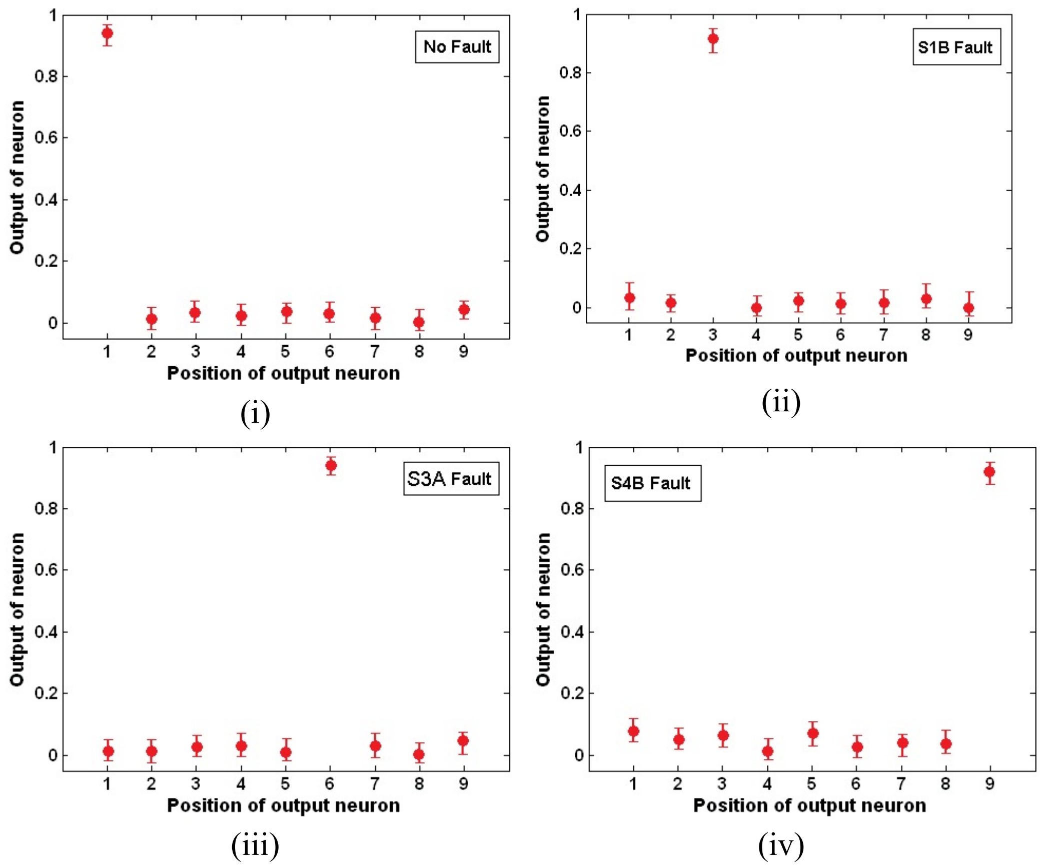


Figure 8.3 Output of neurons in the output layer of the neural network (a) no fault (b) S1B fault (c) S3A fault (d) S4B fault

- Figure 8.3 shows the results of the output of the neuron in the output layer of the optimized neural network (no. of hidden layer neurons=20, η=0.1, convergence criteria=0.01) for the present study.

- For example, if the input pattern corresponds to no fault conditions, then the nine neurons in output layer are trained for a pattern (1 0 0 0 0 0 0 0 0).

- Therefore, when a normal output voltage pattern, which is not trained in the NN is given as an input, it is expected that the output pattern will be closer to (1 0 0 0 0 0 0 0 0).

- Figure 8.3 (a) shows the output of the neurons in output layer for normal condition i.e. no fault input. It is clear that output of 1st neuron is closer to 1 and all other neurons give an output less than 0.2.
- Similarly, Figure 8.3 (b, c and d) shows the output of neurons at other fault conditions. In this work, it is observed that the output of neuron corresponding to that fault position in most of the case is above 0.8.
- It is easier to differentiate the output neuron corresponding to faulty switch from remaining output neurons.
- This indicates that the trained neural network can assess the fault condition of the multilevel inverter effectively.

8.2 FAULT DIAGNOSIS RESULTS OF FFT-ANFIS APPROACH

In this approach, the four features extracted from the FFT analysis of output voltage waveform at different switch fault conditions such as THD, RMS value, 3rd harmonic ratio and 5th harmonic ratio are given as an input to the ANFIS network. The details of the optimized ANFIS network used in the present study are shown in Table 8.4. In this work, ANFIS was implemented by using the fuzzy logic toolbox of MATLAB. Bell shaped membership function 'gbell' is used in the first layer and weighted average defuzzification is adopted to obtain the output (Jun Li 2012 , Jorge & Antonio 2013) .

Table 8.4 Specifications of FFT-ANFIS network

No. of Inputs	4
No. of membership functions	3
No. of fuzzy rules	81
No. of Iterations	500
No. of Training Sets	204
No. of Test Sets	150
Convergence Criteria	0.01
Initial step size	0.01
Membership function	gbell

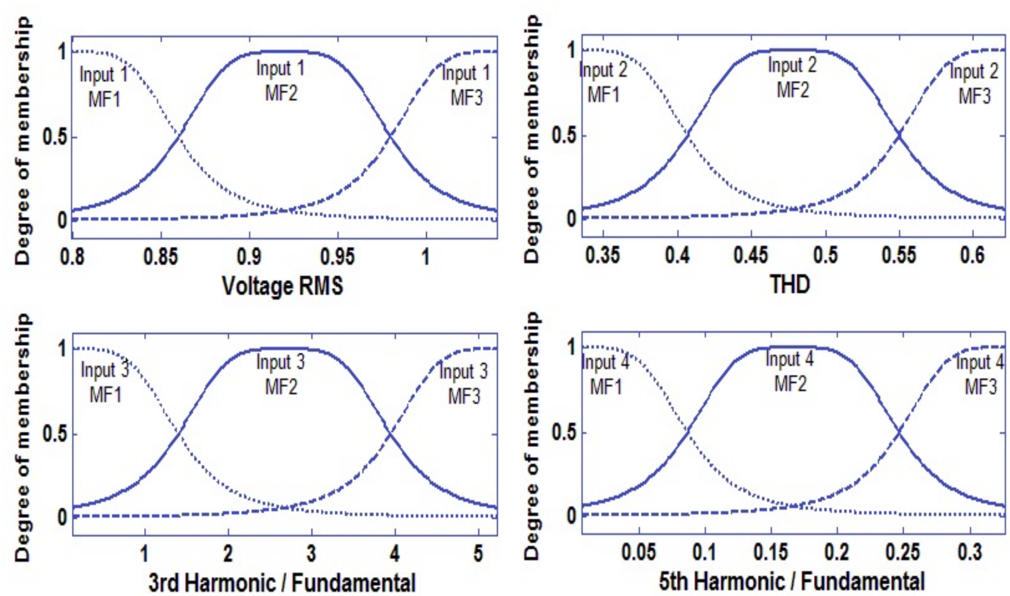


Figure 8.4 Degree of membership of fuzzy gbell membership function for different inputs to FFT-ANFIS network.

- Figure 8.4 shows the 'gbell' membership function of four inputs to ANFIS network such as THD, RMS value, 3rd Harmonic ratio and 5th Harmonic ratio.

- These bell shaped membership functions has a value maximum of '1' and minimum of '0'. Table 8.5 shows the FFT-ANFIS output pattern used for different switch faults of multilevel inverter.

Table 8.5 FFT-ANFIS network output pattern for switch fault

Nature of Fault	ANFIS output
No fault	1
S1A fault	2
S2A fault	3
S3A fault	4
S4A fault	5
S1B fault	6
S2B fault	7
S3B fault	8
S4B fault	9

- Figure 8.5 shows the performance of the ANFIS network during the training process for different iteration numbers with respect to gbell membership function.
- It is noticed that ANFIS network reaches the minimum RMSE convergence criteria near 300 iterations.

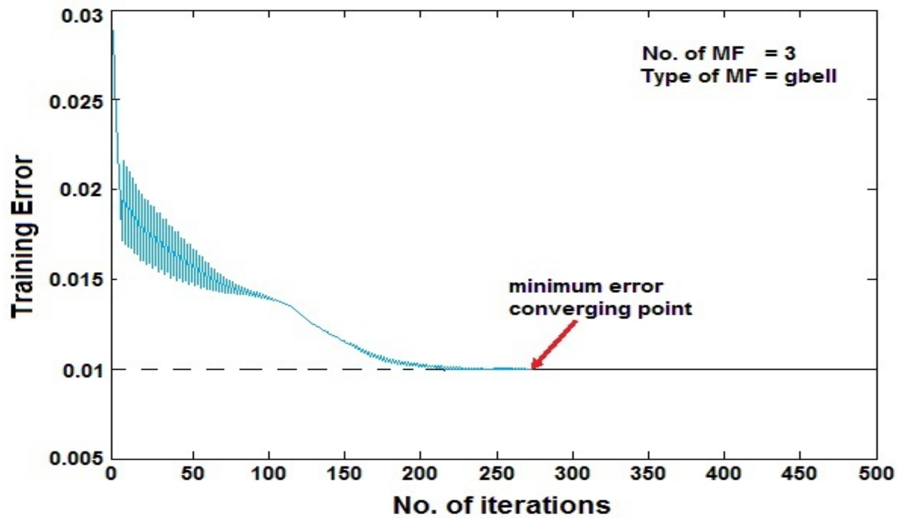
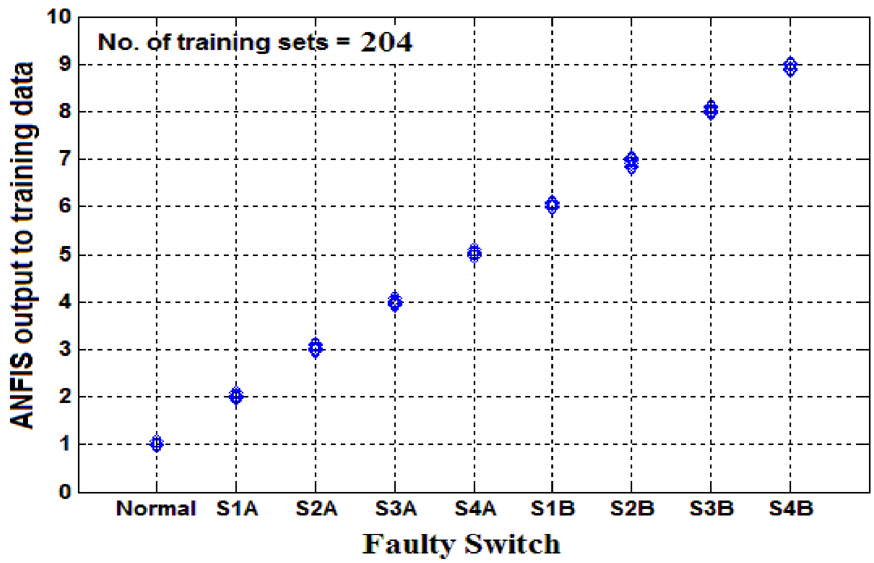
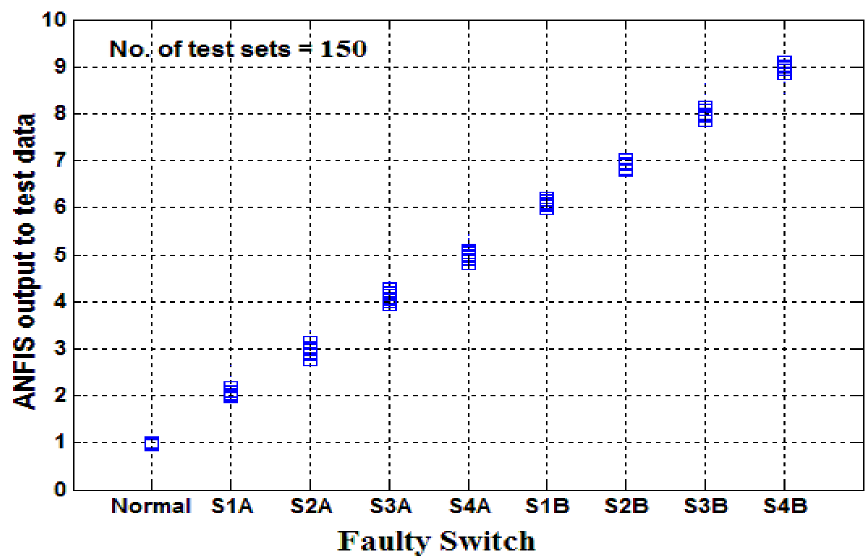


Figure 8.5 Convergence of root mean square error of FFT-ANFIS network during training process with gbell MF

- During the initial stage of training phase upto 100 iterations, more oscillations of root mean square error value is observed in this approach.
- After 150 iterations, the oscillations are settled and the root mean square error takes a smooth variations and slowly reaches the convergence criteria of 0.01.
- It indicates that 300 iterations are sufficient for the successful training of the optimized ANFIS network.
- When compared with earlier discussed DWT-ANN approach, this FFT-ANFIS approach reaches the convergence criterion quickly and takes less number of iterations.



(i)



(ii)

Figure 8.6 Output of FFT-ANFIS network for (i) training and (ii) testing data at different open switch fault case

The ANFIS identification rates have been studied with 204 training sets consisting of each fault conditions at modulation index value ranging from 0.8 to 0.95.

- Figure 8.6 (i) shows the output of ANFIS for training data and it is apparent that output of ANFIS network is closer to the respective trained pattern as shown in Table 8.5.
- This shows that the ANFIS network is trained appropriately and has categorised different switch fault cases successfully for training data.
- Once the ANFIS network is tested with training data, then 150 additional data were simulated at different open switch and short switch fault cases for the testing purpose at different modulation index ranging from 0.8 to 0.95.
- Figure 8.6 (ii) shows the output of ANFIS for test data. It clearly shows that the ANFIS approach could classify different switch fault cases reliably.

Table 8.6 Identification rates of FFT-ANFIS network

Nature of Fault	Identification rate (%) at different MF	
	trimf	gbellmf
No fault	100	100
S1A fault	97	99
S2A fault	97	100
S3A fault	95	97
S4A fault	96	98
S1B fault	96	97
S2B fault	98	98
S3B fault	95	99
S4B fault	96	100

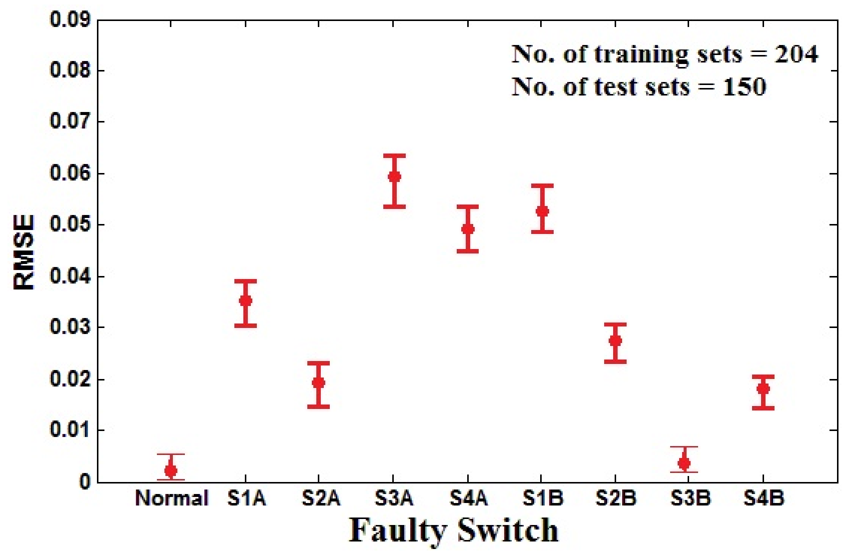


Figure 8.7 Variations in root mean square error value of FFT-ANFIS network at different open switch fault case for both testing and training sets

- Table 8.6 shows the identification rates of ANFIS at two different type of membership functions.
- For comparison purpose, triangular membership function is used and tested with the same training and test data.
- In the case of 'gbell' MF, the network is able to identify 98.8 % accurately all fault cases. In general, performance of 'gbell' MF is better when compared with 'tri' MF.
- Figure 8.7 shows the minimum, maximum and mean values of root mean square error values of ANFIS at different switch fault case for both testing and training sets.
- RMSE of switch faults S3A, S4A and S1B lies above 0.05 and for all other cases RMSE value lies below 0.04.

- The values of RMSE lies in the range of acceptable limit and it shows the effectiveness of the ANFIS based approach in the identification of both open switch and short switch faults of multilevel inverters.

8.3 FAULT DIAGNOSIS RESULTS OF DWT-ANFIS APPROACH

In this methodology, the four features extracted from the DWT multi resolution analysis of output voltage waveform at different switch fault cases such as D6, D7, D8 and D9 energy content are given as an input to the ANFIS network. The details of the optimized ANFIS network used in the present study is shown in Table 8.7.

Table 8.7 Specifications of DWT-ANFIS Network

No. of Inputs	4
No. of membership functions	3
No. of fuzzy rules	81
No. of Iterations	900
No. of Training Sets	204
No. of Test Sets	150
Convergence Criteria	0.01
Initial step size	0.01
Membership function	gbell

ANFIS was implemented by using the fuzzy logic toolbox of MATLAB. Both bell shaped membership function 'gbell' and triangular membership function 'trimf' are used in the first layer and weighted average defuzzification is adopted to obtain the output. Considering the fault diagnosis accuracy obtained with different membership functions in this work, results of 'gbell' membership function are only reported. Three membership functions are used for each input.

Table 8.8 DWT-ANFIS Network Output Training Pattern for Fault Cases

Nature of Fault	ANFIS output
No fault	1
S1A fault	2
S1B fault	3
S2A fault	4
S2B fault	5
S3A fault	6
S3B fault	7
S4A fault	8
S4B fault	9

- Table 8.8 shows the ANFIS output training pattern used for different switch faults of multilevel inverter.
- Figure 8.8 shows the 'gbell' membership function of four inputs to ANFIS such as D6, D7, D8 and D9 DWT MRA energy content. These bell shaped membership functions has a value maximum of '1' and minimum of '0'.

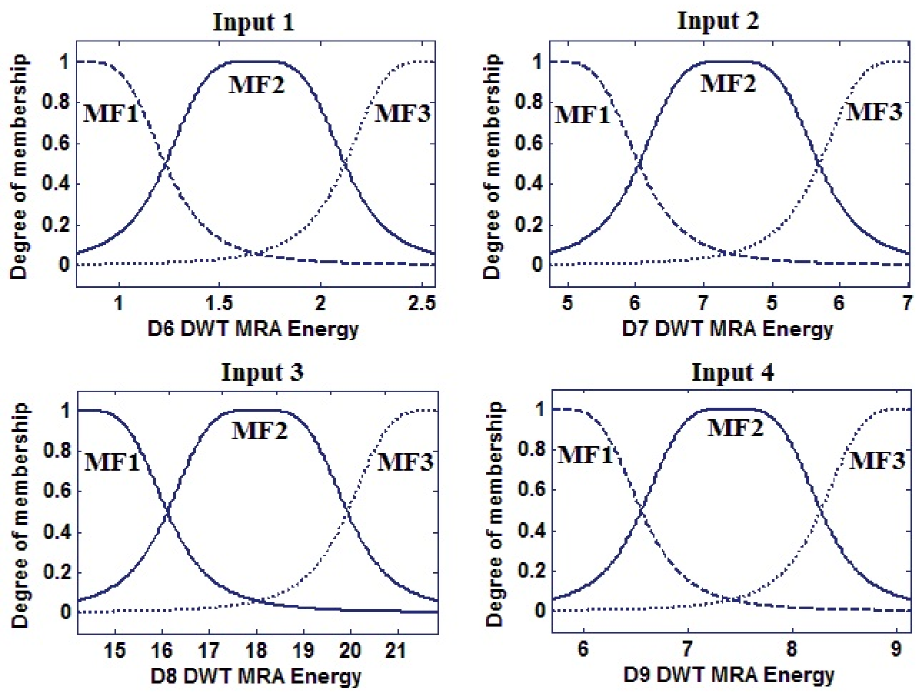


Figure 8.8 Degree of membership of fuzzy gbell membership function for different inputs to DWT-ANFIS network

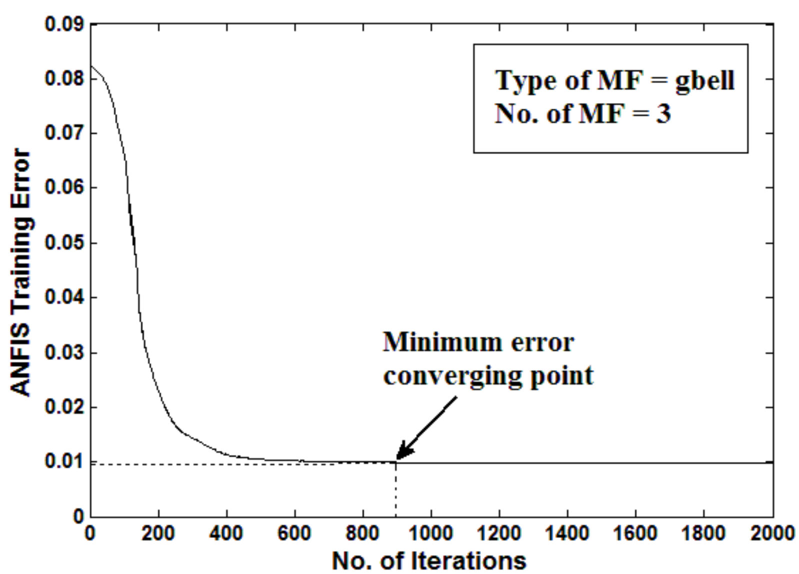
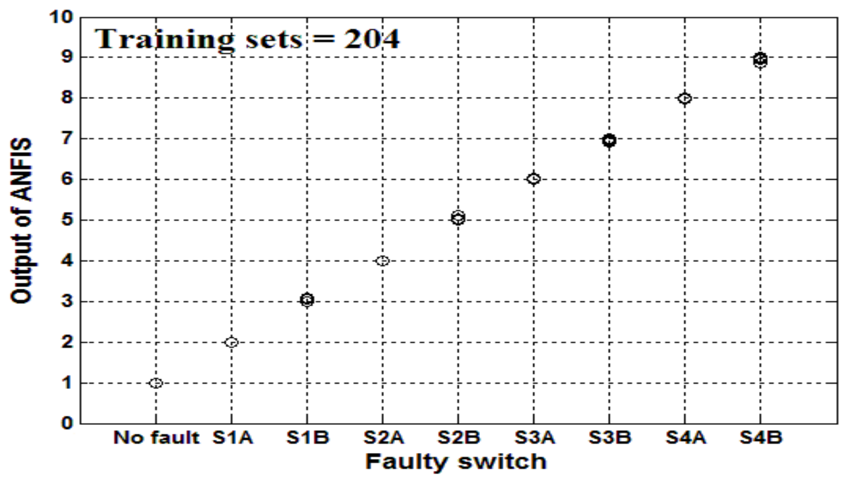
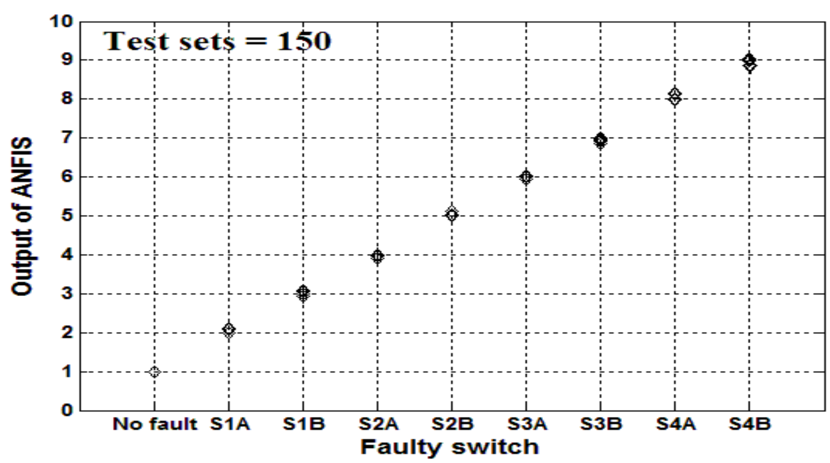


Figure 8.9 Convergence of root mean square error of DWT-ANFIS network during training process with gbell MF

Figure 8.9 shows the performance of the DWT-ANFIS network during the training process for different iteration numbers. It is noticed that ANFIS network reaches the minimum RMSE convergence criteria near 900 iterations. It indicates that 900 iterations are sufficient for the successful training of the optimized ANFIS network.



(i)



(ii)

Figure 8.10 Output of DWT-ANFIS network for (i) training and (ii) testing data at different switch fault case.

- The ANFIS identification rates have been studied with 204 training sets (12 training sets for each fault conditions at different modulation index value).
- Figure 8.10 (i) shows the output of ANFIS for training data and it is apparent that output of ANFIS network is closer to the respective trained pattern as shown in Table 8.8.
- This shows that the ANFIS network is trained appropriately and has categorized different switch fault cases successfully for training data.
- Once the ANFIS network is tested with training data, then 150 additional data were given at different switch fault cases for the testing purpose at different modulation index ranging from 0.8 to 0.95.
- Figure 8.10 (ii) shows the output of ANFIS for test data.
- It clearly shows that the ANFIS approach could classify different switch fault cases successfully and reliably.
- Table 8.9 shows the identification rates of ANFIS at two different type of membership functions.
- For comparison purpose, triangular membership function is used and tested with the same training and test data. In the case of 'gbell' MF, the network is able to identify 100% accurately most of the fault cases.
- In general, performance of 'gbell' MF is better when compared with 'tri' MF.

Table 8.9 DWT-ANFIS Fault Identification rate (%) at different Membership Function

Nature of Fault	Identification rate (%) at different MF	
	'trimf'	'gbellmf'
No fault	100	100
S1A fault	100	100
S1B fault	100	100
S2A fault	95	100
S2B fault	96	100
S3A fault	98	99
S3B fault	95	99
S4A fault	98	100
S4B fault	96	100

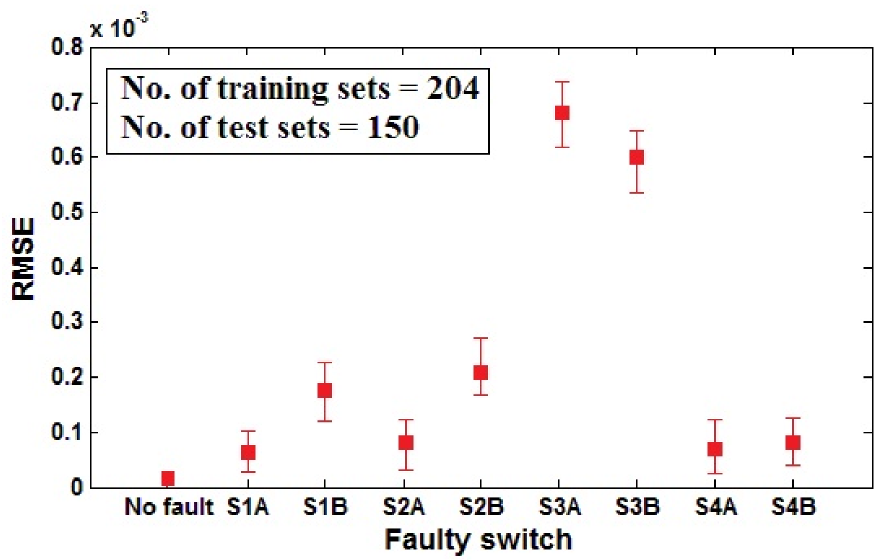


Figure 8.11 Variations in root mean square error value of DWT-ANFIS network at different switch fault case for both testing and training sets.

- Figure 8.11 shows the minimum, maximum and mean values of root mean square error values of ANFIS at different switch fault case for both testing and training sets.
- RMSE of switch faults S3A and S3B lies above 0.0005 and for all other cases RMSE value lies below 0.0003.
- The values of RMSE lies in the range of acceptable limit and it shows the effectiveness of the ANFIS based approach in the identification of switch faults of multilevel inverters.

8.4 COMPARISON OF FAULT DIAGNOSIS PERFORMANCE OF PROPOSED APPROACHES

Table 8.10 Fault Identification rate (%) at different approaches

Nature of Fault	Identification rate (%) at different approach		
	DWT-ANN	FFT-ANFIS	DWT-ANFIS
No fault	100	100	100
S1A fault	100	99	100
S1B fault	96	100	100
S2A fault	97	97	100
S2B fault	97	98	100
S3A fault	99	97	99
S3B fault	96	98	99
S4A fault	95	99	100
S4B fault	96	100	100

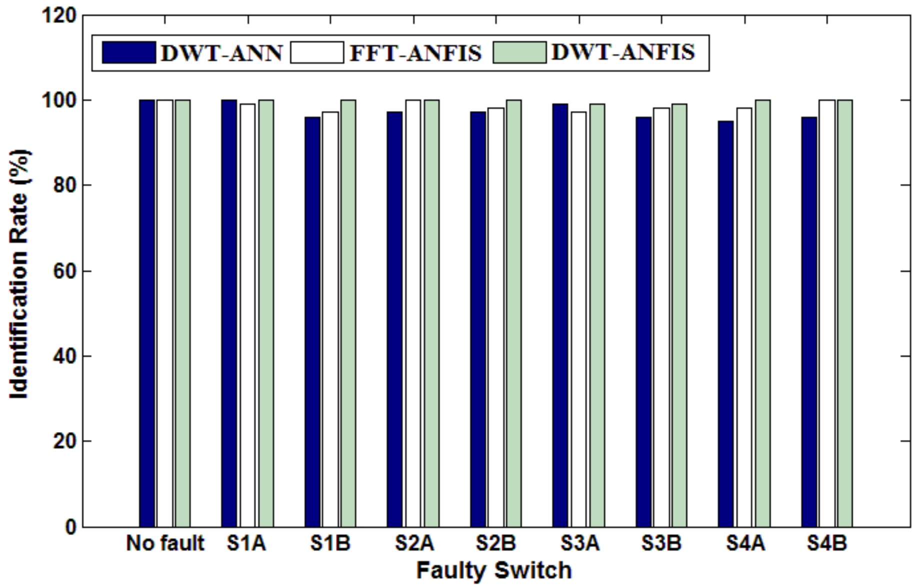


Figure 8.12 Comparison of performance of various approaches in identifying the faulty switch of multilevel inverter

In this research work, various approaches for faulty switch identification of cascaded H-bridge multilevel inverters are proposed. Salient features from the output voltage signals at different open circuit and short circuit fault conditions are extracted using FFT technique and DWT MRA technique. In addition, RMS value of output voltage and two different voltage ratios are evaluated at different fault conditions. Then extracted features are given as an input to various soft computing techniques such as ANN and ANFIS. Based on this, three different fault diagnostic methodologies are proposed in this work such as DWT-ANN approach, FFT-ANFIS approach and DWT-ANFIS approach. Based on the overall performance of these three approaches, Table 8.10 shows the fault identification rate in % at different approaches and Figure 8.12 shows the comparative chart of overall identification rates of three approaches at different switch fault conditions. As already discussed in the earlier sections, overall performance of DWT-ANFIS approach is better when compared with other approaches. From the comparison of three different approaches, the following observations are made,

- Fault diagnosis performance of DWT-ANFIS approach for all fault cases, from normal condition to various open-circuit and short -circuit switch fault conditions, is quite better when compared with FFT-ANFIS and DWT-ANN approaches. Almost 100% identification rate is observed in DWT-ANFIS approach.
- FFT-ANFIS approach took 300 iterations for training the network, whereas DWT-ANFIS approach took 800 iterations and DWT-ANN approach took 2800 iterations. While comparing the other two approaches, FFT-ANFIS approach took less number of iterations and hence the training process is faster in this approach. However, since the previously trained network is only used for fault diagnosis purpose, DWT-ANFIS network can be considered for real time applications
- DWT-ANN approach is trained and tested with 11 inputs. It requires more number of inputs to achieve a considerable performance. Whereas FFT-ANFIS network and DWT-ANFIS network are trained and tested with 4 inputs. Hence the training time is reduced. In addition, structure of the network also becomes simple.
- When compared with DWT-ANFIS approach and FFT-ANFIS approach, DWT-ANFIS approach is trained and tested only with 4 inputs obtained from DWT approach. Hence no intermediate computations such as voltage ratio analysis is required for this approach. Without any additional

inputs such as voltage ratios, the performance of the DWT-ANFIS approach is better when compared with other approaches.

The reported DWT-ANFIS characteristics of output voltage waveform show that faulty switch of multilevel inverter can be easily assessed. When compared with other techniques, DWT-ANFIS technique determines the failure of specific switch (may be due to open-switch fault or short-switch fault) of multilevel inverter accurately. It also drastically reduces the number of inputs to the ANFIS network, which makes faster training process. Proposed DWT-ANFIS technique can be implemented in advanced embedded systems and it will be useful to diagnose the fault quickly. In addition, proposed technique provides 100% identification rate between normal and faulty condition. Hence, once the faulty switch is diagnosed, it can be applied with any reconfiguration technique to maintain the continuous working of the system.