DETECTION OF OPEN – SWITCH AND SHORT – SWITCH FAILURE OF CASCADED H – BRIDGE MULTILEVEL INVERTER THROUGH FFT AND ANN USING LABVIEW

Dr. E. Parimalasundar
Associate Professor, Department of Electrical and Electronics Engineering,
Sree Vidyanikethan Engineering College, Tirupati, India
parimalpsg@gmail.com

Abstract: *In recent times, multilevel inverters are used as high priority in many large industrial drive applications. However, the reliability and performance of multilevel inverters are affected by the failure of power electronic switches. In this paper, failure of power electronic switches of multilevel inverters is identified with the help of high performance diagnostic system during open switch and short condition. Experimental and simulation analysis was carried out on five levels cascaded h-bridge multilevel inverter and its output voltage waveforms were synthesized at different switch fault cases and at different modulation index parameter values. Salient frequency domain features of the output voltage signal were extracted using the Fast Fourier Transform decomposition technique. The real time work of the proposed fault diagnostic system was implemented through the LabVIEW software. The Offline Artificial neural network was trained using the MATLAB software and the overall system parameters were transferred to the LabVIEW real time system. In the proposed system, it is possible to successfully identify the individual faulty switch of multilevel inverters.*

Key words: *Artificial Neural Networks, Fault Diagnosis, FFT, Multilevel Inverter and LabVIEW*.

1. Introduction

In recent years, multilevel power electronic inverters are finding impressive interest in the design of large industrial electric drives in order to meet the high power demands required by them. The foremost advantages of multilevel inverters are the reduction in harmonic distortion of the output voltage waveform with increase in number of levels and flexibility to use a set of batteries or fuel cells in any in-between stages [1-3].

Even though multilevel inverters have made their way successfully in the industrial applications with a proven technology, failure of power electronic switches and its fault analysis is still a recent research topic of many researchers. In industrial applications, where protected and reliable operation is always projected, it is more significant to monitor the condition of power electronic switches in inverters. As the number of level increases in inverter, number of power electronic switches also increases, which leads to raise the probability of failure of any switch and hence any such fault should be identified at the earliest in order to keep away from the operation of drive and motor under abnormal conditions [4-14]. Among the different modes of failures of power electronic switches, an open-switch and short-switch fault is most general and leads to current distortion and generates problems in gate drivers and hence decreases the system performance. Many of the researchers used the inverter current and inverter output voltage to build up the fault diagnosis system [11-15]. Surin khomfoi et al. [13], developed an open-switch fault diagnostic system of a multilevel inverter based on the output voltage using FFT pattern and five parallel neural networks with 40 input neurons per network. Since the size of the neural network is high because of 40 input neurons, in another paper, surin khomfoi et al., proposed another methodology in which combination of FFT, principal component analysis, genetic algorithm and neural network technology was used to discover the fault type and fault location [14].

Identification of faulty switch of multilevel inverters is still a hot research topic and many research people are working hard to find the fault accurately. However, information about real time work of high performance fault diagnostic system for cascaded h-bridge multilevel inverter is inadequate. From the above consideration, in this paper, multilevel inverter output voltages are considered as an important parameter in faulty switch identification of multilevel inverter. Real time implementation of overall proposed fault diagnostic system is executed through LabVIEW software, which is a complicated tool for developing and running real time applications. LabVIEW makes use of graphical programming language created by National Instruments and it has been effectively implemented for data acquisition, instrument control and industrial automation [19-21]. Artificial Neural Network (ANN) is a useful tool in the categorization of patterns through learning and nonlinear mapping. Arranging both LabVIEW and ANN are considered to be essential as an additional test for researchers. Hence, in this paper, real time fault identification process is programmed through LabVIEW based ANN approach [22-23].

2. Structure of H-Bridge Multilevel Inverter

Cascaded Multilevel Inverter is collected by a number of H-Bridge inverter cells linked in series in each phase with a separate DC source. Figure 1 illustrates a typical three phase cascaded multilevel inverter with three H-bridge cells in each phase associated with a three phase induction motor load. The number of levels in the output voltage waveform can be calculated by 2S+1, where ‘S’ is the number of H-Bridge cells utilized in the system. Three Phase multilevel inverter system is generally used in industrial applications, in the present work, the single phase multilevel inverter is only used because the proposed fault diagnostic system can be expanded for three phase applications.

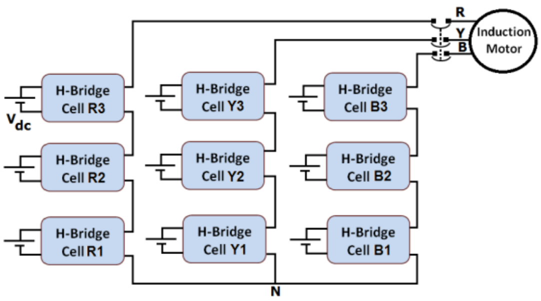


Fig. 1. Representation of a typical three phase cascaded H-Bridge multilevel inverter with induction motor load.

Figure 2 illustrates the representation of single phase five levels cascaded H-bridge inverter used in the present paper consisting of two H-Bridge cells and eight IGBT power electronic switches. Each IGBT switch is named as per their cell position as S1A, S1B, etc. Cascaded Inverter is linked with a dynamic load of 1ψ, 0.5 HP, 50 Hz induction motor. Sinusoidal pulse width modulation (SPWM) technique is applied to produce the necessary switching pulses of IGBT power electronic switches. In the case of SPWM, high frequency triangular carrier signal is evaluated with a reference sinusoidal signal. Figure 3 shows the production of trains of switching pulses of cell A at a particular carrier frequency value of (*fc*) of 3 kHz and modulation index value (*m*) of sinusoidal signal 0.85. In the present work, modulation index is varied in the range of 0.8 to 0.95.

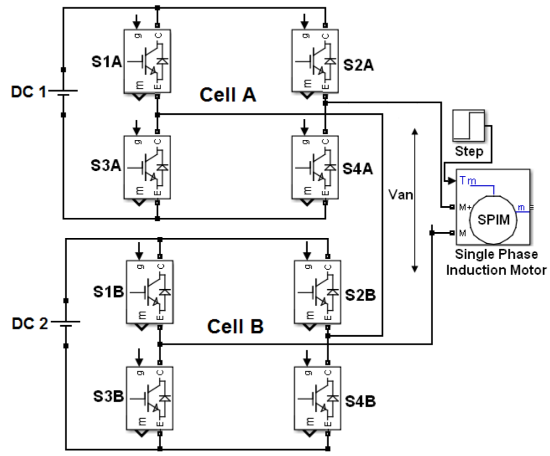


Fig. 2. Representation of simulink model of single phase cascaded H-Bridge five level inverter connected with induction motor load.

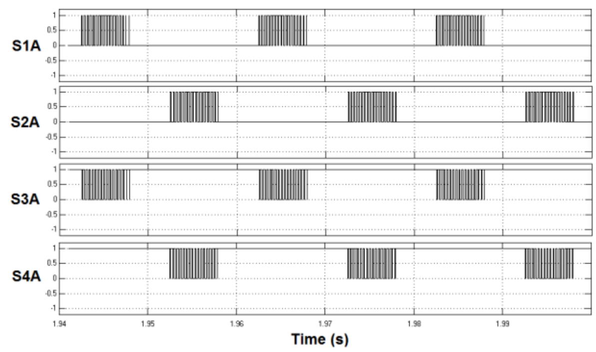


Fig. 3. Illustration of SPWM switching pulses of cell A created with carrier frequency 3 kHz and modulation index value of 0.85.

3. Fault analysis of output voltage and current pattern of cascaded Multilevel Inverter

Simulation fault analysis was carried out with the help of Matlab Simulink software. In order to realize the output voltage and current pattern before and after the fault initiation of multilevel inverter, At very fist open circuit fault is commenced at 1 Sec in the S1A switch of cell A. Figure 4 shows the actual output voltage of the inverter, its magnified view and current pattern before and after the fault of single phase cascaded H-Bridge multilevel inverter associated with induction motor load. Voltage and current patterns are sampled at 20 kHz. Similarly, Figure 5 shows the output voltage and current waveforms after the fault creation of open circuit fault in S2A switch of cell A.

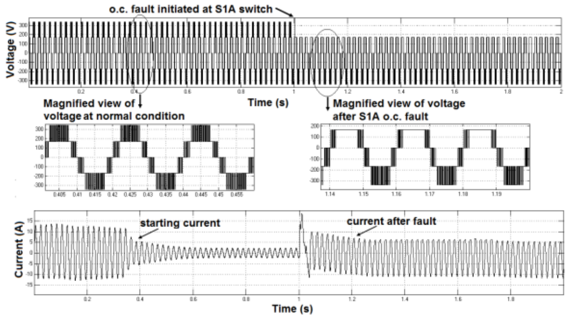


Fig. 4. Voltage and load current waveform analysis of S1A during open circuit fault.

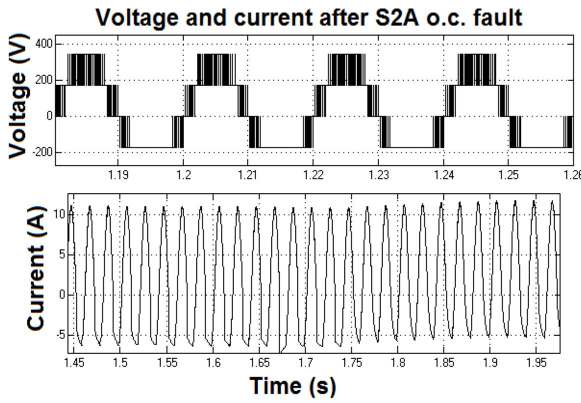


Fig. 5. Voltage and load current waveform analysis of S2A during open circuit fault.

4. Concept of Fast Fourier Transform and Feature Extraction Process

Extraction of the important features of the output voltage data waveform, which in turn eagerly drives, diagnostic in order about raw data, plays a key role in the proposed fault diagnostic methodologies. In order to generate a powerful fault diagnostic method, it is important to perform frequency domain analyses of output voltage patterns. The FFT technique has been recognized to extract different parameters of the output voltage signal. As can be seen, the signals are not easy to rate as an important characteristic for categorizing a faulty hypothesis. Therefore, a signal conversion technique is required. A proper selection of the feature extractor is to give the neural network with sufficient significant details in the pattern set so that the highest degree of precision in the neural network performance can be attained. One probable technique of execution with a digital signal processing microchip is the Fast Fourier Transform [8]. Initiating with the Discrete Fourier Transform in (1), after that the FFT with the decimation in time decomposition algorithm is represented in (2) and (3).

$$F_k = \sum_{n=0}^{N-1} f_n W_N^{nk} \quad \text{for} \quad k=0,\ldots,N\text{-}1 \tag{1}$$

Where $W_N = e^{-j\frac{2\pi}{N}}$

$$F_k = G_k + W_N^k H_k \quad \text{for} \quad k=0,\ldots,\frac{N}{2}-1 \tag{2}$$

$$F_{k+\frac{N}{2}} = G_k - W_N^k H_k \quad \text{for} \quad k=0,\ldots,\frac{N}{2}-1 \tag{3}$$

G_k is for even-numbered elements of f_n, whereas H_k is for odd-number elements of f_n. G_k and H_k can be computed as shown in (4) and (5).

$$G_k = \sum_{n=0}^{\frac{N}{2}-1} f_{2n} W_{\frac{N}{2}}^{nk} \tag{4}$$

$$H_k = \sum_{n=0}^{\frac{N}{2}-1} f_{2n+1} W_{\frac{N}{2}}^{nk} \tag{5}$$

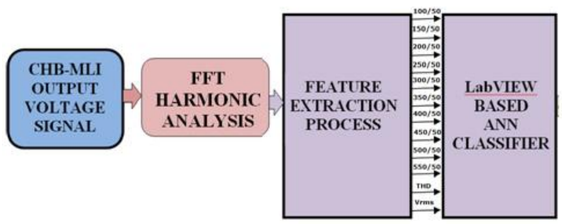
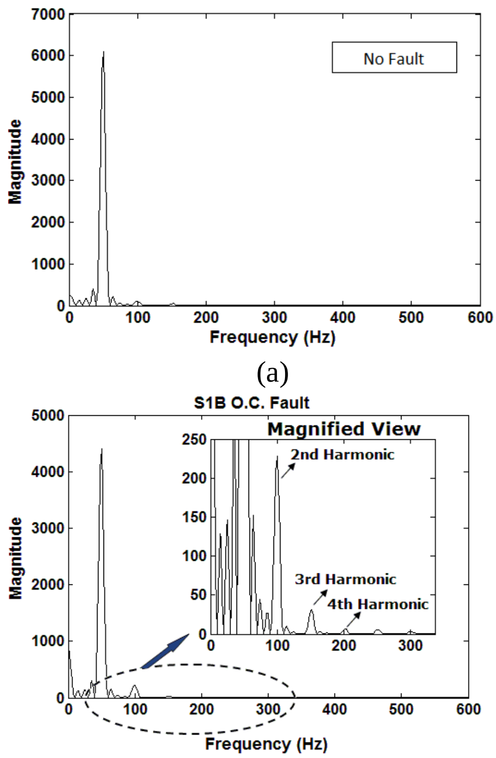


Fig. 6. Schematic diagram of LabVIEW based fault diagnostic system using FFT features

Figure 6 shows the schematic diagram of the fault diagnostic system developed for the identification of failure of power electronic switches using the features extracted from the FFT technique. The output voltage signal is measured in the inverter and using the FFT technique, important features of the voltage signal, i.e. THD (%), harmonic/fundamental ratio (%) values up to 11th harmonic are extracted. Hence the RMS value analysis is also simultaneously carried out in the output voltage signal and the extracted 12 features are given as an input to the artificial neural network. In the Figure 4.1, feature 100/50 represents the ratio of second harmonic to fundamental, feature 150/50 represents the ratio of third harmonic/fundamental and so on. The output of the trained patterns of Artificial Neural Network (ANN) with LabVIEW software identifies the faulty switch of the multilevel inverter.

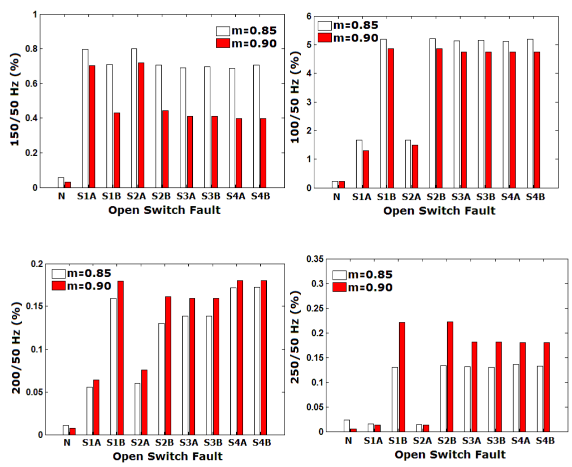
Figure 7 (a, b) shows the typical FFT plot of the output voltage signal obtained at Normal condition and S1B open switch fault respectively. These plots are noticed that the magnitude of fundamental frequency component (50 Hz) is very high when compared to other harmonic frequency components.



(a)

(b)

Fig. 7. FFT frequency plot of output voltage at (a) Normal condition (b) S1B OC fault



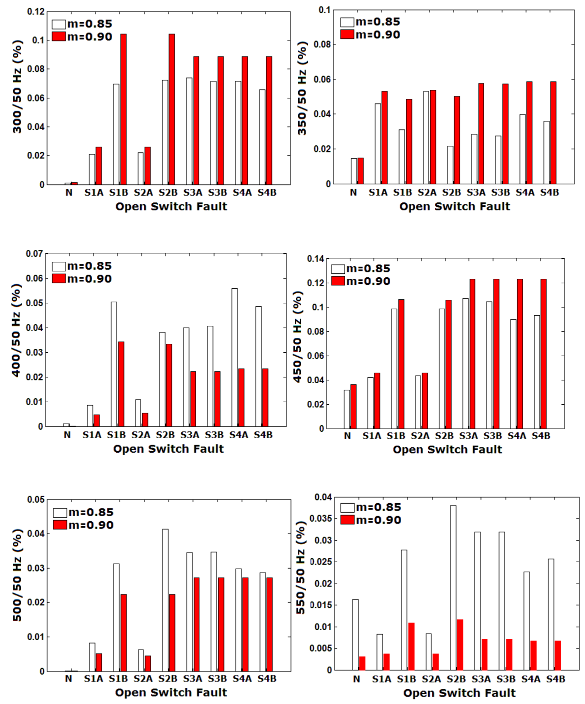


Fig. 8. Features of output voltage waveform obtained from FFT technique at different open switch fault cases from 2nd Harmonic ratios to 11th Harmonic ratios

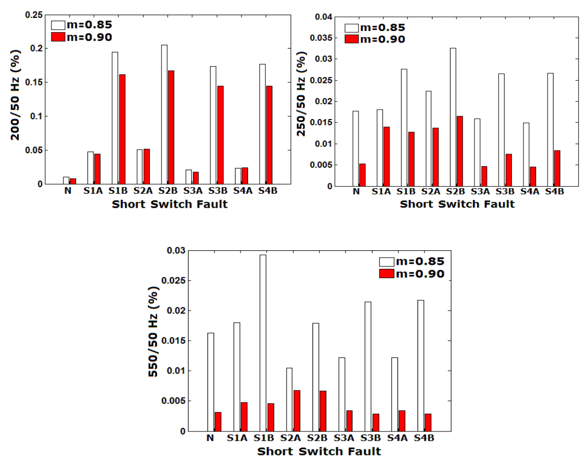


Fig. 9. Features of output voltage waveform obtained from FFT technique at different short switch fault cases (a) 4th harmonic ratio (b) 5th harmonic ratio (c) 11th harmonic ratio

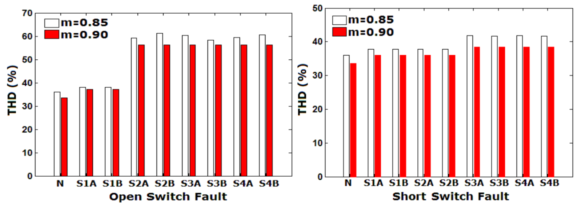


Fig. 10. THD of output voltage waveform obtained from FFT technique at different fault cases and at different modulation index values (a) open switch fault (b) short switch fault

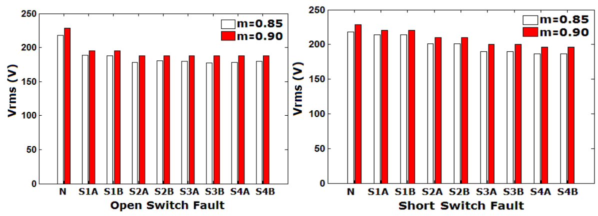


Fig. 11. RMS value of output voltage waveform obtained at different fault cases and at different modulation index values (a) open switch fault (b) short switch fault

However, in order to automate the process of fault diagnosis, it is important to extract distinct features from the output voltage waveform. Hence the FFT technique is applied to all the output voltage waveforms under open circuit fault and short circuit fault conditions with corresponding harmonic level variations, Vrms and THD values. Figure 8 illustrates different features of output voltage waveform obtained from FFT technique at different open switch fault cases from 2nd Harmonic ratios to 11th Harmonic ratios. Figure 9 illustrates features of output voltage waveform obtained from FFT technique at different short switch fault cases for different harmonic ratio values. Figure 10 shows THD of output voltage waveform obtained from FFT technique at different fault cases and at different modulation index values at open switch fault and short switch fault. Figure 11 explains RMS value of output voltage waveform obtained at different fault cases and at different modulation index values at open switch fault and short switch fault.

Figure 12 shows the schematic of the overall fault diagnostic system developed for the identification of failure of power electronic switches in the multilevel inverter. The Hardware system consists of the DC power supply, multilevel inverter, Induction Motor (IM) and Data Acquisition System.

5. Structure of Fault Diagnostic System

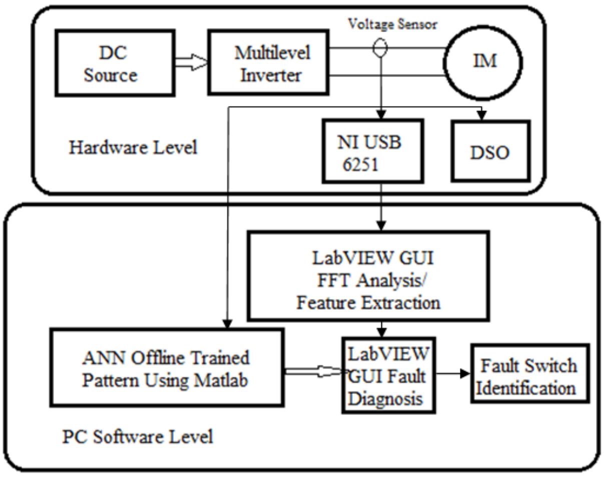


Fig. 12. Schematic of the overall fault diagnostic system.

Initially, both open and short switch faults are created by both simulation and experimental studies at different modulation index values and features are extracted from the voltage signal using FFT harmonic analysis in Matlab. These features are given as an input to the ANN for offline training using Matlab. The trained pattern consisting of weight and bias values of the ANN is fed to the graphical programming language LabVIEW for fault diagnosis. In the case of a real time application, voltage sensor output is given to NI USB data acquisition system which is connected to a PC. Voltage data are processed in the LabVIEW FFT feature extraction analysis and compared with the offline trained pattern. Then LabVIEW GUI indicates the faulty switch of the multilevel inverter, which is very useful for maintaining the reliability of the system.

Figure 13 shows the photograph of the laboratory experimental setup used to collect the output voltage signals of multilevel inverter at different switch fault conditions. Two H-bridge single phase PWM inverter modules are cascaded to get the five level output voltage waveform. IGBTs of rating 600 V, 25A are used as switching devices. PWM control module consisting of reference wave and carrier wave selection, modulation index and switching frequency adjustment is used to get the required gate pulses for the IGBT switches.

Fig. 13. Laboratory experimental arrangement

(a) (b)

Fig. 14. (a) Data acquisition system interfaced with LabVIEW software in PC (b) NI USB-6251 hardware

Figure 14 (a) and (b) show the photograph of the data acquisition system interfaced with LabVIEW software in PC for real time applications. National Instruments (NI) USB-6251 (1.25 MSa/Sec) are used as a data acquisition system and it is connected to PC for storing and further processing of signals. This system is capable of measuring 16 analog input signals, 16 bits. A digital storage oscilloscope, Agilent makes (1 GSa/Sec), is also used to visualize the output voltage waveforms. Open circuit and short circuit faults are created on each switch and corresponding output voltage waveform is recorded. Voltage sensor is used to collect the output voltage signals and it is connected with NI USB-6251. Output voltage signal is measured in the inverter at different modulation index values and FFT harmonic analysis is carried out. An Important feature of the voltage signal, i.e. energy content of the signal at different level of decomposition is extracted.

5.1 Simulation Results at Open Circuit Fault

Initially, open circuit fault is created on S1A switch and corresponding output voltage waveform is stored. Similarly, open circuit fault is created on all switches of both H-Bridges A & B and the corresponding voltage waveforms are stored for further feature extraction process.

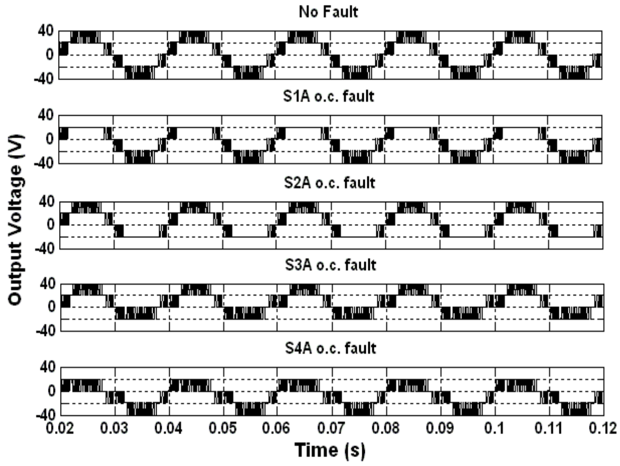


Fig. 15. Output voltage waveforms obtained at open circuit switch fault condition

Figure 15 shows the typical output voltage waveforms obtained at open circuit switch fault conditions of H-Bridge A. For comparison purpose, the voltage waveform obtained at normal (no fault) condition is also shown in the same figure. From the visual inspection of the output voltage waveforms, it is clear that it is possible to easily identify the variations under fault conditions with respect to normal condition.

5.2 Simulation Results at Short Circuit Fault

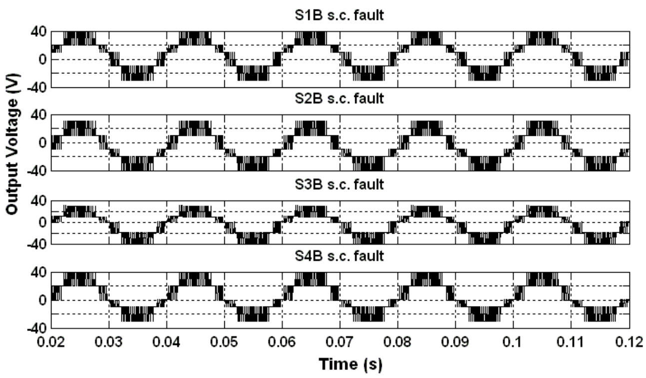


Fig. 16. Output voltage waveforms obtained at short circuit switch fault condition

In this case, short circuit fault is created on all switches of both H-Bridges A & B one by one and corresponding output voltage waveform is stored for further feature extraction process. Figure 16 shows the typical output voltage waveforms obtained at normal (no fault) and short- switch fault conditions of H-Bridges B. It is observed that there is a considerable difference in all output voltage waveforms under short-switch fault conditions when compared with no fault condition. FFT technique is applied to all the output voltage waveforms under short circuit fault conditions and the corresponding FFT harmonic analysis is evaluated.

6. Experimental Validation

6.1 Feature Extraction Analysis using LabVIEW

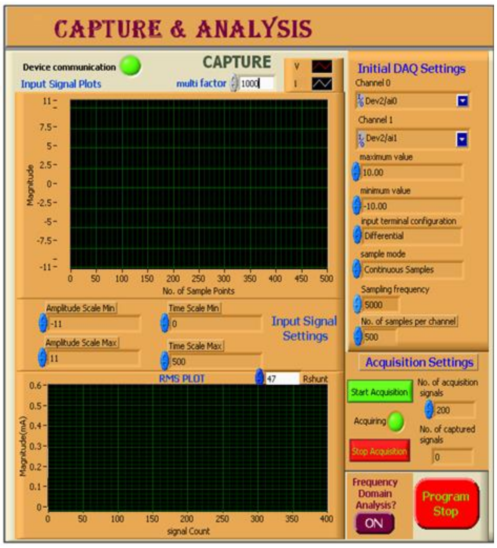


Fig. 17. LabVIEW front panel of the output voltage imprison and analysis of multilevel inverter

The complete fault diagnostic system has been developed using LabVIEW 8.5 software. Figure 17 shows the developed LabVIEW front panel consisting of output voltage capture and analysis module. The graphical user interface developed in LabVIEW displays the acquired output voltage waveforms on the front panel of the program. The front panel acts like a user interface where the user can input and extract data. Once the NI USB device is properly interfaced with this LabVIEW front panel, device communication indicator will blink in green. Front panel has control over output voltage signal parameters such as time scale, magnitude scale, sampling frequency and number of samples of each signal. Also, it is possible to set the number of signals to be captured at a particular time using the acquisition settings such as a Start Acquisition button and Stop Acquisition button. Separate subVI control is given for frequency domain analysis of voltage signals. Since the NI DAS and LabVIEW software has the facility to capture and analyze a set of data at a particular time, signals are captured continuously and stored in PC for further processing. This front panel also shows the variations in the RMS value of the output voltage signal with respect to time which helps in understanding the trend analysis of the V_{rms} parameter.

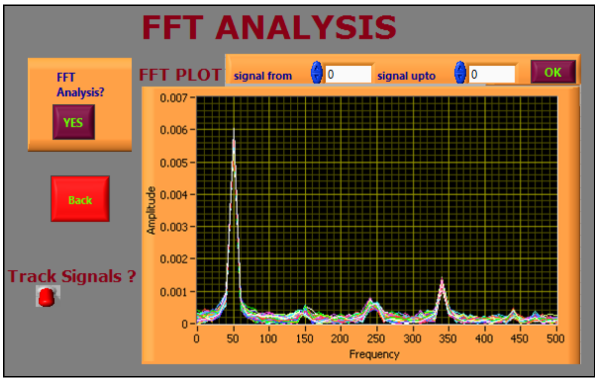


Fig. 18. LabVIEW front panel of FFT based frequency domain analysis

Figure 18 shows the front panel of LabVIEW developed for frequency domain analysis of output voltage signals using FFT technique. This module consists of control over the selection of signals for FFT analysis purpose. In this module, control is also given to track the individual FFT plot of voltage signal. Peak values of the harmonic frequencies are used to evaluate the harmonic ratios with respect to fundamental frequencies.

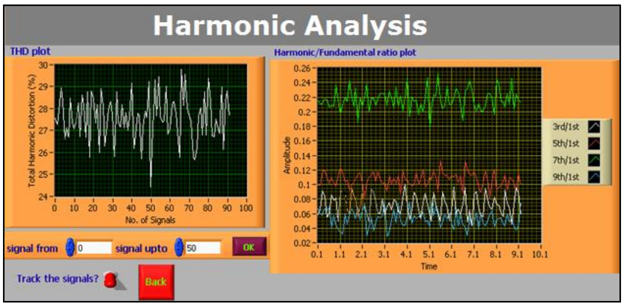


Fig. 19. VI front panel of FFT based THD and harmonic analysis

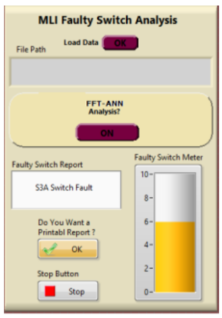


Fig. 20. VI front panel of MLI faulty switch analysis

The FFT frequency domain harmonic analysis of the front panel is developed in this research work and it is shown in figure 19. It is designed in such a way to view the various harmonic/fundamental ratios and THD value of the output voltage signal of multilevel inverter and figure 20 shows that VI front panel of MLI faulty switch analysis. In this window, it is also possible to track the harmonic plot of individual output voltage signals. This software module is developed in such a way to evaluate upto 11th harmonic ratio. Trend analysis of THD value and harmonic ratios is possible in this front panel and faulty switch has to be identified. Figure 21 illustrates the output voltage pattern of multilevel inverter under different faulty switch condition at real time implementation.

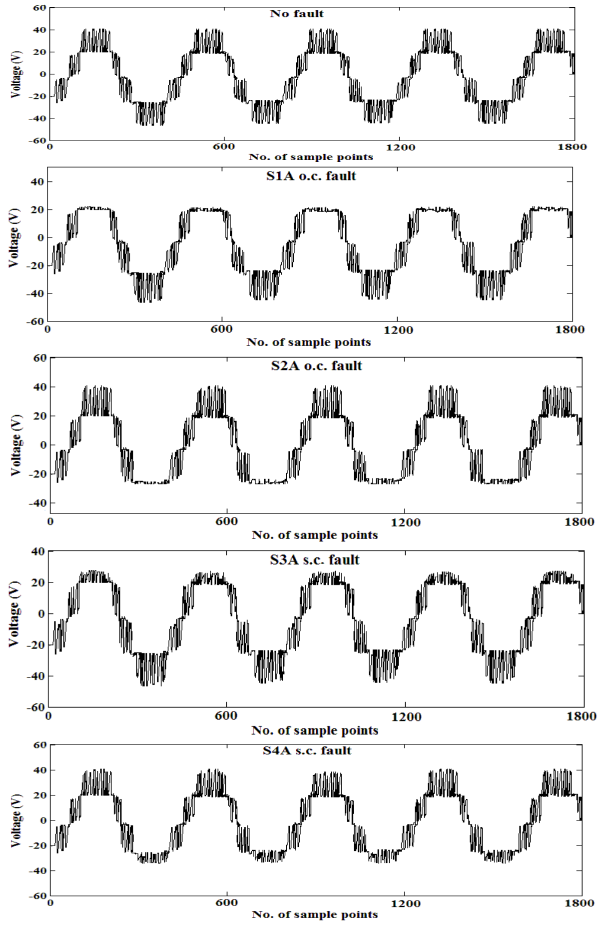


Fig. 21. Typical output voltage waveform obtained at different OC and SC switch fault conditions of H-Bridge A during the experimental studies

6.2 Real Time Fault Diagnosis Results from LabVIEW-ANN Approach

In order to mechanize the development of fault diagnosis of multilevel inverters, multilayer feed forward network along with back propagation learning algorithm has been used [15, 22-23].

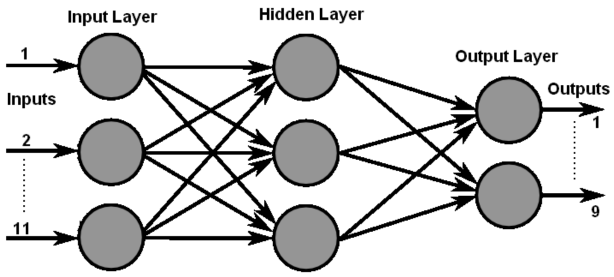


Fig. 22. Schematic of Artificial Neural Network.

Figure 22 shows that schematic diagram of artificial neural network. It has a structure of an input layer, one hidden layer and an output layer. The input and target vectors should be fed primarily for training the network pattern. Training the network is completed by changing the weights and biases of the units depending on the consequential error. In the back propagation training algorithm, for each data set, a forward pass and backward pass is conceded out in anticipation of the Mean Square Error (MSE) is too low. The convergence is achieved when the error between the calculated and the preferred output value is less than the fixed value (convergence criteria). The MSE, which is the average of the amount of the errors for all set of inputs and consequent outputs, is calculated as follows,

$$MSE = \frac{1}{m}\sum_{k}^{m}\left(S_k - Y_k\right)^2 \tag{6}$$

Where S_k and Y_k are correspondingly the desired and measured output for the kth input set and m is the total quantity of input sets [15, 22-23]. The details of the optimized neural network utilized in the present work are shown in Table 1.

Table 1
Specifications of FFT - ANN- Lab VIEW Approach

No. of Inputs	12
No. of Neurons in Hidden Layer	24
No. of Neurons in Output Layer	9
Learning Rate (η)	0.1
No. of Iterations	3800
No. of Training Sets	200
No. of Test Input Sets	150
Convergence Criteria	0.01

In this proposed work, the 12 parameters (10 harmonic ratios, THD and V_{rms}) obtained as features from the FFT technique 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 2 shows the ANN training pattern approached for different switch faults of multilevel inverter. In the training pattern, each neuron in the output layer of the neural network is assigned for a particular fault and then trained for a binary value of 1 or 0 as shown in the Table 2. For example, in the case of no fault condition, first neuron in the output layer is assigned a value of 1 and all other neurons are trained for a value of 0. Similarly, for different fault cases, the output layer neurons are trained for different binary training patterns. Offline training of the neural network was used 200 training sets and the weight matrix of the trained pattern is given as an input to the LabVIEW GUI module for testing purposes with 150 test inputs.

Table 2
Training pattern of Neural Network

Classification of fault	Position of Neuron	Output 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 23 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 3800 iterations. It indicates that 3800 iterations are sufficient for the successful training of the optimized neural network. Therefore, the performance of the back propagation neural network has been studied with 24 hidden layer neurons maintaining the value of the learning rate to be 0.1 and the number of iterations to be 3800.

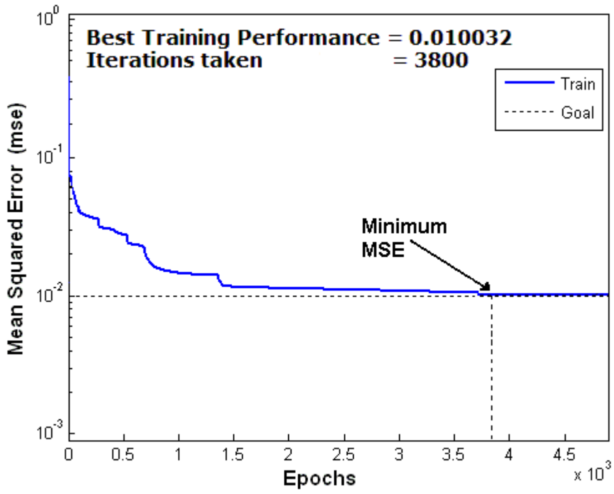


Fig. 23. Variations occurred in MSE of the ANN during training pattern with respect to increase in number of iterations

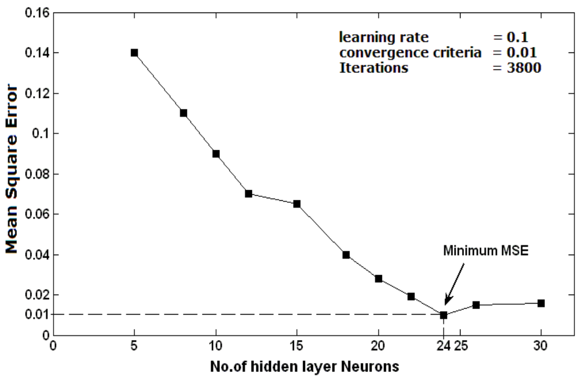
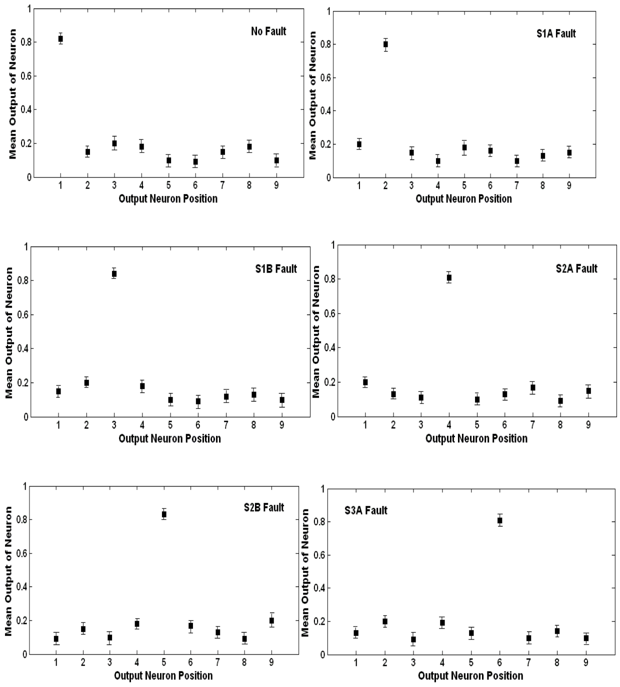


Fig. 24. Evaluation of the mean square error of the neural network at different no. of hidden layer neurons

In general, it is noticed that no fault case is accurately predicted by the neural network at all tested number of hidden layer neurons. Since the network convergence has not reached within the specified optimized neural network parameters in the case of 15 and 20 hidden layer neurons, the accuracy of the identification rate is affected. It is identified that the performance of the neural network is better for 24 hidden layer neurons when compared with other cases. The average identification rate for all fault cases is 100 % in this case and the neural network is able to identify the fault efficiently almost for all fault cases. From Table 3 gives the detail analysis of identification rate and Figure 24 illustrates the evaluation of mean square error of the neural network at different number of hidden layer neurons.

Table 3
Overall Identification rates of FFT-ANN-LabVIEW approach

Classification of Fault	Identification rate (%) at different number of hidden layer neurons		
	15	20	24
No fault	100	100	100
S1A fault	91	92	100
S1B fault	93	95	100
S2A fault	92	95	100
S2B fault	91	92	100
S3A fault	95	95	100
S3B fault	92	96	100
S4A fault	93	95	100
S4B fault	92	94	100



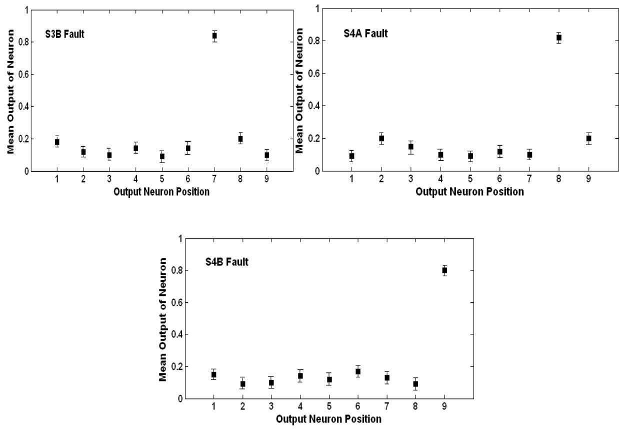


Fig. 25. Output of neurons in output layer of the ANN at different fault cases from the FFT-ANN-LabVIEW approach

During real time testing using LabVIEW fault diagnostic system, when an untrained input pattern corresponding to S1A fault is given as an input, then the output of second neuron should be maximum when contrasted with other neurons. Figure 25 shows the output of the neurons in the LabVIEW fault diagnostic system for different fault cases. It is observed that the output of neuron corresponding to that fault position in most of the cases is above 0.8. It is easier to differentiate the output neuron corresponding to the faulty switch from remaining output neurons. This indicates that the trained neural network can assess the fault condition of the multilevel inverter accurately. In the present paper, the high speed NI USB 6251, 16 bit, 1.25 MSa/Sec Data Acquisition System is linked to a laptop which has Intel core i5 processor with a clock speed of 2.7 GHz and 4 GB RAM. In this proposed method, the LabVIEW GUI takes 10 milliseconds to diagnose the faulty switches.

This real time LabVIEW based testing of fault diagnosis of multilevel inverter with output voltage characteristics such as FFT harmonic content shows that it is possible to discover the failure of particular switch of multilevel inverter exactly. When evaluated with the techniques reported in previous papers [13-14], proposed method considerably reduces the number of inputs to the ANN network and diagnoses the fault cases in 10 milliseconds Also proposed method determines the failure of an exact switch (open-switch fault or short-switch fault) of multilevel inverter. In addition, proposed technique gives 100 % identification rate between normal and faulty condition of a switch. Hence, once the faulty switch is diagnosed, it will be useful for the operator to carry out preventive maintenance.

7. Conclusion

Faulty switch diagnosis of a cascaded H-bridge five level inverter associated with an induction motor load is analyzed in this work. Significant features of the output voltage waveform are examined by both simulation and experimental analysis at different open-switch and short-switch fault cases. Essential features such as harmonic analysis of FFT Technique are specified as an input to the back propagation trained neural network. The Matlab software is applied to make offline training of neural network. Real time function of the proposed fault diagnostic system was executed during the LabVIEW software. From proposed fault diagnostic system, it is potential to accurately identify the individual faulty switch of the cascaded multilevel inverter. This system is capable to categorize 100% accurately the normal and faulty situations. Hence, at that instant switch fault is identified immediately, it will be helpful for the operator to perform protective maintenance work.

References

1. Zedong Zheng, Kui Wang, Lie Xu, Yongdong Li.: *A hybrid cascaded multilevel converter for battery energy management applied in electric vehicles*, IEEE Trans. Power Electron., 2014, vol. 29, p. 3537-3546.
2. Javad Gholinezhad and Reza Noroozian.: *Analysis of Cascaded H-Bridge Multilevel Inverter in DTC-SVM Induction Motor Drive for FCEV*, J Electr Eng Technol, 2009, p. 918 –924.
3. Banaei, M.R, Salary, E.: *A New Family of Cascaded Transformer Six Switches Sub-Multilevel Inverter with Several Advantages*, J Electr Eng Technol., 2013, vol.8, p.1078-1085.
4. Ui-Min Choi, Kyo-Beum Lee, Frede Blaabjerg.: *Diagnosis and tolerant strategy of an open-switch fault for T-type three-level inverter systems*, IEEE Trans. Ind. Appl., 2014, vol. 50, p. 495-508.
5. Chen, A., Hu, L., Chen, L.Y., Deng, He, X.: *A multilevel converter topology with fault-tolerant ability*, IEEE Trans. Power Electron., 2005, vol. 20, p. 405–415.
6. Pablo Lezana, Josep Pou, Thierry A., Meynard, Jose Rodriguez, Salvador Ceballos, Frédéric Richardeau.: *Survey on fault operation on multilevel inverter*, IEEE Trans. Ind. Electron., 2010, vol. 57, p.2207-2218.
7. Mingyao Ma, Lei Hu, Alian Chen, Xiangning He.: *Reconfiguration of carrier-based modulation strategy for fault tolerant multilevel inverters*, IEEE Trans. Power Electron, 2007, vol. 22, p. 2050-2060.
8. Diallo, D., Benbouzid, M.H., D. Hamad, D., Pierre, X.:*Fault detection and diagnosis in an induction machine drive - A pattern recognition approach based on concordia stator mean current vector*, IEEE Trans. Energy Conv., 2005, vol. 20, p. 512–519.
9. Estima, J., Marques Cardoso, A.: *A new algorithm for real-time multiple open-circuit fault diagnosis in voltage-fed PWM motor drives by the reference current errors*, IEEE Trans. Ind. Electron., 2013, vol. 60, p. 3496–3505.
10. Khan, M.A.S.K., Rahman, M.A.: *Development and implementation of a novel fault diagnostic and protection technique for IPM motor drives*, IEEE Trans. Ind. Electron., 2009, vol. 56, p. 85-92.
11. Lezana, P., Aguilera, R., Rodriguez, J.: *Fault detection on multicell converter based on output voltage frequency analysis*, IEEE Trans. Ind. Electron., 2009, vol. 56, p. 2275–2283.
12. Abul Masrur, M., Chen, Z., Murphey, Y.:*Intelligent diagnosis of open and short circuit faults in electric drive inverters for real-time applications*, IET Power Electron., 2010, vol. 3, p. 279–291.
13. Surin Khomfoi, Tolbert, L.M.: *Fault diagnostic system for a multilevel inverter using a neural network*, IEEE Trans. Power Electron., 2007, vol. 22, p. 1062-1069.
14. Surin Khomfoi, Tolbert,L.M.: *Fault diagnosis and reconfiguration for multilevel inverter drive using AI-based techniques*, IEEE Trans. Ind. Electron., 2007, vol. 54, p. 2954-2968.
15. Sivakumar, M., Parvathi, R.M.S.:*Diagnostic Study of Short-Switch Fault of Cascaded H-Bridge Multilevel Inverter using Discrete Wavelet Transform and Neural Networks*, International Journal of Applied Engineering Research, 2014, vol. 9, p. 10087-10106.
16. Sarathi, R., Venkataseshaiah, C., Yoshimura, N.: *Condition monitoring of outdoor polymeric insulation structures using wavelets and neural networks*, IEEE Conference on Electrical Insulation and Dielectric Phenomena, 2003, vol. 10 p.398-401.
17. Sarathi, R., Yoshimura, N.: *Investigations into the surface condition of the silicone rubber insulation material using multiresolution signal decomposition*, IEEE Trans. Power Delivery, 2006, vol. 21, p.243-252.
18. C.Kalaivanan, C., Andrea Cavallini, Gian Carlo Montanari.: *Investigations on leakage current and phase angle characteristics of porcelain and polymeric insulator under contaminated conditions*, IEEE Trans. Dielectr. Electr. Insul., 2009, vol.16, p. 574-583.
19. Sachin Sharma, Gaurav kumar.: *Object classification through perceptron model using LabVIEW*, International Journal of Electronics and Communications Technology, 2011 vol.2, p.255-258.
20. Nagarani, Nithyavathy, Parameshwaran.:*Low cost Mobile Robot using Neural Networks in Obstacle Detection*", International Journal of Scientific & Engineering Research, 2013, vol.4, p.26-29.
21. Parimalasundar, E., Suthanthira Vanitha, N.: *Fault Diagnosis of Multilevel Cascaded Inverter Using Multi Layer Perceptron Network*, Research Journal of Applied Sciences, Engineering and Technology, 2015 vol. 9, p. 336-345.
22. Parimalasundar, E., Suthanthira Vanitha, N.: *Fault Strategy Analysis for Three-phase Cascaded Multi-level Inverter*, Research Journal of Applied Sciences, Engineering and Technology, 2015, vol. 9, p. 327-335.

23. Hochgraf, C., Lasseter, R, Divan D, Lipo, T.A.:*Comparison of multilevel inverters for static VAR compensation*, Proceeding of the Conference Record of the 1994 IEEE Industry Application Society Annual Meeting, 1994, vol. 2, p. 921-928.
24. Kastha, D.K, Bose, B.K.*: Investigation of fault modes of voltage-fed inverter system for induction motor drive*. IEEE T. Ind. Appl., 1994, vol. 30, p. 1028-1038.