Research Journal of Applied Sciences, Engineering and Technology 9(5): 336-345, 2015
DOI:10.19026/rjaset.9.1411
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: September 07, 2014 Accepted: October 11, 2014 Published: February 15, 2015

Research Article

Fault Diagnosis of Multilevel Cascaded Inverter Using Multi Layer Perceptron Network

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Abstract: In this study, a fault diagnostic system in a multi-level inverter using a MLP network is developed. Using a mathematical model, it is difficult to diagnose a Multilevel-Inverter Drive (MLID) system, because MLID system complexity has a non-linear factor and it consist of many switching devices. Therefore neural network classification is applied to fault diagnosis of MLID system. Multilayer perceptron networks (MLP) are used to identify the type and location of occurring faults from inverter output voltage measurement. Here, MLP network based fault identification system for five level cascade H-bridge Multilevel Inverter (MLI) is analyzed. The proposed system identifies the fault with a greater accuracy and the results to various input patterns are presented for easy comprehension.

Keywords: Cascade H-bridge inverter, multi layer perceptron, multilevel inverter, neural network

INTRODUCTION

Demanding higher power ratings is a future scope for industry and MLID systems have become a solution for high power applications. Multilevel inverter is enabling the use of renewable energy sources and also achieves higher power ratings. Two topologies of multilevel inverters for electric drive application have been discussed in Tolbert *et al*. (1999). As an essential qualities fault should be identified as soon as possible, as this persist for a long time, subsequent fault is generated. Ex. If a motor drive runs continuously under abnormal conditions, the drive (or) motor may quickly fails.

The various fault modes of a conventional PWM Voltage Source Inverter (VSI) system for an induction motor are investigated in Kastha and Bose (1994). Three level inverters are now conventional apparatus but other topologies have been attempted this last decade for different kinds of applications (Rodriguez *et al*., 2002). Among them flying capacitors inverters, Neural Point Clamped (NPC), inverter also called imbricated cells and series connected cells inverters called cascaded inverters (Manjrekar, 1999). Cascaded H-bridge MLI is most commonly used due to its flexibility in decreasing and enhancing the no. of output levels required, less number of components to realize a certain levels. MLI as compared to diode clamped (or) flying capacitor MLI's and the provision of using separate DC sources for each module, enhances the stability and performance of the system (Malinowski *et al*., 2010; Ebrahim and Seyed Hossein, 2009).

Figure 1 shows a single phase multilevel inverter system.

Faults on any system lead to instability of the system as it is unavoidable. Hence the system should be built fault-tolerant and should have the ability to recognize the type of faults (Lezana *et al*., 2010). A new topology for a low cost VSI in which true phase current information exists with the use of only one dc link current sensor has been proposed by Blaabjerg and Pedersen (1997). A comparison of features, cost and limitations of fault tolerant three phase AC motor drive topology is investigated in Welchko *et al*. (2004). Practical implementation of Harmonics Elimination Strategy method [HES] method requires memorizing all the firing angles which is complex and needs considerable computational costs. Mathematical solutions with limited computational costs are therefore preferred for real time applications. The approached can be achieved with neural networks which are known as passimonious universal approximators, its learning from examples leads to robust generalization capabilities (Haykin, 1999).

Figure 2 Depicts a m-level cascade MLI with [(m-1)/2-1] modules of conventional four switch inverters with individual DC sources.

MLD drives is an effective drives in the industries in recent times. Many types of multilevel inverter topologies is been discussed (Khomfoi and Tolbert, 2010; Khoucha *et al*., 2010) and for the medium power rating machines the H-bridge multilevel inverter becomes most efficient drive. The industries are relying upon the induction motors for their manufacturing

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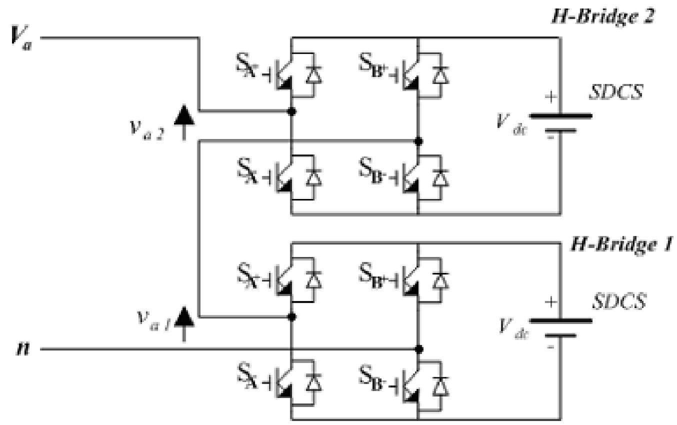


Fig. 1: A single phase multilevel inverter system

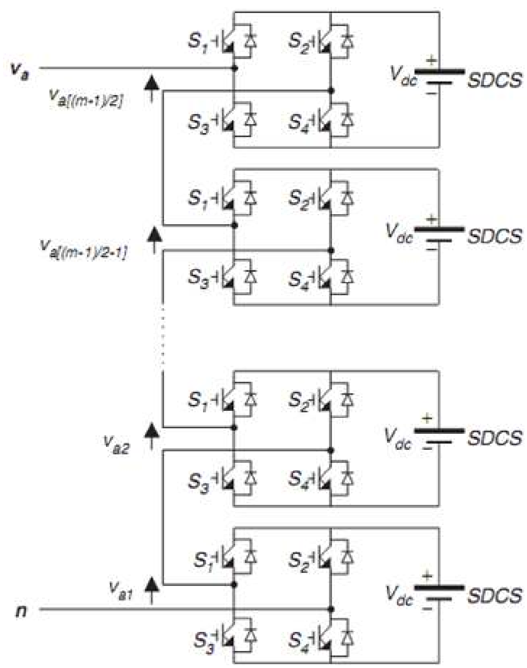


Fig. 2: Depicts a m-level cascade MLI

process and the multilevel inverters are used as the drives for the induction motors. This may lead to affect the production of the industry which incurs loss. So a fault diagnosis method becomes mandatory for the industries when some kind of faults occur in the multilevel inverter drives. Research on fault diagnosis of the inverters initially focused on the voltage source inverters in which some of the fault modes is been discussed in Neelam (2011). Classification of fault for each MLI topology and its remedial action are described in Lezana *et al*. (2010). Neural point coupling inverter play an important role in industrial drives, so the fault tolerant operation of this inverter is compulsory. ANPC inverter is introduced, which operates in faulty condition (Jun *et al*., 2012). Intelligent systems incorporated with meta heuristic algorithm are highly applicable in electrical control system, as it deserves it. Application from neural network to genetic algorithm training has many advantages like fast operation of neural network and provides accurate results. But in this approach Direction of Arrival (DOA) is the problem, which can be solved by Multilayer Perception Neural Network (MLP-NN). Electronic devices and components have limited switching-frequencies. High frequency carriers are therefore limited by this constraints. The HES allows cancelling the critical harmonic distortions and therefore controlling the fundamental component of the signal by using electronic device with low switching frequencies (Taleb *et al*., 2008). Neural networks provide efficient response to any kind of input pattern (Rodriguez *et al*., 2005). They adapt themselves to the input pattern by continuously training themselves by adjusting the weights between the neurons or the layer of neurons. The complex interconnection of the neurons make the ANN fault tolerant as a set of neurons can take over the load of the faulted set of neurons without any change in performance of whole system. A method of operating cascaded multilevel inverters when one or more power H- bridge cells are damaged has been proposed in Khomfoi and Tolbert (2007). The method is based on the used of additional magnetic contactors in each power H- Bridge cell to bypass the faulty cell. Multilayer perceptron networks (MLP) are used to identify the type and location of occurring faults from inverter output voltage measurement. The objective of the proposed system is to analyze MLP network based fault identification system for five level cascade H-bridge multilevel inverter (MLI). The proposed system identifies the fault and the results to various input patterns with a greater accuracy.

GENERAL CONCEPTION OF FAULT DIAGNOSTIC SYSTEM

Structure of fault diagnostic system: The fault diagnosis system is used to diagnose the fault location. The structure of fault diagnostic system is illustrated in Fig. 3.

The system consist of 4 stages feature extraction, Neural network classification, fault diagnosis and switching pattern calculation with gate signal output. The networks are trained with both normal and abnormal data for the MLID. Thus the output of this network is nearly 0 and 1 as binary code. The binary code is sent to fault diagnosis to decode the fault type and its location. Then, the switching pattern is calculated.

Feature extraction system: Simulink is used to simulate data of fault features with 0.7 modulation index (ma) out of 1.0 is illustrated in Fig. 4 and short circuit faults shown in Fig. 5.

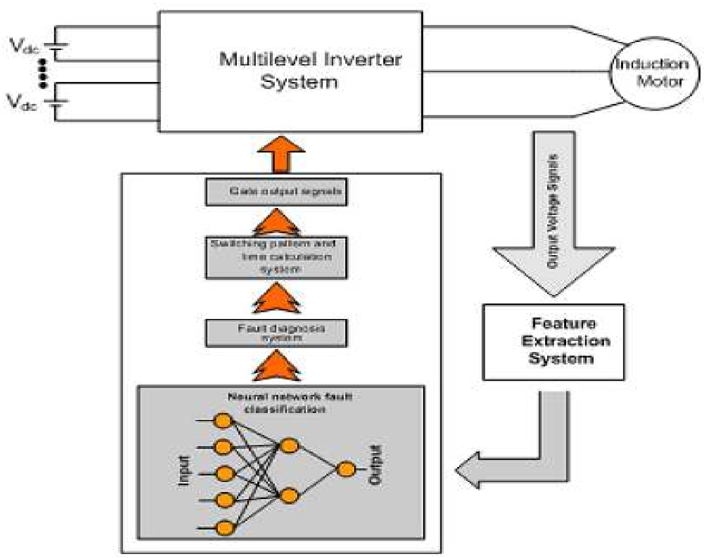


Fig. 3: Structure of fault diagnostic system

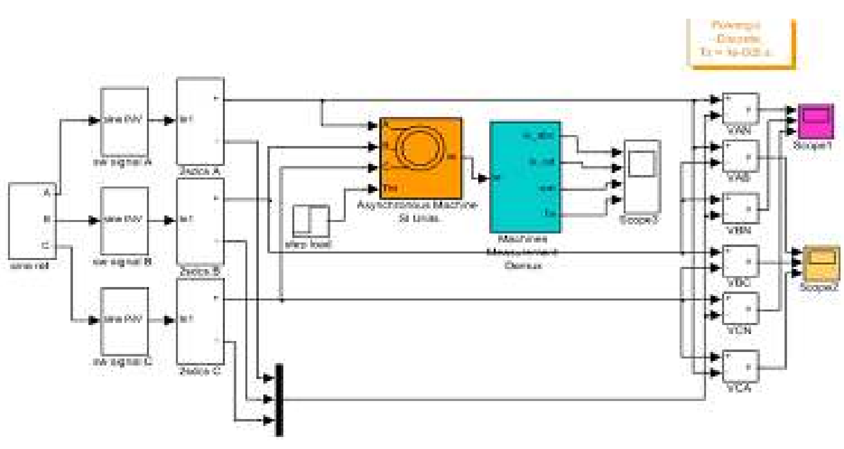
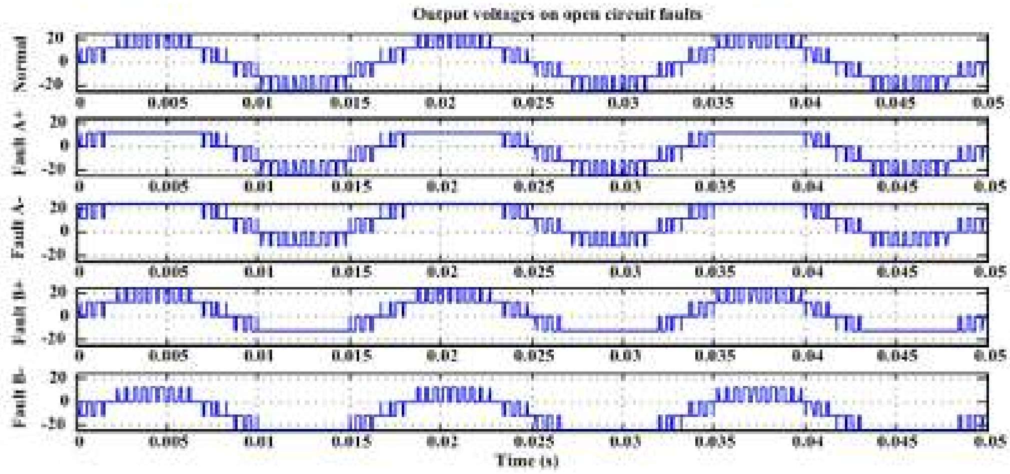
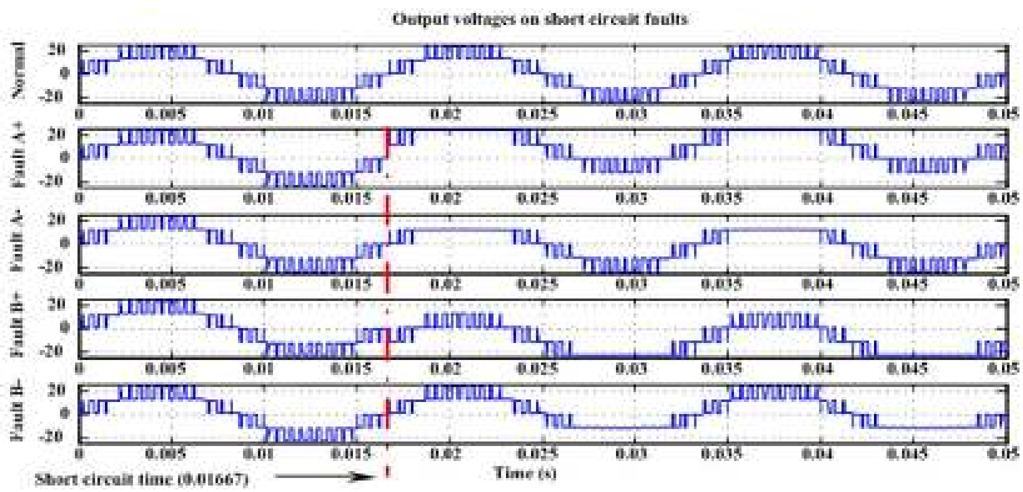


Fig. 4: Simulation of fault feature



(a)



(b)

Fig. 5: Simulation of output voltages signals; (a): open circuit faults; (b): short circuit faults showing fault features at S, S, S and S of H-bridge 2 with modulation index = 0.8 out of 1.0

Output voltage waveform with MLID with open circuit (Fig. 5). The signals in Fig. 5 are difficult to rate as an important characteristics and have high correlation coefficient for classifying a fault hypothesis. Therefore signal transformation technique is required. An appropriate selection of the feature extractor is to provide MLP network with adequate significant details in the pattern set, so that the highest degree of accuracy in MLP network performance can be obtained. One possible technique for implementation with FFT. Computational savings of FFT becomes N logarithmic time (N $\log_2$N) compared to quadratic time for DFT.

RADIAL BASIS FUNCTION MULTI LAYER PERCEPTRON NETWORKS: ARCHITECTURE AND LEARNING

RBF MLP network architecture: As the concept of ANN evolved, various architectures of the artificial neural networks were developed that expertise in a given kind of applications (Son *et al*., 2004; Kim *et al*., 1996). For instance, the perceptron network works flawlessly with the data that is linearly seperable. Whereas, the ADALINE and MADALINE networks work good with hard problems, the BAM, Elman Architecture work better as memory units or data storage networks. The feed forward, Cascade forward architectures (Taleb and Meroufel, 2009; http://en.wikipedia.org/wiki/Backpropagation) and the RBF network can be employed for applications where the network has to deal with continously varying inputs that take continous values ranging over the real domain.

In this study, RBF network architecture is implemented. The RBF network as shown in Fig. 6 has three layers, one input layer, a hidden layer and an output layer. The neurons in the input layer are linked to those in the hidden layer through unit weights. The number of neurons in the input layer equals to the number of samples taken in the input data. The hidden layer neurons consist of non-linear radial basis function

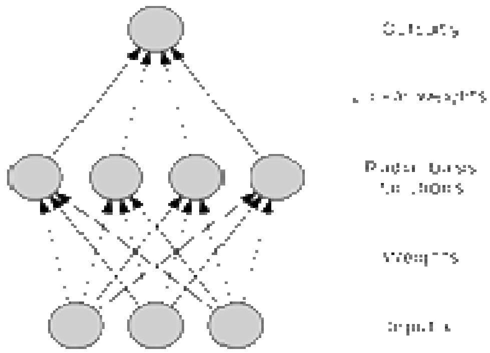


Fig. 6: RBF Network architecture

type activation as shown in Fig. 7, which computes its output value based on the Euclidean distance of the weighted sum of the samples from the center vector of the neuron. The number of neurons in the hidden layer is a variable parameter. The neurons are added and removed from the hidden layer during the training process and the optimum number of neurons is fixed along with their centers and the spread factor of the activation function.

Training of a radial basis function network: The training of an RBFN involves updating of three main parameters apart from the weights as done in other networks, the parameters being the center vectors of the activation functions, the spread or width parameter of the activation functions and the number of neurons in the hidden layer (Neelam, 2011). The optimal number of hidden layer neurons can be obtained from optimization algorithms such as the particle swarm optimization, evolutionary programming, genetic algorithm, modified genetic algorithm, etc. or they can also be determined by adding a fixed number of neurons (preferably one or two neuron) per epoch, updating the weights and validating the patterns. The number of neurons that give the best fit are considered to be the optimal number of neurons in the hidden layer.

The training algorithm for the RBFN (Lezana *et al*., 2010; Jun *et al*., 2012) as stated involves:

Step 1: Computing the number of hidden neurons N by various optimization techniques mentioned.

Step 2: Compute the cluster centers ciusing either the K-means clustering technique or using the random subsets of the training points.

Step 3: Interpolate the weights using the relation:

$$w = G - 1x \tag{1}$$

where,

$$G = gij = \rho(xj - ci) \tag{2}$$

And $\rho\ xj - ci$ is the Gaussian function given by:

$$\rho\ xj - ci = \exp[-\beta\ xj - ci^2] \tag{3}$$

where, β is the spread parameter.

Step 4: Compute the output of the network given by:

$$\varphi x = wi\rho\ xj - ciNi = 1 \tag{4}$$

Step 5: Repeat steps 1 to 4 until the best fit between the output φx and the targets is reached.

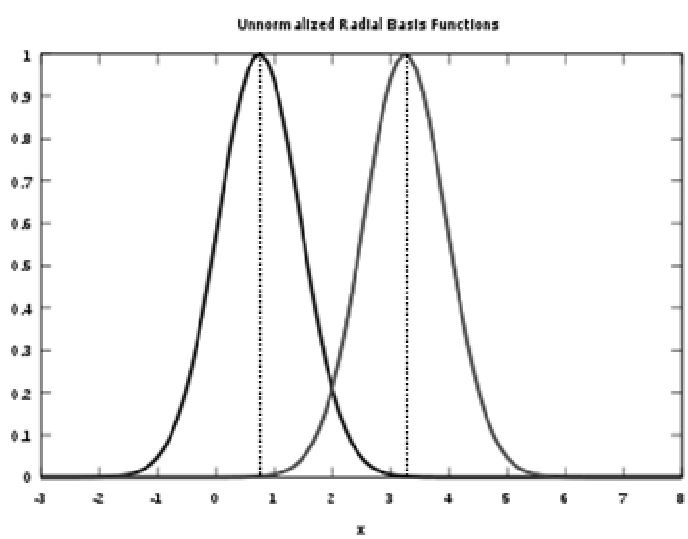


Fig. 7: RBF activation functions with centers at c1 = 0.72 and c2 = 3.35

TESTCIRCUITS AND METHODS

Figure 8 shows the general block diagram of a fault diagnostic system. The output voltages are measured and given as inputs to the ANN controller which identifies the type of fault and provides the gating pulses accordingly to compensate for the fault.

The 5-level cascaded multi-level inverter is simulated for various irregularities in MLI outputs due to misfiring of the switches using Simulink as shown in Fig. 9. The pulses are generated in such a manner that, when a switch is misfired or triggered before it is actually meant to be triggered, there exists a conduction overlap with these conduction switch from the same leg which leads to appreciable distortion in the output waveform of the MLI. This distortion is noticed to be unique to faults due to misfiring.

The firing pulses and the simulated output waveforms of the healthy MLI are shown in Fig. 10 and 11, respectively. The upper and the lower waveforms in Fig. 11 depict the output of the individual stages and the middle waveform gives the total output of the MLI.

Simulations of training patterns: The output waveform patterns of the MLI under faulty conditions are obtained by generating the firing pulses to the MLI in such a manner that combinations of switches are fired prior to their actual instant. To obtain the input data to train the neural network, the following combinations of misfiring are simulated:

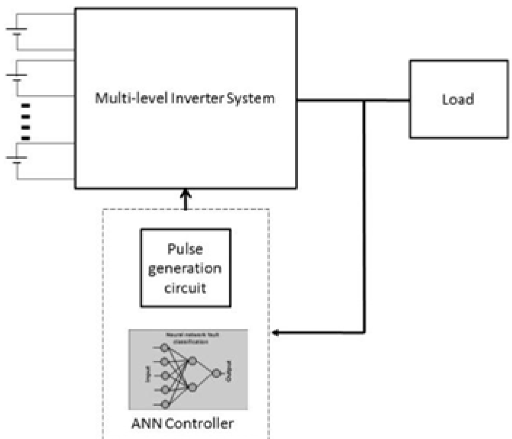


Fig. 8: General block diagram of an ANNcontroller based fault diagnostic system

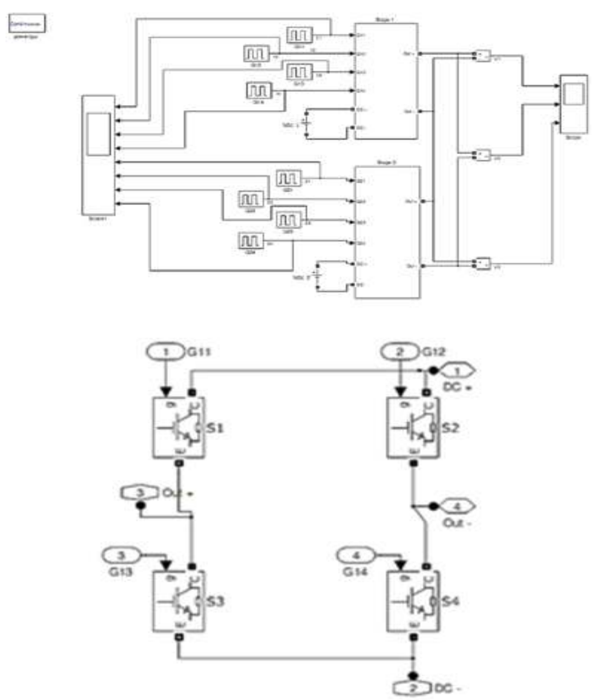


Fig. 9: (a): Single stage of an MLI; (b): Simulink model of a5-level cascaded MLI

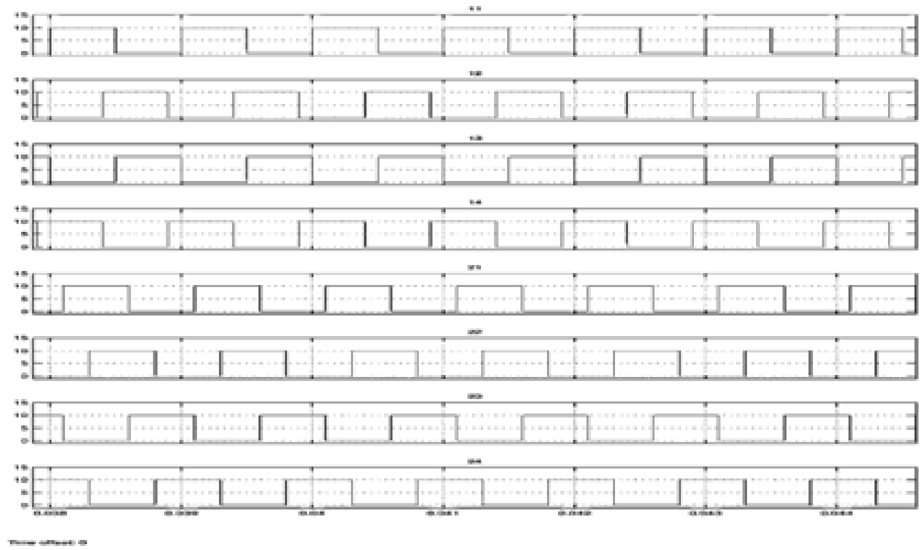


Fig. 10: Firingpulses to the healthy MLI

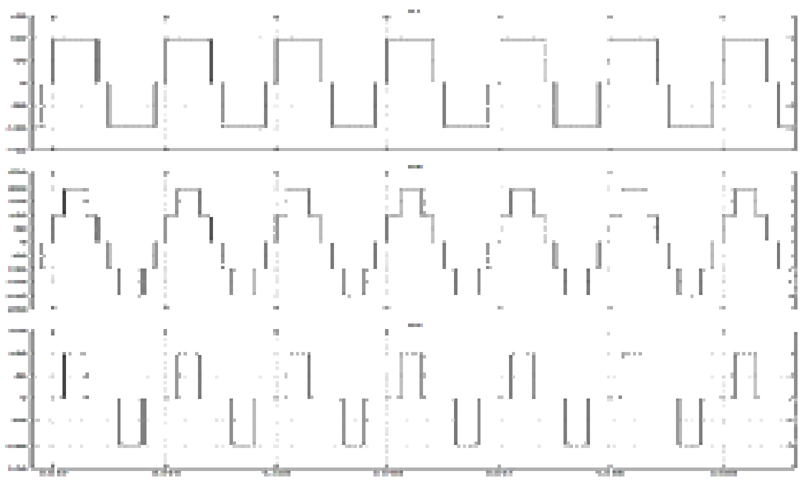
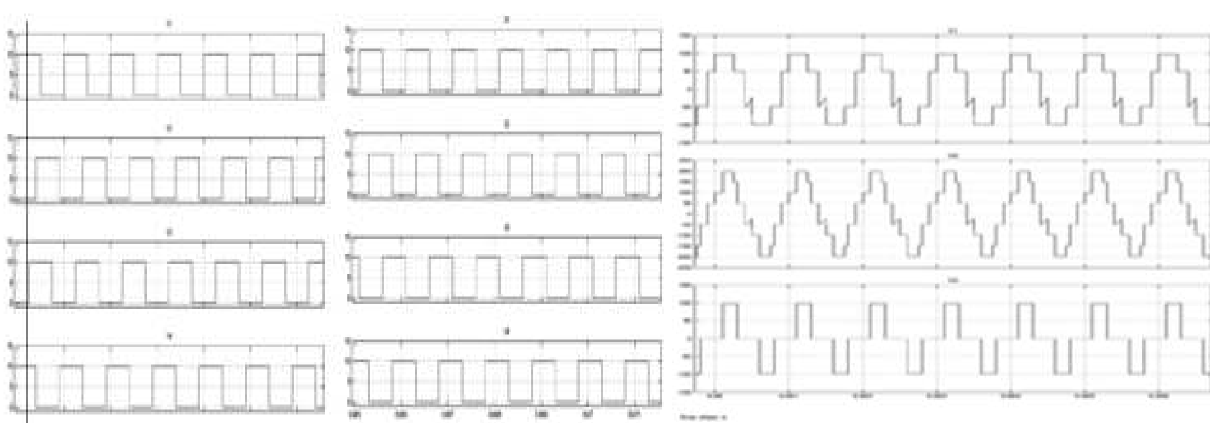


Fig. 11: Output wave forms of a healthy 5-level cascaded MLI



(a) (b)

Fig. 12: Triggering pulses and output waveforms when the Switch S_{13} is triggered 0.25 ms early

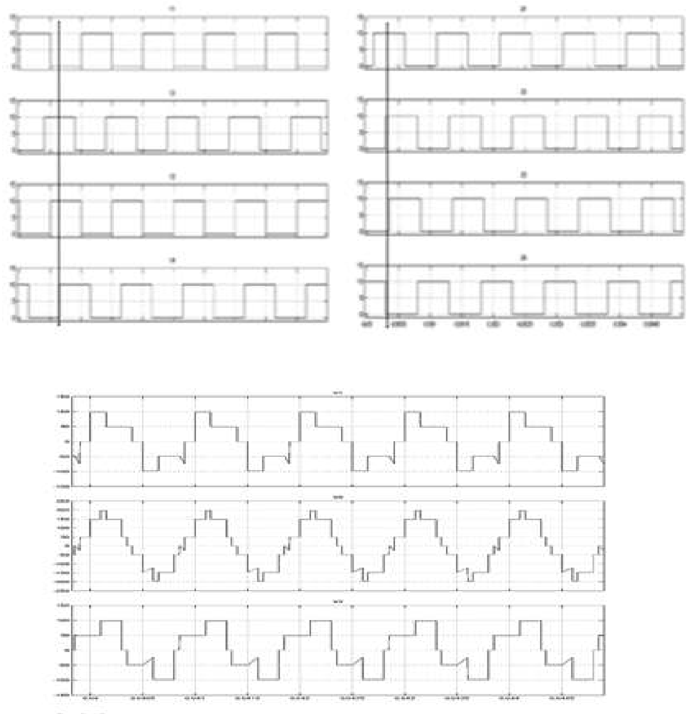


Fig. 13: Firing pulses and output waveforms when switches S_{14} and S_{23} are fired 0.25ms early

- Switch S_{13} is triggered such that there is a conduction overlap between switches S_{11} and S_{13}.
- Misfiring causing conduction overlap in switches S_{12} and S_{14}.
- Misfiring causing conduction overlap in switches S_{21} and S_{23}.
- Misfiring causing conduction overlap in switches S_{22} and S_{24}.
- All combinations of conduction overlap in more than one pair switches, etc.

Figure 12 and 13 show few of the output patterns obtained to train the neural network.

A total number of sixteen patterns of seven thousand sample points each are obtained from all the combinations of faults due to misfiring of the switches which are given as the input training patterns of the RBF network.

Training the RBF network for fault diagnosis: The training patterns thus obtained by simulating the faults are fed to the RBF network generated using newrbe. The generated RBF net contains 7000 input neurons with the Gaussian function as the RBF activation function with a spread parameter of 1 and 12 output neurons with a purelin activation function. The output layer contains 12 neurons as there 12 unique types of faults that can be caused due to misfiring of the various combinations of switches in the MLI. The training target values are as shown in Table 1. Each column represents each type of fault taken in the order of the input patterns provided for training.

Table 1: Targets patterns for various faults

No fault	[1 0 0 0 0 0 0 0 0 0 0 0]
$S_{11}S_{13}$	[0 1 0 0 0 0 0 0 0 0 0 0]
$S_{12}S_{14}$	[0 0 1 0 0 0 0 0 0 0 0 0]
$S_{21}S_{23}$	[0 0 0 1 0 0 0 0 0 0 0 0]
$S_{22}S_{24}$	[0 0 0 0 1 0 0 0 0 0 0 0]
$S_{11}S_{13}S_{21}S_{23}$	[0 0 0 0 0 1 0 0 0 0 0 0]
$S_{12}S_{14}S_{22}S_{24}$	[0 0 0 0 0 0 1 0 0 0 0 0]
$S_{11}S_{13}S_{22}S_{24}$	[0 0 0 0 0 0 0 1 0 0 0 0]
$S_{12}S_{14}S_{21}S_{23}$	[0 0 0 0 0 0 0 0 1 0 0 0]
$S_{11}S_{13}S_{12}S_{14}$	[0 0 0 0 0 0 0 0 0 1 0 0]
$S_{21}S_{23}S_{22}S_{24}$	[0 0 0 0 0 0 0 0 0 0 1 0]
All pairs	[0 0 0 0 0 0 0 0 0 0 0 1]
No fault	[1 0 0 0 0 0 0 0 0 0 0 0]
$S_{11}S_{13}$	[0 1 0 0 0 0 0 0 0 0 0 0]

The trained neural network is tested in two categories. First, the test vectors are selected from the training vectors and the output of the neural networks is observed. In Table 1, the ANN is able to identify the type of the fault and location of the fault occurring on the MLI. To test the trained neural network further, new pattern of data are simulated and provided to the input layer of the net. The pattern of the new data is similar but not identical any of the training data. The net was able to match the new test pattern to the correct pattern.

RESULTS AND DISCUSSION

As stated, the net is tested by applying test input patterns obtained by simulating a fault of any

```
>> out_1 = sim (net, V_12_14);
out_2 = sim (net, V_11_13_21_23);
out_3 = sim (net, V_all);
out_trained = [out_1 out_2 out_3]
%output of the net correspoding to three trained input patterns

out_trained =

   -0.0000   -0.0000   -0.0000
   -0.0000    0.0000    0.0000
    1.0000   -0.0000   -0.0000
    0.0000   -0.0000   -0.0000
    0.0000    0.0000    0.0000
   -0.0000    1.0000   -0.0000
   -0.0000   -0.0000   -0.0000
    0.0000   -0.0000    0.0000
   -0.0000   -0.0000    0.0000
    0.0000   -0.0000    0.0000
   -0.0000    0.0000   -0.0000
         0         0    1.0000

>>
```

Fig. 14: Output of the net corresponding to trained patterns

```
>> out_new = sim (net, V_fault_1_10ms)
%output for 72(deg) conduction overlap on switches S11&S13

out_new =

   -0.0000
    1.0000
   -0.0000
   -0.0000
    0.0000
   -0.0000
   -0.0000
    0.0000
    0.0000
    0.0000
   -0.0000
         0

>>
```

Fig. 15: Output of the net to the new pattern corresponding to 72° conduction overlap misfire fault on switch pair $S_{11}S_{13}$

combination mentioned in Table 1. To train the net, patterns corresponding to faults with conduction overlap period of 450 are applied to the input layer of the generated RBFN. Figure 10 gives the output of the of the neural network when the patterns corresponding to misfiring fault on switch combinations S12S14, S11S13S21S23 and all pair of switches with conduction overlap of 45 are applied which are used to train the net.

Figure 14 shows the output of the net corresponding to trained patterns.

Figure 15 gives the output of the net when an output voltage waveform pattern of the MLI corresponding to a misfire fault with conduction overlap period of 72° between on pair $S_{11}S_{13}$. Though this pattern is an unknown pattern to the net, it is able to correctly associate with the correct type of misfiring fault based on the training patterns.

CONCLUSION AND FUTURESCOPE

A fault diagnostic system to identify faults due to misfiring of switches in a 5-level Cascaded H-Bridge Multi-level Inverter using Artificial Neural Network is proposed. A Radial Basis Function Neural Network is trained with the patterns of the output voltage waveforms during various instances of misfiring of one or more switches in the MLI. Once the network is trained with few training patterns, it is ready to identify the location (s) of the misfiring irrespective of the duration and instance of the misfiring of the switches. The neural network delivered an appreciable performance throughout the operating range of the MLI. It was also observed that, a radial basis function neural network trained with the output waveform pattern is able to efficiently identify the location (s) of the switches that were misfired when compared to training a perceptron model with either the harmonic spectrum or the voltage histogram or any other method. These methods were able to identify the fault only as either an open circuit fault or a short circuit fault but failed to further classify these faults as stated in above Section. Thus, an ANN trained with wave shape of the output pattern provides a superior control over the firing pulses enabling the triggering circuitry to automatically adjust the duty cycle/pulse width or any required parameter such that the MLI continues to produce a healthy output despite switches being misfired accidentally. As the response of an RBFN is quicker than most of the available ANN topologies, the distortion of the output during this response time does not have a considerable impact on the performance of the load systems and hence can be neglected. The proposed RBF Neural Network can be trained further to identify and provide compensation for any type of faults on the MLI stated in above section. The future scope of the presented work includes implementing the proposed RBFN to diagnose all switch level faults, shorting and disconnecting of DC sources and load end faults.

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