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Open Circuit Fault Diagnosis and Fault Classification in Multi-Level Inverter using Fuzzy Inference System

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Abstract: Multi-level inverters (MLIs) have been successfully used to integrated the renewable energy sources (RES) into microgrids. However, the operation of MLI is affected when an open circuit fault (OCF) or a short circuit fault occurs. Among these kinds of faults, there is a high prevalence of open circuit faults in MLI. Any fault in MLI must be identified and classified as soon as possible to maintain the reliability of the power supply. This work is focused on developing a Fuzzy Inference System (FIS) for detecting and classifying the open circuit faults in Cascaded H-Bridge Multi-Level Inverter (CHMLI), thereby improving the fault diagnosis accuracy and efficiency. In CHMLI, the gate pulse is generated by pulse width modulation (PWM) technique. The Mamdani Fuzzy Logic Controller (FLC) identifies and categorizes the different OCFs. Fuzzy logic rules are designed for detecting and classifying open circuit faults simultaneously using the fundamental Discrete Fourier components of voltage and current. Several combinations of open circuit faults have been studied in different switches of the MLI, along with the effect of fault inception angle. Furthermore, the test results support the feasibility of the proposed fuzzy-based fault diagnosis and classification scheme in a practical context. A real-time simulation obtained with the help of FPGA-based OPAL-RT 4510 demonstrates the robustness and effectiveness of the designed topology. All types and fault locations are considered in multiple cases of switch failure.

Keywords: Cascaded H-Bridge Multi-Level Inverter, Renewable Energy Sources, Pulse Width Modulation, Fuzzy Logic Controller, Discrete Fourier.

1 Introduction

The world's energy demands have rapidly increased over the last two decades [1]. With recent breakthroughs in intelligence and microgrids, different Renewable Energy Sources (RES), such as solar, wind, biomass, fuel cells etc., are being used as alternative solutions toward carbon-free energy sources to fulfil sustainable development goals [2]. However, these RES involve converting DC power to AC

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power through inverter technologies, which results in harmonics and degrades the power quality. A practical solution to limit the harmonic intensity is to employ Multi-Level Inverters (MLI). As the number of levels in the inverter increases, the output AC voltage increases, and the power quality of grid-connected distribution systems increases. This type of converter is called a multilevel inverter [3]. With Multi-Level Inverters (MLI), the DC power is converted into AC power by connecting many switches in multiple ways (Diode clamped, Flying Capacitor, Cascade H-Bridge).

The cascaded H-bridge multi-level inverters (CHMLI) are often employed in medium and high voltage high power applications owing to its low switching losses. Different RES, such as photovoltaic cells, wind farms, and fuel cells, can be integrated into the power grid with a Multi-Level Inverter (MLI) system for high-power outputs. MLI topologies like neutral point clamped (NPC), flying capacitors (FC) and cascaded H-bridge (CHB) have been commercialized [4], but with increasing number of voltage levels; the number of device count is also increased. The CHMLI has the following advantages over conventional two-level inverters: power switches under low voltage stress, lower switching losses, low harmonic content in the output voltage and highly efficient. However, due to the mal-function of power electronic modules and occurrence of faults in switches, the system's reliability decreases with a rise in inverter voltage levels [5].

According to the literature, it has been determined that open-circuiting or short circuiting of switch(s) is the most common reason of failure of an inverter in distributed power generators. There is also a greater likelihood of faults arising between the switch elements. An analysis of 200 products from 80 companies has found that the possibility of fault in semiconductors and solder joints is around 21% and 13%, respectively [6]. On the other hand, about 34% of converter system failures are caused by fault in device modules. As a result, the fault in the switch components of the inverter must be diagnosed [7, 8]. After the inverter fails, the CHMLI must run in the fault tolerance control mode so that the system can recover as soon as possible. MLI reliability can be significantly improved by using fault-tolerant configuration and preserving the modularity of its implementation [9 – 13].

MLIs are most vulnerable to malfunction resulting from failure of power devices, which may lead to low reliability and low system performance. Two significant causes of damage in IGBT modules/switches of power converters are open circuit faults (OCFs) and short circuit faults (SCFs). It has been demonstrated in the literature that various techniques have been used to detect and diagnose an open circuit fault in MLI [14, 15], including principal component analysis and Multiclass Relevance Vector Machine Approach (PCA-mRVM) [16], Artificial Neural Networks (ANNs) [17, 18]. AI-based techniques are commonly used in fault diagnosis due to their superior detection and prediction capabilities. These techniques involve two steps. Firstly, features are extracted from the faulty signal using feature extraction techniques such as mean, entropy, median, energy, or standard deviation, along with methods like PCA, KPCA, Sub-Band Wavelet Energy, FFT, DWT, etc. In the second stage, these features are utilized as input to machine learning classifiers, such as SVM, KNN, DT, RF, NB etc., to classify the faulty signal into different output classes representing the faulty switch/s combinations. Several studies have utilized AI- based approach for fault diagnosis in MLI, as demonstrated in references [19 – 22]. Furthermore, a creative method to detect and identify the fault location based on the current distortion is presented in [23]. In [24, 25], Fuzzy logic-based systems have been utilized to detect and locate the failed switches in NPC inverters, as well as to detect the switch faults in CHBMLIs. Nevertheless in [26] combined DWT and fuzzy-based system has been utilized for fault diagnosis, however, the time required for fault detection and classification is not specified. Reference [27] employed a fuzzy-based system to detect and classify faulty switches in NPC inverters. In [27], only single-switch fault detection and classification have been addressed and only two types of faults are classified. The objective of this paper is to develop an algorithm that utilizes fuzzy logic for detecting and classifying different types of open circuit faults in MLI. In CHMLIs, if any switch encounters a fault, a fault signal is generated as a result of the employment of fuzzy logic. Fuzzy logic is an appealing solution in the field of power electronics due to its ease of design, ability to map nonlinearity, and low level of intuition. In particular, the paper shows a 5-level inverter topology that can handle switch open circuit faults. During the evaluation of the recommended configuration, normal and defect conditions are taken into account. Simulations of MLI system in normal and abnormal states are performed using MATLAB/Simulation.

The remaining part of the paper consist of 5 sections. Section 2 describes the proposed topology and open circuit fault attributes of CHMLI. Section 3 analyses the fuzzy-based fault diagnosis and fault classification techniques. The purpose of the fourth section is to provide an in-depth analysis of fuzzy-based fault recognition and classification techniques under a number of possible scenarios along with a detail comparative analysis. Lastly, Section 5 summarizes the findings of this paper.

2 Details of Proposed Topology

In this work, CHMLI topology has been selected to perform the open circuit fault analysis. Detailed information about inverter topology and corresponding switch firing pulse generation methodology is discussed. Different combinations of open circuit faults are considered, and a discussion on the impact of open circuit faults on the inverter output ac voltage is presented in a subsequent subsection.

2.1 Cascaded H-Bridge MLI

Fig. 1 depicts the circuit diagram of a five-level CHMLI.

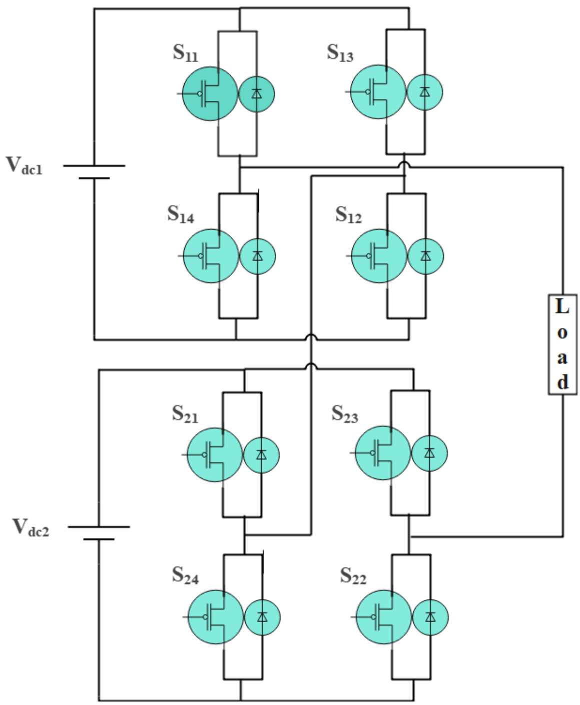


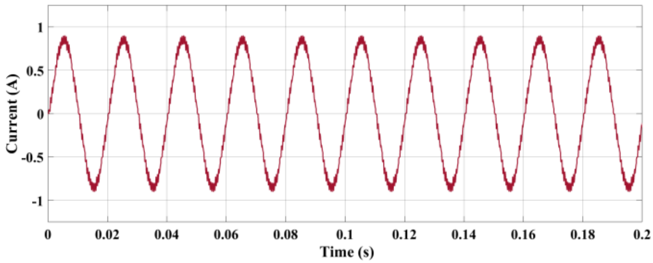
Fig. 1 – *5 levels CHB inverter.*

The parameters of the CHMLI are given in **Table 1**.

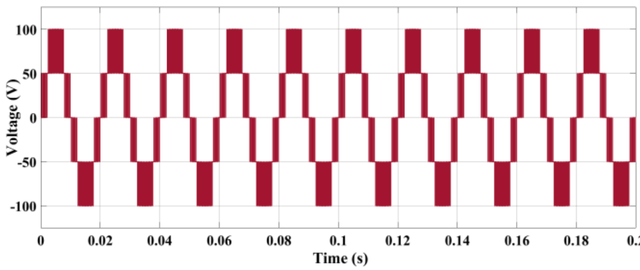
Table 1
System specifications.

Parameters	Specifications
Input voltage	50 V
R	100 Ω
L	40 mH
Frequency	50 Hz
Switching frequency	1000 Hz
Modulation index	0.85
Sampling time	100 µs

Two DC batteries each of 50 V are linked to the respective H bridges by a combination of 4 switches switching configurations. The cascaded H-Bridge (CHB) output voltage level is described as l = 2*n*+1, where ‘*n*’ indicates the no. of DC sources and ‘l’ denotes the output inverter level. Thus, five diverse output voltages can be generated, i.e., (+2Vdc +Vdc, 0, –Vdc and –2Vdc). During normal operating conditions, Figs. 2a and 2b show the output AC voltage and current waveforms, respectively.



(a)



(b)

Fig. 2 – (a) *Waveform of the output current under the expected circumstances*; (b) *The waveform of the output voltage.*

2.2 Phase shift pulse width modulation

In this paper, the CHMLI is operated using phase shift pulse width modulation (PSPWM), an easy-to-implement technique with minimal complexity compared with other modulation techniques. PSPWM compares each carrier signal with the reference signal continuously. A high output voltage is obtained when the reference signal is greater than the carrier signal. Modelling waves are identical for each cell in this technique, but the carrier waves for each cell are phase-shifted. In PSPWM, we give a slight phase shift between the carriers. All cells get an identical reference waveform, but its amplitude is reduced by a factor N. In PSPWM, the effective switching frequency gets multiplied at the output. Suppose the upper and lower switches in the same leg (on or off) operate simultaneously. In that case, the supply to the inverter will be short or open, respectively.

Assume the number of cells in each phase "N" = 4. Number of H Bridge' n' = 2.

The number of levels $L = 2n+1=2\cdot2+1= 5$. Number of carriers required is 2.

A phase shift between the carriers 360°/L–1 or the angle 360° concerns triangular frequency.

2.3 CHMLI: Open circuit fault

Two leading types of fault in IGBT modules are open circuit faults (OCFs) and short circuit faults (SCFs). The switch cannot transmit current to the load under OCF conditions. However, overcurrent will be experienced under SCF conditions. OCF recognition is the main focus of this paper. OCF types in an inverter will determine how many switches are faulty at a given time. In MLI with n devices, (n–1) device faults may occur. For example, a single device may fail, a double device may fail, or (n–1) devices may fail. In this work, faults caused by the open circuit of either single device or dual devices (complicated) have been considered. In 5-level CHMLI, 37 possible open circuit switch faults can occur. All these possible combinations of faults are divided into six classes depending upon the deviation of the magnitude of the fundamental component of voltage calculated using Discrete Fourier, as illustrated in **Table 2**.

Several case studies have been simulated to illustrate the different OCF conditions in CHMLI. In Figs. 3a and 3b, the circuit diagram of the CHMLI and in Figs. 3c and 3d the output voltage waveforms are shown under an OCF condition in different switches such as S_{11}, S_{13} and S_{12} respectively. For example, at 0.1 s, an OCF is created on a switch S_{11}. Consequently, the waveform in Fig. 2b illustrates the inverter AC output voltage waveform, which consists of only one level of +50 V in the positive half cycle and two levels of –50 V and –100 V in the negative half cycle, resulting in a reduction in levels as a result of an OCF condition in one switch. A similar fault condition has also been identified in the second case study in which two switches, S_{13} and S_{12}, have been identified as being open circuited in the upper H-bridge in the right leg, as illustrated in Fig. 3c. In this case of 2 switches OCF, as exemplifies in Fig. 3d, +100 V and –100 V voltage levels in positive and negative half of the AC output of inverter are absent and only +50 V, 0 and –50 V are obtained.

Furthermore, a more substantial number of OCF case studies have been considered and listed in **Table 2**. According to Fig. 3, it can be concluded that the presence of an OCF in the CHMLI results in a distortion of the output voltage waveform due to the OCF in the CHMLI. Moreover, there will also be a reduction in the number of levels. Based on analysis of these distinct changes in output voltage waveforms between faulted and non-faulted conditions, a fuzzy-based fault recognition and classification scheme has been developed in next section.

Table 2
Classification of faults according to the type of OC switch fault.

Class	Fault types	Modes of fault (OC)	Number of cases	Fault situation	Output cases
I	Two Switch	S21, S23	2	Lower leg	1
		S24, S22			2
II		S11, S14	4	Same leg	3
		S13, S12			4
		S21, S24			5
		S22, S23			6
III		S11, S12	20	Diagonal leg	7
		S13, S14			8
		S21, S22			9
		S23, S24			10
		S11, S21		One switch from upper leg and second from lower leg	11
		S11, S22			12
		S11, S23			13
		S11, S24			14
		S13, S21			15
		S13, S22			16
		S13, S23			17
		S13, S24			18
		S14, S21			19
		S14, S22			20
		S14, S23			21
		S14, S24			22
		S12, S21			23
		S12, S22			24
		S12, S23			25
		S12, S24			26
IV		S11, S13	2	Upper leg	27
		S14, S12			28
V	Simple Fault	S13	4	One switch	29
		S14			30
		S23			31
		S24			32
VI		S11	4		33
		S12			34
		S21			35
		S22			36
VII	No-Fault	-	1	Fault Free	37

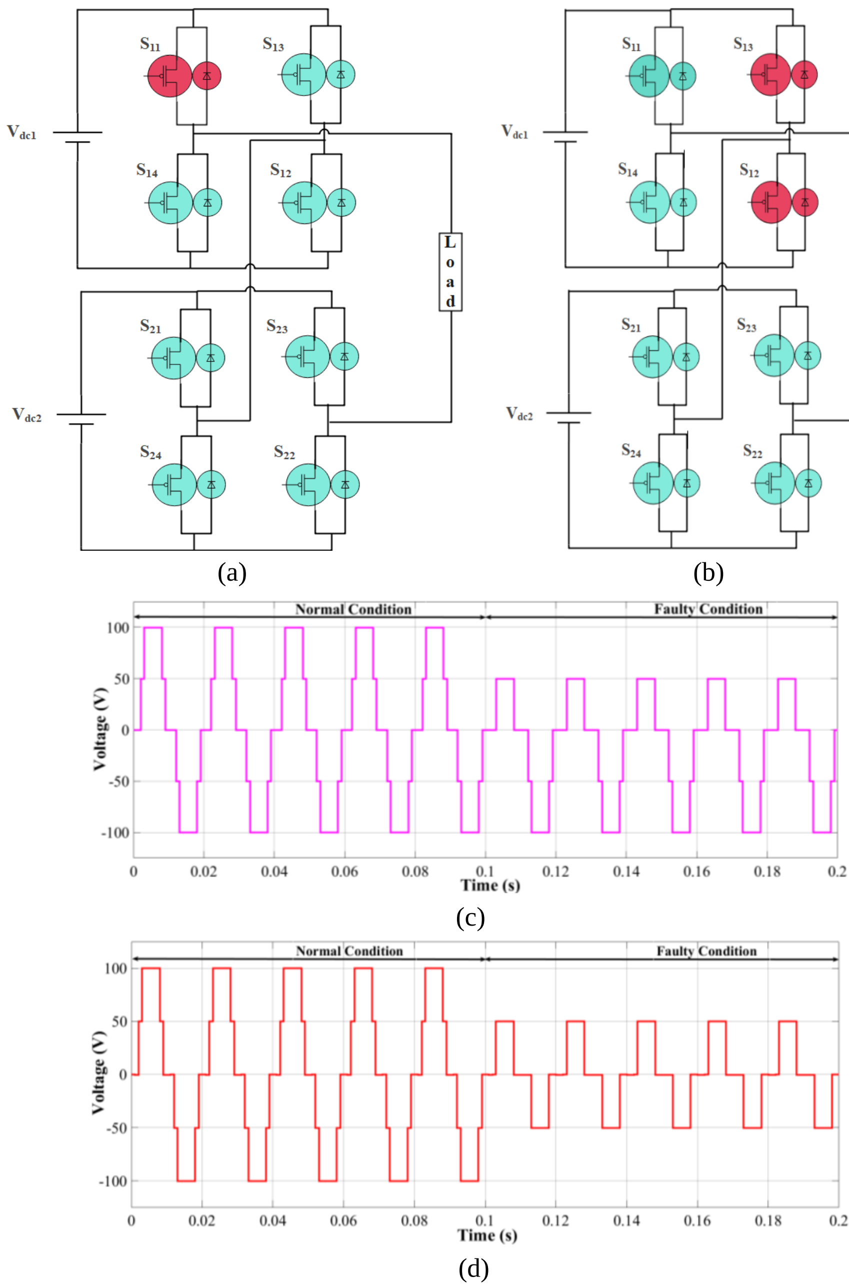


Fig. 3 – (a) *Circuit diagram of the CHMLI when OCF at S_{11};*
(b) *Circuit diagram of the CHMLI when OCF at S_{13} and S_{12};*
(c) *Output voltage waveform when OCF at S_{11};*
(d) *Output voltage waveform when OCF at S_{13} and S_{12}.*

3 Proposed Fuzzy Based Fault Diagnosis and Classification Technique

As seen in the previous section, the output voltage and current have distinct characteristics during the no-fault and post-fault conditions, so they can be used to determine the presence of OCF and establish which switch/s is/are open-circuited. If any switch (IGBT) is open-circuited (OC), the inverter output AC voltage and current signals obtained from the sensitive load side of the CHMLI are preprocessed using Discrete Fourier to extract the fundamental component of voltage and current, which are used as input to Fuzzy based system. The output of the fuzzy based system is fault signal which detects the presence of fault and classify the faults into six different classes representing different combinations of switch faults. In fuzzy logic, inputs and outputs are governed by specific rules, making the process highly efficient and reliable. In the past, the fuzzy logic controller (FLC) was categorised into two models: Mamdani FLC and Takagi-Sugeno FLC. Mamdani FLC is intuitive and more widely accepted than Takagi-Sugeno FLC. This paper uses Mamdani FLC to model fuzzy logic.

3.1 Design of fuzzy logic control system

Fuzzy logic operates with fuzzy sets of fuzzy algebra. Fuzzy logic is also known as fuzzy logic controller (FLC), a method used in many applications, including fuzzy reasoning, fuzzy clustering, fuzzy programming, etc. Out of all these applications, fuzzy logic reasoning is known as fuzzy logic controller (FLC).

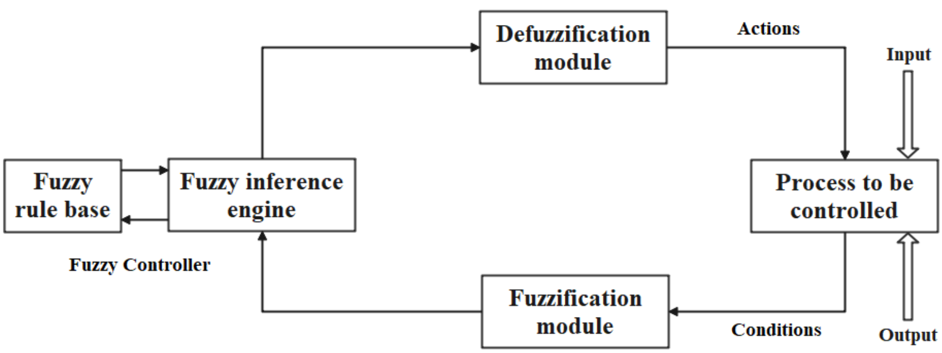


Fig. 4 – *Fundamental features of a fuzzy logic control system.*

Fuzzy controllers have four main modules, as illustrated in Fig. 4:

1. Fuzzification module.
2. Fuzzy inference engine.

3. Fuzzy rule base.
4. Defuzzification module.

3.2 OC fault diagnosis and classification using the fuzzy logic controller

A fuzzy logic controller is used for developing the OCF recognition scheme. In place of proportional-integral (PI) controllers, fuzzy logic controllers (FLC) are usually used to control complex non-linear systems whose mathematical models can't be described. Fuzzy logic will be used in this paper to detect the presence of any open circuit fault in the CHMLI. Further Fuzzy-based classification system can classify the fault into six different categories.

Faults are classified into different categories using a fuzzy-based controller. Depending upon the magnitude of inverter output voltage measured through discrete Fourier block in MATLAB, the fault range in this paper is classified. The magnitude of output AC voltage changes when any fault occurs, such as one switch fault, two switch faults, etc. In addition, the fault level is changed. Thus, these differences in the fundamental components of output AC voltage and current are viewed as unique features that can be used to categorize faults into different types. Let's suppose when the OC fault takes place in switch S_{11}, the fundamental Discrete Fourier voltage decreases from 95 V to 72.36 V, so according to **Table 2** of fault classification, it has come under class VI type fault. Likewise, when any combination of switches is faulted, the class is automatically deducted using the fuzzy-logic controller.

For fault diagnosis and classification, the first step is fuzzification of input crisp signals and defuzzification of output fuzzy signal into crisp output signal through membership functions. Figs. 5a – 5c exemplify the membership function for AC voltage, AC current as input to FLC, and Fig. 5d fault signal as output of FLC, and 3D visualisation of inference rules, respectively. Fuzzy-logic systems classify faulty switches based on discrete Fourier voltages and currents. Input signals are divided into eight ranges based on a triangular membership function that is low1-6, middle, and high. Out of which six membership functions are assigned for the lower voltage ranges, one MF is allocated for the medium value of voltage and one MF is given for high value of Discrete Fourier voltage. Similarly, for input current signals also fuzzification process is carried out. Furthermore, the output fault signal contains eight ranges of membership functions, and these ranges are FS_L, FS_V and six $FS_{H1\text{-}6}$. A set of voltage and current during different types of OCF data is gathered. Physical units are used to measure all inputs and outputs.

The fault classification rules are exemplified in **Table 3**.

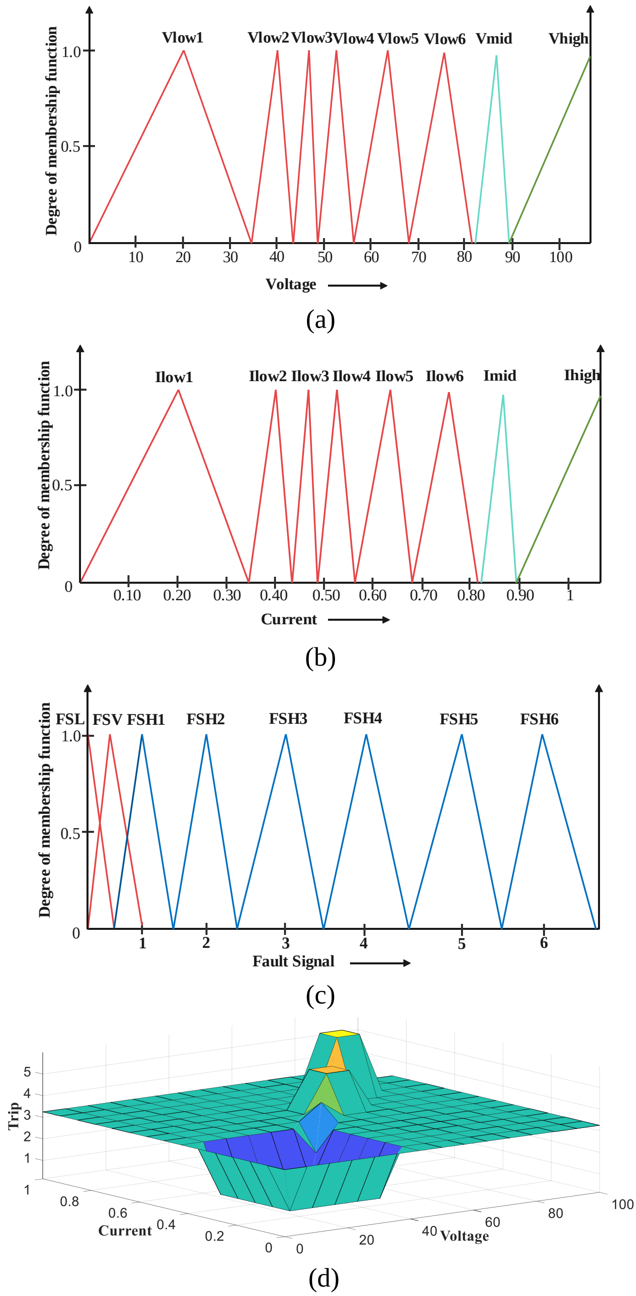


Fig. 5 – *Fault diagnosis and classification:* (a) *AC voltage membership function*; (b) *AC current membership function;* (c) *Output fault diagnosis signal membership function*; (d) *3D visualization of fuzzy rules.*

Table 3
Diagnosis and classification of faults using fuzzy logic rules.

Fuzzy Logic Rule								
Parameters	V_H	V_M	V_{L1}	V_{L2}	V_{L3}	V_{L4}	V_{L5}	V_{L6}
I_H	FS_L	FS_L	FS_L	FS_L	FS_L	FS_L	FS_L	FS_L
I_M	FS_L	FS_V	FS_L	FS_L	FS_L	FS_L	FS_L	FS_L
I_{L1}	FS_L	FS_L	FS_{H1}	FS_L	FS_L	FS_L	FS_L	FS_L
I_{L2}	FS_L	FS_L	FS_L	FS_{H2}	FS_L	FS_L	FS_L	FS_L
I_{L3}	FS_L	FS_L	FS_L	FS_L	FS_{H3}	FS_L	FS_L	FS_L
I_{L4}	FS_L	FS_L	FS_L	FS_L	FS_L	FS_{H4}	FS_L	FS_L
I_{L5}	FS_L	FS_L	FS_L	FS_L	FS_L	FS_L	FS_{H5}	FS_L
I_{L6}	FS_L	FS_L	FS_L	FS_L	FS_L	FS_L	FS_L	FS_{H6}

$FSH_{1, 2, 3, 4, 5, 6}$ =fault signal high for different classes

FS_L = Low fault signal

FSV = Verge fault signal

4 Simulation Results and Discussions

Matlab Simulink toolbox has been used to simulate the proposed system under consideration as illustrated in Fig. 6. CHMLI is illustrated in this Fig. 6 with two DC sources and a R-L load. The fuzzy logic controller (FLC) takes the inverter ac voltage and current signals as input and generates an output fault signal to detect the presence of fault and classify the OCF.

A separate data set has been utilized to assess the enactment of fuzzy logic in detecting and classifying faults. A variety of combinations of switch faults are created to form the test data set. All cases are classified into six different types depending upon the number of switches, which are open circuited at a time and the efficacy of fuzzy logic-based fault diagnosis, and classification is examined. The details are given here under.

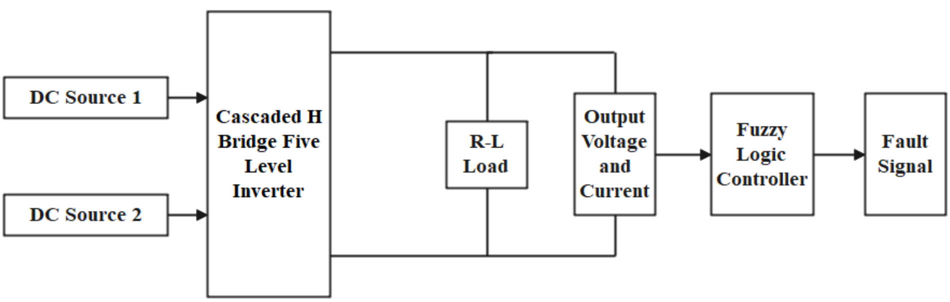


Fig. 6 – *The proposed system under consideration.*

4.1 The performance during faults of class I and Class II

The open circuit fault conditions in Class I and Class II are discussed in this section, as illustrated in **Table 2**. Class I refers to OCF involving two switches in the upper or lower parts of the lower H-bridge. In the same vein, class II refers to two switches in one leg which are open circuited in either the upper H Bridge or the lower H Bridge. The aim of this study is to evaluate the effectiveness of a fuzzy-based fault diagnosis and classification system. A summary of the results of the tests for class I and class II faults is provided in **Table 4**. Additionally, it describes the fault class as well as the faulty switches. Moreover, it also presents the estimated time required for detecting and classifying a fault based on the suggested strategy. In CHMLI when the OCF is incepted at 0.1 s, the FLC needs some time to identify the fault. Consequently, fault diagnosis time (t_d) refers to the time to recognize a fault, and fault classification time (t_c) refers to the time required to categorize the fault.

Table 4

A fuzzy logic approach to fault diagnosis and classification of Class I and II faults.

Class	Fault types	OC fault	t_d	t_c	Total cases	Fault condition	Output cases
I	Two Switch	S_{21}, S_{23}	4 ms	20 ms	2	Lower leg	1
		S_{24}, S_{22}					2
II	Two Switch	S_{11}, S_{14}	5 ms	19 ms	4	Same leg	3
		S_{13}, S_{12}					4
		S_{21}, S_{24}					5
		S_{22}, S_{23}					6

According to Fig. 7, the proposed scheme performs well when the $S_{24}S_{22}$ switches are open circuited. A waveform of the AC output voltage is shown in Fig. 7a, and a fundamental component of the AC output voltage is shown in Fig. 7b. As a result of this information, fuzzy-based fault diagnosis and classification method results are reported as a concluding example in Figs. 7c and 7d, respectively. A fuzzy-based detector will always produce zero output in the absence of faults. According to Fig. 7c, when a fault occurs in the CHMLI switch, the fuzzy-based detector output changes from 0 to 1. It took just four milliseconds to detect the fault. At 0.1 s after opening the two switches, the fuzzy-based classification output increases gradually, indicating an OCF, but the graph settles down to first class at 0.120 s. According to this study, it takes 20 ms for a fuzzy-based classification to classify faults.

Similarly, for class II, Fig. 8 shows how the suggested scheme performs in the OC condition of $S_{13}S_{12}$ switches. In this case, a fault is detected in 5 ms, and the fault is classified in 19 ms time.

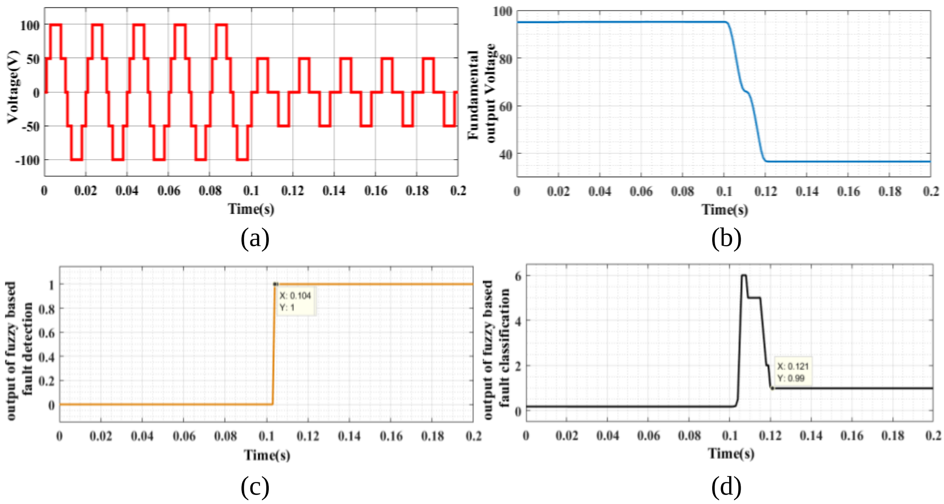


Fig. 7 – *Test findings of the class I fault:* (a) *Output voltage;* (b) *Fourier output voltage;* (c) *Fault diagnosis based on fuzzy logic;* (d) *Classification of faults based on fuzzy logic.*

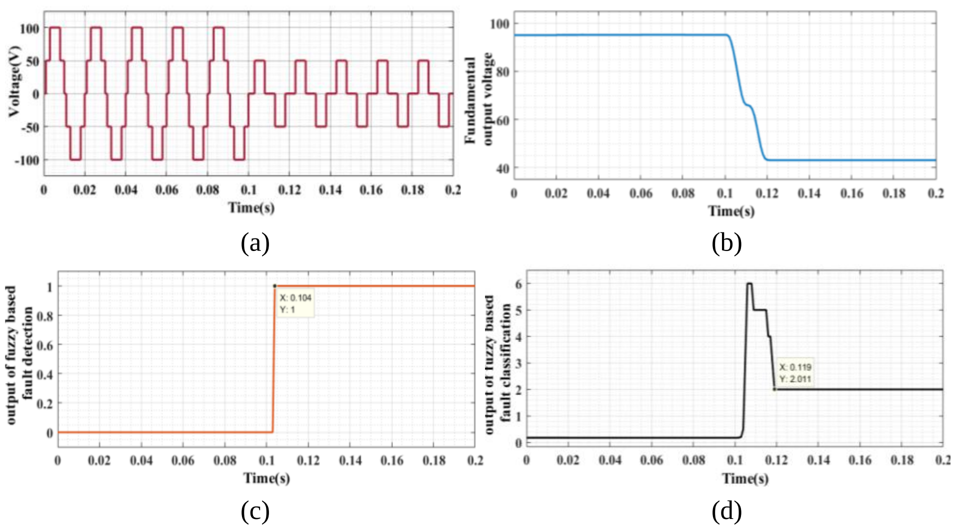


Fig. 8 – *Test findings of the class II fault:* (a) *Output voltage;* (b) *Fourier output voltage*; (c) *Fault diagnosis based on fuzzy logic*; (d) *Classification of faults based on fuzzy logic.*

4.2 The performance during faults of Class III

Class III faults can be classified into two types. The first type of open-switch fault involves two switches that are open-circuited in the diagonal leg of the H-bridge. In this case, four combinations are considered. The second type, wherein one switch from the upper H-bridge and the remaining one from the lower H-bridge are open circuited. In this case, 16 combinations are considered under such fault conditions. To assess the efficacy of fuzzy-based fault diagnosis and classification, a variety of combinations of class III faults were tested and **Table 5** shows the results. Among the information contained in the **Table 5** are the types of faulty switches and their diagnosis and classification times. CHMLI detected and classified the fault within 0.12 s.

Table 5
A fuzzy logic approach to fault diagnosis and classification of Class III faults.

Class	Fault types	OC fault	t_d	t_c	Total cases	Fault condition	Outputcases
III	Two Switch	S_{11}, S_{12}	4 ms	10 ms	4	Diagonal leg	1
		S_{13}, S_{14}					2
		S_{21}, S_{22}					3
		S_{23}, S_{24}					4
		S_{11}, S_{21}			16	One switch from upper bridge and second from lower bridge	5
		S_{11}, S_{22}					6
		S_{11}, S_{23}					7
		S_{11}, S_{24}					8
		S_{13}, S_{21}					9
		S_{13}, S_{22}					10
		S_{13}, S_{23}					11
		S_{13}, S_{24}					12
		S_{14}, S_{21}					13
		S_{14}, S_{22}					14
		S_{14}, S_{23}					15
		S_{14}, S_{24}					16
		S_{12}, S_{21}					17
		S_{12}, S_{22}					18
		S_{12}, S_{23}					19
		S_{12}, S_{24}					20

Fig. 9 illustrates the effectiveness of the suggested concept in the case of open circuit switches $S_{11}S_{12}$. In Fig. 9a, the output voltage waveform of the CHMLI is displayed. Fig. 9b illustrates the magnitude of fundamental component of the AC output voltage. The output of proposed fuzzy-based fault diagnosis and fault classification are presented in Figs. 9c and 9d respectively. In the absence of faults or normal operating conditions till 0.12 s, a fuzzy-based detector will always produce a zero output. The output of the fuzzy-based detector changes from 0 to 1 whenever a fault occurs in the CHMLI switch, as illustrated in Fig. 9c. As demonstrated by a fuzzy-based fault classification, Fig. 9d shows that, until

0.12 s, the CHMLI is considered healthy, but after initiating two switches OCF at 0.12 s, the output of FLC rises, indicating the presence of fault in CHMLI, and eventually fix to third class label at 0.130 s. In light of this, fuzzy-based fault classification is capable of identifying faults within a period of 10 ms.

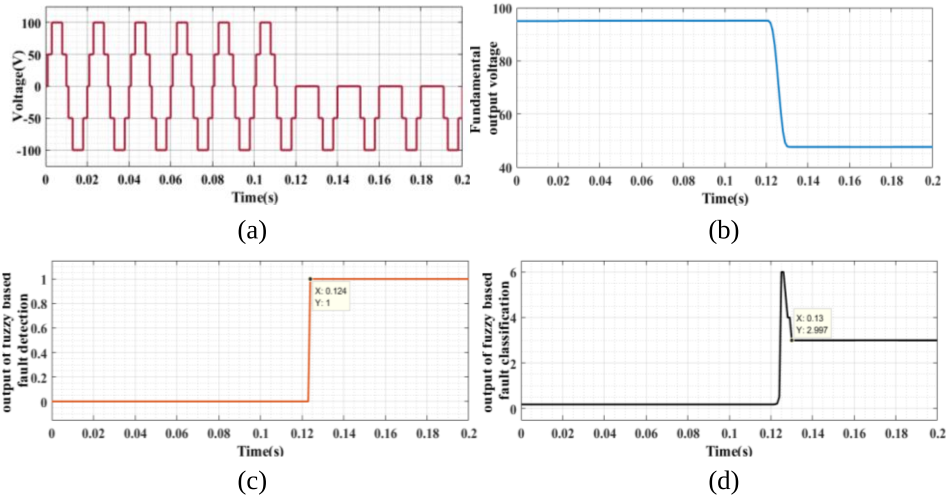


Fig. 8 – *Test findings of the class III fault:* (a) *Output AC voltage;* (b) *Fourier voltage magnitude;* (c) *Fault diagnosis based on fuzzy logic;* (d) *Classification of faults based on fuzzy logic*.

4.3 Performance during class IV, V and VI type fault

In this section, we examine Class IV, Class V, and Class VI Type open circuit fault conditions. Class IV open circuits occur when there is an open circuit between two switches in the upper or lower part of the upper H-bridge. In a similar fashion, Class V and Class VI refer to single switches that are open-circuited either on the upper H Bridge or on the lower H Bridge respectively. As described in **Table 6**, the proposed fuzzy-based fault detector and classification were evaluated against different combinations of Class IV, Class V, and Class VI fault types. In the CHMLI, all the OC fault classes IV, V and VI occurred at 0.15s. The proposed fuzzy-based scheme requires much less time to identify and classify faults within a particular class label, as shown in **Table 6**.

A demonstration of the implementation of the suggested scheme for switches $S_{11}S_{13}$ is presented in Fig. 10 wherein the AC output voltage waveform of the CHMLI can be found in Fig. 10a. As depicted in Fig. 10b the discrete Fourier voltage magnitude as an input to FLC. In Figs. 10c and 10d, fuzzy-based fault diagnosis and classification results are presented respectively. In order to recognize faults, the fuzzy-based system will require approximately one quarter of a complete cycle, whereas in order to classify faults, the fuzzy-based system will require a full cycle. Generally, fault classification takes longer than fault recognition (see **Table 6**). A graphic representation of this scheme can be seen in Fig. 10c, where the output of the fuzzy-based fault recognition system initially shows zero, but after the fault occurs, it settles into one. The fuzzy-based fault classification method, as shown in Fig. 10d, may take longer to settle down after a fault occurs since a complete cycle of discrete Fourier is required for the estimation of the fundamental component of voltage accurately which is used to classify faults using fuzzy data. Similarly, Figs. 11 and 12 demonstrate the appropriate recognition and classification of Class V and Class VI fault types.

Table 6

A fuzzy logic approach to fault diagnosis and classification in CHMLI.

Class	Fault types	OC fault	t_d	t_c	Total cases	Fault condition	Output cases
IV	Two Switch	S11, S13	5 ms	18 ms	2	Upper leg	1
		S14, S12					2
V	Simple Fault	S13	4 ms	9 ms	4	One switch	3
		S14					4
		S23					5
		S24					6
VI		S11	15ms	16ms	4		7
		S12					8
		S21					9
		S22					10

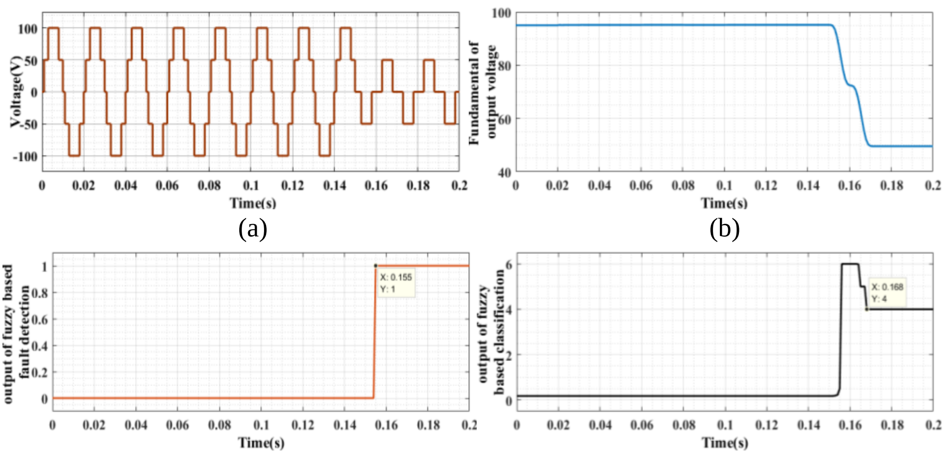


Fig. 10 – *Test findings of the class IV fault:* (a) *Output AC voltage;* (b) *Fourier voltage magnitude;* (c) *Fault diagnosis based on fuzzy logic;* (d) *Classification of faults based on fuzzy logic*.

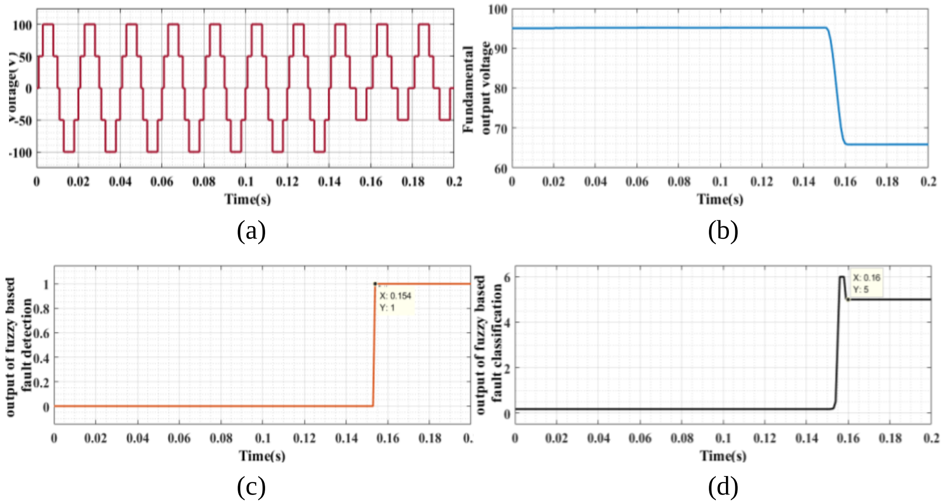


Fig. 11 – *Test findings of the class V fault:* (a) *Output voltage;* (b) *Fourier output voltage;* (c) *Fault diagnosis based on fuzzy logic;* (d) *Classification of faults based on fuzzy logic*.

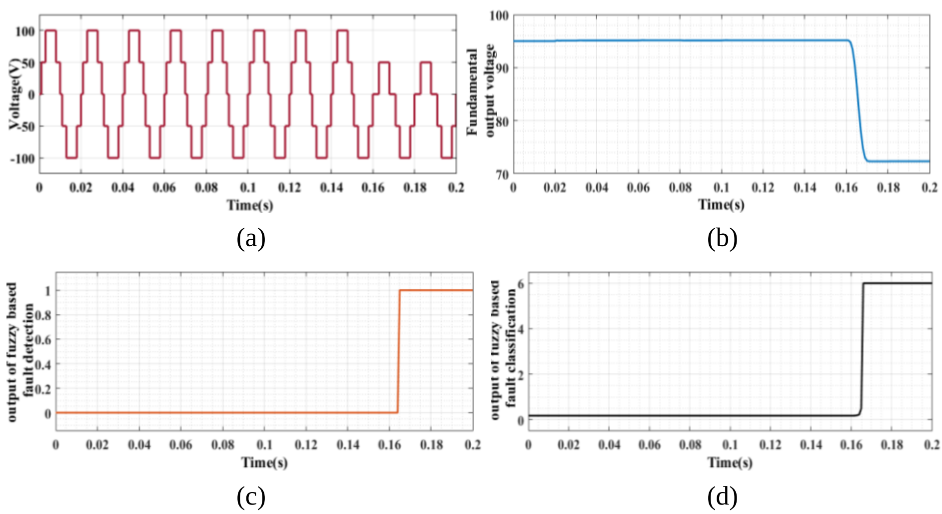


Fig. 12 – *Test findings of the class VI fault:* (a) *Output voltage;* (b) *Fourier output voltage;* (c) *Fault diagnosis based on fuzzy logic;* (d) *Classification of faults based on fuzzy logic*.

4.4 Experimental validation with OPAL-RT's real time-LAB simulator

As part of the experimental validation process, OPAL-RT's RT-LAB simulator was used to validate the proposed methodology in real time. A real-time simulation can be performed using the parallel computing capabilities of

OPAL-RT. Several multicore processors are built into the OPAL-RT so that a large number of parallel computations can be carried out simultaneously. To ensure that there is no time delay between real-time execution and the execution of any complex test system, each subsystem is assigned to a separate execution thread on multiple multicore processors at the same time. Fig. 13 shows an experimental test setup using host PC, OPAL-RT4510, DSO (GWINSTEK MDO-2204EX). It has been demonstrated that fuzzy-based systems can detect and classify faults that occur in different combinations of switches in CHBMLI. Three different types of faults representing Class I, IV and VI have been tested in real time using experimental test set.

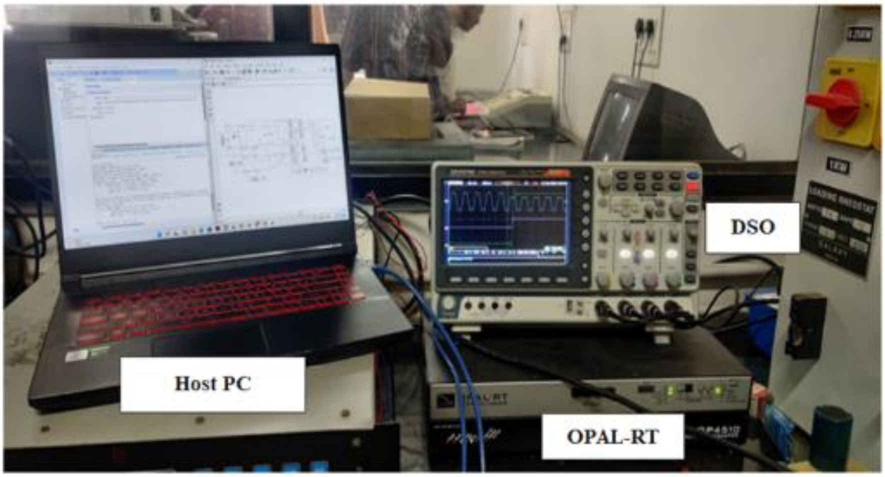
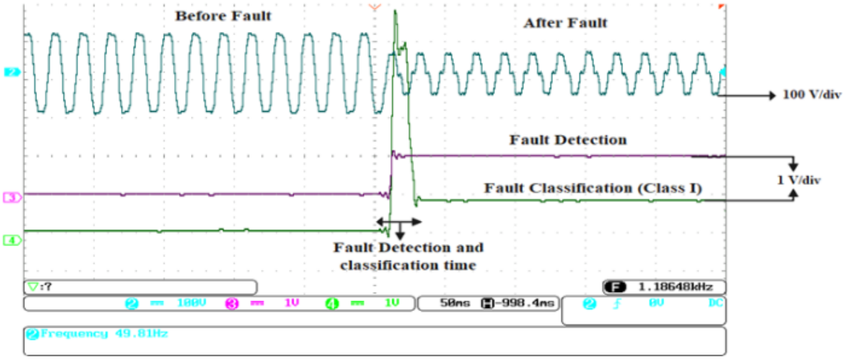


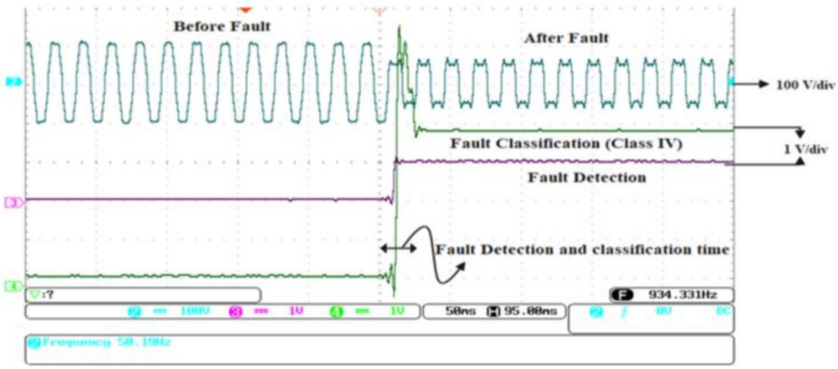
Fig. 13 – *Experimental test set up.*

The experimental results for these three cases for fault diagnosis output is shown in Figs. 14a – 14c using purple line graph. It can be observed that, before the initiation of fault in real time indicated by red arrow at the top of each figure, the output of fault diagnosis is low representing the reference point, and just after the inception of open circuited fault, the fault diagnosis output denoted using purple graph will rise and settle onto one (1) division in y axis. Thus, confirming the presence of fault in switches of CHMLI.

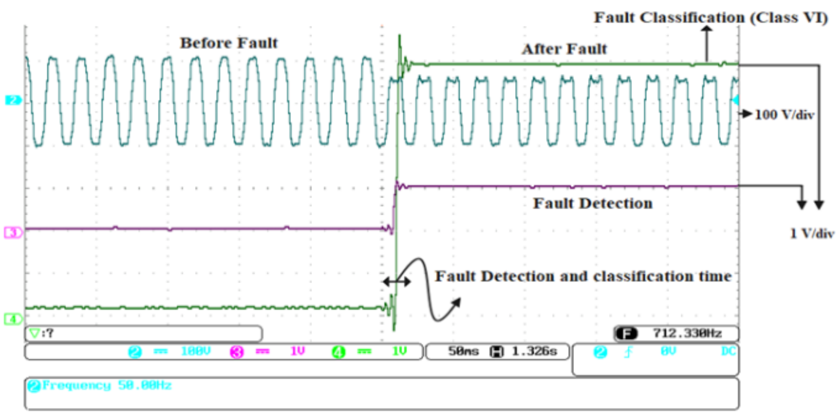
Furthermore, the next task is to classify the fault type according to fuzzy based fault classifier using predefined if-then rules considering the total 37 cases and categorizing them into total VI classes as per **Table 2**. when switches are open circuited, the fuzzy-based system requires some time to settle down to a particular class represented by total 6 divisions in y axis, as shown in Figs. 14a – 14c.



(a)



(b)



(c)

Fig. 14 – *Real-time simulation result when:* (a) *Switch $S_{24}S_{22}$ fault;*
(b) *Switch $S_{11}S_{13}$ fault;* (c) *Switch S_{11} fault.*

For example, when switches $S_{24}S_{22}$ are open circuited, the experimental results are shown in Fig. 14a, the green line graph depicts the output of fuzzy based fault classifier, herein the difference between the reference point and the settling point of the classifier output green line graph is 1 division in y axis, representing a class I type fault. The same applies to the class IV type of fault shown in Fig. 14b, which occurs when switch $S_{11}S_{13}$ is open circuited, and the difference between the reference point and the settling point of the classifier output green line graph is 4V consisting of 4 divisions in y axis representing class IV type of fault. Similarly, as shown in Fig. 14c if switch S_{11} is open circuited then classifier output green line graph settles to 6 divisions from the reference point, finally confirming the occurrence of class VI type fault. Thus, from the experimental test results, it is clearly evident the proposed fuzzy based fault identifier and classifier rapidly detects and classifies the fault type correctly. Thus, the proposed scheme is suitable for practical implementation in real time.

4.5 Impact of fault commencement time

In this segment, the performance of the suggested fuzzy-based concept has been tested for different OCFs occurring at different fault inception time and angles. The test results are tabulated in **Table 7**, from which it is concluded that the suggested system can identify and categorise the fault occurring at any instant of time interval as well as at any fault inception angle.

Table 7
Impact of fault commencement time.

Class	Fault type	Fault mode (OC)	Fault Inception Angle	Fault Inception Time	Fault Diagnosis Time	Fault Classification Time
I	Two Switch	$S_{24}S_{22}$	45^0	0.1025 s	2.5 ms	21.5 ms
II	Two Switch	$S_{13}S_{12}$	90^0	0.1050 s	2.0 ms	21.0 ms
III	Two Switch	$S_{11}S_{12}$	135^0	0.1075 s	15.5 ms	21.5 ms
IV	Two Switch	$S_{11}S_{13}$	180^0	0.1100 s	5.0 ms	18.0 ms
V	Single Switch	S_{24}	270^0	0.1150 s	2.0 ms	21.0 ms
VI	Single Switch	S_{11}	360^0	0.1200 s	5.0 ms	6.0 ms

4.6 Overall performance evaluation

Tests are conducted to evaluate the appropriateness of the fuzzy inference scheme suggested for different modes of switch faults created at different interval of time i.e. Class I at 0.1 s to 0.2 s, Class II 0.3 s to 0.4 s, Class III from 0.5 s to 0.6 s, Class IV form 0.7 s to 0.8 s, Class V from 0.85 s to 0.95 s and finally Class VI from 1.1 s to 1.2 s. As can be seen from **Tables 5**, **6** and **7**, there are 37 possible

OC fault combinations involving single and double devices in a 5-level CHMLI model. All possible faults have been classified into six categories depending on the discrete Fourier output voltage level. According to Fig. 15, in case of any switch or switches malfunctions, the fuzzy-logic system will diagnose the presence of OCF and categorize it to a particular class. As illustrated in Fig. 15, fuzzy-based fault classification has been tested by all six types of OC fault cases. and FLC produces different class labels corresponding to the input samples of a particular type of class of OCF. The output of fault classification rises to corresponding one to six labels depending on the time at which the specific type of fault is created in CHMLI as mentioned above. As can be seen from the figure, the fuzzy-based approach properly identifies all kinds of faults into the proper class labels, so assuring 100% accuracy.

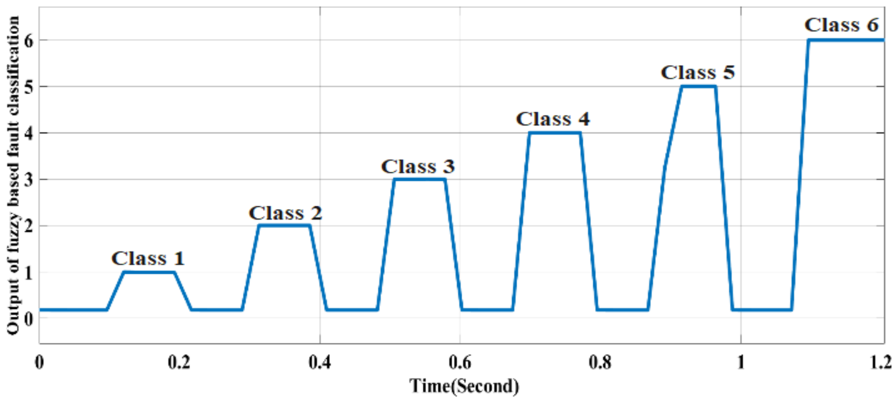


Fig. 15 – *Fault classification scheme based on fuzzy logic.*

The overall performance of fuzzy-based classification methods is calculated by analysis of the confusion matrix (CM) on test data. A confusion matrix for fuzzy-based classification is illustrated in Fig. 16. In order to determine which patterns of a particular class are classified accurately and which are misclassified, a confusion matrix can be computed. Toward the lowermost and rightmost of the CM plot, the last column and last row depicts the individual class accuracies, and the bottommost right corner element of CM visualizes the total accuracy and also inaccuracies recorded for classification of all the output classes. A green color describes the diagonal cells of the confusion matrix, and this color has been used by classification to identify the actual class. Accurate classification is achieved as the number of the events are classified in the diagonal elements of CM only and there are no elements classified in off-diagonal elements of the CM. This case study specifies a false positive rate of 0% at the bottom of the list. Therefore, fuzzy-based fault classification is capable of providing 100% accuracy in OC fault classification.

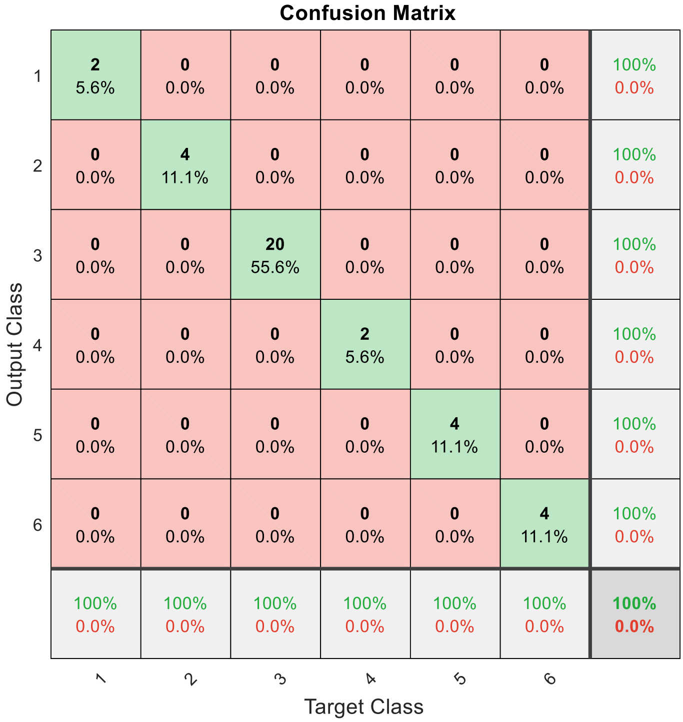


Fig. 16 – *Confusion matrix of the proposed FLC.*

4.7 Comparison and discussion

This section presents a relevant comparative analysis between the suggested methodology and other existing schemes for multilevel inverters. The comparative study between the suggested method and the currently existing system is presented in **Table 8**. The comparison is based on different performance parameters such as the methodology used, whether fault diagnosis/recognition and fault type classification has been carried out or not, and fault diagnosis time, fault classification time and accuracy of the suggested scheme. In [7 – 10], the proposed structure illustrates fault-tolerant capability. Still, there is no methodology to detect the presence of a fault or classify the fault, i.e., it cannot determine when a fault occurs. Open circuit fault diagnosis in CHB has been investigated using PCA- mRVM in [16]; here, fault diagnosis time is more than the proposed work. Furthermore, ANN [18], Sub-Band Wavelet Energy [20] and ML [19, 21] have been applied to detect the OC fault. However, the fault diagnosis time is higher, and the accuracy is less than the proposed work. Moreover, [21] has utilized SVM and kNN to classify OC faults, and the time taken for classification is higher than the proposed scheme and does not detect the fault. Recently SVM has been used for OC fault diagnosis in MLI by using the entropy of wavelet packet and mean of the current signal as input in [22], its accuracy is less than the proposed scheme, but the computation complexity is more as it requires computation of entropy of wavelet packet and mean of current. On the other hand, the proposed scheme simply uses recursive Discrete Fourier to calculate the fundamental voltage component for fault diagnosis using FIS. Furthermore, in the proposed scheme, we have used fuzzy logic controller as a fault detector and faulty switch classification for CHMLI, it is straight forward method based on if-then rules and does not require tedious training data generation and training process compared to another AI-based scheme. The proposed fuzzy-based fault recognition and classification in CHMLI exhibits superior performance over other existing techniques. Besides, the proposed FLC can easily detect and classify the faults with 100% accuracy. The fault recognition time is less than a quarter cycle, and the fault classification time is less than one cycle. Additionally, the proposed scheme has been experimentally validated using OPAL-RT, which confirms its practicability in real time.

Table 8
Comparisons with existing schemes.

References	Fault Type	Methodology	Fault Diagnosis Time	Fault Classification Time	Accuracy
Tianzhen Wang et al. [16]	OC	PCA- mRVM	47 ms to 56 ms	Not considered	100%
Hailin Hu et al. [18]	OC	Neural Network	Not considered	Classify faulty switches of NPC inverter	95.1%
Mahafzah et al. 19]	OC	NB	Not considered	30 ms	25%
		SVM		10 ms	75%
		ANN		10 ms	37.5%
		DT		20 ms	99%
Faisal A. Khan et al. [20]	OC	SVM	Only detect the faulty switch	Not considered	92%
		Decision Trees			88%
		Decision Tree + XG Boost			94.12%
Murad Ali et al. [21]	OC	SVM	Not considered	3.51ms to 11.84 ms	85% to 98%
		KNN		347 ms to 507 ms	
Kumari Sarita et al. [22]	OC	Entropy of wavelet packet and mean of current signal as input to SVM	0.33 ms to One-quarter cycle	Not considered	99.70%
L. M. Halabi et al. [23]	OC	Using current distortion method	50 ms to 100 ms	Not considered	Not considered
Pavan Mehta et al. [25]	OC	Using fuzzy logic controller	5 ms to 40 ms	Not considered	Not considered
Presented work	OC	Discrete Fourier and Fuzzy Logic Controller	2 ms to 5 ms	6ms to 21.5 ms	100%

5 Conclusion

The purpose of this paper is to propose a novel scheme based on fuzzy inference for the recognition and classification of open circuit faults. In this paper, multilevel inverter output voltage and current characteristics are examined in order to determine the malfunction of the power electronics component under an OCF environment. The CHMLI is considered at five levels with different OCFs. A discrete Fourier analysis is used to identify the fundamental components of voltage and current. Based on several switch fault scenarios, it has been found that the fuzzy-based approach is effective. In addition to being accurate, this method also has the advantages of being fast and reliable. According to numerous calculation examples, the OCF diagnosis method based on FIS is superior in terms of classification accuracy and rationality. Different fault circumstances have been considered to validate the performance of the proposed fuzzy-based approach, such as fault type, fault mode, fault inception time, and fault angle. From the test results, its is confirmed that fault recognition and classification can be accurately performed within a quarter of a cycle and within one cycle respectively. The real-time simulation using OPAL-RT4510 confirms the applicability of proposed scheme for practical scenario. Moreover, from the comparison with other schemes published in the literature, the proposed scheme proves to be superior.

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