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ANALYSIS OF OPEN SWITCH FAULT IN THREE - PHASE GRID - TIED MULTILEVEL INVERTER USING MACHINE - LEARNING ALGORITHM

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ABSTRACT

The goal of the project is to use machine learning algorithms to create a fault diagnosis method for three-phase grid-tied multilevel inverters in order to find open switch faults. Using features extracted from the inverter current signals, a machine-learning algorithm is trained to classify the faults according to the proposed fault diagnosis technique. The effectiveness of the suggested method is assessed using experiments and simulations with different fault scenarios. The findings demonstrate the efficacy of the suggested fault diagnosis technique in quickly and accurately identifying open switch faults in multilevel inverters. According to the study's findings, the suggested method may be a trustworthy and effective way to identify faults in multilevel inverters.

Furthermore, real-time monitoring and fault diagnosis are made possible by the integration of the machine learning technique with control systems, allowing for the prompt correction of faults and prevention of system damage or shutdown. The study also emphasises how machine learning algorithms can be used to diagnose faults in power electronics systems, which can lower maintenance costs and downtime while enhancing system performance and reliability. By presenting a novel fault diagnosis technique for open switch faults in three-phase grid-tied multilevel inverters using machine learning algorithms, the research study advances the field of fault diagnosis in power electronics. The suggested method is a flexible and practical tool for fault diagnosis and maintenance since it can be expanded to other kinds of faults and power electronics systems. As a result, the study makes a significant contribution to the field of power electronics fault diagnosis and shows how machine learning algorithms can be used to increase the performance and reliability of power electronics systems.

Keywords: Grid, Inverters, MFCCs, KNN, Machine Learning.

I. INTRODUCTION

An electronic device that changes direct current (DC) into alternating current (AC) is called an inverter. To put it another way, it transforms the energy from a battery or other DC power source into a form of electrical energy that can be used to power electronics and other household appliances that need AC power.

In order to convert the DC power produced by solar panels into AC power that can be used to power homes or businesses, inverters are frequently used in off-grid solar power systems. In order to operate appliances and other devices while driving, they are also utilized in cars to convert DC power from the battery into AC power. Inverters come in different sizes and power capacities, ranging from small inverters used to power individual devices to larger inverters used to power entire homes or commercial buildings. They can also have additional features such as surge protection, battery charging capabilities, and automatic shutdown in case of power surges or other issues.

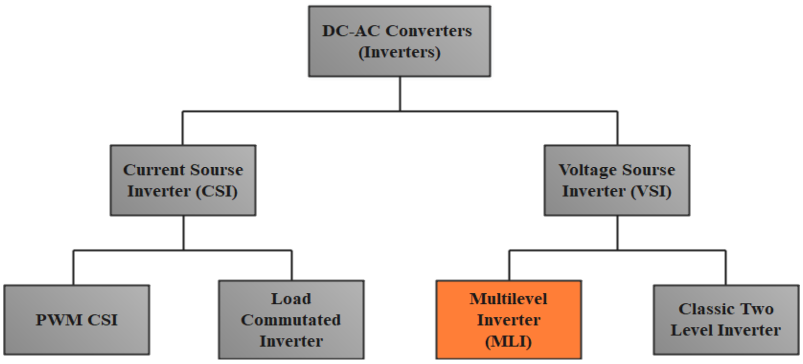

Figure 1: Classification of Inverter

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1.1 Multilevel Inverter

A multilevel inverter is a power electronic device used to convert DC (direct current) power into AC (alternating current) power of higher voltage and/or frequency than the input. It achieves this by synthesizing the output waveform from multiple levels of DC voltages, typically generated using capacitors or DC sources.

Unlike traditional two-level inverters, which use only two voltage levels to generate a stepped output waveform, multilevel inverters use three or more voltage levels to create a more sinusoidal waveform with less harmonic distortion. This can improve the performance and efficiency of AC motors, reduce stress on power system components, and enable the use of renewable energy sources like solar or wind power.

Multilevel inverters (MLIs) can be categorized based on the number of voltage levels, such as three-level, five-level, seven-level, etc. The complexity of the circuit and the number of switching devices required depend on the number of voltage levels. Therefore, the selection of a particular MLI topology depends on the application requirements, including voltage and power rating, switching frequency, and cost [1].

As a result of their ability to meet certain power ratings and electric power quality criteria, MLIs are increasingly being incorporated into systems with low levels of electronic radiation and harmonic distortion. Due to the constant switching frequency, MLIs offer several distinct advantages over traditional two-level inverters that use pulse with modulation (PWM) [2]. Due to these characteristics, MLIs are being investigated as potential commercial solutions for dynamic applications requiring high performance and high power. These applications can range from one megawatt up to thirty megawatts [3].

With their higher voltages and lower total harmonic distortion (THD) output voltage waveforms, MLIs are ideal for high-voltage applications [4]. As well as interacting in a variety of ways with sustainable energy sources, multilayer converter systems can also interact with biofuels, fuel cells, and photovoltaic cells [5]. In general, the control algorithm determines the applications, efficiency ratings, and MLI operation [6].

There have been a number of MLI topologies proposed over the last few decades [7, 8]. The number of DC sources in the topology of MLIs can be divided into two major categories. The fly capacitor, neutral-point clamped (NPC), and cascaded H-bridge topologies are the most widely implemented and utilized topologies in the commercial sector at present [9].

1.2 Types of Multilevel Inverter:

The choice of multilevel inverter topology depends on various factors, including the desired output waveform quality, the cost, the efficiency, and the reliability requirements of the application. There are several types of multilevel inverters, including:

1.2.1. Diode-clamped multilevel inverter:

Also known as, a "neutral-point-clamped" inverter (NPC), this topology uses capacitors or diodes to clamp the voltage at a neutral point, which is typically the midpoint of the DC voltage source. This creates multiple voltage levels between the DC source and the AC output, which can be used to generate a sinusoidal waveform.

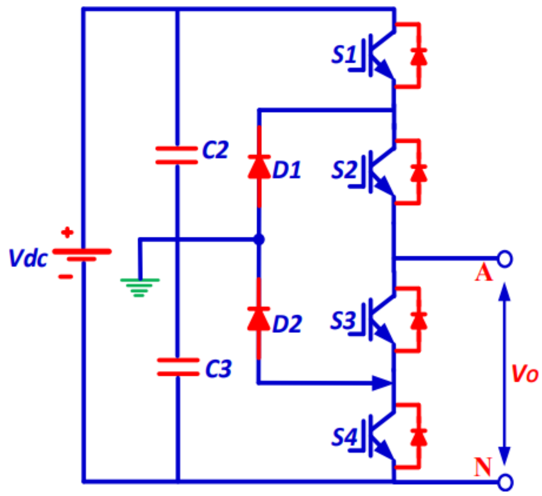

Figure 2: Three-level diode-clamped MLI topology

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1.2.2. Flying capacitor multilevel inverter (FCMLI):

This multilevel inverter topology utilizes multiple capacitors to produce the necessary voltage levels. The capacitors are charged and discharged in a sequence to generate the output waveform, which enables the management of both real and reactive power. However, constructing this architecture from scratch is expensive and challenging due to the significant number of capacitors required. Furthermore, these designs suffer from significant switching frequency losses when transferring actual power.

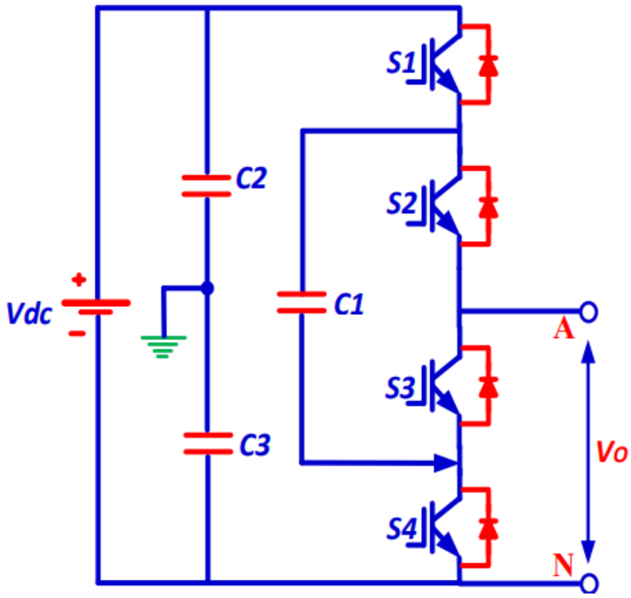

Figure 3: Three-level FCMLI topology

1.2.3. Cascaded H-bridge multilevel inverter (CHB):

This type of inverter uses a series of H-bridge circuits, each consisting of four switching devices (usually power transistors or IGBTs) connected in a bridge configuration. The H-bridges are connected in series to create the required voltage levels.

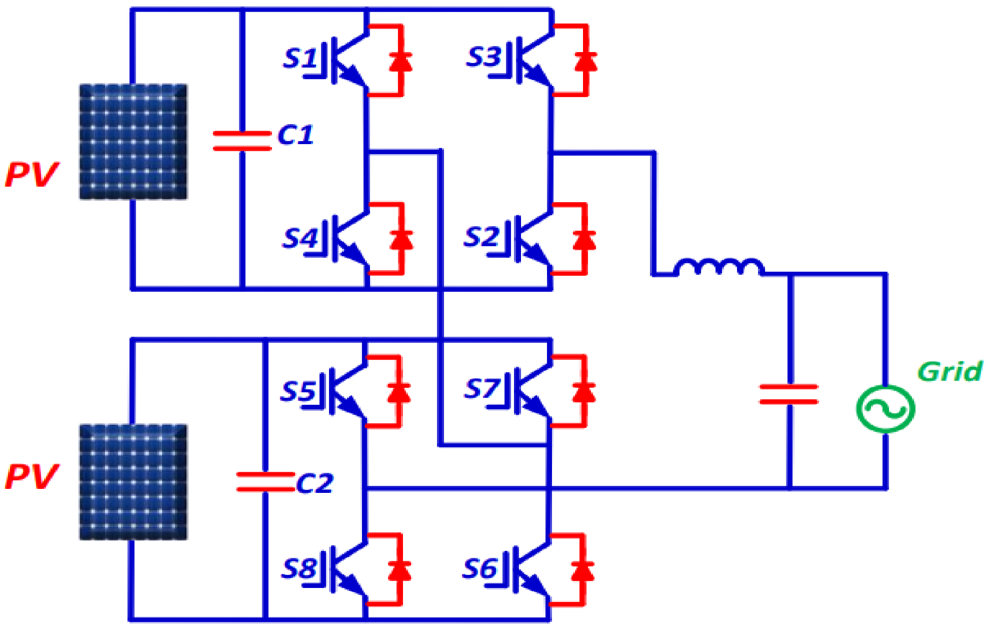

Figure 4: Cascaded inverter

1.3. What MLIs have to offer and what they don't

There are several common inverters around the world, so Table 1.1 shows the advantages and disadvantages of each.

Table 1.1 Different types of MLIs and their advantages and disadvantages

Topology	Advantages	Disadvantages
NPC	- Neutral clamping switches can be used to solve the problem of unbalanced voltage balancing and loss sharing - Reduction of DC source requirements. - Capacitor pre-charging can be performed collectively	- The complexity of the voltage-balancing circuit - Clamping diodes become more needed as the level rises - The losses are unevenly distributed between the inner and outer switches
FLC	- Can be used with fewer DC sources - Power flow can be controlled both in real and reactive modes - Phase redundancy can be used to balance the voltage levels of capacitors	- Complicated voltage balancing circuits - Capacitors become more necessary as the level rises - Losses and switching frequencies will be a problem in real power transmissions
CHB	- Modular design allows for easy expansion to higher levels - Electric shock is less likely to occur since there are separate DC sources - Asymmetric source configurations are possible	- More DC sources are needed for higher output voltages - The input voltage must be matched by the blocking voltage on the switch. - Increased amount of gate driver circuits required

1.4 Application of Multilevel inverter:

Multilevel inverters are used in a variety of applications, including:

1.4.1 Motor drives:

Multilevel inverters used to drive AC motors, including high-power motors used in industrial applications. The improved waveform quality and reduced harmonic distortion can result in smoother motor operation and improved efficiency.

1.4.2 Renewable energy systems:

Multilevel inverters used in solar and wind power systems to convert DC power generated by the panels or turbines into AC power suitable for the grid. The high voltage capability of multilevel inverters can enable the use of higher voltage solar panels or wind turbines, resulting in reduced system cost and improved efficiency.

1.4.3 Grid-tied inverters:

Multilevel inverters used in grid-tied solar or wind power systems to inject power into the grid. The improved waveform quality and low harmonic distortion can reduce the impact of the system on the grid and improve power quality.

1.4.4 High-power electronics:

Multilevel inverters used in high-power electronics applications, such as variable speed drives, uninterruptible power supplies (UPS), and electric vehicle charging systems. The improved waveform quality and reduced harmonic distortion can improve the reliability and efficiency of these systems.

1.4.5 Power transmission:

Multilevel inverters used in high-voltage direct current (HVDC) transmission systems to convert AC power to DC power for transmission over long distances. The high voltage capability and improved waveform quality can reduce the transmission losses and improve the efficiency of the system.

II. LITERATURE SURVEY

With the integration of wind and solar power into the power grid, MLIs have emerged as an essential component for converting and interfacing between various electrical power equipment. The primary purpose of MLIs in this context is to act as DC-AC inverters and DC-DC converters. The initial application of MLIs dates back to 1975, starting with three-level converters and evolving into various topologies over the years [10]. It is possible to send sinusoidal waveforms to the grid as opposed to waveforms with fewer harmonics in grid-tied systems, ensuring compatibility between the grid and the implanted signals. It is generally acceptable to use MLIs with an LC filter in order to generate sinusoidal three-phase currents and voltages with fewer harmonics [11].

Several drawbacks limit the utility of conventional three-level inverters, which were originally developed to connect renewable energy sources to power grids. The first disadvantage is that they require devices with high power ratings, which increases the cost of the inverter and the switching losses. The second disadvantage is that conventional inverters produce a multi-stepped waveform output, which results in a waveform of poor quality with significant harmonics. The MLI has been introduced in the industry as a means to overcome these limitations [12]. MLIs can improve harmonics, provide operational efficiency, reduce strain on MLIs under load, and reduce electromagnetic interference (EMI) over conventional inverters [13]. Different renewable energy sources can be used to provide DC input voltage to MLIs, including solar arrays with DC-DC converters, inductive synchronous/generators, generator-fed windmills, rectifying designs, and fuel cells with DC-DC converters.

2.1 The following factors should be considered when considering the reliability of MLIs:

An effective system is defined as one that has a high probability of achieving its desired lifetime goal. For a converter to be reliable, it must be able to withstand and tolerate any fault that may arise. In order to ensure durable power electronics applications, it has always been a primary goal of research in power electronics to improve the reliability of power electronics systems in an efficient and cost-effective manner. Therefore, the power electronics industry and research must explore highly reliable power electronics in greater depth. It has been a significant barrier to the widespread deployment of grid-connected power electronics for many years due to the lifetime and reliability of silicon power electronics. A significant challenge was compounded by the necessity of aggressively cooling silicon power electronics, which results in higher system costs as well as a reduction in reliability due to redundant cooling systems. With the advent of wide bandgap power electronics, particularly silicon carbide, electric power grid applications have the opportunity to overcome these challenges. An analysis, a design, and a solution can all be regarded as reliability studies in power electronics [14]. Analyzing the causes of power electronics failures is of primary importance, whereas designing a reliable power electronics system is of secondary importance. It is an integral part of solution-oriented studies to develop techniques and control methods that are capable of producing a reliable power electronics system that is robust enough to withstand any problems.

For a deeper understanding of the reliability issues associated with power electronics, several questions need to be addressed. Identifying the most critical components that are susceptible to failure in power electronics and that negatively, impact the reliability of the system is essential. Are power semiconductors the only components that should be considered, or are there other components that should also be considered? It is also interesting to know whether reliability concerns are the same for all power electronics applications and topologies. In addition, as a final question, are there any limitations to the reliable solutions currently available?

It is possible for the entire power electronics system to fail when any one component fails. In addition to semiconductor devices, capacitors, inductors, solder tracks, and PCB boards, there are several other components that should be taken into consideration. Various methods and available standards may be used to calculate a component's failure rate, including element losses, junction temperatures, and other factors.

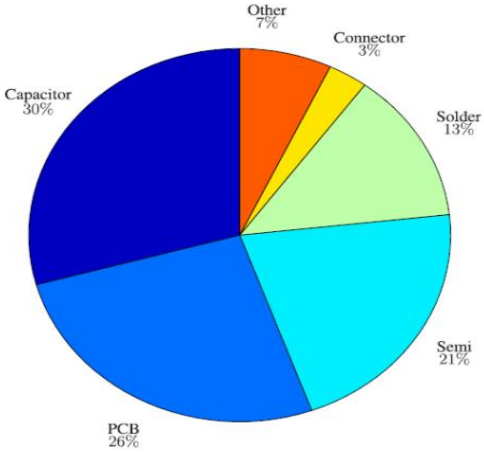

Figure 5: Power converter fault distributions

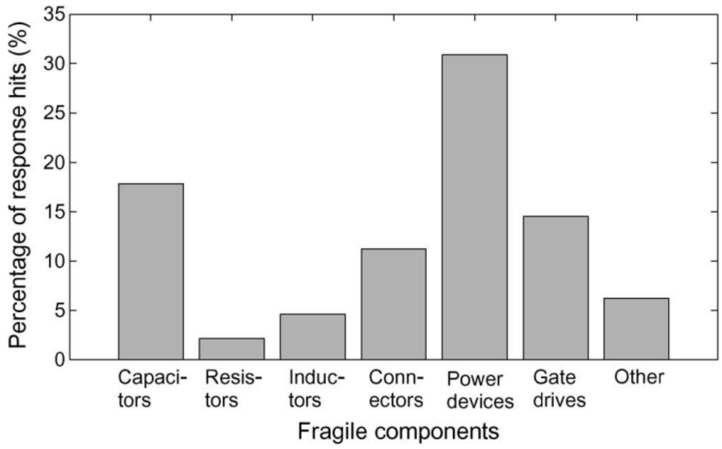

Figure 6: A description of the distribution of fragile components [17].

According to [15] and [16], Power converter failures are due to semiconductor faults in approximately 21% of cases, as shown in Figure 2.1. In comparison, 39% of system failures are due to soldering and PCB faults in about 39% of cases. Among more than 60 companies that participated in a survey conducted by [17], it was found that semiconductor power devices accounted for 31% of all power electronic system failures, which was the highest hazard rate among power electronic components. A survey conducted by the same company also revealed that faults caused 15% of power converter failures in gate drivers.

For this reason, it is important to conduct reliability assessments of power electronics converters in order to ensure their safe operation. Inverters and converters are crucial components in ensuring the performance and reliability of a power system. A variety of power electronics-based Flexible AC Transmission System (FACTS) devices employing power electronic switches can improve power quality [18] as well as enhance power using optimization techniques. In spite of this, the quality of power is affected when renewable energy (RE) is incorporated into the power grid because of variable outputs and converter interfacings [19]. Power quality is reduced when converter switches are faulty [20], resulting in distorted output current waveforms. Because of these distorted waveforms, heating losses may occur in the converters, or the system may change response [21]. In order to avoid distorted waveforms, converter switches must be operated appropriately. It is important to ensure that overcurrent (OC) faults are detected and isolated as quickly as possible in order to ensure that the switches are operated at their best in the shortest amount of time. It was discussed in [22] that a multilevel converter could provide fault-tolerant operation and improved performance by using the converter's structure.

2.2 Fault Diagnostic Survey using machine-learning algorithm:

The power electronics industry has undergone rapid development in recent years, resulting in various fault diagnosis methods for CHMLI. However, some of these methods have limitations, such as slow network convergence, large calculations, or low classification performance. For example, a Bayesian network was used for transformer fault diagnosis in [23], but it had low classification performance for large data samples. A hidden Markov model was employed in [24] for real-time fault diagnosis analysis of multi-level inverters, but it suffered from slow network convergence for large data samples. The Fast Fourier transform (FFT) principle-based CRBPNN was used in [25] for open switch fault diagnosis of CHMLI, but it was slower due to complex matrix operations. In [26], an ANN-based fault diagnosis method was proposed for asymmetric CHMLI, but it was not applicable to symmetric CHMLI.

In order to overcome these limitations, researchers in [27] developed a fast and robust method for diagnosing open circuit faults in voltage source inverters using two-line voltages as the diagnosis variable, which reduced the influence caused by failure rates of information sources. As of yet, CHMLI has not incorporated this method into its open circuit fault detection process. According to [28], an inverter with three levels of power was diagnosed using a back propagation neural network and a genetic algorithm. Using a single-phase line voltage signal, [29] combined extension theory with chaos theory to diagnose faults in a 3-level T-type inverter. Several new structures for multilevel inverters were proposed in [30] in order to supplement open circuit faults.

SVMs and k-NNs are common machine-learning algorithms in the power industry. As an example, in [31], a comprehensive review of machine learning algorithms was presented for the purposes of analyzing energy efficiency in the power industry. In addition to energy regulatory systems and urban environmental planning, SVM and k-NN models have been used in a variety of applications [32,33]. The SVM algorithm was employed in [34] for detecting and diagnosing faults in machines, and the k-NN algorithm was employed in [35, 36] for detecting and diagnosing faults in high-voltage direct current systems. The author is unaware of any literature that explores the application of SVM and k-NN for the detection of faults and the diagnosis of open switch faults in CHMLI. However, to the best of the author's knowledge.

The fault diagnosis of multilevel inverters has been achieved using a variety of machine-learning algorithms in addition to SVM and k-NN. A single sub module of a modular multilevel converter (MMC) was used to diagnose open-circuit faults using an ANN-based classification algorithm [37]. In contrast, sliding mode observers were proposed for fault detection and localization in a triple star bridge cell and parallel multicell converter [38] and [39]. Additionally, a single sub-module of MMC can be operated with a state observer, as described in [40, 41]. Despite their high capabilities, sliding-mode observer-based fault diagnosis technologies require a heavy computational load, which is a significant disadvantage. Conversely, PPCA, which can be used to optimize and process data without altering the original properties and characteristics of the input data, has been demonstrated to be more effective in diagnosing open switch faults in CHMLIs employed in distributed generator units as compared to SVM and k-NN in [42]. Furthermore, the SVM technique has been discussed in [43] for fault detection. It has been demonstrated that it can detect faults more quickly and does not require information about a complete current cycle compared to other fault detection methods.

As part of the fault diagnosis process, machine-learning algorithms perform the following steps: modelling, preprocessing, feature extraction, and feature analysis. The first stage of the process is to develop knowledge, which can be achieved through the use of equations based on physics, models based on a language, or data-driven models. In the second step, input data is preprocessed, including filters to reduce nuisances, frequency domain conversions, or other reference frame transformations. In the third step, features are extracted, which employs a variety of techniques ranging from signal processing to information processing to control theory in order to determine if there are any fault signatures present. A final step of the process involves analyzing the features to determine whether a fault has occurred, classifying the types of faults, isolating the faults, and estimating their severity.

Different techniques have been used for feature extraction, and fast feature extraction techniques have been discussed in [44]. Wavelet packet decomposition (WPD), wavelet packet entropy, such as Shannon and log wavelet entropy, are used in this technique, which has not been implemented in previous literature for fault detection and classification of converter switches.

Fault detection is critical to maintaining the reliability and efficiency of a multilevel inverter system. However, traditional fault detection methods can be time-consuming and require a lot of expertise, making it challenging to implement in real-time systems. Machine learning techniques have emerged as a promising alternative due to their ability to process large amounts of data quickly and accurately.

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In conclusion, the use of machine learning techniques for fault detection in multilevel inverters shows great promise. With the increasing availability of data and computational power, machine-learning algorithms can provide accurate and timely fault detection, improving the reliability and efficiency of the system. However, extensive training and validation of machine-learning models are required to ensure their accuracy and reliability. Further research is needed to optimize and validate these techniques for practical application in real-world systems.

III. PROBLEM IDENTIFICATION

Multilevel inverters are complex systems with a large number of switches that can experience various faults. Switch faults are among the most common types of faults that can occur in multilevel inverters, which can result in a significant reduction in system performance or even complete failure. The following are some of the problems that can arise due to switch faults in multilevel inverters:

3.1 Overvoltage and under voltage: Switch faults can cause overvoltage or under voltage conditions in the system, which can damage the system components or lead to system failure.

3.2 Harmonic distortion: Switch faults can also cause harmonic distortion in the output waveform, which can affect the performance of the system and cause damage to connected loads.

3.3 Increased switching losses: Switch faults can result in increased switching losses, which can cause the system to overheat and reduce the overall efficiency of the system.

3.4 Unbalanced voltage levels: Switch faults can cause unbalanced voltage levels in the system, which can lead to system instability and reduce the system's ability to regulate voltage.

3.5 Increased stress on other switches: Switch faults can also increase stress on other switches in the system, leading to additional faults and reducing the overall reliability of the system.

Therefore, switch faults in multilevel inverters can lead to various problems that can affect system performance, stability, and reliability. Therefore, effective fault detection and mitigation strategies are necessary to ensure the smooth and reliable operation of multilevel inverter systems.

IV. METHODOLOGY AND RESULT ANALYSIS

The process of designing a Machine Learning (ML)-based fault classifier involves several steps as illustrated in Figure 4.1. The first step is to collect a dataset that contains information about various fault conditions that may occur in the inverter. To obtain this dataset, the inverter is subjected to different faults, and the output voltages are measured and recorded. From the acquired output voltage signal, relevant features are extracted and a dataset is prepared that includes the corresponding fault class.

Next, the ML-classifier is trained using the training dataset, and a separate dataset is used to test the trained classifier. The performance of the classifier is evaluated using standard performance metrics, and if satisfactory, the classifier can be deployed for practical use. The selection of appropriate features and classifier is crucial in designing an effective fault classifier, and this has been investigated in this study.

By following these steps, a reliable ML-based fault classifier can be designed, which can accurately identify the faulty phase and classify faulty switches in the inverter system. This enables timely maintenance and repair, improving the reliability and efficiency of the system. It is important to note that extensive training and testing of the classifier is necessary to ensure its accuracy and reliability. With proper design and implementation, ML-based fault classifiers have the potential to significantly improve fault detection in complex systems.

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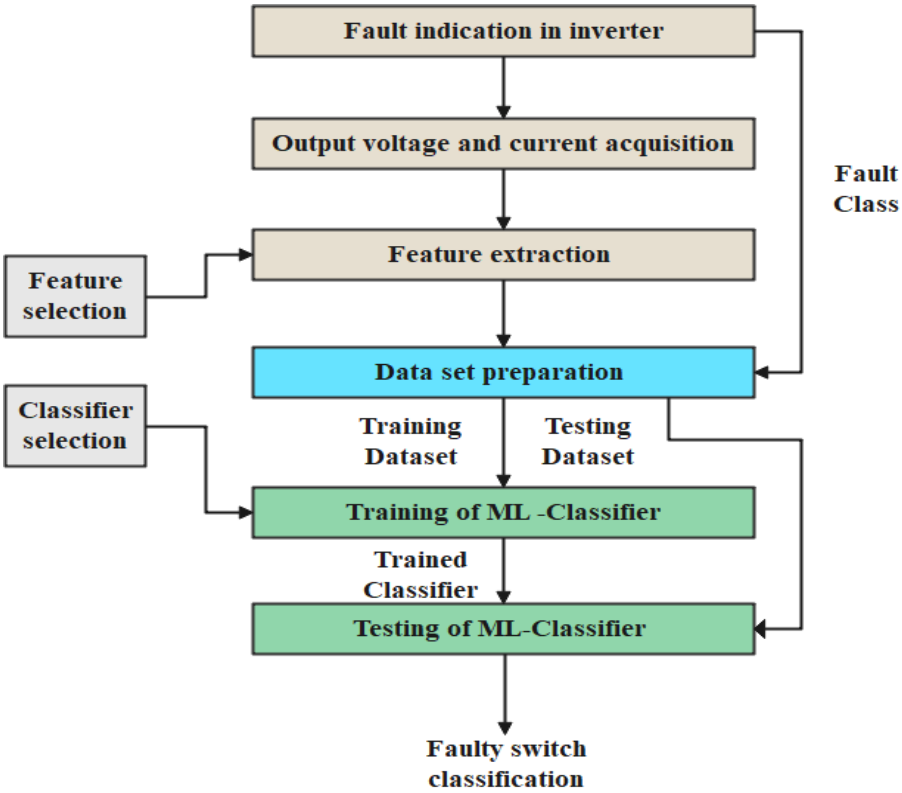

Figure 7: Modeling and classification of faults based on machine learning

4.1. Dataset Preparation

In the proposed fault diagnosis technique, the output voltage and current waveform are considered as significant parameters for diagnosing faults in the inverter system. However, it should be noted that the output current may vary with the load conditions. Therefore, to diagnose faults, faults are intentionally induced in the inverter switches, and the resulting output voltage and current waveforms are recorded. Whenever a fault occurs, the voltage and current waveforms exhibit distinct changes or distortions, which contain information about the fault. These changes in the waveform can be extracted using various signal processing techniques. The output of current or voltage waveforms demonstrates a unique pattern for each switch fault condition, which can be used to identify the fault phase and classify the faulty switch accurately.

4.2. Fault Class Description:

Here is an explanation of the different types of faults examined in the study. Inverter malfunctions are primarily caused by the failure of power semiconductor devices. The current and voltage waveforms of an inverter exhibit abnormal distortions when an open circuit (OC) occurs in its power electronic switches. In this study, the output current and voltage of inverters are tested in relation to switching states. When an O.C. fault occurs in any switch, it causes distortion in the inverter output voltage and current. This distortion depends on the faulty switch's location. The positive or negative cycle of the inverter output current turn out to be distorted when an external switch experiences an O.C. fault. However, when an internal switch experiences an O.C. fault, the positive or negative cycle of the inverter output current suits suppressed. Using the information obtained from the study, the study determines the location of the faulty switch and the position of the three-phase inverter leg by comparing the positive and negative charges that pass through each phase.

4.3. Feature Extraction:

The process of ML-based classification can be divided into two key steps: feature extraction and classification. Feature extraction involves obtaining the necessary features for classification from the measurement signal. Features serve as an abstraction of the measurement signal and provide valuable information for accurate classification. It is often desirable to have a unique combination of features for each class to ensure precise classification. Therefore, the selection of appropriate features is crucial for the effectiveness of the ML-based fault classifier.

Techniques used several feature extraction in machine learning for classification problems. Some of them are:

1. Principal Component Analysis (PCA)
2. Linear Discriminant Analysis (LDA)
3. Independent Component Analysis (ICA)
4. Discrete Wavelet Transform (DWT)
5. Fast Fourier Transform (FFT)
6. Mel Frequency Cepstral Coefficients (MFCC)
7. Local Binary Patterns (LBP)
8. Histogram of Oriented Gradients (HOG)
9. Scale-Invariant Feature Transform (SIFT)
10. Speeded-Up Robust Features (SURF)
11. Gabor Filter
12. Haar Wavelet Transform
13. Gray Level Co-occurrence Matrix (GLCM)
14. Convolutional Neural Networks (CNN)
15. Recurrent Neural Networks (RNN)
16. Auto encoders

These feature extraction processes can be used to extract relevant and informative features from raw data and improve the performance of classification models. For example, in image classification tasks, techniques such as CNNs and HOG are commonly used to extract features from images. In speech recognition tasks, MFCCs are commonly used to extract features from speech signals. The choice of feature extraction technique hang on on the nature of the data and the specific difficult at hand.

4.4. Data preprocessing

Data preprocessing is a critical step in creating a machine learning model as it involves preparing the raw data and making it suitable for analysis. Often, the data we encounter while creating a machine-learning project is unstructured and unformatted, making it difficult to work with. Therefore, it is necessary to clean and format the data to ensure its quality and reliability. In this study, we perform feature scaling to normalize the data into specific values. There are four ways to scale the data, including:

1. Min max scaling
2. Maximum absolute scaling
3. Robust scaling
4. Standard scaling

4.5. ML Based Classifier

There are various machine learning-based classifiers used in different applications. Some of the commonly used classifiers are:

1. Logistic Regression
2. Decision Trees
3. Random Forest
4. Support Vector Machines (SVM)
5. K-Nearest Neighbors (KNN)
6. Naive Bayes
7. Artificial Neural Networks (ANN)
8. Convolutional Neural Networks (CNN)
9. Recurrent Neural Networks (RNN)
10. Long Short-Term Memory (LSTM) Networks
11. Gradient Boosting Machines (GBM)
12. AdaBoost
13. XGBoost
14. CatBoost

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15. LightGBM

These classifiers can be used in various applications such as image classification, natural language processing, sentiment analysis, fraud detection, and many others. The choice of classifier depends on the specific problem and the nature of the data.

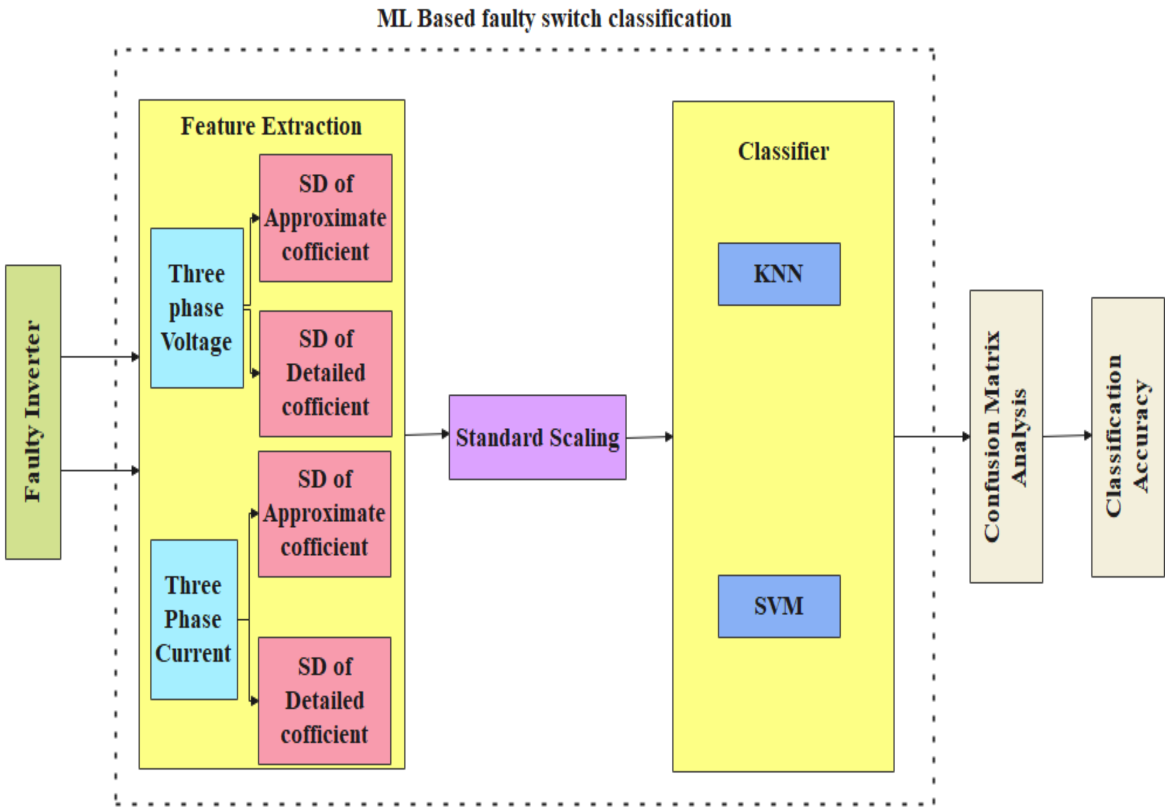

Figure 8: Proposed combined classifier

Table 1: Comparison of various fault-tolerant control methods based on switch fault

Faults considered	**Refer -ence**	**Description of the method**				**Comments**
		Topology discussed	**Switching technique**	**Parameters analysed**	**FTC methods**	
Single switch fault	[25]	NPC	PD-PWM	Energy sharing analysis	Inclusion of bidirectional switches	The addition of series transformer makes system complexity
	[29]	Modified MLI	LSF	THD analysis, switching loss calculation	Using Bidirectional switches	Not easily extendable
	[35]	CMLI	Multicarrier sinusoidal PWM	Reliability analysis	Redundant switching methods	Failed to preserve post fault output voltage level
	[36]	Generalized MLI	Level shifted-SPWM	Reliability analysis using Markov's model	Redundant switching methods	Unidirectional and bidirectional switches are required to make complex circuitry.
Both OC &	[37]	CHB MLI	Variable frequency	THD analysis	Based on CHB MLI	Output voltage magnitude was lowered

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SC fault			inverted sine carrier PWM		structure	due to an inner switch fault
	[38]	FC	PS-PWM	Capacitor voltage balancing	Algorithmic based controller	Hardware-based solution. Not suitable for higher levels
	[40]	CHB	Multicarrier PWM	THD and switching loss analysis	Rotating phase shift	Performance comparison between PS PWM & LS PWM techniques
	[43]	NPC	Multicarrier PWM	Capacitor voltage balancing	Using bidirectional switches	A partial solution to the fault
	[442]	FC	LS PWM	Post fault capacitor voltage balancing	Resonant leg and bidirectional switches	The use of bidirectional switches results in increased losses
	[41]	CHB	LS PWM	Power distribution among CHB module.	Neutral shift and rotational switching mechanism	Eliminate the use of redundant inverter for single switch fault.
	[44]	CHB	Space vector modulation	THD analysis	Auxiliary module	Finding the nearest vector is hard when there are several switch faults
	[15]	FC	LS PWM	Reliability analysis	Redundant leg	Causes unbalanced output voltage
Multiple switch fault	[27]	NPC	Carrier PWM	Power loss	Redundant leg with minimal switches	Suitable for multi-switch OC/SC fault.

The approach proposed in this study involves a combination of Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) for feature extraction. First, DFT is applied to the phase voltage and current signals, and the resulting output is fed into the DWT algorithm to calculate the approximate and detailed coefficients of the standard deviation of the voltage and current waveforms. This process generates a set of features that can be used to classify faults in the NPC inverter when any switch is faulty. The data is then normalized using standard scaling, a technique that transforms the values of a feature to have a mean of zero and a standard deviation of one, to ensure that all features have the same scale and do not dominate the training of the model. The proposed method utilizes two popular classifiers, namely K-nearest neighbor (KNN) and Support Vector Machines (SVM), which have been found to be effective in fault classification applications. Figure 4.2 depicts the proposed combined model for this work and shows the better output than other methods given in above table.

V. CONCLUSION

The open-switch fault of a three-phase inverter was the main focus of this project. A novel fault diagnosis technique for locating and categorizing single and multiple open switch faults is presented in this paper. This was made possible by:

1. The average and RMS values were extracted from the analysis of the inverter's three-phase current waveform. When both parameters are combined, a more reliable fault diagnosis method is produced than when they are used separately.
2. A novel approach to normalization is presented and validated, employing the mean-to-RMS ratio. To categorise various faults, the ensemble-bagged classification method was fed the ratio values.
3. Multiple switch faults, including triple-switch faults, can be detected using the suggested technique. Additionally, it works well with low current.
4. In addition to the simplicity of the fault diagnosis technique, additional sensors are not required, thus facilitating implementation and minimizing the cost to the manufacturer.
5. The proposed fault diagnosis technique was validated through experiments and simulations. The results presented in this paper confirm the robustness of the proposed technique for estimating all possible fault scenarios.

VI. REFERENCES

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