Fault Detection in Cascaded H-Bridge multi-level Inverter Using Machine Learning

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***Abstract*— Multi-level inverters have found considerable applications in renewable energy sources and high-power applications in recent years. MLIS is being utilized for multipurpose applications like communication, manufacturing, aerospace power filter, and many more. Given its wide usage, it is critical to ensure an MLI's stable operation i.e., to discover and fix faults as soon as possible. Using mathematical models for diagnosing faults might be difficult due to the presence of numerous switching devices.**

In this context, we explore Machine Learning techniques to improve fault diagnosis accuracy and efficiency of a cascaded H-bridge multi-level inverter. This exploratory project explores the fault diagnosis technique in Cascaded H-bridge multi-level Inverter for Open Circuit Faults (OCF) by using the K-nearest neighbor (K-NN) classifier algorithm based on principal component analysis (PCA).

Using the Phase Shift Pulse Width Modulation (PSPWM) technique, the output voltage signals under different switching fault conditions of the CHMLI are taken as fault features.

***Index Terms*—** PCA: Principal component analysis, OCF: Open circuit fault, CHMLI: Cascaded H-bridge multi-level inverter, k-NN: k-Nearest neighbors, PSPWM: Phase shift pulse width modulation, PWM: Pulse width modulation

I. INTRODUCTION

THE Cascaded H-Bridge Multi-level Inverter (CHMLI) is a popular topology for multi-level inverters that can be used for both single-phase and three-phase conversion. It utilizes H-bridge units that are made up of switches and diodes to achieve the desired voltage levels. At least three voltage levels are required for a multi-level inverter, which can be achieved by a single H-Bridge unit in the CHMLI topology.

CHMLIs are widely used in medium and high voltage, high power applications due to their small switching losses. This means that they generate less heat and are more efficient, making them a popular choice in modern times. The multi-level converter can achieve high power ratings and is particularly useful for low-power applications that rely on renewable energy sources.

When compared to conventional two-level inverters, CHMLIs have several advantages. Firstly, the power switches in CHMLIs experience low voltage stress, which reduces the likelihood of failure due to over-voltage. Secondly, the output voltage of CHMLIs has low harmonic content, which means that the output waveform is closer to a sinusoidal waveform than that of a two-level inverter. Thirdly, CHMLIs have less switching loss, which means that they generate less heat and are more efficient. Lastly, CHMLIs have high working efficiency, which is beneficial for low-power applications that rely on renewable energy sources.

Overall, the advantages of CHMLIs make them an attractive option for various industries, including renewable energy, electric vehicles, and industrial automation, where precise and reliable power conversion is critical.

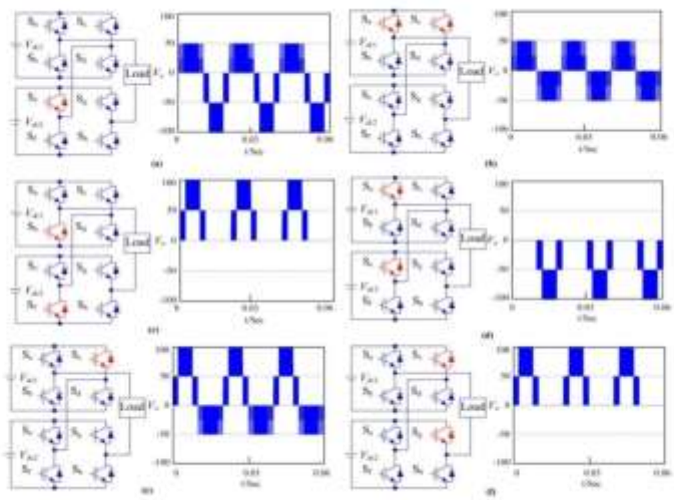
<u>Need Of Research</u>

While the CHMLI topology offers several advantages over conventional two-level inverters, it is important to note that the reliability of these systems can decrease as the number of inverter levels increases. In addition, faults and losses in power electronic components can also impact the reliability of the system. One of the primary causes of inverter failure in distributed power generating units is the short or open circuit in the switching element.

Previous research has explored various methods for detecting faults in inverters, including mathematical models. However , these models can be complex and may not always provide accurate results. In this context, an exploratory project has been undertaken to investigate the use of the k-NN classifier algorithm based on PCA to efficiently and accurately detect faults in CHMLIs.

The k-NN classifier algorithm based on PCA is a machine learning technique that uses principal component analysis (PCA) to reduce the dimensionality of the data and the k-nearest neighbor (k-NN) classifier to classify faults. This approach has been shown to be effective in detecting faults in CHMLIs, offering high accuracy and efficiency.

By leveraging machine learning algorithms, such as the k-NN classifier algorithm based on PCA, faults in CHMLIs can be quickly and accurately identified, allowing for timely maintenance and repair of the system. This can help to minimize downtime and prevent further damage to the system.



III. Approach

A. Overview

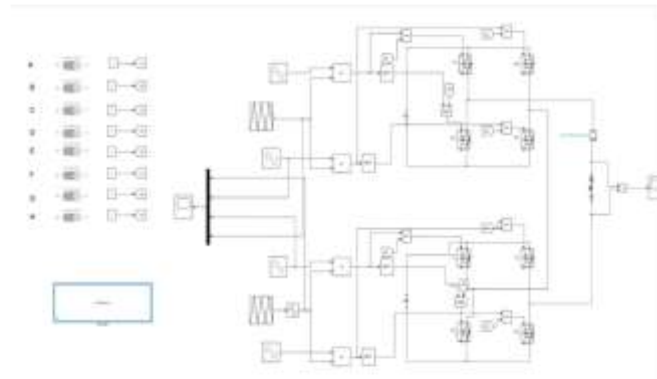
In this project, we use 5-level CHMLI based on Phase-shifted Unipolar Pulse Width Modulation (PSPWM) technique. The project uses a method based on the PCA-k- NN algorithm to enhance the accuracy of fault analysis in the CHMLI system and also reduce the diagnosis duration time. This method can determine the location of the fault from the CHMLI system output voltage waveform. The voltage signal is treated as the fault signal. The output voltage waveform signal data was obtained from the sensitive load side of the CHMLI. This data is then fed to PCA algorithms which convert the high-dimensional data to
low dimensional data. The k-NN classifier takes the output transformed signal (employing PCA). The training of the classifier is done with the output being labels of the switch.
Phase shift pulse modulation is used in the project to control the CHMLI because of the advantage of easier implementation and high modularity as compared to other modulation techniques.

B. Fault Diagnosis technique

The fault detection system in question aims to identify any faults that may occur in the output voltage signal of a system. To reduce the dimensionality of the output voltage signal, the system employs the use of principal component analysis (PCA). PCA is a popular method for reducing the number of dimensions in a dataset while retaining the most important information.

The process of PCA involves transforming the original data into a new set of variables that are uncorrelated with one another. The new variables are called principal components, and they explain the maximum possible variance in the original dataset. By keeping only the principal components that account for a significant portion of the variance, the dimensionality of the dataset can be significantly reduced, while still retaining the most important information.

In the context of fault detection, using PCA-based dimensional reduction can provide several advantages, including easier use of Bayesian methods, and the ability to perform statistical testing to detect faults. Additionally, the PCA projection obtained can be used to identify patterns and trends in the data that may not have been apparent in the original dataset, further aiding in the detection of faults. Overall, the use of PCA in fault detection systems can help improve the accuracy and efficiency of detecting faults in complex systems.



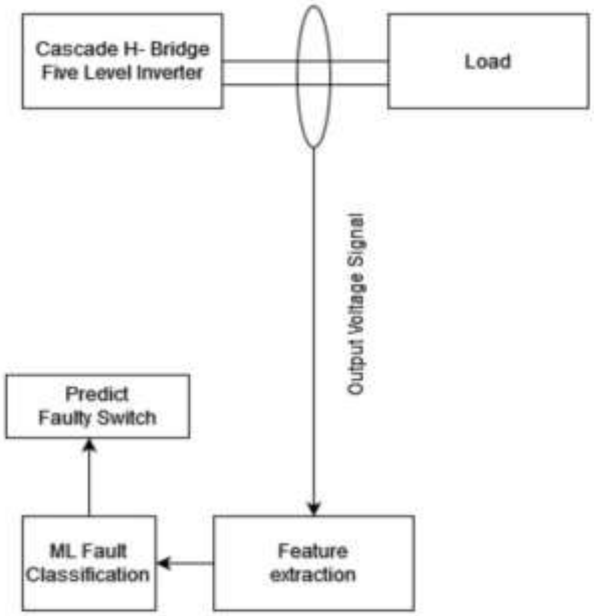
C. PCA-k-NN method

In recent years, machine learning-based algorithms have been increasingly employed for fault detection and classification in various types of inverters. One such technique is the k-nearest neighbors (k-NN) algorithm, which selects the samples having the minimum distance as the nearest neighbors of the test data. Based on the categories of the k nearest neighbors, the classification of the test data is determined.

The proposed fault diagnosis technique utilizes the PCA feature extractor to compress the output voltage of the CHMLI. The PCA technique reduces the dimensionality of the data and provides optimized data. An Explained Variance Plot (Fig 3.2) is used to determine which principal components contribute the most variance, and the number of principal components is chosen accordingly.

The output of the PCA technique is used to create a dataset for the k-NN classifier. A plot is created (Fig 3.3) to determine the optimal value of K for the model. The proposed technique uses K=3, and different parameters such as Euclidian and Manhattan distance metrics are implemented to classify various faults.

The flowchart of the proposed PCA-based k-NN fault diagnosis technique is illustrated below. The output voltage of the CHMLI is input to the PCA feature extractor, followed by the k-NN classifier to classify different faults. The proposed technique offers advantages such as statistical testing facilities, easier use of Bayesian methods, and the ability to obtain PCA projection.

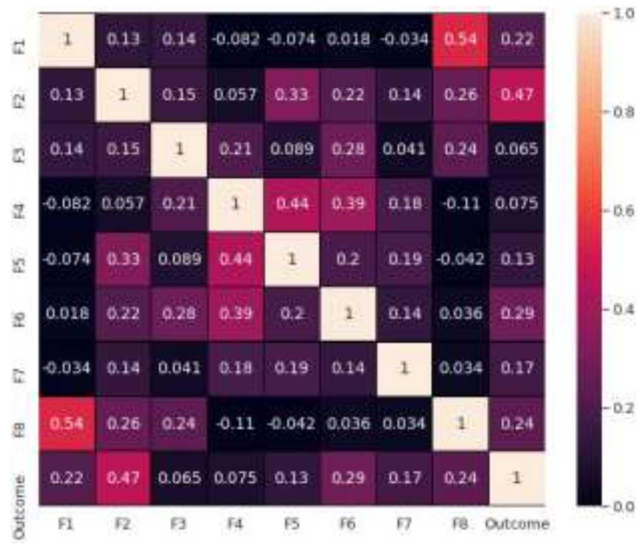


V. RESULT AND PLOT

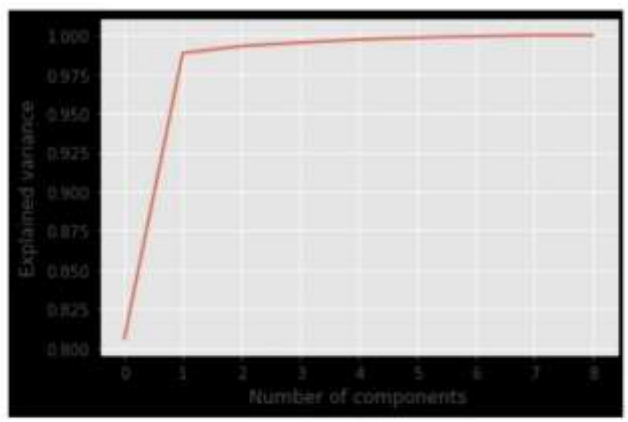
Principal components analysis (PCA) is a statistical technique used to reduce the dimensionality of high-dimensional data while preserving the majority of the variation in the original dataset. PCA works by identifying linear combinations of the original variables, called principal components, that explain the maximum amount of variance in the data.

In the context of fault diagnosis in CHMLIs, PCA can be used to reduce the dimensionality of the input dataset and improve the accuracy of fault detection algorithms. The results presented in Table 3.1 demonstrate that the PCA-k-NN algorithm achieves a 100% accuracy rate, regardless of whether 75% or 95% of the data is used for training. This high accuracy rate is achieved using both Euclidian and Manhattan metrics.

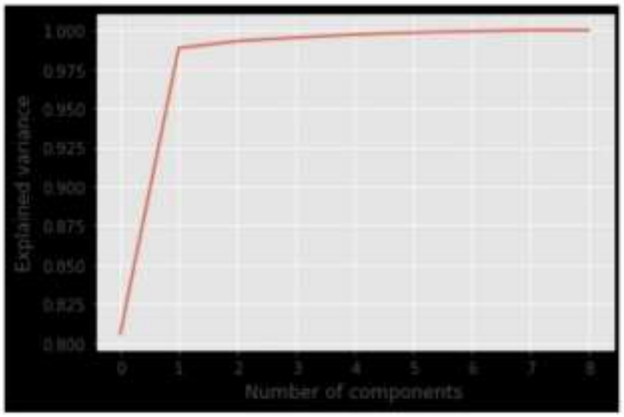
The confusion matrix shown in Figure 3.1 provides a visual representation of the performance of the k-NN classifier method. This matrix summarizes the number of true positives, true negatives, false positives, and false negatives in the classification results, allowing researchers to better understand the strengths and weaknesses of the algorithm.



The plot in Figure 3.2 shows the accuracy of fault diagnosis using the PCA-k-NN algorithm with different values of "k", which determines the number of nearest neighbors used in the classification process. As the plot shows, the accuracy of the algorithm generally increases as the number of nearest neighbors increases, up to a certain point, after which the accuracy begins to plateau or even decrease.



Overall, the use of PCA-k-NN algorithm for fault diagnosis in CHMLIs appears to be a promising approach, with high accuracy rates and the potential for further optimization through the choice of "k" and other parameters.



VI. Conclusion

1.This project has investigated the output voltage characteristics of the multi-level inverter of a distributed power generator under the OCF situation in order to design a good diagnostic tool to recognize the failure of the power electronics circuits.

2. The simulation results are reported on five-level CHMLI at OCF. The most important features from the output signal at different OC fault forms are extracted using PPCA-k-NN techniques.

3. High accuracy for simple faults has been achieved using the proposed techniques.

Scope of Improvement

1.Use SCF fault data.

2. Use Double Switch fault data.

3. Implement other models like SVM and compare it with K-NN.

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