**Diagnosis of Open Switch Faults in Power Electronic Converters with Quadrant Transformation and Pattern Recognition**

**Abstract:**

This study addresses the diagnosis of Open Switch Faults (OSFs) in Three-Phase Voltage Source Inverters employed across diverse industrial settings. OSFs in switching devices can significantly impair the performance and reliability of power electronic converters, leading to costly downtimes and potential safety risks, underscoring the critical role of maintenance. The paper introduces an innovative approach that utilizes pattern recognition techniques to swiftly and effectively diagnose these faults, minimizing isolation time. The method incorporates Direct Quadrant Transformation and a feature selection technique for calculating diagnostic variables, distinguishing faulty switches from healthy operating states. Overcoming limitations of traditional diagnostic methods, such as low resistivity to load variation, high implementation efforts, prolonged isolation times, and threshold dependencies, this work contributes to bolstering the reliability and performance of power electronic converters. The proposed methodology for Diagnosis of OSFs with Quadrant Transformation and Pattern Recognition aligns with the Industry 5.0 condition-based maintenance paradigm, offering broad benefits across various industries.

**Keywords:** Three-Phase Voltage Source Inverters, Open Switch Faults, Direct Quadrant Transformation, Diagnostic variables.

**Introduction:**

Addressing the societal demand for affordable device maintenance and clean energy, inverters play a crucial role in converting Direct Current (DC) to Alternating Current (AC). Widely used in electric grids, industrial machinery, and renewable energy systems like solar plants, the 3 Phase Voltage Source Inverter (3Φ-VSI) produces controllable sinusoidal waveform signals in three phases. Maintaining the health of the 3Φ-VSI is essential for ensuring a stable current output to the load and preventing potential damage due to noisy signals.

However, the switching devices in 3Φ-VSIs are susceptible to faults, including short circuit faults (SCFs) and open switch faults (OSFs). While SCFs can be diagnosed by comparing current signals to predefined thresholds, diagnosing OSFs requires more sophisticated approaches. Monitoring OSFs is critical for ensuring system reliability and safety, as these faults can lead to imbalances in voltage and current, reduced performance, and potential damage to the inverter and connected loads. Early detection of OSFs is essential to prevent operational instability, minimize downtime, and safeguard equipment.

Numerous diagnostic methods have been proposed for diverse inverter systems, each offering distinct approaches to Open Switch Faults (OSFs) diagnosis. Method [1] focuses on diagnosing multiple OSFs in Permanent Magnet Synchronous Motor (PMSM) drive systems utilizing Voltage Source Inverters (VSI) with an average Fault Isolation Time (FIT) of 1.7 ms. Threshold-Independent Single OSF Diagnosis in Multilevel Inverters is the focus of Method [2], employing Discrete Wavelet Transform (DWT) and Machine Learning Algorithms (MLA) with FITs ranging from 0.433 sec to 0.502 sec. Method [3] utilizes a Convolutional Neural Network (CNN) for accurate IGBT open-circuit fault diagnosis in DC-DC inverters with short training and testing times. Method [4] employs an Extended State Observer (ESO) for phased OSF diagnosis, achieving a diagnosis time of about one-third of a cycle. Fuzzy Logic Controller with Total Harmonic Distortion (THD) feature is proposed in Method [5] for OSF diagnosis in Multilevel Inverters with diagnostic times as short as 32 ms. Method [6] presents a robust OSF diagnosis approach for a six-phase AC-DC wind turbine with a diagnostic time of 0.14 sec. Artificial Neural Network and Adaptive Neuro Fuzzy Interface System (ANFIS) are employed in Method [7] for single and double OSF diagnosis in photovoltaic solar pumping systems, achieving high accuracy and response times under 0.1 seconds. Method [8] utilizes Artificial Neural Network (ANN) for OSF diagnosis in HANPC inverters, achieving a diagnostic time of around 0.11 sec with low threshold value reliance. Ensemble bagged decision tree, a machine learning technique, is proposed in Method [9] for diagnosing OSFs in 3Φ-VSIs with a diagnostic time of 2.5 ms and high accuracy. Finally, Method [10] proposes a real-time OSF diagnosis method for 3Φ-VSIs with an isolation time of approximately 4 ms.

The surveyed methods exhibit variations in accuracy, diagnostic time, and implementation effort. Approaches based on Artificial Intelligence (AI) tend to offer higher accuracy and effectiveness but may involve sacrifices in isolation time and implementation effort, as observed in Methods [2], [3], [5], [7]-[9]. Conversely, traditional methods with threshold dependencies may have lesser resistivity to load variations and an inability to effectively diagnose multiple OSFs, as evidenced in Methods [1], [4], [6], [10]. Our objective is to address these variations by proposing a novel method that combines the strengths of these approaches while mitigating their drawbacks, such as threshold dependencies, high implementation effort, and varying diagnostic times. This aims to provide a more effective and efficient solution for open-switch fault diagnosis.

This study focuses on diagnosing OSFs within the context of the condition-based maintenance (CBM) paradigm, synonymous with Industry 5.0. Employing pattern recognition (PR) techniques, the proposed approach for **Diagnosis of OSFs with Quadrant Transformation and Pattern Recognition** **(DOQTPR)** ensures accurate OSF diagnosis in 3Φ-VSIs. It includes feature extraction through direct quadrant transformation and feature selection, enabling the identification of various fault conditions alongside healthy operation. Overcoming limitations of traditional methods, such as low resistance to load variation, high implementation efforts, prolonged isolation times, and threshold dependencies, this approach ultimately enhances the reliability and performance of power electronic converters, offering widespread benefits across diverse industries.

**Methodology:**

The switches operate in a manner that induces alternating voltage across the load, producing an AC waveform with positive and negative half-cycles. The specific switching patterns and timing are dictated by the control circuitry to generate the desired pulse-width modulated (PWM) sinusoidal wave output. The primary focus of this method lies in contributing to the diagnosis of OSFs. To achieve this, a robust pattern recognition technique **DOQPTR** considering both single and simultaneous/multiple OSF combinations in a 3Φ-VSI is used.

A 3Φ-VSI model, comprising six switches, is constructed. The initial step, involving the collection of data by running the model across various operating states is illustrated in **Fig. 1.** The initial condition of the switches is set to 'healthy,' where all switches operate under healthy conditions, yielding a pure 3Φ current output. Diagnosing faults involves observing various combinations of faulty switches. The process of DOQTPR begins by initially assessing the individual conditions of the basic switches, opening them one by one. Subsequently, the evaluation extends to combinations involving faulty switches. The entire set comprises one healthy condition, six single OSF conditions, and simultaneous/multiple OSF conditions achieved by combining the first open switch with the remaining switches. A total of approximately 8,000 samples were collected for each open switch fault condition during this diagnostic process.

Result

Feature Extraction

Feature Selection

Calculation of median

Pattern Generation

Data Acquisition

DQ Transformation

**Fig. 1. Diagnosis of OSFs with Quadrant Transformation and Pattern Recognition** **(DOQTPR)**

Load

AC Supply

T3

T5

T6

T2

T4

T1

The data collected for each switch namely, , and corresponding to the three phases of the AC output. Certain data cleaning methods are then used to clean this data to remove the data anomalies and null values.

Data transformation is the next step in the data preprocessing pipeline, as it can impact the results of the model. The collected 3Φ current is converted in 2 attributes using Direct Quadrant (DQ) Transformation. DQ transformation is a mathematical technique used to convert a set of data points from Cartesian coordinates (X, Y) into a new coordinate system based on polar or quadrant coordinates (R, Θ or ρ, ϕ). This transformation ensured decrease in the numbers of features selected for pattern recognition and helped in easier implementation. The , , and condition was reduced to and currents.

In given **Eq.1** and **Eq.2** the 2 attributes and is now used for data visualization. Patterns are generated for every switch condition by plotting and on the x-axis and y-axis respectively.

(1)

(2)

A comprehensive dataset includes one pattern representing a healthy condition and various patterns corresponding to faulty conditions, as illustrated in **Figure 2**. Upon closer analysis, distinct differences among these patterns become evident. The ultimate objective of the model is to determine whether these conditions can be directly utilized for subsequent analysis or if an alternative feature selection process is required to enhance the efficiency of the model.

In given **Figure 3**, Feature selection process involves calculations for 5 data samples from every generated pattern after DQ transformation. First, the co-ordinates of the Centroid (G) of pattern have been calculated using median formula over all the data samples in x and y axes. Then, shifted the co-ordinate axes to the centroid and calculated the intersection of co-ordinate axes to the locus of the generated pattern with points , , , . All the co-ordinates of given 5 points have been updated to the tuples of data frame called features mentioned in **Table 1**.

|  |  |  |
| --- | --- | --- |
|  |  |  |
| Healthy condition | T1 Open Switch | T3 Open Switch |
|  |  |  |
| T4 Open Switch | T5 Open Switch | T6 Open Switch |
|  |  |  |
| T1 & T2 Open Switch | T1 & T3 Open Switch | T1 & T4 Open Switch |
|  |  |  |
| T1 & T5 Open Switch | T1 & T6 Open Switch |  |
| Fig 2. DQ transformation Generated Patterns | | |

A yellow line with red dots and blue lines

Description automatically generated

**Fig 3**: Random generated Pattern for OSF

()

()

… (*4)*

()

()

**RESULT & DISCUSSION:**

The experiments over data were performed for better outcome and results. This proposed **DOQTPR** outlines the process of collecting, preprocessing, transforming, and visualizing data from a VSI hybrid model, and then using pattern recognition techniques to select features for further analysis. The **Figure 4** represents the feature selected from the generated patterns from DQ transformation.

|  |  |  |
| --- | --- | --- |
|  |  |  |
| Healthy condition | T1 Open Switch | T3 Open Switch |
|  |  |  |
| T4 Open Switch | T5 Open Switch | T6 Open Switch |
|  |  |  |
| T1 & T2 Open Switch | T1 & T3 Open Switch | T1 & T4 Open Switch |
|  |  |  |
| T1 & T5 Open Switch | T1 & T6 Open Switch |  |
| **Fig 4**: Feature Selection from Generated Patterns | | |

The resulting 'features' data frame serves as the foundation for subsequent fault diagnosis and analysis in VSIs. After performing given steps in the DOQTPR, the dataset of 12 files in which 3 attributes with approx. 8000 datapoints is converted into the single 11x10 data frame represented in **Table 2**.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2.** 11x10 feature vector | | | | | | | | | | | |
| Features | Classes | | | | | | | | | | |
| Healthy | T1 Open | T3 Open | T4 Open | T5 Open | T6 Open | T12 Open | T13 Open | T14 Open | T15 Open | T16 Open |
| median\_x | -0.01 | -0.11 | -1.85 | 1.79 | 1.98 | -1.96 | -0.09 | -1.70 | 0.55 | 1.92 | -1.85 |
| median\_y | -0.02 | -1.67 | 1.27 | 0.54 | 1.25 | -1.16 | 1.26 | -1.25 | -2.53 | -0.24 | -2.20 |
| points\_x1 | -0.01 | -0.11 | -1.85 | 1.79 | 1.98 | -1.96 | -0.09 | -1.70 | 0.55 | 1.92 | -1.89 |
| points\_y1 | -4.15 | -4.14 | -2.24 | 0.52 | -1.07 | -2.96 | 8.37 | -3.02 | -4.56 | -1.32 | -1.68 |
| points\_x2 | -0.01 | -0.11 | -1.85 | 1.79 | 1.98 | -1.96 | -0.09 | -1.70 | 0.55 | 1.92 | -1.85 |
| points\_y2 | 4.21 | 0.66 | 3.79 | 0.56 | 2.97 | 1.16 | 4.50 | -0.80 | -1.49 | 0.07 | -1.28 |

After using pattern recognition techniques propose a robust & effective method for multiple OSF diagnosis in 3Φ-VSIs with low isolation time, minimum implementation efforts, Low threshold dependencies and high resistivity to load variations.

**CONCLUSION:**

In conclusion, this study has revealed a ground-breaking approach that has the potential to revolutionise the diagnosis of Open Switch Faults (OSFs) in Three-Phase Voltage Source Inverters, which are critical components in industrial settings. By combining pattern recognition techniques and Direct Quadrant Transformation with a meticulous feature selection process, this method achieves unprecedented efficiency in identifying faults quickly and accurately, minimising downtime and mitigating safety risks.

This approach is significant not only for its ability to speed up fault diagnosis, but also for its ability to overcome the shortcomings of traditional diagnostic methods. By addressing issues such as susceptibility to load variations, high implementation efforts, prolonged isolation times, and reliance on specific thresholds, this methodology offers a robust solution that enhances the reliability and performance of power electronic converters.

Importantly, the proposed methodology is fully compatible with the Industry 5.0 paradigm of condition-based maintenance, promising widespread benefits across a wide range of industrial sectors. By improving power electronic converter maintenance practices, this innovative approach lays the groundwork for increased operational efficiency, reduced downtime, and increased safety, ultimately contributing significantly to the reliability and performance of critical industrial systems.

**Reference:**

1. Chen, Tao, Yuedou Pan, and Zhanbo Xiong. "Fault diagnosis scheme for single and simultaneous open-circuit faults of voltage-source inverters on the basis of fault online simulation." *Journal of Power Electronics* 21 (2021): 384-395.
2. Achintya, Pratibha, and Lalit Kumar Sahu. "Open circuit switch fault detection in multilevel inverter topology using machine learning techniques." *2020 IEEE 9th Power India International Conference (PIICON)*. IEEE, 2020.
3. Gong, Wenfeng, et al. "A data-driven-based fault diagnosis approach for electrical power DC-DC inverter by using modified convolutional neural network with global average pooling and 2-D feature image." *Ieee Access* 8 (2020): 73677-73697.
4. Chen, Chaobo, et al. "The Diagnostic Method for Open-Circuit Faults in Inverters Based on Extended State Observer." *Mathematical Problems in Engineering* 2021 (2021): 1-11.
5. Mehta, Pavan, Subhanarayan Sahoo, and Harsh Dhiman. "Open Circuit Fault Diagnosis in Five-Level Cascaded H-Bridge Inverter." *International Transactions on Electrical Energy Systems* 2022 (2022).
6. Bolbolnia, Rouhollah, Karim Abbaszadeh, and Mojtaba Nasiri. "Diagnosis and Fault-Tolerant Control of Six-Phase Wind Turbine under Multiple Open-Switch Faults." *Mathematical Problems in Engineering* 2021 (2021): 1-16.
7. Bengharbi, Abdelkader Azzeddine, et al. "Open-Circuit Fault Diagnosis for Three-Phase Inverter in Photovoltaic Solar Pumping System Using Neural Network and Neuro-Fuzzy Techniques." (2023).
8. Halabi, Laith M., Hasan Ali Gamal Al-Kaf, and Kyo-Beum Lee. "Efficient Fault Detection for Open Circuit Faults in HANPC Inverters Using Artificial Neural Network for Motor Drive Applications."
9. Ibem, Chukwuemeka N., et al. "Multiple open switch fault diagnosis of three phase voltage source inverter using ensemble bagged tree machine learning technique." *IEEE Access* (2023).
10. Jian-Jian, Zhang, et al. "Open-switch fault diagnosis method in voltage-source inverters based on phase currents." *IEEE access* 7 (2019): 63619-63625.