International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Fuzzy Logic Diagnostics for Open-Circuit Faults in Renewable Energy Voltage Source Inverters with Changeable Load Conditions

N. R. Dhumale[1], R. B. Dhumale[2], M. V. Shelke[3], S. S. Nikam*[4], P. B. Mane[5], A. N. Sarawade[6]

Submitted: 17/08/2023 **Revised**: 05/10/2023 **Accepted**: 21/10/2023

Abstract: In this paper, a three-phase voltage source inverter (VSI) fault diagnosis system based on Fuzzy Logic is proposed. The Fuzzy Logic Fault Diagnosis (FLFD) system consists of four main stages such as PVM-Current Normalizer and Typical Transient Suppressor, Discrete Wavelet Transform, Feature Selection and Fuzzy Logic (FL). The crucial prerequisites for the aforementioned steps, including feature selection, mother wavelet selection, and FL structure, are covered in detail. The time domain waveform is used to clarify the terms PVM-current normalizer and typical transient suppressor. Due to the employment of a PVM-current normalizer and a conventional transient suppressor, this system is less dependent on mechanical or electrical operating conditions than other fault diagnostic methods. The choice of the mother wavelet and the level of decomposition are described in detail. By using the fewest possible features, the FLFD system identifies a variety of potential faults under varied load and different frequency. The approach for selecting features that work well is described. To categories faults, a FL's architecture is built. On a suitable dataset, the system is implemented, and its performance is assessed. The experimental findings demonstrate the suggested system's superior performance and ability to accurately diagnose VSI issues.

Keywords: *Fuzzy logic; voltage source inverter; varied load; Park's Vector Transform*

1. Introduction

Voltage Source Inverters (3Φ-VSIs) overall performance depends heavily on the consistently reliable operation of every one of its parts. Any one of its parts failing could result in significant productivity and capital gain losses. 3Φ-VSI fault diagnosis is therefore a crucial topic of research nowadays. Variable speed drives (VSDs) fed by Voltage Source Inverters (VSIs) are susceptible to a variety of failures, including those involving the inverter, the machine, and the sensors. DC link capacitors and power switch faults are the most common inverter defects [1].

The diagnosis of power switch problems is necessary because they impair the functioning of VSIs. A number of methods have been focused on the diagnosis of short-circuit & Open-Circuit Faults (OCFs) in VSIs, according to the review [2]. Extra hardware circuits are typically used for fault diagnostics since a short-circuit fault is an instantaneous destructive defect [3]. The most recent evaluation of the literature survey in OCF diagnostics reveals that the proposed methods fall under of the following categories [4]: Model-based Methods (MbMs) and Signal-based methods (SbMs).

[22,3,4,5] *AISSMS Institute of Information Technology, Pune, India.* [1,6] *Sinhgad College of Engineering, Pune, India.*
* *Corresponding Author Email:shobha.nikam@aissmsioit.org,*

In order to identify and isolate defects, signal-based approaches, a subset of fault detection techniques, analyses the system's signals. SbMs can be used to diagnose OCFs by looking at the VSI's output voltage waveform. The Fast Fourier Transformation (FFT) is one signal-based approach for VSI OCF diagnosis [5]. The output voltage waveform is evaluated with the FFT in this method to find any missing frequency components from the predicted waveform. These frequency components can be utilized to diagnose flaws in the VSI and can be brought on by OCFs in the VSI. The Discrete Wavelet Transform (DWT) method is another SbM. Using the wavelet transform, the output voltage waveform is evaluated in this manner to find any transient waveform changes that are not visible in the predicted waveform. The OCFs that can produce these transient variations can be exploited to identify the fault. When diagnosing OCFs in VSI, SbMs offer several advantages over MbMs. They can be utilized with any VSI system and don't necessitate a complex mathematical model of the VSI. Also, they are comparatively computationally effective [6]. In summary, OCFs can be identified using SbMs like Fourier analysis and wavelet transform approaches. These techniques have some benefits over MbMs, but they also have some drawbacks that must be considered.

The normalized current average value technique to guarantee a successful OCF diagnosis in AC machine drives proposed in [7]. As [8] suggest using a single DC current sensor to rebuild the currents in the motor stator. The OCF diagnosis is then accomplished using the reconstructed currents and variations in the average current values. In [9], the authors diagnose a total of 27 OCFs and three current sensor failures using only the observed current signals and the combination of the two fault indications. Although this method has the advantage of being applicable for both closed-loop and open-loop control of AC drives, it requires a lot of computational power to be implemented in real time. For the diagnosis of various fault types in VSIs, [10] suggested a mixed technique employing the current Park's Vector Method (PVM) and normalized current average value approach.

As a successful OCF classifier, techniques like Artificial Neural Networks (ANNs) or Fuzzy Logic (FL) have been presented [11]. Whilst they need a lot of technical work, FL and ANN based approaches offer added intelligence for fault diagnosis. It has been demonstrated that the WT and FL combo is a powerful tool for OCF diagnosis and that there is no impact of high frequency noise on the results [12]. Pattern Recognition-based Systems (PRSs) are the name given to these artificial intelligence-based fault detection systems. PRS are frequently employed in the diagnosis of complex systems and which may be quickly put into use in real-time application. Initial training and classifier structure both influence PRS performance. When the PRSs are not trained on a specific problematic data set, they frequently fail to identify the incorrect state [13]. With VSI's fluctuating load conditions, it is exceedingly challenging to get early training data. Implementing a pattern recognition-based fault diagnostic system under varying load conditions is therefore highly challenging.

This study develops a 3Φ-VSI fault diagnosis system. The PVM-Current Normalizer and Typical Transient Suppressor, DWT, Feature Selection, and FL are the four key steps of the proposed Fuzzy Logic Fault Diagnosis (FLFD) system. Prerequisites for the aforementioned processes are described in detail, including mother wavelet selection, feature selection, and FL architecture. The phrases PVM-current normalizer and typical transient suppressor are explained using the time domain waveform. This technique is less dependent on mechanical or electrical operating circumstances than other fault diagnostic systems since it uses a PVM-current normalizer and a standard transient suppressor. The level of decomposition and the mother wavelet selection are detailed in great detail. The FLFD system can identify a range of potential defects under varying load and frequency by using the fewest features possible. The method for choosing functional features is presented. A FL is developed to categories faults. The system is tested and its performance is evaluated on an appropriate dataset. The experimental results show the proposed system's excellent performance and capability to precisely identify VSI faults.

2. Proposed Fuzzy Diagnosis System of Open Circuit Faults

The proposed FLFDS is shown in Fig. 1, which is used to classify twenty one faulty conditions and a healthy condition. To overcome the drawbacks mentioned in previous fault diagnosis systems under variable load at different frequencies detection parameter current is normalized and then features are extracted in frequency domain. 3Φ stator current is used as detection parameter in the proposed FLFDS method. The FLFDS collects the packet of 20 ms and each packet consists of 158 samples. Every packet of samples has unique features at healthy and faulty conditions. The load current sensed from stator of three phase induction motor consist of high frequency noise like harmonics. Three low pass filters are used to remove such high frequency noise.

The OCF diagnosis of switching devices in **3Φ VSIs** using PVM is carried out successfully for single switch OCF. Single OCF of variable speed drive is diagnosed using average values of three phase currents and phase angle, which are calculated using PVM. The d-q transformation or Park's Vector approach is mathematical transformation used to convert stator currents of VSI i_a, i_b and i_c into two phase currents i_d and i_q. **3Φ** current of VSI is given by **Eq. 1**.

$$i_l = \begin{cases} i_a = I_m \sin(\omega_s t + \phi) \\ i_b = I_m \sin\left(\omega_s t - \frac{2\Pi}{3} + \phi\right) \\ i_c = I_m \sin\left(\omega_s t + \frac{2\Pi}{3} + \phi\right) \end{cases} \quad (1)$$

Where l = a, b or c, I_m is the maximum amplitude of current, $\omega_s t$ is current frequency and ϕ is the initial phase angle. The I_d and I_q are calculated using **Eqs. 2 - 3** to generate current patterns under healthy and faulty conditions.

$$i_d = \sqrt{\frac{2}{3}} i_a - \frac{1}{\sqrt{6}} i_b - \frac{1}{\sqrt{6}} i_c \quad (2)$$

$$i_q = \frac{1}{\sqrt{2}}(i_b - i_c) \quad (3)$$

The effective method is implemented using diagnostic variables and normalized three phase current (I_{lpvmN}) values. The normalization of three phase currents is required to avoid the problem of mechanical machine or electric operating condition dependency. The PVMs and normalized **3Φ** current of VSI are calculated using **Eq. 4** and **Eq. 5** respectively.

$$|\overline{is}| = \sqrt{i_d^2 + i_q^2} \tag{4}$$

$$I_{lpvmN} = \frac{i_l}{|\overline{is}|} \tag{5}$$

Because of this normalization process, the normalized phase currents I_{pvmN} will always take values within the range of ± 0.81, which is independent of the measured currents amplitude and given by **Eq. 6**.

$$I_{lpvmN} = \begin{cases} i_{aN} = \sqrt{\frac{2}{3}}\sin(\omega_s t + \phi) \\ i_{bN} = \sqrt{\frac{2}{3}}\sin(\omega_s t - \frac{2\Pi}{3} + \phi) \\ i_{cN} = \sqrt{\frac{2}{3}}\sin(\omega_s t + \frac{2\Pi}{3} + \phi) \end{cases} \tag{6}$$

The time domain waveform of transient caused due to load variation from heavy load to light load during Single Switch OCF condition is shown in **Fig. 2**. Due to load variation, the amplitude of three phase current is changed and generate transient as shown in **Fig. 2.a**, which in turn generates false alarm. Hence, 3Φ current of VSI are normalized in the range of ±1 to avoid false alarm. With this normalization, the transient in the 3Φ current of VSI is increased as shown in **Fig. 2.b**. Therefore, 3Φ current of VSI are normalized using Park's Vector approach which is given by **Eq. 5**. PVM-normalized current is able to suppress transient as shown in **Fig. 2.c**, which shows better results. Insignificant change in the amplitude is observed in Fig. **Fig. 2.c** during load variation, which is no sudden rise or fall in the current signal. Hence, the results of proposed fault diagnostic method will not affect.

The non-stationary normalized 3Φ current signals can be simultaneously analyzed in the time and frequency domain using DWT, which converts1-Dcurrent signals into 2-D space of time and frequency and low frequency components respectively. Selection of the mother wavelet and the decomposition level of signal is more crucial problem in wavelet analysis. In DWT, different mother wavelets can be used for signal analysis. Wavelet analysis will produce different results for analysis of same signal using different mother wavelets. Properties of mother wavelets like symmetry, orthogonality, dense support and vanishing moment are used for mother wavelet selection. On the other hand, different mother wavelets may have same properties. In such condition, mother wavelet matching with original signal is selected for analysis.

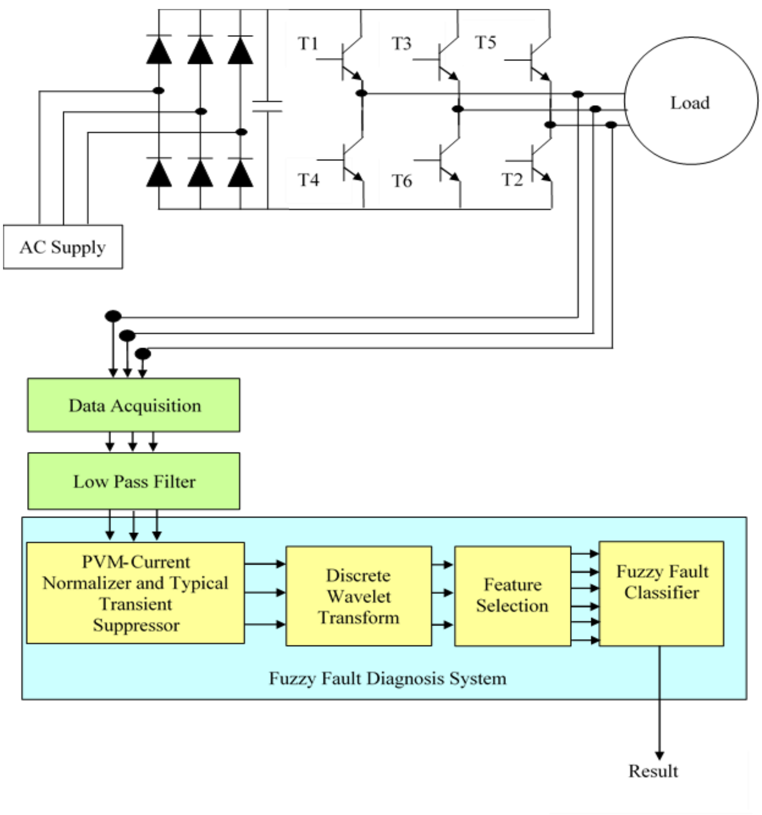

Fig. 1. Proposed Fuzzy Fault Diagnosis system

Mother wavelet matching with signal is selected for analysis and DB mother wavelet is suitable for analysis of transients in current waveform. One more important problem in wavelet study is selection of the level of the mother wavelet function, which was formerly decided by experimentation and based on basic uniqueness of the data. The highest level to apply the wavelet transform is based on number of samples in data set, as data is down-sampled by 2. The maximum values of detail coefficients for different mother wavelets applied on current signal during healthy and T1 open circuit faulty conditions. It is observed that DB mother wavelet is more effective than other mother wavelets for analysis of transients in current signal generated as result of IGBT open circuit fault.

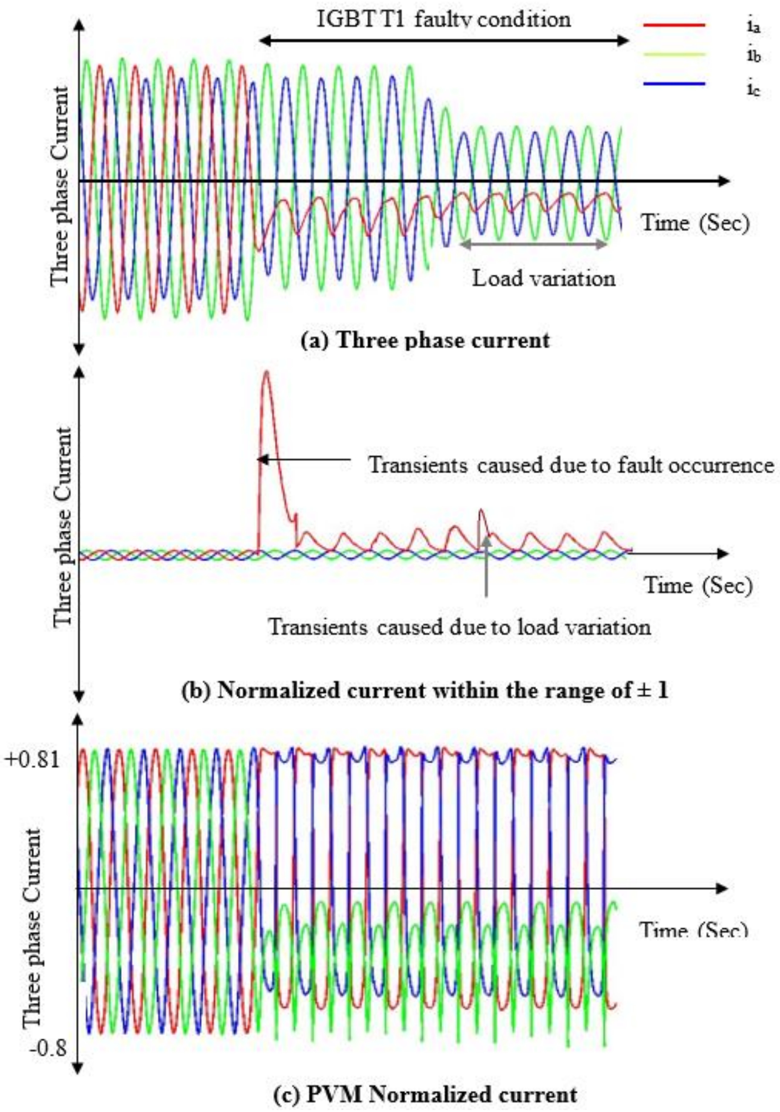

Fig. 2. Results concerning transient in current caused due to fault occurrence and variation in load

A main challenge to meet in fault diagnosis of 3Φ VSI is that how to identify faults using efficient minimum number of features which are measurable. Once the features are extracted, feature selection plays important role in effective classification of faults. In this work, the selected features for healthy and faulty conditions are named as fault diagnostic variables (FDVs) and shown in **Table 1**. The FDVs are calculated for each data packets consisting of 158 samples. Fifteen data packets are collected out of these four packets for healthy condition and eleven packets for faulty condition. It is observed that extracted features are important for analysis of OCF in VSI. These features have definite distinctive values during healthy and faulty conditions; under variable load conditions they have same values.The concept of FL has been there since last three decades. It observed that different faults can be classified using either min or max features. The max features are used for construction of FIS. The max features are **clustered using C-means clustering**; clustered data is shown in **Table 1**.

The triangular membership function is used for input variables. Five membership functions are assigned for every input of fuzzy inference system. These five membership functions are defined as LOW, MED_LOW, MED, HIGH_MED and HIGH. The explanation for selection of membership functions and fuzzy rules is explained in details in results and discussion.

The crisp input is transformed into a fuzzy value using fuzzification. The fuzzy output of the fuzzy inference engine is defuzzified into a crisp value before being sent to the controller. The application where a choice must be made only on crisp values cannot use the generated fuzzy results. Only the crisp output is understandable by a controller. So, the fuzzy output must be transformed into a crisp value. The selection of an effective defuzzification approach does not follow any systematic process. The **Centre of Area** (COA) approach, also known as the centroid method, is the most often used defuzzification technique. This method of defuzzification is used in this work to locate the fuzzy set's centre and get the associated crisp value.

3. Results and Discussion:

The fuzzy inference system is implemented using grid partition. The numbers of membership functions have been decided by observing performance of FL as given below.

- **Three number of membership functions:** Initially fuzzy inference system is implemented with three membership functions in each input which shows very poor accuracy. The mean square error is 0.7.
- **Four number of membership functions:** The performance of FL is improved using four membership functions but it is not satisfactory. The mean square error is 0.09.
- **Five number of membership functions**: Five membership functions are used which give better performance with mean square error is 0.005.

The performance of FL is also tested by taking more number five of membership functions. The performance of FL is shown in **Table 2**. Number of membership function increases complexity of FL. Hence five number of membership functions are selected for fault classifier. The ten-fold cross-validation evaluation method is used for computing fault classification results. In this case the samples to be analyzed are arbitrarily divided so that 165 samples are kept for training and 165 samples are kept for testing and validation. The procedure is started with dissimilar random division and the analysis is done by calculating average of results. The FL accomplished 100% sorting accuracy without including any misidentification out of 165 samples of training data. After successful training, the FL was tested using the testing samples. The total fault classification accuracy for the test data was 99.27% with 3 fault misclassification out of 83 test samples. The actual and targeted output of FL for some conditions during testing is shown in **Fig. 3**.

Table 1. Sample of clustered data of FDVl2

FDVR2	FDVY2	FDVB2
-0.2083	-0.2598	-0.06136
0.0107	0.01120	0.00884
0.2296	0.28220	0.07900
0.4486	0.55320	0.14930
0.6676	0.82400	0.21950
0.8865	1.09500	0.28970

Table 2. Performance of FL for different membership functions

Number of membership functions	Number of Fuzzy rules	Mean square error
3	125	0.70000
4	216	0.09000
5	276	0.00500
6	307	0.00590
7	343	0.00696

The time domain waveforms of three phase load currents for healthy and T-4 faulty condition are shown in Fig. 4. An IGBT T-4 is in the lower part of voltage source inverter. At t = 84.88 ms open circuit fault is introduced in IGBT T-4. It can be observed that the phase current i_a decreases and positive DC level is added into i_a. The currents i_b and i_c shift to negative value. The PVM-normalized current signals are shown in Fig. 4.b. The range of three phase PVM- normalized current signals is ± 0.81. The output fuzzy based classifier 4.02 indicates T-4 is faulty as shown in Fig. 4.d. A fault is isolated at t = 99.96 ms, fault detection time is 15.08 ms.

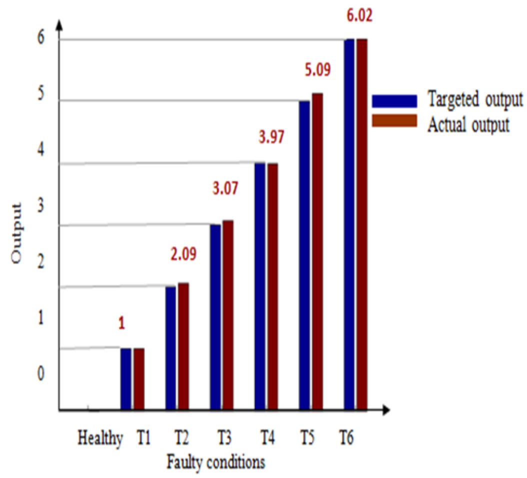

Fig. 3. Output of Fuzzy Fault Diagnosis system using five membership functions

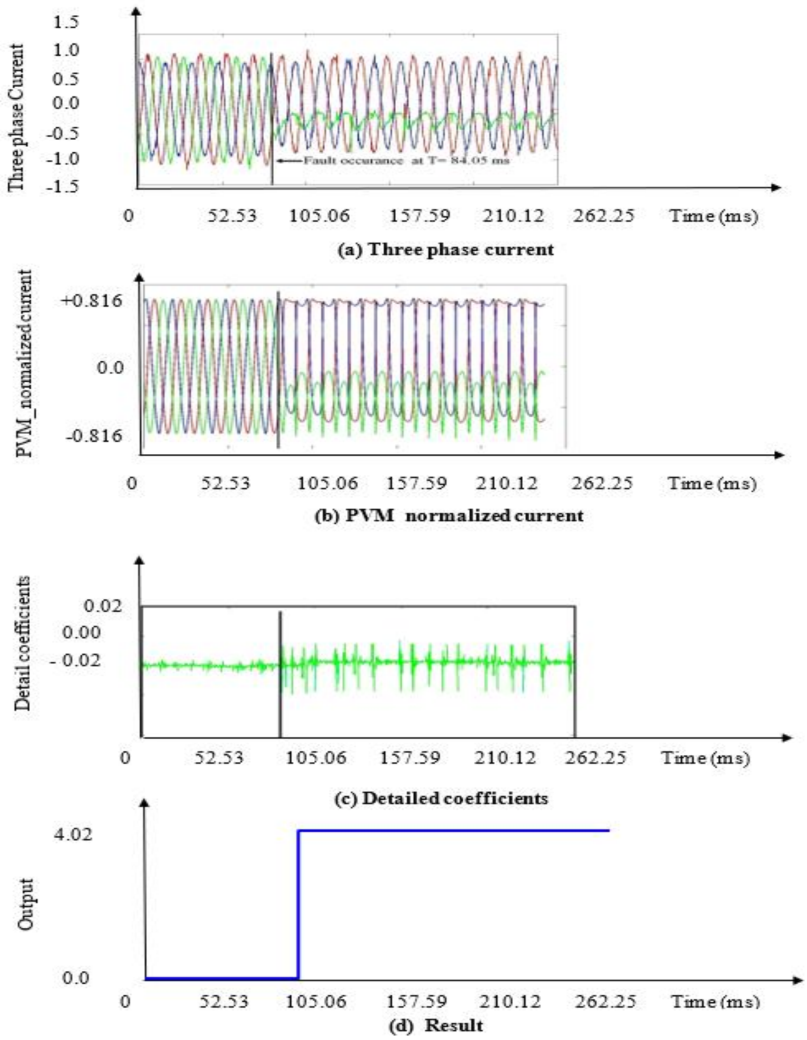

Fig. 4. Experimental results of T1 open circuit fault diagnosis

4. Conclusion:

The FL Fault Diagnosis system consists of four main stages such as PVM-Current Normalizer and Typical Transient Suppressor, Discrete Wavelet Transform, Feature Selection and FL. Feature selection, mother wavelet selection, and FL structure are covered in detail as important prerequisites for the aforementioned steps. The terms PVM-current normalizer and typical transient suppressor are explained using the time domain waveform. This system is less dependent on mechanical or electrical operating conditions than other fault diagnostic methods because it uses a PVM-current normalizer and a conventional transient suppressor. The choice of the mother wavelet and the level of decomposition are described in detail. By employing the fewest feasible features, the FLFD system may identify a range of probable problems under changing load and various frequency. The approach for selecting features that work well is described. To categories faults, a FL's architecture is built. The system is tested, trained, and its performance is evaluated on a suitable dataset. The experimental results show the proposed system's superior performance and capability to precisely identify VSI problems.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] İ. Şahin, "Model Predictive Torque Control of an Induction Motor Enhanced With an Inter-Turn Short Circuit Fault Detection Feature a Thesis Submitted To the Graduate School of Natural and Applied Sciences of Middle East Technical University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Electrical and Electronic Engineering," no. September, 2021.

[2] L. Kou, C. Liu, G. wei Cai, Z. Zhang, J. ning Zhou, and X. mei Wang, "Fault diagnosis for three-phase PWM rectifier based on deep feedforward network with transient synthetic features," *ISA Trans.*, vol. 101, no. xxxx, pp. 399–407, 2020, doi: 10.1016/j.isatra.2020.01.023.

[3] H. S. Khan, M. Aamir, K. Kauhaniemi, M. Mumtaz, M. W. Hassan, and M. Ali, "Improved finite control set model predictive control for distributed energy resource in islanded microgrid with fault-tolerance capability," *Eng. Sci. Technol. an Int. J.*, vol. 24, no. 3, pp. 694–705, 2021, doi: 10.1016/j.jestch.2020.12.015.

[4] E. B. Rocha Junior, O. E. Batista, and D. S. L. Simonetti, "Differential Analysis of Fault Currents in a Power Distribution Feeder Using abc, αβ0, and dq0 Reference Frames," *Energies*, vol. 15, no. 2, pp. 1–22, 2022, doi: 10.3390/en15020526.

[5] J. Liu, H. Tan, Y. Shi, Y. Ai, S. Chen, and C. Zhang, "Research on Diagnosis and Prediction Method of Stator Interturn Short-Circuit Fault of Traction Motor," *Energies*, vol. 15, no. 10, 2022, doi: 10.3390/en15103759.

[6] N. Koteleva, N. Korolev, Y. Zhukovskiy, and G. Baranov, "A soft sensor for measuring the wear of an induction motor bearing by the park's vector components of current and voltage," *Sensors*, vol. 21, no. 23, 2021, doi: 10.3390/s21237900.

[7] M. R. Mullali Kunnontakath Puthiyapurayil, M. Nadir Nasirudeen, Y. A. Saywan, M. W. Ahmad, and H. Malik, "A Review of Open-Circuit Switch Fault Diagnostic Methods for Neutral Point Clamped Inverter," *Electron.*, vol. 11, no. 19, pp. 1–29, 2022, doi: 10.3390/electronics11193169.

[8] J. Kim, S. Park, D. Min, and W. Kim, "Comprehensive survey of recent drug discovery using deep learning," *Int. J. Mol. Sci.*, vol. 22, no. 18, 2021, doi: 10.3390/ijms22189983.

[9] L. Xu, R. Ma, R. Xie, J. Xu, Y. Huangfu, and F. Gao, "Open-Circuit Switch Fault Diagnosis and Fault-Tolerant Control for Output-Series Interleaved Boost DC-DC Converter," *IEEE Trans. Transp. Electrif.*, vol. 7, no. 4, pp. 2054–2066, 2021, doi: 10.1109/TTE.2021.3083811.

[10] H. O. A. Ahmed, Y. Yu, Q. Wang, M. Darwish, and A. K. Nandi, "Intelligent Fault Diagnosis Framework for Modular Multilevel Converters in HVDC Transmission," 2022.

[11] A. Dianov, S. Member, A. Anuchin, and S. Member, "Phase Loss Detection Using Current Signals : A Review," *IEEE Access*, vol. 9, pp. 114727–114740, 2021, doi: 10.1109/ACCESS.2021.3105483.

[12] Y. Wang, Y. Ding, and Y. Yin, "Reliability of Wide Band Gap Power Electronic Semiconductor and Packaging : A Review of," 2022.

[13] R. B. Dhumale and S. D. Lokhande, "Diagnosis of multiple open switch faults in three phase voltage source inverter," J. Intell. Fuzzy Syst., vol. 30, no. 4, pp. 2055–2065, 2016, doi: 10.3233/IFS-151918.

[14] Goyal, A. ., Kanyal, H. S. ., & Sharma, B. . (2023). Analysis of IoT and Blockchain Technology for Agricultural Food Supply Chain Transactions. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3), 234–241. https://doi.org/10.17762/ijritcc.v11i3.6342

[15] Moore, B., Clark, R., Muñoz, S., Rodríguez, D., & López, L. Automated Grading Systems in Engineering Education: A Machine Learning Approach. Kuwait Journal of Machine Learning, 1(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/125