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Original Article

Current Signature Analysis of Open Circuit Fault Diagnosis in 3Φ-Voltage Source Inverter under Variable Load Conditions

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Abstract *- Accurately identifying Insulated Gate Bipolar Transistor switch failures is crucial for ensuring the dependability and durability of the 3Φ-Voltage Source Inverters. For the purpose of monitoring and diagnosing faults in three-phase inverters, signal processing is frequently utilized. The current study then uses an ANN approach to focus on the issue in variable load settings. The suitable Mother Wavelet is a Mother Wavelet with the greatest Energy to Shannon Entropy (ESE) ratio. An innovative technique with normalized characteristics is used to reduce the algorithm's complexity. The ReliefF algorithm is used to choose the best features. The most useful traits are used to instruct an ANN to detect errors. The suitable ANN structure is selected from a pool of training structures depending on accuracy. The recommended technique is novel in that it achieves OCFs in 3-VS Conditions of varying load by using the fewest features and the least amount of training data. To do this, extracted features are normalized before training an ANN. The data gathered shows that rank-based feature selection had improved the ANN classifier's accuracy.*

Keywords *- 3Φ-Voltage source inverters, Artificial neural networks, Current signature analysis, Energy to shannon entropy, Open circuit faults, Relief.*

1. Introduction

The large percentages of industry applications employ 3Φ-Voltage Source Inverters (3Φ-VSIs). In order to keep the production process running smoothly, maintaining them is crucial. Power semiconductor switches Majority inverter problems originate from Insulated Gate Bipolar Transistors (IGBTs)[1]. Open Circuit Faults (OCFs) and Short-Circuit Faults (SCFs) are common problems with power switches. The much more serious defects, SCFs, are often separated by conventional protective components. OCFs are less prone to be extremely damaging than SCFs[2].

Several academics have focused on identifying OCFs, which is crucial in the maintenance area. Yet, if a power switch is subjected to an OCF for an extended period of time, it may result in the failure of further components or even force an unplanned system shutdown. Because of these factors, the research community is becoming more interested in techniques for diagnosing OCFs in 3Φ-VSIs[3]. These Fault Diagnostic Techniques (FDTs) are often either data or circuit-driven.

The primary and extensively used method for identifying IGBT-OCFs is Current Signature Analysis (CSA). It should be observed that the IGBT current signal is often noisy; thus, the fault information may be obscured. Traditional methods like Park's Vector Technique (PVT), Normalized DC Current (NDC) approach, and modified NDC method are difficult to use in these circumstances. The sensitivity of the diagnostic indicators and the quality of the current signal will be improved by the proper processing procedure[1]. In 2-level VSIs, certain research has taken into account all OCFs. In order to detect OCFs and current sensor disconnection problems in 2-level VSIs, the modified Park's vector approach, the application of the average current approach, as well as the Luenberger observer-based approach were each suggested. IGBT and current sensor defects in 3Φ-VSIs were simultaneously diagnosed using the Fast Fourier Transform (FFT) and an independent random functional link network [4, 5]. Line voltage deviations and phase voltage deviations, which are appropriate for current sensor faults having a constant current, were used to diagnose all OCFs as well as current sensor problems for 2-level VSIs. Despite the growing interest in rapidly identifying OCFs, 3-VSIs might easily apply these techniques due to the different fundamentals[6, 7].

SP technologies are used in a number of methods to identify the IGBT-OCFs. The Support Vector Machine (SVM) is used to separate discontinuities in the current signal brought on by the fault after the Wavelet Transform (WT) has detected them. WT was combined with Artificial Neural Networks (ANNs) to automate the identification of OCFs in inverters[8].

The WT-ANN approach was used [3] to locate OCFs in converters. A technique using ANN, feature analysis, and wavelet analysis was developed to identify single and double OCFs in the converter of wind turbine systems with synchronous generators[1]. For finding flaws, data-driven approaches frequently employ cutting-edge Signal Processing(SP) and Artificial Intelligence (AI) algorithms[9]. These techniques are not good for real-time online problem diagnosis since they need a lot of data and complicated calculations[10-13].

ML methods are utilized in [14] to identify abnormalities such as symmetrical and asymmetrical defects in a power system. An actual power system dataset is gathered for this research and splits into training and testing datasets with varying percentages.

The suggested system's accuracy is great, and it is contrasted with other AI methods[14]. Yet, AI approaches for driving system fault diagnosis are developed to decrease the difficulty and quantity of problems and breakdowns caused by the usage of big measurement systems with the standard FDTs. Several AI techniques have been used to identify as well as identify defects in past years, and many proved to be effective. In particular, the authors of [15] suggested a strategy for identifying OCFs using the PVT current approach, and then they used the Fuzzy Logic (FL) technique to recognize malfunctioning VSI switches.

The outcomes of this approach are contrasted with those of OCF's detecting techniques. A combinational logic-based and FL approach is suggested for fault identification [16]. This approach has certain advantages—it is easy to use and has a high degree of diagnostic accuracy—but it must be used with an intelligence redundancy engagement system. Also, the approach that is being provided can only be used to find OCFs.

The numerous FDTs, including the time voltage criterion, switching time-domain OCF detection, asymmetric zero voltage switching, ANN and AI, histogram, harmonic frequency analysis, and the output voltage or current analysis are detailed in the research[2]. The overall method for defect diagnostic is applying several signal systems or mathematical operations to the measured output amount in order to extract any unique characteristics, such as voltage, current, as well as power. The numerous FDTs are divided into three major groups: harmonic frequency analysis, AI-based methods, as well as waveform analysis. For defect diagnosis as well as fault location identification, an ANN was created [17]. In the study, a multiclass ANN was suggested, with extremely careful consideration given to input/output design. Also, this method utilized the torque, voltage, and current signals (CSs). The outcomes showed how valuable and beneficial the FDTs are coupled with ANNs.

The proposed approaches, however, are exceedingly sophisticated and have a very narrow range of applications since a very intricate mathematical model is needed to handle them. A stator current sensor-based ANN was also employed by the authors in [18, 19]. Comparing the proposed technique to the typical current sensors used in similar applications, its key benefit is that it is much faster.

A crucial component of run-time predictive maintenance is fault analysis. The current study Current Signature Analysis of Open Circuit Fault Diagnosis (CSAOCFD), employs an ANN technique to concentrate on the problem under fluctuating load conditions.

A Mother Wavelet(MW) that has the highest Energy to Shannon Entropy (ESE) ratio is chosen as the appropriate MW[19, 20]. A novel approach is employed using the normalized characteristics to decrease the algorithm's complexity. For selecting the optimal features, the ReliefF algorithm is employed.

The most effective characteristics are utilized to teach an ANN to diagnose faults. Out of various trained structures, the appropriate ANN structure is chosen based on accuracy. The new aspect of the suggested strategy is that it uses the fewest features and the smallest amount of training data to diagnose OCFs in 3-VSI under situations of fluctuating load. Before training an ANN, extracted features are normalized to achieve this. The findings demonstrate that rank-based Feature Selection (FeaSel) has enhanced the accuracy of the ANN classifier. The main contribution of the suggested work is listed below.

- To research a technique for fault diagnosis of single and multiple open switches in a 3Φ-VSI system that works with variable load.
- To provide an MW that has the highest ESE ratio is chosen as the appropriate MW.
- To ensure that selected features remain the same for all load circumstances after being extracted for a single load condition.
- To provide a method for selecting the best features to train ANN techniques to improve performance in the 3Φ-VSI fault diagnostic technique.

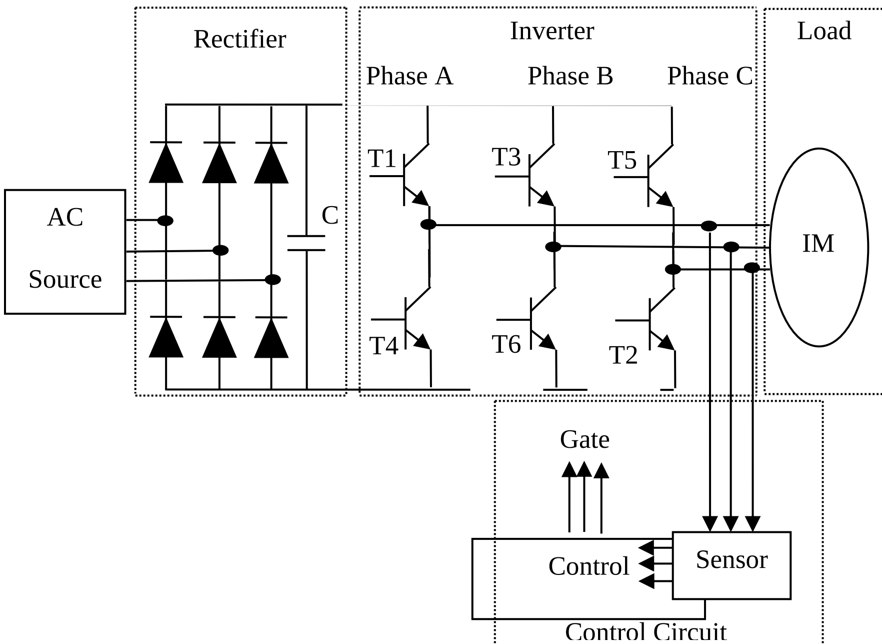


Fig. 1 The circuit diagram of 3Φ-VSI

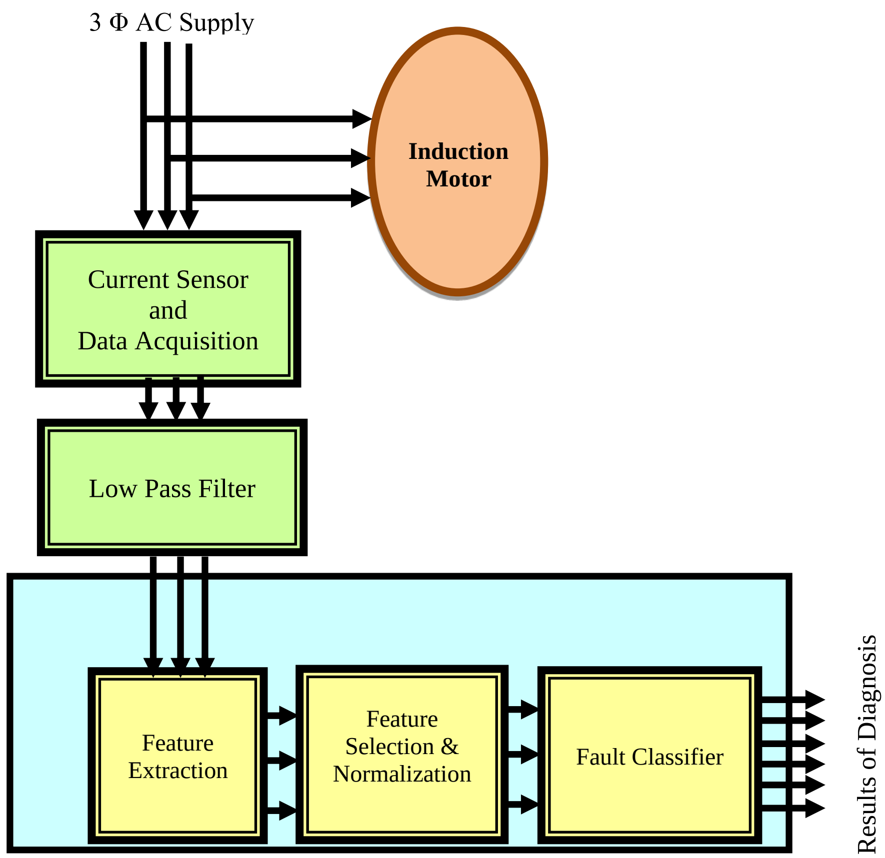


Fig. 2 Proposed current signature analysis of open circuit fault diagnosis in 3Φ-VSI

2. Materials and Methods

The planned CSAOCFD is put into practice to produce signals for both healthy as well as faulty situations, and observations are kept for all circumstances. The circuit diagram of 3Φ-VSI is shown in Figure 1. The general layout of the test rig in operation with an Induction Motor (IM) is shown in Figure 2. A current sensor is installed to measure the 3Φ current I_p—I_R, I_Y, and I_B—described in Eq. 1. For every cycle of the CSs, five packets of CSA are performed once the CSs are transformed into digital form.

$$I_p = \begin{cases} I_R = I_m \sin(\omega_s t + \Phi) \\ I_Y = I_m \sin(\omega_s t + \Phi - \frac{2\pi}{3}) \\ I_B = I_m \sin(\omega_s t + \Phi + \frac{2\pi}{3}) \end{cases} \quad (1)$$

Where I_m is the maximum current amplitude. P is a phase like R, Y and B. In 3Φ-VSI, the OCF is produced artificially. With an OCF, variations in CSs are seen under various switch and load situations. To eliminate undesired signals, these load CSs are filtered. The filtered CSsIRf, IYf, and IBf, as provided in Eq. 2, are employed for feature extraction.

$$I_{pf} = \begin{cases} I_{Rf} = I_m \sin(\omega_s t + \Phi) \\ I_{Yf} = I_m \sin(\omega_s t + \Phi - \frac{2\pi}{3}) \\ I_{Bf} = I_m \sin(\omega_s t + \Phi + \frac{2\pi}{3}) \end{cases} \quad (2)$$

The Discrete Wavelet Transform (DWT) extracts features from the filtered current signal. Using Eq. 3 and Eq. 4, the Detailed Coefficients (DC) and Approximate Coefficients (AC) are determined.

$$DC_{pf} = \sum_{i=0}^{m} I_{pf(i)} \times h_{(n-i)} \quad (3)$$

$$AC_{pf} = \sum_{i=0}^{m} I_{pf(i)} \times g_{(n-i)} \quad (4)$$

Where n is the shifting parameter, and m is the total sample size in one packet of the current signal. The High Pass Filter as well as Low Pass Filter coefficients are denoted by the letters $h_{(n-i)}$ and $g_{(n-i)}$ respectively.

The MW with the highest ESE ratio is the most appropriate MW. The feature like Minimum_{pf} (min_{pf}), Maximum_{pf} (max_{pf}), Kurtosis_{pf}, Skewness_{pf}, RMS_{pf}, and Shannon Entropy (SE_{pf}) values of the DC_{pf} are calculated. The best features are chosen using the ReliefF algorithm. The selected features are normalized using Eq. 5.

$$Norm_{\text{Self\_PF}} = \frac{\max(Self_{pf})}{\max(Self_{pf})} \quad (5)$$

Where, Self_PF is one of the selected features from min_{pf}, max_{pf}, Kurtosis_{pf}, Skewness_{pf}, RMS_{pf}, and SE_{pf} using the ReliefF algorithm. The most beneficial characteristics are utilized to guide an ANN in fault detection. The best ANN structure is chosen based on accuracy from a pool of training structures.

3. Experiment Facilities and Instrumentation

The most crucial component in the training of ANN is a significant collection of real data with the actual problematic situations. It was discovered through the experimental design. A visual representation of the experimental setup is shown in Fig. 3. IGBTs are safeguarded against faults using the protection circuits. An IM may run at various operating speeds with a variable frequency drive. While choosing an IM, the motor speed range is carefully considered.

The CSAOCFD system records 09 defective conditions and one in good condition at varied speeds. Fig. 4 shows the few samples taken at 1200 rpm for various faulty states.

CSs acquired from a current signal is recorded and stored using a Digital Storage Oscilloscope (Tektronix manufacture TBS 1064, 60 MHz, 4 channels, measurement accuracy: vertical 3%, from 10 mV/div to 5 V/div). These signals are subjected to DWT analysis before being taken into account as data input for ANN processing. The input used for the experiment is displayed in Table 1.

4. Results and Discussion

Understanding the sensor data related to non-stationary signals is crucial. Multilevel analysis using DWT makes it feasible to do this. DWT is a frequently used method to gather data in the time and frequency domain. For each of the sample conditions listed in Table 1, the DC_{pf} feature extracted is compared.

The change in DC_{pf} values have been mirrored by the change in CSs under various defective conditions. Fig. 5 compares and illustrates it. It has been noted that DWT is used to investigate the abrupt rise and decrease in CSs in the frequency domain. DWT helps to locate and isolate unusual fault features. It is crucial to choose the right SP approach and the right features in order to extract usable information from nonlinear signals. The following often-used characteristics may be retrieved from the extracted features of CSs: min_{pf}, max_{pf}, Kurtosis_{pf}, Skewness_{pf}, RMS_{pf}, and SE_{pf}. The DWT is used to extract the necessary features from CSs.

Table 1. Input conditions for pilot experimentation

Conditions	IGBTs
Healthy Condition	All IGBTs Healthy
Single Switch OCFs	T1, T2, T3, T4, T5 and T6
Double Switch OCFs	T1-T3, T1-T6
Phase OCFs	T1-T4

DWT's time and frequency domain application efficiently displays the fault existing impulse. As indicated in Fig. 6, several MWs are tried at various levels to choose the optimal wavelet and level based on the highest ESE. The comparison of every MW taken into account is made at various stages of decomposition depending on the ESE ratio. The energy contained in a signal decreases as the degree of signal breakdown rises, as is evident for all MWs considered. As level one provides the most data for choosing wavelets and features, it is taken into consideration.

With the use of DWT, several MW types, including Daubechies (DB), Coiflet, Symlet, HARR, DMEY, Biorthogonal, and Reverse Biorthogonal, are taken into account throughout the analysis. The maximum ESE ratio is used to determine the appropriate amount of MW. For all wavelets considered, this ratio is greatest at level 1. Fig. 7 compares and plots the average ESE for each MW and for each fault class. Fig. 7 makes it obvious that DB2 and SYM2 have greater ESE ratios. Each wavelet's mathematical function is identical; therefore, anyone may be used. Hence, level 1 of DB2 MW is chosen for analysis. More DB2, as well as SYM2 systems, have higher average ESEs.

The DB2 wavelet is chosen as an appropriate MW, as previously stated. The knowledge from the output signal is examined using the 18 statistical features gathered. The RelifF technique is used to optimize the FeaSelon rank basis. The sample CSs for a defective condition at 1200 rpm is considered to provide the research's major aspects. All mother wavelets at level 1 clearly exhibit excellent ESE ratios. The explanation for this fact is that knowledge is more important than entropy at the early stages of signal decomposition. This is the rationale behind selecting level 1 for comparison. The RelieffF method is used to improve the rank basis feature. The rank 1 feature that is noticed is Kurtosis_{pf}. As a result, all signals' Kurtosis_{pf} features are discovered using DB2 at level 1. According to Fig. 8, the efficacy of the Kurtosis_{pf} feature when taken alone is 18.9%. Combined with the top seven ranked features for the fine Gaussian SVM classifier, as shown in Fig. 8, it improves up to 90.7%. It is obvious that the top seven features are all that is required to get the best efficiency for the fine Gaussian SVM classifier used in this implementation. With the help of Eq. 5, which is now known as Eq. 6, the Kurtosis_{pf} characteristic is normalized before being used as an input to train ANN

$$Norm_{\text{Kurtosis\_PF}} = \frac{\max\,(\text{Kurtosis}_{pf})}{\max\,(\text{Kurtosispf}_{pf})} \tag{6}$$

An ANN is trained using the $Norm_{\text{Kurtosis\_PF}}$ parameters as inputs. The $Norm_{\text{Kurtosis\_PF}}$ values for various defective situations for 3Φ current are calculated. Table 2 displays the different ANN architecture combinations that were taken into consideration. Tan sigmoid activation function and the Levenberg-Marquardt method approach have been employed for learning. The quantity of the training data, the neurons in the input, hidden, and output layers, as well as the initial weight given to the input signals, all play a role in choosing the optimum structure.

In ANN training, 7000 samples are taken into account, of which 1600 samples are from good conditions, and 5400 samples are from problematic situations. The samples are divided as follows: 50% of the whole sample is used for ANN training, 25% of the total sample is used for ANN testing, and the remaining 25% is used for ANN cross-validation. Machine Learning Models (MLMs) can ensure the best efficiency since they evaluate multiple models, starting with the most basic ones.

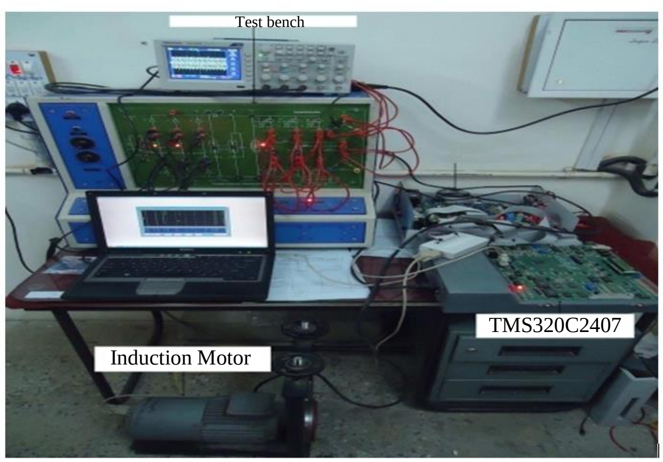


Fig. 3 A visual representation of the experimental setup

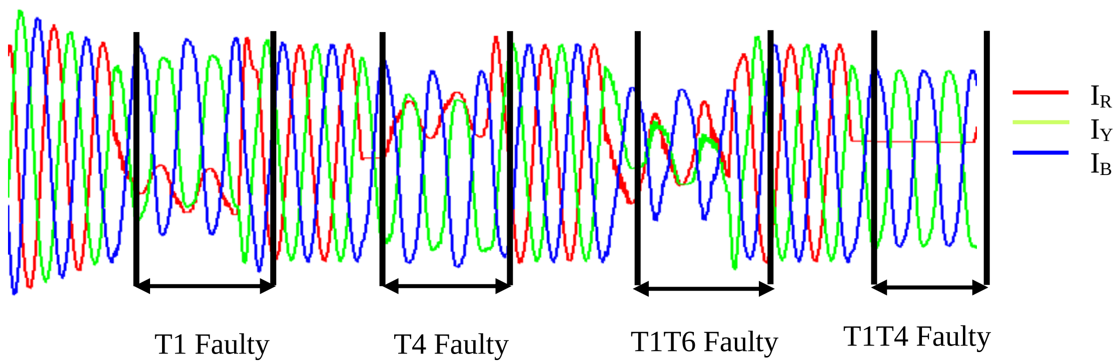
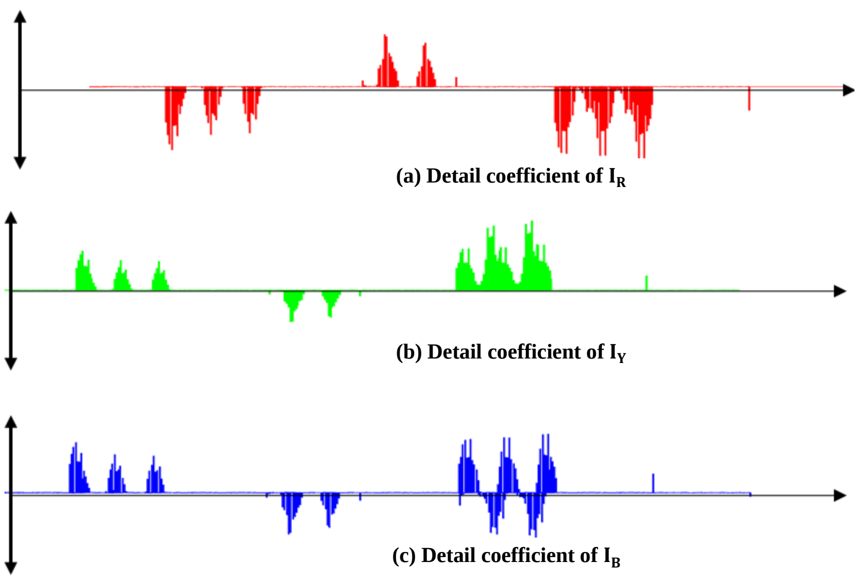


Fig. 4 Three-phase current waveform during healthy and faulty conditions



(a) Detail coefficient of I_R

(b) Detail coefficient of I_Y

(c) Detail coefficient of I_B

Fig. 5 Detail coefficients during healthy and faulty conditions

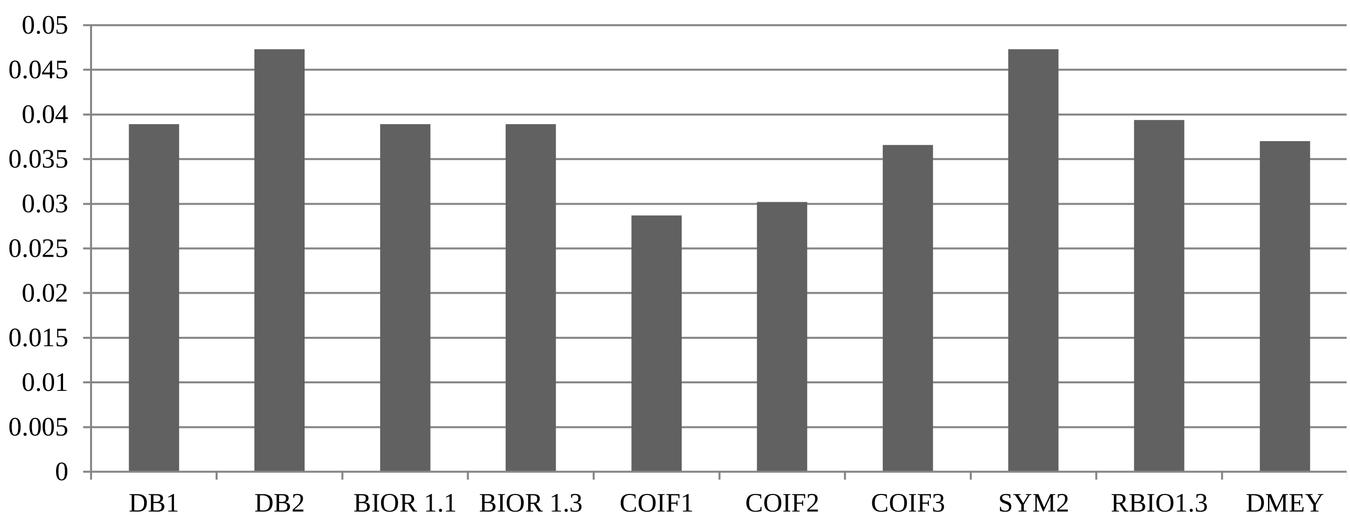


Fig. 6 MW comparison at several levels

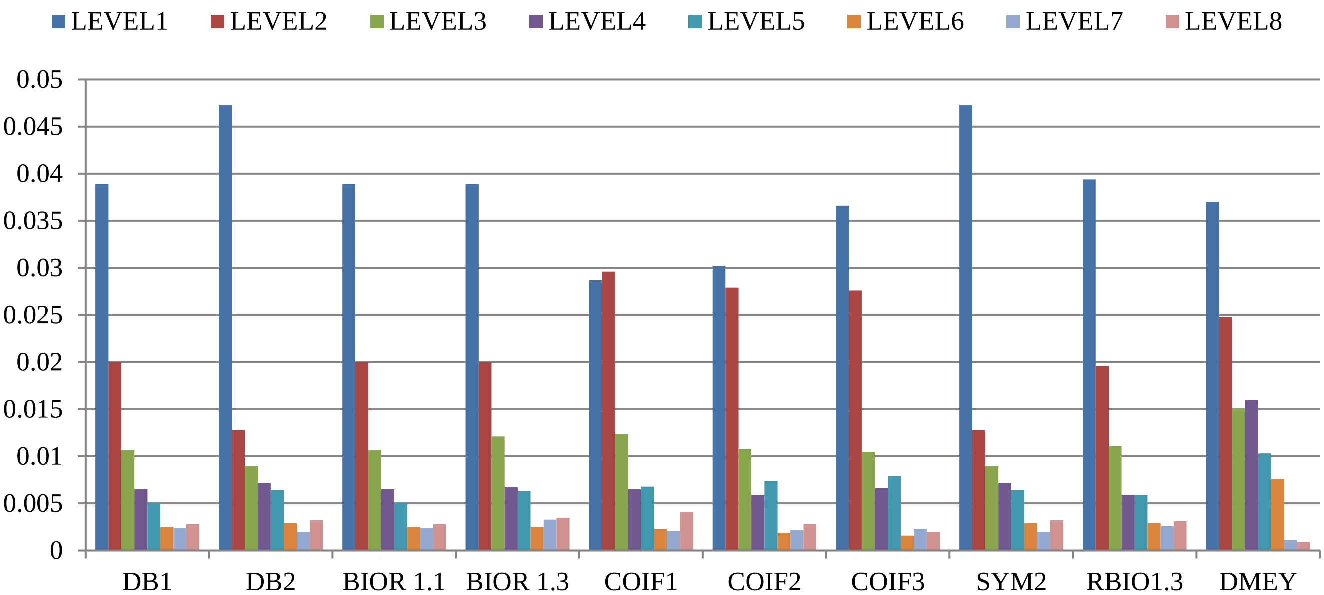


Fig. 7 Comparison of mother wavelet at different levels

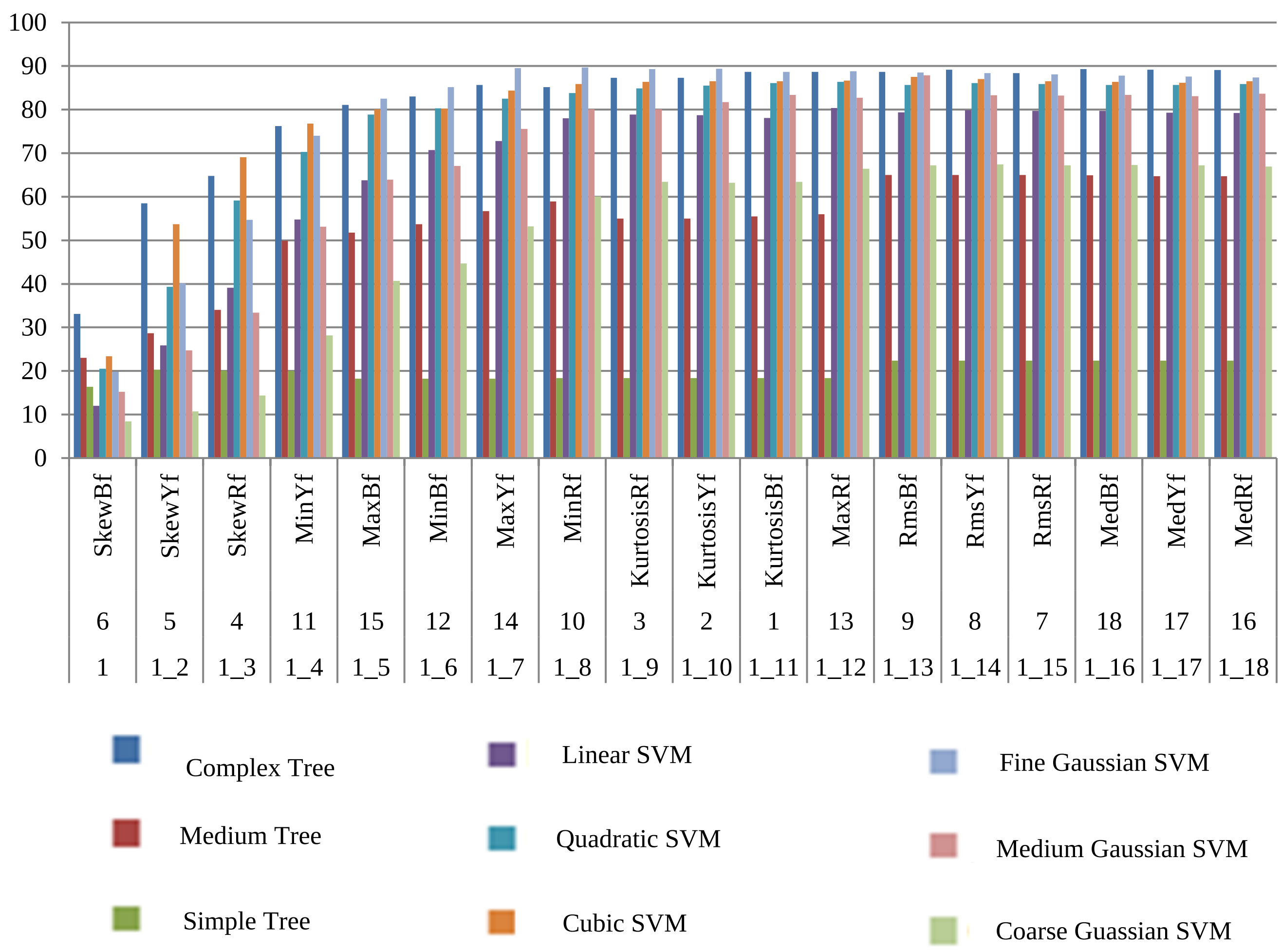


Fig. 8 Ranking-based feature selection using the ReliefF algorithm

Table 2. Evaluation of ANN structure

Structure	Learning rate	Accuracy
3-5-6	0.02	86.79
3-10-6	0.02	90.05
3-15-6	0.02	92.99
3-20-6	0.02	94.98
3-25-6	0.02	92.01
3-5-6	0.01	86.29
3-10-6	0.01	89.00
3-15-6	0.01	90.56
3-20-6	0.01	91.99
3-25-6	0.01	93.00

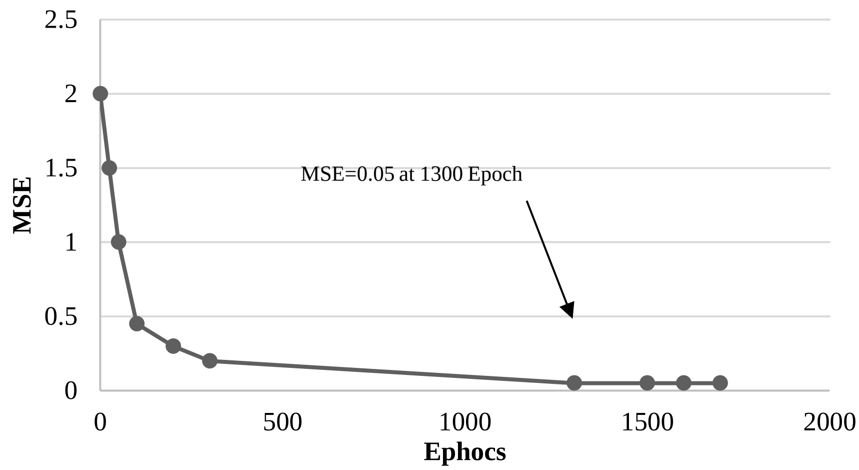


Fig. 9 Variation of MSE in the training of ANN

A technique for evaluating MLMs called cross-validation involves training several MLMs on portions of the available input data but instead evaluating them on the complementary portion of the data. To identify overfitting and MLM failure to generalize, use cross-validation. The three primary components of ANN architecture are input, hidden, and output layers. The three inputs for comparing the proposed structures are still as follows. The number of concealed layers is controlled by accuracy. So, the choice of the number of concealed layers 5, 10, 15, 20, and 25 is based on trial and error. During ANN training, the learning rate varies between 0.01 and 0.04. There are 1800 epochs taken into account. Table 3 displays the various testing and training structures that were considered.

Figure 9 illustrates how the ANN performed while training for structures 3-20-6 with a learning rate of 0.02. At 1250 epochs, an MSE of 0.049 was found. ANNs are trained, tested, as well as validated using MATLAB software. The method for three-phase VSI fault detection and diagnostics has been given. For the purpose of classifying faults, the features are extracted using DWT, and their normalized values are then put into neural networks. Here are lists of effectiveness as well as assessment measures. A technique is effective if it can identify the faulty switch. The implementation and testing of various fault detection and diagnosis systems hamper performance under fluctuating load conditions. The simulation results, displayed in Figure 10, demonstrate the system's accuracy in detecting open circuit failures under varied load conditions. This system has a remarkable ability to accurately classify faults under various load circumstances. It is advantageous to set as few thresholds and tolerances as feasible to create a generally applicable procedure.

The effectiveness of a neural network depends on how well it has been trained. The mean square error and hidden node count will determine how long it takes to train the neural network. The longer it takes to train the neural network, the more hidden nodes there are. For the selection of concealed nodes, there is no specific mathematical word. Consider the neural network trained if there is a smaller error between the target and the actual output. The difficulty of detecting the detection parameter, the complexity of the mathematical processes, and the decision-making process all affect the amount of work needed to execute an algorithm. The CSAOCFD method has a significant implementation effort.

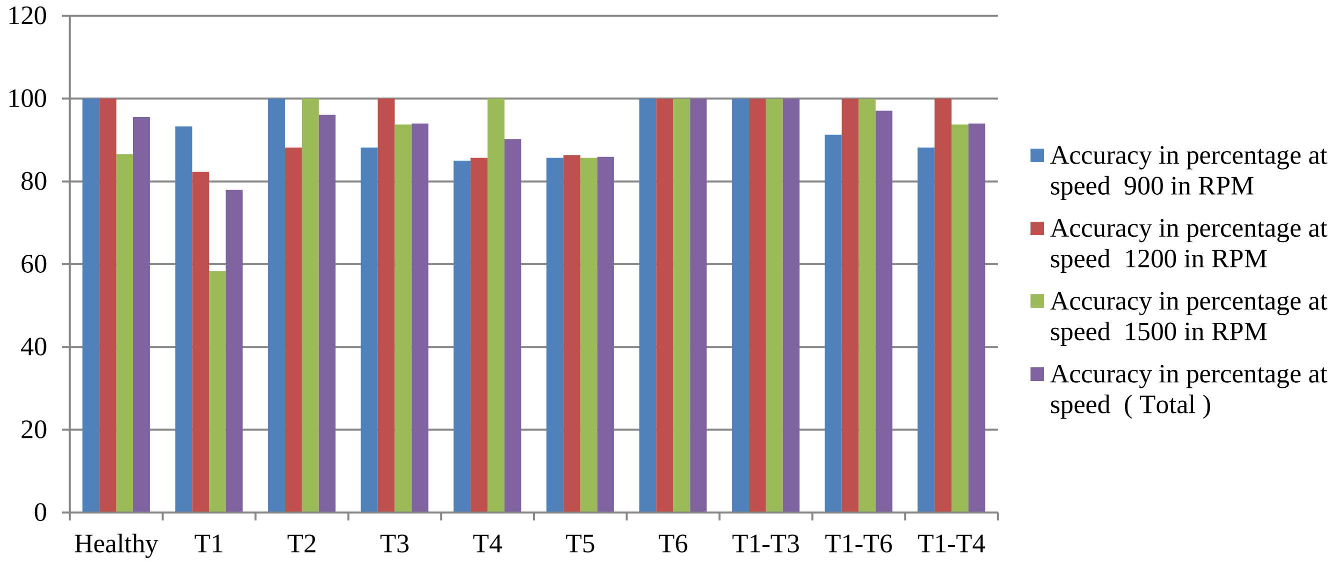


Fig. 10 Accuracy of open circuit fault at different speeds in RPM

5. Conclusion

A new protection algorithm is proposed in the system to enhance the performance, reliability, safety, and efficiency of 3Φ-VSIs. In order to prevent the traditional or catastrophic breakdown and to increase the reliability, efficiency, and performance of the power inverter, a new method for detecting defects in 3Φ-VSIs has been introduced. This is one of the best approaches with characteristics like ageing systems, high-reliability requirements, and cost competitiveness. The relevance of preventive and condition-based maintenance, online monitoring, system problem detection, and diagnosis is also growing. 3Φ-VSIs faults have been identified using the Daubechies wavelet transform of phase currents to demonstrate its efficacy and the faults have been classified using a neural network. The framework for detecting and diagnosing open circuit defects served as the foundation for developing neural networks. The average level of diagnostic accuracy has increased to about 95%. Also, the system displayed a trained, structured neural network system that can identify and isolate any of the nine defects. It can be concluded that the suggested model-based fault diagnostic strategy combined with machine learning techniques reliably and effectively detects the faults occurring in 3Φ-VSIs.

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