Comparative Study of Three Fault Diagnostic Methods for Three Phase Inverter with Induction Motor

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Abstract
In recent times, inverters are considered as the basic building block in an electrical drive system used widely in many industrial drive applications. However, the reliability of these inverters is mainly affected by the failure of power electronic switches. Various faults in inverter may influence the system operation by unexpected maintenance, which increases the cost factor and reduce overall efficiency. In this paper, comparative study of three different fault detection and diagnosis systems for three phase inverter is presented. The basic purpose of these fault detection and diagnosis systems is to detect single or multiple faults efficiently. These techniques rely on the neural network for fault detection and diagnosis by using Clarke transformed two-dimensional features extraction, three-dimensional features extraction and features extraction using discrete wavelet transform (DWT) with a different number of features in each technique. Several features are extracted using different mechanisms and used in the neural network as input for fault detection and diagnosis. Furthermore, a simulation study is carried out to analyze the fault detection and diagnosis response of these techniques. Also, a comparative study has been performed by considering fault detection time and accuracy. Comparison results prove the supremacy of three-dimensional feature extraction technique over other two techniques as it can detect and diagnose single, double and triple faults in a single cycle with high accuracy as compared to other two techniques multi-cycles detection.

Keywords: Fault detection and diagnosis, Electrical drive system, Clarke transformation, Features extraction, Neural network system, Discrete wavelet transform

1. Introduction
Voltage source inverters (VSIs) are widely used in variable speed electric motor drives, uninterruptible power systems and filters, electric vehicles and most recently, in renewable energy conversion systems. There are several types of a fault such as controller faults, current sensor faults, switching device faults, motor faults and dc bus faults. Any of these faults in VSI’s can result in severe damage to human life and the surrounding environment in applications such as aerospace, military and medical. Hence, the reliability of these inverters becomes an important factor in ensuring their safe and efficient performance during different fault occurrence. Furthermore, high costs due to stand still and repair, as well as general need to improve reliability, have led to research in fault detection systems. Usually, fault
tolerant system consists of three major features such as component redundancy, fault detection and isolation and reconfiguration system. Fault diagnosis is the combination of fault detection and identification. Primary detection of faults can guarantee the reliability and safety of the system. Due to high thermal and electrical stress, high probability of switching devices failure exists. These switching device faults can be generally classified into open switch fault and short switch fault. Open switch faults are focused in this research as they need to be handled immediately. Frequently occurring open switch faults don’t only require a halting operation, but noise and vibrations can also be induced in the system. Furthermore, the overcurrent flow in healthy switches can cause additional faults in these switches [9,10]. Regarding diagnostic of these open switch faults, several methods by using output currents have been proposed based on various techniques. Some of these techniques are neural network method [11,12], artificial intelligence [13], wavelet transform [14–16], current deviation method [17], fuzzy logic [18,19] and normalized dc current method [20,21]. In [22], induction machine faults based on time-frequency representation and feature vector size was optimized by PSO. Whereas in [23], a fault tolerant control of five phase induction motor was formulated under the single phase open circuit. Control method was designed based on third harmonic injection. Some other methods were based on the analysis of output voltage of power systems [24,25]. These methods compared the measured and reference voltages to detect faulty switches. The majority of above-mentioned methods are able to detect IGBT open circuit faults in more than one fundamental period or they are unable to detect multiple faults at a time due to unsuitable feature extraction. Some of these techniques are suitable for constant speed environment only.

Keeping in mind the aforementioned problems, this paper presents a comparison of three diagnostic methods based on the Clarke transformed two-dimensional features extraction for neural network method based diagnosis, three-dimensional features extraction for neural network-based diagnosis and two-dimensional feature extraction using DWT technique. In voltage source inverter, single and multiple open switch faults can be diagnosed and identified using these techniques. Simulation studies are carried out to analyze these diagnostic methods response. Furthermore, diagnostic time and efficiency in detecting faults of these methods are compared.

This paper is organized as follows: Section 2 explains the fault detection system structure and fault generation mechanism. Section 3 explains the three diagnostic methods for three phase inverter open switch faults detection. Section 4 illustrates the detailed simulation results along with comparative study whereas Section 5 outlines the conclusion.

2. Fault Detection System Structure

Three-phase inverter with ‘Y’ connected load is shown in Figure 1. Six gate transistors of inverter named T1-T6 are considered for fault scenarios. As we know, fault detection is directly dependent on the output load current or voltage which is sensed using sensors and sampled for further process. Then, efficient but different features extraction techniques are used in discussed three fault detection methods to get the maximum possible effective and versatile features.

2.1 Fault Generation

In all three fault detection and diagnosis techniques, the fault has been generated externally to check the performance of designed systems in faulty scenarios. Single and multiple faults are generated by opening the inverter IGBT’s so that signal without respective phase can be given to the system. There is a high possibility of same phase both gates fault in multiple faults situation.

3. Fault Detection and Diagnosis System Model

Efficient fault detection and diagnosis can avoid standstill and unplanned maintenance, to make possible to run an emergency operation in case of faults. In this research work, we considered two faults situations; i.e., 1) single fault, 2) multiple faults at a time. All three techniques are briefly discussed to understand the process of fault detection.

Figure 1. Common structure of three phase inverter.
3.1 Clarke Transformed Two-Dimensional Feature Extraction for Neural Network based Fault Detection (Technique 1)

Feature extraction is a process which can provide neural network enough significant information in the pattern set to achieve the highest accuracy in neural network performance. Feature extraction system should be universal for different speed references by normalized functions. Also, localization of each pattern class should be in limits defined by the threshold. In this fault detection and diagnosis technique [12], four features are extracted to be used as input of neural network. A high number of features play a vital role to make the system more accurate and effective by differentiating single and multiple faults. Block diagram for Technique 1 is shown in Figure 2.

To get the features in the Simulink environment, these features are explained using equations (1)-(4) For every possible scenario, faults are generated manually to obtain the features in faulty condition. This process is repeated several times for every possible change in data due to noise and other unpredictabilities in a real-time environment. Furthermore, for better neural network training, features data threshold limit is determined in each faulty condition based on data collected previously. The neural network is further trained with this organized data set.

As shown in the block diagram, fault detection using this technique is based on three steps. In the start, measured output three phase current data is transformed to two-phase using Clarke transformation. This transformation is performed to evaluate the stator current pattern evolution when open circuit power switches fault occur in the inverter as shown in Figure 3. The four features extraction is performed: i.e., mean for both axis, angle and surface difference. These features are further given as input to the neural network for fault detection process which generates 0 or 1 as output to identify if the system is in normal or faulty condition respectively.

First two features (mean) for two-dimensional current signal can be calculated as (1) in which $N$ defines the number of samples:

$$I_{\alpha} = \frac{\sum_{i=1}^{N} I_{\alpha}(i)}{\text{length}(I_{\alpha})},$$

$$I_{\beta} = \frac{\sum_{i=1}^{N} I_{\beta}(i)}{\text{length}(I_{\beta})}.\tag{2}$$

As shown in Figure 4, third feature surface difference of the current pattern between normal and fault condition can be calculated as

$$E_S = S_N - S_f,\tag{3}$$

where $S_N$ is current vector surface in normal mode and $S_f$ is current vector surface in faulty mode. Fourth feature angle to the current pattern with $I_\beta$ as center of the $\beta$- frame, and $I_\alpha$ as the center of $\alpha$-frame can be calculated as follows:

$$I_\theta = \tan^{-1}\left(\frac{I_\beta}{I_\alpha}\right).\tag{4}$$

Features data from these equations show the sufficient decorrelation between different fault scenarios.

3.1.1 Neural network

As shown in Figure 5, the architecture of the neural network used in this fault detection technique is a feed forward network with the four inputs. A used neural network composed of one input layer consists of four neurons, one hidden layer with fifteen neurons and one output layer with thirteen neurons and target output of 0 or 1, each of which represents different health condition of the system. The sigmoid activation function is used for hidden and output layers. In the start, the neural network is usually trained with the dataset of normal and faulty data. After that, trained network is further used for fault detection and diagnosis purpose.
3.2 Three Dimensional Feature Extraction for Neural Network-based Fault Detection (Technique 2)

As shown in block diagram in Figure 6, three phase output currents are considered for feature extraction in Technique 2. These three phase current values create a 3D circle in normal/healthy condition. Equation (5) explains the 3D circle.

\[ R^2 = I_a^2 + I_b^2 + I_c^2. \]  

(5)

This 3D circle changes its shape in a specific pattern for each fault scenario. Each single and multiple faults have its own 3D pattern. Various extracted features using three-phase current are explained with equations.

As we mentioned before, voltage 3D plot has a specific and different shape for each fault situation. Hence, it will give a unique value for a mean of each phase in three-dimensional space. Equations (6)-(8) are used to derive mean of each phase.

\[ I_a(\text{mean}) = \sum \frac{I_a}{N}, \]  

(6)

\[ I_b(\text{mean}) = \sum \frac{I_b}{N}, \]  

(7)

\[ I_c(\text{mean}) = \sum \frac{I_c}{N}. \]  

(8)

Next feature to be extracted in this technique is angle calculation for the above-derived mean points. Angles are calculated for every 3D plotted current mean point. As any variation or missing phase will change the mean point location in three-dimensional space, therefore unique angles for each faulty situations can be extracted. Two angles are calculated for each mean value in both directions with respect to each axis which gives us six angles collectively. Equations (9)-(14) are used to derive these six angles.

\[ \text{atanBA} = \tan^{-1}\left(\frac{I_b(\text{mean})}{I_a(\text{mean})}\right), \]  

(9)

\[ \text{atanCA} = \tan^{-1}\left(\frac{I_c(\text{mean})}{I_a(\text{mean})}\right), \]  

(10)

\[ \text{atanAC} = \tan^{-1}\left(\frac{I_a(\text{mean})}{I_c(\text{mean})}\right). \]  

(11)
The neural network structure is same as of the first technique explained in Section 3.1.1 except the number of neurons in the input layer which represents the number of features extracted in specific fault detection technique.

3.3 Feature Extraction using Discrete Wavelet Transform for Neural Network based Fault Detection (Technique 3)

To develop an efficient fault detection and diagnosis system, DWT technique plays an important role for features extraction from output three-phase current signal. In this technique, DWT is used for features extraction and then the extracted data is used as input of neural network for fault identification.

Let \( c_0[n] \) be the original signal sequence. After convolution with \( h \) and \( g \) quadrature mirror filters, it is decomposed into an approximation component \( c_1[n] \) and a detail component \( d_1[n] \) at scale 1. The approximation component \( c_1[n] \) is further decomposed into \( c_2[n] \) and \( d_2[n] \) at the next scale and so on. Mathematically it can be represented by (15)-(16) In these equations, \( m \) represents the scale of decomposition, \( n \) represents the sampling point and \( k \) represents the translation coefficient.

\[
c_m[n] = \sum_k h[k - 2n] c_{m-1}[k], \quad (15)
\]

\[
d_m[n] = \sum_k g[k - 2n] c_{m-1}[k], \quad (16)
\]

In these equations, \( n \) defines the number of samples, \( c_2 \) is approximate component obtained after level 2 DWT, \( d_1 \) and \( d_2 \) are the detailed components.

Another feature named energy of each detailed signal at each level \( j \) and the total energy for all levels can be extracted from (23)-(24), respectively.

\[
E_j = \sum_{j=1}^{j} |D_j(k)|^2, \quad (23)
\]

\[
E_{total} = \sum_j \sum_k |D_j(k)|^2 = \sum_j E_j. \quad (24)
\]
Figure 8. Block diagram for feature extraction using DWT for ANN based fault detection.

Then these extracted features are used as input of the neural network for fault detection. The neural network structure is same as of Section 3.1.1 except the different number of neurons in the input layer which represents the number of extracted features in specific fault detection technique.

4. Simulation Studies

Designed fault detection and diagnosis systems are discussed here in detail. These systems are tested with single, double and triple faults.

4.1 Fault Detection Technique 1

Simulink diagram of the designed system can be seen in Figure 9. As we can see, the induction motor is connected as load whereas three phase output current is used for feature extraction and further as input to the neural network for fault detection as shown in Figure 10. Features extracted for neural network training are shown in Table 1. Simulation results show that this technique can detect single and double faults with high accuracy whereas it can detect triple faults up to 90% accuracy.

4.2 Fault Detection Technique 2

In this technique, the three-phase output current is used for fault detection purposes. System block diagram is shown in Figure 11 whereas the extracted features data is shown in Table 2. Simulation results show that this detection method can detect and identify the single, double and triple faults with high accuracy and one cycle time period.

4.3 Fault Detection Technique 3

As shown in Figures 12 and 13 of Technique 3, we use three phase current and transform it in two dimensions. Furthermore, DWT is used to extract appropriate features for fault detection. Initially, the system is operated a number of times to obtain data
for neural network training as explained in Section 2. Then this extracted data is used in the trained neural network for fault detection. Feature extraction data is shown in Table 3.

4.4 Simulation Results and Comparative Study

Designed neural network-based fault detection and diagnosis systems for the three-phase inverter in a variable speed drive are tested multiple times in the case of single and multiple faults at a time. Simulation results for all explained fault techniques have been discussed here. Feature data mentioned in Tables 1-3 are used to train neural network separately and then same fault types are detected to compare the fault identification methods response. In the simulation test sets, systems show overall satisfactory classification performance in both single and multiple faults cases. As shown in Figures 10, 11, and 13, the neural network will identify faults and give output “1” across respective fault display. Simulation for each technique is carried out more than 65 times to collect the fault detection data for comparative studies. Output results in Figures 14-16 show that Technique 2 is much better in comparison to Techniques 1 and 3 as it can detect single, double and triple faults with 100% accuracy in one cycle period of output current or voltage.

In Technique 1, the system shows high accuracy in single and double faults but 90% accuracy in case of triple faults due to less number of features to differentiate triple faults. The reason behind this issue is that in case of triple faults, two-dimensional
pattern similarity is high and we have a small number of features to identify the specific switch fault. Therefore, the neural network is unable to identify the specific fault due to much similar data and mix up the fault type in the end. In the case of Technique 3, the system shows high accuracy in single and double faults but triple fault accuracy is nearly 70% due to the similarity of feature data in such complex case. As shown in Figure 16, system unable to detect and differentiate the faults due to the similarity between features of respective gate faults. Also, it takes more than 3 cycles of output current to identify faults. The reason behind its slow detection is the complex method to identify and detect the gate faults. In this technique, initially DWT is used to extract the features in separate file due to the system complexity and these features are saved in MATLAB workspace. Then in the separate Simulink file, these features are used to detect and identify the faults using a neural network. Likewise in a real system, this data similarity while detection or dissimilarity with the trained neural network can happen due to random noise or other environmental uncertainties. Comparative data is given in Table 4.

Table 2. Feature data for Technique 2

| System condition | $I_a$ (mean) | $I_b$ (mean) | $I_c$ (mean) | Feature for training |
|------------------|-------------|-------------|-------------|----------------------|
| Normal           | 1.23        | 1.28        | 1.25        | atanBA               |
|                  |             |             |             | atanCA               |
|                  |             |             |             | atanAC               |
|                  |             |             |             | atanBC               |
|                  |             |             |             | atanAB               |
|                  |             |             |             | atanCB               |
| T1               | -2.25       | 1.9         | 1.9         | 310                  |
|                  |             |             |             | 140                  |
|                  |             |             |             | 45                   |
|                  |             |             |             | 45                   |
| T2               | 2.3         | 0.55        | 0.5         | 15                   |
|                  |             |             |             | 15                   |
|                  |             |             |             | 78                   |
|                  |             |             |             | 45                   |
|                  |             |             |             | 78                   |
| T3               | 1.9         | -2.3        | 1.9         | 140                  |
|                  |             |             |             | 45                   |
|                  |             |             |             | 45                   |
|                  |             |             |             | 140                  |
|                  |             |             |             | 310                  |
| T4               | 0.5         | 2.44        | 0.5         | 78                   |
|                  |             |             |             | 45                   |
|                  |             |             |             | 45                   |
|                  |             |             |             | 78                   |
|                  |             |             |             | 12                   |
| T5               | 1.9         | 1.9         | -2.22       | 45                   |
|                  |             |             |             | 140                  |
|                  |             |             |             | 310                  |
|                  |             |             |             | 45                   |
| T6               | 0.5         | 0.5         | 2.3         | 45                   |
|                  |             |             |             | 78                   |
|                  |             |             |             | 12                   |
|                  |             |             |             | 12                   |
| T1&T2            | -1.25       | 1.22        | 1.22        | 315                  |
|                  |             |             |             | 315                  |
|                  |             |             |             | 140                  |
|                  |             |             |             | 45                   |
|                  |             |             |             | 140                  |
| T1&T3            | 1.12        | 1.24        | -1.24       | 45                   |
|                  |             |             |             | 130                  |
|                  |             |             |             | 310                  |
|                  |             |             |             | 45                   |
|                  |             |             |             | 135                  |
| T2&T3            | 2.5         | -2.5        | 1.43        | 135                  |
|                  |             |             |             | 28                   |
|                  |             |             |             | 60                   |
|                  |             |             |             | 150                  |
|                  |             |             |             | 315                  |
|                  |             |             |             | 298                  |
| T4&T6            | -1          | 1.88        | 1.88        | 330                  |
|                  |             |             |             | 330                  |
|                  |             |             |             | 119                  |
|                  |             |             |             | 45                   |
|                  |             |             |             | 119                  |
| T4,T5&T6         | -0.14       | 1.76        | -1.24       | 357                  |
|                  |             |             |             | 260                  |
|                  |             |             |             | 188                  |
|                  |             |             |             | 322                  |
|                  |             |             |             | 96                   |
|                  |             |             |             | 125                  |
| T1,T2&T3         | -1.3        | -2.08       | 1.9         | 238                  |
|                  |             |             |             | 325                  |
|                  |             |             |             | 124                  |
|                  |             |             |             | 135                  |
|                  |             |             |             | 210                  |
|                  |             |             |             | 312                  |

Table 3. Feature data for Technique 3

| System condition | Mean energy | Mean variance | Mean wavelength | Mean energy | Mean variance | Mean wavelength | Mean energy | Mean variance | Mean wavelength | Mean entropy |
|------------------|-------------|--------------|----------------|-------------|--------------|----------------|-------------|--------------|----------------|--------------|
| Normal           | 0.03233     | 0.01607      | 1.314          | 0.01407     | 0.1126       | 3.056          | 0.02534     | 0.567        | 0.3709         | 0.03285      |
| T1               | 0.003952    | 0.0257       | 41.88          | 69.35       | 52.63        | 50.02          | 0.003888    | 0.02458      | 21.15          | 51.6         | 50.67          | 49.69        |
| T2               | 0.003952    | 0.02544      | 41.86          | 69.51       | 53.42        | 49.92          | 0.003876    | 0.02451      | 21.26          | 52.51        | 51.24          | 50.24        |
| T3               | 0.003971    | 0.02534      | 29.87          | 69.42       | 53.33        | 49.91          | 0.003764    | 0.0244      | 38.63          | 51.98        | 50.62          | 50.11        |
| T4               | 0.003963    | 0.02547      | 29.82          | 69.41       | 52.9         | 50.04          | 0.003755    | 0.02445      | 39.62          | 51.49        | 50.46          | 49.89        |
| T5               | 0.003006    | 0.02012      | 32.1           | 73.34       | 54.46        | 50.2           | 0.004419    | 0.02811      | 38.56          | 51.5         | 51.07          | 49.89        |
| T6               | 0.003006    | 0.02013      | 32.1           | 73.29       | 53.46        | 50.02          | 0.004423    | 0.02807      | 38.48          | 51.66        | 50.06          | 49.87        |
| T1&T2            | 0.002201    | 0.0141       | 48.18          | 78.18       | 57.58        | 50.16          | 0.001651    | 0.01074      | 2.345          | 57.89        | 53.3           | 51.97        |
| T1&T3            | 0.00217     | 0.01403      | 22.82          | 77.49       | 56.73        | 49.78          | 0.001385    | 0.009736     | 42.27          | 57.35        | 54.03          | 49.96        |
| T4&T6            | 0.05648     | 0.1175       | 2.615          | 0.008896    | 0.1701       | 0.718          | 4.733       | 0.0145       | 0.567          | 0.8622       | 2.676          | 0.03078      |
| T4,T5&T6         | 0.0007143   | 0.004564     | 46.07          | 90.32       | 66.94        | 45.38          | 0.0005052   | 0.0034       | 3.741          | 66.47        | 56.5           | 59.52        |
| T1,T2&T3         | 0.0002333   | 0.002061     | 23.3           | 98.06       | 82.94        | 46.28          | 0.0008219   | 0.005302     | 41.5           | 59.88        | 55.42          | 46.14
Table 4. Comparison table between three techniques

| Fault detection Technique | Fault scenario (%) | Response time | Comments |
|--------------------------|-------------------|--------------|----------|
|                          | Single | Double | Triple |         |
| Technique 1              | 100    | 100    | 100    | Fast    | Low computational and detection time, independent feature values for all types of single and multiple faults |
| Technique 2              | 100    | 95     | 95     | Medium  | Less complex system due to small number of features, less accuracy in case of triple faults due to Clarke transformed features data mixing |
| Technique 3              | 100    | 90     | 70     | Medium  | High computational time due to large calculations of DWT data, slow response, frequent missing of triple faults due to features data similarity |

Figure 14. Current pattern graph in normal condition.

Figure 15. Current pattern graph in single fault condition.

Figure 16. Current pattern graph in triple fault condition.

As it can be seen in the comparative table, Technique 2 can detect single, double and triple faults with the highest accuracy whereas Technique 1 and Technique 3 lack the accuracy in double and triple faults, respectively. Response time for gate fault detection is also shown in this table. Technique 2 takes less than 2.5 ms to detect the generated fault whereas Technique 1 takes almost 5 ms and Technique 3 takes 8-10 ms for the same fault in same environmental conditions. Furthermore, the reason behind the comments given in this table is discussed briefly in Section 4.

5. Conclusion

In this research work, comparative study of three fault detection and diagnosis techniques for a three-phase inverter with induction motor is presented. This study aims to solve the problem of efficient and robust detection of single and multiple faults in the system. Considered fault types for the system are switch-
ing device open faults. Various feature extraction systems are discussed here. These extracted features play a vital role in fault detection and localization in respective technique. No additional sensors and complicated calculations are required for designed systems. Furthermore, all these three techniques are used in same environment and conditions to detect same faults to verify their performance. Technique 2 based on three phase output current shows the best performance due to the high dissimilarity between extracted features and comparatively simple design model. Additionally As discussed in Section 4.4, comparative studies show that three-dimensional feature extraction for neural network-based fault detection system can detect single and multiple faults with high accuracy as compared to other two techniques. Furthermore, the simplicity of this system also shortens the response time as compared to Technique 1 and 3. In future work, this technique will be used to analyze faults in three-phase motors, generators, and energy management systems.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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