

Comparative Study of Fault Diagnostic Methods in Voltage Source Inverter Fed Three Phase Induction Motor Drive

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Abstract. Three phase Pulse Width Modulation inverter plays vital role in industrial applications. The performance of inverter degrades as several types of faults take place in it. The widely used switching devices in power electronics are Insulated Gate Bipolar Transistors (IGBTs) and Metal Oxide Field Effect Transistors (MOSFET). The IGBTs faults are broadly classified as base or collector open circuit fault, misfiring fault and short circuit fault. To develop consistency and performance of inverter, knowledge of fault mode is extremely important. This paper presents the comparative study of IGBTs fault diagnosis. Experimental set up is implemented for data acquisition under various faulty and healthy conditions. Recent methods are executed using MATLAB-Simulink and compared using key parameters like average accuracy, fault detection time, implementation efforts, threshold dependency, and detection parameter, resistivity against noise and load dependency.

1. Introduction

In many industrial applications the Voltage Source Inverters (VSI) are used to convert DC power into AC power. In automation industries, VSIs are used to drive AC induction motor (ACIM). Different faults can occur in ACIM, 38% faults in ACIM are caused due to failure of power devices, electrolytic capacitors, and other electronic components [1]. The breakdown of switching devices in power electronics like IGBTs or MOSFETs are broadly classified as [2]:

- Base or collector open fault,
- Misfiring fault and
- Short circuit fault

During IGBT collector or base open situation, IGBT remains in off condition. Thermal cycling is one of the reasons for incidence of base or collector open fault, whose root cause is stirring of linking wires. Another reason of IGBT base or collector open fault is fault in driver circuit otherwise a short-circuit-fault. The electrical system is able to work in IGBT base or collector open faulty condition with less performance. The short circuit fault occurs because of an incorrect voltage across gate. This can be reason of driver circuit break down or supplementary power supply breakdown. One more reason for short circuit fault is an intrinsic failure which may occur due to overvoltage/avalanche stress or temperature overshoot. IGBTs can tolerate short circuit fault up to 10 μ s [3]. The



fault diagnostic methods are classified into Knowledge based systems, Model based systems, Signal based system, and Hybrid-Active fault diagnosis approach. In this paper Knowledge based systems and Hybrid fault diagnosis approaches are discussed. These methods are classified shown in Figure 1. The Discrete Wavelet Transform (DWT) and Fuzzy Logic (FL) are collectively applied for fault diagnosis of single IGBT for variable speed drive systems [9][10]. But this combination is not appropriate for fault diagnosis of multiple IGBTs for variable speed drive system. The features extracted from Detailed Coefficients (DC) of DWT are used to train Artificial Neural Network (ANN) in [11]. This method is suitable for fault diagnosis of multiple IGBTs and less than 5% errors are reported. The Fault Diagnostic Systems (FDSs) based on the combination of Park's Vector Transform (PVT) with the Fuzzy Logic (FL), ANN or Clusterive-Adaptive Fuzzy Neural Network (C-ANFIS) is proposed in [6], [7] and [8]. The methods proposed in [1] and [12] are more robust under variable load conditions but not able to diagnose short circuit faults. The combination of Entropy and ANN has been proposed for fault diagnosis of open circuit and short circuit fault diagnosis in [3]. The methods proposed in [3], [6], [8], [9] and [11] are called as NSADDFDS. The diagnostic variables (DV) and average current of 3Φ currents are used for fault classification of base or collector open fault in IGBTs for variable speed drive system [1] and [10]. The fault classifier is implemented using If-Then rules and known as Qualitative KFDM. The If-Then rules are implemented based on the expert knowledge. The Qualitative KFDM has low generality and low expandability [5].

In this paper recent methods which are commonly used in FDS are implemented using MATLAB-Simulink and compared using key parameters like average accuracy, fault detection time, implementation efforts, threshold dependency, detection parameter, resistivity against noise and load dependency.

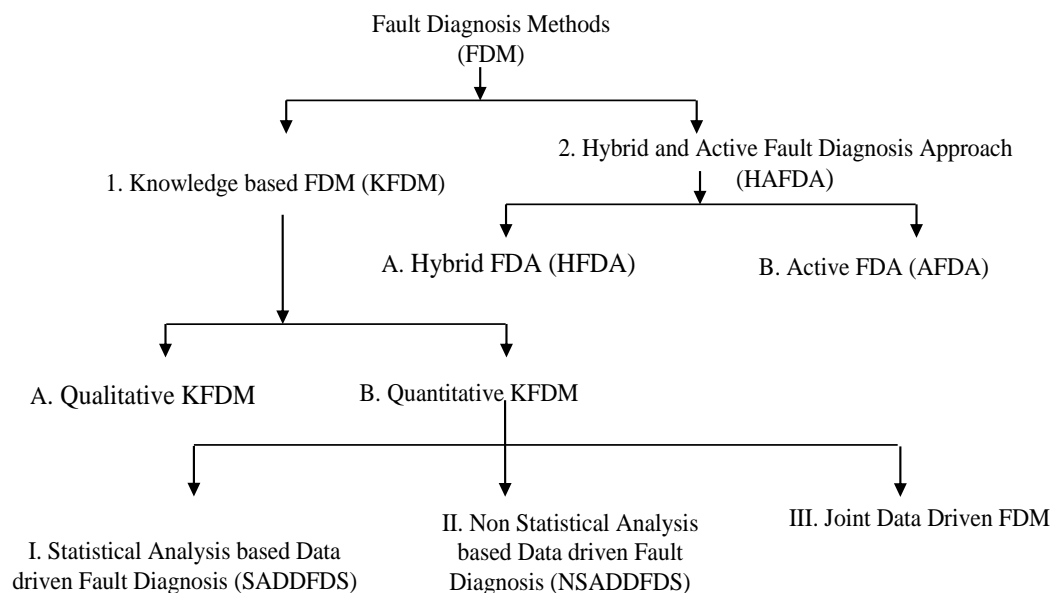


Figure 1. Classification of fault diagnostic methods

2. Voltage Source Inverter

The fundamental arrangement of 3 Φ inverter is shown in Figure 2. In 3 Φ inverter is implemented using six IGBTs which work complimentary. For standard situation, 3 Φ inverter provides entirely balanced 3 Φ sinusoidal currents and voltages as given by equation 1 and equation. 2.

$$i_n = \begin{cases} i_R = I_m \sin(\omega_s t + \phi) \\ i_Y = I_m \sin\left(\omega_s t - \frac{2\pi}{3} + \phi\right) \\ i_B = I_m \sin\left(\omega_s t + \frac{2\pi}{3} + \phi\right) \end{cases} \quad 1$$

Where n = R, Y or B, is the maximum amplitude of current, frequency and initial phase angle are given by I_m , $\omega_s t$ and ϕ .

$$v_n = \begin{cases} v_R = V_m \sin(\omega_s t + \phi) \\ v_Y = V_m \sin\left(\omega_s t - \frac{2\pi}{3} + \phi\right) \\ v_B = V_m \sin\left(\omega_s t + \frac{2\pi}{3} + \phi\right) \end{cases} \quad 2$$

Where maximum amplitude of voltage is given by V_m .

Different FDSs are listed below and detail explanation will be given in Section III. Performance of the FDS is compared in Section IV.

A. DWT-FL [10],

B. DWT-ANN [13],

C. Diagnostic Variables and Average Value of 3 Φ Current [12],

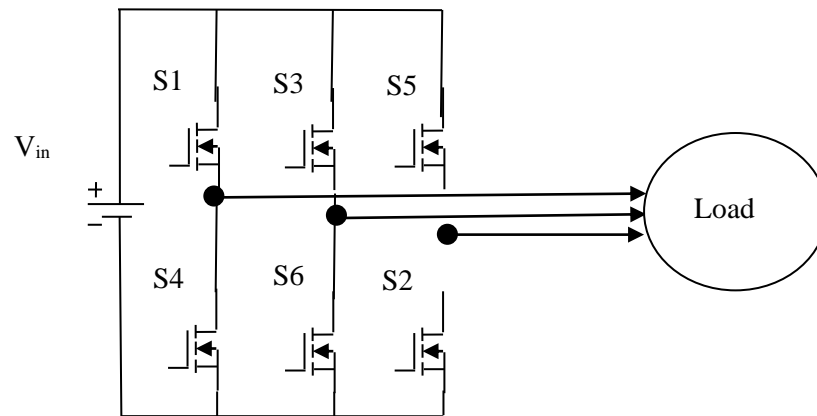


Figure 2. Three Phase VSI

3. Different Methods of Fault Diagnosis

3.1. Discrete Wavelet Transform - Fuzzy Logic (DWTFL)

The block diagram of DWTFL is shown in Figure 3. This method is implemented using three phase currents i_R , i_Y and i_B . Three phase currents are converted into data packets, each data packet consist of samples for 72° of fundamental current signals. The three phase currents are passed through DWT to compute *detail coefficients* (DCs) and *approximate coefficients* (ACs). h_n and g_n are responses of *Low Pass Filter* (LPF) and *High Pass Filter* (HPF) in DWT calculated using equation 3 and equation 4 respectively. Minimum (*min*) and maximum (*max*) values of DCs are extracted at various load

conditions. K_d and K_f are selected as upper and lower threshold values respectively observing different values of DCs. The *min* and *max* values are compared with K_d and K_f to generate *fault diagnosis signatures* as given in equation 5. The fault signatures are created as shown in Table 1. Figure 4 shows the stator currents and *detail coefficients* of S1, S4, S1S6 or S1S4 open-circuit fault. DB4 mother wavelet is used for analysis. IGBT open circuit fault established the direct current offset in stator currents, which is clearly observed in Fig. 4. A higher direct current offset is noticed in phase in which IGBT is faulty, as compared to the healthy phases. Also, the polarity of direct current offset in faulty phase is opposite with the other two phases. A *Fuzzy Inference System (FIS)* is implemented observing fault signatures.

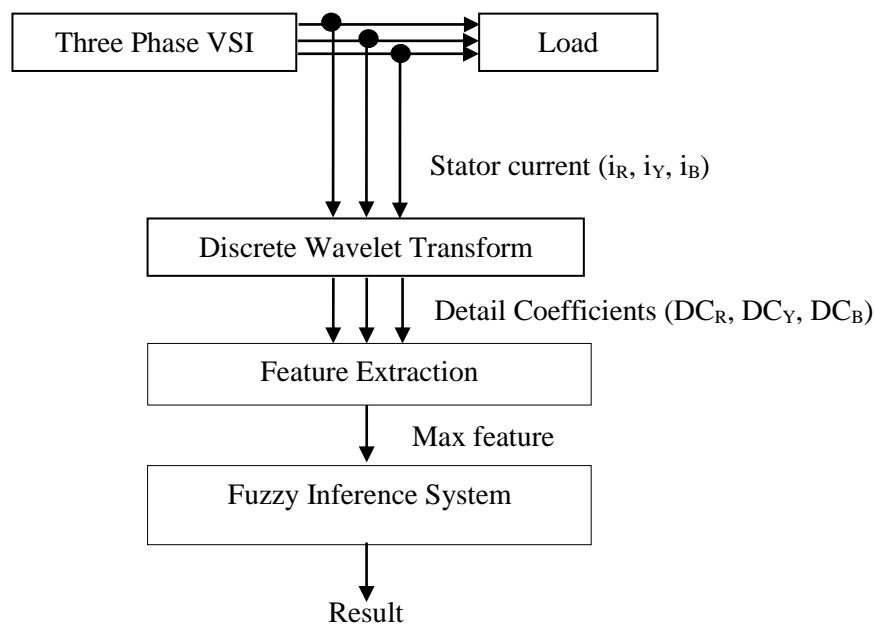


Figure 3. Discrete Wavelet Transform - Fuzzy Logic

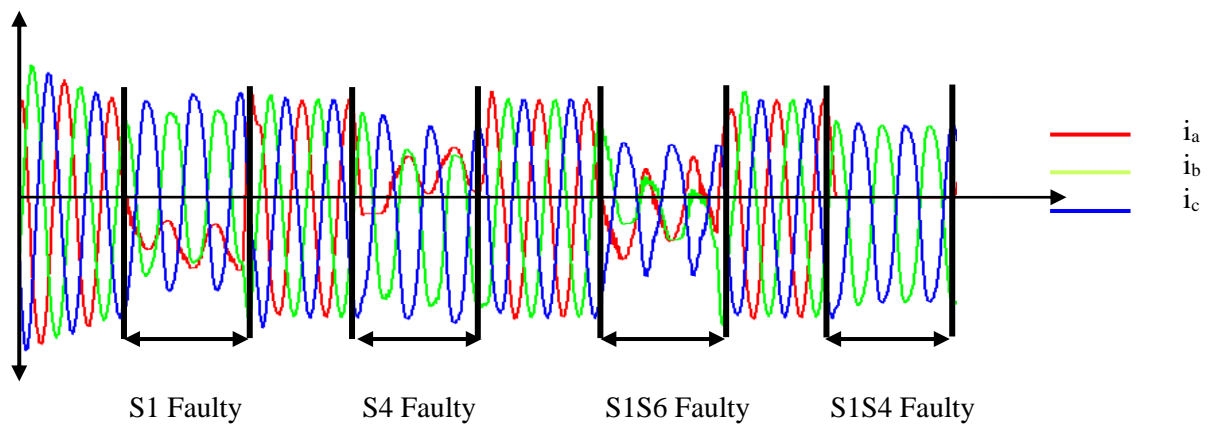
$$DC_n = \sum_{k=0}^l i_n(k) \times h(n-k) \quad 3$$

$$AC_n = \sum_{k=0}^l i_n(k) \times g(n-k) \quad 4$$

Where l is number of current samples in one data packet.

Table 1 Diagnostic signatures of DWTFL

Faulty switches	Diagnostic variable		
	DC_R	DC_Y	DC_B
S1	Neg	Pos	Pos
S4	Pos	Neg	Neg
S3	Neg	Pos	Neg
S6	Pos	Neg	Pos
S5	Pos	Peg	Neg
S2	Neg	Neg	Pos



a) Three phase current waveform during healthy and faulty conditions

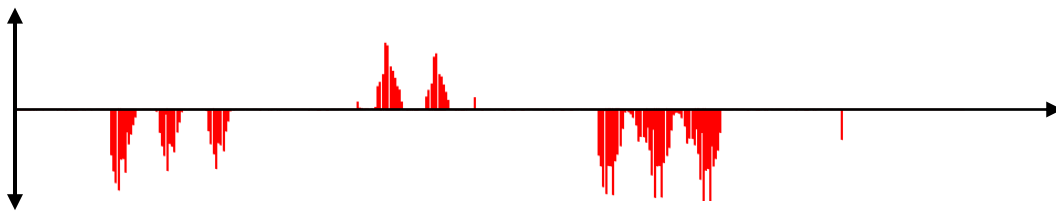
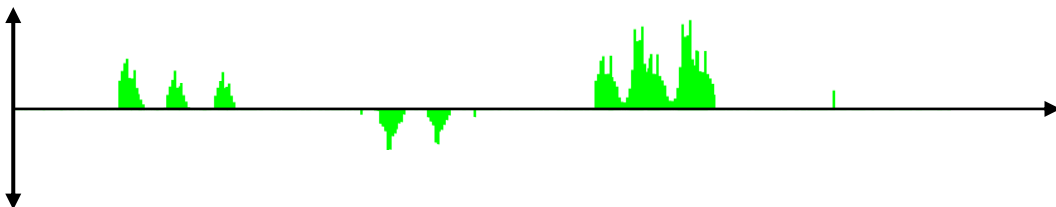
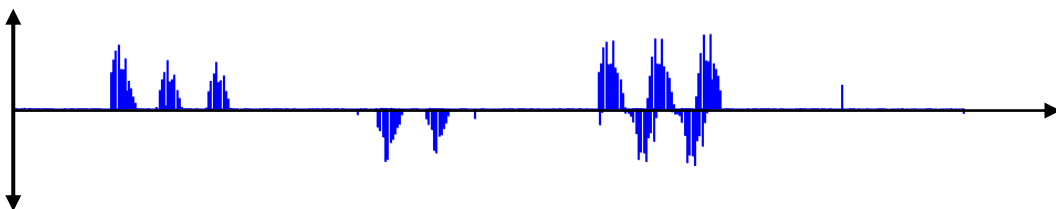
(b) Detail coefficient (DC) of i_a (c) Detail coefficient (DC) of i_b (d) Detail coefficient (DC) of i_c

Figure 4. Detail coefficients during healthy and faulty conditions

$$S_n = \begin{cases} \text{Neg} & \text{if } DC_n < k_f \\ \text{Pos} & \text{if } k_f \leq DC_n < k_d \\ \text{Dbl} & \text{if } k_d \leq DC_n \end{cases} \quad 5$$

3.2. Discrete Wavelet Transform - Artificial Neural Network (DWTANN)

The block diagram of DWTANN is shown in Figure 5. This method is implemented using three phase currents i_R , i_Y and i_B . Three phase currents are converted into data packets, each data packet consist of samples for 72° of fundamental current signals. The three phase currents are passed through DWT to compute *detail coefficients* (DCs) and *approximate coefficients* (ACs) which are given by equation 3 and equation 4 respectively. Minimum (*min*), Maximum (*max*), Median (*med*), Mean (*mean*) and Standard Deviation (*std*) features are extracted. The features are used to train *Feed Forward Back Propagation Neural Network* (FFBPNN). The structure of FFBPNN is decided changing parameters during training of ANN. Neurons in hidden layer, learning rate and training data size are changed to find structure of ANN. ANN with 5 input nodes, 1 hidden layer and 22 output nodes have structure like 15-24-22 is trained and tested for different faulty conditions which gives better performance with less Mean Square Error (MSE).

3.3. Diagnostic Variables and Average Value of 3 Φ Current (DVAC)

The d-q transformation or *Parks Vector Approach* (PVA) is mathematical transformation. This technique is applied to transform 3 Φ Current of VSI i_R , i_Y and i_B into two phase currents i_d and i_q . The Parks vector components are given by equation 6 and equation 7.

$$i_d = \sqrt{\frac{2}{3}} i_R - \frac{1}{\sqrt{6}} i_Y - \frac{1}{\sqrt{6}} i_B \quad 6$$

$$i_q = \frac{1}{\sqrt{2}} (i_Y - i_B) \quad 7$$

The normalization of 3 Φ Current currents is necessary to keep away from the difficulty of machine mechanical operating condition dependency. This method employs the dq transformation. By using Parks vector approach *Parks Vector Modulus* (PVM) can be calculated as equation 8,

$$|\overline{is}| = \sqrt{i_d^2 + i_q^2} \quad 8$$

The normalization is done by dividing 3 Φ currents by PVM. The normalized 3 Φ currents is given by equation 9,

$$I_{pvm} = \frac{i_l}{|\overline{is}|} \quad 9$$

Since this normalization method, the normalized phase currents I_{pvmN} will forever to obtain values inside the range of ± 0.8164966 , which is not dependent of the measured currents amplitude and given by equation 10.

$$I_{pvmN} = \begin{cases} i_{RN} = \sqrt{\frac{2}{3}} \sin(\omega_s t + \phi) \\ i_{YN} = \sqrt{\frac{2}{3}} \sin(\omega_s t - \frac{2\Pi}{3} + \phi) \\ i_{BN} = \sqrt{\frac{2}{3}} \sin(\omega_s t + \frac{2\Pi}{3} + \phi) \end{cases} \quad 10$$

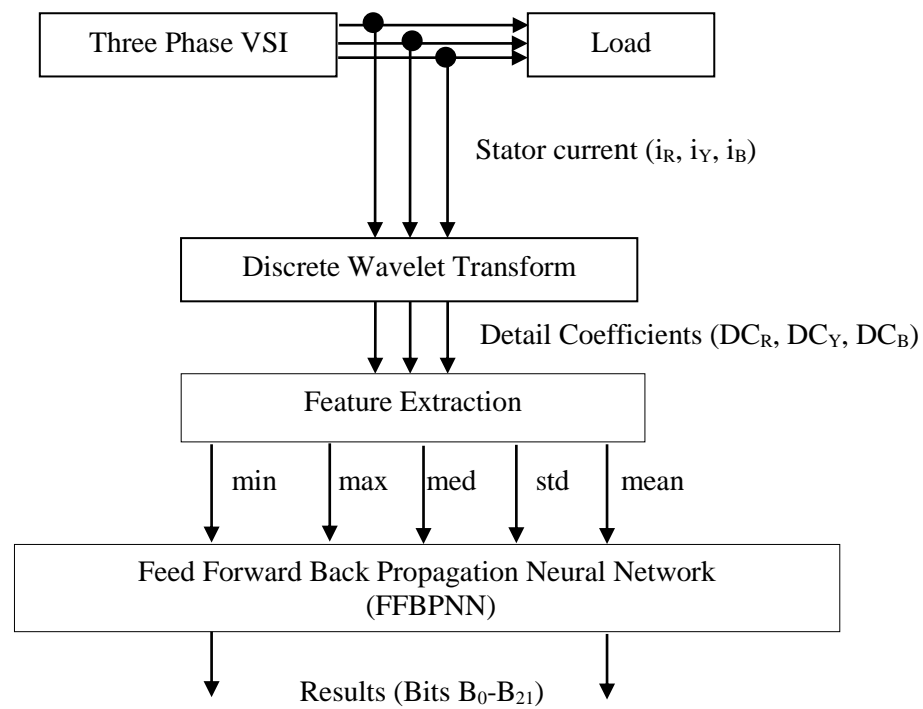


Figure 5. Wavelet Transform – Artificial Neural Network based fault diagnostic system

Average absolute values of normalized 3Φ currents of VSI are applied to calculate diagnostic variables. For 3Φ , three diagnostic variables are needed to be calculated. These three diagnostic variables e_{nN} are obtained from the errors of the normalized currents average absolute values and given by equation 11.

$$e_n = \xi - |I_{pvmN}| \quad 11$$

Where ξ is a stable rate. The rate of ξ is equal to the average absolute value of the normalized 3Φ currents of inverter under healthy working conditions which is given by equations. 12, 13 and 14.

$$\xi_a = 0.5144 \quad 12$$

$$\xi_b = 0.5173 \quad 13$$

$$\xi_c = 0.5287 \quad 14$$

These three diagnostic variables have specific characteristics which are very useful for fault diagnosis. When inverter is in normal operating condition, all three diagnostic variables take approximately zero value. If *Base or collector open fault* is occurred in 3Φ inverter, as a minimum one of the diagnostic variables turn into positive. If fault is set up in IGBT S1, then diagnostic variable of phase which contains that IGBT takes positive value. In such way, diagnostic variables give information about the faulty phase. But it does not give any information about the faulty switches. For this, average current of three phases is used with diagnostic variables. Diagnostic variables detects faulty phase and average current identifies faulty switch from that faulty phase. From equations equation. 15 and equation 16, E_n and M_n are calculated which are used in fault diagnostic process. As the technique is normalized, it is not necessary to change these values for various load and speed conditions.

$$E_n = \begin{cases} F & \text{if } e_n < k_f \\ Y & \text{if } k_f \leq e_n < k_d \\ D & \text{if } k_d \leq e_n \end{cases} \quad 15$$

$$M_n = \begin{cases} N & \text{if } \langle I_{pvmN} \rangle < 0 \\ P & \text{if } \langle I_{pvmN} \rangle > 0 \end{cases} \quad 16$$

These two equations create fault diagnostic signatures. Value of K_d is decided by observing maximum value from e_a , e_b or e_c ; when single switch is faulty. Similarly, K_f is minimum positive value from e_a , e_b or e_c ; when two switches are faulty in different phases. The values of K_d and K_f are 0.20210 and 0.00553 respectively for 10 kW active power as shown in Table 2. These values are decided on experimentation basis observing Table 2. The diagnostic signatures are shown in Table 3.

4. Different Methods of Fault Diagnosis

Lists of evaluation and performance indices are given below:

Effectiveness: Diagnostic system is effective if it effectively pin point the faulty IGBT. Effectiveness of the fault diagnostic systems is calculated using Eq.17.

$$\text{Effectiveness (\%)} = \frac{\text{True Positive Output}}{\text{Total Number of Input Samples}} \times 100 \quad 17$$

Table 2 Diagnostic variables at 10 kW power

IGBT	e_a	e_b	e_c
S1	0.20048	-0.0354	-0.1579
S4	0.20173	-0.0385	-0.1566
S3	-0.1502	0.20192	-0.0456
S6	-0.1577	0.20210	-0.0397
S5	-0.0412	-0.1512	0.20139
S2	-0.0314	-0.1487	0.18745
S1S6	0.51974	-0.1487	0.18745
S3S4	-0.1873	0.51975	-0.1873
S5S2	-0.1873	-0.1873	0.51974
S1S2	0.12251	-0.082	-0.0261
S1S3	0.00553	0.19652	-0.2083

Table 3 Diagnostic signatures

Faulty switches	Diagnostic variable			Average current		
	E_a	E_b	E_c	M_a	M_b	M_c
S1	Y	F	F	N	-	-
S4	Y	F	F	P	-	-
S3	F	Y	F	-	N	-
S6	F	Y	F	-	P	-
S5	F	F	Y	-	-	N
S2	F	F	Y	-	-	P
S1S6	D	-	-	-	-	-
S3S4	-	D	-	-	-	-
S5S2	-	-	D	-	-	-
S1S2	Y	Y	F	N	N	P
S1S3	Y	F	Y	P	P	P
S1S5	F	Y	Y	P	P	P
S1S4	Y	Y	F	P	P	P

Table 4 Effectiveness of different diagnostic methods (in %) under variable load condition

Fault	DWTANN			DWTFL			DVAC		
	5000W	1000W	1500W	5000W	1000W	1500W	5000W	1000W	1500W
S1	70.73	82.63	66.6	100	100	86.6	100	100	100
S2	42.22	62.25	58.33	93.33	82.35	58.33	100	100	100
S3	37.5	57.87	49.89	100	88.23	100	100	100	97.26
S4	38.1443	59.73	43.75	88.23	100	93.75	100	100	100
S5	48.8095	57.89	51.98	85	85.71	100	100	100	100
S6	38.1443	54.45	85.71	85.71	86.36	85.71	100	100	100
S1-S6	65.28	85.37	73.98	100	99.99	99.99	100	100	100
S1-S4	76.19	87.23	81.98	99.99	99.99	99.99	100	100	100
S1-S3	66.13	85.23	72.93	89.46	100	100	96.35	100	100
S3-S2	66.89	87.81	73.29	100	84	83.33	100	100	100
S3-S4	71.67	85.65	76.29	96	100	92.3	100	100	100
S3-S6	67.87	84.69	72.98	99.99	99.9	99.99	100	100	100
S5-S6	53.98	73.75	65.76	96.15	99.99	100	100	100	100
S5-S2	65.98	82.97	71.09	100	99.99	97.94	100	100	100
S5-S4	56.98	72.84	65.98	91.29	99.99	99.99	100	100	100

Effectiveness of fault diagnostic system is tested over 316 samples. Out of these 38 samples are collected for healthy condition and 278 samples for faulty conditions. Effectiveness of different methods is shown in Table 4. In case of DWTFL, by observing polarities of detailed coefficients, significant accuracy is achieved for classification of single switch open circuit fault. Multiple switch open circuit fault diagnostics system requires additional number of fuzzy rules. Some features of detailed coefficients at different faulty conditions are matching with each other or are slight different in coefficients. Hence in DWTFL fault diagnostic system false alarms are increased. The DWTANN shows good results for 10 kW loads, as it is trained for such condition. It is very difficult to collect training data set at variable load conditions. In some faulty cases as mentioned in DWTFL, features are

matching with each other at different conditions. The accuracy of DWTANN depends on the training data and network parameters. It is difficult to train ANN for high and light load conditions. In DVAC fault diagnostic system, accuracy at variable load conditions depends on threshold values. Threshold values are carefully selected Remarkable accuracy of fault diagnostic system is achieved. This method of fault diagnosis is effective under variable load conditions.

Diagnostic System Classifier Performance Metrics:

This type of metrics is used to evaluate performance of diagnostic algorithm, normally considering multiple fault classes. Classifier Performance Metrics is a square metrics consisting of equal rows and columns where its entry corresponds to strength of correlation between its i^{th} and j^{th} elements. It shows the diagnostic outcome into several classes. The classifier performance metrics for different methods are shown in Table 5 to Table 7 for DWTFL, DWTANN and DVAC In Table 7, all conditions of misclassifications and few conditions of good classifications are shown. The tables show the real deficiency as heading across the top of the table and how they were classified as heading down the first column. The diagonal elements shown in metrics are correctly classified faults, whereas subsequent elements in the column represent misclassification of faults. The confusion matrix can be created using percentage or real cases viewed. The probability of isolation or fault isolation rate (FIR) is calculated using equation 18.

$$FIR = \frac{A_T}{A_T + C_T} \times 100 \quad 18$$

$$A_T = \sum_i A_i \quad 19$$

$$C_T = \sum_i C_i \quad 20$$

Where A_i and C_i are the isolated and non isolated faulty conditions. The FIR for DWTFL, DWTANN and DVAC are 57.53%, 76.15% and 99.30% respectively. These values are calculated for 21 faulty and a healthy condition.

Fault Detection Time (FDT): FDT is defined as time interval between instance of fault occurrence and instance of fault isolation. The fault detection time is reliant on the difficulty of the detection algorithm and its resistivity to noise, as the threshold is determined according to that. FDT of different methods is shown in Table 8. The fault detection time required is less in case of fuzzy based diagnostic system as compared to ANN based fault diagnostic systems. The selection of neural network, number of hidden layer, hidden nodes and training of neural network decide the fault detection time of ANN based system. The computational difficulty in case of ANN is extra as compared to fuzzy logic. The fault detection time of DVAC method is low and it is very close to DWTFL; as the computational complexity in both systems is same.

Implementation Efforts (IE): The Implementation efforts of fault diagnostic system depend on the ease of sensing the detection parameter like voltage, current, vibration etc. In above mentioned diagnostic methods current signals are used as detection parameter. Similarly, packet size in case of all mentioned diagnostic method is same i.e. 4 ms except DVAC it is 20 ms. These methods are trained or implemented for fix size of packet as shown in Table 9. This increases data acquisition burden which results into high implementation efforts. The implementation efforts of fault diagnostic system also depend on the mathematical operation and decision-making process involved.

Tuning Effort (TE): It is beneficial to have thresholds independent fault diagnostic system and tolerances to be kept as highest as feasible. The fault diagnostic method based on artificial intelligent

are threshold independent but requires high efforts to train neural network or to build rules in fuzzy inference system. In case DVAC, threshold values are selected to cover overall power region.

Table 5 Confusion matrix used for diagnostic metrics of DWTFL methodology

Fault →													
Classified as ↓	S1	S2	S3	S4	S5	S6	S2S4	S2S6	S3S5	S4S5	S4S6	S5S6	S5S4
S1	56	17	19	18	08	20	07			20	14	12	10
S2	8	44			11	13	06	12					04
S3	11	10	59	12		21		05	05				
S4		12		44	10				03	08	08	10	
S5			05		54	19							
S6	27	17	17	26	17	27	09	05		10			07
S2S4							70				05		
S2S6								78	05				
S3S5									79	04		06	
S4S5										32			
S4S6							08				68		
S5S6									08			65	10
S5S4										18	05	02	72

Table 6 Confusion matrix used for diagnostic metrics of DWTANN methodology

Fault →													
Classified as ↓	S1	S2	S3	S4	S5	S6	S2S4	S2S6	S3S5	S4S5	S4S6	S5S6	S5S4
S1	96								1.2		5.04		
S2		98		2				14			1.00		
S3			97										
S4		2		98									
S5					100								
S6	4		3			94	2.46						
S2S4							97.54						
S2S6								78					
S3S5									98.2				
S4S5										100			
S4S6											95.96		
S5S6												100	
S5S4													100

Table 7 Confusion matrix used for diagnostic metrics of DVAC

Fault →	S1	S2	S3	S4	S5	S6	S1S3	S2S6	S3S5	S4S5	S4S6	S5S6	S5S4
Classified as ↓													
S1	100												
S2		100											
S3			99.35										
S4				100			0.62						
S5			0.65		100								
S6						100							
S2S4							99.28						
S2S6								100					
S3S5									100				
S4S5										100			
S4S6											100		
S5S6												100	
S5S4													100

Table 8 Fault detection Time in millisecond

Faults	DWTFL	DWTANN	DVAC
S1	62.793	96	59.953
S2	64.264	138	74.978
S3	57.919	111	60.842
S4	70.231	126	52.946
S5	57.598	95	47.784
S6	62.37	99	61.277
S1-S6	59.375	91	69.351
S1-S4	62.203	44	58.703
S1-S2	67.669	97	55.597
S3-S2	66.606	92	75.191
S3-S4	48.957	87	63.561
S3-S6	64.074	95	53.416
S5-S6	67.78	98	68.672
S5-S2	68.54	94	59.097

Table 9 Implementation efforts based on different parameters

Parameters	DWTFL	DWTANN	DVAC
Fault detection parameter	Current	Current	Current
	Low	Low	Low
Packet Size	4ms	4ms	20 ms
	High	High	High
Mathematical operation	High	High	High
Decision-making process	High	High	High

Resistivity against False Alarms (R): False alarms can take place during light-load and transient conditions, due to increased noise, i.e., low signal-to-noise ratio. Resistivity against transients can be improved by providing a dead time during transients. However, this approach has the drawback of slower detection. The necessary dead time is an indicator of resistivity against false alarms. Resistivity against noise can be improved by having higher threshold. However, it leads to false alarms during light loads. This can be handled by making a method independent of load. The DWTFL and DWTANN methods are dependent on load as shown in Table 4. DVAC diagnostic method is load independent but threshold dependent. The comparison of fault diagnostic methods regarding tuning efforts and resistivity is shown in Table 10.

Table 10 Comparison with respect to tuning efforts and resistivity against noise

Methods	Parameter		
	Tuning Effort	Resistivity	
		Against noise	Against load
WTFL	High	Low	Low
WTANN	High	Low	Low
DVFL	High	High	High

5. Conclusion

Different methods of Fault diagnosis for voltage source inverter are compared in this paper. These methods are generally based on grouping of 3Φ current transformations from time to other domain and classifier. Three phase currents are generally transformed using Discrete Wavelet Transform or Park Vector Transform. Discrete Wavelet Transform is more robust against high frequency noise but required threshold values to diagnose faults under variable load conditions. This transformation is useful for *Base or collector open fault* diagnosis of IGBTs. Such transformation is generally used with combination of If-Then rules, Fuzzy Logic or Artificial Neural Network. Parks Vector Transform is appropriate for open fault diagnosis of IGBTs in variable speed drive as current is normalized. This method is suitable and threshold values are used which covers overall power region. Fault diagnostic signatures calculated using PVT is combined with If-Then rules. The diagnostic method based on diagnostic variable and average value of three phases current is more suitable for diagnosis of switching devices under different operating conditions.

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