Comparative Study of Open Switch Fault diagnosis inThree Phase Voltage Source Inverter

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Abstract

The fault diagnosis followed by corrective measures involves the human interlinking at every step and it turned out to be a most excellent problem for *Artificial Intelligence.* In the multiple cases the probabilty of fault occurrence articulated is vague and not completely defined. The maintenance engineer during condition based monitoring has to apply intelligenceto get realistic decisions depending on *vast available data*. The fault diagnosis problems are *knowledge based* on one side and *rule based* on the other side. This gives challenging opportunity to pertain theory and idea of Artificial Intelligence in the process of fault diagnosis.This paper presents the recent techniques of fault diagnosis systems based on *Fuzzy Logic and Artificial Neural Networks*. The wavelet transform is very good tool for analysis of non-stationary signals in fault detection process as compared to Fourier Transform, Short Time Fourier Transform or other techniques of signal processing. Selection of the mother wavelet and the selection decomposition level of signal are more crucial problems in wavelet analysis. Hence in this paper the selection of mother wavelet and level of decomposition for analysis of nonstationary signal is discussed with the help of time domain waveforms. Fault diagnosis of Voltage Source Inverter, a complex electrical systemis considered as case study. To study the combined approch of Wavelet Transform-Fuzzy logic and Wavelet Transform-Artificial Neural Networks with their advantages and disadvantages in fault diagnosis is main objective of this paper.

Keywords: Fault diagnosis, voltage source inverter, signal processing techniques, wavelet transform, artificial intelligence, fuzzy logic, artificial neural networks.

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1. Introduction

Since the progress of the **Fault Diagnosis Systems(FDSs)**, there have been persistent progresses in the area of condition monitoring of complex systems. Incessant research and development in this area lead to growth of more successful FDS[1]. The modern FDS of complex systems may be helpful depending on whether the assumed method has ability to diagnose faults under different operating conditions such as frequency, load, speed, temperature, etc[2]. Fault diagnosis is combination of fault detection and classification. The **Signal Processing(SP)** techniques are used to extract features from signals under healthy and faulty conditions to detect fault[3]. Then selected features are given to fault classifier to pin point particular fault. The SP techniques in FDS work in a similar fashion of fault detection which does not carry more information concerning fault[4]. But remember that the fault diagnosis in FDS carry additional information regarding fault like type of fault, location of fault, severity of fault, etc. The extracted features of signals may be in time or frequency domain. **Fast Fourier Transform (FFT)**, Short Time Fourier Transform (STFT), **Wavelet Transform (WT)**, Winger-Ville Distribution (WVD), **Park's Vector Transform (PVT)**, Discrete Cosine Transform (DCT) etc. are the different techniques used for feature extractions in FDSs [5-9]. The WT can analyze signal in both time and frequency domains, for this reasonthis transformation technique is widely used in analysis of transient generated in signal due to occurrence of fault in electrical or mechanical systems[9]. Simple If-Then rules, **Fuzzy Logic (FL)**, **Artificial Neural Networks (ANNs)**, **Fuzzy Neural Network (FNN)**, Classification and Regression Trees (CARTs), etc are utilizedforclassification of the faulty conditions[10-11].

Fuzzy Logic (FL) and Artificial Neural Networks (ANNs) based FDSs are widely applied for complex industry process. Such FL and ANNs based FDSs are known as **Knowledge-based Fault Diagnosis Systems** (KFDSs)[12]. KFDs can be implemented if large historical data of the system is available. Hence, KFDs is also known as **Data Driven Fault Diagnosis (DDFD)**. The knowledge extraction can be either qualitative or quantitative; hence KFDS is classified as Qualitative Knowledge based Fault Diagnosis Systems (QLKFDSs) and Quantitative Knowledge based Fault Diagnosis Systems (QNKFDSs). Recently the combinations of Wavelet Transform-Fuzzy Logic (WT-FL), Wavelet Transform-Artificial Neural Networks (WT-ANNs), Park's Vector Transform-Fuzzy Logic (PVT-FL), Wavelet Transform-Fuzzy NeuralNetworks (WT-FNNs), etc. are commonly developed techniques for fault diagnosis of complex Electrical, Mechanical and Chemical systems [13-15].

Recently researchers are interested in the field of fault diagnosis of **electrical drives**. The PVM based FDS is implemented to diagnose multiple open switch faults in three phase pulsewidth-modulated voltage-source inverters (PWM-VSIs)[16]. Three phase currents are normalized with the help of PVM based current normalizer. Effective results are obtained under variable load conditions of **Permanent Magnet Synchronous Motors (PMSM)**. This method is effectively applied for diagnosis of open circuit fault and sensor fault in three-phase voltage-source inverters (VSIs) fed PMSMs drives [17]. This method demonstratesrobustness against false alarms and its effectiveness in both IGBTs and current

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sensors fault diagnosis.The new method is successfully applied for fault diagnosis of switching devices in three phases VSI under variable load conditions at different frequencies [13]. This method is implemented using combination of PVT, DWT and ANNs. The idea of allelic points is offered and related functions are defined to explain the symmetry of the VSI-topology to diagnose circuit faults. The fault could be located by using combination of functions and residuals depending on the study of VSI-topology[18]. The open circuit fault of switching devices in PWM-VSI for vector-controlled induction motor drivesis proposed in [19]. The d–axis and q-axis current repetitive distortions are related for finding of faulty switches due to its unfussiness and robustness, at the same time as the faulty stages are utilized for the classification of faulty switches. A new method based on ANNsisproposed for open circuit fault diagnosis of **Insulated Gate Bipolar Transistors (IGBTs)**[20]. Only three conditions are considered for study, two conditions are multiple faulty switches in same leg and a condition with faulty switches in different legs. **Clustering Adaptive Neural Fuzzy Inference System(C-ANFIS)**is proposed to detect open circuit fault in single IGBT under variable mechanical or electrical conditions [21]. Better results are obtained with minimum worst-case error. A novel method for real-time diagnosis of single and multiple open-circuit fault in permanent magnet synchronous generator drives for wind turbine applications is proposed in [22,23]. These methods are based on diagnostic variable and average value of three phases current which found very robust method in diagnosis of PWM-VSI.

In this paper the recent techniques of FDSs based on FL and ANNs with merits and demerits under different operating conditions are discussed. The advantages of WT as feature extraction technique over the other techniques, and how the mother wavelet and decomposition level of mother wavelet affect on result of fault detection is discussed. This paper also includes discussion on FL and ANNs in fault diagnosis process. The results with the help of time domain waveform are presented to prove the merits and demerits of WT-FL and WT-ANNs FDSs.

2. Experimental Setup

Before starting to actual concept of fault diagnosis this section gives details of *experimental setup*. The block diagram of three phases *Voltage Source Inverter (VSI)*is shown in Fig. 1having major blocks like AC source, rectifier, inverter, load and control circuit.The actual experimental setup is given in Fig. 2 and specifications in Table 1. An open-circuit fault in the VSI is introduced by opening collector terminal. Such facility is generated in test box. The Data Acquisition System (DAS) consists of a VSI, induction motor and real time interface. A protection circuit is provided to avoid the damage of the IGBTs, caused due to various faulty conditions. The variable load conditions are implemented in the test bench for its application during the proposed methodology assessment using a pulley wheel mechanism which helps to increase or decrease load on induction motor. An induction motor with 0.75kW, 1415 rpm and 1.8 Amp current rating is used for experimentation. The current signalsare acquired using Hall Effect sensor (CR 5420).Thecurrent signals from the

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sensors are collected usingTDS1000C-EDU. The 158 samples are collected foreach cycle of current signal. The data packets arecollected under healthy and all faulty conditions.
Let us consider the waveform shown in Fig. 3presenting the output ofthree phase*Voltage Source Inverter (VSI)*. This waveform is recorded for fault in switching device T1. This waveform consists of healthy and faulty conditions. During healthy condition of VSI the amplitude of current signals in three phases is nearly same. Once the fault is introduced in device T1 the amplitude of current containing faulty device T1 (i.e. Phase A) change the shape of waveform. Transients in the current waveform are generated due to faulty device T1 of VSI. These transients are sudden rise or fall in the current signal of Phase A as shown in Fig. 4.

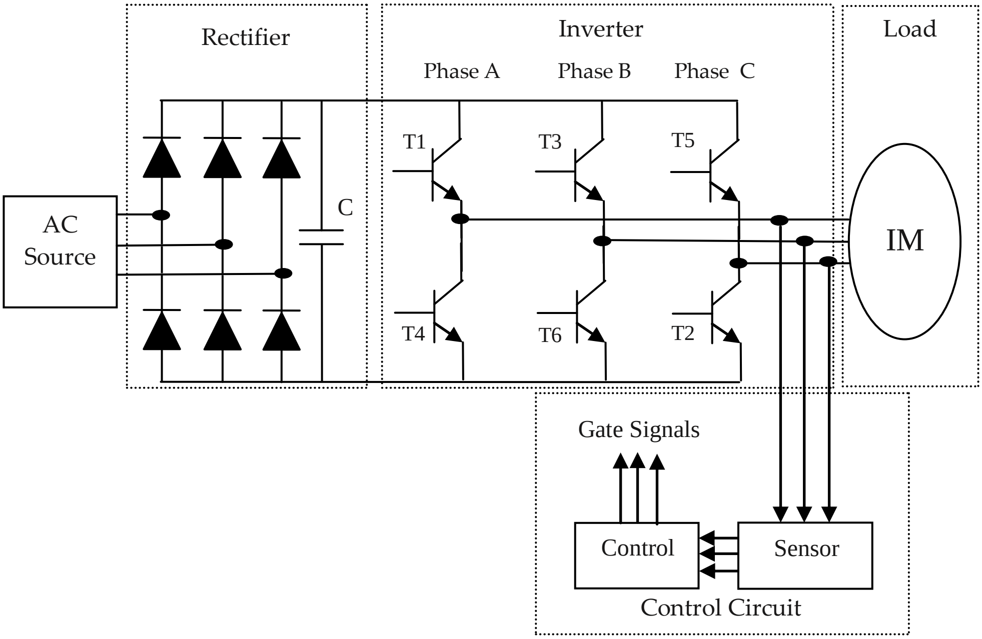


Fig. 1. Three phase Voltage Source Inverter

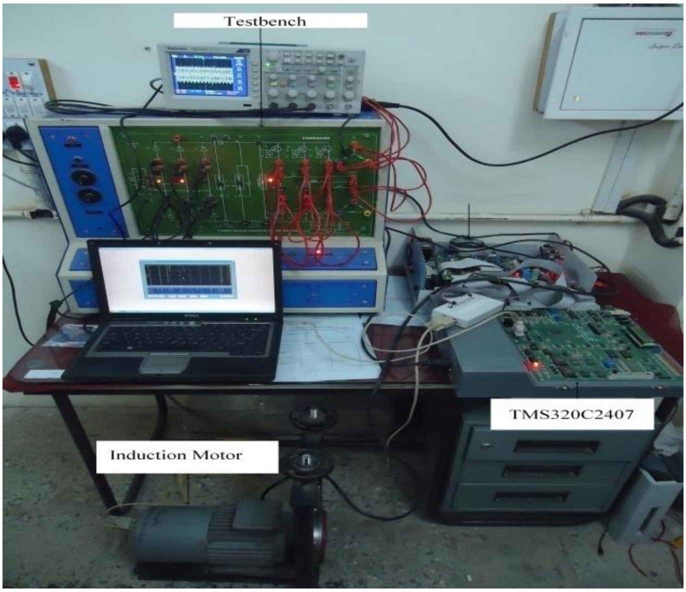


Fig. 2. Experimental setup

Table 1: Specifications of Voltage Source Inverter

Parameters	Values
DC Link Electrolytic Capacitor	5000μF
Load Inductance	10mH
Load Resistor	0.20Ω
Output AC Voltage	230Vp
Output Current	5.0630 Amp
Output Frequency	40Hz – 70 Hz
Load Power (Variable)	5kW – 15kW

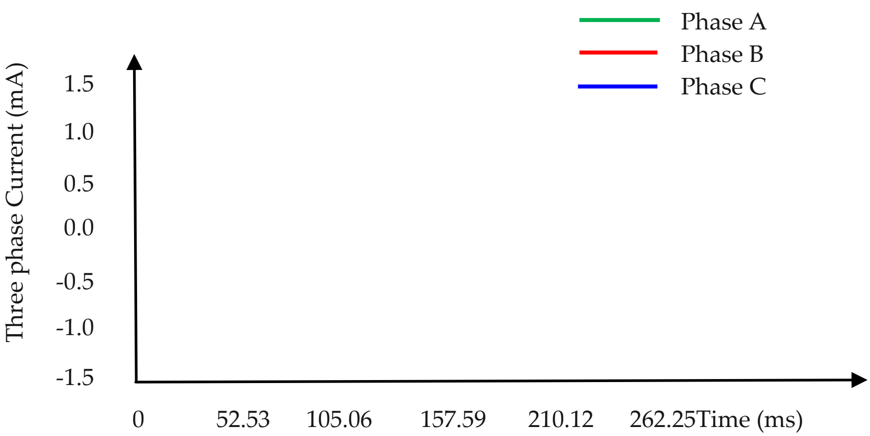
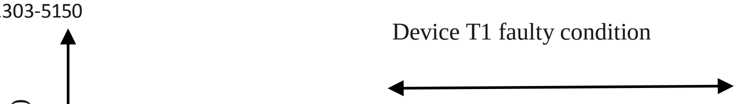
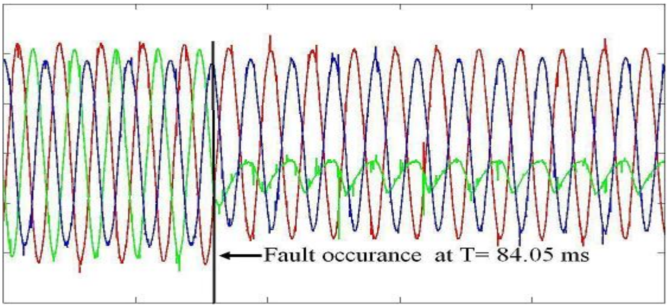
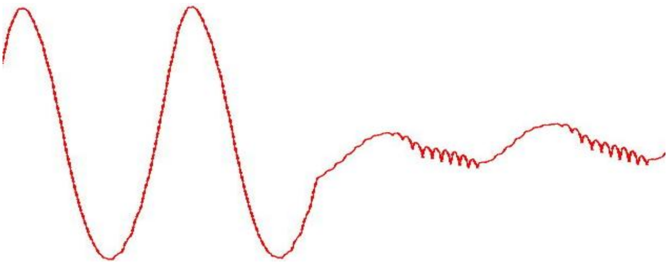
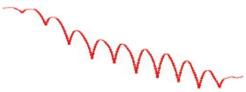


Fig. 3. Three phase current in haelthy and faulty condition









3. Fault Detection using Wavelet Transform

Fault detection is identifying that a problem has occurred, though one doesn't identify the source offault. Faults may be identified by a selection of quantitative or qualitative ways. This consists ofseveralmultivariable or model-based approaches. The recent techniques of fault detection are generally based on analysis of**non-stationary signals** like current, vibration, etc. Non-stationary signals can be simultaneously analyzed in the time and frequency domain using **Discrete Wavelet Transform (DWT)**. The DWT converts One Dimensional (1-D) non-stationary signal into Two-Dimensional (2-D) space of high frequency and low frequency components.The DWT is able to identify abrupt rise or fall in non-stationary signal in time and frequency domain. The process offault detection using DWT starts with passing non-stationary signals through Low Pass Filter (LPF) and High Pass Filter (HPF). The output of LPF is called as Approximate Coefficients (C_{AS}), which holdscharacteristics of signal in time domain andit can be *analyzed into next levels*. The output of HPF is called as Detail Coefficients (CDS) and it holdscharacteristics in frequency domain, which is useful for fault detection.The DWTeffectivelyallow us to recognize bank of analysis filter. One can get original signal if synthesis filters willfunctional. After analyzing signal using filters, both the CAsand CDS are decimated by two to constructsuperior localization of high and low frequency components.

WT does not have a pre-fixed kernel as in other transform like FFT or DCT. As a result, the wavelet kernel can be selected based on the performance of the wavelet filter concerning to the type of application. The main advantege of using DWT then is the capability of fine-tuning the wavelet filters for additional adaptive solutions. Various kernel have shown varying results for fault detection. Such wavelet kernel included **Daubechies (DB), Symmlet, Coiflet,Battle Lamarie** and they need considerably diverse performance.Further the choice of the mother wavelet and the decomposition level of signal are more crucial taskin the analysis of WT. In WT, various mother wavelets can be utilized for fault detection. Analysis of same signal with various mother waveletsprovidesdifferent results. Properties of mother wavelets as symmetry, orthogonality, dense support and vanishing moment are utilized for selecting mother wavelet. In contrast, various mother wavelets possibly will have same properties. In thissituation, mother wavelet identical with original signal is chosen for analysis.One more difficulty in wavelet analysis is choice of the decomposition level of the mother wavelet, which was previously determined by testing and based on fundamental distinctiveness of the data. The maximum level that affects the wavelet transform is based on number of samples in data set, as data is down-sampled by 2.

The analysis of non-stationary current signal with the DB2 mother wavelet at level-2 during healthy and device T1 faulty condition is shown in Fig. 5. The CDS of wavelet transform as shown in Fig. 5 can easily differentiate healthy and faulty conditions. The maximum values of CDS for different mother wavelets applied on non-stationary current signal during healthy and device T1 faulty conditions are shown in Fig. 6. It is observed that DB mother wavelet is more effective than other mother wavelets for analysis of transients in non-stationary signal generated as result of faulty devices.

The above discussion clears that the DB2 at level 2 is suitable to detect healthy or faulty conditions of switching devices in VSI. In this way, it is required to identify mother wavelet for analysis of non-stationary signal which is suitable to that particular fault detection application.

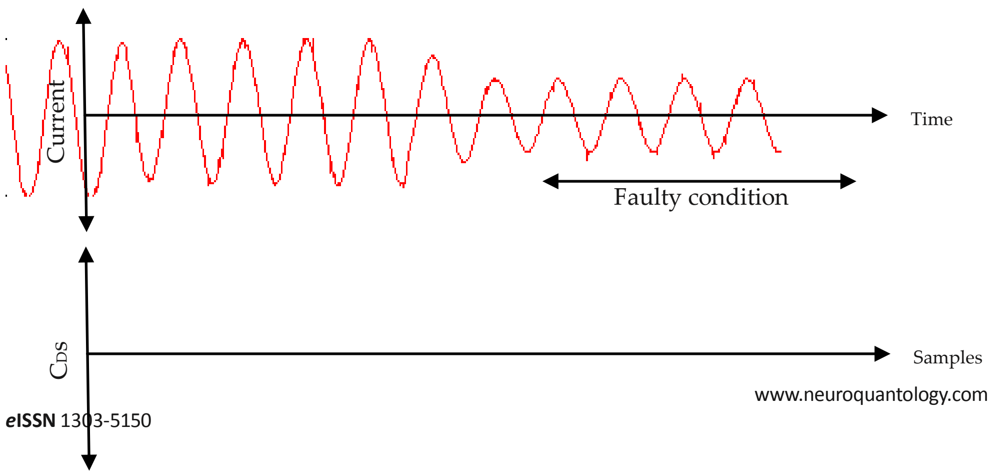
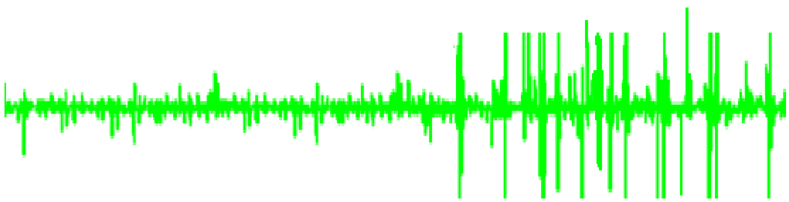


Fig. 5. Analysis of Waveform using DB 2 at level 2.



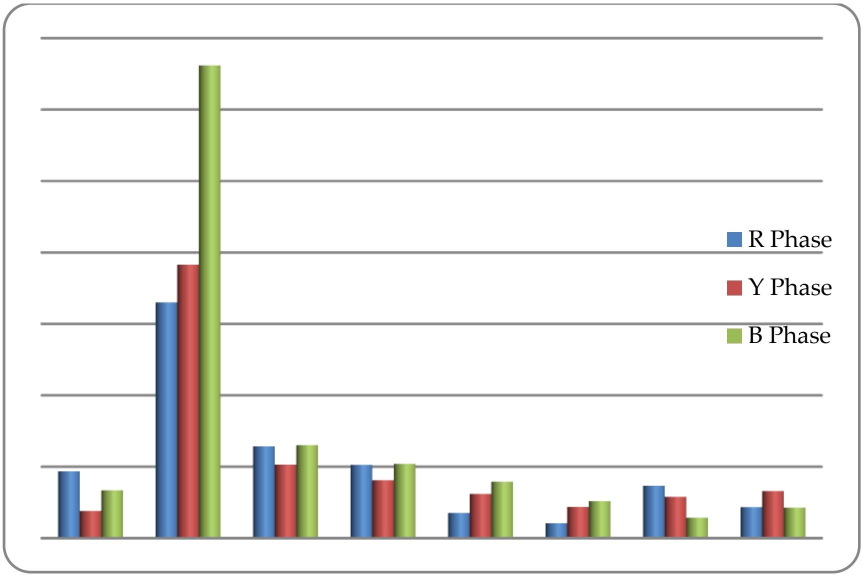


Fig. 6.C_{DS} values of different mother wavelet for healthy and Device T1 faulty conditions

3. Fuzzy Logic Fault Diagnosis

The block diagram of Fuzzy Logic Fault Diagnosis (FL-FD) system is shown in Fig. 7. The non-stationary three phase stator current signal (I_A, I_B and I_C) of 50 Hz frequency is input to FL-FD system. The Low Pass Filter (LPF) is used to remove high frequency noise. three phase stator current signals are shown in Fig. 8.a under healthy and faulty conditions. The packets of 4 msi.e.,72^0 of current signal is formed and given to DWT. The detail coefficients of stator current signal (C_{DS}_A,C_{DS}_B,C_{DS}_C) are extracted to built ***Fuzzy Inference System* (FIS)**. The detail coefficients are shown in Fig. 8.b to Fig. 8.d.The FIS is implemented using three inputs, one output and seven rules. Depending on value of FIS output the faulty device or devices are presented using six bits; each bit is for one device from T1 to T6. Each bit in output string presents healthy or faulty condition of devices T1...T6. If the bit B1 is 0 then device, then T1 will in healthy condition;else for B1 is 1 then device T1 will in faulty condition.

The C_{DS} values for three phases currents are recorded in healthy and faulty condition of devices T1...T6. The C_{DS} values for healthy condition are in the range of $\pm (1.2 \times 10^{-5})$ and in faulty conditions $\pm 1.7 \times 10^{-3}$ which depends on faulty devices as shown in Fig. 8. It is observed that C_{DS} may be positive or negative depending on faulty device. For example, if fault is in device T1, then the C_{DS} values of current signals I_A, I_B and I_C are Negative, Positive and Positive respectively. Similarly, if fault is in same phase but in lower device T4, then C_{DS} values will Positive, Negative and Negative. In such way *Fault Diagnosis Signatures* for FL-FD system are given in Table 2. A Mamdani *Fuzzy Inference System (FIS)* is implementedby observing *Fault Diagnosis Signatures*.

The first step in FIS implementation is membership function assignament. Three detailed coefficients of I_A, I_B and I_C are given to FIS as input. Each input consists of three membership functions which are classified into *linguistic terms* like Low, Med and High; and accomplished using *Triangular Membership Functions*. If the thorough knowledge of the problem has to be known and knowledge regarding Linguistic variable should also be known then ***Intuition method*** is used for membership value assignment. Simillarlly output membership function is also assigned to show conditions of six devices like Healthy, very_Low, Low, Medium_Low, Medium_High, High and Very_ High. The second step is to implement *Fuzzy Rule Base* as shown in Table 3. In fact, the third defuzzification method is not needed in fault diagnosis algorithms. Here, researchers are interested in *consequences of Rule Base*.

This implemented FL_FD system is tested for the different operating conditions like single device fault, multiple (two) devices faulty at a same time, under variable load and at different frequencies. In device T1 faulty condition the waveforms and result of fault diagnosis is shown in Fig. 9. It should be noted that the cause for the event of transients in output current originated due to faulty device T1 can be sensed by studying detail coefficients. This makes typical fault diagnosis signatures that match with the circumstances given in Table 3. The output of FL_FD system is [1 0 0 0 0 0] indicates device T-1 is faulty. An output bit B1 is shown in Fig. 10. A fault is isolated at t = 209.84 ms, fault detection time is 17.79 ms. The output Bits B2 to B6 are zero which are not shown in Fig.14.

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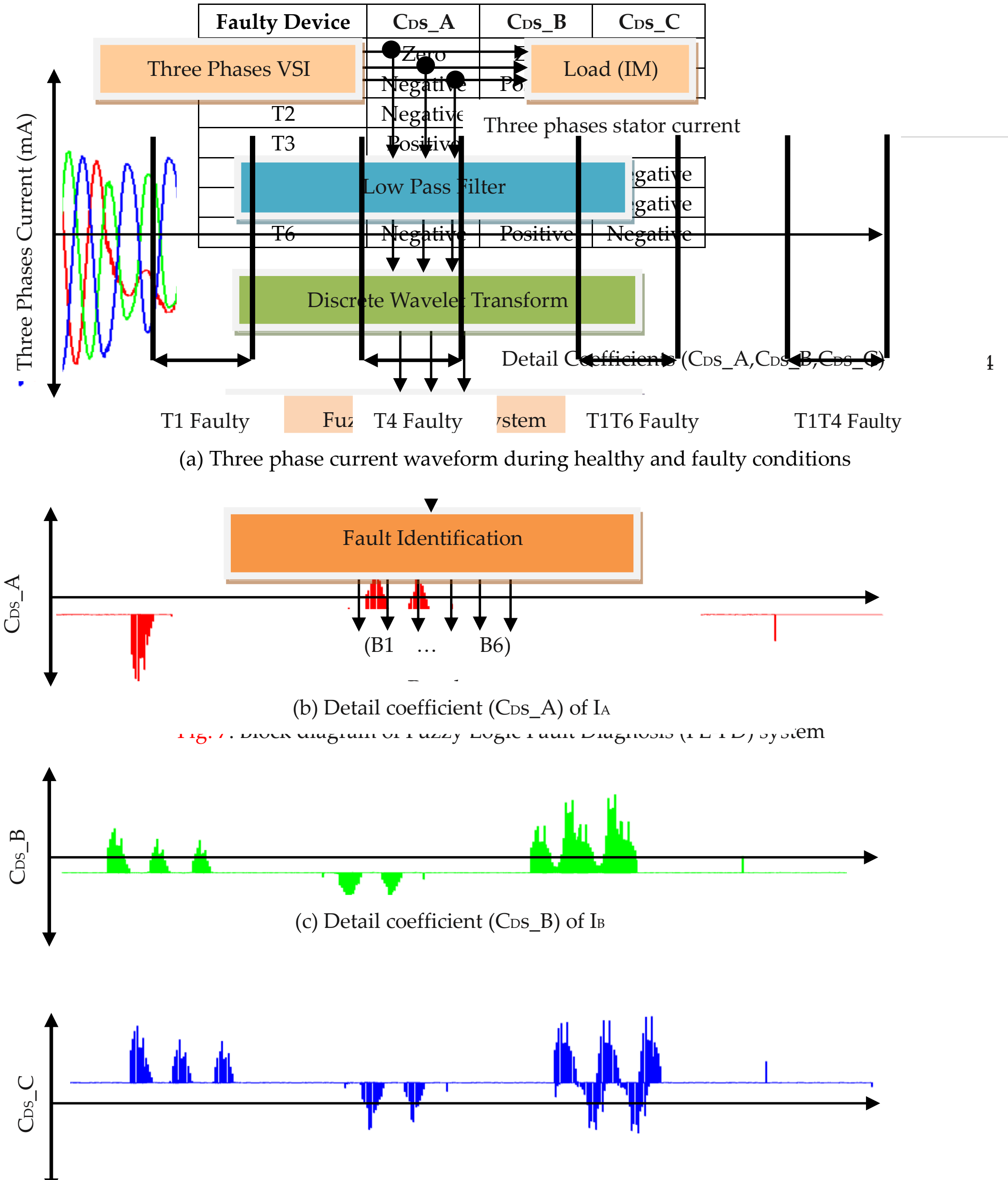
Table 2: Fault Diagnosis Signature



(a) Three phase current waveform during healthy and faulty conditions

(b) Detail coefficient (C_{DS}_A) of I_A

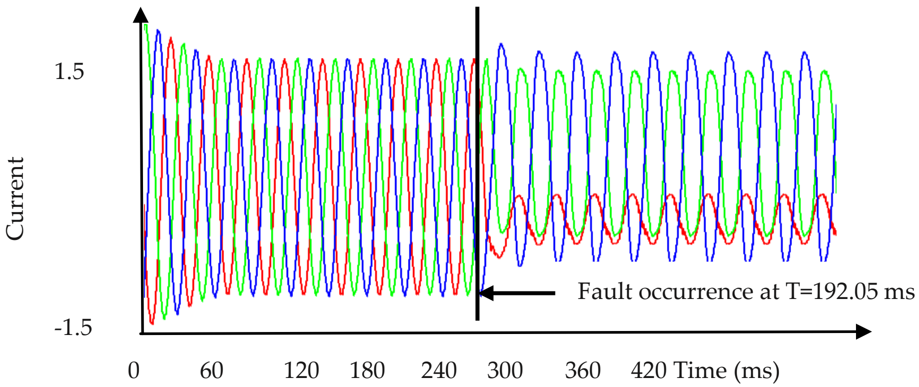
(c) Detail coefficient (C_{DS}_B) of I_B

(d) Detail coefficient (C_{DS}_C) of I_C

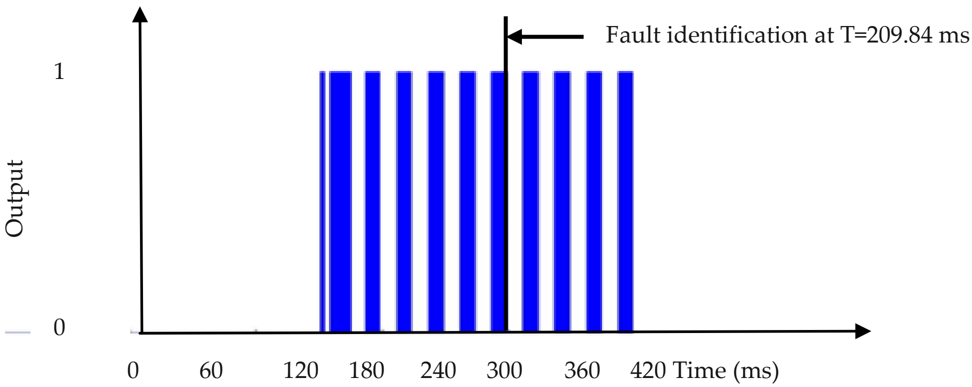
Fig. 8.Detail coefficients during healthy and faulty conditions

Table 3: Fuzzy Rules

Switch	Inputs			FIS Output
	C_{DS}_A	C_{DS}_B	C_{DS}_C	
H	Med	Med	Med	Healthy
T1	Low	High	High	Very_Low
T2	Low	Low	High	Low
T3	High	Low	High	Medium_Low
T4	High	Low	Low	Medium_High
T5	High	High	Low	High
T6	Low	High	Low	Very_ High



(a) Three phase waveform



(b) Output Bit B1

Fig. 9. Results comprising three phase current and output of T1 open circuit fault

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4. Neural NetworkFault Diagnosis

The block diagram of Neural Network Fault Diagnosis (NN-FD) system is shown in Fig. 10. The packets of 4 msi.e., 72^0 of current signal is formed and given to DWT. The detail coefficients of stator current signal (CDS_A, CDS_Band CDs_C) are extracted.*Minimum (min), maximum (max), standard deviation (Std), median (Med) and mean* features are selected. These selected features are shown in Fig. 12; it is clear that *min, max, std and Med* shows major changes for the duration of different faulty conditions. The mean feature does not bring any information therefore this feature is not well thought-out to train ANN. Only two features are utilized to diagnose faulty and one healthy condition to decrease size of training data in ANNs.The ANN is trained to diagnose the faulty conditions at 50 Hz frequency. The 50% of the collected data is utilized to train the ANN and the left behind 50% is utilized as the testing and validation of ANN. The number of hidden nodes varied among 05, 10, 15, 20 and 25. In every run, the stop condition is a combination of the upper limit epoch number and the threshold of errors if the number of the epoch has reached 1500 or the minimum squared error is a smaller amount than 0.001, then the training ends. There are 6 input nodes, 25 hidden layers and 6 output nodes to classify the problem in an ANN. The six output nodes give the faults of six various switches. The trained ANN structure is tested for all possible combinations. The time domain waveform for device T1 faulty condition is shown in Fig. 13. From this result it is clear that the performance of NN-FD is better than FL-FD. As shown in Fig. 13.b and Fig. 13.c the NN-FD system misidentify the faults at the instant which fault occurs because the features are matching at this instant in T1 and T6 faulty conditions. Hence the False-True diagnosis is high in caseof NN-FD system as compare to FL-FD system. 4876

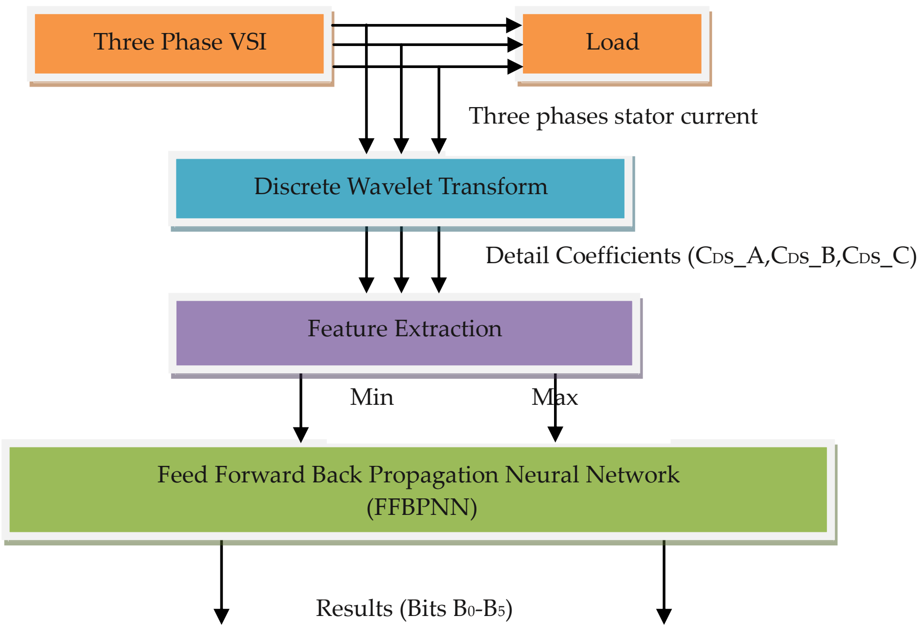

Fig. 10. Block diagram of Neural NetworkFault Diagnosis (NN-FD) system

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5. Results and discussion

The accuracy of fault diagnosis for FL-FD and NN-FD systems is calculated using Eq. 1. The accuracy for different load conditions is given in Table 4. It observed that the accuracy of both the FDSs is good at 1 mA load current because these two systems are implemented for this load condition. For different load conditions it is required to change fuzzy membership functions in FL-FD system and to train ANN architecture in NN-FD system by collecting data at different load conditions.

Accuracy (%) = (True Positive Output/Total Number of Samples) x *100* (1)

In investigation of FL-FD system it is observed that the obtained results are not steady there is misdeed in fault diagnosis as shown in Fig. 9.b. Because, the device T1 is not always in ON state and the detail coefficients obtained with the Wavelet analysis are difficult to differentiate in healthy and faulty conditions during OFF time of the device T1 as shown in Fig. 11. Hence the effectiveness of FL-FD systems is notsignificant. The following observation of FL-FD systems clears that the accuracyis poor: 4877

- The FL-FD system is not suitable to diagnose single phase fault i.e. two devices faulty in same phase (e.g. T1T4, T3T6 and T5T2). Because no current will conduct through faulty phase hence the C_{DS} values for these three phases are not differentiable in healthy and faulty conditions. The current waveforms are shown Fig. 8.a for faulty condition of T1T4 and C_{DS} values are shown in Fig. 8.b to Fig. 8.d.

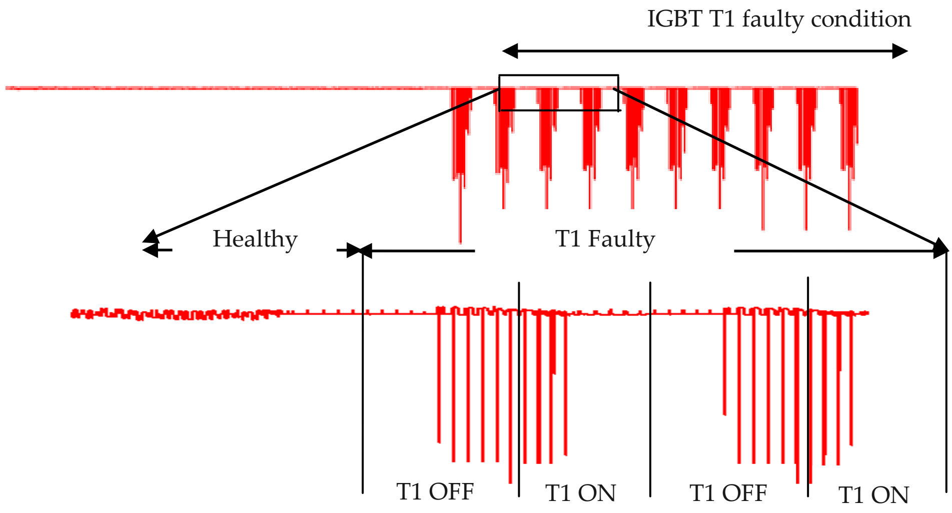


Fig. 11. Detail Coefficients of A-Phase during device T1 faulty condition

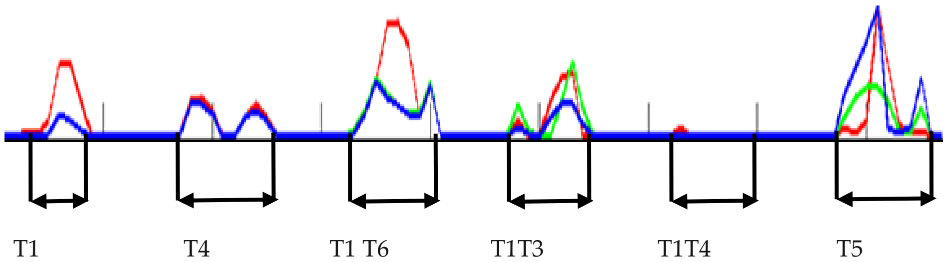
- This method is suitable for finding faults only in ON state and is missing in OFF state of devices.
- It is required to modify fuzzy membership functions under variable load conditions.
- At different frequencies it is required to change sampling rate of data acquisition system.

The main observations of NN-FD systemare given below:

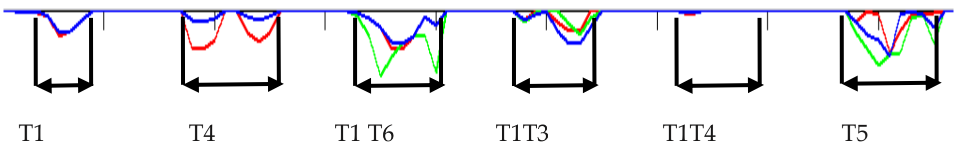
- In case of some faulty conditions features are matching with other faulty conditions hence it increases false-true alarams in NN-FD system as shown in Table 5of confusion matrix.
- It is very difficult to collect training data set under variable operating conditions like variable load, speed, frequency, etc.

Table 4: Accuracy of FL-FD System and NN-FD System

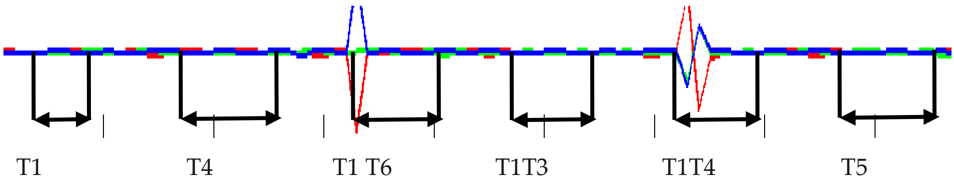
Device	FL-FD System			NN-FD System		
	1.2 mA	1 mA	0.75 mA	1.2 mA	1 mA	0.75 mA
T1	70.73	64.63	66.6	79.5	87.57	66.6
T2	42.22	64.45	56.33	53.33	74.35	66.33
T3	37.5	57.67	49.69	75.99	79.43	77.47
T4	36.64	59.73	43.75	76.43	77.77	73.75
T5	46.60	57.69	55.96	75	75.75	77.6
T6	36.64	54.45	65.75	75.75	76.36	65.75
T1-T6	65.26	65.37	73.96	79.09	77.3	76.4
T1-T4	5.03	6.4	5.03	91.59	99.5	92.94
T1-T2	66.63	65.43	74.93	73.46	86.74	74.76
T3-T2	66.69	67.66	73.49	79.45	84.55	63.33
T3-T4	76.67	65.65	76.49	76	77.57	74.3
T3-T6	6.69	6.66	3.49	34.5	67.34	49.69
T5-T6	53.96	73.75	65.76	66.55	76.04	76.5
T5-T2	3.69	3.66	3.49	65.55	78.04	56.5
T5-T4	56.96	74.64	65.96	75.49	86.7	77.04
Total	51.00	62.45	59.112	71.84	80.33	71.26



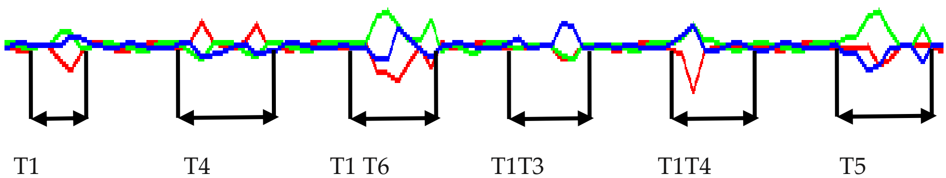
(a) Max features of Detail Coefficients values



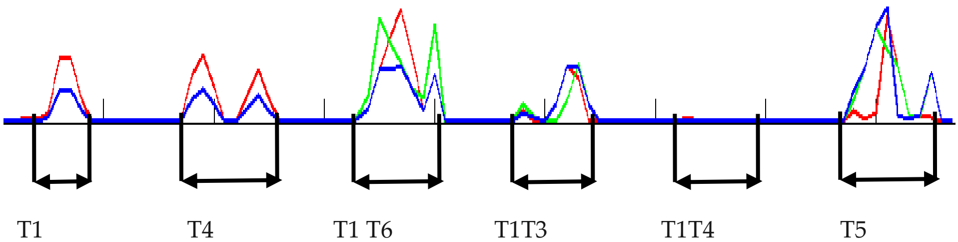
(b) Min features of Detail Coefficients values



(c) Mean features of Detail Coefficients values

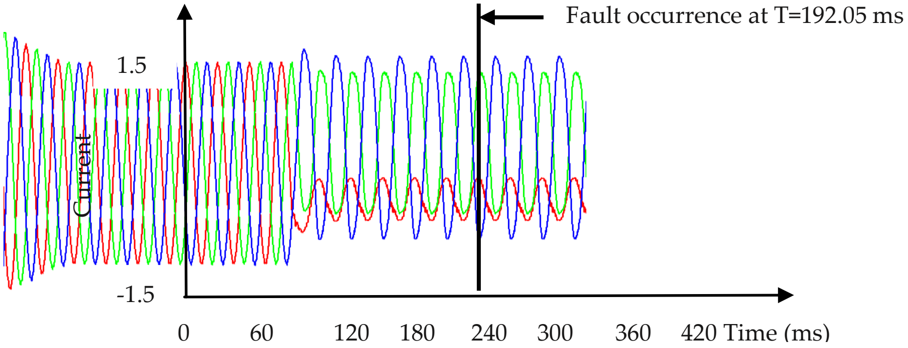


(d) Median features of Detail Coefficients values

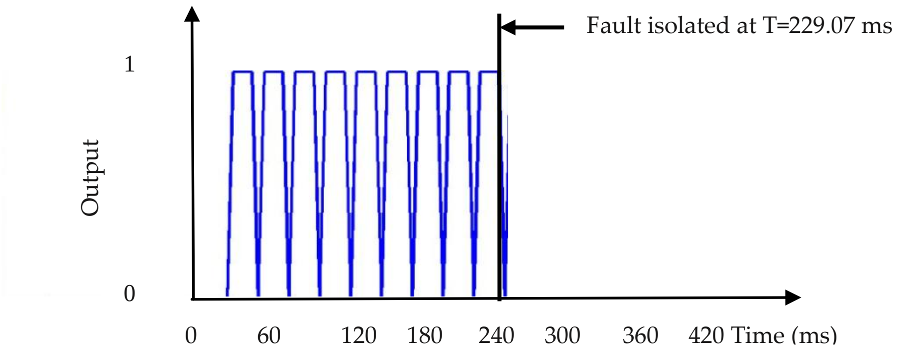


(e) Standerd deviation features of Detail Coefficients values

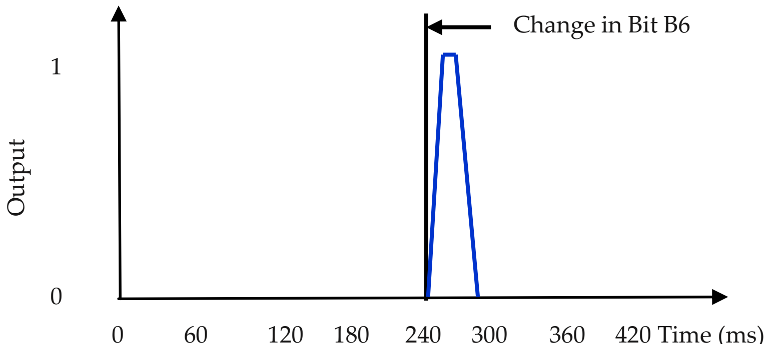
Fig. 12. Features for different faulty conditions



(a) Three phase waveform



(b) Output Bit B1



(c) Output Bit B6

Fig. 13. Results comprising phase current and output bits of T1 open circuit fault

Table 5: Confusion matrix for NN-FD System

Fault → Classified as ↓	T1	T2	T3	T4	T5	T6	T2T4	T2T6	T3T5	T4T5
T1	87.57	6.15	10.23	8.34	8.15	1.43	13.29			
T2	4.10	74.35			12.76					
T3	6.25	6.18	79.43	4.34		12.89		2.93	4.34	
T4		8.21		77.77	10.23				5.23	
T5			5.32		75.75	1.29				
T6	6.13	7.19	7.15	5.32	3.56	76.36	7.67	8.34		
T2T4							78.80			
T2T6								81.90	2.42	
T3T5									82.80	12.45
T4T5										86.40
T4T6							3.56			
T5T6									5.43	
T5T4										14.34

6. Conclusion

This paper presents the fault diagnosis based on artificial intelligence techniques for complex electrical, mechanical or chemical systems. The fault detection techniques based on signal processing are given in detail. Wavelet transform is unbelievable tool for analyzing non-stationary signal as compare to other tools like Fast Fourier Transform, Short Time Fourier Transform, etc. In wavelet transform the selection of mother wavelet and level of decomposition is critical task and it is based on shape of transients caused in non-stationary signal as a result of fault occurrence. In this paper the selection process of mother wavelet and level of decomposition is discussed in detail with the help of time domain waveform. The two recent techniques of fault diagnosis using Fuzzy Logic and Artificial Neural Networks with the help of three phases Voltage Source Inverter as target application are discussed. The Fuzzy Logic-Fault Diagnosis system is implemented by observing fault diagnosis signatures. Mamdani-Fuzzy Inference System is used. Only the consequences of fuzzy rules are sufficient to diagnose the faults. Hence the third stage of fuzzy logic i.e. Defuzzification is not used in Fuzzy Logic-Fault Diagnosis system. This system is easy to implement but have very poor accuracy. The reasons for low accuracy is mentioned and discussed in detail with the help of time domain waveform. The Neural Network-Fault Diagnosis system is implemented by collecting sample data at different healthy and faulty conditions. The selection of hidden layer, learning rate related with the structure of artificial neural network is specified. The accuracy of fault diagnosis system in NN-FD system is 80.33% and FL-FD system is 62.56%. The NN-FD system shows better accuracy than FL-FD system under variable load conditions. The false true output of Neural Network-Fault Diagnosis system is introduced in fault diagnosis system. Fuzzy Logic-Fault Diagnosis and Neural Network-Fault Diagnosis systems are easy to implement if initial training data is available. To improve performance of these two systems some modification is required either in signal processing techniques or in fault classification techniques. In case of variable speed or load conditions, it is very difficult to collect initial training data of artificial neural networks or difficult to modify fuzzy membership functions in Fuzzy Logic. Hence, if the non-stationary fault diagnosis parameter i.e. current in this case is normalized within certain range then it is not required to collect data for different load and speed conditions. Once artificial neural networks or fuzzy logic is trained for single load condition it is applicable to all speed or load conditions. High implementation efforts are required to train the Artificial Neural Networks than Fuzzy Logic. The effectiveness of FL-FD system is good if fuzzy rule is carefully designed. In case of NN-FD system effectiveness is good if initial training data is available. But the other methods like Park's Vector method, Normalized DC current methods and Slope methods are ambiguous at small current. Resistivity at small currents of FL-FD and NN-FD systems is good as compared to other systems as mentioned above. High implementation efforts are required in FL-FD system and NN-FD system as compared to other techniques due to implementation of FIS and initial training of ANN.

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