Chapter 3

RACM of Inverters: 2 Samples Approach

3.1 Introduction

The reliability assessment of power electronics converters is essential for the secure operation of the converters. The overall performance and reliability of power system depend on the reliability and performance of its components [15, 16]. The block diagram representation of the RACM of inverter using the proposed OC fault diagnosis method is shown in Fig. 3.1. The converters and inverters are crucial components of the electrical power system. The quality of power is improved by implementing various power electronics-based FACTS devices that involve power electronic switches [17], and different optimization techniques are also implemented to improve the power [18]. The quality of power is disturbed with RE penetration due to the variable outputs and interfacing converters [19]. The fault in the converter's switches leads to the distorted output current waveforms [20] and hence results in reduced power quality. The distorted waveforms lead to heating losses in the converters or may change the response of the system [21–23]. So, to avoid these distorted waveforms, it requires an adequate operation of converter switches. The OC faults must be detected and isolated to achieve the switches' adequate operation in the minimum possible time. Therefore, fault detection and diagnosis must be reliable and fast. The authors in [24, 25] have discussed the structure of the multilevel converter for getting fault-tolerant operation of the converter with improved performance.

Neural network-based Multilayer Perceptron (MLP) technique, SVM, Self-Organizing map (SOM), and K-means based machine learning techniques are discussed by the authors [52] to detect and classify the faults. The authors observed that supervised learning-based algorithms (MLP and SVM) give accurate results during fault detection. The research papers related to

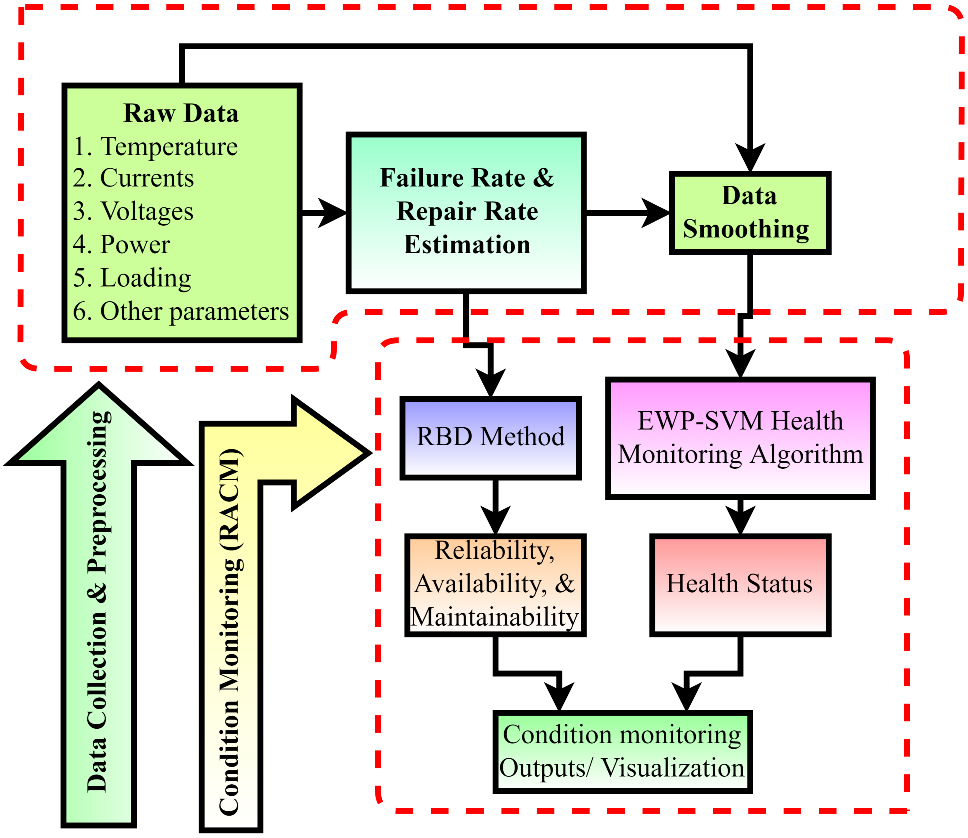

Figure 3.1: RACM using two samples and EWP-SVM based techniques

fault detection of switches based on the analysis of voltage characteristics and current signals are discussed in [56, 59, 65, 69]. The faults are detected after one or more than one cycle of the signals with these techniques. The authors [61, 70] have used the residual-based detection technique to detect the converter's fault. The fault detection technique, including observer-based residual generation and transient energy derived from the superimposed components of voltage and current signals, are discussed in [71] and [72], respectively. These techniques can detect the fault in less than one cycle of the current signal with a low computational burden, but these techniques cannot provide the faulty switch location in less time.

The observer-based condition monitoring of converter is discussed in [20, 67, 73]. The data information of generated voltage, flux linkage, and stator resistance of electrical machines are obtained. The electrical machine is connected to the converter, and all the data information is implemented for the analysis of an observer-based condition monitoring algorithm [20]. The fault detection technique, with more than two parameters, makes the detection system complex. The authors in [67] have also used a residual observer-based fault detection algorithm for detecting the converter OC faults. The fault detection time is observed to be in the range of

15ms to 20ms. The time can be decreased by reducing the computational burden involved in the residual calculation for tripping the faulty switch in the minimum possible time. Also, the detection time should be as minimum as possible.

The authors [52, 74] have discussed the advantages and concepts of the SVM technique, which does not require information on one complete cycle of current signal when compared with other fault detection techniques, including the current signature method and Artificial Intelligence (AI) methods. The SVM technique is faster than other proposed techniques because it gives results in less than half cycle. The fastness and accuracy of fault detection and classification techniques depend on selecting features and its computational time. A fast feature extraction technique is discussed by the authors [60]. This technique includes Wavelet Packet Decomposition (WPD), the entropy of wavelet packets in different forms such as Shannon and log wavelet entropy. The feature extraction technique using the wavelet packet entropy has not been implemented in the previous literature for the fault detection and classification of the converter's switches. Therefore, it is required to investigate this technique with its capability of feature extraction in the fault detection and classification of Insulated Gate Bipolar Transistor (IGBT)s based converters.

An observer-based algorithm based on a single parameter for fault detection is proposed. The parameter is the current signal. The proposed algorithm takes only current coming out to the inverter. It detects the fault in IGBTs using two samples of the current signal. The EWP-SVM technique is used for fault classification and localization of faulty IGBTs of the three-phase inverter. The proposed algorithm can detect the fault in a single IGBT and the fault in multiple IGBTs. The current signals of all three phases are estimated based on the two-samples algorithm using the load impedance and the output voltage. These estimated signals are compared with the actual inverter output currents for fault detection. This makes the detection technique faster and accurate than the other fault detection techniques available in the literature. The comparison of detection time of different supervised and unsupervised machine learning-based algorithms for fault detection of IGBTs is also discussed. The flow chart of the proposed technique is shown in Fig. 3.2. The figure can be divided into three parts: (i) inverter model and current measurement, (ii) OC fault detection, and (iii) classification and localization of faulty IGBTs. In the first part, the three-phase inverter model is Simulated, and currents are measured for fault diagnosis. The second part deals with the detection of OC faults in the IGBTs using a two-samples based fault detection algorithm. The third part is representing the steps involved in the fault classifications

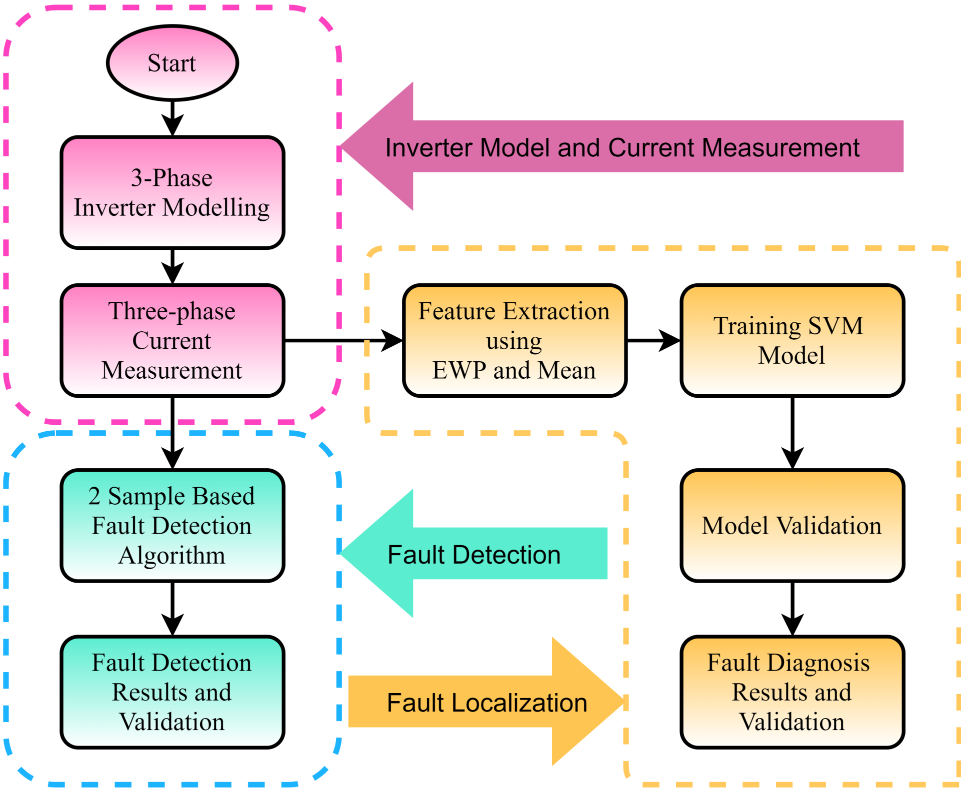

Figure 3.2: Flow chart of the proposed system

and localization of faulty IGBTs. The EWP and mean values of the currents are extracted and used as features for training the SVM based fault classifier, and then, it is validated with the new dataset under different OC faults in IGBTs of the inverter. The SVM algorithm results are the condition of the IGBTs of the inverter, whether they are working normally. If OC fault has occurred in any of the IGBTs, the SVM algorithm outputs the location of the faulty IGBTs.

The faults in three-phase output lines of converters are easy to identify but detection of OC faults in IGBT switches is complicated work. The localization of the faulty switches is a more difficult task. The fault in a single switch may lead to undesirable operation of power electronics-based drives and control systems. Therefore, detection and localization of faults of IGBTs are too essential.

The fastest OC fault detection techniques observed in literature are observer-based techniques. For minimizing the detection time in the order of micro-seconds, the algorithm should involve less computational burden. The detection algorithm becomes slow while considering more processing parameters of the system. Moreover, the selection of features and their extraction is essential for fault diagnosis. The most commonly used features proposed in the literature include entropy [26], WT [27], mean value, phase angle [26], [28], [29] and dq0 transformation of the time series current or voltage waveform [26]. These features sometimes do not accurately detect faults and may result in the wrong classification of faults due to approximately equal values of features under different fault conditions. This chapter proposes a different approach for feature extraction using EWP. It gives accurate results for OC fault detection of IGBTs of three-phase inverter. Furthermore, the classification of faults is significant to distinguish between similar faults. The classification is done using the SVM learning technique. The problem of minimization of fault detection time has also been resolved. The proposed fault detection technique detects the fault within a few microseconds to 0.33 ms time range.

3.1.1 Proposed Fault Diagnosis System

The proposed method is simulated and implemented. The significant contributions of this chapter and the steps involved in the proposed algorithm are given as follows.
(i) Simulation of three-phase IGBTs based inverter model,
(ii) simulation of SPWM for pulse triggering in the IGBTs,
(iii) fault detection using two samples-based algorithms,
(iv) measurement of three-phase currents of the inverter for features extraction,
(v) extraction of features including EWP and mean of the three-phase currents under different fault conditions generated in the Simulink model,
(vi) training of SVM model-based fault classification and localization technique,
(vii) validation and testing of the SVM classifier-based trained model for fault classification and localization of the faulty IGBTs, and
(viii) comparative analysis of proposed algorithm with the available algorithms in the literature used for features extraction and fault diagnosis.

Fig. 3.2 shows the schematic diagram of the proposed fault diagnosis system consisting of three phases inverter, current measurements, fault detection, features extraction, and training of SVM model using the features including EWP and mean of three-phase currents. The inverter model is simulated with six IGBTs, and pulses for these IGBTs are generated using the SPWM technique. The three-phase currents are measured at the inverter's output and sent to two samples-based fault detection algorithm block, which detects the OC fault. The current signals are also sent to the features extraction block, which computes EWP and means the three-phase currents' value. The extracted features of three-phase currents are then used for the training of the SVM algorithm. Afterward, the trained SVM model is validated for fault classification and localization by generating different IGBTs OC faults in the Simulink model. The SVM algorithm provides the condition of IGBTs of the inverter and locates the faulty IGBTs if OC faults have occurred. Fig. 3.3 shows the schematic diagram for two-samples based fault detection algorithm. The load impedance and the voltage are used to estimate the current signals using a two-samples based algorithm. Then the actual current signals of three-phases are compared with the estimated current signals. In Fig. 3.3, e_a, e_b, and e_c are representing the estimated currents of phases a, b, and c, respectively. The comparison of estimated and actual signals is made, and the detector represents the difference between the two outputs d_a, d_b, and d_c, respectively. If the magnitude of any of the detector output is higher than the threshold value of current, it indicates OC fault or noise spike. The OC fault can be distinguished from the noise spike, as discussed in Section 3.2.1. The fault diagnosis is necessary after the fault is detected. The SVM-based fault classification method is used for the fault classification, and localization of faulty IGBT using EWP and mean of current signals as features. The methodologies including two-samples based OC fault detection technique, EWP, SVM techniques are discussed in detail in this chapter.

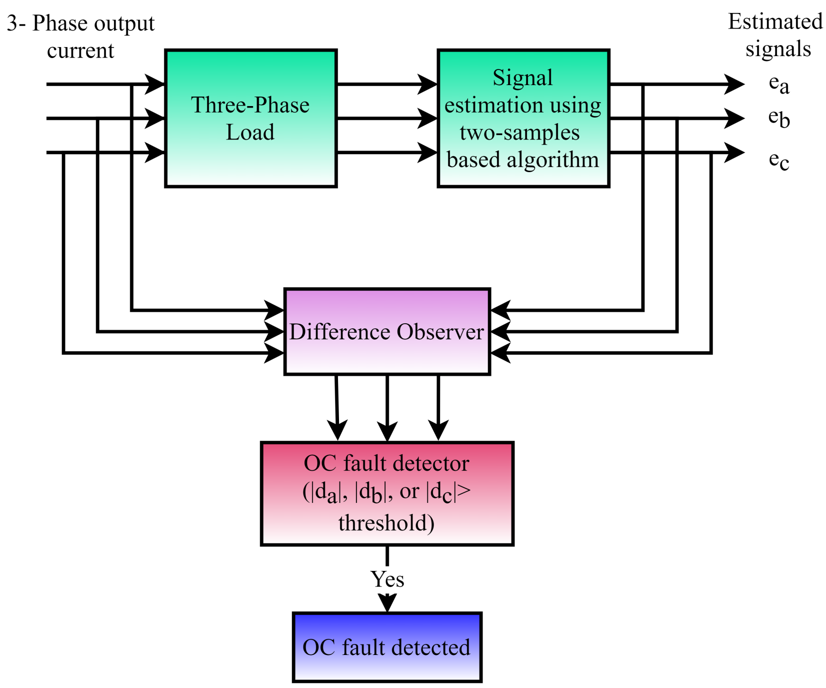

Figure 3.3: Schematic diagram for two-samples based fault detection algorithm

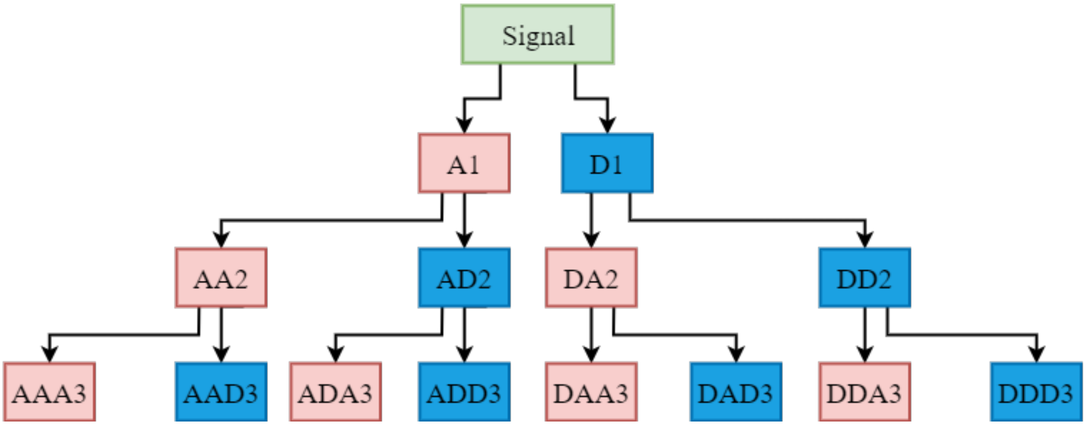

Figure 3.4: WPD of a signal into Approximate (A) and detail (D) coefficients up to 3 levels

3.2 Two Samples-based Method for RACM

The detection of OC faults in IGBTs of the converter is done with three-phase output currents of the inverter. The proposed algorithm is based on processing the two consequent samples of the current signal. In this section, the proposed two samples-based OC fault detection algorithm is explained mathematically. The methodology of feature extraction from the current signal is also discussed in this chapter. The entropy of wavelet packet is used as the feature for fault diagnosis algorithm using SVM technique.

3.2.1 Two-Samples based Fault Detection Technique

The output current and voltage of the converter give the information of OC faults in the switches. The two-samples based OC fault detection technique is shown in Fig. 3.5. The samples of the inverter's output current are taken for detecting the OC fault in the inverter's IGBTs. The peak and Root Mean Square (RMS) values of the signal are estimated using a two-samples algorithm. For this, a window of two samples is used. When the next sample appears, the old sample of current is shifted out. If the estimated value of RMS current of the inverter is observed greater than the threshold value, this indicates the inverter's problem. This is because of either OC fault or noise. The current threshold value is decided based on the value of load connected and the output voltage. The current is determined as the ratio of voltage to the load; the current is calculated each time the load changes, and the current threshold value also changes accordingly. The problem is to distinguish between noise and OC fault. Due to noise, the signal's RMS value may increase and may result in the false operation of the OC fault detector. A fault counter is set to overcome this problem, which is incremented when the RMS value is larger than the current threshold value and decremented when the RMS current value is lesser than the current threshold value. If the counter crosses a particular set limit of counts, it indicates that OC fault in the inverter switches. This way, the OC fault is detected. The threshold count value is chosen as per the severity of noise at the inverter output current. Therefore, the effect of transient and noise can be distinguished from OC faults using the proposed algorithm.

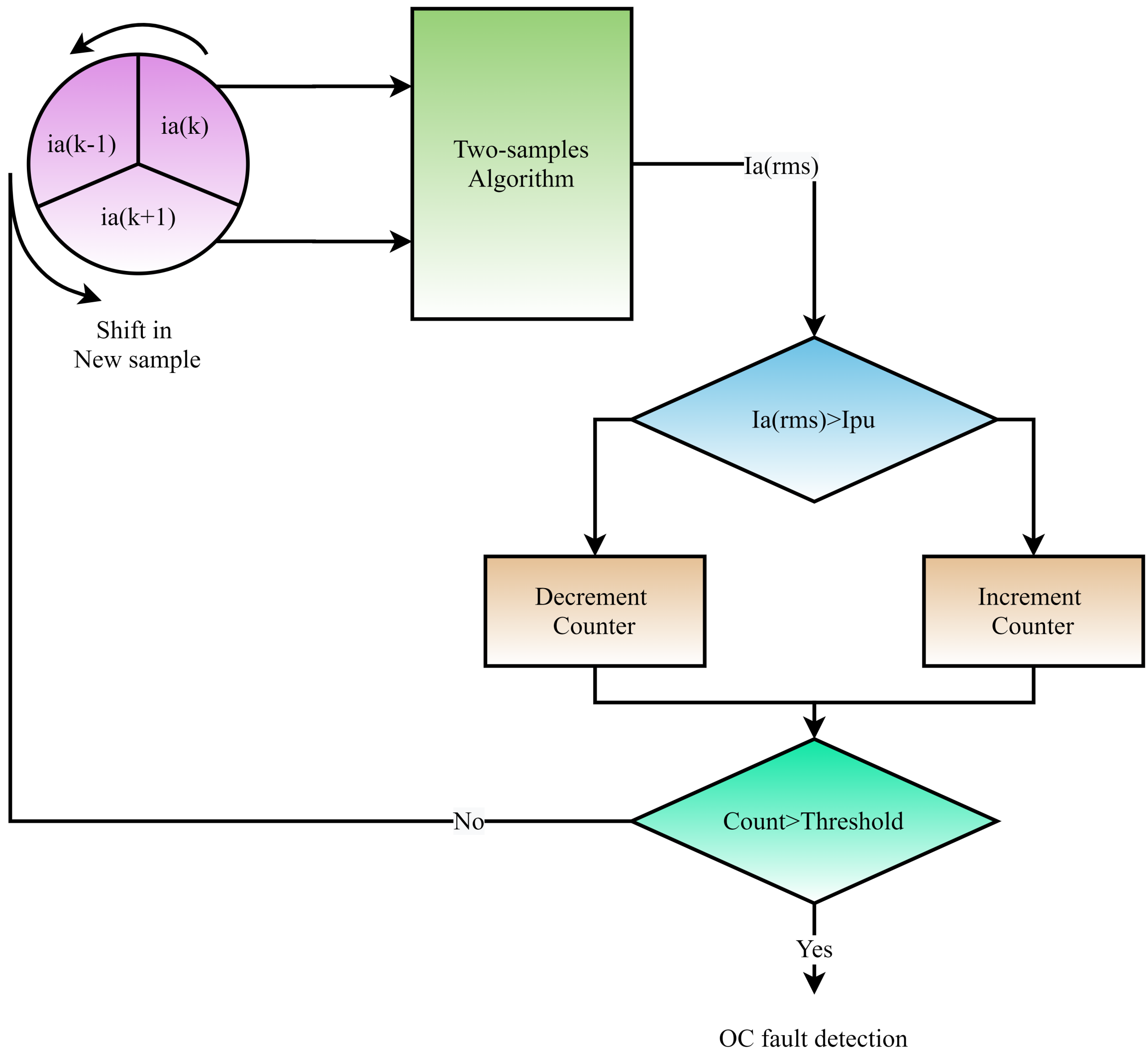

Figure 3.5: Flow chart of two-samples based OC fault detection algorithm

Mathematical model of two samples-based algorithm is as follows. The three-phase currents of the inverter are i_a, i_b, and i_c, respectively. The current of phase-a is taken for the development of mathematical model of the two-samples based algorithm. The expression of current of phase-a for k_{th} time instant is given in equation (3.1). The expression of same current

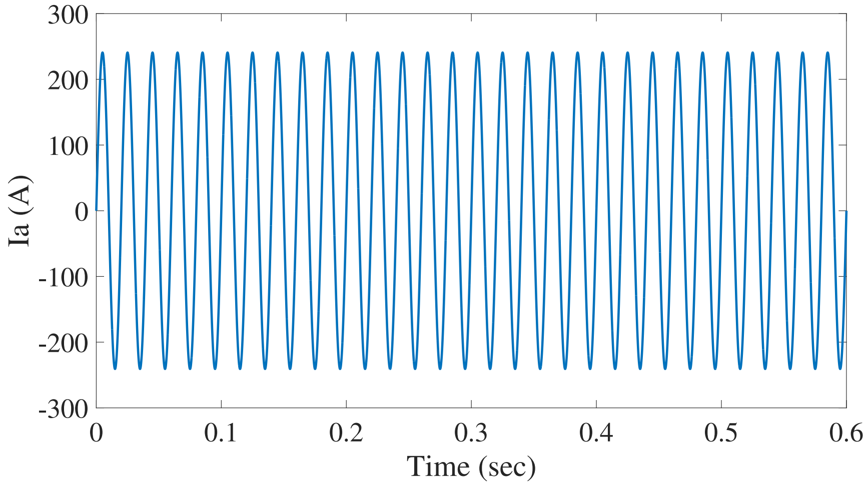

Figure 3.6: Estimated current of phase-a of the inverter under multi-IGBTs OC faults at S1 and S5

for $(k+1)_{th}$ time instant is given in equation (3.2).

$$i_a(k) = I_{am}sin(\omega t_k) \tag{3.1}$$

$$i_a(k+1) = I_{am}sin(\omega(t_k + \Delta t)) \tag{3.2}$$

On simplifying the equation (3.2), the simplified expression is given in equation (3.3).

$$\frac{i_a(k+1) - i_a(k)cos(\omega\Delta t)}{sin(\omega\Delta t)} = I_{am}cos(\omega t_k) \tag{3.3}$$

On adding the squares of equations (3.1) and (3.3), and simplifying the expression, the simplified expression of the resulting equation is given in equation (3.4). The estimated peak value of current of phase-a is given in equation (3.5).

$$I_{am}^2 = \frac{(i_a(k))^2 + (i_a(k+1))^2 - 2i_a(k)i_a(k+1)cos(\omega\Delta t)}{sin^2(\omega\Delta t)} \tag{3.4}$$

$$I_{am} = \sqrt{\frac{(i_a(k))^2 + (i_a(k+1))^2 - 2i_a(k)i_a(k+1)cos(\omega\Delta t)}{sin^2(\omega\Delta t)}} \tag{3.5}$$

The frequency (f) of the current signal is 50 Hz, and the Oversampling Factor (OF) is taken as 200 such that the sampling frequency of the signal becomes $2 * OF * f$ Hz. The OC fault detector signal is constructed using the proposed two samples-based algorithm for all three-phase currents for monitoring the IGBTs of the inverter. The difference between the estimated detection current signal and the inverter's original current signal indicates OC fault in

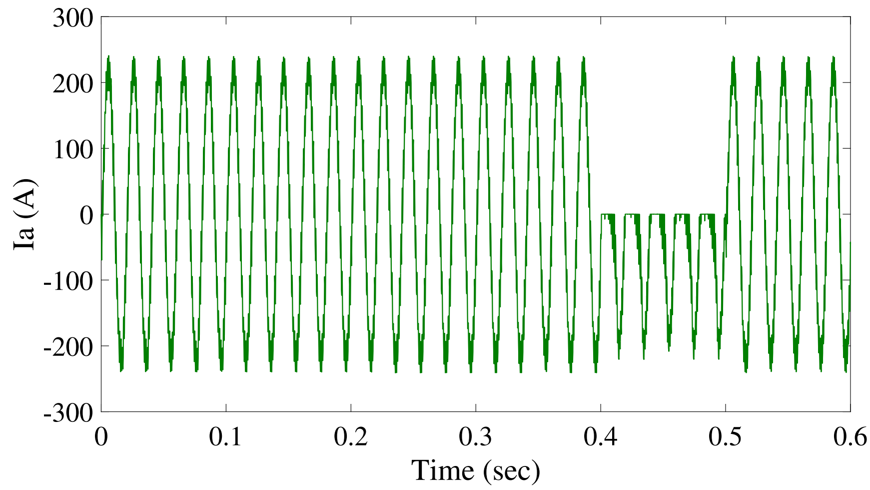

Figure 3.7: Original current of phase-a of the inverter under multi-IGBTs OC faults at S1 and S5

the IGBTs. The constructed signal using the values of loads, voltage, frequency, and estimated peaks is shown in Fig. 3.6. The original phase-a current of the inverter is shown in Fig. 3.7. The OC fault has occurred in the IGBTs S1 and S5 in the time interval of 0.4011 to 0.5011 seconds. The difference between peak values and RMS values of the estimated signal and the original signal indicates OC faults. The setting of the threshold limit is dependent on various factors, including the type of loads, noise spike range, and application range. This chapter selects a threshold value after investigating the difference coming in the current amplitude during OC faults in the IGBTs. When the estimated current's peak value differs with a magnitude more significant than the threshold value of 20 A [75], the OC fault is detected, and a fault detection alarm is generated, as shown in Fig. 3.8. The threshold value may differ as per the factors mentioned earlier. After the fault is removed, the alarm is automatically turned off if the difference between the inverter current signal and the estimated current signal does not cross the threshold limit for one complete cycle. The difference between the estimated signal and the actual signal, along with alarm generation, is shown clearly in Fig. 3.9.

3.2.2 Features Extraction Technique

There are various feature extraction techniques available in the previous literature. These techniques still have some computational complexity, and some are even not fast and accurate. Some of these are always in need of research and development for improving accuracy. In this

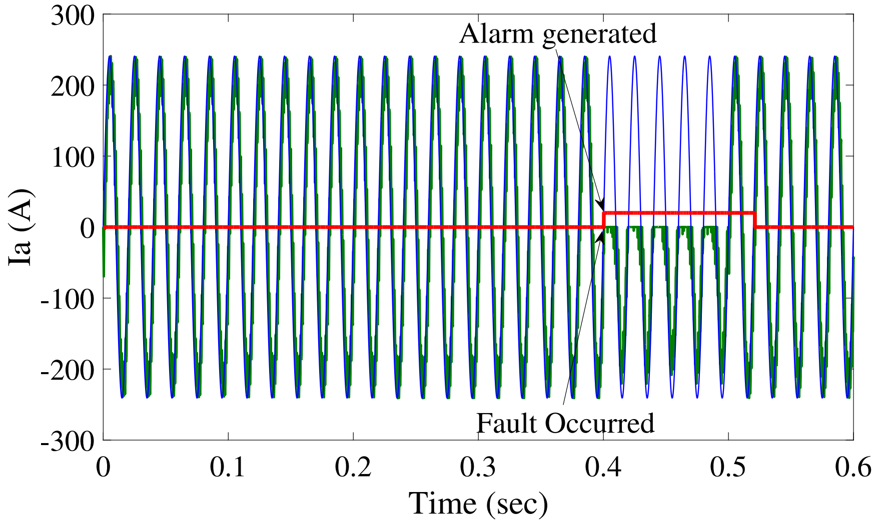

Figure 3.8: OC fault detection by comparing estimated and original current signals

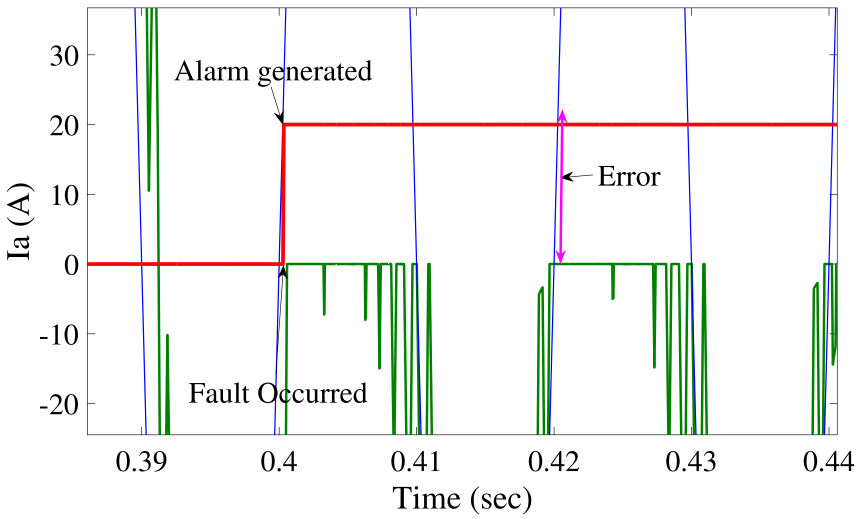

Figure 3.9: The difference of actual and estimated current signal, fault occurring and alarm generation

era, the entropy-based feature extraction technique gives accurate results when it is used for fault detection and classification problem. Entropy's performance as a feature of the signal is better than other statistical techniques, including maximum-minimum values, mean values, WT coefficients, PCA, etc. The entropy-based features extraction technique involves calculating the uncertainty and complexity occurring in the signal during a fault condition. In this section, the decomposition of Wavelet Packet (WP) and entropy feature extraction are discussed as follows.

WPD

WPD is used to extract any signal feature by calculating energy at each node of the WP decomposed. The WPD technique helps to improve the time-frequency resolution, which is not possible by Discrete Wavelet Transform (DWT). In WPD, the features are selected by calculating the energy of coefficients of the decomposed wavelet packets at each node. The approximate and detailed coefficients of wavelets are decomposed in a sequence up to a level specified. Fig. 3.4 shows the decomposition of a signal up to three levels. In this way, if the level of decomposition is N, then the signal is decomposed into 2^N parts of different frequencies [60].

The decomposed wavelet packets are represented in the form of coefficients sequence functions of approximate and detailed parts of the signal. If p(k) and q(k) are the coefficients of approximate and detailed parts of the signal s(t) and length of both, the coefficients are 2N. Then, the WP of the signal can be represented as sequence functions of p(k) and q(k) as given by (3.6) and (3.7).

$$s_{2n}(t) = \sqrt{2} \sum_{k=0}^{2N-1} p(k) s_n(2t-k) \tag{3.6}$$

$$s_{2n+1}(t) = \sqrt{2} \sum_{k=0}^{2N-1} q(k) s_n(2t-k) \tag{3.7}$$

where, n is the integer number (0,1,2,..). For n=0, the signal function is called as scaling function and when the value of n is 1, the sequence gives first wavelet function. The WP sequence function can be represented as given in (3.8).

$$WP_{i,n,k}(t) = 2^{-j/2} s_n(2^{-j}t-k) \tag{3.8}$$

In (3.8), n is equal to 0,1,2,..., $(2^j - 1)$ and this equation satisfies the scaling and WP functions. The terms k, j, and n are used to represent the localizing, scaling, and modulating parameters, respectively. The function represented in (3.8) is modeled mathematically using these parameters for analyzing the fluctuations occurring in the signal. This analysis is done for checking the condition of the signal under different operating conditions at position $2^j.k$, where j is the scaling term at different frequencies of approximate and detailed packets corresponding to a particular value of n. When the signal s(t) is decomposed into WP, its WP coefficients are calculated as the inner product of the signal s(t) and corresponding WP function of the signal as given in (3.9).

$$\begin{aligned} C_{j,n,k} &= innerproduct(s(t), WP_{j,n,k}(t)) \\ C_{j,n,k} &= \int s(t)WP_{j,n,k}(t)dt \end{aligned} \tag{3.9}$$

The WP coefficients in (3.9) gives a measure of frequency in the signal s(t). These coefficients are represented as WP nodes with a particular frequency band and used as features of the signal s(t). When phase current of the inverter is passed through WP function to find the coefficients $C_{j,n,k}$, many coefficients are obtained, which are features at each node of the signal. The features are collected and combined in a single function so that single information can be formed with these coefficients without any loss of information of any coefficient. An entropy function is used to combine these coefficients for getting single information from a large number of coefficients.

Entropy of Wavelet Packet (EWP)

Entropy is found to be a very good tool for feature extraction of the faulty signal. The EWP gives information about the stored energy of the signal. If s is the signal and s_i is signal coefficient on an orthogonal basis. Then, the entropy (S) must be additive function i.e. S(0)=0 and S(s)=$\sum_{i=1}^{N} S(s_i)$. There are different forms of entropy available in the literature involving Shannon, log energy, threshold, etc. [60], [76–79]. The normalized form of Shannon entropy is expressed as given in (3.10). Shannon entropy is helpful in the analysis of uncertainty and also the complexity of the probability distribution.

$$S(s) = -\sum_{i=1}^{N} s_i^2 log(s_i^2) \tag{3.10}$$

where, $s_i^2(i = 1, 2, ..., n)$ denotes the probability density with $s_i^2 >= 0$ and $\sum s_i^2 = 1$. The EWP of the signal s can be expressed as given in (3.11).

$$W_s = -\sum_{i=1}^{n} s_i^2(i) log s_i^2(i) \tag{3.11}$$

Table 3.1: Features extracted from three-phase currents under different conditions

E_a	E_b	E_c	m_a	m_b	m_c	Condition
212824.1	232767.1	230627	0.024232	0.099569	-0.1266	Normal
-528036	226000.2	223641.4	-2.41677	0.022212	-0.09882	S1Fault
206616.5	228515.1	-512955	0.108387	0.038223	2.320638	S2Fault
208682.5	-503301	227831.4	0.107576	-2.38199	-0.20357	S3Fault
-489986	229893.9	227801.7	2.487486	0.065952	-0.15011	S4Fault
203742.8	226072.3	-490194	-0.02133	0.071495	-2.42589	S5Fault
203918.3	-505414	225215.3	0.012456	2.424408	-0.03163	S6Fault
-541682	228799.7	-516510	-2.39018	0.029873	2.320632	S1S2Fault
-499737	-511318	229168.4	2.463128	-2.3676	-0.17466	S3S4Fault
203585.4	-511364	-506902	-0.02416	2.421913	-2.39152	S5S6Fault
209336.5	-506869	-526074	0.111277	-2.37858	2.292185	S2S3Fault
206375	-512002	-487274	-0.02193	-2.3476	-2.47528	S3S5Fault
-504716	-501638	227688	2.415644	2.459758	-0.04989	S4S6Fault
-495512	231168.1	-516056	2.461062	0.091045	2.326121	S2S4Fault
-527081	227833.8	-493525	-2.44417	0.031784	-2.42567	S1S5Fault
-535658	228281.2	-1351997	-2.4254	0.037347	0.000436	S1S2S5Fault
-514149	-507588	-511426	2.396325	2.455514	-2.39738	S4S5S6Fault
-547141	-505682	-527545	-2.38914	-2.37902	2.2975	S1S2S3Fault
204093.7	-1352887	-506057	70.091661	0.00027	2.347946	S2S3S6Fault
-410077	-392293	-399118	-2.41984	-2.37021	-2.48568	VsUpperFault
-381581	-373640	-390125	2.44328	2.481177	2.337141	VsLowerFault

where, s_i^2 represents the wavelet packet energy distribution. Another type of entropy that is used commonly is log energy-based entropy as given in (3.12).

$$W_{log} = -\sum_{i=1}^{n} log(s_i^2) \tag{3.12}$$

For the decomposed wavelet packets, the entropy is computed using (3.11) and (3.12). These equations' entropy values are used as features for training the SVM algorithm to detect and classify the converter switch faults. The use of entropy values gives an advantage of a reduced number of features and less computation.

It is observed that entropy can compute and detect the uncertain changes in the signal easily. Out of the three types of entropy mentioned above, Shannon's entropy is used for calculating the EWP of each node of the signal WP. It is done by creating a MATLAB function. The function computes EWP using the WP coefficients as calculated in (3.9). The (3.13) represents the function to calculate EWP using the calculated coefficients in (3.9). In this equation, j is the length of decomposition or the level of decomposition, and L is the number of WP coefficients in each node for j level WPD with n=0,1,2,....,$(2^j - 1)$. The calculated EWP values of three-phase currents of the inverter are tabulated in Table 3.1 for different fault conditions.

$$EWP_{j,n} = -\sum_{k=1}^{L} log(C_{j,n,k}^2) \tag{3.13}$$

The present work's main objective is to propose a fast and more accurate fault detection and classification technique. The accuracy, along with fastness, is possible with a less computational process in features selection and fewer features, indicating the faults effectively and accurately. For this, the chapter proposes a technique including the concept of fault detection using two samples of the monitoring signal, EWP, and SVM to detect and locate the faults in switches of IGBTs based converter in very less time.

The features extracted from the three-phase currents of the IGBTs based converter under different fault conditions are tabulated in Table 3.1. The EWP of three-phase currents are calculated using the formula given in (3.13) and tabulated in Table 3.1 as Ea, Eb, and Ec for phases a, b and c, respectively. Along with entropy, the mean is also calculated to improve the SVM fault detection algorithm's performance. The mean of the three-phase currents is calculated by using the formula as given in (3.14). In this equation, m_a, m_b, and m_c are the mean values of currents of phases a, b and c, respectively, and N is the number of samples taken.

$$\begin{aligned} m_a &= \sum i_a/N \\ m_b &= \sum i_b/N \\ m_c &= \sum i_c/N \end{aligned} \tag{3.14}$$

3.3 Simulation Studies

The simulation model of a three-phase inverter consisting of six IGBTs switches are used to implement the proposed OC fault diagnosis technique. The inverter switches are triggered using the SPWM model, which is also simulated in the same Simulink. The Simulink model of the fault diagnosis system is shown in Fig. 3.10 consisting of inverter block, features extraction block, SVM based-algorithm block, and fault diagnosis outputs. Various combinations of open circuit faults are simulated, as given in Table 3.1. When the simulation is run under normal and different fault conditions, the fault detection output blocks indicate the condition of each of the fault combinations made in the simulation during the training process. The features are extracted from the three-phase currents using the equations discussed in this chapter. These features are then passed through the SVM-based fault classifier, which is already trained with the training data shown in Table 3.1. The fault detection block shows the output of the fault diagnosis algorithm. The particular fault condition is indicated by '1', and others are shown as '0'. For example, if the Simulink is run under normal condition, the fault detection system outputs 'Normal' block as '1' and others as '0'.

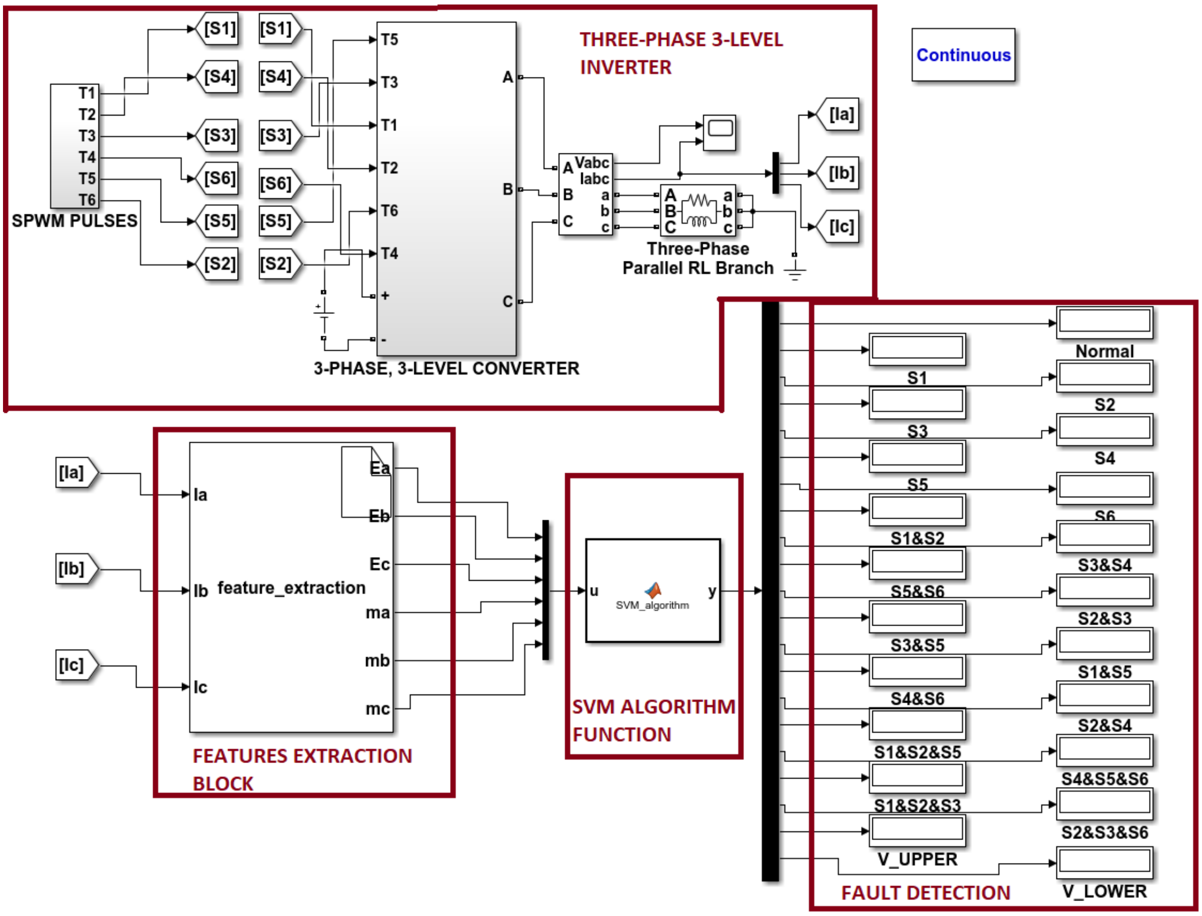

Figure 3.10: Simulink model of the fault diagnosis system

Three-phase output currents of the proposed three-phase inverter are illustrated in Fig. 3.11. The current and voltage waveforms are smooth under the normal operating conditions of the inverter. The EWP values and mean values of all three-phase currents are computed. The MATLAB functions are formed, which consist of the mathematical formulas of EWP and mean values of three-phase currents. The outputs of these functions are used as features for the SVM algorithm. One more function is created, which consists of the SVM algorithm requiring features data as input and giving converter operation condition and switch condition as output. To get the proposed simulation model's desirable performance, firstly, the model is trained for different fault conditions. The simulation model is run under different possible faults, including a single IGBT fault, multiple IGBTs faults, and supply line fault. The current measurement data is used to extract the features to train the SVM model for fault diagnosis. After training the SVM algorithm, it is validated for different faults in the converter. During validation and testing of the proposed algorithm, it is observed that it is giving correct fault detection results. The fault detection outputs under normal and different fault conditions of IGBTs are discussed in this chapter.

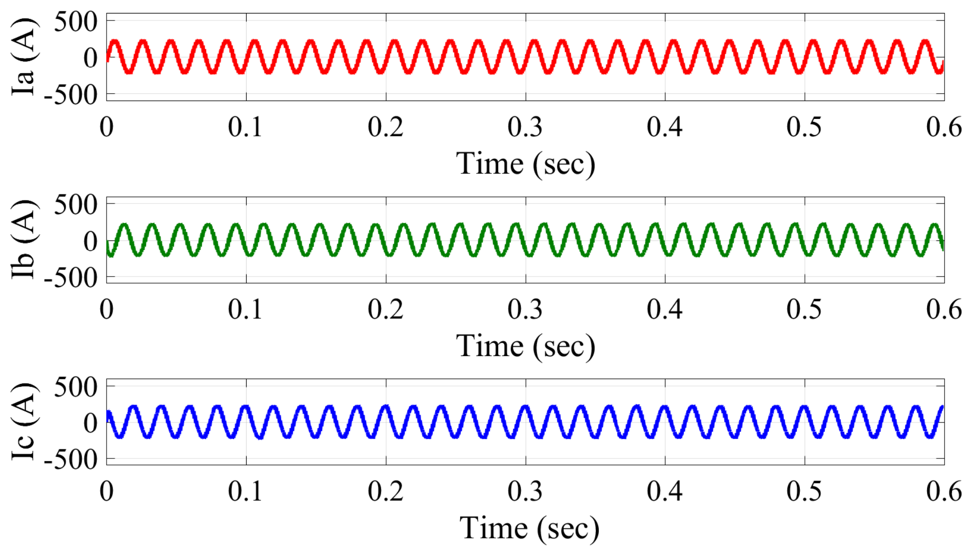

Figure 3.11: Three-phase output currents of the 3-phase, 3-level inverter under normal condition

3.4 Results and Discussion

The current waveforms change when OC faults occur in the IGBTs of the inverter. The EWP is also different for current waveforms under normal and fault conditions. The fault detection system outputs and three-phase currents under OC fault in single IGBT (S1) and under OC faults in multiple IGBTs (S1, S2, and S5) are shown in Figs. 3.12, 3.13, 3.14 and 3.15, respectively. These figures are showing that the fault in a particular switch is detected in less time (microseconds range) when the switch comes into action. All three-phase currents are monitored individually so that whenever OC fault occurs in IGBTs, it can be detected in minimum possible time. For example, if OC fault occurs in S3, the phase-a current will reflect it after a few seconds, but it will be reflected in the phase-b current earlier. Therefore, all phase currents are monitored using a two-samples based fault detection algorithm. The OC fault detection output using the currents of phase-b and phase-c are shown in Figs. 3.16, 3.17, 3.18 and 3.19, respectively. It is clear from Figs. 3.16 and 3.17 that the magnitude of currents of phase-b and phase-c decrease under OC fault in the S1 switch. The differences in the magnitude of currents of phase-b and phase-c with the estimated signals of phase-b and phase-c using the two-samples technique reflect the OC fault in the IGBT of the inverter. However, the effect of S1 OC fault in phase-a current is dominant, and a large difference is visible in phase-a current as compared to the currents of phase-b and phase-c. Similarly, for OC faults in other IGBTs, the effect is detectable in a better way in phase-b and phase-c currents. Therefore, a two-samples-based OC fault detection technique is applied to the currents of all three-phases to detect the fault in the minimum possible time.

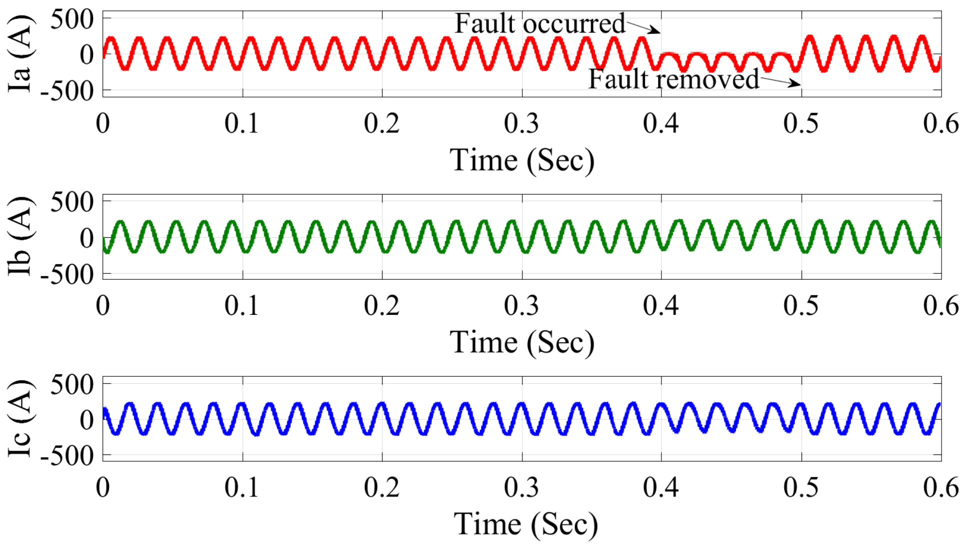

Figure 3.12: Three-phase currents for single IGBT (S1) fault

3.4.1 Fault Diagnosis using EWP-SVM Technique

The SVM model is showing accurate result during training time when EWP is used as a feature for fault classification. Also, while validating the model, it is giving accurate fault diagnosis

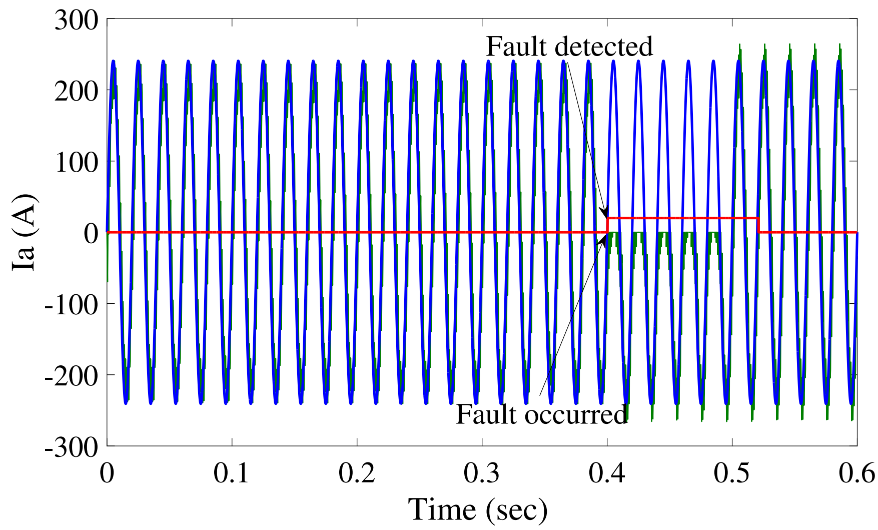

Figure 3.13: OC fault detection for single IGBT (S1) fault

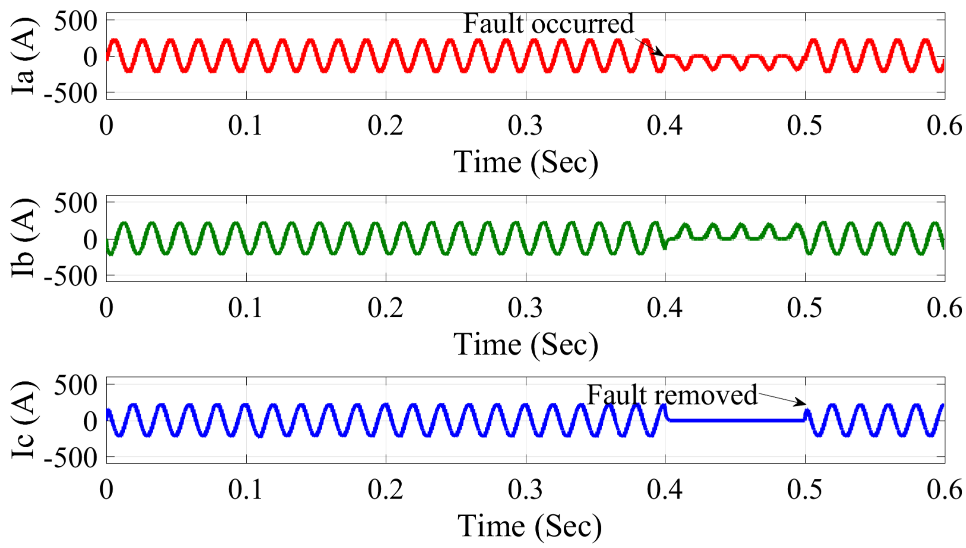

Figure 3.14: Three-phase currents for multiple IGBTs (S1, S2, S5) faults

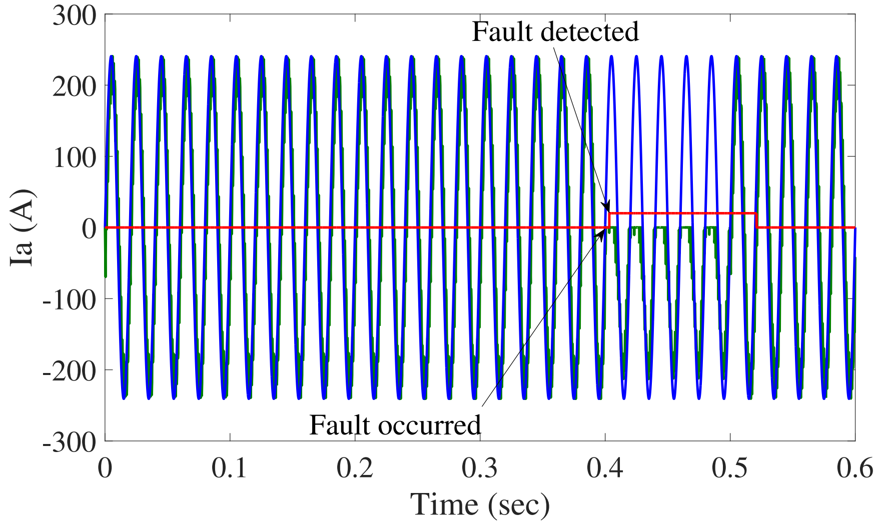

Figure 3.15: OC fault detection for multiple IGBTs (S1, S2, S5) faults

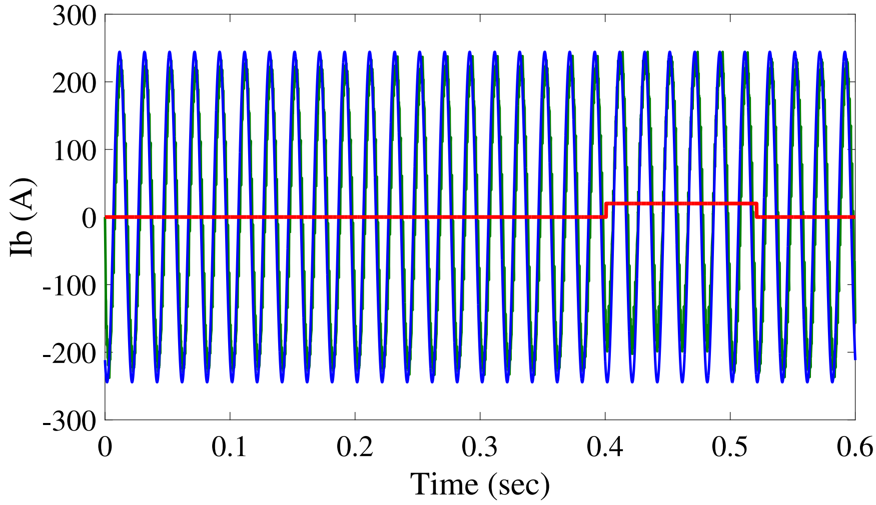

Figure 3.16: OC fault detection output with current of phase-b under OC fault in S1

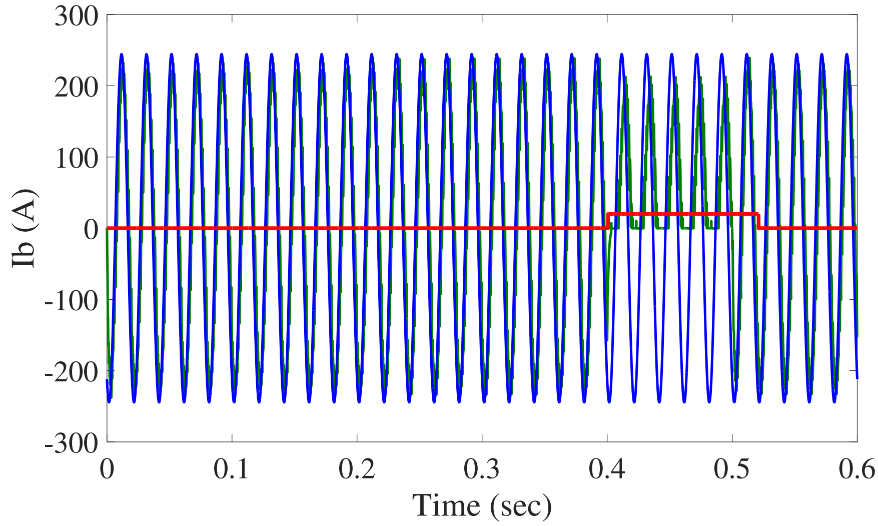

Figure 3.17: OC fault detection output with current of phase-b under OC faults in S1, S2, and S5

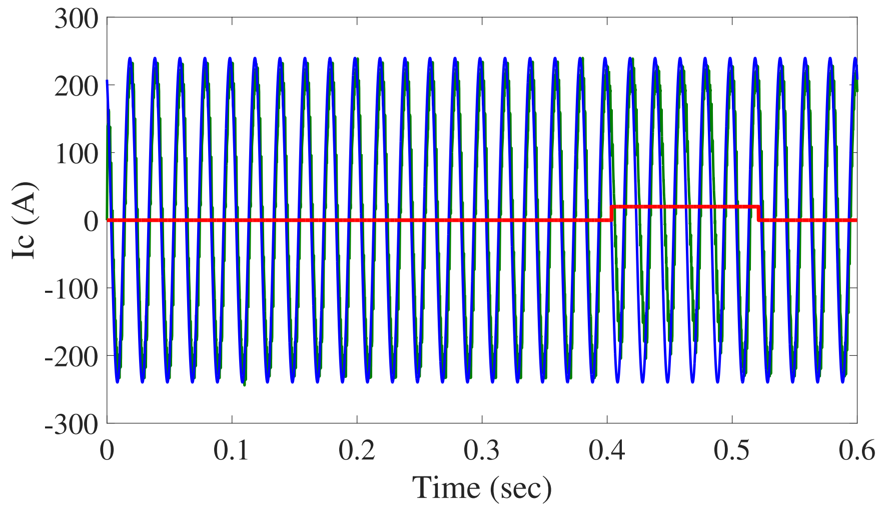

Figure 3.18: OC fault detection output with current of phase-c under OC fault in S1

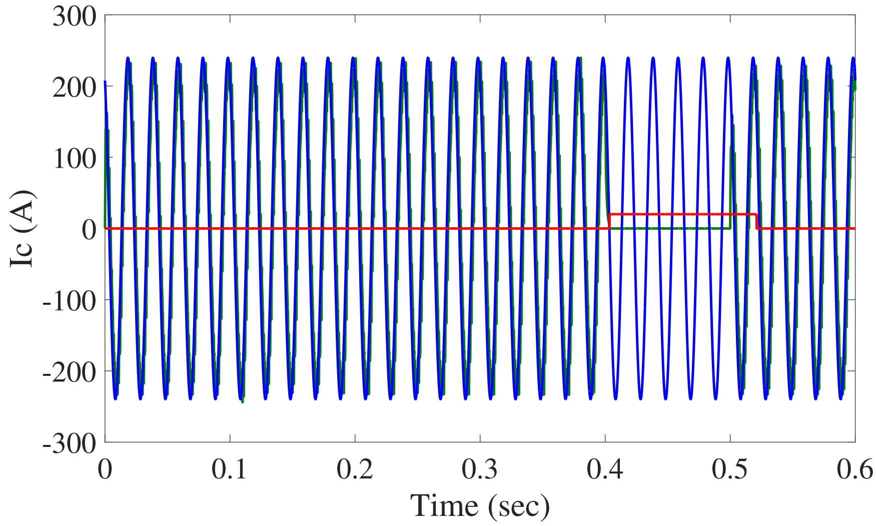

Figure 3.19: OC fault detection output with current of phase-c under OC faults in S1, S2, and S5

and classification results as shown in Fig. 3.20.

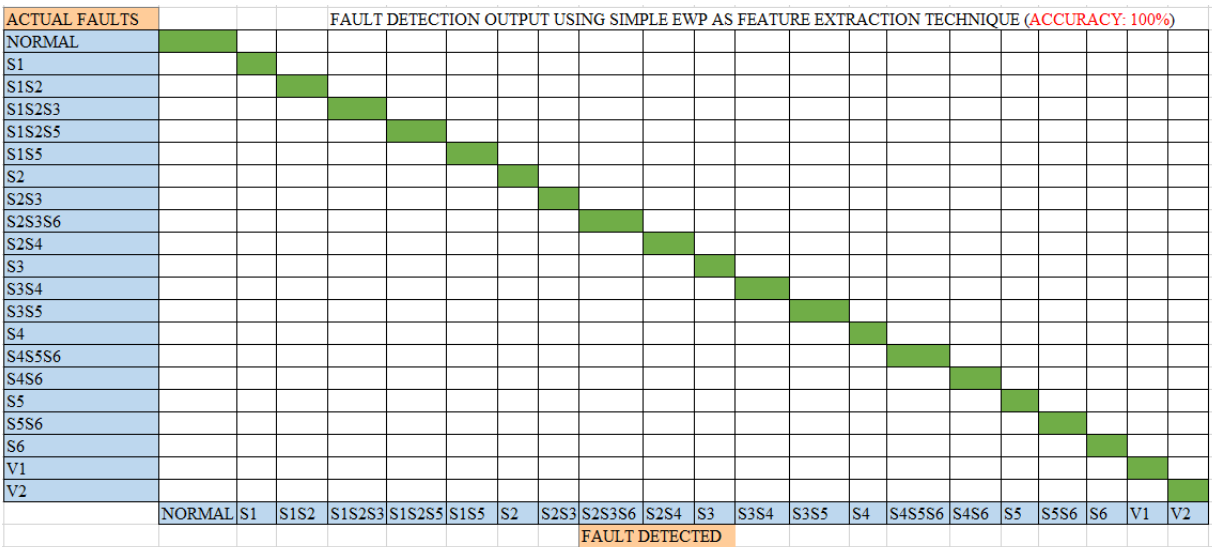

Figure 3.20: Classification results using proposed EWP-SVM technique

The types of OC faults considered for validating the proposed algorithm include six single IGBT OC faults, twelve multiple IGBTs OC faults, and two source terminal OC faults. During validation of the proposed technique of fault diagnosis, the particular class of OC fault is detected correctly, and the faulty IGBTs are localized accurately with an overall accuracy of 99.70%. Further, the model is validated with the training dataset of the features; the accuracy is obtained 100% as shown in Fig. 3.20.

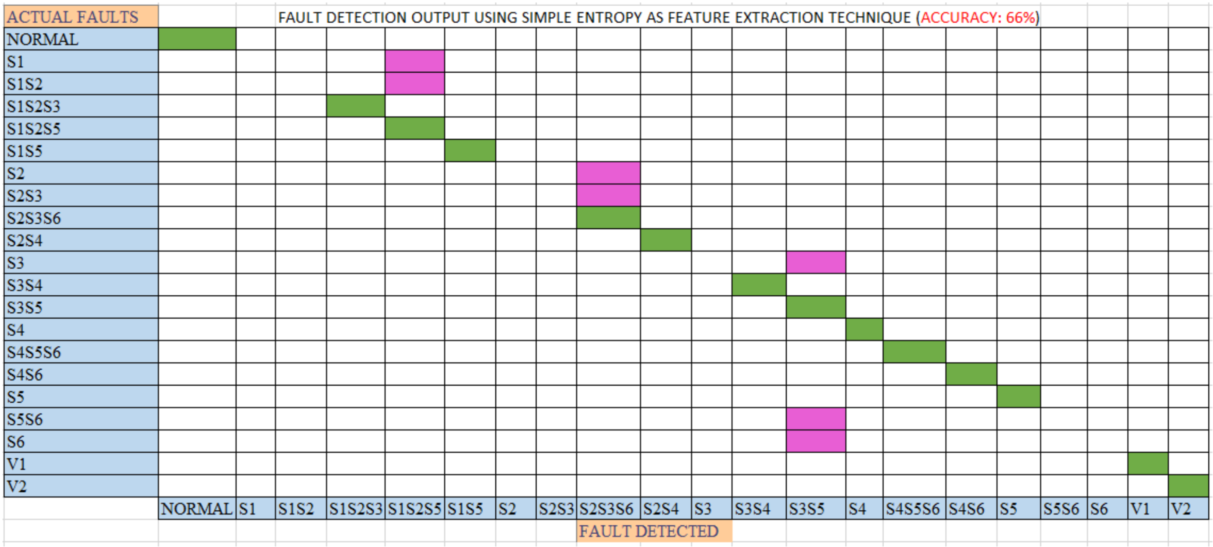

Figure 3.21: Classification results using simple entropy as feature extraction

3.4.2 Comparison between Proposed Technique and Existing Techniques

In this section, various OC fault detection techniques available in the literature are compared with the proposed two-samples based detection technique. A comparison is also made among the simple entropy and EWP methods of feature extraction. Comparing the proposed technique for detection and localization of OC faults in IGBTs of the converter with the other techniques is described.

Fault detection techniques

The important factor in fault diagnosis is the minimization of fault detection time. The literature shows that the fault detection time is less than or equal to the half cycle of the fault waveform using the DWT-SVM technique. The fault detection time in a decreasing manner is as follows: The PCA-MRVM technique gives fault detection result in more than one cycle of samples data; the Extended State Observer (ESO) technique takes 150 ms, Kalman filter, and sliding mode observer techniques takes 100 ms and 50 ms, respectively. In the previous literature, the fastest fault detection technique proposed is the ESO technique, which compares the measured and theoretical values of full-arm voltage for fault detection in less than 15 ms. The technique was applied for the detection of the faulty sub-module in the modular multilevel converter. The technique was not implemented for switch fault detection of the multilevel converter. The other observer-based fault detector is also studied in the literature survey, which involves complex calculations and computational burden. With the proposed EWP-SVM technique, the fault is detected before a one-quarter cycle of the fault current waveform. In fact, the OC fault is detected in the smallest time span by using the two consequent samples of the current signal, which is less time than the time of detection using other techniques proposed in the literature as tabulated in Table 3.2. The proposed algorithm can detect the fault in a single IGBT, faults in multiple IGBTs, and fault in supply. The fault detection system is reliable and faster with the proposed technique. It is also observed that EWP is giving accurate OC fault diagnosis results as compared to other feature extraction method including PCA, WT, SMO, and ESO.

Fault diagnosis techniques

In many papers in previous literature, simple entropy and mean have been implemented for fault diagnosis algorithm. Fig. 3.21 shows the fault diagnosis result when these features are used in a three-phase inverter simulation model. From Fig. 3.21, it is observed that there is a wrong classification issue in this case because the entropy values of signals under different fault conditions and normal conditions are approximately equal. The model is getting confused in classifying the fault from normal condition or one class's fault from another. The entropy values of three-phase currents under single IGBT (S1) OC fault conditions are found to be approximately equal to that of the entropy values under S1S2S5 fault. Therefore, the fault diagnosis output under S1 fault is showing faults in S1, S2, and S5 switches together. Similarly, the entropy of three-phase currents under S2 faults is approximately equal to that of currents' entropy under S2S3S6 faults. Therefore, the S2 switch's fault is detected as S2, S3, and S6 faults together as tabulated in Table 3.3. Due to these types of wrong classification issues, the fault detection algorithm's accuracy using simple entropy is approximately 66 percent when validated for 21 different conditions of the IGBTs, as mentioned in Table 3.1. Therefore, an alternative approach based on the EWP feature is proposed for accurate fault localization as shown in Fig. 3.20.

Hence, from the comparative analysis, the EWP method gives better results than simple entropy. The EWP is enough for fault detection, but the mean value is also considered for the mean value technique's performance analysis in fault detection. It is observed that mean and EWP together are giving better and accurate results as compared to mean and simple entropy together. While implementing the EWP technique in any diagnosis system can be used alone for accurate fault detection to reduce the computational burden.

Table 3.2: Fault diagnosis results using Simple Entropy-SVM technique

Actual Fault	Fault Detected
S1	S1S2S5
S1S2	S1S2S5
S1S2S3	S1S2S3
S1S2S5	S1S2S5
S1S5	S1S5
S2	S2S3S6
S2S3	S2S3S6
S2S4	S2S4
S3	S3S5
S3S4	S3S4
S3S5	S3S5
S4	S4
.	.
.	.
.	.
.	.
S3S6	S3S5

Table 3.3: Comparison of fault detection time of different techniques

Technique	Detection Time (ms)	Reference
ESO	150	[66]
Kalman Filter	100	[53]
SMO	50	[57]
Wavelet-RBFNN	less than half cycle of current waveform	[60]
PCA-mRVM	more than one cycle	[55]
Residual-based observer	15-20	[67]
2 sample-EWP-SVM Technique	less than 0.33 ms	Proposed Technique

3.5 Summary

The proposed two-samples based OC fault detection technique in this chapter is found to be fast and accurate. The OC faults are detected in less than 0.33 ms. The chapter has discussed the EWP-SVM technique, which can diagnose the fault in a single IGBT, multiple IGBTs, and OC fault in the supply terminals. For feature extraction, the EWP technique is more accurate and simple with a less computational burden as compared with the other observer and PCA based features extraction techniques. The SVM algorithm gives accurate fault diagnosis results using the three-phase currents using the EWP feature because only one feature of currents is used, which is entropy. The proposed EWP-SVM technique is fit for implementing a fault diagnosis system to get reliable and faster fault detection schemes. The results show that SVM with simple entropy and energy resulted in the wrong classification in fault diagnosis, which has been avoided by implementing the EWP-SVM technique. The mean value of the signal under a fault condition is also different from its value under normal conditions. Thus mean value alone cannot be used as a feature in fault classification algorithm because of the similarity of signals under different fault conditions. Therefore, it is used along with the EWP feature for better performance of the proposed algorithm. The detection time of the OC fault of IGBTs-based converter can be further decreased, and accuracy can be improved with other supervised based machine learning techniques or by combining the SVM technique with other feature extraction techniques. The level of signal to noise ratio and other transient effects that can be avoided by the proposed detection technique with different types of loads can be analyzed for checking the reach of the proposed technique. In the next chapter, the wavelet entropy based feature is used for OC fault diagnosis which is observed to be better than the two samples based algorithm proposed in this chapter.