Chapter 4

RACM of Inverter: Wavelet Entropy Based PCA-SVM Technique

4.1 Introduction

In the previous chapter, the two-samples based OC fault detection technique was discussed found to be fast and accurate. The OC faults are detected in less than 0.33 ms. The chapter 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 is found to give 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 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 this 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 previous chapter. The block diagram representation of the RACM of inverter using the proposed OC fault diagnosis method is shown in Fig. 4.1. In the literature, various frequency-domain based

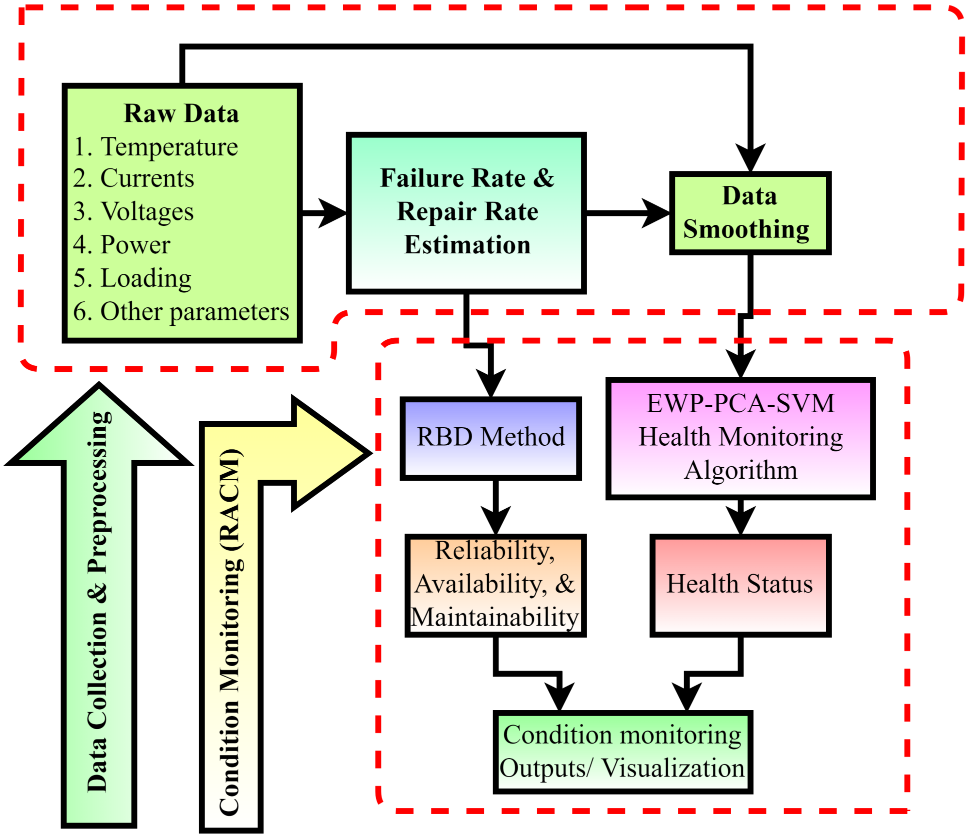

Figure 4.1: RACM using PCA-EWP-SVM technique.

techniques including FFT, WT [52], and machine learning-based techniques including Random Forest (RF), acsKNN, Discriminant Analysis (DA), Naive Bayes (NB), Decision Tree (DT), PCA, SVM [80–83] have been discussed. These techniques have been used to diagnose the faults in the converter system. The WT technique has been used in [52] for the fault detection using the converter three-phase currents. FFT is also used in a frequency-domain based technique for fault detection, but it does not give excellent performance for the transient condition. Mixed Kernel Support Tensor Machine (MKSTM) explained in [54], which uses the data of AC and internal circulation current for extracting the characteristics. The authors have discussed the neural network-based MLP technique, SVM, SOM, and K-means based machine learning techniques in [52] for the fault classification and detection. The authors found the SVM technique as a better and accurate technique for fault classification. Fault detection of IGBTs based on the voltage and current features have been explained [59, 61]. ESO based fault detection method has been discussed briefly [58]. The faulty sub-module is identified in this work, but it cannot show the faulty switch. Thus, fault localization is also necessary. The authors in [84] have proposed a fault diagnosis system using the characteristics of arm voltage and arm voltage error of the sub-module of modular MLI. The algorithm detects and localizes the fault within several control cycles. In [85], the OC faults detection algorithm is proposed using the characteristics of current and voltage. The authors have used the features, including a rise in the magnitude of phase current and DC voltage drop. The fault-tolerant capacity of MLI is improved using various controlling schemes such as clustering of different possible faults and locations [86]. For implementing this type of fault-tolerant control of MLI, the faults should be detected in minimum possible time.

The detection of OC faults of IGBTs using the characteristics of current along with the machine learning technique has been introduced in the literature. The authors [87] have introduced the Hilbert-Huang transform (HHT) for OC fault detection and then, the fault localization has been done using an ANN technique. It is also observed from the literature that SVM gives better performance than ANN. Some available literature [80, 83] have discussed the PCA technique. This technique is implemented only for the extraction and selection of data features. In [80], the selected features are then used in the classifier techniques for fault classification. The authors have observed that SVM's execution time with PCA as a feature extraction and selection technique is larger than other techniques, including RF, KNN, DA, NB, and DT. However, the SVM technique gives improved results during training and testing time intervals in terms of accuracy. The accuracy range of the SVM technique is found to be 94.88% to 99.18%. The authors [83] have discussed that the PCA-SVM technique gives better accuracy than other techniques, including PCA-Extreme Learning Machine (ELM) and PCA-DT. In the present work, the proposed PCA-SVM techniques accuracy is in the range of 90% to 98.89%.

For fault classification, SVM is found to the better technique as compared to other supervised and unsupervised machine-learning-based algorithms [88]. It is used as pattern recognition and classification technique. One significant advantage of the SVM technique is its global boundary of separation of different classes. The authors [88] have mentioned that unlike other fault detection techniques, including the current signature method and AI methods, the SVM technique does not need the information of one complete cycle of the current signal. This technique gives results in less than half-cycle of the current signal, i.e., this technique is faster than other proposed techniques in the literature.

The speed of fault diagnosis systems can be increased by reducing the computational burden and complexity of the features extraction techniques. In [60], the authors have proposed a fast and accurate feature extraction technique. The authors have used the entropy value of the signal as a feature for fault diagnosis. This feature gives better accuracy and faster operation to the classifier.

Sometimes, the fault is needed to found out much early then its localization. When SVM, WT or PCA technique is used individual, the chance of getting false alarm increases. When these are used comprehensively together, the result of fault detection and localization becomes accurate and faster. The time, by which SVM localizes the fault, the PCA based algorithm gives the indication of fault and alarm is generated so that appropriate action can be taken early. Getting fast response is not the only the aim of this chapter, the accuracy is also that much important. Using signal-processing based method for feature extraction gives more accurate fault diagnosis results.

4.2 EWP-PCA-SVM Method for RACM

The process flow of the proposed algorithm is shown in Fig. 4.2. In this work, three-phase inverter is simulated, and triggering pulses are generated using the SPWM technique. The three-phase currents are measured at the output of the inverter. These currents are used to detect the OC faults in the IGBTs using the PCA algorithm. The three-phase currents are also transmitted to the features extraction function, which finds WE of the signal by decomposing the signals into packets. The extracted features of the current signals are then used for the training of the SVM algorithm. Then the trained SVM model is validated for fault detection and classification. Fig. 4.2 shows the schematic diagram, including three-phase inverter, current measurements, PCA-based fault detection technique, features extraction, and training of the SVM model using WE as a feature of three-phase currents. These extracted features are passed to the SVM trained model for fault classification and localization of faulty IGBTs. The three-phase inverter simulated in this work consists of six IGBTs (S1 through S6). The output of the SVM model is the condition of the inverter and its switches.

The most common faults in IGBTs and IGBTs-based converters and inverters are open-

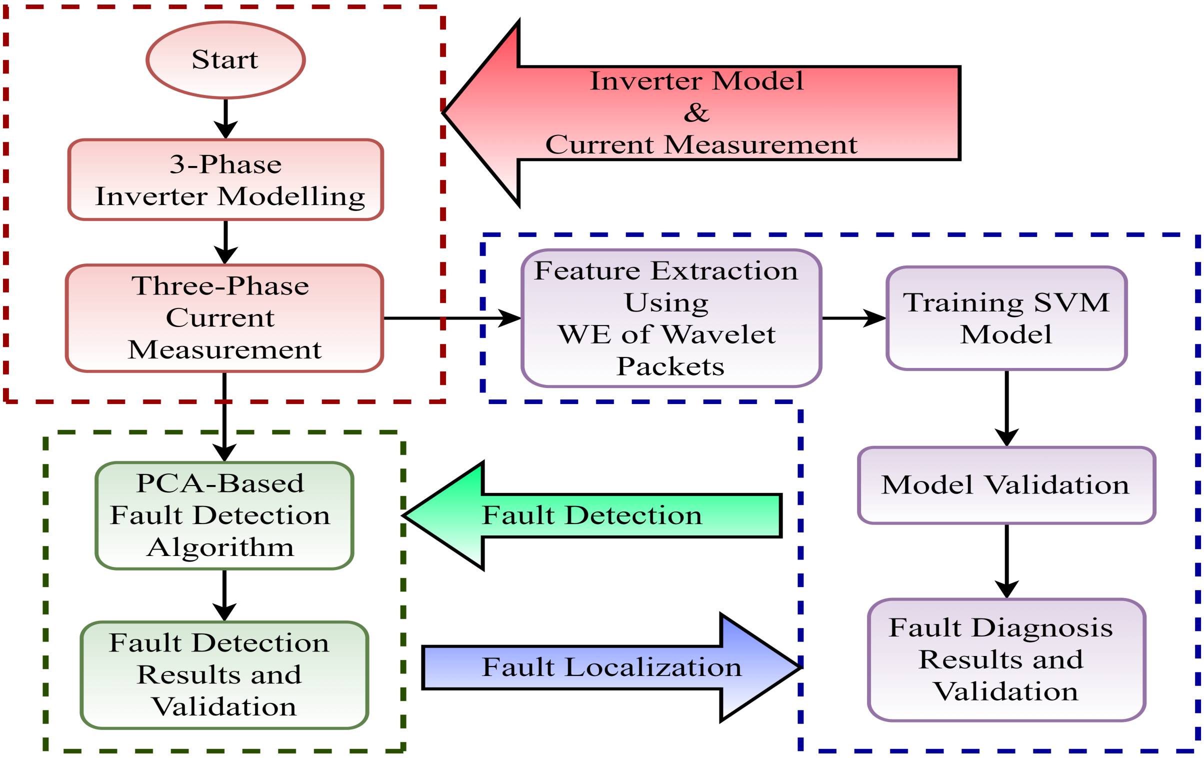

Figure 4.2: Process flow of the proposed algorithm.

circuit faults. A single open-circuit fault in a single IGBT may lead to cause a fault in the whole inverter. In a Modular Multilevel Inverter (MMI), the inverters safety depends on the reliability of the fault detection and monitoring system of the IGBTs. Therefore, detection and localization of faults of IGBTs are essential.

The selection of features and their extraction is a crucial part of machine learning-based fault diagnosis algorithms. The most commonly used features proposed in the literature include entropy, WT, mean, phase angle, and dq0 transformation of the time series current or voltage waveform [26–29]. These features sometimes do not give accurate detection of faults and may results in the false classification of faults due to approximately equal values of features of different fault conditions. In the literature, most of the authors have highlighted the PCA technique as multivariate features extraction and selection technique as in [80–83]. However, PCA itself is an unsupervised type of machine learning technique. This technique is preferred when the fault conditions are unknown, and historical data of fault cases are not available. As load is generally dynamic, the PCA features may change unpredictably, and the classifier may get confused if it uses the features extracted from the PCA technique. The SVM algorithm needs to be trained for every possible change in loads, electrical system parameters, and the inverters. Also, the features extraction and selection for classification is a time-consuming task. There-

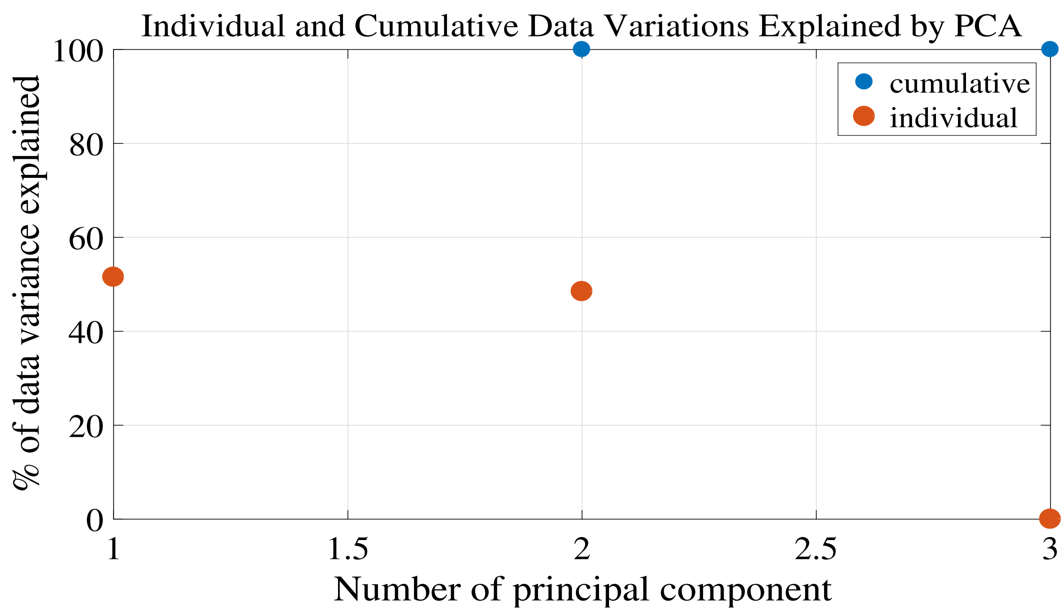

Figure 4.3: Data variance covered by the principal components individually and cumulatively.

fore, the execution time of the PCA-SVM technique is more extensive. The execution time of the SVM technique can be reduced by selecting other practical features extraction techniques. Hence, the WE-based feature is proposed in this work, extracted from the wavelet packets of the current signals. This reduces the computational and execution time and gives faster fault diagnosis response using the SVM technique. The PCA is implemented in this work for OC fault detection. The accuracy is improved, and the execution time is reduced by implementing the proposed fault detection technique (PCA) and classification technique (WE-SVM).

4.2.1 OC Fault Detection using PCA

The PCA technique is not used only as a feature extraction technique; it is also an unsupervised machine learning technique used in this work to detect the OC faults in IGBTs in MLI. From above fig., the percentage of data covered by the first component of PCA is 52%, that by second component is 47.8%, and hence, cumulatively these two components are covering 99.8% data. Therefore, two PCs (PC1 and PC2) are selected for developing the fault detection algorithm. The data variance covered by the individual and cumulative principal components is shown in Fig. 4.3. The PCA-based OC fault detection algorithm is developed using the scores values of the two selected principal components, and the values are updated as the new data comes simultaneously. Therefore, its implementation in real-time is possible. The schematic diagram of the PCA-based fault detection algorithm is shown in Fig. 4.4. The loading matrix is related

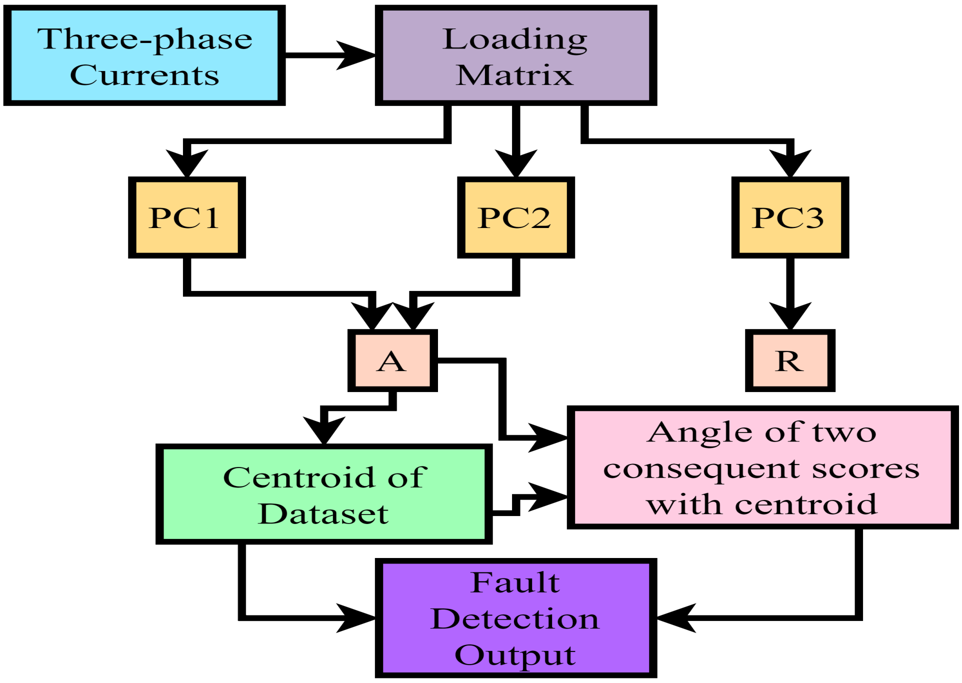

Figure 4.4: Schematic diagram of PCA-based fault detection technique.

to the co-variance matrix 'C' by the relation $C = WAW^T$, where W are the loading matrix, and A is the eigenvalue matrix. In Fig. 4.4, A, and R are the approximated and residual data, respectively. The percentage of the dataset covered by the approximate set is 99.8%, and the rest residual. The approximate centroid of the data set is determined, and the scores values are scattered in the space formed by the two PCs of the PCA. The pattern formed is the hexagonal structure, which is distorted under the OC fault condition. The change in shape is detected by calculating the angle formed by the two resulting scores with the centroid. If the angle is an integral multiple of 60 degrees, then the inverter is working in normal condition. Otherwise, there must be any fault present in the inverter switches. The PCA-based fault detector output under the normal operating condition of the inverter is shown in Fig. 4.5.

The pattern changes when there is any OC fault in IGBTs of the inverter. The PCA-based OC fault detector output pattern under single IGBT (S1) OC fault and multiple IGBTs OC faults (S1 and S5) are shown in Figs. 4.6 and 4.7. The angle formed by the two following score data with centroid when scattered into the space of two principal components gives information of fault condition.

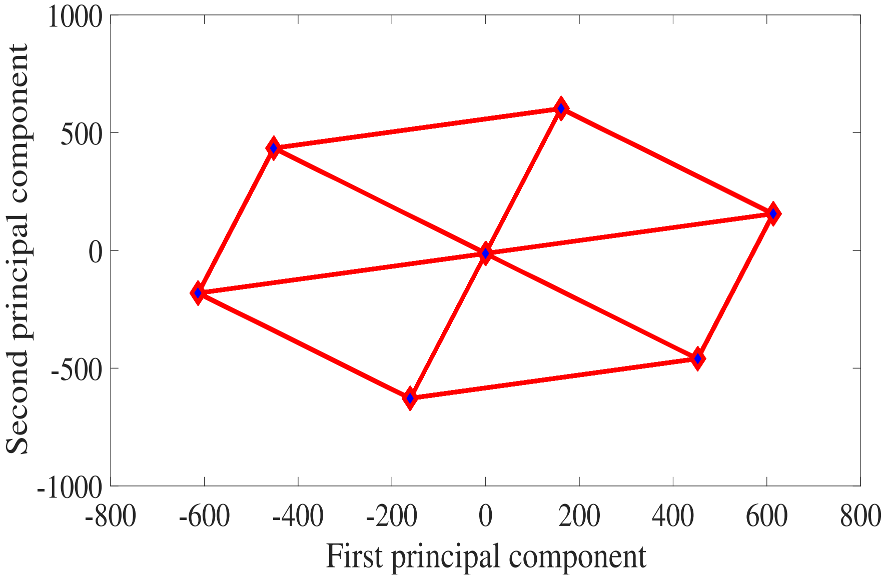

Figure 4.5: OC fault detection output pattern under normal condition.

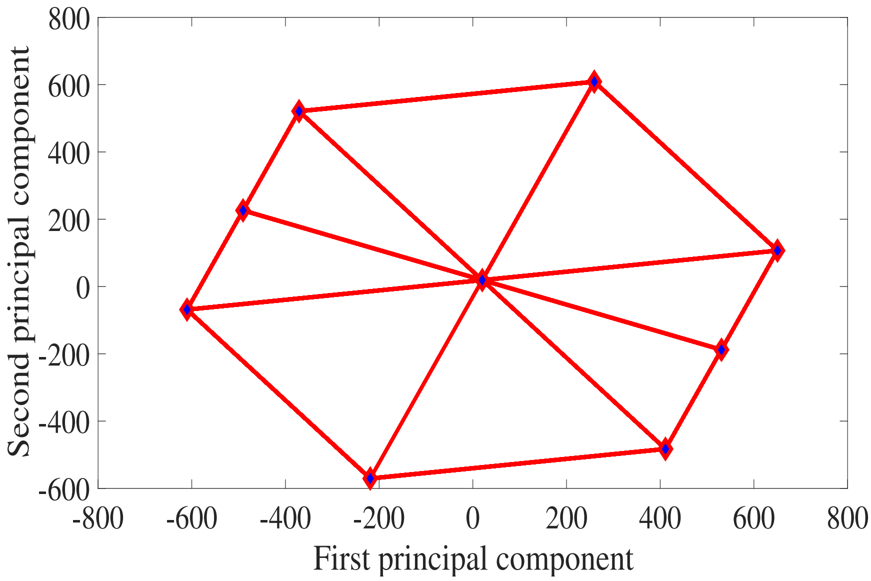

Figure 4.6: PCA-based OC fault detector output pattern for single IGBT.

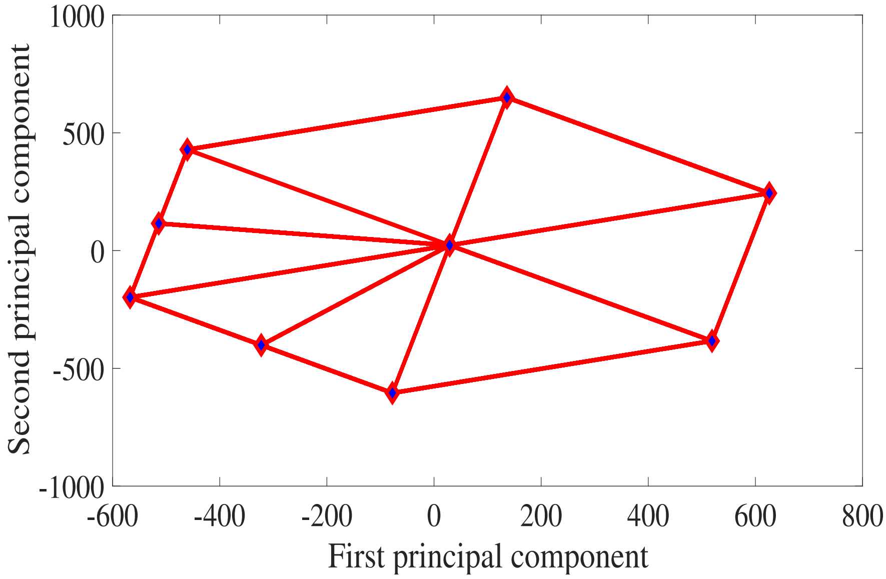

Figure 4.7: PCA-based OC fault detector output pattern for multiple IGBTs.

4.2.2 WPD

The WPD is a better technique than the DWT. The WPD decomposes the signal into two components at each node, but DWT decomposes only one coefficient at each node and neglects the other component. Therefore, the performance of DWT is not excellent under the transient condition and also at high frequency. These demerits are avoided using WPD in place of DWT [60]. The WPD decomposes the signal into two coefficients detail and approximate components at each node. The WE are calculated at each node. If the number of decomposition levels is L, then the number of decomposed coefficients is determined by 2^L. All the coefficients have a different frequency. The signal decomposition up to three-level, and corresponding coefficients are shown in Fig. 4.8. The WPD process can be realized using a low-pass filter and a high-pass filter. These filters decompose the original signal into two components: one with a lower frequency and other with higher frequency. These components are denoted as approximate and detail coefficients, respectively.

The decomposition process of signal $f(n)$ is explained mathematically. The signal is decomposed into components and it can be reconstructed in its original form using Mallat algorithm. The decomposition of $f(n)$ into two components $DE_i(n)$ and $AP_i(n)$ are expressed in eq. (4.1). The filters used for decomposition are denoted by $H(n)$ and $L(n)$ representing high-pass filter and low-pass filter, respectively. The detailed coefficient and approximated coefficient are denoted by $DE_i(n)$ and $AP_i(n)$, respectively. The eq. (4.1) represents the decomposition

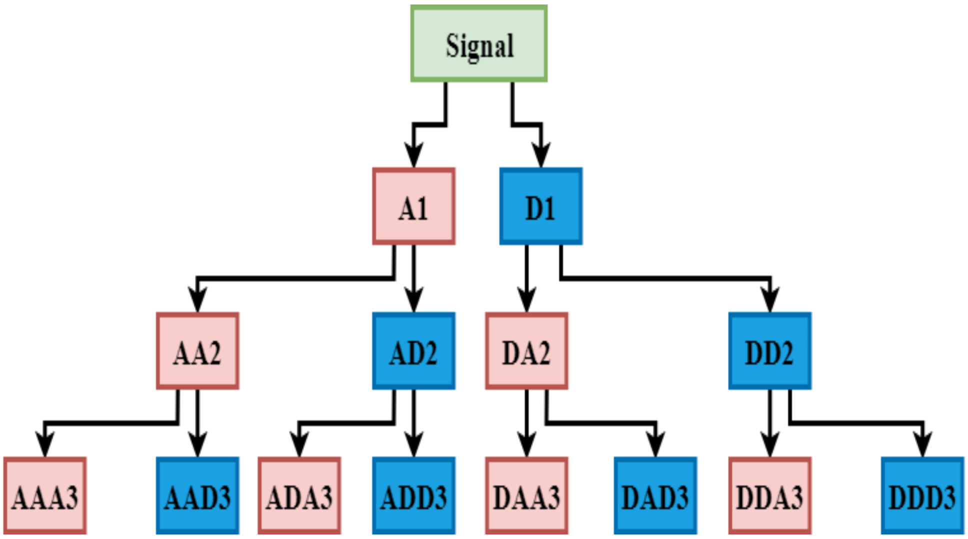

Figure 4.8: Decomposition of wavelet packets into Approximate and detail coefficients.

of signal at i^{th} level.

$$\begin{aligned} DE_i(n) &= \sum_j H(2n-j)g_{i-1}(j) \\ AP_i(n) &= \sum_j L(2n-j)g_{i-1}(j) \end{aligned} \tag{4.1}$$

where, $j >= 1$, $g_0(n) = f(n)$ is the original signal. The value of n is 1, 2, 3......, l; l is the length of $f(n)$. The upper and lower frequencies of decomposed component at i^{th} level are expressed as given in eq. (4.2). The signal $f(n)$ can be found in its original form by adding the decomposed components as given in eq. (4.3). In eq. (4.3), the term $DE_2(n)$ is put in place of AP_1 to make uniform representation of the equation.

$$\begin{aligned} for DE_i(n) &: [\frac{f_{samp}}{2^{i+1}} \& \frac{f_{samp}}{2^i}] \\ for AP_i(n) &: [0 \& \frac{f_{samp}}{2^{i+1}}] \end{aligned} \tag{4.2}$$

Where, f_{samp} is the sampling frequency.

$$\begin{aligned} f(n) &= DE_1(n) + AP_1(n) = DE_1(n) + DE_2(n) + AP_2(n) \\ &= \sum_{i=1}^{j} DE_i(n) + A_j(n) \\ &= \sum_{i=1}^{j+1} DE_i(n) \end{aligned} \tag{4.3}$$

4.2.3 Wavelet Entropy

The entropy of current or voltage signals gives information about the fault condition of the inverter. The authors used WE as the feature, and the mathematical calculations involved in the entropy feature have been discussed in [60, 78]. The stored energy in the signal at each node of decomposition is determined; the entropy of the signal is the additive function of the entropy at each node.

The most commonly used forms of entropy are called as Shannon Entropy (SE), Log Energy (LE), and Threshold-based Entropy (TE). Among these forms, the SE is used when the uncertainty analysis is essential [89] as given in Eq. (4.4). The other two most commonly used entropy forms are given in Eqs. (4.5) and (4.6), respectively. If x is the signal and x_j is signal coefficient at orthogonal basis. Then, the entropy (E) must be additive function, i.e. E(0) = 0 and E(x) = $\sum_{j=1}^{N} E(x_j)$.

$$SE(x) = -\sum_{j=1}^{N} x_j^2 log(x_j^2) \tag{4.4}$$

where, $x_j^2(j = 1, 2...., n)$ denotes the probability density and $x_j^2 >= 0$ and $\sum x_j^2 = 1$. The WE of the signal x can be expressed in Shannon form as given in eq. (4.5).

$$WE_S = -\sum_{j=1}^{n} x_j^2(i) log s_j^2(i) \tag{4.5}$$

where, x_j^2 represents the wavelet packet energy distribution. The WE of the signal x in the log energy form is given in eq. (4.6).

$$WE_L = -\sum_{j=1}^{n} log(x_j^2) \tag{4.6}$$

After wavelet decomposition of the signal, the WE are determined using the algorithm based on Eqs. (4.5) and (4.6). In this work, Shannon WE are used as a feature for fault diagnosis.

The methodologies proposed in this work aim to develop a faster and more accurate fault diagnosis technique. This requires a faster and simple features extraction method involving fewer computations. Therefore, WE is used as a feature extraction method for the three-phase currents of the inverter. For OC fault diagnosis and localization of faulty IGBTs, SVM technique-based classifier is used, which is faster and more accurate as compared to the techniques available in the literature. The WE feature of three-phase currents of the inverter is collected after simulating the inverter under different loading and different OC fault condi-

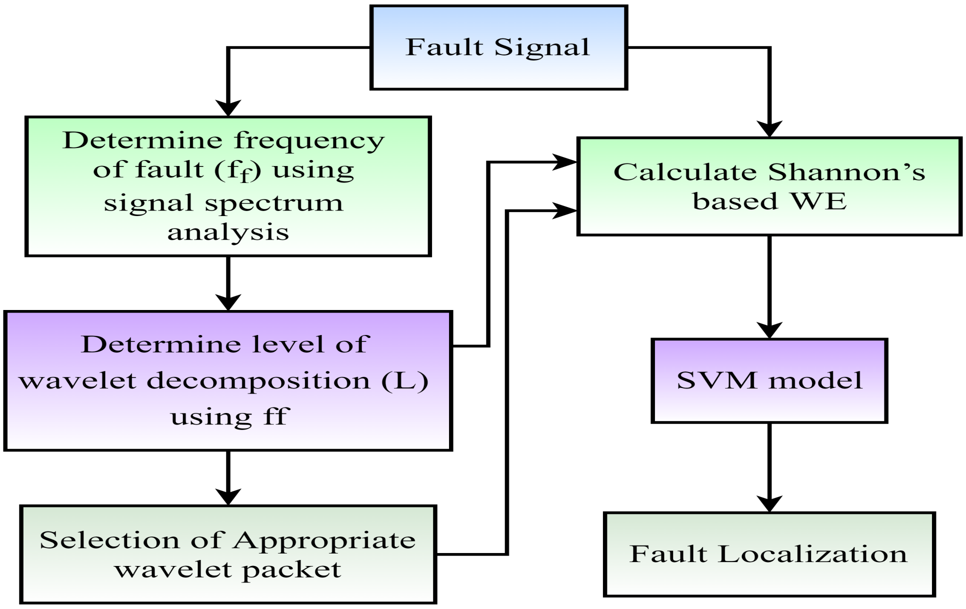

Figure 4.9: Process flow of fault localization using WE feature.

tions. The collected WE features shown in Table 4.1 for WE_a, WE_b and WE_c are the wavelet entropies of the three-phase currents of phase-a, phase-b and phase-c, respectively.

The WE-SVM technique is implemented for fault localization after the fault is detected from the PCA-based detection algorithm. For this, WE are used as a feature for the fault classification and localization. The flow chart of the algorithm involved in fault localization is shown in Fig. 4.9. The fault signal is used to determine the frequency of fault (f_f) using spectrum analysis. The level of wavelet decomposition (L) is determined using the frequency of fault found from the previous step. The values of f_f and L are used to select the appropriate wavelet packet, and then Shannon's-based WE are calculated. This WE are used as a feature for the SVM-based fault classifier algorithm. From the SVM algorithm, the faulty IGBT is localized.

4.3 Results and Discussion

The simulation model is run under different possible loading conditions and faults, including single IGBT OC fault and multiple IGBTs OC faults. The load is variable in nature and it is assumed that the load is varying in only steps: full load and half load. The current requirement under full load is 500 A and that under half-load is 250 A. The current measurement data is used to detect the OC faults using PCA and extract the WE feature to train the SVM model for fault diagnosis. After training the SVM algorithm, it is validated for different faults in the inverter,

Table 4.1

Features extraction under different conditions

WE_a	WE_b	WE_c	Condition
264143.03	261593.75	267353.77	Normal
262364.22	274018.53	264032.72	S1Fault
293682.78	276690.19	286411.71	S2Fault
275630.77	277440.41	292394.12	S3Fault
228417.57	250478.20	230776.74	S4Fault
292808.07	273958.55	284808.06	S5Fault
274916.91	268884.36	289111.55	S6Fault
270791.42	309880.90	289955.38	S1S2Fault
246224.52	255016.85	259463.99	S3S4Fault
268552.26	258693.54	274985.41	S5S6Fault
255623.75	246619.35	267682.23	S2S3Fault
235575.76	207404.19	246060.28	S3S5Fault
177292.20	205213.37	198261.53	S4S6Fault
219752.33	215822.28	199369.98	S2S4Fault
216282.85	211029.26	197062.93	S1S5Fault
248584.32	247875.28	228563.21	S1S2S5Fault
-738269.55	-766083.91	-749037.97	S4S5S6Fault
-510410.99	-544485.91	-520567.42	S1S2S3Fault
220037.02	174570.18	230900.02	S2S3S6Fault

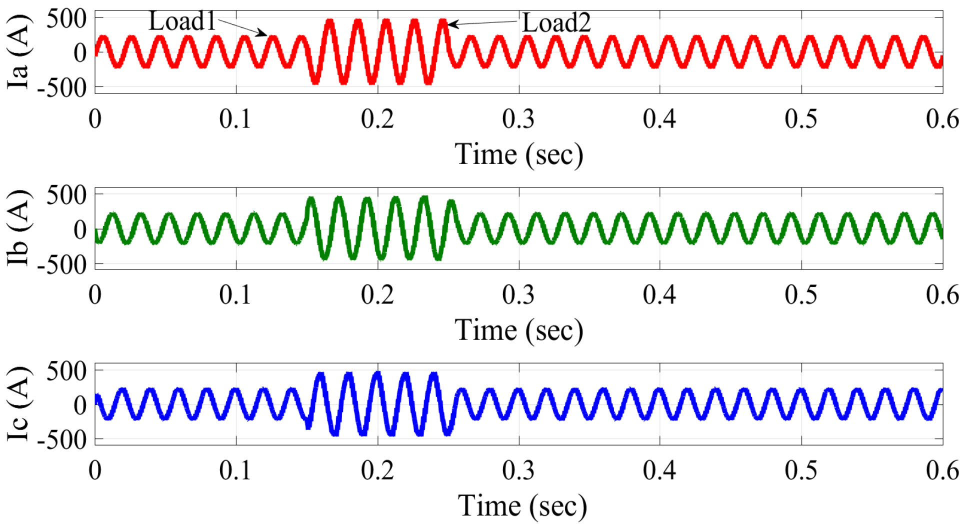

Figure 4.10: Three-phase currents of the inverter under normal condition.

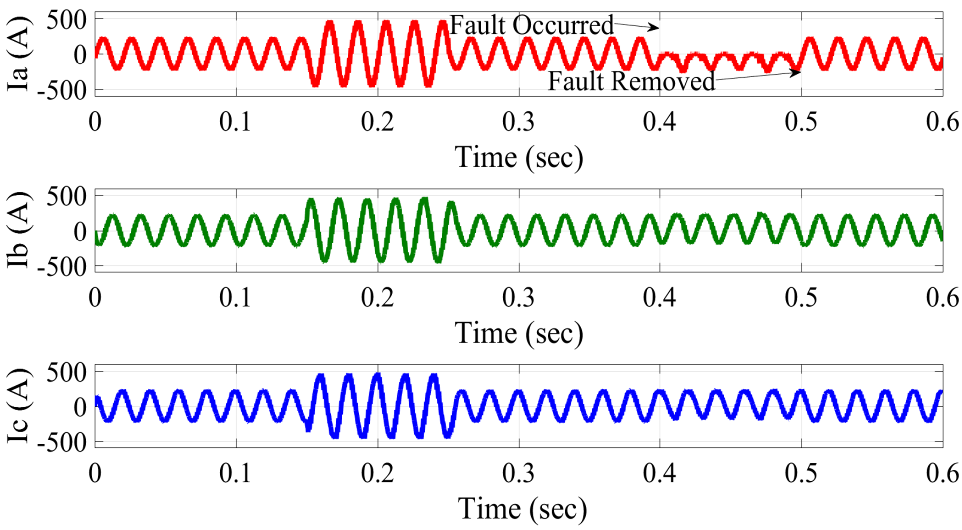

Figure 4.11: Three-phase currents of the inverter under OC fault in single IGBT (S1).

and it is found that the proposed algorithm gives accurate fault detection results.

During OC faults in switches, the current and voltage waveforms change under the fault condition and therefore, the WE are also different for normal and fault condition. The current waveforms under normal condition, OC faults in single IGBT (S1) and multiple IGBTs (S1 and S5) are shown in Figs. 4.10-4.12.

At the occurrence of OC fault, the PCs show the change in scoring values, and the indication is provided by the angle change between the score coefficients from multiple of 60 degrees to other angles. The center of the hexagonal detector structure varies and shifts with variation in load and under fault condition. But with a change in load, the pattern does not change be-

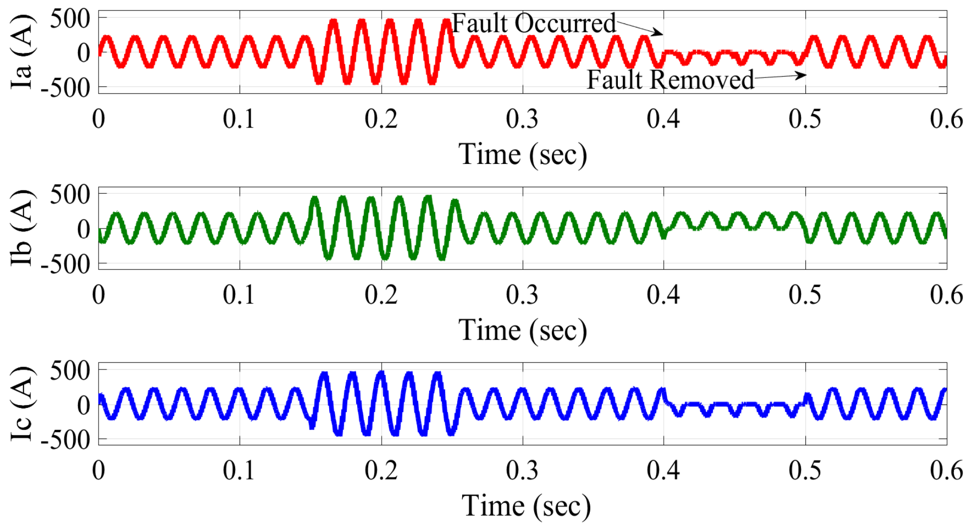

Figure 4.12: Three-phase currents of the inverter under OC faults in multiple IGBTs (S1, S5).

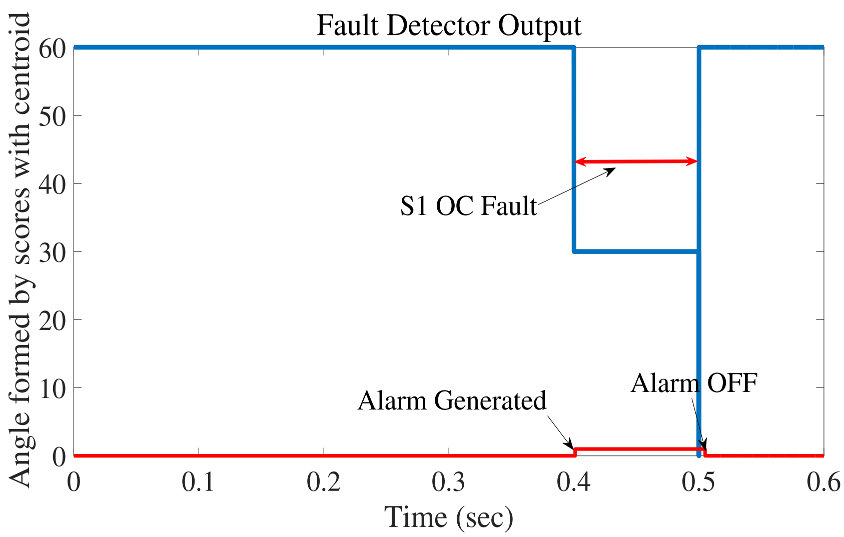

Figure 4.13: PCA-based OC fault detector output under S1 fault.

cause the pattern only changes under fault condition. The OC fault detection output of the PCA technique is shown in Fig. 4.13. As the OC fault occurs, the angle is different from 60 degrees. In response to detecting a fault, an alarm signal is generated automatically, which takes lesser time. The time of detection using this technique is less than 6.6 ms, as shown in Figure 4.13. Once the fault is detected, the SVM algorithm-based fault localization technique outputs the fault IGBT location, which also takes very less time because of the less computational burden involved in the WE feature. This results in a faster fault diagnosis system.

In the published literature, simple entropy and mean have been considered for the fault diagnosis algorithm. Fig. 4.14 shows the result obtained from the SVM technique when simple entropy is used as feature. The different OC faults considered for validating simple entropy-SVM based and WE-SVM based classifiers are tabulated in Table 4.2. The data of normal condition is also taken and represented as N in Table 4.2.

In this case, there is a false-classification issue as the value of simple entropy of signals under fault condition, and the normal condition is approximately equal. Therefore, the model is getting confused in classifying the fault, in the normal condition or with the fault of one class from another. The fault diagnosis output under S1 fault is showing faults in S1, S2, and S5 switches together. Again, fault in the S3 switch is detected as S2 and S3 faults together. The accuracy of the fault detection algorithm using simple entropy is approximately less than 60% when validated for 19 different conditions of the IGBTs, as mentioned in Table 4.1. Therefore, an alternative approach is proposed in this work based on the WE feature. When WE used as a feature for fault detection, the SVM model is showing 100 % accuracy while training time, and also while validating the model, it is giving accurate fault detection and classification results as shown in Fig. 4.15.

Table 4.2

Different OC faults used to train and validate the classifier

Fault	Switches	Fault	Switches
F1	S1	F10	S2, S3
F2	S2	F11	S3, S5
F3	S3	F12	S4, S6
F4	S4	F13	S2, S4
F5	S5	F14	S1, S5
F6	S6	F15	S1, S2, S5
F7	S1, S2	F16	S4, S5, S6
F8	S3, S4	F17	S1, S2, S3
F9	S5, S6	F18	S2, S3, S6

The most important factors in fault diagnosis are the time of detection of the fault and accuracy. The fault detection system would be reliable and faster in the proposed technique as

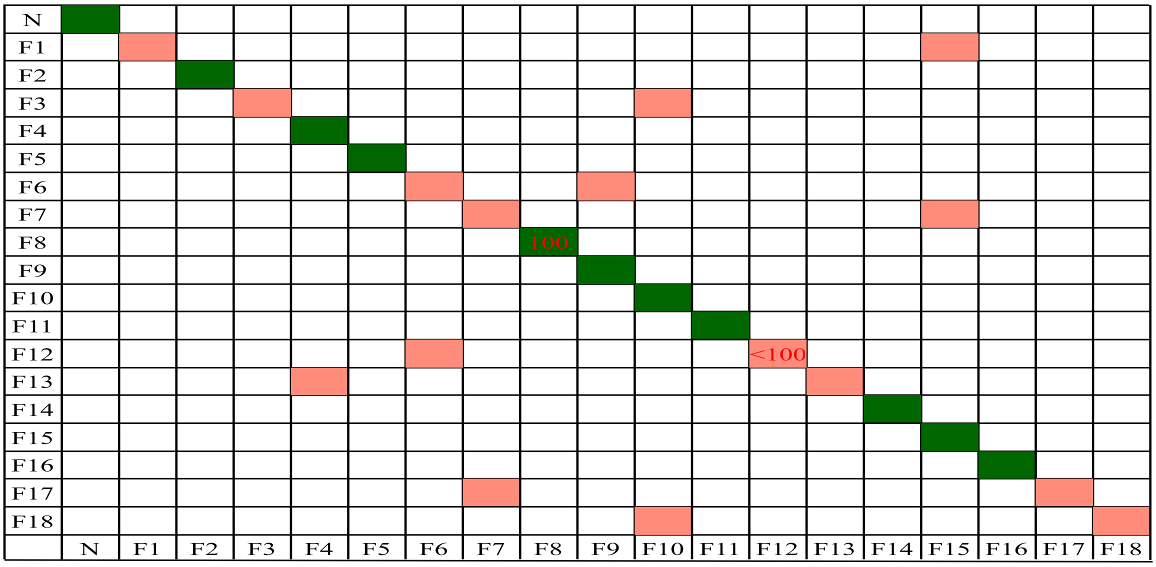

Figure 4.14: Classification results using simple entropy.

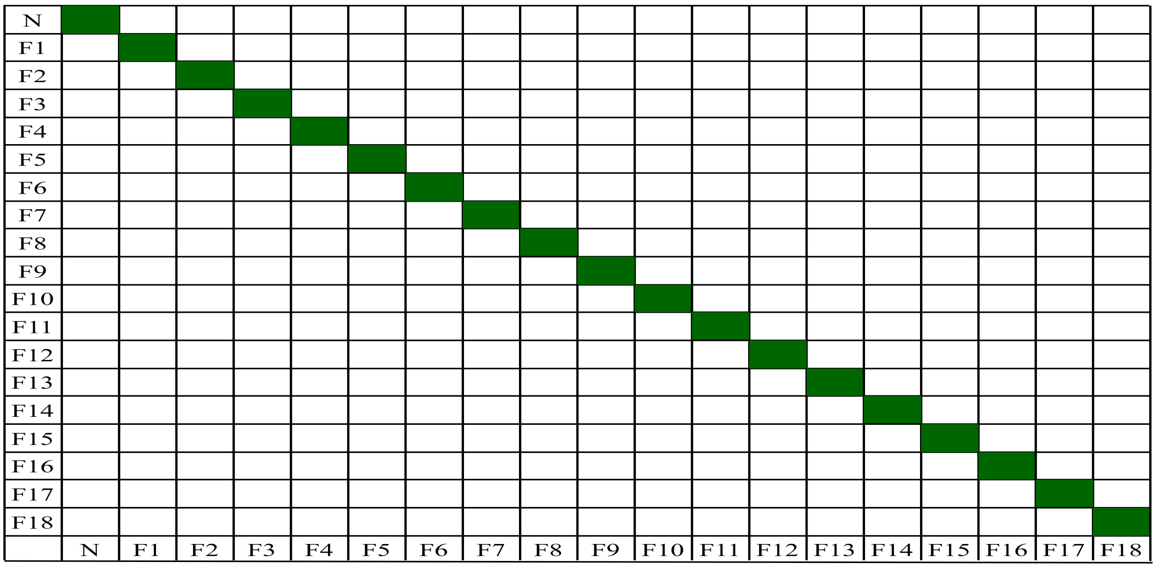

Figure 4.15: Classification results using WE of the current signal as feature.

Table 4.3

Comparison of the accuracy of different fault diagnosis techniques

Technique	Training	Testing	L1	L2	Reference
	✓		88.90	89.99	[90, 91]
KNN		✓	90.07	92.32	
	✓		84.34	84.63	[92]
DA		✓	82.67	80.74	
	✓		87.02	89.96	[93]
NB		✓	90.44	91.61	
	✓		92.78	95.69	[94]
DT		✓	94.84	95.81	
	✓		93.77	95.28	[95]
RF		✓	97.04	98.72	
	✓		94.95	94.98	[96]
SVM		✓	95.98	97.17	
	✓		86.56	85.94	[97]
PCA-ELM		✓	87.51	88.23	
	✓		93.83	95.56	[98]
PCA-DT		✓	94.88	95.35	
	✓		95.96	97.88	[83]
PCA-SVM		✓	97.13	98.05	
	✓		99.71	99.26	Proposed Technique
PCA-WE-SVM		✓	99.94	99.97	

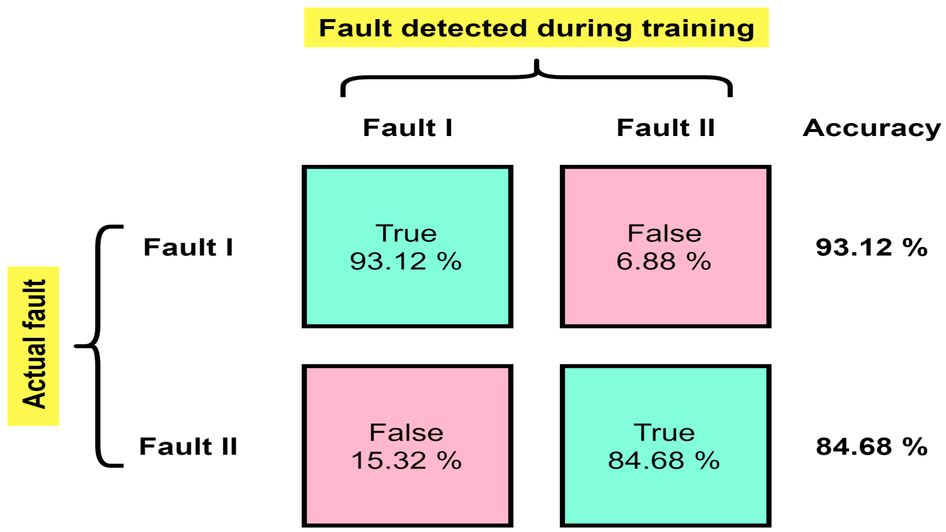

Figure 4.16: Accuracy of fault classification algorithm during training.

it depends only on the single parameter calculation involving the angle between the resulting scores. In Table 4.3, it is clear that using SVM classification technique with WE improves the accuracy of the OC fault diagnosis system as compared to other feature extraction method including PCA, WT, SMO, mean, FFT and ESO. The proposed PCA-WE-SVM technique gives better performance than PCA-SVM, PCA-DT, PCA-KNN, PCA-NB, PCA-RF and PCA-ELM as compared in Table 4.3.

The mentioned techniques are used to train and validate the proposed algorithm using the collected dataset under different loading and OC faults. The accuracies of different classifier techniques are summarized in Table 4.3 where L1 and L2 are representing loading conditions loading 1 and loading 2, respectively. The percentage accuracies of KNN-based fault classifier under loading 1 during training and testing are as shown in Figs. 4.16 and 4.17.

The dataset used for training and validation of the mentioned techniques contain fault data of two types: Fault I and Fault II. Fault I is the group of single IGBT faults and Fault II is the group of multiple IGBTs faults. During training, the KNN classifier gets confused between Fault I and Fault II faults and give false-classification of fault. During testing, the classifier gives false classification between the OC faults of different IGBTs. The overall accuracy of KNN classifier under loading 1 during training and testing period are 88.90% and 90.07%. The other classifiers are also validated under different loading conditions and OC faults. The accuracies are tabulated in Table 4.3.

sectionPrototype of the proposed work The Simulink model of the proposed work is shown

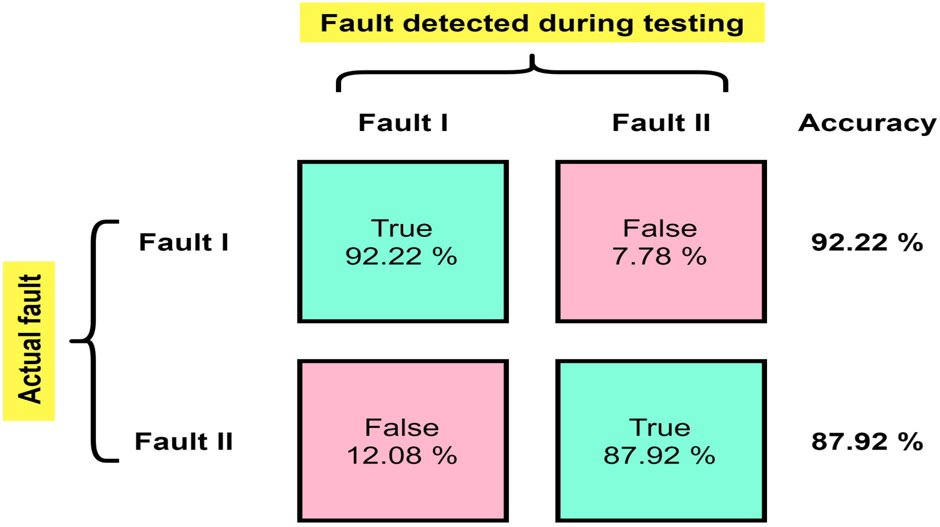

Figure 4.17: Accuracy of fault classification algorithm during testing.

in Fig. 4.18 as prototype. The DC supply voltage is 400 V, the switching frequency is 1 kHz, and the load used is RL (resistor and inductor) type in nature. The current of each phase is measured for feature extraction and fault detection. The detection part is done by the PCA-based algorithm and the localization of the faulty switches is done by WE-SVM based algorithm. This chapter is focused on fault detection and localization only. The disabling of SPWM signals is not done in this chapter as redundant inverter switches are not used. Under normal working condition of the inverter, the fault detection and localization results are shown in Fig. 4.19. Whenever there would be fault in switches, the particular output block will indicate the same as shown in Fig. 4.20.

4.4 Summary

The chapter has discussed the PCA-WE-SVM technique, which can detect the OC faults in a single IGBT and multiple IGBTs of inverters. For feature extraction, the WE technique is more accurate and simpler with a less computational burden. The SVM algorithm gives accurate fault diagnosis results using the WE feature of three-phase currents of the inverter. The fault detection and localization time with the proposed technique are found in lesser execution time than the other techniques available in the literature. The proposed PCA-WE-SVM technique is fit for implementing a fault diagnosis system to get reliable and faster fault detection schemes. In this chapter, results show that SVM with simple entropy and energy resulted in false-classification of the fault, which has been avoided by implementing the WE-SVM technique. The mean value of

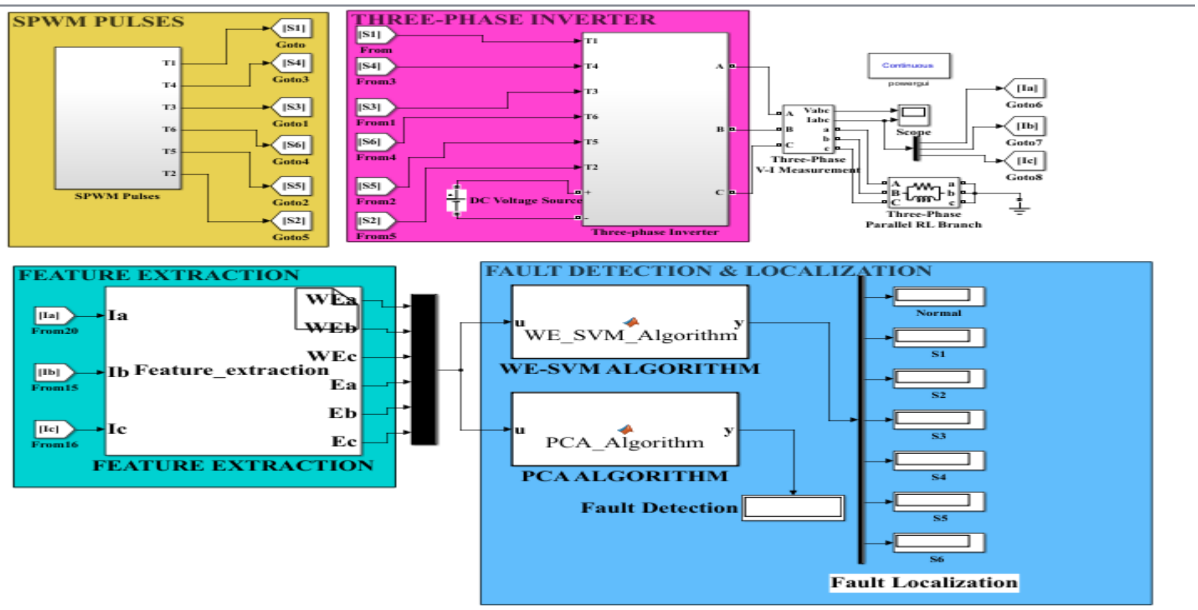

Figure 4.18: Prototype for the proposed algorithm of fault detection and localization.

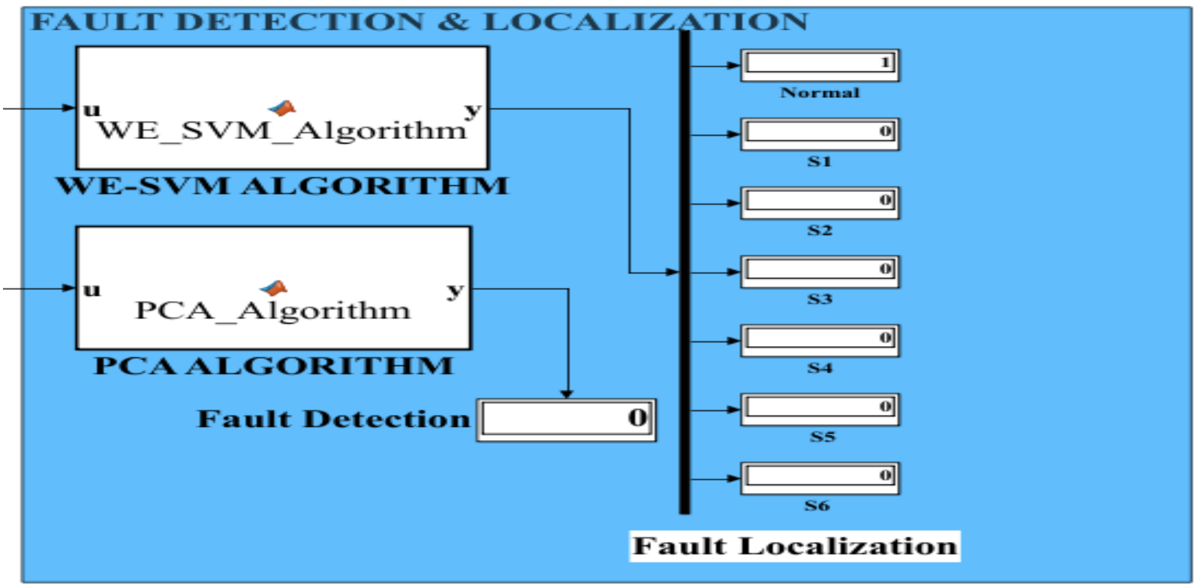

Figure 4.19: Outputs of fault detection and localization algorithms under normal condition.

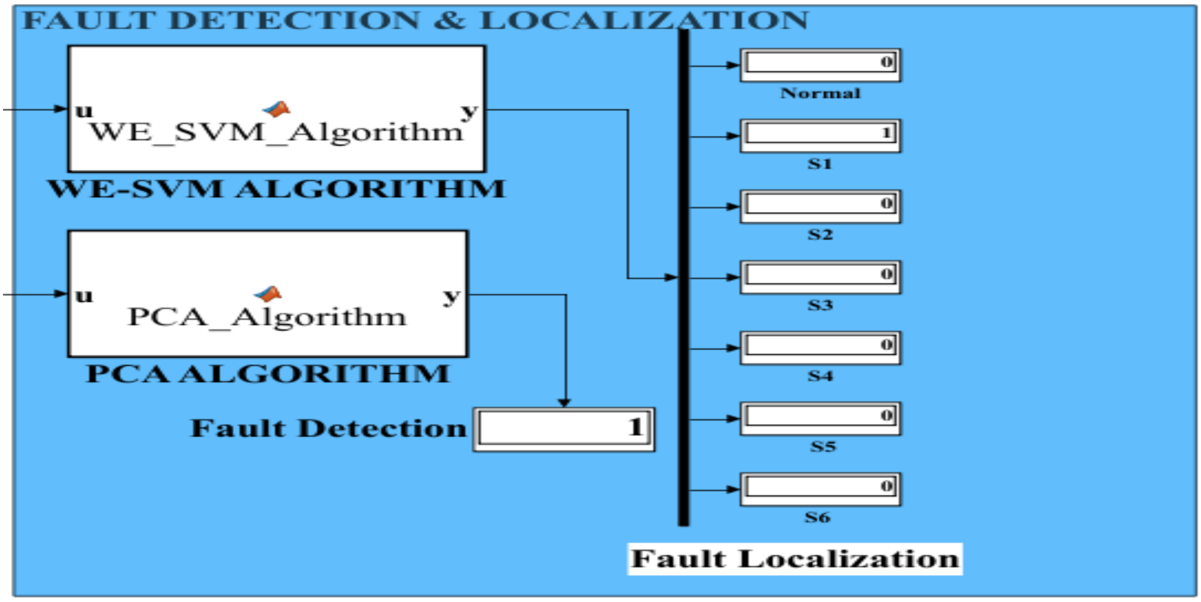

Figure 4.20: Outputs of fault detection and localization algorithms under fault condition in switch S1.

the signal under fault condition also changes. Thus mean value feature cannot be used for fault classification algorithms because of the similarity of signals under different fault conditions. The detection time of the open-circuit fault of IGBTs-based inverter 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. Therefore, next chapter is focused on the OC fault diagnosis system with WF based feature which helps in getting fastest and accurate diagnosis results.