

ENHANCED DIAGNOSIS AND AUTOMATIC MONITORING SYSTEM FOR A FAULTY TWO-LEVEL VOLTAGE INVERTER-FED INDUCTION MOTOR USING A COMBINED SIGNAL PROCESSING AND MACHINE LEARNING

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Abstract

This paper presents a methodology for diagnosing and monitoring open-circuit faults in IGBT switches within inverter–induction motor systems using current signal analysis. The method integrates Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) for signal processing and the Random Forest (RF) algorithm for machine learning-based fault detection and classification. The process begins with applying ICEEMDAN to decompose current signals into Intrinsic Mode Functions (IMFs) that may capture fault-related harmonics. Next, statistical correlation coefficient (Corr) analysis is conducted to identify which IMFs indicate open-circuit faults; IMFs with Corr values ≥ 0.1 (IMF₄, IMF₅, IMF₆, and IMF₇) are selected. These IMFs are used to reconstruct the signal, and spectral envelope analysis is performed on the reconstructed signal to extract fault signatures. The extracted features include key frequency components f_c and f_{oc} , and the phase angle $\varphi(f_{oc}/f_c)$. These features are used to train the RF model for both detection and localization of faults. The RF algorithm achieves a fault detection accuracy of 99.98% and a classification accuracy of 99.99%. Experimental validation confirms the effectiveness of the proposed ICEEMDAN–RF approach, demonstrating a strong potential for accurate diagnosis and continuous monitoring of open-circuit IGBT faults in inverter–induction motor systems.

Keywords: induction motor, inverter, open-circuit fault, EMD, EEMD, CEEMD, CEEMDAN, ICEEMDAN, CC, envelope spectrum, RF.

1. Introduction

The converter–electric machine assembly serves as the core component in electric drives and electromechanical energy conversion. Given its critical role in production systems, it often represents a potential weak link. Consequently, monitoring these assemblies has become increasingly important in the industrial sector. The growing need to enhance the operational reliability of electric drives and extend their service life has driven significant advancements in condition monitoring and diagnosis [1, 2].

Studies in electrical motors and power conversion systems have shown that static converters, particularly inverters, are highly susceptible to defects and exhibit a relatively high failure rate, as illustrated in Fig. 1. Furthermore, researchers specializing in static converters, especially inverters, have identified *direct current* (DC) bus capacitor failures as the most common and likely faults. Following this, failures in the control circuit, power circuit, and power transistors are also prevalent, as shown in Fig. 2 [3, 4].

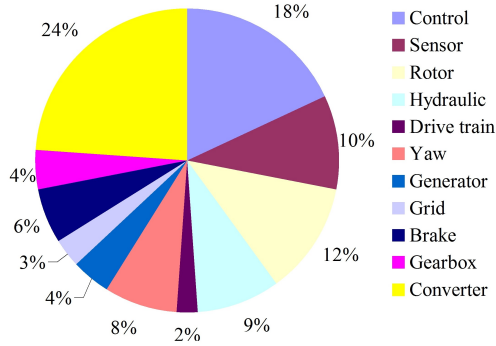


Fig. 1. Failure rate of power conversion system components.

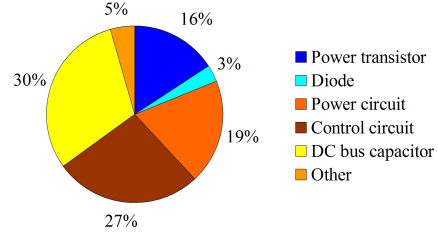


Fig. 2. Fault distribution in a static converter (inverter).

In recent decades, extensive research has focused on the detection and diagnosis of faults in converter–motor assemblies. Various techniques have been developed for this purpose, including vibration, acoustic, and thermographic analysis. However, these methods are mainly recommended for detecting electrical and mechanical faults [5].

In recent years, *motor current signature analysis* (MCSA) has gained popularity as a fault detection technique. This technique is effective because the stator current carries information about nearly all potential faults in the converter–motor assembly. Frequency-domain analysis of stator currents is the most widely used approach, especially under steady-state conditions, since the resulting spectrum provides valuable insights into most electrical and mechanical faults in the system. This technique offers two main advantages [6]:

- The first advantage is its ability to detect a wide range of electromechanical faults using only the stator current, eliminating the need for additional sensors to measure mechanical quantities or vibrations [7].
- The second advantage is that current sensors are already integrated into electric drive control systems, allowing fault detection without disrupting the operation of the converter–motor assembly [8].

An electrical fault in the converter–motor assembly can lead to high replacement costs and production downtime. To reduce these risks, it is important to anticipate possible failures and take preventive measures. Scheduled maintenance enables timely interventions, minimizing unexpected breakdowns and ensuring operational continuity. Therefore, developing predictive detection systems and effective diagnostic methods is essential to identify early signs of degradation and prevent faults before they occur [9].

Among these approaches, machine learning techniques typically rely on two main components: signal processing and artificial intelligence. Signal processing methods include the *Fast Fourier Transform* (FFT), *Discrete Wavelet Transform* (DWT), and *Hilbert–Huang Transform* (HHT). In contrast, artificial intelligence techniques include *artificial neural networks* (ANN), fuzzy logic, and various machine learning algorithms [10, 11].

The HHT, introduced by Huang in 1998, is a powerful time-frequency analysis technique designed for nonlinear and nonstationary signals. Its core principle is the adaptive decomposition of a signal into a set of oscillatory components, each representing a single frequency at a specific time. This process, known as *Empirical Mode Decomposition* (EMD), decomposes complex signals into a finite number of *Intrinsic Mode Functions* (IMFs) that capture localized oscillatory behaviour. The Hilbert transform is then applied to each IMF to obtain its instantaneous frequency and amplitude, thereby providing detailed time-frequency characteristics of the original signal [12]. Although HHT is effective for fault detection, it *does not inherently* provide information about fault localization.

Furthermore, EMD suffers from mode mixing, in which different frequency components coexist within a single IMF or are distributed across multiple IMFs. To address this limitation, the *Ensemble Empirical Mode Decomposition* (EEMD) technique was proposed, which introduces white noise to the signal and averages the resulting decompositions over multiple trials to mitigate mode mixing. A refined version, the *Complete Ensemble Empirical Mode Decomposition* (CEEMD), enhances reconstruction accuracy by using pairs of positive and negative noise realizations, ensuring completeness of the decomposition. The most advanced variant, the *Complete Ensemble Empirical Mode Decomposition with Adaptive Noise* (CEEMDAN), further improves the process by adaptively adding noise at each decomposition stage, producing more accurate, stable, and physically meaningful IMFs. Collectively, these methods represent successive advancements in mode decomposition and form the foundation of modern time–frequency analysis within the Hilbert–Huang framework [13].

To improve the diagnosis process, fault detection should be complemented by fault localization. This combination enables automated learning from features extracted from the processed signal, resulting in more accurate classification of *open-circuit* faults. *Machine learning* (ML) techniques are particularly effective in this regard. Standard ML techniques include *Support Vector Machines* (SVMs), *Naive Bayes* (NB), *K-Nearest Neighbors* (KNN), *Multi-Layer Perceptrons* (MLPs), and *Random Forests* (RFs) [14, 15].

The RF algorithm is a widely used ensemble learning technique for both classification and regression tasks. It constructs multiple decision trees during training and combines their outputs to enhance predictive accuracy and reduce overfitting. Each tree in the forest is trained using a bootstrap sample of the original dataset, and at each node, a random subset of features is selected to determine the optimal split. This randomness introduces diversity among the trees, making the overall model more robust and less sensitive to noise. In classification problems, the final prediction is obtained through majority voting among the trees, whereas in regression tasks, it is typically the average of their outputs. RFs are valued for their high accuracy, stability, and capacity to manage large datasets with complex, nonlinear relationships. Additionally, they provide insights into feature importance, helping to assess the relative contribution of each variable to the model's predictions. Overall, the RF algorithm is a powerful, flexible, and interpretable tool applicable to a wide range of ML problems [16].

It is imperative to review existing research that integrates signal processing and ML techniques for fault detection in inverter–motor systems. In [17], the authors proposed an *insulated-gate bipolar transistor* (IGBT) open-circuit fault detection method based on the HHT. The method employs CEEMDAN to analyse motor stator current signals, producing a set of IMFs. These IMFs capture the characteristic frequency components and harmonics associated with IGBT open-circuit faults. In [18], an *Improved Sliding Mode Observer* (ISMO) was introduced for fault diagnosis. The ISMO is derived from the mathematical model of a *two-phase voltage-source inverter* (TP-VSI) and incorporates a novel power-switching function to mitigate chattering. A key innovation of this method is the extraction of fault features using the average log-likelihood ratio between estimated and measured currents. In addition, a *Delayed Switching Adaptive Threshold* (DSAT), based on logical operations, enables the detection of dual IGBT open-circuit faults while adapting to dynamic operating conditions. Experimental validation confirmed accurate detection of 21 fault

types within less than 75% of a current cycle, ensuring both high precision and robustness. In [19], the authors proposed diagnosis methods tailored for both short-circuit and open-circuit faults in power electronic systems. For short-circuit faults, a classification technique based solely on current magnitude and gate signals was introduced, reducing data requirements and minimizing errors caused by phase deviations and noise. For open-circuit detection, the method applies a specific voltage vector to the inverter and compares the resulting current angle with a predefined lookup table. To further enhance reliability, an iterative diagnosis algorithm was proposed to improve robustness under angle errors and noise. In [20], single- and double-switch open-circuit faults in the drive system of an *electric-discharge* (ED) milling machine were studied. The authors proposed a hybrid method combining wavelet analysis with deep learning, specifically an *Adaptive Gaussian Wavelet Convolutional Network* (AGWCN). Features were extracted from current signals using an adaptive deformable convolution layer, followed by dimensionality reduction through a Gaussian wavelet pooling layer before classification. The AGWCN achieved a fault diagnosis accuracy of 99.72% on both simulated and experimental datasets, significantly outperforming conventional methods.

Furthermore, the model maintained strong robustness under compound noise and variable fault conditions, highlighting its suitability for industrial applications. In [21], a fault-diagnosis method was developed for systems with a two-level inverter architecture, which requires fewer devices than multilevel alternatives for generating nine-level output voltages. While capacitor voltage balancing was managed through an optimised switching strategy, semiconductor switches remained the most fault-prone components. To address this issue, the authors proposed an open-circuit fault detection method based on analysis of the load voltage waveform. The technique applies a wavelet transform to feature extraction, followed by classification with an ANN. Developed in MATLAB/Simulink and validated experimentally; the method demonstrated effective real-time fault detection in two-level inverter systems.

The remainder of this paper is organized as follows:

- Section 2 presents the ICEEMDAN technique and its corresponding algorithm. It also introduces a statistical analysis based on *correlation* (Corr), which is used to optimally select the IMFs containing fault-characteristic frequencies. Finally, this section presents the RF algorithm.
- Section 3 discusses the experimental setup and results, detailing the complete current acquisition process and providing an interpretation of the findings.
- Section 4 provides a comparative analysis of the proposed method with other ML techniques, including *Decision Trees* (DT), and with recent state-of-the-art approaches in terms of diagnosis accuracy.
- Section 5 concludes the paper and outlines directions for future research.

2. Proposed Method for Diagnosis and Automated Monitoring of IGBT Open-Circuit Fault

The proposed method integrates the HHT with ICEEMDAN and RF machine learning.

2.1. ICEEMDAN algorithm

The EMD technique decomposes a signal into several IMFs and a residual component. Each IMF must satisfy the following two conditions [22, 23]:

- The number of extrema and the number of zero crossings must be equal, or differ by at most one.
- The mean value of the envelope defined by the local maxima and minima is zero.

A key limitation of EMD is the occurrence of mode mixing. To address this issue, Wu and Huang [22] proposed the EEMD technique.

In EEMD, the effects of white noise are not completely eliminated, and one of the main drawbacks of this technique is the interaction between the signal and the added noise. To address this issue, the CEEMD technique has been introduced. The key idea of this technique is to add positive and negative white Gaussian noise to the original signal, thereby generating two complementary sets of IMFs [22, 23].

A significant drawback of CEEMD is its high computational cost and the lack of a guarantee that trials x^+ and x^- will yield the same number of modes. To overcome these limitations while preserving the key advantage of CEEMD namely, the elimination of mode mixing the CEEMDAN algorithm [22, 23] was proposed.

In the original CEEMDAN, decomposing multiple realizations $r_k + E_k(\omega^i)$ to extract the $(k + 1)^{\text{th}}$ mode often leads to overlap across scales, resulting in spurious modes and residual noise. To reduce this issue, instead of directly using white noise for mode extraction $E_k(\omega^i)$, operators $E_k(\cdot)$ $M(\cdot)$ are applied to compute the local mean of the signal. The notation $\langle \cdot \rangle$ represents the averaging process over multiple realizations. In both EEMD and the original CEEMDAN, the first mode is defined as:

$$\overline{IMF_1} = \langle E_1(x^i) \rangle = \langle x^i - M(x^i) \rangle = \langle x^i \rangle - \langle M(x^i) \rangle. \quad (1)$$

To minimize the noise present in the modes, only the local mean is computed, and the first mode is then obtained as:

$$\overline{IMF_1} = x - \langle M(x^i) \rangle. \quad (2)$$

The ICEEMDAN algorithm can be outlined in the following steps [22, 23]:

Step 1: Apply EMD to compute the local means of I realizations of $x^i = x + \varepsilon_0 E_1(\omega^i)$, ($i = 1, 2, \dots, I$) and obtain the first residual signal:

$$r_1 = \langle M(x^i) \rangle. \quad (3)$$

Step 2: Calculate the first intrinsic mode function ($k = 1$):

$$\overline{IMF_1} = x - r_1. \quad (4)$$

Step 3: Compute the second residual by averaging the local means of the $r_1 + \varepsilon_1 E_2(\omega^i)$ realizations, and define the second mode as follows:

$$\overline{IMF_2} = r_1 - r_2 = r_1 - \langle M(r_1 + \varepsilon_1 E_2(\omega^i)) \rangle. \quad (5)$$

Step 4: Compute the k^{th} residual as follows:

$$r_k = \langle M(r_{k-1} + \varepsilon_{k-1} E_k(\omega^i)) \rangle, \quad (6)$$

where $k = 3, \dots, K$.

Step 5: Calculate the k^{th} mode as follows:

$$\overline{IMF_k} = r_{k-1} - r_k. \quad (7)$$

Step 6: Repeat Step 4 for the next k iterations.

2.2. Corr analysis

An essential step is identifying the relevant modes that contain the sound signal. The Corr serves as a powerful tool for selecting these modes. For a given time series $x(t)$, the Corr between the original signal and its IMFs obtained through ICEEMDAN is defined by the following equation [24, 25]:

$$\text{Corr}(i) = \sum_{t=1}^L \frac{x(t)IMF_i(t)}{\sqrt{\sum_{t=1}^L x(t)^2} \sqrt{\sum_{t=1}^L IMF_i(t)^2}}, \quad (8)$$

where L is the total number of samples in the signal, and $i = 1, 2, 3, \dots, n$ indicates the number of the IMF.

2.3. RF algorithm

The RF algorithm is a machine learning method based on a *decision tree* (DT) and is implemented through the following steps [26, 27]:

Step 1: Generate B new training sets using bootstrap sampling:

- Perform sampling with replacement, drawing Y observations from the original dataset.
- From p predictors, randomly select a subset of size $m < \text{root}(p)$,

Step 2: Train a DT on each sample using standard techniques, with growth constrained by cross-validation.

Step 3: Record the B predictions of the target variable for each original observation.

Step 4: Obtain the RF prediction through ensemble learning, using majority voting to determine the outcome.

3. Experimental results and discussion

All practical experiments concerned open-circuit faults in IGBTs in a two-level voltage inverter-fed induction motor and were conducted in our laboratory. The test rig consists of a two-level SEMIKRON voltage inverter controlled by a dSPACE 1104 card, supplying a three-phase induction motor coupled to a 2.4 kW DC generator. The induction motor is of the AZAZGA type, 50 Hz, four-pole, 3 kW, with a stator current rating of 7 A. Table 1 presents the main characteristics of the induction motor.

Table 1. Induction motor characteristics.

Motor manufacturer	AZAZGA
Power	3 kW
Nominal supply voltage	380 V
Shaft coupling	Δ
Nominal supply current	7 A
$\cos(\varphi)$	0.83
Number of poles	4
Number of rotor bars	28
Nominal operating speed	1410 rpm
Insulation rating	F

Table 2 presents the characteristics of the DC generator.

Table 2. DC generator characteristics.

DC generator manufacturer	DELORENZO
Power	2.4 kW
Armature terminal voltage	220 V
Armature terminal current	10.9 A
Field excitation current	0.65 A
Field excitation type	separated
Nominal operating speed	1410 rpm
Insulation rating	F

We analysed the system's performance under healthy conditions and six faulty states, each corresponding to an open-circuit fault. In total, tests were conducted across seven operating modes:

- **In Operating Mode 1 (OM1)**, measurements were conducted on a fully functional inverter under healthy conditions.
- **In Operating Mode 2 (OM2)**, an open-circuit fault was introduced at switch S_1 .
- **In Operating Mode 3 (OM3)**, an open-circuit fault was introduced at switch S_2 .
- **In Operating Mode 4 (OM4)**, an open-circuit fault was introduced at switch S_3 .
- **In Operating Mode 5 (OM5)**, an open-circuit fault was introduced at switch S_4 .
- **In Operating Mode 6 (OM6)**, an open-circuit fault was introduced at switch S_5 .
- **In Operating Mode 7 (OM7)**, an open-circuit fault was introduced at switch S_6 .

The structure of a three-phase voltage inverter is illustrated in Fig. 3.

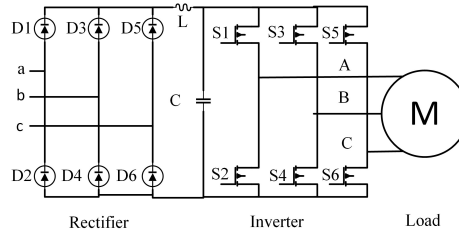


Fig. 3. Inverter-motor system.

The measurement chain consists of three FLUKE i30s AC/DC current clamps and three TEKTRONIX P5200 voltage probes, connected to a dSPACE 1104 data acquisition card and a PC for signal processing and visualization. Due to the random nature of the measured signals, five acquisitions were performed for each scenario to ensure reliable analysis. Each acquisition lasted $T_{\text{acq}} = 5$ s with a sampling frequency of $f_e = 1500$ Hz, yielding 7,500 samples per channel. To study the effect of load on the induction motor signals, only one operating condition was considered: operation at nominal load, with a measured nominal current of 7 A and an estimated torque of 20.33 Nm. To obtain a total of 600 signals across seven operating conditions, the measurement procedure was structured so that each acquisition simultaneously recorded six signals one from each sensor. A total of 100 acquisitions were required, distributed approximately evenly among the seven conditions: 14 acquisitions per condition for six conditions and 16 acquisitions for the

remaining condition. This distribution ensures a balanced representation of all operating scenarios while generating the complete dataset necessary for analysis. Table 3 shows the data distribution summary and Fig. 4 illustrates the acquired current signals for each operating mode.

Table 3. Acquisition distribution by operating mode.

Operating Mode	Acquisitions	Signals (6 per acquisition)
OM1	14	84
OM2	14	84
OM3	14	84
OM4	14	84
OM5	14	84
OM6	14	84
OM7	16	96
Total	100	600

The experimental results shown in Fig. 4 (1 and 2) depict the stator current waveforms for two operating modes: the healthy state and the IGBT open-circuit fault at switch S_1 . In the faulty mode, the electrical quantities, particularly the stator currents, display distinct behaviours compared to regular operation. Specifically, the open-circuit fault at S_1 causes a sudden disruption in the waveform, due to the loss of positive alternations in phase (A). Consequently, the current in phase (A), connected to the faulty leg, can no longer be adequately controlled when its reference is positive, resulting in either negative values or zero. When the phase (A) current drops to zero, the stator currents in the two remaining healthy phases (B and C), which must maintain a zero-sum balance, exhibit an immediate and significant rise to compensate.

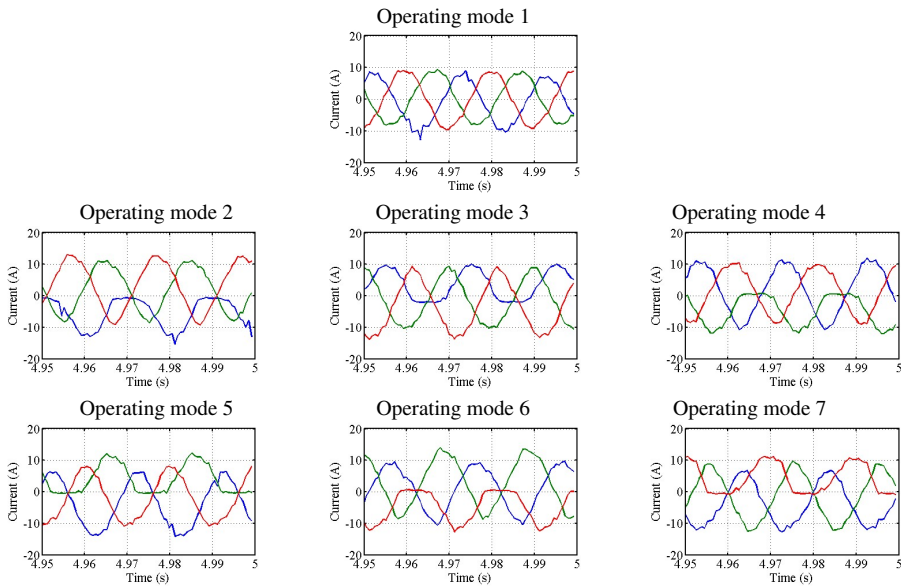


Fig. 4. Current signals.

The proposed process for diagnosing an IGBT open-circuit fault using the hybrid ICEEMDAN and RF technique can be summarised in the following steps:

Step 1: Apply the ICEEMDAN algorithm to decompose the original signal into its IMFs;

Step 2: Calculate the correlation coefficients between the original signal and its corresponding IMFs.

Step 3: Select IMFs with *Corr* greater than 0.1, identifying them as functional components;

Step 4: Reconstruct the signal (*RS*) by summing the selected useful IMFs.

Step 5: Perform envelope spectrum analysis to extract the features of an open-circuit fault in the IGBT.

Step 6: Apply RF-based machine learning to detect and classify open-circuit faults in the IGBT.

Figure 5 illustrates the *Corr* for each IMF under both healthy and faulty conditions. A *Corr* threshold of 0.1 was determined empirically based on preliminary experimental observations. IMFs with correlation coefficients below this value predominantly exhibited noise-dominated behaviour and negligibly contributed to feature discrimination, whereas IMFs exceeding the threshold consistently preserved meaningful signal information across different operating conditions. Sensitivity analyses further showed that small variations around the 0.1 threshold did not influence the IMF selection results. Under all tested scenarios, IMFs 4–7 satisfied this criterion and were therefore selected and summed for *RS*. Consequently, the adopted threshold is robust and does not require readjustment within the investigated operating range.

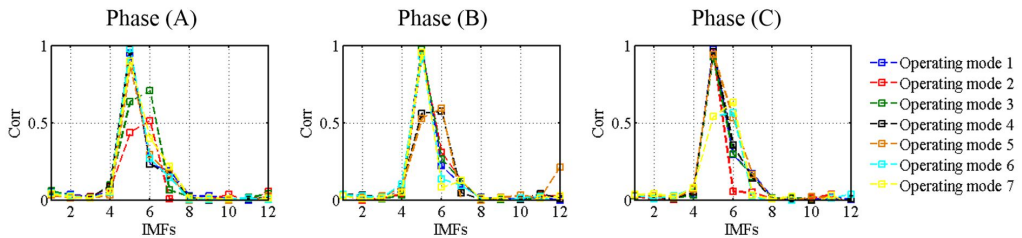


Fig. 5. The *Corr* for each IMF under healthy and faulty conditions.

Fig. 6 presents the useful IMFs and the *RS* for Operating Modes 1 and 2 across each phase.

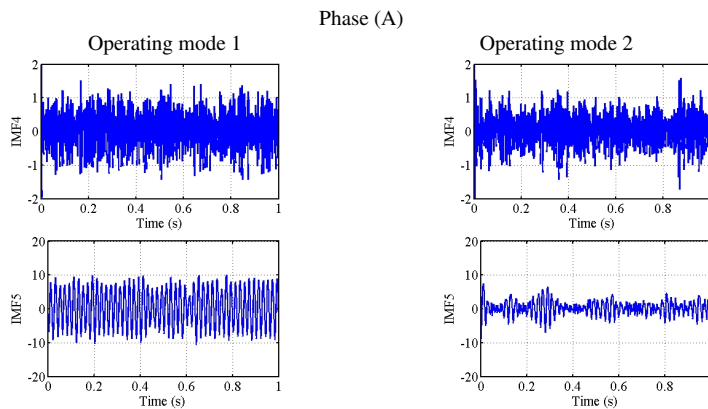


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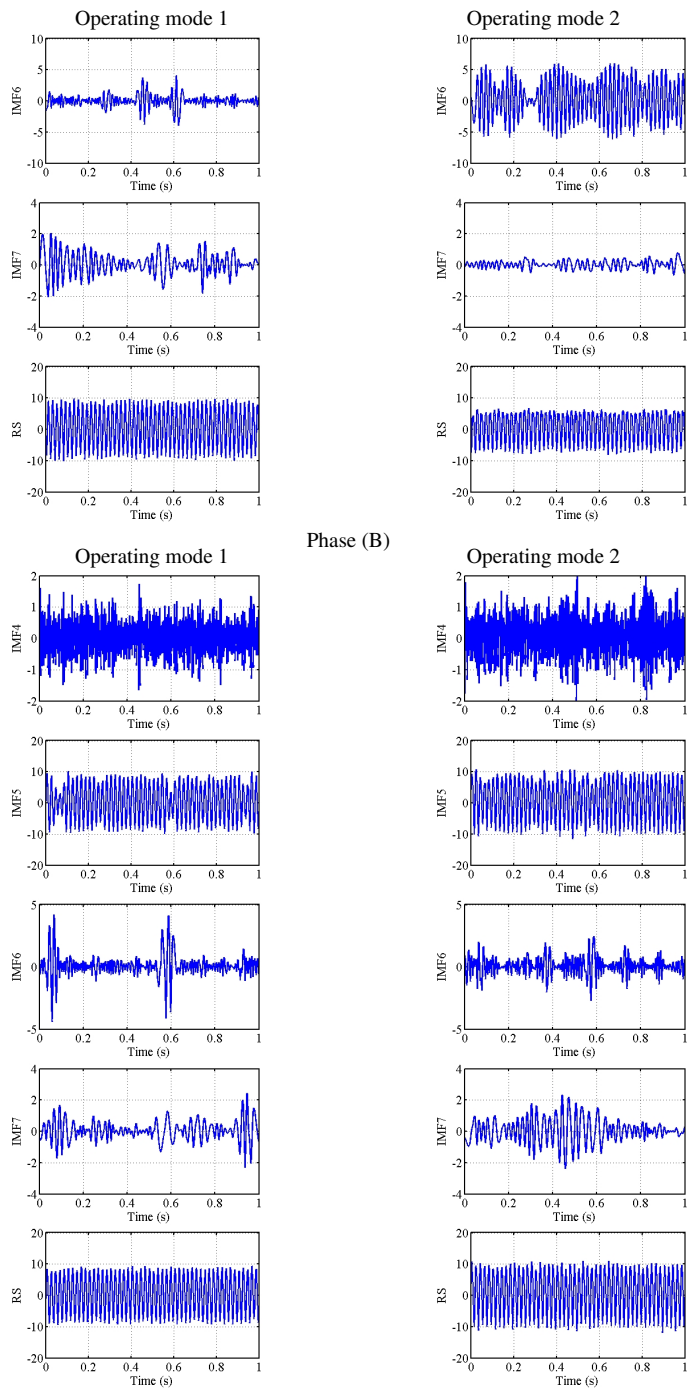


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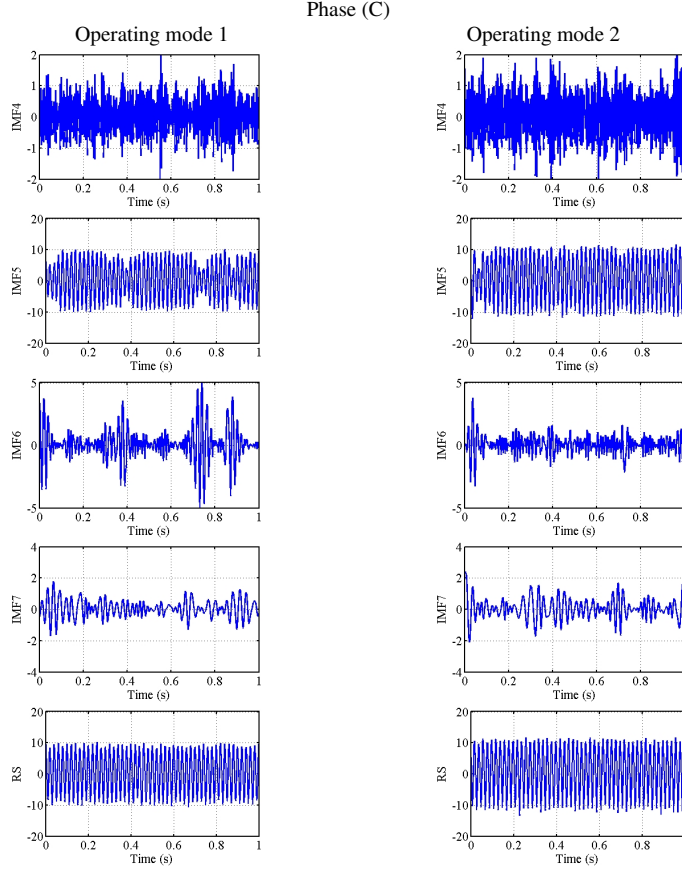


Fig. 6. Useful IMFs and RS.

The remainder of this section focuses on extracting the features of IGBT open-circuit faults to train the RF-based ML system.

The Hilbert transform of a signal $RS(t)$ in the time domain is defined as follows [28]:

$$\overline{RS_i}(t) = \frac{1}{\pi} \int \left(\frac{RS_i(\tau)}{t - \tau} \right), \quad (9)$$

where t denotes the time variable, τ denotes the relaxation time.

The analytical signal $\hat{RS_i}(t)$ of the real signal $RS_i(t)$, constructed using the Hilbert transform, is defined as follows [29]:

$$\overline{RS_i}(t) = RS_i(t) + j\overline{RS_i}(t). \quad (10)$$

The envelope of the signal $RS_i(t)$ obtained as the absolute value of its analytical signal is defined as follows [30]:

$$|\overline{RS_i}(t)| = \sqrt{RS_i(t)^2 + \overline{RS_i}(t)^2}. \quad (11)$$

Figure 7 presents the envelopes spectrums of the RS for Operating Modes 1 and 2 across all three phases.

In operating mode 1, the spectrum shows the presence of f_c harmonics, including a notable 100 Hz harmonic, indicating an imbalance among the supply phases. Additionally, the absence of f_{oc} a harmonic around 50 Hz confirms the system's healthy state. In Operating Mode 2, the spectrum shows the presence of f_c , f_{oc} (around 50 Hz) and 100 Hz harmonics across all three phases (A, B, and C). Notably, the f_{oc} harmonic in phase A exhibits a significantly higher amplitude compared to phases (B and C), with a relationship approximating: $f_{oc \text{ phaseA}} \approx f_{oc \text{ phaseB}} + f_{oc \text{ phaseC}}$. Meanwhile, the 100 Hz harmonic in phase (A) decreases in amplitude, while it remains relatively unchanged in the other two phases, similar to the healthy mode. Finally, the f_c harmonic in phase (A) also decreases significantly compared to phases (B and C), highlighting the impact of the fault.

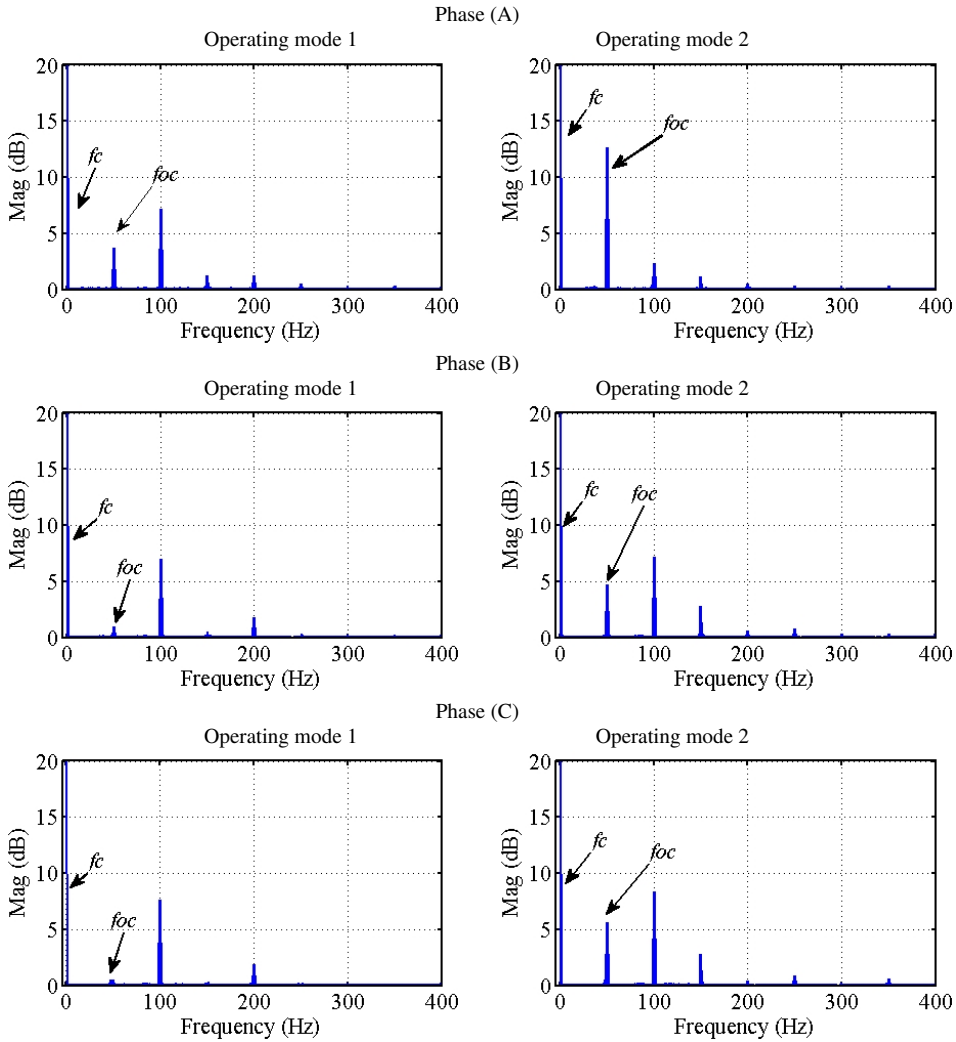


Fig. 7. Envelopes spectrums of RS.

To extract features for training the RF model, the analysis focuses on the amplitudes and phases (arguments) of the two characteristic peaks f_c and f_{oc} for each phase:

$$f_1 = \text{Mag}(f_c), \quad (12)$$

$$f_2 = \text{Mag}(f_{oc}), \quad (13)$$

$$f_3 = \arctan\left(\frac{f_{oc}}{f_c}\right), \quad (14)$$

where f_c is the frequency of the DC component, and f_{oc} is the frequency associated with the open-circuit fault of an IGBT.

The magnitude values of f_1 and f_2 are summarized in Table 4.

Table 4. Magnitude values of f_1 and f_2 .

Phases	Phase (A)		Phase (B)		Phase (C)	
Peaks	f_1	f_2	f_1	f_2	f_1	f_2
Operating Mode 1	22.19	3.73	21.54	0.96	22.23	0.50
Operating Mode 2	23.57 min	12.66 $f_{2(A)} \approx f_{2(B)} + f_{2(C)}$	27.30 max	5.78	27.33 max	6.64
Operating Mode 3	16.86 min	8.38 $f_{2(A)} \approx f_{2(B)} + f_{2(C)}$	24.21 max	3.058	27.5 max	5.256
Operating Mode 4	26.22 max	3.407	18.14 min	11.14 $f_{2(B)} \approx f_{2(A)} + f_{2(C)}$	24.42 max	7.727
Operating Mode 5	28.24 max	9.01	19.32 min	12.41 $f_{2(B)} \approx f_{2(A)} + f_{2(C)}$	24.23 max	3.33
Operating Mode 6	23.48 max	5.20	27.63 max	6.94	19.11 min	12.18 $f_{2(C)} \approx f_{2(A)} + f_{2(B)}$
Operating Mode 7	25.86 max	6.32	26.65 max	5.40	18.96 min	11.72 $f_{2(C)} \approx f_{2(A)} + f_{2(B)}$

Table 5 summarizes the comparison between peak f_1 and peak f_2 , where ε_0 denotes the maximum amplitude of the f_c .

Table 5. Arguments of peak f_1 and peak f_2 .

Phases	Phase (A)	Phase (B)	Phase (C)
Peaks	$\varphi = \frac{f_2}{f_1}$	$\varphi = \frac{f_2}{f_1}$	$\varphi = \frac{f_2}{f_1}$
Operating Mode 1	$ f_2 = \varepsilon_0 = 0^\circ$	$ f_2 = \varepsilon_0 = 0^\circ$	$ f_2 = \varepsilon_0 = 0^\circ$
Operating Mode 2	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$
Operating Mode 3	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$
Operating Mode 4	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$
Operating Mode 5	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$
Operating Mode 6	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$
Operating Mode 7	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 270^\circ$	$ \varepsilon_0 \langle f_2 \rangle \langle f_1 \rangle = 90^\circ$

The RF-based ML technique employs a 70:30 split ratio to divide the dataset into training and testing subsets. The training set comprises 70% of the data (420 signals), while the remaining 30% (180 signals) is reserved for testing. This split ratio was chosen empirically, guided by literature findings, particularly for classifying IGBT open-circuit faults.

To complete the diagnosis of an open-circuit fault in the IGBT switch, an RF-based ML technique is employed to accurately identify the specific fault location, whether it is at IGBT switch S_1 , S_2 , S_3 , S_4 , S_5 , or S_6 .

Figure 8 presents the architecture and schematic representation of the RF model.

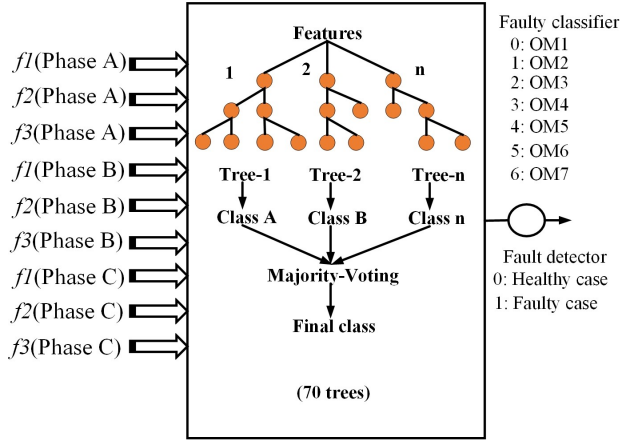


Fig. 8. Schematic representation of the RF architecture.

The RF model was evaluated across 40 independent training and testing runs to account for stochastic variations in model initialisation. The model was configured with nine input features and 70 trees, with key hyperparameters set to ensure robust performance. Specifically, the number of estimators ($n_{estimators}$) was set to 70, the maximum number of features considered at each split ($max_features$) was 9, and the maximum tree depth (max_depth) was limited to 10. Additionally, the minimum number of samples required to split a node ($min_samples_split$) was set to 5, and the minimum number of samples at a leaf node ($min_samples_leaf$) was 2. The model employed bootstrapping ($bootstrap = True$) and used the Gini impurity criterion ($criterion = "gini"$) for classification.

Figures 9 and 10 illustrate the relationship between model accuracy and the number of trees for both fault detection and classification tasks.

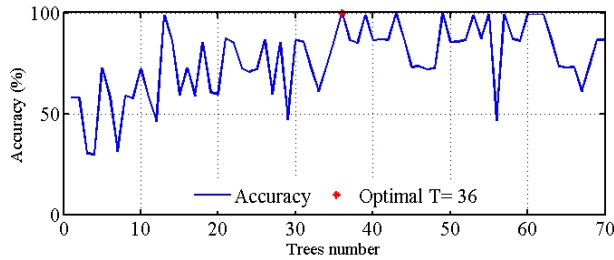


Fig. 9. Variation of detection accuracy with respect to the number of trees in the fault detection model.

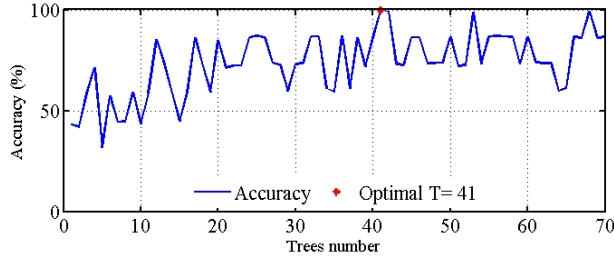


Fig. 10. Variation of classification accuracy with respect to the number of trees in the fault classifier.

As shown in Figs. 9 and 10, the optimal numbers of trees are 36 for the fault detector and 41 for the fault classifier, achieving an exceptional accuracy of 99.98% and 99.99%, respectively. These results highlight the effectiveness of the RF-based ML technique in detecting, classifying, and pinpointing open-circuit faults in the IGBT.

The performance of the fault detector and fault classifier is evaluated using metrics such as accuracy, sensitivity, specificity, precision, G-mean, and F1-score.

- *Accuracy*: the percentage of correctly classified examples is calculated as follows [31,32]:

$$\text{Acc} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (15)$$

- *Sensitivity*: the ability to correctly identify a fault when it occurs is calculated as follows [31, 32]:

$$\text{Sens} = \frac{T_P}{T_P + F_N} \quad (16)$$

- *Specificity*: when the fault is absent, the probability of obtaining a negative result is determined by [31,32]:

$$\text{Spec} = \frac{T_N}{T_N + F_P} \quad (17)$$

- *Precision*: it is the ratio of correctly predicted positive examples to all predicted positive examples, defined as follows [33]:

$$\text{Prec} = \frac{T_P}{T_P + F_P} \quad (18)$$

- *G-mean*: it is the geometric mean of sensitivity and precision, defined as [34]:

$$G\text{-mean} = \sqrt{\text{Sens} \times \text{Prec}} \quad (19)$$

- *F₁-score*: it is a metric that combines precision and sensitivity to evaluate the performance of a classification model, particularly in cases of class imbalance. It is calculated as [35]:

$$F_{1\text{-score}} = \frac{T_P}{T_P + \frac{F_P + F_N}{2}} \quad (20)$$

where: T_P : true positive; T_N : true negative; F_P : false positive; F_N : false negative.

The improved accuracy clearly demonstrates the effectiveness of the process in identifying IGBT faults and classifying fault types, as evidenced by the confusion matrices and output values shown in Figs. 11 and 12.

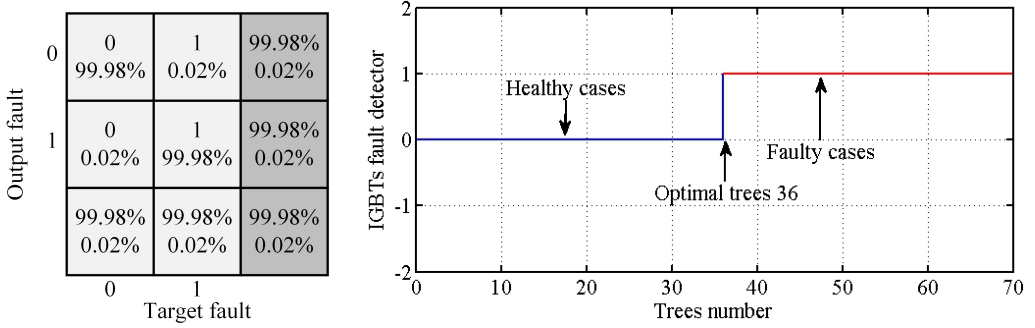


Fig. 11. Performance evaluation of the fault detector using confusion matrices and output values.

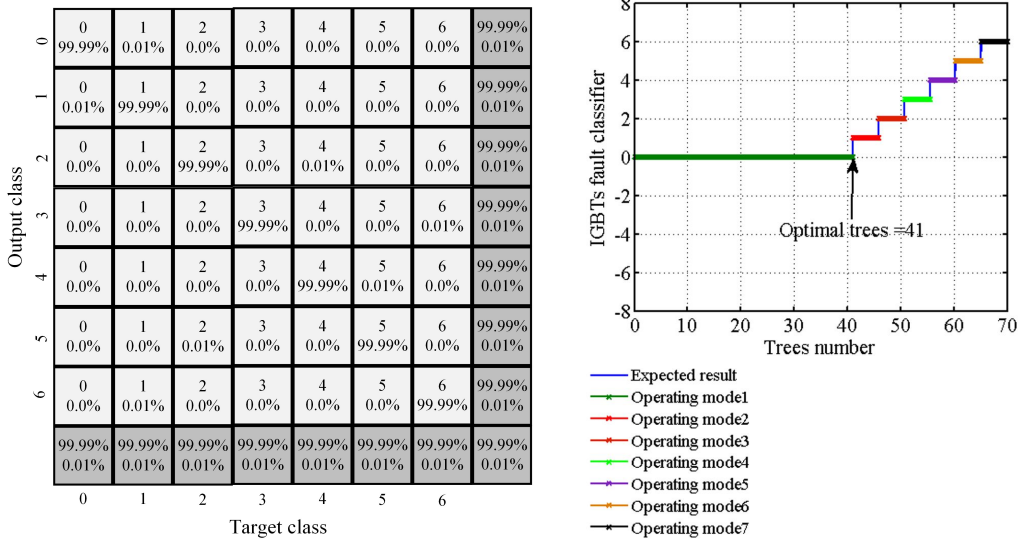


Fig. 12. Evaluation of the fault classifier using confusion matrices and output values.

Table 6 summarises the evaluation metrics and computation time for both the fault detector and the fault classifier.

Table 6. Evaluation metrics and computation time for both the fault detector and classifier.

Techniques	Accuracy	Sensitivity	Specificity	Precision	G-mean	F_1 -score	1/Time normalized
ICEEMDAN-RF fault detector	99.98%	99.96%	99.94%	99.97%	99.96%	98.99%	0.000015
ICEEMDAN-RF fault classifier	99.99%	99.97%	99.98%	99.96%	99.96%	99.95%	0.0002

The ICEEMDAN-RF fault detection model demonstrates outstanding performance across multiple evaluation metrics. In one test scenario, it achieves a sensitivity of 99.96%, reflecting its excellent ability to... accurately detect positive cases when an IGBT is defective. Its specificity, indicating its ability to correctly identify healthy IGBTs, is also high at 99.94%. The classifier attains an overall accuracy of 99.97%, highlighting its reliability in fault identification.

Furthermore, the G-mean, which balances sensitivity and specificity, is reported at 99.96%, confirming the model's robustness under both faulty and non-faulty conditions. The F_1 -score, representing the harmonic mean of precision and recall, reaches 98.99%, demonstrating consistent performance when classifying imbalanced data. The overall detection rate stands at 99.98%, underscoring the model's strong diagnostic capabilities.

In a second evaluation, the ICEEMDAN-RF classifier maintains similarly impressive results. It achieves 99.97% sensitivity and 99.98% specificity, indicating high confidence in both fault detection and non-fault verification. The model also records 99.96% accuracy, 99.96% G-mean, and a 99.95% F_1 -score. Its overall classification rate reaches 99.99%, further affirming its effectiveness and efficiency in IGBT fault diagnosis.

4. A comparative study

Based on established evaluation metrics, we compare the performance of the proposed RF technique with another method from the same family: the DT technique. The comparison is conducted using key performance indicators, including accuracy, sensitivity, specificity, precision, G-mean, F_1 -score, and computation time. Table 7 summarises the results of this comparative analysis.

Table 7. Comparison of the RF technique proposed with the DT technique.

Techniques	Accuracy	Sensitivity	Specificity	Precision	G-mean	F_1 -score	1/Time normalized
ICEEMDAN-RF fault detector	99.98%	99.96%	99.94%	99.97%	99.96%	98.99%	0.000015
ICEEMDAN-RF fault classifier	99.99%	99.97%	99.98%	99.96%	99.96%	99.95%	0.0002
ICEEMDAN-DT fault detector	94.33%	85.23%	90.56%	88.45%	86.82%	77.89%	0.0035
ICEEMDAN-DT fault classifier	95.89%	87.56%	92.83%	89.25%	88.40%	80.23%	0.085

This comparative study clearly demonstrates that the RF technique outperforms the DT technique across various evaluation metrics, including accuracy, sensitivity, precision, G-mean, F_1 -score, and computational efficiency. Despite its relatively simple structure and assumptions, the RF algorithm delivers superior performance in this application. In contrast, while the DT model achieves acceptable accuracy, its overall performance is lower, particularly in accurately identifying the negative class (indicating the absence of a defect), highlighting its limitations in fault-detection scenarios.

Table 8 presents a comparative analysis of the proposed method against recent methods in terms of accuracy.

Table 8. Accuracy and time normalized comparison of the proposed method with existing methods.

Ref	Methods	Classification accuracy (%)	1/time normalized
[36]	EEMD-RF	78.88%	0.0434
[37]	RS-RF	99%	0.0756
[38]	TC-RF	98%	0.0857
Proposed method	ICEEMDAN-RF fault detector	99.98%	0.000015
	ICEEMDAN-RF fault classifier	99.99%	0.0002

The proposed method offers several advantages over existing methods. It achieves higher diagnosis accuracy and significantly reduces normalised diagnosis time, demonstrating superior performance compared to current methods.

5. Conclusions

This article presents an automated method for monitoring open-circuit faults in the IGBT switch of an inverter–induction motor assembly. The proposed method combines signal processing using ICEEMDAN and machine learning using an RF classifier. The method begins with current signal decomposition using ICEEMDAN to identify harmonic components indicative of an open-circuit fault in the IGBT switch and its location. A statistical analysis is then conducted using the Corr to evaluate each IMF. IMFs with a correlation coefficient equal to or greater than 0.1 are considered informative. In this case, IMF₄, IMF₅, IMF₆, and IMF₇ are selected for further analysis. These selected IMFs are used to RS, and a spectral envelope analysis of the RS is performed to highlight IGBT fault signatures. Finally, an RF model is employed to detect and classify the IGBT faults using three extracted features: f_1 , f_2 , and f_3 . The RF model demonstrates excellent performance, achieving detection and classification rates of 99.98% and 99.99%, respectively.

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Appendices

The EMD algorithm can be outlined in the following steps:

Step 1: Identify all local extrema of $r_0 = x$, and connect the local maxima and minima using cubic spline interpolation to form the upper envelope $e_{\max}$ and the lower envelope $e_{\min}$, respectively.

Step 2: Calculate the mean envelope, defined as the average of the upper and lower envelopes:

$$m = \frac{e_{\min} + e_{\max}}{2}.$$

Step 3: Calculate the detail component by subtracting the mean envelope from the signal r_k , i.e., $h_k = r_k - m$.

Step 4: Check whether r_k satisfies the conditions of an IMF:

If yes: Save h_k as IMF_k , compute the residue $r_{k+1} = r_k - h_k$, increment k by 1, and use r_{k+1} as the input for Step 2.

If no: Use h_{k+1} as the input for Step 2.

Step 5: Repeat the process until the final residue r_k satisfies the predefined stopping criterion.

The *stopping criterion* (SD) is computed using two consecutive sifting results, h_{k-1} and h_k , as follows:

$$SD = \sum_{t=0}^T \frac{h_{k-1}(t) - h_k(t)}{h_{k-1}^2(t)}. \quad (21)$$

The procedure (Steps 2–5) involves a series of iterations, known as the sifting process, to extract each mode.

The sifting process terminates when the SD value exceeds a predefined threshold.

The signal can then be represented as:

$$x = \sum_{i=1}^n IMF_i + r_n, \quad (22)$$

where: r_n refers to the final residue, while n indicates the number of IMF.

The EEMD algorithm can be outlined in the following steps:

Step 1: Generate $x^i = x + \varepsilon \omega^i$, where ω^i , ($i = 1, \dots, I$) represents a zero-mean, unit-variance white noise realization, and the noise standard deviation is $\varepsilon > 0$.

Step 2: Decompose x^i , ($i = 1, \dots, I$) using EMD to obtain the modes IMF_k^i , where $k = 1, \dots, K$.

Step 3: Obtain the k^{th} mode $\overline{IMF}_k$ of x by averaging the corresponding modes:

$$\overline{IMF}_k = \frac{1}{I} \sum_{i=1}^I IMF_k^i. \quad (23)$$

The relationship between the amplitude of the added white noise and the number of ensemble trials is given by:

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{I}}, \quad (24)$$

where ε denotes the amplitude of the added noise, while ε_n denotes the final standard deviation of error.

The CEEMD algorithm can be outlined in the following steps:

Step 1: Add white noise to the original signal x in pairs to generate two new datasets, x^+ and x^- :

$$\begin{bmatrix} x^+ \\ x^- \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} x \\ \omega_i \end{bmatrix}. \quad (25)$$

Step 2: Decompose x^+ and x^- use EMD to obtain IMF_i^+ and IMF_i^- from the positive and negative mixtures, respectively.

Step 3: Repeat the above step I times to obtain two datasets, IMF_{ij}^+ and IMF_{ij}^- each containing i^{th} IMFs derived from the positive and negative mixtures j^{th} , respectively.

Step 4: Calculate the final IMF using the following expression:

$$\overline{IMF}_i = \frac{1}{2I} \sum_{j=1}^I (IMF_{ij}^+ + IMF_{ij}^-), \quad (26)$$

where I denotes the number of achievements.

The original signal can be represented as:

$$x = \sum_{i=1}^n \overline{IMF}_i + r_n. \quad (27)$$

The CEEMDAN algorithm can be outlined in the following steps:

Step 1: Apply EMD to the I realizations $x + \varepsilon_0 \omega^i$, ($i = 1, \dots, I$) to extract their first intrinsic mode functions (IMFs) and compute the following:

$$\overline{IMF}_1 = \frac{1}{I} \sum_{i=1}^I IMF_1^i. \quad (28)$$

Step 2: Calculate the first residual component by subtracting the first IMF from the original signal:

$$r_1 = x - \overline{IMF}_1. \quad (29)$$

Step 3: Apply EMD to $r_1 + \varepsilon_1 E_1(\omega^i)$, $i = 1, \dots, I$ extract its first intrinsic mode functions, and define the second CEEMDAN mode as follows:

$$\overline{IMF}_2 = \frac{1}{I} \sum_{i=1}^I E_1(r_1 + \varepsilon_1 E_1(\omega^i)). \quad (30)$$

Step 4: To $k = 2, \dots, K$ compute the k^{th} residual signal:

$$r_k = r_{k-1} - \overline{IMF}_k. \quad (31)$$

Step 5: Apply EMD to the $r_k + \varepsilon_k E_k(\omega^i)$, $i = 1, \dots, I$ realizations and define the $(k + 1)^{\text{th}}$ CEEMDAN mode as follows:

$$\overline{IMF}_{k+1} = \frac{1}{I} \sum_{i=1}^I E_k(r_k + \varepsilon_k E_k(\omega^i)), \quad (32)$$

where $E_k(\cdot)$ is the function used to extract the k^{th} , IMF obtained through EMD, and ε_k is the amplitude of the added white noise.

Step 6: Repeat Step 4 for the next k .

Step 7: Repeat Steps 4-6 until EMD cannot further decompose the residual signal. The final residue is defined as follows:

$$r_n = x - \sum_{i=1}^n \overline{IMF}_i. \quad (33)$$

Consequently, the given signal can be decomposed as follows:

$$x = r_n + \overline{IMF}_i, \quad (34)$$

where n denotes the total number of modes, and ω denotes white noise with unit variance.

The configuration of CEEMDAN and ICEEMDAN hinges on balancing noise-assisted scale separation with computational efficiency. The ensemble size governs the statistical stability of the decomposition, while the noise amplitude controls the level of perturbation used to reveal intrinsic oscillatory structures within the signal. The sifting criteria determine the symmetry and purity of the extracted IMFs, and residue-based stopping rules prevent unnecessary or

redundant decomposition. Owing to its enhanced local mean estimation, ICEEMDAN suppresses noise propagation more effectively than CEEMDAN, allowing the use of smaller ensembles and lower noise levels without compromising the stability or separation of the resulting components. Collectively, these configuration choices influence the robustness, resolution, and computational practicality of the overall decomposition process. Table 9 summarizes the parameter selection criteria for CEEMDAN and ICEEMDAN.

Table 9. Recommended parameter settings for CEEMDAN and ICEEMDAN.

Parameter	CEEMDAN	ICEEMDAN
Ensembles	100–500	50–200
Noise amplitude	0.2–0.3	0.1–0.2
Sifting threshold (SD)	0.2–0.3	0.2
S-number	4–10	4–10
Residue threshold	1%–5%	1%–5%

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