Microgrid Fault Detection and Classification using HHT and Decision Tree

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Abstract: A Microgrid Protection Scheme proposed in this paper is based on the Hilbert-Huang Transform (HHT) and a Machine Learning model. The obtained phasor current signals at first, along with its fundamental components undergo empirical mode decomposition. Decomposing signals into mono components using the Empirical Mode Decomposition (EMD) technique are IMF stands for intrinsic mode function. To derive various practical insights from the chosen IMF, the Hilbert Transform is employed. An approach to machine learning utilization for training the protective system should successfully function and prove best for the protection of the Microgrid System.

Keywords: Microgrid, Hilbert-Huang Transform (HHT), Intrinsic Mode Functions (IMF), Fault Detection, Decision Tree Classifier, Fault Classification.

1. Introduction

Power system breakdowns can create substantial disruptions and jeopardize the electrical grid's dependability and stability. Rapid failure detection plays a vital role in preserving system operational efficiency and reducing outage durations. To extract fault signatures from measured signals, traditional fault diagnosis approaches frequently rely on time-frequency analysis methods. The Hilbert-Huang Transform (HHT) is a driven by data approach with promising results in a range of signal processing applications.

Microgrid protection is quite complicated and difficult problem because of its dynamic operational features. While microgrid undergoes fault condition, the ability of the system's fault detection, protection, and islanded mode of operation should isolate the least defective area. For static situations and radial topologies, conventional power systems typically employ traditional protective mechanisms.

These mechanisms are unreliable for the protection of microgrids because they do not account for the microgrids' changing network configurations, bidirectional power flow, and operational characteristics. [1] Growing Distributed Energy Resources integration in the Microgrid influences the fault current from the grid, which may have an impact on the protection system and protection device settings. [2] Furthermore, the addition of Distributed Energy Resources to the current network may result in contributions from different paths other than the primary connection point, which could lead to sympathetic tripping and blinding. As a result, Microgrids may not be adequately protected by the conventional protection scheme. [3] Thus, because of the above issues, appropriate fault detection and identifying the type of fault have become essential for minimizing the loss during the protection of Microgrid. To overcome various fault related issues in microgrid protection, many authors worked on and proposed different types of solutions for fault diagnosis.

In [4, 30], the authors proposed a protection scheme for microgrids with the help of HHT for obtaining different features and classifying the faults by the use of NBC, SVM, and ELM classifiers. And concluded that the ELM-based approach outperforms SVM- and NBC-based classifiers in detecting the fault events. In [5], the author provided an enhanced threshold-based method for microgrid differential protection by utilizing a VMD-HT based time-frequency

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transform to calculate the differential energy. In addition, the proposed scheme is validated through an OPAL-RT simulator. In a research paper [6], a relaying system is proposed in which fault detection is done with the help of an undervoltage function and fault zone identification is done through the Decision Tree technique.

Some researchers have proposed the ACUSUM algorithm for the detection of voltage depression event and the Decision Tree is applied for the classification of events in microgrid systems [7]. The authors of [8] presented an algorithm for classifying power system faults. They used the RMS values of fault current, voltage dip, and DWT for different fault conditions and then classifying by using Decision Tree. In [9], researchers used HHT with a sliding window strategy for fault detection and classification in microgrids. Combining the advantages of HHT and Decision Tree Classifier techniques is proposed by the authors in [10] for fault recognition in distribution systems penetrated with renewable energy sources. Research in [11] is shows the comparison of two fault classification technique, Support Vector Machine and Decision Tree and based on the results, it is concluded that the accuracy with the Decision Tree classifier is greater than that of another method. The HHT and Decision Tree based on fuzzy rules technique is proposed in [12] for the detection and classification of power quality disturbances in microgrid systems. As per the researcher in [14], HHT proves to be more effective and reliable as compared to the S-transform technique for fault detection in microgrid systems. In [17,18], the whole process of applying HHT is explained for fault detection. The authors of [19-21] give details about the fault occurrence in the microgrid system and different solutions to it. The features extracted from HHT are used as fault characteristics for identifying fault conditions in microgrids. [23]

Thus, based on the above analysis, this paper develops a solution for fault detection and classification through the use of HHT and Machine Learning techniques in microgrid systems. The feature extraction during fault conditions by applying HHT gives characterized fault signals as compared to other signal processing techniques, and applying a Decision Tree classifier to the same extracted feature through HHT performs the best for a set of faults in a microgrid system.

2. IEC Microgrid System

The test model used for this research is an IEC standard microgrid system, as shown below in Fig. 1. It is a 25 kV, 60 Hz system. In this system, there are four distributed energy resources. With a line length of 20 km each, the distribution lines are split into five portions, from DL-1 to DL-5. The operation of a microgrid system is considered to be in grid connected mode. Six loads are connected at specified locations in the system. System parameters and ratings are considered as per Table 1. Various types of faults are assumed to occur on DL-2, and the simulation is performed for the study of different faults in MATLAB/Simulink. The simulated system is shown below in Fig.1.

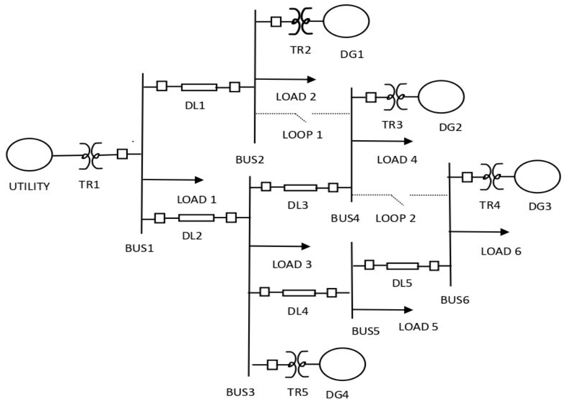


Fig. 1. Microgrid Test Model

Table 1. System parameters and ratings

Grid data	1000 MVA; 120 kV; 60 Hz
Transformer data	(a) TR1: (120/25) kV (Ynd1), 10 MVA, R1 = R2 = 0.00375 pu, 60 Hz; L1 = L2 = 0.1 pu, Xm = 500 pu (b) TR2: (25/0.575) kV (Dyn1), 10MVA, R1 = R2 = 0.00375 pu, 60 Hz; L1 = L2 = 0.1 pu, Xm = 500 pu (c) TR3: (25/0.575) kV (Dyn1) 10 MVA, R1 = R2 = 0.00375 pu, 60 Hz; L1 = L2 = 0.1 pu, Xm = 500 pu
Distribution generation	(a) DG1: DFIG-based wind farm: rated MW: 9; rated kV: 575 V; inertia constant = 0.685 s; 60 Hz, Rs = 0.023 pu, R′ r = 0.016 pu, Ls = 0.18 pu; L′ r = 0.16 pu; Lm = 2.9 pu (b) DG2: Photovoltaic Generation: Maximum Power = 315.7W, Voltage at maximum power point Vmp=54.7V, Shunt resistance Rsh=430.05ohm, Series resistance Rs= 0.43ohm (c) DG3: HTG with 'simplified synchronous machine': 1000kVA, 0.4 kV, inertia constant (H) = 1 s, internal resistance = 0.01466 pu; reactance = 0.22 pu (d) DG4: HTG with 'simplified synchronous machine': 5000kVA, 0.575 kV, inertia constant (H) = 7 s, internal resistance = 0.01466 pu; reactance = 0.22 pu
Transmission line data	R0 = 0.1153Ω/km, R1 =0.413Ω/km, l0 = 1.05e-3 H/km, l1 = 3.32e-3 H/km, C0 = 5.01e-009 F/km, C1 = 11.33e-009 F/km

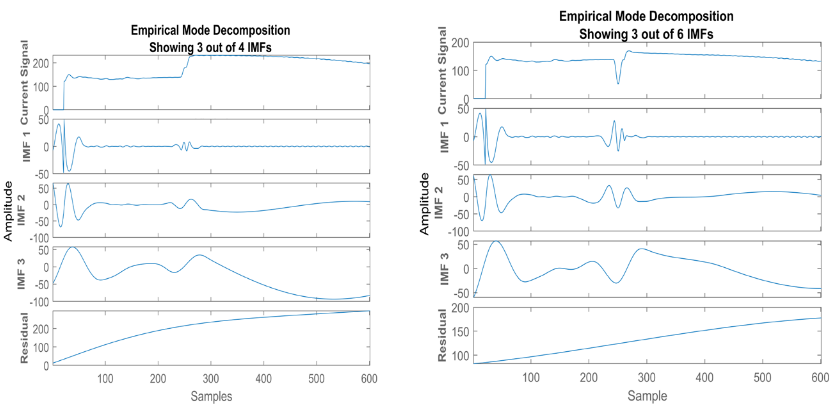
3. Feature extraction from the system

A. Empirical Mode Decomposition:

A data-adaptive multiresolution method called empirical mode decomposition (EMD) can be used to break down a signal into physically significant components. By splitting down signals into constituent parts at various resolutions, EMD can be used to evaluate non-stationary and non-linear signals. The components in EMD are called intrinsic mode functions (IMF). The output of applying the EMD function to a signal will give several intrinsic mode functions and a residue. The following equation explains the performance of EMD.

$$In = \sum_{1}^{M} IMFm(n) + RES_M(n)$$

Where In is the multicomponent signal, IMF_m (n) is the M^{th} intrinsic mode function and $RES_M(n)$ is the residue corresponding to M intrinsic mode. When LG fault is considered on DL-2, and the current signals at bus1 and bus3 are processed through EMD, the IMF will be obtained as shown in fig.2



(a) (b)

Fig. 2. For LG Fault in system (a) All IMF for Bus 1(b) All IMF for Bus 3

B. Hilbert-Huang Transform

The IMFs obtained by applying EMD, detect the presence of different frequency components in the signal and can capture both stationary and non-stationary properties. Based on the Hilbert transform, Hilbert spectrum analysis allows for the investigation of instantaneous energy as well as the frequency of IMFs. Suppose there is a signal x(t). When the Hilbert Transform is applied to x(t), it gives y(t), and the mathematical representation can be as shown below in (1).

$$y(t)=H\,[x\,(t)] = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}\,d\tau \tag{1}$$

where τ is the integration variable.

The analytic signal $z(t)$ as a result of the Hilbert Huang Transform applied to x(t) will be expressed as per (2). $z(t)$ can also be expressed as the combination of a(t) as the instantaneous amplitude of z(t), and θ(t) is the instantaneous phase of z(t) shown in (3).

$$z(t) = x(t) + iy(t) \tag{2}$$

$$z(t) = a(t)\,e^{i\theta(t)} \tag{3}$$

where $a(t) = \sqrt{x^2 + y^2}$

and $\theta(t) = \arctan\left(\frac{y}{x}\right)$

And (4) gives instantaneous frequency which is defined as $\omega(t)$ and given as,

$$\omega(t) = \frac{d\theta(t)}{dt} \tag{4}$$

Thus, when the Hilbert Huang Transform is used to analyze a signal with multiple instantaneous frequencies occurring at the same time, the signal is divided into IMFs through EMD, and the time-frequency distribution of the signal determined by evaluating the instantaneous frequency $\omega(t)$ of the IMF [5].

4. Proposed Methodology for Fault Identification

Data extraction is the measurement of the signals of current and voltage that are gathered from buses at the two ends of the faulted line in the power system under fault circumstances.

Step 1 In the proposed work distribution line, DL2 between bus 1 and bus 3 is the faulted line. The signals are collected through CT connected at bus 1 and 3, as shown in Fig.1.

Step 2 The obtained signals undergo a Discrete Fourier Transform to generate signal samples at a specific sampling frequency. Applying DFT is necessary in HHT for the following reasons:

i. DFT is a preprocessing step to help with the computation of the Hilbert transform and to improve the overall efficiency of HHT.
ii. DFT helps in separating signal components from noise. By filtering noise in the frequency domain, the accuracy of HHT is improved because only relevant frequency components can be focused.
iii. DFT enhances the quality of IMF signals, making them more accurate.

Step 3 The signals obtained from DFT, are processed through the Hilbert Huang Transform. The first step in HHT is to decompose the signals into Intrinsic Mode Functions (IMF) by the use of Empirical Mode Decomposition algorithm. Every IMF stands for a distinct frequency component that the signal contains. But for further processing, the first IMF signal is utilized because it has the fundamental frequency and decaying DC component of the original signal.

Step 4 Using spectral analysis of HHT, the analytical signals are derived for IMF1 at both buses 1 and 3.

Step 5 By using instantaneous amplitude derived from HHT, spectral energy is calculated at buses 1 and 3. Spectral Energy= $[a(t)]^2$.

Step 6 Differential energy is the difference calculated between the spectral energies of bus 1 and bus 3. This differential energy leads to fault detection in the proposed methodology.

Step 7 Machine Learning Technique is used for the classification of faults by using the differential energy feature obtained in the previous step.

The flowchart presented in Fig.3 indicates the proposed process to be followed for fault detection and classification in a microgrid system. As per the process, data of current and voltage at the reference buses Bus 1 and Bus 3 is to be extracted during a faulted condition. Then there is a need of processing the extracted signals with a suitable method to get them in feasible form. So the signal processing is done with the help of Discrete Fourier Transform. The output of the Discrete Fourier Transform is used for the calculation of Intrinsic Mode Function through EMD. Then energy features are derived by applying HHT, and the difference in energy levels between Bus 1 and Bus 3 is calculated, which leads to the detection of a fault in the distribution line DL-2. The same features are provided to the Decision Tree classifier used for classifying the detected faults.

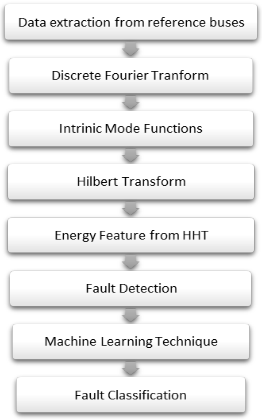


Fig. 3. Flowchart of Proposed Methodology

5. Result

On the IEC standard microgrid system, the suggested fault identification technique utilizing the Hilbert-Huang Transform and Decision Tree is examined. A fault is inserted in distribution line DL-2 connected across Bus 1 and Bus 3 at 0.2 sec (241 sample). A case study is done for Line to Ground fault, Double Line to Ground fault, Line to Line fault. Based on the simulation findings, the robustness with different fault parameter variations, accuracy, and computational efficiency of the proposed fault identification method are assessed.

A. System under Normal Operation:

When the system is running in normal operating conditions, after applying HHT to the IMF generated at two buses, the energy difference should be zero. Fig. 4 shows the differential energy during the no-fault condition of the system. The result is showing almost zero differential energy, which indicates no fault is in the system.

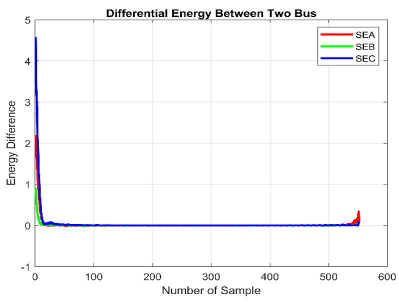
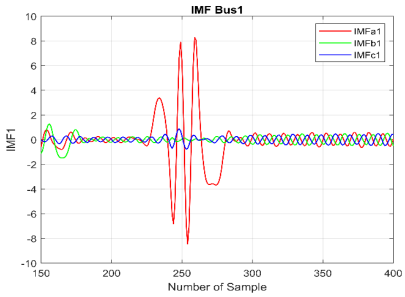


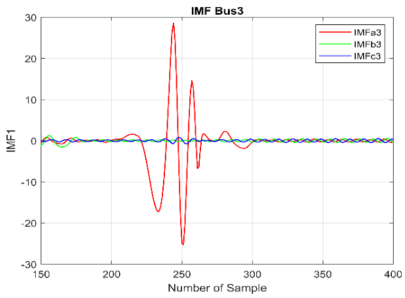
Fig. 4. Differential energy during no fault condition

B. System with LG Fault:

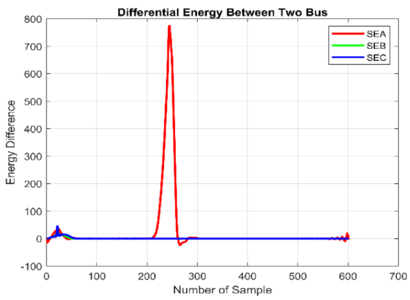
In the power system, the mostly occurred fault is line to ground fault. In first case, single line to ground faults are inserted between bus 1 and bus 3 on distribution line DL2 on phase ‘a’. Fig. 5 (a) and (b) shows the intrinsic mode functions IMF1 for Bus 1 and Bus 3 considered for applying the Hilbert transform. Both figures indicating that the IMF for phase a has a noticeable magnitude during fault occurrence. These IMFs when passed through HHT, the energy feature is captured and differential energy is calculated. This differential energy is shown in fig. 5 (c). It indicates there is a fault in phase a since the differential energy in the other two phase is almost zero.



(a)



(b)



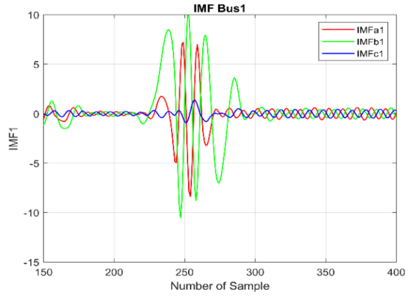
(c)

Fig. 5. For LG Fault in system (a) IMF for Bus 1(b) IMF for Bus 3 (c) Differential Energy for LG fault in phase a

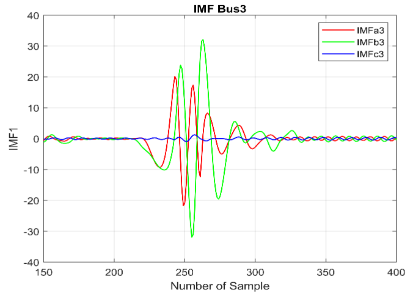
C. System with LLG Fault:

A double line to ground fault is created on line DL2 in the microgrid test system. The IMFs for both faulty phases shown in Fig. 6 (a) and (b) indicate the difference in the frequency component during a fault condition. The peaks in the differential energy shown in Fig. 6 (c) indicate both phase a and b are faulty phases in the system.

Table 2 is listing various types of faults that can occur in the microgrid system. For each type of fault, the whole procedure for calculation of Differential Energy is performed as per Fig.3 and the peak values of differential energy during fault occurrence are tabulated. It is clearly seen that for each type of fault, there is a remarkable difference between the faulty phase and the healthy phase. In the faulty phase, the Differential Energy value is much greater than the other phases, and the healthy phases show almost zero Differential Energy in Fig.7 which shows that the energy at Bus 1 and Bus 3 for the healthy phase is almost same, indicating no fault condition. As compared with the normal operating condition, the discrepancies can be identified as an abnormal condition of the system during a fault condition.



(a)



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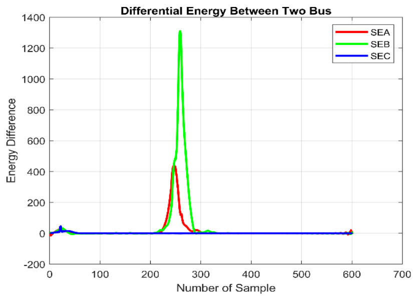


(c)

Fig. 6. For LLG Fault in system (a) IMF for Bus 1 (b) IMF for Bus 3 (c) Differential Energy for LLG fault in phase a and b

Table 2. Differential Energy for different fault condition

Type of Fault	Peak Value of Differential Energy		
	Phase A	Phase B	Phase C
AG	774.6	0	0
BG	0.008	1127	0.008
CG	0.07	0.07	1010
ABG	429.5	1310	0
BCG	0	911.1	1031
CAG	1160	0.279	816.5
AB	783.6	373.9	0.0005
BC	0	834.9	404.8
CA	245.5	0.0005	554.3
ABC	311.3	739.7	701.8

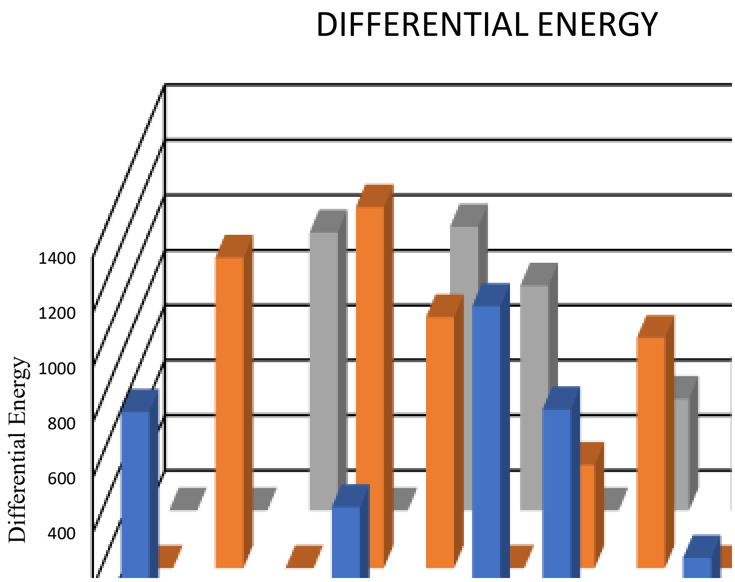


Fig. 7. Differential Energy for different fault condition

6. Decision Tree Classifier

A decision tree is one of the supervised learning approaches of machine learning. It is a prominent classification tool as the performance of the classifier shows the highest accuracy and low-cost computation. [5] Decision trees provide a transparent and interpretable framework for fault detection and classification. [6] As they are capable of capturing nonlinear relationship, this allows the model to adapt to the complex dynamics of microgrid systems more effectively than linear classifiers. [8] Decision trees have a relatively low computational complexity, making them computationally efficient for real-time fault detection and classification tasks in microgrid systems. The simplicity of the decision-making process also facilitates rapid inference, enabling fast response times for critical system events. In this approach, predictions about a collection of data are made using a model in the form of a classification decision tree. In this classifier, partition of dataset is done into subsets based on the most important characteristics of every node of the tree. The process of classification is based on a set of rules known as Decision Rules. These Decision Rules will predict the output of a classifier. The components of a decision tree are the root node, child nodes, and leaf nodes. The initial node of the tree is the root node, followed by node splitting which generates child nodes showing subsets of data, and node becomes a leaf node when the stopping criterion is reached. Thus, leaf node is the output of the classifier.

For the classification of the correct fault type, decision tree can be used, as it is easily interpretable with a tree structure. [6]

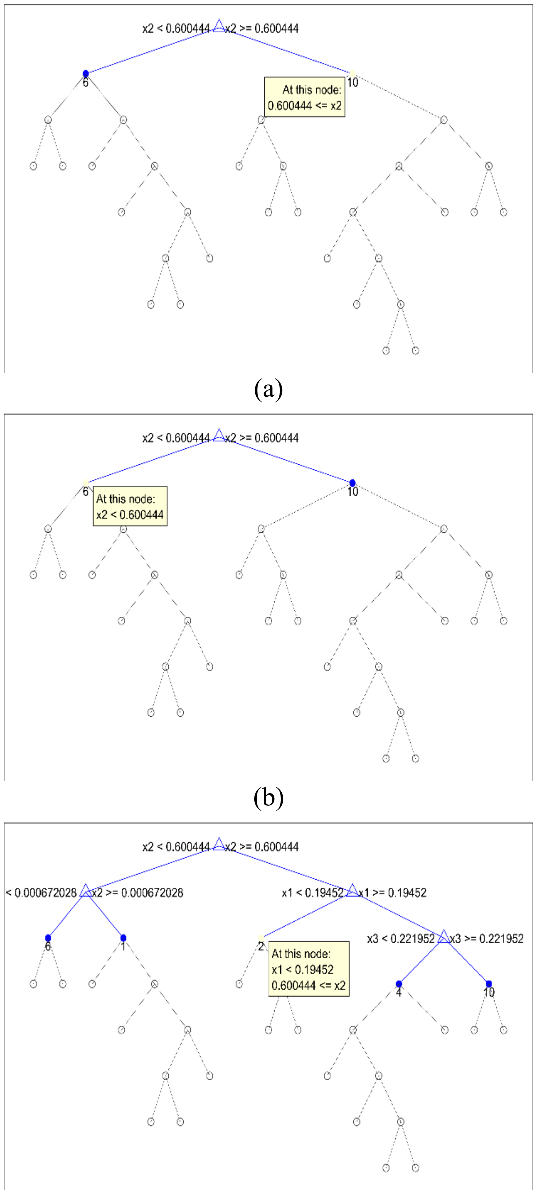
A. Fault Dataset Generation:

For applying decision tree classifier for fault classification, a dataset is required for different fault conditions. All types of unsymmetrical faults along with symmetrical faults are considered on DL-2. Features are extracted with each fault considered by changing fault resistances with a combination of different fault inception angles at different line lengths. The various conditions employed for fault in the microgrid on DL-2 are listed in Table 3. From this generated dataset, 70% of the data is used for training of the Decision Tree Classifier and the remaining 30% is for testing purposes.

The process of classification by the classifier is based on the decision rules. Based on the features and their values at each node in the tree, the classification rules for data are established. The decision tree algorithm divides the dataset into subsets according to the values of particular features in a recursive manner. By analyzing conditions, which are basically the rules, these splits are established.

Table 3. System parameter for training and testing

Fault Type	AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, ABC
Fault Resistance	0 Ω and 10 Ω
Fault Inception Angle	0°, 90°, 180°, 270°
Fault Location	10 % to 90% (in step of 10% of total line length)



(a)

(b)

(c)

Fig. 8. Splits in Decision Tree- (a)First split-right branch (b) First split-left branch, (c) Second split for classification

For fault classification, as per Fig. 8 (a) and (b), the root node splits into two internal nodes. The right branch with the rule x_2 > = 0.600444 and the left branch with x_2 <0.600444 gets divided to classify the data. But after this classifier does not reach a pure decision from which further classification cannot be done. Thus, again, there forms an internal node, which again splits for further classification. So, as shown in Fig. 8 (c), the right-side internal node with the rule x_2 > = 0.19452 gives a right branch and a left branch with x_1 <0.19452 classifies the data. This process is followed till the classifier reaches the leaf node, which give a complete decision tree as shown in Fig. 9 for the proposed HHT based decision tree classifier.

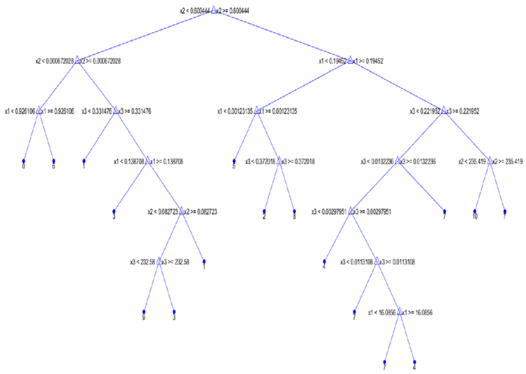


Fig. 9. Decision Tree for classification of fault

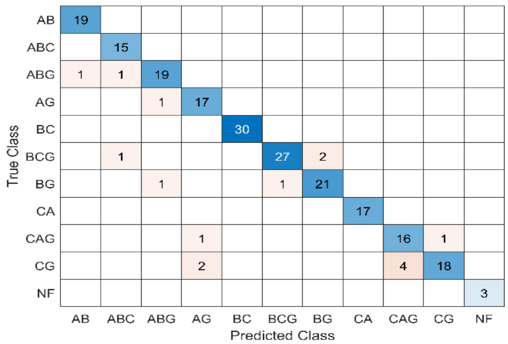


Fig. 10. Confusion Matrix of Decision Tree

The Decision Tree's performance based on various predictor selections and testing samples is displayed in the confusion matrix. Fig. 10 shows the confusion matrix of the decision tree classifier. The row of the confusion matrix indicates the experiments of class, and the column indicates the predictions of class. The value shown by the main diagonal, called True Positive, represents how successfully the classification is done, and the remaining values are those instances that were incorrectly classified. It is 30% of the total data provided to the classifier for testing purposes. Consider the case of AB fault. This fault is classified with 19 samples correctly, but not one sample. For the AB fault, it is True Positive instances. Excluding the instances in the row and column of AB fault is called True Negative instance. The total instances in the row are called False Negative and the total instances in column of the AB fault are called False Negative. Whereas in the case of BC and CA faults, there is not having any value in the row or column of BC and CA faults which indicates all the samples are correctly classified. In the same manner, the confusion matrix clearly represents the classification of data. Thus, the comprehensive evaluation of the classifier model using the confusion matrix is done in terms of accuracy, precision, and recall.

The Accuracy evaluates both positive and negative predictions to determine how accurate the model is. It can be calculated as

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Intances}$$

Precision is one of the matrices for the evaluation of the performance of a classification model. It tells that, from all the positive instances, how many are actually positive. Precision can be calculated using the following equation.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall is also called as True Positive Rate. It is actually giving the count out of all positive instances how many instances are correctly identified by the classifier model.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

For the classifier model trained and tested for fault classification in microgrid, all evaluation parameters as per the equations described above, are listed in Table 4. Different types of faults are classified by the decision tree classifier. And the minimum accuracy of the model is 96%. Precision and Recall are two other important parameters necessary for the evaluation of any classifier. Fig. 11 shows the accuracy plot for various fault classification. As per the results obtained how accurate the model is, for different types of faults can be suggested.

Table 4. Evaluation of Classifier for Different Fault

Fault Type	Accuracy (%)	Precision (%)	Recall (%)
AG	98.16	94.44	85
BG	98.16	91.30	91.3
CG	96.78	75	94.73
AB	99.54	100	95
BC	100	100	100
CA	100	100	100
ABG	98.16	90.47	90.47
BCG	98.16	90	96.42
CAG	97.24	88.88	80
ABC	99.08	100	88.23

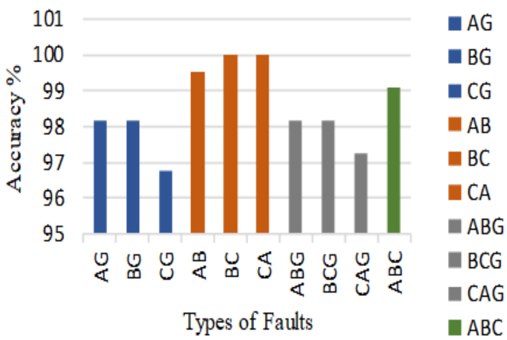


Fig. 11. Accuracy of Decision Tree Classifier Model for different fault conditions

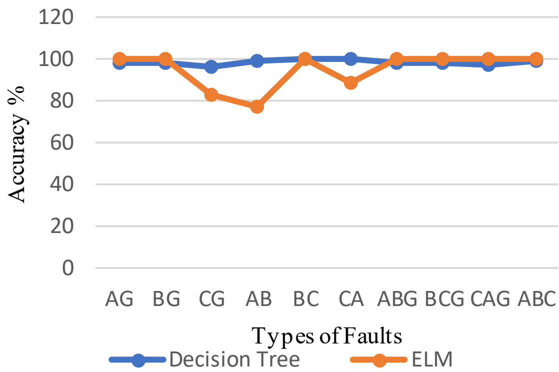


Fig. 12. Comparison of Proposed technique with ELM technique of Machine Learning

7. Conclusion

This paper suggests a protection scheme for microgrid systems which combines HHT and Decision Tree techniques for improving the security of Microgrid Systems as compared to conventional overcurrent protection schemes which typically rely on fixed current thresholds to detect faults. In microgrids with distributed energy resources (DERs) and varying load profiles, these fixed thresholds may not be sensitive enough to detect faults accurately, especially under low fault currents or in networks with high impedance. Thus, in the proposed protection scheme, at the initial stage, the fault currents recovered at both ends of the distribution line under consideration are used for feature extraction through HHT. Then an extracted feature called energy is utilized for the calculation of differential energy between the two buses. This differential energy feature is supplied for the training of a Machine Learning Technique used for classification called decision tree classifier for better classification of fault events. The trained model is tested, and as per the results shown in Table 4, it can be concluded that the

Table 5. Accuracy Comparison of different protection scheme in Microgrid

Protection Scheme in Microgrid	Accuracy (%)
HHT - Decision Tree [Proposed]	98.52
HHT - Extreme Learning Machine [4]	94.98
HHT - Naive Bayes Classifier [4]	92.16
HHT - Support Vector Machine [4]	92.21
S Transform - Naive Bayes Classifier [31]	96.51
S Transform - Extreme Learning Machine [31]	97.23
S Transform - Support Vector Machine [31]	95.55
Time-Time Transform - Decision Tree [27]	88.16
S Transform - Decision Tree [29]	98.45
Wavelet - Decision Tree [26]	97
Decision Tree [6]	98
Mathematical Morphology - Extreme Learning Machine [30]	96.45
Mathematical Morphology - Artificial Neural Network [30]	96.51
Mathematical Morphology - Support Vector Machine [30]	96.25

model is outperforming with the accuracy above 96% for each type of fault event listed in Table 4. Thus, the proposed scheme is found to be robust and adaptable in handling different types of faults and system configurations. As per [4], the microgrid system is protected with HHT-NBC, HHT-SVM, and HHT-ELM. When the accuracy of the proposed protection scheme and HHT-ELM is compared, the proposed technique proves to be more accurate, as shown in Fig.12. Various protection schemes used for microgrid protection are proposed in different research papers, and the accuracy claimed by the authors is compared with the proposed protection scheme in Table 5. The overall accuracy of the proposed scheme achieved to be 98.52% which is best for microgrid protection. The test findings show that the suggested scheme increases the security of the microgrid protection while also offering precise protection. As the signals are complex and non-stationary, the HHT technique enables effective feature extraction from such signals, allowing the Machine Learning model to accurately detect and classify various types of faults. By providing a robust and adaptive protection framework, the scheme enhances the resilience of the microgrid system against various threats, thereby ensuring uninterrupted energy supply to critical loads. Thus, the integration of HHT and Decision Tree in the microgrid protection scheme offers a comprehensive and intelligent approach to addressing the diverse challenges of protecting microgrid systems, ultimately improving their reliability, efficiency, and resilience in dynamic operating environments.

8. References

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