Multifunctional Algorithm for Fault Analysis in Radial Distribution Network with Distributed Generation

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Abstract

Distribution networks along with penetration of distributed generations shows complex operating characteristics that poses challenges to conventional fault analysis methods. To address this problem, this study proposes a multifunctional fault analysis framework that uses advanced signal processing with data-driven learning techniques. The approach starts with the use of the Hilbert transform to voltage and current signals that helps to extract disturbance associated sensitive transient features which+ are used as inputs to a two-stage classification structure. In the first stage, a Random Forest classifier is used for fast and reliable islanding detection and fault detection. In the second stage, an AdaBoost classifier performs the function of classifying fault type and locating faulted bus along with distance from it. Standard IEEE 33-bus distribution system with integrated distributed generators, modeled in MATLAB/Simulink is used to validate the proposed model, while for training and testing the classifiers Python is used. For a range of fault and non-fault scenarios performance is evaluated under grid-connected radial operation. Results confirm that the combined Hilbert–Random Forest–AdaBoost framework achieves higher accuracy in terms of fault detection and classification than conventional techniques such as decision trees and support vector machines. Also, K-fold cross-validation yields a mean accuracy above 90%, and performance metrics such as accuracy, precision, recall, and F1-score all exceed 90%, that confirms the robustness and practicability of the proposed scheme for fault analysis of distribution networks with distributed generation.

Keywords: AdaBoost Classifier, Autocorrelation Function, Distributed Generation, Hilbert Transform, Random Forest Classifier.

1. Introduction

The gradual exhaustion of traditional fossil-fuel energy sources, continuous growth in electricity demand, and the global transition towards sustainable power generation have posed significant challenges for traditional centralized power systems (Manohar et al., 2018; Alam et al., 2019). It has caused wide acceptance of Distributed Energy Resources (DERs) along with the integration of small-scale generation units largely based on renewable energy within distribution networks and close to load. Continuous technological advancements in DERs have caused emergence of the microgrid concept, which is now widely accepted as a basic element of modern power distribution systems (Mohamed et al., 2020; Ola et al., 2020). A microgrid usually consists of interconnected DGs, storage systems, and local loads which mostly operate at low or medium voltage levels in either grid-connected or intentional islanded modes. The islanded mode operation ability is especially important since it enables uninterrupted power supply during grid side disturbances, hence improving system reliability and resilience. Besides that, microgrids also furnish benefits such as enriched power quality, minimized transmission losses, lesser carbon emissions, and boosts economic efficiency by reducing reliance on long-distance transmission infrastructure.

Besides all the benefit of microgrids, the high penetration level of renewable-based DERs also introduces technical as well as operational challenges which are mostly related to power system protection (Chen et al.,2018; Escudero et al.,2018). The inherent intermittency of renewable energy sources and the lesser contribution of conventional synchronous generators results in lower system inertia, making microgrids more vulnerable to frequency instability and severe disturbances during fault conditions. These challenges are more relevant in Nepal, where rapid electrification and expanding industrial activity have led to a notable increase in distributed generation, specifically grid-connected solar photovoltaic's in commercial and industrial facilities. This can result into bidirectional power flows which complicates fault detection and protection coordination. Moreover, as electricity becomes increasingly essential across industrial, commercial, and residential sectors, the need for a highly reliable distribution system becomes essential. Distribution lines being more often exposed to harsh environmental conditions, fast and accurate fault identification, isolation, and islanding detection are extremely necessary to ensure personnel safety, protection of expensive equipments, and maintaining microgrid operation stability, reflecting the need for advanced and adaptive protection strategies.

Several advanced protection techniques have been proposed for microgrids, addressing the challenges posed by distributed generation and inverter-interfaced systems. Adaptive relay techniques using combined fast-recursive discrete Fourier transform and fuzzy-logic decision-making modules have been developed to enhance the speed and accuracy of fault detection (Kumar et al., 2016). Wavelet transform coupled with decision tree classifiers in inverter-interfaced distributed generators (IIDGs) has been employed for fault detection and classification using local current (Mishra et al.,2016). Integration of wavelet transforms and deep neural networks have also shown effectiveness in identifying fault conditions in microgrids (Yu et al., 2016). Also, data mining techniques along with wavelet packet transform have been used for accurate detection of faulted line sections (Jamal et al., 2016). Communication-assisted protection schemes comprised of dual-directional over-current relays provide enhanced coordination in both grid connected and islanded microgrid modes (Sharaf et al., 2016). Phase Measurement Unit (PMU)- based integrated impedance angle methods offer enhanced fault detection and localization capabilities (Sharma et al.,2016). Non-pilot protection strategies for inverter-dominated microgrids to address both balanced and unbalanced faults has been proposed (Lahiji et al.,2016), while current-only polarity comparison techniques serve as a simple and effective method for fault direction detection (Wang et al.,2016). Machine learning methods combined with signal processing approaches has also been applied for fault classification and location in radial distribution grids (Mamuya et al., 2016). Hybrid techniques using Stockwell transform and machine learning have demonstrated improved accuracy in fault location and classification (Aljohani et al.,2016). Finally, convolutional neural networks have been applied to extract internal fault features for intelligent protection strategies (Bukhari et al., 2016).

2. Methodology

2.1 Workflow of Proposed Methodology

The workflow of the proposed multifunctional algorithm, shown in Fig. 1.It is structured as a two-stage protection scheme for accurate fault detection, classification, and location. Three-phase voltage and current signals are continuously measured and processed to remove noise, normalize data, and enhance important signal characteristics which improves learning stability, convergence, and accuracy by restricting dominant features from biasing the model.

From the processed signals, useful features are extracted using mathematical and statistical methods to form a dataset. Feature selection is then performed using standard deviation to eliminate redundant or non-informative features that may affect machine learning performance. In the first stage, the selected features are first applied to a Random Forest classifier to identify the system operating mode as either grid-connected or islanded. If islanding is detected, signal is sent to the distributed generators.

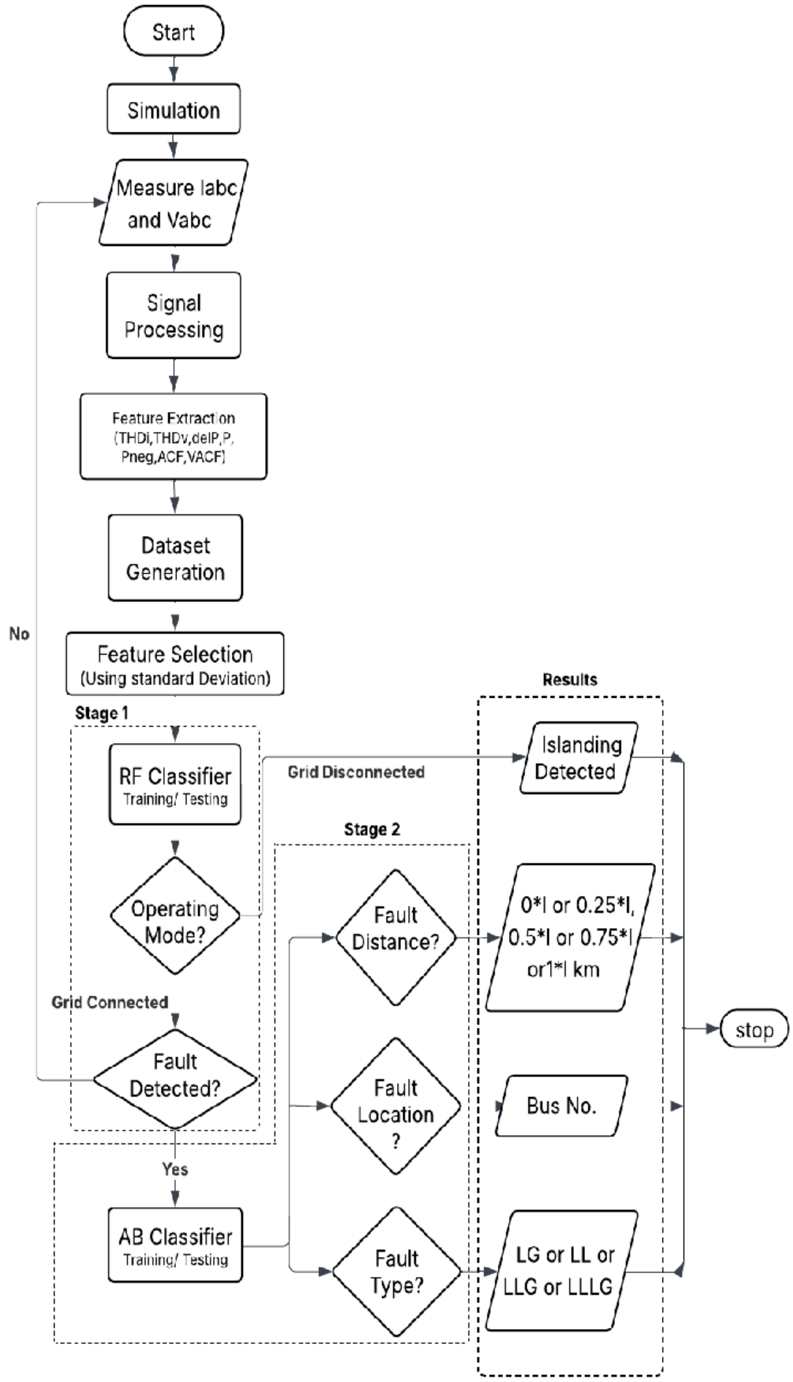

Fig. 1: Workflow of the proposed Methodology

In grid-connected operation, the same classifier is used for fault detection. If no fault is present, the algorithm continues real-time monitoring of system signals; otherwise, it proceeds to the next stage. In the second stage, an AdaBoost classifier is used to classify the fault type (LG, LL, LLG, or LLLG), identify the faulted bus (B7, B11, B16, B21, or B23), and estimate the fault distance (0*l, 0.25*l, 0.5*l, 0.75*l, or 1*l). Based on this structured workflow, the test system is modeled and the machine learning models are trained under various operating and fault conditions to achieve reliable multifunctional protection.

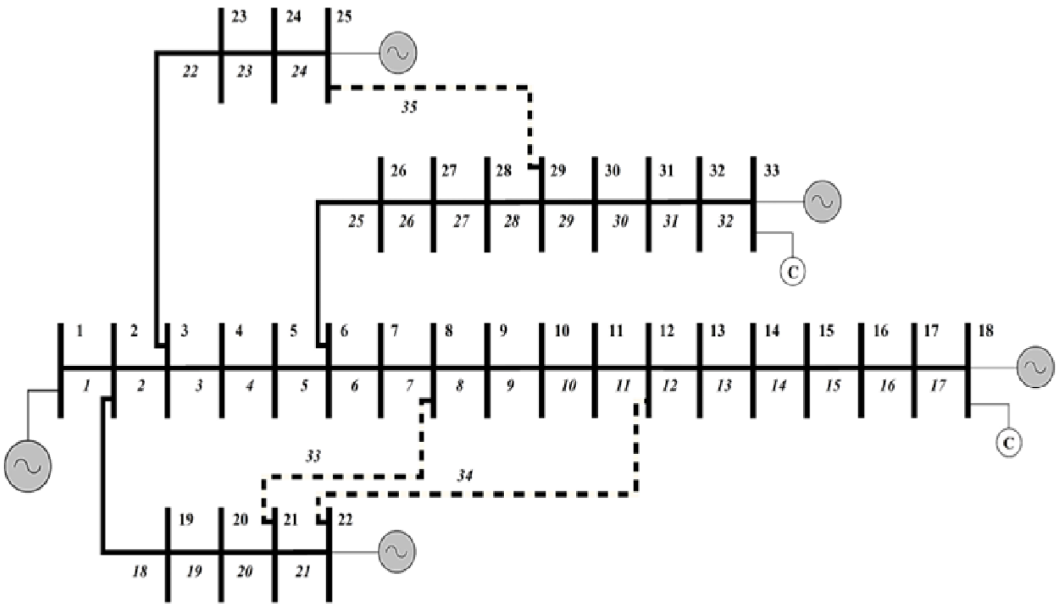

Fig. 2: IEEE 33 Bus test system

2.2 Test System

The IEEE 33 bus test Distribution System with DGs is used for the study of a multifunction Algorithm as shown in Fig. 2. This system consists of 33 buses, with the base values used in this study being 12.66 kV and 50Hz. The test system is comprised of four DGs at buses 18, 22,25 and 33 as in the Figure 3.3. The DG size is 200 KW each that results in 800 KW (26%) of total DG penetration. It also comprises two capacitor banks at Bus 18 and 13 as shown in the Figure, with 0.4MVAR and 0.6 MVAR capacity respectively.

2.3 Simulation Cases

Fig. 3 Shows the Flowchart of Simulation cases. Multiple operating scenarios were simulated to train the proposed ML-based multifunctional algorithm by analyzing voltage and current characteristics under normal and faulted conditions. The IEEE 33-bus distribution system was modeled in MATLAB with a sampling time of 50 µs (50e-6 s). For each selected bus B_k Ɛ{B7,B11,B16,B21,B23}, the system was first simulated for 0.1 s under normal conditions to establish steady state. Subsequently, different fault types F_j Ɛ{LG,LL,LLG,LLLG} were applied at multiple locations along the feeder connected to the selected bus. Fault locations were defined using a normalized distance D_i Ɛ{0ℓ,0.25ℓ,0.5ℓ,0.75ℓ,1ℓ}, where ℓ represents the total line length from the sending to the receiving end. Each faulted condition was simulated for an additional 0.1 s to capture transient behavior. The simulation iterated through all combinations of buses, fault types, and fault locations, resulting in 100 total cases (4 fault types × 5 buses × 5 locations). Throughout the simulations, voltage and current waveforms at the swing bus were monitored to assess system response under different scenarios. Features were continuously extracted at each sampling instant. Since each iteration covered 0.2 s (0.1 seconds for the normal condition and 0.1 seconds for the fault condition), a total of 4000 samples were recorded per case. Consequently, the complete dataset comprised 400,000 samples (4000 × 100). A total of 11 features were used for training, including seven primary features, with THD_i and THD_v contributing three-phase data each. Thus, the final dataset size for the ML algorithm was 400,000 × 11. For islanding detection, the system was simulated for a duration of 0.4 s, with islanding initiated at 0.2 s by disconnecting the main grid.

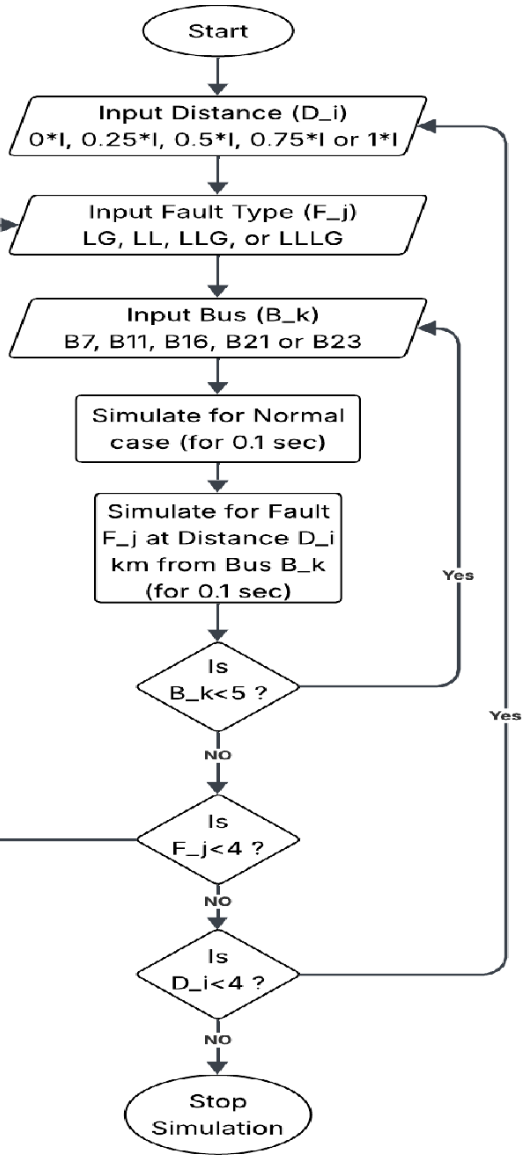

Fig. 3: Flowchart of Simulation Cases

2.4 Signal Processing and Features Extraction

For developing the data mining model of the proposed fault and islanding detection strategy, the signal processing of the electrical parameters was taken into account. Here, 7 features were extracted from instantaneous voltage and current as shown in Fig. 4.

The 7 features used are:

1. Three-phase Total Harmonic Distortion of current (THD_i)
2. Three-phase Total Harmonic Distortion of voltage (THD_v)
3. Transient Power (ΔP)
4. Active Power (P)
5. Autocorrelation function (ACF)
6. Variance of Autocorrelation function (VACF)
7. Negative Sequence Active Power ($P-$)

Hilbert Transform was used to Compute Auto Correlation Function.

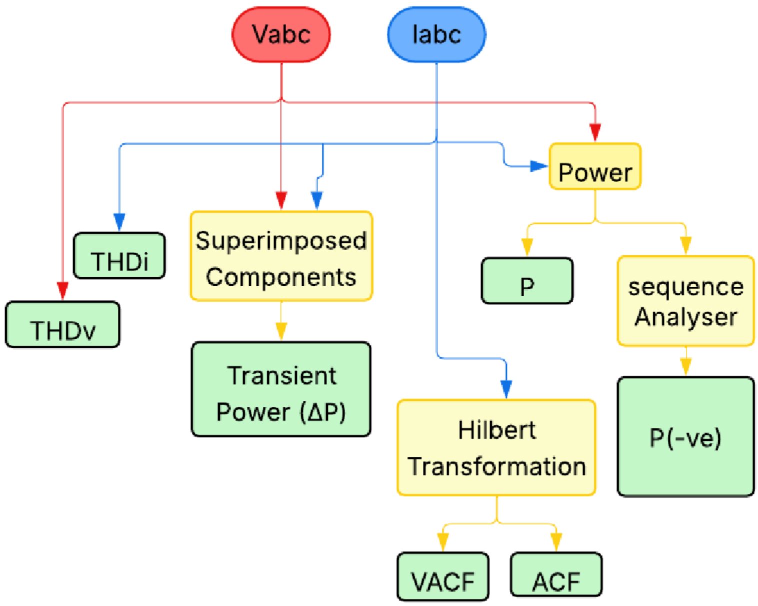

Fig. 3: Features Extraction Scheme

2.5 Dataset Generation

The final set of features extracted from the current and voltage signals (ΔP, THD_i, THD_v, ACF, VACF, P, and P_{neg}) were converted to a Dataset using Scope Data Logging. The datasets were generated from the features waveform for several types of cases discussed above and analyzed as an XLS file Format. The gathered data sets were split into training and testing in the ratio of 4:1, i.e. the training set was about 80%of the total dataset, and the remaining was kept for testing.

2.6 Machine Learning Model Training

The multifunctional fault and islanding detection algorithm was developed using Python in the Jupyter Notebook environment. The process began by importing the simulation dataset generated in MATLAB, which was handled efficiently using the Pandas library. The dataset was pre-processed by separating the input features from their corresponding output labels, followed by normalization using the Standard Scalar to ensure uniform feature scaling. Feature selection was then carried out using a standard deviation–based approach. Feature selection was then carried out using a standard deviation–based approach. The standard deviation of each feature was computed and used to rank them in descending order, as higher standard deviation values indicate greater discriminatory capability for fault classification. Features exhibiting low variation were excluded, as they tend to introduce ambiguity and reduce machine-learning performance. Based on this ranking, 6 highly sensitive and prominent features were selected for model training. Firstly, Random Forest was trained for identifying Grid operating mode and detecting Fault. And then The AdaBoost (AB) classifier was chosen as the primary model, and its performance was compared against the Decision Tree (DT) and Support Vector Classifier (SVC) algorithms for Fault Classification and location.

2.7 Performance Analysis

2.7.1 Confusion Matrix

A confusion matrix summarizes the predictions of a classification model. A typical 2*2 Confusion matrix is shown in Table 1.

Table 1: Confusion Matrix

	Predicted Positive	**Predicted Negative**
Actual Positive	TP	FN
Actual Negative	FP	TN

Where: TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

The proposed model performance is evaluated using following performance metrices. Also comparisons of algorithms were done on the basis of these metrices.

Accuracy:

Definition: The proportion of correct predictions among all predictions. It is given by equation 1.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision:

Definition: Proportion of correctly predicted positive cases out of all predicted positives. It is given by Equation 2.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall (Sensitivity):

Definition: Proportion of actual positive cases correctly identified. It is given by Equation 3.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1-Score:

Definition: Harmonic mean of precision and recall; balances both metrics. It is given by Equation 4.

$$F1 - Score = 2\frac{Precision.\ Recall}{Precision+Recall} \quad (4)$$

2.7.2 Cross Validation

Cross-validation (CV) is a statistical technique used in machine learning and data analysis to assess a model's performance. It works by splitting the dataset into multiple subsets, where the model is trained on some subsets and validated on the remaining ones. This approach helps evaluate how well the model generalizes to new unseen data and aids in reducing the risk of over fitting. While performing this process, K-fold Cross Validation, the most effective CV method, is applied with CV value of 5. CV=5 will choose 80% of data for testing and remaining 20% of data for testing purpose.

3. Results and Discussion

3.1 Load Flow Result

First Backwards/Forward Sweep Load Flow was performed for the proposed system which consists of Bus voltage, Power Angle, Active Power (P) and Reactive Power (Q) at each Bus. Tolerance for load flow was set at 1e-4 pu. The Load flow converged in 9 iterations with a total PQ generation of 3807 KW and 1365.4 KVAR. The System suffered a total loss of 92.45 KW and 65.25 kVAR. The

Voltage at the Swing Bus was kept at 1 pu. for the following Load Flow Analysis. The Generation Value for Swing Bus is 3007.2 KW and 1285.06 KVAR.

3.2 Feature Samples

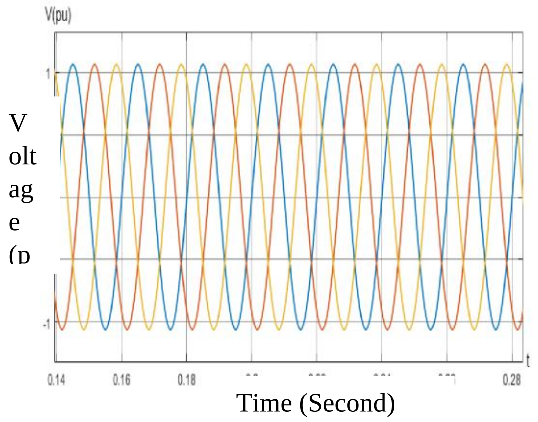

Fig. 4: Voltage waveform

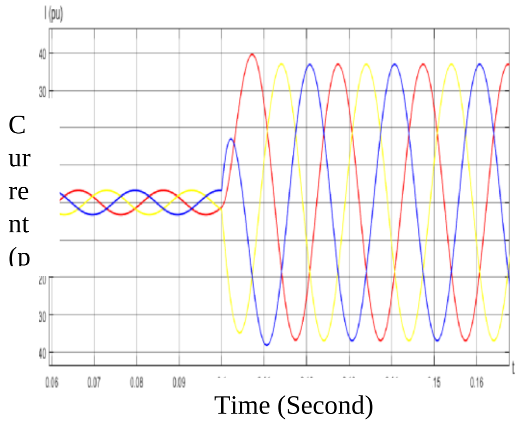

Fig. 5: Current waveform

In the simulation study, voltage and current were measured at Bus 1 in per-unit values with a base voltage of 12.66 kV and base power of 1 MVA. For an LLLG fault applied at Bus 7 at 0.1 s, the voltage waveform showed minimal variation as shown in Fig. 4, while the current waveform as shown in Fig. 5 exhibited a strong transient, with the peak rising from 3.2 pu to 37 pu, indicating high fault sensitivity at this bus.

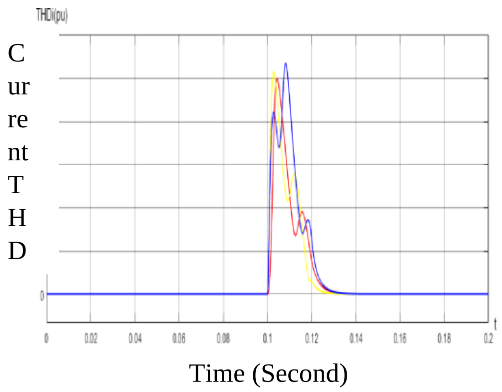

Fig. 6: THDi waveform

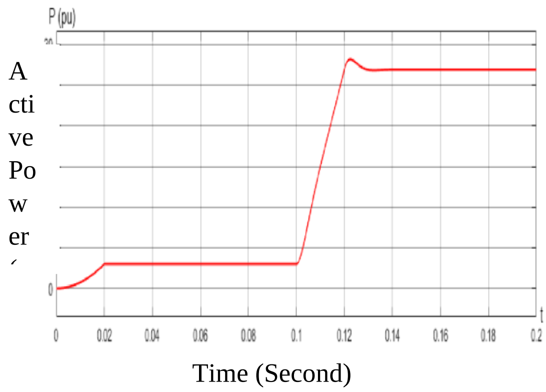

Fig. 7: Active power waveform

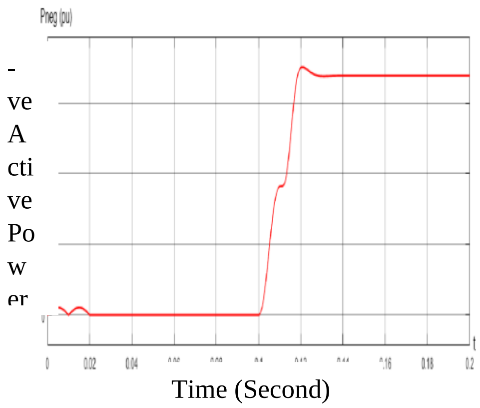

Fig. 8: Negative Active power waveform

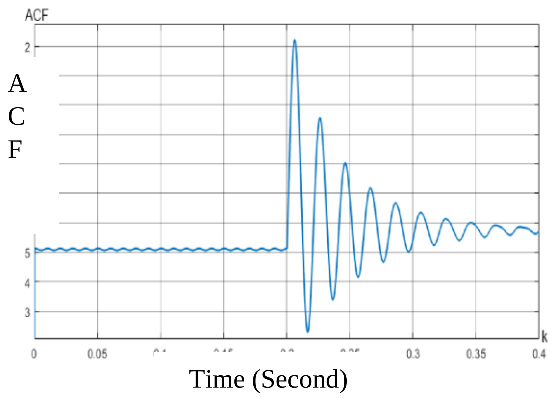

Fig. 9: ACF waveform

The three-phase THDi increased beyond 1 pu during the fault shown in Fig. 6, reflects significant waveform distortion. The active power waveform shown in Fig. 7 also showed a transient response corresponding to the fault current. As expected, the negative-sequence power as Shown in Fig. 8 showed negligible change for the balanced LLLG fault. Additionally, the average autocorrelation function (ACF) shown in Fig. 9 and its variation (VACF) effectively captured the fault-induced disturbances in the current signal. The transient power waveform in Fig. 10 also clearly indicated the fault occurrence.

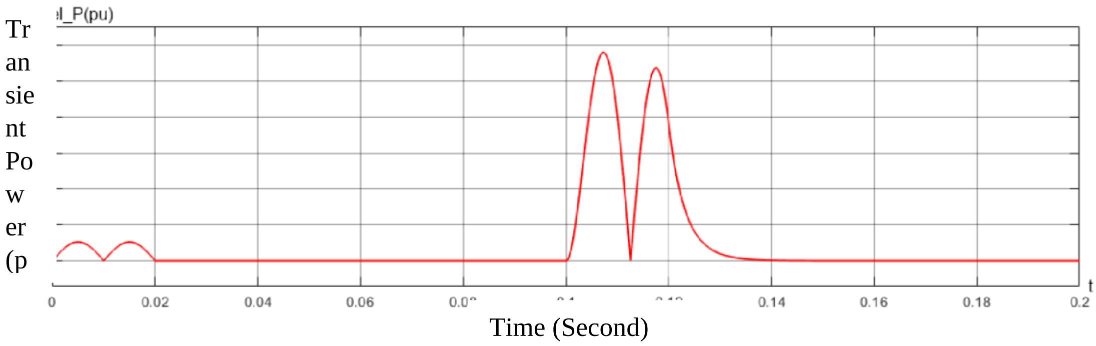

Fig. 10: Transient Power Waveform

These features were extracted for the representative fault case and similarly analyzed for other fault scenarios. The resulting feature sets were used to construct the dataset for training machine learning models to improve fault detection and classification performance.

3.3 Feature Selection Result

The initial feature set included THD_i of phases A, B, and C (THD_{ia}, THD_{ib}, THD_{ic}), THD_v of phases A, B, and C (THD_{va}, THD_{vb}, THD_{vc}), the autocorrelation function (ACF), variance of the ACF (VACF), negative sequence power, transient power, and active power. Based on standard deviation ranking, six features were selected due to their higher variability and stronger relevance to fault conditions. The selected features, in descending order of importance, were THD_{ib}, THD_{ic}, Transient power, Active power, Negative sequence power and Variance of ACF.

THD shows a sensitive effect to the fault cases, which is illustrated by the features ranking. Since most of the faults are unbalanced, and in this simulation, fault lines were used in phase B and C, THD_{ib} and THD_{ic} came to the top rank. Similarly, above 6 features exhibited significant sensitivity to fault-induced disturbances and were therefore identified as the most informative for effective fault detection in the proposed methodology.

3.4 Performance Result

3.4.1 Confusion Matrices

The AdaBoost (AB) and Random Forest (RF) classifiers developed in this study exhibited strong performance as summarized by the confusion matrices in Fig. 11–15. All confusion matrices are presented in percentage form, based on the available dataset.

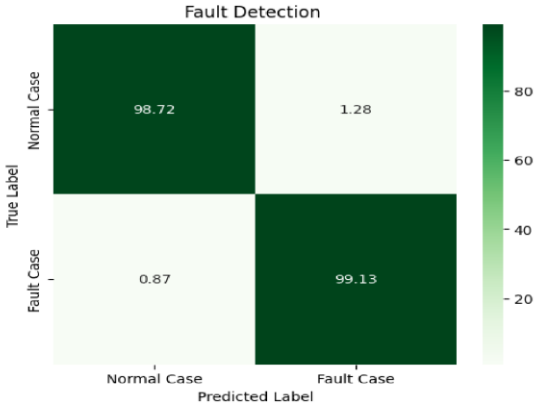

Fig. 11: Fault Detection

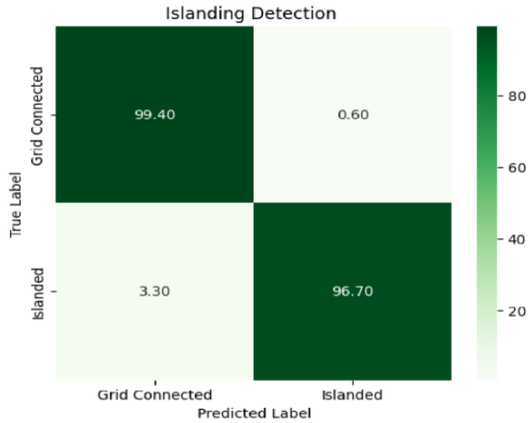

Fig. 12: Islanding detection

For fault detection, the model achieved very high accuracy, correctly identifying normal and faulted states with 98.72% and 99.13% accuracy, respectively, indicating reliable fault detection with minimal misclassification. Islanding detection also showed robust performance, with 99.40% accuracy for grid-connected conditions and 96.70% accuracy for islanded operation, resulting in a low false alarm and missed detection rate.

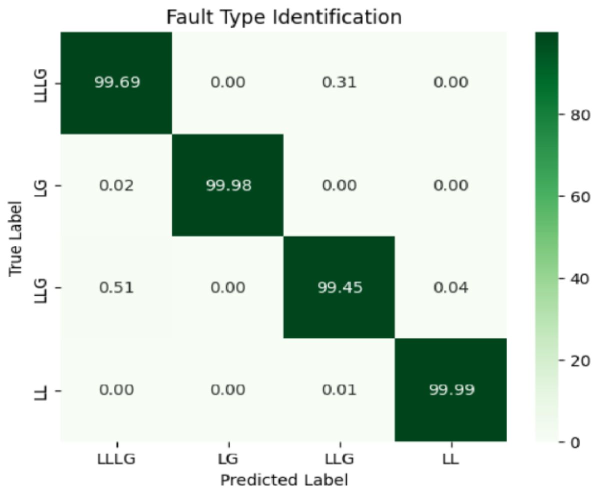

Fig. 13: Fault type identification

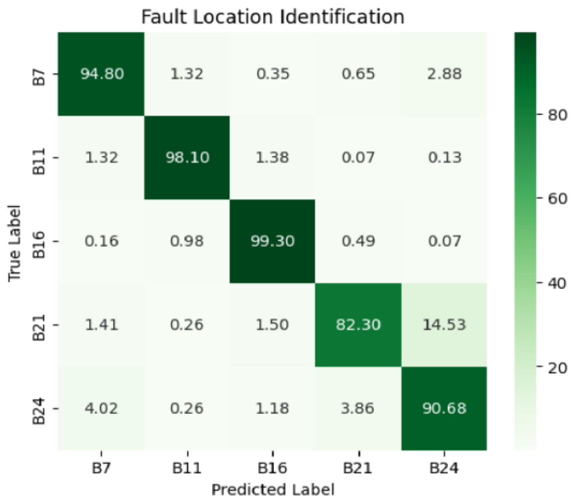

Fig. 14: Fault Location Identification

High accuracy was maintained in fault type identification (>99%). Fault location identification achieved accuracies ranging from 82.3% to 99.3%, with slightly lower performance at buses located farther from the grid. Fault distance identification showed comparatively lower but acceptable accuracy (87%–94.5%) due to limited variation in fault current with small distance changes.

Overall, all major classification tasks achieved accuracies above 91%, confirming the effectiveness and practical viability of the proposed Fault analysis model for modern distribution systems.

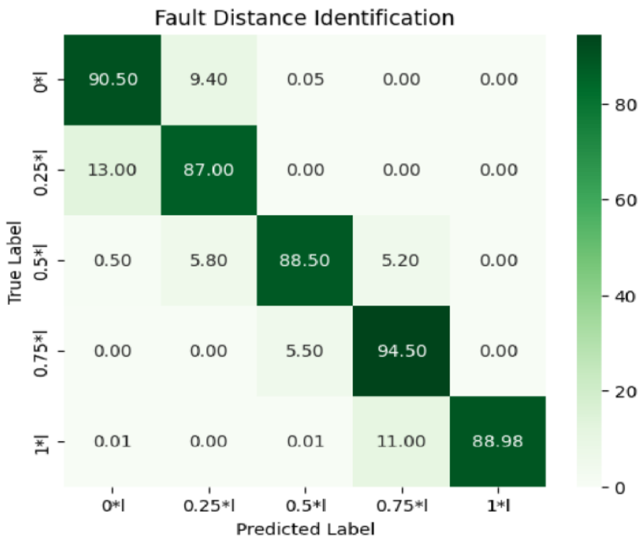

Fig. 15: Fault distance identification

3.4.2 Cross Validation

The summary of cross-validation performance of the proposed model for different fault analysis tasks is presented in Table 2. High fault detection CV score of 96.56% is achieved for fault detection that demonstrates strong reliability in fault detection. Proposed model also shows highly accurate mode of operation identification (96.40%), confirming effective discrimination between grid-connected and islanded operation. It also attained an accuracy of 95.23% for fault type classification. Slightly lower accuracies are observed for fault location (94.33%) and fault distance estimation (92.34%), as these require more precise spatial assessment. Overall, the cross-validation scores are consistently high indicating good generalization ability and confirming the suitability of the model for reliable fault analysis in distribution systems.

Table 2: Cross-Validation (CV) Scores for Different Scenarios

Scenario	CV Score (%)
Fault Detection	96.56
Islanding Detection	96.40
Fault Type	95.23
Fault Location	94.33
Fault Distance	92.34

3.4.3 Performance Comparison

The performance comparison in Table 3 shows that the AdaBoost classifiers superiority over the Decision Tree (DT) and Support Vector Machine (SVM) across all protection tasks. For fault type, fault location and fault distance identification AdaBoost achieves the highest accuracy, precision, recall, and F1-score, demonstrating superior robustness and generalization capability. Although DT and SVM deliver reasonably good performance, their results remain consistently lower than those of AdaBoost.

Table 3: Performance Comparison of ML Models

Scenario	Classifier	Accuracy	Precision	Recall	F1-Score
Fault Detection	RF	98.91	98.70	99.12	98.91
Islanding Detection	RF	98.00	99.28	96.70	97.97
Fault Type	AB	96.48	96.49	97.35	96.92

	DT	94.20	94.10	95.00	94.55
	SVM	95.10	95.00	95.80	95.40
Fault Location	AB	93.20	95.62	94.75	95.18
	DT	92.30	93.70	92.60	92.15
	SVM	91.10	94.60	93.50	94.05
Fault Distance	AB	91.60	93.45	92.70	93.10
	DT	89.40	90.80	90.10	90.35
	SVM	90.30	91.75	91.10	91.40

Table 3 also indicates that both fault detection and islanding detection achieve accuracies of approximately 98%, confirming the suitability of the proposed approach for practical power system applications. Since real-world fault data are often limited and datasets can be highly unbalanced, performance metrics such as precision, recall, and F1-score provide a more reliable evaluation than accuracy alone. Despite this challenge, the proposed model maintains high precision, recall, and F1-score, highlighting its effectiveness and reliability for real-world fault and islanding detection in distribution networks protection schemes.

4. Conclusion

The proposed multifunctional fault analysis algorithm provides a unified and effective framework for fault detection, classification, localization, and islanding identification in distribution networks with high penetration of distributed generation. The scheme was validated on the IEEE 33-bus distribution system under grid-connected and islanded radial operating conditions. By combining Hilbert transform–based feature extraction with data-driven classifiers, the algorithm successfully captured system dynamics under various fault and non-fault scenarios.

Seven discriminative features were extracted by varying fault type, location, and distance in both healthy and faulted states. These features were used to train Random Forest (RF) and AdaBoost (AB) classifiers. The RF module achieved high accuracy in operating mode identification and fault detection, demonstrating strong robustness and generalization. The AdaBoost module provided accurate fault classification and localization, achieving up to 93% accuracy and outperforming Decision Tree and Support Vector Machine methods.

The results confirm that the proposed approach is accurate, computationally efficient, and reliable. Its multifunctional capability makes it well suited for modern distribution networks with significant distributed generation integration.

Conflicts of Interest

The authors declare no conflict of interest.

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