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An Intelligent Particle Filter with Neural Network for Fault Location and Classification in Microgrid

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Abstract

Microgrid concept is initiated due to increasing involvement of distributed generation resources with the utility grid. Microgrid provide reliable and sustainable power but the protection of microgrid become challenging due to bidirectional power flow, dual mode of operation (grid connected and islanded mode). Faults in the microgrid reduce its stability and efficiency. Identification, classification, and location of faults are critical for rapid restoration and microgrid protection. This research proposes a neural network-based intelligent particle filter for microgrid fault detection and classification. Even with low fault current, which is typical of inverter-based DGs, the suggested method seeks to precisely identify fault kinds, locations, and directions. The features are extracted from data using S-Transform, then extracted features are estimated using particle filter. A neural network is then used for classification and finalization of location. The proposed scheme provides extremely precise fault detection, ensuring that the classification and location of the fault are promptly identified for effective protection and service restoration.

Keywords

Microgrid, Microgrid Protection, Fault detection, Fault location, particle filter estimation, neural network

1. Introduction

With the continuous increasing demand of electrical energy and increasing concern of environmental degradation, depletion of fossil fuels and rising fossil fuels price, conventional resources considered to be replaced by renewable resources [1]. The rising use of renewable energy sources (RES), like solar energy, biomass energy, wind farms has allowed formation of microgrid [2]. Microgrid can function both independently and in connection with the main power grid. To improve dependability, resilience, and efficiency on a smaller scale, it includes demand management, storage, and renewable energy sources [3]. Growing DG penetration in the network brings new challenges for the protection of microgrid in case of fault detection and fault localization.

As integration of DG changed the power flow of distribution network from unidirectional to bidirectional. Faults in microgrid affect the stability and reliability of the system [4]. Protection challenges faced by microgrid are fault detection, fault localization, fault classification, coordination between protection devices, detecting between the grid connected mode and island mode, high impedance fault etc. These challenges occur due to the bidirectional flow of electric current due to DGs integration in the grid and topological structure like radial and meshed of microgrid. Traditional fault technique is not suitable for microgrid due their variable fault current. Due to this soft computing techniques like fuzzy logic, neural networks and evolutionary algorithm gain popularity [5].

These technologies are necessary to guarantee microgrid stability and dependability, particularly when there are complex fault scenarios present. A variety of studies have investigated a range of methods for microgrid fault diagnosis and protection, including wavelet transformations, data mining, machine learning, and hybrid approaches. In [6] the author examines fault protection concerns based on the microgrid's integration of distributed generators based on inverters. Two statistical classifiers—Naïve Bayes and decision trees—are compared by the author. In [7] the author employed a deep neural network based on discreate wavelet transform to identify and classify faults in hybrid energy-based multi-area grid-connected microgrid clusters.

In [8] author proposed a combined machine learning and SP based technique. The result shows that the algorithm can provide efficient protection measure for microgrid.

In [9] the author used an approach based on discreate wavelet transform and artificial neural network-based methodology for the detection and localization of the faults in the distributed network of AC microgrid. In [10] Kalman filter based scheme is proposed for microgrid protection. In this one end current signal for the detection and classification of faults. Microgrid fault detection has been effectively accomplished through the use of data mining techniques including random forests, support vector machines (SVM), and decision trees. The efficiency of ensemble learning techniques in fault identification was demonstrated by the author, who investigated gradient boosting trees for fault diagnosis in low-voltage distribution grids [11]. In this study an intelligent data mining-based approach for fault detection in which the first Hilbert transform is used to extract the features from current and voltage signals. AdaBoost classifier for fault classification. The results obtained show 99% accuracy for fault classification [12]. In this study convolutional neural networks (CNNs) based approach is used for features extraction and classification of fault type in microgrids. The proposed technique shows the accuracy of 99% [13].

The comparison results show that suggested schemes outperformed the existing schemes [13]. A transient wavelet energy-based protection strategy was developed specifically for inverter-dominated microgrids to ensure accurate fault identification and classification under a range of operating scenarios. This technique requires lower sampling rate and low-cost communications [14]. This study demonstrated the performance of a time-varying Kalman filtering technique for detection and classification of high-impedance faults in renewable energy-based distribution network [15]. To detect the accurate and early short circuit fault area in the microgrid wavelet transform based algorithm is used in this study. The simulation shows that the proposed technique can detect the short circuit faults faster and more accurately in microgrid.[16].

A alternative protection technique that employed a temporal matrix z-score vector was able to distinguish between fault and normal conditions in microgrids [17]. This study suggests an ensemble wavelet-based approach for detecting AC microgrid faults. Wavelet transformation (WT) is used in microgrids with distributed energy resources (DERs) to extract features from data. These features are subsequently processed by ensemble machine learning models to improve the precision of fault [18].

A dual filtering approach is introduced to enhance security and safety in microgrids with multiple energy sources. This method improves the functionality of fault detection systems and reduces false alarms in complex microgrid settings [19]. In this study, an intelligent fault detection system for microgrids is developed using machine learning methods. The system's real-time fault identification and classification ensures the stability of the microgrid [20]. In this study, faults are detected by combining the Hilbert-Huang transform (HHT) with deep neural networks (DNNs). While HHT gathers time-frequency information from signals, DNNs improve the accuracy of fault detection in microgrids [21].

Identification, categorization, and location of microgrid faults have significantly improved with the protection strategies described above. However, they indicate limits in terms of scalability, real-time performance, and flexibility when utilized in dynamic and challenging microgrid scenarios. This paper presents an intelligent Particle Filter with Neural Network approach to overcome these difficulties. The suggested approach delivers reliable fault detection, identification and classification by combining the state estimation capabilities of particle filters with the fault classification precision of neural networks. This proposed technique is ideal for inverter-dominated and renewable energy-based microgrids because it enhances real-time performance while simultaneously improving accuracy and durability. The paper is arranged as follows. IEC microgrid test system is explained in section II. The introduction of the protection scheme and mathematical formulation is explained in section III. The methodology of the proposed scheme is explained in section IV. Simulation results of the proposed scheme are explained in section V. The last section explains the conclusion

2. System IEC Test System

The microgrid test system used in MATLAB/SIMULINK is shown in figure 1. The microgrid distributed network is connected with the main grid at the PCC by a circuit breaker which changes the operation between grid connected mode and island mode. To test the performance of proposed scheme on various types of DGs in microgrid. In this, four DGs which connect using a step-up transformer in the microgrid. The DG1 and DG2 are wind type DGs and the DG3 and DG4 are photovoltaic type DGs. The CB1 and CB2 have the ability to switch between a radial and meshed microgrid. There are six loads connected in microgrid. Each load is connected at each bus. The total loading considered in this paper is taken as 22 MW, 10MVAR. The frequency of the system is set to 50 Hz. The sampling time used is 5e-5. The base voltage is taken as 13 kV and base power is taken as 45 MVA in the system. The other parameters of the microgrid are taken from [22] [23].

3. Proposed Scheme

3.1. S-Transform

The S-transform is a time-frequency analysis method that provides information on the frequency content of non-stationary signals while preserving temporal localization. It is simply an expansion of the Short-Time Fourier Transform (STFT) that integrates wavelet analysis to address some of its drawbacks. Stockwell et al. (1996) invented the S-transform, which is very useful for evaluating transient or time-varying data, making it ideal for detecting power system faults [24].

The S-Transform (ST) is an effective time-frequency analysis technique that combines features of the Short-Time Fourier Transform (STFT) and the Wavelet Transform. It is especially effective for studying transient signals, such as those generated during faults [25].

$$STFT(\tau,t) = \int_{-\infty}^{\infty} x(t)\, w(\tau - t, f) e^{-2\pi i f t} dt \quad (1)$$

Where, x(t) is the given signal and w (t, f) is the window function. The position of gaussian window is set by t (denoting time) and f(frequency).

$$w(t,f) = \frac{|f|}{\sqrt{2\pi}} e^{\frac{-t^2 f^2}{2}} \quad (2)$$

The gaussian window function ensures that lower frequencies have bigger time windows (excellent frequency resolution) while higher frequencies have smaller windows (good time resolution). This makes the S-Transform adaptable, overcoming the fixed-resolution constraint of STFT. By replacing the w(t,f) with the window function with the gaussian function the above S transform is derived [24], [25], [26].

The equation can be written as.

$$ST(\tau, f) = \int_{-\infty}^{\infty} x(t)\,\frac{|f|}{\sqrt{2\pi}}\,e^{\frac{-t^2 f^2}{2}}\,e^{-2\pi i f t}\,dt \tag{3}$$

For discrete S-transform, x[kt] is the discreate form of x(t) where k = 0,1,2,……,N-1 with sampling interval T.

The discreate Fourier transform of x[kT] is

$$X\left[\frac{m}{NT}\right] = \frac{1}{N}\sum_{k=0}^{N-1} x[kT]\,e^{\frac{i2\pi mk}{N}} \tag{4}$$

Where m = 0,1, 2…., N-1, and N denotes the number of samples.

The discreate S- transform of x[kt]

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=\frac{-N}{2}}^{\frac{N}{2}-1} X\left[\frac{m+n}{NT}\right] e^{\left[\frac{-2\pi^2 m^2}{n^2}\right]} e^{\left[\frac{2\pi m j}{NT}\right]} \tag{5}$$

Where j,m,n = 0,1, 2..., N-1. Making τ = jT and f= n/NT.

The discrete inverse of S transformation can be obtained by Feature Extraction

a. Mean

The RMS value of signal x[n] over N sample.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x\,[n]^2} \tag{6}$$

Where,

X[n] represents the discrete time signal, and N represents total number of samples.

b. Total Harmonic Distortion (THD)

$$THD = \frac{\sqrt{\sum_{h=2}^{H} X_h^2}}{X_f} \tag{7}$$

Where, xf represents amplitude of the fundamental frequency and X_h is amplitude of h th harmonic.

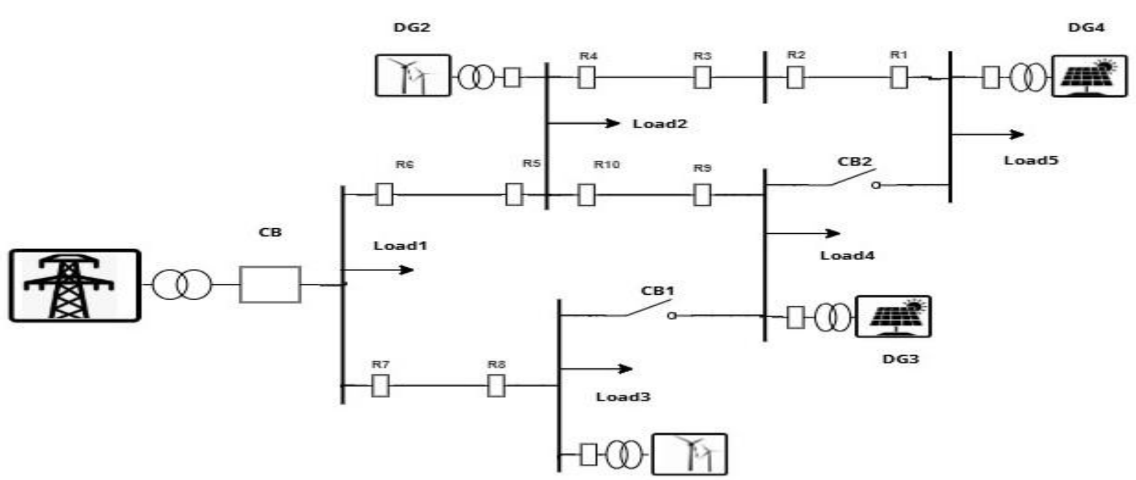

Figure 1. The diagram of IEC microgrid test system.

c. Energy from S-transform

The energy from S- Transform S(t, f) of a signal x[n] is

$$E = \sum_{\tau} \sum_{f} |S(\tau, f)|^2 \tag{8}$$

d. The entropy is an aspect of the frequency distribution's spread. The equation is given by

$$H = -\sum_{i} P_i \log(P_i + \epsilon) \tag{9}$$

Where, Pi represents normalized spectral energy distribution and € is small constant to prevent log (0).

$$P_i = \frac{|S(\tau_i, f_i)|}{\sum S(\tau, f)} \tag{10}$$

2.2. Particle Filter for State Estimation

The Bayesian estimate technique known as the Particle Filter (PF) is designed for nonlinear and non-Gaussian systems. Based on observable measurements z_t, it employs a sequence of particles to predict the system state x_t at a certain time t[15].

a. Initialization

To represent the previous probability distribution p(x0), a collection of n particles is created at the first-time step, at time t=0. Each particle x_0^i sign an equal weight

$$x_0^i \sim \ \mathrm{p}(x_0), \quad w_0^i = \frac{1}{N} \ , i = 1,2,3, \dots N \tag{11}$$

b. Prediction

The particles are propagated through the state transition model to predict their next state.

$$x_t^i = f\left(x_{t-1}^i\right) + \ v_t^i \tag{12}$$

$f(x_{t-1})$ represents nonlinear state transition function and $v_t^{(i)}$ represents the process noise sample from a known distribution.

c. Updates and Normalization

The probability of the observation z_t is used to update the particle weights.

$$w_t^i \propto w_{t-1}^i \cdot p(z_t | x_t^i) \tag{13}$$

Normalize the weights

$$w_t^i = \frac{w_t^i}{\sum_{j=1}^{N} w_t^i} \tag{14}$$

d. Resampling

To prevent particle degradation, resample the particles according to their weights. Higher-weight particles are replicated, and lower-weighted particles are eliminated.

2.3. Pattern Recognition Neural Network for Fault Classification

The PNN classifies the fault type on the basis of estimated data.

a. Input layer

The input layer takes in the estimated data.

$$F_t = [f_1, f_2, \dots, f_n] \tag{15}$$

b. Radial Basis Function Layer

Using a Gaussian kernel, the RBF layer determines how similar the input features and training samples are:

$$G_i(F_t) = exp\left(-\frac{||F_t - \mu_i||^2}{2\sigma^2}\right) \tag{16}$$

Where n is no. of features, μ_i is mean of ith class, σ is smoothing parameters that control speed of gaussian function.

c. Summation Layer and decision layer

The RBF layer's outputs are added up by the summation layer for every class Ck.

$$P(C_k|F_t) = \frac{\sum_{i\in C_k} G_i(F_t)}{\sum_{j=1}^{M} G_j(F_t)} \tag{17}$$

The decision layer assigns the fault type Cˆ to the class with the most likely posterior probability.

$$\hat{C} = argmaxP(C_k|F_t) \tag{18}$$

4. Methodology of Proposed Scheme

An Intelligent Particle Filter with Neural Network (IPFNN) are combined in the proposed methodology for fault detection, identification and location in microgrid. For accurately detecting the type and location of faults in the lines estimate the extracted features. This proposed method is intended to improve fault detection speed and reliability in contemporary power grid, especially in complex systems like microgrids that combine distributed generation with grid-connected operation.

4.1. S Transform features extraction

S- Transform scheme is used to extract the features for fault detection, classification and location. In the proposed scheme we extract the features like mean, entropy, standard deviation, energy and peak values. By evaluating time-frequency characteristics, it enables accurate fault localization, classification and detection in a microgrid. Three-phase voltage (V_{abc}) and current (I_{abc}) data are taken from 10 relays signals from the test model. The S-Matrix, a time-frequency representation produced by the transformation can be used to extract a number of features. Amplitude-based features including the signal total energy, amplitude mean and standard deviation, and magnitude fluctuations at various frequencies are among the features that can be extracted from the S-Transform. Normal and defective circumstances can be distinguished using frequency-based criteria such as energy distribution across various frequency bands and dominating frequency components. Unbalanced faults can be found using phase-based characteristics including inter-phase discrepancies and phase angle variations. Further information on fault characteristics can be obtained by measuring the signal's symmetry and unpredictability using statistical parameters like kurtosis, skewness, and entropy.

4.2. State Estimation Using Particle Filter

After the data has been pre-processed, the state estimate comes next. An Intelligent Particle Filter, which combines the benefits of particle filtering with state-space models, is used to evaluate the system's status in unidentified conditions. For handling the intricacy and non-linearities inherent in power system dynamics, especially in the event of a malfunction, the particle filter is ideal. At the beginning of the process, a set of particles is initialized, each of which represents a possible state of the system. These particles travel across the system's dynamic model, which takes into account the network design and the fault conditions. At each time step, the particles are updated based on the likelihood of the observed measurements (voltage and current) given the predicted state. This probabilistic function helps improve the particle weights by focusing on the most likely states. Resampling is the following step, when low-weight particles are removed, and new particles are made using the higher-weighted ones as a starting point. Through this recursive process, the particle filter may constantly improve the state estimate, providing a more accurate representation of the system's condition over time.

4.3. Fault Detection and Classification

A Neural Network (NN) is used in the fault classification process to accurately identify the type of fault from the pre-processed voltage and current data. As a tool for pattern recognition, the NN is trained to identify and categorize faults by examining the distinct features of the input signals.

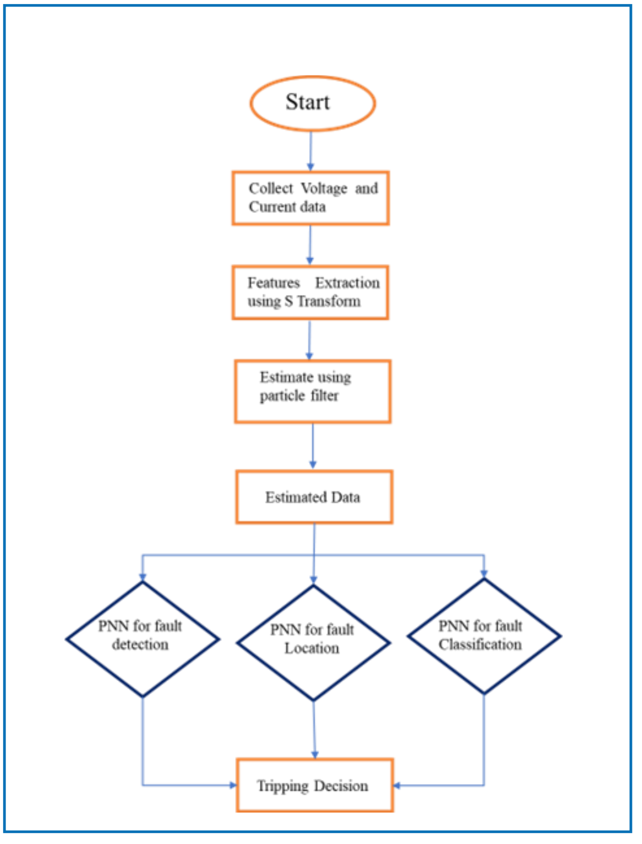

Figure 2. Flow chart of Proposed Scheme.

To capture the complex correlations between input characteristics, many layers of non-linear activation functions—such as ReLU (Rectified Linear Unit)—are employed. The neural network can identify faults in real time after it has been trained. The NN receives the extracted features when a fault is identified and gives the fault type and fault location with the highest probability. For the protective system to react correctly, this classification offers key data. To train the PNN network, we generate the data from the IEC microgrid in different fault and no-fault cases, different operating scenarios, network configurations, fault location. Fig. 2 shows the workflow of the proposed scheme.

5. Simulation Results

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5.1. Fault data generation

The proposed fault detection and classification method's efficacy was evaluated using simulations on a microgrid model that included ten protective relays, five transmission lines (20 km long), a main grid connection, six buses, four distributed generators (three solar-based and one wind turbine-based), and four distributed generators. MATLAB/Simulink2024b simulation was used to conduct the simulation, and multiple fault scenarios—such as grid-connected, island modes, only grid connected mode, partially DG mode were introduced under varied operating conditions.

Name	***Modes/events***	***No.***
Operating condition	Grid connected/islanded/only grid/partially DG connected	4
Network topologies	Loop/ Radial	2
Fault type	AG,BG,CG,ABG,BCG,CAG,AB,BC,CA,ABC	10
Fault resistance	0.01,1,10,100	4
Lines	L1,L2,L3,L4,L5	5

Table 1. Different fault Scenarios.

In order to ensure high-resolution transient analysis, the dataset included three-phase voltage (V_{abc}) and current (I_{abc}) signals from ten relays, sampled at 5e-5 seconds. Table 1 shows the different fault scenarios used in this paper.

5.2. Identify the Headings

An Intelligent Particle Filter with Neural Network (IPFNN) model was trained using the collected characteristics to detect faults, classify the fault. In five fault locations, the model was tested on ten distinct fault types (AG, BG, CG, AB, BC, CA, ABG, BCG, CAG, and ABC).

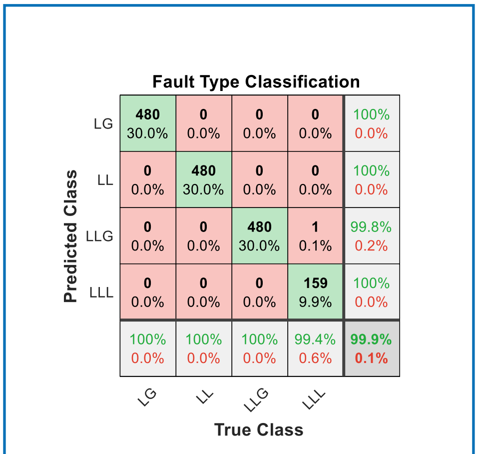

Figure 3. Confusion matrix for fault type.

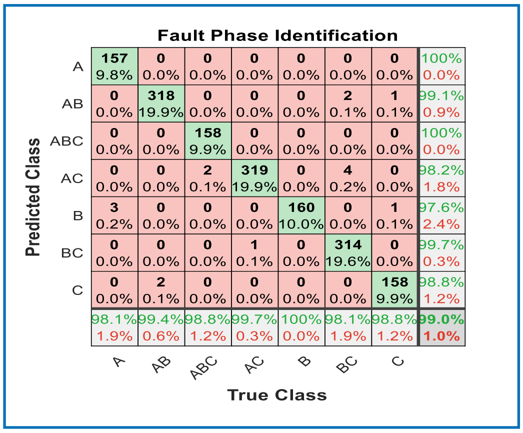

Figure 4. Confusion matrix for fault phase identification.

The estimated data is used to train the neural network. The training was performed using the Levenberg-Marquardt optimization with data samples. Fig.3 shows A confusion matrix is an assessment of efficiency for determining the accuracy of a fault type classification. It is a table that compares real fault kinds to anticipated fault types and displays the number of correct and wrong classifications. Each error type is represented by a matrix including True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). The column represents True fault type and rows represent predicted fault type. The model's performance in detecting and categorizing defects in a microgrid may be evaluated by using important metrics such as accuracy and precision. The proposed scheme achieved 99.9 % accuracy for fault type classification. The IPFNN performance for phase identification is shown in fig.4. The proposed scheme shows 99% accuracy for the fault phase identification.

5.3. Fault Location detection

The proposed scheme for fault location in figure 5 shows the accuracy of 98.7%. Given that most of the predictions match the actual fault locations, the confusion matrix has high classification accuracy. Minor misclassifications point to possible areas for development, such improving feature extraction, improving the classification method, or adding more fault features to help the model distinguish between fault locations that are closely related.

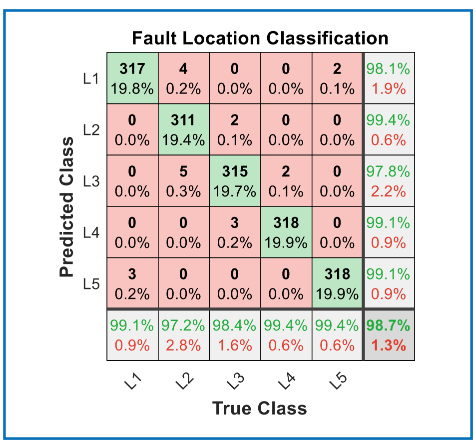

Figure 5. Confusion matrix for fault location.

System Configuration	Existing Protection Scheme			
	[18]	[21]	[20]	Proposed
Operating Mode (grid connected/islanded)	both	both	both	both
Topology (radial or mesh)	both	both	both	both
Accuracy for fault location	99%	Approx100%	99.9%	99.6%
Methods	WT	HHT	PF	IPFNN

Table 2. Comparative analysis of proposed schemes with previously used schemes.

6. Conclusion

Using an intelligent Particle Filter with Neural Network technique, this work proposes an intelligent framework for microgrid detection, location and classification of faults. To improve accuracy and reliability of fault detection, the study combines S-Transform-based feature extraction, particle filter-based feature estimation, and a neural network classifier. To evaluate the efficiency of the proposed scheme, an Intelligent Particle Filter with Neural Network (IPFNN) fault detection analysis was executed. The obtained result shows that the proposed technique achieved the accuracy of 99.9% for fault type and fault location accuracy of 98.7% with different fault scenarios. Hence ensure safe and efficient operation of microgrid is obtained.

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