Research Article

Self-Healing of Active Distribution Networks by Accurate Fault Detection, Classification, and Location

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The power system self-healing concept needs accurate and reliable fault detection, classification, and location (FDCL). This research proposes a novel and robust FDCL approach for distribution networks (DNs) in proportion to self-healing requirements. The proposed algorithm utilized a discrete wavelet transform (DWT) to decompose the measured current and zero sequence current component of only one terminal (substation) to detect and classify all fault types with the identification of the faulted phase(s). The fault location is achieved by integrating DWT and support vector machine (SVM). The data for training were extracted using DWT and collected, and then SVM was trained to locate the faulted section. The simplicity of the applied approach, ignoring DG’s data that is merged into the system, reduced training data and time, ability to diagnose all fault types, and high accuracy are the most significant contributions. The proposed techniques are tested on IEEE 33 bus DN with two distributed generation (DG) units, which are simulated in MATLAB. The simulation results demonstrate that the proposed methods give more accurate and reliable results for diagnosing the faults (FDCL) of various fault sorts, DN size, and resistance levels.

1. Introduction

The primary reasons for energy outages in the electric power system are electrical faults, particularly those faults that occur in distribution networks (DNs), which are about 80% [1]. The fault detection in DN is a complex assignment because of numerous taps along the feeders, various parallel branches, multiple conductors, complex structures, fewer monitoring apparatus, poor communication, data transfer infrastructure [2], and its direct connection with the distributed generators (DGs). Fast and accurate fault detection, classification, and localization (FDCL) along the power system result in power supply reclamation, subsequently decreasing service outage time, enhancing supply continuity and system reliability. Prognostics and diagnostics have been active research areas in recent years [3, 4], and different techniques have been proposed to help operation engineers to diagnose the fault and locate the faulted point as soon as possible.

In recent years, many research works have witnessed the development of various FDCL algorithms in the power system network [5]. In the recent past, many researchers have investigated the power system by following fault diagnosis techniques [6], using techniques based on impedance measurement, traveling wave phenomenon, artificial intelligence (AI), and signal processing. The first technique mainly depends on fundamental frequency, voltages, and current, and it is simple and cheap. It gives erroneous results for huge fault resistance values [7]. In [8–10], the estimation of the fault type and distance in a transmission line (TL) using an impedance-based approach is discussed. The results of these schemes’ simulations show that because of big fault resistance, the fault sort and distance error become more. The second technique employs the forward and backward traveling wave travel times, in addition to the sequential reflections recorded at the measuring points [11–13]. These methods estimate various sorts of faults and find high impedance faults in TLs with acceptable accuracy. However, many measurement units are required for these methods, which makes them uneconomical. The required sample rate is fairly high (above 1 MHz), which is practically difficult to
implement [12]. Therefore, in some papers, the number of the
carried out measurement units is minimized [13].

In a variety of applications, AI is used to diagnose faults
[14–20]. The researchers also gave more emphasis to AI-
based fault categorization and distance estimation skills in
the power system, such as artificial neural networks (ANN),
support vector machines (SVM), fuzzy logic (FL), etc. Fault
classification in a long TL using the FL approach is described
in [21–23]. The current signal’s wavelet transform (WT) is
used in these schemes to feed unseen fault data to the FL
system for fault classification. In these schemes, a simple
computational process is used, however, the fault classifi-
cation error reported is quite large because of the changes in
simulation condition. References [24–28] discuss the em-
ployment of ANN for fault categorization and distance
estimate on long TLs. The simulation results show high
accuracy, however, the training time is quite long, because of
which the task becomes quite complex and tedious.

For the signal processing technique, a number of
methods are available to analyze the frequency charac-
teristics of time-domain signals, however, WT, Fourier
transform (FT), and S-transform are the frequently
employed techniques in fault identification systems/pro-
tection relays. The performance of FT and WT approaches
for detecting various faults in TLs was compared in [29].
The authors clarified that the WT method is better at fault
detection than the FT method. The continuous wavelet
transform (CWT) is utilized to estimate the energy spectrum
of the voltage signal and determination of characteristic
frequencies. This method is improved in [30] using the time
domain analysis. Several studies have been conducted on the
discrete wavelet transform (DWT) for FDCL. The current
signal was decomposed using DWT in [31], where the
current signal was analyzed into detail and approximation
coefficients. These coefficients were used to detect and
categorize the faults. The fault identification method in [32]
was performed using a hybrid of singular value decompo-
sition (SVD) and DWT. DWT was applied to extract features
from high-frequency signals of currents, and then a wavelet
matrix was created. The mother wavelet was Daubechies
(db1) with a sampling frequency of 15.36 kHz. In [33], Fast
FT and wavelet packets are used to determine the charac-
teristic frequencies. Although these approaches rely solely
on substation measurements, they can yield multiple results
in the case of DNs with several ramifications.

Generally, most of the methodologies that identify the
fault are applicable for TLs, unlike DNs. The impedance
measurement technique is influenced by the load changes,
and fault resistance with inaccurate performance in the event
of short-time faults, making these for the purpose of fault
location, and it is unreliable[34]. Furthermore, in the
presence of DG resources, the impedance approaches are
ineffective. The traveling wave technique is suitable for TLs
that generally have a loop structure in contrast to DN, which
is branched. Hence, this method is not useful in DNs, and its
required number of measurement units is high to obtain the
acceptable accuracy. Generally, AI-based technique methods
require considerable training data and time, which make it
unsuitable for the self-healing principle. Although the
transformations approach only uses substation measure-
ments, they may yield various answers in the case of DNs
with several ramifications.

This paper will focus on FDCL of DNs based on self-
healing needs such as the DN must be active power network
and the flexibility to change the topology of the network to
restore customer service quickly. After comparing the ap-
proaches used to implement this task on DNs, DWT from
the signal processing techniques has been chosen, and by one
strong feature extracted from DWT (db 4) analysis for the
measured current and zero sequence current component at
one end, we can detect and classify the fault, its type, loca-
tion, and resistance with any number of DG and DN
topologies. To locate the fault, a combination of DWT and
SVM is applied.

The main contribution of this paper can be summed as
follows:

(1) The method is conceptually simple and can be
implemented in large-branched DNs with several
load taps, laterals, and much fault resistance.

(2) The proposed approach is applicable to DNs that
contain distributed energy sources without requiring
their information. It does not face the multiple so-
lution problem, and it gives accurate results for all
fault types.

(3) To overcome the data and time required for SVM
training, one prominent feature derived from DWT
analysis of the measured current is utilized since it
has a direct relationship with the distance of the fault
place. It greatly helped the good classification using
the SVM of the fault place and reduced the time and
data required for training.

(4) Capacity to diagnose all types of faults with great
accuracy.

This paper is organized as follows: section 1 entails the
review of fault description, zero-sequence component, WT,
SVM, and the proposed methods. In Section 2, the results
and discussion are introduced, and lastly, the conclusion is
presented in Section 3.

1.1. Theoretical Framework of the Implemented Techniques

1.1.1. Fault Description. A fault in a power system is an
abnormal state that occurs when power system equipment
fails electrically. These faults can be labeled as follows:

(a) Series fault (open circuit)
A series fault is one in which the three phases’ im-
pedances are not equal, and it typically occurs when a
power system network has a broken line or one or
more lines have higher impedance than the others.
The frequency, voltage rise, and current drop at the
faulty phases is used to characterize series faults.

(b) Shunt fault
Shunt faults can be categorized into two types,
namely, symmetrical fault and asymmetrical fault.
(1) Symmetrical fault: a fault because of a short circuit in all three lines (LLL) or when the three phases come in contact with the ground (LLLG). It is the most serious fault (maximum fault current and minimum voltage) since it has an equivalent impact on all phases. Generally, symmetrical faults are infrequent, accounting for around 5% of all faults.

(2) Asymmetrical fault: it is unbalanced in nature. This fault occurs as a single line-to-ground fault (LG), line-to-line fault (LL), and double line-to-ground fault (LLG). LG fault manifests when one of the DN’s three-phase conductors comes into contact with the ground because of animal contact, wind, or a line falling on the ground. In DNs, LG faults account for 70% of all faults [35]. LL fault occurs, for example, when strong wind forces one phase to liaison another phase. LL fault accounts for 15% of DN faults [35]. LLG faults include two phases rather than one in the LG circumstance, and LLG faults account for 10% of DN faults. The increase in current and decrease in voltage and frequency are the significant characteristics of the shunt faults.

Distribution systems generally experience all shunt fault types, and hence, all shunt faults were applied to the studied system in this research.

1.1.2. Zero-Sequence Component. The symmetrical components method is a very powerful method for analyzing unbalanced three-phase systems. It facilitates the analysis of the complicated unbalance phenomena in a pretty simple way [36]. Phase voltage or current can be converted into three sets of sequence components, i.e., zero sequence, positive sequence, and negative sequence. The set of zero-sequence current components consists of three phasors with equal magnitudes.

$$I_{a0} = I_{b0} = I_{c0} = I_0,$$  (1)

where $I_{a0}$, $I_{b0}$, and $I_{c0}$ are the zero-sequence current components of phase $A$, $B$ and $C$ respectively. Also, zero phase displacements are explained in Figure 1.

The zero-sequence current component can be computed from the current of phases using the following transformation:

$$I_0 = \frac{1}{3} (I_a + I_b + I_c).$$  (2)

Zero-sequence quantities can be observed only in ground fault conditions. Therefore, the zero-sequence current or zero-sequence voltage can be employed to detect grounded faults in a power system network.

1.1.3. Wavelet Transform. WT is a signal processing algorithm, which is a powerful tool for analyzing power system transient phenomena. It can extract data from transient signals in both the frequency and time domains simultaneously. Hence, in many applications, it has replaced FT [37–41]. Wavelet functions (mother functions) are those that satisfy both frequency and time localization requirements. Wavelets must be oscillatory, decay rapidly to zero, and have a zero average value as a sufficient and necessary condition. WT can be defined in two forms as CWTs and DWT. The enormous computational and the redundancy of information required to determine all potential scales and translations of CWT limits its use. The discretization of the translation and scale components, which principals to the DWT, is an alternate to this analysis, and it can be stated as follows:

$$DWT(m,k) = \frac{1}{\sqrt{a}} \sum_{n} V(n) \psi \left[ \frac{k-b}{a} \right].$$  (3)

where $V(n)$ is the discretized input signal function. $k$ is an integer variable, and it refers to a sample number in an input signal. $\psi$ is the mother function, and $m$ is the dilation parameter. The mother functions can be dilated and translated discretely by adjusting the scaling and translation parameters $a = a_0^m$, $b = na_0^mb_0$, respectively [39] (with fixed constants $a_0>1$, $b_0>1$, and $m$ and $n$ belonging the positive integers set).

(a) Multiresolution analysis (MRA)

There are numerous approaches to present the DWT concept. The multiresolution analysis (MRA), which was advanced in the late 1970s [40], is a highly effective implementation of DWT. As displayed in Figure 2, the original sampled signal $V(n)$ is passed through a low pass filter $l(n)$ and a high pass filter $h(n)$. Following that, the outputs of both filters were decimated by two to get the approximation and detail coefficients at level one (A1 and D1). After that, the approximation coefficients are passed to the second stage, where the previous procedure is repeated. Finally, at the expected level, the signal is decomposed. The following equations can be applied to calculate the wavelet coefficients of a signal $V(n)$ at different levels:

$$A(k) = \sum_{n} V(n).h(2k-n),$$  (4)

$$D(k) = \sum_{n} V(n).l(2k-n).$$  (5)

If the original sampling frequency is F, the signal information acquired by D1 is between F/4 and F/2 of the frequency band, while A1 maintains the rest of the main
signal information between 0 and F/2. D2 extracts the data between F/8 and F/4. D3 debrieﬁes the information between F/16 and F/8, and A3 maintains the rest of the main signal information between 0 and F/16. By doing so, we can simply extract helpful acquaintance from the main signal into multiple frequency bands and simultaneously match the information to the related time period.

1.1.4. Machine Learning. Machine learning is a division of AI that allows a machine or computer to learn and progress its performance based on algorithms that can generalize behaviors and realize patterns from a pre-existing data collection. The two types of supervised and unsupervised learning are determined by how machines learn from data [41]. In the approaches of supervised learning, there are numerous techniques. One of them is known as SVM, and it possesses a good theoretical basis and good generalization capability.

(a) Support vector machines

SVM is a recent multivariate statistical technique that has gained popularity as a result of its regression effects and superior classiﬁcation. As it is founded on the structural risk minimization concept [42], the SVM-based classiﬁer has a stronger generalization property. The SVM algorithm has the nonlinear attribute. Thus, it is capable of dealing with vast feature spaces [43]. Basically, SVM classiﬁcation entails training and testing data collected from several instances. Each instance in the training set comprises of attributes (features) and a class label as a target value. fU_he fundamental principle of SVM is the distance from a data point x, to the separating hyperplane is as follows:

\[ d = \frac{|\langle w, x \rangle + b|}{\|w\|}. \]  

According to Figure 3(d), a separating hyperplane is considered to be optimal if it creates the maximum distance amid the closest vectors and the hyperplane, which is required to maximize the training data margin [44]. The closest points in each class are denoted as support vectors (SVs). The separation margin (in meters) between the classes is given as [45] follows:

\[ m = \frac{2}{\|w\|}. \]  

To maximize m, w is minimized. Thus, the maximum margin can be found by resolving the following quadratic optimization problem [44]:

\[ \min \frac{1}{2}\|w\|^2, \]  

under the constrain

\[ y_i(\langle w^T, x_i \rangle + b) \geq 1, \]  

where \( r \) is the kernel function and a way of computing the inner product \( \Phi(x_i), \Phi(x_j) \) in the feature space directly as a function of the original input data. The solution to the problem provides the values of \( w \) and \( b \), such that the separation between the classes is maximum. The SVMs are acquired by resolving the following dual optimization problem [44]:

\[ \max L(\alpha) = \sum_{i=1}^{N} \alpha_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j r(x_i, x_j), \]  

\( G: \mathbb{R}^m \rightarrow \mathbb{Y}^2 \) \( \Phi(x_i) \rightarrow G(\Phi(x_i)). \) \( (7) \)

A column vector (Y) serves as the class label, and it consist of two entries, −1 and +1. Indicate that \( y_i = 1 \) is related to one class and \( y_i = -1 \) is related to the other. Since the training data set is linearly separable in the feature space (\( \mathbb{F}^m \)), as demonstrated in Figure 3(b), SVM will attempt to separate it using a linear hyperplane.

\[ f(x) = \langle w, x \rangle + b = 0, \]  

where \( w \) is a weight vector, quantity \( b \) is a scalar, and \( \langle \cdot, \cdot \rangle \) denotes the dot product in \( \mathbb{R}^n \). The parameters \( w \) and \( b \) decide the separating hyperplane’s position and orientation. The distance \( d \) from a data point \( x_i \) to the separating hyperplane is as follows:

\[ d = |\langle w, x \rangle + b|/\|w\|. \]  

The mapped data is now in a higher-dimensional feature. The space (\( \mathbb{F}^m \)) may be linearly separable. Hence, another function \( G \) is then applied to map the feature space onto the decision space (\( \mathbb{Y}^2 \)), and this is step two.
under the constrain
\[
\sum_{j=1}^{N} \alpha_j y_j = 0, \quad (14)
\]
where \( \alpha \) is the Lagrangian multiplier, \( N \) is the amount of datasets, and \( x_i \) and \( x_j \) are dimension input vectors. Once the optimization problem is solved, the training points with \( \alpha^*_i > 0 \) are the SVs, and \( w^* \) and \( b^* \) can be determined as follows [44]:
\[
w^* = \sum_{i=1}^{N} \alpha^*_i x_i y_i, \quad (15)
\]
\[
b^* = y_{sv} - \sum_{j=1}^{N} \alpha^*_j y_j r(x_i, x_{sv}). \quad (16)
\]

The optimal decision function is as follows [31]:
\[
f(x) = \text{sign} \left( \sum_{i \in SV} \alpha^*_i y_i r(x, x_i) + b^* \right). \quad (17)
\]

The most extensively employed kernel functions in the literature, namely the polynomial, sigmoidal, and Gaussian radial basis function (RBF), are tested for training and evaluating the SVM classifiers. In this work, the Gaussian RBF kernel is chosen based on its better performance. The Gaussian RBF kernel function is as follows:
\[
k(x_i, x_j) = \exp \left( -\frac{\|x_i - x_j\|^2}{\gamma} \right), \quad (18)
\]
where \( \gamma = (2\sigma^2) \) and \( \sigma \) is the standard deviation of the Gaussian. The kernel function parameter \( \gamma \) is tuned only once to achieve sufficient accuracy. For a more detailed review of SVM, refer to [46].

1.2. Proposed Method for FDCL. The proposed approach is based on the current measurements of the phases, which are available at the substation. The approximation and detail coefficients of the signals are extracted using the relevant DWT based on the MRA technique. By observing the approximation coefficient maximum value for each phase, it is discovered that when the system is healthy, this value is the same for all phases. This value increases very dramatically for the phase (s) in which a fault occurs. Depending on this phenomenon, a robust algorithm has been proposed in this paper to detect and classify the fault type. To pinpoint the section of the fault, DWT was combined with SVM in a way to overcome the training time, since the training was based on one feature directly proportionate to the distance of the faulted section.

1.2.1. Fault Detection Algorithm. As previously stated, DWT will be utilized to detect faults. Determining the mother wavelet function is one of the most essential things to do. In electrical power system applications, the Daubechies (db4) mother wavelet functions are one of the most efficient and famous ones. The fault detection technique was carried out in the following steps:

(1) Simulink is used to build a power system model (active power distribution networks) and measure three-phase currents at the substation.

(2) DWT is obtained for three-phase current signals since the mother wavelet is db4, and the number of decomposition layers is one.

(3) Determine the approximation coefficients for each phase, and assume they are as follows:
   \[ \text{Appcoef}_a = \text{approximation coefficients of phase A} \]
   \[ \text{Appcoef}_b = \text{approximation coefficients of phase B} \]
   \[ \text{Appcoef}_c = \text{approximation coefficients of phase C} \]

(4) Determine the maximum value of approximation coefficients.
   \[ R = \max (\text{Appcoef}_a) \]
   \[ S = \max (\text{Appcoef}_b) \]
   \[ T = \max (\text{Appcoef}_c) \]

(5) The selected value = \( \epsilon \), and the selected value is derived from the approximation coefficient maximum value for each phase.

(6) Compare the maximum value of each approximation coefficient (R, S, and T) with the selected value.

(7) If all maximum values are less than the selected value \( \epsilon \), the system is normal. Otherwise, the system
is faulted. Hence, the next step is to categorize the fault.

The flowchart for fault detection is displayed in Figure 4.

1.2.2. Fault Classification Algorithm. After detecting the fault, the next step is to classify the type of fault. The phenomenon of increasing the approximation coefficient’s maximum value for the phase(s) in which a fault occurs will be used to classify it. Depending on the zero-sequence, quantities can be observed only in ground fault conditions. This quantity will be used to identify ground faults. To conduct the defect classification algorithm, the steps applied will be as follows:

1. Fault detected
2. Calculate zero-sequence current component (2).
3. Apply DWT to zero-sequence current component signal since db4 is the mother function, and the level of decomposition is one.
4. Determine the approximation coefficients for zero-sequence current component, where, \( \text{Appcoef}_0 \) – approximation coefficients of zero-sequence current component.
5. Determine the maximum value of (Appcoef_0).
6. If \( R > \varepsilon \) & \( S < \varepsilon \) & \( T < \varepsilon \) & \( Z > 0 \), the fault type is LG in phase A.
7. If \( R < \varepsilon \) & \( S > \varepsilon \) & \( T < \varepsilon \) & \( Z > 0 \), the fault type is LG in phase B.
8. If \( R < \varepsilon \) & \( S < \varepsilon \) & \( T > \varepsilon \) & \( Z > 0 \), the fault type is LG in phase C.
9. If \( R > \varepsilon \) & \( S > \varepsilon \) & \( T < \varepsilon \) & \( Z > 0 \), the fault type is LLG in ABG.
10. If \( R > \varepsilon \) & \( S < \varepsilon \) & \( T > \varepsilon \) & \( Z > 0 \), the fault type is LLG in ACG.
11. If \( R < \varepsilon \) & \( S > \varepsilon \) & \( T > \varepsilon \) & \( Z > 0 \), the fault type is LLG in BCG.
12. If \( R > \varepsilon \) & \( S > \varepsilon \) & \( T > \varepsilon \) & \( Z > 0 \), the fault type is LLLG in ABG.
13. If \( R > \varepsilon \) & \( S > \varepsilon \) & \( T > \varepsilon \) & \( Z = 0 \), the fault type is LLL in ABC.
14. If \( R > \varepsilon \) & \( S < \varepsilon \) & \( T < \varepsilon \) & \( Z = 0 \), the fault type is LL in AB.
15. If \( R > \varepsilon \) & \( S < \varepsilon \) & \( T > \varepsilon \) & \( Z = 0 \), the fault type is LL in AC.
16. If \( R < \varepsilon \) & \( S > \varepsilon \) & \( T > \varepsilon \) & \( Z = 0 \), the type fault type is LL in BC.
17. The next stage is to pinpoint the location of the fault.

1.2.3. Fault Location Algorithm. According to the simulation, it turns out that the fault location has an impact on the summations of the maximum values of approximation coefficients (\( \tau \)), where this value increases as the fault approaches the substation and vice versa.

\[
\tau = R + S + T.
\]  \( \text{(19)} \)

This characteristic is utilized as feature to SVM training. All sorts of faults occur in every section of the examined system, and the data (\( \tau \)) for each fault is recorded. SVMs are utilized in four ways. The first is trained on LG fault data, the second on LLG fault data, the third on symmetrical fault data, and the fourth on LL fault data, as depicted in Figure 5.

Because of the fact that the DN structure is radial and there are several shunted branches, from the viewpoint of the operational engineers, there is a great similarity between some branches and each other, and this was one of the biggest problems in other ways applied to locate the fault location. It was suggested to put some guiding devices, such as voltage measuring devices, and they should be placed at the branching point of the long branches alone, however, there is no need for the short branches, and this will appear more clearly in the next section.

2. Case Study Results and Discussion

To attain the efficacy of the approaches, the established algorithms were implemented and tested on a standard IEEE 33 bus system. The substation voltage is deemed as 1 pu. The studied system is implemented by MATLAB/SIMULINK environment. The base kV and MVA of the system are 12.66 kV and 100 MVA, respectively.
The system’s active and reactive load power are 3.715 MW and 2.3 MVar, respectively. The system under investigation contains two DGs. The approach described in the reference [47] is utilized for DG allocation, with the exception that DGs are located in two locations rather than one. The DG places, capacities, and the reduction of power losses are as given in Table 1.

Table 1 shows that the DGs will provide 60% of the total load. The distribution system integrated with the DG single line diagram is displayed in Figure 6.

2.1. Fault Detection and Classification. The proposed approach is performed in MATLAB coding based on phase current measurements, which are available at substation, and they are sent from MATLAB/SIMULINK. The maximum values of approximation coefficients (R, S, and T) and the approximation coefficients for zero-sequence current component (Z) for healthy and faulted system at some buses with 0.01 pu fault resistance are shown in Table 2.

Table 2 presents that the values of R, S, and T for healthy phase (s) are nearly similar, ranging between 102 and 106. It is the suggested value (ε) used in the comparison to determine if the system is faulty or healthy. However, the selected value (ε) must be higher than this to avoid treating a correct system that is overloaded as a faulted system. As a result, the suggested worth for the selected value (ε) is as follows:

$$\varepsilon = 1.2 \times 106 \equiv 1.27.$$

Figure 6 shows that bus 18 is the furthest away bus from the substation. Table 2 presents that as we get further away from the substation, the values of R, S, T, and Z decrease, indicating that bus 18 is the critical bus (R, S, T, and Z have minimum values). As a result, the focus shall be put on the results obtained for bus 18. When the system is healthy, all of the approximation coefficients’ maximum values (R, S, and T) are smaller than the prescribed value (ε), and the Z value is equal to zero, indicating that the system is healthy. When a failure of type LG occurs, for example, on phase A, we discover that the maximum value of approximation coefficient of phase A (R) is the only one bigger than the specified value (ε), indicating that the system has an error in phase A. Thus, it is discovered that the value of Z is bigger than zero, indicating that the fault is grounded. We can detect any fault type using this procedure.

2.2. Fault Location

2.2.1. Analysis for Fault Locations. Eleven types of faults may occur in all sections of the active power distribution networks, which are LG (AG), LG (BG), LG (CG), LLG (ABG), LLG (ACG), LLG (BCG), LLL, LLLL, LL (AB), LL (AC), and LL (BC). The τ values are quite close for one fault type, regardless of the phase or phases in which the fault occurs, as long as it happens on the same section. The values of τ for a variety of short circuit faults that can occur on any bus are represented in figures 7(a)–7(d).

According to Figure 7, the results can be summarized as follows:

(1) The τ value falls as the fault distance from the substation increases in the linear form.
(2) Depending on the error type, the values of τ change.
(3) The τ values correspond to different faults on different sections, for example, when an LG fault occurs on section 1 (S1), τ corresponds to the LL fault on section 7 (S7). It occurs multiple times.
(4) For one fault type, there is symmetry between DN sections (only on long branches) in the τ value because DN construction is radial and branching.

Regarding the summary, the items verified are as follows:

(1) The τ values are excellent for training the SVM to identify the faulted section.
(2) More than one SVM must be used, each of which is trained on specific fault data. Four SVMs are employed here. The first is trained on LG fault data, the second on LLG fault data, the third on symmetrical fault data (LLL ≡ LLLL), and the fourth on LL fault data.
(3) The SVM’s perplexity caused by similar data values (τ) in some sections of the lengthy branches is resolved using auxiliary devices.

2.2.2. SVM Training. SVM is trained with 432 samples (τ) using Gaussian RBF for the classification of 4 classes.
every fault type, it has 108 samples to pinpoint the faulted section. The feature vector ($\tau$) and the target vector (fault section) for LG fault, for example, are given in Table 3.

Table 3 demonstrates that the values of $\tau$ at the same section are nearly the same regardless of the phase in which the mistake occurred, and hence, Table 4 only gives one $\tau$ value of LL, LLG, and LLL-LLLG at all sections.

Figure 6 shows that branch 2 is a lengthy branch, and it led to the similarity of $\tau$ values for some sections in it with branch 1, which is part of the main branch. Tables 3 and 4 give what was mentioned, where the $\tau$ values are very similar in sections S12-S13-S14 (branch 1) and S31-S32-S33 (branch 2), respectively, and it is found for all fault types.

If SVM is trained on the dataset ($\tau$) for one type of fault for the entire network once, it will confuse SVM during the identification of the fault section, especially if the fault occurs in sections where $\tau$ values are similar. As a result, for one sort of fault, the SVM was trained in two parts. The first part contains the $\tau$ values of this fault type for the whole network, except branch 2, and the second part contains the $\tau$ values of this fault type for the entire network, except branch 1. It is the procedure for SVM training for all fault types. Figure 8 illustrates the structured training of the LG fault.

As illustrated in Figure 8, after SVM training, we can export the training structure from the classification learner. To determine the suitable structure, two devices were installed to measure the voltage, with the device that gives a lower reading. It indicates that the fault is in the branch in which it is placed. These devices were placed as displayed in Figure 6. If the two devices have the same reading, it means that the fault is on neither branch one nor branch two, and in this case, any structure is suitable to locate the fault section. Figure 9 shows the suitable structure detection flowchart.

2.2.3. Timeframes for Proposed Algorithms. Time elapsed to detect, classify, and locate the fault was critical information. After getting the current reading per phase from the SIMULINK, the proposed algorithm requires 0.01 second to detect the fault. The second stage is the classification, which begins as soon as a fault is discovered, and the total duration for them (detection and classification) is 0.2 seconds.

The four SVM were trained as previously mentioned to pinpoint the location of the fault, and the training duration for each type is given in Table 5.

The classification algorithm’s confusion matrices (part 1 & part 2) are depicted in Figure 10. The number of properly classified faulty sections is represented by the diagonal cells in the confusion matrix, whereas the number of misclassified faulted sections is represented by the off-diagonal cells. It is obvious that the classification was done meticulously until 100 percent correctness was achieved.

The proposed algorithm for fault location, the third level, use the structure was exported from classification learner. The collector algorithm’s maximum time to achieve the goal

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**Table 1: DG allocation and power losses reduction.**

| DG number | DG location | MW     | M var   | Power loss reduction (%) |
|-----------|-------------|--------|---------|--------------------------|
| 1         | 13          | 0.8465 | 0.3961  | 86.4                     |
| 2         | 30          | 1.1392 | 1.0611  |                          |
### Table 2: R, S, T, and Z values at some buses for healthy and faulted system.

| Fault type | 1 | 6 | 18 | 21 | 24 | 32 |
|------------|---|---|----|----|----|----|
| **R (Bus 1)** | 103.5099 | 104.1115 | 103.5181 | 103.5099 | 104.1115 | 103.5181 |
| **S (Bus 6)** | 0 | 103.5099 | 104.1115 | 103.5181 | 103.5099 | 104.1115 |
| **T (Bus 18)** | 0 | 0 | 103.5099 | 104.1115 | 103.5181 | 103.5099 |
| **Z (Bus 21)** | 0 | 0 | 0 | 103.5099 | 104.1115 | 103.5181 |
| **R (Bus 24)** | 0 | 0 | 0 | 0 | 103.5099 | 104.1115 |
| **S (Bus 32)** | 0 | 0 | 0 | 0 | 0 | 103.5099 |
| **T (Bus 21)** | 0 | 0 | 0 | 0 | 0 | 0 |
| **Z (Bus 24)** | 0 | 0 | 0 | 0 | 0 | 0 |
| **R (Bus 32)** | 0 | 0 | 0 | 0 | 0 | 0 |

---

### Additional Data Points for Specific Fault Types:

**AG**
- Bus 1: 103.5099
- Bus 6: 104.1115
- Bus 18: 103.5181
- Bus 21: 103.5099
- Bus 24: 104.1115
- Bus 32: 103.5181

**BG**
- Bus 1: 103.5099
- Bus 6: 104.1115
- Bus 18: 103.5181
- Bus 21: 103.5099
- Bus 24: 104.1115
- Bus 32: 103.5181

**CG**
- Bus 1: 103.5099
- Bus 6: 104.1115
- Bus 18: 103.5181
- Bus 21: 103.5099
- Bus 24: 104.1115
- Bus 32: 103.5181

**ABG**
- Bus 1: 103.5099
- Bus 6: 104.1115
- Bus 18: 103.5181
- Bus 21: 103.5099
- Bus 24: 104.1115
- Bus 32: 103.5181
Figure 7: The \( r \) values at all buses: (a) at LG fault, (b) at LLG fault, (c) at LL fault, and (d) atLLL and LLLG fault.

| Feature vector (\( \tau \)) | Target (fault section) | Feature vector (\( \tau \)) | Target (fault section) |
|-----------------------------|------------------------|-----------------------------|------------------------|
| AG 1857.138                 | BG 1857.3              | CG 1857.167                 | S1 1683.813            | BS 1654.301            | GS 1687.845            | S19 1188.847            | BS 1188.865            | GS 1189.00             | S20 1496.769            | BS 1496.428            | GS 1497.66            | S21 1196.772             | BS 1196.796             | GS 1196.974            | S22 |
| 1792.337                    | 1791.933               | 1792.121                    | S2 1093.302             | S3 1093.616             | S4 1093.613             | S23 1056.796             | BS 1056.839             | GS 1059.017            | S25 |
| 1664.042                    | 1664.485               | 1663.949                    | S5 1956.772             | S6 956.796              | S7 956.974              | S26 1066.807             | BS 1066.734             | GS 1066.795            | S27 |
| 1594.966                    | 1595.003               | 1595.191                    | S8 1233.99              | S9 1233.211             | S10 1233.493             | S30 1267.31             | BS 1267.309             | GS 1267.424            | S31 |
| 1527.983                    | 1528.193               | 1528.161                    | S11 1058.898             | S12 1058.839             | S13 1058.845             | S32 1066.807             | BS 1066.734             | GS 1066.795            | S33 |
| 1354.851                    | 1353.742               | 1355.133                    | S14 1496.796             | S15 1497.66             | S16 1497.66              | S34 1093.845             | BS 1093.639             | GS 1094.017            | S35 |
| 1216.921                    | 1216.949               | 1217.177                    | S17 554.243             | S18 554.117             | S19 554.1489             | S36 554.3621             | BS 554.3432             | GS 554.3329            | S37 |
Table 4: Feature and target vector for LL, LLG, and LLL-LLLG faults.

| Feature vector ($\tau$) | Target (fault section) | Feature vector ($\tau$) | Target (fault section) |
|-------------------------|------------------------|-------------------------|------------------------|
| LL ($AB \cong AC \cong BC$) | LLG ($ABG \cong ACG \cong BCG$) | LLL-LLLG | LL ($AB \cong AC \cong BC$) | LLG ($ABG \cong ACG \cong BCG$) | LLL-LLLG |
| 2822.643 | 3306.614 | 4861.824 | S1 | 2614.992 | 3027.313 | 4393.327 | S19 |
| 2774.389 | 3218.704 | 4696.100 | S2 | 1797.140 | 2063.875 | 2938.972 | S20 |
| 2595.139 | 3000.128 | 4344.210 | S3 | 1637.786 | 1873.884 | 2654.205 | S21 |
| 2509.253 | 2868.270 | 4144.692 | S4 | 1399.706 | 1601.891 | 2246.583 | S22 |
| 2379.042 | 2738.897 | 3950.992 | S5 | 2323.251 | 2675.866 | 3856.438 | S23 |
| 2085.417 | 2393.620 | 3435.258 | S6 | 1875.985 | 2154.259 | 3074.111 | S24 |
| 1848.056 | 2121.412 | 3025.410 | S7 | 1577.323 | 1806.949 | 2553.733 | S25 |
| 1717.192 | 1968.574 | 2796.063 | S8 | 2021.239 | 2321.976 | 3325.399 | S26 |
| 1474.321 | 1686.317 | 2373.054 | S9 | 1936.599 | 2223.234 | 3175.450 | S27 |
| 1296.823 | 1478.921 | 2063.928 | S10 | 1592.604 | 1823.691 | 2578.992 | S28 |
| 1278.184 | 1456.002 | 2029.640 | S11 | 1412.155 | 1614.147 | 2265.007 | S29 |
| 1241.478 | 1414.348 | 1967.304 | S12 | 1341.828 | 1532.300 | 2142.419 | S30 |
| 1071.146 | 1216.410 | 1670.503 | S13 | 1113.248 | 1266.476 | 1744.011 | S31 |
| 963.22098 | 1090.754 | 1482.132 | S14 | 1052.006 | 1195.236 | 1637.238 | S32 |
| 894.745 | 1010.794 | 1362.275 | S15 | 980.976 | 1112.632 | 1513.420 | S33 |
| 831.843 | 937.197 | 1251.934 | S16 | 2544.992 | 2937.313 | 4192.327 | S34 |
| 713.248 | 798.713 | 1044.107 | S17 | 2219.900 | 2471.300 | 3751.700 | S35 |
| 679.869 | 759.291 | 984.962 | S18 | 1922.220 | 2129.996 | 3199.299 | S36 |

Figure 8: $\tau$-LG training structure.

Figure 9: Training structure detection flowchart.
of detecting, classifying, and locating the fault is 0.33 seconds.

3. Conclusion

In this paper, a new FDCL approach has been presented for DNs containing DGs. The techniques to detect and classify short circuit faults in active power distribution networks using the maximum value of approximation coefficient are extracted from DWT based on the MRA decomposition technique for the current and zero sequence current component at one terminal (substation). The combination between DWT and SVM is proposed for fault location. To show the accuracy and efficacy of the proposed algorithms, simulation results have been presented for a radial DN with several laterals (IEEE 33 bus) and two DGs with a 60% level of penetration. The proposed method was able to accurately detect and classify all types of faults, which were investigated. The DWT-SVM proposed scheme was demonstrated to be very robust, yielding a 100 percent accuracy rate.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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