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Classification and Localization of Faults in AC Microgrids Through Discrete Wavelet Transform and Artificial Neural Networks

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ABSTRACT The widespread integration of renewable energy sources to the main electrical grids has led to the increased adoption of AC microgrids. However, the protection of AC microgrids is a challenging task due to inverter interfaces, bidirectional power flow, multiple modes of operation and the requirement for selective phase tripping. This paper presents an innovative artificial neural network (ANN) based approach for fast and accurate identification and localization of symmetrical and asymmetrical faults occurring in the distribution networks of AC microgrids. In the proposed methodology, the three phase and the neutral currents which are sampled at either ends of the distribution lines, undergo discrete wavelet transform to extract the features exhibited during faults in the network. These features are used by two neural networks for classification and localization of the fault. To achieve high accuracy and computational efficiency, the network architectures of the ANNs are optimized, and the extracted features contain the detailed information required for ANNs to clearly distinguish different fault types and locations. A comprehensive evaluation and validation reveal that the proposed scheme accurately and efficiently classifies and localizes faults in AC microgrids. The existing research gap of fault localization in AC microgrids is also addressed through this approach.

INDEX TERMS AC microgrids, artificial neural network (ANN), discrete wavelet transform (DWT), fault classification, fault localization.

I. INTRODUCTION

THE integration of distributed energy resources (DERs), such as solar photovoltaic (PV) systems, wind turbines, and energy storage units, has transformed the traditional power grid into a more decentralized and dynamic entity. AC microgrids are an effective method used to integrate these DERs into the main grid. Microgrids offer several advantages, including increased reliability, improved power quality, and reduced carbon emissions [1], [2]. They can operate in both grid connected and in islanded modes of operation, allowing them to function autonomously during grid disturbances and contribute to the overall resilience of the power system.

However, the integration of diverse DERs and the complex nature of AC microgrid operations introduce new challenges, particularly in terms of detection and localization of the faults. Detection and localization of faults occurring in the distribution network are crucial tasks in any microgrid. Early detection and accurate localization of these faults are vital for minimizing downtime, preventing further damage, and facilitating prompt recovery, thereby improving the reliability of the microgrid.

Detection and localization of faults in AC microgrids is challenging due to the various modes of operation, bi-directional power flow, and presence of DERs with inverter interfaces. DERs such as solar panels and battery energy storage systems are connected to the microgrid through inverter interfaces. Since the current carrying capacity of these Inverter Interfaced Distributed Generators (IIDGs) is lower, the contribution by them to the fault current during islanded mode of operation is insignificant [3]. Conventional protection relays depend on large fault currents to detect faults in the distribution network. Due to the IIDGs, the fault currents are lower rendering the use of conventional relays ineffective in microgrids. Bidirectional power flow occurring in a microgrid can cause conventional protection strategies to function incorrectly [4]. Issues such as sympathetic tripping, protection blinding, variation in fault current, and coordination mismatch arise when such methods are used [4], [5], [6]. Furthermore, during a fault, the non-faulted phase or phases must continue to operate in a microgrid, to ensure that supply is not completely lost. Therefore, the faulted phase must be identified, and selective phase tripping must be done so that only the faulty phases are isolated during an unbalanced fault. This is essential to prevent the complete shutdown of an islanded microgrid and it is not a task achievable with conventional protection methods [7]. The accurate localization of the fault reduces the time for restoration of the supply during a fault and this feature is especially useful if the distribution network is underground.

The analysis of the literature related to this research area revealed that methods used for fault detection in AC microgrids can be broadly categorized into two types as model-based and data-driven approaches. The evaluation method of the model-based approach is to confirm that the evaluated variables are coherent with the model. The foundation of data-driven approaches is the analysis of system data or finding the relationship between input and output state variables. Data-driven fault methods are capable of finding abnormalities that may not be successfully detected by a model-based methods due to their lack of comprehensive knowledge about the system.

In [8], the authors introduced a novel approach that combines wavelet singular entropy theory and fuzzy logic for efficient fault detection and classification in distribution lines, specifically in the presence of distributed generations. The method employed wavelet singular entropy theory to analyze voltage and current signals, extracting relevant features indicative of faults. Subsequently, fuzzy logic was applied to classify faults based on these features. In the paper by A. R. Haron et al. [9], the authors proposed adaptive overcurrent protection settings for microgrids. This involved continuous monitoring and analysis of system conditions, adjusting protective device settings to adapt to changes in the microgrid's operation. The paper also suggested developing fault detection algorithms tailored for microgrids, considering parameters such as fault currents, voltage profiles, and power flow patterns. In [10], the authors recommended using different relays in microgrids for varied fault protection. Authors stressed the importance of coordinated protective devices, suggesting communication-based schemes for real-time information sharing. However, drawbacks include increased costs and reliance on communication channels. In [11], the authors proposed a multi-agent-based method for fault detection in power systems, relying on agent communication. Limitations include potential communication failures, resulting in an ineffective protection scheme, slower fault detection, and a lack of discussion on the impact of renewable energy penetration. In [12], the authors proposed an intelligent protection scheme for microgrids, combining wavelet analysis and decision trees. Wavelet transform decomposed signals to identify abnormal patterns associated with faults, and decision trees classified the system conditions. In [13], the authors suggested a differential protection scheme for microgrids using Hilbert space-based power setting and fuzzy decision processes. Hilbert space theory optimized the power settings in multidimensional space, enhancing sensitivity, and fuzzy logic handled imprecise information in decision-making. In [14], the authors focused on fault detection and location in the low voltage DC bus of a DC microgrid using artificial neural networks (ANNs). The solution involves training two ANNs with historical fault data to learn fault patterns and locations. In [15], the authors proposed a fault classification method for microgrids using wavelet transform and machine learning. Features from faulty signals were extracted using wavelet and wavelet packet transforms, and they were fed to an ANN, a neuro fuzzy (NF) and a wavelet neural network (WNN). The paper [16] introduced a deep learning-based approach for fault classification in a simulated microgrid using wavelet transform and multi-resolution analysis. Long short-term memory (LSTM) and convolutional neural networks (CNN) were employed, with LSTM exhibiting higher accuracy using only half the data of the CNN. In [27], the authors proposed a fault diagnosis method for microgrids based on restricted Boltzmann machine (RBM) within multiple layers of an ANN. The effectiveness of the model was studied under varying inputs, sampling frequencies and added noise. The paper [28] introduced a fault classification method for microgrids based on CNNs. In this approach, current and voltage signal images were converted to scalograms using wavelet transform, and they were used as inputs to the CNN.

Thorough analysis of the literature revealed the shortcomings of the existing schemes for fault classification and localization in AC microgrids. The lack of versatility of the existing schemes hinders them from being used for microgrids with different architectures and this also limits the performance when the operating conditions of the microgrid changes. Conventional, analytical methods used for protection of the microgrids are slower to generate an output, and they require advanced hardware to process the complex algorithms. Some protection schemes rely on communication between devices which could lead to problems during the operation. It was also revealed that the localization of the faults in AC microgrids is not discussed in existing literature. In an effort to bridge the existing research gap, innovative approach combining discrete wavelet transform (DWT), wavelet energy entropy (WEE), and ANNs to achieve accurate and efficient fault analysis is proposed in this paper. Compared to transmission lines, the protection of AC microgrids is significantly different due to use of IIDGs, bi-directional power flow and different modes of operation [6], [20], [28]. Therefore, the already existing work using DWT and ANN for transmission line protection cannot be directly applied to the protection of AC microgrids. A comprehensive analysis and testing were done prior to adapting these techniques for fault classification and localization in AC microgrids. Furthermore, compared to deep learning models such as CNNs, the use of ANNs for a protection scheme is more suitable due to the significantly lower computational power, and faster fault classification and localization ability.

The rest of the paper is structured as follows: Section II describes the proposed approach for accurate and fast fault classification and localization in AC microgrids. Section III provides the details about the simulated AC microgrid used in this research for generating current waveforms. A description on DWT and the techniques used for extracting the required input features from the current waveforms are described in Section IV. The ANN models used for fault classification and localization is explained in Section V of this paper. Section VI discusses the performance and results of the models used for fault classification and localization. The validation of the models using an alternative software and the results are described in Section VII. Finally, Section VIII gives the conclusion and possible future works for this research.

II. PROPOSED FAULT CLASSIFICATION AND LOCALIZATION SCHEME

The proposed protection scheme combines DWT, WEE, and ANNs to achieve accurate and efficient fault analysis. The conceptual framework of the proposed protection scheme is shown in Fig. 1. To gather the necessary data, current measuring devices (CMDs) are installed at either ends of the distribution lines to sample the currents flowing through the three phase conductors and the neutral conductor. These four current waveforms are then subjected to DWT, which enables the extraction of suitable time and frequency information from the fault current waveforms. To accomplish this task, two separate DWT models are developed for fault classification and fault localization. The DWT model for fault classification extracts the four maximum and four minimum detailed coefficients of the fault currents in the three phases and the neutral. These coefficients are taken after the fourth decomposition level. The DWT model for fault localization extracts the maximum horizontal scale and the WEE of the horizontal component of the zero-sequence current at either end of the distribution line. These values are obtained after second decomposition level.The extracted features are given as inputs to the neural networks for fault classification and localization tasks. A classification type ANN is used for the fault classification function, and it gives the fault type and faulted phase or phases as the output. A regression type ANN is used for the fault localization function and the output of fault classification ANN is also given as an input to the fault localization ANN. Information about the specific location of the fault is developed by the fault localization ANN.

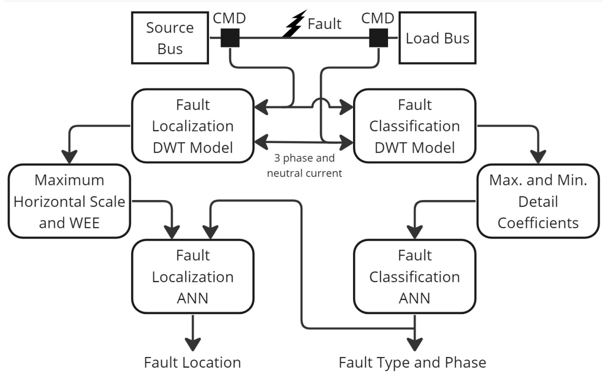

FIGURE 1. Flowchart of the proposed fault classification and localization scheme.

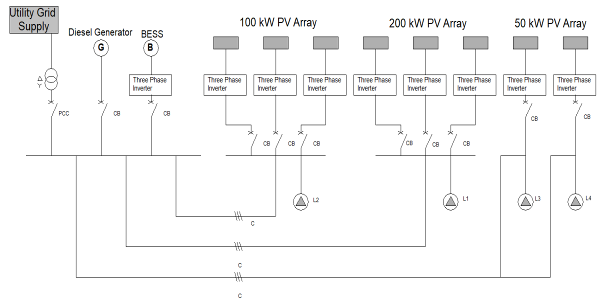

FIGURE 2. Single line diagram of the AC microgrid model.

III. THE AC MICROGRID

The AC microgrid system used in this paper is the microgrid at University of Moratuwa, Sri Lanka and this is the first intelligent protection system developed for this microgrid. This AC microgrid operates at a nominal voltage of 400 V and a frequency of 50 Hz. The simplified single line diagram of the microgrid is illustrated in Fig. 2, and it can function in either grid-connected or islanded modes, with mode control facilitated by the switch at the Point of Common Coupling (PCC). Comprising three types of DERs—specifically, three PV arrays of varying capacities, a Battery Energy Storage System (BESS), and a synchronous diesel generator—the microgrid features Circuit Breakers (CB) for each DER to disconnect them from the system. The PV arrays and BESS are linked to the distribution network through voltage source inverters. Within the microgrid, four loads L1 (200 kW, 50 kVAr), L2 (100 kW, 25 kVAr), L3 (24.4 kW, 6.1 kVAr) and L4 (25.6 kW, 6.4 kVAr) are present. Three distribution lines with lengths of 313 m, 160 m, and 160 m respectively constitute the microgrid infrastructure. To gather the necessary current signals for neural network data generation, CMDs are strategically placed at both ends of each distribution line.

The study involves simulating the same microgrid using MATLAB/Simulink software. The simulation is used to generate data for training and testing of the two ANNs. The data used for training of the two ANNs encapsulate data obtained during both islanded and grid connected modes of operation of the microgrid. Furthermore, changing levels of irradiance for solar PV, varying generation combinations, varying fault distances, and varying loads are also considered when generating the data for training.

IV. DISCRETE WAVELET TRANSFORM (DWT) AND FEATURE EXTRACTION

The DWT is a highly effective method in digital signal processing for decomposing time-series signals into orthogonal components. It has significant utility in fault analysis and detection, as it allows for the identification of concealed time-frequency characteristics within fault currents. In the proposed fault detection scheme, the DWT assumes a critical role in pre-processing the input data before utilizing it in ANNs for subsequent analysis. Utilizing a feature extraction method such as DWT, instead of using current signals directly to classify and localize faults provides several advantages which can be outlined as follows. A major benefit of DWT is multi-resolution analysis capability where high frequency transient details and low frequency trends can be extracted from current signals for improved accuracy [24]. Dimensionality reduction is another advantage where a large time series data such as a current signal can be represented in a compact manner. This reduces the computational burden and allows for rapid classification and localization of the fault [24], [25]. Features taken from DWT is capable of capturing the specific fault dynamics information compared to raw current signals. This characteristic is vital for better generalization of the ANN models. Furthermore, the use of DWT allows denoising of current signals by focusing on the signal components at various levels [26].

An advantageous aspect of the DWT lies in its efficacy in analyzing transient phenomena, which commonly occur during fault conditions. Transients contain crucial information regarding the fault type and location, and the DWT excels at capturing and representing these transient components. Consequently, it is a suitable tool for tasks such as fault classification and localization. In addition to its analytical capabilities, the DWT offers practical benefits for fault analysis. It provides fast and reliable fault analysis capabilities, enabling efficient processing of extensive datasets. Moreover, the implementation of the DWT is relatively straightforward, and it demands less computational time and resources compared to alternative wavelet transform techniques, such as the continuous wavelet transform. Utilizing the DWT as a pre-processing step in fault detection schemes, allows the input data to be effectively prepared for subsequent analysis using ANNs. The capability of DWT to analyze transients and its practical advantages make it a valuable tool in fault analysis applications, offering insights into fault classification and localization while ensuring efficient and reliable fault analysis.

Wavelets are mathematical functions characterized by having a mean value of zero over time. The wavelet function $\varphi_{a,b}(t)$ can be derived from a mother wavelet $\varphi(t)$ through scaling and shifting operations [20].

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\varphi(\frac{t-b}{a}) \tag{1}$$

The scaling parameter a and the shifting parameter b determine the size and position of the wavelet, respectively.

The DWT of a signal $s(t)$ can be derived as shown in (2) [20],

$$d_{j,k} = \int_{-\infty}^{\infty} s(t)\varphi^*_{a,b}(t)\,dt =< s(t), \varphi_{a,b}(t) > \tag{2}$$

where, $d_{j,k}$ is the wavelet detail coefficient at a specific decomposition level j and location k, and $\varphi^*_{a,b}(t)$ is the complex conjugate of $\varphi_{a,b}(t)$. This coefficient represents the contribution of the signal at a decomposition level j and location k, providing a detailed representation of the time-frequency components of the signal.

In practical applications, finding analytical solutions for most signals can be challenging. However, a technique that provides a solution by decomposing the signal into a multi-resolution representation is introduced in [23]. This approach, widely accepted as a standard method for calculating the DWT, overcomes the analytical complexities. The multi-resolution decomposition, described by (3), involves computing approximation coefficients, denoted as $a_{M,k}$. These coefficients capture the low-frequency components of the signal, while the detail coefficients represent the high-frequency components. By applying this transformation, the original signal $s(t)$ is decomposed into an approximation coefficient, A_M and a series of detail coefficients, $D_j(t)$, at level M. This decomposition enables a comprehensive analysis of the signal's frequency content at different resolutions [20].

$$\begin{aligned} s(t) &= \sum_k a_{M,k}\frac{1}{\sqrt{2^M}}\varphi(\frac{t}{2^M}-k) \\ &\quad + \sum_j^M \sum_k a_{M,k}\frac{1}{\sqrt{2^j}}\varphi(\frac{t}{2^j}-k)A_M(t) + \sum_j D_j(t) \end{aligned} \tag{3}$$

A. MOTHER WAVELET AND DECOMPOSITION LEVEL

The selection of mother wavelets and decomposition levels is crucial in the DWT for fault detection and feature extraction. Previous research has explored various wavelet families, including coif, db, dmey, haar, bior, and sym, to leverage their unique time-frequency characteristics [18]. However, exhaustively testing all possible combinations of wavelets is impractical. Therefore, the choice of mother wavelets should be based on the specific properties of the data being analyzed. The db and sym families are generally preferred due to their robustness across different data properties, making them reliable choices regardless of the length and number of samples [20]. Conversely, wavelets with longer filter lengths may limit the achievable levels of decomposition and impair feature extraction capability. Thus, when selecting mother wavelets, it is crucial to consider their filter lengths and compatibility with the desired decomposition levels.

Decomposition level is another critical parameter that significantly affects the performance. It determines the level of detail captured in the signal decomposition and subsequent feature extraction. A higher decomposition level provides a more comprehensive description of the input signal, but it increases computational complexity. The maximum decomposition level is determined by the size of the input signal and the filter size of the chosen mother wavelet.

By carefully choosing suitable mother wavelets and decomposition levels, the input signal can be effectively decomposed into approximation and detail coefficients. This decomposition enables a thorough analysis of the signal's frequency content at different resolutions, facilitating fault detection and feature extraction tasks. Strategic choices based on wavelet properties and consideration of the input signal's characteristics enhance the effectiveness of the DWT in revealing time-frequency domain characteristics and improving fault detection capabilities

B. FEATURE EXTRACTION

1) FAULT CLASSIFICATION MODEL

In the fault classification phase, the DWT-based approach involves decomposing the signal into different frequency bands using the DWT. The DWT effectively captures both high and low-frequency components of the signal, allowing for better fault detection. The resulting wavelet coefficients are then utilized as input features for a neural network. This approach has demonstrated its ability to accurately and efficiently detect faults in AC microgrids, while also significantly reducing the volume of input data required for the neural network, thereby enhancing computational efficiency [5].

To implement this approach, the three-phase and neutral current signals are taken as inputs and subjected to the DWT for feature extraction. MATLAB/Simulink model of the microgrid is used to simulate different faults at different distances in the microgrid. In this particular study, a One-Dimensional DWT with the Daubechies family and a DB4 filter is employed. The signals are decomposed at a resolution level of 4 to analyze faults occurring in distribution lines.

To generate faulty waveforms for analysis, the distance parameter is modified incrementally. This allows for the simulation of various fault scenarios at different distances within the microgrid. For each fault scenario, the maximum and minimum detail coefficients of the line current at level 4 are extracted as features. These coefficients provide valuable information about the fault characteristics and contribute to distinguishing different fault types, such as single-phase to ground fault, double-phase fault, double-phase to ground fault, three-phase fault, and three-phase to ground fault.

The faults are applied by varying the distance to the fault and operating conditions of the AC microgrid. By considering both sides of the distribution line, a total of 8 coefficients are obtained for each fault scenario. These coefficients consist of 4 maximum and 4 minimum coefficients for each of the three phases and the ground. This comprehensive set of coefficients serves as the input data for an ANN, which performs fault classification tasks with high accuracy. To ensure robust training and testing of the neural network, a sufficient amount of data is necessary. Therefore, 1000 data points are generated for each fault scenario, providing a substantial data set for analysis.

2) FAULT LOCALIZATION MODEL

The proposed methodology centers around the analysis of the zero-sequence current acquired from recorded data subsequent to a fault incident at the starting and ending points of a distribution line. The initial phase of the approach entails the utilization of the Fortescue transform on the three-phase current obtained through simulation. This transformative process facilitates the extraction of the zero-sequence current at both terminals of the distribution line, forming a fundamental basis for further analysis.

To capture specific fault characteristics, the wavelet transform is applied to the zero-sequence current at both terminals, resulting in the generation of four components (approximate, horizontal, vertical, and diagonal) for each level of signal decomposition. The primary focus of the current research is on analyzing the horizontal components at the second level of signal decomposition. Following that, the maximum scales of the horizontal components are extracted from both ends of the transmission line. The energy stored in each horizontal component is then calculated, resulting in the acquisition of four input data points for the ANN. These data points comprise two energy values stored in the horizontal components and two maximum scales of the horizontal component on each side of the line. The selection of training data is crucial as it should intelligently capture changes in resistance, angle, and fault type. This ensures that the neural network can effectively recognize and distinguish these variations, preventing any issues during operation.

The Fortescue method is a valuable technique employed to analyze asymmetric faults in transmission lines, encompassing scenarios such as short-circuits, line impedance, equivalent impedance of lines with ground, or conductor interruptions. This method showcases the ability to divide any unbalanced n-phase system into n-balanced phase systems. Specifically, in the case of unbalanced three-phase systems, the Fortescue method provides insights into three distinct components: the positive sequence component system, the negative sequence component system, and the zero-sequence component system. By utilizing the Fortescue method and examining these individual components, a comprehensive understanding of the characteristics and behavior of unbalanced three-phase systems can be attained, enabling effective fault analysis and identification in distribution lines.

To extract the fault characteristics with minimal training data and optimal accuracy, the transformation of three-phase current into zero-sequence current can be employed. This method allows for efficient processing of current data with reduced complexity. This approach aims to further reduce the amount of data needed by focusing solely on the zero-sequence current at both sides of the line. The zero-sequence current for an ABCG fault is shown in Fig. 3.

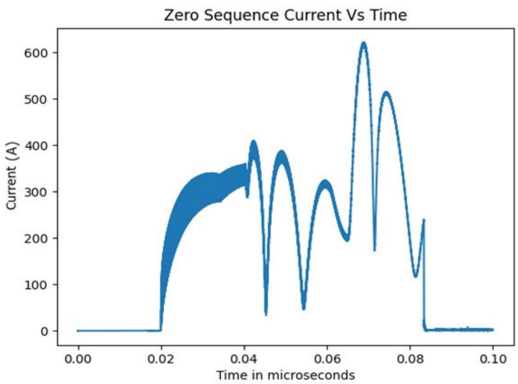

FIGURE 3. Zero-sequence current for an ABCG fault.

Fig. 4 shows the wave separation of the zero-sequence current signal at one corner of the distribution line through second level of decomposition using db4. This separation results in two components, approximate and detailed, at each decomposition level, with the latter including horizontal, vertical, and diagonal elements that relate to the high-frequency information of the signal. In this approach, the focus is on the horizontal component of the second level of decomposition (H2) as it provides essential information about the fault characteristics [22].

To extract meaningful features from these horizontal components for fault localization, WEE is employed to measure the stored energy within them. Additionally, previous studies have indicated that the maximum scale of the horizontal components exhibits variation depending on the specific fault type being examined. Therefore, two properties of the horizontal component of the zero-sequence current of the faulty waveform, namely the maximum scale of the horizontal component and the WEE are extracted.

The wavelet energy of the horizontal component of zero-sequence current at scale j and moment k is obtained using the (4) [22],

$$E_{j,k} = |H_j(k)|^2. \tag{4}$$

There are various methods for signal analysis, and one effective approach is to use entropy as an algorithm for signal decomposition. Entropy provides a measure of the amount of information contained within a signal. To perform this analysis, consider a signal on scale j, where $k = 1, 2, 3, \ldots,$ N (the number of moments or coefficients on the j scale), and L is the number of decomposition levels. The wavelet energy spectrum of the horizontal component on the j scale can be expressed as (5) [22].

$$E_j = \sum_{k=1}^{N} E_{jk}, \quad j = \overline{1, L} \tag{5}$$

Equation (6) represents the distribution of energy in the form of relative wavelet energy [21].

$$P_{jk} = \frac{E_{jk}}{E_j}, \quad j = \overline{1, L} \tag{6}$$

Equation (7) allows for the calculation of the WEE of the horizontal component of zero-sequence current [21].

$$WEE = -\sum kP_{jk0}.log(P_{jk0}), \quad j = \overline{1, L} \tag{7}$$

The maximum scale of the horizontal component and the wavelet energy entropy are extracted from both ends of the distribution line, resulting in a total of four features. These features are utilized as inputs for the ANN. A data set of 1000 data points was generated for each fault, and the faults are applied at varying distances and under different operating conditions of the AC microgrid.

V. ARTIFICIAL NEURAL NETWORK MODELS

A. ANN MODEL FOR FAULT CLASSIFICATION

The classification ANN Model is designed to classify different types of faults based on the inputs provided to it. The inputs for this model are derived from the fourth level of DWT decomposition, specifically the four maximum and four minimum detail coefficients obtained from this level. The model's objective is to accurately determine the type of fault, whether it is symmetrical or asymmetrical, based on the given inputs. There are 11 fault types that fall into categories such as LL (line-to-line), LLG (line-to-line with ground), LG (line-to-ground), LLL (three-phase), LLLG (three-phase with ground), as well as a no-fault condition. These fault types represent various fault scenarios that can occur in the microgrid.

The architecture of the fault classification ANN consists of eight input nodes, corresponding to the four maximum and four minimum detail coefficients obtained from the fourth level of DWT. These coefficients capture important information about the fault characteristics. The model's output layer consists of twelve nodes, representing the different fault types and the no-fault condition. Each output node corresponds to a specific fault type, and the model determines the fault type by activating the appropriate output node.

During the training process, the ANN learns from a labeled data set where fault scenarios are simulated and the corresponding fault types are provided. The network adjusts the connection weights between the neurons using an optimization algorithm, such as back-propagation, to minimize the discrepancy between the predicted fault type and the actual fault type. This iterative training process allows the model to improve its accuracy over time. Once trained, the fault classification ANN can be deployed in real-time applications to classify faults based on the input coefficients obtained from the fourth level of DWT.

B. ANN MODEL FOR FAULT LOCALIZATION

The fault localization ANN model is specifically designed to determine the location of the fault in a distribution line.

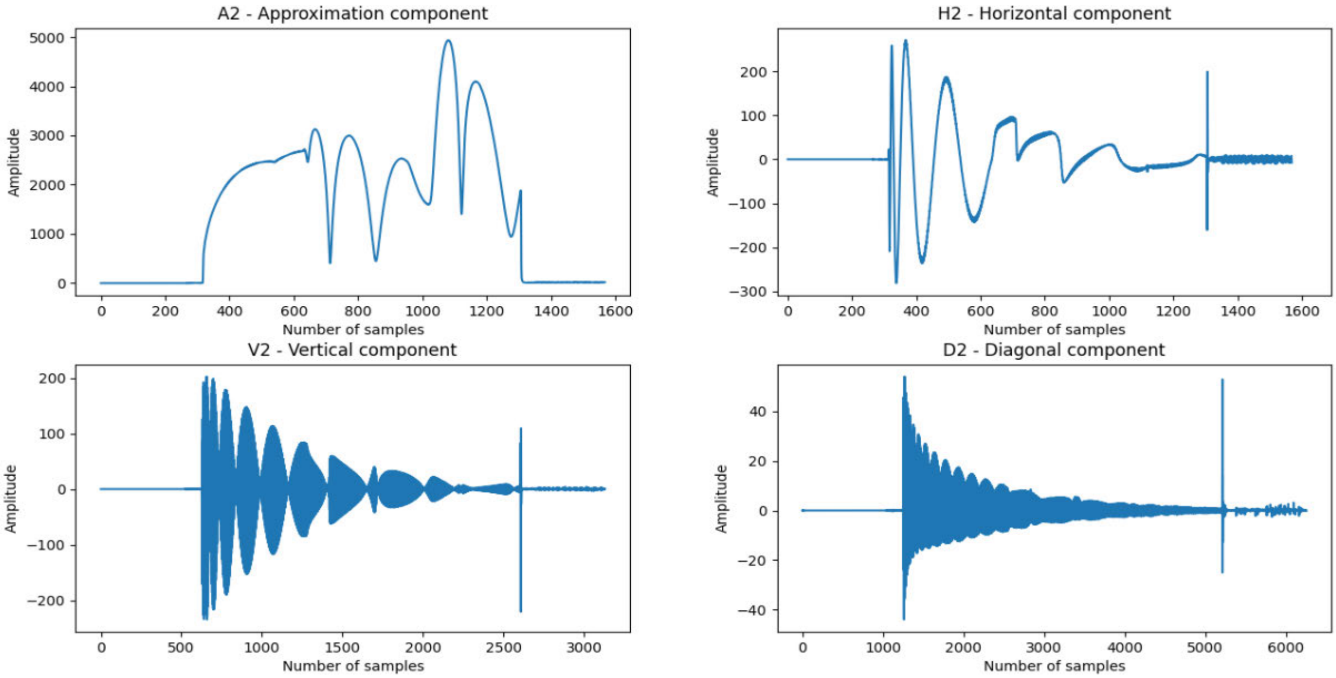

FIGURE 4. **Approximate (A2), horizontal (H2), vertical (V2), and diagonal (D2) components after second level decomposition.**

Unlike the fault classification model, this model utilizes a regression approach as the objective is to determine the distance to the fault on the distribution line of the microgrid. To train the neural network effectively, it is crucial to identify a set of fault properties that can accurately localize faults. In this case, two key characteristics are considered: the maximum horizontal component and the WEE of the horizontal component. These characteristics are derived from both sides of the distribution line after the second level of decomposition using the DWT. These properties provide valuable information about the fault location. In addition to the fault properties, the fault type obtained from the fault classification ANN model is also provided as an input to the localization ANN model. By incorporating the fault type information, the accuracy of fault localization can be further improved, as different fault types may exhibit distinct localization patterns.

This model consists of five input nodes, representing the five input features. These features include the maximum horizontal component, the WEE of the horizontal component, and the fault type obtained from the fault classification ANN model. These inputs serve as the basis for the regression model to predict the distance to the fault on the distribution line. The output layer of the fault localization ANN model consists of a single node, representing the predicted distance to the fault. The neural network is trained using a data set that includes labeled examples with known fault properties and corresponding fault distances. The network adjusts the connection weights during training to minimize the error between the predicted fault distance and the actual fault distance, optimizing the model's ability to accurately localize faults. Once trained, the fault localization ANN model can be utilized in real-time fault localization applications. By providing the required input features, the model predicts the distance to the fault on the distribution line. This information is crucial for efficient fault management and enables prompt actions to be taken to restore the system's normal operation.

VI. RESULTS AND PERFORMANCE

A. RESULTS OF FAULT CLASSIFICATION MODEL

The fault classification ANN model demonstrated exceptional performance, achieving a remarkable training accuracy of 99.83% and a validation accuracy of 99.39%. The training accuracy of 99.83% suggests that the model achieved near-perfect classification results on the training data set. It accurately identified the fault types with only a marginal error rate. Similarly, the validation accuracy of 99.39% indicates that the model performed exceptionally well on unseen data, demonstrating its robustness and ability to generalize effectively. Training and validation accuracy graphs are shown in Fig. 5. This ANN model has a training loss of 0.0004 and a validation loss of 0.0212.

The confusion matrix was also examined to evaluate the model's performance in classifying fault types. The confusion matrix provides a detailed breakdown of the model's predictions compared to the actual fault types. In the confusion matrix, the events which were correctly classified are represented in the diagonal cells, whereas the erroneously classified events are indicated in the off-diagonal cells. The confusion matrix obtained for the classification ANN is shown in Fig. 6. In Fig. 6, A, B, and C represents the three

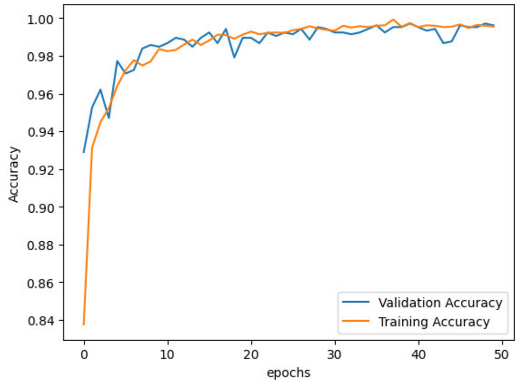

FIGURE 5. **Training and validation accuracy graphs for classification ANN model.**

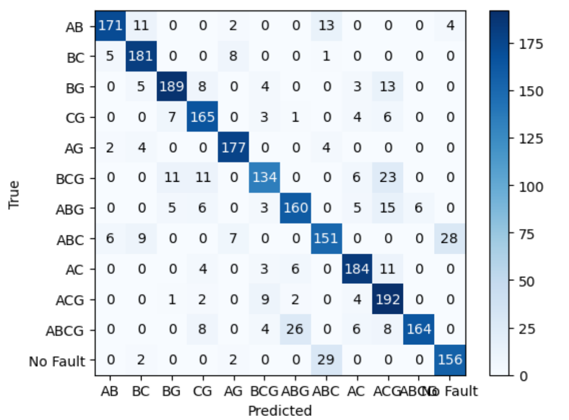

FIGURE 6. **Confusion matrix for fault classification ANN model.**

phases while G represents the ground. As evident from the confusion matrix, the classification ANN model was able to determine the type of the fault with high accuracy when tested with previously unseen inputs.

The proposed scheme for fault classification is capable of generating the fault type information within a very short time duration as well. The average total time for providing the fault type information since receiving the faulty current signals from the current sensing devices is less than 72.5 ms. The total time comprises of a feature extraction time of less than 0.8 μs and 72 ms of classification process time in the fault classification ANN. Lower computational time for the proposed fault classification model makes it suitable for real-time applications.

B. RESULTS OF FAULT LOCALIZATION MODEL

The fault localization ANN model achieved notable performance, as evidenced by various evaluation metrics. The Mean Absolute Error (MAE) value of 0.2122 indicates the average absolute difference between the predicted fault distances and the actual fault distances on the distribution line. A lower MAE signifies better accuracy in estimating fault distances. The Mean Squared Error (MSE) value of 0.1413 represents the average of the squared differences between the predicted and actual fault distances. The MSE considers both large

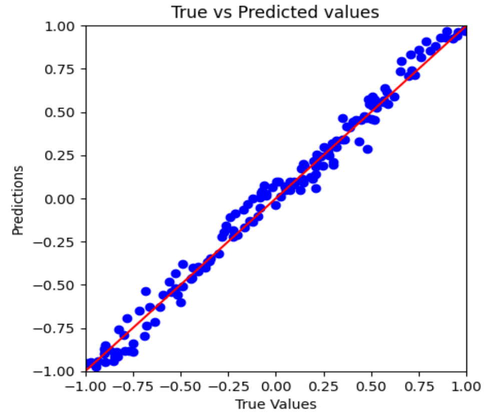

FIGURE 7. **Predicted vs. true value graph of fault localization ANN model.**

and small errors, with a lower value indicating a better fit of the model to the data. The Root Mean Squared Error (RMSE) value of 0.3759 is the square root of the MSE and provides an estimate of the average magnitude of the errors. A smaller RMSE value indicates better precision in predicting fault distances. The R2 score of 0.8660 measures the proportion of variance in the fault distances that can be explained by the fault localization ANN model. A higher R2 score suggests that the model accounts for a significant portion of the variability in the fault distances. The adjusted R2 score of 0.8650 adjusts the R2 score based on the number of predictors in the model. It takes into account the complexity and potential overfitting of the model. A higher Adjusted R2 score indicates a better balance between model performance and complexity.

This ANN model has a training loss of 0.07 and a validation loss of 0.05. Low training loss suggests that the model successfully minimized the errors between the predicted fault distances and the actual fault distances during the training process. Moreover, a low validation loss implies that the model demonstrated good generalization ability by accurately predicting fault distances for unseen data. The predicted versus true value graph for the fault localization ANN model is shown in Fig. 7. The close alignment of the data points to the perfect prediction line demonstrates the ANN model's ability to make accurate predictions, as the predicted fault distances closely match the actual values. This suggests that the model has successfully learned and captured the underlying patterns and relationships in the input features, enabling it to make reliable predictions for fault localization.

The proposed scheme for fault localization is capable of generating the fault location information within a very short time duration as well. The average total time for providing the fault type information since receiving the faulty current signals from the current sensing devices is less than 80.5 ms. The total time comprises of a feature extraction time of less than 0.6 μs and 80 ms of localization process time in the fault localization ANN. Fast localization of the fault location using the proposed scheme allows for prompt recovery of faults and to minimize downtime of the microgrid.

VII. VALIDATION OF RESULTS

In order to validate the simulation results and assess the performance of the ANN models for fault classification and localization, an alternative software, PSCAD/EMTDC software was utilized. The same microgrid described in Section III was simulated within PSCAD, replicating the operational conditions and various fault scenarios. The validation using PSCAD software was done for varying irradiance levels, varying loads, varying combination of sources, and for both islanded and grid connected modes of operation of the AC microgrid. Fault waveforms were generated within this simulated environment, closely resembling real-world fault conditions.

Once the fault waveforms were obtained from the PSCAD simulation, the features of these waveforms were extracted using DWT algorithms. These features served as inputs to the neural network models for classification and localization tasks. The neural network models were then tested using these features to predict the fault types and fault locations. By comparing the predicted results from the neural network models with the actual fault types and locations obtained from the PSCAD simulations, the accuracy and effectiveness of the proposed classification and localization models were evaluated.

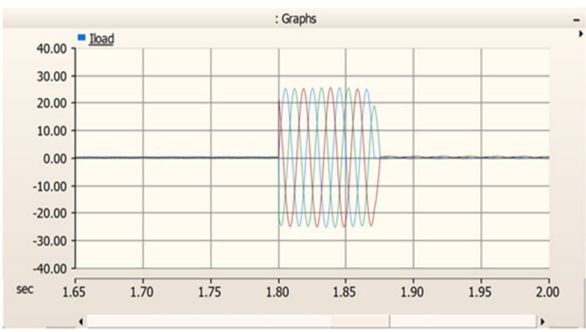

FIGURE 8. ABC fault waveform obtained using PSCAD software.

Validation process for both classification and localization models performed for an ABC fault is described subsequently. The waveform obtained using PSCAD for validation of the ABC fault applied at a distance of 0.0025 km is shown in Fig. 8. The maximum and minimum DWT coefficients obtained using the PSCAD waveform for an ABC fault is shown in Table 1, while an image of the output generated by the fault classification ANN model is shown in Fig. 9. As seen here, the classification model was able to determine the fault type accurately. The ABC fault was applied at a distance of 0.0025 km from one end of the distribution line, and maximum horizontal scale and WEE obtained from the corresponding waveform at both ends are shown in Table 2. In Table 2, Max(H2) represents the maximum horizontal scale after second level of decomposition. When these features were given as inputs to the fault localization ANN, the model was able to predict the distance to be 0.00235 km as shown in Fig. 10. The error of the prediction for this particular scenario was 6.38%.

TABLE 1. Maximum and minimum detailed coefficients values for the ABC fault.

	Phase A	Phase B	Phase C	Ground
Maximum coefficients	259.35	201.55	324.91	0.0368
Minimum coefficients	-214.62	-228.36	-153.75	-0.0398

```
[[ 2.593500e+02  2.015458e+02  3.249074e+02  3.678100e-02 -2.146220e+02
  -2.283580e+02 -1.537470e+02 -3.981000e-02]]
1/1 [==============================] - 0s 72ms/step
ABC
```

FIGURE 9. Result obtained from classification ANN for the ABC fault.

TABLE 2. Maximum horizontal scale and WEE for the ABC fault.

Terminal 1		Terminal 2	
Max($H2_1$)	WEE_1	Max($H2_2$)	WEE_2
20.0314	6.3995	35.0762	6.1849

```
1/1 [==============================] - 0s 80ms/step
Input Data: [[10.         20.03143685  6.39953782 35.07623568  6.18489698]]
Predicted Distance: 0.00235
```

FIGURE 10. Result obtained from localization ANN for the ABC fault.

Similarly, for the validation of the proposed fault classification model, 533 fault waveforms were generated using PSCAD. The features of these waveforms were extracted, and given as inputs to the classification ANN model. Out of the total faults generated, 511 faults were correctly predicted by the model. Table 3 presents the number of generated faulty waveforms for each fault type, the number of faults correctly predicted, and the prediction accuracy for each fault type.

TABLE 3. Validation results for prediction accuracy of fault classification model.

Fault	Number of faults generated	Number of faults correctly predicted	Prediction accuracy (%)
AB	50	47	94.00
BC	52	51	98.08
BG	45	41	91.11
CG	33	30	90.91
AG	43	39	90.70
BCG	40	38	95.00
ABG	45	42	93.33
ABC	40	36	90.00
AC	50	45	90.00
ACG	58	53	91.38
ABCG	55	50	90.91
No Fault	42	39	92.86

TABLE 4. Validation results for prediction accuracy of the fault localization model.

Fault type	Number of predictions considered	Mean of absolute error for predicted results (%)
AB	10	4.56
BC	10	5.32
BG	10	3.22
CG	10	6.45
AG	10	2.64
BCG	10	3.65
ABG	10	3.86
ABC	10	3.32
AC	10	5.67
ACG	10	4.87
ABCG	10	5.32

For validation of the fault localization model, ten faults for each fault type were applied at varying distances along the distribution lines of the AC microgrid under different loads, irradiance levels, and different modes of operation. The goal was to evaluate the performance of the localization ANN by calculating the mean value of absolute error for the predicted results. The faulty waveforms at varying distances were generated using PSCAD software and relevant features were extracted as inputs to the ANN. For each fault type, the mean value of absolute error was measured for the predicted results as a percentage. The fault types included AB, BC, BG, CG, AG, BCG, ABG, ABC, AC, ACG, and ABCG. By considering ten different distances for each fault type, a comprehensive assessment of the localization model's accuracy across a range of scenarios was performed. The summary of the results of the validation for localization model is shown in Table 4 and it can be seen that the mean error values range from 2.64% to 6.45% across different fault types.

VIII. CONCLUSION

A novel approach for fault classification and localization in AC microgrids using DWT and ANNs is presented in this paper. The input features required for the ANNs can be extracted from the three phase and ground current signals sampled at either end of the distribution line. The inputs to the fault classification ANN model include maximum and minimum detailed coefficients obtained through DWT of fault current waveforms. For fault localization ANN model, inputs consist of the maximum scale and WEE of the horizontal component, along with the fault type. The use of ANNs in the proposed scheme enables the accurate classification and localization of the faults unaffected by the mode of operation of the AC microgrid, loading and generating conditions, fault resistance and other events. The ANN model for fault classification shows a training accuracy of 99.89% and a validation accuracy of 99.39%. The ANN model for fault localization shows an adjusted R2 score of 0.8650 indicating a higher accuracy. In addition to the higher accuracy, the proposed scheme is capable of generating the outputs within a short duration allowing the fast isolation of faults and thereby minimize possible damages to the microgrid. Hence, this approach is suitable for real time application in AC microgrids. Furthermore, the proposed deep learning-based approach can minimize the risk of damage or outages, ultimately leading to cost savings and increased reliability of the AC microgrid. The generalization of the proposed scheme for other AC microgrid architectures is possible mainly due to the utilization of DWT and modular design of the ANNs. DWT of the three phase and neutral current signals capture the essential temporal features of a fault which are common for any AC microgrid and this is crucial for generalization. Furthermore, the ANN architecture is easily scalable by changing the number of layers or neurons based on the size and complexity of the AC microgrid.

In the future work related to this research, simulations and experimental setups that accurately represent high impedance faults, converter faults, and other variations in weather conditions will be developed to comprehensively assess the effectiveness of the proposed approach. Also, this approach will be expanded to include more complex microgrid architectures, and testing the approach in real-world scenarios with data from physical AC microgrids.

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