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Online Fault Detection and Classification of a Grid-Connected Microgrid System Based on Discrete Wavelet Transformation

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***Abstract*— The increasing integration of renewable energy sources and distributed energy resources in modern power systems has led to the emergence of microgrids as a viable solution for enhancing energy resilience and sustainability. However, the dynamic and decentralized nature of microgrids poses challenges in ensuring their reliable operation, which calls for developing efficient fault detection and identification methods. In this research, discrete wavelet transformation (DWT) presents a unique online fault detection and identification method for a grid-connected microgrid system. The focus of the research is mainly on the detection and identification of faults by collecting the detailed coefficients of various types of faults, such as line-line fault, line-to-ground fault, double line-to-ground fault, etc., with the help of multi-resolution analysis (MRA) in DWT at different parameters (type of fault, line length, fault resistance, ground resistance) with the ideal selection of the mother-based wavelet. To validate the effectiveness of the proposed methodology, an extensive simulation of the grid-integrated microgrid model consisting of a PV powerplant and Battery storage system has been carried out in the MATLAB/SIMULINK software. The simulation results illustrate the effectiveness and robustness of the suggested technique based on DWT in detecting and classifying various types of faults of a microgrid system with satisfactory results.**

Keywords*— *Discrete wavelet transformation (DWT), fault classification, fault detection, microgrid (MG), multiresolution analysis (MRA).

I. Introduction

The quest for more sustainable and efficient energy systems has captured the focus of researchers, leading to increased exploration of the concept of distributed microgrids (MG). Potential electrical challenges might arise in an MG due to several distributed energy resources (DERs), communication equipment, and fluctuating loads that constitute the MG. The MG can function both in grid-connected as well as islanded modes. The diverse qualities of microgrid components can impact safety, underscoring the imperative to prioritize safety measures before introducing technologies [1].

Various types of fault detection methods have been proposed by researchers for the protection of different power system networks. The detection, classification, and localization of faults in an MG system utilizing a long short-term memory (LSTM) network based on deep learning, demonstrates its superiority over many other techniques as discussed in [2], [3]. However, it can only be implemented in a time-based sequential network and it is more complicated than traditional recurrent neural networks (RNN). Md. Daisy *et. al* [4], identify faulty branches through a comparison between the actual fault voltage magnitude difference and the simulated faults; however, its precision decreases in the presence of faults with high resistances, leading to a reduction in the fault voltage difference. The phase difference between the positive-sequence fault element of the bus voltage and the positive-sequence fault elements of the currents in the feeders presented in [5], can only be used in grid-connected mode. DC line short circuit fault detection scheme was proposed based on RSFC as given in [6], which needs communication requirements for backup protection. A low-cost micro phasor presented by G. S. Dua *et. al* [7] is used as differential protection for a microgrid system based on the positive sequence current angle of the line. Phase angle, the magnitude of voltage and the voltage-based classifier's phase angle are used for the classification of fault in a PV microgrid system or any three-phase system [8]. The fault detection for the LVDC distribution system is based on mathematical morphology as suggested in [9], and [10]. A. Q.Khan *et. al* [11], present a unique hybrid approach that uses readings from phase measurement units (PMUs) for fault detection and the location of transmission lines in an interconnected network. The majority of these fault detection schemes either have communicational requirements, complexity in training, problems regarding noise, only based on time domain or inability to function efficiently during high impedance conditions.

Discrete wavelet transformation (DWT) is specialized in extracting features both in time and frequency [13], [14]. Wavelet transformation is most suited for the feature extraction and fault analysis of nonlinear transient signals of a network [15], [16]. DWT has become a prominent method for the

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detection and classification of faults in a power system network because of their high accuracy and simplicity of operation.

Considering the survey above, the contribution of this study can be summed up as:

1) A novel yet simple fault detection and identification technique of a grid-connected microgrid based on multiresolution analysis of DWT is proposed.

2) Employed a five-level decomposition using Daubechies (Db5) as the mother wavelet for feature extraction for the analysis of all types of three-phase faults (symmetrical & unsymmetrical) in a grid-connected microgrid system.

3) The effectiveness of the proposed algorithm is studied by varying certain parameters such as types of faults, line length, fault resistance and ground resistance.

4) The main characteristic of the proposed algorithm is its simplicity of operation, accuracy, sensitivity and reliability.

In accordance with the contribution mentioned above, the organization of this paper can be given as: Section II briefly describes the modelling of the microgrid and application of the proposed methodology. Section III gives the result and discussion of the fault analysis of the grid-connected microgrid systems. Finally, Section IV addresses the conclusion of the proposed work.

II. MODELLING OF MICROGRID AND METHODOLOGY

A. *Modelling of the microgrid system*

The power system consisting of a utility grid, PV plant, and the battery is simulated in the MATLAB Simulink software, and various fault conditions are introduced in the system to carry out the detection and identification of faults. The block diagram of the grid-integrated microgrid is given in Fig 1.

The system consists of 154MW,35.5kV, 50Hz Main grid and PV power plant as sources, a Battery energy storage system is incorporated to maintain a constant power supply, a 3.4/0.4kv step-down transformer, a transmission tine parameter network to set the desired length of transmission line, VI measurement to measure the current and voltages, Constant AC as well as DC load, a three-phase fault parameter to introduced different types of faults.

B. *Methodology: Wavelet transformation*

The wavelet transform is an efficient signal analysis tool that represents signals in the time-frequency domain, offering a unique capability to localize features in both time and frequency. This is particularly advantageous in applications of fault detection, where precise time and frequency information is crucial, wavelet transform excels by extracting transient details from nonstationary signals like fault currents. Its ability to provide a detailed time-frequency representation makes it a valuable tool for identifying faults in dynamic systems.[12][13][14].

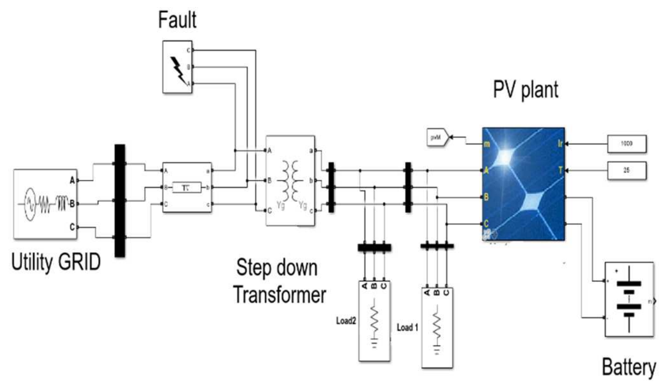

Fig.1 Block diagram of the grid-connected microgrid system.

1) Continuous Wavelet Transform: The Continuous Wavelet Transform (CWT) is a mathematical technique utilized for the analysis of signals across time and frequency domains. In contrast to the Discrete Wavelet Transform (DWT), it utilizes a continuous spectrum of wavelet scales, allowing for the investigation of signals at various frequencies and time scales.

2) Discrete wavelet Transformation: Discrete wavelet transformation is mostly preferred for the practical application of wavelet transformation because of its ability to decompose any time series signal into approximation and detailed coefficient using scaling function and mother wavelet respectively [13]. Discrete wavelet transformation can be represented as

$$\mathrm{DWT}(f,n) = \frac{1}{\sqrt{a_0}} \sum_{k=0}^{N-1} f(k)\varphi\left(\frac{n-ka_0}{a_0}\right) \tag{1}$$

where, n and k are integers, f, a_0, ka_0 are frequency, scaling and translational constant and $\varphi(n)$ is the mother wavelet.

The signals undergo decomposition as they pass through a high-pass filter and a low-pass filter producing the detail and approximate coefficient [15]. The process of decomposition is carried out in multi-resolution analysis until the desired detailed

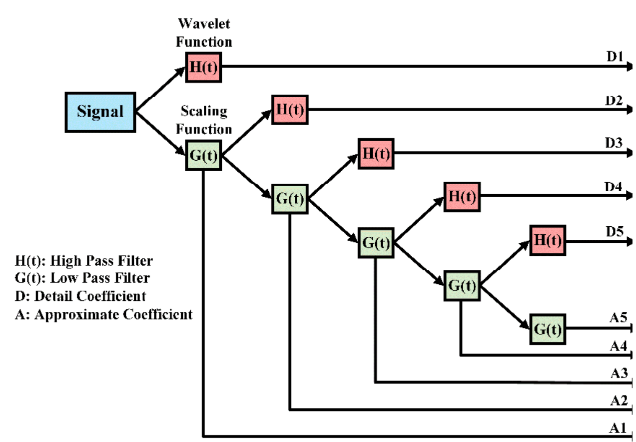

Fig 2: Five-level decomposition of multi-resolution analysis of DWT

TABLE I: FAULTS PARAMETERS WITH CONSIDERING CONSTRAINTS.

Types of Faults	Fault location	Fault resistance, R_f	Ground resistance, R_g	Frequency
LL, LLL, LLLG, LG, LLG, no fault	10km, 15km	0.001 Ω, 4 Ω	0.01Ω, 1 Ω	50Hz

coefficient is obtained. Fig 2 shows the 5-level decomposition of multi-resolution analysis (MRA) of DWT.

3) Data collection: The fault analysis of the system is carried out by running the system with various parameters given in Table I. To implement wavelet transformation, data for the three-phase currents (I_a, I_b, I_c) and ground current (I_g) are initially collected.

A detailed flowchart of the fault detection and classification using discrete wavelet transformation is shown in Fig 3.

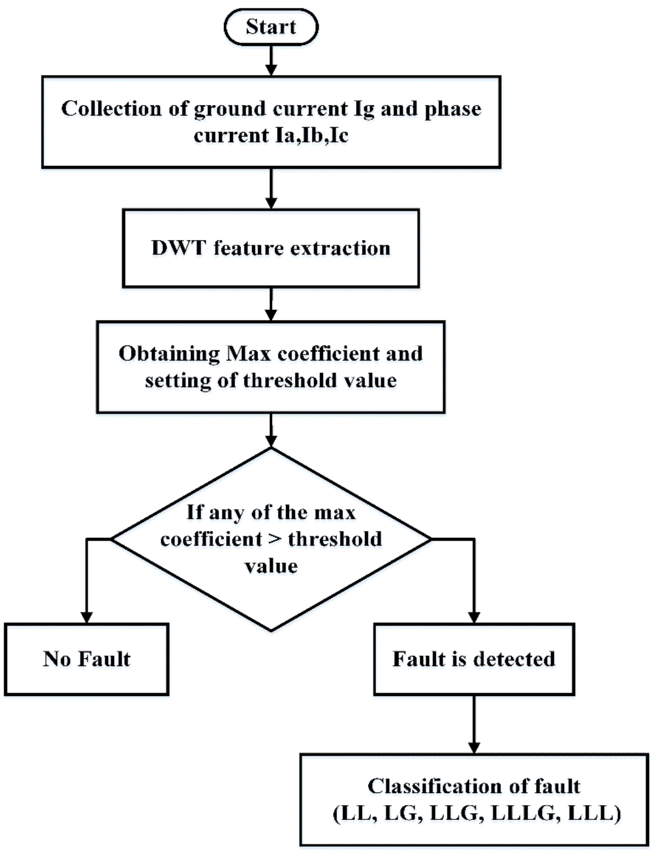

Fig 3: Flowchart of the proposed fault detection and classification technique

4) Feature Extraction: A five-level decomposition using Multi-Resolution Analysis for the Discrete Wavelet Transform (DWT) is performed, with db5 chosen as the mother wavelet. Detailed and approximate coefficients are collected from the multi-level decomposition, allowing the calculation of the maximum coefficient for each phase.

5) Detection and Classification of Faults: Comparing the maximum coefficient values of each phase under various fault conditions, a threshold value is determined. If the maximum coefficient value exceeds this threshold, the fault is detected. Conversely, if the maximum coefficient value is below the threshold, the system is considered to be operating under normal conditions.

In summary, the implementation involves collecting current data, performing a five-level DWT decomposition, calculating maximum coefficients for each phase, and comparing these values against a predetermined threshold to detect and identify faults or confirm normal system operation.

III. RESULT AND DISCUSSION:

For the fault analysis of the Microgrid system through wavelet transformation, twelve different types of fault case conditions are considered at two different locations and by varying the fault resistance and ground resistance. The max coefficient of each phase and ground current during each fault condition at two different locations obtained from the 5-level wavelet decomposition are given in Table II and Table III.

TABLE II: MAX COEFFICIENT OF ALL PHASES AND GROUND CURRENT AT FAULT LOCATION=10 KM, R_F=0.001Ω, R_G=0.01Ω

Type of fault	Max coefficient of I_A	Max coefficient of I_B	Max coefficient of I_C	Max coefficient of I_G
LLLG fault (ABCG)	331.0906	293.2174	456.1936	228.3255
LLL fault (ABC)	257.0019	257.0019	456.1936	**0.0078**
LL fault (AB)	258.0296	294.4383	**0.7683**	**0.0118**
LL fault (BC)	**1.3998**	312.2131	466.7824	**0.0016**
LL fault (AC)	156.6219	**1.8915**	217.1023	**0.0011**
LG fault (AG)	414.4931	**1.8915**	**1.8915**	407.6142
LG fault (BG)	**2.0781**	228.6775	**1.9875**	226.9005
LG fault (CG)	**3.7479**	**4.0071**	346.6666	344.5329
LLG fault (ABG)	220.4998	253.5786	**1.9917**	348.6715
LLG fault (BCG)	**2.9639**	311.5292	459.7038	238.0438
LLG fault (ACG)	244.6850	**3.7223**	364.0455	292.5052
No fault condition	**1.3998**	**1.8915**	**0.7683**	**1.7667e-11**

The maximum coefficient of all the phase currents and ground currents, at the fault location is 10km, R_f=0.001 Ω and R_g=0.01 Ω is given in Table II. It can be seen from all the fault case conditions considered in the table above that the maximum coefficient of the current during no fault condition is remarkably smaller (with the highest maximum coefficient of the healthy line recorded as 4.0071) than that of the maximum coefficient value of the phase with fault.

From Table III, it can be observed that during fault conditions the value of the max coefficient of the faulty phase is considerably larger than that of the phase with no fault. The highest value of the max coefficient of phase current under no fault is found to be 4.0071. It can be concluded from both

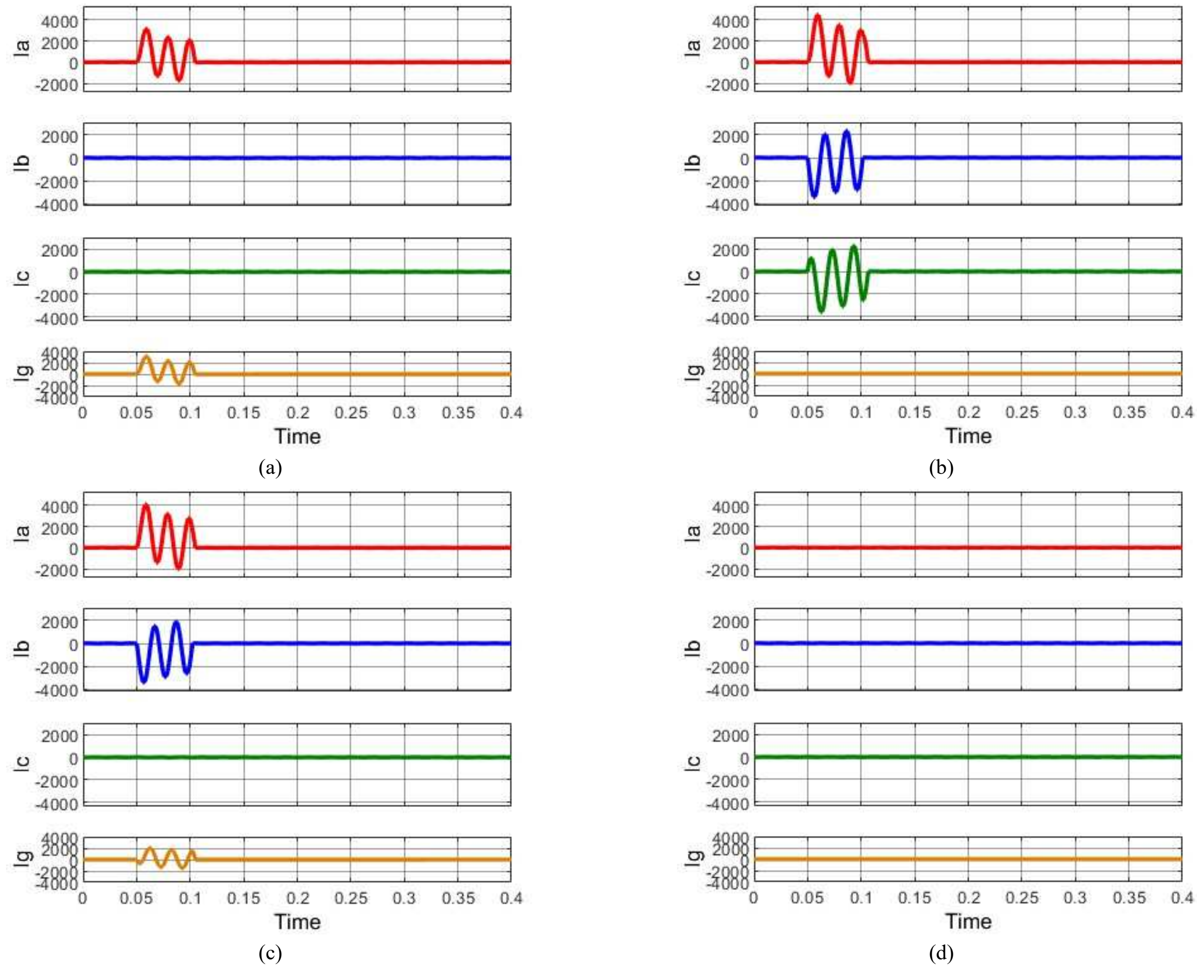

Fig. 5 Current waveform when a fault is applied from 0.05 to 0.1 sec during (a)AG fault (b)ABC fault (c)ABG fault (d) no fault condition.

TABLE III: MAX COEFFICIENT OF ALL PHASES AND GROUND CURRENT AT FAULT LOCATION=15 KM, R_f=4Ω, R_g=1Ω.

Type of fault	Max coefficient of I_A	Max coefficient of I_B	Max coefficient of I_C	Max coefficient of I_G
LLLG fault (ABCG)	412.9636	232.2204	392.9984	256.1650
LLL fault (ABC)	59.6944	232.2204	392.9984	**0.0119**
LL fault (AB)	218.8406	105.7227	**0.6970**	**0.0120**
LL fault (BC)	**1.4017**	242.3942	404.3273	**0.0068**
LL fault (AC)	136.8620	**1.7772**	184.7678	**0.0069**
LG fault (AG)	34.5555	**2.0688**	**2.0617**	32.9325
LG fault (BG)	**3.5333**	165.1459	**3.5892**	164.1666
LG fault (CG)	**2.9413**	**1.8156**	277.5770	276.2598
LLG fault (ABG)	128.9696	227.2795	**2.3721**	159.2801
LLG fault (BCG)	**2.1810**	237.1425	397.8139	97.0552
LLG fault (ACG)	396.2905	**2.4061**	298.6797	271.4048
No fault condition	**1.4017**	**1.7772**	**0.6970**	**3.1167e-12**

observations that fault can be distinguished by comparing the maximum coefficient value of all the phase currents to a common standard reference value. If the max coefficient value of any phase current exceeds 10, it indicates the presence of a fault in that phase. This simple threshold comparison allows for the straightforward identification of faults based on the magnitude of the maximum coefficient value.

From the current waveform given in Fig 5 (a), it can be seen that the magnitude of phase current Ia and ground current Ig drastically increases from 0.05 to 0.1 sec when the fault is introduced, which indicates the presence of a fault in I_a and I_g resulting in AG fault. Likewise in the case of Fig. 5(b) magnitude of I_a, I_b and I_c, increases drastically giving rise to ABC fault. In Fig. 5(c) huge rise in the magnitude of I_a, I_b and I_c can be seen, indicating the presence of ABG fault, while in Fig. 5(d), no sudden changes in the magnitude of current are observed, which indicates that there is no fault in any line. From Fig. 6 it can be observed that the phase current in I_a, and I_b, abruptly increases from 0.05 sec to 0.1 sec which informs the presence of a fault in lines A and B (i.e. AB fault). It can be concluded from the observation that the phase current of the

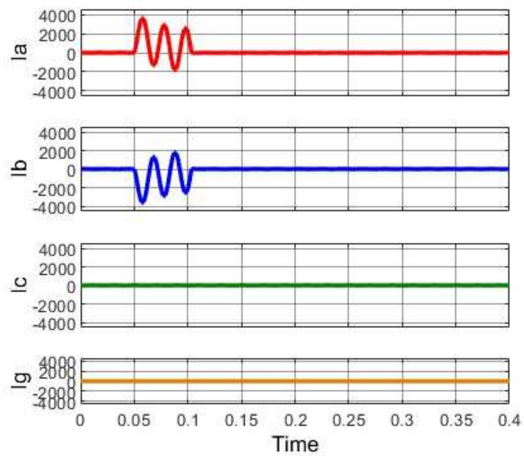

Fig. 6 Current waveform when a fault is applied from 0.05 to 0.1 sec during (e) AB fault

faulty line abruptly increases during fault conditions and under no-fault conditions there is not a sudden rise in current.

It can be observed from the comparative analysis of the proposed technique, that DWT is superior to the conventional ANN in classifying symmetrical and unsymmetrical fault, unlike the ANN which classifies only the symmetrical fault[17]. Also, DWT is not limited to the detection and classification of faults in a power system network with a short transmission line and low impedance network like that of the fuzzy logic [18] and voltage magnitude difference technique[4].

IV. Conclusion

This study emphasizes the utilization of Discrete wavelet transformation for real-time fault detection and classification in a grid-connected microgrid system. The multi-resource analysis decomposition of discrete wavelet transformation proves effective in differentiating the faulty and healthy lines under different fault conditions. Notably, the results demonstrate that the fault of the microgrid system can be analyzed effectively by distinguishing standard fault index values.

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