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WAVELETS AND ANN BASED FAULT LOCATION IN UNGROUNDED PHOTOVOLTAIC SYSTEM

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Abstract- Solar PV farm used for simulation studies involve of the large number of PV module connected to grid-connected inverter through ungrounded DC cables. Constructor report that about 1% of installed PV panel fails annually. Detecting phase to ground fault in ungrounded underground DC cables is also difficult and time-consuming .therefore Identifying ground faults is an important problem in ungrounded photovoltaic (PV) systems because such earth faults do not provide abundant fault currents for their detection and location during system working. If such ground faults are not cleared rapidly, a subsequent ground fault on the healthy phase will produce a complete short circuit in the system.

This paper presents a novel fault-location scheme in which high-frequency noise patterns are used to identify the fault location. The high-frequency noise is produced due to the switching transients of converters combined with the parasitic capacitance of PV panels and cables. A discrete wavelet transform is used for the decomposition of the monitored signal (midpoint voltage of the converters) and features are taken out. Feature extraction of the measured waveform at different frequency bands give feature information of voltage signal at different fault locations and are used as the feature vectors for pattern recognition. Then, backpropagation artificial neural networks classifier, which can automatically classify the fault locations according to the extracted features, is investigated. The proposed fault-location scheme has been primarily expanded for fault location in the PV farm (PV panels and dc cables). The method is assessing for ground faults as well as line-line faults. These faults are simulated with MATLAB and the data are then analyzed with wavelets. Finally, the value of the designed fault locator is tested with varying system parameters. The results illustrate that the proposed approach has accurate and robust performance even with noisy measurements and changes in operating conditions.

Key words- *Ungrounded Photovoltaic system (PV), discrete wavelet transform (DWT), Multi-resolution analysis (MRA), Artificial neural network (ANN)*

1. INTRODUCTION

The photovoltaic market has quickly grown in the last years over the world. One of the main reasons for this high growth in the PV industry is the relaxation of PV generation costs. On the other hand, some specific governmental policies have been encouraging the introduction of grid-connected PV systems in most developed countries. This important growth has not been accompanied by important development in the field of PV system diagnosis, supervision, and fault detection. Most PV systems, in use nowadays, are working in the absence of any supervisory mechanism, especially PV systems in output power levels below than 25 kWp. Maybe the reason has been that monitoring systems have only been implemented in big PV generators, where it compose a very few cost increment respect to the whole system cost, but without the help of a minimum monitoring system is not possible to expand any effective supervision, diagnostic or control of the PV system. Electrical diagnostic methods specifically use the electronic signature of faults. They continuously monitor the PV module performance until the arrival of a fault. The deformation of the resulting output provides information on the occurrence, location, and nature of the default. The first indication of module decay is provided by a decrease in its output power. After detection, microscopic analysis can be performed to understand the causes of the decay. Photovoltaic (PV) generation systems have made important progress and have gained popularity in the past few years as a prominent renewable energy source. The fault location approach at present employed in most industrial ungrounded PV systems uses a pulse generator to send a high frequency signal into the faulted system and traces the signal to locate the fault. This type of fault locating method for high impedance grounded and the ungrounded system is discussed in [1]. Locating ground faults in ungrounded systems is inherently troublesome as a result of such faults do not offer extended fault currents for tracing the fault location. Moreover, the locating method must be performed whereas the system stays operational, a salient feature of ungrounded power systems. Presently out there fault locating techniques [2]-

[5] are either time overwhelming or need giant amounts of dedicated hardware like sensors that increase value and complexness. A novel ground fault location approach was developed by the authors and conferred in [6]. It is supported the principle of pattern recognition of inherent high-frequency noise introduced by the repetitive shift events of power electronic (PE) converters interacting with system parasitic components (such as cable insulation capacitance and stray inductance). The planned approach applies to all or any ungrounded systems containing parasitic components to make a ringing circuit through the ground and that contains a mechanism to excite that ringing circuit. The initial study conferred in [6] demonstrates the effectiveness of the approach through a theoretical account of an appropriate system.

2. MODELING AND SIMULATION OF PV MODULES

A test system shown below in Figure 1 was modeled and simulated in MATLAB (2015). A multi-string ungrounded PV system was connected to the grid using 5 kW, three-phase, two-level voltage source inverter (VSI), which converts DC power generated from PV array into AC power. Each PV array has 4 parallel strings, and each string consists of 4 modules connected in series. The parameter of PV modules is shown in Appendix A. The VSI and DC-DC converters were controlled based on the sinusoidal pulse-width modulation (SPWM) technique. The harmonic filter connects the output terminals of the VSI to respective phases of the point of common coupling (PCC). Station service load of 100 kW and a 210 V, unity pf, the three-phase dynamic load was connected to the output of the inverter at PCC. The mid-point voltages (Vmid1 or Vmid2) of DC-DC converters to grounding were measured and analyzed using a signal processing method for the detection and location of the fault in the PV system. Ground faults at different locations are shown in Figure 1 to implement the proposed fault location method.

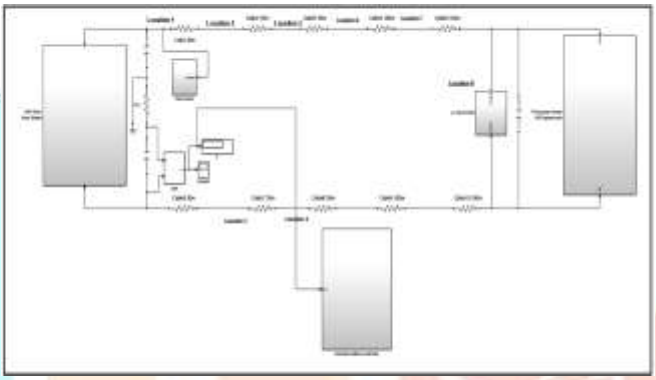


Fig 1: 5kW grid integrated multi-string converter type PV system

The ground and line-line cable fault location are shown in figure 1 and marked as loc. #1 to loc. #6. Here, the fault location 1 to 6 simulates ground fault on cable #1 to #10. Locations 7 to 9 are used to simulate the line-line fault in the DC and AC part of the PV system.

3. PROPOSED METHODOLOGY

Figure 2 shows the block diagram of the proposed approach in which solar PV module interconnected system design. Then after designing, different fault conditions were simulated using resistance inserted in the circuit. The output voltage, current, and power were measured at different and that measures parameters were transferred to an excel sheet for a generation of training data set. That training data set was utilized for training ANN for the classification of different PV system fault conditions.

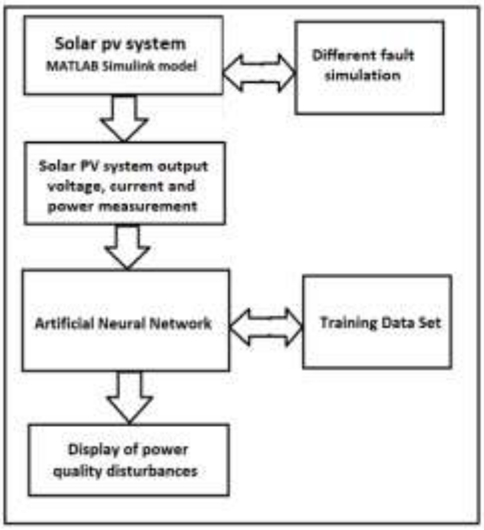


Fig 2: Block diagram of the proposed methodology

4. WAVELET TRANSFORM AND MULT RESOLUTION ANALYSIS

Consider the input signal f (t) that is discretized where integer variable n refers to the sample number of a discrete series. To obtain a discrete version of the WT, the scaling As an alternative to STFT (Short-Time Fourier Transform) and to overcome limitations related to its time-frequency analysis properties, a linear transform is introduced, defined as the wavelet transform (WT). The WT is a powerful mathematical tool that decomposes a given signal into different frequency components and then analyzes individual components with desired time and frequency resolutions. To achieve good time-frequency resolutions, it must have a varying window function whose size increase in time during analysis of the low-frequency content and decrease in time while dealing with the high frequency component of the signal. These requirements are fulfilled with the development of wavelet functions (t), so called as mother wavelet. Parameter (s) and translation parameter (u) are discretized with s= a^j and u =ku_0a^j Then, the DWT of the sampled input sequence, f (n), can be defined as

$$DWT_{\varphi}^{f}(\text{j, k}) = 1/\sqrt{a^j}\sum_{n=-\infty}^{\infty} f(n)\varphi\left(\frac{n-ku_0a^j}{a^j}\right)$$

Where, k, j, a, and $u_0$are integer numberswitha > 1 and $u_0 \neq 0$. The MRA introduced by Stephane G. Mallet [7] is a signal decomposition procedure that divides the signal into a set of frequency bands using a series of low-pass and high-pass filters. The time domain signal f (t) can be represented in terms of scaling, f^3 (t), and wavelet, $f\mu$ (t), functions as given below:

$$\text{f (t)}=\sum_{k=-\infty}^{\infty} a_N(k)\emptyset_{N,K}(t) + \sum_{j=1}^{N}\sum_{k=-\infty}^{\infty} d_j(k)\varphi_{j,t}(t)$$

Where$d_j$the detail coefficient at various resolutions is levels and a_N is the last approximation coefficient at level N.

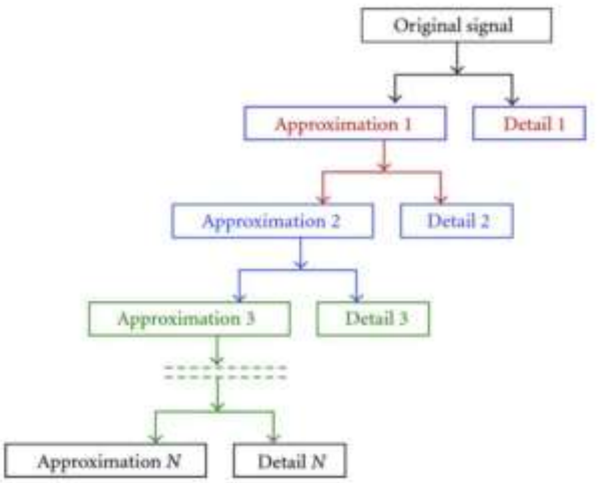


Fig 3: Multi-resolution analysis using DWT

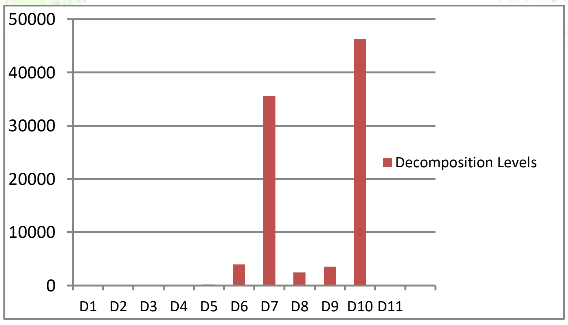


Fig 4: Energy spectrum of Vmid1 for ground fault at Loc6# with DB10 Mother Wavelet

Fig. 4 is an energy spectrum diagram of the measured signal, Vmid1 (for the fault at loc. #6).In db10 the energy is more concentrated at the 10th resolution level and a very small part of the signal energy is leaked to neighboring resolution levels. Therefore, a db10wavelet is selected for WT-based MRA to extract the unique features.

B. Selection of Decomposition Level

The noise signal is decomposed into 11 frequency bands to cover frequencies from 83 Hz to 170 kHz, which will accommodate the resonant frequencies in the system; these are provided in Table I. The optimum number of decomposition levels is determined as presented in [8, 15].

Table 1: Different decomposition levels for cable fault

Decomposition Level	Frequency Band(Hz)
1	85 k – 170 k
2	42.5 k - 85 k
3	21.25 k – 42.5 k
4	10.625 k – 21.25 k
5	5.3125 k-10.625 k
6	2.656 k – 5.3125 k
7	1.328 k – 2.656 k
8	664 – 1.328 k
9	332 – 664
10	166 – 332
11	83 – 166

5. CLASSIFIER BASED ON ANNs

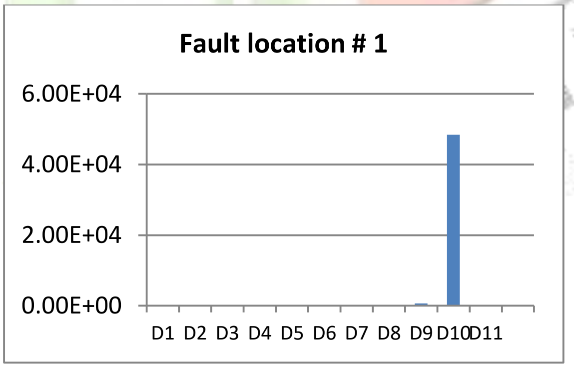
In this study, a backpropagation network was used for the fault locator. The number of neurons in the input layer (q) is the same size as the feature vector take out from the WT-based MRA technique (i.e., q = 11). Similarly, the number of neurons in the output layer (m) is considered equal to the number of fault locations to be examined. After analysis with various hidden neuron numbers, feed-forward networks with 10 hidden neurons were found to be sufficient for this fault location technique. Tan-sigmoid and log-sigmoid activation functions are utilized in the hidden layer and output layer of the network, respectively. The supervised Levenberg-Marquardt back-propagation (trail) training algorithm is selected due to its faster convergence rate and efficiency in providing good results when compared with other optimization techniques [9]. The training of the ANN is repeated until a predetermined mean squared error (MSE), 0.2%, is achieved.

6. SIMULATION RESULTS

A. Cable Faults

The underground cables used in large PV systems are permitting to ground faults or line-line faults. These faults are usually due to failure of cable insulation or unconscious short circuits between conductors with different polarities.

1. Result of feature Extraction with DWT –based MRA: The fault locating method was first analyzed by PV system at standard test condition (STC) with an irradiance od 1000 W/m^2, temperature of 25^0Cand resistance fault of 10 mΩ[10]. The mid-point voltage of DC-DC converter 1 with respect to grounding (Vmid1) was analyzed using WT- based MRA with db10 mother wavelet. This signal is decomposed into 11 resolution levels as shown in Table .using the wavelet MRA decomposition result of Vmid for ground fault at location 1 and 2 as shown in fig.



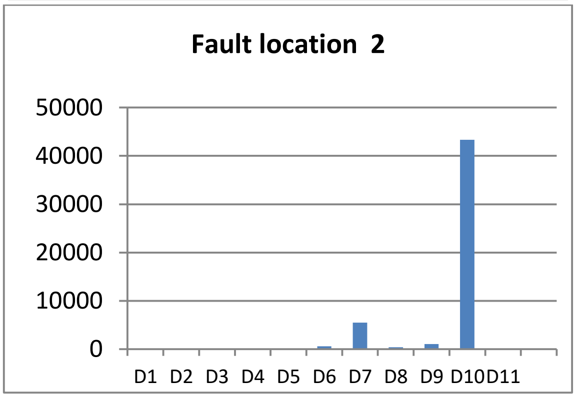


Fig 5: Feature vectors extracted for ground faults at Loc. # 1 and loc. # 2

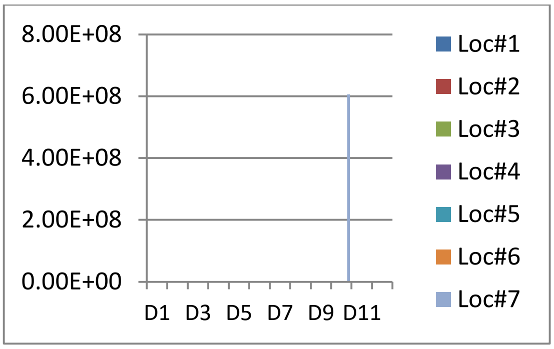


Fig 6: Feature pattern for ground faults at different locations

Fig 6 shows the feature patterns for ground fault at location 1 to 7 for specific PV system operating condition. Similarly, a unique signature of line-line fault location at different frequency bands can be obtained as shown in fig 7, a pattern corresponding to this feature can be used to determine the line-line fault location for DC and AC side of the PV system [18].

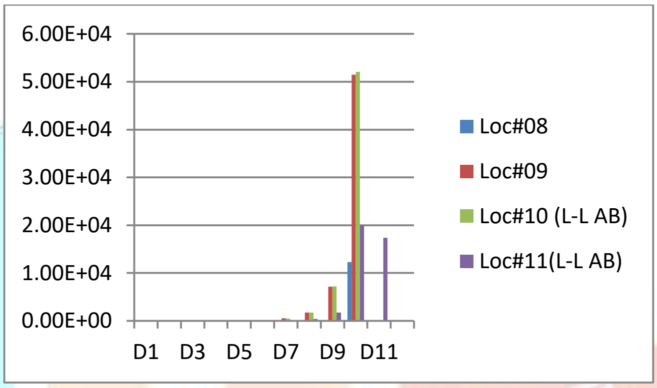


Fig 7: feature patterns for the line-line fault on the DC and AC side of the PV system

2) Result of ANN classifier: The different values of the parameters used for the simulations are given below:

Solar irradiance: 250, 550, 700, 900, and 1000 W/m2 which varies the output power of the PV array from 200 to 500 kW. Temperature: 10, 15, 20, 25 and 30 °C Fault resistances: 10 mΩ, 50 mΩ, 0.1 Ω, 0.2 Ω, and 0.5 Ω PV parasitic capacitance (*Clek)*, series resistance (*Rs)*, and parallel resistance (*Rp)* values are given below in parenthesis [11].In this paper, 12 fault locations and no-fault condition for a total of 13 possibilities are considered. The outputs of the ANN vary from 0 to 1 due to the use of a log-sigmoid activation function in the output layer. Because the outputs of a multi-layer neural network rarely give exactly the target of 0 or 1 for each output neuron, a decision threshold output level of 10% is built into the ANN, i.e., outputs <0.1 are classified as normal conditions and outputs>0.9 are considered as faulty cases. Table 3 illustrates the fault location result for cable fault in the PV system. A 98.2% correct fault location rate obtained for ground fault where a 100% success rate is found for line-line fault. Thus overall fault location accuracy of the proposed fault location method for cable fault in the PV system is 99.10%. For line-line faults at DC cables, no circulatory loop is formed by the fault point and the parasitic elements of the PV modules and cables. Hence, only a small amount of high-frequency noise due to leakage currents to the ground would be produced, and this is what was used to locate the line-line fault locations. Therefore, the fault location accuracy for DC line-line faults is marginally lower compared to the ground fault location accuracy[17].

Table 2: Fault location result for cable fault in the PV system.

Fault location	**Accuracy**	**Average**	**Overall accuracy**
No fault	100%	98.21%	99.10%
Loc. # 1	87.5%		
Loc. # 2	100%		
Loc. # 3	100%		
Loc. # 4	100%		
Loc. # 5	100%		
Loc. # 6	100%		
Loc. # 7	100%		
Loc. # 8	100%	100%	
Loc. # 9	100%		

B. PV Panel Faults

Ground and line-line type faults (intra-string faults) are the most common type of faults in PV systems. Some of the utility engineers report that about 1% of installed PV panels fail annually. The PV module configurations of 285W PV array of the PV test system each PV array consists of 4 parallel strings with 4 modules in each string. The arc fault model used in this paper is based on a differential equation of the arc conductance described in [12, 14].

1. Selection of decomposition level: The signal was recorded with 9 resolution levels covering frequencies from 195 Hz to 10 kHz, as shown in Table 3. The signal was measured and analyzed using DWT- based MRA with db10 mother wavelet.

Table 3: Different decomposition levels for PV panel fault.

Decomposition Level	Frequency Band(Hz)
1	5 k- 10 k
2	2.5 k- 5 k
3	1.25 k-2.5 k
4	625 – 1.25 k
5	312.5 – 625
6	156.25 – 312.5
7	78.125 -156.25
8	39 – 78.125
9	19.5 – 39

For standard operating condition of the PV system, the fault location is extracted for each frequency band and pattern are plotted in fig 8

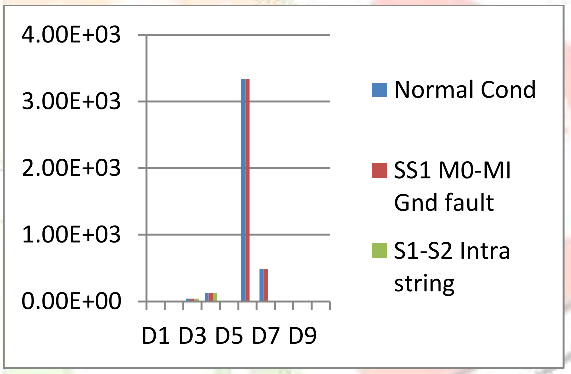


Fig 8: Feature patterns for fault in PV modules

In this case, 0.5, 2.5, 5, 7.5, and 10Ω arc fault resistance are used to simulate arcing fault in PV array [13,16]. The ANN classifier with none input, 10 hidden, and three output neurons were trained until the MSE was ≤ 0.6%. The proposed algorithm can correctly classify 100% for ground fault, 100% of line- line fault in the PV array as shown in Table 4.the The overall location accuracy of 87.5% can be obtained for PV panel fault with proposed fault location method.

Table 4: Fault location results for PV module fault

Fault location	Accuracy	Average	Overall accuracy
No-fault	100%	100%	100%
Ground fault	100%		
Intra string	100%		

7. CONCLUSION

A fault location scheme for ungrounded PV systems has
Been presented in this paper. The ungrounded PV system was subjected to various faults (line to ground, line-line, and arc faults) on both the DC and AC sides of the system. The DWT-based MRA technique was studied to extract the unique features like spectral energy of the noise signal measured at the mid-point of the DC-DC converter. Then, a multi-layer three-layer backpropagation ANN was adopted as a classifier of the pattern recognition to identify exact fault locations for the cables and PV modules of the ungrounded PV systems. Finally, the results show the proposed method is promising, accurate, and robust to changes in operating parameter values and with noisy inputs.

Appendix A

5 kWp UNGROUNDED PV SYSTEM DATA

PV Data (1000 W/m^2)	**Value**
Modules power	285W
Module voltage	62 V0c
Module current	5.7A
No-string	4
String voltage	248 V
String current	6.2 A
Inverter	Omnion 2400 Series
Short circuit current(ISC)	5.7 A
Open circuit voltage(Voc)	7.75V
Parallel string(Np)	4
Series cell	8

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