IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Detection of Arc Fault and Flash in Photovoltaic Systems based on Wavelet Transformation and Support Vector Machine

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Abstract: The main focus of this paper is on detection of arc fault and flash in DC photovoltaic (PV) system and DC grid which may causes fire hazard, personnel shock hazard and damage other system elements or appliances. A notable complication to their detection is that arc in dc system is not periodic, and thus may not have easily perceptible amplitude or frequency signature for pattern recognition based detection technique. Wavelet transform (WT) provides a time and frequency approach to analyze target signals with multiple resolutions. This paper proposes an effective method based on WT and support vector machine (SVM) for detection arc fault in DC PV systems. The process of detecting an arc fault involves signal analysis and then feature identification from system voltage signals. SVM is then used to identify arc fault location. Simulation results are synthesized to study and verify the accuracy of proposed methodology.

***Index Terms*: PV system, arc fault detection, wavelet transformation, multi-resolution signal decomposition, support vector machine.**

I. INTRODUCTION

The increasing amount of PV systems and the trend toward increasing DC voltage levels have a high potential of creating DC arc faults. An electrical arc is the current that flows from one conductor to another when there is a gap between these two conductors [1]. The arc generates heat which can create fire. DC arc occurrence is expected to increase continuously because of cables, connectors, conductors or insulation breakdown, and components aging. Arc faults are common events in PV systems.

Arc faults are classified as series or parallel faults as shown in figure 1. Series arc faults occur due to loose electrical connections and parallel faults can be caused by scraping of conductors due to vibration, puncture of the insulation, or other failures within the DC system.

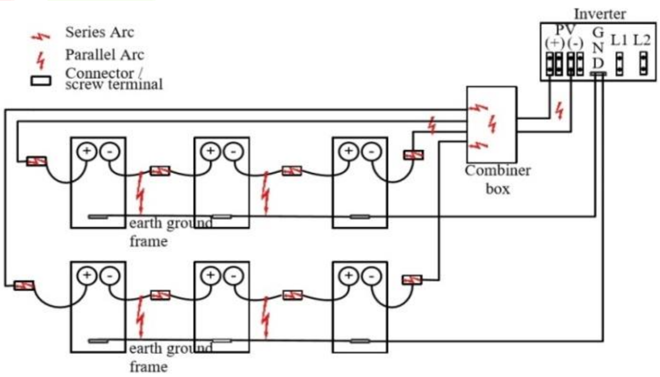
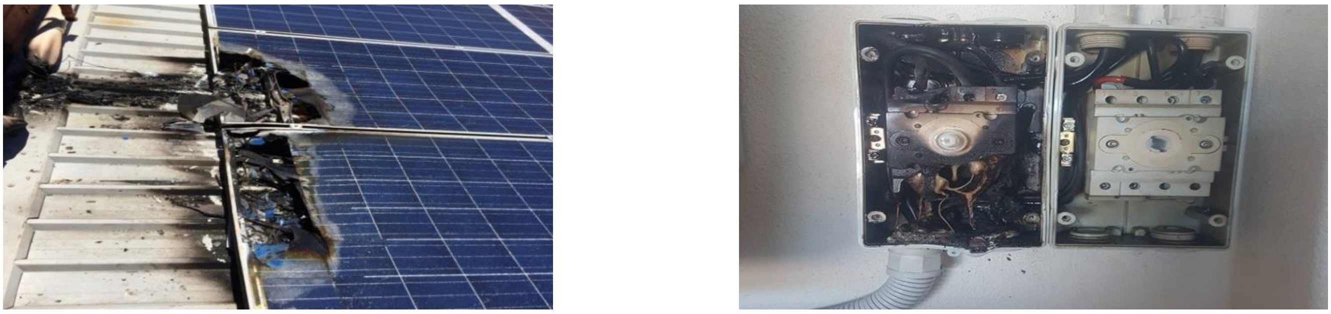


Fig.1. Example of location of dc arcing may occur in PV system

Arc faults can occur in lower rating load residential systems as well as large PV grid systems and can causes inadequate effect to human safety. The arc generates high temperature plasma that can burn adjacent material, such as shown in figure 2 (a & b). Thus, arc fault detection is more important for reliable and safe operation. Also it is more important to detect arc flash, the pre-fault events of sparking, and dielectric breakdown. Arc flash may only last for a short duration (less than a second), but serves as an early indicator of incipient arc faults. Detecting arc flash is a difficult problem because it involves short-term current flowing through ionized air or along an ion path and may not draw sufficiently high root-mean-square current, or have a high enough I^2t energy to trip a thermal circuit breaker [2]. This is particularly occurs in DC micro grid and renewable grid like wind, solar etc. In these cases, an arc can be sustained for hours or even days because the over-current protection devices never activate. Thus, the fire and safety hazard is left undetected and sustained.

DC arc fault in PV systems is an unintended, self-sustaining discharge of electricity with high energy. A DC series arc is the result of the failure of the intended continuity of a conductor or connector in an electrical circuit, while a parallel arc occurs due to an unintended current path between conductors. Parallel arc fault often draws a large amount of fault current because of the sizeable different potential, which is easier to be detected by traditional protection devices [3]. However, in general, a DC series arc fault has less energy than a parallel arc fault, but it has a much higher probability of occurring due to the large number of connections in PV systems. Consequently, the DC series arc fault current will not be sufficient to melt the fuse or activate the over-current protection devices. Compared with the parallel arc fault, DC series arc fault detection is more challenging and more difficult to be detected [4]. Fig. 3 shows dc wiring in ground mounted PV array.



(a) (b)

Fig. 2. Damage due to an arc fault (a) PV system, (b) combiner box

The nature of arc fault in power system is not periodic. Hence conventional signal processing techniques such as discrete Fourier transform (DFT) or FFT have some drawbacks, detailed in [5]. If there is a transient or spike in the signal, it will contribute to the Fourier transform (FT), but its location on the time axis will be lost [6],[7]. The discrete short time fourier transform (STFT) might be suitable for time frequency domain analysis of harmonic-related disturbances, but it is not suitable for capturing abrupt disturbances or short transient signals. However, wavelet analysis mitigates the shortcomings of the Fourier transform methods as it has capability to localize on both time and frequency.

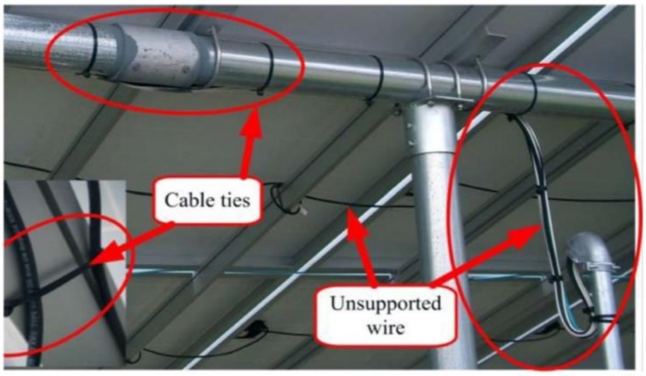


Fig. 3. PV array mounting

In this paper, new approach using WT for arc fault analysis in dc system is proposed. The process of detecting arc faults involves signal analysis and its feature identification and SVM as a classifier. The rest of the paper is organized as follows: Section II described the theory of proposed approach. The implementation of system in MATLAB/Simulink is presented in section III. The results of Simulink model are shown in section IV. Section V concludes the paper.

II. PROPOSED APPROACH:

A. Arc Model:

In order to simulate the arcing condition, black box modeling is commonly used to describe the interaction between the arc and the electrical circuit. The "black box" models are represented by one differential equation relating the arc conductance with magnitudes such as voltage and arc current. Many of these models are based on the equations proposed by Cassie and Mayr models [8],[9]. The mathematical model is adapted to a set of measured data by means of a proper selection of arc parameters including the time constant and the cooling power, which is normally taken as a function of arc current and voltage. In this paper, series arcing is created in Simulink based on the Cassie arc model which detailed in [9]. The differential equation of Cassie arc model is written as

$$\frac{1}{g}\frac{dg}{dt} = \frac{d\ln g}{dt} = \frac{1}{\tau}\left(\frac{u^2}{U_C^2} - 1\right)$$

Where, g is the conductance of the arc, u is the voltage across the arc, i is the current through the arc, Uc is the constant arc voltage, τ arc time constant.

B. Wavelet Transform:

Wavelet transform (WT) are one of the new and effective mathematical tool for signal processing, which was first introduced at the beginning of the 1980s [10]. The wavelet-based techniques have large number of application in the field of physics, mathematics, and engineering because of its capability of analysis time and frequency domain, which is its unique characteristic. The applications of wavelet transform in power system have been recorded for fault detection, fault classification, power system disturbance modeling and identification, power quality analysis, etc. [10]. The fundamental theory and mathematics of the wavelet transform was broadly studied and can be established in [11]–[13].

The performance of the wavelet transform mainly depends on the selection of the mother wavelet. The selecting criteria adopted for selecting mother wavelet in this paper are summarized in [2],[14]. All mother wavelets have the common characteristics i. e. the mother wavelet should be attenuating and oscillating [10].To perform wavelet transform, there are several well-known orthogonal wavelet families such as Harr, Meyer family, Symlets family, Coilflets family, Daubechies family, Biorthogonas family etc [14]. The performance of wavelet-based methods will affected by different mother wavelet. Hence selecting the appropriate mother wavelet is imperative to implement the wavelet analysis [10]. In this paper we choose daubechies wavelet due to their outstanding performance in detecting waveform discontinuities [2].

B.1. Discrete Wavelet Transform:

The discrete wavelet transform (DWT) is defined as

$$C(j,k) = \sum_{n \in Z} s(n) g_{j,k}(n) \qquad (1)$$

$$j \in N, k \in Z$$

where

$C(j,k)$ - wavelet coefficient,

n - sample number,

$s(n)$ - signal to be analyzed, and

$g_{j,k}(n)$ - discrete scaling function (also called as the father wavelet),

which for dyadic-orthonormal WT is defined

$$g_{j,k}(n) = 2^{-j/2} g(2^{-j} n - k) \qquad (2)$$

The auxiliary function to this is the mother wavelet.

$$s = A_J + \sum_{j \geq J} D_j \qquad (3)$$

With this initial setting, the DWT can be easily implemented by multiresolution analysis. As shown in Fig. 4, at each level j, the approximation signal Aj (represented by linear combinations of father wavelets at the jth level) and detail signal Dj (represented by linear combinations of mother wavelets at the jth level) can be created signifies that s is the sum of its approximation AJ improved by the fine details [15].

B.2.Multiresolution Analysis:

The multiresolution analysis (MRA) will be a best tool for decomposing the signal at the expected levels [14] where the faulted-derived signals can be represented in terms of wavelets and scaling functions, associated with a high-pass[H(n)] and a low-pass[G(n)] filter, respectively as shown in figure 5. Thus, we can easily extract the desired information from the input signals into various frequency bands related to the same time period.

On each level of decomposition, the input signal is split into a lower frequency component i.e. scaling coefficient [also called approximation coefficient] and a higher frequency component i.e. wavelet coefficient [also called detail coefficient]. In dyadic wavelet filters, only the low-frequency part is further decomposed. In comparison, binary-tree wavelet filters (wavelet packets), which split both low- and high-frequency components on each level, lead to decomposed signals with an equal bandwidth [15]. In this paper, only dyadic wavelet filter implementation is discussed.

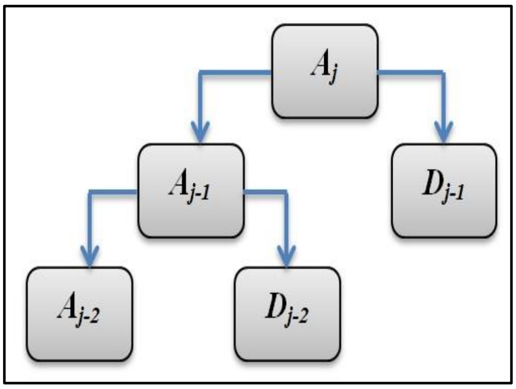


Fig 4. Dyadic Wavelet Decomposition

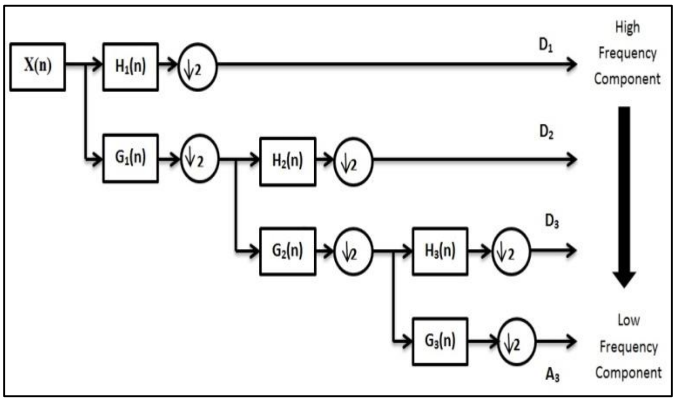


Fig.5: WT- based MRA technique

B.3. Spectral Energy Calibration

Wavelet analysis has been used to determine the signals that arrive at the relaying point as a result of faults and switching operations. This can be obtained through the analysis of details' spectral energy of the current traveling wave signal. The optimum level of wavelet details' coefficients is selected based on its energy content over an window interval of twice of the transmission line travel time and is defined as, the number of samples of the moving window which depends on the travel time *TT* of the transmission line under investigation.[13]

$$DE_j = \sum_{k=N-M}^{N} D_j^2(k)$$

Where $M = 2\left(\frac{TT}{dt}\right)$, *dt* is the sampling interval, *N* is the number of samples of the recorded signal, *Dj* is the *j*-th wavelet details coefficients and *DEj* is the *j*-th details energy.

C. Support Vector Machine

In [5], demonstrated that wavelet transform has superior processing results with arc fault signal analysis than Fourier based methods, when it comes to practical application, classification is still needed to set up a boundary that enables the microcontroller or digital signal processing (DSP) to determine if an arc fault has occurred**.**

SVM is supervised machine learning algorithm which used for fast solving binary classification problem [16]. The main parameter of SVM is hyperplane as shown in Fig. 6 which separates data with maximum margin between two adjacent classes [17]. Fig. 6 illustrates a two class problem where a linear separation is adopted using a straight line. Linear separation is not possible in case of clustered data points.

Let n-dimensional inputs xi (i = 1,2,…,M, where M is the number of samples) belong to class-1 or class-2 and associated to labels yi= 1 for class-1 and yi= -1 for class-2, respectively. For linearly separable data, a hyperplane f(x) = 0 which separates the data can be determined

$$f(x) = \omega^T x + b = 0$$

Where
ω - n-dimensional vector
b - intercept term.

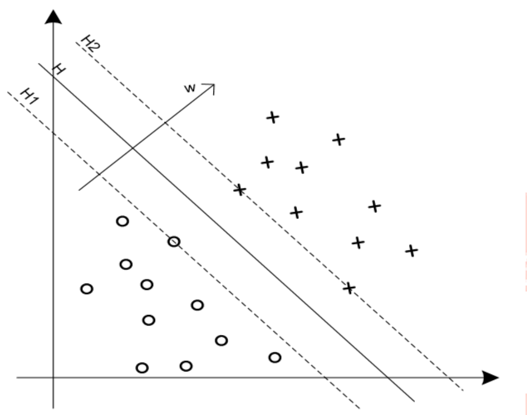


Fig.6. An SVM trained samples from two classes

The separating hyperplane that makess the maximum distance between the plane and the nearest data is called the optimal separating hyperplane as shown in Fig. 6. The geometric margin is found to be 1/||ω||2. Considering noise with the slack variable ξi and error penalty Ci, the optimal hyperplane can be initiated by solving the following convex quadratic optimization problem.

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m}\xi_i$$

$$y_i(\omega^T x_i + b) \geq 1 - \xi_i \text{ , i=1,….,m}$$

$$\xi_i \geq 0 \text{ , i=1,…,m}$$

III. SYSTEM IMPLEMENTATION

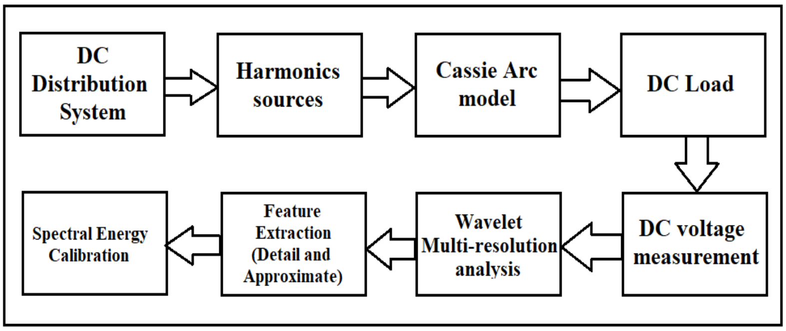


Fig. 7: Flow diagram of proposed approach

In this Paper, the fundamental feasibility of applying wavelet theory to analyze arc fault and arc flash in dc PV systems is examined first in simulation using synthetic waveforms. The flow diagram of this proposed approach is shown in figure 7. We will propose one of the methodologies in which Arc fault or flash location at a different location on the solar PV system or DC grid. For that Cassie arc model utilized for arc generation at different locations of solar PV dc line or DC grid line. The Cassie arc model is connected at different location of dc grid and which is consider as standard arc model for dc grid system for different locations. Then the voltage of the system will be measured at the end of the line and then the measured voltage will be transfer to a discrete wavelet transform using daubechies mother wavelet for signal energy calibration.

Then calibrated spectral energy will be utilized for designing the support vector machine (SVM) which will act as a classifier for arc flash locations on the dc grid. This complete system will be designed in MATLAB Simulink software.

The Simulink model of PV array dc system having voltage source of 100V dc component with small amplitude ac component of 100 and 2000 Hz which represents double frequency power line ripple and inverter switching ripple respectively. The cassie arc model are listed in [2]. The arc model initially behaves as an ideal conductance with the value 1e4 Siemens until the arc switches on, and then it is governed by cassie arc model differential equation. This simulates the separation of electrode that initiate the arc. The two cassie arc model is used, which is separated by using underground 2 km long cable for showing two separate zone.

IV. SIMULATION RESULTS

MATLAB simulation results are classified in three sections, first section shows results for system and arc parameters, second section shows results for wavelet multiresolution analysis for different arc flash location and third section shows result of wavelet spectral energy calibration for different fault conditions. This spectral energy data is useful for arc zone classification using SVM.

A. System and Arc Parameter Result:

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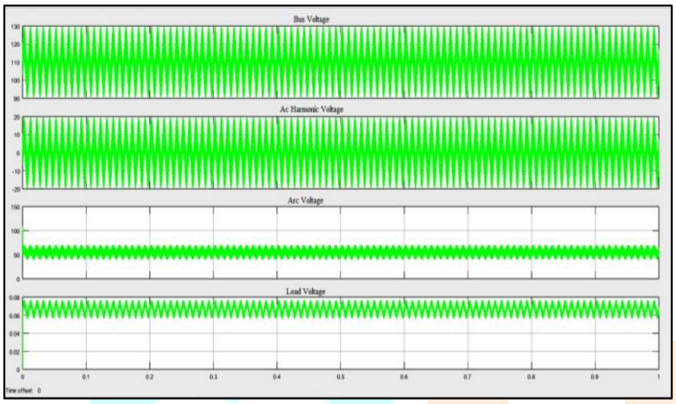

Fig. 8: Bus voltage, AC harmonics voltage, Arc voltage and dc load voltage during normal condition

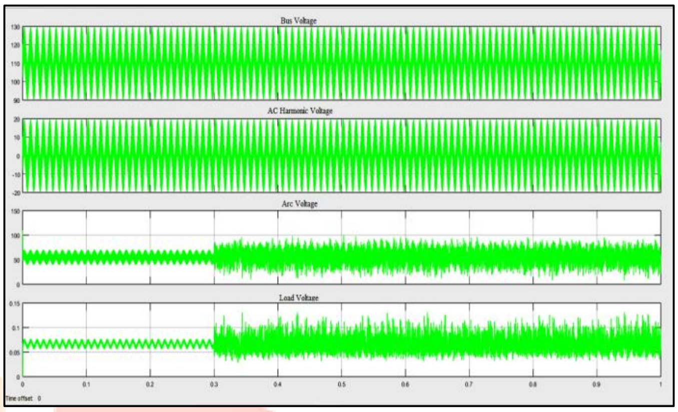

Fig. 9: Bus voltage, AC harmonics voltage, Arc voltage and dc load voltage during arc occurs in zone-1 at 0.3 sec simulation time

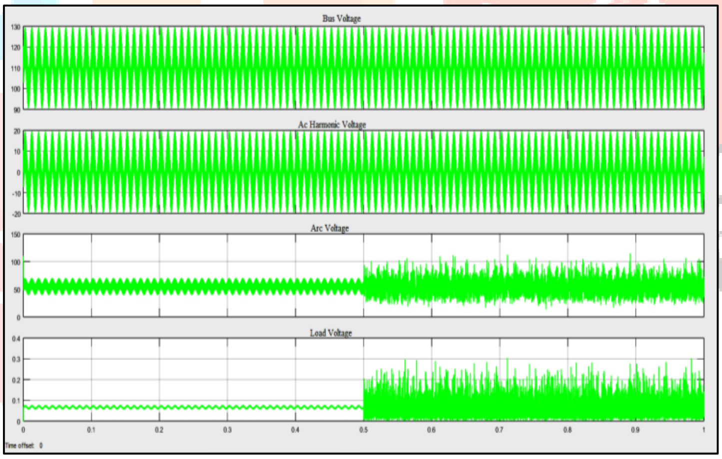

Fig. 10: Bus voltage, AC harmonics voltage, Arc voltage and dc load voltage during arc occurs in zone-2 at 0.5 sec simulation time

Figure 8, 9 and 10 shows DC bus bar voltage, AC harmonics voltage, arc voltage and DC load voltage during normal condition, arc occurs in zone-1 at 0.3 sec simulation time and arc occurs in zone-2 at 0.5 sec simulation time in model respectively. It is observed that there are no any variations in arc voltage and load voltage during normal condition and there are variations and harmonics components present in arc voltage and load voltage for zone 1 and zone 2. Also in DC bus voltage there are only switching ripples and inverter ripples presents no any other changes present in that voltages.

B. Wavelet Multiresolution Analysis Results.

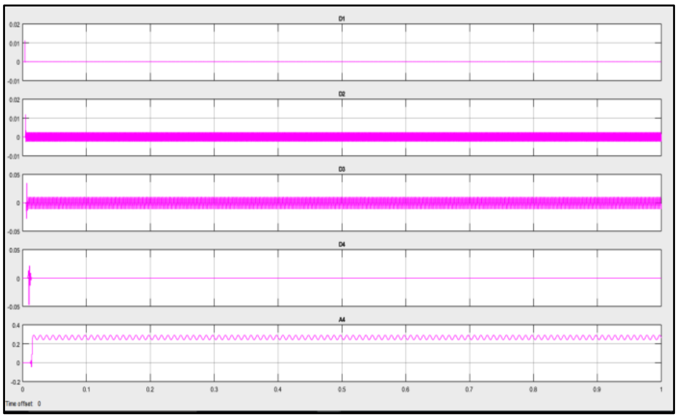

Fig. 11: Wavelet multi-resolution analysis details and approximate coordinators during normal condition

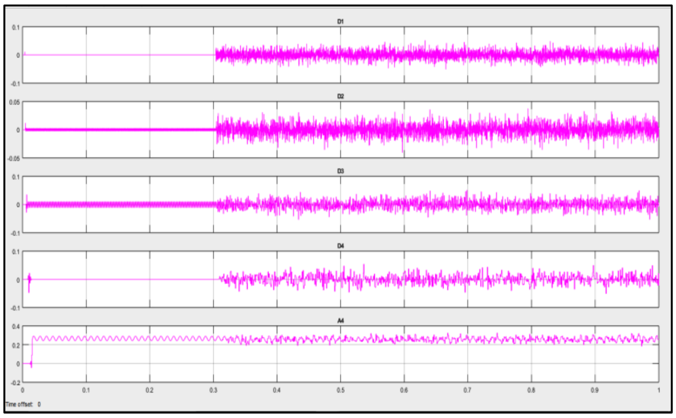

Fig. 12: Wavelet multi-resolution analysis details and approximate coordinators during arc fault or flash in zone-1 occur at 0.3 sec simulation time

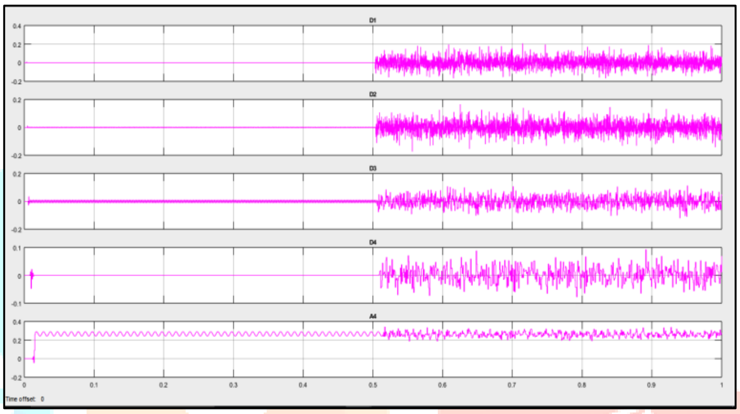

Fig.13. Wavelet multi-resolution analysis details and approximate coordinators during arc fault or flash in zone-2 occur at 0.5 sec simulation time

Figure 11, 12 and 13 shows the wavelet multi-resolution analysis window which shows the detail and approximate coordinator data during normal operation, arc flash occur in zone 1 and zone 2 of dc cable. In case of normal operation arc is not strict or not consider for operation. So that in this case detail coordinator data that is D1, D2, D3, D4 and Approximation A4 is constant data throughout the operation. In case of arc is initiated in zone 1 and zone 2 of DC cable. So that in this case detail coordinator data that is D1, D2, D3, D4 and Approximation A4 is constant before arc initiated while arc is initiated at time 0.3 sec for zone 1 and 0.5 sec for zone 2 then coordinator data changes. Db9 mother wavelet is used for multi-resolution analysis of wavelet transform.

C. Wavelet Spectral Energy Calibration Results

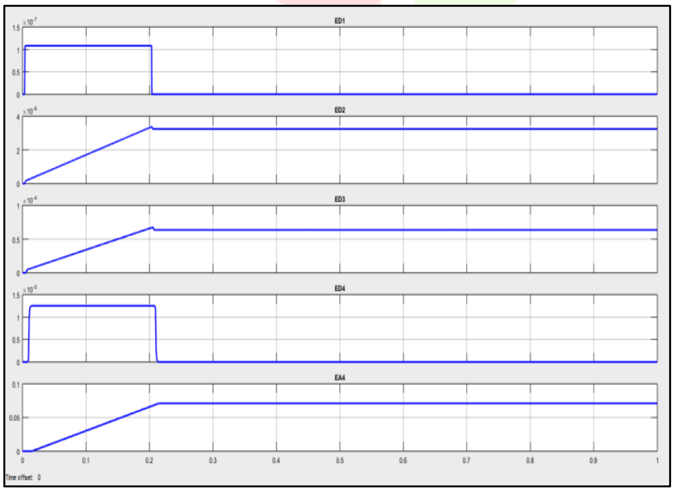

Fig. 14: Wavelet multi-resolution analysis details and approximate coordinators after spectral energy calibration during normal condition

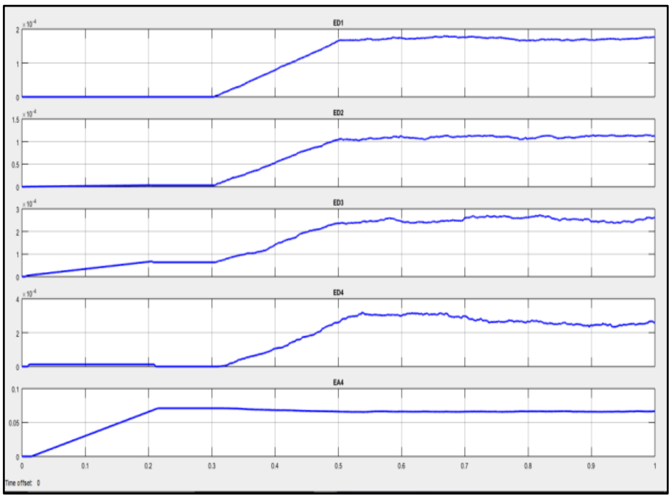

Fig. 15: Wavelet multi-resolution analysis details and approximate coordinators after spectral energy calibration during arc flash or fault occur in zone-1 at 0.3 sec simulation time

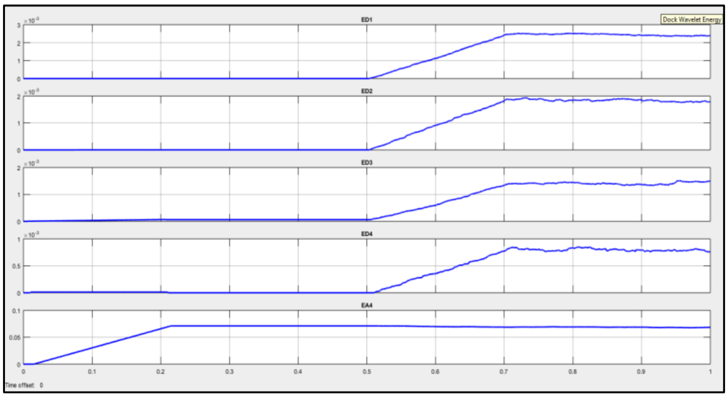

Fig. 16: Wavelet multi-resolution analysis details and approximate coordinators after spectral energy calibration during arc flash or fault occur in zone-2 at 0.5 sec simulation time

Figure 14, 15 and 16 shows the wavelet spectral energy of detail signals D1, D2, D3, D4 and Approximate signal A4 at level 4 of multi-resolution analysis. In this window it is observed that spectral energy of signals is constant throughout the operation during normal condition and it changes from 0.3 sec time duration for zone1 and 0.5 second for zone 2 and which is increased in case of normal condition energy.

D. Results of Support Vector Machine

The input data set and output class data set are given to the SVM for arc zone classification. In which inputs are five of spectral energy of Detail signals D1, D2, D3, D4 and Approximation single at level 4 i.e. A4, while output classes are three in single column 1 for normal condition, 2 for arc zone-1 condition and 3 for arc zone-2 condition. The values are takes place for different arc time i.e. 0.2, 0.4, 0.5, 0.6, 0.8 at different zones.

In SVM data selection window in MATLAB Simulink software, consider columns 1 to 5 of spectral energy of Details D1 to D4 and Approximation A4 as predictor i.e. input while column 6 consist of classes of different arc zones selected as a response of SVM. It is observed that 100 % data set is classify by the linear support vector machine tool for different arc zone classification. Fig. 17 to 20 shows the classification data behavior in between input D1 & D2, D1 & D3, D1 & D4 and D3 & A4 respectively. Red dots shows the zone -1 arc faults while light blue dots shows the zone-2 arc faults classification behavior.

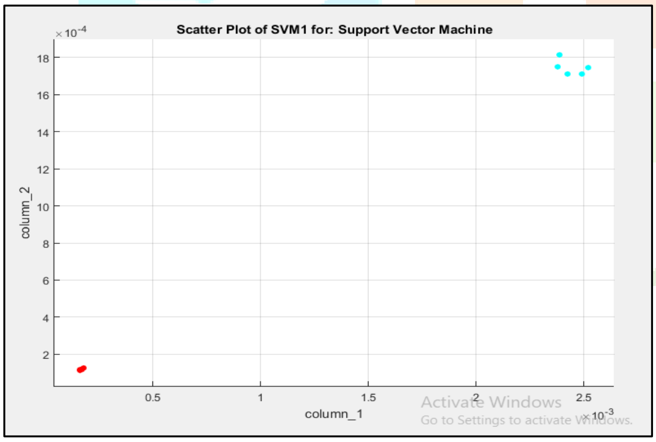

Fig. 17: Scatter plot for SVM between Detail 1 energy and Detail 2 Energy

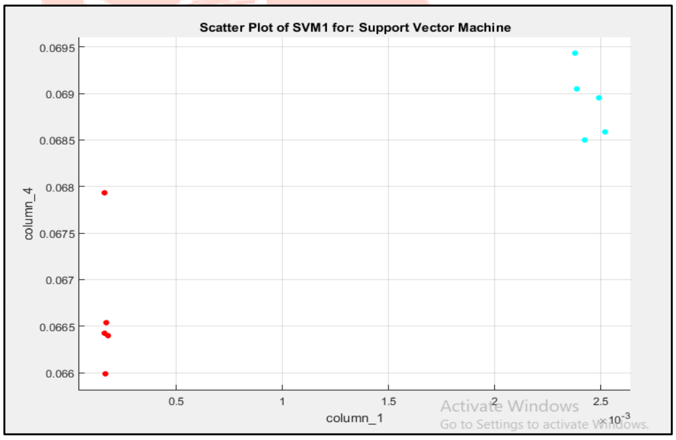

Fig. 19: Scatter plot for SVM between Detail 1 energy and Detail 4 Energy

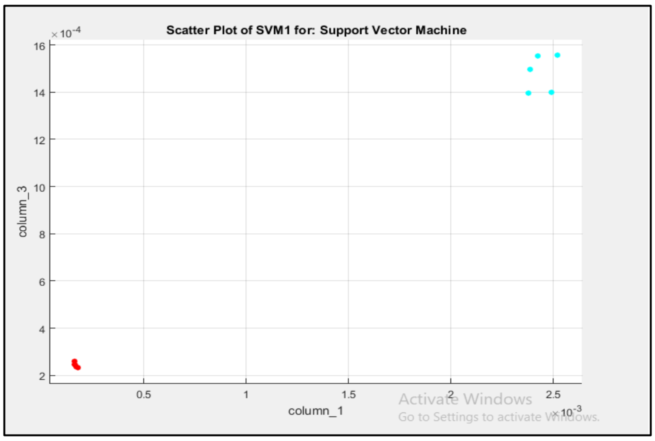

Fig. 18: Scatter plot for SVM between Detail 1 energy and Detail 3 Energy

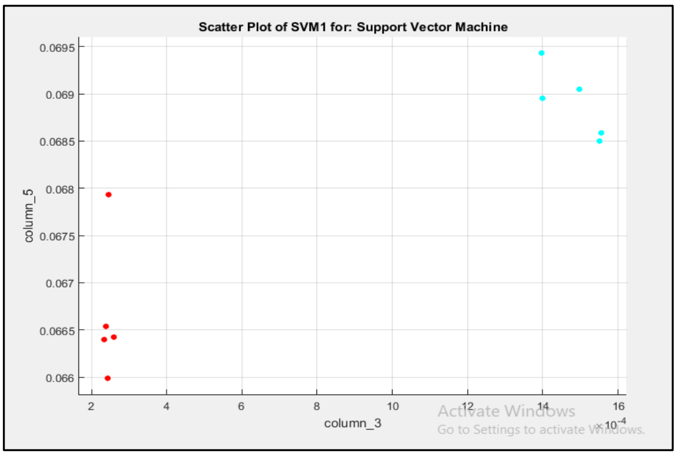

Fig. 20: Scatter plot for SVM between Detail3 and Approximation 4 energy

V. CONCLUSION

This paper has proposed a new approach for arc fault detection in PV DC systems based on WT for feature extraction and SVM for classification. The fundamental feasibility of applying WT has been presented. The presence of ambient electrical noise and switching harmonics and can mask the arc signal, making detection of an arc difficult. Fourier analysis is usually not able to calibrate transient signals and abrupt changes like sudden arc faults and arc flashes. However, WT is extraordinarily effective with detecting the exact instant the signal changes. The results shows that the WT approach is not just capable of analyzing arc fault in dc systems but that it also provides a more readily detectable signal and better performance than the FFT method.

In addition with wavelet transform, this technique extends and calibrates wavelet spectral energy of wavelet multi-resolution signal like detailed and approximate signal. That signal data is then useful for arc zone classification using Support vector machine (SVM) model for dc arc zone classification. It is observed that 100 % data was classify by the SVM technique for different arc zone data which extracted from wavelet spectral energy calibration subsystem model with fast response and high accuracy.

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