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Auto Encoder and DWT for Arc Fault Prediction in Electrical Systems

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Abstract
The most frequent reasons for arc faults are electrical problems, such as outdated wiring and bad connections. Electrical fires are caused by arc faults because they release molten metal and produce high temperatures. These kinds of flames result in a great quantity of loss and disaster each year. A novel approach to identifying residential series and parallel arc faults is presented in this research. To simulate arc failures in series and parallel circuits, an arc simulation model is used. The fault detection algorithm is then used to develop the Discrete Wavelet Transform (DWT) signal processing technique in MATLAB/Simulink, which is used to obtain the fault features. Next, it was discovered that db2 and one level of the wavelet transform were the proper mothers and levels for extracting arc-fault features. MATLAB Simulink was utilized to construct and model
Keywords: *Arc Fault, Discrete Wavelet Transform (DWT), Arc Fault Circuit Interrupter (AFCI).*

1. Introduction

In DC electricity distribution systems, a significant quantity of electrical connectors and lengthy wire lengths are anticipated. Electric arcs can be caused by a high direct current voltage, aging-related deterioration of the wire insulation, rodent bites, and abrasion from chaffing with trees, building walls, or conduit during installation. These DC arcs could cause the micro grid to malfunction or fail, posing a risk of shock hazards and fires. [1&2] Arc faults can be either series or parallel, as Figure 1 illustrates. Loose electrical connections are frequently the cause of series arc faults, *whereas* rodent punctures, heat cycling, vibration, abrasion of wires, and other internal malfunctions can result in parallel faults.

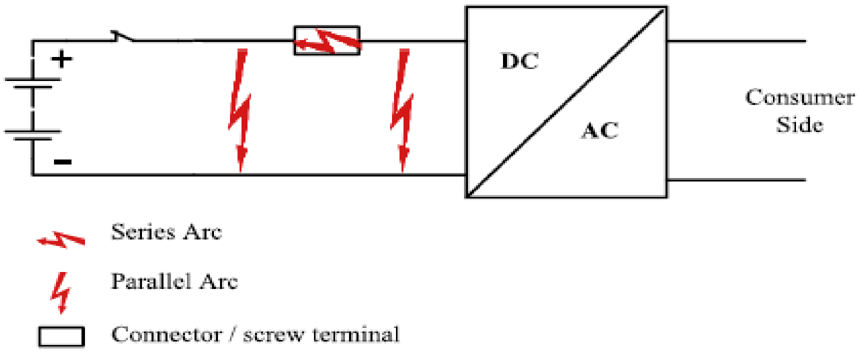

Figure 1 Example of Locations Where Series and Parallel Dc Arcing May Occur in A Dc Distribution System

The Arc Fault Circuit Interrupter (AFCI), which was introduced in 1998, is one of several methods used to identify arc faults, including the Short-Time Fourier Transform (STFT) approach, the Fast Fourier Transform (FFT), and others. The backdrop for the AFCI's intended function of identifying arcs that might serve as fire triggers is provided in this presentation. The AFCI is

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compared to ground-fault circuit interrupters and overcurrent protective equipment; the current models of AFCI devices have ratings of 15 and 20 A at 120 V. There are currently no devices available for commercial or industrial application. [1& 2& 5] This approach provides a key sequence arc fault detection mechanism based on even and odd harmonics (STFT), three parameters to the 50Hz fundamental variable. Real Time Series AC Arc Fault Detection Based on Fast Fourier Transform was also introduced. 2018 saw the implementation of Fast Fourier Transform-Based Real-Time Series AC Arc Fault Detection. With this tool, one may identify current interference and determine the device's arcing fault condition based on the spectrum from the FFT measurement. This method, however, does not work with power source current that has interruptions in it. This study uses MATLAB/Simulink with the arc gap energy-balance theory to construct a suitable Simulink of series and parallel arc fault. The arc current signal's transient information was extracted using the wavelet transform. Subsequently, the fault moment is ascertained by analysing the uniqueness of the fault signal [2&11]. The simulation results demonstrate how well this model can capture the features of real-world series and parallel faults.

2. Fourier Transform and Existing Commercial Method

Commercial equipment is currently on the market for detecting arcs in domestic air conditioning systems, and in certain cases, these products are even necessary. Referred to as an arc fault combo interrupter (AFCIs), these devices are necessary to identify arc faults in both series and parallel. In order to obtain a filtered analog current signal in a certain frequency range—where the arc fault signal is thought to be the most detectable—AFCIs normally use current sensors and analog filters. The filtered time domain current stream is subsequently processed in a digital signal processor (DSP) or microprocessor, typically using specially designed threshold settings and proprietary detection algorithms. [5 & 11] Yet, certain studies have revealed that neither combination AFCI nor branch/feeder AFCI could reliably identify every series arc defect. Studies on AC arc faults are extensive. AC arc fault detection has advanced significantly, with insurance laboratories listed for safety and commercial equipment specialized for this purpose. In contrast, the commercialization of sensing and protection devices and arcs in DC electrical systems are relatively newer fields of study. The fact that arcs in DC systems are not periodic means that their amplitude or frequency signatures may be difficult to identify for methods that rely on pattern recognition, which makes detecting them extremely difficult employing Fourier analysis to break out the frequencies of a bolted fault or continuous arc.

3. Series and Parallel Arc Fault Model

Two types of arc faults exist, the series and the parallel arc fault. The first model type is shown in Figure 2(a). It is the most common fault type. It happens when a single power conductor fails. The maximum arc current is therefore limited by the load current owing to the connection in series, which is significantly less than the CB current rating and, thus, the arc current may or may not generate enough heat to start a fire, depending on the load.

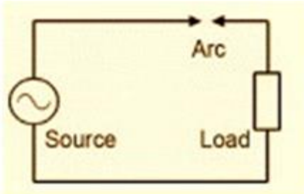

Figure 2(A) Series Arc-Fault

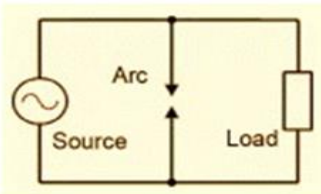

Figure 2(B) Parallel Arc-Fault

Figure 2(b) shows the parallel arc fault. When the insulator is degraded by mechanical, temperature stress, or aging, it develops between the neutral/ground and phase conductor. In this situation, the high-impedance arc melts and carbonizes the insulator first, followed by the low-impedance current route. The trail forms due to

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extreme heat and, if left unattended, it might start a fire. Here, the low impedance current path melts and carbonizes the insulator first, then the high-impedance arc does the same. The intense heat causes the trail to build, which could ignite a fire if ignored [11]. A number of models were constructed to explain its behavior. The most well-known of these are Mayr's arc model and Cassie, which are used to analyze the arc at high current and high plasma temperature conditions. The latter illustrates arc conductance around 0 current while maintaining a consistent arc diameter and power loss. This model performs effectively at low currents (tens of Amperes), making it ideal for modeling arc faults in home and office wiring. Energy balancing theory served as the foundation for the Mayr arc model, and as such, the Mayr arc-fault model expression [7&11&13&14].

Arc Mathematical Model

$dq/dt = e \times i - P_{loss}$

Where: dq / dt: storing energy changes per unit arc length.

$e \times$i: input power per unit arc length.

i: arc current.

e: electric intensity in arc column.

P loss: power loss per unit arc length.

Because arc resistance value is very small, therefore the model can be expressed as the form of conductance

$g = 1/R = i / u = F(q(t))$

$dg / dt = d/dt\,(1/R) = dF(q)/ dq \times dq/ dt$

$= (e \times i) \times dF(q)\, dq$

For Mayr's arc model, the differential equation given by:

$F(q) = k \times e^{q/q0}$

$dg/ dt = (e \times i) \times k/ q0 \times e^{q/q0}$

$1/g \times dg/dt = P_{loss}/ q0 \times ((e\times i/ Ploss) - 1)$

Let $T = q0 / P_{loss}$

$1/ g \times dg/ dt = 1/T \times ((e\times i / P_{loss}) - 1)$

$1/g \times dg/dt = 1/T \times ((L\times e\times i/ L\times P_{loss}) - 1)$

$1/g \times dg/dt = 1/T \times ((u\times i /P0) - 1)$

Where:

- u: arc voltage, $u = L \times e$
- $P0$: Power loss in arc column,
- $P0 = L \times Ploss = u_c^2 \times g$
- u_c: arc voltage constant
- g: arc conductance

Model Parameters

Determination of T

T: reflects the rising velocity of arc voltage in the arc volt – ampere Characteristic curve, and can be expressed as below:

$$T = \alpha \times Ip / Lp$$

Where:

Ip: is the peak current in the arc volt-ampere characteristic curvet. $IP = 25A$

Alpha is the empirical value, take α=2.9 × 10-5

Lp: is the arc length which is approximate-constant.

$$Lp = 2mm$$

Determination of u c

A large number of experimental studies have shown that voltage drop per unit length along the main arc column is independent of the arc current. It is a constant, so this voltage constant is expressed below

$$uc = 25 \times Lp$$

Lp: is the arc length which is approximate-constant.

$$Lp = 2mm$$

Similar to the Fourier transform, the WT is a linear transformation. However, it permits the time localization of distinct frequency components within a given signal, in contrast to FFT. WT has several uses in power engineering because of the diverse range of signals and issues that arise. Some of these uses include fault detection, load forecasting, and power system measurement. [11] Furthermore, pertinent data on power disturbance signals is frequently a conglomerate of precisely localized properties, such as power system transients, either geographically or temporally. This calls for the use of flexible analytic techniques to handle signals in terms of their time-frequency localization, which is a great place to leverage the unique feature of waves. [1&3&9&12]

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4. Arc Fault Simulation and Analysis

Based on a wavelet prototype function known as a "mother wavelet," which offers a localized signal processing technique to dissect the differential signal into a number of wavelet components, each of which represents a time-domain signal covering a certain range of frequencies. Wavelets are very good at estimating functions that have abrupt or discontinuous changes, such as failure signals in power systems. Wavelet transformation is a useful tool for signal analysis and defect feature extraction when the mother wavelet is properly chosen. [1&5]

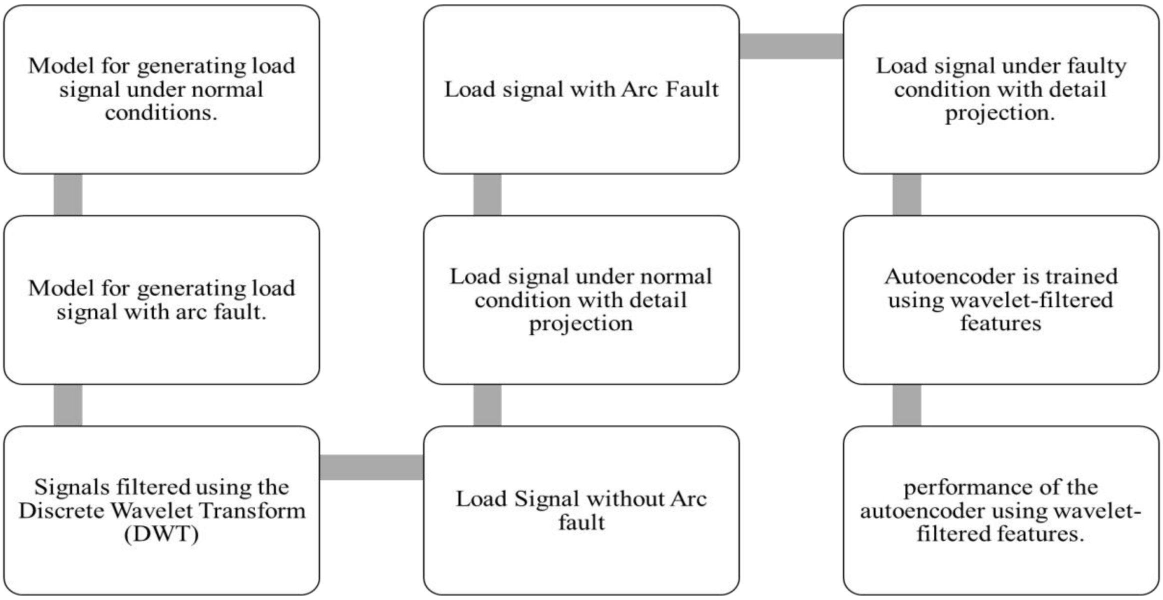

Figure 3 Procedure to ARC Fault Simulation

4.1. Design of Cassie Arc Model to Generate Arc Fault

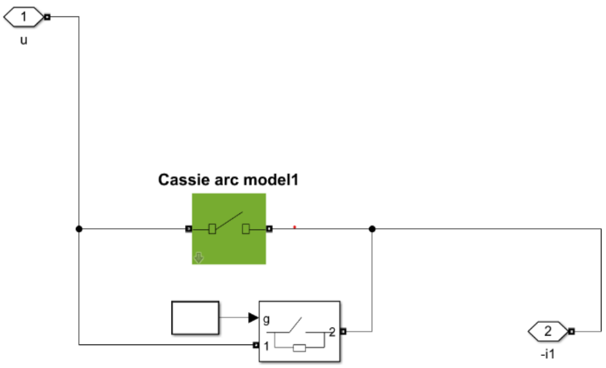

Figure 4 Cassie Arc Model [8&11&12]

The Cassie arc models were implemented in Simulink using the following parameter values:

- Initial conductance g (0) is 1e4 Siemens
- Constant arc voltage Uc = 100 V
- Arc time constant is 1.2e-6 seconds
- $dg/dt = g/\tau\,(u2/U2c-1)$
- *g* is the conductance of the arc
- *τ* is the arc time constant in seconds
- *u* is the voltage across the arc in volts
- *Uc* is the constant arc voltage in volts

4.2. Selection of parameters in Cassie Arc model to generate Arc fault

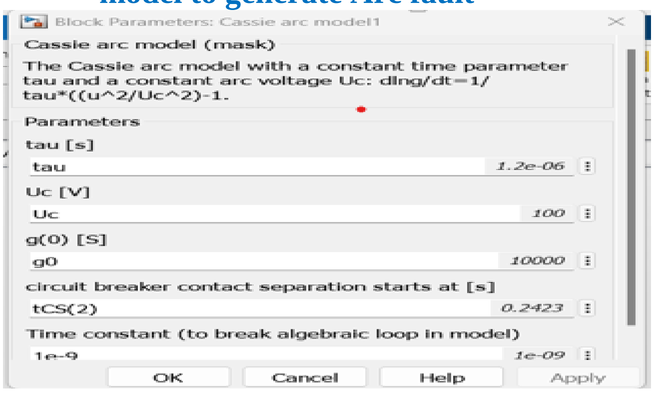

Figure 5 Parameter Seletion for Gegeration of Cassie Arc Model

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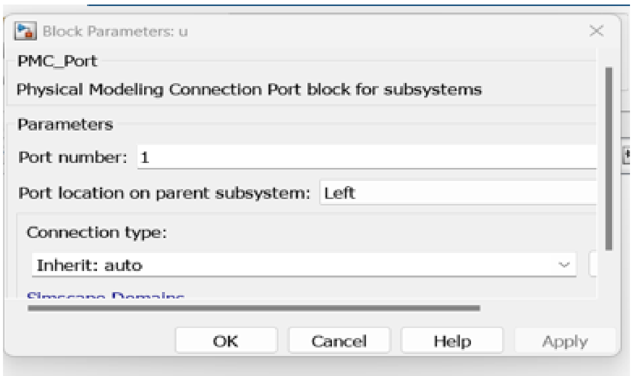

Figure 6 Selection Port for Modeling

4.3.Logic Analyzer output of 10 Cassie Arc Models to Generate Arc Fault

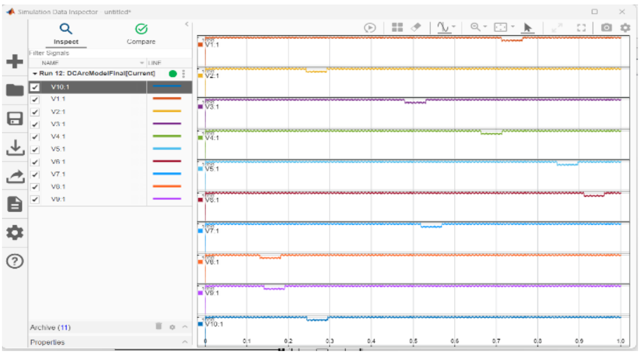

Figure 7 Cassie Arc Model Output Waveforms

4.4.Model preparation in Deep learning using MATLAB Using Configuration Parameters

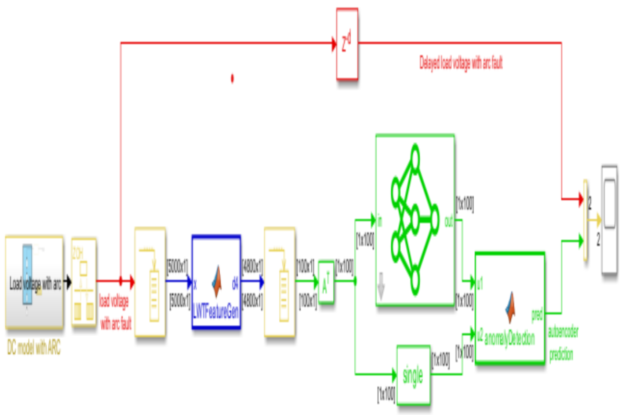

Figure 8 Simulation Model for Auto encoder and DWT in Arc Fault Prediction

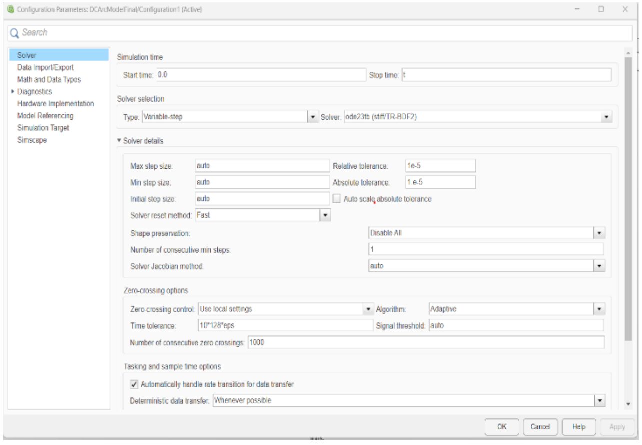

Figure 9 Parameter Configuration for Deep Learning Model

Autoencoders are employed to identify signal irregularities. Data without any anomalies is used to train the autoencoder. Thus, for load signals without arc faults, the learned network weights reduce the reconstruction error. [2&3&7] The threshold in the anomaly detection block that controls the autoencoder's detection performance can be chosen using the statistics of the reconstruction error for the training set. When a reconstruction error exceeds a threshold, the detection block reports the anomaly's existence. The reconstruction error metric in this example was the root-mean-square error, or RMSE. In this instance, we used the load signal to train two autoencoders in a non-arc faulting environment. The raw load signal was used as training data for one autoencoder. [10&12&14]

4.5.Feature Extraction

Discrete wavelet transform (DWT)-filtered signals were used to train and evaluate the wavelet-based autoencoder. The Daubechies db3 wavelet was applied after. [11] The wavelet-filtered load signals under ideal and problematic circumstances are depicted in the accompanying figures. The variance caused by arc faults is captured in the wavelet-filtered defective signal. The wavelet-filtered signals are divided into 100-sample frames for training and testing. [4&7&11]

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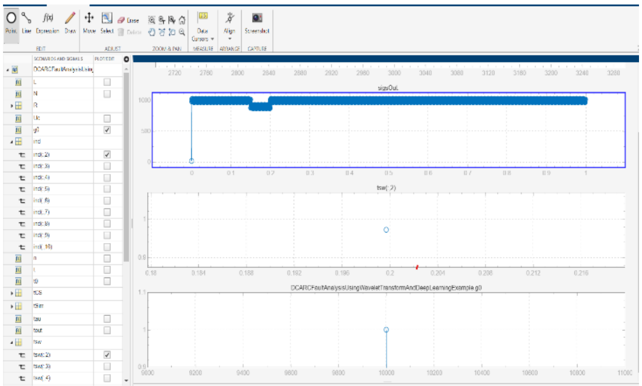

Figure10 Feature Extraction for DWT

A fundamental tool for researching the function's singularity is the Fourier transform. It is difficult to ascertain the distribution of their singular points in space, and because of the lack of spatial localization, it can only ascertain the general character of the strangeness. The arc moment can be effectively localized using wavelet analysis, so circumventing the limitations of the Fourier transform. The analysis will be more effective and space-saving if these steps are selected based on a dyadic basis because the CWT will produce quite a redundancy of data because it considers every conceivable scale and shift step. This concept has been used in the discrete wavelet transform (DWT), a potent and useful filtering method. [9] As was mentioned in a previous subsection, signal analysis applications could need the signal's low-frequency components. High-frequency ones can be needed for other purposes. Because of this, the DWT often adheres to the standards of approximations and details. [3&6&7&11]. The DWT uses a corresponding set of low- and high-pass filters to generate the approximations and details of signals. Two different kinds of functions—the scaling function and the wavelet function, which are particular to particular kinds of mother wavelets—are required for the existence of such a collection of filters. The signal enters the low pass filter (LPF) associated with a particular mother wavelet scaling function during the first step of decomposition. Following the convolution of signal samples with the transfer function coefficients of such a filter and downsampling by two, the approximation coefficients (CA) will be obtained. [1&9&11]

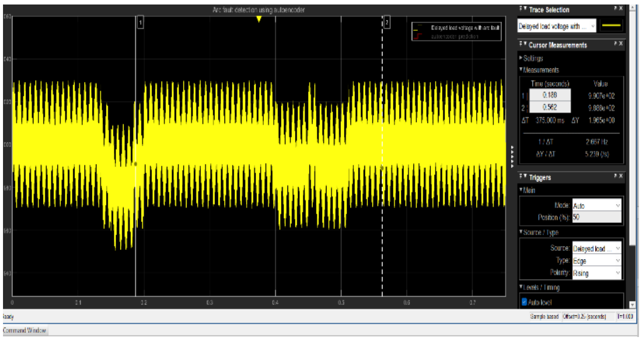

Figure 11 Output Signal of DWT Extraction After Simulation

4.6.Auto encoder Design for Predation of Arc Fault

Reconstructions of the input are produced by autoencoders. An encoder and a decoder are the two smaller networks that make up the autoencoder. The encoder uses input data to teach itself a latent representation, or collection of features. In parallel, these features are used to train the decoder to reconstruct the data. After then, inputs that have never been seen before can be predicted using the autoencoder. Autoencoders can be used to a variety of data formats, such as text, pictures, and time series, and they are very generalizable. [1& 9& 11]

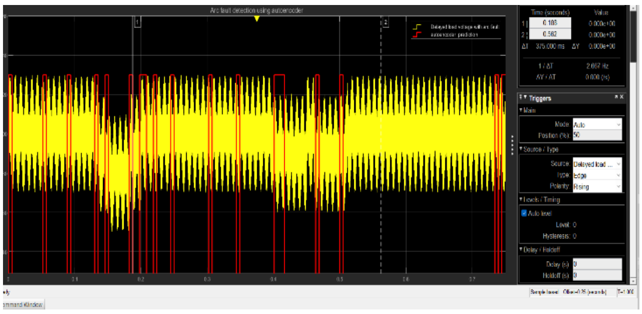

Figure 12 Auto Encoder Prediction from DWT and Deep learning

Conclusion

In this paper, we explored the effectiveness of combining Autoencoder neural networks and Discrete Wavelet Transform (DWT) for the detection of arc faults in electrical systems. The

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proposed methodology leverages the feature extraction capabilities of DWT and the anomaly detection strengths of Autoencoders to achieve high accuracy in identifying arc faults, which are critical for preventing potential hazards in electrical systems. The fusion of DWT and Autoencoder neural networks presents a promising approach for arc fault detection, combining the strengths of signal processing and deep learning. This study provides a foundation for future advancements in the field, with the potential to significantly improve the safety and efficiency of electrical systems.

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