# Series Arc Fault Detection in DC Power Systems and Electric Vehicles

*Final Year Project Report*

*submitted by*

**S JAGAN (EC20B1012)**

*in partial fulfillment of requirements*
*for the award of the degree of*

**BACHELOR OF TECHNOLOGY**

**Department of Electronics and Communication Engineering**
**INDIAN INSTITUTE OF INFORMATION TECHNOLOGY,**
**DESIGN AND MANUFACTURING KANCHEEPURAM**

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# DECLARATION OF ORIGINALITY

I, **S JAGAN**, with Roll No: **EC20B1012** hereby declare that the material presented in the Project Report titled **Series Arc Fault Detection in DC Power Systems and Electric Vehicles** represents original work carried out by me in the **Department of Electronics and Communication Engineering** at the Indian Institute of Information Technology, Design and Manufacturing, Kancheepuram.

With my signature, I certify that:

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- I have understood that any false claim will result in severe disciplinary action.
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**S JAGAN**

Place: Chennai

Date: 13.05.2024

# CERTIFICATE

This is to certify that the report titled **Series Arc Fault Detection in DC Power Systems and Electric Vehicles**, submitted by **S JAGAN (EC20B1012)**, to the Indian Institute of Information Technology, Design and Manufacturing Kancheepuram, for the award of the degree of **BACHELOR OF TECHNOLOGY** is a bona fide record of the work done by him/her under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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# ABSTRACT

This study examines techniques to detect arc faults in DC systems. The goal involves creating ways to identify these events occurring in series circuits, using signal processing techniques, with special emphasis on its application to electric vehicles (EVs). Series arc faults (SAF) carry critical safety risks and usually occur due to damaged insulation lines, and poor line connections. It can cause serious hazards such as fires, explosions, and loss of assets if left undetected on time. Hence in this work, an efficient detection system capable of accurately identifying SAF in real-time to enhance the safety and reliability of DC power systems, particularly in EVs is proposed.

The methodology involves acquiring normal and series arcing signals of a DC-operated system and applying signal-processing algorithms for pre-processing and feature extraction. Certain key features such as entropy, median, mean, maxima, minima, and peak-to-peak are extracted to characterize the SAF signatures. Additionally, advanced techniques including wavelet transform, Fourier analysis, and statistical analysis are employed to improve detection accuracy.

The proposed method integrates sophisticated filtering methods such as moving average and moving median filters to remove noise and isolate fault signatures from the acquired signals. Peak detection algorithms are then utilized to identify abnormal variations indicative of SAFs.

As a primitive work, this work proposes an SAF detection method using the strength of high-frequency components that occur in the current signal during series arcing. When an arc fault occurs, distinct abnormal electrical signals emerge, characterized by elevated harmonics compared to normal states. The proposed method underscores the efficacy of utilizing peak-to-peak features from both normal and arcing states to differentiate between their respective current signals accurately, thus enhancing safety and mitigating potential hazards associated with DC and EV systems

KEYWORDS: Series arc fault detection; DC systems; Signal processing techniques; Electric vehicles (EVs); Wavelet transform; Fourier analysis

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# ABBREVIATIONS

| | |
|---|---|
| **SAF** | Series Arc Fault |
| **DSP** | Digital Signal Processing |
| **FFT** | Fast Fourier Transform |
| **CWT** | Continuous Wavelet Transform |
| **EV** | Electric Vehicle |
| **STFT** | Short Time Fourier Transform |
| **DC** | Direct Current |
| **DWT** | Discrete Wavelet Transform |
| **IDWT** | Inverse Discrete Wavelet Transform |
| **PSD** | Power Spectral Density |

# CHAPTER 1

# Introduction

## 1.1 Arc faults in electrical systems

Electrical arc faults represent a significant safety concern in electrical systems, posing fire risks and equipment damage. These faults can occur in various areas, including in railway traction, ship, aircraft power systems, industrial machinery, and electric vehicles (EVs), and are challenging to detect especially in direct current (DC) systems. The phenomenon of arc discharge is complex, and influenced by factors such as voltage, current, and electrode gap. Also, an arc is similar to a non-stationary resistance depending on various environmental factors.

These faults show a substantial amount of power/energy and can result in frequent fluctuations, posing significant risks of fire and equipment damage. With the increasing adoption of direct current (DC) systems, the prevalence of various types of arc faults is expected to rise.

There are three primary types of arc faults:

1. **Series Arc Faults:** These occur on the same phase line and are caused by wire fractures or poor contacts at junctions and typically occur in faulty insulation in the same phase connection.
2. **Parallel Arc Faults:** These occur between phase lines and are often caused by wire insulation damage.
3. **Ground Arc Faults:** These occur between phase lines and ground, which involve a short circuit between the phase line and ground shell.

Fig. 1.1 shows the comprehensive diagram of various arc faults mentioned above.

Common short-circuit protective devices can mitigate safety risks associated with parallel and grounding arcs. However, the detection and mitigation of SAF is laborious as it exhibits non-linear arcing patterns. Moreover, during an SAF, the current

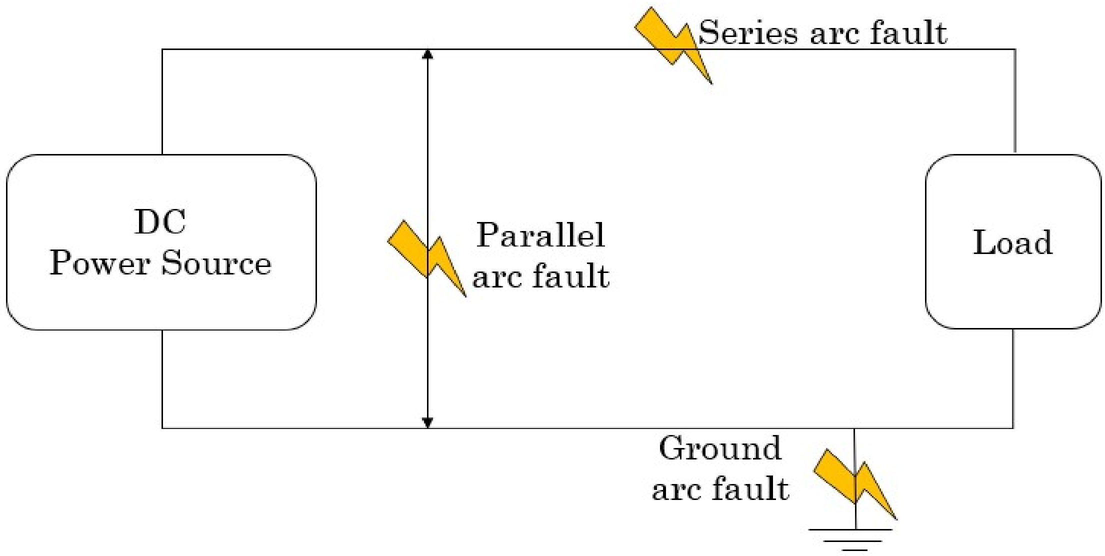



Figure 1.1: Types of Arc Faults [1]

significantly decreases, making it difficult for traditional protective devices to operate effectively. As a result, series arcs can persist and lead to fires or other accidents. Series arc causes the following phenomena [3]

- Heat generation,
- Intense flame emission,
- Acoustic waves,
- Pressure perturbations,
- Leaping of charge carriers,
- Electromagnetic radiation, etc...

Since the exact location of the arc fault is unknown in practice, detecting SAF using the above-mentioned attribute still stands back. To address the challenges associated with SAF detection, signal processing methods [4] are utilized in this work. Time-domain analysis relies on voltage and current signals when an arc occurs, while frequency-domain analysis utilizes the Fast Fourier Transform (FFT) to extract characteristic features of arcs. These features are then combined with signal analysis methods and pattern-matching recognition to detect and classify faults in DC systems. Additionally, time-frequency domain analysis and wavelet transform techniques further improve accuracy in arc fault detection.

It's important to note that in photovoltaic systems, noise is primarily generated by inverters, and DC systems, such as EVs, can feature multiple fixed loads, including lights and motors. To mitigate the impact of external noise, employing diverse types of loads is recommended when utilizing arc fault detection methods.

# CHAPTER 2

# Background and context

## 2.1 Literature survey

Many approaches can be seen in the literature attempting to detect the SAFs in PV systems, DC microgrids, and other DC-operated systems. In [5], the pink noise injected into the current signal during series arcing is used as a notifier of SAF in PV systems. Further, a threshold is used to identify the occurrence of an SAF. In [6], the Differential Power Processing (DPP) structure is employed to analyze the voltage relationships during series arcing in PV systems, utilizing intrinsic voltage sensors from the DPP and inverter. A threshold is then applied to detect SAF based on the analysis results. In [7], the detection of an SAF utilizes RMS values of the arc fault characteristic within a specific bandwidth of the current signal in the PV systems. Additionally, a pre-fault current threshold is incorporated to enhance SAF detection accuracy. In [8], a Principle Component Analysis (PCA) -based SAF detection algorithm utilizing the data points from the current signal during series arcing is proposed in the PV systems. This approach involves setting a threshold for each PCA parameter to detect SAF. In [9], SAF detection characterization and detection are proposed for inverters and transducers (PV field) and observed that a DC series arc does not have zero crossing segments, thus it can be more persistent. Current signals dropped as the arc occurred having fluctuation in decreased current. In [10], the DC SAF identification method for PV systems by studying a differential power processing structure is presented. A prototype of the PV system is done and the utilization of the PV simulator, arc fault detector, grid-connected inverter, and voltage signals as a key feature to estimate time and frequency data can employ a multi-resolution analysis and use an identification method based on a statistical method to detect a faulty activity, which uses statistics-based thresholds to detect SAF

In[11], the intermittent discharges observed at the fault onset are attributed to the high input capacitance of the interface. Delving into the characteristics of this phenomenon, a proposed detection mechanism leveraging spark signatures and cross-correlation during series arcing of current signal in DC-microgrid. Subsequently, a threshold is applied in the SAF detection process. In [12], the intermittent discharges observed at the fault onset are attributed to the high input capacitance of the interface. Delving into the characteristics of this phenomenon, a proposed detection mechanism leveraging spark signatures and cross-correlation during series arcing of current signal in DC-microgrid. Subsequently, a threshold is applied to the SAF detection process. In [13], a window-by-window current change detection approach is proposed. The method utilizes All-Phase FFT (APFFT) for frequency analysis. In [14], a hardware implementation of a SAF is proposed for different DC resistive systems. When an arc fault occurs, a large pulse (spark) occurs, and there is distortion in voltage (decreased) and current (increased). When the arc fault occurs time window is up to 7 times during the recent 10 windows, it can be inferred that the arc fault occurs and can switch an alarm/notification.

In [1], a binary classification model (logistic or SVM) for the DC-powered series arc detection is implemented, for the combined loads such as a permanent magnet synchronous motors (PMSM), an inverter, and a resistance box. Whereas in [15], loads such as a 3-phase inverter, and resistors are used and current signals were taken at 5A, and 8A, with switching frequencies from 5-20kHz. Further, windowed FFT is proposed in the detection mechanism to classify series arcing current signals from the normal state with the proposed model to improve the detection accuracy. In [16], the experimental setup involved the utilization of a three-phase inverter, a single-phase inverter, and a resistor as loads in a DC network, operating at varying current levels of current (3A, 5A, and 8A), with switching frequencies (ranging from 5kHz to 20kHz). This setup facilitated the analysis of certain statistical features such as average, FFT, median, RMS, Variance, and peak-to-peak in both the time and frequency domains. These features were utilized in differentiating between normal and series arcing states using Artificial Neural Networks. In [17], A work is carried out using a data-enhanced ML model that is proposed for DC SAF detection in electric vehicle power systems. Loads such as motor (PMSM), and DC-DC converter are combined in series. STFT/wavelet transform is used to analyze the frequency band of the current signal. When an SAF is present in the EV system, the voltage will rise suddenly in the arcing state, and there is a slight decrease in current amplitude, which relates to the transient/abrupt change of the current in the time domain. In[3], a research study was proposed to develop an algorithm for fast electric arc detection using incremental decomposition of the signal over time in a DC network. Experimented with resistor load and frequency spectra are analyzed, which shows that there is no change in shapes at various voltages, various loads, or various distances between electrodes. The shape of the spectrum changes only when a change happens from normal to abnormal activity, so it is possible to detect whether the arc has occurred using FFT. In,[18], a study on DC SAF diagnosis is proposed using artificial ML with the technique focused on switching the frequency component elimination. A three-phase inverter load is used with a resistor, and operating conditions are 5-20kHz switching frequencies, 5-8A, found that there is distortion in current amplitude typically decreased, and the distortions happen from arc occurrences and present in the frequency range of (3-30)kHz, with independent of the switching frequency.

So, the problem of arc fault detection is multifaceted, requiring a comprehensive understanding of the underlying electrical phenomena and the development of robust detection methods. Traditional detection techniques often rely on threshold-based approaches, which may result in false alarms missed detections, or lack of efficiency. Furthermore, the unique characteristics of DC series arc faults, including their subtle signatures in both time and frequency domains, present additional challenges for detection.

## 2.2 Problem Statement

The increasing adoption/popularity of electric vehicles (EVs) in recent years has led to a growing need for robust safety measures in their DC power systems. One of the critical challenges faced in this domain is the detection and mitigation of DC SAFs, which can result in hazardous conditions such as fires and electrical malfunctions. Developing effective arc fault detection methods tailored specifically for EV DC power systems is essential to ensure the safety and reliability of these vehicles. However, existing detection techniques often lack the precision and reliability required to accurately identify arc faults in real-time and most of them depend on artificial machine learning algorithms (requiring large datasets), highlighting the urgency for advanced solutions in this field.

In the realm of DC power systems, particularly within the context of electric vehicles (EVs), ensuring safety and reliability is paramount. The unique characteristics of DC series arc faults pose significant challenges, as they can occur unpredictably and are often difficult to detect using traditional methods. Moreover, the increasing complexity of EV power systems, including components such as batteries, inverters, motors, and power electronic controllers, exacerbates the difficulty of detecting and mitigating arc faults effectively. Consequently, there is a need for innovative approaches and algorithms to enhance the detection and response capabilities of EV DC power systems, thereby mitigating the risks associated with arc faults and ensuring the continued safety of EV users and the general public.

## 2.3 Objectives

From the literature, it can be concluded that the problem of SAF detection for DC and EV systems is still open as there exists scope for increasing the efficiency of SAF detection in real-time. Hence in this work, certain signal processing techniques (such as Wavelet Transform (WT), and Fast Fourier Transform (FFT)) for identifying DC SAFs in electrical systems (with an emphasis on EV) are explored and utilized. The study includes:

- Exploring the characteristics of DC SAFs and their implications for electrical system safety.
- Investigating signal processing methods such as Fourier transforms, wavelet analysis, statistical analysis in the time domain, and windowed Fourier transforms for feature extraction.
- Developing and evaluating detection systems, including signal processing and threshold-based (empirical) detection, for SAF detection.
- Assessing the effectiveness of different feature extraction techniques and threshold algorithms under various operating conditions and environmental factors.
- Proposing novel approaches that integrate both time and frequency domain features for improved arc fault detection accuracy and reliability.

## 2.4 Focus Areas

The objectives intended in this work will focus on the following aspects.

- Investigating the characteristics of DC series arc faults and their impact on electrical systems.
- Exploring signal processing techniques such as time-domain features, Fourier transforms, and wavelet analysis for feature extraction.
  - **Time-domain features (using statistical analysis):** deriving features in this domain from the time-series data of a signal. These features describe the signal's characteristics within the time interval it was recorded.
    Time-domain features include: *Mean, Median, Variance, Peak Amplitude, Entropy, etc,...*
  - **Frequency domain features:** These features are extracted from the frequency representation of a signal obtained through techniques like Fourier Transform or Wavelet Transform. These features describe the signal's behavior in the frequency domain, revealing information about its spectral composition and frequency components.
    Frequency domain features include: *Power Spectrum Density (PSD)*
  - **Time-Frequency Features:** Time-frequency features capture the time-varying characteristics of a signal, providing information about how its frequency content changes over time. These features are obtained using techniques like STFT, CWT

# CHAPTER 3

# Methodology

## 3.1 Data gathering

The information required for this study has been gathered from the simulation and experimental setup. The experimental setups involve the creation of controlled environments to induce arc faults in the DC network, allowing for the collection of real-time data on current, voltage, and other relevant parameters. Simulations were conducted using MATLAB Simulink software and a real-time experimental setup was conducted to collect normal and series arcing data in a DC network.

### 3.1.1 Circuit diagram:

To study and analyze the normal and series arcing characteristics of a load powered by a DC source, a simulation study has been conducted. The Electric Arc as a Circuit Component developed by J. Andrea et. al [2] has been used to mimic the series arc in simulation. The simulation circuit's components consist of a DC Voltage Source, Simscape IdealArc block (acts as an arc generator), loads, current and voltage sensors, and scope (display) are connected in series, where both the normal (without IdealArc block) and series arcing (with IdealArc block) circuits are presented as shown in Fig.3.1. The data thus obtained is used for further analysis.

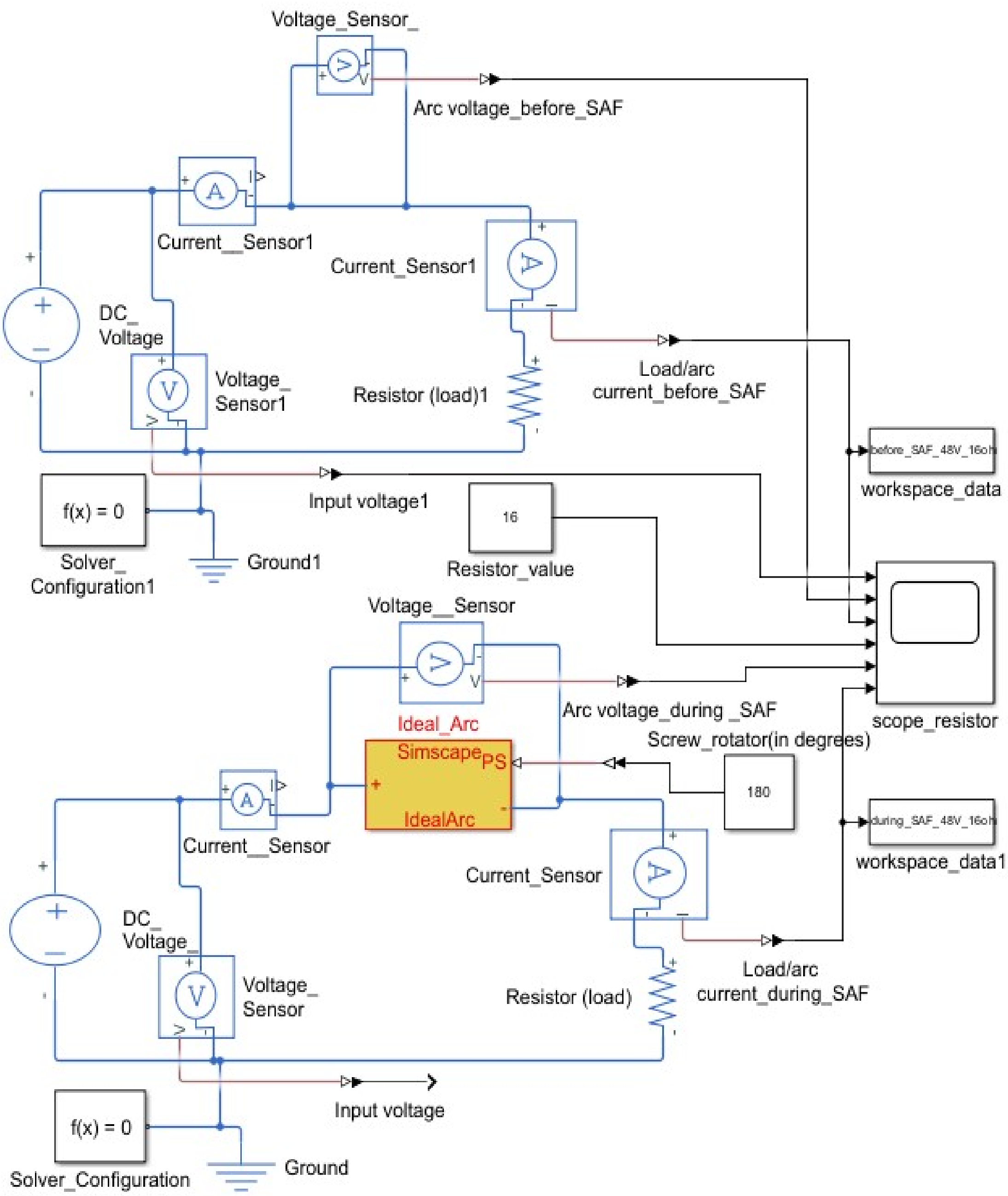



Figure 3.1: Simulation circuit (with and without SimscapeIdealArc block) [2]

### 3.1.2 Experimental setup:

An experimental setup is developed to observe normal and series arcing behavior in real time. The setup consists of a DC energy source($48V, 50Ah$ Li-ion battery), an arc generator, and loads such as a resistor/BLDC (Brushless Direct current) hub motor. The current and voltage signals of both normal and series arcing states are acquired with the help of a signal conditioning circuit connected to the NI ELVIS II board, which is connected to the PC. Subsequently, the analysis is carried out with MATLAB software, as depicted in Fig.3.2

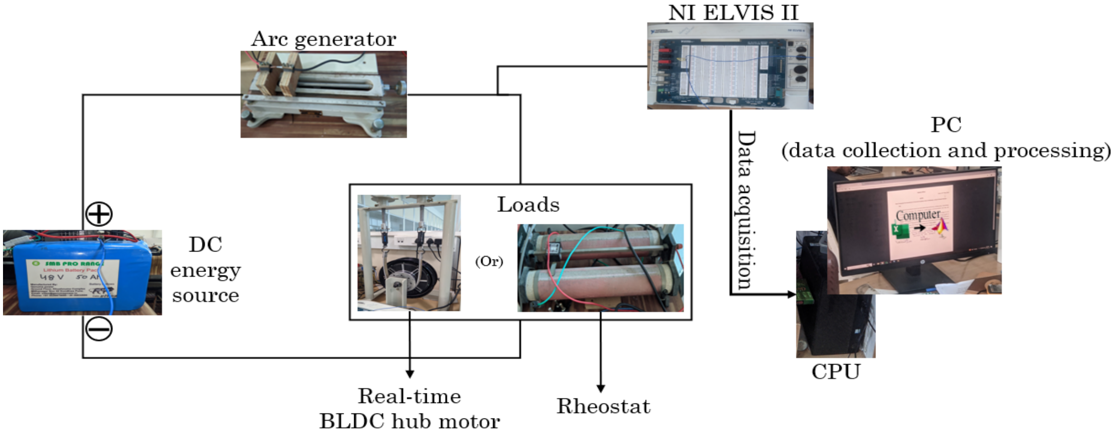



Figure 3.2: Experimental Setup for Series Arc Fault Testing

Creating a series arc is a tedious task in practice, to aid this, an arc generator is developed as shown in Fig.3.3. The arc generator consists of two electrodes placed oppositely. One of the electrodes is fixed and the other is movable using a rotating knob. A well-calibrated scale is fixed along the axis of electrodes for measuring the gap. The frame of the arc generator is made of hard steel and the electrodes are kept over wooden pieces.

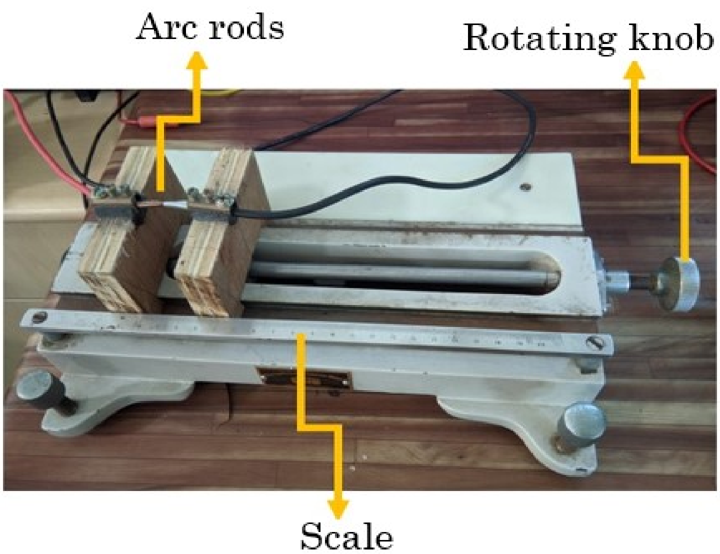
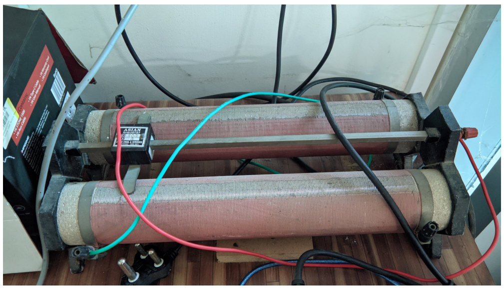



Figure 3.3: Arc generator

Figure 3.4a shows the DC energy source, a lithium-ion battery with a $48V$ and $50Ah$ capacity. Lithium-ion batteries are rechargeable and commonly employed to power various electronic devices. In Figure 3.4b, we observe the rheostat, a resistor load with a resistance value of $16\Omega$. In this experiment, the rheostat serves as a crucial component, acting as a load to test and analyze the characteristics of the power supply.


(a) DC energy supply (Li-ion battery)



(b) Rheostat

Figure 3.4: DC energy supply $(48V, 50Ah)$ and rheostat $(16\Omega)$

### 3.1.3 Data collecting Procedure

The data-gathering procedure is the acquisition of comprehensive data under various environmental conditions. For experimental setups, specific tests are configured to simulate the experimental setup under different types of loads (such as rheostat) by varying environmental conditions, such as the level of gap. Data acquisition systems capture voltage and current signals during normal and series arcing fault events. The process of collecting voltage/current signals from the experimental setup is shown in 3.2, where the NI ELVIS II board, which is connected to the computer and subsequently data is gathered in LabVIEW software, thereby exporting data to excel format for further analysis using MATLAB software.

## 3.2 Analyzing gathered data

### 3.2.1 Statistical Analysis

Statistical analysis techniques were employed to characterize the collected data and identify patterns or anomalies associated with arc faults.

**Time-domain analysis used statistical features** include:

- Mean: represents the mean value of the signal.
- Median: represents the middle value of the sorted signal dataset, separating the higher half from the lower half.
- Variance: Measures the spread or dispersion of the signal values around the mean.
- Skewness: Describes the asymmetry of the signal distribution.
- Kurtosis: Measures the "peakedness" or "tailedness" of the signal distribution.
- Entropy: Captures the uncertainty or randomness in the signal.
- Integral: Represents the cumulative sum of the signal values over a given time.
- RMS (Root Mean Square): Represents the square root of the arithmetic mean of the squares of the signal values.
- Peak Maximum: The maximum values attained by the signal.
- Peak Minimum: The minimum values attained by the signal.

The above features are calculated to summarize the central tendency and variability of the signals. Furthermore, Frequency-domain analysis using the Fast Fourier Transform (FFT) is employed to mitigate misjudgment and analyze the frequency response of the signal.

**Frequency-doamin features** include:

- Power Spectral Density (PSD): Represents the power of a signal distributed over different frequencies. It provides insight into the frequency content of the signal.

Also, Time-Frequency domain analysis is employed to observe the change of frequency over time:

**Time-Frequency domain features:**

- Short-Time Fourier Transform (STFT): Decomposes a signal into its frequency components over short, overlapping time intervals. It provides information about how the frequency content of the signal changes over time.
- Since STFT employs fixed-length windows, it may not give an accurate representation. Therefore, CWT is utilized to analyze the non-stationary signals.
- Continuous Wavelet Transform (CWT): Analyzes a signal at different scales and frequencies simultaneously. It is useful for detecting transient or non-stationary features in the signal.

## 3.3 Wavelet Transform and Signal Decomposition

A wavelet is a waveform, which is a short-duration oscillation with a zero average value that decays very rapidly to zero amplitude. Wavelet Transform is a powerful tool used for signal analysis that enables both time and frequency localization. It decomposes a signal into its constituent frequency components, providing a time-frequency representation that is particularly useful for analyzing non-stationary signals. Wavelet decomposition involves breaking down a signal into its various frequency components using small wavelet functions, oscillating waveform with finite duration [19].

The signal is analyzed at different scales or resolutions during the wavelet decomposition process. This decomposition results in coefficients representing the signal's energy at different frequency bands and time intervals. By decomposing the signal into different scales, Wavelet Transform allows us to capture both high-frequency details and low-frequency trends in the signal simultaneously as shown in Fig.3.5

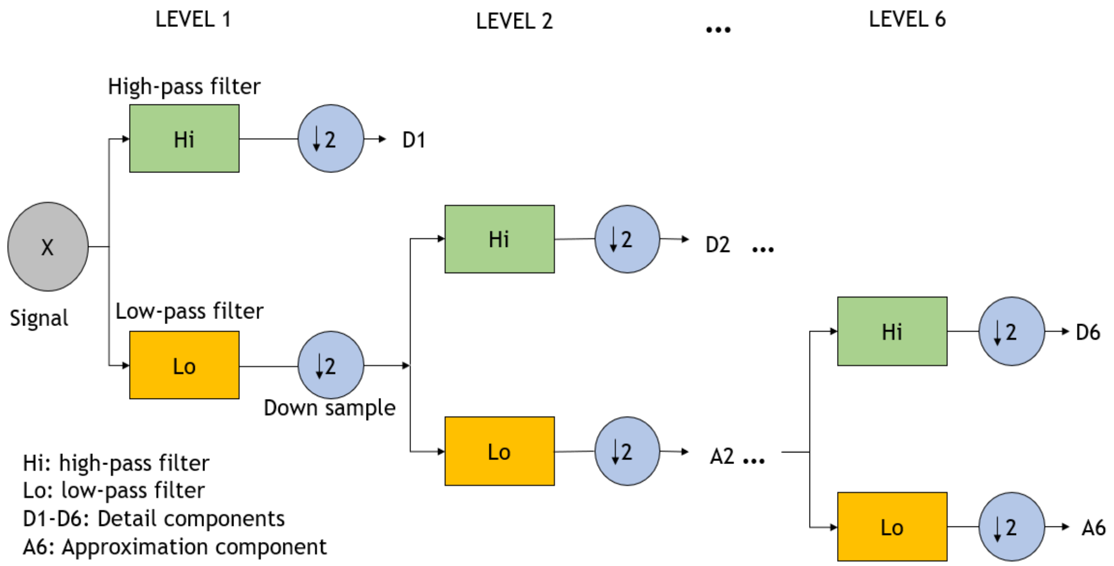



Figure 3.5: Wavelet Transform

### 3.3.1 Detecting maxima peaks based on wavelet transform

After decomposition and reconstruction of the signal, maxima peaks are detected as wavelet coefficients in the current signals using the empirical (threshold) method. To dynamically detect the maximum peaks during the series arcing state, it's necessary to establish a threshold based on the normal current's average value. This threshold is crucial for identifying significant spikes, such as the large spike observed from the onset of the arcing state (as illustrated in Fig.4.6). To find the time of this initial spike, we first determine the maximum peak from both signals, thereby isolating the prominent spike marking the onset of the series arcing. Subsequently, we employ a sliding window approach to calculate the maximum values within sequential intervals from the beginning of the normal current until the time corresponding to this specific spike. Within each window, the maximum value is computed, facilitating the subsequent calculation of an average value derived from these maximums. This dynamic threshold value is employed in the peak detection algorithm to detect only the abnormal spikes that occurred during the arcing state apart from the normal state (as shown in Fig.4.6). These points represent significant changes in signal amplitude, indicating potential fault conditions or anomalies. Analyzing coefficients across different scales detects maxima peaks present in current signals at various frequency bands and time intervals, aiding in the identification of transient events. This process extracts crucial features for signal analysis and classification. Fig.3.6 illustrates the comprehensive processing of the current signal through the proposed techniques for SAF detection.

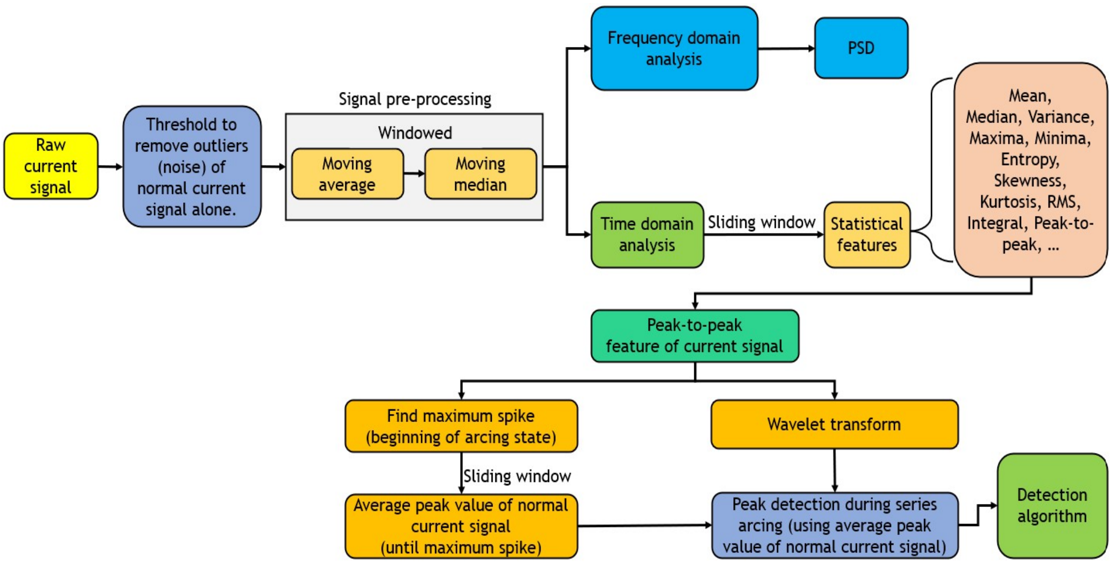



Figure 3.6: Proposed methodology on raw current signal

## 3.4 Detection algorithm

This study employs feature extraction and filtering of the signal utilizing signal processing techniques combined with threshold-based approaches to detect and characterize arc faults in DC systems.

The proposed detection algorithm uses peak-to-peak (Fig.4.7) features in the time domain. The detection algorithm initiates by establishing two thresholds: one dynamically derived from the average peak value of the normal current signal, and the other based on a minimum threshold for the number of fault peaks (say a range of 4-7 fault peaks). This threshold is particularly crucial in scenarios where sudden transients occur, abruptly deviating from the normal signal flow. By setting this threshold, the algorithm ensures robustness against such transient events. It employs a certain window size (say 0.5seconds-2seconds) for the detection process as illustrated in Fig.3.7, which represents the proposed algorithm.

Initially, a flag is set to false. The algorithm then progresses by considering the window's start and end within the peak-to-peak feature signal. It iterates through the data points (samples) within this current window, while simultaneously iterating through the maximum fault peaks (previously detected). During this process, it evaluates whether any pre-detected fault peaks fall within the current window's data. If a fault peak is found within the current window, the algorithm increments the fault peak count. If no fault peaks are present, the count is reset to 0. Subsequently, the algorithm assesses whether all fault peaks within the current window exceed the minimum threshold (obtained from an average value of normal current signal) and also if the count of fault peaks exceeds the minimum threshold within the same current window. If both conditions are met, the flag is set to true, which indicates the SAF, otherwise, it remains false, and the algorithm proceeds to the next window. This iterative process enables the algorithm to dynamically adjust its thresholds and accurately detect the onset of series arcing based on the observed data characteristics.

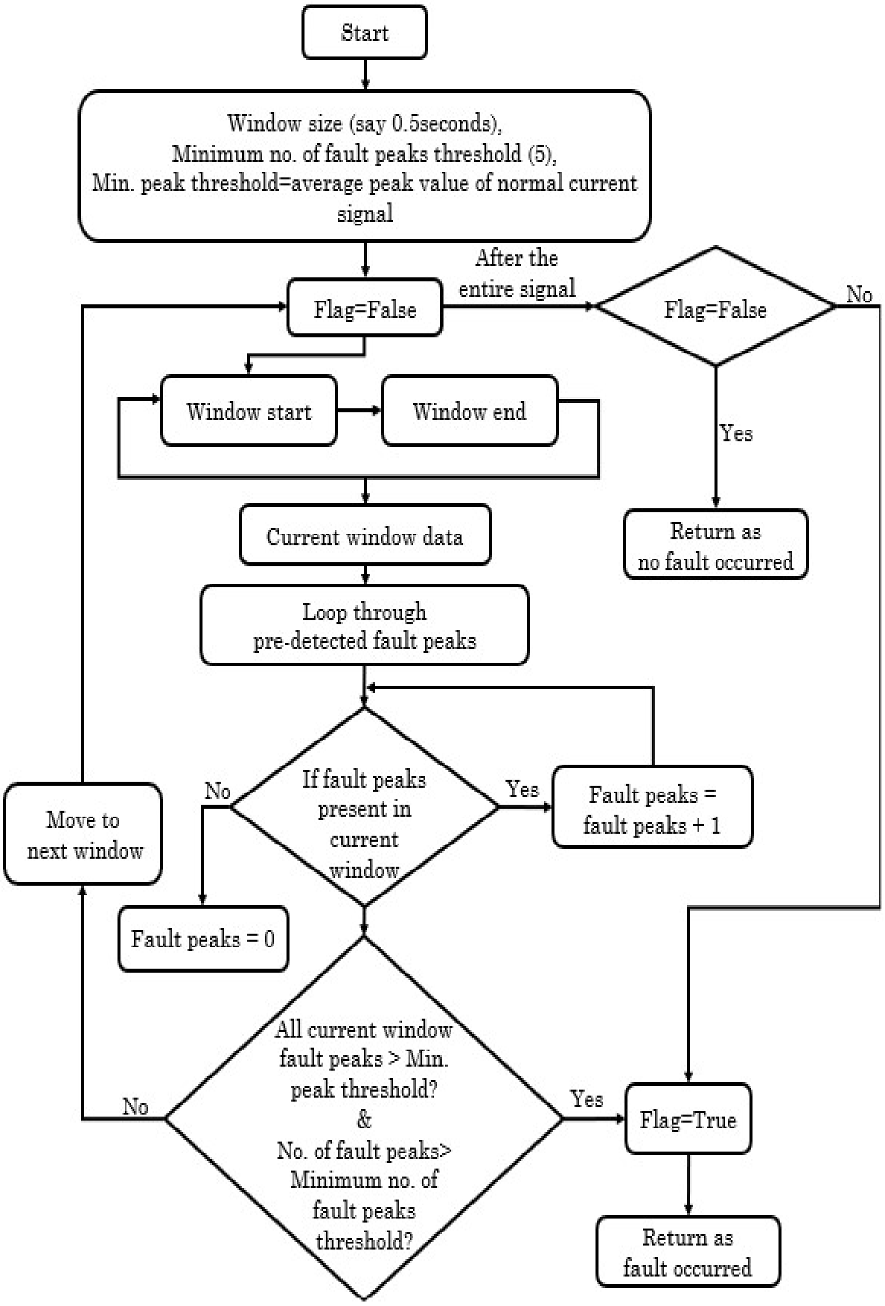



Figure 3.7: Proposed SAF detection algorithm

# CHAPTER 4

# Results and Discussion

## 4.1 Results

### 4.1.1 Overview of Findings

Based on analyzation of the collected data has yielded significant insights into the behavior of SAF in the DC system. Key findings include the identification of anomalies in current and voltage signals, the characterization of their environmental conditions, and the challenges associated with their detection and mitigation.

### 4.1.2 Simulation with an R (Resistor) load

Initially, the normal and series arcing data of a $16\Omega$ resistor with a DC power source of $48V$ are acquired in MATLAB Simulink as shown in Fig.3.1. The detailed results of the analysis are shown below:

The V-I characteristics with $48V$ source and a resistor load of $16\Omega$ during normal and the series arc are shown in the table 4.1, where the normal current value is 3A here.

### 4.1.3 Simulation observation of V-I characteristics with resistor load

On observing that data tabulated for resistive load in simulation at various conditions in the tab: 4.1, it is observed that:

- When there is no arc present in the circuit, there is normal current flow. The voltage across the ideal arc block is zero because the ideal arc block represents a perfect conductor with zero resistance, so the potential difference is zero.
- When an arc is introduced to the circuit, there is a significant increase in voltage and a gradual decrease in current amplitude.

Table 4.1: V-I characteristics with $48V$ source and a resistor load of $16\Omega$.

| | Normal state | | Arcing state | |
|---|---|---|---|---|
| Degree (gap between electrodes) | Voltage (V) | Current (A) | Voltage (V) | Current (A) |
| 0 | 0 | 3 | 0 | 3 |
| 5 | | | 3.763 | 2.765 |
| 10 | | | 7.649 | 2.522 |
| 20 | | | 16.068 | 1.996 |
| 30 | | | 27.525 | 1.280 |
| 50 | | | 47.717 | 0.017677 |
| 70 | | | 47.751 | 0.015536 |
| 90 | | | 47.536 | 0.029003 |
| 100 | | | 47.605 | 0.024719 |
| 120 | | | 47.569 | 0.073588 |
| 150 | | | 46.823 | 0.073588 |
| 180 | | | 47.967 | 0.002048 |

### 4.1.4 Simulation with a motor load

Similarly, the simulation employs a universal motor as the load, powered by a $48V$ DC supply, as shown in Figure 4.1. The circuit consists of two sets, one with (series arcing) the SimscapeIdealArc block (acts as an arc generator) and the other one without (normal) the SimscapeIdealArc block. This configuration enables the examination of the motor's performance characteristics under varying operating conditions. By analyzing the motor's response to the applied voltage, current, and load variations, valuable insights can be gained into its efficiency and behavior within the DC network. The circuit

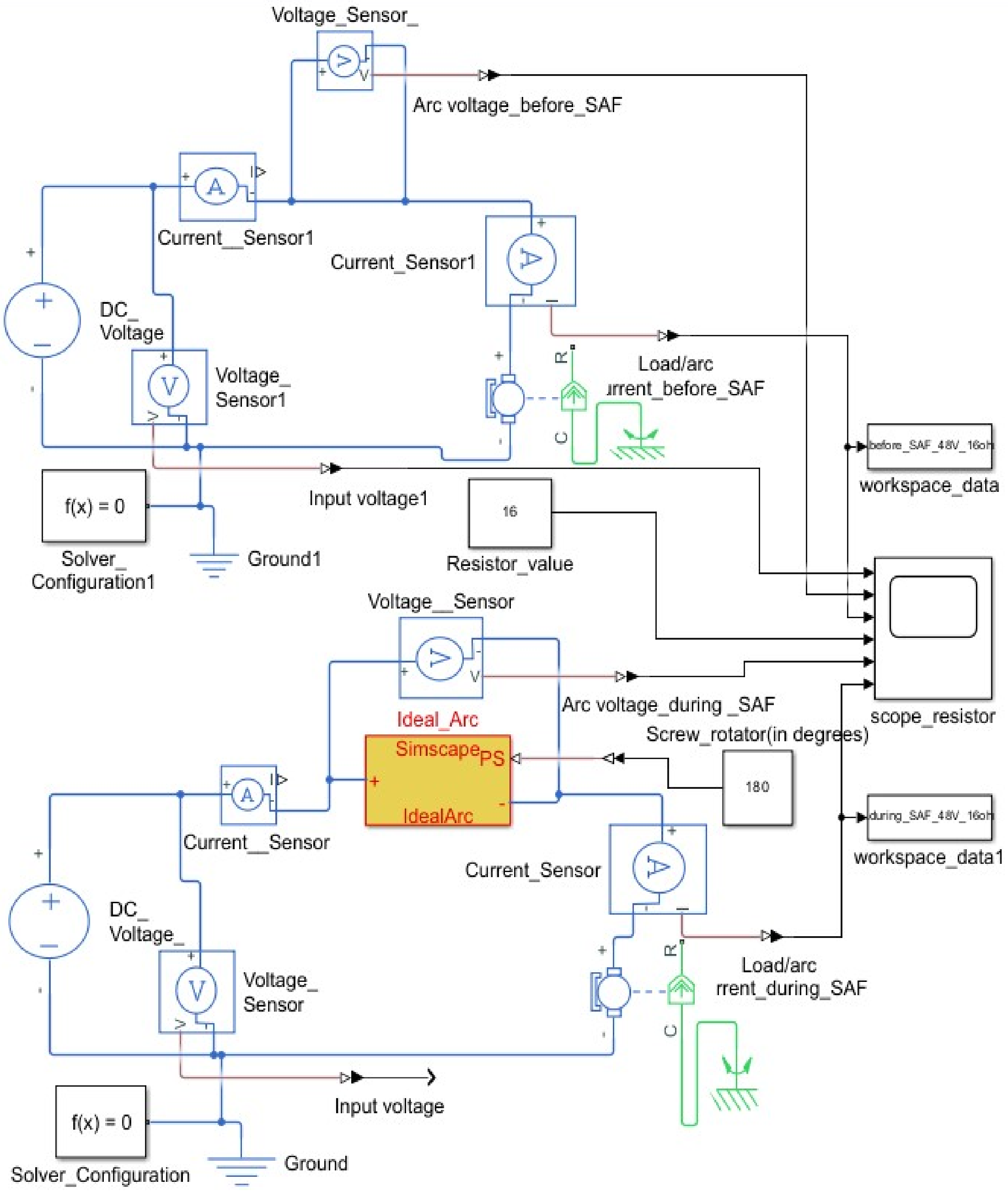



Figure 4.1: DC series circuit with 48V and a universal motor

The V-I characteristics with a $48V$ source and a universal motor during both the normal and the series arc are shown in the table.4.2.

### 4.1.5 Simulation observation of V-I characteristics with the motor load

- When there is no series arc, there's no potential difference between electrodes and the current usage depending on factors such as its mechanical load, speed,

Table 4.2: V-I characteristics with $48V$ source and a universal motor

| | Normal state | | Arcing state | |
|---|---|---|---|---|
| Degree (gap between electrodes) | Voltage (V) | Current (A) | Voltage (V) | Current (A) |
| 0 | 0 | 0.357785 | 0 | 0.357785 |
| 5 | | | 43.344 | 0.035054 |
| 10 | | | 44.822 | 0.023926 |
| 20 | | | 45.094 | 0.021879 |
| 40 | | | 45.200 | 0.021084 |
| 50 | | | 45.219 | 0.020938 |
| 70 | | | 45.240 | 0.020777 |
| 90 | | | 45.252 | 0.020689 |
| 100 | | | 45.256 | 0.020658 |
| 120 | | | 45.262 | 0.020613 |
| 140 | | | 45.266 | 0.020581 |
| 150 | | | 45.268 | 0.020568 |
| 180 | | | 45.272 | 0.020539 |

and efficiency.

- When there's a series arc, there is an abrupt change in the voltage (increases) and a gradual decrease in current amplitude.

### 4.1.6 Experimental raw current characteristics

The experiment utilized a rheostat as a load (with a value of $16\Omega$) to obtain the current signal at a sampling frequency of $250kHz$ during both normal and arcing states. The raw current signal is shown in Fig.4.2, and the current signal during series arcing decreases in magnitude level as compared to the normal signal, also the current signal consists of some noise due to environmental factors.

We leverage our initial understanding of the normal current flow to effectively filter out outliers, or generated noise, from the normal signal. This process involves applying a threshold value say $2-5\%$ of the normal current value (normal current value + $(2-5)\%$ of its value) to identify and eliminate noise (this process is important for eliminating false alarms during SAF detection in the proposed detection mechanism) as shown in Fig.4.3. By doing so, we enhance the detection mechanism's accuracy. However, this approach cannot be extended to the arcing state, as the signal exhibits fluctuating DC flow during this phase.

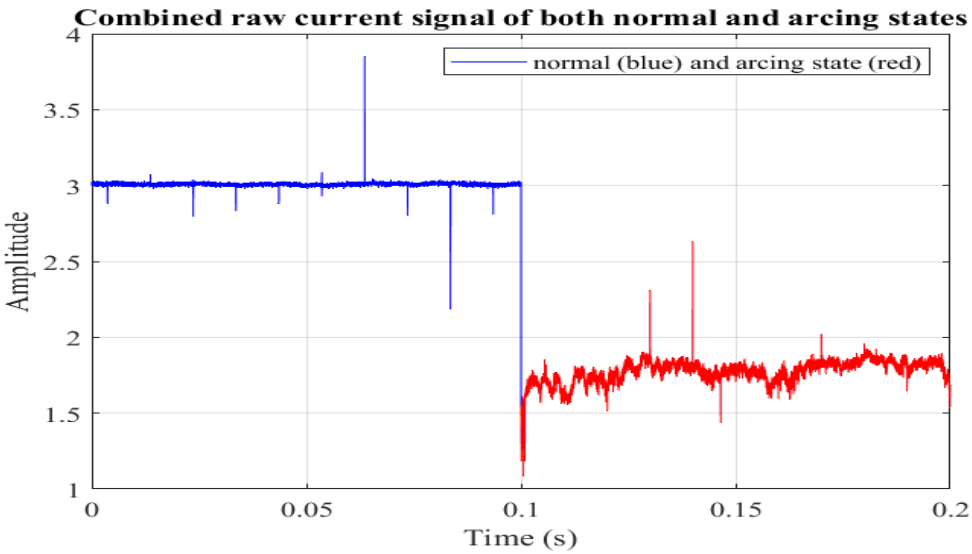



Figure 4.2: Raw current signal in normal(blue) and arcing(red) state

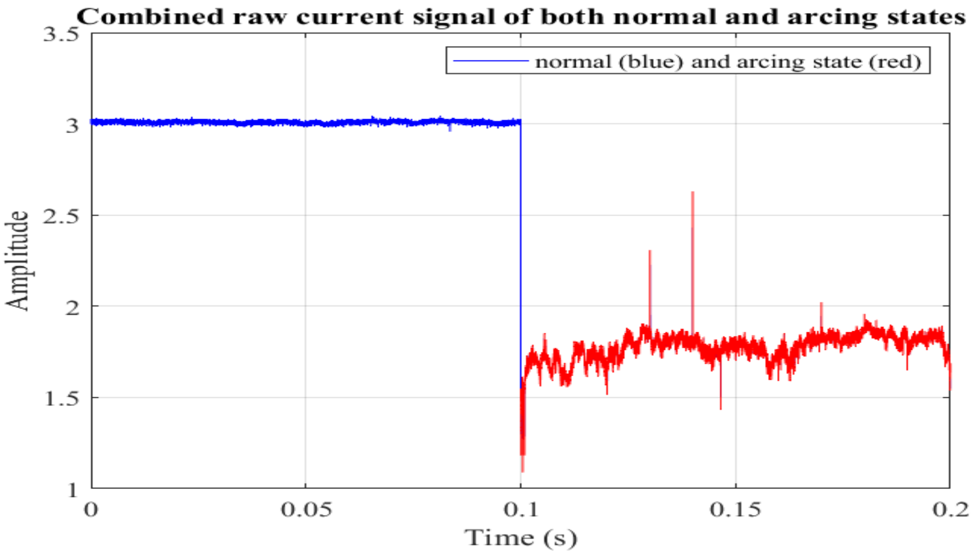



Figure 4.3: Removed outliers in normal(blue) current

## 4.2 Time domain characteristics

### 4.2.1 Removing noise from raw current signal

We begin by addressing the presence of noise within the current signal through a series of filtering processes. Initially, we employ a windowed moving average filter to mitigate noise. Subsequently, a windowed moving median filter is applied to further refine the signal by eliminating noisy data points. The effectiveness of these filtering techniques is illustrated in Fig.4.4, showcasing the resultant filtered current signal.

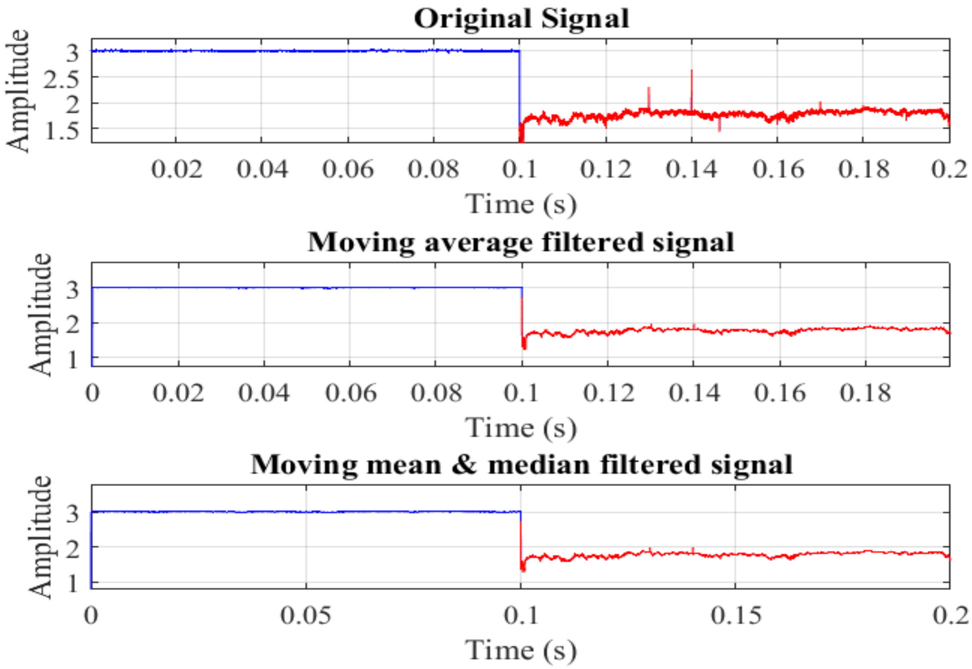



Figure 4.4: Noise removal from normal(blue) and arcing(red) using moving average and median filters

With the signal now filtered, our focus shifts to feature extraction. Using the sliding window technique, we conduct statistical analysis to gain insights into the behaviors of both normal and arcing states in the time domain. This analysis encompasses the computation of various statistical features such as mean, median, variance, RMS, entropy, kurtosis, skewness, integral, and peak-to-peak (maximum-minimum data points) features. The results of this statistical examination are depicted in Fig.4.5.

### 4.2.2 Statistical analysis in time domain

As depicted in Fig.4.5, it is evident that certain features such as mean, median, entropy, kurtosis, skewness, and RMS exhibit limited capacity to distinguish between normal and series arcing signals. Conversely, variance and peak-to-peak features emerge as effective discriminators between the two states. Particularly, the peak-to-peak feature demonstrates a pronounced ability to differentiate based on magnitude levels. Thus, it emerges as a pivotal feature for the detection process.

Further, wavelet transform is employed on the peak-to-peak feature to identify max-

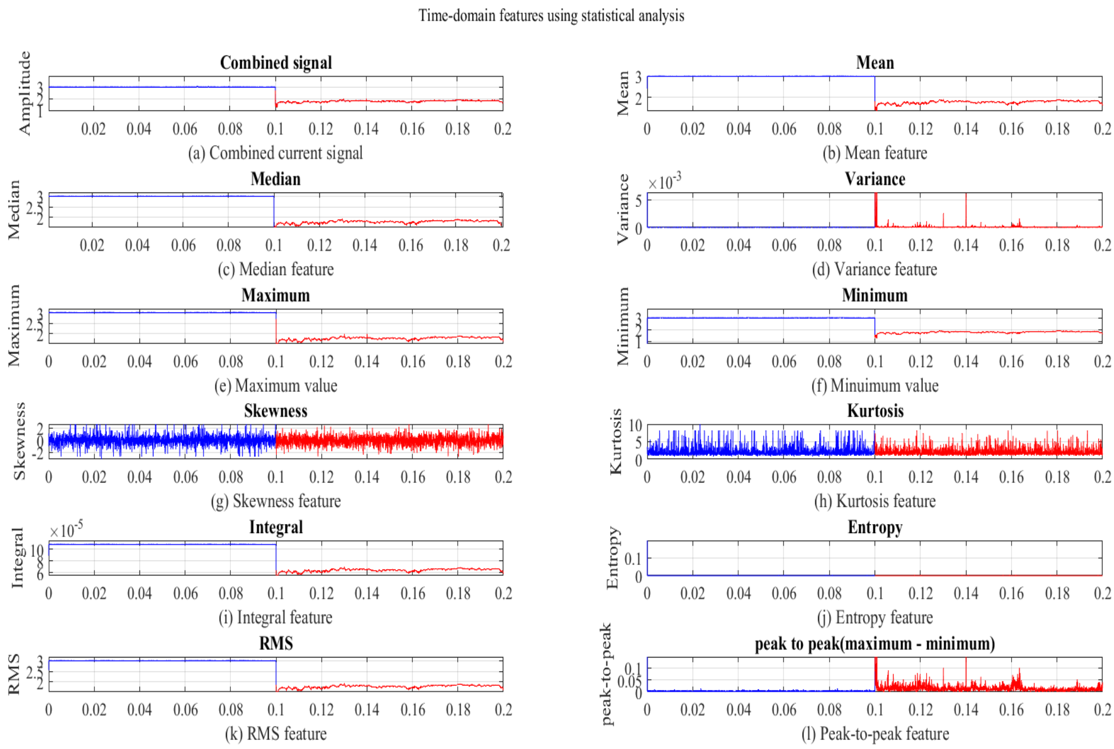



Figure 4.5: Statistical features in the time domain of normal(blue) and arcing(red) current signal. (a)Combined current signal, (b)Mean, (c)Median, (d)Variance, (e)Maximum values, (f)Minimum values, (g)Skewness, (h)Kurtosis, (i)Integral, (j)Entropy, (k)RMS, (l)Peak-to-peak

imum peaks occurring during the series arcing state. This method effectively detects high magnitudes present in the signal, distinct from the normal peaks of the current signal.

## 4.3 Employing wavelet transform on the feature-extracted current signal: Peak-to-Peak analysis

The peak-to-peak feature extracted from the current signal is subjected to wavelet transform, involving signal decomposition and subsequent reconstruction. Using a dynamic threshold (as illustrated in the proposed methodology) based on the average value of normal current during series arcing, maxima peaks are detected as wavelet coefficients in the current signals as depicted in Fig.4.6. Fig.4.7 clearly illustrates the detection of maxima peaks during series arcing, effectively distinguishing them from the normal state.

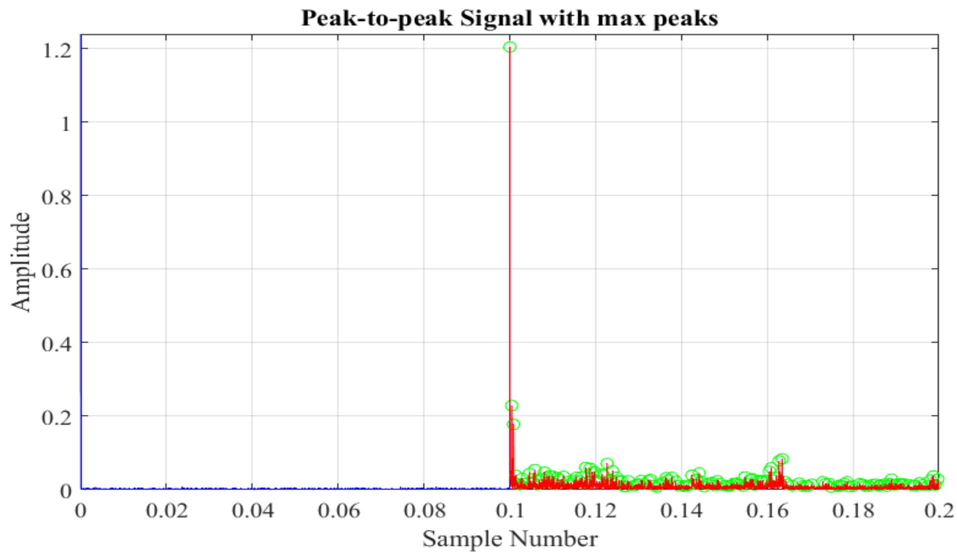



Figure 4.6: Maxima peaks during series arcing(red) state

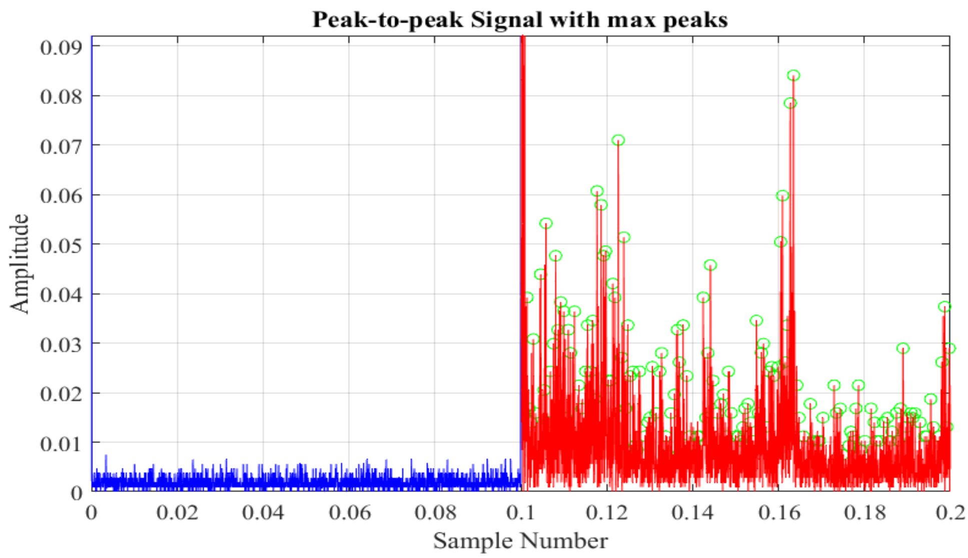



Figure 4.7: Observation of maxima peaks during series arcing(red) state

This dynamic threshold ensures that only abnormal spikes occurring during the series arcing state are identified, distinguishing them from normal fluctuations. These detected points indicate significant changes in signal amplitude, suggestive of potential faults or anomalies. By analyzing coefficients across different scales, maxima peaks present in current signals at various frequency bands and time intervals are identified, aiding in the detection of transient events. This process extracts crucial features for signal analysis and classification.

## 4.4 Frequency domain characteristics

Time-domain analysis depends on the jumping signal of voltage and current when an arc occurs. But more measurements need to be taken to prevent misjudgment caused by other interference, so frequency-domain characteristics are analyzed using the Fast Fourier transform (FFT). Frequency domain features describe the signal's behavior in the frequency domain, revealing information about its spectral composition and frequency components.

In Fig.4.8, the frequency domain representation of current signal during both normal and series arcing states reveals notable differences. Specifically, the frequency components present during series arcing exhibit elevated harmonic components with higher magnitudes compared to those observed during the normal state. This observation suggests that the magnitude levels of frequency components are elevated during series arcing, distinguishing it from the normal state.

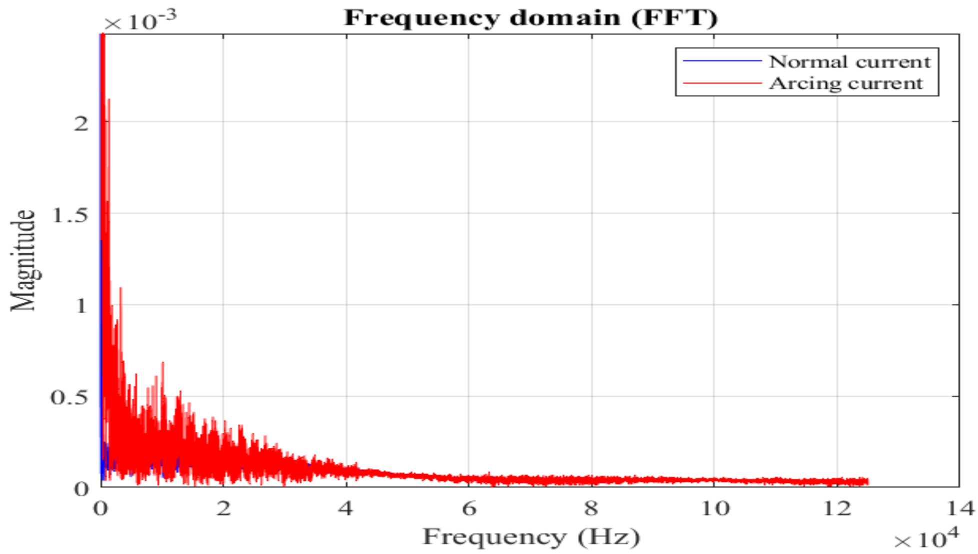



Figure 4.8: Frequency characteristics of normal(blue) and arcing(red) states

### 4.4.1 Power spectral density

The power spectral density (PSD) of frequency obtained during both normal and series arcing states is illustrated in Fig.4.9. Fig.4.10 presents a comparative analysis of the PSDs between normal and series arcing states. Notably, the PSD of the series arcing state exhibits higher magnitude levels compared to the normal state. Therefore, the proposed detection mechanism can be utilized in the frequency domain for SAF detection.

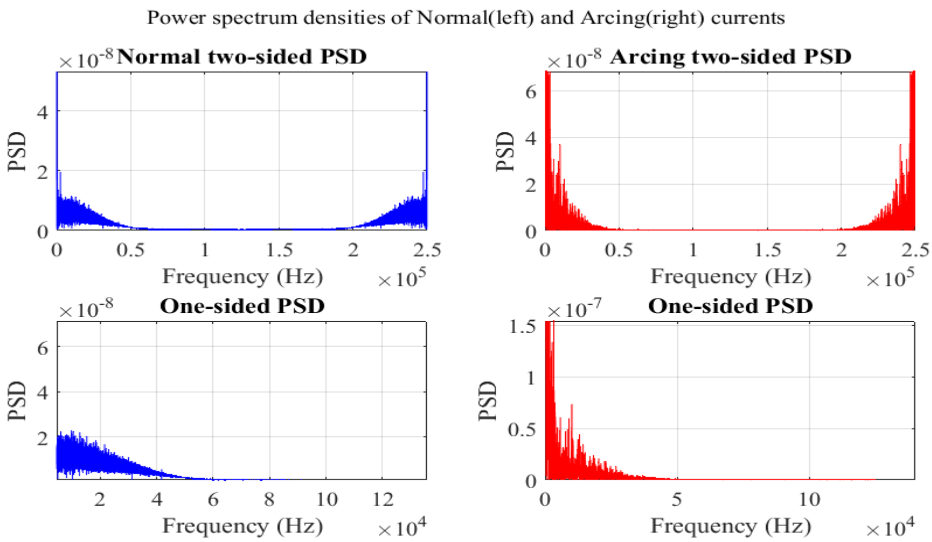



Figure 4.9: Power spectral density of normal(blue) and arcing(red) states

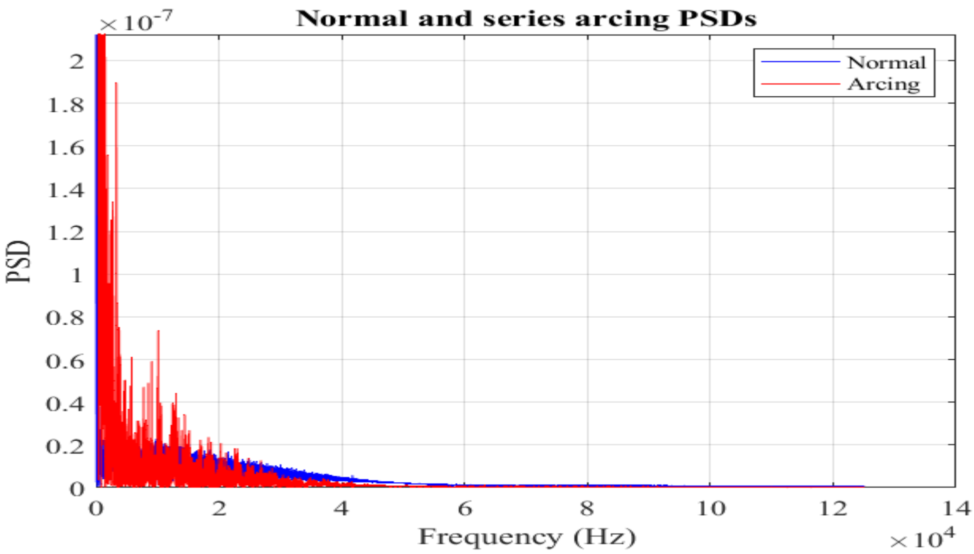



Figure 4.10: Power spectral density of normal(blue) and arcing(red) states

## 4.5 Time-frequency domain characteristics

To further observe the characteristic behavior of the current signal during normal and series arcing in the time-frequency domain, a continuous wavelet transform (CWT) method is utilized. The response for the filtered current signal is shown in Fig. 4.11.

As shown here, at 0.1 seconds the magnitude level is abruptly changed, thereby more harmonica can be seen after this particular time compared to the signal before it. This kind of time-frequency information can be observed using CWT.

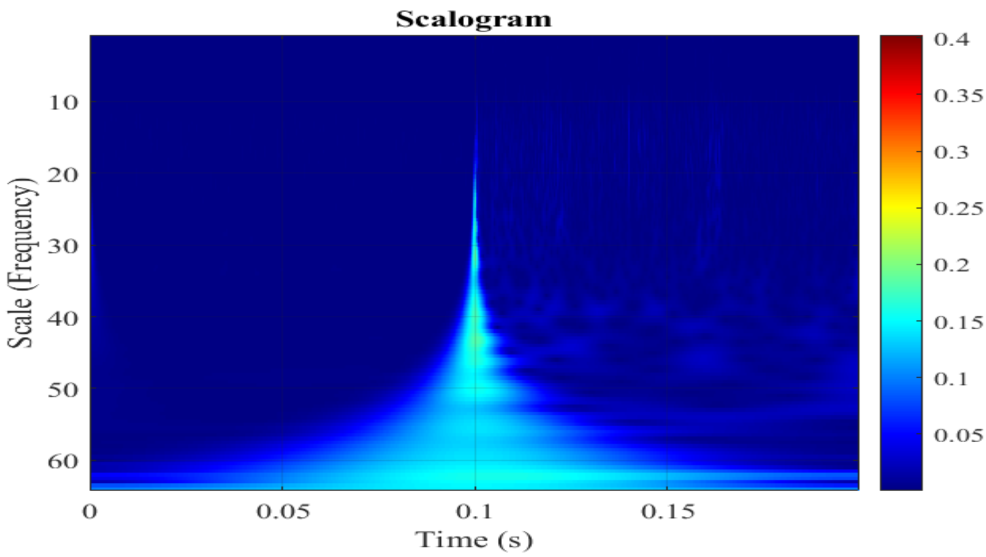



Figure 4.11: Spectrogram of current signal

## 4.6 Detection results for SAF using proposed algorithm

The data gathered from the experimental setup has been analyzed and the proposed detection algorithm has been implemented on this current signal that was recorded during both normal and series arcing.

Fig.4.12 shows that the SAF is not detected when the normal current signal is passed in the proposed detection algorithm, where the maxima fault peak detected is one (ignored) during the normal state. Whereas in Fig.4.13 SAF is detected when normal and series arcing of the current signal is passed in the detection algorithm, in which more maxima fault peaks are present during the series arcing state and the detection time it took was around 0.01 seconds for the proposed algorithm.

The proposed algorithm was executed over ten times (10 iterations), consistently yielding identical results with each test. This uniformity across multiple trials suggests a success rate of approximately 100% for the current data acquired under a rheostat load within the DC network.

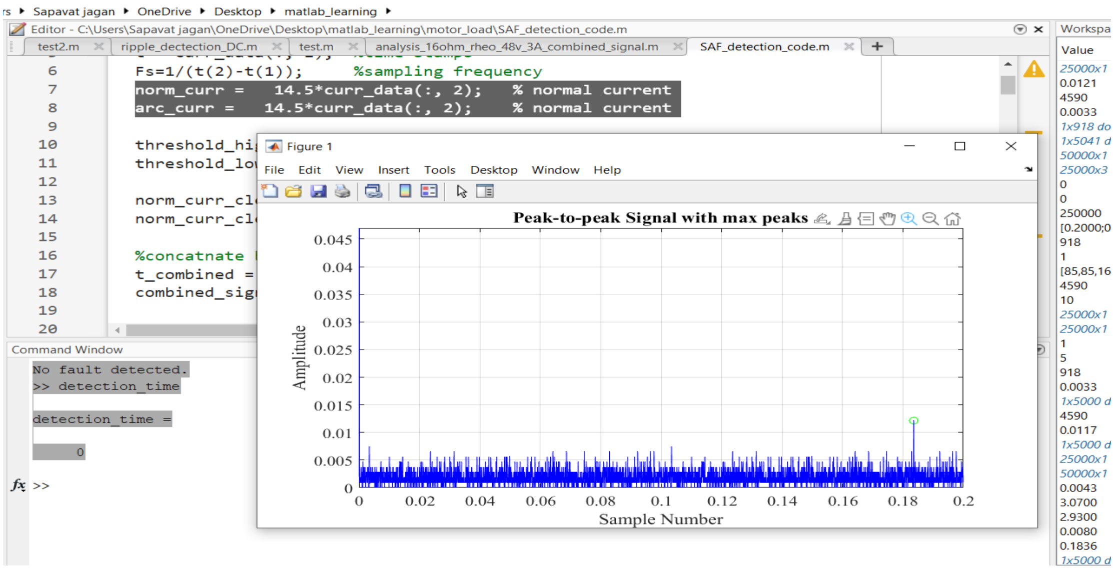



Figure 4.12: SAF not detected

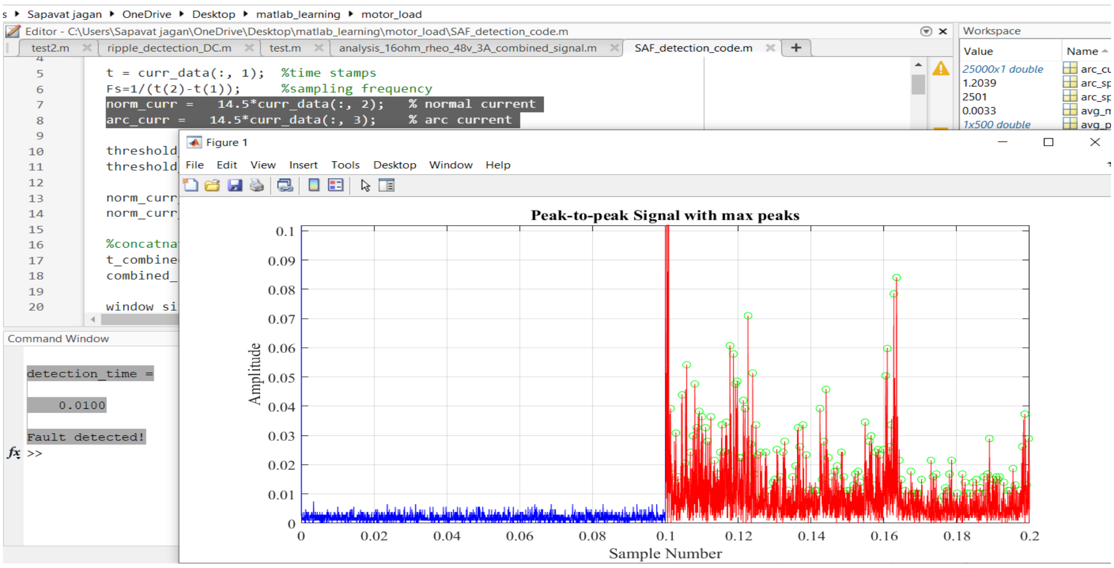



Figure 4.13: SAF detected

### 4.6.1 Interpretation of Results

Based on the above features extracted from the current signal in the time domain (mean, variance, entropy, maximum peaks, minimum peaks) and frequency domain (power and energy spectral), a dynamic empirical approach(threshold-based approach) for SAF detection is proposed. Through empirical analysis, threshold values are determined for each of these features, outlining the boundary between acceptable operation and the presence of an arc fault. During real-time monitoring, the current signal is continuously assessed against these predefined empirical thresholds. If any feature exceeds its respective threshold, indicating a deviation from expected behavior, an alarm or fault notification is triggered, prompting timely intervention to mitigate potential hazards. This methodology offers a practical and effective means of detecting arc faults in DC power systems, leveraging insights derived from empirical data to ensure robust fault detection performance

The results reveal the critical importance of understanding the characteristics and behaviors of different arc faults under various environmental conditions. SAF in particular, poses significant challenges due to their decreased current and difficulty in extinguishing the faults, highlighting the need for specialized detection and mitigation strategies.

### 4.6.2 Limitations of threshold-based analysis

- Threshold-based fault detection in DC power systems relies on a specific threshold value.
- The threshold value is not universal and must be determined each time based on signal type.
- Re-evaluation of the threshold value is necessary for accurate classification of different fault types in new power systems.

### 4.6.3 Overcoming limitations of threshold-based detection:

ML techniques such as ANN, Random Forest (RF), Support Vector (SVM), etc..., can be used to overcome this problem using the large datasets provided to the models. Machine learning offers enhanced fault classification in power systems by adapting to system characteristics, handling nonlinear relationships, addressing uncertainties, and optimizing decision boundaries for robust performance.

# CHAPTER 5

# CONCLUSION AND FUTURE SCOPE

## 5.1 Conclusion

This work, carried out as mentioned above, provides valuable insights into the analysis and development of SAF detection in DC and EV systems. Based on the observation of both simulation and real-time experiment current signal, it is observed that when there is an arc fault occurs, there is an abnormality/fluctuation introduced in current and voltage signals involving elevated harmonics. Voltage significantly increases and current gradually decreases during the series arcing. Also, current signals do not cross zero and current signals show prominent features such as peak-to-peak to detect abnormality in the DC system and EVs.

By employing feature extraction methods and signal processing techniques such as discrete wavelet transform and dynamic empirical techniques, the proposed detection mechanism can effectively identify and characterize arc occurrences in the DC system. The utilization of the moving average and moving median filters, and by leveraging peak-to-peak features of normal and series arcing of the current signal, this method effectively distinguishes arc-related distortions while requiring less data compared to traditional approaches relying on larger datasets. This work presents a robust method for SAF detection. It declares the potential of the proposed approach to significantly enhance the safety and reliability of electrical systems powered by DC in series connection.

## 5.2 Future Scope

### 5.2.1 Enhanced/Advanced Signal Processing and Machine Learning Techniques:

- Advanced signal processing algorithms and machine learning approaches can be utilized to improve SAF detection accuracy in DC networks.
- Implementation of these techniques to the unique requirements of Electric Vehicles (EVs), considering the presence of multiple loads as in EV hardware.

### 5.2.2 Real-Time Monitoring Systems:

- Developing a real-time monitoring system capable of continuous surveillance of DC power systems, particularly in EV setups, to detect arc fault occurrences promptly.
- Implement immediate alert mechanisms to mitigate potential hazards associated with arc faults in EV power systems.

### 5.2.3 Experimental Validation:

- Conducting experimental validation studies using physical DC power system setups, with a focus on EV configurations, to assess the effectiveness of proposed methodologies.
- Validate the performance of SAF detection techniques in real-world scenarios, particularly in the context of EV applications.

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