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REVIEW OF ARC FAULT ANALYSIS IN AC DISTRIBUTION SYSTEMS

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ABSTRACT

This paper offers a quick overview of arc faults occurring in AC distribution systems and discusses different detection methods currently in use. It also examines real-time fault incidents observed at industrial levels. Furthermore, the study explores the distinct Arc signal (current) characteristics of diverse electrical loads, such as resistive elements, inductive loads like fans, and switching loads such as laptops. This exploration includes analyses using time-domain analysis, Empirical Mode Decomposition (EMD), and Hilbert Spectrum analysis. Finally, the paper concludes by proposing directions for future research in this field.

Keywords: —Arc Faults, AC distribution system, High Impedance fault (HIF), Uninterruptible Power Supply (UPS), Empirical Mode Decomposition (EMD), Intrinsic Mode Functions (IMFs).

I. Introduction

Arc faults in distribution systems are unintended electrical discharges that occur when current flows through an unintended path, often caused by damaged or deteriorated wires, excessive thermal insulation, stray currents and overvoltage, poor connections. These faults can generate significant heat, leading to fires and damage nearby infrastructure. Detecting and mitigating arc faults is crucial for maintaining the safety and reliability of electrical distribution systems. Understanding the nature and behavior of arc faults is essential for improving the resilience and safety of power distribution networks. Various detection techniques have been developed to identify and address these faults promptly.

II. Literature

High impedance fault (HIF) is the most commonly occuring fault in distribution system. These can be caused by events such as downed power lines contacting the ground, trees, or other non-conductive surfaces. HIF results in several physical and electrical characteristics [9], including:

a. **Intermittence of the arc:** the arc does not generate current in a steady state pattern, instead it generates a few conduction cycles followed by several non-conduction cycles.

b. **Asymmetry in the current waveform:** due to difference in the break-down voltage against positive and negative voltage values, there is a difference between the peak value and shape of positive and negative half cycles of HIF current.

c. **Current buildup and shoulder:** current magnitude gradually escalates (builds up) until it reaches and maintains a constant value for several cycles (shoulder).

d. **Non-stationary Current:** the current frequency spectrum varies with time.

e. **Randomness:** both the current magnitude, and its conduction/non-conduction intervals are random values.

f. **Non-linearity:** voltage–current characteristic of the HIF is nonlinear due to the existence of the arc.

g. **Low frequency components in current and voltage waveforms:** due to non-linearity of HIF the waveforms contain harmonics up to 600 Hz for the current and up to 300Hz for voltage.

h. **High frequency components in current waveforms:** arc results in high frequency components in the current waveform.

These characteristics helps in detecting the type of fault easily. Various detection techniques proposed for this high impedance faults. Wavelet transforms are employed to decompose the complex signals associated with HIFs into different frequency components, making it easier to isolate the unique characteristics. Denoising techniques are applied to filter out noise and enhance the signal quality, thereby improving the reliability of fault detection [1].

Although these techniques are designed to enhance signal quality by filtering out noise, external ambient noise can overlap with the low-level signals of HIFs, making it difficult for the algorithms to detect them. The Advanced Distortion Detection Technique (ADDT) utilizes waveform analytics to distinguish and detect HIFs by analyzing minute-level distortions in AC sinusoidal voltage and current waveforms [2]. As this technique depends on signal quality external factors may affect the reliability. On the other hand, series arc faults cause severe hazardous situations in low voltage distribution systems which are typically, due to loosen connections, damaged wiring, or broken conductors. Series arc faults occur within the circuit itself, potentially causing intermittent or complete interruptions in the flow of electricity.

A detection technique that combines empirical mode decomposition (EMD) and support vector machine (SVM) algorithms proposed and analyzed for the electromagnetic radiation (EMR) signals under the experimental setup [3]. ArcNet, a model based on convolutional neural networks (CNNs), is introduced. It was trained using a database of signals gathered from various loads, utilizing raw current data [4]. But ArcNet's ability to detect uncommon or previously unseen arc patterns may be limited. If the model encounters novel arc fault scenarios that differ significantly from those in the training data, its accuracy may decrease, leading to potential false positives or negatives.

Arc faults resulting from overloads occur when excessive current flows through electrical circuits, leading to overheating and insulation breakdown [5]. These faults can occur in various components of the electrical system, including wires, switches, outlets, and appliances. When one phase is overloaded, the current flowing through that phase exceeds the cable's rated capacity. This excessive current generates heat due to the resistance in the cable. Continuous overheating can degrade the cable's insulation, reducing its effectiveness and eventually leading to insulation failure. Once the insulation is compromised, the risk of short circuits increases significantly, as the bare conductors may come into contact with each other or with grounding surfaces.

The heat can also cause the cable to expand and contract, leading to mechanical stress and potential physical damage. Regular inspection, proper wiring, and the use of circuit breakers or arc fault circuit interrupters (AFCIs) [7] are essential measures to prevent and mitigate the risks associated with overload-induced arc faults in electrical system. Many distribution systems suffer from imbalances in their three-phase loads due to uneven distribution of single-phase loads among the three phases. This imbalance can lead to inefficiencies and operational issues. Enhancing three phase balancing ensures a more even distribution of power, improving overall system performance and reliability. An expert system is developed to optimize the rephasing of laterals and distribution transformers, improving three-phase balancing in distribution systems [8].

2.1 Field Study

This section focuses on real-time faults that occur in industrial distribution systems, exploring their causes and impacts. It examines fault occurrences by analyzing operational data, historical fault records, and real-time monitoring insights. The primary goal is to identify common fault patterns, investigate their root causes, and assess their effects on system reliability, equipment performance, and overall operational stability. Additionally, this section reviews case studies to highlight real-world instances of failures, their resolutions, and the effectiveness of maintenance strategies. By leveraging data-driven analysis and diagnostic methods, this study aims to enhance the understanding of fault behavior and improve the reliability of industrial distribution networks.

Figure 1: Batteries which has completely burned

Uninterruptible Power Supply (UPS) system is to provide a clean, well-regulated electric power to the critical load equipment, when the normal utility supply fails or out of specification [11]. A UPS system works by constantly monitoring the incoming utility power. When the power supply is stable, the UPS allows it to pass through to the connected equipment while also charging its internal batteries. In the event of a power failure or fluctuation outside the acceptable range, the UPS immediately switches to battery power to provide an uninterrupted supply of electricity. This seamless transition ensures that critical equipment continues to operate without interruption, protecting against data loss, hardware damage. Once the utility power is restored to a stable state, the UPS switches back to utility power and recharges its batteries.

Figure 2: Burned out UPS

An incident occurred in the power room housing the UPS and battery bank, resulting in a fre that engulfed the entire room. All equipment within the room was destroyed in the blaze. Figure 1 and Figure 2 both illustrate the outcomes of the incident. Various factors can contribute to such incidents involving battery banks and UPS systems. The following sections discuss some of the causes that might have led to the fire.

Thermal management is crucial for the reliability of UPS systems. Overheating can accelerate the degradation of battery components and lead to thermal runaway, particularly in lithium-ion batteries. Phase Change Materials (PCMs), Battery Thermal Management System (BTMS), provides efficient temperature control by absorbing excess heat during high load conditions and releasing it during low load conditions, ensuring the battery operates within an optimal temperature range [13].

Battery life can be significantly shortened by overcharging or over-discharging. During overcharging, batteries show increased temperatures, which escalates more rapidly with higher charging rates, often leading to failure. Elevated temperatures near the battery opening results from
the release of high-temperature gases generated internally. Over-discharge similarly affects battery capacity [14]. In high-voltage energy storage systems, numerous battery cells and modules are

interconnected through series and parallel connections. Over time, the cyclic use of these battery systems leads to aging and mechanical stress.

This stress can cause the batteries to expand, resulting in the loosening or breakage of solder joints at the connections between the batteries. Such issues can potentially lead to arc formation, posing significant safety risks [15]. A technical research report on Lithium-Ion UPS Battery [12] presents that the various electrolyte mixtures contain hydrocarbons that are themselves combustible, and that degrade to short-chain hydrocarbons which may be explosive.

Figure 3: Damaged Phase due to Overload

Fig 3 shows the supply mains at the distribution level, in which a phase wire got fire and cut off from the system. This fault happened due to overload on that phase. Fire can easily start by overloading on the cable [10]. Overloads often happen when too many devices are connected to a single circuit, the current increases beyond the rated capacity of the circuit, the insulation materials may degrade, creating a conductive path between conductors or between conductors and ground. When an arc breakdown is initiated, energy gets deposited into the arc channel at a rate much greater than can be removed from the area by the shock wave that is created. This causes a rapid pressure to rise and, if the arc energy is sufficiently high, this will be perceived as an explosion [6].

2.2 Experimental Setup

An experiment focused on studying arc generation is meticulously designed to systematically observe and analyze the behavior of electrical arcing under controlled conditions. The main aim is to observe and document the behavior of arcing signals, identify their unique characteristics, and assess the influence of various parameters. The experiment involves constructing an electrical circuit with essential components such as a power source (e.g., battery or power supply), a load (either resistive or inductive), and suitable wiring, all ensuring they can safely manage the expected current and voltage levels. To generate controlled arcs, specialized equipment like a spark gap is used. Data acquisition is performed using a Digital Phosphor Oscilloscope (DPO), which records both arcing and non-arcing current waveforms. Critical experimental parameters, including the type of arc, its duration, current levels, and fault locations, are predefined. Multiple experiments are conducted with varying parameters to explore different arc fault scenarios.

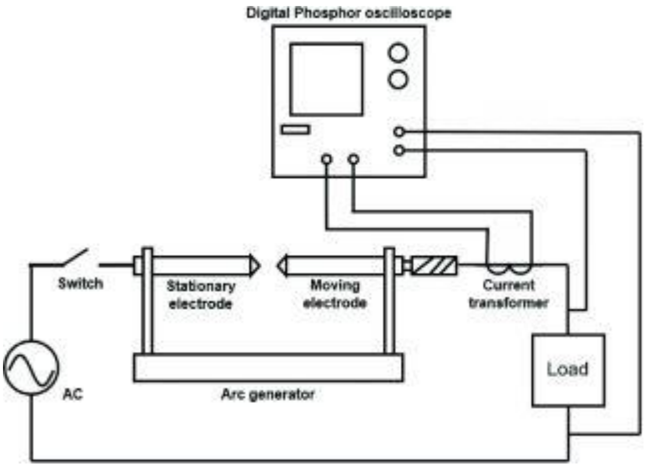

Figure 4: Diagrammatic Representation of Arc Generation Circuit

Data recording is facilitated by DPOs, which offer flexible sampling rates; in this experiment, a sampling rate of 1,000,000,000 samples per second (1Gs/s) is employed to convert analog input into digital data for detailed analysis.

2.3 Theoretical Framework

This section presents the theory behind the techniques applied in analysis of arc signals.

2.3.1 Emperical Mode Decomposition (EMD):

Empirical Mode Decomposition (EMD) is a data-driven technique used primarily for analyzing non-stationary and nonlinear time-series data. EMD aims to decompose a complex signal into a finite number of intrinsic mode functions (IMFs) and a residue. IMFs are functions that oscillate around zero with a local mean frequency.

Sifting Process: The core of EMD is the sifting process, which iteratively extracts IMFs from the original signal. It involves:

a. Identifying local maxima and minima (” extrema”) in the signal.

Interpolating upper and lower envelopes using these extrema.

b. Subtracting the average of these envelopes from the original signal to obtain an IMF.

c. Repeating this process until a stopping criterion is met.

Let x(t) be the original signal. At each iteration k, the k-th Intrinsic Mode Function (IMF), $c_k(t)$ is obtained by,

$$c_k(t) = x(t) - \sum_{i=1}^{k-1} c_i(t)$$

Where, $c_i(t)$ are the previously extracted IMFs.

The process stops when the residual r(t) becomes a monotonic function or exhibits other predefined characteristics. The residual is defined as:

$$\mathrm{r}(t) = x(t) - \sum_{i=1}^{N} c_i(t)$$

2.3.2 Hilbert Spectrum:

The Hilbert Spectrum is a powerful tool used in signal processing and time-frequency analysis, especially for analyzing nonlinear and non-stationary data. It is derived from the Hilbert-Huang Transform (HHT), which consists of two main steps: Empirical Mode Decomposition (EMD) and the Hilbert Transform. To apply the Hilbert Transform to each IMF $c_i(t)$:

$$z_i(t) = c_i(t) + jH(c_i(t))$$

Compute the instantaneous amplitude $A_i(t)$ and frequency $\omega_{\mathrm{i}}(t)$:

$$A_i(t) = |z_i(t)|$$

$$\omega_{\mathrm{i}}(t) = \frac{d\theta_i(t)}{dt}$$

Construct the Hilbert Spectrum $H(\omega,t)$:

$$H(\omega, t) = \sum_{i=1}^{N} A_i(t)\delta(\omega - \omega_i(t))$$

2.4 Real Time Signal Analysis

This section presents the analysis of the gathered arc signals utilizing Empirical Mode Decomposition (EMD). This method allows us to make a comprehensive examination of their characteristics and behaviors.

2.4.1 Analysis of Signals on Individual Loads

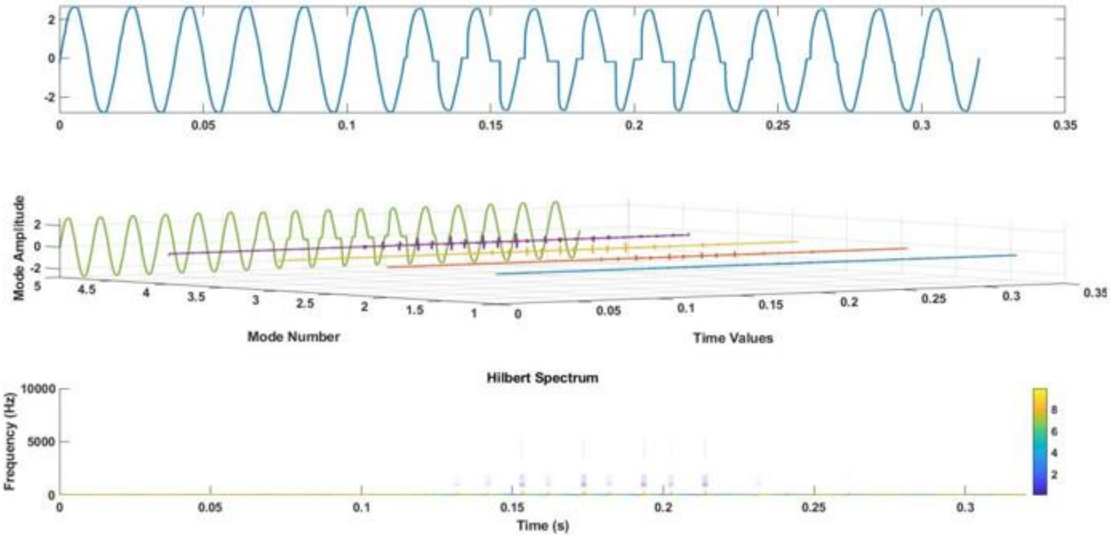

Figure 5: The plots for the corresponding arc signal produced by resistive load.

Figure 5 illustrates three key plots: the time-domain signal, the empirical mode decomposition (EMD), and the Hilbert spectrum of a current signal generated by an arc in a resistive load. The time-domain plot displays the original signal, which shows variations in amplitude and waveform over time. Initially, the waveform is smooth and sinusoidal, but around 0.15seconds, it becomes more complex with sharp transitions, indicating the presence of non-linearities or additional frequency components.

The EMD plot shows the Intrinsic Mode Functions (IMFs) derived from the decomposition of the original signal. Each mode, represented in different colors, highlights a distinct component of the signal. The green mode (IMF 1) has the highest amplitude and corresponds to the dominant frequency of the original signal. The Hilbert Spectrum offers a time-frequency representation of the signal, where color intensity reflects the amplitude of frequency components at each time point, as indicated by the color bar. The majority of the energy is concentrated at specific frequencies, but there is a noticeable dispersion around 0.15 seconds, where additional frequencies emerge.

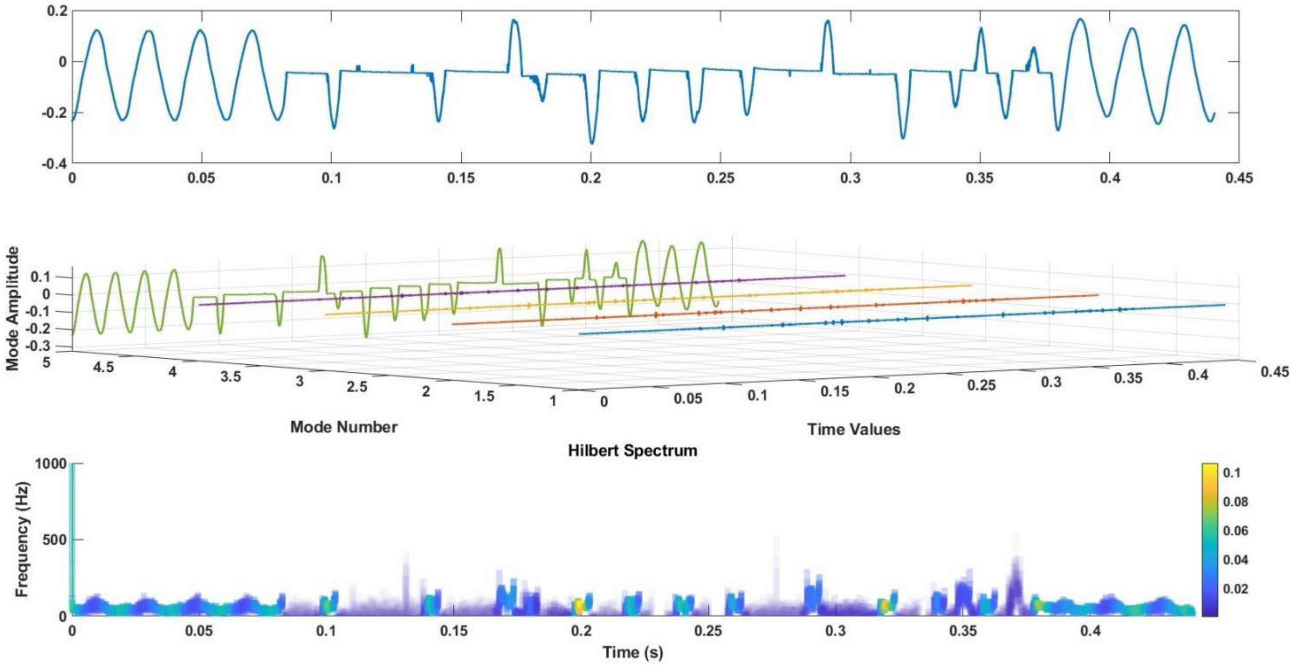

Figure 6: The plots for the corresponding arc signal produced by Inductive load.

The current signal of an inductive load, like a fan, is seen in Figure 6 changing from a smooth sinusoidal waveform to irregular patterns at the beginning of an arc, which occurs at about 0.1 seconds. The identification of later arc occurrences is made more difficult by these abrupt changes and abnormalities. The primary high-frequency component in the EMD plot is captured by the first Intrinsic Mode Function (IMF), while lower frequencies and general trends are represented by subsequent IMFs. After 0.1 seconds, the Hilbert Spectrum shows several frequency components that have emerged. The color intensity of the spectrum indicates amplitude fluctuations, with blue representing lower amplitudes and yellow representing larger ones.

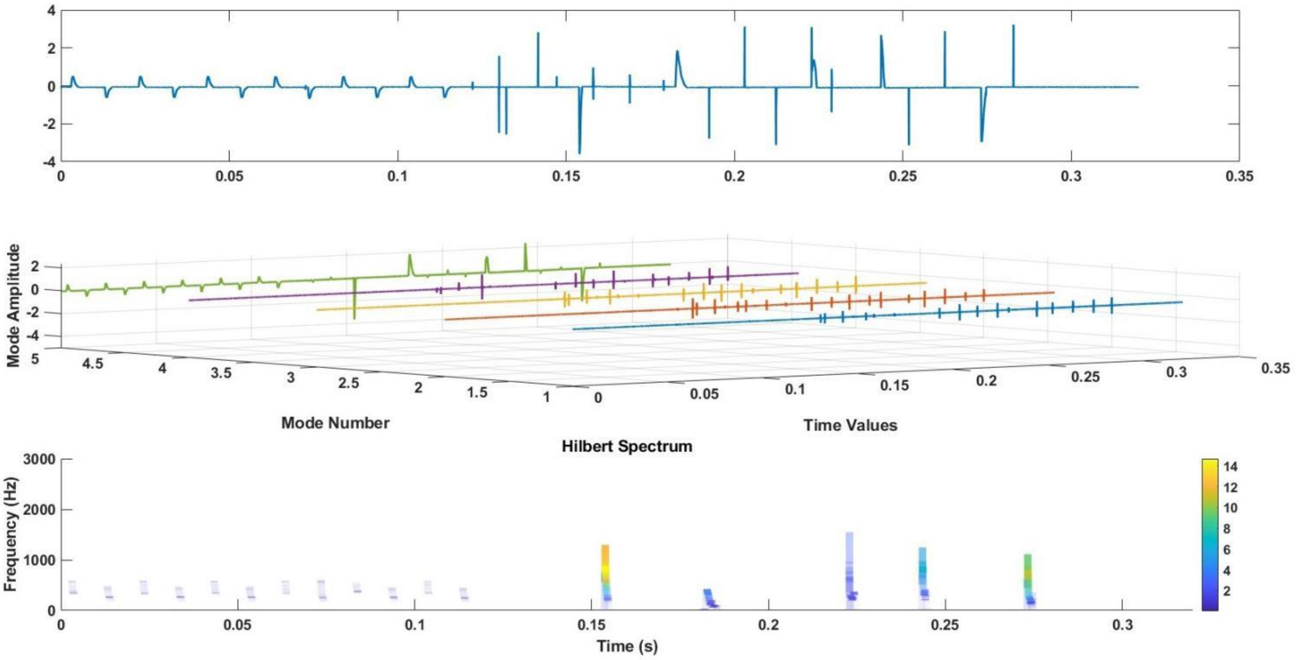

Figure 7: The plots for the corresponding arc signal produced by switching load.

Figure 7 presents the time-domain plot, EMD plot, and Hilbert Spectrum of an arc signal generated by a switching load (laptop). The time-domain signal shows significant amplitude variations, particularly between 0.15 and 0.3 seconds, with periodic spikes that indicate switching events. These spikes occur at irregular intervals, reflecting the intermittent nature of the laptop's load switching.

The EMD plot reveals varying amplitude behaviors among the IMFs. The green IMF, which corresponds to the first IMF, shows noticeable spikes that align with the sharp transitions in the original signal, suggesting that these instances may represent arc occurrences. The Hilbert Spectrum illustrates the frequency components from 0.15 to 0.3 seconds, highlighting the introduction of higher frequencies and increased amplitude due to the switching events. This is evidenced by high amplitude bursts, depicted by intense yellow and orange regions at 0.15 seconds, confirming the presence of these spikes.

2.5 Analysis of Signals on Combined Loads

Three categories of loads which are resistive, inductive and switching loads are connected in parallel. The arcing will take place on any branch corresponding to the particular load.

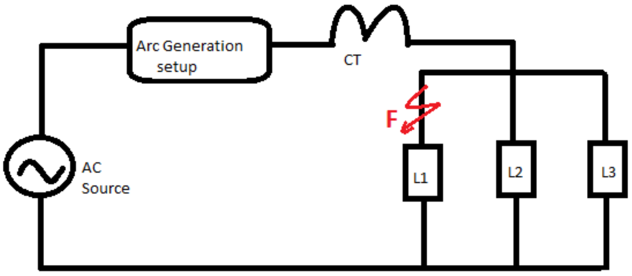

Figure 8: The diagrammatic representation of combined load.

In Figure 9, the time-domain plot exhibits periodic behavior with stable amplitude and frequency, indicating a regular arc current in the resistive branch.

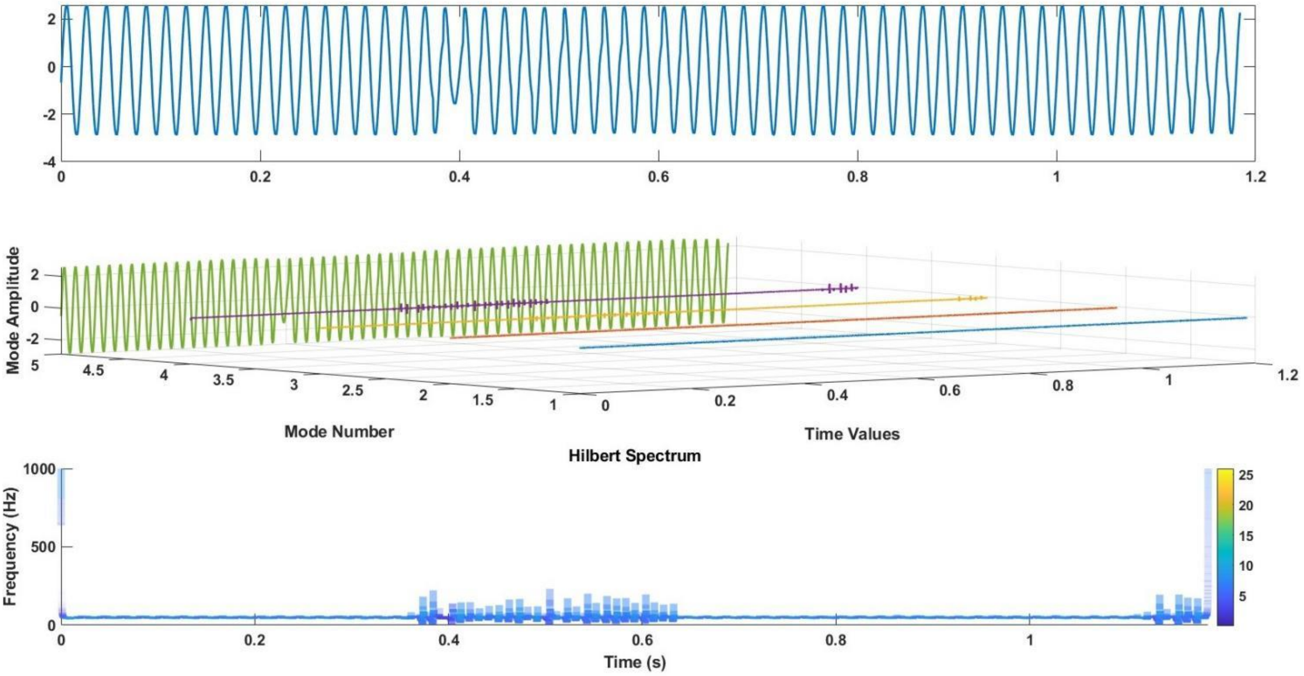

Figure 9: The plots for the corresponding arc signal produced by resistive branch in combined load.

The amplitude ranges from -4 to 4 units over 1.2 seconds, showing minor variations likely due to interactions with inductive and switching branches. The green IMF, with the highest amplitude, represents the fundamental frequency of the arc in the resistive branch. Other IMFs (purple, orange, blue) with lower amplitudes reflect additional frequency components introduced by the inductive and switching branches.

The Hilbert Spectrum reveals significant energy concentration at low frequencies, consistent with the dominant low frequency arc in the resistive branch. Higher frequency components appear around 0.4 to 0.6 seconds and again from 1 to 1.2 seconds, suggesting transient events or disturbances from the switching branch.

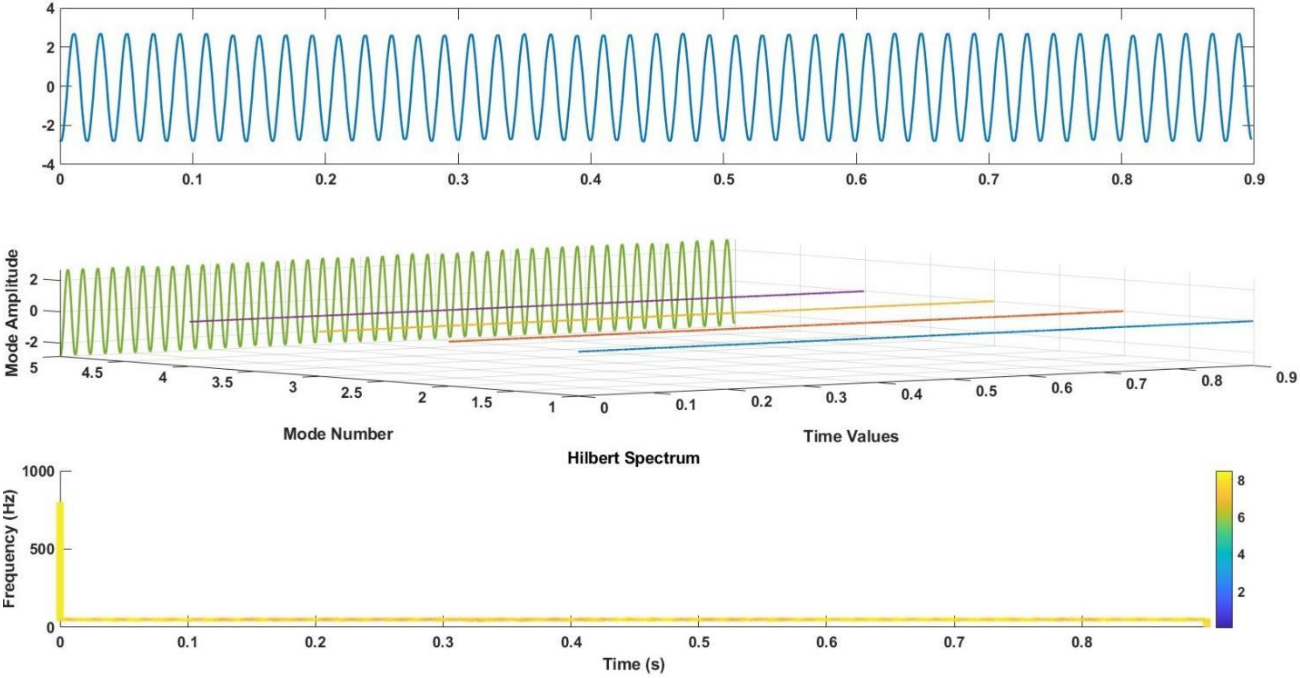

Figure 10: The plots for the corresponding arc signal produced by inductive branch in combined load.

The original signal in Figure 10 shows a periodic arc current in the inductive (FAN) branch with stable amplitude and frequency, characteristic of inductive loads. EMD decomposition reveals that the dominant frequency remains stable over time, while lower amplitude modes reflect influences from other branches and higher harmonics. The spectrum shows a significant concentration of energy at lower frequencies (near 0 Hz), which is consistent with the dominant frequency component of the arc in the inductive branch. The Hilbert Spectrum highlights a dominant low-frequency component, indicating the primary behavior of the arc in the inductive branch, with minimal higher frequency components, suggesting fewer transient events compared to switching loads.

III. Conclusion

By examining real-time faults in the industrial distribution electric system, valuable insights have been gained into the root causes of incidents. Time-domain analysis reveals that different load types (resistive, inductive, and switching) introduce unique patterns in the current signal. Resistive loads exhibit smoother variations, inductive loads (such as fans) show periodic components, and switching loads (such as laptops) produce sharp spikes. The Hilbert Spectrum offers a time-frequency representation, demonstrating how various load types affect the signal's frequency content over time. High-frequency components are particularly noticeable in switching loads due to transient switching events. Understanding the unique current signal patterns associated with different load types (resistive, inductive, and switching) can inform the development of more effective monitoring and diagnostic tools. The findings can also support the design of advanced predictive maintenance strategies, enhancing reliability and reducing downtime. Additionally, insights from the Hilbert Spectrum can be utilized to refine signal processing techniques, leading to improved fault detection algorithms and overall performance optimization in electrical systems. To enhance system reliability, real-time monitoring systems should be developed to continuously analyze the current signals of various loads, facilitating early detection of faults. Additionally, implementing predictive maintenance strategies based on current signal analysis can help prevent failures and optimize the performance of electrical systems.

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