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Review, Analysis, Challenges, and Future Directions

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TOPICAL REVIEW

Incipient Fault Detection in Power Distribution Networks: Review, Analysis, Challenges, and Future Directions

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ABSTRACT This review paper explores the landscape of incipient fault detection methodologies within power distribution networks. It aims to provide insights into the current state-of-the-art techniques, their effectiveness, and potential avenues for future research. Incipient faults, often imperceptible and challenging to detect, pose significant risks to the stability and reliability of power distribution systems. Detecting these faults early ensures uninterrupted service and prevents catastrophic failures. The review begins by outlining the fundamental concepts of incipient faults and their implications on power distribution networks. It then surveys various detection methods, categorizing them into conventional and advanced techniques. Conventional methods include rule-based approaches, while advanced techniques encompass machine learning, artificial intelligence, and data-driven methodologies. Each category is examined in terms of its principles, advantages, and limitations. Furthermore, the review identifies key challenges and emerging trends in incipient fault detection, such as integrating smart grid technologies, utilizing big data analytics, and developing hybrid detection approaches. This thorough review enables stakeholders in the power distribution sector to enhance their comprehension of existing incipient fault detection techniques, thereby enabling informed decisions to enhance network reliability and resilience. Moreover, it offers invaluable insights for researchers and practitioners striving to drive advancements in the field through innovative methodologies and technologies.

INDEX TERMS Incipient fault detection, incipient fault, distribution network, reliability, resilience.

I. INTRODUCTION

In the modern era, the reliable operation of power distribution networks is indispensable for sustaining the functioning of societies. The occurrence of faults within these networks can disrupt the seamless flow of electricity, leading to significant economic losses, inconvenience to consumers, and, in some cases, posing risks to life and property. Among these faults, incipient faults, which are in their early stages of development and often exhibit subtle symptoms, pose a particular challenge for timely detection and mitigation. Incipient faults, also known as "intermittent faults," may be termed "arc faults" if they result in short-circuit arcs. Incipient faults, if left undetected, have the potential to disrupt the seamless flow of electricity and compromise system reliability. In response to the growing demand for an uninterrupted power supply, the identification and timely mitigation of incipient faults emerge as pivotal aspects in ensuring the continued effectiveness of power distribution networks. The abbreviations used in this paper are listed in table 1.

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TABLE 1. Abbreviations.

Short form	Full form
DN	Distribution Network
RTU	Remote Terminal Unit
RT	Real-time
AI	Artificial Intelligence
SLD	Single Line Diagram
STG	Siamese Temporal Graph
RMT	Random Matrix Theory
FE	Feature Extraction
RMS	Root Mean Square
SOM	Self Organising Map
AC	Alternating Current
UG	Underground
OHL	Overhead Lines
TR	Transformer
TP	Tramsmission Power
CB	Circuit Breaker
DDC	Disturbance Data Characteristic
ANN	Artificial Neural Network
WA	Wavelet Analysis
NM	Numerical Modeling
TFDA	Time-Frequency Domain Analysis
KF	Kalman Filter
SIC	Sequence Impedance and Current
CUSUM	Cumulative Sum
ADALINE	Adaptive Linear Neuron
FL	Fuzzy Logic
VD	Voltage Distortion
VM	Waveform Matching
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
PT	Power Transformer
PS	Power System
LSTM	Long Short-term Memory
RNN	Recurrent Neural Network
DL	Deep Learning
WVE	Waveform Vector Embedding
HLCL	Human-Level Concept Learning
HLWD	Human-Level Waveform Decomposition
HPL	Hierarchical Probabilistic Learning
ST	S-Transform
SVM	Support Vector Machine
SM	Synchronized Measurements
RF	Random Forest
AD-TFM	Adaptive Time-Frequency Memory
WMU	Waveform Measurement Units
PSCAD	Power Systems Computer Aided Design
EMTDC	Electromagnetic Transients Program for Digital Computers
RTDS	Real-Time Digital Simulator
RBF	Radial Basis Function
DDBN	Dropout Deep Belief Network
CIF	Cable Incipient Faults
PD	Partial Discharge
SCIF	Single-cycle Cable Incipient Fault
MCIF	Multi-cycle Cable Incipient Fault
IED	Intelligent Electronic Devices
FADS	Failure Anticipation and Diagnosis Scheme
PMU	Phasor Measurement Unit
EPRI	Electric Power Research Institute
DFA	Distribution Fault Anticipator
LTC	Load Tap Changer

Incipient faults in both overhead and underground power distribution systems arise from various factors such as environmental conditions, vegetation interference, mechanical stress, corrosion, animal contact, equipment failures, and human error. Mitigating these risks requires proactive maintenance, regular inspections, and technological advancements to ensure network reliability and safety. Similarly, power distribution transformers are vulnerable to incipient faults due to overloading, voltage surges, moisture ingress, contamination, aging, mechanical stress, faulty components, and environmental conditions. These issues can lead to insulation degradation, short circuits, or component failures. Utilities must implement preventive measures like regular maintenance, inspections, and operational safeguards to uphold transformer reliability. Proactively managing these factors is crucial for minimizing downtime, preventing significant disruptions, and preserving the integrity of the power distribution system. The utilization of IEDs for real-time monitoring in power systems offers the potential to forecast specific failures. As detailed in [1], there typically exists a transitional phase known as the pre-failure period, situated between normal operation and an outage. This concept is depicted in Figure 1. Fast detection and processing of incipient failure signatures is critical for grid failure anticipation. FADS, employing real-time monitoring of electrical waveforms via IEDs, utilizes Waveform Analytics to identify abnormalities. It aims to detect failures, including High Impedance Faults, ensuring effective grid monitoring and real-time failure detection [2].

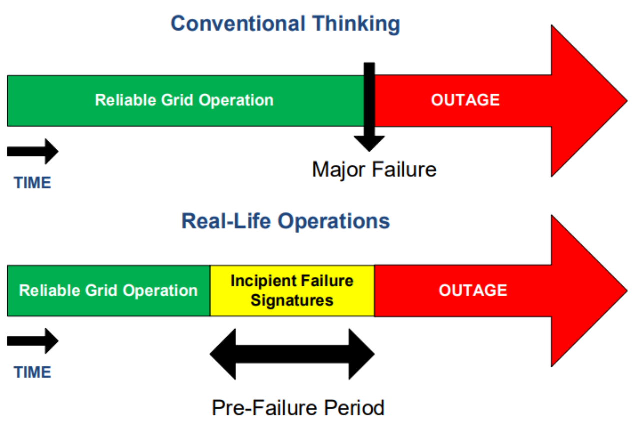

FIGURE 1. Different paradigms of grid operating conditions [2].

Various power system failures, ranging from incipient faults to equipment damage or adverse weather effects, originate from minor events, progress over time (during the pre-failure period), and fully manifest after a delay. Unfortunately, it may be too late to respond effectively by the time these failures fully manifest. The duration of this pre-failure period can vary from seconds to weeks or even months. Throughout this period, normal grid operations experience strain, causing a gradual deterioration in grid stability, ultimately culminating in a complete outage. However, indicators of grid stress are often evident in the electrical waveforms (current and voltage) during the pre-failure period, manifested as subtle deviations from fundamental waveform properties. IEDs are capable of recording these waveforms in high resolution, providing enhanced observability of these minute deviations. These deviations in the electrical waveforms collectively constitute what are known as incipient failure signatures.

The advent of advanced technologies and methodologies has provided unprecedented opportunities for enhancing the reliability and resilience of power distribution systems. In recent years, there has been a surge in research and development efforts aimed at devising effective techniques for the early detection of incipient faults. The imperative has driven these efforts to minimize downtime, optimize maintenance activities, and improve overall network performance. This paper introduces a systematic literature review concerning incipient fault detection in power distribution networks, which is crucial for consolidating existing knowledge, identifying gaps, and charting future research directions. This review seeks to comprehensively analyze the various approaches, methodologies, and technologies employed in detecting incipient faults, encompassing both traditional and emerging techniques. By systematically examining and analyzing the literature, this study seeks to contribute valuable insights that can guide future advancements in the field. The significance of this research lies in its potential to offer practical solutions to the challenges posed by incipient faults in power distribution networks. Early fault detection is crucial not only for preventing disruptions but also for optimizing maintenance efforts and resources. As the demand for electricity continues to rise, addressing these challenges becomes imperative for maintaining a robust and reliable power distribution infrastructure. The insights derived from this systematic review can inform decision-makers, researchers, and practitioners in devising strategies to fortify power distribution networks against the impact of incipient faults. The subsequent sections of this paper delve into a systematic examination of existing incipient fault detection methodologies. It navigates through the intricacies of waveform restructuring, temporal modeling, machine learning applications, and other pertinent technologies employed in early fault detection. The analysis encompasses case studies, real-world implementations, and discussions on challenges and future directions. Through this structured approach, the paper aims to provide a comprehensive understanding of the current landscape of incipient fault detection in power distribution networks and pave the way for advancements in ensuring their enhanced reliability and resilience.

The contributions and enhanced value of this research can be outlined as follows:

- A systematic review of incipient fault detection in power distribution networks, detailing the investigated methodologies, utilized data, software applications, measurement techniques, and the network configurations subjected to testing.
- Evaluating the effectiveness and limitations of existing detection methodologies and technologies.
- Investigating emerging trends, innovations, and potential future directions in the field of incipient fault detection aimed at advancing the reliability and resiliency of the power distribution network(DN).

The subsequent sections of this paper are structured as follows. Section II provides a comprehensive outline of the DN. Section III delineates the significance of incipient fault detection within the DN context. Section IV outlines various methods employed for incipient fault detection. Section V provides a comparative analysis of these methods. Section VI delves into the challenges associated with incipient fault detection. Lastly, Section VII presents the paper's conclusion, accompanied by insights into potential future research avenues in Section VIII.

II. POWER DISTRIBUTION NETWORK OVERVIEW

DN play a critical role in transporting electricity from generation sources to end-users, with their structure and components varying based on factors like network size, load type, and geographic location. Typically, a DN comprises primary substations, which transform high transmission voltages to lower distribution levels using transformers, circuit breakers, and protective relays. Secondary substations further reduce voltage levels for distribution, incorporating additional transformers, switchgear, and protection devices. Feeders serve as primary distribution lines, delivering power from substations to various areas via overhead lines or underground cables. Transformers step down voltage levels for end-users, while switchgear and circuit breakers regulate electricity flow and protect against faults. Distribution lines transmit electricity to homes, businesses, and other consumers, either overhead or underground. Distribution transformers located closer to end-users further adjust voltage levels as needed. Metering equipment measures electricity consumption, employing traditional or digital smart meters.

Protective relays and control systems monitor the distribution system's health, automatically isolating faults to prevent widespread outages. Communication systems, including SCADA, enable real-time network monitoring and management, while remote terminal units and sensors collect and transmit data for centralized control. Advanced distribution automation technologies, such as smart grids, enhance DN efficiency, reliability, and responsiveness. Figure 2 illustrates a medium voltage (11kV) distribution network supplied by a 33/11kV primary substation. This network steps down the voltage to 0.4kV for end-user loads via an 11/0.4kV secondary substation. While the Single Line Diagram (SLD) provides a typical representation of the distribution network, it is important to note that system architectures and components may differ based on specific design and operational criteria. Additionally, contemporary systems are incorporating advanced smart technologies to enhance monitoring, control, and sustainability.

III. IMPORTANCE OF INCIPIENT FAULT DETECTION

Electric power distribution networks are critical infrastructure systems responsible for delivering electricity from generation sources to end-users. Ensuring the reliability and safety of these networks is paramount for utilities and consumers alike. Incipient fault detection plays a crucial role in achieving these objectives by enabling utilities to identify and address potential faults at their early stages before they escalate into larger problems. By leveraging advanced monitoring and diagnostic technologies, such as sensors, communication systems, and data analytics, utilities can detect subtle changes in network conditions indicative of impending faults. These technologies provide real-time insights into the health and performance of distribution assets, allowing utilities to implement proactive maintenance strategies and minimize the risk of outages and safety hazards.

Early detection of incipient faults offers several benefits to utility power distribution networks. Firstly, it enables utilities to conduct preventive maintenance activities, such as equipment inspections, repairs, and replacements, in a timely manner, reducing the likelihood of unexpected failures and downtime. This proactive approach helps optimize the reliability and resilience of the distribution infrastructure, ensuring continuous power supply to customers. Secondly, incipient fault detection enhances safety by mitigating the risk of electrical accidents, fires, and other hazards associated with faulty equipment. By promptly identifying and addressing potential issues, utilities can minimize the exposure of workers and the public to unsafe conditions, thereby improving overall operational safety. To gain deeper insight into the significance of detecting incipient faults in distribution networks, we refer to pertinent case studies carried out by the EPRI team, employing their Distribution Fault Anticipator(DFA) prototype [3]. The details and results of the investigated case studies are listed below.

A. CASE STUDY 1: PRECURSORS ASSOCIATED WITH INTERNAL TRANSFORMER WINDING FAILURE

The DFA prototype intermittently detected subtle precursor signals on numerous occasions within the one-week time-frame preceding the internal failure of a customer service transformer. Illustrated in Figure 3 is one of the initial measurements captured during this period. The load current measured at the substation was approximately 105 RMS amperes, and the failure precursors manifested as intermittent increases ranging from five to ten amperes.

Figure 4 displays the waveforms corresponding to the identified episode, with a circled region indicating slightly accentuated peaks above the load-current envelope. This distinctive behavior was promptly identified as indicative of an incipient failure, although the specific cause remained unknown at that juncture [3].

B. CASE STUDY 2: CABLE FAILURE

A substation equipped with a DFA prototype, monitoring eight of its 25 feeders, experienced a significant failure shortly after 11:00 AM. The substation, which uses multiple large step-down transformers to deliver 12.47-kV distribution, has cables running from the transformers to the control house to supply multiple feeders. A catastrophic failure

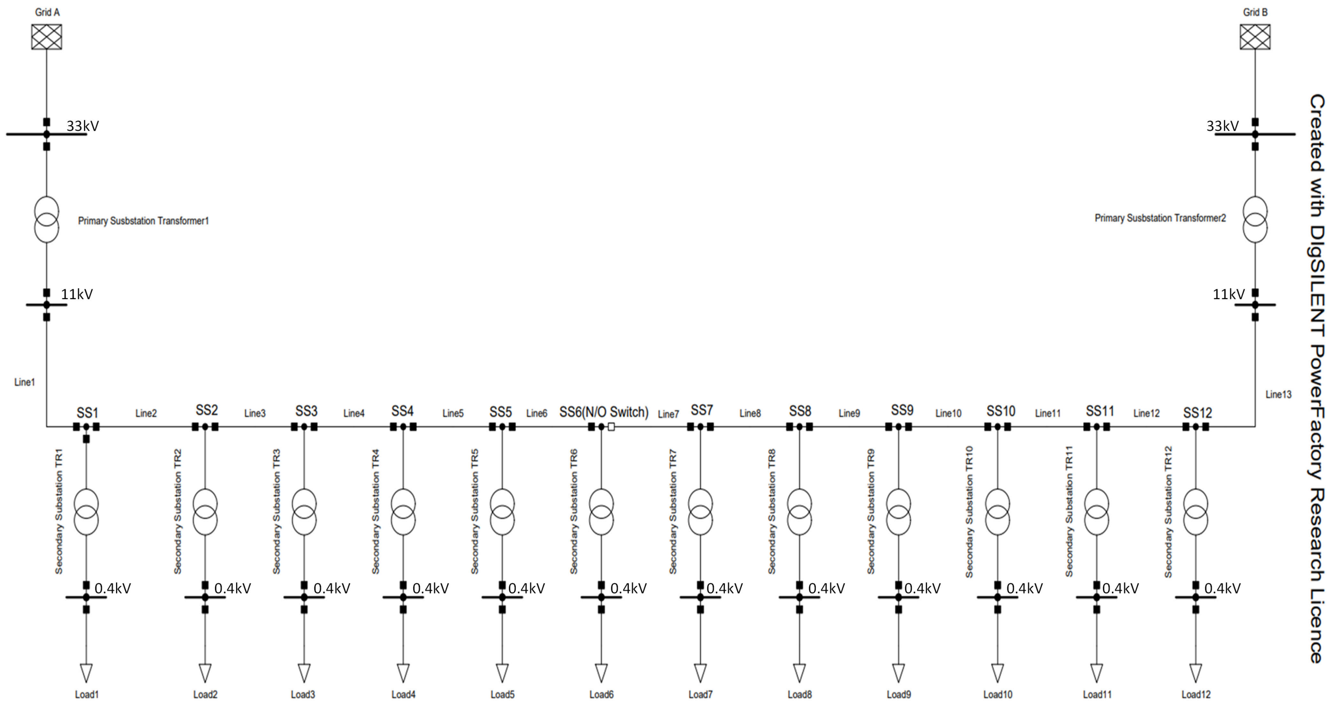

FIGURE 2. Typical power distribution network.

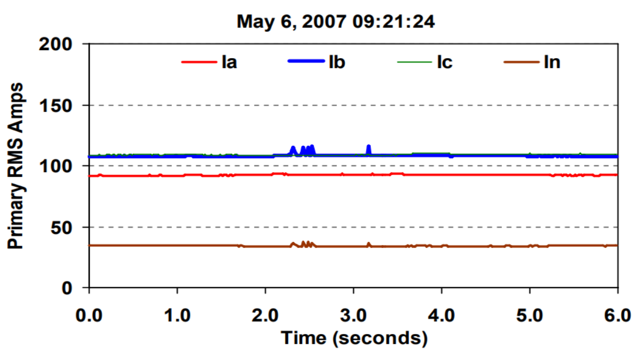

FIGURE 3. Precursors one week before transformer failure (RMS) [3].

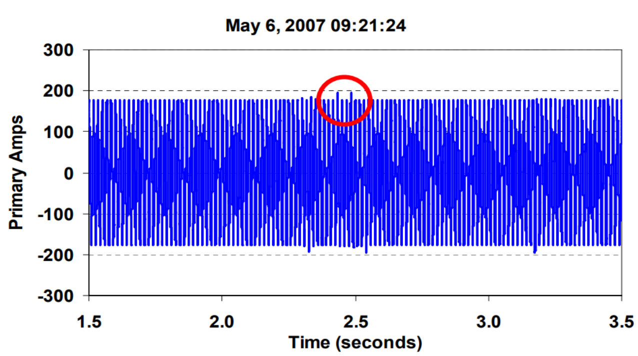

FIGURE 4. Precursors one week before transformer failure (EMT) [3].

occurred in one of the substation cables located in the ductwork between a transformer in the yard and the control

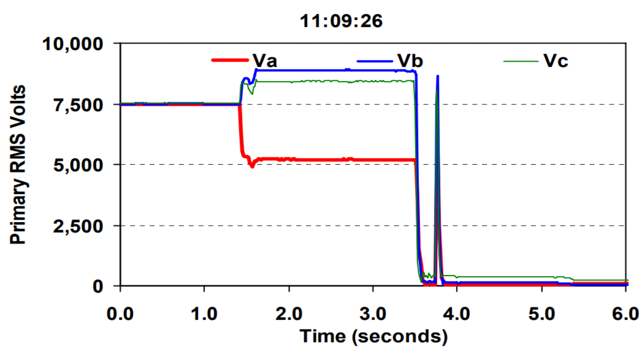

FIGURE 5. Voltages during cable failure (RMS) [3].

house. This failure caused a fault that led to extensive damage, necessitating the tripping of all feeders and resulting in an outage. Consequently, 26,000 customers were left without power for several hours [3].

During the cable failure depicted in Figure 5, RMS bus voltages were recorded showing a significant drop in phase-A voltage to 69% of nominal for 2.1 seconds until the substation protection tripped the transformer. Concurrently, phase-B and phase-C voltages swelled to 118% and 112% of nominal, respectively. Interestingly, 13 cycles after the transformer tripped, power momentarily returned for about 1.5 cycles with similar voltage levels, likely due to an automatic closure of the normally open bus tie switch, feeding the fault from another transformer [3].

Approximately 110 seconds before the cable failure, Figure 6 shows voltage anomalies beginning at 11:07:38,

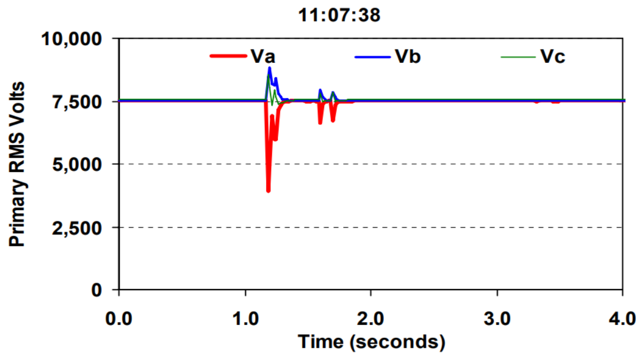

FIGURE 6. First voltage anomaly preceding cable failure (RMS) [3].

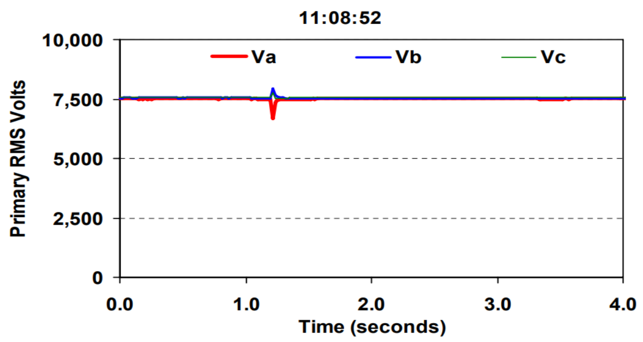

FIGURE 7. Fourth voltage anomaly preceding cable failure (RMS) [3].

including multiple dips over half a second and four distinct anomalies over the next 80 seconds, one illustrated in Figure 7. These anomalies culminated in the ultimate fault, causing the transformer to trip 2.1 seconds later. The DFA system has documented multiple cable failures, often preceded by precursors varying in detection time from minutes to weeks. This specific failure event adds valuable data to the DFA database, despite its statistical infrequency. The resulting 26,000-customer outage for 2.5 hours significantly impacts reliability metrics, adding 3,900,000 customer minutes to reliability indices like SAIDI [3].

The observed instances of cables serving end users have demonstrated that early-stage failures often produce detectable precursors hours or days before a complete failure. This advanced warning period could provide utilities with the necessary time to take preventive action, thereby mitigating significant damage and avoiding extended outages like the one discussed.

C. CASE STUDY 3: WIND-INDUCED CONDUCTOR SLAP

A DFA prototype detected two unusual faults, each beginning as a 600-amp phase-C fault that escalated after several cycles. Occurring minutes apart, both faults necessitated a single operation of the feeder breaker. The first incident, shown in Figure 8, prompted a utility engineer to investigate due to its unusual signature and recurrence.

Noting windy conditions, he suspected wind-induced conductor slap. Comparing fault-current studies to DFA measurements, he located slack-span phase conductors with

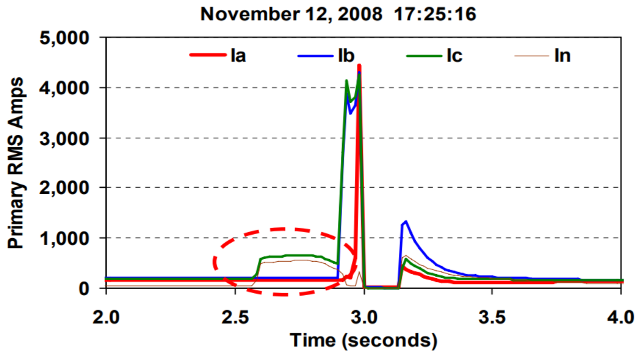

FIGURE 8. Unusual fault current of Wind-Induced Conductor Slap (RMS) [3].

enough sag to contact a nearby slack-span guy. Figures 9 and 10 show the damaged area and conductor damage, demonstrating that DFA-initiated action prevented further damage and potential conductor burn-down.

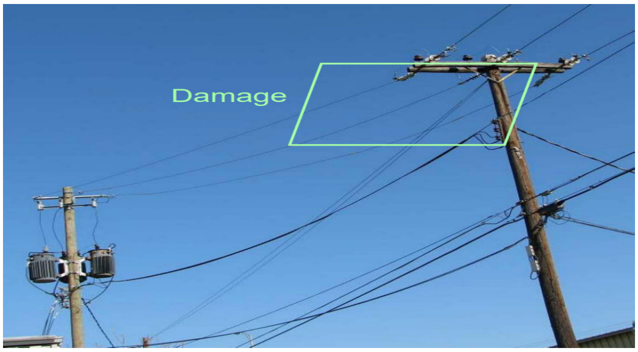

FIGURE 9. Wind-Induced conductor slap in the overhead line [3].

FIGURE 10. Conductor damage from wind-induced conductor slap [3].

D. CASE STUDY 4: PARTS DAMAGE AND EQUIPMENT AGING

Figure 11 depicts currents from an overcurrent fault recorded by a DFA prototype on December 11, 2005, at 07:39:58. The fault generated around 2,400 RMS amps, tripping a single-phase, pole-top recloser after two cycles, which reclosed two seconds later without persistent fault, outages, or customer complaints. A similar fault occurred on December 13, 2005, at 08:21:05, with identical characteristics and results.

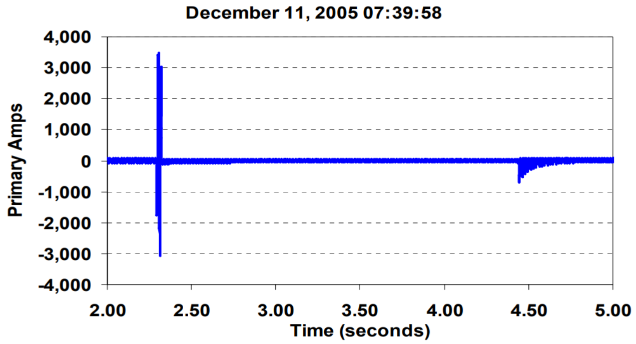

FIGURE 11. Single-Phase fault cleared by pole-top re-closer [3].

FIGURE 12. Damaged external bushing that caused intermittent faults [3].

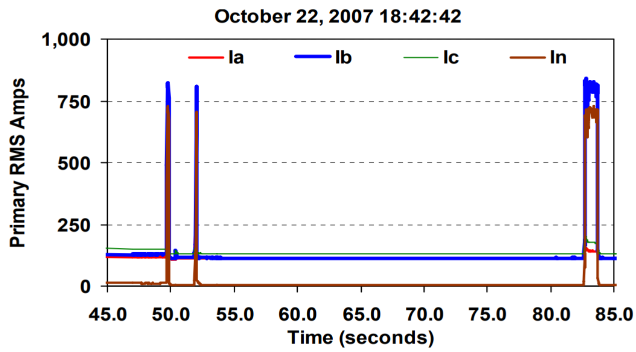

FIGURE 13. Permanent fault with incomplete recloser sequence [3].

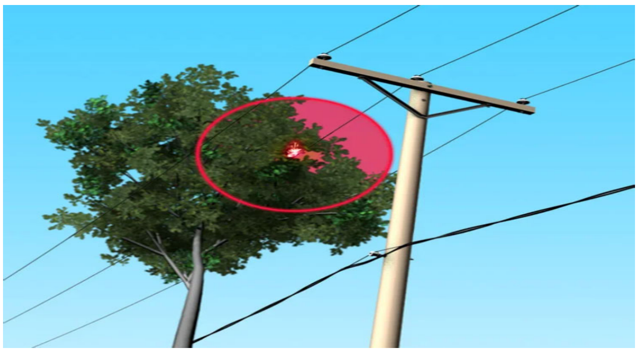

FIGURE 14. Representation of tree limbs touching the three-phase lines.

The DFA alerted utility personnel, who identified the issue—a damaged bushing (shown in Figure 12) on a pole-top service transformer caused by a dead squirrel. The fault recurred on December 18, 2005, prompting expedited repair. This incident highlighted the risks of leaving damaged insulators unaddressed, which can lead to repetitive faults, arc damage, and potentially catastrophic transformer explosions.

E. CASE STUDY 5: RECLOSER MALFUNCTION CAUSED BY CORRODED PARTS IN VEGETATION INDUCED FAULT

Figure 13 illustrates RMS current during a permanent fault caused by a tree limb falling on a three-phase primary as represented in figure 14. The three-phase recloser is designed to lock out after four trips: two on a fast curve and two on a slow curve.

At the 50-second mark, an overcurrent fault triggered the first fast-curve trip, followed by a reclose two seconds later. After the second fast-curve trip and a 30-second pause, the recloser performed a third trip on its slow curve. However, it failed to reclose after this third trip due to contact issues from corrosion or improper seating. This failure left the recloser open but not locked out, posing a safety hazard for repair crews unaware of its potential to re-energize the feeder unexpectedly.

Over time, a wide range of failure modes have been recorded by the DFA, including one or more instances of each as an incipient fault in distribution networks. The table 2 categorizes the various types of failures in distribution networks, their causes, impacts, remedies, and how incipient fault detection methods support these failures before they lead to permanent failures.

The table 2 on distribution network failures outlines a range of critical challenges impacting electrical grid reliability. From voltage regulator and LTC controller malfunctions to issues with lightning arrestors, tree limb contacts, and capacitor problems, each failure type arises from factors such as aging infrastructure, environmental conditions, and mechanical wear. Voltage regulator failures, due to aging components and environmental stressors, lead to voltage instability and degraded power quality. Addressing these issues requires regular maintenance and timely replacements, bolstered by advanced detection methods that monitor for abnormal voltage fluctuations. Similarly, LTC controller failures, attributed to aging components and software errors, necessitate software updates and precise anomaly detection to prevent improper tap changes and voltage disruptions. Proactive maintenance practices are crucial for lightning arrestors and tree limb contacts, involving regular testing, vegetation management, and insulation assessments to prevent equipment damage, short circuits, and service interruptions. Detecting early signs of degradation in underground and secondary cables, such as moisture ingress and mechanical damage, requires improved materials and installation techniques, supported by advanced fault detection methods that identify partial discharges and repeated faults early on, enabling timely replacements and infrastructure upgrades. Integrating these strategies enhances distribution network

TABLE 2. Comprehensive categorization of distribution network failures: causes, impacts, remedies, and the role of incipient fault detection.

Type of Failure	Causes	Impacts	Remedies	What an Incipient Fault Detection Methods Support
Voltage Regulator Failure	▪ Aging ▪ Environmental factors ▪ Mechanical wear	▪ Voltage instability ▪ Power quality issues	▪ Regular maintenance ▪ Timely replacement	▪ Detects abnormal voltage variations ▪ Enabling early intervention
LTC Controller Failure	▪ Component aging ▪ Software errors	▪ Incorrect tap changing ▪ Voltage issues	▪ Software updates ▪ Component replacement	▪ Monitors control signals for anomalies ▪ Preventing improper tap changes
Lightning Arrestor Failure	▪ Lightning strikes ▪ Degradation over time	▪ Equipment damage ▪ Outages	▪ Regular testing ▪ Replacement after significant events	▪ Identifies degradation signs ▪ Ensuring timely replacement
Tree Limb Contacts	▪ Vegetation growth	▪ Short circuits ▪ Outages	▪ Regular trimming of vegetation	▪ Detects minor faults caused by contact ▪ Prompting preventative trimming
Overhead Service Cable Insulation Failure	▪ Weathering ▪ Mechanical damage	▪ Outages ▪ Safety hazards	▪ Insulation testing ▪ Cable replacement	▪ Monitors insulation resistance ▪ Detecting deterioration early
UG Cable Failures	▪ Aging ▪ Moisture ingress ▪ Mechanical damage	▪ Outages ▪ Repair costs	▪ Improved cable materials ▪ Proactive replacement	▪ Detects partial discharges ▪ Indicating impending failures
Repetitive UG Secondary Service Cable Failures	▪ Age ▪ Poor installation ▪ Mechanical damage	▪ Frequent outages ▪ Repair costs	▪ Improved installation practices ▪ Cable upgrades	▪ Identifies repeated minor faults ▪ Suggesting the need for comprehensive repairs
Repetitive Overcurrent Faults	▪ Overloading ▪ Equipment malfunctions	▪ Equipment damage ▪ Safety risks	▪ Load balancing ▪ Protection system upgrades	▪ Monitors current levels ▪ Detecting abnormal patterns
Tree Limbs in Secondary Service Cables	▪ Vegetation growth	▪ Short circuits ▪ Outages	▪ Regular vegetation management	▪ Detects minor disturbances ▪ Indicating the need for trimming
Line Switch/Cutout Failure	▪ Mechanical wear ▪ Environmental factors	▪ Outages ▪ Switching issues	▪ Regular inspections ▪ Timely replacement	▪ Monitors operation cycles ▪ Detecting abnormal behavior
In-Line Splice Failure	▪ Poor installation ▪ Mechanical stress	▪ Outages ▪ Repair needs	▪ Improved installation techniques ▪ Regular testing	▪ Detects increased resistance at splices Indicating potential failure
Substation Bus Capacitor Bushing Failure	▪ Aging ▪ Contamination	▪ Reduced power quality ▪ Equipment damage	▪ Regular maintenance ▪ Timely replacement	▪ Monitors capacitance and dielectric losses ▪ Detecting early signs of failure
Customer Transformer Bushing Failure	▪ Aging ▪ Environmental factors	▪ Outages ▪ Equipment damage	▪ Regular inspections ▪ Bushing replacement	▪ Detects increased bushing temperature ▪ Indicating potential failure
Capacitor Problems	▪ Aging ▪ Harmonic distortion ▪ Overloading	▪ Power quality issues ▪ Equipment damage	▪ Regular maintenance ▪ Harmonic filtering	▪ Monitors capacitance changes ▪ Detecting degradation early

resilience, minimizing downtime, optimizing operational efficiency, and ensuring reliable power delivery.

Furthermore, incipient fault detection supports efficient resource allocation and asset management within utility distribution networks. By accurately pinpointing the location and nature of potential faults, utilities can prioritize maintenance activities and allocate resources more effectively. This optimizes the utilization of manpower, equipment, and materials, leading to cost savings and improved operational efficiency. Additionally, incipient fault detection helps utilities comply with regulatory requirements and industry standards related to network reliability, safety, and performance. By demonstrating proactive maintenance practices and adherence to established guidelines, utilities can maintain regulatory compliance and avoid potential penalties or sanctions. Overall, incipient fault detection is a fundamental aspect of modern utility power distribution systems, enabling utilities to enhance reliability, safety, and efficiency while meeting the evolving needs of customers and regulatory authorities

IV. INCIPIENT FAULT DETECTION METHODS

Power system operators have a crucial role in accurately identifying faults within the network to mitigate adverse consequences such as damage to devices, service interruptions, and network instability, which diminish overall reliability. These issues lead to financial repercussions affecting both customers and electricity companies. Traditional fault location methods, particularly in extensive DN, prove inefficient and costly in terms of manpower, equipment, and time. Consequently, there is a growing need for expedient and automated incipient fault detection and localization in DN. Adopting automatic methodologies provides advantages such as time and resource savings, increased system preparedness for power maintenance, adaptive scheduling, and improved economic factors. These benefits contribute to higher customer satisfaction and enhance the reliability indices of the power system [4], [5].

The incipient fault is a form of transient in the power system's underground cables that might lead to an intermittent arc fault. There are two common forms of incipient faults: multi-cycle incipient faults and sub-cycle incipient faults. When the arc ignites, the sub-cycle incipient fault always happens close to a voltage peak. It lasts for about one-quarter of a cycle and self-clears when the current crosses zero. The multi-cycle incipient fault, which lasts 1-4 cycles and self-clears after the arc is extinguished, is similarly likely to occur close to a voltage peak [6].

Cable faults progress in four stages as shown in Figure 15 [7]. Initially, in Stage 1, the cable is healthy. Over time, defects accumulate, letting moisture seep into cable joints and causing partial discharge (PD) due to distorted local field strength. PD can worsen to intermittent arc discharge, defining a cable incipient fault (CIF) before permanent faults occur. In Stage 3, incomplete insulation deterioration and gas from insulating material can cause self-extinguishing faults. CIF events may repeat until insulation fully breaks down, leading to a permanent fault in Stage 4. Monitoring and addressing early signs of fault development are crucial to preventing significant disruptions and ensuring cable network reliability.

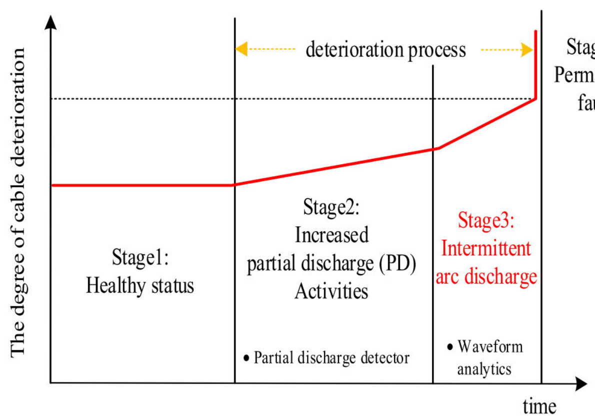

FIGURE 15. Cable deterioration process [7].

Incipient faults are typically described as faulty occurrences characterized by relatively low fault currents and short durations, ranging from one-quarter cycle to multiple cycles. Traditional distribution protection schemes often fail to detect these short-lived current fluctuations due to their brief duration and minimal increase in magnitude. However, it is crucial to detect such faults at an early stage to prevent potential catastrophes resulting from their progression and degradation. Figures 16 and 17 display the fault phase current waveforms of Single-cycle Cable Incipient Fault (SCIF) and Multi-cycle Cable Incipient Fault (MCIF), respectively, for Phase A. The current waveform of CIF encompasses both healthy and fault periods [6]. The methodology includes extracting shallow features through stationary wavelet transform and subsequently constructing a dropout deep belief network (DDBN) to identify cable incipient faults (CIF) distinctively from other similar disturbance events.

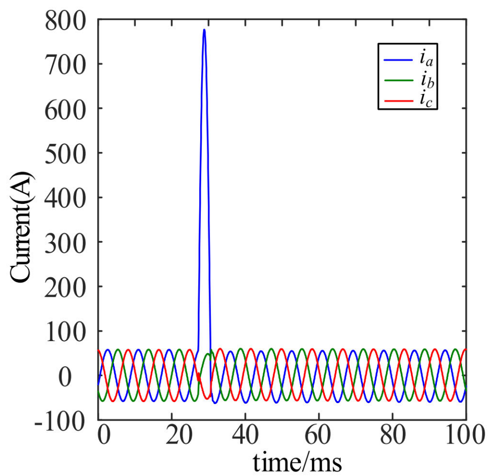

FIGURE 16. Current waveform of SCIF [6].

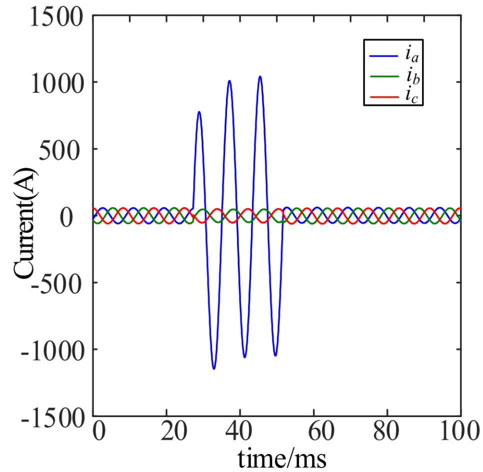

FIGURE 17. Current waveform of MCIF [6].

The approach in [8] introduces the Siamese Temporal Graph technique for detecting early-stage faults. This method encompasses waveform restructuring, the application of Temporal Graph Convolution for mapping, and the derivation of an optimal mapping function through distance metrics. The model's transfer learning capability facilitates its deployment for detecting faults in field data. A methodology shown in [9] involves analyzing and processing online monitoring data, applying random matrix theory, designing a real-time fault detection algorithm, using linear eigenvalue statistics, and justifying the approach through theoretical laws. The feasibility and effectiveness of the methodology are supported by case studies on synthetic and real-world data. The methodology used in [10] involves feature extraction of events and fault detection classifiers, with a comprehensive analysis of statistical characteristics. The findings suggest that the proposed framework, utilizing the Transformer Network, outperforms related works in terms of performance. characteristic analysis and extraction, simulation of abnormal conditions, the establishment of a feature database, and the use of a topic search algorithm for correlation matching in investigated [6]. In [11], extraction methods and feature measures are used to obtain peculiar features from voltage waveforms, followed by a feature selection method and support vector machine combined with particle swarm optimization for classification.

Methodologies for incipient fault detection in power transformers using artificial neural networks for off-line fault detection and wavelet transforms for on-line fault detection are investigated in [12]. The approach in [13], encompasses the collection of videos from distribution lines, dataset preparation, identification of incipient fault types and severity levels, and the application of diverse techniques during video processing. These techniques include frame extraction, device detection and tracking, color thresholding, and median filtering. The methodology explored in reference [14] introduces a precise approach utilizing Cumulative Sum (CUSUM) and Adaptive Linear Neuron (ADALINE) for the early detection of incipient faults in underground cables. In [15], a neural-fuzzy network is utilized to model the thermal condition of power transformers, comparing the output to measurements and processing residuals for fault detection and isolation, with validation through simulation experiments. Wavelet analysis is employed for the detection and classification of incipient faults in underground cables at the distribution voltage level. The results demonstrate the creation of a practical method applicable to real systems, capable of distinguishing various fault conditions, system configurations, and other transients induced by permanent faults, capacitor switching, load changes, etc. [16].

The proposed approach in [17] involves adaptive modeling through the transmission line method for incipient fault detection and identification in transformers. It incorporates continuous wavelet transform (CWT) on residuals for fault identification, supplemented by an adaptive fuzzy reasoning technique to accurately discern various types of incipient faults in transformers. In [18], the methodology utilizes numerical modeling, self-organizing map technology, and wavelet domain-specific energy features for detecting incipient faults, employing modified modeling errors in a chronological sequence for change detection and assessing the performance of three modified algorithms using field-recorded data from underground cable lateral.

The approach detailed in [19] utilizes wavelet analysis alongside the scrutiny of superimposed fault current and negative sequence current for the detection and classification of incipient faults in underground cables at distribution voltage levels. The methodology described in [20] entails the time domain and time-frequency domain analysis of incipient events in single-phase distribution transformers, employing data derived from simulations and experiments and conducting time-frequency analysis through discrete wavelet transform (DWT). In [21], the explored methodology involves utilizing measured current and voltage at one end of the cable for the detection of incipient cable failures, employing an innovation signal derived from the measured fault current through a Kalman filter. The methodology presented in [22] introduces a novel approach for detecting inter-turn faults in transformers, utilizing the computation and application of differences in positive sequence impedance and negative sequence current. Additionally, the method involves creating a new characteristic plot from transformer nameplate details and test results, along with adapting algorithm settings for on-load tap changer operation. The technique is validated through simulation and experimentally verified on a specially designed 10 kVA transformer.

The methodology outlined in [23] introduces an innovative approach for detecting and pinpointing multicycle incipient faults in cables. It includes modeling the incipient fault, utilizing the distortion degree of calculated voltage and waveform match to detect and locate faults, enhancing accuracy through the consideration of fault angle and power loss characteristics, and validating the method through simulations and laboratory experiments. In [24], the paper provides insights into the percentage of cable faults preceded by incipient faults and the duration for their transition to permanency, introducing a detection method validated through field cases and a digital simulator, with security ensured through checks on factors like load consistency and fault component characteristics, and discussing simplified implementations using modern microprocessor-based relays along with application recommendations. In [25], a novel approach is introduced wherein an adaptive time–frequency memory (AD-TFM) cell, incorporating learnable scale and translation parameters of the wavelet transform within the long short-term memory (LSTM), is proposed to extract features from nonstationary incipient fault signals in both time and frequency domains. This forms the basis for the development of a recurrent neural network (RNN) with an attention mechanism, termed the AD-TFM-AT model, enabling multiresolution and multidimensional analysis for incipient fault detection.

A new method called waveform vector embedding (WVE) is introduced to transform incipient fault waveforms from various devices into waveform vectors, which they then structure into a waveform dictionary. To optimize the embedding process during the learning of power system waveforms, the authors devise a specialized loss function to prevent overflow and overfitting of the softmax function [26]. A detection method is proposed based on human-level concept learning (HLCL), featuring human-level waveform decomposition (HLWD) and hierarchical probabilistic learning (HPL), where HLWD breaks down waveforms into primitives inspired by human perception, and HPL learns waveforms through a generative process based on these primitives, yielding hierarchical probability calculations for abnormal events; experiments on simulation and field data, including various fault scenarios, demonstrate the superior performance of the proposed method over three commonly used classifiers [27]. A novel method is presented for locating transient events, including incipient faults, in power distribution systems, utilizing synchronized measurements from waveform measurement units (WMUs) capturing voltage and current waveforms in the time domain. The method comprises three steps: characterizing oscillatory modes through multi-signal modal analysis, constructing a circuit model for the distribution feeder at the identified dominant mode(s) of the transient event, and identifying the event's location through forward and backward analyses of the constructed circuit model [28].

In [29], a supervised machine-learning approach is introduced for identifying incipient faults, employing the PSCAD platform for simulation, utilizing wavelet-based feature extraction, and assessing the performance on both balanced and unbalanced datasets using various Support Vector Machine techniques. In [30], the methodology suggests a multiple anomaly detection scheme utilizing a random forest algorithm to detect and classify incipient faults in power equipment, involving the filtration of irrelevant waveforms from recorded data and evaluating the performance of the random forest algorithm against three other machine learning algorithms. A study employs the S-transform and support vector regression, with a focus on the radial basis function (RBF) kernel, for detecting incipient faults in underground cable networks [31]. As evidenced by multiple articles, incipient failures exhibit a wide range of time scales and waveform patterns [32], [33]. In [11] and [34], it's noted that there's a recognized absence of a comprehensive, holistic, yet efficient approach for implementing failure anticipation techniques. Therefore, solely relying on classifying waveform distortions from a PQ disturbances perspective may prove insufficient and impractical [2].

In [35], an approach is presented for real-time fault detection and identification of faulted lines within active distribution networks. This method integrates fault detection and location functionalities through the utilization of phasor-measurement unit (PMU)-based state estimation. In [36], the dimensionality of PMU data is assessed, and an online application for early event detection using reduced dimensionality is proposed. Reference [37] introduces a density-based detection algorithm designed to identify local outliers, capable of distinguishing high-quality synchrophasor data from low-quality data during system physical disturbances, and [38] presents a real-time power state detection algorithm utilizing massive streaming phasor measurement unit data, based on multiple high-dimensional covariance matrix tests.

In [19], two algorithms are introduced for the identification and categorization of early faults within underground cable systems. These algorithms rely on wavelet analysis and the evaluation of superimposed fault current and negative sequence current within the time domain. In [18], the authors propose a method centered on numerical modeling of early fault patterns, leveraging Self Organizing Map (SOM) technology. This approach involves acquiring specific energy characteristics in the wavelet domain for use in the modeling process. In [39], the multi-scale wavelet transform is employed to extract characteristic features from the cable current signal. High-frequency details, low-frequency approximation coefficients, and the maximum module of current are utilized to identify transient over-current processes. Furthermore, gray correlation analysis is utilized to distinguish early faults from other instances of over-current. Reference [40] utilizes the sum of single-end sheath currents for early fault detection. Both over-current events and the maximum modulus of the wavelet transform of the sum of sheath currents are examined for detection purposes. However, this method lacks evaluation using practical, real-world data. Finally, authors in [41] conduct a Time-Frequency Multi-Resolution Analysis and apply Artificial Neural Networks for early fault detection.

In [42], a straightforward algorithm is introduced, which relies on five primary characteristics of voltage and current waveforms during incipient fault conditions. In [43], field data collected from an underground distribution feeder is analyzed to identify system parameters and characterize observed incipient behavior, employing techniques spanning both time and frequency domains. Authors in [44] investigate the application of pattern analysis methodologies, specifically employing K-Nearest Neighbor (KNN) classifiers, to classify load change transients and incipient abnormalities within an underground distribution cable. The approach outlined in [45] is designed to detect self-clearing transient faults based on both the magnitude and the rate of change in magnitude of the neutral current. Furthermore, [46]presents a method employing an intelligent system, while in [31], a frequency domain-based approach utilizing S-transform is introduced, considering harmonic components of the arc current and/or voltage. Reference [47] employs rule-based and Support Vector Machine (SVM)-based pattern classifiers to classify transient patterns within underground cables.

Drawing from the systematic review of the techniques [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], the characteristics of incipient cable failures can be synthesized as follows: They serve as precursors to permanent failures within the same phase of the cable.; Typically, they manifest at the moment of peak voltage.; In terms of duration, they can be categorized into half-cycle incipient failures lasting approximately 1/4 cycle and multi-cycle incipient failures with durations ranging from about 1 to 4 cycles.; They do not trigger the protective devices to operate.; The majority are single-phase ground faults.

These characteristics of incipient cable failures shape the voltage and current waveforms associated with them. Most failures occur in proximity to the peak voltage due to the heightened voltage stress on the cable insulator during this period, increasing the likelihood of insulation breakdown. When an incipient fault occurs, an intermittent arc develops within the cable, causing an instantaneous surge in fault phase current and a rapid drop in fault phase voltage. However, the arc's duration is short, and it extinguishes automatically at the zero crossing of the AC current, thereby clearing the incipient fault. Consequently, cable current and voltage return to normal levels. Notably, since phase-to-phase and phase-to-phase ground faults often originate from single-phase ground faults, incipient cable faults primarily constitute single-phase ground faults capable of automatic recovery.

V. COMPARATIVE ANALYSIS OF THE METHODS

The literature review presents a diverse array of incipient fault detection methods and approaches, each with its strengths and weaknesses in the context of power DN. A systematic analysis of the relevant investigated incipient fault detection methods in the distribution network has been carried out, and the results are shown in table 3. Out of the reviewed methods, Feature extraction, Fuzzy logic, and Wavelet analysis methods are mostly used for the investigation of incipient faults in power DN.

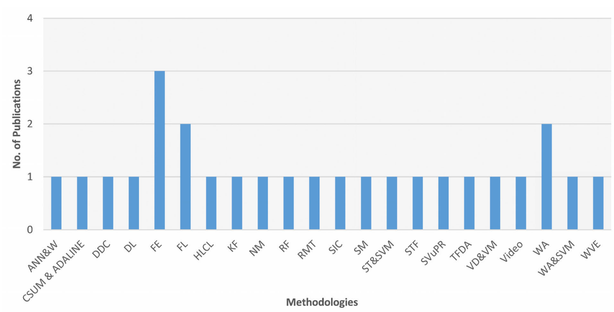

FIGURE 18. Incipient fault detection methodologies.

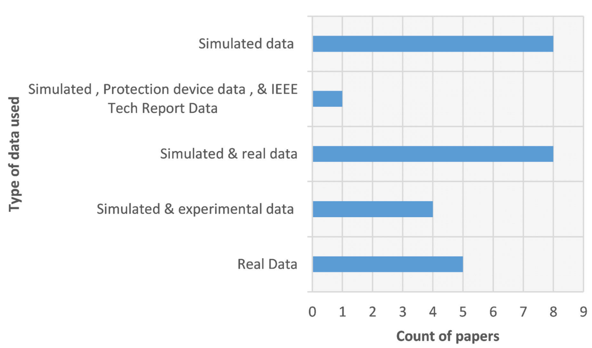

FIGURE 19. Types data used for Incipient Fault detection.

The statistics of the methodologies are shown in Figure 18. Most research uses both simulated and real data to test and validate proposed techniques. However, a few studies have examined protection devices and field-recorded data for analysis, as depicted in Figure 19.

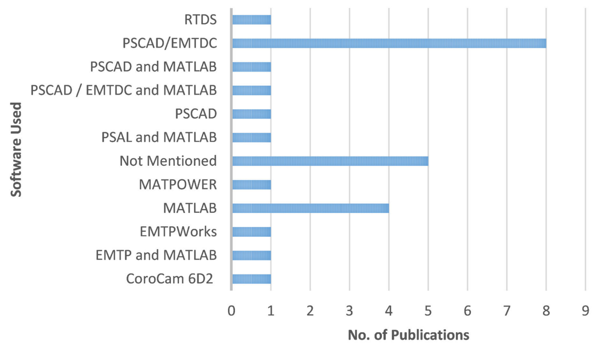

FIGURE 20. Software used for data generation and analysis.

Figure 20 shows the list of commercial software used for incipient fault detection in DN. PSCAD/EMTDC stands first in the utilization mainly for the simulation and data generation, while MATLAB was also used for countable analysis along with a camera/video-based lab-level research works. Voltage and Current are two main parameters used together as the variable inputs for incipient fault detections and further analysis. Three-phase line currents are yet another important parameter utilized in notable studies. Apart from these parameters, active power (P), frequency, weather data, oil samples of the transformer, recorded Power quality recorder data, and videos of the distribution lines were also used for offline and online analysis. The statistics of these parameters are detailed in figure 21.

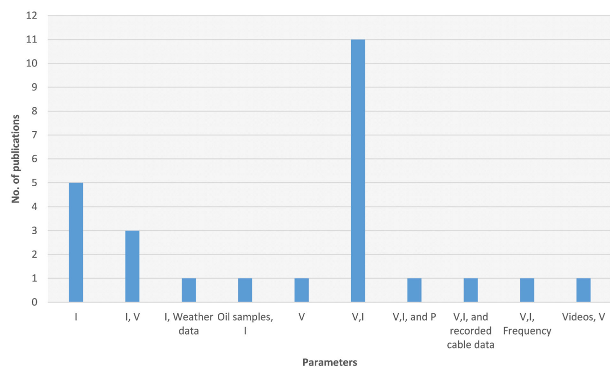

FIGURE 21. Parameters selected for analysis.

While there has been a notable focus on detecting incipient faults in UG cables, it's important to recognize that substantial research efforts have also explored fault detection in OHL and power transformers. These studies cover a wide range of fault detection aspects and examine various locations within the DN. Figure 22 illustrates the distribution and scale of these studies across different sites within the DN. These studies provide invaluable insights into fault detection techniques, thereby bolstering the resilience and reliability of power distribution systems, whether underground or overhead.

TABLE 3. Systematic analysis of incipient fault detection methods.

Paper	Methodology	Data Used	Software Used	Input Measurements	Components Tested
[7]	STF	Simulated & Real	PSCAD/EMTDC	I	OHL
[8]	RMT	Simulated & Real	MATPOWER	V,I, and P	Cable and TR
[9]	FE	Simulated & Real	PSCAD	V,I	OHL
[10]	DDC	Simulated Data	PSCAD& MATLAB	V,I	UG Cable
[11]	FE	Simulated & Real	MATLAB	V	PS Components
[12]	ANN&W	Simulated Data	MATLAB	Oil samples, I	PT
[13]	Video	Real Data	CoroCam 6D2	Videos, V	OHL
[14]	CUSUM & ADALINE	Simulated & Real	EMTPWorks	I	UG Cables
[15]	FL	Simulated & Real	Not Mentioned	I, Weather data	TR
[16]	WA	Simulated Data	PSCAD/EMTDC	V,I	UG Cables
[17]	FL	Real Data	MATLAB	V,I	TR
[18]	NM	Real Data	MATLAB	V,I, & cable data	UG Cables
[19]	WA	Simulated Data	PSCAD/EMTDC	I, V	OHL & UG Cables
[20]	TFDA	Simulated & Experimental	PSAL and MATLAB	I, V	1Ph. transformers
[21]	KF	Simulated & Real	EMTP and MATLAB	I, V	UG Cables
[22]	SIC	Simulated & Experimental	Not Mentioned	V,I	PT
[23]	VD&VM	Simulated & Experimental	PSCAD/EMTDC	V,I	UG Cables
[24]	SVuPR	Simulated Data	RTDS	I	UG Cables
[25]	DL	Simulated & Experimental	PSCAD/EMTDC	V,I	OHL
[26]	WVE	Simulated , Protection, & IEEE	Not Mentioned	I	OHL, UG Cables& TR
[27]	HLCL	Simulated & Real data	PSCAD/EMTDC	V,I	OHL and UG Cables
[28]	SM	Simulated Data	PSCAD/EMTDC	V,I	UG Cables
[29]	WA&SVM	Simulated Data	PSCAD and MATLAB	I	UG Cables
[30]	RF	Real Data	Not Mentioned	V,I	Cable, TR, & CB
[31]	ST&SVM	Real Data	Not Mentioned	V,I, Frequency	UG Cables
[32]	FE	Simulated Data	PSCAD/EMTDC	V,I	UG Cables

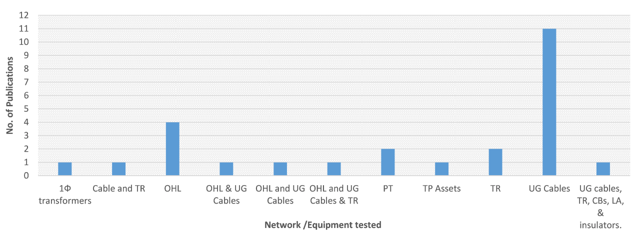

FIGURE 22. Investigated networks and components.

Table 4 shows a comparative analysis of the relevant studies highlighting the key aspects of various methods reviewed in this work.

The current trends and technologies in incipient fault detection underscore a significant integration of machine learning methodologies, signaling a broader adoption of data-driven approaches for incipient fault detection in power systems. Advanced signal processing techniques, such as wavelet transforms and time-frequency analysis, remain pivotal in extracting pertinent features from signals, contributing to the effectiveness of fault detection methodologies. Furthermore, there is a notable exploration of video and image processing techniques, suggesting a potential evolution towards incorporating visual data analysis for improved incipient fault detection in power systems. Hybrid approaches, combining methodologies like AD-TFM with LSTM and attention mechanisms, indicate a growing preference for integrated models that aim to enhance fault detection accuracy. Additionally, the emphasis on real-time implementation underscores a shift towards developing more responsive and adaptive systems, reflecting the industry's increasing demand for timely and efficient incipient fault detection in power networks.

This study provides a systematic analysis of incipient fault detection methods in power distribution networks, emphasizing quantitative metrics such as fault detection accuracy, reliability indices, and overall benefits. Methods are classified into simulation-based, real data-based, and hybrid approaches, utilizing data from various sources like advanced sensors and historical records. Data-driven approaches, particularly those integrating machine learning and real-time data, significantly enhance fault detection accuracy and network reliability. Hybrid methods stand out for their robustness and scalability. Emerging trends highlight the adoption of advanced signal processing and image analysis techniques, and an emphasis on real-time implementation reflects the industry's demand for responsive and adaptive systems. Overall, this analysis reveals an evolving landscape of fault detection methodologies, moving towards integrated, data-driven solutions that optimize the efficiency and reliability of power distribution networks. Future research should focus on refining hybrid approaches and incorporating diverse data sources to develop comprehensive and effective fault detection systems.

VI. CHALLENGES IN INCIPIENT FAULT DETECTION

Incipient fault detection in power DN faces numerous challenges spanning technical, infrastructural, and operational domains. A significant hurdle is ensuring data quality and availability, as power DN generate vast amounts of data from heterogeneous sources like PMUs, smart meters, and SCADA systems. The inherent complexity and diversity of DN, which cover extensive geographical areas

TABLE 4. Comparative review of incipient fault detection/detection methods.

Method	Strength	Limitations
STF	Model's transfer learning capability	Scalability and deployment challenges
RMT	Online monitoring, real-time insights	Complex network configuration challenges
TN with FE	Superior performance, analysis	Scalability, adaptability in diverse network.
ANN and WT	Effective for both offline and online fault detection in power transformers.	Computational Complexity and training challenges.
Video Processing	Unique video data perspective	Scalability, environmental sensitivity.
CUSUM and ADALINE	Precise approach	Scalability, applicability in diverse networks
WA	Practical applicability, fault distinction.	Tuning for diverse configurations
AM and CWT	Adaptable, accurate fault detection.	Scalability to larger systems
NM and SOM	Utilize advanced technologies	Resource-intensive computational needs.
AD-TFM and RNN	Hybrid-detects multi-dimensional faults	Real-time challenges,intensive training.

and encompass various equipment configurations, introduce variability in fault characteristics, making it challenging to develop universally applicable detection methods. Maintaining consistency and quality across these diverse datasets is problematic, and incomplete or inaccurate data can lead to erroneous fault detection. Reliable historical data is crucial for training machine learning models, but many networks lack comprehensive historical datasets, limiting the effectiveness of data-driven approaches. The scarcity of labeled field data for training and validating predictive models further hinders the robustness of developed algorithms in real-world scenarios.

Real-time data processing is another major challenge. Advanced algorithms such as machine learning and signal processing techniques require high computational power, which can introduce latency and hinder timely fault detection. As the network size increases, the volume of data to be processed in real-time grows exponentially, necessitating scalable solutions. Additionally, the dynamic nature of power systems, influenced by factors like load fluctuations and environmental conditions, complicates the accurate detection of incipient faults. Ensuring algorithm robustness and adaptability is also essential, as models trained on specific datasets may not generalize well to other network conditions or fault scenarios. Hybrid methodologies, which integrate different approaches like simulation-based and real data-based methods, can enhance fault detection accuracy. However, developing and fine-tuning these hybrid models is complex and requires significant computational resources. The integration of diverse technologies, including machine learning algorithms, waveform analysis, and video processing, demands careful consideration of interoperability and scalability issues.

Implementation and integration of advanced detection methods into existing infrastructure pose further challenges, particularly since many networks operate with legacy systems not designed to support these technologies. Seamless interoperability between different systems and devices within the network requires standardized communication protocols and data formats. The economic aspect, including the high initial investment and maintenance costs, is also a significant concern. Evaluating the cost-effectiveness of these systems and quantifying the benefits, such as reduced outage durations and improved reliability indices, are necessary to justify the investment. Regulatory and compliance issues, including the lack of standardized protocols and benchmarks, complicate the assessment and comparison of different methodologies. Ensuring compliance with regional and international standards is essential for the deployment and operation of fault detection systems. Addressing these multifaceted challenges through advancements in data processing, algorithm development, system integration, and regulatory compliance will enhance the reliability and efficiency of power distribution systems. Developing versatile and adaptive fault detection solutions capable of handling the intricacies of diverse distribution network environments will necessitate a multidisciplinary approach involving collaboration between power system engineers, data scientists, and domain experts, ultimately leading to more resilient and sustainable power infrastructure.

The integration of distributed generation sources into modern power distribution systems introduces complexities that challenge the reliable detection of incipient faults. These complexities include bidirectional power flows and variable fault currents, which deviate from traditional unidirectional flow patterns. Moreover, the intermittent nature of renewable energy generation adds further intricacy, disrupting the predictability of fault detection mechanisms designed for stable power flows. Overcoming these challenges necessitates the development of advanced fault detection algorithms and robust monitoring technologies. These technologies must effectively handle the dynamic behaviors and diverse characteristics associated with distributed generation sources, ensuring accurate and timely detection of faults to maintain system reliability and performance.

VII. CONCLUSION

The review examines methods for detecting incipient faults in power distribution networks, with the goal of clarifying the effectiveness of current techniques and identifying future research directions. Incipient faults, which are often elusive and difficult to detect, present substantial risks to the stability and reliability of power distribution systems. Traditional fault location methods are deemed inefficient and costly, prompting a growing need for expedient and automated approaches. Various methodologies, such as Siamese Temporal Graph, random matrix theory, Transformer Networks, and wavelet transforms, are discussed, showcasing a diverse range of techniques tailored to address specific challenges in fault detection. The adoption of artificial neural networks, machine learning algorithms, and innovative modeling approaches represents a paradigm shift towards more efficient, accurate, and automated fault detection processes. The reviewed methodologies address diverse scenarios, including incipient faults in transformers, underground cables, and distribution lines. Techniques like waveform restructuring, feature extraction, and adaptive modeling contribute to the development of robust fault detection systems. Advanced technologies such as recurrent neural networks, attention mechanisms, and waveform vector embedding reflect the continuous evolution of fault detection methodologies. The literature suggests a promising trajectory toward achieving enhanced system preparedness, reduced downtime, and improved economic factors, ultimately contributing to higher customer satisfaction and reliability indices in power systems.

The importance of incipient fault detection in enhancing power distribution network reliability is a recurring theme throughout the literature. This emphasis reinforces the significance of proactive measures to identify and address potential faults before they escalate, minimizing damage, service interruptions, and network instability. As the field advances, further research and innovation are crucial. Future endeavors could explore novel approaches, integrate emerging technologies, and focus on real-time incipient fault detection to continually improve the efficiency and effectiveness of fault detection systems. The potential for cross-disciplinary collaboration and the integration of cutting-edge methodologies highlight avenues for ongoing research and development in this critical area of power system management.

VIII. FUTURE DIRECTIONS

In the realm of power distribution networks, future research in incipient fault detection holds significant promise for advancing the reliability and resilience of electrical infrastructure. One avenue for exploration lies in the integration of advanced technologies such as edge computing, advanced machine learning algorithms, and big data analytics. By harnessing the power of these technologies, researchers can enhance fault detection accuracy and efficiency, enabling early identification of incipient faults before they escalate into major failures. Additionally, the utilization of diverse data sources, including heuristic network data, meteorological data, and geospatial data, presents an opportunity to gain a comprehensive understanding of incipient faults and improve prediction capabilities. Finally, the following can be suggested for future work in order to improve the accuracy of the predictions: Use of Generative AI to generate synthetic data to train the model further with more data. To collect comprehensive data for incipient fault detection in power distribution networks, install smart sensors, PMUs, and fault indicators to monitor key parameters. Integrate data from SCADA systems, smart meters, and historical records. Use machine learning models and advanced analytics for predictive insights, ensuring data accuracy with validation and correction algorithms. Conduct controlled experiments and pilot projects for real-world data. Collaborate with utilities and research institutions, sharing data and adopting industry standards. Establish feedback loops for continuous model improvement and ensure compliance with regulatory and ethical guidelines. These steps provide essential data for advancing incipient fault detection.

Another key focus area for future research is enhancing fault prediction models through integration with cyber-physical systems. This integration can facilitate the development of adaptive and resilient networks capable of dynamically responding to emerging fault conditions. Addressing data quality and interpretability is also crucial, with efforts to improve data quality through advanced cleaning techniques and incorporate explainable AI methods to enhance the transparency and reliability of fault prediction models. Furthermore, Investigate the integration of Internet of Things (IoT) devices and advanced sensor technologies for real-time data collection and monitoring. This could include the development of smart sensors capable of detecting subtle changes in network behavior indicative of incipient faults. Enabling continuous model updating and optimizing sensor networks strategically can ensure that fault prediction models remain accurate and effective in dynamic operating environments. Collaboration and standardization efforts are essential to fostering collaboration and facilitating the development and deployment of innovative fault prediction technologies. Through these research endeavors, advancements in incipient fault detection can lead to more reliable, resilient, and efficient power distribution networks, ensuring uninterrupted power supply and minimizing the risk of catastrophic failures.

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REFERENCES

[1] J. A. Wischkaemper, C. L. Benner, B. D. Russell, and K. Manivannan, "Application of waveform analytics for improved situational awareness of electric distribution feeders," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 2041–2049, Jul. 2015.

[2] R. Bhandia, "Failure analysis and diagnosis scheme in distribution systems," Doctoral thesis, Delft Univ. Technol., Delft, The Netherlands, 2021, doi: 10.4233/uuid:e94efb97-b56d-415f-9044-57da2cb57fb9.

[3] *Phase III System Integration and Library Enhancement*, document 1016036, Distribution Fault Anticipation EPRI, Palo Alto, CA, USA, 2009.

[4] S. Zhang, Y. Wang, M. Liu, and Z. Bao, "Data-based line trip fault prediction in power systems using LSTM networks and SVM," *IEEE Access*, vol. 6, pp. 7675–7686, 2018.

[5] A. M. I. Haleem, M. Sharma, K. S. Sajan, and K. N. D. Babu, "A comparative review of fault location/identification methods in distribution networks," in *Proc. 1st Int. Conf. Adv. Res. Eng. Sci. (ARES)*, Jun. 2018, pp. 1–6.

[6] C. Zhang, N. Song, and Y. Li, "Incipient fault identification of distribution networks based on feature matching of power disturbance data," *Electr. Eng.*, vol. 103, no. 5, pp. 2447–2457, Oct. 2021.

[7] H. Lu, W.-H. Zhang, Y. Wang, and X.-Y. Xiao, "Cable incipient fault identification method using power disturbance waveform feature learning," *IEEE Access*, vol. 10, pp. 86078–86091, 2022.

[8] W. Li, E. Xiang, and K. Wang, "Incipient fault identification in power distribution systems based on Siamese temporal graph," in *Proc. Power Syst. Green Energy Conf. (PSGEC)*, Aug. 2021, pp. 789–794.

[9] S. Xin, R. Qiu, and H. Xing, "Incipient fault detection and location in distribution networks: A data-driven approach," *DeepAI*, vol. 58, pp. 56–63, Mar. 2022.

[10] C. Haolan, W. Mengmeng, W. Zhenghao, P. Yuchen, L. Donghuang, and L. Yadong, "Incipient fault detection of power distribution system based on statistical characteristics and transformer network," in *Proc. Power Syst. Green Energy Conf. (PSGEC)*, Aug. 2022, pp. 669–674.

[11] G. W. Chang, Y.-H. Hong, and G.-Y. Li, "A hybrid intelligent approach for classification of incipient faults in transmission network," *IEEE Trans. Power Del.*, vol. 34, no. 4, pp. 1785–1794, Aug. 2019.

[12] N. Yadaiah and N. Ravi, "Fault detection techniques for power transformers," in *Proc. IEEE/IAS Ind. Commercial Power Syst. Tech. Conf.*, May 2007, pp. 1–9.

[13] N. Davari, G. Akbarizadeh, and E. Mashhour, "Intelligent diagnosis of incipient fault in power distribution lines based on corona detection in UV-visible videos," *IEEE Trans. Power Del.*, vol. 36, no. 6, pp. 3640–3648, Dec. 2021.

[14] M. Jannati, B. Vahidi, and S. H. Hosseinian, "Incipient faults monitoring in underground medium voltage cables of distribution systems based on a two-step strategy," *IEEE Trans. Power Del.*, vol. 34, no. 4, pp. 1647–1655, Aug. 2019.

[15] G. Rigatos, P. Siano, and A. Piccolo, "Incipient fault detection for electric power transformers using neural modeling and the local statistical approach to fault diagnosis," in *Proc. IEEE Sensors Appl. Symp.*, Feb. 2012, pp. 1–6.

[16] T. S. Sidhu and Z. Xu, "Detection and classification of incipient faults in underground cables in distribution systems," in *Proc. Can. Conf. Electr. Comput. Eng.*, May 2009, pp. 122–126.

[17] O. Ozgonenel, E. Kilic, M. A. Khan, and M. A. Rahman, "A new method for fault detection and identification of incipient faults in power transformers," *Electr. Power Compon. Syst.*, vol. 36, no. 11, pp. 1226–1244, Oct. 2008.

[18] M. J. Mousavi and K. L. Butler-Purry, "Detecting incipient faults via numerical modeling and statistical change detection," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1275–1283, Jul. 2010.

[19] T. S. Sidhu and Z. Xu, "Detection of incipient faults in distribution underground cables," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1363–1371, Jul. 2010.

[20] K. L. Butler-Purry and M. Bagriyanik, "Identifying transformer incipient events for maintaining distribution system reliability," in *Proc. 36th Annu. Hawaii Int. Conf. Syst. Sci.*, Jan. 2003, pp. 1–8.

[21] T. Ghanbari, "Kalman filter based incipient fault detection method for underground cables," *IET Gener., Transmiss. Distrib.*, vol. 9, no. 14, pp. 1988–1997, Nov. 2015.

[22] P. A. Venikar, M. S. Ballal, B. S. Umre, and H. M. Suryawanshi, "Sensitive incipient inter-turn fault detection algorithm for power transformers," *IET Electr. Power Appl.*, vol. 10, no. 9, pp. 858–868, Nov. 2016.

[23] W. Zhang, X. Xiao, K. Zhou, W. Xu, and Y. Jing, "Multicycle incipient fault detection and location for medium voltage underground cable," *IEEE Trans. Power Del.*, vol. 32, no. 3, pp. 1450–1459, Jun. 2017.

[24] B. Kasztenny, I. Voloh, and C. G. Jones, "Detection of incipient faults in underground medium voltage cables," in *Proc. Power Syst. Conf.*, Mar. 2009, pp. 1–12.

[25] Q. Li, H. Luo, H. Cheng, Y. Deng, W. Sun, W. Li, and Z. Liu, "Incipient fault detection in power distribution system: A time–frequency embedded deep-learning-based approach," *IEEE Trans. Instrum. Meas.*, vol. 72, pp. 1–14, 2023.

[26] Y. Wang, Q. Cui, X. Tang, D. Li, and T. Chen, "Waveform vector embedding for incipient fault detection in distribution systems," in *Proc. IEEE Sustain. Power Energy Conf. (iSPEC)*, Dec. 2021, pp. 3873–3879.

[27] S. Xiong, Y. Liu, J. Fang, J. Dai, L. Luo, and X. Jiang, "Incipient fault identification in power distribution systems via human-level concept learning," *IEEE Trans. Smart Grid*, vol. 11, no. 6, pp. 5239–5248, Nov. 2020.

[28] M. Izadi and H. Mohsenian-Rad, "Synchronous waveform measurements to locate transient events and incipient faults in power distribution networks," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 4295–4307, Sep. 2021.

[29] M. Das, S. Mishra, S. C. Swain, and T. Biswal, "DWT and SVM approach based incipient fault detection methods for underground distribution system," in *Proc. 14th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Jul. 2023, pp. 1–5.

[30] G.-Y. Li and G. W. Chang, "A multiple anomaly detection scheme and random forest algorithm for identifying the incipient faults in transmission network," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Jul. 2022, pp. 1–5.

[31] M. F. Faisal, A. Mohamed, and H. Shareef, "Prediction of incipient faults in underground power cables utilizing S-transform and support vector regression," *Int. J. Electr. Eng. Informat.*, vol. 4, no. 2, pp. 186–201, Jun. 2012.

[32] B. Li, Y. Jing, and W. Xu, "A generic waveform abnormality detection method for utility equipment condition monitoring," *IEEE Trans. Power Del.*, vol. 32, no. 1, pp. 162–171, Feb. 2017.

[33] L. A. Irwin, "Real experience using power quality data to improve power distribution reliability," in *Proc. 14th Int. Conf. Harmon. Quality Power (ICHQP)*, Sep. 2010, pp. 1–4.

[34] W. Freitas, T. A. Cooke, and K. Kittredge. *IEEE Working Group on Power Quality Data Analytics*. Accessed: Apr. 2019. [Online]. Available: https://grouper.ieee.org/groups/td/pq/data/

[35] M. Pignati, L. Zanni, P. Romano, R. Cherkaoui, and M. Paolone, "Fault detection and faulted line identification in active distribution networks using synchrophasors-based real-time state estimation," *IEEE Trans. Power Del.*, vol. 32, no. 1, pp. 381–392, Feb. 2017.

[36] L. Xie, Y. Chen, and P. R. Kumar, "Dimensionality reduction of synchrophasor data for early event detection: Linearized analysis," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2784–2794, Nov. 2014.

[37] M. Wu and L. Xie, "Online detection of low-quality synchrophasor measurements: A data-driven approach," *IEEE Trans. Power Syst.*, vol. 32, no. 4, pp. 2817–2827, Jul. 2017.

[38] L. Chu, R. Qiu, X. He, Z. Ling, and Y. Liu, "Massive streaming PMU data modelling and analytics in smart grid state evaluation based on multiple high-dimensional covariance test," *IEEE Trans. Big Data*, vol. 4, no. 1, pp. 55–64, Mar. 2018.

[39] C. Zhou, N. Zhou, S. Pan, Q. Wang, T. Li, and J. Zhang, "Method of cable incipient faults detection and identification based on wavelet transform and gray correlation analysis," in *Proc. IEEE Innov. Smart Grid Technol. Asia (ISGT ASIA)*, Nov. 2015, pp. 1–5.

[40] C. Zhang, X. Kang, X. Ma, S. Jiang, and X. Qu, "On-line incipient faults detection in underground cables based on single-end sheath currents," in *Proc. IEEE PES Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Oct. 2016, pp. 795–799.

[41] K. L. Butler-Purry and J. Cardoso, "Characterization of underground cable incipient behavior using time-frequency multi-resolution analysis and artificial neural networks," in *Proc. IEEE Power Energy Soc. Gen. Meeting Convers. Del. Electr. Energy 21st Century*, Jul. 2008, pp. 1–11.

[42] A. Edwards, H. Kang, and S. Subramanian, "Improved algorithm for detection of self-clearing transient cable faults," in *Proc. IET 9th Int. Conf. Develop. Power Syst. Protection (DPSP)*, Mar. 2008, pp. 204–207.

[43] R. Moghe, M. J. Mousavi, J. Stoupis, and J. McGowan, "Field investigation and analysis of incipient faults leading to a catastrophic failure in an underground distribution feeder," in *Proc. IEEE/PES Power Syst. Conf. Expo.*, Mar. 2009, pp. 1–6.

[44] M. J. Mousavi, K. L. Butler-Purry, R. Gutierrez-Osuna, and M. Najafi, "Classification of load change transients and incipient abnormalities in underground cable using pattern analysis techniques," in *Proc. IEEE PES Transmiss. Distrib. Conf. Expo.*, Oct. 2003, pp. 175–180.

[45] N. Stringer and L. A. Kojovic, "Prevention of underground cable splice failures," in *Proc. IEEE Ind. Commercial Power Syst. Tech. Conference. Conf. Rec.*, May 2000, pp. 83–93.
[46] S. Ebron, D. L. Lubkeman, and M. White, "A neural network approach to the detection of incipient faults on power distribution feeders," *IEEE Trans. Power Del.*, vol. 5, no. 2, pp. 905–914, Apr. 1990.
[47] M. J. Mousavi and K. L. Butler-Purry, "A novel condition assessment system for underground distribution applications," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1115–1125, Aug. 2009.

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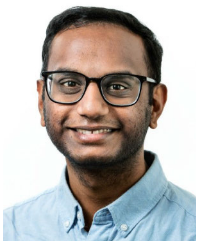

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