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Fault Identification and Predictive Maintenance Techniques for High-Voltage Equipment: A Review and Recent Advances

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Abstract

This paper reviews fault identification and predictive maintenance techniques essential for the reliable operation of high-voltage power systems. The increasing integration of renewable energy sources and distributed generation imposes significant operational challenges, necessitating advanced maintenance strategies beyond traditional reactive and preventive approaches. Emphasis is placed on condition-based and online monitoring techniques that leverage artificial intelligence, machine learning, and IoT for timely fault detection and accurate prediction of equipment lifespan. The study examines methodologies applied to critical high-voltage components such as circuit breakers, transformers, and cables, detailing their operational principles, advantages, limitations, and evaluation metrics. While substantial progress has been made in enhancing system reliability and reducing downtime, challenges related to data quality, model complexity, and cybersecurity remain, highlighting areas for future research and development.

Keywords

High-Voltage Power Systems, Fault Identification, Predictive Maintenance, Condition-Based Monitoring, Artificial Intelligence, IoT, Online Monitoring

1. Introduction

High-voltage power systems are critical for modern society and economic activity. These networks face increasing demands from renewable energy integration and distributed generation [1]. Equipment failures cause financial losses, power outages, and safety hazards, making effective maintenance strategies essential.

Traditional reactive and preventive maintenance approaches have limitations.

Reactive maintenance leads to unplanned downtime and increased costs, while preventive maintenance may involve unnecessary actions and fail to prevent unexpected failures between scheduled intervals, necessitating more proactive, condition-based strategies.

Fault identification techniques diagnose existing problems, enabling timely repairs and preventing minor issues from escalating. Predictive maintenance anticipates failures by monitoring equipment condition and predicting remaining useful life, optimizing maintenance schedules and reducing costs. The complexity and operational demands of high-voltage equipment require sophisticated maintenance strategies addressing electrical load fluctuations, environmental conditions, and mechanical wear.

Detecting incipient faults and predicting operational lifespan present challenges due to equipment complexity and diverse failure modes [2]. Non-invasive online monitoring techniques are preferred to minimize service disruptions [1]. Implementation requires robust data acquisition, integration, and analysis systems from various sensors, plus cybersecurity protection.

This review examines peer-reviewed research on fault identification and predictive maintenance for high-voltage equipment, covering circuit breakers, transformers, and cables. For each technique, we analyze underlying principles, applications, detectable faults, advantages, limitations, and evaluation metrics. The paper provides comparative analyses, identifies literature themes, and discusses future research directions.

2. Fault Identification Techniques for High-Voltage Equipment

2.1. High-Voltage Circuit Breakers

2.1.1. Faults in Circuit Breakers

Circuit breakers, essential for protecting power systems from overcurrents and short circuits, are primarily susceptible to mechanical faults. Contact faults include wear, burning from arcing, insufficient pressure, and improper opening/closing. Mechanism failures encompass stiff operation, component deformation, and shaft seizing. Other mechanical issues involve bolt loosening, spring fatigue reducing force, and connecting rod breakage or deformation. Electrical faults also threaten operation, including control circuit failures from damaged components, connection faults, or missing control signals. Shunt release malfunctions include coil breakage, turn-to-turn short circuits, or insufficient supply voltage preventing opening [3]. Undervoltage release mechanisms may fail due to inadequate tripping force or stuck mechanisms [3]. Insulation faults manifest as external/internal flashovers, phase-to-phase flashovers, lightning-induced flashovers, and bushing failures [4]. Overload faults arise from poor isolating plug contact, causing melting or burning [4]. Temperature rise issues result from insufficient contact pressure, loose main circuit connections, or severely worn contacts [3]. Sticking and misoperation faults have mechanical and electrical origins, representing common high-voltage switchgear failures [4]. Excessive noise from undervoltage release mechanisms can indicate underlying faults. The predominance of mechanical faults [5] emphasizes the importance of predictive maintenance techniques like vibration analysis for assessing mechanical condition. The diverse electrical faults necessitate comprehensive testing and monitoring for reliable operation. Potential operational errors underscore the need for rigorous maintenance protocols and thorough operator training.

2.1.2. Fault Identification Techniques

Voiceprint Analysis

Voiceprint analysis examines acoustic signals during circuit breaker operation, offering non-intrusive fault identification [6]. The technique captures sounds during opening/closing using specialized acquisition devices. These signals are processed using S-transform for time-frequency representation, creating amplitude matrices. Singular Value Decomposition (SVD) extracts key features, which train Machine Learning algorithms like Support Vector Machines (SVM) for fault classification [6]. This method primarily diagnoses mechanical faults, effectively detecting iron core jamming, loose components, and pushing rod jamming [6]. Advantages include low-complexity equipment that is reliable and easy to install in substations. SVM handles small sample sizes and nonlinear problems effectively. However, proper installation location selection is critical for universal results, and environmental noise may affect data quality and accuracy. Performance is evaluated using fault classification accuracy [6].

Vibration Analysis

Vibration analysis identifies mechanical faults by monitoring vibration signals from strategically placed sensors during operation [7] [8]. It detects operating mechanism malfunctions and developing failures that could prevent proper opening [9]. Analysis involves signal preprocessing, feature extraction, and fault classification using time-frequency methods like Wavelet Transform and Short-Time Fourier Transform [7]. Machine Learning algorithms including CNNs, SVM, and multi-layer classifiers classify extracted features for fault identification [7]. Applications include detecting contact faults, mechanism seizures, bolt loosening, spring fatigue, and energy storage spring issues [7] [10]. Advanced techniques use phase-space reconstruction and geometric features like mean center distance [11]. Key advantages include early fault detection enabling proactive maintenance [12]. Multi-sensor data fusion enhances accuracy by providing comprehensive mechanical behavior understanding [10]. However, sensor placement is critical, and noise requires sophisticated signal processing [7]. Performance metrics include accuracy, precision, recall, and F1-score [12].

Coil Current Analysis

Coil current analysis offers another non-intrusive approach for assessing the operating performance and detecting faults in high-voltage circuit breakers by examining the current signature of the trip and close coils [5]. Current waveforms reflect mechanical movement and electrical characteristics, with anomalies indicating faults [7]. Recent ML methods examining coil current and contact travel waveforms show promising results [13] [14]. Time-domain algorithms detect key features and event timing, while mathematical morphology enhances critical point detection in noisy environments [5]. This technique detects tripping device jams and coil plunger motion issues, providing opening/closing time information [5] [7]. Advantages include computational efficiency and easy implementation in low-cost microprocessors for embedded monitoring [5]. However, distinguishing normal variations from actual faults requires careful analysis, especially with noise present [5]. Effectiveness is evaluated by accurate critical point detection and fault identification [14].

Other Techniques

Beyond voiceprint, vibration, and coil current analysis, other techniques are also employed for fault identification in high-voltage circuit breakers. One such approach involves analyzing the stroke curve and current signal of the breaker, combined with ML algorithms like Random Forest, to achieve improved diagnostic accuracy in defect diagnosis [10]. Additionally, few-shot transfer learning approaches, utilizing attention mechanisms with one-dimensional CNNs, have been developed for on-site fault diagnosis, aiming to enhance the robustness and accuracy of diagnoses even with limited fault data [10]. Simple, low-cost online monitoring systems that continuously monitor vital parameters have also been proposed [15] [16]. The trend in circuit breaker fault identification is clearly moving towards the adoption of more sophisticated artificial intelligence-based methods that can integrate data from multiple sources to provide a more comprehensive and accurate assessment of the breaker's condition, even when the availability of fault data is limited.

2.2. High-Voltage Transformers

2.2.1. Faults in Transformers

Transformers, serving as pivotal components in voltage transformation across power systems, are susceptible to various faults that can compromise their operation. Coil faults represent a significant concern, accounting for a substantial proportion of total transformer failures [17]. These faults often originate from insulation breakdown due to electrical, thermal, and environmental stresses, leading to short circuits between turns or layers within windings [2]. Transformer core overheating is another common issue, potentially stemming from multi-point grounding, short circuits within silicon steel laminations, or zero-sequence magnetic flux presence. Insulation degradation is a critical failure mode, frequently caused by overloading, switching surges, lightning strikes, and natural aging of insulating materials [2]. Moisture ingress and oil contaminants significantly accelerate this degradation. Oil and winding insulation faults can arise from reduced dielectric strength due to polar contaminants like water and cellulose breakdown byproducts.

Transformer bushing failures occur due to capacitor core deterioration, moisture intrusion, and joint heating. On-load tap changers (OLTCs), critical for voltage regulation, are prone to failures involving poor contact and component aging [18]. The transformer oil condition can be influenced by OLTC operation, as gases from the OLTC compartment can leak into the main tank, potentially masking or indicating other issues [19]. Other common faults include conductive current loop overheating due to poor tap changer contact or loose lead wire connections, cooling system failures such as oil seepage, air leakage, metal particle contamination, and oil pump/cooling fan mechanical failures. Oil storage cabinet breathing issues involve pressure release device and gas relay malfunctions [18]. Core faults can develop if core insulation is damaged or lamination structure is bridged by conductive materials, causing eddy currents and overheating [19]. In DC high-voltage generators, common faults include abnormal output voltage, unstable output voltage, excessive operating temperatures, arc or discharge phenomena, and control circuitry failures [20]. High-voltage reactors experience core and clamp overheating, coil insulation damage, and partial discharge (PD) [18]. The high prevalence of coil faults underscores the necessity for robust insulation monitoring and protection strategies [17]. The multifaceted nature of insulation degradation highlights the complexity in managing transformer health [2]. The interplay between OLTC operation and transformer oil condition suggests that comprehensive oil analysis should account for gases originating from the OLTC [19].

2.2.2. Fault Identification Techniques

Differential Protection

While more a protection scheme than fault identification technique, differential protection is present on every high-voltage transformer. It compares currents entering and leaving the protected zone using percentage-differential relays [21]-[23]. Under normal conditions, currents should be balanced; significant discrepancies indicate internal faults like short circuits or winding failures, triggering protective action [24]. This method effectively detects internal faults but faces challenges distinguishing between fault currents and inrush currents during energization.

Primary advantages include sensitivity to internal faults while maintaining immunity to external disturbances. The differential-restraining characteristic discriminates between internal faults and external phenomena like load fluctuations or transient inrush currents, offering rapid response crucial for minimizing damage [21]. However, magnetizing inrush currents during energization can cause false tripping. Traditional solutions include slow-speed relays or desensitizing during inrush periods, but these reduce sensitivity and slow fault detection [25]. Advanced techniques include harmonic-restraint and voltage-restraint current differential protection [26], and flux-restraint principles [26].

Digital and numerical relays have replaced electromechanical relays, enhancing precision and enabling SCADA integration. Recent research explores wavelet transforms and principal component analysis (PCA) for improved feature extraction [27] [28]. AI and ML techniques enhance fault detection accuracy, with fuzzy logic, neural networks, and SVM differentiating between fault and non-fault conditions [29]-[31]. Advanced approaches include CNNs and Deep Learning for discriminating internal faults from inrush currents [32] [33]. New methods like power differential protection and sequence-component-based protection aim to enhance performance [34] [35]. However, differential protection provides limited insight on transformer condition or lifetime and is primarily used for external threat protection, making it inapplicable for predictive maintenance.

Dissolved Gas Analysis

Dissolved Gas Analysis (DGA) is a cornerstone technique for transformer fault identification [36] [37]. The principle involves analyzing combustible gases (hydrogen, methane, ethane, ethylene, acetylene) produced when insulating oil and solid materials decompose under thermal and electrical stresses. Standard interpretation methods including IEC and IEEE ratio methods and graphical methods like the Duval Triangle identify fault types based on gas concentrations [38]. ML algorithm integration shows promise for improved accuracy by analyzing complex relationships between gas concentrations and fault conditions.

DGA effectively detects thermal faults (overheating), electrical faults (PD, arcing), and insulation degradation [39]. Advantages include early incipient fault detection and recognition as a primary diagnostic tool [36]-[38]. However, interpretation can be ambiguous in complex scenarios [36] [40], and regular oil sampling requires time-consuming, costly laboratory analysis [36]. ML and AI approaches address these limitations, with models like KosaNet showing improved classification for multinomial DGA data [40]. Techniques like correlation coefficient density clustering and gene expression programming demonstrate promising results [41] [42].

Vibration Analysis

Similar to circuit breaker applications, vibration analysis identifies mechanical faults in transformer cores and windings [43] [44]. Vibration sensors on transformer tanks monitor operational signals revealing mechanical integrity information. Analysis involves frequency analysis, statistical methods, and ML algorithms for fault classification [43]. Different faults generate distinct frequency components, enabling accurate identification [45]. Short-circuit winding faults can be identified by comparing vibration signal cumulative probability distribution curve slopes and analyzing energy spectra [43].

Primary applications include detecting iron core, winding, and short-circuit faults [43]. Key advantages include non-invasive operation without service interruption. However, noise reduction can be complicated and costly, requiring improvement for enhanced accuracy [43]. Mathematical statistics methods minimize noise influence on accuracy. Advanced approaches include mathematical statistics methods for optimizing short-circuit failure detection [43]. Continuous wavelet transform (CWT) converts signals into RGB images preserving time-frequency relationships [46]. ML and DL show promising results, with improved

CNN models achieving 99.95% accuracy [46]. Joint learning frameworks combining vibration and sound signals integrate multi-branch input and multi-scale residual learning [46]-[48]. Hidden Markov Models achieve 95% accuracy for OLTC mechanical fault diagnosis [45].

Frequency Response Analysis

Frequency Response Analysis (FRA) is a powerful and sensitive technique used to assess the mechanical integrity of the core, windings, and press frames within power transformers [49]. It is particularly effective in detecting winding deformations, core issues, and other faults without the need for invasive procedures [50] [51]. The method involves injecting a sinusoidal voltage signal into one winding of the transformer over a wide range of frequencies (typically from a few Hz to a few MHz) and measuring the resulting frequency response in another winding or at the same winding [52]. This measured frequency response, often represented as a magnitude and phase plot against frequency, serves as a unique "fingerprint" of the transformer's internal electrical and mechanical structure [51] [53]. Any significant changes in this frequency response compared to a baseline measurement (obtained at the time of manufacture or after a known healthy state) can indicate the presence of mechanical deformations or electrical faults within the transformer [49]. FRA is particularly sensitive to winding deformations such as axial or radial displacement, short-circuited turns, and core movements, which can occur due to manufacturing defects, transportation stresses, installation errors, or in-service short circuits [49]. It can detect failures in both windings and the iron core, making it a versatile diagnostic tool [54].

However, FRA is not without its challenges. Traditionally, FRA required taking the transformer out of service, which could cause interruptions to the electricity grid [55]. Interpretation of FRA signatures has also been a significant hurdle, often requiring expert analysis due to the lack of standardized interpretation codes worldwide [51] [54]. Additionally, FRA measurements can be affected by disturbances or minor changes during the testing process, potentially leading to inaccuracies in fault detection [54] [56]. Furthermore, it often requires a reference signature for comparison and can be challenging to interpret without sufficient expertise [49]. FRA is capable of identifying faults even without a reference fingerprint in some cases, but having original fingerprints significantly improves the reliability of diagnosis [55] [57]-[59].

Recent progress in FRA technology has addressed some of these limitations. New variations of FRA, such as the Sweep Frequency Impedance (SFI) method, have been introduced to address issues like low signal-to-noise ratio and instability caused by changes in measuring voltage [60] [61]. While traditional interpretation of FRA results often relies on visual comparison of frequency response curves, which can be subjective and require expert knowledge, there is a growing trend towards integrating ML algorithms to automate the interpretation process and provide more objective and quantitative fault diagnosis [62]. Compared to other methods like the low-voltage pulse method, FRA offers strong anti-interference capabilities and good measurement repeatability [43]. Advanced signal processing techniques, such as the discrete wavelet transform, have also been employed to improve the robustness of FRA and reduce the influence of measurement disturbances [63]. AI techniques have been developed to estimate high-frequency electric circuit parameters from FRA signatures, facilitating more reliable fault identification and interpretation [64]-[67].

Polarization and Depolarization Current Measurement

Polarization and Depolarization Current (PDC) measurement assesses insulation system condition non-destructively [68] [69]. The method applies DC voltage across windings, measuring polarization current, then short-circuits windings measuring depolarization current [68]. Current behavior provides dielectric response information about oil and paper insulation [70]. The technique estimates trapped charges from oil-paper insulation interfacial regions [71] and effectively detects insulation failures from moisture, PD activity, contamination, and overheating [68].

PDC is an offline, time-consuming process requiring several hours [68] [70]. Interpretation complexity involves multiple factors including oil/paper conductivity, water content, temperature, and aging [72]. Sensitivity to insulation geometry variations limits data transferability between transformers [69]. Efforts focus on reducing measurement duration [68] [70] and using DL techniques like residual LSTM networks for forecasting [71]. The Modified Debye Model better models non-uniform aging [69]. Multi-method approaches combining PDC with FDS and RVM provide comprehensive evaluation [73] [74]. AI algorithm integration improves analysis efficiency [75] [76].

Thermography Analysis

Thermography uses infrared cameras to detect component heat emission, becoming increasingly important for transformer monitoring and diagnosis [77] [78]. Primary advantages include non-invasive, contactless, real-time monitoring without service interruption [79] [80]. It efficiently identifies overheating components, hot spots, contact issues, unbalanced loads, and high-voltage component cracks [81]. However, it cannot measure internal temperatures directly, observing only surface heating, and environmental factors like ambient temperature and reflections affect accuracy [77] [82] [83].

Recent research combines thermography with advanced data analysis. Modern thermal cameras with higher sensitivity and ML pattern recognition significantly enhance diagnostic accuracy. DL approaches applied to infrared images achieve high automated defect analysis accuracy [81]. In conclusion, thermography techniques have proven to be valuable tools for condition monitoring of high-voltage transformers, offering non-invasive, real-time diagnostics. Integration with other monitoring methods and advanced data analysis continues enhancing effectiveness.

Other Techniques

In addition to the aforementioned techniques, other methods are also employed for fault identification in high-voltage transformers, each offering unique insights into transformer health while presenting distinct advantages and disadvantages [18] [84], although they are not as popular amongst grid operators yet due to their limitations.

Negative sequence current analysis, although just an optional add-on to classic differential relay schemes, seems to be an effective technique that monitors the negative sequence component of current, which arises during asymmetrical faults such as inter-turn short circuits [85] [86]. This method is highly sensitive to minor winding faults and integrates well with differential protection schemes, providing real-time fault detection. Nevertheless, its effectiveness is limited during no-load conditions, and its complexity increases with unbalanced loads, necessitating precise current transformer calibration [87]. Advances in algorithm development have improved fault discrimination accuracy, particularly in detecting winding faults.

Another important method is RVM, which assesses the dielectric response of transformer insulation by applying a DC voltage and measuring the recovery voltage after disconnection. This technique is particularly useful for evaluating moisture content and insulation degradation [88] [89]. RVM is simple, non-destructive, and capable of providing valuable insights into moisture levels and insulation aging [90]. However, its interpretation is complex and requires expert analysis [91]. Furthermore, it is sensitive to external factors such as temperature and the aging characteristics of the insulation [92] [93]. Recent advancements have focused on improving signal processing and automation, reducing reliance on expert interpretation and enhancing accessibility for routine diagnostics [91], [94]-[97].

Excitation current analysis involves applying a voltage to the high-voltage winding and measuring the magnetizing current. Variations from expected values indicate potential core and winding issues [98]. This method is advantageous as it detects core delamination, short circuits, and turn-to-turn faults without requiring baseline values, making it suitable for routine monitoring [98]. However, residual magnetism can affect results, and fault localization remains challenging without supplementary diagnostic tools. Recent developments have integrated digital signal processing and historical data analysis, enhancing detection sensitivity [99] [100].

Voltage and current measurements (referred to as ΔV-I analysis) offer another means of fault identification. This technique compares input voltage and current with the instantaneous output voltage to create a ΔV-I locus [101]. Deviations from the normal locus indicate internal faults [102] [103]. The main advantage of this method lies in its ability to perform real-time monitoring while being largely immune to variations in load levels and power factors [104]. Nonetheless, it requires continuous data acquisition and is sensitive to harmonic content and noise [102]-[104]. However, this technique—much like differential protection—rarely ever detects early signs of a problem.

The power factor or dielectric dissipation factor (PF/DDF) technique measures the dielectric loss of insulation by applying an AC voltage and assessing the ratio of resistive to capacitive current [105]-[107]. This method effectively detects moisture and contamination in insulation and can be performed both offline and online [108]. However, accurate results require temperature correction, and the technique is sensitive to external noise and test conditions [109]. There is also very limited field data for establishing proper criteria. Recent research seeks to improve the availability of comparative data and the accuracy of the measurements [110].

Acoustic emission analysis is another significant method that detects sound waves generated by PDs, mechanical impacts, or structural changes within the transformer [111]-[113]. It offers high resistance to electromagnetic interference and excels in locating mechanical faults and PDs [114] [115]. However, signal attenuation in oil limits its detection range, and sophisticated signal processing is required to accurately interpret the data [113]. The combination of acoustic analysis with ML has notably enhanced fault localization accuracy, while recent research also strives to reduce costs [116]-[119].

2.3. High-Voltage Cables

2.3.1. Faults in Cables

High-voltage cables, responsible for transmitting electrical power over distances, are primarily susceptible to insulation breakdown [120]. This is the most frequent cause of failure in underground networks and can be triggered by physical damage such as cuts or abrasions to the cable sheath, electrical stress leading to overstressing or PD initiation, and water treeing, particularly in cross-linked polyethylene (XLPE) insulation cables. In older oil-impregnated paper insulation cables, paper degradation from moisture ingress despite waterproof lead-alloy sheaths is a significant concern [120]. Manufacturing defects including insulation eccentricity, uneven shielding thickness, material impurities, and internal/external shielding protrusions contribute to insulation failures. Core short circuits occur when two or more conductor layer cores contact, creating unintended current paths. Core open circuits signify conductor continuity breaks within the cable. Sheath corrosion represents another failure mode caused by long-term operational stresses including thermal expansion/contraction and electrolytic or chemical corrosion, leading to sealing component aging and potential lead sheath wear or cracking, resulting in localized insulation damage and moisture ingress. Poor metal sheath sealing facilitates moisture intrusion and excessive induced currents in metallic protective layers [121]. Cable joint failures constitute a significant portion of overall faults, often from improper installation creating "hot" joints [120]. External mechanical damage, frequently from excavation activities, poses substantial threats potentially causing immediate insulation breakdown. Other fault types include low/high resistance faults, flashover faults, breakdown faults, and operation faults, each requiring specific diagnostic approaches [122] [123]. Cable breakdown occurs when insulation is completely punctured, causing direct short circuits between inner conductors and grounded metal mesh, increasing secondary current. Given insulation integrity's paramount importance for reliability, PD measurement stands out as crucial for early breakdown detection [120] [124]-[126]. Significant failures from external mechanical damage underscore the necessity of stringent cable laying protocols and precise location marking. Maintaining high manufacturing standards to minimize defects is essential for ensuring long-term high-voltage cable system reliability [123].

2.3.2. Fault Identification Techniques

Partial Discharge Analysis

PD analysis is a critical technique for assessing the insulation health of high-voltage cables and identifying potential fault locations [127]. PDs are localized electrical discharges that occur within the insulation without completely bridging the electrodes. These discharges are precursors to insulation breakdown and cable failure [127] [128]. PD activity can be detected using acoustic sensors, electromagnetic sensors (such as Transient Earth Voltage or UHF sensors), and chemical sensors that detect byproducts of PD activity [62]. The analysis involves measuring parameters such as PD inception voltage, discharge magnitude, and occurrence patterns over time. Different insulation defects, including electrical tree discharge, surface sliding discharge, air gap discharge, and floating discharge, produce characteristic PD patterns, allowing identification of the problem type and severity [127] [128]. PD analysis can be performed through both off-line and on-line monitoring systems. On-line systems enable continuous, proactive asset management of medium-voltage (MV) cable networks, reducing unexpected failures [127] [129]. Online systems often employ UHF sensors, High Frequency Current Transformers (HFCT), and Rogowski air coil sensors (RACS) concurrently [127] [130] [131].

While highly effective for early detection of insulation problems, PD analysis can be susceptible to noise interference, and signal interpretation requires specialized expertise [132]. Wavelet-based denoising techniques, such as discrete wavelet transform (DWT) and second generation wavelet transform (SGWT), have been applied to improve signal quality [128]. Advanced features for noise and PD defects separation based on synchronous multi-channel techniques have been developed [130]. Ongoing research focuses on developing more sensitive sensors, improving signal processing techniques, and automating knowledge acquisition from on-line condition monitoring data [129] [131] [133].

Time Domain Reflectometry

Time Domain Reflectometry (TDR) diagnoses faults in electrical wiring and interconnect systems by sending a high-frequency signal down the cable and analyzing the reflected signal to detect impedance changes [134]-[136]. When the pulse encounters a discontinuity, such as a cable break, short circuit, or open circuit, a portion reflects back to the source. By measuring the reflection time and analyzing the reflected pulse shape and amplitude, the fault location and nature can be determined [134]. TDR is particularly effective for detecting hard faults such as open circuits and short circuits, making it useful for pinpointing exact locations of physical breaks or significant impedance changes [137] [138].

While effective for certain fault types, TDR's sensitivity is limited for high impedance faults or insulation degradation that do not cause significant impedance mismatches [136] [137] [139]. Signal interpretation may require expertise to distinguish between different discontinuities. Fault responses exhibit strong dispersive behavior, meaning peak amplitude does not directly correlate with fault severity. The echo response depends on multiple factors, including test signal frequency content and physical fault length [140]. Fault detection in transmission lines constitutes an ill-posed problem, necessitating a priori knowledge of fault characteristics. These complexities require advanced signal processing techniques to improve TDR's diagnostic reliability. To enhance TDR capabilities, researchers have proposed integrating TDR with wavelet analysis to improve fault detection accuracy and reduce noise interference [139]. Another advancement applies transfer function analysis in the time domain, using adaptive filters and optimization techniques to increase measurement precision for both hard and soft faults [134]. Multi-level wavelet analysis has been introduced to mitigate the "blind spot" problem in fault localization [141].

Impedance Spectroscopy

Impedance Spectroscopy (IS) has emerged as a promising technique for fault identification in high-voltage cables, offering advantages over traditional methods like TDR and PD detection, particularly for detecting soft faults and incipient failures [142]-[145]. IS measures the input impedance of the wiring system across a frequency range, detecting and locating both hard faults (open and short circuits) and soft faults (small impedance changes) [146] [147]. Cable impedance is influenced by physical and electrical properties, including insulation characteristics. Changes in the impedance spectrum, particularly in magnitude and phase as a function of frequency, can indicate insulation degradation, buffer layer ablation, local aging, or other fault types, including inductive and capacitive faults [145]. Cable capacitance can vary due to aging, affecting the impedance spectrum. Fourier series analysis can be applied to impedance and frequency measurement data to improve fault detection performance [146].

Impedance spectroscopy provides a frequency-domain perspective on cable insulation health and offers insights into overall cable condition and degradation [146]. Sweep Frequency Response Analysis (SFRA) can be used with impedance spectroscopy to construct the driving point impedance function, enabling short-circuit fault location estimation through poles and zeros analysis [148]. However, interpreting complex impedance spectra requires specialized knowledge and modeling to accurately diagnose fault type and severity. Further research is needed for specific challenges in complex cable configurations, such as cross-bonded cables [1] [149]. Recent research focuses on applying data-driven and AI-based decision tools for fault identification [150]-[152].

Other Techniques

Besides PD analysis, TDR, and impedance spectroscopy, other methods are being explored for high-voltage cable fault identification. Acoustic detection methods are mentioned, with [153] noting that PD problems can be tracked using acoustic emission, though the acoustic method is inefficient for cable fault detection and limited to precise localization where the approximate location is already identified. A fuzzy comprehensive evaluation method uses operation monitoring data to assess fault likelihood in high-voltage power cables [154]. This method involves selecting relevant indices from operational data, establishing fuzzy evaluation sets based on cable condition specifications, and using fuzzy logic to evaluate overall cable condition [154]. Another method involves applying DC voltage to the cable and using capacitor coupling to detect insulation faults and broken conductor strands by listening for noise created at the fault location when the cable is disturbed [137]. These diverse approaches highlight ongoing efforts to develop more effective and comprehensive fault identification techniques for high-voltage cables.

3. Predictive Maintenance Techniques for High-Voltage Equipment

3.1. High-Voltage Circuit Breakers

The shift from time-based to predictive maintenance for high voltage circuit breakers represents significant advancement in power system reliability and asset management [155]. Condition-based maintenance (CBM) has emerged as a key strategy in this transition, offering more efficient and cost-effective approaches to maintaining high voltage circuit breakers [156]. Predictive maintenance relies on various diagnostic signals and intelligent modeling techniques to assess circuit breaker condition in real-time. This approach utilizes any combination of techniques analyzed in paragraph 2.1 to detect potential faults and predict failures before they occur [6] [8] [157].

The transition to predictive maintenance has led to novel approaches for assessing high voltage circuit breaker health. These include life-cycle assessment using control circuit condition monitoring data [158], RankBoost-based data-driven methods for determining maintenance priority [159], and hybrid prognostics models that integrate deterministic and stochastic operations [160]. Recently, AI application is becoming increasingly prevalent in predictive maintenance for high-voltage circuit breakers [161] [162]. Advanced ML techniques and AI algorithms such as neural networks, support vector machines, and Light Gradient Boosting Machine (LightGBM) have been employed to improve fault diagnosis accuracy and efficiency [14] [163]. By identifying complex patterns and anomalies in this data, AI models can predict potential failures before they occur, allowing for proactive maintenance planning and optimized maintenance schedules [161] [164]. This approach can significantly reduce downtime, optimize maintenance resource allocation, and potentially extend equipment lifespan.

While AI-driven predictive maintenance offers numerous benefits, it requires large quantities of high-quality data for effective model training [164]. Challenges also exist in model complexity, interpretability, and ensuring cybersecurity of the data and systems involved. The performance of these AI-based systems is typically evaluated based on prediction accuracy, lead time for predicting failures, and resulting reduction in equipment downtime [162].

3.1.1. Vibration Analysis for Predictive Maintenance

Vibration analysis plays a significant role in the predictive maintenance of high-voltage circuit breakers by continuously monitoring vibration signals to assess the mechanical health of the equipment over time [155]. By analyzing trends in vibration characteristics, such as changes in frequency content or amplitude, it is possible to detect the gradual degradation of mechanical components and predict potential failures. Techniques like multi-resolution analysis can be used to decompose the vibration signals into different frequency bands, allowing for a more detailed assessment of various sub-wave levels and the capture of subtle features indicative of wear or damage [155]. Furthermore, optimizing fuzzy rules using genetic algorithms can help in classifying the severity of the degradation and predicting the remaining useful life of components such as springs. Continuous vibration monitoring provides insights into the progression of faults, enabling timely maintenance interventions before a critical failure occurs [2].

3.1.2. Coil Current Analysis for Predictive Maintenance

Analyzing the trends in coil current signatures over time is another valuable technique for the predictive maintenance of high-voltage circuit breakers [5]. By continuously monitoring the current flowing through the trip and close coils and comparing the current waveforms to baseline signatures established during normal operation, deviations can be detected that may indicate developing mechanical or electrical problems. For example, changes in the timing or shape of the current pulses could signify increased friction in the operating mechanism or deterioration of coil insulation, potentially leading to jams or failures [5]. This non-intrusive method can provide early warnings of performance degradation, allowing for proactive maintenance to address the underlying issues before they escalate into more serious faults.

3.1.3. Infrared Thermography

Infrared thermography offers a non-contact and visual method for predictive maintenance of high-voltage circuit breakers by detecting abnormal heating in various components [165]. Infrared cameras capture thermal images of the circuit breaker, revealing temperature distributions across its surface. Elevated temperatures in specific areas can indicate problems such as loose electrical connections, overloaded components, or increased resistance due to corrosion or wear, all of which can lead to equipment failure if left unaddressed. ML algorithms, such as Multilayered Perceptron (MLP), can be used to analyze the thermal images and classify the thermal state of the circuit breaker components into "non-defect" and "defect" categories, providing an objective assessment of potential issues [165]. This technique allows for the early identification of thermal anomalies, enabling timely maintenance to prevent failures and ensure the reliable operation of the circuit breaker.

3.2. High-Voltage Transformers

Being the most critical equipment of transmission grids, the shift from time-based to predictive maintenance for high voltage transformers represents significant advancement in power system management. Traditionally, utilities relied on routine preventative maintenance programs combined with regular testing [82]. However, this approach has been gradually replaced by CBM, which reduces or eliminates routine time-based maintenance in favor of performing maintenance only when equipment condition requires it [82]. This transition is driven by several factors. Deregulation in the power industry has accelerated competition among power companies, pushing them to maximize profit while minimizing maintenance costs [166]. Additionally, the large number of substations and their specific locations make CBM particularly useful as part of the system's on-demand response [167].

Predictive maintenance strategies offer practical advantages over traditional approaches. Scheduled maintenance often fails to prevent sudden failures, causing costly disruptions and safety risks [162] [168]. It allows more accurate fault detection, reduces unnecessary maintenance, and can prevent failures [162]. The move is supported by better non-intrusive diagnostic tools that assess transformer internal condition and provide early failure warnings [82]. When combined with IoT technologies, predictive maintenance can become prescriptive maintenance, offering advantages over offline preventive approaches [169].

ML and DL techniques are increasingly applied to enhance predictive maintenance for high-voltage transformers, helping identify vulnerable transformers with high accuracy and enabling operators to prioritize maintenance [168] [170] [171]. These algorithms analyze data from DGA results, temperature readings, load data, and vibration measurements to identify patterns and predict failures. Random Forest classifiers predict short circuit faults using wavelet transform and feature selection [172]. K-means clustering groups transformers with similar behavior patterns to identify failure-prone units [170]. Linear Regression and PCA predict transformer conditions based on electrical parameters. Deep neural networks analyze historical data to predict degradation and failures by identifying complex anomalies [173]. While AI-based approaches offer potential for accurate predictions, they require significant historical data for training, and model complexity and interpretability present challenges [172]. Input data quality is crucial for model performance. Digital twins combined with AI improve predictions with promising results [174].

3.2.1. Predictive Maintenance Based on DGA

Dissolved Gas Analysis (DGA) is not only used for fault identification but also plays a crucial role in the predictive maintenance of high-voltage transformers. By monitoring the trends in the concentrations of dissolved gases over time, it is possible to track the progression of insulation degradation and predict potential failures [175]. A sudden increase in the concentration of certain key gases or a rapid change in gas ratios can indicate an accelerating fault condition, providing an early warning of an impending failure. Analyzing historical DGA data using statistical methods and ML algorithms can help to develop models that predict the rate of fault progression and estimate the remaining useful life of the transformer [176]. This allows maintenance personnel to plan interventions proactively, minimizing unplanned outages and maximizing the operational lifespan of the transformer. While DGA is a powerful tool for predictive maintenance, it requires regular oil sampling and analysis, and the accuracy of predictions depends on the frequency and quality of the data collected.

3.2.2. Thermal Monitoring for Predictive Maintenance

Continuous monitoring of the temperature of critical components within high-voltage transformers, such as windings, core, and oil, is essential for predictive maintenance [177]. Abnormal temperature rises can be indicative of various issues, including overloading, problems with the cooling system, or the presence of developing faults like short circuits [177] [178]. Temperature monitoring can be achieved using permanently installed sensors or through periodic inspections using thermal imaging cameras. Real-time temperature data allows operators to identify potential problems early and take corrective actions before they lead to more severe damage or failure [177]. For example, a gradual increase in winding temperature under normal load conditions might suggest a developing fault within the winding insulation. Effective thermal monitoring requires appropriate sensor placement and calibration, and the interpretation of temperature data needs to consider the transformer's load and ambient environmental conditions.

3.3. High-Voltage Cables

AI and ML algorithms are also being applied to predictive maintenance for high-voltage cables [127] [179]. By analyzing historical data collected from cable monitoring systems, including PD activity, temperature readings, and load information, AI models can learn to identify patterns and predict potential cable failures [127] [180] [181]. These data-driven approaches can often identify complex relationships that are not apparent through traditional analysis methods, leading to more accurate predictions of failure and optimized maintenance interventions [127] [154] [182] [183]. For example, ML algorithms can be trained to predict the likelihood of cable failure based on various operational and environmental factors, allowing for proactive maintenance scheduling [132] [183]. Implementing AI-based predictive maintenance for cables requires access to sufficient historical data for training the models effectively.

3.3.1. Condition Monitoring using Partial Discharge

Continuous monitoring of PD activity is a key predictive maintenance technique for high-voltage cables [127]. By tracking the occurrence and characteristics of PD over time, it is possible to assess the ongoing health of the cable insulation and predict potential breakdowns [127]. An increase in the magnitude or frequency of PD events, or a change in the PD pattern, can indicate the progressive deterioration of the insulation, signaling an increased risk of failure. Online PD monitoring systems allow for the continuous assessment of cable condition without the need for service interruption, providing valuable insights into the aging process and the development of insulation defects [127]. Analyzing trends in PD parameters enables maintenance personnel to prioritize cables with deteriorating insulation for inspection and potential repair or replacement, thus preventing unexpected outages.

3.3.2. Other Techniques

Other techniques are emerging for the predictive maintenance of high-voltage cables. Drones equipped with thermal imaging cameras can be used to quickly and thoroughly evaluate the health of cables, particularly overhead lines, by detecting temperature variations that may indicate hotspots or defects [184]. Ground-based thermal inspections using infrared cameras are also valuable for identifying early signs of deterioration in cable systems. Furthermore, technologies that combine innovative data analytics and IoT capabilities are being developed to predict the remaining useful life of underground cable systems. Integrated monitoring systems that utilize various sensors and data analytics platforms are also crucial for comprehensive condition monitoring and predictive maintenance of cables [127].

4. Comparative Analysis

Voiceprint analysis presents a cost-effective method for detecting mechanical faults in high-voltage circuit breakers, particularly advantageous for substations where ease of installation and maintenance is paramount [6]. Its primary advantage lies in simplicity and efficacy for common mechanical issues. However, dependence on acoustic signals renders it vulnerable to environmental noise, necessitating optimal sensor placement [6]. Conversely, vibration analysis, while potentially more sensitive to a broader spectrum of mechanical faults, demands advanced signal processing and meticulous sensor positioning [7]. Multiple sensors and sophisticated algorithms can enhance accuracy, albeit at higher cost and complexity [10]. Coil current analysis offers a distinct perspective by concentrating on electrical signals that drive mechanical operations, providing computationally efficient online monitoring of breaker health and detecting operating mechanism anomalies [5]. Its non-intrusive nature and ease of implementation render it a valuable complementary technique. AI-driven predictive maintenance signifies substantial advancement by integrating data from various monitoring techniques, such as vibration and coil current analysis, to deliver comprehensive and accurate failure prediction. Despite its promise, successful implementation depends on large, high-quality datasets and overcoming challenges related to model complexity and cybersecurity. Continuous vibration monitoring provides focused assessment of breaker mechanical health, facilitating component degradation tracking over time and enabling timely maintenance [155]. Similarly, analyzing trends in coil current signatures offers non-intrusive means to monitor operating mechanism performance and predict potential issues [5]. Infrared thermography serves as a valuable supplementary technique for identifying thermal anomalies that may indicate developing problems [165].

In high-voltage transformers, DGA remains the most widely adopted technique for identifying internal faults, particularly those associated with insulation degradation and thermal or electrical stresses [38]. Its capability to detect incipient faults at early stages is invaluable in preventing catastrophic failures. However, the off-line nature of DGA and potential for ambiguous interpretations necessitate complementary techniques. Vibration analysis offers insights into transformer mechanical integrity, providing non-invasive detection of issues such as winding deformations or core looseness [43]. FRA stands out for its high sensitivity to mechanical changes within the transformer, making it excellent for detecting winding deformations caused by various stresses [62]. However, interpreting FRA signatures often requires specialized expertise and reliable baseline for comparison [53]. PDC measurement is particularly useful for assessing overall transformer insulation health, detecting faults caused by moisture, contamination, or aging [68]. While non-destructive, its time-consuming nature limits routine application, and analysis requires careful consideration of various influencing factors. Thermal imaging is a promising, low-cost monitoring application that can identify faults before turning severe but will not identify insulation deterioration until significantly progressed [177]. In high-voltage transformers, predictive maintenance heavily relies on long-term trend analysis of dissolved gases through DGA. This method provides crucial insights into insulation condition and allows failure prediction based on gas generation rate. However, inherent time lag in gas accumulation necessitates other techniques for comprehensive assessment [185]. Furthermore, online monitoring DGA systems are expensive and complex to retrofit onto existing equipment [186] [187]. Continuous thermal monitoring offers real-time information on transformer operational status and can detect immediate issues related to overloading or cooling system malfunctions [177] [184]. The increasing application of ML and DL to transformer predictive maintenance enables analysis of complex data patterns from various sources, leading to more accurate fault occurrence predictions and remaining useful life estimation. These advanced techniques hold potential to revolutionize transformer maintenance, but require significant historical data and careful model development.

For high-voltage cables, PD analysis is paramount for evaluating the integrity of the insulation system and detecting potential failure points [127]. Analyzing trends in PD parameters allows for proactive maintenance interventions [127].

TDR excels at locating physical discontinuities in the cable, such as breaks or short circuits, providing precise fault localization for efficient repairs [137] [138]. However, it is not particularly useful for CBM as it practically cannot identify severe faults before they occur. Impedance spectroscopy offers a frequency-domain perspective on cable health, providing information about insulation properties and the presence of certain fault types like aging or buffer layer issues [146]. The interpretation of impedance spectra often requires expertise, but it provides valuable insights into the overall condition of the cable insulation. The application of AI to cable monitoring data, including PD information, temperature, and load, can further enhance the accuracy of failure predictions and enable more effective predictive maintenance strategies [127]. Techniques like drone-based thermal imaging and integrated IoT-enabled monitoring systems also contribute to a more comprehensive approach to predicting and preventing cable failures [127].

Table 1 summarizes and compares the primary fault identification techniques for high-voltage equipment.

5. Challenges and Limitations of Current Techniques

While fault identification and predictive maintenance techniques offer significant advantages in ensuring high-voltage equipment reliability, they face inherent challenges and limitations. One significant hurdle lies in difficulties with data acquisition and interpretation. Vibration signals from High-Voltage Circuit Breakers are characterized by nonlinearity, nonperiodicity, and transient nature, complicating meaningful feature extraction that can reliably indicate specific faults [12]. Accurately interpreting vast amounts of vibration data requires substantial expertise to differentiate between normal operational vibrations and subtle patterns signifying problem onset [188]. Similarly, PD signals crucial for assessing insulation health can be significantly influenced by environmental noise, making accurate detection and interpretation of these faint signals challenging [12]. The magnitude and pulse characteristics of PD events vary considerably depending on time, applied voltage, operating temperature, load, and humidity, adding complexity to their analysis [189]. Early logging and online monitoring systems for power lines suffered from limitations such as low sampling rates, hindering their ability to capture transient overvoltage signals with sufficient accuracy [1]. Even with modern techniques like voiceprint analysis for circuit breakers, collected data can be voluminous and contain multiple information types, posing difficulties in isolating specific features indicative of particular faults [9]. Collecting data on electrical system condition can be challenging, especially with equipment in remote or inaccessible areas. The analysis of large volumes of sensor data from predictive maintenance programs can be complex and time-consuming, requiring specialized software and analytical skills. Furthermore, predictive maintenance effectiveness relies heavily on underlying data quality; inconsistencies, inaccuracies, or errors can lead to missed fault detections, inaccurate remaining useful life predictions, or high false alarm rates, undermining program value [190].

Table 1. Comparison of fault identification techniques for high-voltage equipment.

Equipment Type	Technique	Underlying Principles	Typical Applications (Fault Types)	Advantages	Limitations
Circuit Breakers	Voiceprint Analysis	Analysis of acoustic signals generated during operation	Mechanical faults (iron core jamming, loose components, pushing rod jamming)	Low equipment complexity, high reliability, easy installation, good for small/nonlinear data	Installation location critical, potential susceptibility to environmental noise
	Vibration Analysis	Monitoring and analyzing vibration signals produced during operation	Mechanical faults (contact faults, mechanism seizures, bolt loosening, spring fatigue)	Early detection possible, multi-sensor fusion enhances accuracy	Sensor placement critical, noise can affect accuracy, requires sophisticated signal processing
	Coil Current Analysis	Analyzing the current signature of trip/close coils	Jams in tripping devices, issues affecting coil plunger motion, opening/closing time anomalies	Non-intrusive, computationally inexpensive, can be embedded in microprocessors	Requires careful analysis to distinguish normal variations from faults, especially in noisy environments
Transformers	DGA	Analyzing dissolved gases in transformer oil	Thermal faults, electrical faults, insulation degradation	Widely used, detects incipient faults early	Interpretation can be ambiguous, requires regular oil sampling and lab analysis
	Vibration Analysis	Analyzing vibration signals from the transformer tank	Iron core and winding faults, short-circuit faults in windings	Non-invasive, mathematical statistics can minimize noise influence	Noise sensitivity can still be a factor, requires proper sensor placement and signal processing
	FRA	Measuring frequency response of transformer windings	Winding deformations, short-circuited turns, core movements	Highly sensitive to mechanical changes, detects faults from manufacturing to service life	Interpretation complex and often requires expert knowledge, requires a reference signature
	PDC	Assessing dielectric response of insulation by measuring polarization/depolarization currents	Insulation failure faults due to moisture, PD, contamination, overheating	Non-destructive, evaluates oil-paper insulation without opening tank	Time-consuming off-line process, results affected by various factors, requires demanding analytical models
Cables	PD Analysis	Detecting and analyzing PDs within cable insulation	Insulation defects (voids, cracks, contamination)	Effective for early detection of insulation problems, online monitoring possible	Susceptible to noise, requires specialized equipment, signal analysis can be complex
	TDR	Sending pulse and analyzing reflections	Cable breaks, short circuits, open circuits	Can pinpoint fault location along the cable	Sensitivity limited for certain fault types, interpretation of reflections can be challenging
	Impedance Spectroscopy	Measuring impedance over a range of frequencies	Buffer layer ablation, local aging, inductive/capacitive faults, open circuit faults	Provides information about insulation condition and degradation	Interpretation of impedance spectra may require expertise

Environmental factors significantly impact measurement accuracy from predictive maintenance techniques. Ambient temperature influences transformer characteristics and thermal imaging readings [191]. UAV-based thermal inspections can be limited by adverse weather conditions such as storms, severe winds, and snow [191]. High winds can cool components experiencing elevated temperatures, potentially masking thermal signatures indicating problems [192]. Pollution affects insulator performance and interferes with PD measurement accuracy [193]. High humidity reduces dielectric strength of insulation materials and accelerates degradation [194]. In circuit breaker vibration analysis, external electromagnetic environments introduce noise into collected signals, potentially obscuring patterns indicative of mechanical faults [9].

Cost and complexity associated with implementing predictive maintenance techniques present significant limitations, particularly for smaller organizations or those managing vast equipment quantities. Establishing continuous online condition monitoring systems involves substantial financial investment [195]. Broader implementation requires significant costs for sensor procurement, data infrastructure development, and specialized software acquisition. Transitioning from traditional time-based to predictive maintenance often necessitates considerable initial capital outlay [190]. Successful implementation requires skilled workforce with expertise in data analytics, ML, and monitoring technique principles. Lack of personnel with specialized skills challenges many organizations.

Each fault identification and predictive maintenance technique has limitations regarding specific fault types it can effectively detect. Thermal imaging may be less effective detecting certain faults in dry-type transformers where operating coil temperatures are inherently much higher than ambient temperature [196]. Substation-based devices designed to detect high-impedance faults may not reliably detect all such faults due to often low fault current [197]. Traditional electrical monitoring techniques may suffer from spurious indicators and lack of sensitivity, potentially leading to missed detections or false positives [198]. In PD testing for cables, online methods might not be sensitive enough to detect minor electrical treeing within insulation [199]. The rate at which different insulation materials erode due to PD activity varies significantly, making it challenging to establish reliable predictions based solely on PD measurements [189]. Vibration analysis might be less accurate identifying motor-related defects compared to methods like Electrical Signature Analysis (ESA). These limitations underscore that no single predictive maintenance technique is universally effective for detecting all fault types. Comprehensive condition monitoring strategies necessitate judicious application and integration of multiple complementary techniques.

6. Common Themes and Future Directions

Fault identification and predictive maintenance for high-voltage equipment continuously evolves, driven by technological advancements and growing emphasis on enhancing power system reliability. Several emerging trends significantly impact this domain. The most prominent trend is increasing integration of AI and ML technologies into predictive maintenance strategies [168] [170] [171] [183] [200]. AI and ML algorithms analyze vast sensor data, identify complex patterns indicative of impending failures, and predict remaining useful life with greater accuracy [190]. DL techniques prove particularly effective in recognizing overheating fault locations in transformers from thermal images and classifying PD signal patterns to identify insulation defect types and severity [201]. AI is explored for optimizing power electronic device performance like IGBT inverters by dynamically adjusting switching strategies based on real-time conditions [202]. In circuit breaker diagnostics, explainable AI approaches provide insights into vibration signal features most indicative of specific fault conditions [12]. Digital twins, virtual replicas of physical equipment, are enhanced by AI integration, allowing sophisticated simulations of equipment behavior and enabling more proactive maintenance planning [203]. Unsupervised learning algorithms identify patterns in unlabeled data, detecting previously unknown anomalies in high-voltage power system operation [204].

IoT and sensor technology advancements play increasingly vital roles in enabling continuous condition monitoring. Affordable IoT sensors continuously collect real-time data on operational parameters including temperature, vibration, pressure, and electrical characteristics. This continuous data stream facilitates early detection of subtle anomalies indicating initial equipment degradation stages, enabling proactive maintenance interventions before critical breakdown. IoT-enabled predictive maintenance strategies yield significant economic benefits, including reduced unplanned downtime, extended asset service life, and optimized maintenance costs. Wireless sensor networks are utilized for medium-voltage cable condition monitoring, providing flexible and cost-effective approaches [205]. Edge computing emerges as a key trend, enabling real-time equipment data analysis directly at source, reducing latency and enhancing data privacy.

Digital twin technology development represents another significant future direction. Digital twins continuously monitor actual working conditions and provide platforms for visualizing potential future scenarios based on simulated operational stresses and environmental factors [206]-[211]. These virtual representations allow operators to simulate different operational conditions and understand risk factors affecting high-voltage asset performance. This capability enables more proactive and optimized maintenance planning based on predicted needs rather than fixed intervals.

Ongoing signal processing technique advancements are crucial for improving fault detection accuracy and sensitivity. Improved methods such as wavelet transform, empirical mode decomposition, and spectral analysis techniques extract more meaningful features from sensor data collected through vibration analysis and PD measurement [12]. Advanced filtering and denoising algorithms continuously develop to improve acquired signal quality [212]. Wavelet transform effectively reduces noise in PD signals, and anisotropic diffusion filtering applies for thermal imaging enhancement [212]. FRA increasingly detects mechanical defects within transformers by analyzing electrical response across frequency ranges [213]. ESA and Motor Current Signature Analysis (MCSA) emerge as powerful tools leveraging electrical data analysis to diagnose equipment conditions and predict potential failures. Voiceprint analysis, capturing and analyzing acoustic signatures from high-voltage circuit breakers during operation, is explored for identifying mechanical faults [6]. An ellipse-based method for fault detection in transformers analyzes voltage versus current image features to identify distortions indicating internal or external faults [214] [215].

7. Conclusion

This review has provided a comprehensive overview of fault identification and predictive maintenance techniques for high-voltage equipment, focusing on circuit breakers, transformers, and cables. Various techniques, from traditional methods like DGA and vibration analysis to advanced AI and IoT approaches, have been discussed with their principles, applications, advantages, and limitations. Comparative analyses have highlighted strengths and weaknesses of different techniques for specific equipment types. The analysis reveals significant advancements, particularly increasing AI and ML integration, growing IoT and sensor technology roles, and trends towards online and continuous monitoring. These developments enhance high-voltage power system reliability and longevity, reduce operational costs, and ensure safe electricity supply. While challenges remain in data quality, model complexity, and cybersecurity, opportunities for innovation are substantial, promising more intelligent and proactive maintenance strategies for critical high-voltage equipment.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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