

A Comprehensive Review of AI-Driven DC Arc Fault Detection in Photovoltaic Systems

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Abstract—Photovoltaic (PV) systems now account for over 1.3% of global electricity generation and are expanding rapidly. DC arc faults pose severe safety risks among PV system faults, including fire hazards, equipment damage, and system failures. Traditional protection methods such as overcurrent devices and threshold-based detection often fail to distinguish arc faults from normal system noise reliably due to series arcs' intermittent and low-current nature. To address these problems, intelligent methods, including machine learning (ML), deep learning (DL), and hybrid approaches, have emerged as promising solutions offering superior accuracy, adaptability, and real-time performance. This paper presents a state-of-the-art intelligent approach for DC arc fault detection in PV systems. We explicitly compare ML and DL algorithms, highlighting trade-offs in computational efficiency, data requirements, and hardware constraints. Key implementation challenges, limited real-world datasets, and high computational costs for edge deployment are analyzed. Future directions focus on bridging gaps such as edge computing for real-time detection, synthetic data generation, and interpretable AI models. The findings aim to advance PV safety standards and enable scalable renewable energy integration.

Keywords—Photovoltaic (PV) Systems, DC Arc Fault Detection, Machine Learning (ML), Deep Learning (DL), Artificial Intelligence (AI)

I. INTRODUCTION

PV system have emerged as an integral aspect of global renewable energy infrastructure, globally solar PV installed capacity with yearly additions expected to increase from 252 GW in 2022 to 700 GW in 2025 [1]-[4], as illustrated in Fig. 1 Global Solar PV Installed Capacity Growth. As solar energy usage grows, it becomes more important to ensure PV system dependability and safety [5]. PV systems with DC arc faults commonly experience fires that endanger human safety and cause property damage. Preventing catastrophic events requires early diagnosis [6], [7].

DC arc faults, which can occur due to improper installation, aging components, or environmental factors, are particularly challenging to detect and mitigate. Two types of arc faults exist: series and parallel. A ground fault is also included in this category [8]. As shown in Fig. 4. Parallel arc faults result from insulation breakdown between conductors or a conductor and ground, causing arcing across the conductors. The ground and parallel arcs are easily identifiable due to their high current draw [9]. A series arc fault occurs when a single wire in a circuit break, causing an arc to form across the gap. This can occur owing to faulty wires, loose connections, or broken conductors [10]. Besides, detecting series arc faults in PV systems presents significant

technical challenges due to the inherently low fault current magnitudes, the absence of current zero-crossing phenomena unlike AC systems, and interference from multiple noise sources within PV system components [11]. Conventional protection often fails to detect series arc faults due to their low-current signatures, which overlap with normal operation noise. Arcs generate highly concentrated energy, causing rapid power dissipation in a small region, which leads to extremely high temperatures of up to 20,000K. Arc faults primarily contribute to PV fires, accounting for 60% of all such incidents [12]. An arc fault evidences these limitations on 24 July 2021 in Jilin province. As shown in Fig. 2. It was preliminarily verified that 14 people had been killed, 12 were seriously injured, and 14 suffered ordinary bone injuries and trauma [13].

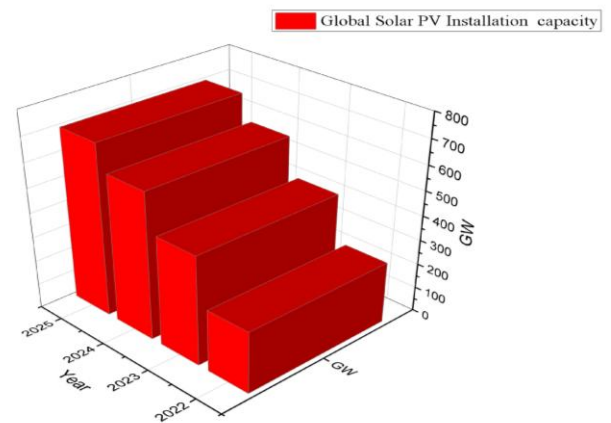


Fig. 1. Global solar PV installation capacity [2]

In response to the destructive impact of arc faults in PV systems, the National Electrical Code (NEC) mandated in 2011 that photovoltaic systems with DC voltages exceeding 80V must be equipped with DC arc fault circuit breakers. This requirement was further reinforced and expanded in 2018 to mitigate the risk of arc faults and enhance system safety [5], [14]. Therefore, advanced detection methods capable of distinguishing subtle fault signatures from noise can accurately identify and mitigate these faults and ensure the safety and reliability of PV installation's compliance with safety standards.

Modern computational algorithms, particularly ML and DL, have considerably improved fault detection capabilities in PV systems by achieving over 98% accuracy in experimental setups and inference time 25ms [15], [16], increasing accuracy and response times. Conventional detection systems, while generally effective for gross

faults, frequently have limits in reliably finding faults and struggle with dynamic conditions, irradiance fluctuations, or partial shading under dynamic operating situations, such as changing weather and environmental factors. ML and DL methods Contemporary data-driven techniques, particularly ML and DL, demonstrate superior performance in processing large datasets and identifying subtle operational anomalies indicative of system faults. These methods enable precise differentiation between normal and faulty states through multimodal analysis of electrical parameters and thermal data, reducing false alarms compared to threshold-based methods [6], [15]. Hybrid models wavelet transforms combined with convolutional neural networks [CNNs] [17] further enhance robustness by integrating signal processing with feature learning [18], [19]. Incorporate combined approaches and DL, which provide high accuracy for detecting DC arc faults in PV systems [19]. Furthermore, its real-time processing capabilities allow quick response to identified abnormalities, with arc extinction within 200 ms according to UL 1699B [14], [20]. This is crucial for reducing system downtime and avoiding safety issues.



Fig. 2. Arc Incident in Jilin province [13]

This review examines AI and ML integration for DC arc fault detection. While these techniques offer superior accuracy, challenges remain in computational complexity and edge-device deployment [16], [22]. Including time-frequency analysis and hybrid AI models benchmarking performance against standardized PV datasets and identifying gaps in generalizability and edge-computing optimization. In addition, this paper summarizes the top techniques and compares performance-efficient models, establishing clear benchmarks for DC arc fault detection in PV systems. It provides practical recommendations for developing next-generation detection systems and proposes a framework to transition from research concepts to field-deployable solutions.

The research contributes a taxonomy of AI-driven detection methods, showcasing top-performing models, and discusses DC arc fault detection challenges facing PV systems. It also provides a complete review of AI-based and traditional-based techniques, addressing their benefits and limitations and laying a road map for future PV system research.

II. OVERVIEW OF DC ARC FAULT IN PHOTOVOLTAIC SYSTEM

A. Photovoltaic System

A PV system converts sunlight into electricity through interconnected components Fig. 3, beginning with PV cells -

semiconductor devices that generate direct current (DC) when exposed to sunlight. These cells are built in series to form modules, which are then combined into arrays through series connections, increasing system voltage or parallel connections and boosting current output with total power governed by $P=IV$ relationships [22], [23]. A complete PV system includes four key components: solar panels, arrays of interconnected modules, inverters that convert DC to grid-compatible alternating current (AC), battery storage systems for excess energy, and monitoring systems that track performance and detect faults [24]. While these systems enable renewable energy integration for applications like electric vehicle charging and microgrids [25], [26], they face significant operational challenges that may reduce energy yield and pose serious fire risks.

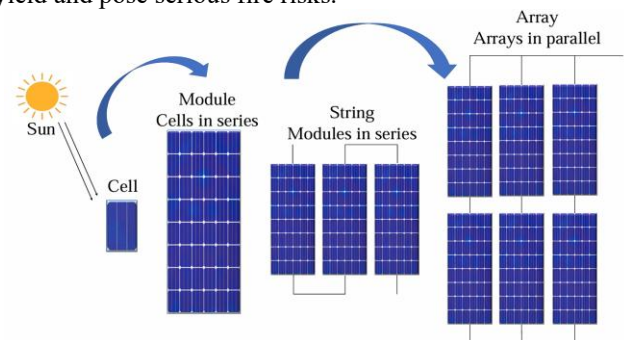


Fig. 3. Basic structure of photovoltaic system [5]

B. Classifications of Faults in PV System

In the PV system, faults may occur in all parts of a PV system, such as PV arrays, transmission cables, combiner boxes, controller systems, converters, inverters, and batteries, and faults in photovoltaic systems are both on the DC side and AC side [27]. Faults (Table 1) in solar PV systems can significantly impact their performance, efficiency, and reliability. These faults are generally categorized into three main types:

- Physical
- Environmental, and
- Electrical
- Physical Faults

Physical damage to PV modules, including glass breakage and cell cracking, represents a significant failure mode in PV systems, typically caused by environmental stressors or manufacturing defects, with consequent reductions in power output and potential safety risks [28], [29]. Electrical interconnection faults manifested through connector degradation or cable insulation failure induce increased series resistance, leading to power dissipation and hotspot formation [30], [31]. Structural integrity issues in mounting systems, such as frame deformation or fastener failure, can result in module misalignment, adversely affecting irradiance capture efficiency and potentially accelerating other degradation mechanisms [32]. These physical failure modes contribute to system performance decline and underscore the importance of robust design and regular maintenance in photovoltaic installations.

- Environmental Faults

Several environmental and operational factors significantly influence PV system performance. Partial shading caused by transient obstructions or permanent design

flaws can dramatically reduce power output by creating current mismatches between cells [32], [33]. Surface contamination from accumulated particulates, including dust, pollen, or snow deposition, forms an optical barrier that diminishes light transmittance, necessitating periodic cleaning protocols to maintain optimal efficiency [29]. It can reduce power output by 8.80% and efficiency by 11.86% [34]. Thermal effects represent another critical consideration, as elevated operating temperatures induce material thermo-mechanical stress, accelerating degradation mechanisms while simultaneously reducing conversion efficiency through negative temperature coefficients [35]. These interrelated factors underscore the importance of proper site selection, system design, and maintenance practices in maximizing photovoltaic system performance and longevity.

- Electrical Faults

Photovoltaic systems are susceptible to critical electrical faults compromising performance and safety. Short circuits, typically caused by insulation degradation or improper connections, create low-resistance paths that reduce system voltage and may lead to hazardous conditions [36], [37]. Open circuit defects, caused by conductor breaks or connector failures, disrupt current flow and reduce power generation capacity [32], [36]. Power conversion subsystems are especially susceptible because inverter failures can interrupt the crucial DC-AC conversion process and perhaps result in whole system shutdowns [32], [20]. Most importantly, arc faults occur when high-impedance connections generate continuous electrical discharges, which can cause localized overheating that damages system components and poses serious fire risks [36]. To guarantee system dependability and safety, these electrical failure modes, taken together, call for strong protection plans and routine maintenance.

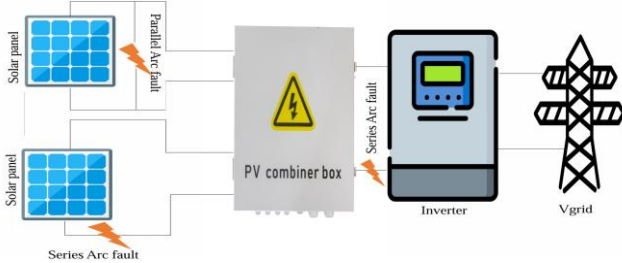


Fig. 4. Potential faults in various location in PV system

III. BACKGROUND OF DC ARC FAULTS DETECTION USING ARTIFICIAL INTELLIGENCE

A. Conventional Approaches

The conventional techniques for DC arc fault detection in PV systems are based on monitoring electrical parameters like voltage fluctuations, current spikes, and high-frequency noise signatures; they frequently use threshold-based algorithms, frequency domain analysis, wavelet transform and Fast Fourier transform, and impedance measurements to identify fault conditions as shown Fig. 5, for understanding DC arc fault detection using traditional method. Several studies have studied these conventional approaches.

Current-based methods employ threshold algorithms to identify characteristic abrupt current reductions associated with arc faults, offering implementation simplicity and low cost though exhibiting reduced reliability under variable

irradiance conditions [6], [38]. Voltage-oriented techniques detect fault-induced transients through peak detection or derivative analysis yet demonstrate compromised performance in electrically noisy environments or during partial shading operation [7], [8]. More sophisticated impedance-based approaches utilize spectroscopy to measure sudden impedance variations, providing enhanced accuracy without requiring specialized measurement hardware and increased system complexity [39]. The research paper discusses detecting DC series arc faults in photovoltaic (PV) systems using Fast Fourier Transform (FFT) techniques. FFT converts time-domain signals to the frequency domain, allowing for the identification of high-frequency components indicative of arc faults [40]. This study combines time and time-frequency domain analysis of loop current and PV-side voltage to enhance the algorithm's anti-interference ability [41]. Proposed a new approach to fault arc monitoring and positioning based on Variational Mode Decomposition (VMD), which extracts time and frequency-domain features from signals collected under different working conditions to detect and locate series DC arc faults in PV systems [42]. Time-domain and frequency-domain features have been employed to detect arc faults by identifying electrical signal characteristics [43]. These methods, however, may struggle with real-time detection and adaptability to varying conditions. Distinguishes between system noise and arc noise, preventing false detections. Techniques like periodic feature analysis and zero-range density analysis are used to differentiate arc noise from other types of noise in the system and detect arc faults [44]. The study proposes an arc detection algorithm that utilizes differential discrete wavelet transform (DWT) analysis, which enhances the distinction between inverter noise and arc noise, allowing for quick and effective detection of series arcs [45]. The proposed fault detection and localization algorithm for PV systems achieves a detection accuracy of 98.3%, demonstrating its effectiveness in identifying arc faults in complex electrical environments, including power electronics and maximum-power-point tracking [46].

Table 1. Classification of PV system faults causes and effects

Fault Type	Primary Causes	Effects	Detection/Mitigation Methods
Physical Faults	Solar cell cracks, delamination, Hot spot, Broken cells, Junction box, Backsheet, Failure, Bird Dropping, Shading faults,	Reduced power output. Increased maintenance costs and system downtime	Installation of rodent-proof conduits and protective mesh, Regular inspections and maintenance.
	Soiling, Moisture ingress, Temperature Extreme, UV radiation, Snow cover, Dust Accumulation	Significant reduction in energy output. Potential for long-term damage if not addressed.	Installation of bypass diodes to mitigate shading effects, Implementation of machine learning-based reconfiguration techniques
Electrical Faults	Short Circuits, Open circuits, Ground Fault, L-L faults, Bypass diode fault, Arc fault	Fire hazards, system shutdowns, Reduced lifespan of system components	Arc fault detectors, circuit breakers, Current Sensors, I-V Curve Tracing

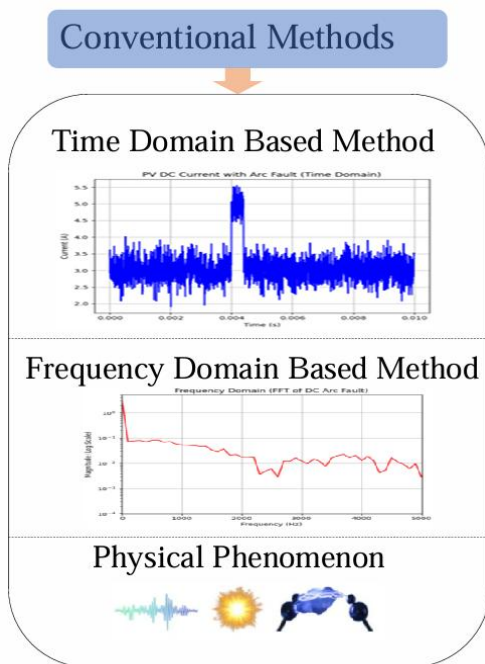


Fig. 5. Conventional Based Methods for DC arc fault detection [77]

Detecting DC arc faults in PV systems remains a significant challenge due to the arc's unpredictable and transient nature. While traditional detection methods are computationally efficient, they often struggle to distinguish arc faults from normal system transients, such as inverter switching MPPT adjustments, leading to false alarms and missed detections. These limitations arise from inherent trade-offs between accuracy, computational complexity, and robustness across varying operating conditions, including partial shading, irradiance fluctuations, and different arc types and series-parallel. Although hybrid techniques that include signal processing and heuristic principles have potential, they have drawbacks, such as erroneous triggers and delayed reactions in dynamic PV situations. With improved precision and adaptability for real-world deployment, new AI-based solutions are emerging as a possible solution to these restrictions.

B. Intelligences Approaches

Recent Progress in AI, particularly in ML and DL, has enabled more effective and efficient fault detection in complex systems, including PV installations as show Fig. 6, DC arc fault detection using AI. DC arc fault detection and AI techniques are especially valuable because of their ability to analyze complex datasets, recognize patterns indicative of faults, and minimize false positive rates, even under diverse operational conditions. Various methodologies have been explored, from traditional techniques to advanced ML, DL, and hybrid approaches. Although these algorithms may not always get the best accuracy compared to deep learning and hybrid methods, they can handle large datasets and recognize intricate patterns [47]. As a result, various studies have been investigated.

DC series arc fault detection for PV systems have leveraged ML and DL techniques to improve accuracy and robustness. One approach combines adaptive local mean decomposition (ALMD) and multiscale fuzzy entropy for

data preprocessing before classification with a support vector machine (SVM), achieving 98.75% accuracy [48]. Another study employs random forests to enhance detection reliability in PV arrays, addressing challenges posed by environmental instability [49]. To mitigate misjudgment caused by fluctuating PV output, an adaptive method integrating principal component analysis (PCA) and ϕ -statistic has been proposed, demonstrating strong environmental adaptability [50]. Lightweight convolutional neural networks (CNNs) have also shown promise, with one architecture reaching 98.15% accuracy [51], while a hybrid model combining 1D CNNs, long short-term memory (LSTM) networks, and an attention mechanism further improves classification performance [52]. Other methods, such as variational mode decomposition with extra tree classifiers, achieve 98.75% accuracy under diverse operating conditions [53]. CNNs have been particularly effective, with one study attaining 98.9% accuracy in discriminating arc faults from short circuits [54] and the TL-LEDarcNet method achieving 95.8% accuracy for low-energy arcs [55]. Further optimizations include a lightweight CNN high 98.81% accuracy [56] and an explainable attention-based model that reduces parameters by 51.52% while achieving 99.63% accuracy, enabling real-time inference on embedded hardware [57]. Advanced techniques like CNN-based distance matrix analysis achieving 99.00% accuracy [65] and neural networks with 4ms detection latency achieving high 99.5% accuracy [66] highlight progress in real-time applications. The ArcNN framework, integrating temporal convolution networks (TCNs), PCA, and a single hidden layer neural network (SHLNN), achieves 99.88% test accuracy [68], while a multi-stage mathematical morphology filter paired with a recurrent neural network (RNN) attains 98.24% accuracy [72]. Semi-supervised ensemble learning methods, combining labelled and unlabeled data with traditional algorithms like SVM and decision trees, have also achieved exceptional performance 99.9% accuracy, showcasing adaptability in DC distribution systems [76].

The study emphasizes that conventional AI-based methods for arc fault detection are frequently "black boxes," meaning they are hard to comprehend and alter, which might reduce their usefulness in real-world scenarios. These models present potential solutions because they can manage complicated data and detect difficult patterns using conventional techniques. However, they also have limitations that must be addressed to improve their effectiveness and reliability in real-world applications.

A hybrid model for DC arc fault detection in PV systems is gaining traction due to their ability to enhance detection accuracy and reliability. These methods usually integrate signal processing, ML, and optimization algorithms to overcome the difficulties brought on by the dynamic and intricate nature of PV systems. Combining several detection techniques, hybrid models can more effectively differentiate arc faults from system noise and transient disturbances like MPPT adjustments or inverter switching. This integrated method is appropriate for real-time deployment in PV installations since it improves fault classification while preserving computing efficiency. Consequently, compared to traditional single-technique solutions, such approaches greatly increase system safety and operating effectiveness. Several hybrid approaches have been proposed.

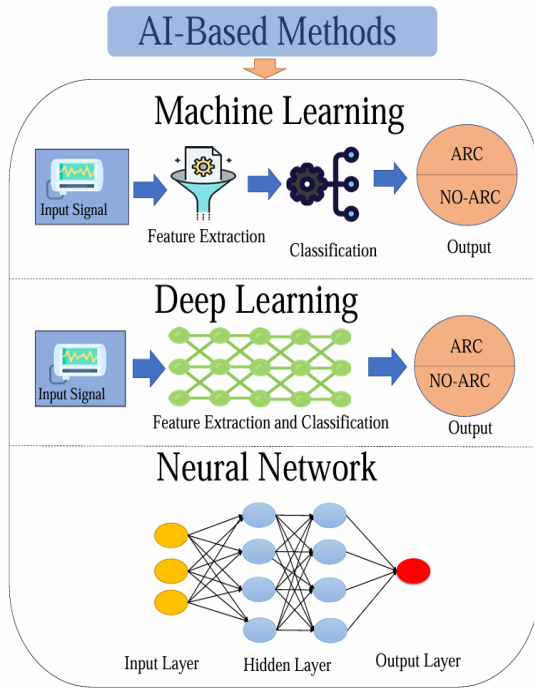


Fig. 6. AI-Based Methods for DC arc fault detection [77]

Proposed an advanced recognition procedure that hybrids time domain current filtering, frequency domain noise removal, and time-frequency feature extraction with artificial learning models for improved DC arc fault detection and achieving high detection precision [58]. Recommends combinations of six feature parameters from both time and frequency domains with various artificial intelligence techniques for effective fault detection [59]. Proposes a hybrid deep learning model that combines the equilibrium optimizer algorithm (EOA) and long short-term memory (LSTM-SAE) for real-time automatic fault detection and classification in grid-connected photovoltaic systems. Demonstrating its efficacy in detecting symmetrical and asymmetrical faults with improved computation time and noise robustness [60]. The paper focuses on an EMD-GRU-NN hybrid model for DC arc fault detection, achieving over 98.7% accuracy and enhancing adaptability across different PV stations, which can effectively improve the reliability and efficiency of solar power generation systems [61]. The study employs optimized variational mode decomposition (VMD) to extract fault features from current signals and uses a particle swarm optimization (PSO)-enhanced support vector machine (SVM) classifier for arc fault detection and achieves over 98.21% [62]. This method combines WPT for feature extraction with SVM for classification. It is particularly effective in detecting arc faults in grid-connected PV systems and enabling accurate detection of arc faults [63]. The method uses Local Mean Decomposition (LMD) to extract fault-related frequency bands, fuzzy entropy and harmonic power to assess current complexity, and standard deviation of supply voltage as additional features, with SVM for classification, enhancing DC series arc fault detection in PV systems [64]. The study explores advanced AI techniques for detecting and classifying DC series arc faults in PV systems. One proposed method employs a Multilayer Perceptron combined with Bi-Directional Long Short-Term Memory

(MLP-BiLSTM), utilizing nine series arc fault models and PSCAD-based simulations to achieve a high detection accuracy of 99% [67]. Another approach, DA-DCGAN, integrates domain adaptation with deep convolutional generative adversarial networks for fault diagnosis, attaining 98.5% accuracy [69]. Additionally, an AI-based detection method is introduced, demonstrating 97.5% accuracy in identifying DC arcs in PV systems [70].

Advanced AI techniques, particularly ML, and hybrids, have demonstrated superior performance in detecting DC arc faults in PV system; traditional system methods still play a role in specific scenarios where computational resources are limited or where simpler solutions are preferred. The comparative studies of PV fault detection methodologies in recent years, as summarized in Table 2, show that different approaches have different performance characteristics. The integration of AI in PV fault detection is on the rise, with high levels of accuracy and effectiveness. However, challenges remain in real-time diagnosis and early warning systems, as well as in adapting these technologies to diverse environmental conditions.

Table 2. Comparison of AI Based dc arc fault detection

Ref	Year	Method	Accuracy
[16]	2024	CNN	98.15%
[56]	2022	Lightweight CNN	96.16%
[65]	2022	CNN	99.00%
[55]	2022	transfer learning	95.8%
[66]	2022	Neural network (NN)	99.5%
[67]	2023	MLP-BiLSTM	99%
[68]	2023	TCN	99.88%
[69]	2019	DCGAN+CNN	98.5%
[70]	2024	BPNN+FFT	97.5%
[71]	2023	Empirical Filtering-Based AI Learning	Not specified
[61]	2023	EMD and GRU-NN	98.7%
[53]	2025	TFCRP and ET	98.75%
[72]	2024	Mathematical Morphology and RNN	98.24%
[73]	2022	FFT and ANN	98.2%
[62]	2022	VMD and PSO-SVM	Over 98.21%
[54]	2020	DL algorithm	98.9%
[74]	2020	EMD+SVM	Not specific
[75]	2021	CNN-LSTM	98.43%
[48]	2022	Fuzzy-SVM	98.75%
[76]	2019	Ensemble ML	99.9%

IV. CHALLENGE IN AI BASED DC ARC FAULT

The accuracy and applicability of ML and DL techniques for fault detection in PV systems are affected by the problems with AI-based DC arc fault detection, which are primarily caused by data variability, computational limitations, and the requirement for dependable real-time processing. Table 3 systematically compares their respective advantages and limitations.

A. Data Quality and Imbalance

- The sensors' precision and dependability may impact the quality of the collected data. Inaccuracies and errors can be introduced by noise, interference, and malfunctioning sensors. This can result in inaccurate feature extraction and, ultimately, impact the effectiveness of the AI-based detection model.
- Acquiring enough labeled data to train AI models is sometimes difficult and expensive. Because DC arc failures in photovoltaic systems are relatively uncommon, gathering sufficient real-world fault samples is difficult.

Due to a lack of data, the model may become underfitted, reducing its ability to properly generalize to other fault scenarios.

- The dataset typically contains far more samples of regular operation than samples of faults. Because of this mismatch, the AI model may be more likely to forecast the majority-class normal signal and struggle to identify the minority-class arc fault correctly.
- Data scarcity for DC arc fault detection in PV systems is a serious difficulty, as real-world fault incidences are infrequent and difficult to recreate in controlled situations. The scarcity of diverse and high-quality datasets impedes the creation and evaluation of dependable ML algorithms for arc fault diagnosis.

B. Model Complexity and Training

- Essential to choose the right model designs and parameters. The model may perform badly on new, unseen data if it is very complex. It may overfit the training set, memorizing the particular patterns instead of understanding the fundamental correlations. However, if the model is overly straightforward, it might underfit the data and miss the intricate details of DC arc faults. The practical use of these models in real-time monitoring systems may be limited by the time-consuming nature of the training process, particularly when working with huge datasets.
- Optimizing the model's hyperparameters to attain optimal performance is a difficult undertaking. It frequently calls for a great handle of trial and faults as well as the application of optimization methods, which could not always converge to the global optimal solution, leading to less-than-ideal detection accuracy.

C. Environmental and Variability

- Environmental variables such as temperature, humidity, irradiance, and dust accumulation significantly impact DC arc fault detection in photovoltaic systems. These factors alter the system's electrical characteristics through temperature variations that affect conductor resistance and semiconductor properties, humidity alters insulation properties, and dust accumulation alters surface conductivity. Therefore, a detailed understanding of these environmental interactions is necessary to create robust fault detection algorithms that maintain accuracy under varying operating conditions.
- Photovoltaic system components, including solar panels, inverters, and connectors, may deteriorate and age over time. This can alter the system's electrical properties and cause other failures, which the AI model trained on data from a more recent or well-maintained system might not be able to detect.
- The identification of DC arc faults may become more complex when solar systems are linked to the grid because of their interactions with grid-side electrical equipment as well as grid voltage and frequency changes. The nature of the arc faults and the effectiveness of the AI-based detection techniques may be impacted by the various operating modes and control strategies of the grid-connected inverters.

D. Black-Box AI Interpretability

- In particular, DL-based models are often viewed as "black boxes" in the context of artificial intelligence. Understanding the model's decision-making process and which features are most important in identifying DC arc faults is challenging. Engineers and operators may find it difficult to test and trust the model's conclusions due to its lack of interpretability. This is especially true in sensitive applications where inaccurate detection could have serious consequences.
- Adversarial challenges and unanticipated input fluctuations might have an impact on AI model performance. To avoid false alarms or missed detections in the context of DC arc fault detection, it is imperative to make sure the model is resilient to different kinds of noise, interference, and malevolent theory.

E. Standards and Regulations

- There are currently no industry-wide or uniform standards for AI-based DC arc fault detection in PV systems. Comparing and accurately evaluating the performance of different models can be difficult, as different manufacturers and research organizations may use different methodologies and evaluation standards.
- AI-based detection systems must implement applicable safety and regulatory criteria. However, due to the dynamic nature of AI technology and the unique characteristics of DC arc faults, it can be difficult to ensure that photovoltaic systems meet the required regulatory standards.
- To ensure safety and reliability, key standards govern DC arc fault detection in PV systems. UL 1699B mandates arc-fault circuit interrupters (AFCIs) for PV systems, requiring rapid fault detection and shutdown. NEC Article 690.11 enforces AFCI use in systems over 80V, while IEC 63027 standardizes DC arc fault detection testing methods. These regulations drive advancements in detection technologies, ensuring compliance and reducing fire risks in PV installations [14].

V. DISCUSSION AND FUTURE DIRECTION

A. Discussion

Advanced analytical techniques in ML, DL, and signal processing algorithms, as well as hybrid approaches, show great promise for improving DC arc fault detection in PV systems, although several implementation challenges remain. Current advanced methods demonstrate superior performance to conventional approaches threshold-based, and Fourier transform methods through their ability to detect complex patterns and transient anomalies in system operating data [58]. These techniques allow for more accurate differentiation between normal variations and actual fault conditions.

The most effective modern approaches use specialized pattern recognition architectures. Spatial feature analysis methods such as wavelet transforms, and convolutional neural networks excel at processing high-dimensional signal data. In contrast, temporal analysis techniques in long-term memory networks effectively handle sequential system measurements [52]. These methods retain high fault detection

rates while drastically lowering false alarms by automatically extracting crucial features from raw input data.

Table 3. Different method of strengths and limitation AI dc arc fault

Model	Strengths	limitations
Support Vector Machine (SVM)	Effective for small datasets with high accuracy, Strong classification decision boundary	Computationally expensive for large datasets, requires feature selection, sensitive to parameter tuning
K-Nearest Neighbors (KNN)	Simple and easy to implement, good for small datasets, non-parametric	Computationally expensive for large datasets, performance highly dependent on distance metric, sensitive to irrelevant features
Artificial Neural Network (ANN)	Effective for handling structured data and general-purpose fault detection	Limited in handling high-dimensional data without complex architectures
Convolutional Neural Network (CNN)	Excellent for extracting spatial features and accurate fault detection	Computationally intensive and requires large datasets
Long Short-Term Memory (LSTM)	Handles long-term dependencies well, enhancing fault detection accuracy in sequential data	High computational cost and potential overfitting without large data
Ensemble Machine Learning (EML)	Combine multiple classifiers to improve accuracy and robustness	Requires careful model selection and weighting methodology to increase computational cost
Recurrent Neural Network (RNN)	Effective in processing sequential data for time-series analysis	Prone to vanishing gradient issues and struggles with long sequences
Generative Adversarial Networks (GANs)	Can generate synthetic data, improving model robustness in fault detection	Challenging to train and prone to instability

However, important restrictions need to be solved for widespread use. Since arcing occurrences are rare in operating systems, a significant challenge is the lack of diversified fault data. In practical applications this paucity of data may result in subpar generalization.

Furthermore, the dynamic nature of PV systems' working environments which include ever-changing temperature, irradiance, and configuration variables makes implementation extremely difficult. Significant computational requirements are another barrier, especially for real-time applications in resource-constrained devices such as inverters. The complexity of these analytical models also creates verification challenges, as their decision-making processes can be difficult to interpret, which is a critical concern for safety applications. To address this, explainable AI (XAI) techniques, such as Shapley additive explanations (SHAP) values and Local Interpretable Model-agnostic Explanations (LIME), could enhance model transparency [57].

Future developments should be hybrid approaches combining physics-based arc models with data-driven classifiers that integrate physical system modeling with data-driven analysis and optimized algorithms for practical implementation. Overcoming these challenges will enable more reliable and efficient Arc fault detection in photovoltaic systems.

B. Future Direction

Although AI-based fault detection for PV systems has advanced significantly, there are still a number of areas that need to be investigated further in order to produce more reliable, accurate, and flexible solutions. To overcome

current constraints and improve DC arc fault detection capabilities, the future research avenues are proposed.

- **Synthetic Data Generation:** Arc faults can be modeled under various conditions by creating physics-based simulations with programs like MATLAB/Simulink and Real-Time Digital Simulators (RTDS). These simulations, which generate realistic current and voltage waveforms that capture arc characteristics, reduce the risks and expenses of conducting physical experiments. Combining synthetic data with real-world measurements can enrich AI model training datasets, enhancing generalization and reducing false alarms.
- **Hybrid algorithmic approaches:** Integrating complementary techniques, such as neural networks with fuzzy logic or expert systems, can leverage the strengths of each method. For instance, combining signal processing with deep learning may improve detection accuracy and robustness.
- **Comprehensive fault modeling:** Expanding DC arc fault models to incorporate environmental factors like irradiance, temperature, and component aging effects can improve algorithm generalization in real-world conditions.
- **Embedded detection devices:** Designing cost-effective, compact hardware for real-time onboard fault detection within inverters or PV components can reduce reliance on external systems. Such embedded solutions can enhance system responsiveness and reliability.
- **IoT-Enabled Monitoring:** Implementing distributed IoT networks for system-wide fault tracking, combining edge devices with cloud analytics, can facilitate predictive maintenance and rapid response. This approach enables real-time monitoring and enhances the scalability of PV systems.
- **Explainable AI (XAI) for Fault Detection:** Arc defect detection systems can become more transparent and reliable by including explainable AI approaches. By providing clear insights into the decision-making process of AI models, XAI facilitates better understanding and acceptance among engineers and stakeholders, aiding in maintenance and troubleshooting efforts.
- **Standardization and Benchmarking:** Developing unified standards and benchmarking protocols is crucial for consistently evaluating arc fault detection technologies. Standardization facilitates the comparison of different methods and promotes the adoption of best practices across the industry.
- **Future Work Priorities:** Embedded devices and hybrid algorithms are particularly urgent due to their direct impact on real-world deployability, while IoT integration offers long-term scalability benefits.

VI. CONCLUSION

In conclusion, this comprehensive review paper has thoroughly analyzed the current status of DC arc fault detection in PV systems, focusing on various methodologies, both traditional and AI-based. Traditional methods are cost-effective and simple, but they have limitations in terms of reliability under dynamic operating conditions and often struggle to recognize arc faults from system noise. In contrast, present computational approach improvements have

shown greater arc fault detection performance, offering enhanced precision and adaptability through advanced pattern recognition and real-time processing capabilities.

Our analysis of various algorithms and their accuracy reveals that most models achieve high accuracy, and we have summarized their strengths and limitations. Although many achieve potential results, false alarms and unwanted tripping persist. Future research should focus on developing robust, lightweight models that maintain high detection accuracy while minimizing computational overhead. Improved data collection methods, including synthetic data generation and enhanced sensor technologies, could address existing gaps in training datasets. Furthermore, standardized evaluation metrics and testing will be required to validate and compare detection methodologies across different PV system configurations.

Addressing these challenges can enhance the reliability and safety of next-generation fault detection systems and the wider and safer use of PV power. The transition from theoretical advances to practical deployment will be critical for enhancing the reliability and sustainability of PV systems in global renewable energy markets.

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