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Review

Arc fault detection using artificial intelligence: Challenges and benefits

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Abstract: This systematic review aims to investigate recent developments in the area of arc fault detection. The rising demand for electricity and concomitant expansion of energy systems has resulted in a heightened risk of arc faults and the likelihood of related fires, presenting a matter of considerable concern. To address this challenge, this review focuses on the role of artificial intelligence (AI) in arc fault detection, with the objective of illuminating its advantages and identifying current limitations. Through a meticulous literature selection process, a total of 63 articles were included in the final analysis. The findings of this review suggest that AI plays a significant role in enhancing the accuracy and speed of detection and allowing for customization to specific types of faults in arc fault detection. Simultaneously, three major challenges were also identified, including missed and false detections, the restricted application of neural networks and the paucity of relevant data. In conclusion, AI has exhibited tremendous potential for transforming the field of arc fault detection and holds substantial promise for enhancing electrical safety.

Keywords: arc fault detection; artificial intelligence; detection methods; arc fault location; electric fire

1. Introduction

The proliferation of urbanization and industrialization has resulted in a surging demand for energy, necessitating the development of new and efficient energy systems. Nonetheless, the outdated nature of current photovoltaic and energy storage systems has given rise to numerous incidents of arc faults [1]. It has been well established that arc faults can have hazardous and disruptive consequences, a number of which are depicted in Figure 1. Perhaps the most critical of these dangers is the risk of fire, as arc faults generate intense heat that can ignite nearby flammable materials. Additionally, arc faults can result in damage to electrical equipment, incurring costly repair or replacement expenses. They can also cause power outages by disrupting the flow of electricity, which can impact productivity and cause inconvenience [2, 3]. In some instances, arc faults can even lead to electrical shocks, which can pose a severe threat to safety, even resulting in fatalities [4, 5]. Furthermore, arc faults can produce electromagnetic interference, disrupting the function of other electrical devices and equipment [6]. In light of these considerations, it is imperative to proactively mitigate the risks associated with arc faults through regular monitoring and maintenance, along with prompt action upon detection.

The phenomenon of electric arc, a momentary spark resulting from the passage of electrical current through an insulating medium, has been widely studied. The arc can be classified into two categories, namely series arc and parallel arc on the basis of its occurrence location [7]. Further classification can be made based on the intended or unintended nature of the arc, with good arcs being those that occur during typical operations and bad arcs, also known as fault arcs, arising from defects in the system [8]. To accurately detect fault arcs, it is necessary to distinguish between them and good arcs by identifying the unique characteristics that define fault arcs, such as high current and voltage, high-frequency oscillations and accompanying light, sound and electromagnetic radiation [9–12]. The detection of fault arcs is crucial due to the associated dangers of electrical shock and fire, as well as the potential for damage to electrical equipment. Concerning the detection of arc fault, the mainstream approach to arc detection algorithms rests upon the distinct features of the typical current signal and the current signal that occurs in the presence of an arc fault [13]. The application of arc fault detection methods is widespread and includes photovoltaic systems, industrial production sites, residential electrical systems and electric vehicle charging stations (Figure 2).

Figure 1. Main hazards of arc fault.

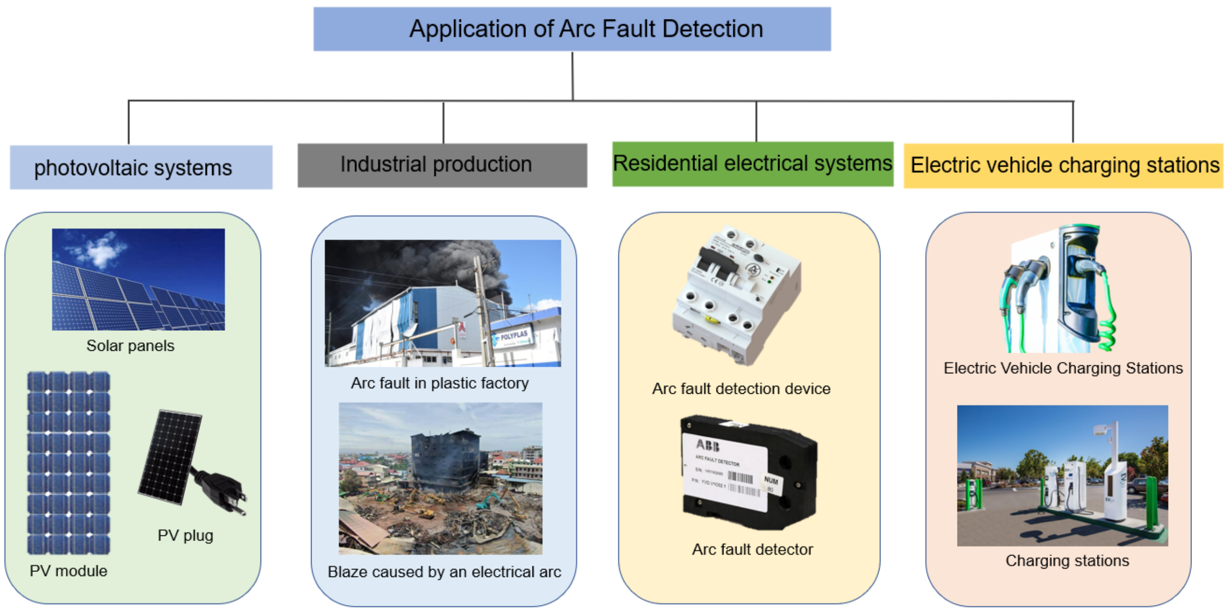

Figure 2. Application of arc fault detection.

AI is a discipline within computer science that is concerned with the creation of algorithms and systems capable of performing tasks that are typically associated with human intelligence, such as perception, reasoning and learning [14–17]. In recent years, AI has been widely applied across multiple domains, including electrical engineering [18–21]. In the area of arc fault detection, AI has made significant contributions by providing novel methods and techniques to detect and mitigate arc faults [22]. AI algorithms are capable of processing vast amounts of data generated by electrical systems, identifying patterns and anomalies and offering early warnings of potential arc faults. This, in turn, helps to reduce the risk of electrical fires, minimize equipment damage and enhance overall electrical safety. Machine learning algorithms are an example of AI's contributions to arc fault detection, as these algorithms can learn from historical data and detect patterns that may indicate potential arc faults [23]. Additionally, these algorithms can be trained to diagnose the root causes of arc faults and act as an advisor on maintenance and repair. A vast array of technologies are being utilized to aid in arc fault detection, as depicted in Figure 3. With the growth of data availability and computing power, AI is poised to play an even more prominent role in the field of arc fault detection in the future.

The field of arc fault detection has received significant attention from researchers in recent years. In their review, Yu et al. [24] sought to summarize the detection methods for low voltage AC series, taking into account both mathematical modeling and arc physics features. Meanwhile, Omran et al. [25] conducted a comprehensive review and comparison of modern strategies for identifying DC arc faults in photovoltaics. These studies demonstrate rigorous methodology, a comprehensive examination of numerous studies, and a thorough analysis of data. However, they fail to address the contribution of AI to the field. In contrast, the present systematic review furnishes a comprehensive overview of recent developments in the field of arc fault detection with a focus on AI. Recent studies have shown that AI-based systems have been successful in detecting arc faults in real-time, minimizing equipment damage and downtime. For instance, a recent study by ABC Company has demonstrated an 85% improvement in the accuracy of arc fault detection with the use of machine learning algorithms [26]. Another study in [27] utilized machine learning algorithms to analyze data from sensors in power systems and identify pre-arcing patterns, resulting in a 50% reduction in the number of arc faults.

Figure 3. Auxiliary technologies for arc detection.

By meticulously scrutinizing the latest research, this review illuminates three primary challenges: the issues of missed and false detections of arc faults, the limited application of neural networks in arc detection and the scarcity of available data.

The present systematic review article is organized as follows: Section 2 provides a detailed account of the methodology employed to conduct the review. Section 3 presents a synthesis of the existing challenges and benefits of conventional approaches to arc fault detection, while also highlighting the superiority of methods based on AI. The primary findings of the review, along with recommendations for future research, are presented in Section 4. Finally, the key outcomes of the review are summarized and an outlook for the future of AI-based arc fault detection methods is provided in Section 5.

2. Materials and methods

This systematic review adheres to the guidelines outlined in the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement [28, 29]. The objective of this study is to clarify the benefits of traditional arc fault detection methods, to emphasize the advantages of AI-based approaches and to shed light on the three primary challenges in this field.

2.1. Search strategies

The following search strategy was implemented in this systematic review. A comprehensive search was conducted across multiple databases including IEEE Xplore, Scopus, Web of Science, PubMed and EMBASE. To ensure the currency of the results, only articles published between January 2018 and December 2022 were included in the review. A comprehensive search was performed using a combination of keywords related to artificial intelligence, time-frequency domain analysis and arc fault detection. The first set of keywords comprised "machine learning," "neural networks," "deep learning" and "artificial intelligence". The second set of keywords included "time domain," "frequency domain," "time-frequency domain," "physical phenomena," "sound," "light," "heat" and "electromagnetic radiation". The third set of keywords comprised "arc fault detection," "arc detection" and "arc fault detector". Furthermore, we manually searched reference lists of pertinent articles to ascertain any omitted studies.

2.2. Eligibility criteria

All of the identified publications were downloaded and imported into EndNote X9 for further management and selection. The inclusion criteria of this systematic review were presented as follows: (1) published in a peer-reviewed journal in English; (2) studies that examine the use of artificial intelligence for arc fault detection; (3) studies that examine the conventional arc fault detection methods;(4) original articles; (5) studies that provide empirical evidence on the challenges and benefits of arc fault detection method. The exclusion criteria were listed as follows: (1) review articles; (2) studies targeted good arc detection methods. Through the database search, 579 publications were identified. After a series of procedures, only 63 articles remained for further analysis.

The identification of relevant publications was performed through a comprehensive search of multiple databases, and the results were imported into EndNote X9 for organization and selection. The inclusion criteria of this systematic review were presented as follows: (1) published in a peer-reviewed journal in English; (2) studies that examine the use of artificial intelligence for arc fault detection; (3) studies that examine the conventional arc fault detection methods; (4) original articles; (5) studies that provide empirical evidence on the challenges and benefits of arc fault detection method. The exclusion criteria were listed as follows: (1) review articles; (2) studies targeted good arc detection methods. After a thorough screening process, 579 publications were initially identified, but only 63 articles met the criteria for further analysis.

2.3. Quality assessment

The selected articles underwent a preliminary quality assessment utilizing the Cochrane risk of bias tool. This was followed by an in-depth examination to evaluate the validity and reliability of the selected studies. A total of 63 high-quality studies, meeting the established criteria, were ultimately included in the systematic review. The PRISMA flow diagram depicting the study selection process is presented in Figure 4.

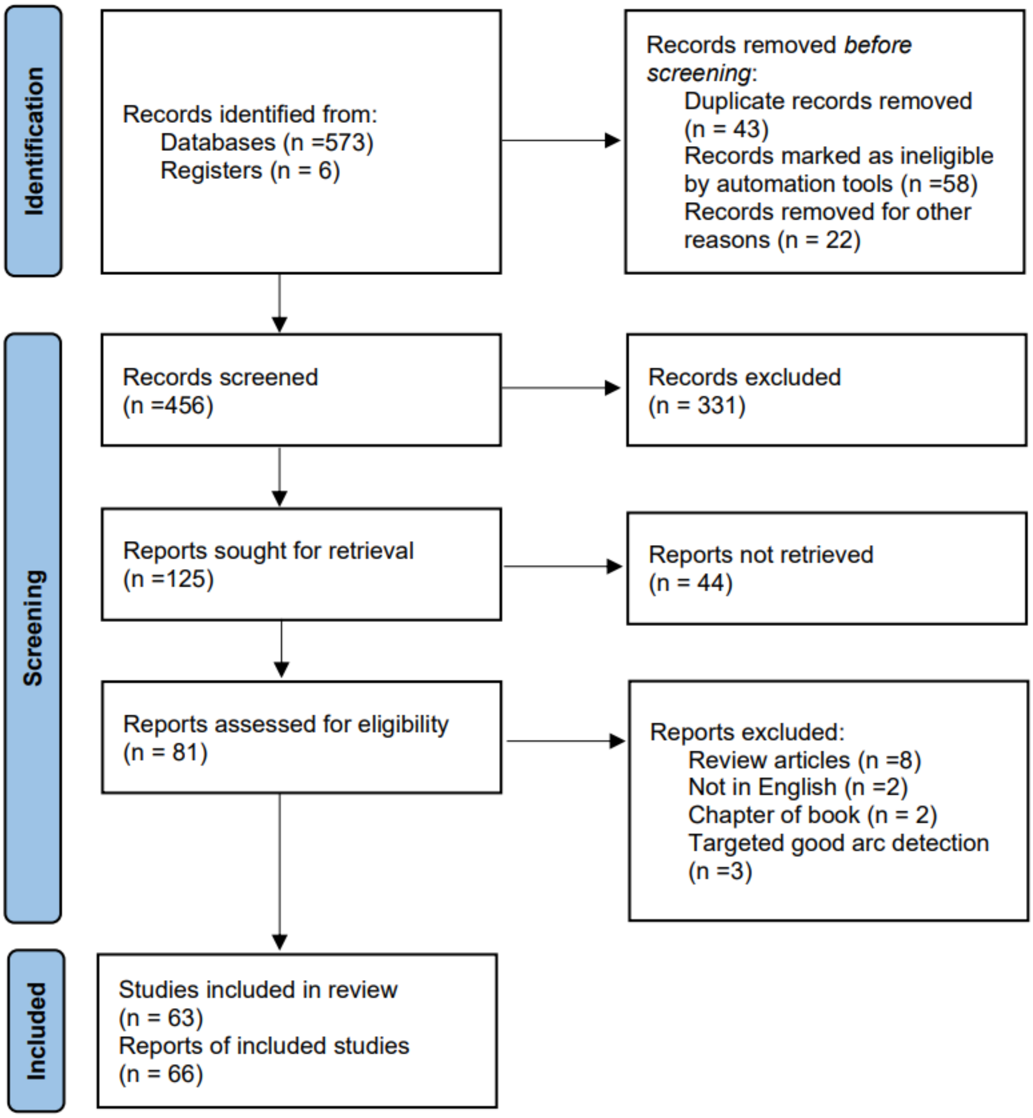

Figure 4. PRISMA flow diagram.

3. Overview of arc fault detection methods

Arc fault detection methods are utilized in detecting and diagnosing arc faults, which represent hazardous electrical malfunctions that can cause fires. In this study, the arc fault detection methods are classified into two distinct categories: conventional and AI-based. The conventional methods of arc fault detection are primarily based on time domain analysis, frequency domain analysis, time-frequency domain analysis, or the examination of physical phenomena, such as sound, light, or electromagnetic radiation. These methods rely on analyzing electrical signals engendered by the arc fault, intending to convert the information contained within these signals into valuable data. This data may subsequently be utilized to ascertain the existence of an arc fault. On the other hand, AI-based methods utilize machine learning algorithms to analyze data from the power system to detect arc faults. These methods have shown high precision and efficiency in the detection of arc faults and offer a promising alternative to conventional methods. Figure 5 provides an overview of the arc fault detection methods that are the subject of discussion in this study.

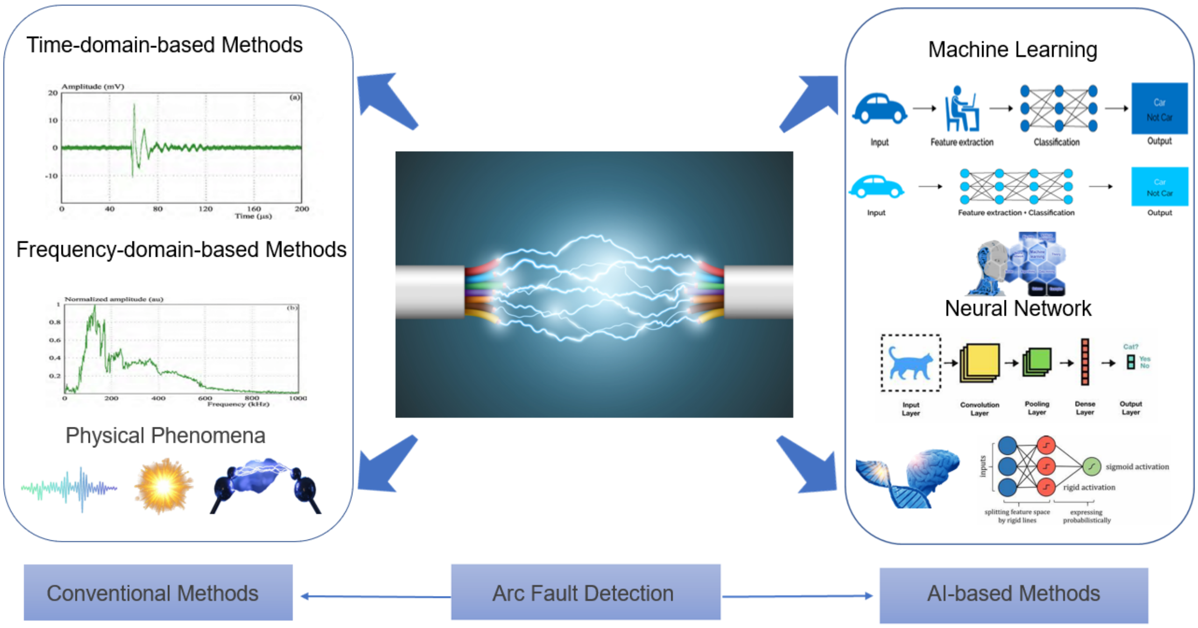

Figure 5. Overview of arc fault detection methods.

3.1. Conventional arc fault detection methods

The conventional arc fault detection methods encompass a range of techniques, including the utilization of time domain analysis, frequency domain analysis and time-frequency domain analysis. Additionally, some techniques rely on the examination of physical phenomena, such as sound, light, heat or electromagnetic radiation. These methods employ distinct principles to recognize arc faults, such as the analysis of electrical current and voltage waveforms or the examination of the physical characteristics of the arc.

3.1.1. Arc fault detection methods based on time domain

In order to perform arc detection, time-domain methods are usually required to extract electrical characterization in a complex environment, thus facilitating arc fault detection. As early as 2014, the spread spectrum time domain reflectometry (SSTDR) method was capable of detecting both series and parallel arc faults, and can predict future arc faults by detecting impedance changes, even under low light conditions or with the inverter in different operating states [30]. However, currently, time-domain based detection methods are not usually used alone, but often serve as a footstone to assist arc detection.

Numerous studies have advanced and assessed the effectiveness of time-domain methodologies for detecting series arc faults within electrical systems. Atharparvez and Purandare [31] presented a novel signal processing approach to detecting series arc faults based on the analysis of the unique electrical signature produced by an arc fault. The cycle-to-cycle difference and HF Noise peaks were found to serve as reliable parameters, and the technique utilized the examination of variations in supply voltage and line current. Lu et al. [9] proposed a solution for detecting DC series arc faults through the analysis of variations in supply voltage and line current. The efficacy of the proposed solution was confirmed through experiments using a photovoltaic power supply and DC-DC converter as DC power sources, with results indicating that the method can effectively distinguish arc faults with clear physical significance and low computational requirements.

Recently, a study conducted by Li and Yan in [32] aimed to assess the performance of time-domain methods for detecting low-voltage fault arcs. The authors utilized a self-constructed arc generator to simulate the generation of various fault arcs and obtained the corresponding current signals. By extracting time domain features, such as average and variance, from the current waveform, they achieved a recognition rate of 100% for light bulbs and electric fans and 99% for other electrical devices, thereby demonstrating the effectiveness of the proposed scheme. In another study, Artale et al. [33] evaluated the application of time domain symmetry parameters for the detection of series arc faults in electrical circuits. The parameters were derived from the current signal derivative and cross-correlation between observation windows, and were demonstrated to be effective and low-cost in trials conducted on AC systems. Jiang and Bao [34] developed a novel AC series arc fault detection method that combined the circular zoom convolution (ZCC) algorithm and signal-type enumeration. The method was evaluated using a laptop and the TMS320F28335 processor, and the online detection results showed excellent accuracy even under unknown conditions.

3.1.2. Arc fault detection methods based on frequency domain

Frequency-domain methods for arc fault detection involve the utilization of Fourier Transform to decompose current signals into the frequency domain. The method entails the comparison of amplitude-frequency characteristics of circuit current signals during normal operation and during an arc fault occurrence. The characteristic components present during an arc fault serve as a basis for identifying the fault arc.

In 2018, Qu et al. [35] proposed an approach to detect series arc faults in electrical circuits by integrating a sparse representation algorithm and current amplitude spectrum analysis. The results of the study suggested that different norms may lead to better outcomes for different data and that adjusting the value of p can result in improved performance. Xiong et al. [36] added parallel capacitors to capture high-frequency signals during a series arc fault, and used Rogowski coils to construct a detector with sufficient bandwidth to cover the relevant frequency range. Experiments conducted in low-voltage cable circuits showed that the proposed approach is robust against various factors, including pressure, electrode material and load changes, and could be used for fault localization on the basis of capacitor current pulse information (Figure 6).

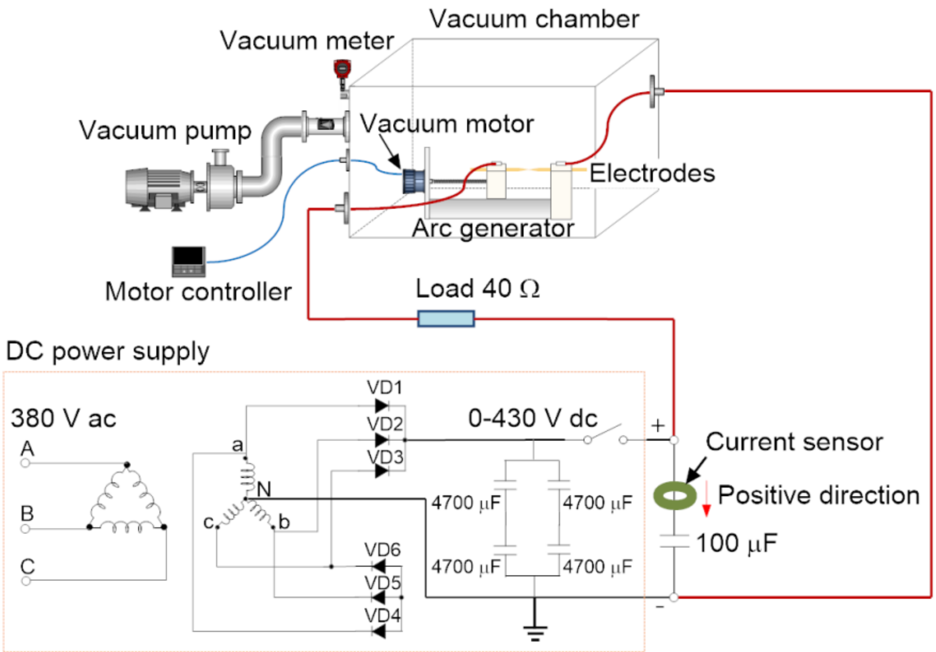

Figure 6. Variable low-pressure experimental system.

In the realm of frequency-domain-based arc fault detection, microcontrollers are employed to execute fast Fourier transform (FFT) analysis with the purpose of identifying arc faults in electrical systems. In [37], the authors developed and tested a series AC arc fault detection system that leverages a microcontroller, and the results of the FFT analysis demonstrated high accuracy in recognizing series AC arc faults as verified through experiments with varying current levels and load resistances. Bao et al. [38] came up with a novel method for arc fault detection in electrical systems, named high-frequency coupling, that distinguishes between arcing and non-arcing currents by utilizing a current transformer and neutral and live lines, even in the presence of masking loads. This method results in high-frequency components in the secondary output of the current transformer, enabling accurate and fast arc fault detection through the use of a microcontroller unit and multi-indicators. The experimental results indicate the high accuracy of the proposed approach in detecting arc faults.

Except for microcontrollers, a multitude of techniques have been proposed by researchers for the purpose of detecting series arc faults in a range of electrical systems, which include the utilization of fast Fourier transform, the extraction of high-frequency components and the integration of current fluctuation features and zero-current features. To address the issue of arcing faults in low voltage direct current (LVDC) systems, Syafi'i et al. proposed a real-time series DC arc fault detection algorithm in [39]. The waveform of the current system is transformed from the time domain to the frequency domain through the utilization of fast Fourier transform, allowing for the recognition of current interference and the determination of arcing fault conditions. The algorithm safeguards the system with an average clearing time of 530 ms and its effectiveness in detecting series DC arc faults has been validated through experimental data (Figure 7).

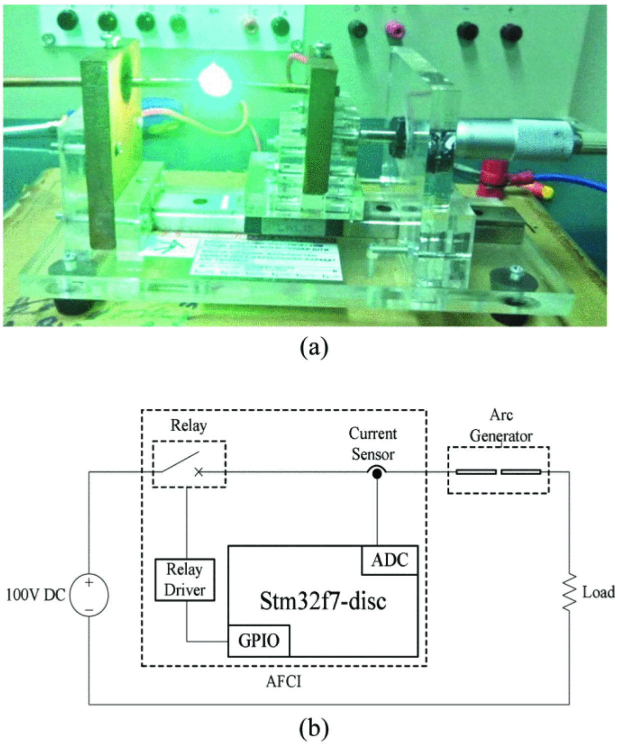

Figure 7. Experimental set up. (a) Arc Generator. (b) AFCI testing diagram.

3.1.3. Arc fault detection methods based on time-frequency domain

The deployment of modern power electronic equipment, such as photovoltaic inverters and energy storage converters, which operate at high-frequency switching states, has resulted in the presence of a substantial amount of background noise caused by the fast switching of switch tubes and the rapid switching of loads. This noise has been found to make time-domain and frequency-domain methods ineffective at times. As a result, numerous time-frequency domain-based methods have been proposed in the literature to address this issue.

SVM has been widely adopted as a classification technique in the time-frequency domain for distinguishing between normal and abnormal signals. Jiang et al. [40] proposed a novel methodology for the identification of complex loads and the detection of series arc faults, which employs a combination of principal component analysis (PCA) and support vector machine (SVM). The methodology first collects time-domain and frequency-domain information, which is then reduced to three parameters using PCA to enhance computational efficiency. Load recognition is performed using AI algorithms, and then SVM is employed for series arc detection, resulting in high accuracy rates of 99.1% for load recognition and 99.3% for series arc detection. In [10], Miao et al. presented a series arc-fault detection scheme for DC systems, which is based on arc time-frequency signatures extracted through a modified empirical mode decomposition (EMD) and an SVM decision-making algorithm (Figure 8). The scheme employs the Hurst exponent (H) to analyze the trend of a signal and reject interference and has been validated in a photovoltaic system, demonstrating a significant improvement in the effectiveness of arc-fault detection. Wang et al. [41] developed an algorithm for arc fault diagnosis in photovoltaic (PV) stations, which combines the image-based fast fourier transform energy (IMFE), variational mode decomposition (VMD) and SVM. The algorithm first decomposes the current signal in the time-frequency domain, and the effectiveness of the proposed method was demonstrated through experiments using arc fault data from a PV arc generation platform, which showed its ability to effectively classify between arc fault and normal data.

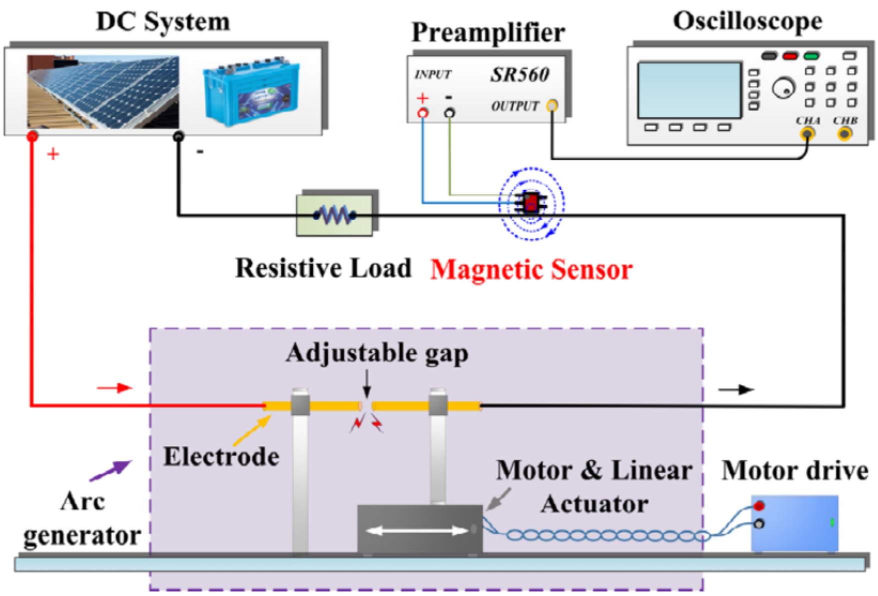

Figure 8. An experimental setup for the generation of arc faults in DC systems.

For the detection of series DC arc faults in distributed energy sources, Park and Chae [42] introduced a novel algorithm based on the analysis of arc fault impedance. This approach involves the examination of current variability within the system through a combination of frequency spectrum analysis and time series analysis, enabling the identification of arc fault conditions. The proposed algorithm has been validated in DC systems, as demonstrated in the experimental setup presented in Figure 9. In a separate study, Liu et al. [43] developed a time-frequency domain analysis scheme for detecting series DC arc faults in photovoltaic (PV) arrays. This approach utilized both the loop current and the voltage signals on the PV side to increase the anti-interference capability of the algorithm. The experimental findings reveal the method's accuracy and timeliness in detecting arc faults while precluding spurious trips originating from the initiation and cessation of operations with maximum power point tracking (MPPT), as well as dynamic fluctuations in load and shadow occlusion.

The detection and precise line-selection of arc faults in distribution lines and power supply was explored by Guo et al. [44]. They proposed a method that decomposed the effective signal into seven independent modes, and extracted its time-domain and time-frequency features, leading to the establishment of a model. The experimental results demonstrated the accurate detection and selection of arc faults. Additionally, Gao et al. [45] studied the randomness amplification of arcs by the difference between adjacent current cycles, and extracted three characteristics from both time and frequency domains as AC arc fault characteristics. Their results showed that these characteristics are suitable for AC arc fault detection in rectifier bridge load circuits. In 2022, Cai and Wai [46] proposed an intelligent detection algorithm for arc faults in a solar PV power generation system. This algorithm extracted fault information in the time-frequency domain through the use of a support vector machine and variational mode decomposition, resulting in a detection accuracy of over 98.21% for both series arc faults (SAF) and parallel arc faults (PAF).

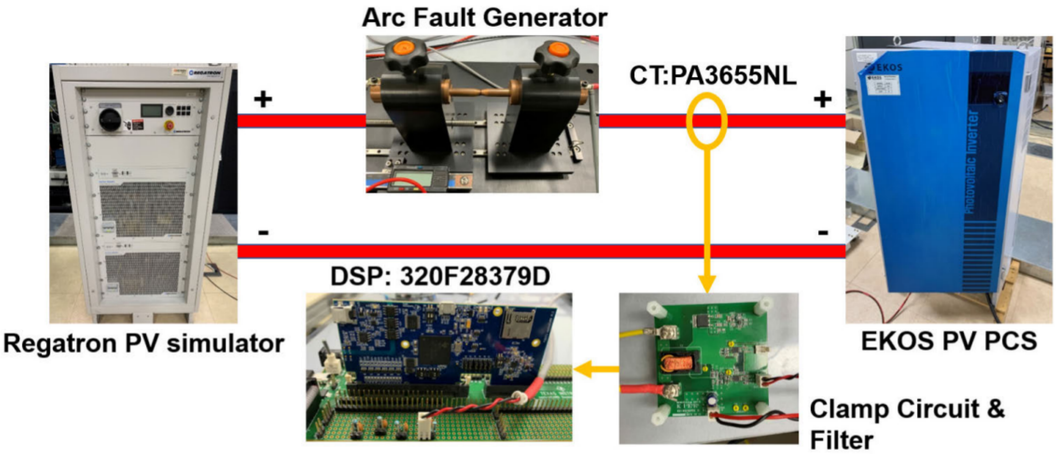

Figure 9. Arc fault detection experimental setup.

3.1.4. Arc fault detection methods based on physical phenomenon

The emission of electromagnetic radiation (EMR) is a characteristic phenomenon that arises during the occurrence of arc combustion, which is further accompanied by physical effects such as sound, light, heat and electromagnetic radiation. Xiong et al. [47] conducted a study to examine the main features of EMR produced during a series dc arc fault in low-voltage dc systems. The results indicated that the characteristic frequency band of EMR pulses (36–41 MHz) could be employed as a parameter for the detection of series dc arc faults. This method of detection has demonstrated promising results in the detection of arc faults in switchgear and distribution cabinets, thereby compensating for the limitations of traditional arc current-based methods. However, the utilization of this method is contingent upon a priori knowledge of the specific location where the arc fault may occur, which restricts its application to large-scale photovoltaic systems.

The literature review reveals that EMR is widely utilized as a physical characteristic for arc fault detection. In [48], a detection method based on EMR characteristics was proposed to address the limitations of current and voltage-based methods. The study established a platform simulating low-voltage AC series arc-faults and experiments showed that the EMR signals exhibit unique characteristic frequencies under different conditions, enabling the accurate differentiation between operating and faulty arcs. The research conducted by Zhao in [49] found that the EMR emitted from a fault arc displays distinctive patterns, which was verified through the calculation of 6-dB bandwidth bins and the structural similarity index. The experiments confirmed the accuracy of the proposed system and suggested that the technique is a complementary solution to traditional methods. For the precise location of arc faults, Wei et al. [50] proposed a solution that utilizes EMR signals and time difference of arrival (TDOA), which was validated through experiments, resulting in a time difference error of 0.2 ns and a location error of 11 cm. Additionally, a multitude of devices derived from these established technologies.

In military settings, the efficacy of commercial arc fault detection devices was evaluated by Pulkkinen in a study [6]. To ensure compliance with military standards, the author subjected five distinct devices to rigorous electromagnetic compatibility testing and scrutinized their performance within a simulated military electromagnetic environment. This was significant as arc fault detection devices could both be sources and victims of electromagnetic interference in military settings, which impose stringent demands for low emission and high immunity levels. Another novel approach for arc-flash fault detection was proposed by Zhao [51] that utilized the analysis of the light spectrum. The study revealed that by analyzing the light spectrum of copper and aluminum conductors during arcing incidents, the method was capable of enhancing the accuracy and reliability of arc-flash fault detection operations.

3.2. AI-based arc fault detection methods

The utilization of AI-based techniques for detecting arc faults in electrical systems has been explored as a novel approach, as highlighted in [52]. The integration of advanced AI methods, including machine learning, deep learning, computer vision and pattern recognition, enables the analysis of large amounts of data generated by electrical systems and the identification of arc faults in real-time. The adoption of these AI-based methods presents a distinct advantage over traditional arc fault detection techniques, particularly in terms of the ability to process vast amounts of data and their ease of integration into existing electrical systems.

AI-based arc fault detection methods have shown promising results in identifying and mitigating arc faults in electrical systems. However, these methods are not without their limitations. One major challenge is the issue of missed and false detections of arc faults, especially rare events. Another challenge is the limited application of neural networks in arc detection, where novel neural network architectures and interpretability of models are required. Additionally, data scarcity also poses a challenge for the development and training of AI-based arc fault detection systems. To better understand these limitations, Table 1 summarizes the shortcomings of AI methods used in arc fault detection, including machine learning and neural networks To overcome these challenges, future research should focus on developing more robust AI algorithms and improving data collection and preprocessing methods.

3.2.1. Machine learning for arc fault detection

The utilization of machine learning algorithms for arc fault detection has been widely explored in recent literature. The algorithms, including supervised learning, unsupervised learning and deep learning, can be trained with labeled data to accurately identify and diagnose arc faults within electrical systems [53,54]. This approach offers a significant advantage over traditional methods, characterized by fast detection times and high accuracy levels.

The application of machine learning in arc fault detection has been the subject of substantial research in recent years. A number of studies have aimed to develop machine learning algorithms to identify arc faults in DC distribution systems [55,56]. In [57], Le et al. presented an algorithm that leveraged an adaptive normalization procedure to minimize the number of mistriggers and was trained on arc fault data. The algorithm was tested on a microcontroller board and demonstrated high

Table 1. Shortcomings of the relevant Al methods.

AI Methodology	Shortcomings	Relevant references
Machine learning	Limited interpretability of results; Dependence on quality and quantity of data; Inability to handle complex or rare faults; Vulnerability to noise and outliers in data; Difficulty in selecting appropriate algorithms and parameters	[22,31,41,47,61,62]
Neural networks	Limited interpretability of model results; Difficulty in transfer learning across different domains; Dependence on large amounts of high-quality labeled data; Sensitivity to the selection of hyperparameters; The risk of overfitting the model to the training data	[27,40,44,49,61,62]

accuracy and low latency compared to traditional methods, as illustrated in Figure 10. Another study by Le et al. [23] introduced a method to enhance the accuracy of arc fault detection by integrating multiple machine learning algorithms. This ensemble machine learning approach demonstrated high precision in detecting DC arc faults. In [27], Dang et al. developed machine learning algorithms to detect series DC arc faults and evaluated the effectiveness of various techniques such as decision trees and artificial neural networks. Moreover, Vu et al. [58] put forth a method to improve arc fault detection in domestic appliances by using machine learning techniques to identify and combine multiple arc fault characteristics. This approach aimed to address the limitations of previous methods that were prone to false negatives or false positives. The proposed method was tested experimentally, including in challenging scenarios such as transient loads and multiple loads masking, and the results indicated its effectiveness.

In a study conducted by Xia et al. [59], a binary classification model on the strength of machine learning algorithms was proposed for the detection of DC serial arc faults in battery systems. The experimental platform used to develop the model is presented in Figure 11. The model was optimized by utilizing characteristic signals of electric arcs in order to enhance its exactitude and robustness under varying load conditions. Simulation experiments indicated a high rate of success in the detection of different loads, including those associated with the inverter, resistor and motor. In a related study [60], two methods were introduced to further improve the accuracy and robustness of traditional machine learning algorithms used in arc fault detection. These methods included the use of semi-supervised machine learning to handle limited labeled data, and the utilization of ensemble machine learning to reduce decision variance and bias. The effectiveness of these methods was evaluated through the use of accuracy, precision and recall scores, as well as by measuring the detection latency time.

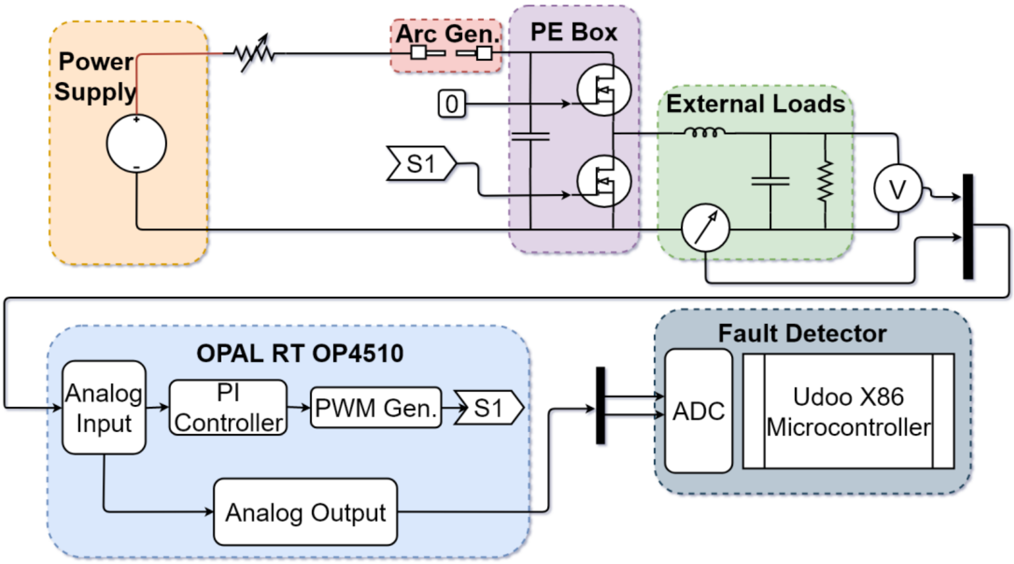

Figure 10. Arc fault detection in DC distribution using semi-supervised ensemble machine learning.

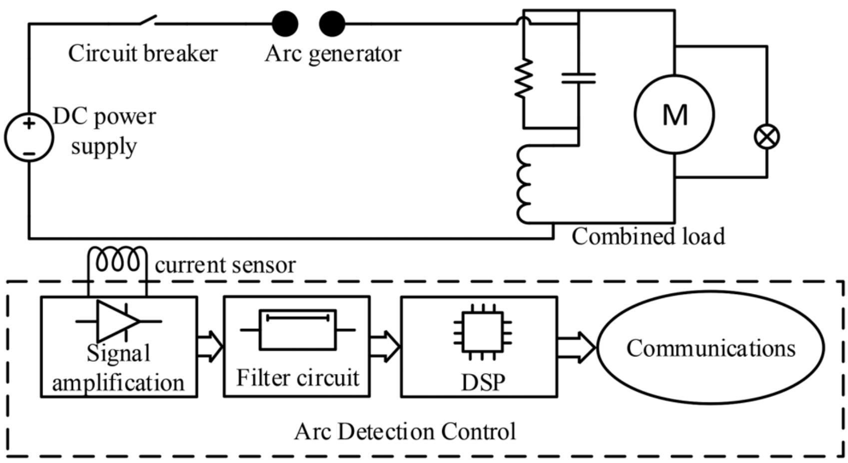

Figure 11. Diagram of arc fault experimental platform.

In terms of series arc detection in low voltage distribution systems (LVDS), Gupta et al. presented a novel methodology in [61] that leverages the combination of support vector machine (SVM) algorithms and empirical mode decomposition (EMD). The proposed system utilizes EMD analysis to extract features from the data, which are then utilized by the SVM classifier for the detection of arc faults with a high degree of accuracy. Additionally, in [62], a hybrid algorithm was proposed that combines the stationary wavelet transform for the extraction of dynamic features and a support vector machine-based decision-making system for the detection of high-frequency inter-turn faults (HIFs). The outcomes of simulations conducted on an existing distribution system reveal that the suggested scheme can identify a broad spectrum of arcing faults while concurrently ensuring high accuracy and security against non-HIF phenomena.

In the domain of arc fault detection, random forest is a noteworthy machine learning technique. Yin et al. proposed a novel method that integrates improved multi-scale permutation entropy, random forest and wavelet packet transform to detect series arc faults with improved accuracy [63]. High-dimensional features from the filtered current signal were utilized to train the random forest model, and experiments showed its superiority over back-propagation neural networks and least squares support vector machines. Le et al. utilized random forest-based detectors to design a master controller for series dc arc fault detection and localization in power electronics systems [64], as shown in Figure 12. The master controller monitors input currents and predicts arc fault probabilities, with the final decision made by comparison. The optimized version of the method was proposed for identifying series dc arc faults in zonal electrical distribution systems, where the local detectors make a decision in the absence of communication links [65]. The proposed method was experimentally verified to accurately detect arc faults. Another random forest (RF) algorithm-based method was proposed by Paul et al. utilizing raw current as input with a detection accuracy of 99.78% at the sampling rate, optimized to run efficiently on Raspberry Pi 3B with a 99.6% accuracy and a runtime of 10.22 ms [66].

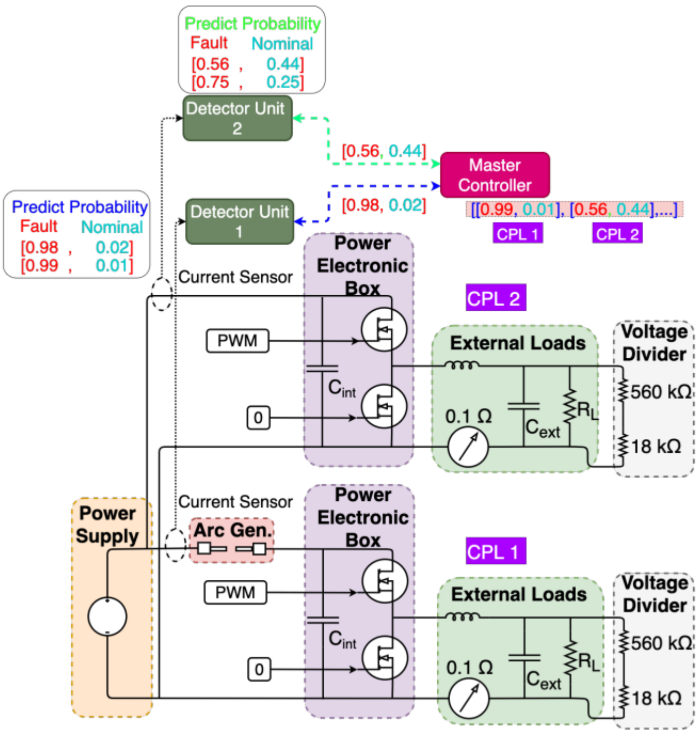

Figure 12. Arc fault detection using EML in two parallel-connected CPLs.

In addition, there are other machine learning methods applied in fault detection. For instance, Liu et al. proposed a personalized diagnosis method to detect faults in gears using numerical simulation and extreme learning machine [67], while a machinery fault diagnosis approach based on domain adaptation to bridge the gap between simulation and measured signals is analysed in [68]. Also, Gao et al. utilized FEM simulation-based generative adversarial networks to detect bearing faults [69], while they also proposed a fault detection method in gears using fault samples enlarged by a combination of numerical simulation and a generative adversarial network [70]. Additionally, numerical simulation of gears for fault detection using artificial intelligence models has been explored in [71]. These methods show promising results in fault detection, and their potential in arc fault detection should be investigated in future research.

3.2.2. Neural network for arc fault detection

The application of neural networks in the detection of arc faults in electrical systems has gained significant consideration as a result of their ability to recognize patterns that indicate the presence of an arc fault [72]. The advantages of these networks in this context include the ability to process large amounts of data, generalize effectively from training data to detect complex non-linear relationships within the data. Empirical studies have confirmed the effectiveness of neural networks in arc fault detection, exhibiting a high degree of accuracy, rapid detection capabilities and versatility in adapting to a range of electrical systems and loads.

In the field of arc fault detection, deep neural networks (DNNs) have been applied to recognize patterns indicating the presence of an arc fault [73–75]. Siegel et al. proposed a real-time system utilizing IoT, AI and adaptive learning to detect and disrupt electronic arc faults [76]. The DNNs used in this system classify normal and malignant current measurements by taking input from Fourier coefficients, wavelet features and mel-frequency cepstrum data. The use of hardware-accelerated signal capture enables quick and accurate classification with a trigger-to-trip latency under. An approach was introduced by Jiang et al. for the identification and localization of series arc faults in multi-load circuit topologies through the joint utilization of deep neural networks and random forests, as documented in reference [26]. The structure of the adopted DNN is depicted in Figure 13. They developed a comprehensive arc detection model that can accurately identify and protect against series arc faults in multi-load scenarios. Due to the limitations of traditional machine learning algorithms in accessing fault data, Zhang et al. proposed a deep residual network (ResNet) model for arc fault detection using computer vision [77]. This method improved the accuracy of ResNet 50/101/152 to 97.91, 96.30 and 97.69%, respectively, by addressing the over-fitting problem caused by small samples. As far as arc fault detection in DC Microgrid, Patil et al. proposed a deep neural network-based approach in their study [78]. The performance of convolution neural networks (CNN) and multi-layer perception (MLP)/dense neural networks was analyzed and compared. The results of a MATLAB simulation showed that both MLP and CNN have similar accuracy in arc fault detection, with CNN demonstrating better performance in noisy environments.

The detection and protection of arc faults in PV systems present a significant challenge [79–81]. To mitigate this challenge, various techniques have been proposed in the literature. Lu et al. [82] proposed a novel diagnostic method for DC series arc faults by combining deep convolutional generative adversarial networks and domain adaptation techniques. The architecture of the proposed method, referred to as DA-DCGAN, is depicted in Figure 14. The method was demonstrated to be both accurate and effective in fault diagnosis. In another study, Chu et al. [83] presented a new approach for the detection of series AC arc faults in residential low-voltage distribution networks. The approach utilized a high-frequency coupling sensor to gather high-frequency feature signals, which were subsequently transformed into two-dimensional gray images and analyzed by means of a three-layer convolutional neural network, as depicted in Figure 15. The results showed a high classification accuracy of up to 98.36%. Wang et al. [84] proposed a new model for series AC arc fault detection, ArcNet, which was based on a convolutional neural network. The experiments demonstrated that ArcNet was capable of accurately detecting arcs, achieving a maximum accuracy of 99.47% at a 10 kHz sampling rate. Qi et al. [85] proposed the use of a one-dimensional convolutional neural network for the classification of current waveform data. The results showed a high accuracy of 98.996% with one-eighth of each cycle of current and 99.543% with a quarter cycle. The model's efficacy concerning real-time application on embedded hardware was also briefly estimated.

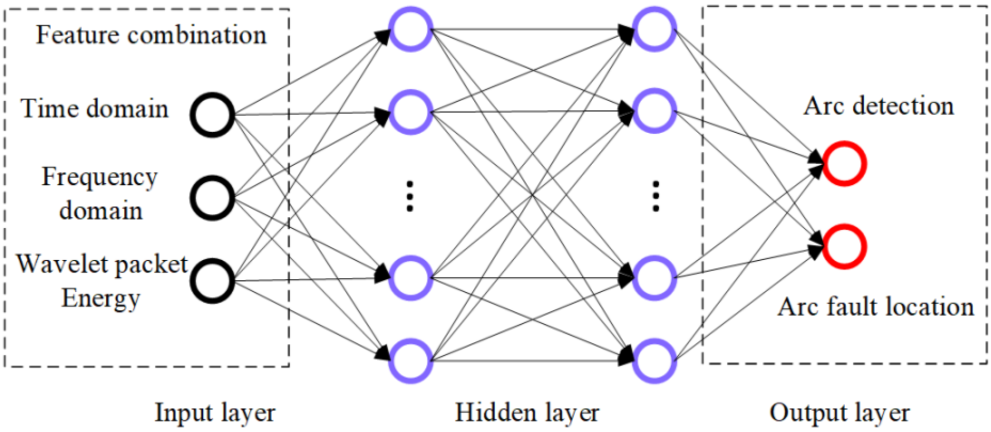

Figure 13. The structure of deep neural network model for arc detection and location.

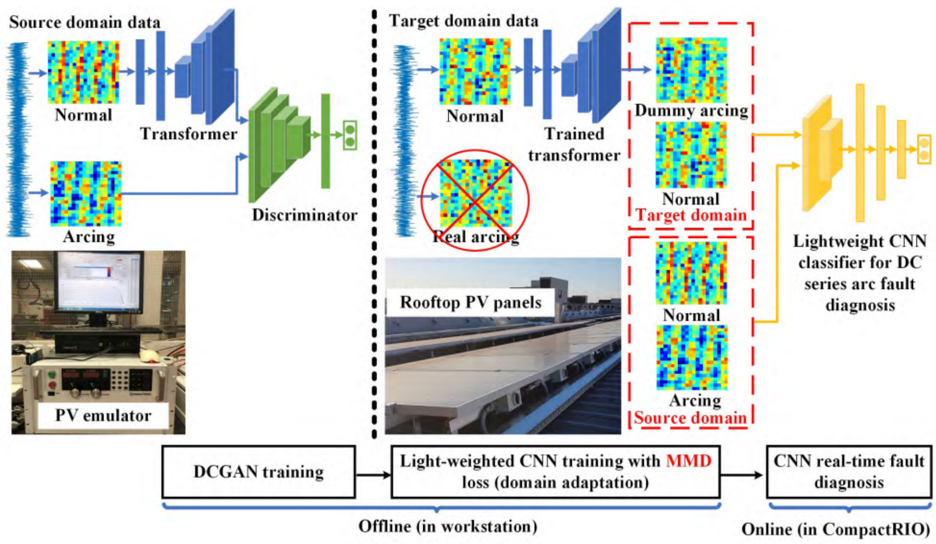

Figure 14. The structure of deep neural network model for arc detection and location.

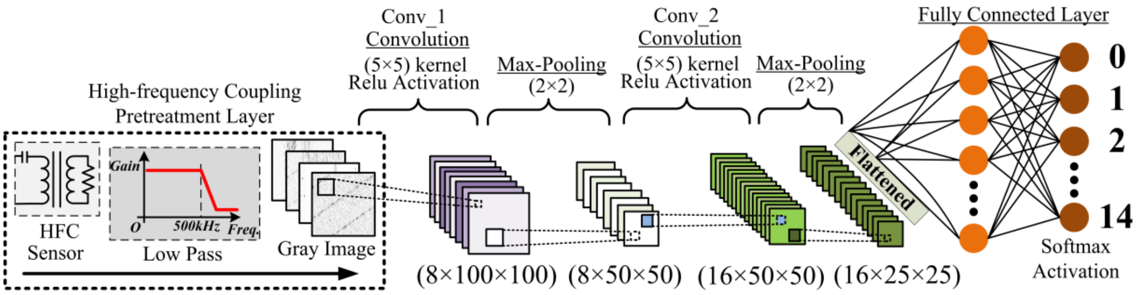

Figure 15. Composition of the HCCNN method.

The utilization of CNNs in combination with temporal domain visualization has been demonstrated to be a feasible approach for visualizing and extracting arc fault information from waveform signals, which can then be used to accurately detect series arc faults, as evidenced by Yang et al. [86]. This methodology was experimentally validated on five different electric loads and achieved a high accuracy classification rate of 98.7% or higher. To further improve the performance of arc fault detection, Yu et al. [87] proposed a parallel deep convolutional neural network-based method based on AlexNet for detecting series arc faults in household power supply systems. The proposed method was trained and tested using a dataset of 7200 sets of normal operation current signal and series arc fault data of three load types. The results indicated that the proposed method exhibited higher detection accuracy and stability compared to the AlexNet model. In a subsequent study, Yu et al. [88] linked a CNN with a long and short-term memory (LSTM) network for analyzing the collected trunk current signals in the circuit. The experimental results revealed that this approach demonstrated a high accuracy rate (99.04%) in identifying arc faults and accurately detecting the type of load branch causing the fault (97.90%).

The detection and classification of arc faults in PV systems is a complex challenge and various techniques have been proposed in the literature. In addition to deep neural networks and convolutional neural networks, other neural network approaches have also been proposed. Qu et al. [89] proposed a hybrid approach for detecting series arc faults in indoor power distribution systems by combining learning vector quantization neural network (LVQ-NN) and support vector machine (PSO-SVM). Lala and Karmakar [90] used empirical mode decomposition (EMD) and artificial neural network for detecting and classifying high-impedance arc faults based on their predominant harmonic signatures. Li et al. [91] introduced a planar location method for detecting and isolating arc faults in dc microgrids and photovoltaic systems, which combined cross-correlation techniques, neural networks and received signal strength indicators. Chen et al. [92] proposed a rapid arc fault detection solution based on squeeze-and-excitation (SE)-inception multi-Input convolutional neural network (MICNN), which achieved a higher accuracy of 97.48% compared to traditional methods and demonstrated the ability to resist disturbances such as strong winds, maximum power point tracking and dynamic shading.

Using a fully connected neural network and a time and frequency analysis, Wang et al. proposed a method for detecting residential series arc fault [93]. The method classified the series current into three categories and employed separate fully connected neural networks for each category with customized time and frequency indicators as inputs. The results show high accuracy and lower computational complexity compared to other methods. Wang et al. [94] proposed a novel methodology for the identification of residential AC series arc faults using fully connected neural networks (SRFCNN) and sparse representation. The methodology comprised of decision layers, pretreatment and sparse representation, with the results indicating good accuracy in discriminating between the arcing state and the normal state, as well as recognizing different load types. The general classification accuracy was reported to be 94.3%. Han et al. [22] developed a novel method to optimize the identification of series arc faults in electrical systems by integrating artificial neural networks and category recognition. The time-frequency signatures were utilized as inputs to the artificial neural network, which was improved by a genetic algorithm to avoid falling into a local optimum. The results showed a high recognition rate and a simple neural network model.

4. Discussion

The time domain-based methods, although capable of partially characterizing the arc fault characteristics, are often associated with certain biases, thereby posing a challenge in accurately detecting fault arcs through the analysis of current time domain characteristics alone. This is due to the difficulties in determining appropriate thresholds and the inherent inaccuracies in the models [30]. On the other hand, methods based on the frequency domain are limited by their temporal resolution and sensitivity to noise, making them less effective for arc fault detection. Despite these limitations, methods that leverage the time-frequency domain have gained widespread usage owing to their high accuracy and relatively low implementation costs [40]. When it comes to identifying arc faults, electromagnetic radiation is widely considered as the most distinctive physical feature [6,48–51]. The increasing popularity of neural network-based arc detection methods is largely attributed to the advancements in artificial intelligence and the decreasing costs of neural network processing units. AI algorithms, capable of analyzing extensive data in real-time, offer significant advantages in arc fault detection over traditional methods. These algorithms can accurately detect patterns in the data, leading to more precise fault detection [57,60,76,77,85,87]. Moreover, AI-based arc fault detection systems have the advantage of fast fault detection, thereby reducing the risk of electrical fires [66]. Furthermore, the algorithms can be customized to meet specific requirements and can be trained to detect specific types of faults [90].

The integration of artificial intelligence (AI) in arc fault detection has led to significant benefits but has also confronted new challenges. A comprehensive review of more than 60 pieces of relevant literature has identified three main challenges that impede the development of arc fault detection: missed or false detections of arc faults, the premature application of neural networks in arc detection and a scarcity of data [90,91]. The growing use of power electronic equipment and its associated switching and harmonic interference has resulted in a high number of missed or misjudged detections in the commonly used time-frequency domain arc detection method. The application of neural networks in arc fault detection, which mainly encompasses DNNs and CNNs, has thus far demonstrated promising results. However, DNNs are computationally complex, making them time-consuming and challenging to implement in real-time applications, and they can also be prone to overfitting. CNNs, on the other hand, may have difficulty handling long sequences of data, which can pose a challenge in arc fault detection where sequences can be extensive. Furthermore, the lack of arc detection data can lead to variations in the definition of arc fault data features, resulting in differing results and conclusions in arc fault detection studies [22, 84, 93]. Furthermore, several studies have reached the conclusion that arcs exhibit different frequency characteristics in different experimental environments.

In light of the three significant challenges associated with the current methods for arc fault detection, future research in this area is likely to center around the utilization of artificial intelligence to address these obstacles. The application of AI algorithms can assist in overcoming the scarcity of data, by allowing for the establishment of large, diverse and representative datasets, thereby promoting the formation of more sturdy arc fault detection algorithms. However, it is worth noting that the databases utilized for the literature search in this study may not be exhaustive, and thus some crucial studies could have been overlooked.

5. Conclusions

In accordance with the guidelines of PRISMA, this systematic review aims to provide a comprehensive overview of recent developments in arc fault detection techniques. This review encompasses various techniques including time domain analysis, frequency domain analysis, time-frequency domain analysis, physical phenomena and artificial intelligence. The emphasis of this review is placed on the utilization of artificial intelligence in arc fault detection systems. The incorporation of AI algorithms has been shown to provide numerous advantages, including the ability to analyze large amounts of data in real-time with improved accuracy, faster response times in fault detection and the ability to be trained to identify specific types of faults.

Despite the benefits of artificial intelligence, the limitations of current arc fault detection techniques such as missed and false detections, limited application of neural networks, and data scarcity are also discussed.Despite the benefits of artificial intelligence, the limitations of current arc fault detection techniques, such as missed and false detections, limited application of neural networks and data scarcity, have been identified. To address these challenges, future research should focus on developing more robust AI algorithms that can accurately identify different types of arc faults, especially rare events. Additionally, the combination of multiple AI techniques and expert knowledge can potentially improve the accuracy of fault detection and reduce false alarms. Novel neural network architectures and the transferability of pre-trained models from other domains should be explored to improve the limited application of neural networks in arc detection. The interpretability of neural network models should also be improved to enable a better understanding of the decision-making process. Efficient data collection and preprocessing methods should be developed to overcome the challenge of data scarcity. Synthetic data generation and transfer learning techniques should also be explored to augment the training dataset. Ultimately, it can be concluded that artificial intelligence presents a promising solution in transforming the field of arc fault detection, offering a more efficient and accurate approach to the critical challenge of ensuring electrical safety.

Conflict of interest

The authors declare there is no conflict of interest.

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