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Review

Artificial intelligence techniques for ground fault line selection in power systems: State-of-the-art and research challenges

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Abstract: In modern power systems, efficient ground fault line selection is crucial for maintaining stability and reliability within distribution networks, especially given the increasing demand for energy and integration of renewable energy sources. This systematic review aims to examine various artificial intelligence (AI) techniques employed in ground fault line selection, encompassing artificial neural networks, support vector machines, decision trees, fuzzy logic, genetic algorithms, and other emerging methods. This review separately discusses the application, strengths, limitations, and successful case studies of each technique, providing valuable insights for researchers and professionals in the field. Furthermore, this review investigates challenges faced by current AI approaches, such as data collection, algorithm performance, and real-time requirements. Lastly, the review highlights future trends and potential avenues for further research in the field, focusing on the promising potential of deep learning, big data analytics, and edge computing to further improve ground fault line selection in distribution networks, ultimately enhancing their overall efficiency, resilience, and adaptability to evolving demands.

Keywords: artificial intelligence; ground fault cable selection; machine learning; deep learning

1. Introduction

Power systems serve a pivotal role in delivering energy to residential, commercial, and industrial sectors [1–3]. As the energy demand escalates, power systems must tackle challenges in fulfilling this demand while maintaining reliability and safety. The distribution network, accountable for the transmission and distribution of electricity to consumers, plays a quintessential role in the overall performance of the power system [4]. Addressing high energy demand necessitates developing and implementing energy production and distribution systems capable of providing the requisite energy in a sustainable and economical manner. The distribution network is integral to the transmission and distribution of electrical power. Regular maintenance, upgrades, and investments in novel technologies are imperative to guarantee the secure and dependable functioning of the distribution network. [5]. This may encompass the integration of smart grid technologies to facilitate real-time monitoring and control of systems. Conventional artificial intelligence (AI) methodologies exhibit limitations in precision and dependability [6]. For example, rule-based approaches rely on predefined rule sets, but they struggle to handle the complex variations and diverse fault patterns in power systems. Traditional machine learning methods require manual feature engineering and data preprocessing, which can be time-consuming and may not capture all relevant information. Moreover, they demand extensive manual effort for development and maintenance and typically lack the ability to learn and adapt to new situations or data. Consequently, more advanced AI techniques have been devised to tackle these limitations in ground fault line selection. Ground fault line selection is a crucial task in the realm of electrical power systems. It involves pinpointing the location of a fault in the power system and subsequently isolating it to avert further damage to the system [7]. AI can enhance the accuracy and efficiency of ground fault line selection. One approach employs machine learning algorithms to analyze data from various sensors and devices in the power system, such as voltage and current sensors. This data can then be utilized to identify patterns and anomalies indicative of a fault [8]. Another approach leverages artificial neural networks [9], which can be trained to discern and categorize diverse fault conditions based on historical data [10]. The neural network can then predict the fault location and suggest suitable actions for isolation [11]. By implementing AI in ground fault line selection, power system operators can detect and respond to faults more expeditiously and accurately [12]. This can help minimize downtime and mitigate the risk of damage to the power system, ultimately enhancing the reliability and safety of the entire system [13].

Ground faults within an electrical distribution system arise when a conductor establishes contact with the ground or a grounded object [14]. Various types of ground faults exist, encompassing single-line-to-ground fault [15], double-line-to-ground fault [16], line-to-line fault [17], and three-phase fault [18]. Additionally, ground fault line selection in power systems is a complex task due to the technical intricacies involved. The configuration and structure of power systems, with multiple supply points, substations, transmission lines, and distribution lines, add to the complexity. Factors such as fault current, soil resistivity, human error [15] and physical location [16] further contribute to the challenges. To maintain the safety and dependability of the electrical distribution system, it is crucial to identify and tackle the underlying causes of ground faults.

In an electrical system, ground faults can give rise to phenomena such as low resistance, current leakage [19], voltage drop [20], arcing [21], and GFCI activation [22]. To circumvent hazards, it is vital to promptly address ground faults and adopt appropriate safety measures such as employing GFCIs, implementing proper grounding systems, and conducting equipment maintenance. Ground fault line selection relies on several factors, including electrical system configuration, fault current [23], soil resistivity [24], and physical location. The algorithm characteristics encompass executing a fault analysis, appraising soil resistivity, determining the grounding method [25], calculating fault current limit [26], selecting the grounding fault line [27], and designing the grounding system [28].

The inherent features of distribution networks can present multiple challenges to grounding fault line selection, encompassing fault detection, location precision, and response velocity [29]. These challenges can be addressed through an amalgamation of artificial intelligence technologies and best practices in grounding system design and maintenance [30]. By deploying these solutions, distribution networks can enhance fault detection, location accuracy, and response speed, ensuring that the grounding system delivers effective protection against electrical hazards. A ground fault in a distribution network may precipitate an array of issues, including voltage fluctuation, device damage, and power supply disruption [31]. This leads to a voltage decline in the electrical system when a ground fault occurs, as a significant amount of current flows through the fault and into the ground. This voltage drop can induce fluctuations that may trigger equipment malfunction or shutdown, leading to downtime and diminished productivity.

Artificial intelligence (AI) is a field within computer science that focuses on the creation of algorithms and methodologies that empower machines to acquire and perform tasks typically associated with human intelligence [32, 33]. These tasks include perception [34], reasoning [35], learning [36], and decision-making, which require cognitive abilities [37]. Within the realm of power systems, AI can be employed to augment the performance and dependability of the electrical grid by furnishing advanced fault detection, diagnosis, and response capabilities [7]. AI techniques can also optimize the design and operation of power systems, facilitating more efficient and sustainable energy consumption [38]. Artificial intelligence (AI) techniques have surfaced as a promising solution to tackle the challenges of ground fault line selection in power systems. AI-based approaches boast several advantages over traditional methods, encompassing high accuracy, rapid response time, and diminished false alarms [39]. Deep learning techniques, such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN), have been successfully implemented in ground fault line selection to enhance fault detection and response [40–42]. Evolutionary algorithms and fuzzy logic represent other AI-based methods employed in ground fault line selection [43]. Evolutionary algorithms utilize principles of natural selection to identify optimal solutions for complex problems, while fuzzy logic is a mathematical methodology permitting imprecise reasoning and decision-making [44]. These techniques have demonstrated considerable potential in improving the accuracy and expediency of ground fault line selection in power systems. AI-based techniques offer substantial advantages over traditional methods in ground fault line selection within power systems.

This systematic review presents a comprehensive overview of contemporary AI techniques in ground fault line selection, focusing on deep learning methods, evolutionary algorithms, and fuzzy logic. It highlights their advantages over conventional approaches and examines three primary challenges, encompassing fault detection, location precision, and response speed. Moreover, this review emphasizes the need for further research to address these challenges and contributes to the development of advanced AI-based techniques for ground fault line selection in power systems.

The structure of the article adheres to a prescribed format comprising an introduction, methodology, results, discussion, and conclusion. The introduction establishes the context for ground fault line selection and AI techniques. And the methodology describes the selection and evaluation of relevant articles. Then, the results section summarizes key findings, while the discussion interprets these results, their implications, and critically evaluates the reviewed studies. Finally, the conclusion highlights main points and suggests future research directions and practical recommendations.

2. Materials and methods

In accordance with the PRISMA guidelines [45], we conducted a comprehensive systematic review to identify relevant research articles on artificial intelligence techniques for ground fault line selection in power systems. We searched three prominent electronic databases, including the web of science, EBSCO, and EMBASE, which are known to contain a vast amount of academic literature. To ensure that we captured the most relevant articles, we used the search query ((Artificial Intelligence) or (Ground Fault Line Selection) or (Machine Learning) or (Deep Learning)). After removing duplicates, a total of 270 articles remained out of 300 initially selected. Studies that focused on topics other than ground fault line selection, or those that did not use artificial intelligence-based techniques, were excluded from the analysis. Ultimately, we identified and analyzed 57 articles that met our inclusion criteria. A PRISMA flow chart illustrating the screening process of the selected articles is presented in Figure 1.

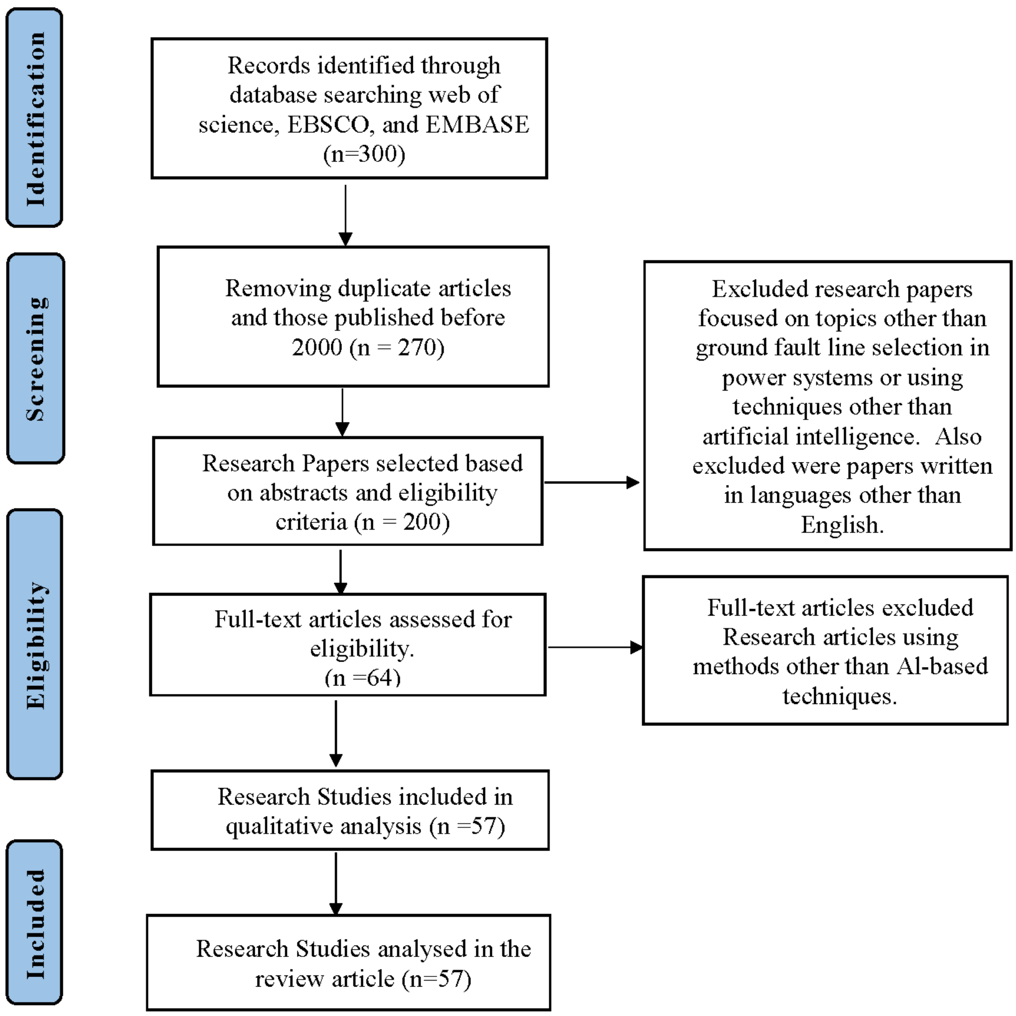

Figure 1. PRISMA flow chart.

The study selection process involved two independent evaluators who screened the articles for relevance. Disagreements were resolved through discussion or third-party arbitration. The data extraction process included various aspects of AI techniques, such as machine learning algorithms, artificial neural networks, evolutionary algorithms, and fuzzy logic. The studies' quality was assessed based on internal and external validity, bias, and risk. The overall evidence level was evaluated by combining the data's credibility, internal and external validity, consistency, and other factors.

The synthesis and analysis of the studies' data involved categorizing and summarizing different findings, integrating the data from different sources, and identifying patterns, trends, and anomalies. The presentation of the data included tables, figures, graphs, and other visual aids. The discussion and interpretation of the data focused on their significance, implications, and limitations, and the critical evaluation of the reviewed studies' strengths and weaknesses.

In conclusion, the materials and methods section of this systematic review adhered to the PRISMA guidelines and included a comprehensive search strategy, study selection criteria, data extraction, synthesis and analysis, quality assessment, and overall evidence-level assessment. The systematic review approach ensured that the analysis was rigorous and transparent, and that conclusions were based on high-quality evidence.

3. Research results of literature review (5 major ground fault line selection methods)

The distribution network makes extensive use of the low-current grounding system. A challenging step in the fault handling procedure has always been choosing the fault line in single-phase ground faults. Although, nowadays, many related studies and experiments have been carried out, as shown in Figure 2, the existing line selection theory and line selection methods need to be further improved in terms of accuracy and sensitivity. Hence, this study will investigate the following 5 aspects in order to maximize the precision and efficacy of its fault line selection.

Figure 2. The on-field single phase to ground fault experiments.

3.1. Research based on short circuit current method

During operation, the distribution network may experience a variety of faults, with the majority being single-phase ground faults. If a single-phase ground fault arises, the system can continue to operate with power for a brief period. However, if the fault persists and is not promptly resolved, it can lead to insulation breakdown between lines and the expansion of the fault's scope. Due to the current characteristics of distribution lines, such as their short length, extensive branching, and predominantly mixed cable frame structure, the successful identification and localization of faults in the field exhibit a low rate, primarily due to the susceptibility to complex fault factors. As a result, it is critical to promptly determine the location of the fault point in order for the distribution network to operate safely and reliably. The line selection process is sometimes the same as in Figure 3.

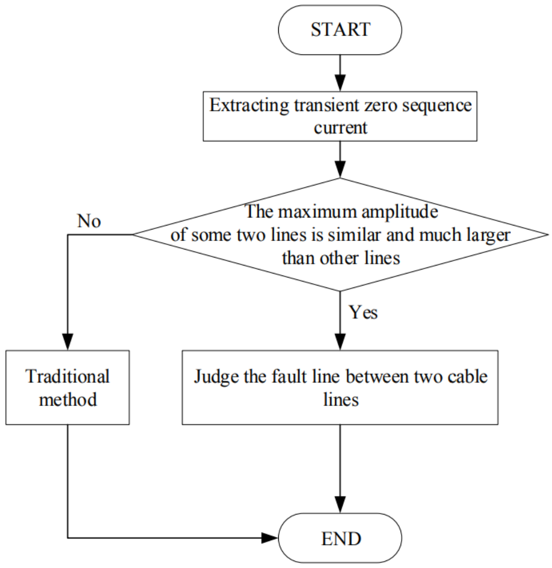

Figure 3. Process of fault line selection.

Numerous studies have been conducted to determine the fault by measuring the short-circuit current and combining it with relevant test equipment. Díaz et al. [46] introduced a short-circuit current estimator based on a Takagi-Sugeno fuzzy model of the PV array aimed at addressing the primary limitations of the short-circuit current method. The estimator is capable of real-time estimation under any weather condition without disconnecting the photovoltaic generator and measuring it. The effectiveness of the estimator is validated through experiments conducted on a two-stage, single-phase, grid-connected inverter. Then, a new MPPT method for PV systems was introduced by Sher et al. [47], which used the fractional short-circuit current (FSCC) method to improve tracking and power harvesting. It is an irradiance sensorless scheme and is validated with computer software simulation and experimental confirmation. A fast technique was proposed in [48], which used the slope of a PV inverter current to predict if the current exceeds its rated value due to grid faults. It quickly disconnects PV solar systems and transforms them into a dynamic reactive power compensator STATCOM for voltage support. PSCAD-based simulation studies using PSCAD are conducted to showcase the efficacy of this technique. In addition, Li et al. [49] devised a generic method for calculating pole-to-pole short-circuit fault current in DC grids. This method is more efficient than EMT simulations, suitable for all types of dc grid networks, and can be applied to multiple areas with different dc voltage levels linked with dc/dc converters.

A novel modeling approach for short-circuit studies that integrate superconducting fault current limiters (ScFCLs) was proposed by Castro [50] in 2018. The operating point of the ScFCL is computed in the abc reference frame, whereas the symmetrical components are employed to achieve a solution for the entire network. Besides, in 2021, Mohsenzade et al. [51] introduced a protection strategy to limit the junction temperature increase during Short Circuit Fault (SCF) events by adding a low-value resistor to the IGBT emitter. This reduces the SCF current to a level significantly lower than the saturation current, thereby preventing substantial IGBT failure. The study's outcomes are verified through simulation and experimentation.

It can be known from the above researches that the short-circuit current method is effective for ground fault line selection.

3.2. Research based on time domain inversion

Besides the short-circuit current method, the time domain inversion method is another viable approach for ground fault line selection.

The failure of power transformers may result from the application of electromagnetic transients, leading to the generation of dielectric stresses. The study [52] primarily examines a specific phenomenon where excessive overvoltages result from resonance. Laboratory experiments indicate that a step voltage excitation on a 27-m cable generates a 24-p.u. overvoltage on the open low-voltage side. Figure 4 displays a portion of the actual laboratory configuration. According to the simulations, the maximum overvoltages that may arise reach 43 p.u. when the cable length is at its most disadvantageous.

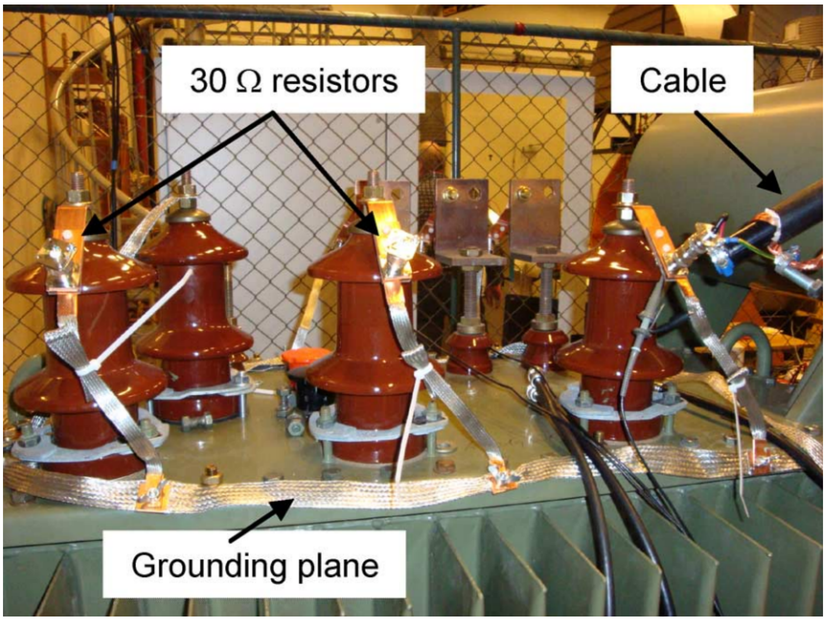

Figure 4. Connections on the transformer.

Choi et al. [53] suggested the utilization of source-independent time-domain waveform inversion that utilizes convolved wavefields to eliminate the impact of the source wavelets. The misfit function is computed by back-propagating the residual seismograms and applying the imaging condition. Synthetic data tests demonstrate that the inverted models closely approximate the actual model but have certain limitations when introducing random noise. Using an average of traces as the reference trace is preferable to utilizing a single trace.

In 2015, A research study [54] carried out by Vignoli revealed that time-domain electromagnetic data can be inverted using 1D models with a fixed vertical discretization. However, this approach can result in imprecise reconstruction of resistivity distributions. To address this limitation, a focusing regularization technique is introduced to combine the advantages of both methodologies. The method centers on minimizing the number of layers with a non-zero resistivity gradient rather than minimizing the norm of the model variation itself. This approach can also be extended to the horizontal direction to facilitate the reconstruction of lateral boundaries. Moreover, Stoller et al. [55] introduced the Wave-U-Net, a modified version of the U-Net that is tailored for the one-dimensional time domain. This approach resamples feature maps to compute and merge features at various time scales. Experimental results demonstrate that the Wave-U-Net achieves performance similar to a state-of-the-art U-Net architecture that is based on spectrograms.

3.3. Research based on impedance ratio method

Due to the complexity and variability of modern distribution networks, the traditional transient steady-state routing method is influenced by external factors and the accuracy of routing is limited. Therefore, a variety of methods are needed to perform fault assessment.

Based on the impedance comparison method, many researchers have introduced some new algorithms for fault location and line protection by current measurement, and have conducted field tests. Zhi et al. [56] investigated the impact of distributed generation on inverter performance in microgrids. They employed QPR dual loop control, introduced odd harmonics, and analyzed system stability using impedance ratio Nyquist curves to enhance the output voltage quality and load capacity. The study offers theoretical support and parameter optimization guidelines. Experts conducted a study [57] in 2015 to assess the ratios of electrical impedance measurements reported in prior research to identify factors contributing to electronic apex locators' accuracy (EAL). Data were analyzed to determine correlations between impedance and log-scaled frequency, and the accuracy of the impedance ratio method employed to detect the apical constriction (APC) was evaluated using linear ramp function fitting. A transient measured impedance (TMI)-based DC line backup protection approach was presented in [58], which can properly identify faults while being unaffected by fault resistance and DC line attenuation. When compared to traditional precautions, the results are positive.

In addition, Bains et al. [59] introduced a precise algorithm for fault location that employs synchronized measurements from both ends of the SCCTL. The algorithm delivers fault-location outcomes without utilizing the MOV model or natural fault loop, and it can also be applied to double-circuit transmission lines. Based on the energy of the transient zero-sequence current in the SFB, a fault finding approach is suggested in a study [60]. Study and analysis of the phase-frequency characteristics of the equivalent impedance of the distribution network with lateral branches. Field tests and numerical simulations confirm the viability and efficacy of the suggested approach.

Overall, the detection by this method is effective, and compared with the traditional method, it can better reflect its advantages.

3.4. Research based on model matching method

Despite the fact that ground fault line selection has several challenges, such as the difficulty of precise positioning and the inefficiency of existing approaches, the model matching method is still recommended. Experts have proposed the following related points of view.

As early as 2009, Pereira et al. [61] proposed a distribution feeder fault location methodology based on matching during-fault voltage sags to determine the problematic node or region. The algorithm is adequate, according to the test findings, because it not only located the flawed spot, but also identified the damaged region, giving critical information for repairing any damage. Bakar [62] proposed a novel method for fault section location using the matching technique. This technique involves calculating the difference between wavelet coefficients derived from the voltage signal and wavelet coefficient samples stored in databases, resulting in the Average of Absolute Difference (AAD). A study examined the efficacy of impedance-based techniques and matching procedures to locate three-phase to-ground faults (LLLGF) [63]. It presented the basic concept of the fault distance calculation in Figure 5.

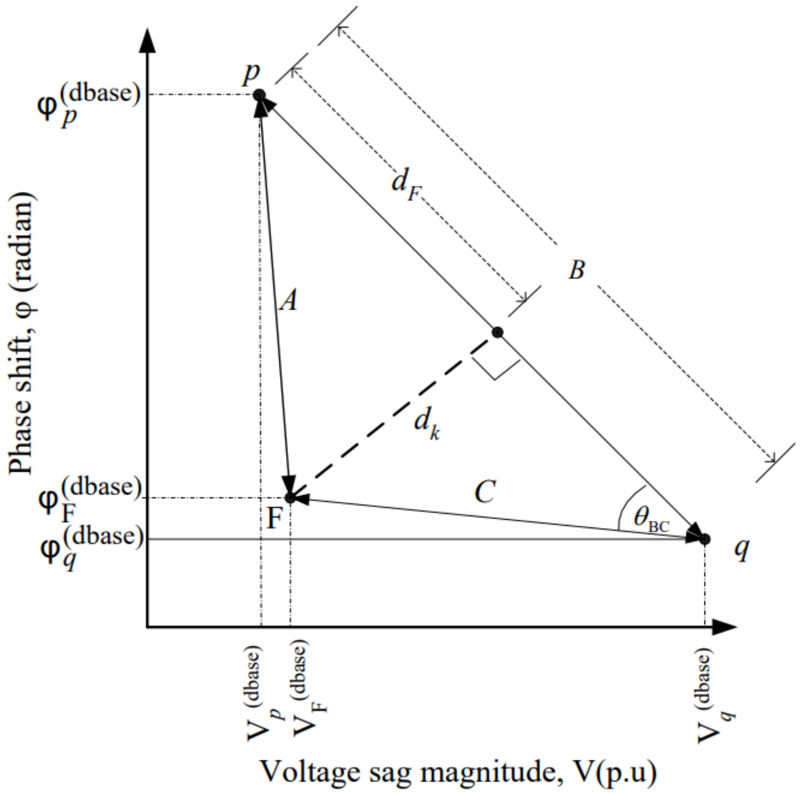

Figure 5. Basic concept of the fault distance calculation.

A non-homogeneous distribution network was utilized as a test network, and actual data from Malaysia's TNB (Tenaga National Berhad) was used to replicate the network. Both methods were assessed to determine the precision of the fault distance estimation, and the findings revealed that the accuracy levels were contingent upon the particular section being analyzed.

Apart from the aforementioned studies on matching techniques to locate the faulty parts, there were other studies that presented new ideas in combination with the model matching method. In 2020, a method [64] was proposed for selecting fault lines in distribution networks. The technique involves feature extraction, constructing a feature database, and conducting a topic search using power disturbance data from a power quality monitor. This method is practical and straightforward and can accurately locate faults without being impacted by factors such as initial fault angle, fault location, and power grid structure. Furthermore, another approach [65] utilized the SVM fault branch selection algorithm and similarity matching. This method involves constructing an SVM-based fault branch filter classifier using the positive sequence component feature matrix data at each monitoring point. To define the objective similarity function of fault location, the Euclidean distance and Pearson correlation coefficient are employed, resulting in accurate fault location. The findings demonstrated that the suggested strategy is both effective and precise.

Therefore,the above studies illustrated that model matching can accurately locate the fault location.

3.5. Application of artificial intelligence techniques in ground fault line selection

The fundamental causes of ground faults in power distribution systems can include compromised insulation, equipment malfunctions, human errors, lightning strikes, and environmental factors. These faults can result in hazardous phenomena such as low resistance, current leakage, voltage drops, and arcing. The impact on the safety and reliability of distribution systems includes equipment damage, power interruptions, and safety risks. Therefore, we need advanced methods, especially AI-related techniques to tackle these issues.

3.5.1. *Artificial neural networks*

The utilization of artificial neural networks can enhance the detection of ground fault lines, which is crucial for ensuring the stable and efficient operation of the current transmission network and preventing harm to both people and equipment caused by recent. A scheme of it is shown in Figure 6.

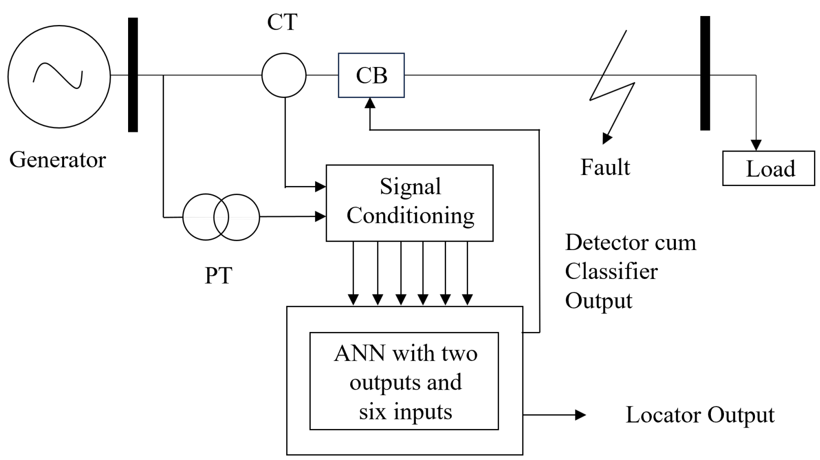

Figure 6. Artificial neural network scheme.

Research on artificial neural networks has become increasingly intense in recent decades and yielded significant progress. These networks have effectively addressed numerous practical problems that modern computers struggle to solve, such as pattern recognition, automatic control, prediction estimation, and more. Artificial neural networks demonstrate impressive, intelligent capabilities. Therefore, it has also been commonly used in ground fault line selection. Many studies have proposed different theories through the combination of this technique with other measurement methods. In a study, Li et al. [66] came up with an approach to increasing the dependability and security of power systems by utilizing artificial intelligence (AI) approaches. In a wide range of system settings, the artificial neural network (ANN) is utilized to diagnose fault location as well as fault resistance. The ANN training is quite straightforward and quick, and the predicted outcomes are correct. Besides, Singh et al. [67] investigated the application of artificial neural networks to detect faults in electric power transmission lines. They employed a 300km, 25kv transmission line to validate the proposed fault detection system, which was simulated using MATLAB Simulink. The fault detection system was also implemented on TMS320C6713 hardware.

In addition, by using artificial neural networks, Jamil et al. [68] illustrated the identification and categorization of problems in electrical power transmission lines. The simulation results suggest that the approach is efficient and may be expanded to the Power System's Distribution network. In 2017, a study conducted by James et al. [69] proposed that fault detection is vital for microgrid control and operation, yet conventional fault detection techniques are ineffective because of their reliance on large fault currents. In order to swiftly provide information concerning fault type, phase, and location, the present study suggests an intelligent technique for fault detection that utilizes wavelet transform and deep neural networks. The simulation findings show effectiveness. Then, another study [70] utilized wavelet transform and statistical analysis to extract fault characteristics, which are then used to train an artificial neural network for fault location in a power system. The neural network demonstrated good performance in identifying faults with varying angles, locations, and resistances. In 2021, research conducted by Yadav et al. [71] aimed to use artificial neural networks to detect faults in electric power transmission lines (ANN). Simulations show that AI-based methods are effective in detecting problems and achieving satisfying results. Figure 7 illustrates an artificial neural network model.

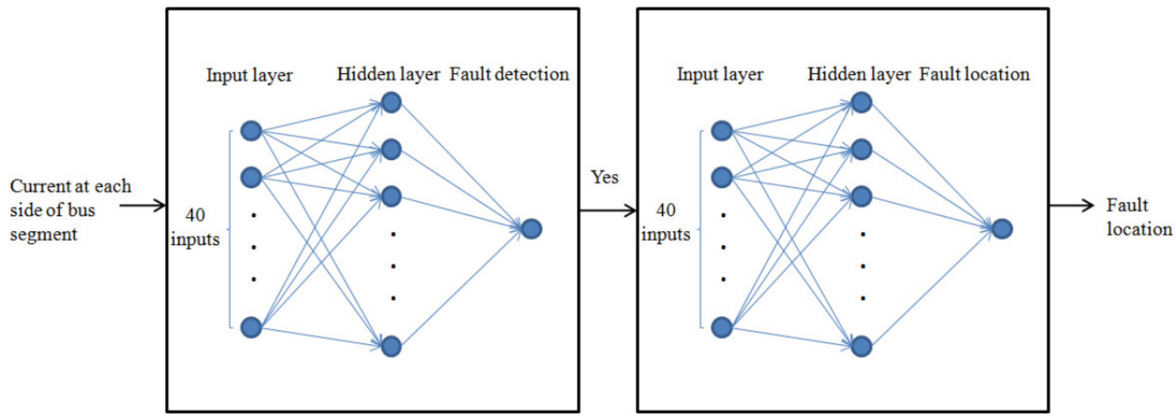

Figure 7. Artificial neural network model.

Additionally, empirical evidence has shown that artificial neural networks can enhance fault location precision and transmission line monitoring for training. In their work, OGAR et al. [72] utilized

Artificial Neural Networks to train a 330 kV, 500 km three-phase transmission line. Notably, the objective was to detect faulty current and voltage data, achieving a fault detection accuracy of 100% and a fault localization accuracy of 99.5%. This model is the foundation for transmission line fault protection and management systems. According to a study [73], High Impedance Fault (HIF) is a danger to human life, and an algorithm has been created to detect it utilizing signatures in both the time and frequency domains. To increase accuracy, features such as phase current rate of change, sequence current angle change, and relative energy of WT coefficients are used. An approach [74] based on Artificial Neural Networks (ANNs) is recommended to classify faults in hybrid power distribution systems. This involves monitoring the voltage signal at the PCC while utilizing Discrete Wavelet Transform (DWT) to extract various characteristics. The simulation is carried out in MATLAB, and hardware implementation is used to validate the findings. Using the suggested methods, the Total Harmonic Distortion (THD) is reduced by 4.3%.

Therefore, it is shown through various experiments and studies that artificial neural networks are suitable for providing circuit fault detection promptly.

3.5.2. *Support vector machines*

The main methods of urban power supply networks are neutral point ungrounded and arcs suppression coil grounded. The advancement of urban planning has resulted in a need for enhanced security in power grid operations. In practical applications, single-phase grounding faults are the most common fault. Therefore, it is essential to focus research on the selection and location of single-phase grounding faults. Under such circumstances, some experts suggested that support vector machines can be used as the theoretical basis to apply it to ground fault line selection.

In order to resolve uncertainty linear division relations for high voltage transmission line fault types, fuzzy set theory and Support Vector Machines (SVM) with significant generalization abilities were employed in [75]. The suggested approach is appropriate for all model architectures and is capable of appropriately classifying fault kinds. Parikh et al. [76] developed a fault classification method for a transmission line with fixed series capacitor was proposed by Parikh et al., which utilized support vector machines (SVM). The algorithm was evaluated on a 300 km, 400 kV transmission line with 25,200 test instances and found to be quick, accurate, and resilient over a wide variety of system and fault circumstances.

Then, in a study, a novel technique for categorizing fault types and forecasting fault location in high-voltage power transmission lines was presented utilizing Support Vector Machines (SVM) and Wavelet Transform (WT) [77]. The method yielded an average fault location inaccuracy of under 0.26%, with the maximum error being 0.95 km. In 2016, Ray et al. [78] conducted a study that examined a support vector machine-based technique for determining fault type and distance estimates in a lengthy transmission line. The results of this study demonstrated a remarkable level of precision, with the smallest fault distance estimation error recorded at 0.21% and an overall accuracy of 99.21%. The fault classification method's layout is depicted in Figure 8.

Meanwhile, a novel approach for identifying energy and financial losses as well as fire risks associated with Line-to-Line (L-L) faults in Photovoltaic (PV) arrays was introduced in a study [79]. Maximum Power Point Tracking (MPPT) has the potential to conceal some defects, rendering them invisible to security measures. Moreover, In [80], the authors proposed a fault detection algorithm based on multiresolution signal decomposition for feature extraction and two-stage support vector ma-

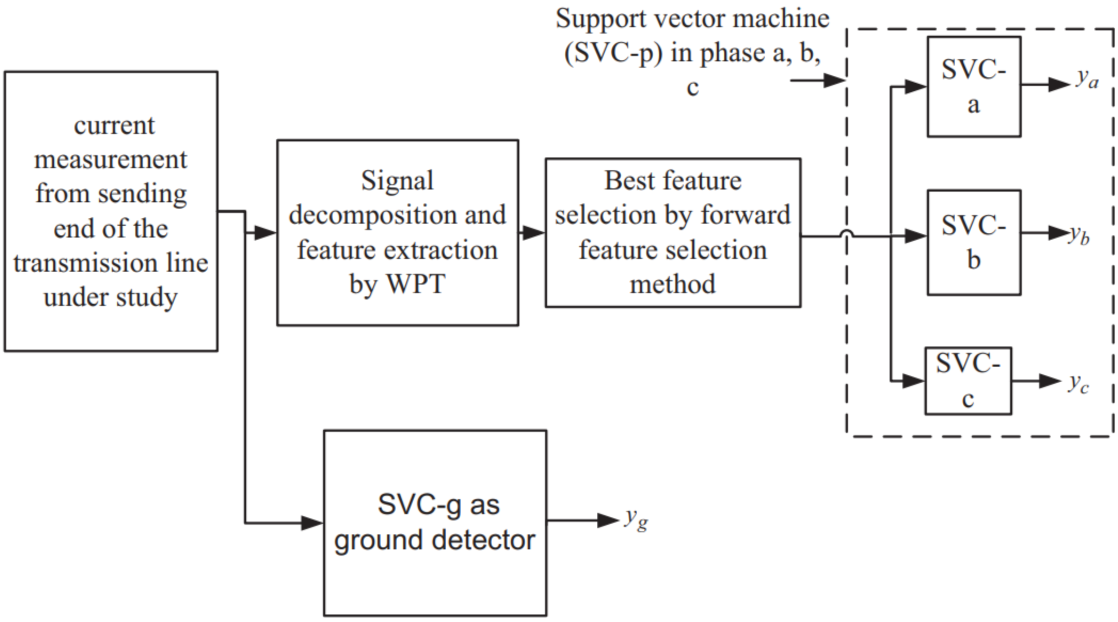

Figure 8. Detailed layout of support vector fault classifier.

chine (SVM) classifiers for decision making. It requires data of the total voltage and current from a PV array and labeled data for training the SVM. Simulation and experimental case studies verified the accuracy of the proposed method. In a separate study, Shafiullah et al. [81] aimed to identify different types of faults in a distribution grid through the use of wavelet transform (WT) to extract features from three-phase fault currents and employing an enhanced support vector machine (SVM) for classification. To establish the efficacy of the proposed model, a backtracking search is executed to optimize the SVM parameters, and the outcomes are compared with those of a general/non-optimized support vector machine. In 2019, Awalin et al. [82] provided an efficient fault type classification approach based on Support Vector Machine (SVM) for identifying different fault kinds in distribution systems. The suggested approach uses the size and angle of voltage sags detected at a distribution system's principal substation to determine the fault types. Results indicate that the suggested method's accuracy is satisfactory. Sarwar et al. [83] proposed an accurate high impedance fault (HIF) detection and isolation scheme in a power distribution network. The technique utilized Principal Component Analysis, Fisher Discriminant Analysis, and Binary and Multiclass Support Vector Machine algorithms for fault detection and identification. Simulation results demonstrate the effectiveness of Support Vector Machines in accurately detecting and locating high impedance faults. Recently, a study investigated high-frequency transient current for fault detection in a 500-kV long overhead transmission line (OHTL). An Optimized Support Vector Machine (OSVM) is proposed, achieving fault location within 0.012 seconds and 99.85% accuracy, regardless of fault distance, resistance, noise, or inception angle. The OSVM enhances line system dependability and advances nuclear system development. [84]

The research on support vector machines has introduced novel approaches for selecting round fault lines, resulting in improved fault detection efficiency.

3.5.3. *Decision tree*

In addition to the above two methods, combining decision trees with other theories can also improve the detection and classification of circuit system defects.

A method for identifying and categorizing power system failures on transmission lines was presented in [85]. To detect and categorize defects, it employed a rule-based decision tree and a Stockwell transform-based multi-resolution analysis of current signals. Faults analyzed in this research work include line-to-ground fault, and other 3 different faults. In September 2018 at the International Conference on Computing, Power and Communication Technologies (GUCON), there was a study [86] about a discrete wavelet transform and a rule-based decision tree are employed to detect and categorize power system defects using bus current and a fault index. Apart from that, a proposed method in [87] is based on machine learning algorithm application in distance protection for fault detection and classification in power transmission network. Post fault current data is taken into account for fault classification and detection. In addition, Asman et al. [88]came up with a statistical approach for identifying fault sources on power transmission lines using RMS current duration, voltage dip, and discrete wavelet transform(DWT). To acquire the best classification results, the classifier performance of several parameters was evaluated in the form of a confusion matrix.

Recently, a novel method for identifying faults in a TCSC-compensated transmission line by utilizing just local end current measurements as input to a DT-based classifier was introduced by Mohanty in [89]. The proposed approach exhibits a sensitivity of 100%, surpassing the performance of current methods. The decision tree will handle the numerical and categorical variables by ruling out features condition using the splitting method,and an example can be shown in Figure 9.

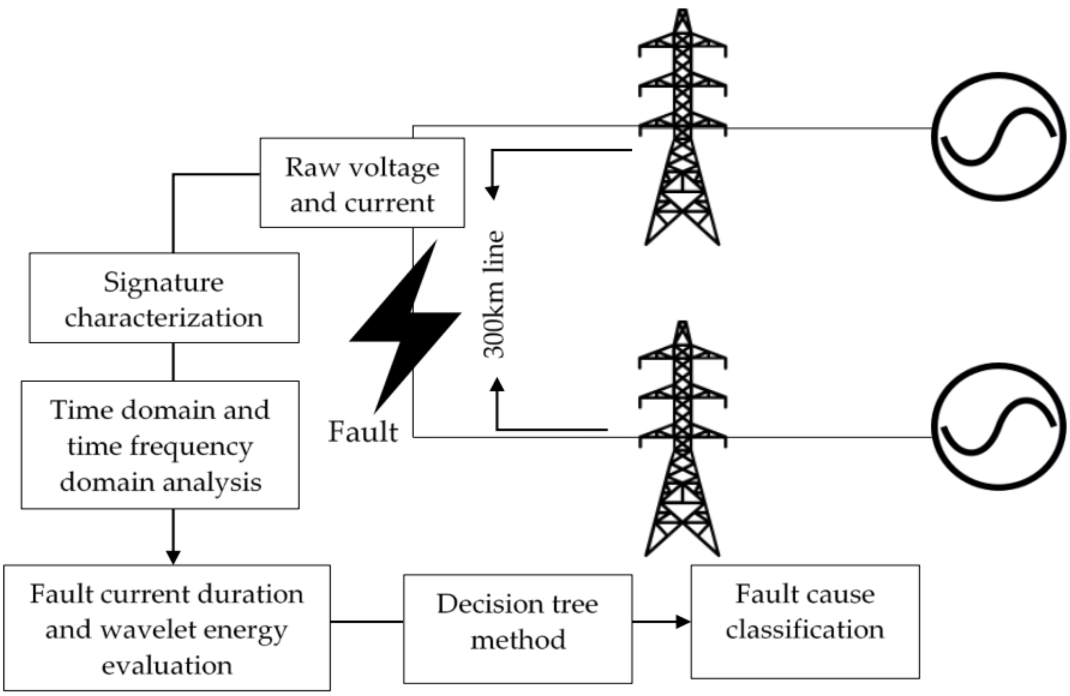

Figure 9. Transmission line fault simulation process.

3.5.4. *Fuzzy logic*

The problem of fault line selection remains unresolved, owing to the intricate nature of the power distribution network structure and the constraints associated with adopting a single-line selection approach. However, as artificial intelligence advances, professionals continue to suggest new solutions, such as the use of fuzzy logic.

In 2016, Adhikari et al. [90]presented fuzzy logic-based online fault detection and classification of transmission lines utilizing Programmable Automation and Control technology and National Instrument Compact Reconfigurable i/o (CRIO) devices. At the same year, in [91], the experts used wavelet transformations in conjunction with a fuzzy logic system to classify 11 different types of transmission line failures without compensation. The results revealed that under system settings and in a noisy environment, the technique can classify all fault kinds with large distinctions. Also, Dehghani et al. [92]came up with a new method of fault detection and classification in asymmetrical distribution systems with dispersed generation to detect islanding and perform protective action. Indexes are defined based on wavelet singular entropy in positive components and three phase currents to detect and classify faults. The major priority is the reduction in time (10 ms from event inception) in distinguishing islanding and protection transmission lines. Furthermore, in 2018, a study conducted by Lekie et al. [93]proposed that fuzzy logic controller was developed to detect single line to ground fault, double line to ground, line to line fault and three phase fault on Notore fertilizer plant 11KV distribution. Results were 0.0439, 0.616, 0.375 and 0.5 respectively, showing that the proposed fuzzy logic is optimal. Bhat et al. [94] proposed a fuzzy logic system (FLS) for detecting and classifying three-phase faults in a distributed power system network. The suggested system successfully identifies and detects various failure kinds.

Through simulation experiments, it verifies the feasibility of the application of the theory in the ground fault line selection.

3.5.5. *Genetic algorithms*

The adoption of a single fault line selection approach for ground fault line selection is associated with certain limitations that can result in erroneous or overlooked selections. Therefore, the genetic algorithm-based method for indirectly grounding power systems is put forth. By using the system failure stable states of the active power line selection method and the reactive power line selection method, as well as the transition condition parameter-based wavelet route selection method, the algorithm is able to determine a trustworthy selection criterion for the indirectly grounding power systems.

Using genetic algorithms (GAs) and response surface technique, Hasanien et al. [95]proposed an optimal design process for the controller utilized in the frequency converter of a variable speed wind turbine (VSWT) powered permanent magnet synchronous generator (PMSG). (RSM). It is discovered that the fault-ride-through of VSWT-PMSG may be enhanced by applying the frequency converter parameters derived from GAs-RSM. In another study [96], the authors compared the Whale Optimization Algorithm (WOA) to the Genetic algorithm(GA) for estimating fault location in power systems and transmission networks. Both three-phase to ground faults and single-phase to ground faults are analyzed, with the aim of determining the fault location efficiently, precisely, and with high accuracy. An objective function is employed to achieve this goal within a short duration.

In addition, genetic simulated annealing algorithm GSAA-BP is a BP neural network algorithm used to select fault lines for small current grounding systems. The diagram of BP neural network structure was shown in Figure 10.

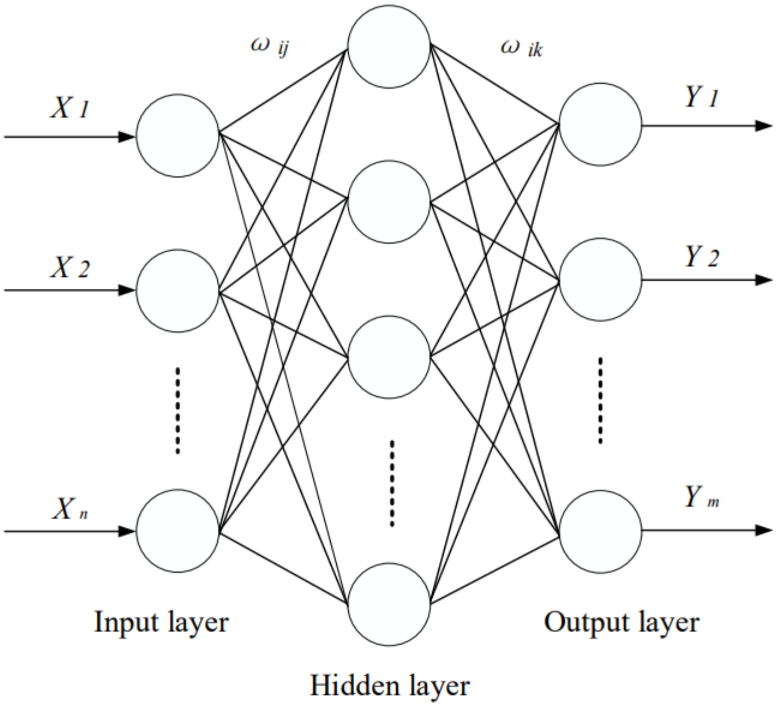

Figure 10. Schematic diagram of BP neural network structure.

To circumvent the challenges posed by the initial weight and threshold in conventional BP neural networks, an approach has been devised that enhances population diversity and leads to greater convergence speed, flexibility, and precision in judgment accuracy. [97]. With the use of a discrete wavelet transform (DWT), genetic algorithm (GA), and neural network(NN), Moloi et al. [98] proposed a protective fault method. The fault current signals are analyzed using DWT, statistical characteristics are removed to reduce the size of the original signal, and GA is used to find the best settings. On a real network, the system is tested, and a high level of fault detection accuracy is attained. In 2022, Hichri et al. [99]discussed fault detection and diagnosis (FDD) in grid-connected PV (GCPV) systems using tools for feature extraction and selection and fault classification. The proposed approach utilizes the genetic algorithm technique for selecting optimal features and applies an artificial neural network classifier to diagnose faults. The outcomes validate the feasibility and effectiveness of the proposed method, which exhibits a short computation time. The results confirm the feasibility and effectiveness of the proposed approach with a low computation time. Lately, a rapid diagnosis technology for short circuit faults in DC microgrids is proposed. It includes fault classification and location. The rate of change of transient current is used to classify faults and a converter fault location criterion is established. Line fault location is achieved through a multi-objective optimization algorithm based on genetic algorithm. The proposed method improves fault diagnosis efficiency and considers the impact of new energy sources [100].

From the simulation results, the method has the characteristics of high reliability and good selectivity, and has good adaptability to different structures of power grids.

3.5.6. *Other methods*

The continuous evolution of science and technology and the in-depth analysis conducted by experts in related fields have led to the introduction of numerous other techniques and methodologies. In 2017, a study presented an intelligent fault detection scheme for microgrids based on wavelet transform and deep neural networks [69]. The scheme enables fast and accurate fault detection, including fault type, phase, and location information, without the need for communication. It demonstrates superior performance compared to existing methods and can adapt to different operating modes and network topologies. In Figure 11, power signature inputs measured by NIFM methods are reduced using AI approaches for SLGF identification was presented in [101].

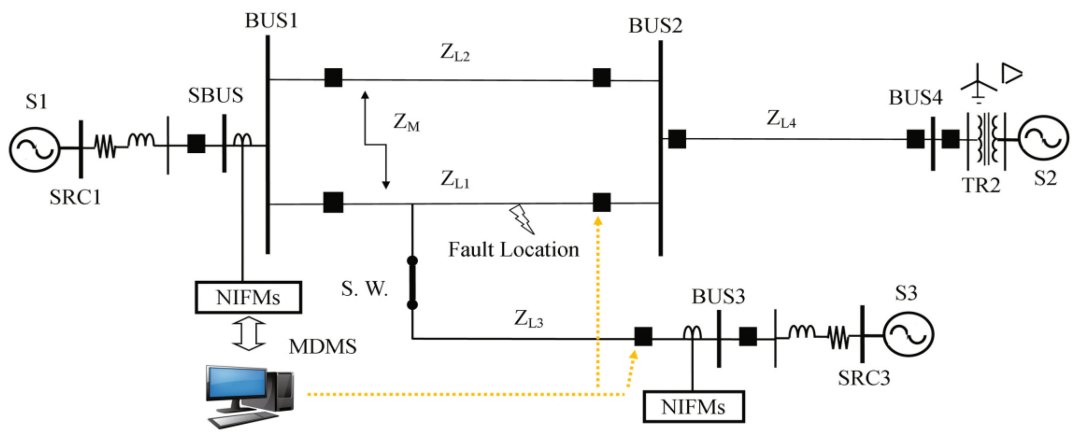

Figure 11. Fault protection scheme on power transmission networks for a NIFM system.

In an NIFM system, several machine learning approaches are employed to compare whether classification algorithms are acceptable for diagnosing the SLGF for various power signatures. Aljohani et al. [102] introduced a hybrid method for locating single-line-to-ground (SLG) faults in a modeled distribution feeder using the Stockwell Transform (ST) and Machine Learning Techniques (MLT). Under measurement noise and load demand uncertainties, the results are satisfactory.

Due to the single line to ground fault(SLGF) is the most prevalent in the distribution network. A study conducted by Jabbar et al. [103] proposed the Adaptive Neural-Fuzzy Inference System (ANFIS) approach for controlling the PC, which produces the best results by detecting the fault, lowering the electrical arc, limiting the fault current, and suppressing the fault current by analyzing its higher and lower peaks. The structural concept of the approach can be shown in Figure 12.

In order to extract features from enormous amounts of data for single-line-to-ground (SLG) fault finding, [104] conducted by Mou-Fa Guo presented a unique technique for fault-section location utilizing a 1-D convolutional neural network (1-D CNN) and waveform concatenation. The proposed technique was found to be successful even when a few DFIs are out of order, according to the results. Besides, a new method for selecting single-line-to-ground fault feeders in power distribution systems is proposed in a study [105]. Effectiveness and reliability are demonstrated by simulation tests. The

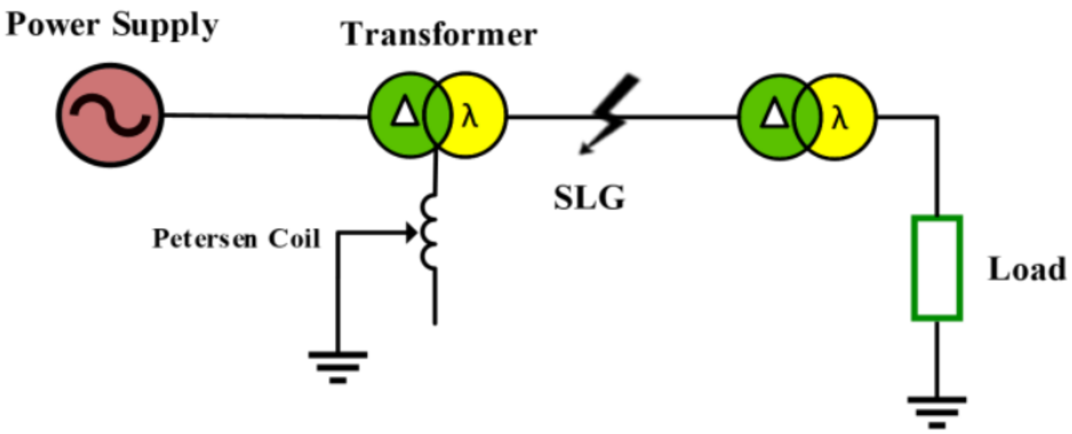

Figure 12. OLD showing SLGF and its protection by using PC.

advantages are demonstrated by reverse installation tests and comparisons. A new method for single-phase ground fault line selection was proposed in 2021, utilizing a Long Short-Term Memory (LSTM) network [106]. The simulation example gathers real-world operational data and builds an LSTM fault line selection model using the Keras framework. When LSTM is compared to other algorithms, it has a high level of prediction accuracy.The detailed application of ground fault line selection based on big data flow chart is shown in Figure 13.

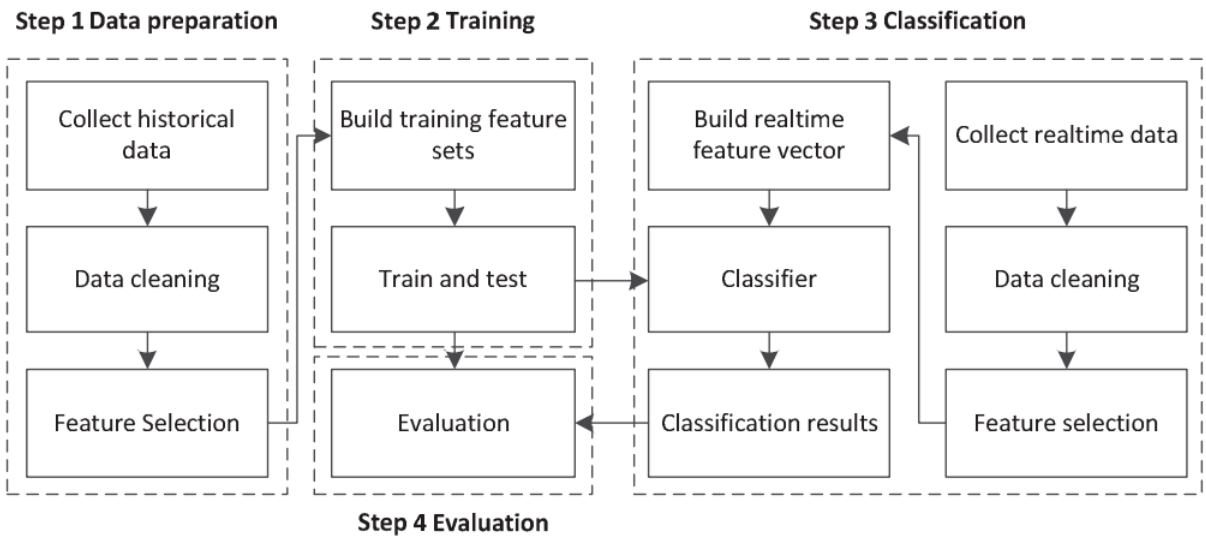

Figure 13. Application flow chart.

In power system fault analysis and location, a large part of the research still uses methods such as signal processing and statistical analysis for feature extraction. However, shallow machine learning models are being replaced by deep machine learning models. The research results generally show that compared to traditional AI technology, the new generation of AI technology has higher accuracy and precision in identification. Table 1 provides some comparative data on the identification and analysis accuracy between new generation AI technology and traditional machine learning in fault analysis and location research. By comparing these studies, it was found that the recognition accuracy and precision of new generation AI technologies, such as CNN, DBN, SAE and other deep learning models, are generally higher than those of traditional machine learning models.

Table 1. Summary of New Generation AI Applications in Power System Fault Analysis and Location.

Application Area	New Generation AI Technology	Compared Technology	Recognition Results (Accuracy or Precision)
	Deep Learning \ [107]	Rule-based systems	Accuracy: 98.9%
Fault Identification	Decision Tree \ [108]	Traditional machine learning	Accuracy: 99.93%
	Support Vector Machine \ [109]	Traditional machine learning	Accuracy: 99.44%
Fault Distance Estimation	Convolutional Neural Networks \ [110]	Classical regression methods	Error: <0.8%, Accuracy:86.4-100%
	Recurrent Neural Networks \ [111]	Time-frequency analysis methods	Accuracy: 97.2%
	Artificial Neural Networks \ [112]	Traditional grid search methods	Average error: 0.1683
Fault Location	Fuzzy Logic \ [113]	Particle Swarm Optimization	Error range of less than 0.1 to 0.4
	Genetic Algorithm \ [114]	Traditional grid search methods	Error: 1.13% Accuracy: 98.87%

With the advancement of artificial intelligence, the method of ground fault line selection will be further optimized to achieve higher accuracy and assist the safe and efficient operation of the distribution network.

4. Discussion

After reviewing a large number of literature, it is found that there are numerous grounding fault line selection methods available, which have improved the accuracy of grounding fault line selection. However, these methods still have limitations and need further improvement.

The traditional short-circuit current method is widely used and relatively mature [115], which can quickly determine the location and type of grounding fault and is applicable to various types of grounding faults. Moreover, the calculation of this method is relatively simple, without requiring additional hardware equipment or complex system modeling. However, this method cannot accurately locate the fault, and it is sensitive to the system model parameters, which may lead to misjudgments when there are significant errors [116]. The time-domain inversion method can accurately locate the grounding fault, determine its type and location, and is effective for complex systems or multiple faults occurring simultaneously. This method has high resistance and robustness against the system. However, using this method requires high computing power and storage space, which may require additional computer support. The impedance ratio method is a very simple method that only requires comparing two measured values without additional calculation or complex modeling. It is applicable to both single-phase and multi-phase grounding faults and can be used in conjunction with other selection methods. whereas this method has high requirements for the power grid, requiring stable and accurate grounding resistance values [63, 117]. Additionally, it can only determine the fault area, and is not suitable for precise fault location. The model matching approach, which relies on the system model, provides an accurate means of detecting and identifying ground faults. It has good adaptability for multiple faults occurring simultaneously and can be simulated and analyzed using existing computer simulation tools. However, this method has some drawbacks, such as the need for precise system modeling and parameter estimation, and high computational and storage requirements. Additionally, it cannot determine the precise fault location. Meanwhile, obtaining accurate and comprehensive data is complex, time-consuming, and can lead to unreliable fault detection. Developing algorithms that handle diverse fault scenarios and provide reliable results is crucial for effective fault detection. Moreover, immediate responses to faults require efficient algorithm design and fast data processing to meet real-time requirements. Inadequate data collection results in false alarms and compromised safety, while poor algorithm performance leads to inaccurate fault detection. Furthermore, the lack of real-time capabilities hampers fault isolation and system stability.

In modern society, grounding fault line selection can benefit significantly from the integration of artificial intelligence (AI). This collaboration can bring together domain knowledge from power systems engineering and expertise in AI algorithms, leading to the development of more effective and practical AI techniques for ground fault line selection. AI algorithms excel at processing large amounts of data in real-time, resulting in faster and more accurate detection and diagnosis of grounding faults [118, 119]. Moreover, AI-based methods can take a holistic approach to fault analysis by leveraging multiple data sources and parameters simultaneously, which can lead to a more proactive and preventive approach to fault management. Additionally, AI-based methods are highly adaptable to different types of grounding faults and power system configurations, providing a versatile solution to fault management. Finally, AI-based methods can facilitate the advancement of AI technologies and their applications in power systems, fostering further innovation and progress in fault management and related fields.

In general, distinct grounding fault line selection techniques exhibit unique merits and demerits, necessitating the selection of a suitable approach that aligns with the specific situation at hand. When selecting the method, factors such as power grid requirements, cost, and accuracy should be considered, and sufficient testing and verification should be conducted to ensure the accuracy and reliability of the selection method. Moreover, the combination of multiple fault line selection methods can enhance the accuracy and reliability of the selection process.

Due to the complex structure of the distribution network, it is difficult to establish a mathematical model that precisely described its characteristics, while artificial intelligence, especially artificial neural networks, can deal well with the pair of nonlinear problems, and with its fault tolerance and good self-adaptability, so the application in the small current grounding system fault has a good prospect.

By establishing a database of fault characteristics, the information is compared and analyzed to infer which line is at fault. In addition, the fault information of each line provided by each feeder terminal in the distribution network is used to select the line in the system where the fault occurs by combining the basic idea of genetic algorithm, relying on the fitness function of genetic algorithm, then, the overall optimal solution is found by calculation. Artificial neural networks are commonly employed to process fault information by using fault characteristic quantities as input and the relative fault line selection as output, offering reliable fault line selection. At the same time, artificial neural networks can fuse a variety of fault characteristics to carry out the selection of the low-current grounding system. Since most of the existing fault line selection methods use the amount of features after a certain fault for fault line selection, but the complex structure of the distribution network leads to variable fault factors during single-phase grounded short-circuit faults, often leading to some single fault features are not obvious, making the use of these fault features for line selection methods can not accurately select the fault line [71, 120, 121].

In addition to the above research directions, transient signals are also an important part of the ground fault selection. The transient signal after the fault is very rapid, and the process is very short. However, the transient signal amplitude is large, the fault characteristics difference between fault line and non-fault line is obvious, and the use of transient signal for line selection is not affected by the neutral grounding mode, for intermittent arc grounding fault is also applicable [122].

Despite significant improvements in ground fault line selection methods over the years, technical limitations still pose certain challenges. Firstly, most of the current methods are used for a single fault characteristic, the selection method can not accurately determine the fault line selection problem in the low-current grounding system. Secondly, some line selection methods are more influenced by external factors, resulting in lower detection sensitivity and less reliability. Moreover, relevant data are still lacking.

This research has significance for power management and academic research. In terms of power management, AI-based grounding fault line selection technology can improve the safety and stability of power systems, reduce the impact of power faults on users, and minimize repair time and costs. It can also help power management departments monitor and predict grounding faults, improving the reliability and efficiency of power systems. And for academic research, this review on AI-based grounding fault line selection can promote the development of fault diagnosis and treatment technology in power systems, broaden the research direction of fault line selection in power systems, and promote the application of AI technology in power systems. In addition, this research can provide inspiration and reference for fault diagnosis and treatment in other fields.

As the accuracy and effectiveness of ground fault line selection still faces challenges, future research is likely to be developed further in conjunction with artificial intelligence. The application of artificial intelligence can further help detect faults in the distribution network since it is capable of powerful data extraction and inference, it can reduce human errors and eliminate repetitive tasks. However, it is worth noting that the literature search in this paper is not exhaustive and some important studies may have been overlooked.

Table 2. Summary of Artificial Intelligence Techniques for Ground Fault Line Selection in Power Systems.

Direction of Application	Application Area	Research Progress	Technical Advantage	Bottleneck	Future Research Direction	Long-term Vision
Supervised learning	Power Distribution Systems	Advanced	High accuracy, rapid response times, ability to handle complex data	Large data requirements, risk of over fitting	Developing hybrid models with unsupervised learning	Integrating AI models into real-time monitoring systems
Unsupervised learning	Power Transmission Systems	Emerging	Detecting unknown patterns and anomalies Potential for real-time monitoring	Insufficient labeled data, potential for false positives	Developing methods for fault localization and diagnosis	Developing explainable AI models for better decision-making
Reinforcement learning	Renewable Energy Systems	Early stage	Learning from experience, optimizing complex control problems	Extensive computation resources required, slow learning potential	Incorporating domain knowledge and physical models into AI algorithms	Developing AI-based adaptive protection systems for enhanced reliability

5. Conclusion

In accordance with the guidelines of PRISMA, this systematic review aims to illustrate the importance of AI-based ground fault line selection in power systems protection. It presents the potential of AI techniques to improve the accuracy and speed of fault detection and isolation. The review focuses on the advantages of AI approaches, such as artificial neural networks, in analyzing power system data and predicting fault locations. AI-based approaches can be easily integrated into existing protection systems and can be adapted to different types of power systems.

One promising AI-based approach involves using artificial neural networks to analyze power system data and identify the location of the fault. The technique is trained on historical data to recognize patterns and predict the location of the fault based on real-time measurements of voltage and current.

Artificial intelligence techniques are innovative and have great potential in the field of power systems. Ongoing research and development in advanced technologies show continuous interest in the area. This systematic review of artificial intelligence techniques for ground fault line selection in power systems explores the direction of application, technical advantages, research progress, bottlenecks, future research directions, and long-term vision. The main contents are shown in Table 2. By delving into the shortcomings of AI in power systems and proposing potential development directions, this study aims to contribute to the advancement of AI technologies in the field of power systems.

Although AI-based ground fault line selection offers great potential benefits, it is still in its early stages of adoption, and further research is necessary to apply AI to ground fault line selection because it can enhance fault detection accuracy, reduce response time, and improve power system reliability. Continued exploration will enable the development of more robust algorithms, address challenges specific to different power system configurations, and maximize the benefits of AI in mitigating ground fault risks. Moreover, there are still challenges to be overcome. Gathering and annotating large-scale datasets can be time-consuming and resource-intensive. Additionally, the possibility of false alarms remains a concern, as the AI models may incorrectly identify certain conditions as ground faults, leading to unnecessary interventions and disruptions in the power system operation. Therefore, further research and development efforts should focus on exploring data augmentation techniques and developing advanced algorithms and models. Overall, the review highlights the potential of AI-based ground fault line selection as a promising approach to improve power systems protection against ground faults.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare there is no conflict of interest.

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