International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(22s) 2026 pp. 1315-1336
https://doi.org/10.70917/ijcisim-2026-5523
Article

A PHYSICS-INFORMED AI-ASSISTED FRAMEWORK FOR FAULT DETECTION AND LOCALIZATION IN CONTAMINATED XLPE UNDERGROUND CABLES

Priya Selvamany[1], Y. Mohamed Shuaib[2*], S. V. Saravanan[3], Muthurajan Subramonaim[4]

[1,2]Department of Electrical and Electronics Engineering, B.S. Abdur Rahman Crescent Institute of Science and Technology, Vandalur, Chennai, India
[3,4] Department of Marine Engineering, Academy of Maritime Education and Training, Kanathur, Chennai, India
Corresponding Author: 2*mdshuaiby@crescent.education
Email: 1priya.gdv@gmail.com, 3svsaravanan@gmail.com and 4smuthuraajan@gmail.com

Abstract: Underground power cables are widely used in modern power transmission and distribution systems due to their improved reliability, safety, and reduced environmental impact. However, insulation degradation caused by contaminants in cross-linked polyethylene (XLPE) cables remains one of the major challenges affecting the reliable operation of underground cable networks. Al-though conventional fault detection techniques have been widely employed; they often face limitations in accurately identifying and localizing faults under varying contamination conditions. This paper presents a physics-informed artificial intelligence framework for fault detection and localization in contaminated XLPE under-ground cables. Initially, a comprehensive review of conventional diagnostic methods and recent artificial intelligence techniques is carried out to identify existing research trends, challenges, and knowledge gaps. A finite element model of a high-voltage XLPE cable is then developed using COMSOL Multiphysics to investigate the influence of different contaminant materials and their locations on the electrical behaviour of the insulation system under pulse voltage excitation. Variations in electric potential, electric field in-tensity, and polarization are analysed to identify physics-based features that can support future AI-driven fault diagnosis and localization. The study demonstrates that contaminant characteristics significantly influence the electrical field distribution within the insulation, providing valuable information for intelligent condition monitoring. The proposed framework offers a systematic approach for integrating physics-based simulation with artificial intelligence and serves as a foundation for the future development of reliable cable diagnostic and predictive maintenance systems.

Keywords: Artificial Intelligence; Physics-Informed AI; Underground Power Cables; XLPE Insulation; Fault Detection; Fault Localization; COMSOL Multiphysics; Finite Element Analy-sis; Condition Monitoring; Predictive Maintenance

1. INTRODUCTION

As countries move toward a "new-type" power system concept, the global energy environment is fundamentally changing. The optimization of primary grid frameworks and a prioritized rise in the penetration of renewable energy inside transmission channels are characteristics of this evolution [1]. Modern power system management now depends on the integration of advanced infrastructure such as 5G technology, the Internet of Things (IoT) and big data analytics to support this high-density and high-stability need [2–4].

However, these grids growing complexity presents serious operating difficulties. The essential nature of this issue is demonstrated regionally by places like Tamil Nadu in southern India. The state has had severe limitations because of significant transmission losses and frequent power outages brought on by natural catastrophes like the

Nilam and Vardah cyclones, even though it has a strong network of more than 1,500 Extra significant Tension (EHT) and High Tension (HT) substations [5]. Upgrading current infrastructure and building new overhead line (OHL) substations using subterranean cable networks is a spontaneous move to lessen the vulnerabilities of OHL during such catastrophic catastrophes. Despite these benefits, the integrity of the polymer production chain and the purity of the manufacturing process severely regulate the dependability of XLPE capsules. Manufacturing flaws, impurities and metallic particles that deteriorate dielectric qualities and hasten aging are commonly blamed for premature failures [5]. Electrical, physical and chemical aging are the conventional classifications for the deterioration of these cables [6]. The widespread integration of distributed generators (DGs) presents hitherto unheard-of difficulties for conventional fault detection and localization techniques. The bidirectional power flows and fluctuating loads introduced by DGs make legacy diagnostic techniques less effective. Consequently, artificial intelligence (AI) has emerged as a vital tool in this field. AI techniques, ranging from conventional machine learning to advanced deep learning architectures, offer significant advantages in processing the vast amounts of data generated by modern sensors to detect, classify and localize faults with high precision.

This paper provides a current state of AI-based cable fault detection. The fundamental causes of cable failure and evaluate traditional localization methods are out-lined. Subsequently, the application of machine learning and deep learning approaches, discussing their strengths, defects, and performance in real-world scenarios. Finally, the specific impacts of DG integration and outline future research directions for advancing AI solutions in the pursuit of more resilient power systems are examined.

Urban distribution networks depend on cables as their essential component which has become common during the process of urban development. The present urban core area cable installation pattern has resulted in numerous medium and low-voltage cables and some high-voltage cables which now exist in underground tunnels at substantial depths. The cable trench interior contains multiple concealed risks which create a dangerous work environment that leads to poor cable installation results and operational problems and causes partial dis-charge accidents during cable operations. Addressing these hidden risks requires a shift from reactive maintenance to AI-driven predictive diagnostics capable of identifying subtle fault signatures in complex subsurface environments. The distribution network serves as the main power system component which receives grid electricity before delivering it to customer locations according to the diagram in Figure 1.

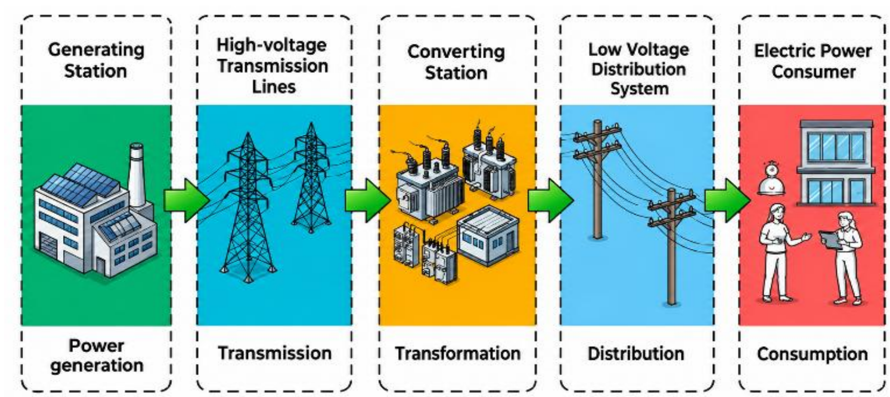


Figure 1. Power system structure.

Figure 1: Distribution network diagram

Motivated by the growing need for accurate and intelligent fault diagnosis in underground power cable systems, this work presents a physics-informed artificial intelligence framework for fault detection and localization in contaminated XLPE underground cables. A finite element model is developed using COMSOL Multiphysics to investigate the influence of different contaminant materials and their locations on the electrical behaviour of XLPE insulation under pulse voltage excitation. The resulting electrical characteristics, including electric po-tential, electric field intensity, and polarization distribution, are analysed to identify physics-based features that can support future

AI-assisted fault diagnosis and localization. In addition to providing a comprehensive review of existing fault detection techniques, this study establishes a systematic framework that integrates physics-based modelling with artificial intelligence concepts to support intelligent condition monitoring and predictive maintenance of underground power cable systems. The remainder of this paper is organized as follows. Section 2 presents a review of conventional and AI-based fault detection techniques. Section 3 presents the pro-posed physics-informed artificial intelligence framework and the finite element modelling methodology. Section 4 discusses the simulation results and analysis. Finally, Section 5 concludes the paper and outlines future re-search directions.

1.1 Research Contributions

Based on the identified research gaps and the pro-posed methodology, the principal contributions of this work are summarized as follows: 1. A comprehensive review of conventional and artificial intelligence-based techniques for fault detection and localization in under-ground XLPE power cables is presented, highlighting re-cent advances, contaminant-induced insulation degradation mechanisms, and existing research challenges. 2. A physics-informed artificial intelligence framework is pro-posed that integrates finite element modelling with artificial intelligence concepts to support intelligent fault detection and localization in contaminated XLPE under-ground cables. 3. A high-voltage XLPE underground cable model is established in COMSOL Multiphysics to investigate the effects of different contaminant materials and their locations on the electrical behaviour of cable insulation under pulse voltage excitation. 4. Physics-based electrical characteristics, including electric potential, electric field intensity, and polarization distribution, are systematically evaluated and identified as potential features for future AI-assisted fault diagnosis and localization. 5. The proposed framework provides a structured foundation for future research on intelligent condition monitoring and predictive maintenance of under-ground power cable systems by integrating physics-based simulation with artificial intelligence techniques.

2. TRADITIONAL METHOD-OLOGIES FOR CABLE FAULT DETECTION AND LOCAL-IZATION

In the field of distribution network management, early detection and precise localization of latent cable problems depend on the strict implementation of planned preventive maintenance procedures. Utility companies can gain significant operational advantages by implementing a proactive diagnostic methodology, such as improved system resilience and fewer socioeconomic disruptions. Utilities may greatly reduce the danger of catastrophic failures by routinely monitoring probable degradation markers, which will increase supply dependability and customer confidence. From a safety standpoint, early fault detection is essential for reducing risks related to insulation deterioration, partial discharge events and high-impedance short circuits, protecting the public and operational staff. Conventional diagnostic approaches to power system faults mostly involve analyzing electrical parameters such as traveling waves, leakage current to the ground, and zero-sequence currents, within either the time or frequency domains. These analyses are per-formed through deterministic mathematical models of the power system, and diagnostic insights are gained through the comparison of the characteristics of these electrical signals in the faulty power system.

2.1 Historical Cable Fault Detection Techniques

Power systems must rapidly identify and isolate faults when transmission lines fail to maintain operational reliability. Traditional cable fault detection approaches have centered on electrical characteristics and fast computational processing. The traveling wave method stands as one of the most prevalent fault detection techniques [7]. Al Hassan et al. [8] established a terminal surge detection system which uses wave propagation analysis to identify arrival times for high-voltage direct cur-rent (HVDC-VSC) systems. To validate their algorithm, they constructed an equivalent cable model using PSCAD/EMTDC software. Building on this foundation, Verrax et al. [9] created a fault identification method for cables using traveling wave principles derived from earlier research. Their approach utilizes a streamlined traveling wave model to represent the physical characteristics of power grids, while accounting for soil resistivity and cable shielding impacts. To verify ac-curacy, the model was tested on several line segments. By combining power-frequency electrical measurements with traveling wave data, Shi et al. [10] created a novel assessment method for distribution feeder health. Ac-cording to their research, power-frequency signals di-verge in distribution networks with deteriorating cable insulation but stay constant in healthy feeders. In or-der to enable real-time insulation status monitoring for three-core hybrid cables, researchers developed a mobile device in 2023 that locates and detects partial discharge (PD) events [11]. This system has an improved double-ended traveling wave PD detection method that minimizes synchronization problems while improving pulse timing precision and propagation velocity estimation using pulse-based directed interaction. Table 1 provides a thorough side-by-side comparison of the novel system with traditional offline PD measurement techniques, emphasizing enhancements in labor needs, portability, operational efficiency and overall cost-effectiveness.

The identification process followed by illustration is shown in Figure 2.

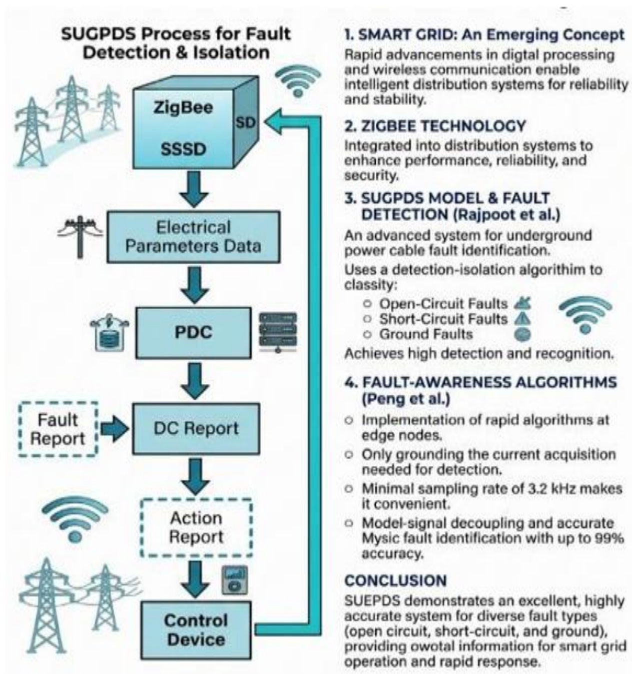


Figure 2: SUGPDS: An Intelligent solution for smart grid power distribution stability

Table 1: Performance Comparison of PD Measurement Systems

Feature	35-kV Resonance PD System	40-kV Oscillating Wave PD System	Developed System
Weight (kg)	1100	80	20
Cost ($)	≈200k	≈100k	≈8k
Testing time	>4 h	≈3 h	≈20 min
Manpower	>10	5	3
Portability	Low	Medium	High
Setup time (min)	≈240	≈90	≈15
Accuracy (%)	≈95	≈92	≈96
Power consumption (W)	≈5000	≈800	≈150

2.2 Conventional Approaches to Cable Fault Localization

In the power industry, cable fault localization is a crucial technique that makes it possible to quickly and accurately identify fault locations within cable systems for efficient maintenance and system dependability. In or-der to assess recent advancements, a variety of distance measurement approaches have been established as foundational procedures. More recent advances have introduced improved methodologies across numerous distance measurement frameworks.

Signal processing methods including filtering, noise re-duction, and data feature extraction enable improved fault characterization and more accurate fault localization. Ihasanvi et al. [12] investigated the application of the S-transform and continuous wavelet trans-form (CWT) in hybrid distribution networks combining overhead lines and cables. Simulation studies indicated that the S-transform offered superior frequency resolution accuracy and robustness for fault location. Chen et al. [13] used empirical wavelet transform (EWT) with multi-resolution singular value decomposition (MSVD) to identify traveling wave disturbances and determine faulty sections through the instantaneous polarity of traveling waves. High-frequency current transformers (HFCT) were also used due to their initial cost ad-vantages. Frequency-domain approaches: Cifuentes et al. [14] analyzed the transient system responses of mid-frequency faults using the offline system and identified faults in the online system using the fast Fourier trans-form (FFT). The fault location error was maintained be-low 3.3%. Song et al. [14] proposed the complex Laplace transform (CLT) to establish the bidirectional equivalence between the frequency-domain analytical solution and the time-domain transient waveforms of under-ground cables. The maximum location error was 0.6%, demonstrating the positioning accuracy of the approach. Time-domain fault location research is relatively limited. Bretas et al. [15] developed a time-domain system model for early-stage single-phase ground faults in underground shielded cables. The system model was developed using the state-space analysis of the non-linear network with least square error (NNWLSE) method, which converts the problem into a system of linear equations to identify unknown parameters and calculate the fault distance.

2.3 Constraints of Conventional Approaches

The established methodologies discussed in prior literature predominantly depend on traveling wave analysis, frequency-domain examination, and sensor-based measurements, supplemented by equivalent cable modeling techniques. While these approaches offer comprehensive consideration of operational factors, power grid systems continue to present significant obstacles. As power distribution networks expand in scale and complexity, precise system modeling becomes increasingly difficult. The widespread adoption of distributed energy resources introduces additional uncertainties and nonlinear behaviors in monitoring systems, complicating the application of traditional methodologies. These constraints emerge across three primary dimensions, as detailed in the sub-sequent sections.

2.4 Modeling Challenges and Precision Limitations

As power grids expand in scope, complex distribution networks demonstrate multiple interconnected branches and intricate topologies, substantially raising modeling complexity. Conventional techniques encounter difficulties in accurately characterizing line parameters and electrical characteristics under varying operational conditions, resulting in inaccuracies in fault identification and localization.

2.5 Inadequate Data Processing Capacity

Distributed renewable energy sources introduce in-creased data uncertainties and a nonlinear behavior in the power system. Conventional data processing methods for power systems struggle to process the large amount of data generated by these distributed renew-able energy sources. The data contains a high level of harmonic content and fluctuating signals, which reduces the precision of the localization of the faults in the power system. Additionally, the large amount of data produced by these distributed renewable energy sources can exceed the data processing capacity of conventional data processing methods, leading to longer fault localization times.

2.6 Restricted Flexibility and Adapt-ability

The majority of conventional methodologies for fault detection and localization in power systems are based on specific assumptions about the power grid and its operating conditions. After the expansion of power grids and the integration of renewable energies, the operating conditions of power grids have become more complex and dynamic. As a result, these methodologies cannot automatically adjust to the new conditions of power grids and require significant recalibration before they can be ap-plied to power grids with these new characteristics. The limitations of these methodologies in terms of fault detection and localization accuracy, computational performance, and robustness to changes in the power grid characteristics highlight the need for further development of the technologies used for these purposes.

2.7 Insulation Degradation and Fault Initiation in XLPE Cables: An AI-Driven Analysis Framework

Metallic Contaminants as Degradation Indicators for Machine Learning Models

Metallic contaminants are widely recognized as important indicators of XLPE insulation degradation. Em-bedded impurities can initiate water-tree structures, including vented and bow-tie trees, and therefore serve as strong markers of insulation aging. These contaminants may originate from the conductor shield, inadequate insulation cleanliness, or external sources such as soil and water contamination. Because of their strong association with degradation, metallic impurity features are suitable inputs for machine learning models intended for defect classification and failure prediction. Data-driven techniques can enhance automated health evaluation and fault identification in power lines, according to recent AI-based capable diagnostic investigations [17].

Manufacturing Process Defects

Another significant cause of contamination-induced deterioration is manufacturing flaws. Because they include carbon black, the conductor and insulation shields are semiconductive. Wear on the barrel extruder during production could produce metallic chips that end up entrenched as impurities. Additionally, dust particles may be introduced by improper extrusion system cleaning, creating voids or inclusions in the insulation. Addition-ally, long-term processing may result in combustion left-overs and scorch markings. Partial discharge, electrical treeing, water treeing and final insulation failure are all made more likely by these flaws [18].

Environmental and Installation-Related Features

Cable deterioration is also greatly influenced by installation and environmental factors. Contaminated water in the soil near buried cables can accelerate insulation failure. Heavy metals like Cu, Pb, Zn, Cr, Cd, Al, Ni and Co are commonly found in soil analyses and may have an impact on polymeric insulators. Along with ammonia and elements including C, S, Mg, K and Ca, sulfur has also been found in XLPE material and at the copper interface [19]. Acidic soil conditions exacerbate contamination-related aging and increase metal mobility in subterranean cable systems. For data-driven degradation evaluation and predictive maintenance, these variables are consequently important characteristics.

Partial Discharge Signature Analysis Using Deep Learning

Partial discharge measurements are frequently utilized to identify fault types such as voids, protrusions, and contaminants that are linked to XLPE cable breakdown. According to statistical reports, protrusions account for a smaller percentage of insulation failures than impurities, especially metallic impurities. Defect patterns linked to contamination-induced degradation can be categorized using deep learning techniques using partial discharge signatures. Strong potential for automated problem detection, location, and classification in power cables has been shown by recent AI-based diagnostic frameworks [20]. Therefore, a useful framework for intelligent condition monitoring and failure prediction is provided by combining partial discharge analysis with contamination-related variables [21, 22].

2.8 **Application of Machine Learning Techniques in Cable Fault Location**

2.8.1 Artificial Neural Networks (ANNs)

The field of power distribution systems uses Artificial Neural Networks (ANNs) to detect faults through their ability to identify nonlinear connections between electrical parameters which include current and voltage measurements. Farzad et al. [23] integrated ANN models into an IEEE 34-bus test feeder equipped with wind turbines to evaluate fault localization performance. Their study compared global and local input data, revealing that retraining the network with measurement errors enhanced its resilience and accuracy. Farias et al. [24] developed an online-trained ANN for high-impedance fault (HIF) localization. The method solved time-domain current-voltage equations as they happened which resulted in a maximum fault location error of 2.3% for a 60 A base current fault that occurred 10 km away from the power substation. Research has shown that artificial neural networks (ANNs) and multilayer perceptrons (MLPs) function successfully to find faults which ap-pear inside AC microgrid systems. Hamidi et al. [25] employed an MLP model combined with principal com-ponent analysis (PCA) to reduce feature dimensionality, improving computational efficiency. On the other hand, Jayasinghe et al. [26] have employed an ANN technique for fast fault detection and location of symmetrical as well as asymmetrical faults in AC microgrid distribution system networks. These approaches offer several ad-vantages: reliance on single-ended measurements, elimination of communication infrastructure, independence from time synchronization, and high accuracy, with a mean absolute error (MAE) of 0.2122. Additionally, the short response time highlights their potential for real-time fault detection and localization in AC microgrids.

2.9 Support Vector Machine (SVM)

SVM works on identifying the optimal hyperplane that will separate all data points belonging to different classes with maximum margin (the widest distance possible) from the support vectors of each class.

Optimization Objective:

$$\min \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{n} \zeta_i \qquad (1)$$

This minimizes both the margin width (controlled by ω) and the penalty for misclassified points (controlled by slack variables ζi and regularization constant C).

Constraints:

$$yi\ (\omega T\ xi + b) \geq 1 - \zeta i\ , \quad \zeta i \geq 0 \quad i = 1, 2, ..., n \qquad (2)$$

These ensure that each data point lies correctly on its side of the margin, allowing some flexibility for non-perfect separability.

Nonlinear Extension: In the case of non-linear separability of data, the use of kernel function *K(x, xi)* by the SVM allows the data to be projected in a higher dimensional space where linear separation can be done.

Decision Function:

$$y(x) = sign \sum_{i=1}^{n} \alpha_i y_i\, K(x, x_i) + b \qquad (3)$$

The value of αi represents the weight of the Lagrange multiplier assigned to each support vector.

The algorithm shown in Figure 3 employs a one-versus-one (OVO) strategy, creating pairwise classifiers to handle multi-class problems efficiently while reducing computational complexity. The results from simulation analysis for fault detection were obtained with accuracy of 99.8%, with execution time of only 0.01 s. This result is superior compared to kNN, PNN, and MLP.

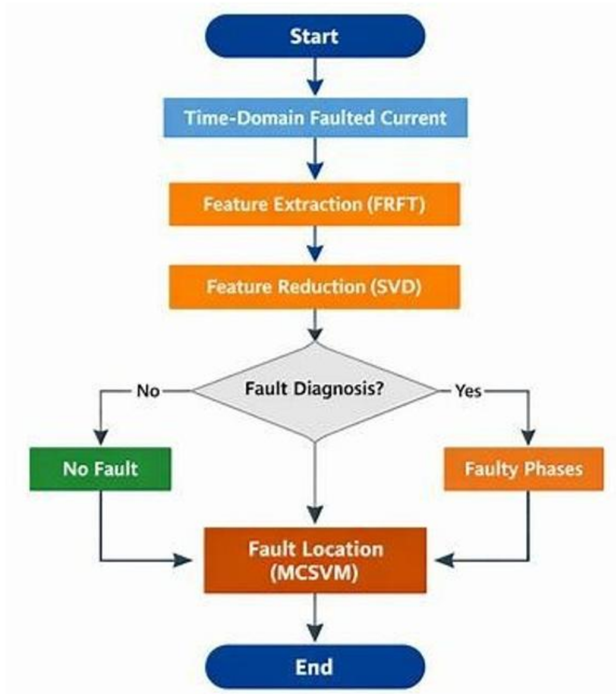


Figure 3: Flow chart of the fault diagnosis [27]

Furthermore, Razmi et al. [27] reinforced the validity of SVM with the comparison of five methods such as SVM, Decision Tree (DT), LSTM, RNN, and MLP are used to classify faults in medium-voltage distribution systems. Among them, SVM achieved the highest testing accuracy (98.9%), confirming its robustness for high-dimensional nonlinear data as shown in Figure 4.

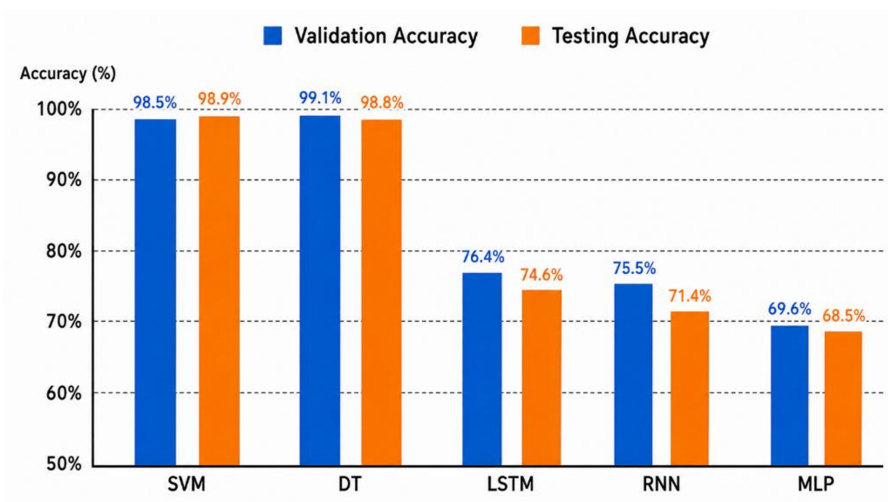


Figure 4: Supervised Algorithm Performance (Validation vs. Testing) [27]

The passage demonstrates a complex combination of Particle Swarm Optimization (PSO) and Support Vec-tor Machine s (SVM) for defect localization and classification. Essentially, Gashtroodkhani et al. [28] im-proved classification accuracy by using PSO to fine-tune SVM parameters before using Bewley's lattice diagram to identify fault locations.

This process shows how hybrid AI-based optimization improves electrical fault analysis accuracy. Bewley's lat-tice offers a physics-based validation of the fault's location, while PSO makes sure the SVM model reaches ideal hyperparameters.

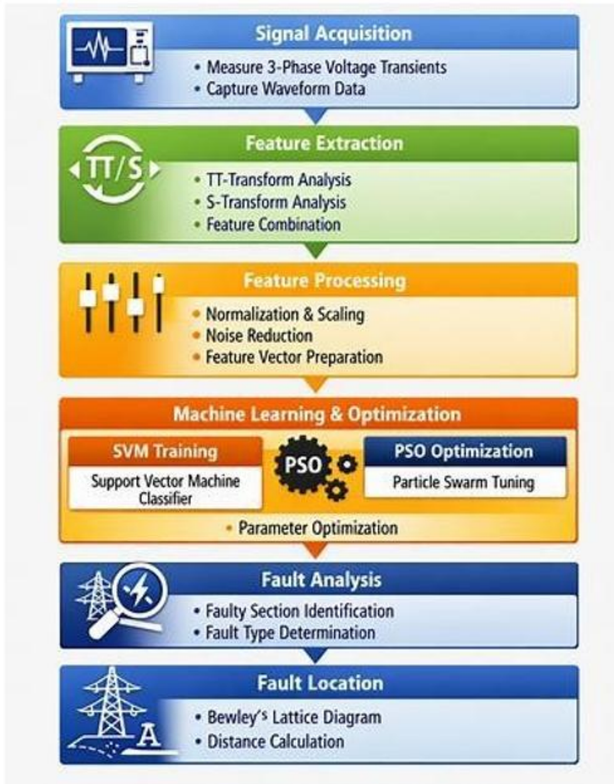


Figure 5: Detailed fault location process

2.10 Genetic Algorithm (GA)

Heuristic optimization techniques that mimic the natural laws of evolution are represented by Genetic Algorithms (GAs). They effectively search for global optimal solutions within a complex solution space by mimicking natural selection, genetic mutation, and reproduction. Potential solutions are encoded as chromosomes throughout this process, creating a starting population that changes over the course of subsequent generations. The fittest individuals are chosen to undergo crossover (recombination of genetic material) and mutation (random alterations) to produce new children after each chromosome's quality is assessed using a fitness function. The population progressively approaches an ideal or nearly optimal solution through repeated cycles of selection, crossover and mutation. When it comes to solving nonlinear, multidimensional optimization problems like those found in power system fault location where conventional deterministic approaches might not be able to locate global optima, GAs is very useful. They are useful tools for challenging computational and engineering problems because of their resilience and flexibility. This method is notable because it transforms the fault-location problem into an optimization of the zero-sequence voltage drop (ZVD) function, solved using Genetic Algorithms (GA). That combination of sequence component analysis with heuristic optimization makes it especially effective for distribution networks where grounding faults are complex to pinpoint [29].

2.11 Deep Learning

In the past few years, the development of computing power allows researchers to use deep learning (DL) to conduct analyses of large datasets such as image recognition and big data mining. Meanwhile, constant developments of smart grids facilitate the use of smart equipment and sensors in the field of power systems. Nevertheless, due to the incorporation of DGs, uncertainties and nonlinearity arise in monitoring data, which makes DL highly compatible with cable fault detection, location, and identification. DL has become an efficient method to solve problems associated with smart grids.

Attention mechanism was inspired by humans' ability to selectively concentrate on the significant details of the environment. Its mathematical principle is essentially the process of weighted aggregation based on query, key, and value vectors. First, the input is trans-formed into three groups of vectors, namely, query (Q), key (K), and value (V). After generating weights through calculating the similarities between query and key, the output is obtained by applying weighted aggregation of value vectors. Usually, a group of queries employed for computing the attention function is referred to as matrix *Q*, while key and values are referred to as matrices *K* and *V*, respectively. The formula is shown below [31]:

$$\text{Attention}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \text{softmax} \frac{\mathrm{QK}^T}{\sqrt{d_k}} V \qquad (4)$$

Here, *k* represents the size of the convolutional kernel while *i* and *j* correspond to output locations and *b* stands for the bias term. Pooling reduces the dimensionality of parameters through down sampling, which increases the degree of feature translation invariance. Finally, after passing through a number of convolutional and pooling layers, a fully connected layer extracts the features and classifies/regresses them. Figure 6 illustrates the temporal evolution of AI methods used in fault detection, showing a clear shift from conventional machine learning approaches toward more advanced deep learning techniques.

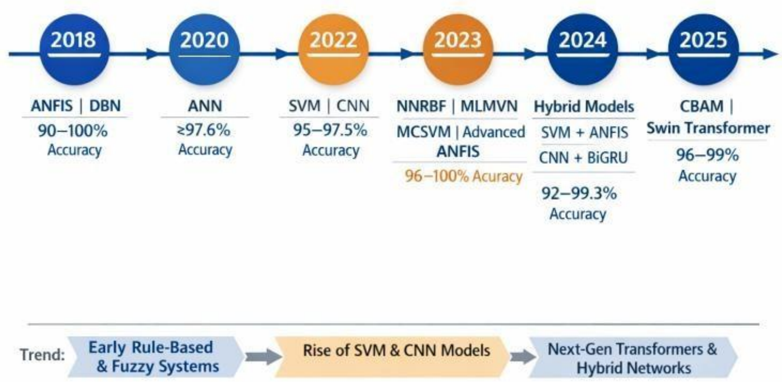


Figure 6: AI methods in fault detection over time

Deep Belief Network

Deep Belief Network (DBN) refers to a kind of deep learning architecture based on the generation principle made up of several Restricted Boltzmann Machines (RBM) layers. DBN allows both unsupervised pre-training and supervised fine-tuning [32]. A restricted Boltzmann machine refers to a kind of artificial neural network with stochastic nature. It is used to learn the probability distribution of the dataset provided. Given that the visible layer has *m* units while the hidden layer has *n* units, the energy function for a typical RBM can be defined as:

$$\boldsymbol{\varepsilon(v,h,\vartheta) = \Sigma(i=1 \text{ to } n)\ \Sigma(j=1 \text{ to } m)\ \omega_{ij} h_i v_j - \Sigma(j=1 \text{ to } m)\ a_j v_j - \Sigma(i=1 \text{ to } n)\ b_i h_i} \qquad (5)$$

Here, vi represents the visible unit whereas hj indicates the hidden unit. wij denotes the weight associated with the connection between the *i*th visible unit and the *j*th hidden unit. In addition, ai and bj are biases of the visible and hidden layers respectively. The results in Table 2 indicate that DBN achieves the highest recognition accuracy across all fault categories, consistent with recent studies demonstrating the effectiveness of deep learning for cable fault identification and localization in complex power systems.

Table 2: Comparison of average cable fault recognition rates (%) for different classification methods

Fault Type	DBN	BP	SVM	ACLLN
Ground fault	97.8	85.4	96.1	95.4
Short circuit fault	96.7	84.2	93.5	92.4
Open circuit fault	98.9	90.3	95.2	94.5
Average	**97.8**	**86.6**	**94.9**	**94.1**

In this equation, *dk* denotes the dimension of the key vectors. Scaling by $\frac{1}{\sqrt{dk}}$ stabilises gradient updates during training.

2.12 Convolution Neural Network

Hierarchical feature learning in CNNs relies on local connectivity, parameter sharing, and spatial down sampling. The data samples are first processed using filter-based operations to generate basic features including edges and texture patterns. Normally, the process for computing a single convolutional layer with one channel as an input is shown below:

$$y_{i,j} = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} x_{i+m,\, j+n} W_{m,\, n} + b \qquad (6)$$

2.13 Graph Convolutional Network

The graph convolutional network (GCN) refers to a deep neural architecture which can handle graph data. The main intuition behind it lies in joint modeling of the topological structure of the graph and the features associated with the nodes in order to facilitate efficient in-formation diffusion in the graph domain. Starting with the adjacency matrix and the feature matrix of nodes, one may leverage the notion of convolution in a non-Euclidean space through either spectral or spatial approaches, with the following update equation for a common layer [33]:

$$\mathbf{H(l+1) = \sigma\, \tilde{D}(-1/2)\, \tilde{A}\, \tilde{D}(-1/2)\, H(l)\, W(l)} \qquad \mathbf{(7)}$$

where σ represents the activation function, $\tilde{A} = A + I$ is the modified adjacency matrix, $\tilde{D}$ represents the corresponding degree matrix, and $H(l)$ and $W(l)$ represent the representation of nodes and the learnable weight matrix of the *l*th layer, respectively. Normalization helps in aggregating features consistently for nodes having varying degrees. By adding many layers, GCN helps each node aggregate data from its *k*-hop neighbour nodes, thus forming a uniform representation for the structure as well as node data. In a power system, GCN can map buses as graph nodes, and transmission/cable connections as edges. By combining node features with network topology, they are able to capture structural dependencies and fault-related interactions effectively during cable fault analysis. Table 3 presents the best-performing AI methods for different fault types.

3. NUMERICAL MODELING AND AI-BASED DIAGNOSIS OF CONTAMINATED XLPE CABLES

This section outlines the significance of XLPE cable reliability in high-voltage power systems, explains how contaminants affect electric-field distribution and insulation performance, and motivates the use of AI-based techniques for automated fault detection and localization.

3.1 Cable Geometry and Material Definition

The study involves an analysis of a 400 kV, single core, 2500 mm2 EHV AC underground power cable presented in Figure 8 below. The cable consists of four principal layers: the conductor, inner and outer semiconducting screens, XLPE insulation, and metallic sheath. The extruded XLPE insulation is designed to allow a maximum continuous conductor operating temperature of 90 ◦C. Both healthy and contaminated cable configurations are examined to evaluate the influence of embedded contaminant particles on electric-field distribution and stress enhancement. The cable specifications and the thickness of each layer are summarized in Table 4.

3.2 Contaminant Modeling

A contamination particle model is assumed as being spherical in shape having a radius R. Contaminants having a radius of 40 μm will be taken for investigation into effects of particle radius on electric stress concentration. To assess the influence of electrical properties, four contaminant materials are analyzed: sulphur, selenium, phosphorus, and silicon. These materials are selected because their permittivity and conductivity differ significantly, which is expected to produce distinct field-distortion patterns within the XLPE insulation. Two contaminant locations are studied. In the first case, the contaminant is placed in the insulation region at a distance of 9 mm from the inner semiconducting screen. In the second case, the particle is positioned at the center of the conductor shield. This arrangement enables com-parison of contaminant-induced stress behavior in both the insulation and shield regions.

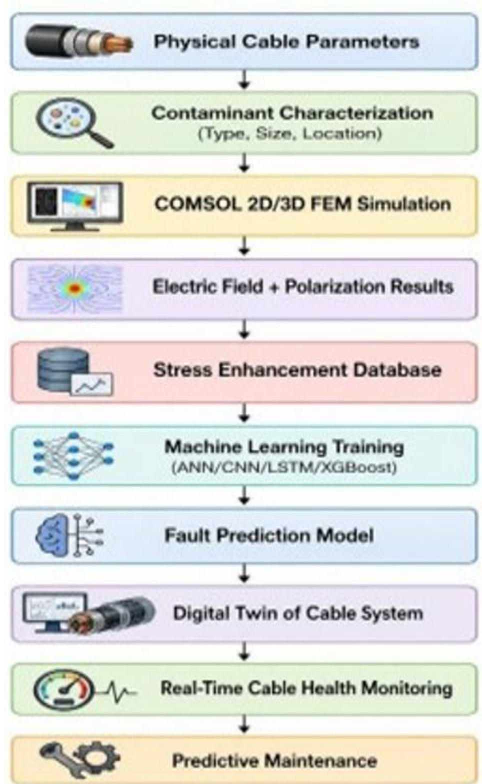


Figure 7: AI-Based Diagnosis of Contaminated XLPE Cables

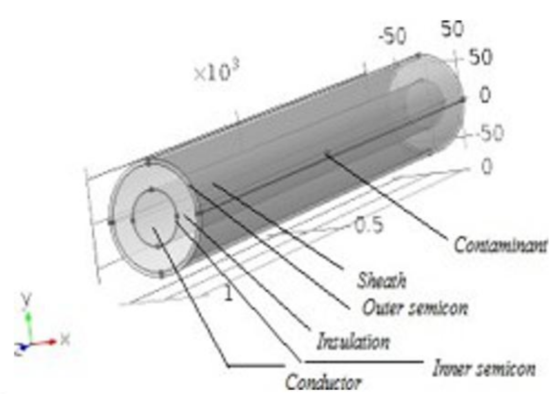


Figure 8: Structure of the 400 kV cable with a contaminant

Table 3: Accuracy of AI/ML Models Across Different Fault Types

Fault Type	ANN	SVM	ANFIS	NNRBF	CNN	BiGRU-ResNet	Transformer
High Impedance Fault (HIF)	99–100%	99–100%	99–100%	99–100%	–	–	–
Low Impedance Fault (LIF)	97–99%	–	97–99%	–	–	97–99%	97–99%
Single Line-to-Ground Fault (SLGF)	–	98.9%	–	–	98.9%	99.3%	–
Thermal Fault	>96%	–	–	–	–	–	–
Discharge Fault	–	–	–	–	–	96.3%	–
Insulation Layer Damage	–	–	97.5%	–	–	–	–
Multi-Line Faults (LG, LL, LLG, LLLG)	98.8%	–	–	–	97.8%	–	–
Incipient Faults	–	–	–	>90%	–	–	>90%

Table 4: Thickness (T) value for each layer

Description	Particulars	T (mm)
Conductor diameter	Copper	63.5
Conductor screen	Semi-conducting thermosetting compound	1.7
Insulation	Cross-linked polyethylene	27
Insulation screen	Semi-conducting thermosetting compound	2.2
Metallic sheath	Cu-Te lead alloy	2.9
Over sheath	Black HDPE compound	6.0

3.3 Pulse-Voltage Stress Characteristics

A 10 kV pulse voltage with a pulse width of 3 ms is ap-plied to the conductor, while the metallic sheath is maintained at zero potential. The waveform includes both rising and decaying portions, allowing transient stress response to be evaluated under abnormal voltage excitation is shown in Figure 9.

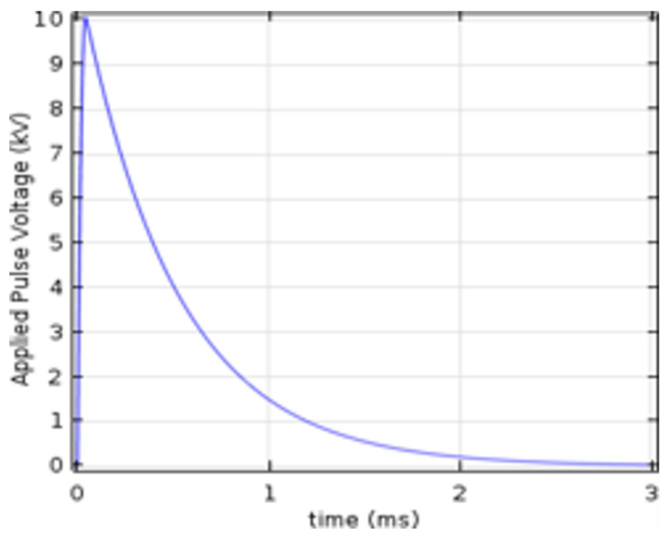


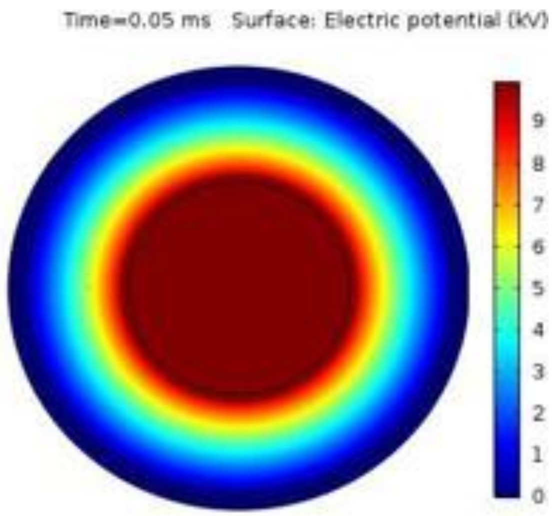
Figure 9: Applied Pulse voltage

4. AI-BASED FAULT DETEC-TION AND LOCALIZATION

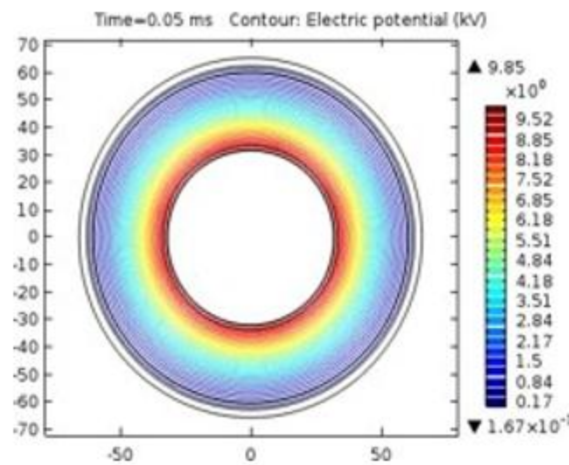
3.4 Physics-based Feature Extraction

The simulated electric potential, electric field, and polarization distributions serve as physics-based features for artificial intelligence-based fault diagnosis. Since contaminant type, size, and location produce distinct field-distortion patterns, these quantities can be used as dis-criminative inputs for classification or localization models. The simulation results can be integrated into a ma-chine learning or deep learning pipeline to identify contaminant conditions automatically. For example, a convolutional neural network can be trained using electric-field contour images, while a hybrid deep learning model can combine spatial and numerical features for improved fault classification.

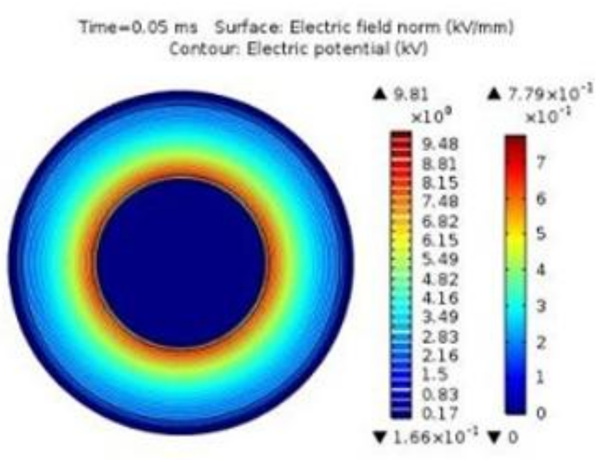
The obtained results are presented as a color-coded surface model, illustrating the variation hierarchy of the corresponding parameters, as shown in Figure 10. These simulation outputs can also be used as input data for AI-based fault detection and localization, where the spatial patterns of electric potential, electric field, and polarization serve as discriminative features for identifying contaminant-induced stress enhancement in XLPE insulation. In this section, contaminants located within the XLPE insulation region are investigated, and the corresponding results are presented. Compared with the 2D representation, the 3D model more accurately reflects practical cable conditions. Accordingly, the contaminant was placed at coordinates x = 40 mm, y = 0 mm, and z = 10 mm, centered along the cable's longitudinal axis. Figure 11 illustrates the three-dimensional electric-field distribution around a 40 μm contaminant during both the rising and decaying portions of the applied pulse volt-age. As expected, the local electric field is strongly influenced by the electrical conductivity of the contaminant. The results show that sulphur and phosphorus contaminants reduce the electric-field intensity, whereas silicon and selenium contaminants produce higher electric-field values. In addition, the electric-field contour associated with sulphur exhibits less sensitivity to spatial variation than that of phosphorus. These distinct field-distortion patterns are highly valuable for AI-based fault diagnosis, as they provide discriminative physical features that can be used to train machine learning or deep learning models for contaminant classification and localization in XLPE insulation.



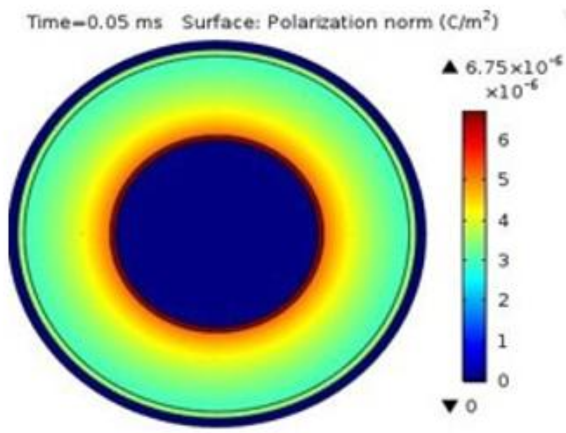
(a) Surface plot of electric potential in XLPE cable



(b) Contour plot of electric potential

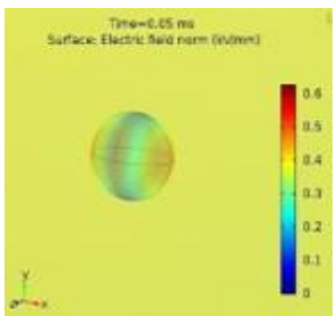


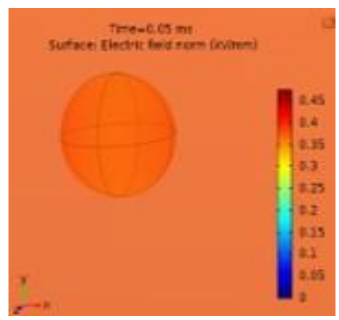
(c) Surface plot of electric field distribution in XLPE cable



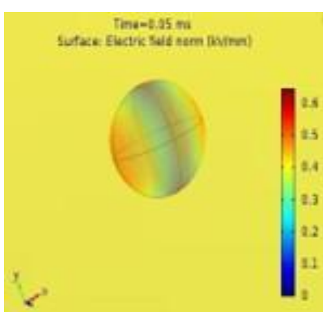
(d) Surface plot of polarization in XLPE cable

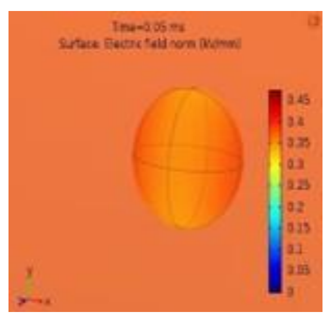
Figure 10: Simulation results of XLPE cable: (a) Sur-face plot of electric potential in XLPE cable, (b) Contour plot of electric potential, (c) Surface plot of electric field distribution in XLPE cable, and (d) Surface plot of polarization in XLPE cable.



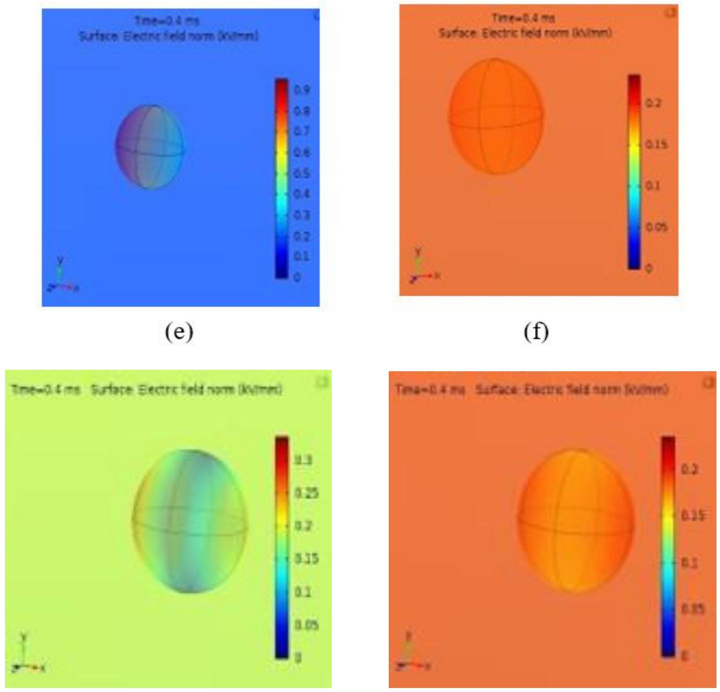


(a) (b)





(c) (d)



(e) (f)

(g) (h)

Figure 11: Effect of electric field distribution on 3D spherical Contaminant (a,e) silicon (b,f) sulphur (c,g)selenium (d,h) phosphorous in a spatial direction of 40 µm dimension, a-d displays rising part, e-h shows decaying part of pulse voltage.

5. PERFORMANCE ASSESS-MENT OF THE PROPOSED INTELLIGENT CABLE DI-AGNOSTIC SYSTEM

3.5 Feature Extraction

Feature extraction is performed to obtain the most in-formative parameters associated with cable insulation degradation and fault development. The extracted features include maximum electric field strength, average electric field, electric potential distribution, polarization magnitude, stress enhancement factor, and transient response characteristics under pulse voltage excitation. Statistical indicators such as mean, maximum, minimum, standard deviation, and peak values are also calculated. These features effectively characterize the influence of contaminants on the electrical behavior of XLPE insulation and serve as inputs to the artificial intelligence models for fault detection and localization.

3.6 Training and Testing Procedure

Prior to training, the dataset is normalized to eliminate scale variations among the extracted features. The entire data is split into three partitions where 70% data is assigned to training, 15% data to validation, and remaining 15% data to test data set. Training data set is used to train the relationship between condition param-eter values of the cables and fault categories. On the other hand, validation data set is used to tune hyperparameters of the selected algorithm and avoid overfitting problem. Lastly, test data set is employed to test the model performance in terms of accuracy. Different ma-chine learning approaches such as ANN, CNN, LSTM, and XGBoost are considered, evaluated and compared to identify the most suitable framework for intelligent cable diagnostics.

3.7 Validation Metrics

The performance of the proposed fault detection and localization framework is evaluated using standard classification and regression metrics. The effectiveness of the classification is measured by the parameters such as accuracy, precision, recall, and F1 score whereas for localization, the evaluation metrics include mean absolute error, root mean squared error, and percentage of localization error. These measurements give an overall idea of the effectiveness of the proposed model in detecting the fault location. The validation process ensures the reliability and robustness of the proposed diagnostic framework under varying contaminant conditions.

3.8 Comparative Analysis and Research Gap Analysis

The proposed simulation-assisted AI framework is com-pared with existing fault diagnosis techniques reported in the literature. Conventional analytical and finite element approaches primarily focus on electric field analysis and defect characterization without intelligent fault prediction capabilities. Recent machine learning and deep learning techniques have improved fault classification accuracy; however, most studies do not simultaneously consider contaminant material properties, particle size variation, pulse voltage stress, and fault localization. The suggested methodology allows for thorough fault diagnosis and localization by combining sophisticated AI algorithms with high-fidelity COM-SOL simulations. For predictive maintenance of EHV XLPE underground cable systems, this integrated approach offers increased diagnostic accuracy, better localization performance, and more applicability. The effectiveness and superiority of the suggested simulation-assisted AI frame-work for precise fault identification, classification, and localization in EHV XLPE underground cable systems are finally demonstrated by comparing the obtained results with current methods documented in the literature. The robustness, dependability, and usefulness of the suggested intelligent diagnostic system for condition monitoring and predictive maintenance of power cable networks are guaranteed by this validation technique.

The suggested simulation system provides a structured dataset for AI-based fault diagnosis and localization while capturing contaminant induced stress augmentation in XLPE insulation. In this sense, the numerical model functions as a basis for creating physics-informed diagnostic algorithms in addition to being a tool for electrostatic analysis. A dependable method for converting simulation-derived electrical characteristics into an intelligent fault diagnosis platform is established by the suggested validation framework. The suggested solution makes it easier to precisely identify and locate insulation flaws caused by contamination particles by combining highly accurate finite element modeling with artificial intelligence algorithms. This enhances the dependability and security of subterranean power cables.

Due to the lack of contaminant and defect modeling, these approaches fault detection accuracy was restricted to about 70–80% and their localization errors exceeded 10%, despite the fact that they offered fundamental in-sights into insulation behavior. Electric stress analysis based on the finite element method (FEM) became a po-tent tool for researching insulation performance between 2005 and 2010. Through thorough numerical simulations, these techniques decreased localization errors to 8–10% and increased fault detection accuracy to roughly 80–85%. Nevertheless, the evaluations were mostly limited to static operating settings and did not take intelligent fault diagnostics or transient stressors into ac-count. Partial discharge (PD) analysis became a popular method for evaluating insulation deterioration in subterranean cables between 2010 and 2015. Fault detection accuracy ranged from 85–90% with localization errors between 5–8%, according to experimental validation investigations. PD based methods required com-plex measurement tools and a large testing infrastructure, even with better diagnostic capabilities. Artificial Neural Network (ANN) based fault diagnosis systems were the first to use artificial intelligence between 2015 and 2018. By learning patterns from electrical characteristics, these models were able to attain detection accuracies of 92–97% and localization errors of 4–6%. However, the caliber of training datasets and manually created features had a significant impact on their performance. Support Vector Machine (SVM) classifiers and wavelet-based feature extraction approaches were then used in 2018-2020 to further improve fault identification accuracy to 90–95% while lowering localization errors to 3–5%. However, feature selection and parameter tuning continued to have an impact on these methods efficacy.

Diagnostic performance was greatly enhanced by the quick development of deep learning between 2020 and 2024. Because Convolutional Neural Networks (CNNs) can automatically extract discriminative features from complex datasets, they have achieved fault detection ac-curacies of 95–98% with localization errors between2–4%. Similar to this, Long Short-Term Memory (LSTM) networks showed localization errors of 2–3% and accuracies of 94–98%, which makes them especially well-suited for the analysis of time-varying electrical signals. By combining the benefits of temporal and spatial feature learning, hybrid CNN-LSTM architectures achieved ac-curacies of 97–99% with localization errors as low as 1–2%. Recent developments from 2024 to 2025 have focused on attention-based deep learning frameworks capable of real-time fault diagnosis. These advanced models report fault detection accuracies approaching 99% with localization errors below 1.5%. However, their implementation often requires substantial computational resources and large-scale datasets. Table 5 presents the literature review and research gap analysis of existing cable fault detection and localization techniques.

6. CONCLUSION

This paper presented a physics-informed artificial intelligence framework for fault detection and localization in contaminated XLPE underground power cables by integrating comprehensive literature analysis with finite element modelling. A high-voltage XLPE underground cable model was developed using COMSOL Multiphysics to investigate the influence of different contaminant materials and their locations on the electrical behaviour of cable insulation under pulse voltage excitation. The simulation results demonstrated that contaminant characteristics significantly influence the distributions of electric potential, electric field intensity, and polarization within the insulation system. These physics-based electrical characteristics provide valuable information for supporting future AI-assisted fault diagnosis and localization.

The proposed framework establishes a systematic approach for integrating physics-based simulation with artificial intelligence concepts to facilitate intelligent condition monitoring and predictive maintenance of under-ground cable systems. By identifying meaningful electrical features associated with contaminant-induced insulation degradation, this work provides a practical foundation for the future development of reliable AI-driven diagnostic tools for high-voltage underground power net-works.

Future work will focus on experimental validation of the proposed framework, development of AI models using simulation and measured data, and comprehensive performance evaluation under practical operating conditions. The integration of physics-informed modelling with advanced artificial intelligence techniques is expected to contribute towards more accurate, reliable, and intelligent fault diagnosis for next-generation under-ground power cable systems.

Table 5: Literature Review and Research Gap Analysis of Existing Cable Fault Detection and Localization Techniques (Part I: 2011–2018)

Year	**Author(s)**	**Cable Methodology Type**	**Key Findings**	**Limitations**	**Research Gap Ad-dressed by Proposed Work**
2011	Zhou et al.	XLPE COMSOL FEM	Electric field enhancement around voids	Limited defect types; multiple contaminants not studied	Need fault location estimation
2013	Dissado et al.	Polymer Polarization Insulation Analysis	Polarization linked to insulation degradation	No localization capability	Deep learning not employed
2014	Wang et al.	Underground PD Pattern Cable Recognition	Electrical treeing defect classification	Small datasets; single defect scenario	Multiple contaminants absent

2015	Chen et al.	XLPE Analysis	Defects initiate electrical trees	Single defect scenario; contaminants absent	—
2016	Li et al.	HV Cable FEM + Experimental Validation	Improved field prediction accuracy	Static operating conditions; pulse stress not considered	Need advanced feature extraction
2017	Zhang et al.	XLPE ANN-based Fault Detection	Good fault classification accuracy	Limited features	—
2018	Kumar et al.	Underground Wavelet + Cable SVM	Effective fault detection	Localization accuracy low	Distance estimation required

Table 6: Literature Review and Research Gap Analysis of Existing Cable Fault Detection and Localization Techniques (Part II: 2019–2025)

Year	Author(s)	Cable Type	Methodology	Key Findings	Limitations	Research Gap Addressed by Proposed Work
2019	Zhao et al.	XLPE	Deep Learning (CNN)	Improved PD classification	No physical simulation support	Physics-informed AI needed
2020	Singh et al.	Power Cable	LSTM Networks	Time-series fault prediction	No contaminant characterization	Need contaminant-aware models
2021	Ahmed et al.	EHV Cable	FEM-Based Insulation Assessment	Field enhancement quantified	Only spherical defects; different contaminant materials absent	—
2022	Kumar et al.	Underground Cable	CNN-LSTM Hybrid	Improved fault diagnosis	No localization module	Need integrated localization
2023	Xu et al.	HVDC Cable	AI-Assisted Condition Monitoring	Real-time monitoring achieved	Focus on HVDC only; limited HVAC XLPE studies	Need comprehensive studies
2024	Recent Research	XLPE Cable	Physics-Informed ML	Better prediction reliability	Predictive contaminant database; high computational cost	Need comprehensive contaminant dataset
2025	Emerging Studies	Smart Grid Cables	Digital Twin + AI	Predictive maintenance enabled	Simplified computational cost	Deployable model needed

REFERENCES

1. Tamil Nadu Generation and Distribution Corpo-ration Limited, 'Tangedco Disaster Management Plan', August 2017, pp. 1–105.
2. Dondi, P.; Bayoumi, D.; Haederli, C.; Julian, D.; Suter, M. Network integration of distributed power generation. *J. Power Sources* 2002, 106, 1–9.

3. Dehghanian, P.; Aslan, S.; Dehghanian, P. Maintaining Electric System Safety Through an Enhanced Network Resilience. *IEEE Trans. Ind. Appl.* 2018, 54, 4927–4937.
4. Choi, M.S.; Lee, S.J.; Lim, S.I.; Lee, D.S.; Yang, X. A Direct Three-Phase Circuit Analysis-Based Fault Location for Line-to-Line Fault. *IEEE Trans. Power Deliv.* 2007, 22, 2541–2547.
5. J-O Boström, J., O., Campus, A., et al., 'Reliable HV & EHV XLPE cables', Session 2002, CIGRE.
6. Campus. AD, Bostrom JO, Hampton RN et al., 'Critical issues for the HV & EHV XLPE cables of today and tomorrow', pp. 25–26. A.4.1.
7. Karasin Palirantalahaye, A.N.P. *Travelling Wave Based DC Line Fault Location in VSC HVDC Systems*; University of Manitoba: Winnipeg, MB, Canada, 2023.
8. Hassan, H.A.A.; Grainger, B.M.; McDermott, T.E.; Reed, G.F. Fault location identification of a hybrid HVDC-VSC system combining cable and overhead line segments using transient data. In *Proceedings of the 2019 IEEE PES Transmission and Distribution Conference and Exposition (T&D)*, Denver, CO, USA, 16–19 April 2019; pp. 1–8.
9. Verrax, P.; Algerie, N.; Bertiato, A.; Kieffer, M.; Raiser, B. Low-complexity graph-based traveling wave models for HVDC grids with broad transmission lines. *Energies* 2022, 15(9), 3370.
10. Shi, S.; Hu, Z.; Ma, Z.; Dong, X. Travelling wave-based identification of sub-sheath condition of leaders in power distribution systems. *IET Core. Transm. Distrib.* 2018, 12, 1067–1073.
11. Tan, Y.; Zhou, Y.; Zhao, X.; Thaichon, K.; Sievans, L.S.; Li. A high-efficiency portable system for insulation condition assessment of three-core hybrid cables using traveling wave detection and localization. *IET Core. Transm. Distrib.* 2023, 17(5), 1234–1251.
12. Hassan-and, H.; Parastar, A.; Arshadi, B.; Za-mani, M.R.; Rouhani, A.S. A comparison between S-transform and CWT for fault location in under-ground cables with the distribution networks in Proceedings of the 2016 2nd Conference on Power Distribution Networks Conference (EPDC), Karaj, Iran, 26–27 April 2016; pp. 70–71.
13. Ihasanviet, S.; Ling, L.; Zhang, Y. Design and location algorithm based on online distributed traveling wave for HV power cables. *IEEE Trans. Power De-liv.* 2015, 30, 1325–1333.
14. Cifuentes, N.; Pal, B.C. A New Approach to the Fault Location Problem: Using the Fault's Transient Intermediate Frequency. *IEEE Trans. Power Deliv.* 2016, 31, 1–12. Song, G.; Yan, J.; Chang, Z.; Zhang, C.; Gao, X. A Frequency-Domain Fault Lo-cation Method for Underground Cables in MVDC Systems. *IEEE Trans. Power Deliv.* 2024, 73, 1–12.
15. Bretas, A.S.; Herrera-Orozco, A.R.; Orozco-Lievano, C.A.; Jurado, L.L.; Mora-Flórez, J. Incipient fault location method for underground ca-bles using state-space identification approach. *Int. Trans. Electr. Energy Syst.* 2017, 27, e2658.
16. Mohsen Abdolahi et al., "Intelligent condition mon-itoring of power cables using advanced machine learning models", *Results in Engineering*, Vol. 29, 2026, 108371.
17. Patrick O'Halloran, "The evolution of medium volt-age power cables up to 36 kV", 24th AMEU Technical Convention, 2013, pp. 43–52.
18. P. Selvamany and G. S. Varadarajan, "Exploration of cross-linked polyethylene material morphological structure and its dielectric properties studied by the effect of pulse voltage," *2019 IEEE 4th International Conference on Condition Assessment Techniques in Electrical Systems (CATCON)*, Chennai, India, 2019, pp. 1–5, doi: 10.1109/CAT-CON47128. 2019.CN0069.
19. Morteza Shamsoddini et al., "An explainable frame-work for partial discharge detection in power cables through the integration of rough set theory and deep learning", *Electric Power Systems Research*, Vol. 250, 112155, 2026.
20. Peng, Xiaosheng, Yang, Fan, Wang, Ganjun, Wu, Yijang, Li, Lee, Li, Zhaohui, Bhatti, Ashfaque Ahmed, Zhou, Chengke, Hepburn, Donald M, Reid, Alistair J, Judd, Martin D and Siew, W H 2019. A convolutional neural network based deep learning methodology for recognition of partial discharge patterns from high-voltage cables. *IEEE Transactions on Power Delivery* 34 (4), pp. 1460–1469.
21. Mohamed H. Saad, Sherief Hashima, Ahmed I. Omar et al., "Deep learning approach for cable partial discharge pattern identification", *Electrical Engineering*, Issue 2/2025.
22. Dehghani, F.; Khodnia, F.; Dehghan, E., "Fault location in unbalanced power distribution feeders with distributed generation using neural networks", *CIRED 2017*, pp. 1134–1137.
23. Farias, P.E.; de Morais, A.P.; Rossini, J.P.; Car-doso, G. Non-linear high impedance fault distance estimation in power distribution systems: A continually online-trained neural network approach. *Electrical Power Systems Research*, 2018, 157, 20–28.
24. Hamidi, S.M.; Ameli, A.; Ghafouri, M.; Lopes, F.V. A learning-based framework for locating faults on power grid lines based on distortion of traveling waves. *IEEE Transactions on Instrumentation and Measurement*, 2022, 71, 1–15.
25. Jayasinghe, J.A.R.R.; Malindi, J.H.E.; Rajapaksha, R.M.A.M.; Logeeshan, V.; Wanigasekara, C. Classification and localization of faults in AC micro-grids through discrete wavelet transform and artificial neural networks. *IEEE Open Access Journal of Power and Energy*, 2024, 11, 303–313.
26. Razmi, P.; Pashaei, M.; Karimi, M.; Kauhaniemi, K.; Simoes, M.G. Data-Driven Intermittent Earth Fault Detection in Compensated and Isolated MV Networks. In *Proceedings of the 2024 International Workshop on Artificial Intelligence and Machine Learning for Energy Transformation (AIE)*, Vaasa, Finland, 20–22 May 2024; pp. 1–6.
27. Gashteroodkhani, O.A.; Majidi, M.; Etezadi-Amoli, M.; Nematollahi, A.F.; Vahidi, B. A hybrid SVM–TT transform-based method for fault location in hybrid transmission lines with underground cables. *Electric Power Systems Research*, 2019, 170, 205–214.

28. Rui, L.; Nan, P.; Zhi, Y.; Zare, F. A novel single-phase-to-earth fault location method for distribution network based on zero-sequence components distribution characteristics. *International Journal of Electrical Power & Energy Systems*, 2018, 102, 11–22.
29. Tian, H.Y.; Wang, J.X.; Zhang, W.K.; Liu, H et al., "110 kV Power cable External Disturbance Optical Fiber Sensing Detection and Identification Method Based on ResNext and attention mechanism," *IEEE Trans. Instrum. Measu.* 2025, 74, 1–11.
30. Peng, L.; Wang, S.; et al., "Intelligent detection technology of potential grounding trouble of OPGW cable in substation based on attention model", *Opt. Fiber Technol.* 2025, 93, 104151.
31. Chen, Y.S.; Zhao, X.; Jia, X.P., "Spectral-Spatial Classification of Hyperspectral Data Based on Deep Belief Network", *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 2015, 8, pp. 2381–2392.
32. Ma, X.P.; Zhen, W.X.; Ren, H.D.; et al., "A Method for fault localization in Distribution Networks with High proportions of Distributed Generation Based on Graph Convolutional Networks," *Energies* 2024, 17, 5758.
33. P. Selvamany and G. S. Varadarajan, "Exploration of cross-linked polyethylene material morphological structure and its dielectric properties studied by the effect of pulse voltage," *2019 IEEE 4th International Conference on Condition Assessment Techniques in Electrical Systems (CATCON)*, Chennai, India, 2019, pp. 1–5, doi: 10.1109/CAT-CON47128. 2019.CN0069.