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AI-Based Predictive Maintenance for Underground Power Cables Using Deep Learning

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Abstract - *In this paper, we present the use of Artificial Intelligence (AI) and Deep Learning (DL) for predicting maintenance of underground power cables. Traditional diagnostic methods, like Partial Discharge (PD) analysis, are common for finding insulation defects. However, these methods rely heavily on experts' interpretations, making them slow and less effective in real-time situations. To tackle these problems, we use advanced DL models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) models. These models automatically extract features from PD waveforms and Phase Resolved Partial Discharge (PRPD) patterns. They show higher accuracy, can adapt to noisy signals, and generalize better than traditional methods. This allows for better classification of fault types and more accurate estimation of defect locations. Field trials and studies using reflectometry underline their ability to cut downtime, improve maintenance schedules, and prolong the lifespan of power assets. Overall, using DL in PD diagnostics is a significant shift from reactive to predictive maintenance, helping to support reliable and cost-efficient underground power systems.*

Key Words: Artificial Intelligence, Deep Learning, Predictive Maintenance, Underground Power Cables, Partial Discharge, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Condition Monitoring, Fault Diagnosis.

1.INTRODUCTION

Underground power cables are essential for modern urban and industrial power distribution systems. They offer aesthetic, safety, and space-saving benefits compared to overhead lines. Despite these advantages, cable networks can develop hidden insulation defects over time due to manufacturing flaws, mechanical stress, moisture ingress, or electrical aging. These defects often show up as partial discharges (PD), which are transient localized ionization events that can lead to severe insulation failures. Therefore, finding PD activity early and accurately is crucial for preventing unplanned outages, cutting repair costs, and prolonging asset life.

Traditional PD diagnostic methods, such as time-domain pulse analysis, phase-resolved partial discharge (PRPD) patterns, and reflectometry, have been effective in labs and real-world scenarios. However, they usually need expert interpretation, manual feature extraction, and extensive post-processing. These drawbacks limit scalability and real-time use, especially in large-scale distribution networks that require quick, automated decision-making. Recent studies have applied classical machine learning to PD classification, but these models are still sensitive to noise, data imbalance, and manually designed features.

This paper explores how to integrate deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, into a framework for predictive maintenance of underground cables. By learning hierarchical representations from raw PD waveforms and PRPD images, DL methods can lessen reliance on manual preprocessing, increase robustness against noisy environments, and generalize across various defect types. We present a methodology for data acquisition, preprocessing, model design, and evaluation, and we validate our approach using reflectometry-based localization and representative field-like datasets.

1.1 Problem Statement

In this paper, we tackle the important issue of localized insulation defects in underground power cables. These defects lead to partial discharges (PD), which often happen before costly, unplanned failures. Traditional PD diagnostics rely on expert interpretation and manual feature extraction. This limits scalability and reliability in noisy, real-world conditions.

Although deep learning (DL) methods have shown promise for automated PD classification, practical use is still held back by a lack of labeled field data, class imbalance, sensor quality issues, and placement sensitivity. There are also challenges with interpretability and inconsistent performance across different cable types and environments.

This work presents a complete framework that merges DL-based PD detection and classification with reflectometry-based localization and data enhancement strategies. Our approach aims to improve early fault detection accuracy and provide reliable spatial localization for targeted repairs. It reduces the need for human experts and increases resilience to noise and changing cable conditions, all while keeping computational and explainability concerns in mind.

1.2 Objectives

In this paper, the goals are to examine the role of partial discharge in insulation breakdown and identify shortcomings in traditional PD methods. We aim to design and implement a practical data acquisition plan that captures time domain PD waveforms and PRPD patterns in noisy field conditions. We will develop and compare deep learning models, including CNN, LSTM, and hybrid CNN LSTM, for automated PD detection and fault classification. Additionally, we will create data augmentation and preprocessing strategies to address class imbalance and enhance the model's ability to handle noise and different cable conditions. We will also integrate deep learning-based classification with reflectometry timing for accurate spatial localization and measure localization error. We plan to evaluate model performance using standard classification and localization metrics and test how well it works across various cable types and sensing setups. Finally, we will assess deployment feasibility by measuring computational latency and memory usage and exploring techniques to improve explainability and increase operator trust.

2. METHODOLOGY

In this paper, the methodology starts with gathering data using High Frequency Current Transformers (HFCT), Ultra High Frequency (UHF) sensors, and Transient Earth Voltage (TEV) sensors to capture Partial Discharge (PD) signals as time-domain waveforms and Phase Resolved Partial Discharge (PRPD) patterns. The collected signals go through preprocessing steps, including noise filtering, normalization, windowing, and generating spectrograms using Short-Time Fourier Transform (STFT). Data augmentation is also done to balance rare PD types.

For feature extraction and classification, Deep Neural Networks (DNNs) are used. Convolutional Neural Networks (CNNs) process spectrogram and PRPD images. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models analyze sequential waveforms. Hybrid CNN-LSTM structures manage multi-modal inputs. Training employs the Adam optimizer, dropout, class weighting, and early stopping to minimize overfitting. Generative Adversarial Networks (GANs) may be applied to expand datasets.

3. CLASSIFICATION OF PARTIAL DISCHARGE

Partial Discharge (PD) classification is vital for identifying the type and severity of insulation defects in underground cables. Traditional methods require manual feature extraction from PD waveforms or Phase Resolved Partial Discharge (PRPD) patterns. They then use statistical or machine learning classifiers like Support Vector Machines (SVMs) or Artificial Neural Networks (ANNs). These methods often face challenges with noisy signals, overlapping discharge sources, and scalability issues. Deep Learning (DL) addresses these problems by learning features directly from raw or pre-processed PD data.

Convolutional Neural Networks (CNNs) are commonly used to classify PRPD images and spectrograms created from Short-Time Fourier Transform (STFT) of PD signals. CNNs can automatically identify spatial patterns, such as intensity clusters and textures, which relate to different defect types like voids, corona, or surface discharges. Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) models, effectively classify PD when treated as time-series pulses. They capture temporal dependencies and repetitive discharge signatures. Hybrid CNN-LSTM models combine spatial and temporal learning, leading to higher accuracy in varying field conditions. Autoencoders (AEs) are also used for unsupervised feature learning. They compress PRPD or waveform data into low-dimensional representations before classification. Generative Adversarial Networks (GANs) help by generating synthetic PD signals, which balance datasets and enhance model robustness.

Comparative studies reveal that CNNs perform better for image-based PRPD classification, while LSTMs excel with noisy sequential waveforms. Hybrid models consistently outperform single models, achieving accuracy above 95% in experimental studies. These models not only classify PD types but also enable severity grading. This sets a foundation for predictive maintenance strategies in underground power cable networks.

3.1 Partial Discharge Pulse Waveform

The figure shows a typical partial discharge (PD) pulse voltage measured over time. The sharp spike near time zero indicates a sudden release of energy from localized dielectric breakdown in the cable insulation. The pulse reaches a maximum amplitude of 8.21 V and then quickly decays with damped oscillations before stabilizing close to zero. This waveform reflects the transient and high-frequency nature of PD activity. Its amplitude, polarity, and decay pattern are important indicators for identifying defect types and evaluating insulation condition in underground power cables.

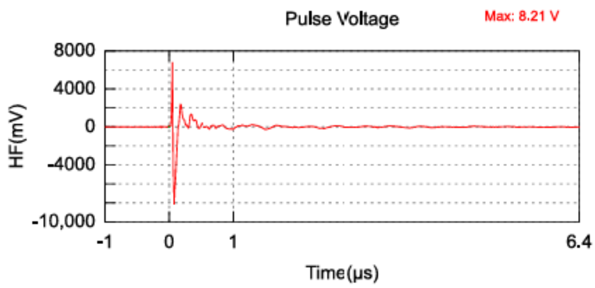

Fig -1: Partial Discharge waveform in time-domain.[2]

Such waveforms are essential for both traditional and AI-based diagnostic methods. In conventional analysis, features like peak amplitude, rise time, pulse width, and repetition rate are taken from these signals to evaluate the severity and type of defect. However, differences in noise levels, sensor placement, and cable conditions often make manual interpretation difficult. In deep learning frameworks, raw PD waveforms are fed directly into models like Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks, which automatically learn the temporal dependencies in the signal. This removes the need for extensive manual feature engineering and allows for higher classification accuracy in real-world operating conditions.

3.2 Convolutional Neural Network Architecture for Partial Discharge classification

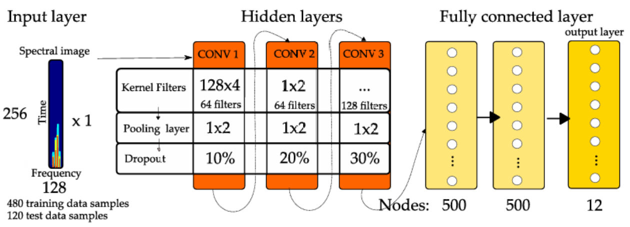

Fig -2: CNN structure proposed by used to classify PD spectrograms.[2]

The figure shows a Convolutional Neural Network (CNN) model created to classify partial discharge (PD) signals using spectral images as input. The input layer takes a two-dimensional spectral representation of PD data that measures 256 (time) × 128 (frequency). This layer includes a dataset of 480 training samples and 120 test samples. The hidden layers have three convolutional blocks: CONV 1, CONV 2, and CONV 3. Each block uses kernel filters of different sizes, followed by pooling layers that lower dimensionality and dropout layers set at 10%, 20%, and 30% to avoid overfitting. The convolutional layers learn more complex spatial and temporal features from the PD spectral images.

The features extracted then go to fully connected layers, which include two hidden layers with 500 nodes each, before reaching the output layer with 12 nodes. These nodes represent classification into 12 different PD types or categories. This feature learning structure allows the CNN to automatically recognize complex patterns in PD data. It provides greater accuracy and reliability compared to traditional machine learning methods that rely on manual feature extraction.

3.3 Comparison of PD Detection Methods

The table compares the performance of different Partial Discharge (PD) detection methods based on three main parameters: detection rate, recognition accuracy, and detection time cost. The Convolutional Neural Network (CNN) method shows the best performance, with a PD detection rate of 95.73%, recognition accuracy of 95.58%, and a reduced detection time of 12 seconds. This makes it a strong choice for real-time applications. The pulse current method has a similar detection rate of 95.36% but lower accuracy at 90.81%, and it takes more than 30 minutes, which makes it less practical for quick diagnostics. Ultrasonic detection has moderate accuracy at 85.73% but the lowest detection rate at 48.10%. This shows its limited effectiveness for PD classification, even though it has a faster time cost of about 5 minutes. The existing Transient Earth Voltage (TEV) method achieves a detection rate of 80.68% and recognition accuracy of 80.90%, with a time cost of around 10 minutes, but it still does not match the CNN-based detection. In summary, this comparison shows that CNN-based models provide higher accuracy and more reliable detection while significantly cutting down the time needed, proving their value for predictive maintenance of underground cables.

Table -1: Results comparison between CNN and traditional method.[2]

Methods	**PD Detection Rate (%)**	**Recognition Accuracy (%)**	**Detection Time Cost**
CNN	95.73	95.58	12 sec
Pulse Current	95.36	90.81	More than 30 min
Ultrasonic	48.10	85.73	Approx. 5 min
Existing TEV	80.68	80.90	Approx. 10 min

4. PROS AND CONS

4.1 Pros

- Automated Feature Extraction: Deep learning removes the need for manual feature engineering, which lessens reliance on experts.
- High Accuracy: Models like CNN, LSTM, and hybrids reach 96 to 100% accuracy in PD classification, surpassing traditional methods.
- Scalability: These models can manage large real-time datasets and adjust to various cable systems and settings.
- Early Fault Prediction: They allow for predictive maintenance by spotting PD activity before failures occur, which enhances reliability and cuts downtime.

4.2 Cons

- High Data Requirement: It needs large amounts of labeled PD data, which is costly and takes a lot of time to gather.

- Computational Cost: Training deep networks requires powerful hardware, like GPU or TPU, and a lot of memory.
- Black Box Nature: The limited interpretability makes it harder for operators to understand decision-making.
- Generalization Limits: Models might not work well with different cable types unless they are retrained.
- Data Imbalance: Rare PD types can skew models unless they are carefully balanced.
- Sensor Dependence: Accuracy depends on the right sensor type, placement, and calibration. Poor data capture can lower performance.
- Noise Robustness: These models deal with complex, noisy, and overlapping PD signals more effectively than standard techniques.

5. CONCLUSION

The review shows that using Artificial Intelligence (AI) and Deep Learning (DL) for Partial Discharge (PD) diagnostics provides a new way for predictive maintenance of underground power cables. Traditional diagnostic methods are reliable but depend on manual interpretation. They also have slow response times and are affected by noise. In contrast, deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks significantly improve automated feature extraction, classification accuracy, and resistance to complex, noisy signals. Experimental results and comparisons show that DL-based methods achieve higher detection rates and reduce diagnostic time. This makes them suitable for real-time applications.

However, adopting DL in this field comes with challenges. High data needs, computational demands, limited interpretability, and reliance on sensor quality must be resolved for practical use in the field. Future work should aim to build large, balanced datasets, create explainable AI models to boost operator trust, and improve architectures for quicker, more efficient implementation. Combining these methods with reflectometry also enhances the potential by allowing for fault detection and precise localization, which supports targeted maintenance strategies.

In conclusion, using DL in PD diagnostics marks a shift from reactive to proactive cable maintenance. As data handling, model design, and explainability continue to improve, these methods could set a new standard for reliable, cost-effective, and smart monitoring of underground power infrastructure.

REFERENCES

[1] Steffen Ziegler, Member, IEEE, Shishir Shekhar, Senior Member, IEEE, Daniel Scherle, P.E., Member, IEEE, Malaquias Pena, Member, IEEE, “Deep Learning Signal Waveform Characterization of Partial Discharge for Underground Power Cable Conditions”, 2023, IEEE

[2] Sonia Barrios, David Buldain, María Paz Comech, Ian Gilbert and Iñaki Orue, “Partial Discharge Classification Using Deep Learning Methods—Survey of Recent Progress”, 2019, MDPI

[3] Matthew S. Mashikian, Life Fellow, IEEE, “Partial Discharge Location as a Diagnostic Tool for Power Cables”, 2000, IEEE

[4] IEEE 400 Guide for Field Testing and Evaluation of Insulation of Shielded Power Cable Systems Rated 5 kV and above, IEEE, Piscataway, NJ, Jun. 5, 2012

[5] Montanari, G.C.; Cavallini, A. Partial discharge diagnostics: from apparatus monitoring to smart grid assessment. IEEE Electr. Insul. Mag. 2013, 29, 8-17

[6] J. McBride, V. Harper, L. Coffeen, F. Stanley, H. Ng, "Examination and Location of PD Sites in Severely Aged Underground Distribution Cables", IEEE Transactions on Power Delivery., Vol. 9, No. 2, April 1994