Artificial Intelligence-Based Condition Monitoring and Predictive Maintenance of Medium Voltage Cables: An Integrated System Development Approach

Author(s): Kumar, Haresh; Shafiq, Muhammad; Kauhaniemi, Kimmo; Elmusrati, Mohammed

Title: Artificial Intelligence-Based Condition Monitoring and Predictive Maintenance of Medium Voltage Cables: An Integrated System Development Approach

Year: 2024

Version: Accepted manuscript

Please cite the original version:

Kumar, H., Shafiq, M., Kauhaniemi, K., & Elmusrati, M. (2024). Artificial Intelligence-Based Condition Monitoring and Predictive Maintenance of Medium Voltage Cables: An Integrated System Development Approach. In *2024 10th International Conference on Condition Monitoring and Diagnosis (CMD)*, 191-195. IEEE. https://doi.org/10.23919/CMD62064.2024.10766104

Artificial Intelligence-Based Condition Monitoring and Predictive Maintenance of Medium Voltage Cables: An Integrated System Development Approach

Haresh Kumar
School of Technology and Innovations
University of Vaasa
Vaasa, Finland
haresh.kumar@uwasa.fi

Muhammad Shafiq
Centre for Advanced Power System
Florida State University
Tallahassee, Florida, USA
ms22ds@fsu.edu

Kimmo Kauhaniemi
School of Technology and Innovations
University of Vaasa
Vaasa, Finland
Kimmo.Kauhaniemi@uwasa.fi

Mohammed Elmusrati
School of Technology and Innovations
University of Vaasa
Vaasa, Finland
moel@uwasa.fi

***Abstract*—In order to minimize power supply outages in electrical distribution systems, the reliable operation of medium-voltage (MV) cables is of paramount importance. These cables may experience unplanned downtime and failures, which can result in large financial losses and interruption of the processes. This study investigates the use of artificial intelligence (AI) in developing a system for condition monitoring and predictive maintenance of Medium Voltage (MV) cables. It uses historical data to train models for predicting potential cable failures, with the goal of increasing reliability and decreasing downtime. The study also investigates the effectiveness of machine learning (ML) algorithms in forecasting maintenance needs under various environmental conditions and factors. The findings suggest that ML can optimize MV cable maintenance strategies, resulting in increased efficiency and cost-effectiveness in electrical infrastructure management. Using cutting-edge technologies like sensors, data analytics, and ML, this paper proposes an integrated monitoring system development approach for MV cable predictive maintenance. The purpose of the proposed system is to improve the reliability of MV cable network by facilitating proactive maintenance strategies through timely insights into cable condition. This research provides useful insights for industry professionals, researchers, and policymakers who want to optimize maintenance strategies and ensure continuous power supply in modern electrical infrastructure.**

Keywords—MV cable, condition monitoring, AI, big data platform, maintenance strategies

I. INTRODUCTION

A medium-voltage (MV) network can include tens of thousands of assets and electrical devices, requiring demanding diagnostics and long-term monitoring under a variety of operating situations. It is difficult to effectively manage technical asset management when dealing with long-term incomplete and limited information about essential assets. To meet this difficulty, it is important to reduce the quantity of electrical equipment to a manageable size and limit the precision for individual equipment [1].

This work has been done as a part of “Smart Grid 2.0”-project funded by Business Finland with grant No. 1386/31/2022. The first author acknowledges Fortum and Neste Foundation for providing grant (grant reference No. 20220101) for this research work.

Paper-insulated cables and XLPE cables are examples of medium-voltage cables that have been deployed and utilized extensively for many years. Computer-aided measurement tools and sophisticated material analysis techniques have been used to study their aging and electrical breakdown mechanisms. Many failures of MV cables are caused by damage from excavation activities [1]. The deterioration of insulating system components, frequently brought on by stress factors including thermal, chemical, or electrical impacts, is one of the most frequent reasons of failure in electrical components. Partial Discharge (PD) activity causes the majority of electrical problems. If preventive maintenance is not carried out, PD activity damages and deteriorates the insulating system, ultimately leading to equipment failure. [2].

Maintenance procedures were traditionally carried out at predetermined intervals without taking the equipment's actual age and condition into consideration. Premature or delayed maintenance, neither of which effectively prevents failures, could result from this time-based strategy. Condition-Based Maintenance (CBM) strategies are being adopted by modern utilities. These strategies link maintenance activities with the real aging of electrical assets. PD analysis assists asset managers in optimizing maintenance plans based on the actual condition of electrical equipment by providing quantitative information on insulation deterioration, consequently reducing maintenance and replacement costs [2].

Predictive maintenance methods use artificial intelligence (AI) and machine learning (ML) techniques to extend the lifespan of electrical systems by anticipating when maintenance is most essential. These techniques lower maintenance costs both financially and in terms of time, particularly in situations where dependability and safety are critical [3]. The effectiveness of conventional ML algorithms for predictive maintenance can be assessed by producing data and testing them in real time environment. From time-based maintenance to condition-based solutions, machine learning algorithms can enhance component failure prediction accuracy [3].

Predictive maintenance generates massive amounts of data, which require big data platforms like Hadoop, Kafka, and Spark to handle. These platforms allow the deployment of AI-driven predictive maintenance systems by facilitating the effective storage, processing, and real-time analysis of data. Predictive maintenance with AI and big data platforms offers an innovative approach to manage MV cables in electrical distribution systems. For industry experts, researchers, and regulators looking to optimize electrical infrastructure management, this strategy offers considerable benefits by utilizing real-time data, predictive models, and advanced analytics to improve safety, reduce operating expenses, and increase dependability[4]. This study examines how AI and ML can be used to create predictive maintenance systems that can monitor the health of MV cables and predict any failures, improving the reliability and efficiency of power distribution networks.

The main contributions of this paper include the following:

- Development of an integrated system approach that can benefits from AI for condition monitoring and predictive maintenance of MV cables. Highlighting the potential of the integrated approach to improve the overall reliability and operational efficiency of MV cable systems in power distribution networks.
- Proposing the usage of big data platforms such as Hadoop, Kafka, and Spark to manage enormous amounts of data created during predictive maintenance. Facilitating effective data processing, real-time analysis, and storage to enable AI-driven predictive maintenance systems
- Systematically addressing data requirements, complexity, interpretability, regulatory compliance, and integration issues throughout predictive maintenance system development and implementation.

The structure of the paper is as follows: An overview of partial discharge in MV cables and maintenance strategies is provided in Section II. Section III gives an overview of artificial intelligence (AI), big data platforms, and predictive modeling. The system development approach is discussed in Section IV, and Section V concludes this paper.

II. Partial Discharge in MV cable and Maintenance strategies

A localized electrical discharge known as a partial discharge (PD) can happen inside the insulation of MV cables. PD may degrade the insulating material, causing the cable to eventually break. Early diagnosis of insulating issues requires careful observation of PD activity. The detection of PD by sophisticated sensors and diagnostic equipment yields important information for evaluating cable quality and pinpointing spots in need of maintenance [5]. While PD is a key indicator to assess the condition of MV power cables, continuous monitoring generates a considerable amount of data to analyze. PD signals are high frequency, requiring high frequency sensors and a suitable sampling rate, leading to large data sizes. Considering a Rogowski coil sensor with a frequency of 60.7 MHz, a sampling rate of 125 MS/s is needed [6]. Given the nature of PDs and the required analysis, PD pulses (with typical pulse widths of 0.1 µs to 0.5 µs) require 80.64 MB of data to be observed over one day. If 10 sensors are needed to monitor 10 terminations of the feeders in an MV cable network over a whole year, approximately 2060 GB of data needs to be processed. This highlights the significant amount of data to be dealt with for a real cable network.

In the industrial sector, maintenance expenditures make up between 15% and 60% of total operating expenses. Effective equipment maintenance is critical for discovering and resolving machine irregularities, which impact operational time and efficiency [7]. The three main categories of maintenance are as follows:

1. Reactive Maintenance: This kind of maintenance is only conducted in response to equipment failure, which results in direct expenses related to unplanned failures.
2. Preventive Maintenance: This strategy, which is carried out on a regular basis in accordance with a planned schedule, may result in needless maintenance procedures and related expenses.
3. Predictive Maintenance (PDM): PDM initiates repairs only when necessary or shortly before a breakdown occurs, eliminating interruptions to operation of equipment and lowering maintenance costs [7].

Table 1 illustrates the advantages and disadvantages of three distinct types of maintenance.

TABLE I. Types of maintenance [7], [8]

Type of Maintenance	**Advantages and Disadvantages**	
	Advantages	***Disadvantages***
Reactive Maintenance	Minimum staff is required, as well as minimum planning	-Very expensive -Employers at minimal risk -Random failures
Preventive Maintenance	-Less expensive maintenance than reactive maintenance -Minimize failures	-Needs time for planning -Repairs even in the absence of a defect
Predictive Maintenance	-Economical -Time-saving -Improve dependability and productivity	-First-time expenses are significant. -Employee education is necessary for data analysis.

PDM outperforms the others in terms of safety and maintenance costs. Conventional PDM systems require a deep comprehension of fault processes because they depend on physical models that describe failure modes based on fundamental concepts. However, when these physical models are not fully developed, it would be difficult for conventional PDM systems to describe failure modes [8]. Due to high accuracy in anomaly detection and prediction, ML techniques, in particular deep learning (DL) approaches, have attracted a lot of attention recently from both academia and industry [7].

III. AI, Big data platform and predictive modeling

In recent years, the combination of AI and Big Data platforms has transformed the field of predictive maintenance, particularly for MV cables. AI-driven prediction models are able to precisely predict future failures and maintenance requirements by utilizing massive volumes of data gathered from various sensors and monitoring devices [4]. In order to demonstrate how artificial intelligence and big data platforms work together to improve the efficiency and dependability of medium voltage cable networks, this section examines the technological basis of these technologies.

A. AI

In predictive maintenance, AI and ML are essential components that provide advanced methods to improve equipment dependability and operational effectiveness. For predictive maintenance applications, ML techniques are divided into four categories: supervised, unsupervised, semi-supervised, and reinforcement learning methods. Each has a specific purpose [5]. Table 2 illustrates the advantages and disadvantages of four categories of ML techniques.

TABLE II. TYPES OF ML MODELS [5]

Type of ML model	Advantages and Disadvantages	
	Advantages	*Disadvantages*
Supervised Learning	Reliable forecasts based on past failure data; effective with labeled data.	Getting independent labels takes a lot of time
Un-Supervised Learning	Can find trends and abnormalities in unlabeled data, lowering maintenance expenses	Lacking a clear measure of accuracy for assessment
Semi-Supervised Learning	It combines labeled and unlabeled data, which saves money and time.	Ensuring that data without labels does not conflict with data with labels
Reinforcement Learning	Learn from weakly labeled and vast unlabeled data in parallel.	High computation costs; challenges with convergence, particularly for big data sets

B. Big Data Platform

Robust big data platforms are necessary for the successful handling of various and huge amounts of data for implementing predictive maintenance systems in industrial environments, including power networks. Important issues and strategies consist of [4], [9]:

- **Difficulties with Data Acquisition:** Gathering data from several sources, sometimes in different forms, is essential to predictive maintenance. This comprises operational data from supervisory control and data acquisition (SCADA) systems and sensor data for condition monitoring. Reliable prediction models depend on the smooth integration of data from many sources.

- **Demands on Data Processing:** The volume and complexity of data collected in predictive maintenance may provide challenges for traditional data processing approaches. Scalable methods for effectively processing and storing huge datasets are provided by big data analytics tools like Apache Spark, Kafka, and Hadoop.

- **System Architecture and Integration:** Predictive maintenance systems are more responsive and reliable when data analytics tools are integrated with already-existing systems, like SCADA, and make use of real-time data transmission technologies like fifth generation(5G) mobile networks.

C. Predictive Modeling

To guarantee optimal equipment performance and save downtime, predictive maintenance significantly depends on extensive data gathering and sophisticated analytics. In real-time, a range of data types, including event, condition, and operational data, are captured from tools, equipment, and combined systems.

Processing data is essential; it requires a great deal of preprocessing in order to extract relevant characteristics and get the data suitable for predictive modeling. This data may be stored in relational databases and Hadoop HDFS systems, which handle streaming data requirements and enable multi-dimensional time series analytics. Recent developments suggest ML frameworks designed for independent diagnostics under different network situations in the context of cable diagnostics and maintenance. However, finding the most effective ML algorithms and characteristics for specific diagnostics tasks remains difficult, demanding global investigation into universally applicable techniques [10].

We classified PDs from MV cables [11], [12] using a variety of ML methods, including K-means, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), which may be used to predictive maintenance tasks. It is important to use time series analytic techniques to assess the condition of equipment across successive time intervals in order to guarantee that models such as artificial neural networks (ANN) are trained and validated optimally, employing separate periods for training, validation, and testing. A variety of measures are used in model evaluation, depending on the kind of prediction (classification or regression), including accuracy, F1 score, mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) [13]. These measurements direct future improvements in predictive maintenance techniques and offer crucial insights into the functioning of the models.

Reducing downtime and improving maintenance schedules are two major advantages of predictive modeling for PDM. However, some obstacles and problems [3] must be overcome for effective adoption in the industrial environment:

- **Data Requirements**: ML algorithms used in predictive maintenance require a large amount of high-quality data for testing and training. It can be difficult and time-consuming to gather and prepare this data from several sources, which includes operational, condition, and event data from various sources such sensors and historical records.
- **Complexity of Data Structures:** ML models may struggle to extract information from complicated data structures commonly seen in industrial environments. Predictive models may be less accurate and reliable as

a result of this limitation, particularly when addressing significant equipment characteristics and failure patterns.

- **Interpretability and Maintenance**: It is still difficult to understand ML models, especially DL algorithms. Models frequently operate as "black boxes," making it challenging for operators to understand the reasoning behind forecasts. In maintenance operations, this lack of transparency might make decision-making more difficult.
- **Regulatory Compliance:** Highly regulated industries, including electricity distribution, need commitment to strict safety regulations and standards. To maintain operational and legal compliance, automated predictive maintenance system implementation must negotiate numerous regulatory environments.
- **Integration and Deployment:** There may be difficulties in integrating predictive maintenance solutions with current processes and infrastructure. To fully reap the benefits of predictive modeling, smooth deployment and interaction with running systems are crucial.

A predictive modeling framework is introduced in this paper that is shown in Figure 1. The proposed predictive modeling framework for MV cables comprises of four precisely constructed steps:

- **Operational Assessment:** A comprehensive operational assessment of MV cables is carried out in this first step, with an emphasis on data needs and operating circumstances. Establishing an extensive understanding of the system's current state and identifying critical variables that affect cable health are the goals.

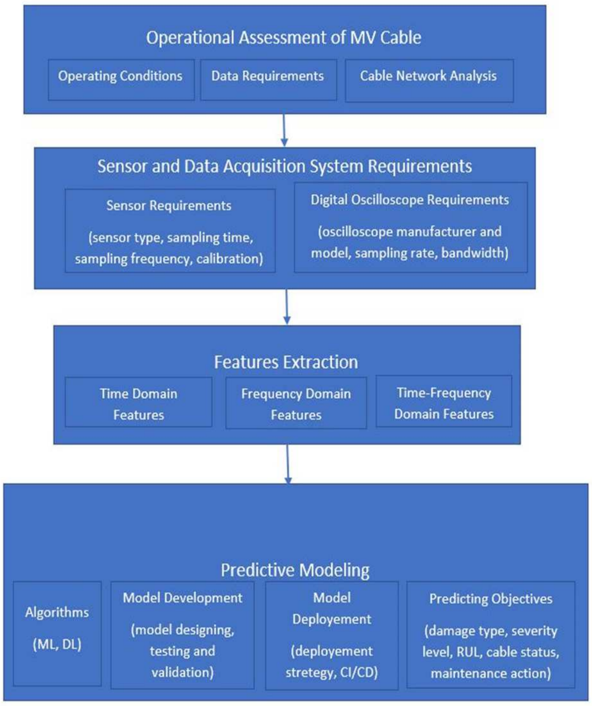

Fig. 1. Predictive Modeling framework

- **Data Acquisition:** In this step, comprehensive event, condition, and operational data from the cables are systematically gathered using advanced sensors and digital oscilloscopes. This guarantees an extensive dataset that captures all aspects of cable performance in many conditions.
- **Feature Extraction:** Three crucial domains are handled with the data at this stage: time, frequency, and time-frequency. By capturing significant characteristics and trends in the data, this multidimensional analysis makes it possible to identify key variables that affect the efficiency and overall condition of the cable.
- **Predictive Modeling:** The final stage employs ML and DL techniques to develop predictive models. These models aim to achieve specific predictive objectives such as identifying damage types, sensitivity levels, remaining useful life (RUL), cable status, and necessary maintenance actions. This stage integrates sophisticated algorithms to deliver high-accuracy predictions, supporting predictive maintenance strategies.

IV. AN INTEGRATED SYSTEM DEVELOPMENT APPROACH

The suggested system development approach for AI-driven predictive maintenance of MV cables is divided into three complete stages, each with a distinct purpose within the overall system. The proposed system development approach is shown in Figure 2 and three complete stages of this system are:

Data Capture (Level 1): This level focuses on collecting a wide range of data, such as partial discharge (PD), equipment, and environmental data. The objective is to develop a complete dataset that depicts the MV cable's real-time operational state as well as external variables impacting them.

Big Data Platform (Level 2): This level has been divided into two major sections:

- Data Storage Section: This section, which includes historical data, time series data, feature extraction, and cable ID components, guarantees effective data management. It enables the effective storage, retrieval, and structuring of huge amounts of data, resulting in smooth data processing.
- Data Processing and PD Classification Section: This section employs AI, ML, and DL approaches to focus on effective data classification and processing. Advanced algorithms analyze the data to find trends, abnormalities, and possible failure warnings.

Application Layer (Level 3): This layer includes predictive maintenance applications such as RUL prediction, fault diagnosis and monitoring, cable health index, maintenance strategies, and cable status and degradation assessment. It estimates the remaining operational lifespan of MV cables, identifies and monitors faults in real-time, informs maintenance decisions, and develops optimized maintenance schedules based on real-time data and predictive insights.

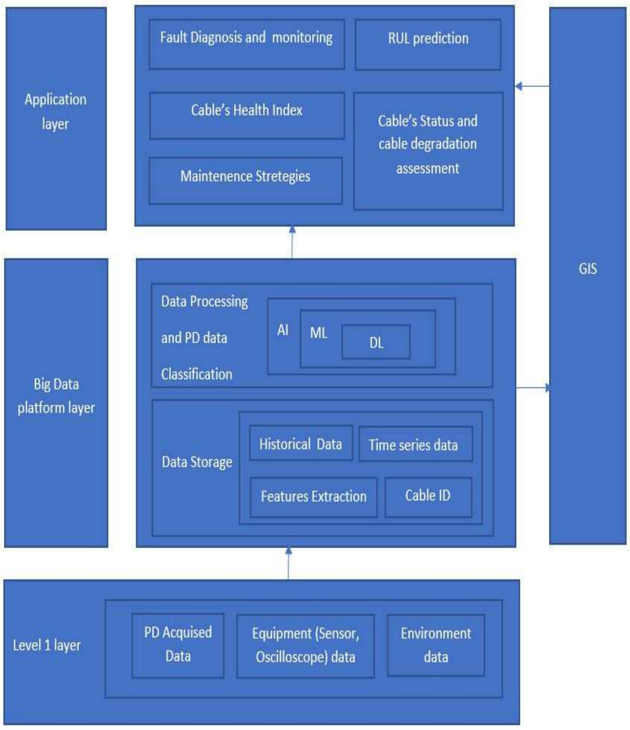

Fig. 2. System development approach

This helps extend cable lifespan and ensure reliable performance.

V. CONCLUSION

The proposed integrated system development approach for condition monitoring and predictive maintenance of medium voltage (MV) cables, utilizing artificial intelligence (AI), addresses challenges in industrial environment such as data requirements, complexity, interpretability, regulatory compliance, and integration. This study is based on extended work of our previous studies (performance evaluation of AI based algorithms, and use case development for condition monitoring and predictive maintenance). The proposed integrated system development approach is structured into three stages: data capture level, big data platform, and application layer. This methodology ensures robust data acquisition, efficient processing, and actionable insights for maintenance operations. The use of advanced ML and DL techniques enhances the accuracy and reliability of predictive models, facilitating optimized maintenance strategies, reducing downtime, and improving the overall reliability and operational efficiency of MV cable systems. Big data platforms like Hadoop, Kafka, and Spark are instrumental in handling large volumes of data generated in predictive maintenance, enabling efficient storage, processing, and real-time analysis. This system facilitates optimized maintenance strategies, reduces downtime, and improves the overall reliability and operational efficiency of MV cable systems.

This study expands on past research by demonstrating real-time interaction among other systems, addressing an important limitation of previous use case. Continuous research and development in this field are required to improve processes for maintenance, save operating costs, and assure the long-term dependability and efficiency of MV cable systems. Future study will focus on improving the presented model framework and investigating real-world applications to test and improve the effectiveness of the suggested system development approach methodology in a variety of industrial situations.

REFERENCES

[1] Xiang Zhang, E. Gockenbach, and H. Borsi, "Life asset management of the electrical components in medium-voltage networks," in 2005 IEEE Russia Power Tech, IEEE, Jun. 2005, pp. 1–7. doi: 10.1109/PTC.2005.4524482.

[2] A. Caprara, G. Ciotti, and F. Bartoloni, "On-Line and Off-Line Partial Discharge Scouting on MV Networks," in International Symposium on Electrical Insulating Materials, 2020, pp. 83–86. Accessed: Jul. 06, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/9275784

[3] O. Serradilla, E. Zugasti, J. Rodriguez, and U. Zurutuza, "Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects," Applied Intelligence, vol. 52, no. 10, pp. 10934–10964, Aug. 2022, doi: 10.1007/s10489-021-03004-y.

[4] S. Koziel, P. Hilber, and R. Ichise, "Application of big data analytics to support power networks and their transition towards smart grids," in 2019 IEEE International Conference on Big Data (Big Data), IEEE, Dec. 2019, pp. 6104–6106. doi: 10.1109/BigData47090.2019.9005479.

[5] A. Tag, S. S. Refaat, S. M. Kameli, and M. A. Saleh, "Machine Learning Applications for Online Partial Discharge Detection, Classification, and Localization in Power Transformers: A Review," in 4th International Conference on Smart Grid and Renewable Energy, SGRE 2024 - Proceedings, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/SGRE59715.2024.10428725.

[6] M. Shafiq, K. Kauhaniemi, G. Robles, M. Isa, and L. Kumpulainen, "Online condition monitoring of MV cable feeders using Rogowski coil sensors for PD measurements," Electric Power Systems Research, vol. 167, pp. 150–162, Feb. 2019, doi: 10.1016/j.epsr.2018.10.038.

[7] Z. Chen, Y. Gao, and J. Liang, "LOPdM: A Low-Power On-Device Predictive Maintenance System Based on Self-Powered Sensing and TinyML," IEEE Trans Instrum Meas, vol. 72, 2023, doi: 10.1109/TIM.2023.3308251.

[8] T. Abbasi, K. H. Lim, N. S. Rosli, I. Ismail, and R. Ibrahim, "Development of Predictive Maintenance Interface Using Multiple Linear Regression," in 2018 International Conference on Intelligent and Advanced System (ICIAS), IEEE, Aug. 2018, pp. 1–5. doi: 10.1109/ICIAS.2018.8540602.

[9] F. J. Maseda, I. López, I. Martija, P. Alkorta, A. J. Garrido, and I. Garrido, "Sensors Data Analysis in Supervisory Control and Data Acquisition (SCADA) Systems to Foresee Failures with an Undetermined Origin," Sensors, vol. 21, no. 8, p. 2762, Apr. 2021, doi: 10.3390/s21082762.

[10] M. Achouch et al., "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges," Applied Sciences (Switzerland), vol. 12, no. 16. MDPI, Aug. 01, 2022. doi: 10.3390/app12168081.

[11] H. Kumar, M. Shafiq, G. A. Hussain, L. Kumpulainen, and K. Kauhaniemi, "Classification of PD Faults Using Features Extraction and K-Means Clustering Techniques," in 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), IEEE, Oct. 2020, pp. 919–923. doi: 10.1109/ISGT-Europe47291.2020.9248984.

[12] H. Kumar, M. Shafiq, and K. Kauhaniemi, "Performance Evaluation of AI-based Algorithms for Condition Assessment of Power Components," in 2022 9th International Conference on Condition Monitoring and Diagnosis (CMD), IEEE, Nov. 2022, pp. 231–236. doi: 10.23919/CMD54214.2022.9991719.

[13] I. F. Galiev, M. S. Garifullin, I. P. Alekseev, A. R. Gizatullin, and A. M. Makletsov, "Development of an Integrated Expert System for Distribution Network Diagnostics Based on Artificial Intelligence Technology," in Proceedings - 2023 International Russian Smart Industry Conference, SmartIndustryCon 2023, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 6–14. doi: 10.1109/SmartIndustryCon57312.2023.10110786.