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Emerging Technologies based Use Case Development for Condition Monitoring and Predictive Maintenance of MV Cables

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***Abstract*— Condition monitoring (CM) and predictive maintenance (PM) techniques can provide a system to achieve a high quality of service with minimal maintenance costs. Using CM-based data, repairing assets is possible based on predictions of the occurrence of faults in assets. Underground medium voltage (MV) cables are vulnerable to deterioration due to stress factors and degradation of the insulating material that lead to cable failure. The gradual deterioration produces incipient faults that lead to MV cable breakdown if not diagnosed at early stages. Efficient diagnosis avoids unscheduled outages and partial discharge (PD) analysis is the most effective method for CM and diagnostics of MV cables. The health of the MV cable can be monitored by collecting and processing a huge amount of data. A use case is developed that shows how data is transferred using emerging technologies to the supervisory control and data acquisition (SCADA) system for diagnostic purposes.**

***Index Terms*-- condition monitoring, electrical insulation, medium voltage cable, partial discharge, use case**

I. Introduction

In order to evaluate the condition of the medium voltage (MV) cables, the demand for an online condition monitoring system is rising. With the help of a condition monitoring system, many benefits can be yielded, such as; better power quality, early detection of faults, reduction of the failure rate, repair strategies to reduce maintenance costs, and the early management of the distribution network. Moreover, the accelerated ageing of MV cables is a rising concern for the long-term reliability of the distribution network. In polymeric insulation, the most dangerous defects are caused by electrical degradation in the form of cavities and cracks and grow in the form of electrical trees and hence causing PDs. To provide useful information about the status of the insulation systems, an advanced condition monitoring system is required that can ensure a high capability of detecting incoming faults based on the analysis of PD signals emerging from the insulation defects accelerating the ageing of the affected electrical components [1] such as; gas-insulated switchgear, power transformers, and cables.

To determine the overall health of MV cables, online condition monitoring is an excellent way. The maintenance alerts can be provided by PD measurements to allow scheduling of outages depending on actual condition data as compared to schedules depending on time intervals. With the help of PD measurements, information about the insulation system is gained that is impossible to extract with other methods. Continuous PD measurements help operators to make the right decisions about maintenance procedures performed on their assets. Moreover, remote monitoring plays an essential role in asset management by providing accurate and immediate feedback on asset performance. The collected data from an advanced condition monitoring system can also be beneficial to designers and manufacturers to improve their reliability and service quality. The collected data will contribute to filling the remaining gaps in understanding the PD's physics and its impact on the remaining useful life of an asset [2].

Remote monitoring plays a significant role in continuous condition monitoring by involving remote experts and emerging technologies. Emerging technology such as Artificial Intelligence (AI) can be used for remote maintenance support in many ways. For example; by applying advanced analytics and machine learning to data from various sources and formats. It can also provide predictions based on data analysis and pattern recognition techniques. AI can not only improve the quality, speed, and accuracy of remote support but also provide new opportunities for maintenance optimization. With the help of remote monitoring, many advantages can be yielded, such as; creating automatic alarms, instant analysis by PD experts without needing the experts on-site, and remote data access/storage. As PD alerts/alarms

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predict future failure, the plant personnel can schedule outages for suitable times to identify and repair the faults [2].

The main contributions of this paper include the following:

- Developing a use case that explains how an advanced condition monitoring system is designed and how it can be used for analytics and decision-making purpose. The proposed condition monitoring system focuses on medium voltage (MV) cables, which are often imposed too much stress during manufacturing and deploying periods.
- Presenting a unique system architecture. The presented architecture collects PD data from sensors at level 1, extracts features and classifies the PD data at level 2, and sends the classified PD data toward the level 3, where different algorithms or knowledge-based rules can be applied to determine cable's health index and decisions can be made for predictive maintenance.
- Presenting our previously developed incipient faults classification algorithm that can be implemented in our developed advanced condition monitoring system and in system architecture.

The paper is organized as follows: Section II gives an overview of use case by explaining the potential applications of an advanced condition monitoring system. The use case based on emerging technologies is developed in Section III in addition of describing the system architecture, and Section IV concludes this paper.

II. OVERVIW OF USE CASE

Implementing advanced techniques for diagnosing MV cables using an advanced condition monitoring system can achieve dynamic information on the condition and operation of MV cables. Moreover, these techniques enable effective planning of maintenance actions. This may keep the reliability of MV cables at a suitable level, reduce the outage rate, extend life, and maintain the return on investment (ROI).

MV cable is a critical asset for a cost-effective and reliable power supply. An unexpected failure of a MV cable can lead to an unplanned shut down of power supply and interrupt various technological and domestic processes and this causing huge economic burdens on the power utilities in terms of larger repairs, and compensation penalties along with customer dissatisfaction. The prognostics and health management (PHM) strategies could be applied to determine cable's health. These strategies periodically investigate the health of the cable to diagnose faults, identify early indicators of anomalies and predict the remaining useful life (RUL) [3]. While the MV cable is in operation and once any defect has been observed, the remaining lifetime of the MV cables depends on type of the insulation defects and their rate of progression which must be evaluated accurately using effective data measurement and data analysis/processing techniques. The two potential applications that can be developed or designed using our designed an advanced condition monitoring system are cable's health index and identification of prognostic parameters. These two applications can be used to predict RUL of MV cables. However, there are different methods for predicting cable's RUL, and in this paper our focus is on data driven method that can be implemented in our designed condition monitoring system and proposed architecture.

A. Cable's health index

To track a cable's health state, it is critical to identify parameters/patterns consistent over time until cable failure. The cables's performance is affected by different stresses and ageing factors. In addition to regular ageing, generally, the leading causes of MV cable deterioration are abnormal increase (instantly or sustained) thermal, electrical, mechanical, and environmental stress [4]. Based on the measured data from cables considering PDs for insulation defects from the sensors, the outcomes of measured data be converted into a health index form that indicates the health status of the cable based on specific properties. An individual cable's life can be predicted using a key parameter like the health index, which indicates cable's failure probability. Therefore, the maintenance and replacement of an cable are entirely dependent on the health index parameter limit[5].

One straightforward method is to use cable's health indexing system in which several health index levels could be assigned to cables based on their health condition data. In [6] the author designed health index system for assets that can be utilized for MV cable's case. The Table 1 shows the health index levels for cables's case. For each level, the status and maintenance action are shown in Table 1.

TABLE I. Health Index Levels [6]

Health Index	Status	Maintenance Action
1	Cable has deteriorated to the stage where failure is about to happen	Cable has reached its end life and should be replaced immediately
2	Has many serious problems. Problems may cause cable failure without intervention	Start planning process for cable replacement
3	Has many minor problems or a major problem? Problem(s) would accelerate ageing rate without intervention	Increase cable inspection and maintenance frequency
4	Has some minor problems or evidence of ageing	Normal Maintenance
5	In "as new" condition	Minor Maintenance

At this stage, we propose that health index of MV cables can be calculated using emerging technology (AI technology) after machine learning based classification of PD sources. Once calculation of health index is done, the levels could be assigned and predictive maintenance actions would be taken based on health index levels.

B. Identification of prognostic parameters

The condition of MV cables is evaluated based on the information obtained from various predefined predictive indicators (prognostic parameters). Such indicators or variables are considered critical drivers for representing the condition of a power component [7]. For PDs cases, these variables can be obtained from PD pulses using time-domain analysis, frequency-domain analysis and time-frequency domain analysis [8]. However, there are alternatives to extract predictive parameters and they have different advantages and disadvantages (complexity of extracting, processing time). All these predictive variables provide valuable information about the continuous condition of a power component. In all the cases, the obtained values and their rise over time are considered to predict the condition of the MV cable from different points of view. For all of them, ranges of threshold values can be set, that will be used to identify their condition by characterizing such categories using numeric values as Good (G), Moderated (M) or Bad (B). The challenging part is to gather all these predictive variables in a meaningful metrics and evaluate the results as a whole in an integrated and detailed way as a condition indicator system (features extraction system) that contains all such information [7].

The information gathered by prognostic (predictive) parameters can be used by AI algorithms to predict the failure of cable and to schedule maintenance in advance. The unplanned downtimes can be avoided using AI based algorithms which results the more effective usage of resources[9]. The advantage of predictive maintenance is that it may improve the quality of the power supply, minimize the repair costs and reduce failures by assuming that sufficient amounts of data is present and AI based algorithms identify data patterns that lead to incipient faults with sufficient predictive accuracy [9].

III. USE CASE DEVELOPMENT

The objectives that can be achieved from use case development by utilizing an advanced condition monitoring system are: Improving the role of supervisory control and data acquisition (SCADA) in asset/grid operation, and scheduling maintenance actions at proper times and only when needed, which results in a reduction of maintenance costs. The development of tools for identifying predictive variables and determining MV cables's health index could achieve such objectives [10].

Designing an effective decision-making system like an advanced condition monitoring system comprises several challenges: data acquisition, preprocessing, feature selection, and implementation of machine learning-based techniques. The data acquisition part consists of raw data collected by the different sensors. Before the acquired data set is implemented in machine learning-based techniques, the preprocessing is required [11]. In preprocessing, one can clean the data to achieve the required data (high-quality or useful data). After preprocessing, the data is applied to machine learning-based techniques and split into training, testing and validation data. Finally, the machine learning techniques classify the data and show the classified data patterns. The classified data can be used to determine the predictive maintenance strategy of an asset/component under consideration[5].

The main purpose of this work is to develop an advanced condition monitoring system which provides necessary information (early warning of faults, asset's health index, fault location, and critical events) to distribution system operators or PD support engineers. PD detection-based condition monitoring methods have gained large popularity, especially for transformers and cables. Transformers and cables are essential components of the power distribution network, and they constitute primary problems in power supply in the distribution network. Both offline and online PD data can be used in the proposed system. The stages involved in an advanced condition monitoring system for data transfer from the power component to the SCADA system are shown in Fig.1.

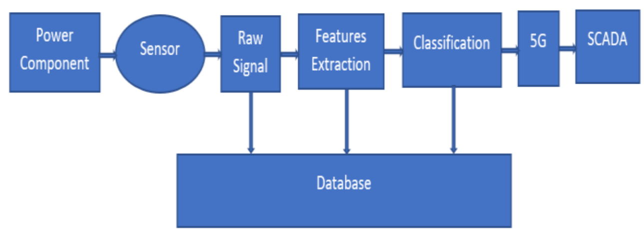

Figure 1. Advanced condition monitoring system

The advanced condition monitoring system is made up of the following main components: 1. Power Component 2. Sensors 3. Raw Data 4. Features Extraction 5. Classification 6. 5G (fifth generation) communication 7. SCADA system. The advanced condition monitoring system uses HFCT/Rogowski coil sensors to record the PD signals from cables. The features are extracted (by applying discrete wavelet transform on PD pulses) from the raw PD signals, and they are sent to the classification system in addition to sending them to the central database. The classification system classifies the data based on PD sources using clustering or classification techniques depending upon whether known or unknown labels and sends the classified data to the SCADA system using 5G communication technology. The classification system is used to identify the type and to quantify and predict the severity of PD activity. The central database is used here to record the system's information at different stages so that further actions can be taken based on recorded data. The central database gathers raw data, extracted features, and classified data. The SCADA system shows the type of PD activity to the operating personnel at the SCADA. The operating person can request further information (raw PD data, features) from the central database to determine the PD sources and severity of PD at different periods.

The 5G technology offers a significant advance in the combination of latency reduction and reliability enhancement. Electricity distribution is one of the significant use cases of 5G for Ultra-Reliable Low-Latency Communications (URLLC). 5G has replaced optical communication technology by achieving improved flexibility, reliability, and cost savings. The low latency and high reliability make 5G a new option for replacing fixed-line communication connections. SG communication often has special performance requirements, especially very low latency (≤ 1 ms). 5G meets the requirements for SG implementation, with highly reliable communication, low latencies, robust security mechanisms to prevent malicious intrusion, and high scalability [12].

A. Features Extraction and Classification Algorithm

The data-driven faults diagnosis process is widely used for condition monitoring of power components. This process consists of four steps: data collection, data preprocessing, feature extraction, and fault classification. At first, useful features are extracted and used them as input for classifiers/ML algorithms. Our previously extracted features are shown in [8], [13] for input of classifiers, and an algorithm for classification of PD defects is shown in Fig. 2.

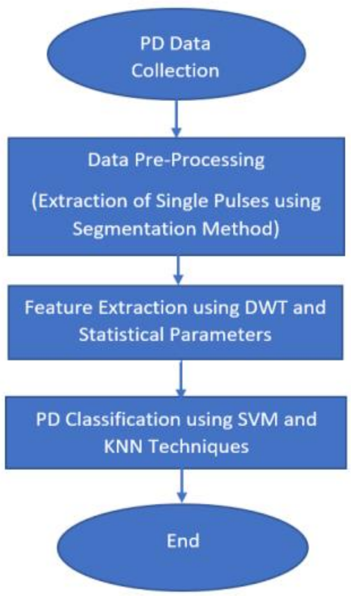

Figure 2. Flow chart of classification algorithm [13]

B. System Architecture

In order to meet the needs of our use case, the system architecture should have the following functions:

- It can collect the PD data of components and can store the data in large capacity
- It connects with a database, which includes data preprocessing, feature extraction and selection, RUL prediction and other methods for training and verification of the algorithms.
- It has high-performance computing capabilities and can process acquired status data in real time [14].

The above-mentioned functions could be obtained using our previous developed system architecture from FUSE project. The proposed system architecture can process the massive amounts of data generated from components of MV network along with the time-critical events to guarantee asset management, and forwards the intelligence and decision making towards the SCADA. Therefore, by considering requirements such as guaranteed asset management, early warning of faults, and predictions of faults, an architecture created in the FUSE project [15] is shown in Fig. 3.

The FUSE Architecture [15] was designed to implement only a three-tier hierarchy, and this architecture can be extended up to many levels depending on the requirement of power distribution network. Basically, the three-tier hierarchy consists of three levels, namely; level 1, level 2 and level 3. Layer 1 acts like an edge layer. The edge layer consists of sensors, actuators, and IoT nodes and sends the data to level 2. In FUSE architecture, level 1 was designed in a way that its hardware consists of a processor for high-level data analysis plus a programmable FPGA for low-level data pre-processing and parallel computations. We can deploy PD sensors (HFCT/Rogowski coil) in this architecture to identify and localize PD sources from cables. Moreover, the transient PD patterns can be analyzed to predict faults in the MV grid.

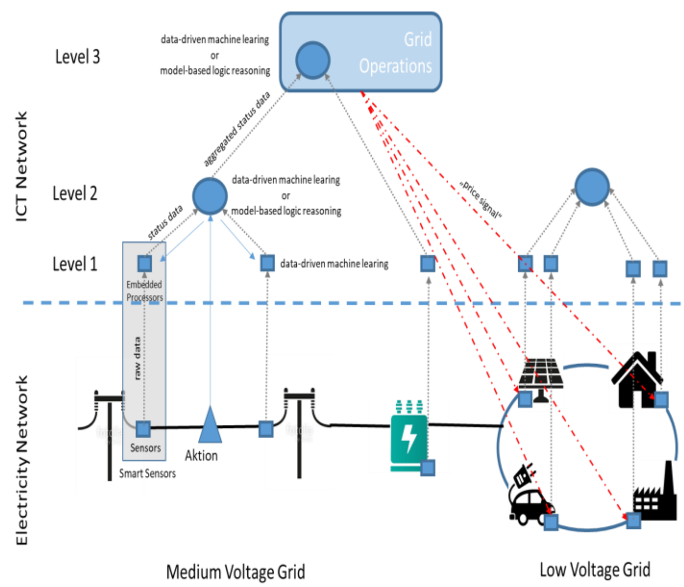

Figure 3. FUSE Architecture [15]

Level 2 works as a fog layer that preprocess extracts features and classify the collected data from layer 1. In addition of classification, other algorithms, such as; state estimation, anomaly detection, calculation of health index, and prediction analysis can be implemented in layer 2. From our previous works [9], [13], we have extracted features and developed a classification algorithm that can be implemented in level 2 for determining the cable's health index and making decision for predictive maintenance. The developed algorithm for classification of PD sources is shown in Fig. 2.

The level 3 acts as an application layer. At Level 3, data and information from multiple Level 2 nodes are brought together and visualized using the Things board framework[15]. Distribution system operators or PD support engineers can view and evaluate the information created by the Level 2 nodes, to make decisions regarding maintenance strategies. The Level 3 provides real-time online and comprehensive offline RUL support capabilities (RUL prediction, health assessment, decisions for predictive maintenance) which helps SCADA to take the necessary actions. For communication and data exchange between the Level 2 and Level 3, the 5G communication technology is proposed. For implementing 5G communication technology, Level 2 requires 5G user equipment (UE) and this could be achieved by deploying 5G modems and attaching them to the Level 2 embedded devices. Level 3 comprises of 5G access network and a 5G core network, which is controlled and maintained by a telecommunications operator.

IV. CONCLUSION

Emerging technologies can improve fault diagnosis and condition monitoring process, and guide future replacement of MV cables. An advanced condition monitoring system offers to meet today's high quality of service by giving information about repairing MV cables that are based on predictions of PD behavior and the occurrence of incipient faults. Data transfer and time criticality parameters play a crucial role in the classification results. The proposed advanced condition monitoring system offers a robust solution to perform prediction by using emerging technologies (AI, machine learning and 5G communication technology). The work presented in the current paper is based on our previous approaches, which have already been applied based on machine learning techniques for the classification of PD sources. In this paper, a detailed use case based on our previous studies was presented. The data processing benefits the previously developed machine learning algorithms and system architecture. The presented use case provides the basis for the development of an advanced condition monitoring system benefitting the latest technological solutions. The limitation of this use case is that it does not show the interaction with the system from the operational staff or other systems or databases. Future work could be to overcome this limitation by designing the use case for real-time operation conditions.

The importance of condition monitoring systems in power distribution networks is continuing to grow with the importance of understanding ageing mechanisms, ageing assessment and condition monitoring techniques for power components. The developed use case shows how MV cables and an advanced condition monitoring system can be combined as a product which could be deployed in real real-time in a power distribution network for condition assessment of MV cables and predicting their RUL.

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