Multi-level Defects Classification of Partial Discharge Activity in Electric Power Cables using Machine learning

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Abstract – Condition monitoring of power system is an important and crucial step to ensure the reliable and healthy operation over time. The classification, identification and characterization of flaws in elements of power systems can be significantly done using partial discharge (PD) pattern recognition. The multi-level classification approach is proposed in this paper to monitor, identify, and discriminate defects that cause partial discharges in insulation systems. Three-dimensional (3D) finite element analysis based model was developed to create significant partial discharge activities within different voids located in a solid dielectric cable. The proposed scheme utilized different types of support vector machine (SVM) models for obtaining maximum accuracy. The proposed machine learning models predicted the presence of voids with an accuracy of 94.5% and the different void diameter with an accuracy of 77%.

Keywords: Machine Learning, Support Vector Machine, Partial Discharge, Power System, FEA.

1 Introduction

The implementation of smart grid requires reliable operation and effective condition monitoring of all operating units. The need for improved reliability, continuous service, and optimal economic performance of electric grids has seen great focus in recent years. Most failures occur in power system are originated from insulation degradation, which makes insulation’s health as an important indicator for power system aging and performance capability [1]. High and medium voltage level power equipment’s insulation health has been globally tested using partial discharge (PD) diagnostics approach [2].

Partial discharges are small electrical discharges that occur prior to failure condition which exists in the insulation and dielectric materials under electric imbalance stress, contaminants presence or due to imperfection in electric insulation. Partial discharges are intermittent pulses of certain amplitude at certain phase. PD causes thermal, physical, electrical, and acoustic effects which can be detected, localized, analyzed and quantified for condition monitoring of any power system component. [3].

When discharges occur, there is a high instability risk for the insulation system. However, the detection and localization of PDs in electric cables is a difficult task. Therefore, many research efforts have already been conducted to measure, detect, and identify PD severity in the dielectric materials [4].

Discharges can be detected with conventional testing system, which requires de-energizing of the whole system or isolating the testing component from rest of the grid. Advanced techniques were proposed to detect discharges in offline mode, using the concept that all discharges emit electromagnetic wave under detectable ranges which can be utilized to quantify the partial discharges in any location of power grid remotely.

PD detection via the ultra-high frequency (UHF) sensor shows the most promising results as the discharge’s signals are fall under the range of MHz to GHz which is similar to the working range of UHF sensor. The measured PD raw signal in electric power cable is usually mixed with external signal and noise [5]. The noisy signals require denoising schemes as well as advanced PD diagnostic techniques for PD source identification and its separation [6]. In recent years, different feature extraction tools have been considered in the literature to classify or identify the severity of PD activities such statistical features extracted from wavelet decompositions, short time frequency transform (STFT) and phase resolved PD pattern (PRPD) which includes PD patterns in frequency, time and phase domain, before implementing data reduction techniques. Many computer-aid classifier tools have been proposed and developed over the last few decades with their own pros and cons [7]. The main contribution of this paper is to present an automated PD diagnosis approach with pattern analysis and machine intelligence of solid dielectric insulating material for electric power cables.

The paper investigates and reports on several scenarios for the most common defect with different variation in solid insulation. A 3D finite element model for high voltage power cable has been built using the multiphysics software. In this paper, we simulate the most common defect with different variations in solid insulation i.e. power cable or GIS spacer. The PD parameters are determined through the finite element analysis simulated model. The features extracted from the raw data is corrupted with interferences and then further utilized in machine learning tools to classify the defects. The results are intended to show the potential capability of machine learning models in identifying defects and to give a correlation with the change in the defect’s physical specification. The paper will first give an extensive overview of the 3D finite element model for high voltage power cable, and then focus on the machine learning for PD recognition and classifications of defects.
2 Three dimensional finite element model for high voltage power cable

Pre-breakdown phenomenon is a well-known condition in insulated power cables. Discharge’s origin could be initiated at any place in the whole insulation of electric power cable. Discharge is a multiphysics phenomenon which consists of interdepending electrostatic, thermal and electromagnetic changes [8]. The changes in the finite element simulation model at each node of power components are simulated using discretized boundary analysis. 3D finite element modeling is the most suitable approach to emulate such phenomenon.

![Figure 1. The simulated model of 220 kV power cable with air-filled void.](image)

The cavity is the most common internal defect that exists in solid insulation like cracks, gas-filled voids, air and pockets which originate due to manufacturing flaws, over lifetime stress, or physical accidents. These defects remain unnoticed with small undetected discharges which grow over time. When becoming spherical or elliptical voids of specific size, they create large discharges, and if unchecked they lead to breakdown or failure in the insulation system. The 3D finite element model for high voltage power cable is shown in Figure 1 which utilizes Poisson’s equation based electrostatic physics for discharges when the electric field in the cavity that exceeds the inception field limits [9]. PD can be expressed as given in equation 1.

\[ \nabla^2 V(x, t) + \frac{\rho(x, t)}{\varepsilon \varepsilon_0} = 0 \]  
(1)

Where, \( V \) is the applied voltage on conductor, \( \rho \) is the surface charge density, \( \varepsilon \) is the relative permittivity.

The conductivity in the void increases due to the ionization of gas inside the cavity. Furthermore, small pico-scaled PD current start flowing for a certain time causing changes in temperature and pressure in the cavity which is utilized in analyzing the changes in inception field and conductivity. The process happens in the nano-scaled time range and continues depends on the results based on solving partial differential equations.

The variation in electric field in cavity can be seen in Figure 2 at time before (-), after (+) and, during (0) partial discharge event. Negative sign illustrates the electric field prior to partial discharge happening, 0 represents electric field variation within cavity during PD, the positive sign represents the electric field after partial discharge occurrence.

![Figure 2. Plots of the variation of the electric field at different time, +Time$_{PD}$ & -Time$_{PD}$ signifies the time before and after, Time$_{PD}$ signifies the time instant during PD.](image)

The void varies in shape and size over different voltage levels. The shape of the voids are spherical as well as elliptical. The size of voids is limited to 1 cm due to multiple points of discharges and initiation of the treeing phenomenon. Specific type of defect is necessary to be considered in order to investigate the performance of the machine learning algorithm. The data recorded from models with partial discharges pattern consists of apparent charge, number of PD pulses, and time of discharge events. The data is recorded from up to 20 power cycles for each kind of defect to measure the variation, where one power cycle duration is equivalent to one cycle with power frequency (i.e. 50 Hz).

To accurately model the system, the initial raw data obtained needs to include noises and interferences. The two different types of interferences considered are common in practical conditions: discrete spectral interference (DSI) and white Gaussian noise. The selection of the interferences was randomized from a one out of 100 scale in order for the system to be trained in maximum interference conditions. The partial discharge data recorded by different detection and data acquisition tools depend on the requirement and accessibility of installation of the detection system. The recorded data resolved pattern that includes PD charge, number of PD event, and phase, act as identifying parameters for classification of PD defect in solid dielectric cable.
3 Machine learning for PD recognition

Machine learning, a subset of artificial intelligence, is a scientific study of algorithms and statistical models that uses computational effort to characterize the behavior of a specific task without the explicit use of any instruction, thus primarily relying on patterns and statistical analysis [10]. The fundamental premise of machine learning is to feed the model with training data as such to use mathematical and statistical analysis to predict the outcome. Machine learning can thus be further categorized into two categories, supervised and unsupervised learning. Supervised learning refers to the use of machine learning algorithms to predict the outcome of input data given that the training data includes the respective outcomes. In turn, unsupervised learning algorithms are not trained with data sets that include the respective outcome, thus relying primarily on pattern recognition, as well as deep learning, and neural networks. In this research study, only supervised classification algorithms will be considered to predict partial discharge, primarily linear and quadratic support vector machines. The main goal of using machine learning is to predict the existence of PD in solid insulation, as well as the PD magnitude and classify the diameter of voids. This is achieved through the provided simulation data without using formulas and equations that represent partial discharge which simplifies the process. In other words, through the use of machine learning algorithms, developing a meta-model of a system is possible to predict possibly existing partial discharge.

3.1 Support vector machines

The support vector machine (SVM) is a supervised learning model [10]. It is a representation of the examples as points in space separated by a clear gap that is as wide as possible. The boundary that classifies different classes is known as a hyperplane, and the points closest to the hyperplane are known as support vectors. Support vector machine was first proposed by Vladimir Vapnik in 1995 [9]. SVM provides a great advantage in small sample quantity training data, nonlinear, and high dimensionality pattern recognition problems. Due to the size and high dimensionality of the training data proposed earlier, SVM is proposed to be most appropriate for this application. Successful applications have demonstrated that SVMs can perform as well or better than neural networks in a wide variety of fields, including engineering, information retrieval, and bioinformatics [9].

A. Linear SVM

A linear SVM models the data and divides them into different regions separated by a linear hyperplane (linear boundary). A linear SVM algorithm finds a linear boundary that separates regions with the least error by maximizing the distance between the boundary and the support vectors. Linear SVM is restricted as they are ideal for linearly separable data and may fail to achieve high accuracy when dealing with non-linear data set.

B. Quadratic SVMs

Linear SVM is limited to linearly separable data sets. However, there are different methods conventionally used to solve the issue of using support vector machines for non-linearly separable data. The most common method is known as the kernel trick or kernel function. The key idea behind the kernel trick is to map data sets to higher dimensionality feature space.
by using reproducing kernels [9]. The kernel trick allows performing operations in the input space as opposed to the higher dimensional feature space. In turn, the computational complexity is enhanced and made easier as the inner product space does not need to be calculated in the higher dimensional feature space. In addition, this allows for avoiding issues regarding dimensionality. However, the computation is still critically dependent upon the number of training patterns and to provide a good data distribution for a high dimensional problem will generally require a large training set [10]. The algorithm for quadratic SVM assumes the equations for the polynomial kernel trick, however, with degree 2. The appropriate equations for a general polynomial function are as follows [11]:

\[ K(x, x') = (x, x')^d. \]  \hspace{1cm} (6)

\[ K(x, x') = ((x, x') + 1)^d. \]  \hspace{1cm} (7)

Where \( K(x, x') \) represents the kernel function performing the non-linear mapping into feature space.

4 Results

The partial discharges classification consists of a set of layered classification. The initial classification is choosing between healthy and defect case. The second aspect is dealing with the classification of different categories of the defect type. The present data set including 1020 different instances with 57 attributes, were modeled with 5-fold cross-validation. According to various experimental studies, this value generally results in a model prediction with low and modest variance, particularly for small quantity samples. The models assumed 56 predictive attributes and one non-predictive attribute. The outcome attributes included 6 different classes, which are as followed: healthy, void_I, void_II, void_III, void_IV, and void_V representing the different void levels. Compared to linear SVM, the quadratic SVM model yielded a higher accuracy. The initial quadratic SVM resulted in prediction accuracy of 94.5% for distinction of healthy system vs systems with voids as shown in Figure 4. The linear SVM contains fewer false positive predictions, its overall accuracy is 90.1% with a high false negative prediction.

With further analysis, the confusion matrices seen in Figure 5 show the performance of the quadratic SVM along with the linear SVM in predicting the different categories of voids.

![Figure 4](image.png)

**Figure 4** - Confusion matrix for healthy and defect condition using (A) Quadratic SVM and, (B) Linear SVM, respectively.

In the confusion matrix in Figure 5, the categories that caused the greatest inaccuracy for the quadratic SVM model were void_I void_II primarily due to the similarities and small variance between the two classes. Overall the quadratic SVM was able to predict the category of voids with an accuracy of 77%, with the decrease in accuracy corresponding to similarities between the void classes. Whereas, the accuracy for the linear SVM was only 68.1%. Figure 6 shows the ROC graph for the quadratic SVM performance for void_II, which had the greatest inaccuracies, as well as the ROC for void_IV which had the least amount of inaccuracies. The ROC curve plots the true positive rate (TPR) against the false positive rate. Ideally, the desired ROC curve should have a sharp edge at the top corner with an area of 1.0, depicting ideal accuracy. From Figure 6 it is evident that the model works best for predictions of void_IV however, partially lacks the accuracy for void_II as mentioned earlier.
Moreover, a three-level classification is possible with this proposed algorithm. Further improvements include but are not limited to improved feature selection, including further deep analysis on strongly correlated features that directly influence the presence of partial discharge. Addition of different voltages applied to the model may allow better prediction of existing partial discharge within the model. The addition of more data sets may increase accuracy as to find improved pattern recognition and potentially higher accuracies. The implementation of actual experimental data would further provide a more accurate meta-model representation that can be further enhanced to be used for real life partial discharge prediction.

5 Conclusion

Advanced condition-monitoring system based on partial discharges pattern recognition has been introduced which provides the benefits of self-recognition and characterization of defects existing in solid insulation of power components. The power utilities require such advance monitoring system to keep power system operation reliable and avoid unplanned outages in electric power networks. The PD identification system proposed based on machine learning tool-SVM further supports the promising application of machine learning for partial discharge detection. Advancement in machine learning tools provides various specifications that are not possible with traditional commissioning techniques. The simulated modeling of defects in cables helps us to create the features at a very remote location of power system which acts as classifying parameters for training. The classifier provides multilevel details about defects and condition of power system components.

6 Acknowledgement

This publication was made possible by NPRP grant [10-0101-170085] from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

7 References


