COMPARISON OF PARTIAL DISCHARGE PATTERNS IN XLPE CABLES BASED CLASSIFICATION DEFECTS USING EXPERIMENTAL AND THEORETICAL INVESTIGATIONS

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Abstract: Partial Discharge (PD) condition monitoring provides an early warning of critical problems in the power cable, so that corrective measurements can be taken before costly damages occur. Under circumstances where the cable defects are recognized and classified early enough, the situation can be contained by temporal reparation of the cable to extend cable life. In this direction paper aims to recognize and classify defects of cable cavities rapidly and accurately once the PD test is carried out. So, the implementation of the off-line PD test on cross linked polyethylene (XLPE) cable network has been accomplished. The experimental investigation of 3D patterns of partial discharge measurements due to artificial cavity defects on different size are proposed, the automated classification of defects is done through Artificial Neural Network (ANN), by using the statistical feature extraction technique. The evaluation of ANN is also presented to ensure the effectiveness of such classifications. From the obtained results we can say that the classification of the electrical behavior of a region with a strong cavities concentration is done with success by many cavities for cable samples, and the successful and accurate automated classification of defects was achieved even at high deformation shapes. Where, feature extraction statistical technique improves the performance of ANN, and decreases the processing time for classification.

Keywords: Partial Discharge- XLPE Power Cables- Artificial Neural Network- Pattern Classification

1 INTRODUCTION

Partial Discharge (PD) is known as the factor of the insulation deterioration in high-voltage equipment, especially in the power system cables. Therefore it was necessary to classify PD with the objective of identifying discharges of unknown origin and classification the defect which causes discharge. This classification provides vital clues to the health of dielectrics. For every defect of these defects has a direct impact on the shape of three-dimensional 3D-PD pattern. Therefore, the visual system can be used for a 3D-PD pattern to identify different types of defect. But often visual observations lead to contrary to truth of sources of PD. This visual system can be successful only if there is valuable information on the partial discharge analysis devices, and the long experience of the engineers of the work test. It is now possible to classify PD sources quickly and effectively with rapid developments in digital signal recognition techniques and the emergence of high-speed computers.

The use of statistical parameters in the classification work has become the preferred classification technique to replace the old style of classification [1]. The measurements of PD are determined which are classified by many various techniques, including, Fuzzy neural networks (FNN) [2], Probabilistic neural networks (PNN) [3], extension theory [4], Grey Clustering Approach (GCA) and Genetic Algorithm (GA) and neural networks (NNs) [5, 7]. Statistical parameters are used to develop the conventional classification technique [8-10]. All the fore mention researches haven”t applied this classification on XLPE cable with artificial cavity. In this paper, Five types of experimental models with artificial defects are carried out to produce five common PD cavity events in XLEP high-voltage cable. The proposed method has been implemented according to the off-line PD test 3D-patterns collected from laboratory. In order to classification, various statistical features are extracted from the experimental of 3D pattern shapes.

2 PARTIAL DISCHARGE AND CAVITIES IN XLPE CABLE

Cavities or voids are formed in solid insulation during manufacture; installation exceeds the breakdown strength of gas within the void or operation, when the electric stress in the void, partial discharges will occur. The electric stress in the void is the critical factor for the generation of partial discharges at known temperature and pressure.

Internal cavity frequently occurs in the form of spherical or elliptical gas filled cavity. If the voltage is applied to the insulation system, the electric field in the cavity will be higher than that the surrounding insulation medium. This is due to the
low dielectric constant of the gas inside the cavity than the dielectric constant or the insulation medium. The presence of defects in cable system represents weak points in cable system operation. In the case of newly installed HV cable system, all cable parts are considered as PD-free components as they have passed the type and routine test at the cable factory. However, there is still a risk of the presence of defects in the newly installed HV cable system. These defects can be a result of improper on-site assembling (poor workmanship) process of the cable accessories or hidden defects in the design of cable accessory. It would therefore be of great interest to study simultaneously the PD activity in a different cavity size and the magnetized shape of PD in the XLPE power cable. The results of such a study could give some idea on the relation between cavity size and PD.

3 EXPERIMENTAL INVESTIGATIONS

For the experimental investigation's purpose there are four artificial defects which applied in the cable sample. These defects are the missing of outer semi-conductive screen, XLPE insulation in the cable sample and the electrode-bounded cavity. These four artificial defects represent the different case of PD occurrences. The first and second artificial defect represents the surface discharge along the interface of insulation material. This type of PD can result in failure of cable system even if the extruded insulation is totally immune to PD-induced electrical tree initiation. The third and fourth artificial defect represents the case of electrode-bounded cavity between the outer semi-conductive screen and the cable insulation

3.1 Model Sample and configuration

The sample is a single core XLPE insulated cable 38/66 (72.5) kV, diameter of the conductor is 27.5mm and the thickness of the XLPE dielectric insulation is 17mm. In order to make four defects in this cable, The artificial cavity are drilled in the surface of cable below the outer semi-conductive screen of a different depths, where the depths form 1mm to 4mm, the drilling diameter of cavity is 1mm. The PD measurements at 1.73U₀ for the five models of the cable cavity with depth 0mm,1mm, 2mm, 3mm and 4mm are carried out.

3.2 Experimental Setup

Partial discharges activity is measured using resonant tuned frequency 50 Hz AC energizing and conventional IEC 60270 in the Extra High Voltage Research Center (EHVRC), PD laboratory which has designed to house a shielded enclosure to prevent any electromagnetic interference. As a result the background noise level is less than 2pC, and the control room consists of similar panels as the shielded enclosure with glass windows for direct view of the test area, test circuit of cable inside a shielded enclosure as shown in the “Figure 1”.

![System configuration of the PD detecting system](image)

**Figure 1:** System configuration of the PD detecting system

It includes a step up transformer, capacitor coupling circuit, a commercial PD detector, and the cable under test. Through the testing processes, all the data measured were digitally converted in order to save them in the computer memory. Digital PD detectors provide the possibility for post-processing of the instantaneous PD signals for 2 minutes time period. Most commercially available instruments have a computerized option which can provide 2 dimensional or 3 dimensional pattern of the PD activity. In this paper will focus on the 3D pattern of PD (φ–q–n), which represents the relationship between the PD magnitude “q” and the pulse count or frequency \(H_n(\phi, q)\) in the test measuring time is 2 min as a function of phase angle, and the PD TE571 detect was applied in the carrying out experiments to detect the discharge signals in the five XLPE power system cable. The experimental setup and sample configuration are shown in “Figure 2”.

![Experimental set up including sample](image)

**Figure 2:** Experimental set up including sample
3.3 Experimental Investigations Results

The typical 3D pattern of PD measurement results 3D $H_n(\phi, q)$ are presented the magnitude for the five kinds of depth models (0mm, 1mm, 2mm, 3mm and 4mm) of the different artificial cavities in XLPE cable at a test voltage of $1.73U_0$, that are shown in “Figures 3 to 7”, respectively. The maximum PD magnitude may be summarized in “Figure 8” as a function of cavity depth.

**Figure 3**: 3D $H_n(\phi, q)$ processed for discharge in XLPE cable 38/66 kV without cavities.

**Figure 4**: 3D $H_n(\phi, q)$ processed for discharge in cable sample with spherical cavities 1mm.

**Figure 5**: 3D $H_n(\phi, q)$ processed for discharge in cable sample with cylindrical cavities 2mm depth and 1mm diameter.

**Figure 6**: 3D $H_n(\phi, q)$ processed for discharge in cable sample with cylindrical cavities 3mm depth and 1mm diameter.

**Figure 7**: 3D $H_n(\phi, q)$ processed for discharge in cable sample with cylindrical cavities 4mm depth and 1mm diameter.

**Figure 8**: Apparent charge as a function of cavity depth of an XLPE sample cable 38/66 kV.

It is clear that, the PD patterns of different defects have display discriminative features. From “Figure 3” it can notice that, the cable exhibits insignificant low magnitude of discharge $q$, which are distributed broadly over the phase $\phi$. This cable could be considered as a healthy cable. It is evident from “Figure 4” that, the magnitude of the discharge is increased, and concentrated in the negative half cycle (around $\phi=270$). Meanwhile, it’s concentrated in the raising of both positive and negative cycles in “Figure 5”. The behavior began in “Figure 5” is continued in “Figures 6&7”, with significant increase in both the magnitude $q$ and the numbers or frequently $H_n(\phi, q)$ of PD. “Figure 8” shows that the increase of apparent charge as cavity depth increase which is calculated at 72.5 kV.

It’s concluded from the results of PD measurements that, the experienced monitors can reasonably visual classify from the 3D PD pattern the defects that occur in High voltage XLPE cables due to cavities, but this isn’t always the case. The need of automated classification method has emerged as shown in the following sections.

4 ANNE BASED PD CLASSIFICATION

The type and structure of ANN, which are used in this work to classify the cable defect models and creation training set (input/target) of the ANN, will be explained in this section.
4.1 ANN Pattern Classification Structure

The using of ANNs for PD pattern recognition and classification due to that ANNs were originally designed as pattern-recognition and data analysis tools that mimic the neural storage and analytical operations of the brain. ANN approaches have a distinct advantage over classification methods in that they are non-parametric and require little or no a priori knowledge of the distribution model of input data. Additional superior advantages of ANNs include parallel computation, the ability to estimate the nonlinear relationship between the input data and desired outputs, and faster generalization capability, therefore ANNs may be learn without difficulty the various PD patterns. In this paper, ANN has been built to classify inputs into a set of target five categories such as 0mm, 1mm, 2mm, 3mm, and 4mm depth cavities for XLPE power system. Neural Network Pattern Recognition Tool MATLAB (R2010a) are used to solve statistical system. Neural Network Pattern Recognition Tool 3mm, and 4mm depth cavities for XLPE power system. The using of ANNs for PD pattern recognition and classification due to that ANNs were originally designed as pattern-recognition and data analysis classification due to that ANNs were originally designed as pattern-recognition and data analysis. The results of statistical feature extraction of the database creation 150 sets have been classified into five categories. We repeat the database creation 150 sets at ±60% deformation factor. In order to improve the performance, pre-processing schemes that extract relevant statistical features from the PD patterns are presented for the proposed ANN-based classifier.

5 STATISTICAL FEATURE EXTRACTION

Feature extraction is a technique essential in PD pattern recognition to reduce the dimension of the original data and make effective discrimination of the statistical feature patterns for different PD status. In this work, the significant statistical features are extracted from 3D-pattern of charge-phase frequency distribution; the output vector of the ANN-based classifier is the PD pattern of the defected cable models, and the input vector is the values of twelve (360°/30°) phase windows. Six statistics of feature extraction are calculated for electric charge q in the phase 30° width and its frequency H_n(φ,q) or f, to obtain the input vector scheme to ANN as follows:-

\[
\mu = \frac{\sum_{i=1}^{200} \sum_{j=1}^{30} f_{ij}q_i}{\sum_{i=1}^{200} \sum_{j=1}^{30} f_{ij}}
\]

Where:
\( \mu \) = Mean value of the charge
\( q_i \) = charge magnitude for i=1,..,360 at j=1,..,2
\( f_{ij} \) = frequency H_n(φ,q) at q and q_i for j=1,..,2

\[
\sigma = \sqrt{\frac{\sum_{i=1}^{200} \sum_{j=1}^{30} (q_i - \mu)^2}{\sum_{i=1}^{200} \sum_{j=1}^{30} f_{ij}}}
\]

Where: \( \sigma \) = Standard Deviation value of the charge

\[
CV = \frac{\mu}{\sigma}
\]

Where: \( CV \) = Coefficient of variation of the charge

\[
K_H = \frac{\sum_{i=1}^{30} \sum_{j=1}^{30} (q_{ij} - \mu)^2}{\sigma_q^2 \sum_{i=1}^{30} \sum_{j=1}^{30} f_{ij}}
\]

Where: \( SK \) = Skewness value of the charge

\[
q_{max} = \max_i \left\{ q_{ij} \right\}
\]

For i=1,..,222 & j=1,..,2

Where: \( q_{max} \) = Maximum Value of \{q_i\} for i=1,..,n at j-column, \( f_{ij} = \max_i \) at \( q_{ij} \)

The results of statistical feature extraction of the 3D-patterns of the experimental PD measurement
results are shown in the “Figures 10 to 15” at schemes I to VI, respectively.

6 RESULTS AND DISCUSSIONS

To verify the proposed approach, a practical experiment is conducted to demonstrate the effectiveness of the PD pattern classification scheme. The experimental tests were carried out on five defects models of XLEP high-voltage cable. The test results show that the proposed method is able to accurately classify the testing defects. Associated with their real defect types, there is a total of 150 sample data for different PD events. Each PD event contains 30 patterns of sample data, of which 20 patterns are training data, 5 patterns are validating data, and 5 patterns are testing data.

The statistical feature extraction technique is used to extract 6 statistical features for each pattern. The significant features are extracted from statistical features. After the feature extraction process, all the features in the feature vectors were normalized to set up the training sets. After setting up the training sets, the training procedure of ANN-based classification is started. The classification time consuming without using statistical features is 200 time of time consumed with it.

Table 1: Classification accuracy of the ANN

<table>
<thead>
<tr>
<th>Statistical features</th>
<th>Classification Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scheme I</td>
<td>100%</td>
</tr>
<tr>
<td>Scheme II</td>
<td>100%</td>
</tr>
<tr>
<td>Scheme III</td>
<td>100%</td>
</tr>
<tr>
<td>Scheme VI</td>
<td>100%</td>
</tr>
<tr>
<td>Scheme V</td>
<td>100%</td>
</tr>
<tr>
<td>Scheme VI</td>
<td>99.34%</td>
</tr>
</tbody>
</table>

Table 1 shows the test result of the training data. The data in Table 1 show that the proposed method has 100% accuracy for the 150 training feature vectors; there are only 3 errors of classification at maximum value (Scheme VI) with the deformation factors 30%, 60%, and Kurtosis value (Scheme V) with the deformation factor 90%.

MSE (Mean Square Error), measures the network’s performance according to the mean of squared errors between the output result and the target that is with the validation and testing set. “Figure 16” shows the MSE of an ANN with statistical schemes and in the case of no scheme at two data sets, which have 30% and 60% deformation factor. It is clear from the figure that the using of mean, standard deviation (STD), and coefficient of variation (CV) features improved the performance of the ANN than in the case of no scheme the mean, standard deviation and coefficient of variation statistical features is better.
than the maximum value, skewness and kurtosis statistical features when using to classify the defected cable models. The figure also shows that the performance of network for data set when used 30% deformation factor is better than used 60% except in the case of skewness scheme due to the more feature effect of the deformation factor with this statistical value.

Figure 16: MSE of an ANN with statistical schemes and in the case of no scheme.

7 CONCLUSION

This paper presents The experimental investigation of 3D patterns of partial discharge measurements due to artificial cavity defects on different size are proposed. Also, the proposed was implemented using ANN by source ceding in MATLAB, and it was proved that;

- The experimental analysis of 3-D patterns of PD measurements due to artificial spherical and cylindrical cavities for many samples show that changing the size of artificial cavities increase of PD amplitude as a function of voltage is steeper for the bigger size of the cavity.
- The extracted feature vectors from 3D-PD patterns can significantly reduce the size of the PD pattern database and save time processing of classification.
- The ANN-based PD pattern classification is very effective for identifying the defects of XLPE cable even the case of high deformation of shape of 3d patterns of PD dataset.
- The statistical feature extraction schemes can making significantly improve the performance of ANN-based classification of defected cable special with using mean, standard deviation and coefficient of variance schemes.

8 ACKNOWLEDGMENTS

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9 REFERENCES


