

AC and Lightning Breakdown Voltage Prediction Based on PD Measurements

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Abstract: Partial discharge (PD) measurements are a standard method to determine insulation integrity since many years. For new equipment, the partial discharge level should be below a certain standardized level to be commissioned successfully. However, what is when a monitoring system detects upcoming partial discharges during the lifetime of an electrical equipment? Unfortunately, the discharge magnitude is not directly proportional to the remaining lifetime or the breakdown risk or breakdown voltage. Expert systems or experienced professionals can identify the PD defect root cause with a good certainty. This helps to determine the given risk. Nevertheless, clear risk quantification is missing. In this paper, a new approach is presented to predict the AC and lightning breakdown voltages of the equipment based on patterns from PD measurements. The method is validated with PD test data of several tip-plate configurations in air. A neuronal network is trained with these measurements. For control measurements with a different tip, it can be shown that the breakdown voltage can be predicted with an average failure of 5.3% for AC and 9.1% for lightning.

Key words: Breakdown voltage prediction, partial discharges, risk evaluation, neural networks.

1. Introduction

Reliable supply of electrical energy is an essential requirement for modern industrial societies. With the increasing demand on electricity and volatile energy sources like wind or sun, the power grid operators are obligated to be flexible and to offer their services for moderate costs. Therefore, the operators have to utilize equipment to their absolute maximum ratings and eventually to postpone necessary inspections.

The wear of the high voltage (HV) equipment on one hand and possible errors during fabrication or repair of HV equipment on the other hand can cause partial discharges (PDs) and impair the quality of service. PD presence and evolution is a good indicator for the equipment insulation integrity. Such information shall help to estimate the actual risk of a system breakdown.

Advances in sensors, electronics and digital signal processing have helped engineers in past decades to detect PDs and to monitor the HV equipment. For

example, monitoring by means of ultra-high frequency (UHF) partial discharge measuring techniques in gas-insulated switchgear (GIS) is today a routine in industry. The PD monitoring of GIS is done using UHF-sensors [1-13]. In generators and transformers capacitive couples are used to monitor PD. Unfortunately, the discharge magnitude measured with all such monitoring systems is not directly proportional to the remaining lifetime or breakdown risk of the HV equipment. For some PD defect types physical or statistical models exist to calculate the AC or lightning breakdown voltages, which correlates to the remaining insulation strength. In general, the exact defect geometry is required to perform such calculation. However, this defect geometry is just known after defect localization and repair. To the authors knowledge just one approach exists for bouncing particles in GIS to calculate the AC breakdown voltage based on the measured PD data [14, 15].

Today PD expert system or experienced professionals can identify the defect root cause with a good certainty. This helps to get a certain idea on the given risk. Nevertheless, clear risk quantification is

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missing. In this paper, a general approach is presented how AC and lightning breakdown voltages can be predicted based on PD measurement data.

2. Neural Networks

Artificial neuronal networks (ANN) have been used in the last decades to solve pattern recognition tasks or to predict output data based on complex input data in which normal regression algorithms fail due to the complexity of the problem. In general, an ANN can be described as an adaptive learning algorithm that is inspired by our brains structure [16]. At the synapse—the nerve cell releases a chemical compounds called neurotransmitters, which excite or inhibit a

chemical/electrical discharge in the neighboring nerve cells. The summation of the responses of the adjacent neurons will elicit the appropriate response in the neuron. An ANN consists of a set of algebraic equations and functions, which determine the best output given a set of inputs. These equations simulate the behavior of our nerve cells (Fig. 1).

To solve complex problems a multitude of such base cells are connected in rows and layers. To predict the AC and lightning breakdown voltage an ANN was chosen with 512 cells in the inputs layer, 23 cells in the hidden layer and 3 cells in the output layer. The 512 input data are the repetition rates of a pixel reduced PRPD-pattern (Fig. 2).

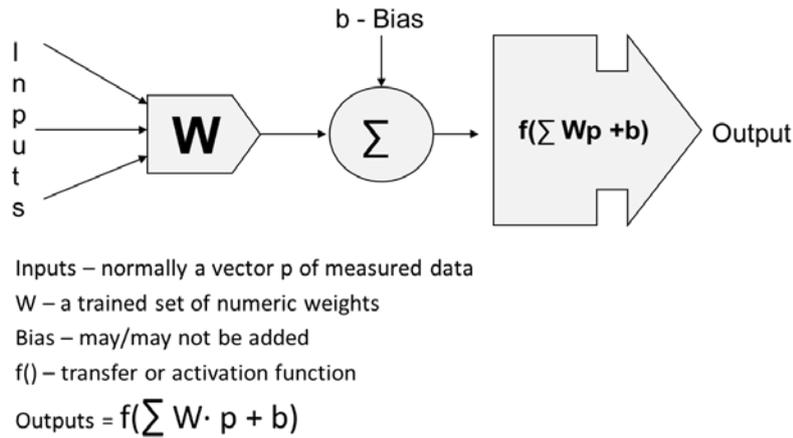


Fig. 1 Base cell of an artificial neural network.

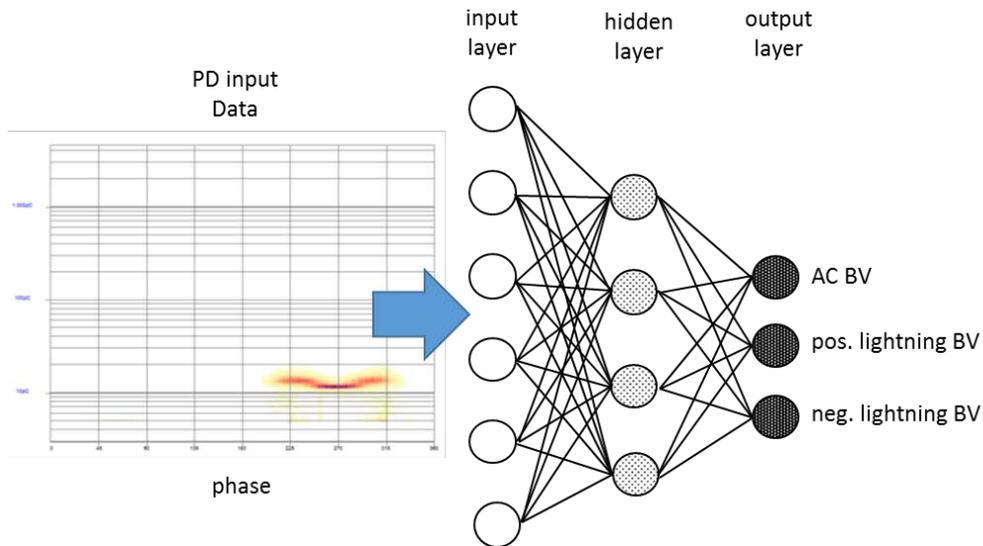


Fig. 2 ANN structure to predict breakdown voltages (BV) from PRPD-patterns.

3. Data Acquisition and ANN Training

To train the ANN for good results excessive data pairs consisting of PRPD pattern and associated breakdown voltage (BV) are required. For simplicity, a tip plane configuration in air was chosen to validate this relatively general approach. Fig. 3 shows the experimental set up. The air gap between the electrodes is 25 mm. Tips with four different tip radius (150 μm , 0.35 mm, 0.5 mm and 1.25 mm) have been investigated.

For all, the tip length into the air gap was modified in for steps (0 mm, 5 mm, 10 mm and 15 mm).

3.1 Breakdown Voltages Measurements

For all these $4 \times 4 = 16$ configurations the 50% breakdown voltages have been tested for AC, positive lightning and negative lightning.

3.2 Partial Discharge Measurements

Also the PD activity has been measured (PRPD-pattern). As the algorithm is intended to predict the breakdown voltage (which is hopefully well above the actual operation voltage) PD data have been measured at several voltages below the measured AC breakdown voltage (40%, 50%, 60%, 80% of AC BV).

The measurements were repeated 10 times to gain some statistical variance.

3.3 Training of the Neuronal Network

For the training of the ANN the breakdown voltages are normalized to the BV value of the 25 mm plate/plate air gap representing the sound insulation status. These normalized BV values can be interpreted as percent of remaining insulation strength. Fig. 4 shows four training datasets from a tip with 150 μm radius protruding 10 mm into the air gap. They belong all to the same AC or lightning breakdown voltages.

4. Results

Fig. 5 shows the data of the same tip protruding 15 mm into the air gap. They look similar but relate to significantly different breakdown voltages. This explains why this prediction is relatively difficult for humans.

Based these $4 \times 4 \times 10 = 160$ datasets obtained in the experiments the ANN algorithm has been training and validated. Data from only 3 of the 4 different tips were used to train the ANN. The algorithm learned the BV voltages of these 3 tips after only 1,500 learning cycles with an acceptable error of less than 1% (back error propagation method). Then the PD data of the not trained tip were presented to the network and the predicted BV was recorded.

The results obtained with relatively small number of training datasets for an ANN are surprisingly good.

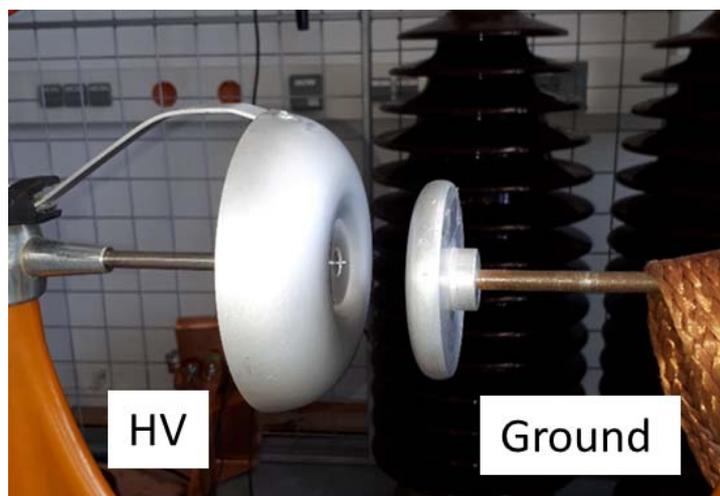


Fig. 3 Adjustable tip/plane configuration.

150 μ m tip protruding 10mm into the air gap

Normalized Breakdown Voltages: AC: 31%, neg. lightning: 68% pos. lightning: 55%

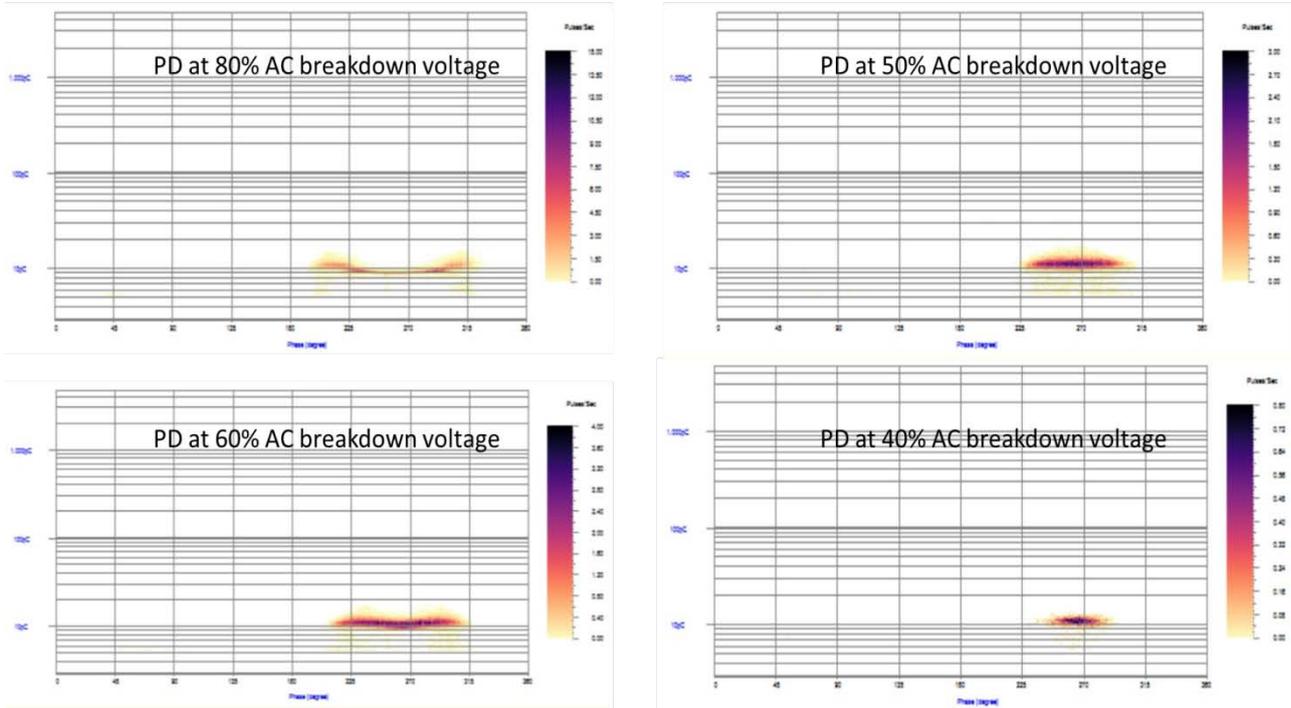


Fig. 4 Training datasets from a tip with 150 μ m radius protruding 10 mm into the air gap.

150 μ m tip protruding 15mm into the air gap

Normalized Breakdown Voltages: AC: 25%, neg. lightning: 49% pos. lightning: 43%

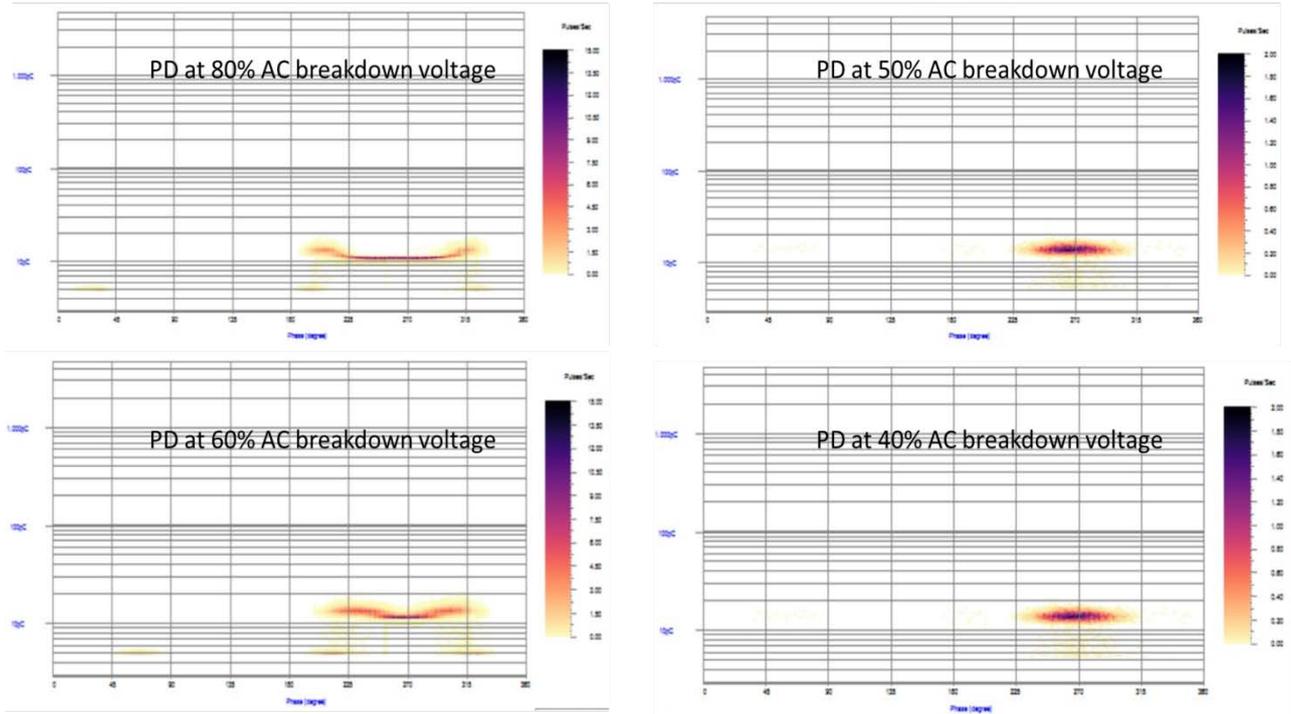


Fig. 5 Training datasets from a tip with 150 μ m radius protruding 15 mm into the air gap.

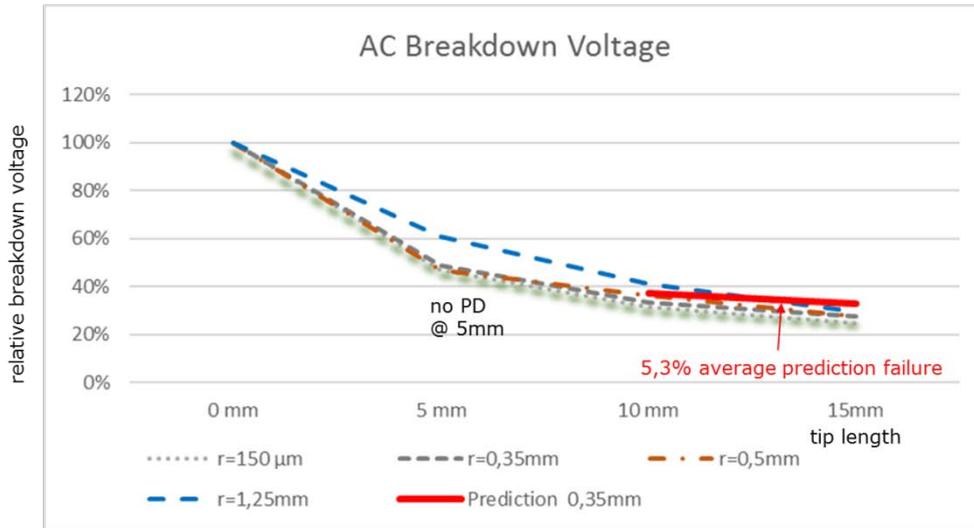


Fig. 6 Prediction of the normalized AC breakdown voltage of an “untrained” 0.35 mm tip.

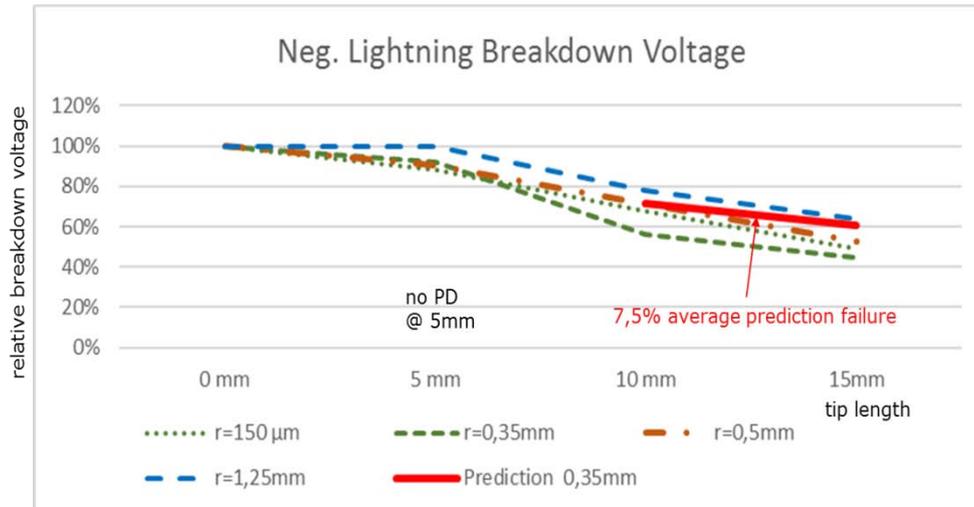


Fig. 7 Prediction of the normalized negative lightning breakdown voltage of an “untrained” 0.35 mm tip.

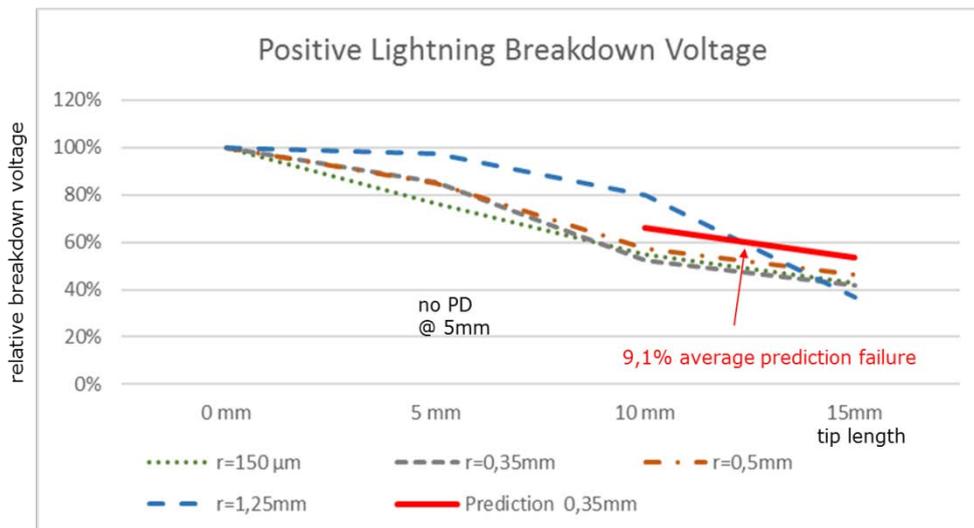


Fig. 8 Prediction of the normalized positive lightning breakdown voltage of an “untrained” 0.35 mm tip.

Figs. 6-8 show the results for the tip with 0.35 mm radius, which has not been trained to the ANN before. The AC breakdown voltage can be predicted with an average failure of 5.3%. The negative lightning BV is with an error of 7.5% and for positive lightning voltages with 9.1% error.

5. Conclusion

The approach of predicting the remaining insulation strength/breakdown voltages based on PD data by an artificial neural network was validated successfully. Even if the results are encouraging, it has to be pointed out that they have been archived at an academic set up only. It is clear that this approach must be further investigated for full-scale equipment and for insulation systems with higher relevance like SF₆, oil or PE. But it is also clear that this approach is general and open to all types of equipment and insulations where PD can be measured and a significant amount of training data sets can be obtained.

Approximately 50 years ago researchers have started to measure PD. Twenty-five (25) years ago we introduced first classification algorithms to identify the PD root cause type. The author hopes that with this work a small contribution can be made to quantify insulation breakdown risk based on PD data by predicting the actual breakdown voltage.

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