Characterization of Tools for Recognizing Phase Resolved Partial Discharge Pattern Based on Deep Learning Models

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ABSTRACT

Smart grids are growing with large scale deployments including between others partial discharge sensors for monitorization of insulation condition. This paper describes the application of permanent monitoring solutions using artificial intelligence to generate reliable alerts base on pattern recognition. Three different data models initially with high level of accuracy have been implemented and compared using different type of architecture and training data sets. A characterization for the three models has been designed to show the performance in real conditions where data is completely different to the training data set, noise is mixed with the defect, sensitivity is lost, and clustering techniques where needed to separate multiple defects. Finally, the results of the characterization permit to distinguish how critical is the implementation of the data model and the quality of the acquisition hardware.

KEYWORDS

Partial discharge; Phase Resolved PD Pattern; Artificial Intelligence; Deel Learning; Characterization.

INTRODUCTION

The implementation of smart grids deploying sensors to monitor different parameters in high voltage cables has been increasing in recent years [1]. Companies are accumulating a high volume of data that requires automatic treatment to generate reliable alerts. In the case of partial discharge (PD) monitoring, alerts generated by level are not effective enough, since noise events or external phenomena that do not pose a risk to the internal insulations can be superimposed. Monitoring systems are evolving to integrate artificial intelligent (AI) tools to automatically identify phase resolved PD patterns of defects in solid, SF6, air and oil insulation. Normally these models are trained with a very small database that in many cases comes from laboratory measurements, which ends with a high overfitting, preventing the model from generalizing well to new patterns. Despite obtaining accuracies close to 99%, these metrics are not reliable since they are validated on a dataset with little variability. When the model is evaluated using real field samples, it is appreciated that the results obtained do not reach 75%. This is evidence that laboratory samples do not provide enough variability to train a reliable production model. These tools must be robust to discriminate noise from PD defects. They also must be able to identify the type of defect regardless of the affected phase in which the PD pulses are generated or the amplitude with which they reach the sensor.
This article describes how three different Deep Learning models designed to identify different PD phenomena have been characterized. The architecture chosen for the first two models was VGG16. This architecture belongs to the Convolution Neuronal Network family, proved very effective at computer vision problems. Such architecture is publicly available in several open-source libraries. The first model was trained on laboratory data. The second model with the same architecture has been trained with samples of real field measurements. And a third model belongs to the recognition tool implemented by Ampacimon that is used in online monitoring solutions. All the samples of the dataset made up of samples of real field measurements have been previously validated by a diagnostic expert.
In the first characterization test, the behaviour of each of the three models using a data set from real field measurements is analysed. The second test is done using different noise situations, gradually increasing the noise with respect to the pattern of PD to identify when the model stops recognizing the sample. This noise will affect both the density and the amplitude. The third test of the characterization consists of eliminating part of the base of the pattern progressively to simulate an attenuation of the pulses equivalent to that of the propagation of the discharges in the real installation, as well as progressively decreasing the number of pulses that form the pattern.
The characterization results allow to see the differences between a model trained with real field samples and one trained with data generated artificially in a laboratory. Obtaining real field data for training is not an easy task, however, as shown in the study, it is essential to obtain reliable Deep Learning models capable of performing well in the field.

PD DIAGNOSIS BASED ON PATTERN RECOGNITION AND ITS APPLICATIONS

The measurement of PD is not easy as it is a small pulse with picocoulomb levels mixed in the background noise of the installation, but even if detection could be solved with noise suppression tools, the interpretation of the pulses is also requiring a lot of experience. The interpretation for AC installations has been done until now analysing the phase resolved PD pattern to identify the physical phenomena of the partial discharge permitting to assign the criticality.

Phase Resolved PD Pattern

The PRPD pattern is built with the set of pulses detected during the acquisition, representing in the vertical axis the charge of the pulses over the 360 degrees of 1 period of the voltage in the horizontal axis [2]. Depending on the type of phenomena (corona, surface, floating potential, void, particles…) and type of insulation (air, solid, oil SF6) the pattern will have different shape.
Recognition of clean patterns use to be possible, but difficulties may arise depending on:

- Rate of the defect (number of pulses per cycle).
- Noise conditions.
- Attenuation of the signal to reach the sensor.
- Affected phase.
- Mix of multiple defects overlapped.