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Acoustic cloud based approach for Corona early detection on Hydropower Equipment

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ABSTRACT

The Hydropower Generation market is facing globally high operational flexibility, compelling the operator to look forward to reach maximum availability and performance.

The early detection of incipient electrical failures at the generator winding, transformers and conventional substations will help reach these targets.

This paper presents a monitoring system which identifies through sound emission the acoustic emissions produced through small electrical discharges, called “Corona”. The Corona has a characteristic acoustic signature, containing specific frequency components in the range between 7 to 19 kHz. Acoustic Corona monitoring can also be used in combination with Partial Discharge Monitoring Systems, improving the early detection of incipient failures.

The approach along with using control system data, including historical machine behavior, and applying cloud based machine learning algorithms allows the continuous monitoring of the Corona effect. This allows to cluster machine “normal” behavior and to detect corona anomalies, allowing early warning before failures.

The output provides a web-based visualization to the operator, indicating unusual behavior that the support engineer can investigate possible issues in an early phase. The automated system provides a continuous monitoring of the equipment and raises a warning or alarm just in case of a corona acoustic behavior.

This solution allows an easy retrofit of existing hydropower plants as it requires no physical modifications of the equipment.

Keywords: acoustic, Corona, Machine learning

1. INTRODUCTION

Acoustic monitoring and cloud computing introduce a new approach of a monitoring system for Hydro Power plants: the “integral” approach.

This approach is based on the use of non-localized measurements which promotes the use of information from a larger set of equipment, e.g. inside the generator, turbine pit, conventional substations, or in the area of auxiliary systems such as high-pressure units.

The acoustic monitoring system is capable of detecting anomalies or deviations from typical behavior of the machine (1). This approach has advantages over classical monitoring systems, where sensors are mounted to fixed locations. Integral sensors like microphones supervise a larger space and thus supervise more equipment with a smaller number of sensors. It is very interesting, for example, how the vibration signals of classical monitoring systems relate to signals of acoustic monitoring. (1).

Although the use of microphones will lead to obtain signals which will be a mixture of the contribution of several sound sources, it can be possible to detect specific events if a proper set of acoustic features is selected and techniques of blind source separation is used.

Most of the malfunctions detected in the hydro power units are caused by following type of phenomena:

- Mechanical: Due to shaft misalignment, anisotropy of bearings, instability of the bearing oil film, mechanical or magnetic imbalance and friction.
- Hydraulic: Due to self-generated forces, hydrostatic, cavitation, instabilities in the draft tube or flow in the hydraulic ways. They can also come from transient regime period excitations
- Electric: Due to unbalanced magnetic forces, lack of uniformity in the generator gap or phenomena known as Partial Discharge or Corona.

Mechanical phenomena and their translation into vibrations and correlated acoustic effects have been studied and published in previous papers (1). Our new goal is to investigate Corona as electric malfunction potentially causing degradation of the insulation system in the power unit (generator) and as part of the future investigations we will focus on one of the most typical hydraulic phenomena: cavitation (2).

The Corona effect can occur in generators or transformers. The corona is produced by partial discharges which may occur in high voltage equipment due to unforeseen high electric field strengths. The occurrence of partial discharge does not mean the total loss of the insulation system as it does not cause a complete conductor to ground connection. Partial discharge can also occur along the surface of solid insulating materials. This happens if the surface tangential electric field is high enough to cause a breakdown along the insulator surface. However, with the passage of time the Corona may end up deteriorating the insulation, causing increased aging of the insulation material.

Figure 1 – Corona on generators (source ofilsystems.com)

Evidence of the Corona is often visible to the eye with a white powder also appearing that sprinkles the surface of the stator winding. Past research also talks about the possibility of detecting the corona at the same time by means of acoustic (3), visual monitoring and through the detection of gases, since a secondary product of the Corona is the appearance of ozone (4).

In practice, the Corona is evaluated during two different situations:

1.1 During Commissioning

During the dry commissioning of the generator, a high-power test (executed in accordance with e.g. IEEE 56-1979 (§ 8.1.5.2)) is carried out manually, which ends with the visual inspection of the machine. Thus, the test is normally executed by night with reduced illumination; if necessary, a dark covering must be provided.

Under certain circumstances, this test involves the presence of personnel in the generator pit, which entails risks. For safety reasons, all metallic non-energized parts of the machine as well as the HV power supply should be grounded and the windings must be free from dust or other kind of dirty. It will be also necessary to isolate the area around the stator and provide security/safety advertises. Only qualified personnel should be allowed to execute the test.

Due to all these points, an acoustic monitoring system detecting corona and avoiding the presence of personnel in the generator pit and the generator stator during the test would be a significant improvement for hydropower plants commissioning and maintenance personnel.

A similar scheme to the wiring schematic (Figure 2) for testing corona during commissioning has also been used for the laboratory tests of our system.

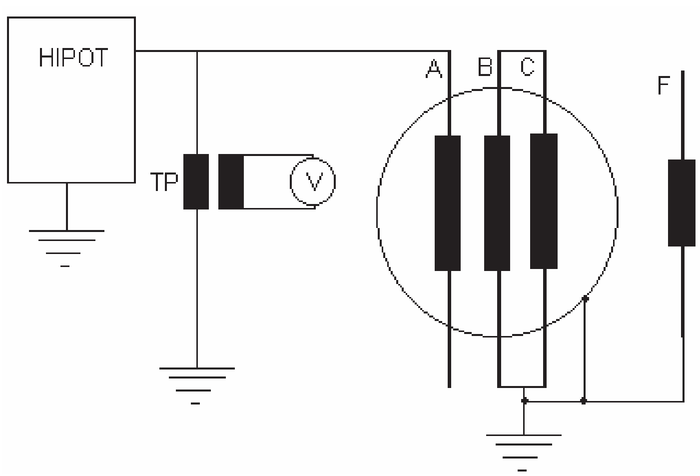

Figure 2 – Wiring schematic for alternating voltage test of the stator winding

Where:

HIPOT	-	HV test equipment;
TP	-	Voltage transformer;
V	-	Voltmeter AC;
A, B e C	-	stator winding phases;
F	-	rotor winding.

1.2 During Operation period

In the medium and long term, special equipment is needed to detect the Corona by means of couplers. These couplers are installed mainly to detect Partial Discharge, but they also measure the Corona. For diagnosis, it is essential to make a temporary tendency of the measure Partial Discharge because the machines have different reference values.

Figure 3 – Mounted couples inside a generator pit (source sparks instruments)

The doubling of Corona levels over a six-month period is cause for concern. The machine must be opened and inspected visually.

The acoustic cloud-based approach could be an easy way to equip the generator and both do stand-alone Corona monitoring and correlate the results and analysis of the classical Corona Monitoring system.

2. PROCEDURES FOR EVALUATING THE CORONA

2.1 Tests description

For Corona generation, both in the laboratory and in the field, it is necessary to apply the high voltage source defined previously and shown in figure 2.

In both cases, the high voltage source is connected to the voltage transformer. In the case of the laboratory, the experiment is closed by connecting the high voltage source with an electrical conductor. In the case of the field, the voltage source is connected to one of the bars of the stator winding, on the generator output bus

In both cases, special attention must be paid to conveniently storing the unused elements. The metallic surfaces must be clean and free of dust and to achieve the Corona special conditions of temperature and humidity are required.

Once the electric part is assembled, the voltage of the high-power source is raised in steps until the Corona appears. As a result it appears a time signal like the one in figure 4 containing multiple Coronas over time. This Corona must be very similar for the experiment done in the laboratory as in the field experiment.

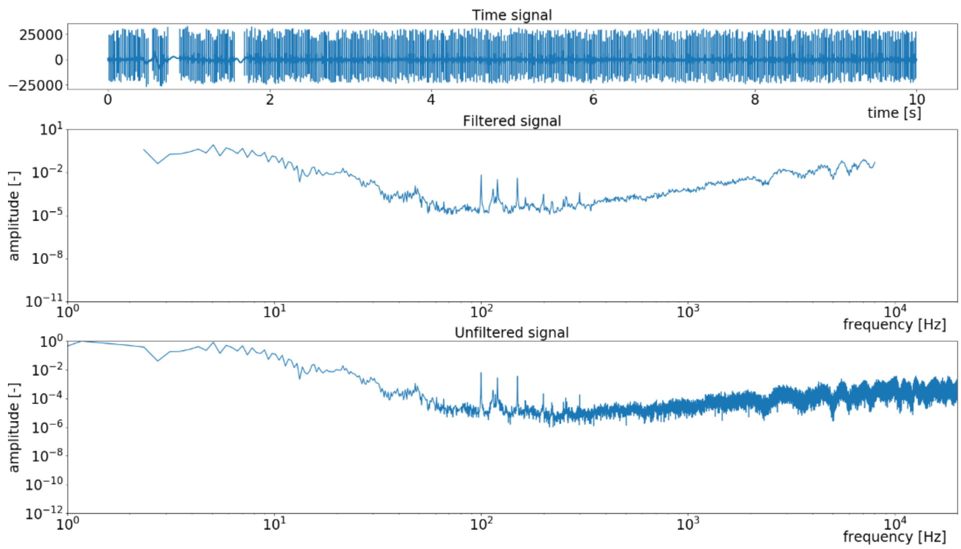

Figure 4 – Pure Corona Signal

As the purpose of this work is the separation and detection of Corona in running machine conditions, and to achieve an effect similar to that of the generator running in a hydraulic power station, in the laboratory a simulated background noise with similar intensity and shape to the real one was added.

The superposition of the Corona signal to the background noise of the machine in nominal operation can be seen in Figure 5. In addition, in other experiments other noises, such as fans, are added.

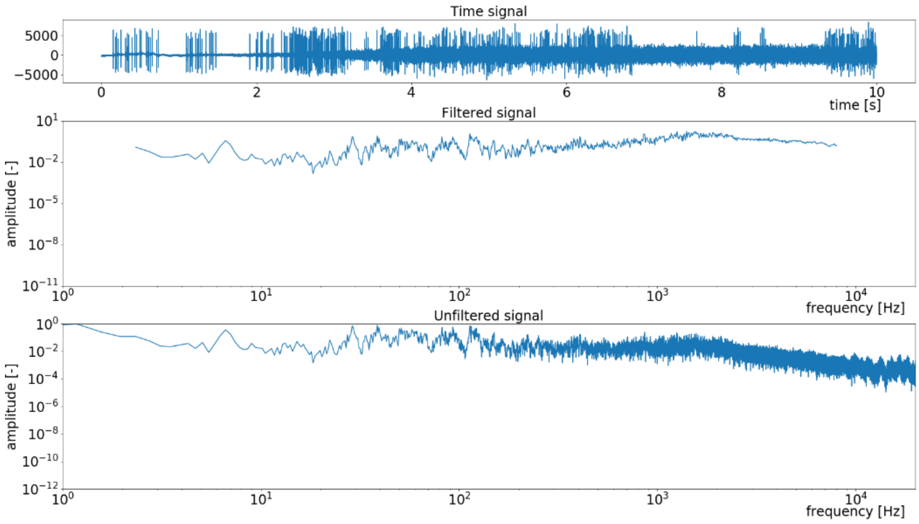

Figure 4 – Corona Signal and Running Machine background noise added

For all these scenarios, different samples of different lengths are taken to better perform the training of the algorithms.

For the analysis and separation of the Corona, two different techniques have been chosen that have given very interesting and promising results:

- In the first one, MFCCs (Mel Frequency Cepstral Coefficients) were used as features and reduced in dimensions under the PCA. Finally, 3 dimensions were used to visualize the data set.
- In the second one, a CNN (Convolutional Neural Network) was established using gray scale spectrograms of input size 300X300 for binary classification of test data

2.2 MFCCs (Mel Frequency Cepstral Coefficients)

The first classification strategy that we have carried out is MFCCs. Mel Frequency Cepstral Coefficients (MFCCs) are widely used features for automatic speech and speaker recognition. In addition, applications in environmental noise are becoming more frequent.

The cepstral coefficients are derived from the Fourier transform (FFT – Fast Fourier Transform) or the discrete cosine transform (DCT), but the basic feature is that in MFCC the frequency bands are logarithmically located, according to the Mel scale.

The short time Fourier transform of the signal is evaluated to follow the temporal changes of the frequency components. Then the next step is the calculation of the periodogram of the power spectrum of each frame.

Following, the filter bank according to the Mel scale is applied to the power spectra and the resulting energy is summed.

Then the logarithm of all filter bank energies is calculated, and through the DCT we obtain the cepstral coefficients of the Mel frequencies, which will form the MFCC vector.

After the MFCCs were extracted as features, the dimensions of the data set were reduced using the PCA (Principal Component Analysis) clustering. Finally, we only used three dimensions of the dataset to represent the data in three-dimensional space.

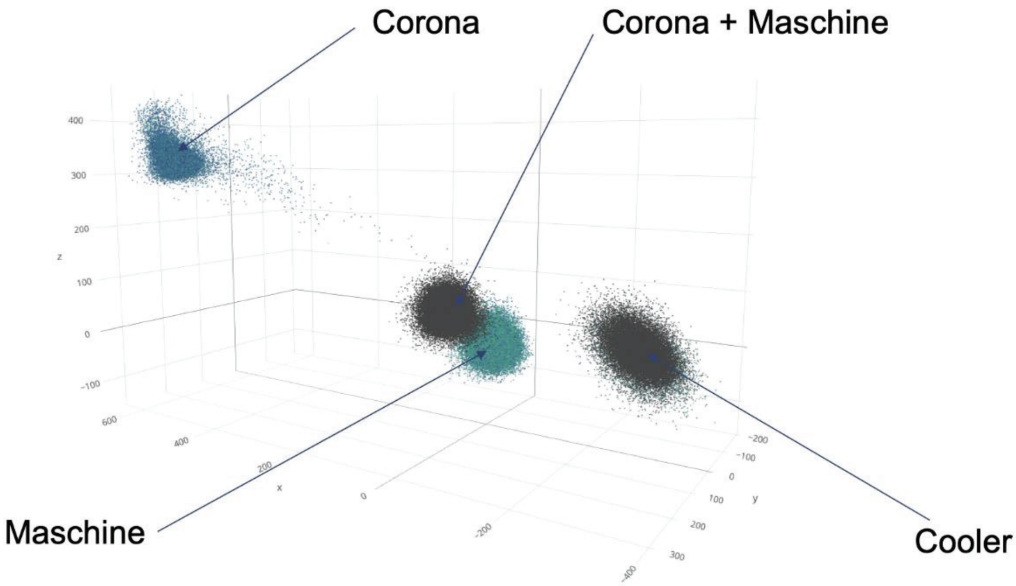

Figure 5 – PCA Clustering of the Corona estimation after MFCCs calculation

2.3 Convolutional Neural Network

The second classification strategy that we have carried out is CNN (Convolutional Neural Network). CNN is a type of Artificial Neural Network with supervised learning that processes its layers imitating the visual cortex of the human brain to identify different characteristics in the inputs that ultimately make it possible to identify objects and "see".

In our case, we will work with spectrograms of the different noises as input for the CNN. Figure 6

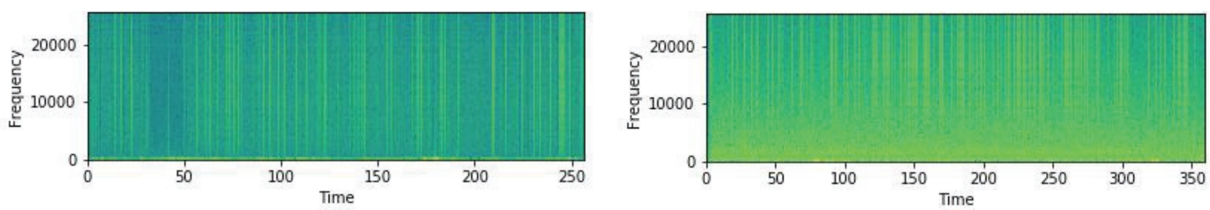

Figure 6 – Corona spectrogram (Left) and Corona+ Machine spectrogram (Right)

The CNN contains several specialized hidden layers and a hierarchy: this means that the first layers can detect lines, curves and are specialized to reach deeper layers that recognize shapes. These consist of taking "groups of nearby pixels" from the input image and operating mathematically (scalar product) against a small matrix called a kernel. That kernel supposes a of size 3×3 pixels "runs" all input neurons (left-right, top-bottom) and generates a new output matrix which will ultimately be our new layer of hidden neurons.

In our case, our CNN Model (containing 5 layers) was trained with the same number of samples from the running power unit and from the running power unit + Corona.

In addition, the concept of data augmentation was used hereby artificially generated data was added to the original training data. Finally, the trained model was tested on the data of a second experiment under the same conditions as the first experiment. Figure 7

Training data Set	Samples
Running Power Unit	458
Running Power Unit + Corona	458
Totally	**916**

Data- Augmentation (Overlapping, Noise)

N=916 → **N=6512**

Test data Set	Samples
Running Power Unit	326
Running Power Unit + Corona	326
Totally	**652**

Figure 7 – CNN Training Data Set and Test Data Set

The results of the bi-class decision model are very positive, giving rise to very small decision errors, with very high accuracy and precision. Figure 8

N= 652		Predicted: No Corona	Predicted: Corona
Real	No Corona	325	1
Real	Corona	0	326

Acuracy:	
(325+326)/652=	0.998
Missclassification Rate:	
(0+1)/652=	0.001
Precision:	
326/327=	0.996

Figure 8 – Results of the application of the CNN Model on Corona

3. CONCLUSIONS

It has been possible to separate and detect the Corona by means of a bi-class detector based on neural networks with very high hit rates and by means of clustering based on the MFCCs algorithm with very promising results.

The next step is to integrate it into Voith's standard acoustic monitoring algorithms and apply this approach also to the special Corona tests performed during the start-up of hydraulic machines.

The acoustic monitoring is conceived as an integral monitoring system. Not only the components from the vibrations can be isolated (1), but also the spectral components of other aggregates of a hydroelectric power plant (air compressors, etc.), or electrical effects as Corona, allowing monitoring of the anomalies of these systems.

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