# Automating the Classification of Field Leakage Current Waveforms

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*Abstract*— **Leakage current monitoring is widely employed to investigate the performance of high voltage insulators and the development of surface activity. Field measurements offer an exact view of experienced activity and insulators' performance, which are strongly correlated to local conditions. The required long term monitoring however, results to the accumulation of vast amounts of data. Therefore, an identification system for the classification of field leakage current waveforms rises as a necessity. In this paper, a number of 500 leakage current waveforms recorded on a composite post insulator installed at a 150 kV High Voltage Substation suffering from intense marine pollution, are investigated. The insulator was monitored for a period of 13 months. An identification system is designed based on the considered data employing Fourier analysis, wavelet multiresolution analysis and a neural network. Results show the large impact of noise in field measurements and the effectiveness of the discussed system on the considered data set.**

***Keywords-insulator; leakage current; field; neural network; wavelet; pattern recognition; STD_MRA***

## I. INTRODUCTION

Outdoor insulation is an important part of transmission and distribution systems, since a single insulator failure may cause an excessive outage of the power system. During operation, electric, mechanical, thermal and chemical stresses apply to outdoor insulators. One of the most influential mechanisms however, is the pollution phenomenon. The basic stages of the phenomenon as described in [1,2], are as follows: the first step is the accumulation of contaminants on the insulators' surface. In the case of hydrophilic insulation (e.g. porcelain), the presence of a wetting mechanism (e.g. rain, fog, humidity) transforms the contaminants layer into a conductive film and the flow of leakage current (LC) on the surface is permitted. Initially, this current is resistive and sinusoid but as activity advances distorted sinusoid current is recorded. The surface heats and dries up unevenly and areas of higher resistance, called dry bands, are formed. The voltage distribution along the insulator is altered. Increased stress along the dry bands is observed and dry band arcs appear, which, under favorable conditions, may propagate and ultimately lead to a complete flashover of the insulator. The presence of the arc in the current path is indicated from the on-set time delay of LC waveform in every half-cycle, which causes a knee-like shape. Polymer insulators and coatings are used to prevent film formation, and therefore suppress activity, due to their hydrophobicity. However, such materials experience cycles of hydrophobicity loss and recovery [3-7]. The phenomenon is highly correlated with environmental and surface conditions (temperature, wind, location etc) [1-8]. Therefore, only field measurements can offer an exact view of the experienced activity and insulators' performance. It should be noted that during a hydrophobicity loss period, the waveform shapes recorded on hydrophobic insulators are similar to those recorded on hydrophilic ones [8]. The main issue regarding field leakage current monitoring however, is that activity is rapid, rather rare and cannot be safely predicted. Therefore, continuous long term field monitoring is required. The long term monitoring combined with the necessary high sampling rate results to the accumulation of vast amounts of data. Further, field conditions exaggerate the noise factor and therefore a percentage of the gathered data may be incoherent [9]. In this paper, a data set of 500 LC waveforms recorded on an insulator located in the field during a period of 13 months, is investigated. An identification system capable of identifying four different types of waveforms is designed based on the considered waveforms. The identification system employs Fourier analysis in order to identify noise generated waveforms, wavelet analysis and especially STD_MRA in order to extract patterns from activity portraying waveforms and a neural network to automate the identification process.

## II. MEASUREMENTS SETUP

The waveforms investigated in this paper have been recorded on a 150 kV post composite insulator located in the Linoperamata 150 kV High Voltage Transmission Substation of the Greek Network. The monitoring period was 13 months. The Linoperamata Substation is located next to the coast and suffers from intense marine pollution. The Greek Public Power Corporation (P.P.C.) has issued a large project to cope with the problem, and as a part of that project several insulators and coatings have been, or still are, monitored and investigated. Some of the published results can be found in [8-11]. A schematic representation of the measuring apparatus employed to monitor leakage current is shown in Fig. 1.

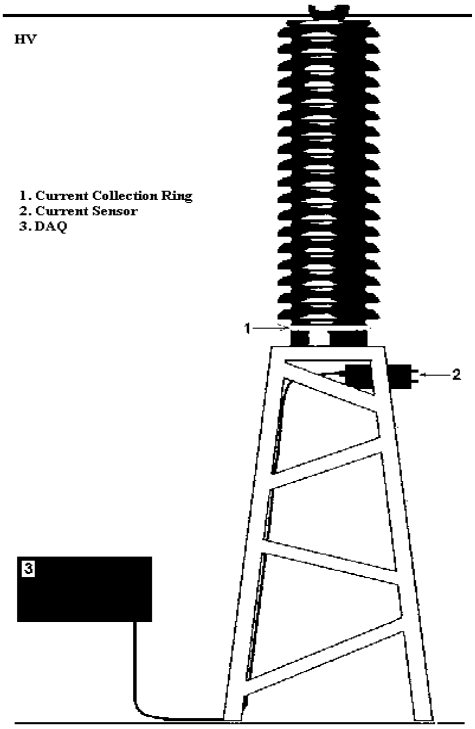


Figure 1. A schematic representation of the LC measuring apparatus

The measurement of leakage current is acquired by inserting in the LC path a collection ring and a Hall sensor. The acquired data are transmitted to a central data acquisition system (DAQ) and sampling is performed at a rate of 2 kHz**.** A user-defined time window is set (e.g. 24 hours) and the DAQ records one waveform for each time-window (e.g. one waveform per day). The waveform that is recorded is the one portraying the highest peak value. Various time-windows have been applied during the 13 months of monitoring. Each waveform has a length of 480ms which with a 2 kHz sampling rate corresponds to 960 data points. The DAQ is periodically connected to a laptop in order for data to be retrieved. The MATLAB software has been employed for further processing of retrieved data and for the design and evaluation of the identification system.

## III. WAVELET ANALYSIS AND THE STD_MRA TECHNIQUE

Wavelets are a mathematical tool for signal analysis. Extended wavelet theory can be found in [12,13]. Wavelet analysis allows simultaneous time and frequency analysis of signals. A wavelet function is an oscillatory function, with an average value of zero and a band-pass like spectrum. The basic concept in wavelet analysis is to select an appropriate wavelet function $\Psi$ (the mother wavelet) and then perform the analysis of a signal using translated (shifted) and scaled (dilated) versions of the mother wavelet. The continuous wavelet transform is given by (1) where $\alpha$ represents the scale, $b$ represents the position, and $\Psi^*$ represents the complex conjugate of $\Psi$ .

$$\langle f,\Psi_{a,b}\rangle = \int_{-\infty}^{\infty} f(t)\Psi_{a,b}(t)dt = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} f(t)\Psi^*(\frac{t-b}{a})dt \qquad (1)$$

In case a digitized signal and discrete values of $a$ and $b$ are used then the Discrete Wavelet Transform is given by (2) where $a = s_0^j$ , $b = ka = ks_0^j$ and $k, j \in Z$ .

$$DWT(f,j,b) = \frac{1}{\sqrt{s_0{}^j}}\int_{-\infty}^{\infty} f(t)\Psi(\frac{t-k\cdot s_0{}^j}{s_0{}^j}) \qquad (2)$$

Multiresolution analysis (MRA) is a wavelet based filtering algorithm, which was created as a theoretical basis to represent signals that decompose in finer and finer detail [12,13]. The main idea is to use wavelet analysis to decompose the original signal in two parts: the approximation, which contains the low-frequency part of the signal, and the details, which contains the high-frequency part. The first stage of decomposition will give the first level approximation (a1) which if decomposed will give the second level approximation (a2) and so on. Detail analysis is performed with a contracted, high frequency version of the mother wavelet, while approximation analysis is performed with a dilated, low frequency version of the same wavelet. An example of MRA performed in a LC waveform is shown in Fig. 2.

In this paper, the STD_MRA technique is used in order to extract patterns from LC waveforms. Each LC waveform is decomposed in six levels using MRA and the standard deviation (STD) of the details (d1, d2, …, d6) extracted in each level of the MRA is calculated. The normalized six-point vector, called STD_MRA vector, is then used as a pattern for the corresponding waveform. The STD_MRA vector is normalized because similar LC waveform shapes can portray various amplitudes. The mathematical expression of the standard deviation $\sigma$ for a n-point vector $x$, is given in (3), where $\bar{x}$ is given in (4). Considering that the shape of the mother wavelet should be similar to the shape of the signal, Daubechies 4 wavelet is chosen as a mother wavelet. The form of the approximation and details during the MRA is directly linked to the shape of the mother wavelet, which means that decomposition will produce Daub4-like wavelets, as shown in Fig. 2. The frequency band of approximation and details for each decomposition level is showed in Table I.

$$\sigma = (\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2)^{\frac{1}{2}} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2} \qquad (3)$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (4)$$

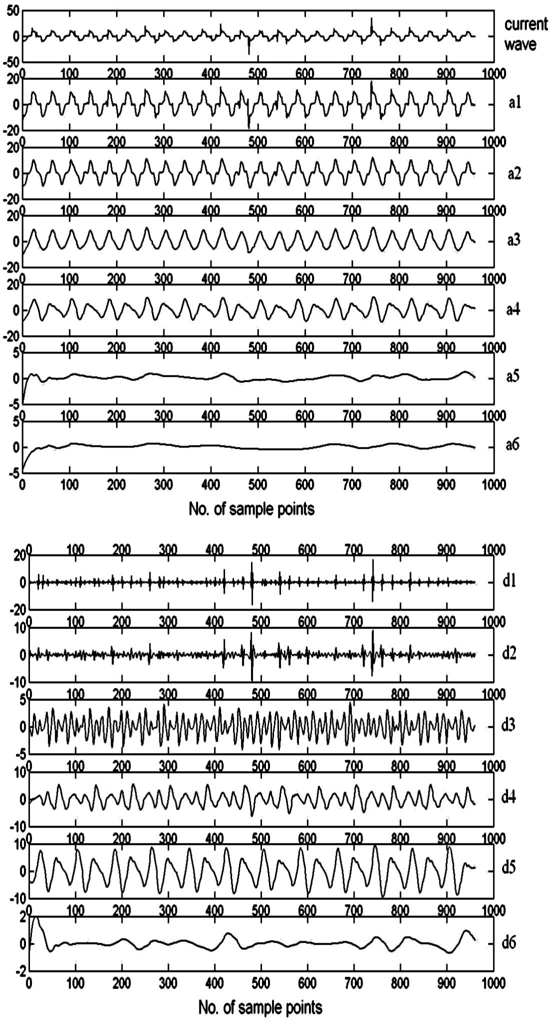


Figure 2. Six level MRA analysis of a LC waveform. a1-a6 shows the approximation and d1-d6 shows the details through levels 1-6.

TABLE I. FREQUENCY BANDS FOR DIFFERENT MRA LEVELS

| *Decomposition Level* | *Approximation* | *Details* |
|---|---|---|
| 1 | 0~500 (Hz) | 500~1000 (Hz) |
| 2 | 0~250 (Hz) | 250~500 (Hz) |
| 3 | 0~125 (Hz) | 125~250 (Hz) |
| 4 | 0~62.5 (Hz) | 62.5~125 (Hz) |
| 5 | 0~31.25 (Hz) | 31.25~62.5 (Hz) |
| 6 | 0~15.625 (Hz) | 15.625~31.25 (Hz) |

## IV. ACTIVITY PORTRAYING WAVEFORMS AND EXTRACTED PATTERNS

Three different categories for activity portraying waveforms were set after the investigation of the considered data set. Sinusoid and distorted sinusoid current are described as Type A. Dry band arcs that are sustained for a limited number of half cycles are described as Type B and excessive arcs that are sustained throughout the whole waveform are described as Type C. An example of each type and the corresponding pattern derived from STD_MRA is portrayed in Fig. 3,4 and 5 respectively.

## V. THE ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) are highly parallel, adaptive learning systems that can learn a task by generalizing from case studies of the tasks. If a problem can be posed as a problem of mapping outputs to inputs, then an ANN can be used as a black box that learns the mapping from examples of known cases of correlated inputs-outputs. The selection and the design of the ANN was done considering the attributes described in [14-16] related to simplicity, speed and efficiency. Among the various forms of ANN architectures, the multilayer Feed Forward network with back propagation learning algorithm was chosen. This architecture (also known as Multi-layer Perceptron architecture) is suitable for recognizing patterns that don't evolve with time.

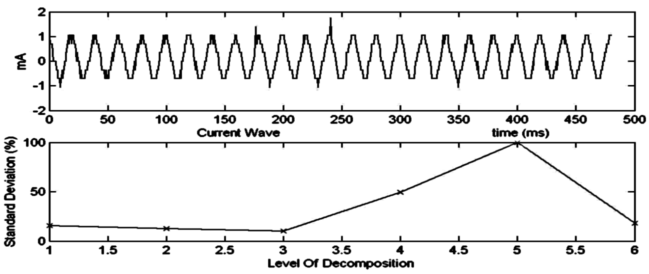


Figure 3. A Type A waveform and it's the STD_MRA pattern

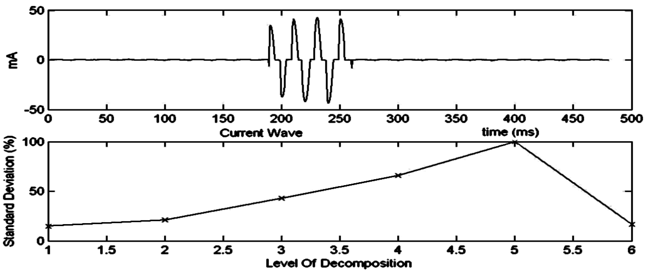


Figure 4. A Type B waveform and the STD_MRA pattern

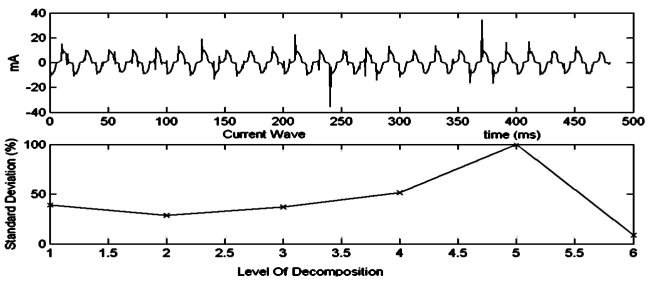


Figure 5. A Type C waveform and the STD_MRA pattern

In order to identify categories that are located in the same area, but are not linearly separated (such as the patterns extracted in this study), one hidden layer is sufficient. The number of inputs is six (equal to the elements of the pattern-vector) and the ANN must identify 3 categories, therefore three output neurons are sufficient. Each Type is correlated to a three-element output vector easily separable from the others. Type A to [1 0 0]',Type B to [0 1 0]' and Type C to [0 0 1]'. In order to minimize the risk of "trapping" the algorithm around a local minimum, the number of neurons per layer should decrease from the input layer to the output layer. Hence, five neurons are selected for the hidden layer. The hyperbolic tangent function is chosen for the hidden layer for its speed and efficiency. The Log-Sigmoid function is chosen for the output layer in order to compress the outputs into the [0,1] domain. The learning algorithm used is the Levenberg-Marquardt due to its speed in the case of medium-sized ANNs. The train set consists of 4 Type A waveforms, 3 Type B waveforms and 6 Type C. A schematic representation of the ANN is illustrated in Fig. 6.

## VI. NOISE GENERATED WAVEFORMS

Noise generated waveforms can be attributed to various field related conditions (cable faults, equipment faults, operation of circuit breakers, switching of heavy loads etc) [9]. Noise generated waveforms vary in form, and some typical waveforms are shown in Fig. 7. Those waveforms will lead to erroneous results if fed to the neural network. Therefore, it is highly desirable to be identified and discarded at the early stages of the identification system, using deterministic criteria. The voltage frequency in the Greek system is 50 Hz and therefore the fundamental frequency of every leakage current waveform should be 50Hz. This criterion can be used to discard waveforms as the first three in Fig. 7. However, waveforms similar to the last one in Fig. 7, can exhibit a 50Hz fundamental. An example is shown in Fig. 8. An amplitude criterion could be applied in order to discard such waveforms. However, a noise generated spike, can be superimposed on such waveforms, as shown in the first waveform of Fig. 7, and thus allowing them to exceed any threshold. Therefore, a simple low pass filter with a cut off frequency of 200Hz is employed, in order to remove spikes while maintaining the main part of the waveform, and then an amplitude criterion is applied.

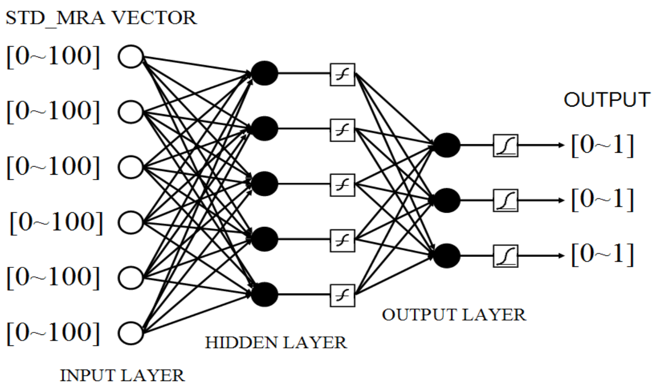


Figure 6. A schematic representation of the ANN

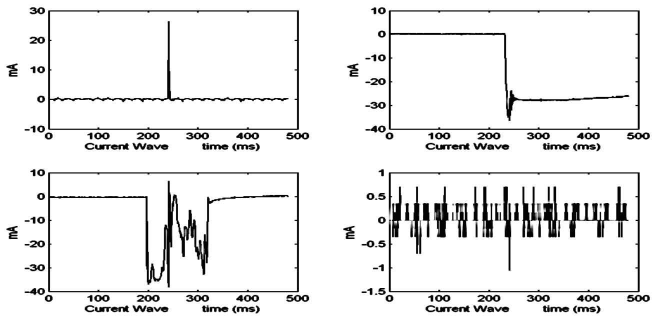


Figure 7. Noise generated waveforms

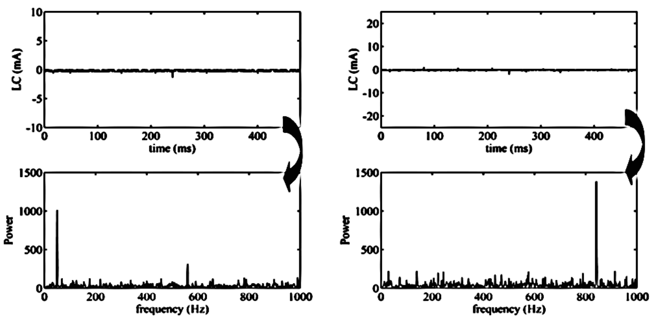


Figure 8. Two noise generated waveforms and their frequency content

## VII. THE IDENTIFICATION SYSTEM

A block diagram of the identification system is shown in Fig. 9. Initially, the frequency content of each LC waveform is calculated using the Fourier transform. If the fundamental frequency of the waveform differs from 50 Hz then the waveform is attributed to noise. If the waveform exhibits a 50 Hz fundamental, then it passes through the low-pass filter and the amplitude of the filtered waveform is calculated. If the amplitude of the filtered waveform is found smaller than 1 mA, then the waveform is attributed to noise. Otherwise, STD_MRA is performed on the original waveform (not the filtered one). The extracted pattern (the STD_MRA vector) is then fed to the Artificial Neural Network which identifies the waveform type.

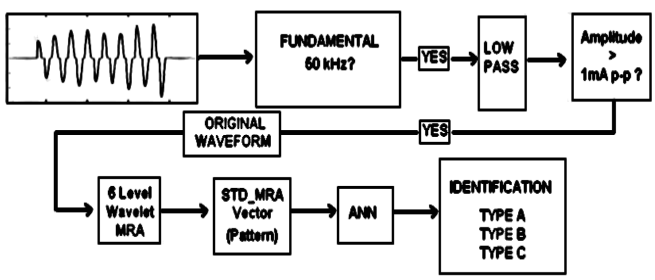


Figure 9. Block diagram of the identification system

## VIII. RESULTS AND DISCUSSION

The identification system was able to successfully identify all 500 waveforms and results are shown in Table II. The results show the significant impact of noise in field leakage current waveform monitoring. Further it is shown that the discussed identification system can successfully recognise and further categorize activity portraying waveforms.

TABLE II. NUMBER OF WAVEFORMS PER TYPE

| *Waveform type* | *Number of waveforms* |
|---|---|
| NOISE | 460 |
| TYPE A | 9 |
| TYPE B | 7 |
| TYPE C | 24 |
| SUM | 500 |

However, it should be mentioned that the design of the discussed identification system is based upon the considered data set, which is relatively small. Further investigation of field waveforms is required. However, results show that the STD_MRA technique combined with neural networks can be applied in order to identify different types of field leakage current waveforms, although it is highly probable that further investigation may result to the modification of the system and possibly to the add of new categories.

## IX. CONCLUSION

Leakage current monitoring is widely employed in order to investigate surface activity on high voltage insulators and to evaluate their performance, which are both strongly correlated to local conditions. Field monitoring can offer an exact view of the insulators' performance and the experienced activity. However, the necessary long term monitoring results to the accumulation of vast amounts of data and the implementation of an identification system rises as a necessity. In this paper a number of 500 waveforms recorded over a 13 month period on a 150 kV post composite insulator located at a 150 kV High Voltage Substation suffering from intense marine pollution, is investigated. An identification system is designed, capable of identifying four basic types of waveforms, including noise generated waveforms. Results show that noise is significantly exaggerated in the field. In addition, it is shown that wavelet analysis, and especially the STD_MRA technique, combined with neural networks can be successfully employed to automate the classification of field leakage current waveforms.

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