Recurrence Quantification Analysis as a Novel LC Feature Extraction Technique for the Classification of Pollution Severity on HV Insulator Model

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ABSTRACT
Recently, Recurrent Plot (RP) was introduced to study Leakage Current (LC) for polluted insulator performance monitoring. Based on complex graphical representations, RP only provides a qualitative overview of the insulator state. To overcome this issue, we present in this paper a novel technique, named Recurrence Quantification Analysis (RQA) able not only to indicate RP structures, but also to quantify LC dynamics during the contamination process. RQA is introduced to investigate RP structures, quantify LC dynamics and extract features from LC waveforms for polluted insulator monitoring and performance diagnostic. For this purpose, LC acquisition is firstly carried out on a plan insulator model uniformly polluted with saline solution. Eight RQA indicators are presented to investigate LC waveforms under various pollution conductivities. Finally, mean values of RQA indicators are proposed as input for three well-known classification methods (K-Nearest Neighbors, Naïve Bayes and Support Vector Machines) in order to classify the contamination severity into five classes. Results show excellent correlation between RQA indicators and the pollution severity level.

Index Terms - Leakage current, recurrent plot, recurrence quantification analysis, feature extraction, polluted insulator monitoring, classification methods.

1 INTRODUCTION
In order to improve power networks reliability, many researches are focused on High Voltage Insulators. This important element of the electrical transmission and distribution system remains, yet, vulnerable to various environmental conditions. Indeed, high voltage insulators are susceptible to electrical flashover occurrence under natural and industrial pollution [1-3]. To examine this phenomenon, many authors studied the effect of pollution accumulation on the insulator surface and found that the Leakage Current (LC) is closely related to the contamination level [4-19].

To predict the contamination level and monitor high voltage insulators, several methods, known as feature extraction techniques, have been developed to study the characteristics of LC. Ramirez-Vazquez et al [6] were interested to measure the pulse number and the peak value of LC as well as the cumulative charge value to assess pollution severity. Similarly, Li et al [7] highlighted the mean value, the maximum value and the standard deviation of the LC as suitable quantities to study LC under pollution conditions. Moreover, Jiang et al [8] proposed to examine the phase angle between LC and applied voltage, the maximum pulse amplitude of LC and the total harmonic distortion as characteristic parameters to assess polluted insulators state. To determine LC characteristics, the Fast Fourier Transform (FFT) analysis, power spectrum analysis and wavelet analysis are used respectively by Suda [9], Song and Choi [10], Douar et al [11] and Pylarinos et al [12]. As main result found by Suda, magnitudes of 3rd, 5th and 7th harmonics (corresponding to 50 Hz, 150 Hz and 250 Hz respectively) increase within the flashover process. Wavelets are useful for decomposing LC into low frequency, medium frequency and high frequency components. According to Song et al [10], the high frequency components of LC are helpful to monitor the contamination process on HV insulators. Also, Douar et al [11] analyzed the flashover process and examined the frequency characteristics of LC using Standard Deviation-Multi Resolution Analysis (STD-MRA) representation. Recently, Pylarinos et al [12] compared classification performance of LC waveforms for temporal and frequency features. Results showed that frequency components provide better results. However, classical LC feature extraction, computed from temporal and frequency domains, are very limited in number. Moreover, interpretation of LC temporal and frequency features does not offer an overview about the insulator performance. These features have to be used as inputs of artificial intelligence tools, such as Artificial Neural Networks [13-18] or Fuzzy Logic [19-20], in monitoring of pollution severity and diagnostic of the insulator performance.

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The Recurrent Plot (RP) is recently introduced in this area. Initially, this technique was conceived to detect non-linearities and eventually chaotic dynamics in experimental signals in physics [21], in financial data time series [22] and ecosystem time series [23]. Recently, it has been successfully applied to study LC and monitor the flashover process [24-25] and also to Dynamic Drop Test for Hydrophobicity Evaluation of Silicone Rubber Insulator [26]. According to these studies, RP provides a rapid overview about the insulator state during the contamination process. However, RP delivers only a qualitative overview, based on complex graphical representation that requires tedious interpretation work.

Besides, an investigation of LC waveforms during the contamination process shows that the LC is sinusoidal for low pollution levels [24]; the higher the pollution level, the more distorted the LC waveform. This latter contains large peaks and differs from its sinusoidal shape during the discharge propagation until flashover [25]. Such change in LC shape should suggest the use of non-linear methods to investigate and control LC dynamic variation during the contamination process.

RQA is one of non-linear methods able to study the dynamic of a given signal based on the chaos theory [27]. This theory claims that small differences in initial conditions, of a given system, yield widely to diverging outcomes, causing thus the output prediction very difficult in general [28]. Used numerous in the medical domain to analyze the dynamic of physiological systems [29-39], RQA allows to discern between healthy and unhealthy patients. RQA applied to the heart beat signal revealed successful monitoring of heart diseases [29-31]. Electromyography (EMG), which represents the electrical activity of a muscle during contraction, was investigated through RQA [32-33]. For instance, RQA has been used by Ito et al [32] to detect muscle fatigue, and by Ouyang et al [33] to identify hand grasp movement. Furthermore, Electroencephalograms (ECG) have been analyzed using RQA to monitor the most common and chronic neurological epilepsy disorder [34-35]. Moreover, RQA revealed successful early detection of seizure on ECG deducted from rats [36]. Whereas, Yang et al [37] announced the ability of RQA to prevent Myocardial infarction (heart attack) when used to study Spatial Vectocardiogram (VCG) signals.

Since RQA revealed successful disease detection and unhealthy pattern recognition in the medical domain, we propose it in this paper to study and monitor polluted insulators performance based on LC investigation. To achieve this purpose, LC waveforms acquisition is firstly carried out on a plan insulator model uniformly spread by a saline solution. Five conductivities of this solution have been chosen. For each conductivity, Recurrent Plot (RP) is applied on LC temporal waveform. RP diagrams show specific graphics and morphologies for every pollution conductivity value. Hence, RP monitors well enough the insulator performance during contamination conditions. RP seems to be an excellent tool to flashover monitoring. However, it requires rigorous interpretation and provides only a qualitative overview of the insulator state. To overcome this deficiency, we propose the Recurrence Quantification Analysis (RQA). RQA is able not only to quantify appearing structures on RP diagram, but also to examine the variation and shifting of LC dynamic. Eight RQA indicators are studied. Two dimensional scatter plots of these eight indicators point out the high correlation between their mean values and the pollution conductivity value. Consequently, these mean values are used as inputs for three well-known classification algorithms (K-Nearest Neighbors, Naive Bayes, Support Vector Machines), while the output is the pollution conductivity value class. As a novel LC feature extraction technique, RQA seems to be a very effective technique not only to monitor and diagnose the insulator performance, but also to study LC dynamic under pollution.

2 EXPERIMENTAL ARRANGEMENT

Experiments were carried out using the experiment arrangement shown in Figure 1. It comprises a High Voltage Test Transformer (300 kV/50 kVA, 50 Hz) supplied by a Regulating Transformer (220/500 V, 50 kVA, 50 Hz). The applied voltage is recorded through an AC capacitive voltage divider (the ratio is 1000:1). The laboratory model is constituted by a glass plate (500 mm x 500 mm x 5 mm). Made up of aluminum paper, two rectangular electrodes (500 mm x 30 mm x 0.003 mm) have been used on both HV and ground sides. The distance between the two electrodes represents the leakage path of the 1512 L cap and pin insulator (292 mm).

The contaminating pollution is composed of distilled water and NaCl and is uniformly and continuously spread all over the model surface. To ensure good reproducibility of the pollution, the saline solution is pulverized 25 times on each side of the insulator model using a sprayer placed above this model and at a distance of 50 cm from it, as shown in Figure 2. To reproduce the different levels of the outdoor insulators pollution (from light to extreme pollution conditions), the adopted pollution conductivity values are: 0.01, 0.19, 0.71, 1.2 and 10.1 mS/cm. Before tests, the insulator surfaces were washed with ethyl alcohol and rinsing with distilled water, in order to remove any trace of dirt.

Tests are conducted under a fixed applied voltage equal to 12 kVrms. A Tektronix digital oscilloscope of bandwidth of 500 MHz and PC are used to record the leakage current and applied voltage waveforms. Note that, leakage current signal is measured trough a non-inductive resistance of 1 kΩ.
3 THEORETICAL BACKGROUND

In this section, we expose a concise theoretical background of methods used in this paper. First, RP computation concept is explained. Then, typical RP structures and their corresponding interpretations are detailed. Further, RQA method is presented. In this work, we study eight RQA indicators. Calculation and physical interpretation of these indicators is exposed. Finally, a brief theory about three of the most known classification methods (K-Nearest Neighbors, Naïve Bayes and Support Vector Machines) is given. These supervised classification methods are used to determine the pollution severity value.

3.1 RECURRENT PLOT (RP)

Recurrence plots are graphical tools which visualize the recurrence behavior of the phase space trajectory of dynamical systems. RP was first proposed in 1981 by Maizel and Lenk [40] as a method of visualizing patterns in sequences of genetic nucleotides. It has since been introduced to study dynamical systems. RP is computed as shown in equation (1).

\[ R_{i,j}(\varepsilon) = \Theta (\varepsilon - \| x_i - x_j \|), \quad i, j = (1, ..., N) \]  

where \( \| \cdot \| \) is the norm (in this research, Euclidian norm is adopted), \( \Theta (\cdot) \) is the Heaviside function and \( x \) is the studied time series. Equation (1) means that if the distance between \( x_i \) and \( x_j \) is less than \( \varepsilon \), then \( R_{i,j} = 1 \) and a dot is placed at \((i, j)\) in the RP, else \( R_{i,j} = 0 \) and a blank is placed at \((i, j)\).

To interpret RP diagrams, the use of Table 1 is more than helpful. In fact, this table summarizes most common explanations about RP typologies and textures based on studies carried out by Marwan et al [28].

<table>
<thead>
<tr>
<th>RP Structures</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Homogeneous</td>
<td>Stationary process</td>
</tr>
<tr>
<td>Diagonal lines</td>
<td>Periodicity</td>
</tr>
<tr>
<td>Isolated points</td>
<td>Strong fluctuations</td>
</tr>
<tr>
<td>Periodic/quasi-periodic patterns</td>
<td>Cyclicities in the process</td>
</tr>
<tr>
<td>White bands</td>
<td>Non-stationary data; presence of abrupt transitions</td>
</tr>
<tr>
<td>Vertical and horizontal line</td>
<td>Laminar states; Some states do not change or change slowly</td>
</tr>
<tr>
<td>Long bowed line</td>
<td>Similarity in state evolution</td>
</tr>
</tbody>
</table>

Figure 2. Pulverization method of the pollution on the insulator model.

3.2 RECURRENT QUANTIFICATION ANALYSIS (RQA)

The RQA is a method of non-linear data analysis for the investigation of dynamical systems. This method, developed by Webber and Zbilut [27], aims not only to quantify different appearing structures in RP through indicators, but also to study the shifting of a given signal’s dynamic. In this paper, we focus on eight fundamental indicators [28]:

1. Recurrence Rate (RR) is the density of recurrence points in a RP. RR corresponds to the probability that a specific state will recur. RR is calculated by equation (2).

\[ RR(\varepsilon) = \frac{1}{N^2} \sum_{i=1}^{N} R_{i,i}(\varepsilon) \]  

2. Determinism (DET) is the ratio of recurrence points on the diagonal structures to all recurrence points. DET, computed according to equation (3), is related with the determinism of the system and points out the predictability of the system. Diagonal lines represent epochs with similar time evolution of states. A high DET indicates that RP contains more and longer diagonal line structures compared with the stochastic process.

\[ DET = \frac{\sum_{l=l_{min}}^{R} P(l)}{\sum_{l=l_{min}}^{R} P(l)} \]  

where \( P(l) \) is the frequency distribution of the lengths of the diagonal structures in the RP. \( l_{min} \) is the threshold, which excludes the diagonal lines formed by the tangential motion of a phase space trajectory.

3. Average diagonal line length (L) represents the average time where two segments of the trajectory are close to each other, and can be interpreted as the mean prediction time. \( L \) is given by equation (4).

\[ L = \frac{\sum_{l=l_{min}}^{R} P(l) N_{l}}{\sum_{l=l_{min}}^{R} P(l)} \]  

4. Maximum of average diagonal line length (\( L_{max} \)), which represents the longest diagonal line found in the RP, is calculated as in equation (5).

\[ L_{max} = \max(l_i; i = 1 ... N_i) \]  

where \( N_i = \sum_{l=l_{min}}^{R} P(l) \) is the total number of diagonal lines.

5. Laminarity (LAM) is analogous to determinism except that it is defined by the ratio of recurrence points forming vertical structures to all recurrence points. LAM indicates the probability that a state will not change for the next time step and is expressed according to equation (6).

\[ LAM = \frac{\sum_{l=l_{min}}^{R} P(v)}{\sum_{l=l_{min}}^{R} P(v)} \]  

where \( P(v) \) is the distribution of the lengths \( v \) of the vertical structures.

6. Trapping time (TT) represents the average length of vertical structures. Its computation requires the consideration of a minimal length \( v_{min} \). TT estimates the mean time that the system will abide at a specific state or how long the state will be trapped. TT is calculated as in equation (7).

\[ TT = \frac{\sum_{l=l_{min}}^{R} P(v) N_{l}}{\sum_{l=l_{min}}^{R} P(v)} \]
7. Maximal length of the vertical lines ($v_{max}$) is analogous to the standard indicator $t_{max}$ ($N_v$ is the absolute number of vertical lines). $v_{max}$ can be regarded as the maximum time that the system will remain at a specific state and is computed by equation (8).

$$v_{max} = \max\{v_i^{N_v}\}$$

8. Entropy (ENTR) refers to the Shannon entropy of the probability $p(l) = P(l)/N_t$ to find a diagonal line of exactly length of $l$ in the RP. $ENTR$, calculated by (9), reflects the complexity of the RP concerning the diagonal lines.

$$ENTR = -\sum_{l=l_{min}}^{l_{max}} p(l) \ln p(l)$$

### 3.3 CLASSIFICATION METHODS

Three of the most commonly used classification techniques are employed in this paper: the k-nearest neighbors' classifier (Knn), the Naïve Bayesian classifier and the Support Vector Machine (SVM). These three algorithms have already been used in many domains [40-44].

### 4 RQA RESULTS

In this section, we expose results of RP and RQA for LC waveforms investigation. For various pollution conductivities, LC waveforms with their corresponding RP and RQA are exposed. Results show that these indicators are highly correlated to the pollution severity level. Consequently, to extract features from LC waveforms, we propose to compute the mean values of these eight indicators. Finally, two dimensional scatter plots indicate the ability of RQA mean values to distinguish between various levels of the pollution severity.

### 4.1 RP DIAGRAMS

Using experimental arrangement described in chapter 2, the recorded LC waveform on 10000 points is presented in Figure 3a, RP diagrams are computed using equation (1) and exposed in Figure 3b. To interpret RP, we use Table 1. In case of 0.01 mS/cm conductivity value, few points compose the RP indicating weak discharge activity on the insulator model. For 1.2 mS/cm, formation of white bands is noticed which designates the apparition of local arcing discharges on the insulating surface. Finally, for 10.1 mS/cm, RP contains very dense points and larger white bands. The white segments point out the intermission of intensive discharges and the dense points indicate the intensive arcing discharges.

### 4.2 PHASE SPACE RECONSTRUCTION

Before computing RQA, a phase space reconstruction, of LC time series, has to be performed. This is a primordial processing step, because it converts the LC signal into a recurrence plot in order to extract their features using RQA. Therefore, by using the Takens' embedding theorem [45], LC time series are transformed into phase space trajectories as described in (10).

$$\tilde{x}(t) = [x(t), x(t_i - \tau), ..., x(t_i - (m - 1) \tau)]$$

where $i = (0, 1, 2, ..., N)$, $N$ is the length of the time series, $m$ represents the embedding dimension, $\tau$ defines the delay between samples and $\tilde{x}(t_i)$ is phase space trajectory describing the dynamical behavior of LC. According to [23], $m$ and $\tau$ should be chosen equal to 5 and 20 respectively. That is to say, by transforming the LC from a high dimensional space to an $m$-dimensional sub-space, RPs and RQA can be established to investigate more efficiently LC properties.

### 4.3 RQA INDICATORS

Since RP describes time series visually (i.e. through graphical and morphological structures) but not quantitatively, the RQA quantifies a time series through the indicators based on the RP. Therefore, by setting $l_{min}$ and $v_{min}$ equal to 2, RQA indicators shown in Figure 3c are computed, using equations (2) to (9). The higher the conductivity, the higher the LC waveforms amplitudes and the more pulses around the maxima.

All the indicators show higher variations, bigger peaks and lower values when conductivity increases. $RR$, which quantifies recurrent points, varies from 1 to 0.45 for a conductivity equal to 0.01 mS/cm, decreases until 0.81 for 1.2 mS/cm and reaches almost 0 for 10.1 mS/cm. $RR$ shows also tight peaks for 0.01 mS/cm, while larger ones are observed with the increase of the conductivity. High values of $RR$ indicate the presence of recurrent points on the RP, suggesting the predictability of LC dynamic. However, small values of $RR$ indicate few recurrent points inferring white bands on the RP. Thus, lower $RR$ minimal values point out absence of recurrences, signifying the shifting of LC dynamic from predictable to non-stationary one.

Similarly, $DET$ values decrease when the pollution severity increases. $DET$, which points out the dynamic of a system, is high for 0.01 mS/cm indicating that LC dynamic is determinable and periodic. However, for a more severe contamination, $DET$ values diminish indicating that LC waveforms move from a stochastic dynamic to non-periodical one. This is due to the apparition of stronger discharges.

$L$ represents the average time that two segments of the trajectory on the RP are close to each other. It can be interpreted as the mean prediction time. It shows larger variations with the increase of pollution conductivity. Its diminution indicates that LC is becoming less predictable. Likewise, $L_{max}$ signal is composed of peaks. These peaks are larger for 10.1 mS/cm suggesting the unpredictability of LC when the contamination is intensified.

$LAM$ is an important indicator. Although being analogous to $DET$, $LAM$ brings valuable information. It shows lower minimal values for the greater conductivity (10.1 mS/cm) informing about the fewer occurrences of laminar states in the LC. Thus, there are more single recurrent points and larger white segments to describe the RP. Such structure predicts more random and unstable behavior of LC.

High values of $TT$ indicate the absence or slight change of LC in time; that is to say that LC is trapped for some time. This is a typical behavior of laminar states (intermittency). Low values of $TT$ suggest a fast incoming transition of the LC to an unknown state predicting a forthcoming transition in LC dynamic. Also, $v_{max}$, which is analogous of $L_{max}$, varies in the same way.

Concerning $ENTR$ (entropy), it is used for measuring the complexity of a given signal. For 0.01 mS/cm, $ENTR$ is close to 3, but shows peaks due to LC deformations. For 10.1 mS/cm, $ENTR$ presents lower minimal values and looks like a sinusoidal signal. Such signal indicates the changing complexity of the LC waveform. Therefore, LC signal behavior is becoming non-periodical.
Figure 3. RQA for LC investigation under pollution, (a) LC waveforms for various conductivities, (b) RP representation, (c) RQA indicators waveforms.
The higher the conductivity value, the lower the RQA indicators minimal values. In fact, low values of these indicators correspond to blank spaces on the RP and suggest a non-periodical LC signal. Such RQA values result from contamination which causes distortions and pulses on the LC waveforms, especially near peak regions. Therefore, RQA values are composed of small magnitudes and tight peaks for pollution conductivities less than 1.2 mS/cm. However, for 10.1 mS/cm, RQA values contain big and large magnitude peaks. Such variation quantifies and describes LC dynamic under pollution. In other words, the deterioration of the insulator performance is highlighted by the diminution of RQA indicators minimal values. These indicators announce the shifting of LC dynamic from periodical dynamic to non-stationary one indicating the possible occurrence of the flashover.

4.4 RQA FEATURE EXTRACTION

From Figure 3, RQA indicators are proven to be highly correlated to the pollution severity, thus to extract a feature vector from RQA indicators, we opt for computing their mean values. Indeed, to study the correlation between RQA indicators and the pollution level, we plot RQA indicators mean values two by two, for various pollution levels, on a two dimensional space. To plot the eight indicators, $2^8$ combinations are possible. Among them, we have randomly chosen the characteristics shown in Figure 4. It can be seen from these scatter plots that the mean values of the eight indicators decrease with the increase of the pollution conductivity. Moreover, in every plot, we observe that RQA mean values are gathered in five groups corresponding to the five pollution conductivity values. Such plots suggest that RQA means values are directly related to the pollution level. These indicators plots proof the ability of RQA to discern between the pollution severity levels. Indeed, for a given pollution conductivity, values of RQA indicators are situated in a specified interval. Consequently, RQA is chosen as a feature extraction technique to determine and classify the pollution severity based on LC examination. Hence, RQA indicators mean values are chosen as inputs for classification methods, while the output is the pollution conductivity value. Flowchart of the algorithm using RQA for pollution conductivity classification is exposed in Figure 5.

5 CLASSIFICATION RESULTS

Three classification techniques used in this paper consist in the k-nearest neighbors’ classifier (Knn), the Naïve Bayesian
classifier and the Support Vector Machines (SVM). The k-nearest neighbors (Knn) classifier [42] is simple and easy to implement. It requires no training and assigns an object to the most common class among its k-nearest neighbors. Several distances can be used to determine the nearest neighbors. The Euclidian distance was chosen in this paper, with k equal to 1. The Naïve Bayes classifier [43] is a simple probabilistic classifier based on Bayes theory. It implies the assumption that variables are statistically independent. It is known to be rather effective. The Support Vector Machines (SVM) [44] is considered as one of the most accurate machine learning classifiers because of its ability to solve problems of linear and non-linear classification by finding the maximum margin hyper plane that separates the classes. Several kernel functions can be used, including linear, polynomial, RBF, and sigmoid. However, SVM suffers from multi-class categorization problem and has to be adapted in the case of multi-class recognition problem (one vs. one or one vs. all strategies). In this work, “one vs. all” strategy and linear kernel function were used.

To estimate the pollution severity through LC classification, five labels are assigned to five pollution conductivities, from the lightest to the heaviest ones (class 1 corresponds to 0.01 mS/cm, while class 5 corresponds to 10.1 mS/cm), as described in Table 2. Previously plotted in Figure 4, the LC database is composed of 100 LC waveforms (20 per conductivity). 90 % of this database is used for training and the rest for testing.

As shown in Table II, the obtained classification results are successful for the 10 samples in the case of SVM and Knn algorithms. However, Naïve Bayes classifier offers bad results with 4 misclassifications out of 10. These results are somehow predictable. Having the ability to deal with linear and non-linear classification problems, SVM is known to be a high performance classifier [43]. Knn seems also to be a very good choice in this work. However, Naïve Bayes classifier, although being simple and fast, shows low performance especially when dealing with a limited database.

The classification accuracy comparison of the three cited methods highlights the importance of choosing the proper classification technique. Indeed, to build an efficient classification algorithm, both choices of the feature extraction technique and the classification method are highly decisive.

### 6 CONCLUSION

In order to monitor the insulator performance and build a proficient pollution severity diagnostic tool, an examination of LC signals through RQA was established. Showing an undoubted efficiency for signal dynamic analysis, eight RQA indicators of LC are computed and examined for various pollution levels. These indicators characterized very well LC signal behavior. Indeed, the higher the pollution conductivity value, the lower RQA indicators minimal values. Two dimensional scatter plots confirm that the eight indicators mean values are highly linked to the pollution severity level. Indeed, five groups are clearly noticeable corresponding to the five pollution levels. Thus, these eight indicators mean values are chosen as input for three classification algorithms. Results

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**Table 2.** Classification results.

<table>
<thead>
<tr>
<th>Sample</th>
<th>RR</th>
<th>DET</th>
<th>L</th>
<th>Lmax</th>
<th>LAM</th>
<th>TT</th>
<th>Vmax</th>
<th>ENTR</th>
<th>Pollution conductivity (mS/cm)</th>
<th>Assigned class</th>
<th>Obtained class</th>
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</thead>
<tbody>
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<td>17.368</td>
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of classification announce SVM and Knn classifiers as the suitable algorithms to choose instead of the Naive Bayes classifier and also RQA as an excellent LC feature extraction technique. Moreover, RQA allows to study LC dynamic during the contamination process. In fact, LC dynamics is noticed to be non-linear. For low pollution levels, LC is sinusoidal. However, for the highest conductivity, LC waveform becomes distorted and contains peaks suggesting, thus, a non-stationary dynamic. This paper presents an original technique to monitor and study LC signal under contamination process. RQA is, not only, a novel method to study and investigate LC dynamics during the contamination process, but also an efficient LC feature extraction technique to determine the pollution severity level and monitor the insulator performance.

REFERENCES


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