Transient power grid phenomena classification based on phase diagram features and machine learning classifiers

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***Abstract*—Electrical transmission lines are the most significant part of a power systems in terms of their spread and length with respect of other components. With their huge development due to the growing demand, network losses are an issue that needs the permanent attention of power network providers and distributors. The difficulties of predictive maintenance of power grids are related to the detection of early warning indicators of weaknesses of electrical cables. These indicators might be defined by partial discharges, corona effects, electrical arcs, all these phenomena being characterized by transient signals propagating in cables. Identifying such signals can be very helpful to assess their sources usually located in the weak parts of the grid. In this paper, we present a new approach for the detection and characterization of these types of transient phenomena in power grid using the phase diagram domain. The extracted features are classified using Support Vector Machine, Naïve Bayes and k-Nearest Neighbors. The experimental results indicate that the proposed method provides interesting results in the classification of real-life power grids signals, being a potential solution for predictive maintenance of electrical cables.**

***Keywords*—machine learning, power grid, phase diagram, signal classification, transient phenomena.**

I. Introduction

Energy transmission and distribution networks are one of the areas intensively studied in recent years due to their importance. Identification and characterization of the dynamic phenomena of the power system have received a considerable attention.

It has been widely accepted that the lack of accuracy of measurement of power system states is one important cause of failures in the power system. Based on this, the interest of monitoring transient phenomena is very high, because they are the precursors indicating the weaknesses in the electric cables and which, sooner or later, lead to power outages [1].

The arbitrary transient behavior combined with the complex geometry of the power grid make the power system transient studies very complicated. The primary goal should be to maintain the integrity of the power system by deploying simple automatic analysis schemes. On the basis of monitoring systems, different control strategies can be applied through development and implementation of new analysis tools [2].

Considering these aspects, this paper proposes a way to characterize the transient phenomena of power grids, which will help to define the early warning indicators of cable weaknesses. The first step is to detect all the transient activities in the power grid under surveillance, after which we classify these activities.

As a signal processing framework, we use the analysis in phase diagrams which is a data driven technique (model free) leading to the capacity to deal with a wide variety of transient signals. The representation of transient signals in phase diagram domain allows us to define meaningful descriptors and define the AI framework for the classification of these transient phenomena.

The structure of the paper is as follows: Section 2 presents theoretical notions that underlie the analysis method derived from the phase diagram domain, as well as the presentation of the classification algorithm and the features used as inputs. Section 3 describes the results obtained by applying the method of analysis and classification algorithms previously proposed and Section 4 presents the conclusions of this paper and future perspectives.

II. Theoretical Aspects

A. Phase Diagram based Entropy

Phase diagram-based entropy is a way in which we can highlight the changes that take place in the state of an analyzed system, being extremely suitable for non-linear data analysis [3]. To determine this measure, we start from a signal $x[n]$ expressed in the form of a time series that is transposed into a new multidimensional representation space by the phase space vectors presented in (1).

$$\overrightarrow{v_{[i]}} = \sum_{k=1}^{m} x[i+(k-1)d] \cdot \overrightarrow{e_k},\ i = 1,2,...,M \tag{1}$$

In the description of these vectors, two essential parameters appear for the new representation form. The delay *d* between samples is given by the mutual information and the encapsulation dimension *m* is determined by the false nearest neighbor method [4]. Also $\overrightarrow{e_k}$ are the axis unit vectors and $M = N-(m-1)d$, where N is the length of the time series. The quantification of the degree of similarity between two vectors from the phase diagram is evaluated by (2):

$$C_i^m(r) = \frac{1}{N-(m-1)d}\sum_{j\neq i}\Theta\left\{\left\|\overrightarrow{v_{[i]}}-\overrightarrow{v_{[j]}}\right\|-r\right\} \tag{2}$$

The main parameter to be considered is the tolerance threshold r used to establish the range in which the data fluctuations are considered similar. Also $\|\cdot\|$ is the operator of Euclidian distance and Θ is the Heaviside function. To determine the entropy [3], we quantify this degree of similarity on a logarithmic scale in order to capture the occurrences of similar vectors as in (3).

$$\Phi_m = \frac{1}{N-(m-1)d}\sum_{i=1}^{N-(m-1)d}\log\left(C_i^m\right) \tag{3}$$

Thus, in defining the entropy, we take into account the variation of the degree of similarity once we increase the encapsulation dimension of the representation space.

$$PDEn = \Phi_m - \Phi_{m+1} \tag{4}$$

A low value of this parameter expresses the fact that the analyzed system is one defined by regularity, while a higher value of it highlights the less predictable character of the system.

B. *Phase Diagram Features*

In this subsection, we describe three features used to build our machine learning approach. To illustrate their definition, we consider a *2D* representation of a time series as presented in Fig. 1.

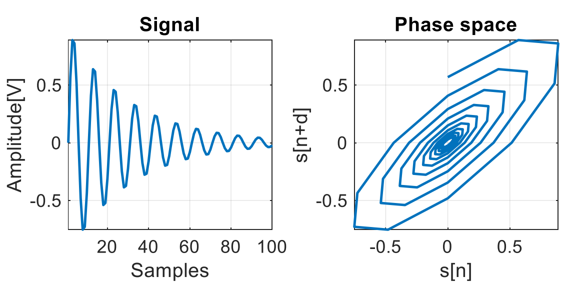

Fig. 1. The signal in time domain and its 2D phase diagram representation

1) *Angular mean*

Each representation in the phase space consists of several vectors. Each two successive position vectors of the representation form an angle. The angular mean involves the quantification of all existing angular values. Thus, after summing all the angles of the representation, we refer to their totality, using (5) to obtain the first feature AM [3].

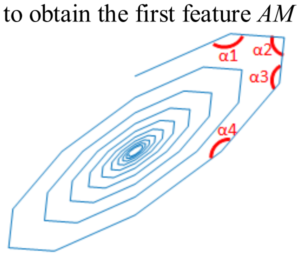

Fig. 2. Angular mean representation

$$AM = \frac{1}{M-1}\sum_{i=1}^{M-1}\arccos\left(\frac{\overrightarrow{v_{[i]}}\cdot\overrightarrow{v_{[i+1]}}}{\left|\overrightarrow{v_{[i]}}\right|\cdot\left|\overrightarrow{v_{[i+1]}}\right|}\right) \tag{5}$$

The graphical representation of the angular mean is shown in Fig.2.

2) *The length of the first gap*

As it can be seen in Fig. 3, the representation of the time series in the phase diagram consists of several spirals due to the positioning of the vectors in the phase space [3].

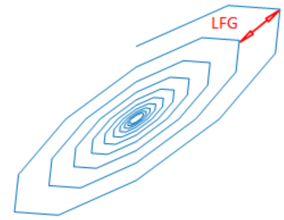

Fig. 3. The length of the first gap representation

The length of the first gap is the distance between the first two spirals. Let $A(x_1, y_1)$ and $B(x_2, y_2)$ be the two points furthest from the center of the representation on the two spirals, we can quantify the length of the first gap as in (6).

$$LFG = \sqrt{(x_2-x_1)^2+(y_2-y_1)^2} \tag{6}$$

These two necessary points are determined as the intersection of the major axis of the ellipse in which the representation can be inscribed with the first two spirals of the phase diagram.

3) *Spatial entropy*

The points that form the representation of the time series in the phase diagram can be inscribed in the four quadrants, as can be seen in Fig.4. Depending on the type of time series, the points can be found mainly in different quadrants. For example, in the case of transient signals, it is observed that most of the points are grouped in quadrants Q1 and Q3 [3].

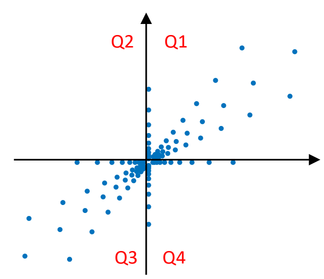

Fig. 4. Spatial entropy representation

To quantify spatial entropy, we use (7):

$$SE = \log\frac{N_{Q1}}{N_{Q3}} \tag{7}$$

where N_{Q1} and N_{Q3} represent the total number of the representation points found in quadrants Q1 and Q3.

In order to show the interest of the proposed features we compare them with some classical features based on the spectrogram, wavelet and statistical approaches. We use a significant signal from each class identified in the experimental part (more information in Section 3). As it can be seen in Fig.5, the three transient signals have a specific shape.

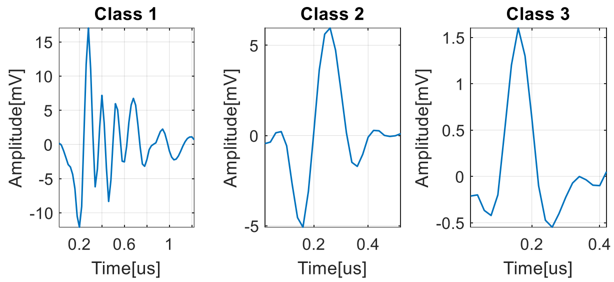

Fig. 5. The three classes of transient signals

The first classical approach is based on the spectrogram. In Fig.6 the spectrograms of the signals can be observed. The information we can take from this approach is not enough. It is observed that the covered frequency area is approximately identical. Spectrograms similarity would also lead to problems in an image-based classification algorithm.

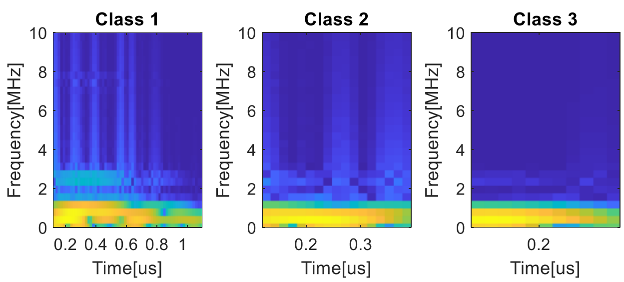

Fig. 6. The spectrograms of the three transient signals

The wavelet-based approach is also problematic. The scalograms shown in Fig.7 have a lower degree of similarity than the spectrograms. This may be more useful in image classification algorithms for signal classification. From the perspective of the information extracted, the impossibility of identifying a suitable scale is a real impediment.

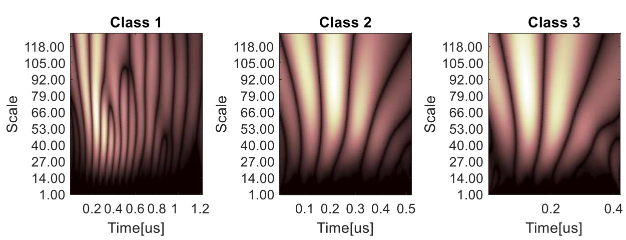

Fig. 7. The scalograms of the three transient signals

One of the most used approaches in classifying signals in various fields is the statistical approach. The feature set used is based on some information extracted from the signal in time domain. The most used are based on the minimum, maximum, mean value, standard deviation and skewness [5]. Fig. 8 shows the values of these features for a set of 10 signals specific to the three classes.

The degree of signal separation based on this approach has several shortcomings. As can be seen, the signals of Class 2 and Class 3 can be confused based on the mean values. Class 1 and Class 2 signals can also be confused based on standard deviation and skewness.

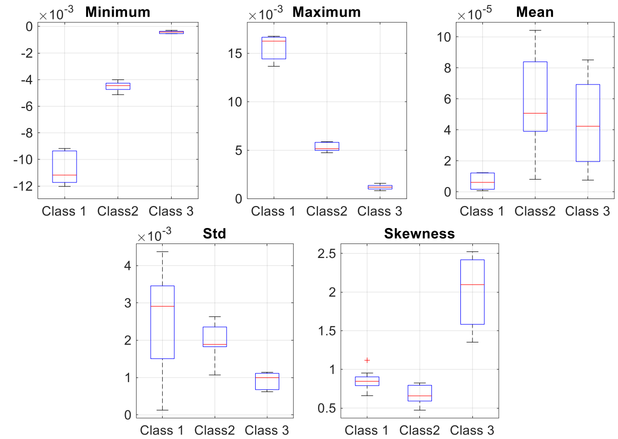

Fig. 8. The boxplots of the classical statistical features

Analyzing the feature-based approach in the phase diagram, we observe a complete degree of separation. Fig. 9 shows the variation of the three features for the same set of 10 signals. The three classes of signals are highlighted and separated, there is no possibility of confusion between them.

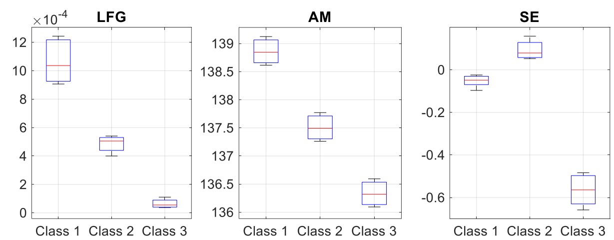

Fig. 9. The boxplots of the phase diagram features

Thus we can conclude that from the features perspective the approach proposed by us has a high advantage compared to the existing and used methods.

C. *Classification Techniques*

In this subsection we briefly present the three machine learning techniques used to classify the signals.

The first one is Support Vector Machine (SVM). The goal of this algorithm is to find an optimal hyperplane between the possible outputs, that distinctly classifies the data [6]. In its most simple type, SVM supports binary classification. For multiclass classification, we must break down the multiclassification problem into multiple binary classification problems. This is called a one-to-one approach. In this approach, we need a hyperplane to separate between every two classes, neglecting the points of the third class. The computations of data points separation depend on a kernel function. This function determines the smoothness and efficiency of class separation. In our paper, we use a second order polynomial kernel function.

The second one is Naive Bayes (NB). The NB method is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. It assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature [7].

The last one is the k-Nearest Neighbors (KNN). KNN algorithm is a non-parametric supervised classification algorithm based on simple mathematics theory. KNN algorithm classifies by comparing the unknown test data points with the training data points to which it may be similar [8]. Similarity is measured by a metric distance. In this study, the Euclidean distance presented the best results and the k nearest neighbors was set to five.

The performance metrics used to evaluate the classifiers are recall, specificity, precision and accuracy. A perfect classifier is described by 100% recall and 100% specificity.

III. Experimental Configuration And Results

The first stage of our experimental work is the analysis of an electrical network in order to obtain the necessary electrical signals. Thus, a real three-phase power grid, consisting of two main stations, a source station and a distribution station was analyzed. The network analysis system consists of three high frequency current transformer sensors and one acquisition board. The configuration can be seen in Fig.10.

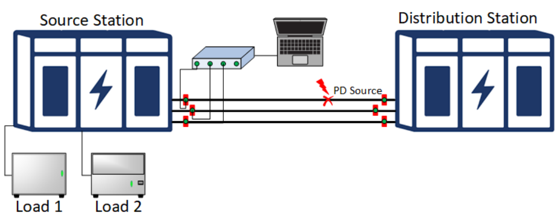

Fig. 10. The experimental benchmark

The signals from the source station are analyzed. As expected, the analysis of the cable from the source station highlights several transients carried in the network. Fig. 11 shows the signal recorded at a sampling frequency equal to $f_s = 50\ MHz$. Three different types of transients can be distinguished, specific to three generating sources.

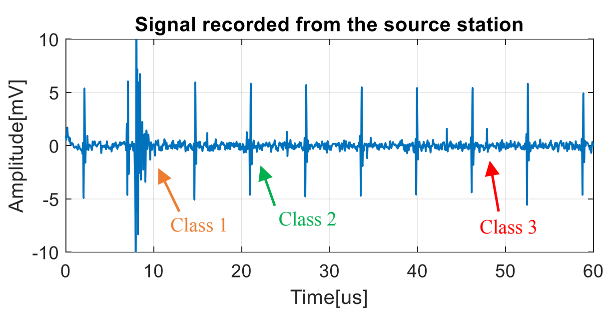

Fig. 11. The signal recorded from source station

Thus, to Class 1 we assign the strongest signal in terms of amplitude and with the longest duration, to Class 2 we assign the periodic signal, with a pulse repetition rate of $T = 6\ us$ and to Class 3 we assign the signal specific to the partial discharge. The first two classes of signals correspond to external loads connected to the network, which can cause a confusion with the rising fault signal – partial discharge. This is actually the third class of signals which is the sign of cable portion weakness. In Fig.5 we can see a specific signal from each class.

For the detection part of the transient signals using phase diagram-based entropy, the following aspects are considered. A 10-sample chosen window is slid over the entire duration of the signal to highlight entropy variations. For the tolerance threshold, the value of 0.75 is chosen from the standard deviation of the signal contained in the sliding window. The results in terms of detection can be seen in Fig.12.

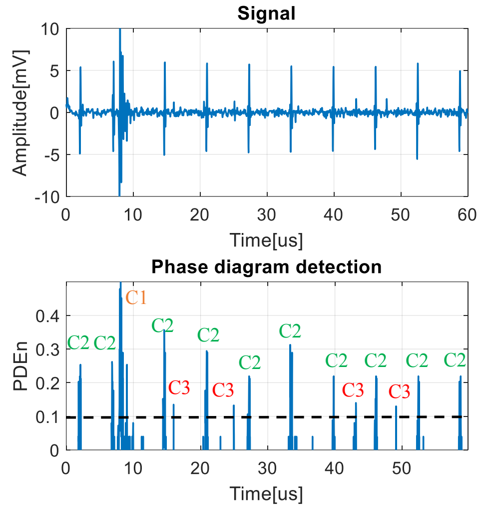

Fig. 12. Phase diagram-based detection

As can be seen, this detection method highlights all the moments of occurrence of transient signals, regardless of their class. Even partial discharge signals, which are much smaller in amplitude than the other two types of signals, are detected using a threshold of 20% from the maximum value of the entropy. In order to evaluate the performance of the detection result, we compare the obtained result using one of the methods currently used for the detection of transient signals based on wavelet transform. Fig.13 shows us the result of the detection process which has a lower accuracy because the partial discharge is not detected.

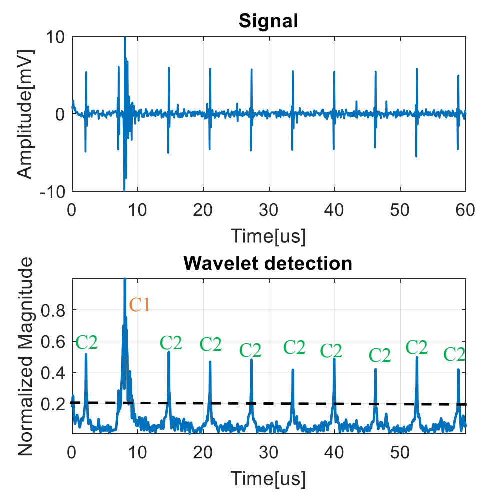

Fig. 13. Wavelet transform detection

Without any knowledge on the shape and size of the analysis signal, there are some problems in choosing the wavelet, requiring a stage of visualizing the signals. The type of wavelet used in this paper was given by the Daubechies family, because it corresponded the best results obtained via many trials.

The next step in our analysis is based on the classification part of the signals. We created a database using several measurements at different times. In this sense, we gathered 1500 signals specific to the three classes. Of these signals, 70% were used for training and 30% for the testing part of the classification algorithms. The confusion matrix for the train and test data sets using the algorithms are shown in Fig.14.

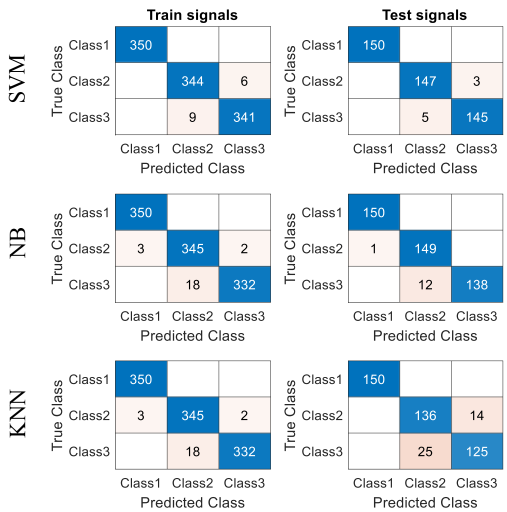

Fig. 14. The confusion matrix using SVM, NB and KNN

Table I shows the results obtained using this approach in signal classification.

TABLE I. PERFORMANCE REPORT OF THE CLASSIFIERS

SVM	***Class1***	***Class2***	***Class3***
Recall	100%	96.7%	97.9%
Specificity	100%	98.3%	99%
Precision	100%	98%	96.6%
Accuracy	98.2%		
NB	***Class1***	***Class2***	***Class3***
Recall	99.3%	92.5%	100%
Specificity	99.6%	96%	100%
Precision	100%	99.3%	92%
Accuracy	97.1%		
KNN	***Class1***	***Class2***	***Class3***
Recall	100%	84.4%	89.9%
Specificity	100%	91.6%	95.3%
Precision	100%	90.6%	83.3%
Accuracy	91.3%		

As we can see, all classifiers based on features extracted from phase diagram domain have very good results. In particular, the best performance is obtained by using the SVM classifier. Despite the fact that it presents the best classification performance, SVM presented the longest training and testing times. The KNN algorithm presented the best training times. The maximum performance value obtained for the SVM classifier is 98.2%, and the recall, specificity and precision metrics for each class are over 96.6%. In contrast, the minimum value of performance is obtained with KNN classifier giving an accuracy of 91.3% and values over 83.3% for the others metrics.

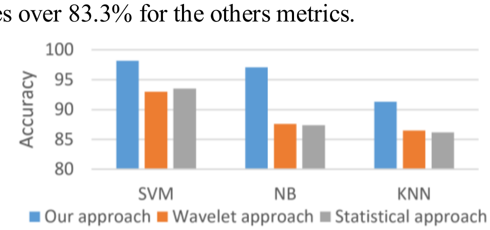

Fig. 15. Performance comparison of the three approaches

In order to check the accuracy of the features, we compare our approach with the set of statistical features described in Section 2. We also extract these statistical features from the detail coefficients obtain by wavelet decomposition of the signals. Fig. 15 shows a comparison in terms of the accuracy of the classification process for the three approaches. The results obtained with our proposed set of features are superior to those obtained with the statistical and wavelet approach. With the statistical features, the best results in the classification are also given by SVM with an accuracy of 93.5% and the weakest also by KNN with an accuracy of 86.2%, which are very close to the ones obtain with the wavelet approach.

IV. CONCLUSIONS

This paper presents a new approach based on phase diagram analysis of a power grid in order to characterize and classify each existing transient phenomenon. Depending on this, decisions regarding the state of the system can be made.

The machine learning algorithms that classify power grid signals provide a valuable decision support. The best one is SVM, which offers a high classification accuracy and solve the separation problem without introducing a number of large features in the training process.

Our future work is based on creating an automated global system through which each analysis on a power grid will allow the detection of each external signal and the localization and classification of their generating sources. Also, a future research direction will be based on extraction of the best combination of nonlinear features from the phase diagram.

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