Wavelet transform and fractal theory for detection and classification of self-extinguishing and fugitive power quality disturbances

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Abstract— **In this paper, fractal theory and wavelet transform are combined to detect and classify self-extinguishing and fugitive scenarios of power quality disturbances (PQDs). After deciding whether the disturbance is simple or complex, the additional voltage is denoised through Discrete Wavelet Transform (DWT); the denoising process is adapted according to whether the distorted voltage contains oscillatory transients or not. At the detection stage, the grille fractal dimension of the DWT decomposition detail is computed. Then, a threshold is deduced to detect the start and end moments of the disturbance. The results reveal that the proposed detection scheme yields accurate location of PQDs even in the presence of high oscillatory transients. An algorithm based on geometric and statistical approaches is developed at the classification stage to recognize PQDs automatically. The geometric classification is based on Continuous Wavelet Transform (CWT), whereas the statistical classification is based on Multifractal Detrended Fluctuations Analysis (MFDFA) and an energy metric. The results prove that the combination of geometric and statistical classification can serve as an effective discrimination tool for PQDs. The major strength of the proposed approach is its ability to interpret the impact of each disturbance on the multifractal behavior of the nominal voltage, thus giving the possibility to draw the necessary generalizations for real-time applications.**

Keywords—Grille fractal dimension, Multifractal Detrended Fluctuations Analysis, singularity spectrum, Discrete wavelet transform, Continuous wavelet transform, Energy metric.

I. INTRODUCTION

In recent years, power quality concerns have attracted considerable attention in the power industry. The deployment of smart grid technologies and the extensive penetration of decentralized energy resources have made power systems more vulnerable to perturbations. Poor power quality can lead to innumerable disturbances in electrical networks. Thus, to meet the requirements of the energy market, there is a persistent need for a powerful technique to detect and classify power quality disturbances, such a method should be of high precision, meaning that the detection algorithm must be able to differentiate between the transients produced by electrical disturbances and those caused by switching events. For example, the switching of loads or capacitors should not trigger the protection devices of the electrical system because such a situation will generate untimely interruptions and thus affect the continuity of the power supply. On the other hand, the proposed schema should reveal the main features of the distorted signal so that the pattern recognition module could be able to distinguish one disturbance from another. Such an asset will be valuable for engineers, especially during the development of the monitoring equipment.

The literature addressing the issues of PQDs can be divided into detection and recognition approaches. In the first category, several techniques have been put forward to detect PQDs. An adaptive threshold was proposed in [1] to detect single and combined PQDs. In reference [2], wavelet packet, Tsallis entropy, and singular value decomposition are combined to detect PQDs. A high decomposition level has been adopted for all the disturbances, which may lead to considerable loss of information in the case of simple disturbances.

Owing to the evolution of signal processing techniques, the fractal theory has emerged as an alternative for recognizing PQDs [3]-[7]. With this method, the abrupt changes in the distorted voltages are rapidly identified through a fast calculation process. Its main strength lies in is its ability to detect singularities and self-similarities that may differ from one signal to another. The simplicity of the calculation process has motivated the use of fractal theory in different fields of modern science, including in medicine, finance, and geology. However, in existing fractal detection methods, further analysis is performed on the calculated fractal dimension before defining the detection threshold. Such methodologies may become expansive in real-time applications [3], [6].

In existing PQDs recognition methods, once a disturbance is detected, the distorted signal is processed by a feature extraction technique so that the most significant features are extracted. Regarding feature extraction techniques, various techniques have been proposed in the literature [8]. Fourier Transform (FT) and short-time Fourier transform (STFT) have been the subject of several studies. However, their application has been limited to the extraction of features from stationary signals. The fact that non-stationary signals vary with time made them unsuitable for determining the exact location of small

discontinuities and fast changes in the signal. With the emergence of wavelet transform (WT), the problems encountered with FT and STFT have been solved. The major strength of this approach is the flexibility of its windows, meaning that it uses wavelets with a short time window at high frequencies and long windows at low frequencies, thereby providing an excellent resolution for each scale of the signal [9]-[10]. However, the literature reports that the wavelet transform is highly sensitive to noise. This limitation has been overcome with Stockwell Transform (ST) [11] at the cost of a higher computational burden. EMD is an adaptive technique that decomposes the signal into multi-intrinsic modes functions [12]. However, the mixing mode problem still compromises the efficiency of this method. HHT [13] combines EMD and Hilbert Transform for analyzing non-stationary PQDs, but some issues such as the effect of EMD and cubic spline interpolation need to be addressed.

The data resulting from the feature extraction technique serve as inputs to an intelligent classifier to recognize the PQD. In this context, the authors in [14] used Discrete Wavelet analysis with multi-resolution analysis MRA to extract features from the distorted signals; the optimal features have been delivered to the PNN classifier for PQD recognition. However, there is little evidence that a fixed number of features can lead to accurate results for all the disturbances encountered in real life. In article [15], a dual neural network-based method was proposed to detect and classify PQDs. However, the black-box nature of neural network classifiers makes the interpretation of results difficult. Interpretability is decisive for the proper recognition of PQDs. In [16], Tunable-Q wavelet transform and dual multiclass Support Vector Machine (SVM) for online automatic detection of power quality disturbances were proposed. However, the high computational burden of this technique makes it inappropriate for real-time applications.

In the approaches recently proposed in the literature, the parameters such as the signal energy, maximum deviation, and kurtosis are calculated. Then, an original feature set is built to be fed to the classification system [17-19]. In the paper by [19], statistical features are used to define decision rules for classification. The proposed Decision Tree (DT) classifier has 5 layers structure which may cause delay for real-time analysis. On the other hand, DT classifiers have poor generalization ability.

Depending on its duration, the PQD is:

Self-extinguishing: if the disturbance is so short that it does not trigger the protection devices. The extinction transients appear on the voltage waveform during the disappearance of the disturbance.

Fugitive: when removed after triggering and reclosing the protection devices.

In all the papers cited above, only the fugitive scenarios of PQDs have been considered, the self-extinguishing ones haven't been involved. When self-extinguishing PQDs occurs, the extinction transients still affect the voltage waveform even after the end of the disturbance. In some

cases, the voltage waveform is contaminated by strong harmonics that it becomes difficult to discriminate the fault oscillatory transients from those of extinction. This fact may complicate the detection of the end moment of the disturbance.

Considering the above analysis, it can be concluded that the majority of existing methods cannot meet the requirements of a real-time application due to their complexity. In fact, they require a considerable amount of calculation without providing a meaningful interpretation of results. On the other hand, wavelet transform and fractal theory, each own some potential assets but does not perform well when used individually. In this paper, based on the idea that the combination of both techniques can lead to accurate detection of PQDs, the scanning ability of CWT is used to investigate the singularities of the distorted voltage, the high sensitivity of Discrete wavelet transform (DWT) to noise is used to prepare the data to be delivered to the detection module. Thereafter, the performance of the grille fractal dimension in detecting signal singularities is used to detect the start and end moments of the disturbance.

In the power system field, the distorted voltage holds a considerable amount of singularities that -if properly interpreted-can tell a lot about the disturbance dynamics. Following an intuitive rezoning, the distorted signal may hide a similarity between its local and global properties. Self-similarity is one of the relevant properties of fractal sets that can serve as a tool for PQDs recognition. In this paper, the classification step is based on a geometric and statistical classification of self-similar features contained in PQDs signals. The geometric classification is based on CWT, whereas the statistical classification is based on (MFDFA) and an energy metric.

The novelty in this paper is:

• An algorithm for detecting and classifying PQDs is proposed not only for the fugitive scenario but also for self-extinguishing scenarios.

• The denoising process is tailored to whether the disturbance is simple or complex.

• At the classification stage, self-similarity is taken as a criterion for PQDs classification. The geometric classification is achieved by CWT, whereas the statistical classification is performed utilizing (MFDFA) and an energy metric. The combination of geometric and statistical classification is adopted to meet the requirements of real-time analysis. The proposed approach is easy to implement, allows a proper interpretation of the results, and possesses good generalization ability.

The rest of the paper is organized as follows: in section 2, the theoretical basis of the wavelet transform, the grille fractal dimension, and the MFDFA approach are detailed. In section 3, the proposed algorithm is presented. The simulated system is described in section 4. The detection results are presented in section 5. The classification results are detailed in section 6. Discussion of the results is presented in section 7. The concluding remarks are given in section 8.

II. THEORY

A. Wavelet transform

The wavelet transform is a decomposition technique dedicated to the analysis of non-stationary signals. Two versions of WT exist: continuous and discrete. Continuous wavelet transform CWT is generally used to reveal scale-invariant patterns and their location in time series. Mathematically, CWT is carried out according to the following equations:

$$CWT(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \quad a,b \in R, \ a \neq \quad (1)$$

ψ is the mother wavelet, a and b are scaling and translating parameters.

During the CWT process, the mother wavelet is translated over the whole signal and the correlation coefficients between the wavelet and the whole signal are calculated for all scales and positions.

The calculation amount needed in CWT can be limited by choosing scales and positions based on the power of 2, this leads to Discrete Wavelet Transform DWT, which consists of dividing the signal $s(t)$ into approximations A_j and details D_j by means of high pass $g(n)$ and low pass $h(n)$ filters [20]. The approximations result from the process of filtering the signal with high pass filters, whereas details are the results of the signal filtration by low pass filters [21]. The scaling function and wavelet function can be defined respectively by the following equations:

$$\varphi(t) = \sqrt{2}\ \Sigma\ h(n)\varphi(2t - n) \quad (2)$$
$$\psi(t) = \sqrt{2}\ \Sigma\ g(n)\varphi(2t - n)$$
$$(3)$$
$$g(n) = (-1)^n h(1 - n) \quad (4)$$

n is the number of samples
The approximations and details can be expressed by:

$$A_{j+1}(t) = \Sigma\ h(n - 2t)\ A_j(n) \quad (5)$$
$$D_{j+1}(t) = \Sigma\ g(n - 2t)A_j(n) \quad (6)$$

B. The grille fractal dimension

The grille fractal dimension $N(\delta)$ is defined as the number of squares of length δ required to cover the signal s. For a signal having $(n + 1)$ sampling points $(s_1, s_2, \dots s_{n+1})$ during the interval $(t, t + \Delta t)$, $N(\delta)$ can be expressed as follows:

$$N(\delta) = \frac{1}{\delta}\Sigma_{i=1}^{n}|s_i - s_{i+1}| \quad (7)$$

With δ is the time interval between two consecutive sampling points, it's defined as:

$$\delta = \frac{\Delta t}{n} \quad (8)$$

C. Multifractal Detrended Fluctuation Analysis

Multifractal Detrended Fluctuation Analysis (MFDFA) is a strong technique introduced by [22] to investigate the multifractal behavior of time series. By means of this method, the parameters named: the singularity spectrum, the scale function, and other parameters are to be drawn to decide if the signal possesses multifractal properties. The steps needed in this method are as follows:

Step 1: The profile of the time series $\{x_i\}$ of the length N is calculated according to:

$$Y(i) = \Sigma_{j=1}^{i}(x_j - \langle x \rangle) \quad i = 1 \dots \dots \dots \dots N \quad (9)$$

$\langle x \rangle$ is the mean of the signal $\{x_i\}$

Step 2: the profile $Y(i)$ is divided into $N_s = int(N/s)$ equal non-overlapping segments of size s. Since N may not be a multiple of s and the function int takes the integer part of N_s. A short part at the end time of the signal could remain. In order to not miss this part of the time series, the same process is repeated but starting from the opposite end of the series. This leads to $2N_s$ for each value of s.

Step 3: a polynomial is fitted to the data to reveal the local trend for each $2N_s$. To this end, a first variance is calculated:

$$F^2(s,v) = \frac{1}{s}\Sigma_{i=1}^{s}\{Y[(v-1)s+i] - y_v(i)\}^2$$
for $v = 1, \dots \dots N_s$ $\quad (10)$
And

$$F^2(s,v) = \frac{1}{s}\Sigma_{i=1}^{s}\{Y[(N - (v - N_s)s + i] - y_v(i)\}^2 \quad \text{for}$$
$v = N_s + 1, \dots \dots 2N_s \quad (11)$

$y_v(i)$ is the fitting polynomial of the order m representing the local trend in the segment v. m is generally between 1 and 3.

Step 4: average all the segments to compute the order q of the fluctuations function:

$$F_q(s) = [\frac{1}{2Ns}\Sigma_{v=1}^{2Ns}\ [F^2(v,s)]^{\frac{q}{2}}]^{\frac{1}{q}} \text{ for } v = 1 \dots N_s \quad (12)$$

Step 5: Determine the scaling of the fluctuation function by analyzing the log-log plot of $F_q(s)$ versus s for each value of q. The fluctuation function $F_q(s)$ exhibits the following power law:

$$F_q(s) \sim s^{h(q)} \quad (13)$$

If a scaling behavior governs the time series $\{x_i\}$.

$h(q)$ is the generalized Hurst exponent. Monofractal time series have the same value of h for all the values of q whereas, in multifractal time series, the function $h(q)$ decreases with q. The order q is generally between -5 and +5.

Step 6: The generalized Hurst exponent is related to the Renyi exponent via the following equation:
$$\tau(q) = qh(q) - 1 \quad (14)$$

This equation permits the confirmation of the signal multifractality. If $\tau(q)$ presents a non-linear curve, the time series is multifractal, otherwise, the time series exhibit monofractal behavior. The singularity spectrum $D(h)$ can be related to $\tau(q)$ by means of a Legendre transform:

$$D(h) = qh(q) - \tau(q) \quad (15)$$

The typical shape of the singularity spectrum for a multifractal set is shown in Fig. 1. The strength of multifractality is quantified by measuring the multifractal width Δh.

$$\Delta h = h_{max} - h_{min} \quad (16)$$

The width Δh quantifies the density of weak and strong singularities in a signal. A broader multifractal width Δh indicates that the signal under study is rich in self-similar patterns. h_0 reveals the dominant irregularity in a multifractal set. A high value of h_0 informs that large fluctuations for which (q>0) dominate the signal dynamics, whereas a low value of h_0 indicates that weak singularities with (q<0) are dominant.
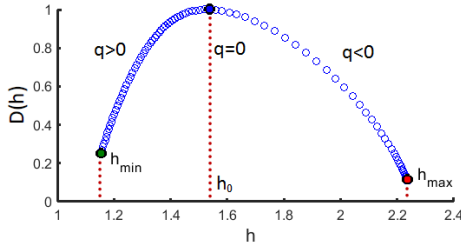
Fig. 1. Typical shape of the singularity spectrum for multifractal set.

III. THE PROPOSED ALGORITHM

The main steps of the proposed algorithm are summarized in Fig. 2. When a disturbance occurs, the initial voltage $V(t)$ recorded at normal operation is contaminated with an additional signal $V_d(t)$. The contamination level depends on the nature of the disturbance being investigated. The distorted voltage $V_f(t)$ can be expressed as:

$$V_f(t) = V(t) + V_d(t) \qquad (17)$$

Where $V_d(t)$ is the signal that contains the fault information. In many cases, the PQD does not induce a noticeable distortion in the voltage waveform. In others, the frequency contents of distorted voltage are similar to those generated during switching events. In such situations, the disturbance may not be detected when analyzing $V_f(t)$. To cope with this problem, the fault information can be extracted by isolating $V_d(t)$ that holds the relevant information contained in the distorted voltage.
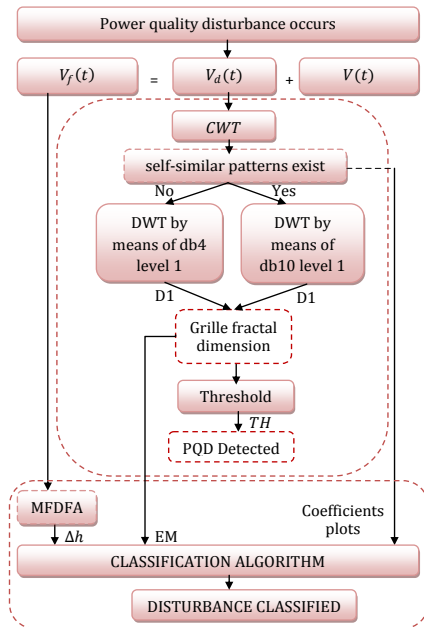
Fig. 2. Flowchart of the proposed detection and classification approach

A. Denoising process

After separating the additional signal from the distorted voltage, a decision should be made as to whether the disturbance is simple or complex. Since the self-extinguishing scenario of PQDs is considered in this paper, two types of transients are to be differentiated: oscillatory

transients that appear in the voltage waveform when a complex disturbance occurs and the extinction transients that encode the disturbance (simple or complex) extinguishing. In this paper, the transients nature is investigated using CWT, the technique possesses the ability to traduce the transients contained in a given signal into self-similar shapes. For this purpose, CWT is conducted to reveal the self-similar features masked in the fault information $V_d(t)$. Through CWT, the wavelet is translated over the entire signal and the correlation coefficients between the wavelet and the main signal are plotted to allow the visualization of all the signal characteristics. The choice of the mother wavelet is the key factor that decides the accuracy of PQD classification. In an attempt to reveal the self-similarities hidden in the signal $V_d(t)$, a deep analysis of wavelet families has been carried out. After drawing comparisons between the coefficient plots of those wavelets, it was found that db10 led to the highest coefficients. Furthermore, due to its number of vanishing moments, db10 has captured the smallest self-similar patterns that other wavelets have missed.

B. Detection

The detection schema is based on the fractal theory for its ability to reflect the singularities contained in complex signals. For this purpose, the fractal dimension is selected as a tool to detect the start and end moments of PQDs. In the field of power engineering protection, the rapidity of the detection process is highly required. Therefore, the grille fractal dimension is implemented for its fast computation process and its robustness in analyzing non-stationary signals. Once the signal $V_d(t)$ is processed, the grille fractal dimension of the decomposition detail is computed to locate the start and end times of the disturbance. To eliminate the transients between the start and end times of the disturbance or those due to the disturbance extinguishing, a threshold based on the second max of the grille fractal dimension is defined:

$$N(\delta)_i \geq sd \max(N(\delta)) \qquad (18)$$
$$TH = 1$$
$$Else$$
$$TH = 0$$

C. Classification

The classification stage is based on a combination of geometric and statistic classification. Geometric classification is based on CWT, whereas statistical classification is based on Multifractal Detrended Fluctuation Analysis (MFDFA) and an energy metric.

D. Geometric classification

The geometric classification is based on CWT. The aim is to investigate whether the distorted voltage contains self-extinguishing transients or not. The disturbance is self-extinguishing if CWT coefficient plots contain self-extinguishing self-similarities. Otherwise, the disturbance is fugitive.

E. Statistic classification by MFDFA

Given the complexity and non-stationary nature of the distorted voltages, the associated time series exhibit a multifractal behavior; this implies that a single scaling exponent will not be sufficient to describe the behavior of these series. Non-stationary signals do not exhibit the same

singularity over time but they are characterized by local singularities that vary with time. The singularity spectrum is the parameter that measures the signal fluctuations during a time t. If the Holder exponent H defines the local singularity of a signal. The singularity spectrum $D(h)$ corresponds to the Hausdorff dimension of a set of points whose local holder exponent is H. Two methods are generally used to quantify the multifractality of a signal: Multifractal Detrended Fluctuation Analysis (MFDFA) [22] and Wavelet Transform Modulus Maxima (WTMM) [23]. In reference [24], it has been concluded that MFDFA leads to better detection of multifractality compared to WTMM that in some cases, may suggest a spurious multifractality. Furthermore, it has been mentioned that the performance of WTMM is strongly dependent on the chosen wavelet. In the paper [20], it has been stated that in addition to its simplicity, MFDFA leads to more significant results compared to WTMM. Taking this into consideration, the MFDFA method has been selected in this paper to estimate the singularity spectrum of PQD voltages.

F. Statistic classification by energy metric

Further to CWT and MFDFA, a metric is developed in this paper based on the energy of the grille fractal dimension; the proposed metric is defined as:

$$EM = n * \frac{En(N(\delta))}{En(N(\delta)_V)} \qquad (19)$$

$En(N(\delta))$: The energy of the grille fractal dimension $N(\delta)$ obtained from the detection module.

$En(N(\delta)_V)$: The energy of the grille fractal dimension of the voltage $V(t)$.

n is the number of the sampling points. The proposed metric is calculated for all PQDs under consideration. Then, the range of EM is defined for each disturbance.

IV. THE SIMULATED SYSTEM

In order to prove the efficiency of the proposed methodology, a total of 4 disturbances are simulated in Matlab Simulink Software. The investigation included: outage, sag, phase to phase fault, three-phase fault. For each PQD, self-extinguishing and fugitive scenarios are considered. All the disturbances start at t_0=0.1s and end at t_1= 0.14s. For each disturbance scenario, the distorted voltage recorded in the scope is logged in the workspace with 8001 samples. The sampling frequency is 20003.2 Hz and the rate frequency is 60Hz. In several publications, PQDs have been simulated based on mathematical models. This may be far from the reality where the distorted voltages are contaminated by strong oscillatory transients. In this paper, the power network considered in simulations is a three-phase 735 KV real compensated system supplying an equivalent load via 2 transmission lines [25]. The system (Fig. 3) transmits power from 6*350 MVA generators to an equivalent system via a 600 km transmission line. The equivalent system consists of a 300 MVA transformer feeding a load of 250 MW. The transmission line is divided into 2 lines of 300 Km; line 1 between buses B1 and B2 and line 2 between buses B2 and B3. CB1 and CB2 are the circuit breakers of line 1. To improve the transmission efficiency, series and shunt compensation are used. For that, a capacitor bank whose reactance represents 40% from the

line reactance is connected to the end of each line (series compensation). For shunt compensation, a shunt reactance consisting of 330 MVAR is connected to both lines. The protection of the capacitor bank is carried out via metal oxid varistors (MOV1 and MOV2).
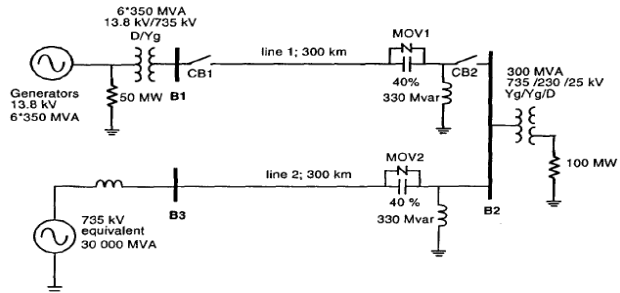

Fig. 3. The three phase 735 KV real compensated system

V. DETECTION RESULTS

A. Outage

In order to simulate the self-extinguishing scenario of the outage, a short circuit is created in phase A of line 1. The corresponding distorted signal $V_f(t)$ is shown in Fig. 4; the transients appearing on its waveform are due to the extinction of the disturbance. These transients are gradually attenuated until they definitively disappear. To decide whether the disturbance is simple or complex, CWT is applied to the differential voltage utilizing the db10 wavelet (Fig.4). The coefficients denoting the correlation index between the signal and the wavelet are generated from the scale 1 to 220. The colour at each point of the scalogram encodes the coefficient magnitude; bright colours refer to high coefficients, whereas dim colours refer to low coefficients. The bright region depicted after the end of the disturbance corresponds to the extinction transients; it progressively disappears with the extinction of the disturbance. The branches appearing at the smallest scales are the modulus maxima of the wavelet transform; they encode the signal singularities. As can be seen from Fig. 4, the modulus maxima extend to high scales in a self-similar manner, thereby reflecting the self-similar behavior of the extinction transients. However, those self-similarities do not exist for all the scales; it can be seen in the figure that the self-similar patterns disappear beyond scale 140.
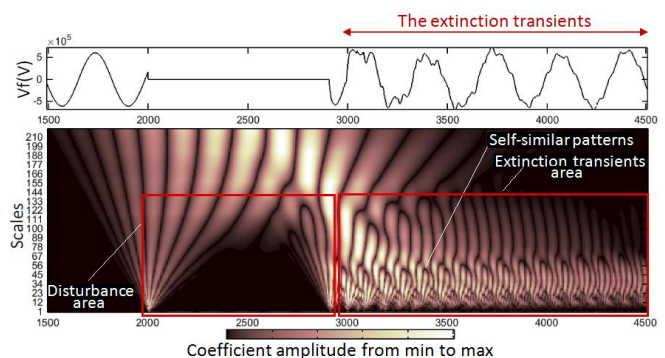

Fig. 4: CWT applied to the differential voltage of self-extinguishing outage
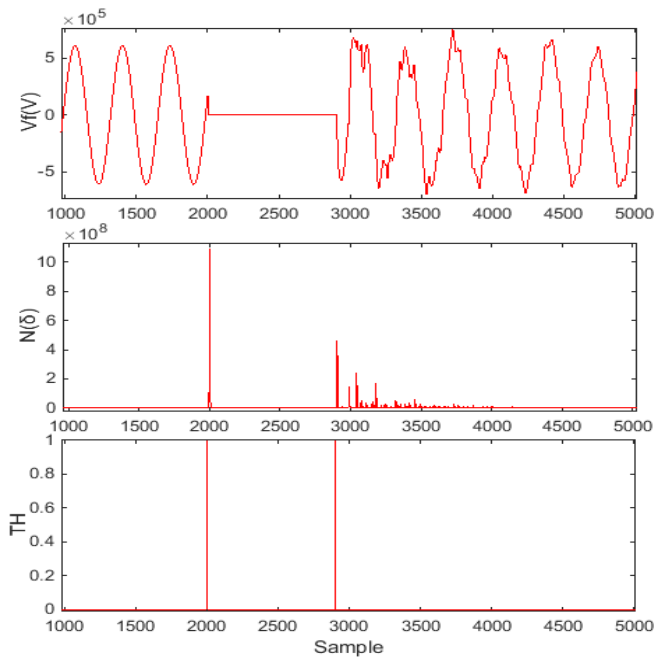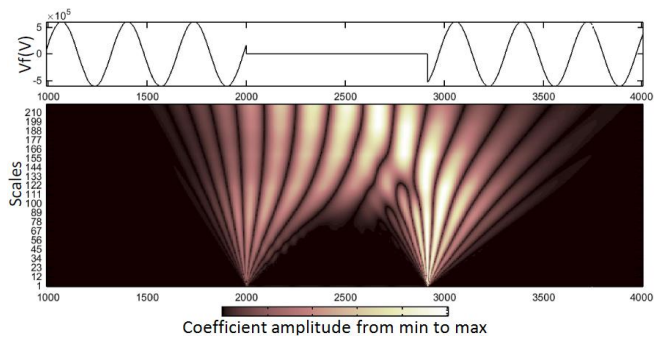
Fig.5: Detection results of self-extinguishing outage

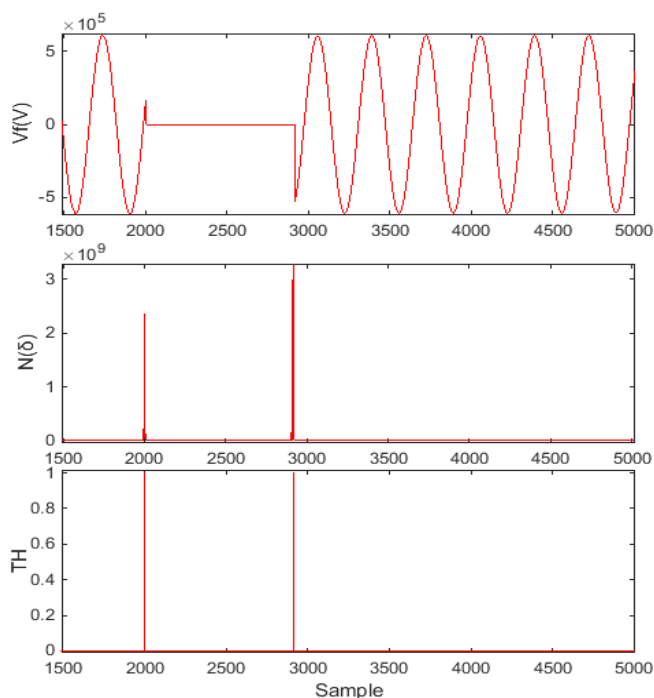Fig. 6. CWT applied to the differential voltage of fugitive outage

Fig. 7. Detection results of fugitive outage

As can be seen from Fig. 4, self-similar patterns do not appear during the disturbance, which means that we are

dealing with a simple PQD. For this reason, the differential voltage is processed by means of db4 level 1 decomposition. The computed fractal dimension $N(\delta)$ and the threshold TH are shown in Fig. 5. From this figure, it can be seen that the presence of the extinction transients does not influence the detection accuracy; the start and end moments of the disturbance are located efficiently.

Similarly to the self-extinguisher outage, the fugitive outage is qualified as a simple disturbance since the corresponding additional voltage does not show self-similar patterns during the disturbance (Fig. 6). The fractal dimension $N(\delta)$ and the threshold TH are presented in Fig. 7. From the curve of TH, it can be seen that the first peak depicts the start moment of the disturbance, whereas the second corresponds to its end.

B. Voltage sag

Following a self-extinguishing short circuit applied to line 1, the voltage on B3 dropped from its initial value. The corresponding coefficients are displayed in Fig. 8. Similarly to the self-extinguishing outage, self-similar patterns identifying the extinction transients are depicted. This self-similarity is loosed after the scale 140.
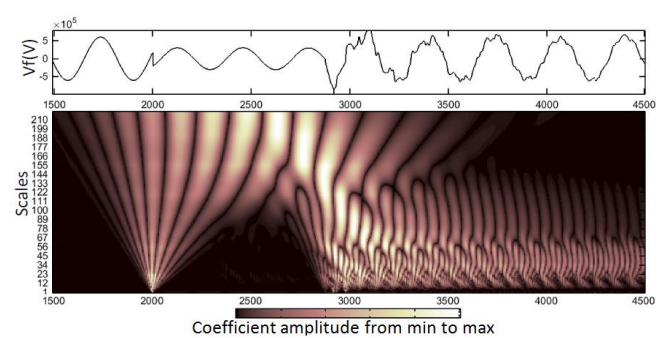

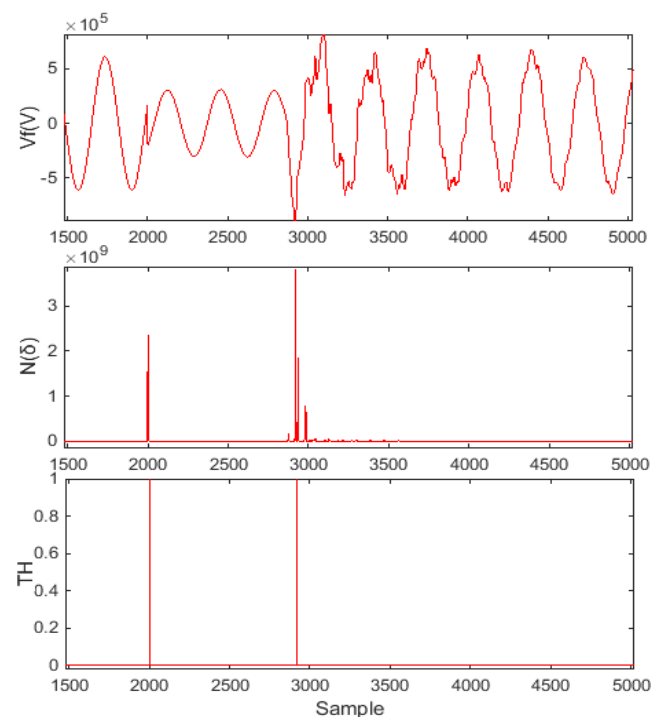Fig. 8. CWT applied to the differential voltage of self-extinguishing sag

Fig. 9. Detection results of self-extinguishing sag

The differential voltage is processed through db4 level 1 decomposition due to the absence of self-similar patterns during the disturbance. The detection results are drawn in Fig. 9. A drastic variation is depicted at the start moment of the disturbance. The second peak of the grille fractal dimension $N(\delta)$ is followed by transients recording the extinction of the disturbance. The extinction transients have been eliminated by means of the threshold TH and the end moment of the disturbance was accurately detected.

For the fugitive sag, the bright spots are centered on the start and end moments of the disturbance (Fig.10). The detection results in Fig. 11 reveal that the proposed algorithm can detect the disturbance accurately.
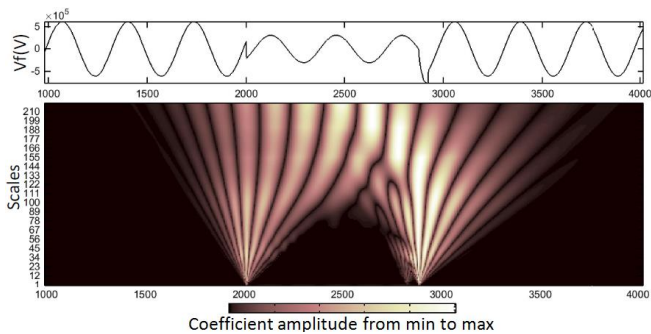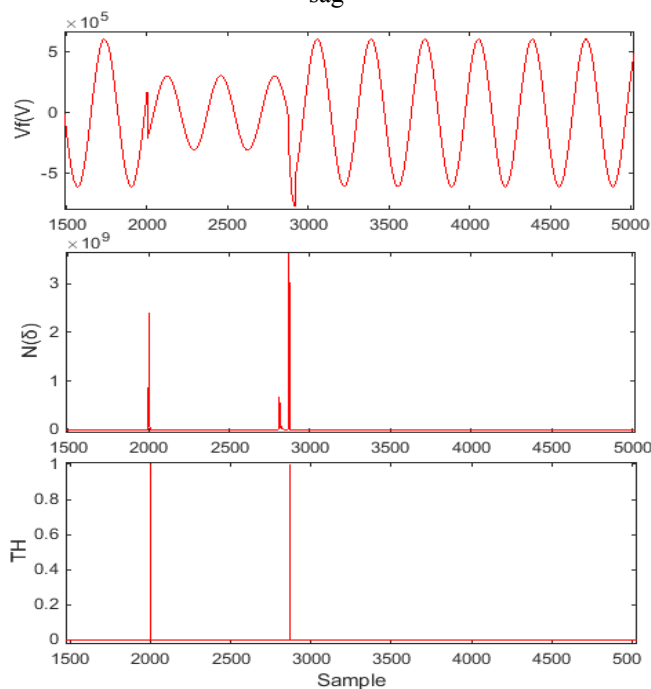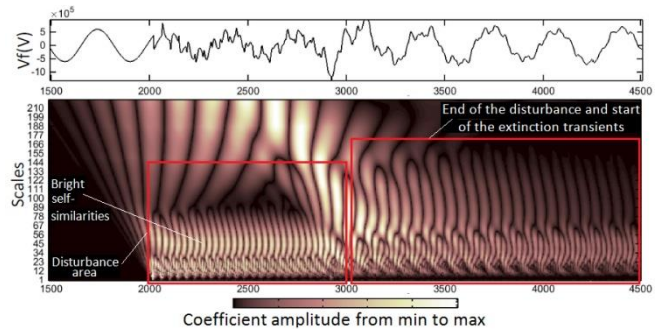

Fig. 12. CWT applied to the differential voltage of self-extinguishing phase to phase fault.

The self similarities depicted during the disturbance prove that we are facing a complex disturbance. For this reason, the differential voltage is processed using the db10 level one decomposition. After having tested several supports, it turned out that the db10 level one decomposition allowed an effective detection of the disturbance even in the presence of strong oscillatory transients. This result is clearly illustrated in the fractal dimension plot (Fig. 13) where a drastic change is depicted at the end of the disturbance. The proposed threshold TH eliminates the transients between the two strongest peaks of $N(\delta)$, allowing accurate detection of the start and end moments of the disturbance.
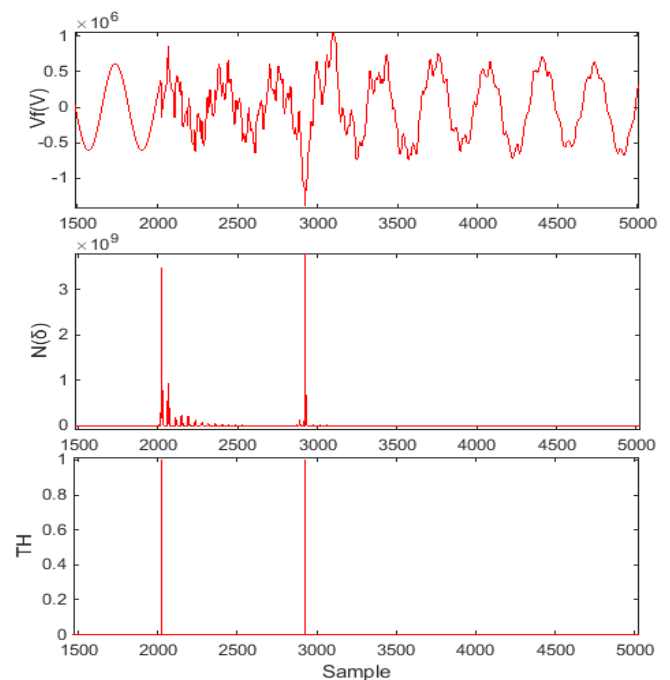

Fig. 10. CWT applied to the differential voltage of fugitive sag

Fig. 11. Detection results of fugitive sag

Fig. 13. Detection results of self-extinguishing phase to phase fault

C. Phase to phase fault

A double phase fault is simulated by short-circuiting phases A and B of line 1. The coefficients plot shown in Fig. 12 can be divided into two areas. The first area describes the disturbance period, whereas the second region denotes the end of the disturbance and the start of the extinction transients. The first area is characterized by bright self-similarities that extend from small scales up to scale 80. The second region is distinguished by bright spots extending to large scales and dim self-similar patterns that disappear with the extinction of the disturbance.
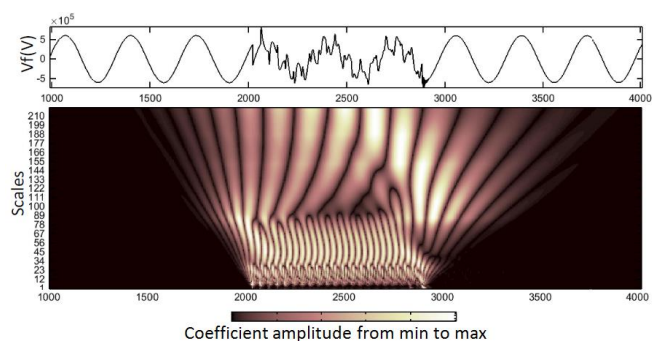

Fig. 14. CWT applied to the differential voltage of fugitive phase to phase fault
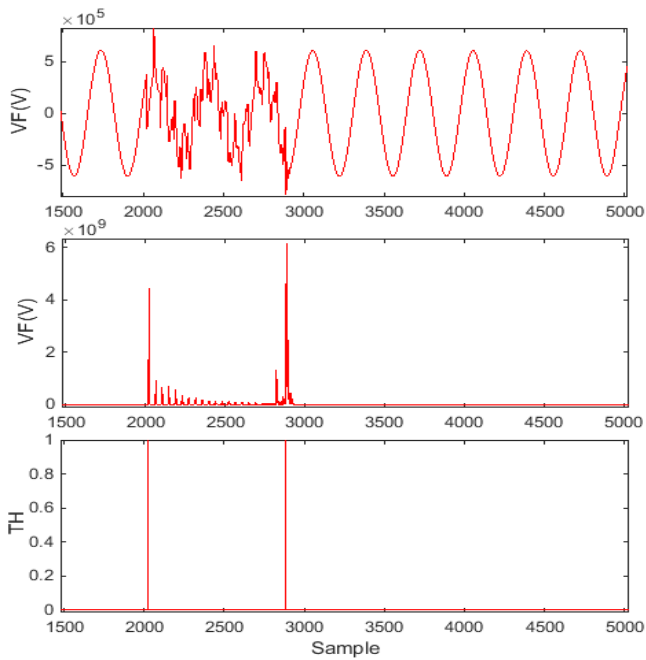
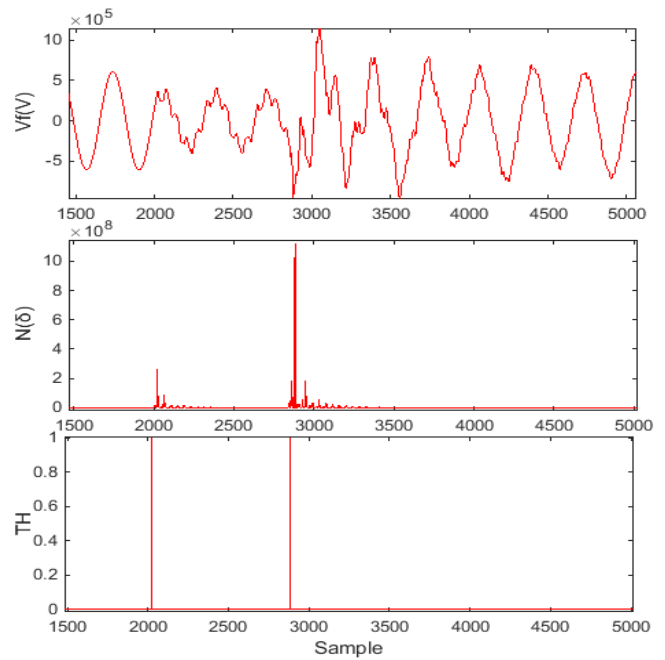Fig. 15. Detection results of fugitive phase to phase fault

Fig. 17. Detection results of self-extinguishing three-phase fault.

Similar coefficient plots are identified in the fugitive scenario of phase to phase fault; the only difference is that the part representing the extinction transients in the self-extinguishing scenario has disappeared (Fig.14). The grille fractal dimension $N(\delta)$ is shown in (Fig. 15). The two peaks detect the disturbance well despite the presence of strong transients between them. These transients are eliminated by means of the proposed threshold TH, and the occurrence moments of the disturbance are detected accurately.

D. Three-phase fault

Following a three-phase fault, voltage sag with harmonics was recorded on phase A. The coefficients drawn in Fig. 16 refer to the self-extinguishing scenario of a three-phase fault. Whereas bright self-similarities are identified during a two-phase fault, dim self-similarities are identified during a three-phase fault with a small bright region ranging from scale 30 to scale 40.
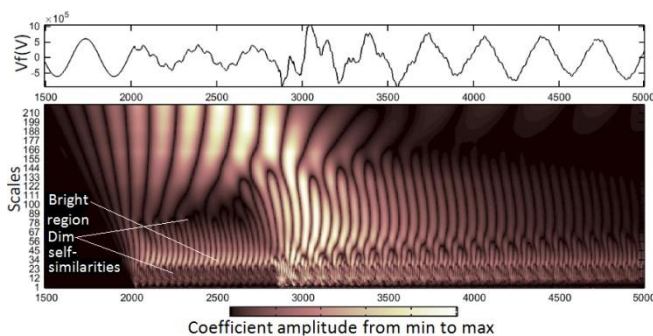

Coefficient amplitude from min to max

Fig. 16. CWT applied to the differential voltage of self-extinguishing three-phase fault.

Given the presence of self-similar patterns during the disturbance, the differential voltage is processed through db10 level 1 decomposition. The grille fractal dimension shown in Fig. 17 proves the effectiveness of the proposed algorithm. The extinction transients are eliminated using the threshold TH, and the occurrence times of the disturbance are detected.
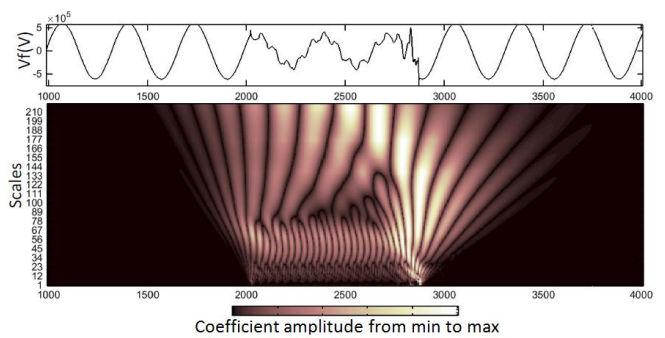

Coefficient amplitude from min to max

Fig. 18. CWT applied to the differential voltage of fugitive three-phase fault.
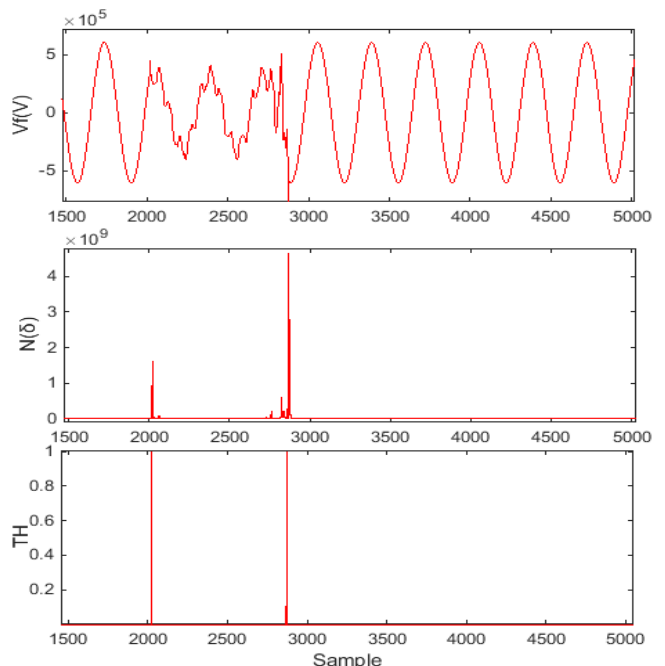

Fig. 19. Detection results of fugitive three-phase fault.

As can be seen in Fig. 18, the self-similar patterns depicting the extinction transients disappear in the fugitive scenario. The detection results shown in Fig. 19 locate well the occurrence moments of the disturbance.

VI. CLASSIFICATION RESULTS

A. Multifractal Detrended Fluctuation Analysis

In this section, the MFDFA algorithm is applied to all distorted voltages and the multifractal behavior hidden in each disturbance is quantified. The singularity spectrums related to all the examined disturbances are shown in Fig. 20. From Fig. 20.a, it can be seen that the self-extinguishing outage holds a broad range of multifractal patterns ($\Delta h = 2.29$) with a dominance of small fluctuations (long right tail). In the fugitive outage, the disappearance of the extinction transients narrowed the right tail representing the small fluctuations; this led to ($\Delta h = 2.22$) instead of 2.29 for the self-extinguishing outage.

The curve of the singularity spectrum is more concave for the self-extinguishing sag (Fig. 20.b) with a narrowing in the multifractal width ($\Delta h = 1.2$); this can be explained by the fact that the voltage sag represents a drop of the fluctuations magnitudes (voltage waveform) whereas, during the outage, the voltage is completely loosed which is considered as an intense transformation from the fluctuation point of view. The multifractal width narrowed more in the fugitive scenario of sag ($\Delta h = 1.04$) with a dominance of weak fluctuations at the expense of large ones (long right tail).

In the self-extinguishing phase to phase fault, the multifractal width is richer than that of sag due to the strong oscillatory transients that appear in the voltage waveform (Fig. 20.c). In the fugitive scenario, the peak of the singularity spectrum shifts to the right, thereby reflecting the shrunk of the right tail representing the weak singularities. For self-extinguishing three-phase fault, the distorted voltage is rich in singularities which explain the wide width ($\Delta h = 1.35$) of the singularity spectrum (Fig. 20.d). In the fugitive scenario, the multifractal width becomes ($\Delta h = 1.06$).
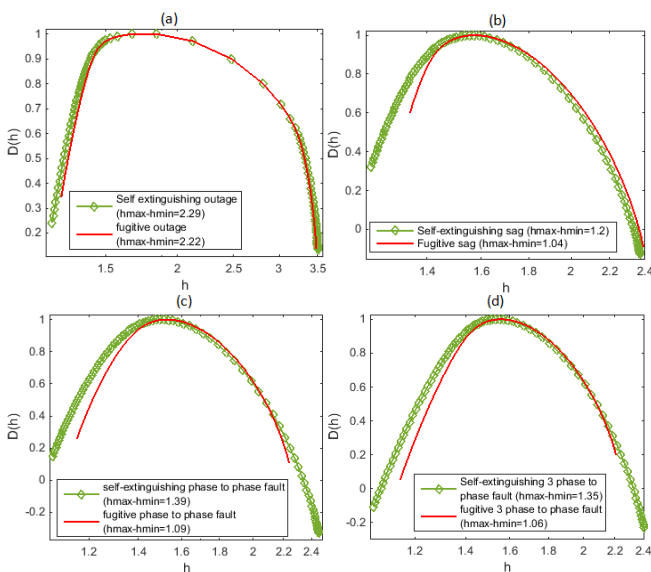
B. Automatic classification of PQDs

For an automatic classification of the studied PQDs, an algorithm is developed based on CWT coefficient plots, MFDFA singularity spectrum, and the proposed energy metric EM. For this reason, 150 samples of each disturbance have been created with different parameters. The voltage swell was also considered. The maximum and minimum values of EM and Δh for all the studied PQDs are detailed in tables I and II. The proposed algorithm is given in figure 21.

Table I: Range of EM for all the considered disturbances

Disturbance	The range of EM
Self-extinguishing outage	145<EM<196
Fugitive outage	1524< EM <2638
Self-extinguishing sag	614 < EM <994
Fugitive sag	992< EM<1706
Self-extinguishing phase to phase fault	1205< EM <1783
Fugitive phase to phase fault	2010< EM <3346
Self-extinguishing three-phase fault	12 < EM <14
Fugitive three-phase fault	147< EM <1087
Self-extinguishing swell	239< EM <12064
Fugitive swell	331< EM <607

Table II: Range of Δh for all the considered disturbances

Disturbance	The range of Δh
Self-extinguishing outage	1.85< Δh < 2.30
Fugitive outage	1.85< Δh < 2.20
Self-extinguishing sag	1.10< Δh < 1.85
Fugitive sag	1.10< Δh < 1.70
Self-extinguishing phase to phase fault	1.10< Δh < 1.85
Fugitive phase to phase fault	1.01< Δh < 1.3
Self-extinguishing three-phase fault	1.01< Δh < 1.5
Fugitive three-phase fault	1.01< Δh < 1.35
Self-extinguishing swell	0.8< Δh < 1.01
Fugitive swell	0.8< Δh < 0.9
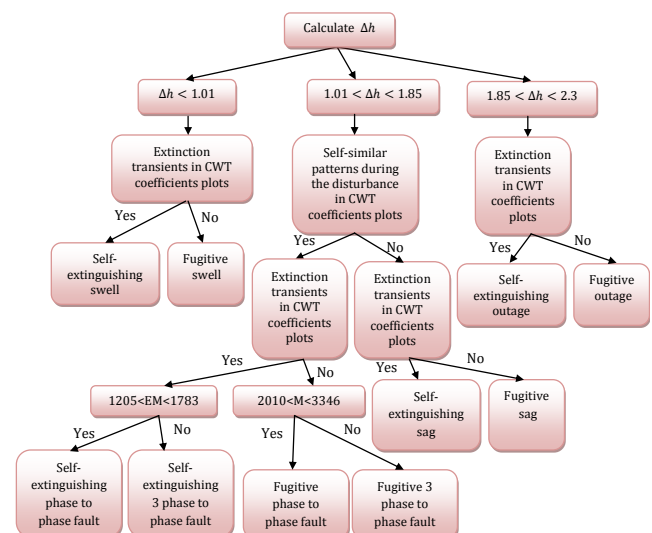
Figure 21. Algorithm for automatic classification of self-extinguishing and fugitive PQDs

Fig. 20. Singularity spectrum of PQDs voltages (a- outage, b-sag, c-phase to phase fault, d- three-phase fault)

The proposed classification algorithm has been developed from the obtained results. For all the studied disturbances, the self-extinguishing and fugitive scenarios have close singularity spectrums. However, the extinction transients scanned in CWT plots can be used to discriminate between them. Swell, sag, and outage show similar CWT coefficient

plots, but they have different singularity spectrum Δh. As for three-phase fault (sag + harmonics) and phase to phase fault (harmonics), they can be distinguished by the proposed energy metric EM. The proposed classification algorithm is easy to implement, provides a proper interpretation of the results, and shows good generalization ability.

Table III: Comparison of the classification accuracy of the proposed approach with DT, PNN, PSO-ELM and ANN.

Type of the disturbance	Classification accuracy %				
	DT	PNN	PSO-ELM	ANN	Proposed approach
Self-extinguishing outage					100
Fugitive outage	99.9	100	100	100	100
Self-extinguishing sag					100
Fugitive sag	99.9	98	98	99	98.66
Self-extinguishing phase to phase fault					100
Fugitive phase to phase fault	100	99	100	100	100
Self-extinguishing 3 phase fault					99.33
Fugitive 3 phase fault	99.99	98	98	98	99.33
Swell	100	99	100	96	100
AVG	99.97	99	98.75	98.84	99.29

The classification accuracy of the proposed approach is compared with DT [19], PNN [14], PSO-ELM [26], and ANN [27]. The self-extinguishing scenario of each disturbance is considered even if it was not studied in the other methods. The results in (Table III) show that the recognition accuracy of the approach is 100% for several disturbances. For three-phase fault (sag + harmonic), the recognition rate reached is 99.33% which is higher than PNN, PSO-OLM, and ANN. The average accuracy of the method is 99.29% which demonstrates that the proposed algorithm can achieve an excellent classification for all the disturbances.

VII.   DISCUSSION

Among the advantages of the proposed approach, the denoising process is tailored depending on whether the disturbance is simple or complex. As a result, accurate detection of PQDs was achieved even in the presence of high oscillatory transients. Some of the exiting approaches have used the same wavelet decomposition for simple and complex disturbances. However, experience has shown that a wavelet decomposition that may be appropriate for complex disturbance can lead to information loss if applied to a simple disturbance. Within simulations, we have found that db4 is suitable for simple disturbances, whereas db10 is appropriate for complex ones.

Contrary to the existing fractal approaches, the proposed threshold is found to yield efficient detection results without a need for further analysis of the grille fractal dimension.

This fact reduces the computation time and allows rapid detection of PQDs.

The detection scheme demonstrates high robustness against self-extinguishing transients. As shown in detection results, the start and end moments of self-extinguishing PQDs have been accurately detected. In all the papers cited above, only the fugitive scenario has been considered. However, the self-extinguishing scenarios are frequent in real-life PQDs. Some references consider the noisy environment by adding the Gaussian white noise to the PQDs voltages [10]. However, in real-life disturbances, it's frequent to have different levels of distortion on the same distorted voltage. Consequently, adding one level of the Gaussian white noise cannot accurately simulate real disturbances.

In the approaches proposed in [17-19], several parameters were calculated to define the feature set of the classification module. In the proposed approach, the classification of PQDs is based on 3 parameters: CWT coefficient plots, the singularity spectrum and the energy metric EM. The three parameters are used as inputs to the classification algorithm for automatically classifying PQDs. This fact reduces the calculation burden and increases the generalization ability of the method.

Compared to ST [11] and Gray image [18] approaches, the proposed recognition approach has the advantage of revealing and quantifying the self-similar patterns that discriminate one disturbance from the other. This property is of immense value, especially for real-time engineering applications in which fast and interpretable results can make a great difference. In fact, through CWT and MFDFA, an algorithm with low computational burden and high generalization ability has been built. The interpretation of CWT coefficients plots allows us to decide whether the disturbance is self-extinguishing or fugitive. As for the singularity spectrum, it permits the identification of the disturbance nature. The algorithm has been supplemented by the energy metric EM to recognize PQDs.

In the paper [7], global and local fractal indexes of the wavelet coefficients were extracted and used to divide the disturbances into 3 groups according to their perturbation degree. However, as shown in this paper, disturbances such as sag and outage have similar fractal dimensions. As a result, the fractal dimension alone does not allow precise classification of PQDs. There is a need for a statistical approach to meet this need.

VIII.   CONCLUSION

Fractal theory and wavelet transform are widely used in power network issues. In a previous paper, the fractal theory was used to study the dynamic behavior of the power network [28]. In this paper, the high sensitivity of wavelet transform to noise and the performance of the grille fractal dimension in detecting singularities have been combined to detect the start and end times of PQDs. In the classification stage, CWT was used to perform a geometric classification by scanning the self-similarities that distinguish one disturbance from another. Furthermore, the density of self-similar features has been quantified through MFDFA and an energy metric was proposed to complete the statistic classification algorithm.

The main contribution of this paper is:

- The proposed recognition algorithm is efficient not only for fugitive PQDs but also for self-extinguishing ones.

- The denoising process is adapted according to whether the disturbance is simple or complex.
- The proposed threshold yields efficient detection results without a need for further analysis of the grille fractal dimension.
- The detection approach has good robustness against oscillatory and self-extinguishing transients.

- The proposed approach is easy to implement, allows a proper interpretation of the results, and possesses good generalization ability.

Our findings related to PQDs can be summarized as follows:
- For all the studied PQDs: two and three-phase faults, each of them have its own signature on the CWT coefficients and the energy metric. However, outage, sag, and swell, their coefficient plots are images of each other, whereas their singularity spectra differ significantly. This proves the major importance of the singularity spectrum in quantifying the impact of each disturbance on the voltage dynamics.
- For the same disturbance, the multifractal width varies from one scenario to another. Due to the extinction transients, it has been shown that the self-extinguishing scenario posses the broadest width compared to the fugitive scenario.
- Strong oscillatory transients result in brilliant self-similar shapes, whereas weak transients result in dim self-similarities.

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S. Lakrih proposed the detection and recognition approach of this paper, carried out the simulations and wrote the paper.

J. Diouri guided and revised the paper.