Applying Machine Learning Algorithms for Classifying Time-Frequency Failures in Power Grid Systems

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Abstract. In power grid systems, Power Quality (PQ) disturbances affect manufacturing process, cause malfunction of equipment and induce economic losses. This paper presents ten new features to identify PQ disturbances such as voltage sag, swell, interruption, harmonics and combined defaults. At first, Hilbert Transform (HT) and Phase Locked Loops (PLL) techniques are applied to estimate the frequency and phase of harmonic components of voltage signals in real time. Then new descriptors, i.e., features, based on Time-Frequency (TF) representations are used. These TF features are obtained from the Rényi and Shannon entropy obtained with the Short-Time Fourier Transform (STFT), the Stockwell Transform (ST) and the Optimized Stockwell Transform (OST). In order to evaluate the proposed TF descriptors, machine learning algorithms are applied to effectively discriminate the different types of disturbances. Classification results show an accuracy of more than 99.4% even in 5 dB SNR high-noise condition.

Keywords: Power quality, power grid failure, time-frequency feature, classification, machine learning.

1 Introduction

In power distribution grids non-linear loads introduce current harmonics and voltage disturbances that affect the performance of other loads [1]. On another side, large penetration of renewable power generation into the existing power grid injects the inevitable issues related to the Power Quality (PQ) [2]. Therefore, it is very important to detect and eliminate the power quality disturbances and failures in order to reach and maintain quality power. So, one of the important issues in PQ problems is to detect and identify disturbance waveforms automatically in an efficient and fast manner. PQ monitoring considers four calculations as it is represented by Figure 1: The phase angle detection, fundamental frequency estimation, amplitude estimation, and frequency content analysis.

There are several techniques for detecting or identifying PQ disturbances [3]: Methods for analysing PQ parameters, filtering methods and Fourier analysis techniques. The most widely adopted approach in signal processing is the spectral analysis using Fourier analysis. This technique is tremendous for analysing stationary signal because the characteristics of the signal do not change with time, but it is unfavourable for non-stationary signals because of its inadequacy in tracking the changes in the magnitude, frequency or phase. The Time-Frequency representation (TF) can be provided by methods like the Stockwell Transform (ST), the Hilbert-Haung Transform (HHT) or either the Wavelet

Transforms [4]. The TF representation gives the energy distribution of a signal according to two variables, the time and the frequency.

This paper uses the TF analysis for characterizing non-stationary electrical signals and detecting PQ disturbances. This means that PQ disturbances are characterized by ten features in the TF domain. The new relevant parameters allows then to apply Machine Learning (ML) algorithms for classifying PQ failures. PQ disturbance classification is achieved by using ML algorithms such as the K-Nearest Neighbors (K-NN), the Random Forest (RF), and the Support Vector Machine (SVM). These algorithms are trained on the ten selected TF-features extracted from the grid voltage system.

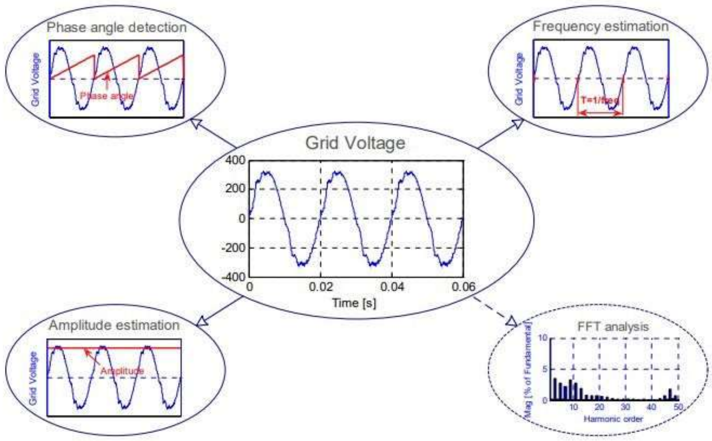

Fig. 1. General overview of power quality monitoring and analysis

2 Time-frequency domain for the evaluation of the power quality

2.1 Context of power quality

The term power quality may be defined as a wide variety of electromagnetic phenomena that characterize the voltage and current at a given time and location in the power system. Voltage swell, sag, flicker, notch, harmonics, interruptions, oscillatory transient and their combinations are some of the common PQ events [1]. Traditionally, the conventional methods to address PQ analysis issues lead to the main descriptors that are the Power Factor (PF), the Total Harmonic Distortion (THD) and the unbalance:

- The PF is the ratio between the active power and the reactive power and is expressed by the $\cos\phi$. This means that if $\cos\phi = 1$, then there is no reactive power flow and the phase angle between the voltage and current is zero.
- The THD is often used to define the degree of harmonic content in an alternating signal. The THD is the ratio of the square root of the sum of all harmonic components except fundamental to the fundamental component. For a signal, the term THD represents the percentage of distortion from its fundamental wave shape. Harmonics for example are more present on the current.
- In a three phase power grid, the voltage unbalance is a condition in which the three-phase voltages differ in amplitude or are displaced from their normal 120° phase

relationship, or both. The degree of unbalance is usually defined by the ratio of the negative sequence voltage component to the positive sequence component. In power grids with high penetration of solar PV generators, they are typically not allocated equally between the three phases.

Theses indicators are simple PQ descriptors and are not representative of the quality of the waveforms of a power supply system, i.e., the voltage and the current. In other words, they are not able to distinguish the previously listed common PQ events, i.e., they are not able to calculate the parameters of the waveforms.

These events occur on the voltage or on the current signals and affect their waveforms. In this study, the objective is not to calculate the parameters of the waveforms but to identify the PQ events. Our choice consists in using TF-descriptors because they are able to handle non-stationary signals which are more common rather than stationary signals and to take into account frequencies variations over time which is very relevant to discriminate PQ faults [5].

2.2 System modelling and fault description

In this study, the power grid is defined by the two following signals:

$$u(kT_s) = U\sin(2\pi f kT_s + p) \tag{1}$$

$$i(kT_s) = I\sin(2\pi f kT_s + p + \theta) \tag{2}$$

where $u(t)$ and $i(t)$ are respectively the voltage and the current of amplitude U and I. f is the fundamental frequency ($\omega = 2\pi f$), p is the phase angle and θ is the phase angle between the voltage and the current. T_s represents the sampling period and k is the time index or the iteration because the power system is considered as a full discrete system.

Voltage and current waveforms which are supposed to be a periodic (sinusoidal) waveforms may contain PQ event/events. This paper classifies 10 different situations of the PQ. These are the standard and pure waveform (C_0) corresponding to (1) or (2), and 9 conditions with the voltage with PQ disturbances like sag (C_1), swell (C_2), interruption (C_3), sag + harmonic 3 (C_4), sag + harmonic 3 + harmonic 5 (C_5), swell + harmonic 3 (C_6), swell + harmonic 3 + harmonic 5 (C_7), harmonic 3 (C_8), and harmonic 3 + harmonic 5 (C_9). The PQ events are fully formalized by mathematical expressions in Table 1. These situations of the PQ are refered as classes C_i with $i = 0...9$ and where the considered signal is $x_i(kT_s)$ with $h(kT_s, \tau)$ the Heaviside step function defined as (T is an instant):

$$h(kT_s, \tau) = \begin{cases} 1 & \text{if } kT_s \geq \tau \\ 0 & \text{if } kT_s < \tau \end{cases} \tag{3}$$

In the following, all the developments and proposed methods can indifferently handle the voltage or the current measured on the power grid.

2.3 Proposed TF features

A complete detection and classification scheme of the PQ disturbances is proposed. An overview of this scheme is represented by Figure 2. The following three main steps are considered: A - the detection processing, B - the TF-feature extraction processing, and C - the classification processing.

Table 1. Description of the PQ events

PQ disturbance	**signal**	**parameters values**
C_0: Pure sine wave	$x_0(kT_s) = A\sin(\omega kT_s)$	$A = 1$, $f = 60\text{Hz}$, $\omega = 2\pi f$
C_1: Sag	$x_1(kT_s) = A\Big(1 - \alpha h(kT_s, T_1) + \alpha h(kT_s, T_2)\Big)\sin(\omega kT_s)$	$0.1 \leq \alpha \leq 0.9$
C_2: Swell	$x_1(kT_s) = A\Big(1 + \alpha h(kT_s, T_1) - \alpha h(kT_s, T_2)\Big)\sin(\omega kT_s)$	$0.1 \leq \alpha \leq 0.8$
		$T \leq t_2 - t_1 \leq 9T$
C_3 : Interruption	$x_3(kT_s) = A\Big(1 - \alpha h(kT_s, T_1) + \alpha h(kT_s, T_2)\Big)\sin(\omega kT_s)$	$0.9 \leq \alpha \leq 1$,
C_4: Sag	$x_4(kT_s) = A\Big(1 - \alpha h(kT_s, T_1) + \alpha h(kT_s, T_s)\Big)$	
+ Harmonic 3	$\Big(\sin(\omega kT_s) + \alpha_3\sin(3\omega kT_s)\Big)$	$0.1 \leq \alpha \leq 0.9$, $0.05 \leq \alpha_3 \leq 0.15$, $\sum \alpha_i^2 = 1$
C_5: Sag5	$x_5(kT_s) = A\Big(1 - \alpha h(kT_s, T_1) + \alpha h(kT_s, T_2)\Big)$	
+ Harmonics 3 &	$\Big(\sin(\omega kT_s) + \alpha_3\sin(3\omega kT_s) + \alpha_5\sin(5\omega kT_s))$	$0.1 \leq \alpha \leq 0.9$, $0.05 \leq \alpha_3, \alpha_5 \leq 0.15$, $\sum \alpha_i^2 = 1$
C_6: Swell	$x_6(kT_s) = A\Big(1 + \alpha h(kT_s, T_1) - \alpha h(kT_s, T_2)\Big)$	
+ Harmonic 3	$\Big(\sin(\omega kT_s) + \alpha_3\sin(3\omega kT_s)\Big)$	$0.1 \leq \alpha \leq 0.8$, $0.05 \leq \alpha_3 \leq 0.15$, $\sum \alpha_i^2 = 1$
C_7: Swell	$x_7(kT_s) = A\Big(1 + \alpha h(kT_s, T_1) - \alpha h(kT_s, T_2)\Big)$	
+ Harmonics 3 & 5	$\Big(\sin(\omega kT_s) + \alpha_3\sin(3\omega kT_s) + \alpha_5\sin(5\omega kT_s))$	$0.1 \leq \alpha \leq 0.8$, $0.05 \leq \alpha_3, \alpha_5 \leq 0.15$, $\sum \alpha_i^2 = 1$
C_8: Harmonic 3	$x_8(kT_s) = A\big(\sin(\omega kT_s) + \alpha_3\sin(3\omega kT_s)\big)$	$0.05 \leq \alpha_3 \leq 0.15$, $\sum \alpha_i^2 = 1$
C_9: Harmonics 3 & 5	$x_9(kT_s) = A\big(\sin(\omega kT_s) + \alpha_3\sin(3\omega kT_s)$ $+\alpha_5\sin(5\omega kT_s)\big)$	$0.05 \leq \alpha_3, \alpha_5 \leq 0.15$, $\sum \alpha_i^2 = 1$

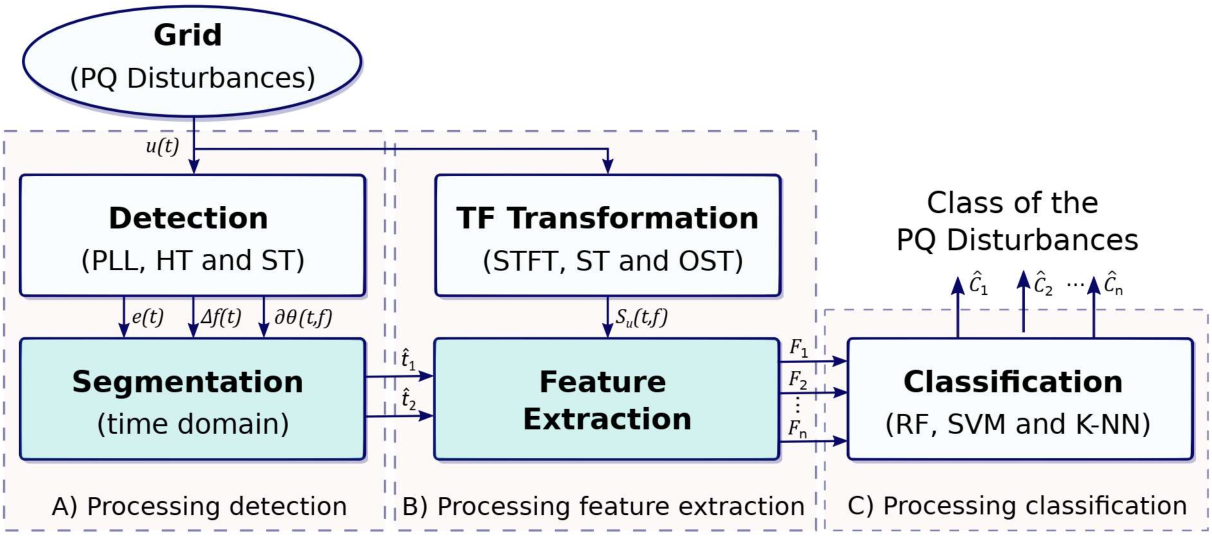

Fig. 2. Proposed workflow for the detection and classification of power quality disturbances

A) In the detection processing, with a signal measure x from the grid, the following values are calculated by the detection block: e, Δf and $\partial\theta$ depend on the time. They are:

$$e = sin(\theta - \hat{\theta}) \approx \theta - \hat{\theta}, \tag{4}$$

$$\Delta f = f - \hat{f}, \tag{5}$$

$$\partial\theta(kT_s, \hat{f}) = \frac{\partial\Phi_x^w(kT_s, \hat{f})}{\partial kT_s}. \tag{6}$$

where

- e which represents the phase angle deviation;
- Δf which is the instantaneous frequency deviation compared to the constant frequency;
- $\hat{f}$ is the estimated frequency and $\hat{\theta}$ the estimated phase angle at instant k; This can be achieved in real-time by PLL techniques [6] or more sophisticated techniques or signal processing tools like the Hilbert Transform (HT) and the Stockwell Transform (ST);
- $\partial\hat{\theta}(kT_s, \hat{f})$ is the estimated value of the instantanneous phase with respect to time;
- $w(kT_s)$ is the sliding Gaussian widow.

The segmentation steps consists in estimating instants t_1 and t_2, i.e., in calculating $\hat{t}_1 = k_1T_s$ and $\hat{t}_2 = k_2T_s$ in order to robustify the TF features. Indeed, $\hat{t}_1$ represents the start time and $\hat{t}_2$ represents the end time of the event. This allows to handle high quality descriptors in the TF-frame. They are thus relevant and significant in the TF frame even in the case of non-stationary signals measured from the power grid. New and recent techniques have been developed to exceed system performance traditional, in terms of image quality, size, weight, energy consumption [7].

B) The "TF Transformation" uses TF-methods like the ST, the Short-Time Fourier Transform (STFT), or the Optimized Stockwell Transform (OST). These methods outputs $S_u(kT_s, \hat{f})$ which is the TF representation of the signal u at a given instant [8]. It is a $n \times m$ matrix that contains the frequency content of the signal over the last period of time.

The "Feature Extraction" block consists in using $S_u(t,f)$ from whom $\hat{t}_1$ and $\hat{t}_2$ serves to trigger the calculation of ten TF-descriptors. These ten TF-descriptors are called features F_i (with $i = 1...10$) and are:

- $F_1 = Nf(t)$ is the number of components as a function of time. Unlike conventional features designed to evaluate harmonic distortion such as the Total Harmonic Distortion (THD), F_1 aims to track the number of harmonics and allows to know precisely when any harmonic component may appear or disappear.
- $F_2 = SER$ is the Shannon entropy ratio obtained by the STFT.
- $F_3 = CM$ is the energy concentration obtained by the STFT, it is a statistical measurement to assess the quality of time-frequency representation. It is often used to evaluate the degree of energy dispersion around the instantaneous signal frequency in the time-frequency plane.
- F_4, F_5 and F_6 are transient features based on the Shannon energy. They characterize the shape of the transient signals at specific frequencies, i.e., 60, 180 and 300 Hz.
- F_7, F_8, F_9 and F_{10} are the parameters that control the OST's Gaussian window. They are obtained by maximizing the energy concentration F_3 [7].

Obviously, some of these TF-descriptors have already been used in the literature to describe the PQ disturbances. The new TF-descriptors that have been introduced in this study to enhance the significativity of the PQ under non-stationary conditions are F_1 and F_2 [9].

C) The classification processing will be detailed in the next section. It is based on three ML techniques that only take into account the 10 features.

3 TF-failures classification with machine learning techniques

The sources of distortion in waveforms are present at generation, transmission and distribution parts of the power grid. For better processing and identification of the PQ events, features are extracted from the raw signal. The feature set extracted is used as an input to the classifier system which classifies the disturbance. Traditional PQ disturbance classification methods are susceptible to noise interference, transients, time-varying events, feature selection and feature quality. The quality of the feature, also referred as veracity, is related to accuracy, biases, noise, and abnormality in signals. Therefore classification of the PQ disturbances requires advanced algorithms such as Artificial Neural Networks (ANN) and other ML techniques [14–18].

This paper proposes a PQ disturbance classification based on algorithms such as the K-Nearest Neighbors (K-NN), the Random Forest (RF), and the Support Vector Machine (SVM). They have been chosen because of their simplicity. If the features are relevant, the classification problem can be simplified. These algorithms are trained on the ten TF-features F_i previously defined. The PQ classification consists in recovering the class $\hat{C}_i$ that characterises waveform distortions and deviations from the ideal sine wave. The waveform patterns are the ones expressed by signals $x_i(kT_s)$ corresponding to a class C_i of a PQ event or a specific distortion of the pure sine waveform.

3.1 Dataset description

The sampling rate is $T_s = 1$ ms ($f_s = 1$ kHz) and without any loss of generality $f = 1/T$ =60 Hz. The amplitude of the pure sine wave is chosen as $A = 1$. A total of 1000 PQ events have been generated with 100 different signals for each of the 10 C_i classes.

For each class, the numerical values of parameter α have been uniformly chosen between the limits given in Table 1. The duration of the signals is 1 second and the duration of the failure (PQ event) within a signal has a duration of 80 μs. For each situations $T \leq T_1 \leq T_2 \leq 9T$ and $T \leq T_2 - T_1 \leq 9T$ i.e., $0.016667 \leq T_2 - T_1 \leq 0.1500$ seconds. Each PQ situation related to the classes C_i has been generated 100 times with different levels of Gaussian noise: No noise, 20 dB and 5 dB noises.

Then, the features are calculated for all the signals with the tree methods (STFT, ST and OSTO). These data represents a database composed of 300 000 data. for the learning process of the ML algorithms and 75% of the data has been randomly selected and used for training the algorithms and 25% for the tests.

3.2 Design of the ML classifiers

The K-NN is one of the simplest of classification algorithms that is often used as a benchmark for more complex classifiers. It is a supervised learning that does not make any assumptions on the underlying data distribution.The K-NN has been implemented with the Euclidean distance as the distance metric in the multidimensional feature space and a neighbourhood size $K = 1$. The numerical value of K has been obtained by applying a cross validation over the data.

The RF is made up of multiple decision trees which are common supervised learning algorithms. Their predictions are aggregated to identify the most popular result. It is an ensemble method. The implementation of the RF uses the following configuration: It is composed of 30 Bagged Trees with a maximum number of splits of 1025.

SVM works by mapping data to a high-dimensional feature space so that data points can be categorized, even when the data are not otherwise linearly separable. A separator between the categories is found, then the data are transformed in such a way that the separator could be drawn as a hyperplane. The mathematical function used for the transformation is known as the kernel function. The SVM has been designed with the followings: The Kernel function is Gaussian with a scale of 0.79, a box constraint level of 1 and all the data are normalized.

4 Evaluation of the PQ event classification and results

All the calculation and simulation have been conducted by using the Matlab environment. A primary result is presented in Figure 3 where two signals are mapped in the two dimensional TF-space by using the three methods previously described: STFT, ST and OST. It can be seen that for the disturbed signals, with only a sag, and with a sag with additional harmonic components of rank 3 and 5, that it relatively easy to detect the start and end times of the fault. From here, $\hat{t}_1$ and $\hat{t}_2$ are estimated from the image, i.e., energy represented in the TF-space. Once these instants have been determined, the 10 TF-descriptors F_i can be calculated. One can also see for example, that during the period (between $\hat{t}_1$ and $\hat{t}_2$) the presence of 2 higher-order harmonics in the second signal (i.e., $\hat{F}_1 = 3$).

Figure 4 shows the resulting classification in the 2-dimensional frame of $\hat{F}_1$ vs $\hat{F}_2$ for the three types of signals: Without noise, with a 20 dB noise and with a 5 dB noise. $\hat{F}_1$ and $\hat{F}_2$ are obtained with the OST method. Each dot represents a PQ event and its class is color-coded. The extracted features separate all the classes successfully. It can be seen that it is more difficult to separates the classes of PQ events in noisy signals. Without noise, classes can be well separated event with simple ML techniques. However, one must

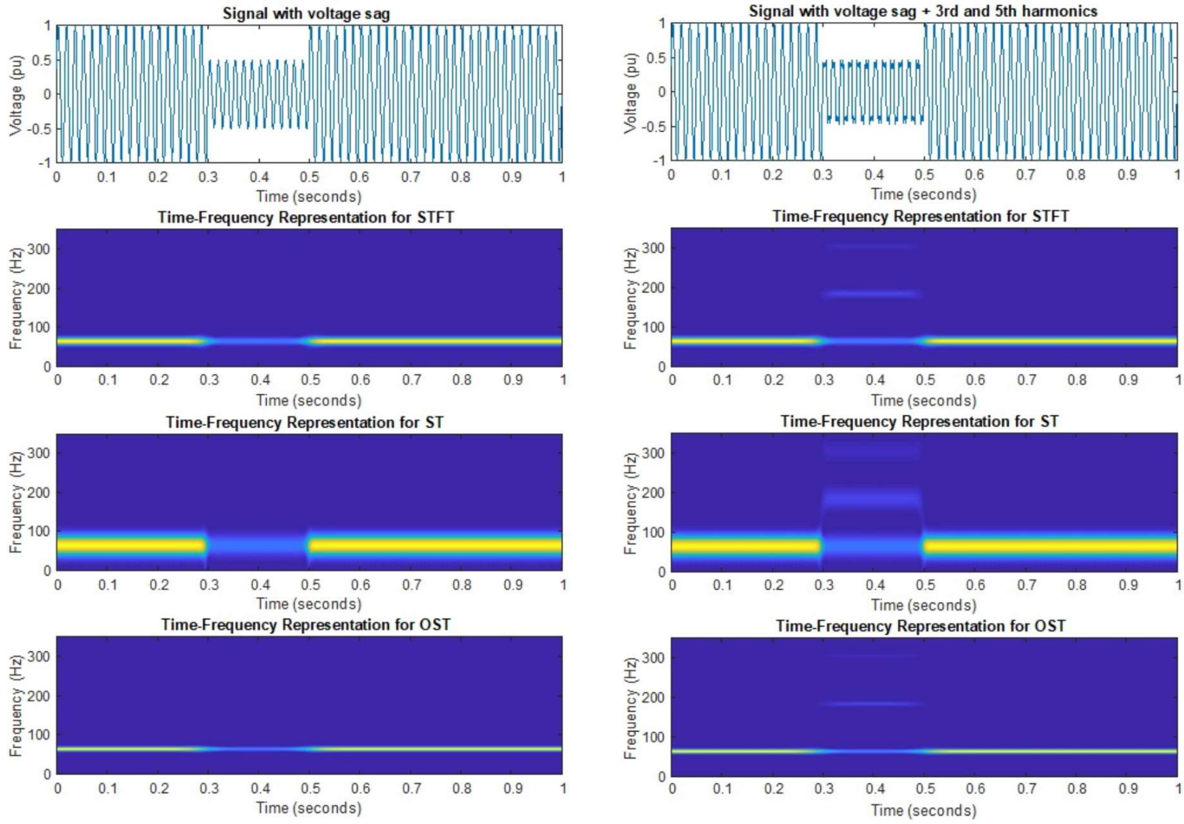

Fig. 3. TF-analysis of a signal with sag (left) and a signal with sag but also disturbed by harmonic components of rank 3 and 5 (right)

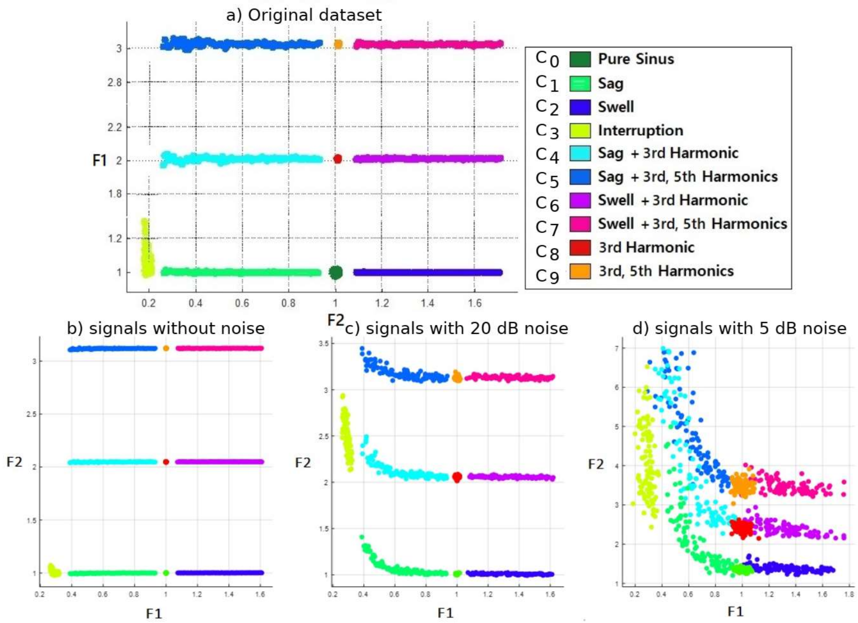

Fig. 4. Representation of the classified PQ events in the $\hat{F}_1\hat{F}_2$-frame with different levels of noise by using the OST method

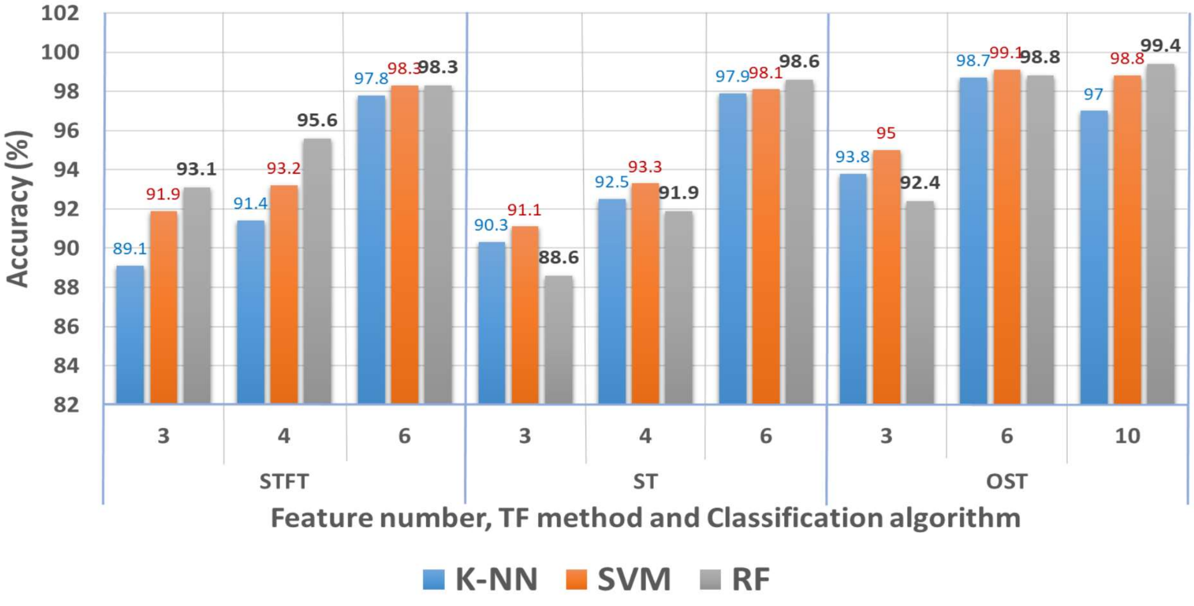

Fig. 5. Overview of the PQ events classification performance

remain that the classification was achieved in a 10-dimensional space, it is thus not easy to see the decision boundaries of all the classes.

Finally, a complete analysis of the PQ events classification performance is presented by Figure 5. Results show the ML-classification performances by taking into account only the 3 first, 4 first, 6 first or all the 10 $\hat{F}_i$ features by using the 3 different TF methods. The RF algorithm leads to a classification rate higher than 99,4% in each situations of PQ disturbances and noise. K-NN and SVM algorithms reaches a classification rate higher than 97% under the same test conditions with 10 features. In some situation, the classification accuracy is 100%. This is the case when the SNR is high. It can be concluded that the proposed descriptors are able for effectively discriminate the different types of disturbances even in the presence of noise.

5 Conclusions

The issue of power quality in the power system is of great importance for the smooth and long-lasting operation of the electrical devices. It is very important to detect and eliminate the power quality disturbances in order to obtain quality power. This paper presents a work to evaluate the classification of PQ events in realistic power distribution systems. The goal consists in handling non-stationary disturbed signals which are ubiquitous in a large number of power grids. Ten time-frequency descriptors have been proposed by using three different time-frequency methods: The Short-Time Fourier Transform (STFT), the Stockwell Transform (ST) and the Optimized Stockwell Transform (OST). Once calculated, the ten are gathered to serves as inputs to different machine learning techniques in order to identify and classify the PQ events even under noise conditions. For this, simple machine learning techniques have been used and evaluated. Indeed, three classifiers, such as K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), and Random Forest (RF) are utilized to recognize the PQ events categories. The results showed that the time-frequency features are relevant to estimate physics-related meaningful parameters of the noisy and non-stationary signals and thus to better understand the origin of the failures. Furthermore, the complete approach is new and effective in classifying with a high accuracy different varieties of PQ events occurring in power grids.

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