



An effective Power Quality classifier using Wavelet Transform and Support Vector Machines



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ABSTRACT

In this paper we propose a method based on a combination of binary classifiers which are optimized for those special cases where the real signals contain a multitude of events within the analyzed temporal window. These type of events are known as complex events. The proposed Power Quality (PQ) classifier is based on Wavelet Transforms (WT) and Support Vector Machines (SVM). The method uses a One vs. One multiclass SVM. We propose a novel method which is simple, easy to train, and can be implemented with low computational cost. The proposed algorithm consists of a set of simple binary SVM classifiers. Each SVM node is trained separately allowing them to be parallelized. The training stage is performed using single events, however due to the structure of the SVM methodology selected, it allows the system to detect complex events. Tests and training were performed using real complex signals and the results show the proposed methodology to be highly efficient.

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1. Introduction

With the new investment in power distribution systems and the increased proliferation of renewable energy and the associated equipment there is a renewed focus on the quality of power supplied to the customers. Additional interest and pilot programs in Smart Grid technology has heightened these issues as it is reflected by a call for policies and compliances throughout the world. From a utility perspective, additional requirements by customers concerned with a high level of quality have increased these requirements. The main reasons are due to the use of sensitive equipment and an economic need to operate their system reliable whilst maintaining good Power Quality and performing root cause to all deviations. Historically, a lot of research has been done (des [Merces Machado, Bezerra, Pelaes, de Oliveira, & de Lima Tostes, 2009](#); [Math et al., 2010](#); [Olofsson, 2009](#); [Reaz, Choong, Sulaiman, Mohd-Yasin, & Kamada, 2007](#); [Roscoe, Burt, & McDonald, 2009](#); [Santoso, Powers, Grady, & Parsons, 2000](#); [Soo-Hwan, Gilsoo, & Sae-Hyuk, 2010](#); [Stockwell, Mansinha, & Lowe, 1996](#)) in this realm, yet ubiquitous implementations by most utilities of these techniques are yet to be seen. A recent critical review regarding the detection and classification of Power Quality events, illustrates

the importance that this issue has today ([Mahela, Shaik, & Gupta, 2015](#)). There are several factors that have inhibited this, namely: lower priority on guaranteeing high Power Quality, in-house manual root cause analysis, lower incorporation of Power Quality sensitive equipment, low customer demand and education regarding Power Quality, deficiency of robust tools that can be cheaply and easily incorporated to help in classification of all Power Quality deviations.

Due to the aforementioned reasons, utilities will need to initiate aggressive programs to address Power Quality issues in their systems. They will also have to have a system of quickly performing root cause analysis on deviations observed on their system for maintaining compliance. Any tool that can help them to detect, identify and classify any PQ event in order to undertake perturbances in-house analyses is highly desirable. The tool should also be easy to implement, train and adjust for any variations often experienced due to the growth of nonlinear sensitive equipment (such as Smart Grid technologies, FACTS devices etc). Currently the manual process of detection and classification of such PQ events will need to be bolstered or replaced with an offline or real-time tool integrated with the Distribution Management System (DMS).

In a modern grid context, the most important PQ issues are: Fault analysis and location, Capacitor bank operation, Volt/Var fluctuation, and harmonic contamination.

A description of all the steps and methods that can be applied for PQ is presented in [Bollen and Gu \(2006\)](#), [IEEE Recommended](#)

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Practice for Monitoring Electric Power Quality (2009). In particular, classification methods based on Wavelet analysis are presented in Gaouda, Salama, Sultan, and Chikhani (1999), Jaehak, Powers, Grady, and Bhatt (2002), Liyan Liu, and Zeng (2008), Santoso, Powers, Grady, and Hofmann (1996). Classification methods based on Artificial Neural Networks (ANN) are presented in (Cheng, 2012; Monedero et al., 2007; Santoso et al., 2000; Wijayakulasooriya, Putrus, & Minns, 2002). In recent years new methodologies based on Support Vector Machines are suggested. A general description of the method can be found in Cristianini and Shawe-Taylor (2000). Since then the application of this technique to PQ related issues has been proposed (Biswal, Biswal, Dash, & Mishra, 2013). All methods based on linear learning techniques need to be trained before the installation on the real scenario. They require considerable amount of data containing the different PQ events. Since it is very difficult to obtain real signals from measurement devices these systems are trained using simulated signals. Publications that suggest the use of SVM to detect PQ events are based on simulated signals. Some of them use a mathematical models of the system to simulate the perturbation behavior (Biswal, Biswal, & Dash, 2013; Biswal et al., 2013; Chen, Xu, Piao, & Yuan, 2009; Garcia, Gualdron, & Plata, 2007; Janik & Lobos, 2006; Jinsha, Yinghui, & Tiefeng, 2009; Li & Bao, 2011; Mohapatra, Sinha, Panigrahi, Mallick, & Hong, 2011; Osman, 2007; Vega, Kagan, Ordóñez, & Duarte, 2009). Others use commercial software that simulates a power system in order to reproduce PQ events. These signals are exported to a data base and used to train the detection algorithm (Hamzah, Anuwar, Zakaria, & Tahir, 2009; Ismail, Zakaria, & Hamzah, 2009; Ming & Kai-Cheng, 2009; Thukaram, Khincha, & Ravikumar, 2006; Weiming, Xuelei, Jingbo, & Zhiheng, 2006; Whei-Min, Chien-Hsien, Chia-Hung, & Fu-Sheng, 2008). Although these approaches are very useful, they are not always effective when they are applied to a real event. For example, in Axelberg, Gu, and Bollen (2007) it is concluded that the classifier reduces its effectiveness when tested for field signals. Despite the fact that some authors focus their research using real signals (Axelberg et al., 2007; Eristi & Demir, 2012; Susukh, Premrudeepreechacharn, & Kasirawat, 2009), these waveforms present only one event at a time. However, this is not the typical case, since it is very frequent to have more than one event within the same time frame. These kinds of disturbances are usually called complex disturbances and cause great difficulties during the identification stage due to co-existence of different disturbance characteristics. The difficulties includes wrong characteristic calculations, incorrect evaluation, and low classification accuracy.

Recently, different approaches were proposed; (Biswal, & Dash, 2013) presents a method where the S Transform is used to extract the features and classify the events based on a decision tree methodology. Although it is an efficient methodology, the classifier is designed using different optimization techniques, and the results are obtained after several decision steps which causes time delay in classification.

Cheng-Long, Yen-Ling, Tsong-Liang, Ying-Tung, and Joe-Air (2005) implemented a classifier based on Wavelet Transforms and a Dynamic Structure Neural Network. Features were extracted from several wavelet coefficients; therefore it is sensitive to the presence of noise in the input signals and do not perform adequately.

Nowadays, classifiers based on Support Vector Machines (SVM) have increased the interest of the research community, due to their simplicity. Liu, Li, and Wen (2013) present a method that uses the normalized energy of different WT coefficients and it is combined with Principal Component Analysis (PCA) in order to extract the main signal features. Then, the classification is performed using a SVM. This methodology becomes complex mainly during the training stage. In addition, each complex event needs to be previously uniquely identified before the training stage.

The method proposed in Liu, Cui, and Li (2015) considers the complex disturbance classification as a multi-label classification problem. The paper suggests a method based on the Ensemble Empirical Mode Decomposition (EEMD) technique to extract the signals features and a multi-label classification technique named Rank Wavelet Support Vector Machine. The main advantage of this work is the correlation preservation between different event types which improve the method's accuracy. However, the maximum number of decomposition levels is set to eleven in order to cover all characteristic of complex disturbances; this issue may become expensive from the point of view of computational cost. In addition, since Rank Wavelet SVM is a complex classification scheme, it makes the samples belong to multiple categories.

Based on the analysis of the current needs and the evaluation of the different methodologies presented, it can be inferred that there is a need of developing a new set of algorithms that can handle complex events, be easy to implement and present low computational cost.

This paper proposes a method based on a combination of binary classifiers which is optimized for complex event real signals. The proposed PQ classifier is based on Wavelet Transforms (WT) and Support Vector Machines (SVM). The method uses One vs. One multiclass SVM.

The main contribution of the proposed approach is that the classifier needs to be trained using only individual PQ events, and due to its parallel processing structure, can successfully identify perturbations that contains more than one event within the same time frame. This identification is successfully performed by training the system using only single event signals. The use of the proposed SVM based method, allows one to tune each binary classifier individually, in addition, since each classifier are handled individually, can be used in parallel, becoming very computationally cost efficient. Moreover, the proposed method allows the system to select a set of features specifically for each binary classifier according to the individual disturbances that needs to be classified, thus improving the performance.

Due to the use of less number of coefficients better performances are obtained, and since it is a single-label classification method it is simpler than the one presented in Liu et al. (2015).

The tests were performed with real signals captured in the field instead of simulated ones making it a realistic robust classifier. These important features differentiate our proposal with respect to those classifiers from previous works.

The paper is organized as follows: First it presents an overview of a disturbance processing system, then, a detailed explanation of the most important concepts related to Support Vector Machine is presented. After that, the proposed methodology is described and the most relevant results are shown. Finally the pertinent conclusions are discussed.

2. Disturbance processing system

According to Fig. 1 a typical disturbance processing system can be comprised by: A preprocessing module, a detection module, a feature extraction module and a classification module:

2.1. Preprocessing module

A typical waveform obtained by measuring a Power System usually is contaminated with additive noise.

The noise will affect the ability of the detection module and also the performance of the classification process. The objective of this module is to filter the noise and prepare a clean data set to be used by the detection module.

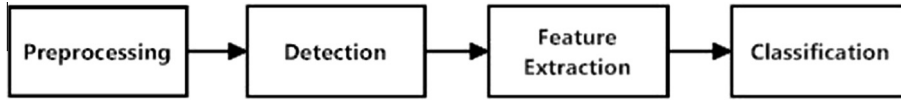


Fig. 1. Disturbance processing system.

2.2. Detection module

Because of the random nature of a disturbance, its occurrence cannot be predicted. For this reason a monitoring system must continuously sample and sense parameters which indicate the presence of an anomaly in a current or voltage waveform. One strategy to detect a disturbance is to analyze the rms value of the waveform or to sense the high frequency wavelet coefficients.

2.3. Feature extraction module

Normally the amount of data obtained by sampling a waveform is considerably large. Therefore this data needs to be transformed into a reduced set of features. This process is known as feature extraction.

2.4. Classification module

The classification module is responsible in characterizing the information according to a set of predefined classes.

3. Support Vector Machine

The SVM method is a supervised learning technique used for pattern recognition and regression analysis. In general the SVM is used where the data are represented by two different classes, whose objective is to find the best hyper plane that divides the data into these two classes.

Finding the best hyper plane requires that the distance between the training samples and the hyper plane be maximized.

Fig. 2 illustrates the input spaces formed by two data classes. It shows the separation hyper plane, the margin m , and the data values over the hyper planes H_0 and H_1 . The data that determine these planes are known as *Support Vectors*.

If the data can be separated in the input space, then a group of data d can be defined as $\{(x_i, y_i)\}$, where:

$$x_i \in \mathcal{R}^d, \quad y_i \in \{1, -1\} \tag{1}$$

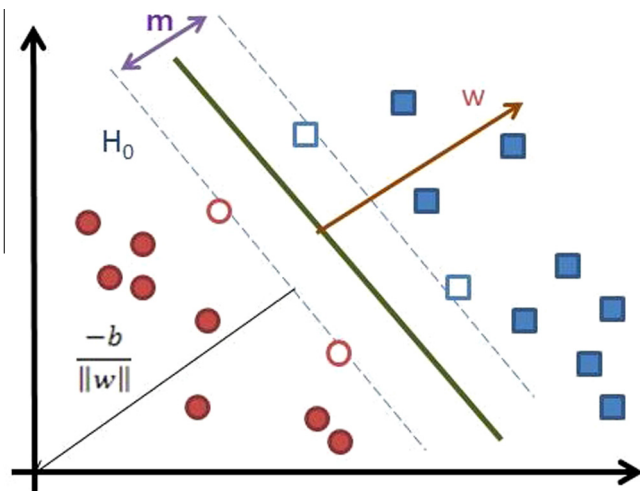


Fig. 2. Separation hyper plane.

Considering the hyper plane $\in \mathcal{R}^d$, the problem can be formulated as an optimization problem, where the objective equation can be defined as $\langle w \cdot x + b \rangle$.

Then, the optimization problem is to minimize $\|w\|$ subject to:

$$y_i(w \cdot x_j + b) \geq 1 \tag{2}$$

At the border, the restriction becomes:

$$y_i(w \cdot x_j + b) = 1 \tag{3}$$

The separation between the classes is $2/(\|w\|)$. The optimal plane can be found solving the minimization of:

$$\varphi(w) = 1/2\|w\|^2 \tag{4}$$

Subject to:

$$y_i(w \cdot x_j + b) \geq 1 \tag{5}$$

This problem can be also formulated mathematically as follows:

$$\min_{w,x} \max_{\alpha_i} \{1/2\|w\|^2 - \sum_{i=1}^n \alpha_i [c_i(w \cdot x_i - b) - 1]\} \tag{6}$$

where α_i is a Lagrange multiplier, the non-zero values of x_i are known as the *Support Vectors* (Cristianini & Shawe-Taylor, 2000).

The linear approximation can be represented as follows:

$$\min \varphi(w, \varepsilon) = \frac{1}{2}\|w\|^2 + C \left(\sum_{i=1}^N \varepsilon_i \right) \tag{7}$$

where ε is a slack variable and C a penalty factor.

If data are not linearly separable a conversion method is needed to transform the original data space into a new one. The conversion is nonlinear and the new space dimension is higher than the dimension of the original one. These transformations are performed by *Kernel functions*.

With the introduction of a Kernel function the SVM problem does not need to be modified significantly.

To find the α_i it is necessary to solve the following problem:

$$\max \sum_{i=1}^l \alpha_i - 1/2 \sum_{i,j=1}^l y_i y_j \alpha_i \alpha_j K(x_i x_j) \tag{8}$$

Subject to:

$$\sum_{i=1}^l y_i \alpha_i = 0 \tag{9}$$

$$0 \leq \alpha_i \leq C_i = 1, \dots, l \tag{10}$$

The most commonly used Kernel functions are: Polynomial, Gaussian, Radial Basis function (RBF), and Neural Network based kernel function (Cristianini & Shawe-Taylor, 2000).

Since originally SVM was developed for binary classification, if a multi class classifier is needed, such as the case of PQ classification, particularly where the signals contain more than one disturbance, the SVM needs to be implemented in several steps. The natural extension is to combine several binary classifiers to conform a binary decision tree; however, the size of the problem and consequently the performance is influenced by this fact. In addition, for the particular case analyzed in this paper, if a combination of events wanted to be detected, the binary decision tree needs to

be built taking into consideration all possible combinations. The training of a classifier based on binary decision tree architecture is much more complex. Moreover, the incorporation of a new class (i.e. a new type of disturbance) is more difficult because the classifier needs to be re-structured and, in consequence, re-trained.

Therefore, as an alternative, in this paper a classifier based on methods known as *one versus one* (OVO) or *one against one* (OAO) method, and *one versus all* (OVA) is implemented and described below.

3.1. One versus all method

Its main idea is to build k SVM models where k is the number of classes. Mathematically this optimization problem can be formulated as follows:

$$\min 1/2w^T w^i + C \sum \epsilon_j^i w^{iT} \tag{11}$$

Subject to the following constraints:

$$y(w^i x + b^i) \geq 1 - \epsilon_j^i \quad \text{if } y = i \tag{12}$$

$$y(w^i x + b^i) \leq -1 + \epsilon_j^i \quad \text{if } y \neq j \tag{13}$$

Once the optimization problem is solved, the solution is selected based on the following condition:

$$x = \arg \max (y(w^i x + b^i)) \tag{14}$$

3.2. One versus one method

This method was proposed by Ismail et al. (2009), its main idea is to build $k(k-1)/2$ classifiers where each one is trained using data from two classes. Based on the nomenclature used in the previous section and considering classes i and j , the following optimization problem is solved:

$$\min 1/2w^{ijT} w^{ij} + C \sum \epsilon^{ij} w^{ijT} \tag{15}$$

Subject to the following constraints:

$$y(w^{ij} x + b^{ij}) \geq 1 - \epsilon^{ij} \quad \text{if } y = i \tag{16}$$

$$y(w^{ij} x + b^{ij}) \leq -1 + \epsilon^{ij} \quad \text{if } y = j \tag{17}$$

Once all $k(k-1)/2$ classifiers are built, a voting strategy is performed. In this work, the vote is based on $sign(y(w^{ij} x + b^{ij}))$. If x is in class l , then the vote for class l is incremented. The predicted x is based on the maximum voted class.

4. Proposed method

4.1. Preprocessing

Since the proposed method is focused on real signals it is necessary to apply a low pass filter to smooth out the high frequency components of the signal (Hong-Tzer & Chiung-Chou, 2001).

This module also narrows the signal duration to a fixed numbers of fundamental cycles.

4.2. Detection

The detection module is based on the Wavelet Transform (WT) since its capability for signal classification and identification is proven (Santoso et al., 1996)

Once the mode and the signals are selected, the detection process starts; the signal is decomposed into Wavelet coefficients

using Wavelet Transform, and based on these coefficients, the program detects whether any of the PQ disturbances is present in the signal and calculates the duration of the event.

By means of the detailed coefficients d_1 and d_2 the algorithm identifies the presence of some impulses; these signals are the ones that the program uses to automatically detect the presence of a perturbation. The duration of the perturbation is calculated by comparing the coefficients with a threshold signal.

As an example, Fig. 3 illustrates the d_1 coefficient from a signal with a swell and a random noise. The first and the last peak in this case are used to set the start and end of the event.

4.3. Feature extraction

Once a disturbance is detected, the next step is to minimize the dimension of the data that is delivered to the classification stage.

The approximation scales and the detail coefficients d_1-d_n of the Wavelet Transform are processed to obtain different parameters that characterizes a given event.

As an output of the detection module and as an input of the classification module, 31 parameters are calculated. These parameters are the energy of the seven first WT coefficients, these energies are calculated as the difference between the normalized coefficients and the total energy of a pure sinusoidal signal, and these energies are calculated based on the Parseval theorem. Then, four additional components are calculated; k_1 which is the normalized measurement of the samples which values are greater than 1, k_2 the number of samples that are in the interval $[-0.1, 0.1]$, k_3 counts for the samples in the interval $(0.1, 1]$ and k_4 represents a normalized value of the amount of d_1 Wavelet coefficients over the selected threshold.

$$k_{1Norm} = \frac{\sum_{i=1}^N k_1(i)}{N} k_1 = \begin{cases} 1 & \text{if sample } (i) \geq 1 \\ 0 & \text{if sample } (i) \leq 1 \end{cases} \tag{18}$$

$$k_{2Norm} = \frac{\sum_{i=1}^N k_2(i)}{N} k_2 = \begin{cases} 1 & \text{if sample } (i) \leq 0.1 \\ 0 & \text{if sample } (i) \geq 1 \end{cases} \tag{19}$$

$$k_{3Norm} = \frac{\sum_{i=1}^N k_3(i)}{N} k_3 = \begin{cases} 1 & \text{if sample } (i) \leq 1 \\ 0 & \text{if sample } (i) \geq 0.1 \end{cases} \tag{20}$$

$$k_{4Norm} = \frac{\sum_{i=1}^N d_1(i)}{M} k_4 = \begin{cases} 1 & \text{if } d_1(i) \geq \text{Threshold} \\ 0 & \text{if } d_1(i) \leq 0.1 \end{cases} \tag{21}$$

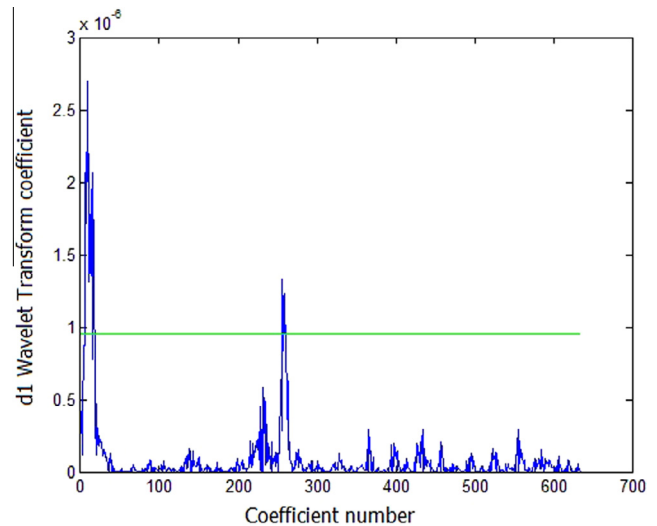


Fig. 3. d_1 Wavelet Transform coefficient.

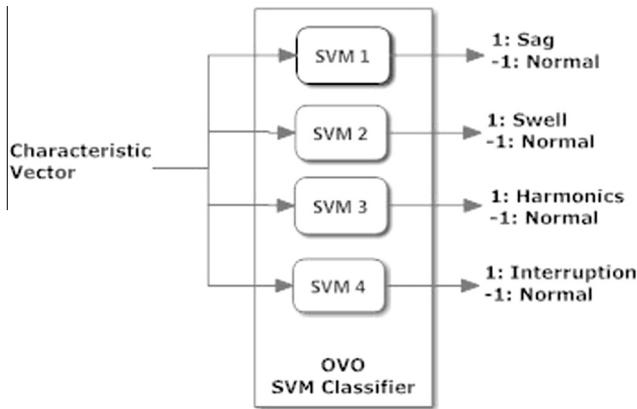


Fig. 4. SVM classifier.

Table 1
Training set.

PQ event	Simulated	Real	Total
Sag	200	300	500
Swell	200	300	500
Harmonic	100	400	500
Interruption	200	200	400

Table 2
Results test 1.

PQ event	Sag	Swell	Harmonic	Interruption
Sag	30	0	0	0
Swell	0	13	3	0
Harmonic	0	0	20	0
Interruption	2	0	0	8

Then, the mean, median, standard deviation and variance for d_1 , d_2 , d_3 , d_4 and d_5 Wavelets coefficients complete the 31 parameters used to characterize a signal.

The feature extraction module reduces the dimension of the data from approximately 2000 samples to 31 parameters. Therefore, the reduction factor is around 65.

4.4. Classification

Fig. 4 shows the developed classifier. It comprises four SVM nodes and its architecture is based on one versus one strategy.

The first node is responsible to identify the Sags, the second one the Swells, the third one Harmonics and the last one Interruptions. This architecture allows the system to have a very good performance when more than one event is present in the same analysis window time. This classification does not need to include and train additional steps of combined signals.

This feature represents an advantage with respect to the binary tree decision classifier that is normally used in Hamzah et al. (2009), Ismail et al. (2009) and Ming and Kai-Cheng (2009).

5. Results

5.1. Training set

To train the classifier, a set of data was selected using simulated and real signals. For simplicity only four types of PQ events were considered: Sags, Swells, Harmonics and Interruptions. Table 1 summarizes the considered signals.

To analyze the results, two different types of experiences were performed; the first one considers 76 field signals that contain only one event at a time with the following distribution: 30 Sags, 16 Swells, 20 Harmonics and 10 Interruptions. For the second test 62 field signals that contain two events at the same analysis time were considered: 42 Sags and Harmonics, 8 Swell and Harmonic and 12 Sags and Swells. In addition to this, real signals with only one event were added to this test; 30 signals with Sags, 16 with Swells, 20 with Harmonics and 10 with Interruptions.

Table 2 presents the results of the detection process considering real signals that contain a single PQ event in the analyzed window. The developed monitoring system was capable to detect and classify correctly 93.43% of the disturbed waveform.

Figs. 5–7 illustrate different analyzed signals that comprise disturbances conformed by a combination of Harmonics, Sag and Swells.

Table 3 presents the results using real signals that contain two different disturbances within the same analyzed time window. The developed software was able to successfully detect and classify 92.65% of the disturbed waveforms. It is important to mention that

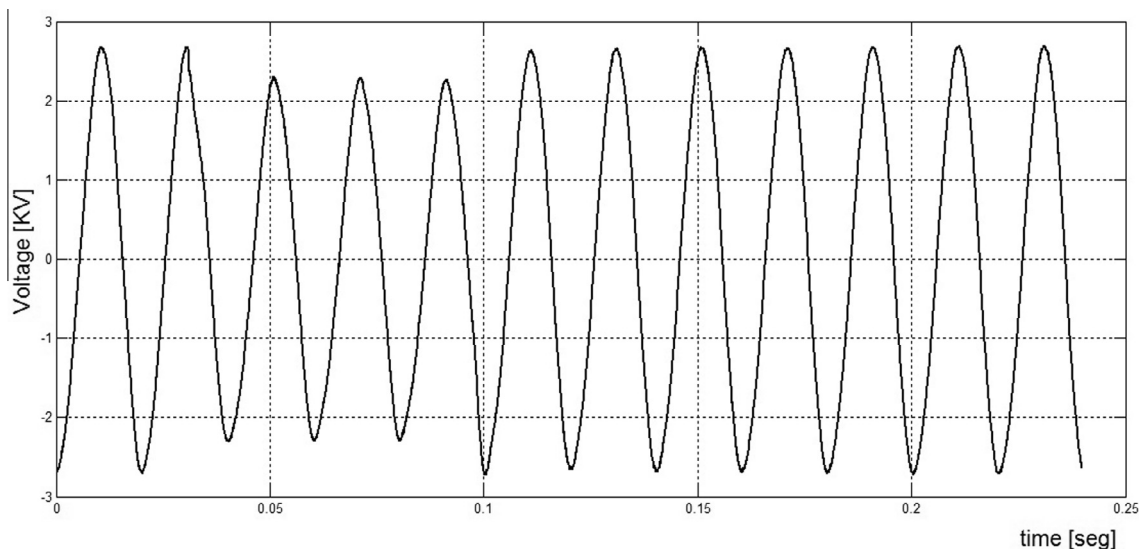


Fig. 5. Voltage harmonics and sag.

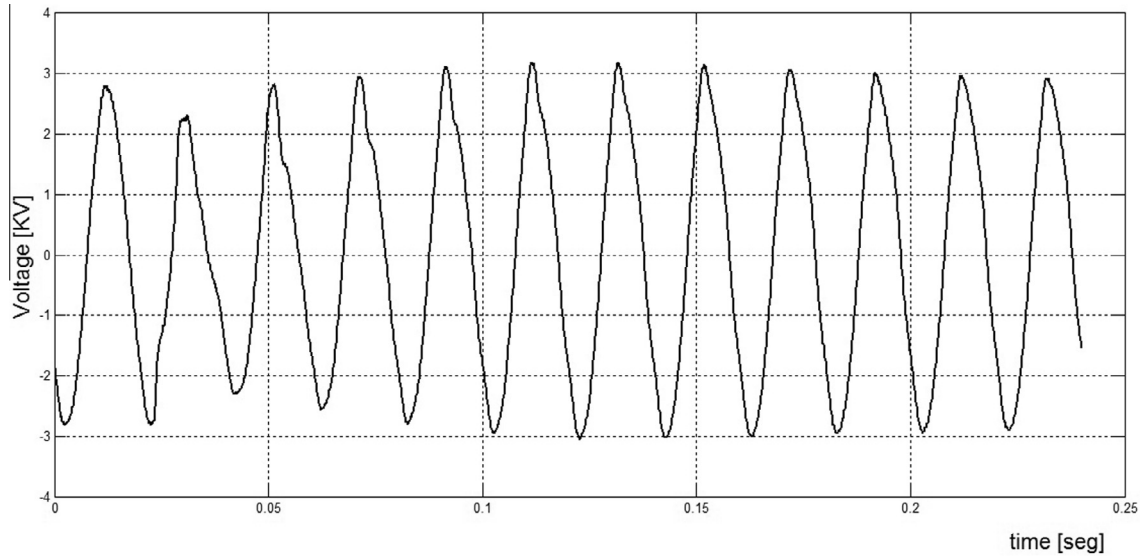


Fig. 6. Voltage harmonics and swell.

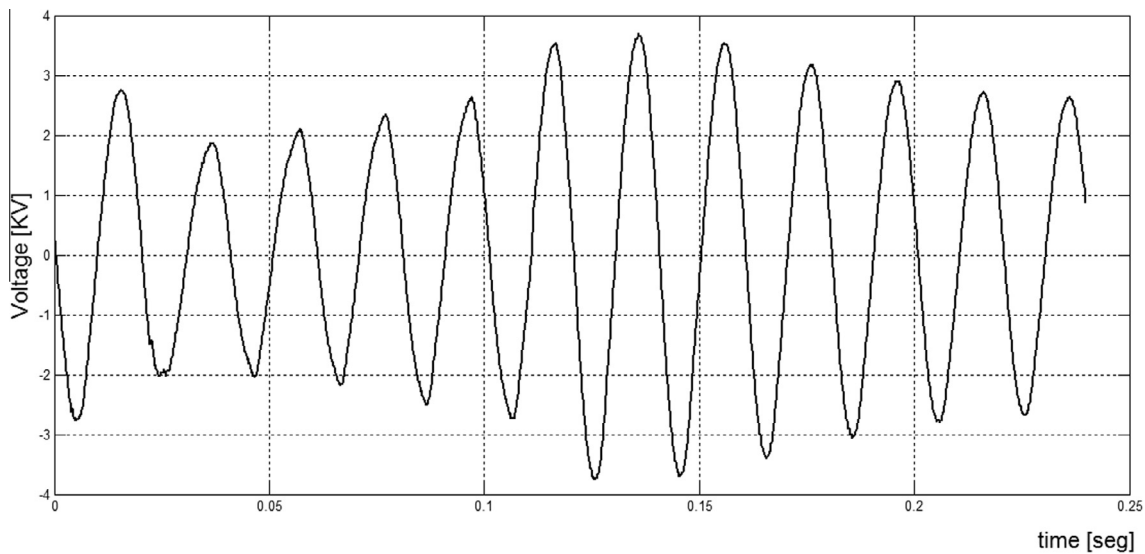


Fig. 7. Voltage sag and swell.

Table 3
Results test 2.

PQ Event	Quantity	Signals that detect only one event
Sag + harmonics	42	3
Swell + harmonics	8	0
Sag + swell	12	2

the remaining 7.35% were partially detected because the system was capable to find one of the two PQ events. Another important remark is that the classifier was not re-trained with the specific combination of disturbances that were used in this second experience in order to test the performance of the monitoring system.

6. Conclusions

This paper proposes an efficient and computationally cheap method to detect and classify PQ events containing complex

perturbation present in distribution power system signals. The methodology is based on Wavelet Transforms (WT) that is used to extract the main features of the signals. Then a One vs. One multiclass SVM built as a binary node array is used in classifying the extracted features. The main advantage of this type of methodology is to allow the classification of complex events using a simple array of binary structures. In addition, it reduces the computational cost because each node can be processed independently allowing parallelization. Moreover, since each node is treated independently, the input parameters can be individually tweaked and optimized. Therefore each classifier can be specialized to recognize assigned event type in a more efficient way. In the future signals that exhibit correlation between different events may be evaluated. Correlation features allow a sense of robustness and decrease the amount of false positive classification.

To train the system, a combination of signals comprising of real power system events and simulated events were used as inputs. Only signals that included single events were used to train the classifier. Then, to evaluate and test the results complex real power

system events were used. The classifier successfully detected both single events as well as complex events.

To summarize, the methodology presented in this paper allows one to classify complex events without the need of a sophisticated training set. Since it is based on binary classifiers, it is very easy to design, implement, modify, train and optimize and can be parallelized reducing the computation time.

To improve the method, in a future work several issues will be analyzed such as evaluating the event correlation, reducing and weighting features for classifying unique subset of events, studying how to adaptively optimize the parameters used per node and to improve the de-noising preprocessing stage before the WT transformation.

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