A. Rahmani, L. Slimani, T. Bouktir

UNBALANCED LOAD FLOW WITH HYBRID WAVELET TRANSFORM AND SUPPORT VECTOR MACHINE BASED ERROR-CORRECTING OUTPUT CODES FOR POWER QUALITY DISTURBANCES CLASSIFICATION INCLUDING WIND ENERGY

Purpose. The most common methods to design a multiclass classification consist to determine a set of binary classifiers and to combine them. In this paper support vector machine with Error-Correcting Output Codes (ECOC-SVM) classifier is proposed to classify and characterize the power quality disturbances such as harmonic distortion, voltage sag, and voltage swell include wind farms generator in power transmission systems. Firstly three phases unbalanced load flow analysis is executed to calculate difference electric network characteristics, levels of voltage, active and reactive power. After, discrete wavelet transform is combined with the probabilistic ECOC-SVM model to construct the classifier. Finally, the ECOC-SVM classifies and identifies the disturbance type according to the energy deviation of the discrete wavelet transform. The proposed method gives satisfactory accuracy with 99.2% compared with well known methods and shows that each power quality disturbances has specific deviations from the pure sinusoidal waveform, this is good at recognizing and specifies the type of disturbance generated from the wind power generator. References 22, tables 8, figures 9.*
Key words: **unbalanced load flow, wavelet transform (WT), support vector machines (SVM), power quality disturbance, wavelet energy.**

Цель. Наиболее распространенные методы построения мультиклассовой классификации заключаются в определении набора двоичных классификаторов и их объединении. В данной статье предложена машина опорных векторов с классификатором выходных кодов исправления ошибок (ECOC-SVM) с целью классифицировать и характеризовать такие нарушения качества электроэнергии, как гармонические искажения, падение напряжения и скачок напряжения, включая генератор ветровых электростанций в системах передачи электроэнергии. Сначала выполняется анализ потока несимметричной нагрузки трех фаз для расчета разностных характеристик электрической сети, уровней напряжения, активной и реактивной мощности. После этого дискретное вейвлет-преобразование объединяется с вероятностной моделью ECOC-SVM для построения классификатора. Наконец, ECOC-SVM классифицирует и идентифицирует тип возмущения в соответствии с отклонением энергии дискретного вейвлет-преобразования. Предложенный метод дает удовлетворительную точность 99,2% по сравнению с хорошо известными методами и показывает, что каждое нарушение качества электроэнергии имеет определенные отклонения от чисто синусоидальной формы волны, что способствует распознаванию и определению типа возмущения, генерируемого ветровым генератором. Библ. 22, табл. 8, рис. 9.
Ключевые слова: **несбалансированный поток нагрузки, вейвлет-преобразование (WT), машины опорных векторов (SVM), нарушение качества электроэнергии, энергия вейвлета.**

Introduction. The quality of energy has become an important issue for electric users and their customers. With the rapid increase of wind energy, this quality can be easily disturbed by the distortion in the supply of the electric power network that can lead to high costs and create many problems.

Problem statement and definition. To improve and ensure the quality of the electrical energy, the disturbances must be detected and if possible the detection must be close to the source of these disturbances. Several criteria can set the quality of energy which includes the voltage waveform, harmonics, inter harmonics, transient voltage, frequency voltage, frequency stability, voltage fluctuations (flicker)...etc [1]. To improve the power quality in [2] found that the load flow analysis is an important part and essential step for any power system network computation and it has always been useful by many power system engineers in this domain. Furthermore, they propose a novel approach using a 25 IEEE bus test system to solve the reorder of the unbalanced distribution network including optimal distribution network including optimal location of dispersed production units. By the comparison with other results obtained before, the results of this new technique are better to reduce losses and improve the PQ characteristics in distribution network level. With a same way, In [3] a modification has been done for the CPC power theory to four-wire unbalanced power, for

objective to gives the smallest possible line losses in the same transferred of the active power to the load in non symmetrical and unbalanced distribute voltage. For this reason a load flow is an important analysis tool to improve the PQ [4].

On the other hand, the wavelet transform has an important part in power system, and the development of this tool allowed many scientists to operate in various domains among them power quality. First applied of wavelets transform in power system by Ribeiro and Robertson in 1994 [5, 6]. From this year till now the number of publications in this domain has increased and the most popular wavelet analysis in power systems are used and applied for amelioration of power quality.

Overview of the most well-known evolutionary classifier on the topic. In the literature various methods based on wavelet transform (WT), fuzzy logic, neural network (NN), support vector machine (SVM), particle swarm optimization (PSO) and genetic algorithm (GA) have been proposed and implemented for PQD identification and classification.

In [7] present a combination of binary classifiers method, the proposed PQD classifier is based on WT and SVM, this method uses a one-vs-one multiclass SVM (four SVM nodes) each node is contain one event and trained individually allowing them to be parallelized. In general, the results display a good performance and the

PQ events can be detected. A novel method of automatic classification of hybrid or single PQD is proposed by [1], this proposed algorithm depend of the Discrete Wavelet Transform (DWT) and Probabilistic NN based Artificial Bee Colony (PNN-ABC) optimal feature selection of PQD, the DWT utilized for the feature extraction of the disturbances and the PNN is applied as an operative and dynamic classifier for the classification of the PQD. After the results, they found that the proposed algorithm is a significantly upper technique forcharacterize and identifying the single and various PQD. On the other hand, [8] are presents a new approach consisting linear Kalman filter and fuzzy-xpert system for identification and classification of voltage and current disturbances in power systems. Linear Kalman filter together with DWT is used to extract the parameters and these parameters are the inputs to fuzzy-xpert system that uses to identify the class of the PQD. A new method to classify and detect PQD in power system based fuzzy logic (FL) and neural networks basis radial function (RBFNN) are suggested in [9], RBFNN used the feature extracted by wavelet as inputs to generate membership function in FL and features to collect various events using FL detection and classification. The comparison showed that the classification accuracy of the fuzzy logic is improved just by the help of PSO, more details in [10]. Other techniques based on fuzzy and WT have been presented in [10, 11]. In [12] is presented another methodology that uses a maximal overlap discrete wavelet transform (MODWT) technique to recognition and locating of different PQD, the coefficients extracted from MODWT used like input for the classifiers. The obtained results show that the Decision Tree (DT) provides better classification accuracy than the SVM at every case with and without noise. Otherwise, the selection tree is working satisfactorily with synthesized or real signals. Probabilistic neural network (PNN) has been used in [13] as a function approximation tool for PQD classification and genetic algorithm (GA) is used to optimize the PNN parameter and the results demonstrate that the method is more accurate than the other methods presented. Another method has been presented in [14], S-transform with double-resolution (DRST) combined with directed acyclic graph based on support vector machines (DAG-SVMs). First, DRST are used for an effective feature extraction from power signals. Then, the DAG-SVMs classify and predict the PQD. Obtained results of this proposed show that the automatic classification algorithm is powerful and has the ability to distinguish and to detect different power quality phenomena classes easily. In [15] is displayed a performance enhancement scheme for the recently developed extreme learning machine (ELM) for classifying PQD using particle swarm optimization (PSO), the results indicated that the proposed algorithm faster and more accurate in discriminating PQD, and overall accuracy was 97.6 %. Other methods based on SVM and WT have been presented in [7, 16], wavelet and neural network [1, 17].

Generally, each research has a different strategy and this is good for providing information and to predict the classes of PQD and each method has its negatives and positives, also the significance of the importance of unbalanced load flow analysis is needed for more information and good contribution and to generalize all PQD especially in transmission network to reduce power losses and to improve the PQ characteristics for electric users and their customers.

The goal of the paper is to overcome the advantages we propose in this paper a recognized method based unbalanced load flow to extract and calculate difference system data such as voltage, reactive and active power. After, this data are used to calculate the energy deviation of the waveform signal using the discrete wavelet transform, in which the support vector machines with Error-Correcting Output Codes (ECOC-SVM) locates the importance values including to classify some kinds of power quality disturbances produced from the wind energy.

Wavelet transform. Discrete wavelet transform (DWT) is an implementation using a discrete set of scales and wavelet translations obeying certain rules. With $a = a_0^m$ and $b = n b_0 a_0^m$, where $a_0 > 1$, $b_0 > 0$, and m, n are integers

$$DWT = (m, n) = \int_{-\infty}^{+\infty} x(t) \psi^*(t) dt ,\qquad (1)$$

where «m» scale and «n» shift (translation)

$$\psi^*(t) = a_0^{\frac{m}{2}} \left((t - n a_0^m b_0) / a_0^m \right).\qquad (2)$$

In other words, this technique decompose the signal into a set of mutually orthogonal wavelets, which is the major difference with continuous wavelet transform.

Energy of signal. The energy of the disturbed signal will divided into different resolution levels by different ways depending on the power quality events at hand. So, the standard deviation at different resolution levels of the decomposed signal (Equations (1) and (2)) and MRA is proposed in this technique as feature to classify different power quality problems. The energy used in our study in equations (3), is the vector containing the percentages of energy corresponding to the details at different resolution levels, given by

$$E_d(K) = \frac{\sum (C_{d_K})^2}{\sum C^2} \cdot 100 ,\qquad (3)$$

where C is the vector contains the wavelet decomposition and C_d is the vector contains the detail coefficients at level k, using the DWT.

All of the waveforms in this paper are simulated in MATLAB Simulink with IEEE 9 Bus system [18]. We generated pure sine wave (frequency 60 Hz and the amplitude in p.u).

Proposed method. The block diagram in Fig. 1 demonstrate the proposed method. Where the Support Vector Machine (SVM) with Error-Correcting Output Codes (ECOC) classifier is proposed to classify and characterize the power quality disturbances such as voltage sag, voltage swell and harmonic distortion, which are possible to be produced from the wind energy.
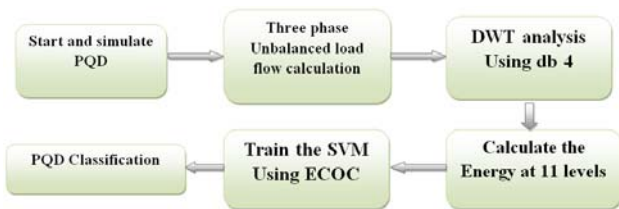
Fig. 1. Block diagram representing the simulation steps

Firstly, 3 phases unbalanced load flow analysis is executed to calculate different electric network characteristics, levels of voltage, active and reactive power. After, a wavelet transform is applied to decompose the signal by DWT. Using the equation (3), we calculate the energy of the decomposed signal. Finally, the ECOC-SVM classifies and identifies the disturbance type according to the energy deviation of the DWT.

Applications and results. Possible causes of the voltage sag include short circuit faults, electric motors starting, turning on of heavy equipment, capacitor switching, etc. Sag can occur on multiple-phase or on a single phase, and are often accompanied by voltage swells on other healthy phases. Where, the harmonic currents produced by some nonlinear loads on the system, such as adjustable speed drives, arc furnace loads, computers, copiers, etc. The wind power generator has a possibility to generate all this kinds of disturbances. By this way, we have generated different power quality problems using the IEEE 9 Bus model (Fig. 2).
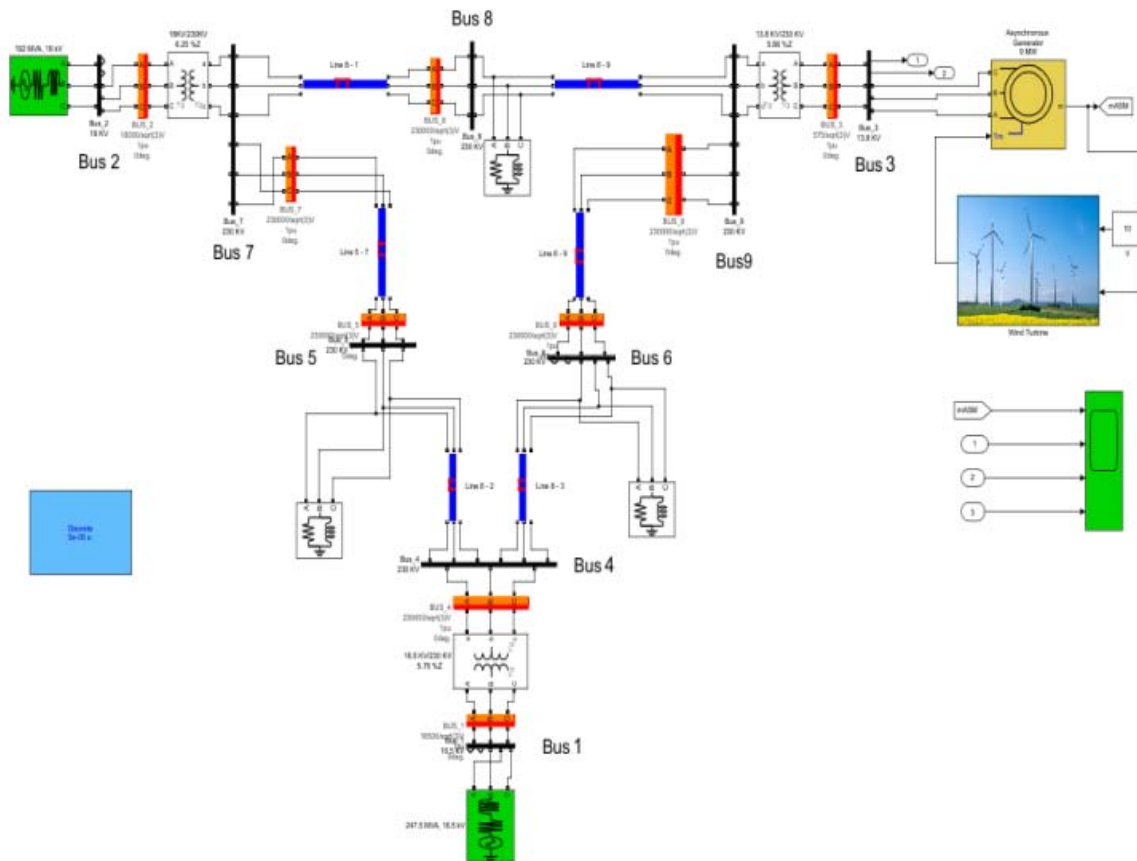

Fig. 2. IEEE 9 bus system network

In this study, sag and swell voltages caused by a short circuit fault at bus 6 and the rectifiers (diode) are used in our study as source of harmonics on the network at the same bus with 90 % power factor (cosθ = 0.9) in Bus 6, take in consideration the main characteristics of event in power system [19].

Unbalanced Load Flow Results. Load flow analysis is an important part and essential step for any power system network computation and it has always been useful by many power system engineers in this domain to improve the power quality and to reduce the power losses. Most methods use a balanced load flow (single or simple phase), this gives low information quantity, especially in three phase system in transmission or distributed network. For this reason, unbalanced load flow is needed to extract a maximum of information in each phase. Table 1, 2 and Fig. 3 presents 3 phase unbalanced load flow results.
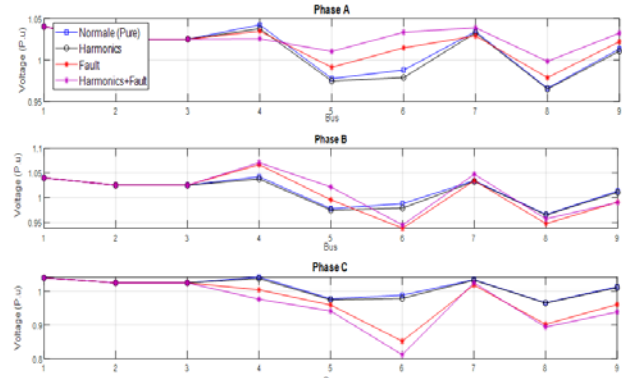

Fig. 3. Voltage profile of the three phase load flow results

Table 1 represents the phase magnitude voltage, angle, active and reactive powers in each generator bus and Table 2 represent the load buses. It can be seen the non-symmetrical values in some buses, especially in case of the manager's fault (phase C), where Fig. 3 shows in detail the voltage profile and the minimum voltage found in case 4 (harmonics + fault), especially in phase C at bus 6 and its observed also near to this bus. Furthermore, in the harmonic disturbance results, there is a difference between all buses, this is due to the location of the harmonic source (bus 6) and the total distortion harmonic (THD) in each bus when THD in bus 1 was 1.16 % in bus 6 30.29 % and 21.3 % in bus 5, The same thing for the other disturbances.

DWT Results. The appropriate select of the mother wavelet perform an important part in detecting, localizing and analysing different kinds of signal variations, the choice relies on the nature of the application. For detection of low amplitude, short duration, fast decaying and oscillating type of signals, the most popular wavelets are Daubechies and Symlets families (db2, db3 and sym2, sym3… etc). Wavelet Daubechies «db4» is used to execute the DWT with 11 decomposition levels.

Figure 4 shows the distorted energy distribution at each level, we could not actually recognize the features. High and low frequency disturbance come in 5th, 6th and 9th level. The results showed that the sag energy deviation levels are less than the pure energy deviation levels, and minimum values concentrates between 6th and 9th levels. Contrary to the value of energy in voltage swell is more than the pure signal, also the voltage swell has the maximum energy deviation at level 8. These figures have been tested and proved using the IEEE 9-bus network (Fig. 2).
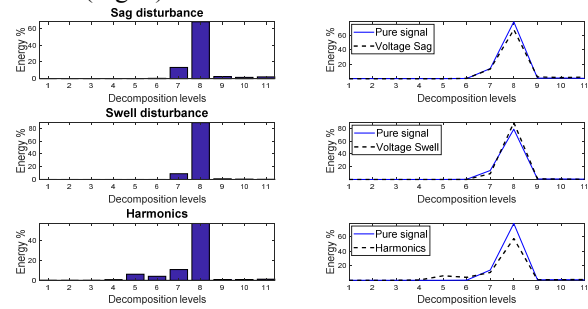

Fig. 4. Distortion energy distribution in each level

Table 1

Unbalanced load flow results for the Generators Buses

		Phase A				Phase B				Phase C				Total			
		Voltage		Power		Voltage		Power		Voltage		Power		Voltage		Power	
		p.u	angle	MW	Mvar	p.u	angle	MW	Mvar	p.u	angle	MW	Mvar	p.u	angle	MW	Mvar
BUS 1	Normal (pure)	1.04	0	27.4	−0.67	1.04	−120	27.4	−0.67	1.04	120	27.4	−0.67	1.04	0	82.21	−2.02
	Harmonics	1.04	0	25.89	2.04	1.04	−120	25.89	2.04	1.04	120	25.89	2.04	1.04	0	77.67	6.13
	Fault (phase C)	1.04	0	25.72	3.87	1.04	−120	31.33	−15.15	1.04	120	106.98	31.07	1.04	0	164.04	19.80
	Harm + Fault	1.04	0	8.85	8.81	1.04	−120	12.92	−18.22	1.04	120	106.74	47.96	1.04	0	128.51	38.57
BUS 2	Normal (pure)	1.025	9.54	54.32	−2.36	1.025	−110.46	54.32	−2.36	1.025	129.54	54.32	−2.36	1.025	9.54	162.97	−7.07
	Harmonics	1.025	9.96	54.33	−1.54	1.025	−110.04	54.33	−1.54	1.025	129.96	54.33	−1.54	1.025	9.96	163	−4.63
	Fault (phase C)	1.025	14.26	54.33	0.53	1.025	−114.3	54.33	−2.4	1.025	113.85	54.33	6.30	1.141	4.61	163	4.44
	Harm + Fault	1.025	19.15	54.33	−4.82	1.025	−111.17	54.33	−9.57	1.025	114.46	54.33	2.58	1.0091	7.49	163	−11.81
BUS 3	Normal (pure)	1.025	2.74	28.3	7.61	1.025	−117.26	28.3	7.61	1.025	122.74	28.3	7.61	1.025	2.74	84.90	22.83
	Harmonics	1.025	3.16	28.33	9.14	1.025	−116.54	28.33	9.14	1.025	123.46	28.33	9.14	1.025	3.46	85	27.42
	Fault (phase C)	1.025	9.93	28.33	2.43	1.025	−122.03	28.33	20.59	1.025	101.67	28.33	38.26	1.0042	−3.46	85	61.28
	Harm + Fault	1.025	15.32	28.33	−3.53	1.025	−118.58	28.33	20.94	1.025	100.97	28.32	51.27	0.9942	−0.73	84.99	68.69

Table 2

Unbalanced load flow for the Load Buses

		Phase A				Phase B				Phase C				Total			
		Voltage		Power		Voltage		Power		Voltage		Power		Voltage		Power	
		p.u	angle	MW	Mvar	p.u	angle	MW	Mvar	p.u	angle	MW	Mvar	p.u	angle	MW	Mvar
BUS 5	Normal (pure)	0.9777	−3.66	41.63	16.58	0.9777	−123.66	41.63	16.58	0.9777	116.34	41.63	16.58	0.9777	−3.66	124.89	49.75
	Harmonics	0.9748	−3.44	41.67	16.67	0.9748	−123.44	41.67	16.67	0.9748	116.56	41.67	16.67	0.9748	−3.44	125	50
	Fault (phase C)	0.9713	−1.85	41.67	16.67	0.9957	−125.56	41.67	16.67	0.9093	104.58	41.67	16.67	0.9541	−7.42	125	50
	Harm + Fault	1.0103	2.33	41.67	16.67	1.0495	−122.4	41.67	16.67	0.9413	105.86	41.67	16.67	0.9933	−4.48	125	50
BUS 6	Normal (pure)	0.9879	−4.73	29.88	9.93	0.9879	−124.73	29.88	9.93	0.9879	115.27	29.88	9.93	0.9879	−4.73	89.64	29.78
	Harmonics	0.9789	−3.86	28.47	13.8	0.9789	−123.86	28.47	13.8	0.9789	116.14	28.47	13.8	0.9789	−3.86	85.4	41.4
	Fault (phase C)	1.0646	−0.74	30	10	0.9382	−124.77	30	10	0.7239	86.77	30	10	0.8835	−10.62	90	30
	Harm + Fault	1.0933	2.09	28.47	13.8	0.9448	−119.96	28.46	13.8	0.5869	80.18	28.45	13.8	0.8369	−7.67	85.38	41.39
BUS 8	Normal (pure)	0.9661	−1.72	33.42	11.65	0.9661	−121.72	33.42	11.65	0.9661	118.28	33.42	11.65	0.9661	−1.72	100.25	34.94
	Harmonics	0.9651	−1.1	33.33	11.67	0.9651	−121.1	33.33	11.67	0.9651	118.9	33.33	11.67	0.9651	−1.1	100	35
	Fault (phase C)	0.9788	4.54	33.33	11.67	0.9475	−126.1	33.33	11.67	0.9023	99.21	33.33	11.67	0.9276	−7.09	100	35
	Harm + Fault	0.9984	10.31	33.33	11.67	0.9572	−122.34	33.33	11.67	0.8940	99.2	33.33	11.67	0.9273	−3.54	100	35

Using the proposed rules extracted from MRA technique at different levels with MRA curve the recognizing waveform problem becomes more easily and we can localize and detect and also classify several PQ events. When sag occurs, the 8th level also when the signal suffers harmonic distortion the 5th and 6th levels show noticeable variations, and this is clear in Fig. 5.

The percentages of energy depend on many factors, value of the disturbance, the duration, the location of this disturbance (in which bus) also the parameter of the network system as lines, load, voltage source…etc.

However, to preserve the complete information Std-MRA curve values of all levels of MRA are considered as an input to SVM to classify the power quality events.
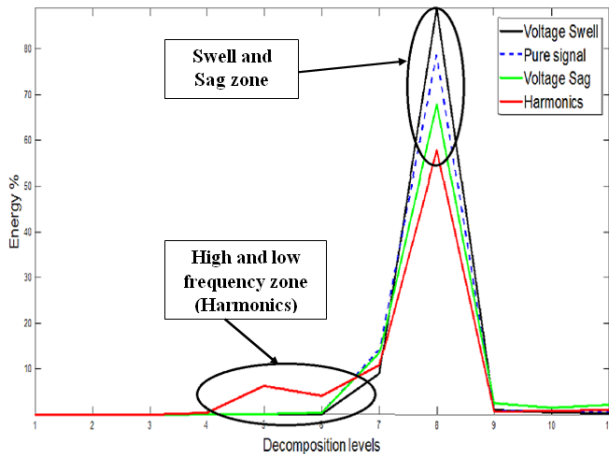

Fig. 5. Families of energy deviation curve for different PQD

Support Vector Machine results. A Support Vector Machine (SVM) is a special classifier formally and known by a separating hyperplane. In the other words, given name as training data (supervised or control learning), the algorithm outputs an optimal hyperplane which classify new examples (Fig. 6). For that reason our objective should be to obtain the line passing as far as possible from all points. Then, the process of the SVM algorithm is based on locate the optimal hyperplane that determinate the largest distance between the two class to the training examples. In this case, the classification becomes very dynamic and more precise. Different kernel functions are used and applied in the literature. The Gaussian kernel (Equation (4)) is an example of radial basis function kernel which gives the best results is selected [20]

$$k(x,y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right). \qquad (4)$$

The adjustable parameter σ represent a significant role in the behavior of kernel, and should be carefully adjust to the problem at hand. If overestimated, the exponential will behave almost linearly and the higher-dimensional projection and forecast will start to lose its non-linear capacity. In the other hand, if underestimated the function will miss regularization and the decision limit will be highly sensitive to unrest in training data.

Two-Class Support Vector Machine. From the simulated signals, DWT is applied to the signals waveforms. After, the energy of the decomposition levels

obtained using the DWT are used for SVM. The basic idea of SVM is to plan the training data from the input area into a higher dimensional feature space through Gaussian kernel function. By this away, space optimal hyper plane is specified and determined to maximize the generalization ability of the classifier. Before the training process, input data are normalized and divided into 500 sets for training and 300 sets for test. A structure of the support vector machines consists of 2 or 3 inputs (Energy level), for example [Ed6 – Ed8] or [Ed6 – Ed8– Ed9] as illustrated in Table 3. The output variables of the support vector machines are designated as value range from 1 to 6, which corresponds to the different power quality problems:

A: «1» corresponds to Voltage swell;
B: «2» corresponds to Voltage sag;
C: «3» corresponds to Harmonic;
D: «4» corresponds to Voltage swell + Harmonic;
E: «5» corresponds to Voltage sag + Harmonic;
F: «6» corresponds to pure (without problems).

We have 5 Two-Class SVM models are used and each model contains 2 types of the power quality problems (Table 3). For each SVM model, the adjusted parameters out-of sample classification error are investigated as the most appropriate parameters so that the obtained output is only specified or determined the effect of choice or with energy level are good for the training of the SVM and also for the classification. After the training process, case studies are varied so that the decision algorithm capability can be verified. The total numbers of the case studies are 300.
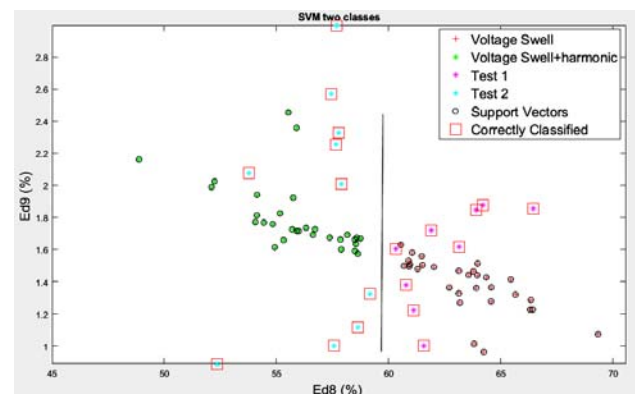

Fig. 6. Classification by two-class SVM between Voltage swell and Voltage swell + Harmonic

Table 3

Out-of sample classification error for two-class SVM

SVM Models	Ed 6 & Ed 9	Ed 8 & Ed 6	Ed 8 & Ed 9	Ed 6 & Ed 8 & Ed 9
A & B	0 %	2 %	2 %	0 %
B & C	0 %	0 %	0 %	0 %
C & E	27 %	7 %	10 %	0 %
C & D	16 %	13 %	21 %	9 %
D & E	12 %	3 %	5 %	0 %
Average	12 %	5 %	7.6 %	1.8 %

Multi-Class SVM (ECOC-SVM). The most common framework or methods already used Kernel functions. Well known classic SVM was developed for binary classification, if a multi class classifier is needed

such as the case of PQD classification, particularly where the signals include more than one disturbance or more problems, in this situation the SVM needs to be achieved in several steps. The natural extension is to combine various binary classifiers to response and to comply a binary decision tree. Error-Correcting Output Codes (ECOC) represent a effective structure to handling with these kinds of problems. However, the performance is influenced by the size and degree of the problem. In addition, for the particular case analyzed in this paper, multi ECOC technique or Fit multiclass models for support vector machines (fitcecoc) are used [21]. Multi ECOC technique is based on a reduction of multiclass classification problems to a set and combination of binary SVM where certain decoding scheme and coding design are used for the prediction of classification results according to binary SVM predictions (Fig. 7):

- max objective evaluations of 30 reached;
- total function evaluations: 30;
- total elapsed time: 50.6946 sec;
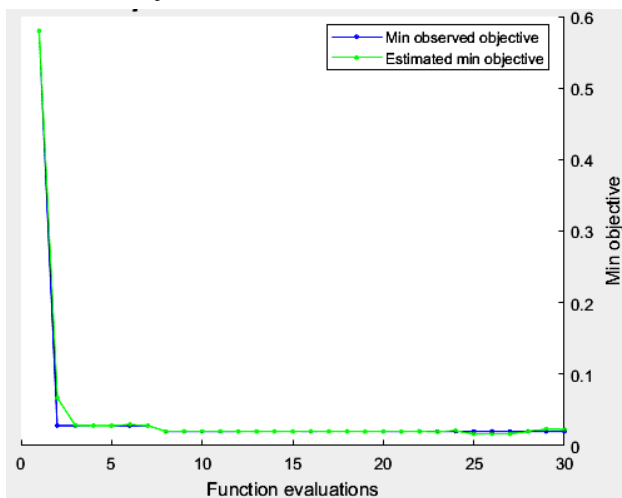- total objective function evaluation time: 8.1846.

Fig. 7. Min objective vs Number of function evaluations

Table 4

Out-of sample classification error for ECOC-SVM

	Ed 8 & Ed 6	Ed 6 & Ed 8 & Ed 10	All Energy levels (Ed1-Ed11)
Out-of sample classification error ECOC-SVM	10.8 %	10 %	3.2 %

Wind turbine simulation and results. In this section, reconfiguration of the transmission network in the presence of power wind generator. As we know, this reconfiguration can disturb the network parameters and create some PQD (Harmonics and voltage perturbation), as seen in Fig. 9, by replacing the generator in bus 3 by a wind farm power generation and keeping the same power generation 85 MW (figure 2).

Figures 8 and 9 represent the simulation results, where Fig. 8 represent the mechanical power of the turbine and the speed of the asynchronous machine. On the other hand, Fig. 9 present the frequency, current and voltage waveform at bus 3 and table 8 represent the 3 phase load flow results with and without wind energy.
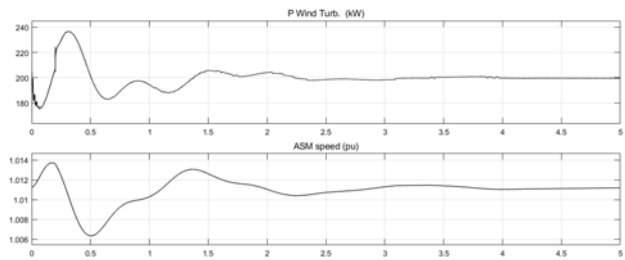

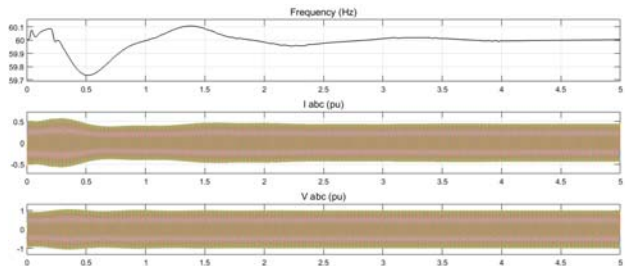Fig. 8. Turbine mechanical power and the ASM speed

Fig. 9. Frequency, current and voltage waveform at bus 3

In this part we will divide the signal produced from the wind generator at bus 3 into 3 parts (0-0.5 s, 0.5-1 s, 1-5 s), and we will try to detect the different perturbation on this signal using ECOC-SVM classifier. Table 5 shows the classification results.

Table 5

PQD classification generated by the wind generator using Ecoc-SVM classifier

SIGNAL PART	[0 – 0.5 s]	[0.5 – 1 s]	[1.5 – 4.5 s]
PQD class	D	E	F

Comparing performance with other classifiers. Tables 6 and 7 demonstrate the ability of the proposed method to identify and classify PQD with very high accuracies averaging to 99.2 %.

Table 6

Percentage of classification by ECOC-SVM and other existing classifiers

Type of power quality problem	ST with CFDT [22]	S-transform and DAG-SVMs [14]	Proposed ECOC-SVM
A	98.66 %	98.5 %	100 %
B	97.33 %	99 %	100 %
C	100 %	99.5 %	98 %
D	98 %	97 %	98 %
E	–	99.5 %	100 %
Average	98.49 %	98.7 %	99.2 %

Table 7

Classification accuracy rate of the proposed method compared with other methods

Method	Classification
Proposed method (ECOC-SVM)	99.20 %
Neural network with DWT and fuzzy logic [10]	98.17 %
Wavelet and fuzzy logic [11]	98.02 %
Wavelet and SVM [7]	93.43 %
PSO-ELM [15]	97.60 %
Fast Dyadic ST with CFDT [22]	98.66 %

The performance and the efficiency of the proposed method and algorithm is also compared with other existing classifiers, including wavelet transform and neural network, wavelet transform and neural fuzzy, wavelet and SVM. The most common methods to design multiclass classification is to determine a series of binary classifiers and to combine or collect them [14-16]. This work represents an effective framework to compact with these types of problems.

The results showed significant performance by different device and strategy of new problem dependent designs based on the ternary ECOC-SVM with out-of sample classification error are relatively low with 3.2 % (Table 4).

Table 8

Load flow results with and without wind energy in some buses

		Phase A				Phase B				Phase C				Total			
		Voltage		Power		Voltage		Power		Voltage		Power		Voltage		Power	
		p.u	angle	MW	Mvar	p.u	angle	MW	Mvar	p.u	angle	MW	Mvar	p.u	angle	MW	Mvar
BUS 3	Without wind	1.025	2.74	28.3	7.61	1.025	–117.26	28.3	7.61	1.025	122.74	28.3	7.61	1.025	2.74	84.90	22.83
	With wind	1.02	1.11	28.33	5.14	1.02	–116.1	28.33	5.14	1.02	123.5	28.33	5.14	1.02	1.15	85	15.42
BUS 8	Without wind	0.9661	–1.72	33.42	11.65	0.9661	–121.72	33.42	11.65	0.9661	118.28	33.42	11.65	0.9661	–1.72	100.25	34.94
	With wind	0.9555	2.1	33.99	10.41	0.9555	–117.9	33.99	10.41	0.9555	121.96	33.99	10.41	0.9555	1.88	101.97	31.23
BUS 6	Without wind	0.9879	–4.73	29.88	9.93	0.9879	–124.73	29.88	9.93	0.9879	115.27	29.88	9.93	0.9879	–4.73	89.64	29.78
	With wind	0.9620	3.27	29.77	8.96	0.9620	–115.84	29.77	8.96	0.9620	122.90	29.77	8.96	0.9620	3.52	89.33	29.6

Conclusion.

The paper introduces the application and the implementation of wavelet transform and multiresolution analysis signal decomposition as a powerful analysis tool in power system, the property of this wavelet demonstrate the capacity of this technique to extract significant information from the analyzed distorted signal. This information is partitioned into different zones where each zone can be used to observe and classify power quality problems. The results show clearly that the precision of the combination of discrete wavelet transform and support vector machines algorithm is highly acceptable as shown in previous tables. In the other hand, the proposed method is able to recognize and classify different power disturbance types efficiently with 99.2 % compared with well known methods. The further work will be the improvement of the algorithm by taking in consideration the real signals for the development of the practical protection system, it can also help in finding and locating the source and the cause of disturbance.

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Ala eddine Rahmani[1], *Ph.D Student in Electrical Engineering*,
Linda Slimani[1], *Doctor in Electrical Engineering, Professor*,
Tarek Bouktir[1], *Doctor in Electrical Engineering, Professor*,
[1] Department of Electrical Engineering,
Université Ferhat Abbas Sétif 1, Algeria,
phone: +213 658 210 102,
e-mail: alaaeddinrahmani@yahoo.fr,
slimaniblinda@gmail.com,   tbouktir@univ-setif.dz