Çağrı ARIKAN[1], Muammer ÖZDEMİR[2]

Yıldız Teknik Üniversitesi (1), Ondokuz Mayıs Üniversitesi (2)

Classification of Power Quality Disturbances at Power System Frequency and Out Of Power System Frequency Using Support Vector Machines

***Abstract**. In this paper, firstly it is tried to classify pure sine and power quality disturbances (PQD) such as voltage sag, voltage swell, voltage with harmonics, transients and flicker at power system frequency (50 Hz). Wavelet transform (WT) is used to extract distinctive features. Wavelet energy criterion is applied to wavelet detail coefficients. It is seen that classification performance of support vector machine (SVM) used as classifier is well. Then pure sine and PQD, that are out of power system frequency, are tried to classify. Curve fitting approach is used for estimating frequency. It is observed that SVM classifies PQD signals well when frequency of pure sine is updated with the frequency of PQD even if they deviate from 50 Hz.*

Streszczenie.** W artykule przedstawiono sposób wykorzystania transformaty falkowej do wykrycia i analizy podstawowych zaburzeń napięcia jakości energii w sieci elektroenergetycznej (50Hz). W celu estymacji częstotliwości zastosowano metodę dopasowania krzywej. Stwierdzono, że metoda wektorów nośnych (ang. Support Vector Machine) poprawnie klasyfikuje zakłócenia mocy, nawet dla częstotliwości odmiennych niż 50Hz. **(Klasyfikacja zakłóceń jakości energii w systemie elektroenergetycznym w częstotliwości sieciowej i poza nią – metoda wektorów nośnych).

Keywords: power quality disturbance, wavelet transform, support vector machine, curve fitting approach, classification.
Słowa kluczowe: zakłócenia jakości energii, transformata falkowa, maszyna wektorów nośnych, metoda dopasowania krzywej

1. Introduction

In the last few years, electrical power quality (PQ) has become an important issue. Any PQ problem, which manifests itself in changes of voltage, current or frequency, appeared when malfunction or poor operation occurred in customers' equipment [1, 2]. PQ is defined as ‘‘the concept of powering and grounding sensitive equipment in a manner that is suitable to operation of that equipment” in the IEEE Std. 1159-1995 [3]. As in [4], PQ is ‘‘set of parameters defining the properties of PQ as delivered to the user in normal operating conditions in terms of continuity of supply and characteristics of voltage (symmetry, frequency, magnitude and waveform)” [5].

Before any appropriate mitigating action can be taken, reliable and fast detection of disturbances and causes of disturbances must be known. For determining effects of disturbances and analyzing supply of disturbances, classification must be done accurately. So appropriate precautions can be taken for these disturbances.

PQD could downgrade the service quality. PQD and the resulting problems increased because of using solid-state switching devices, power electronically switched loads and non-linear, data processing equipment, lighting controls, unbalanced power systems, industrial plant rectifiers and inverters [6]. These loads cause voltage distortions.

Determination of PQD waveforms is traditionally was judged by visual inspection. In this case engineers occupied with too much data for inspection [7]. Also, the detection of PQD was done according to pre-determined threshold value, but lack of this method is large amounts of data logged by the monitoring systems [8]. Therefore, preprocessing of the data is required. In literature there are many methods that represent the data without losing main feature. Also, these methods are used for reducing the size of the data. The methods used in this area are Fourier transform (FT), fast Fourier transform (FFT), fractal based method [9], S transform method [10], time-frequency ambiguity plane [11], short time power and correlation transform method [12], WT method [13, 14], Hilbert transform [15], chirp-Z transform (CZT) method [16], d-q transform method [17] and Kalman filter [18].

FT shows spectrum components in signals but it does not include time information of these components. FT gives highly successful results for analyzing the frequency content of a stationary process, but it is insufficient to analyze for non-stationary signals. Then short time Fourier transform (STFT) was developed. Fast changing high frequency components of the signal are not analyzed in time domain because window function used in STFT is fixed width [6,7]. In fractal based method, beginning and ending point of disturbances can be seen as a visual but frequency information of disturbances can't be obtained because fractal doesn't have frequency information [9]. While Chirp-Z transform method such as discrete Fourier transform (DFT) does not provide sufficient time information but WT provides suitable time frequency resolution [19, 20]. S transform has complex calculations and it requires Gauss window parameter [10], fractal based method and Hilbert transform don't have the high classification accuracy [6, 9] Because of these reasons traditional methods are not sufficient.

Proposed new signal processing methods and intelligent systems used in monitoring systems are needed since the early 2000s. The most widely used artificial intelligence tools for classifying PQD are expert systems, fuzzy logic, artificial neural network (ANN) and genetic algorithms [21]. In recent years, probabilistic neural networks and SVM appear to be more effective new learning machines [6]. Rule based expert systems and chaos synchronization are the methods used for classifying PQD signals [22,23,24,25].

In this paper, firstly pure sine and five PQD such as voltage sag, voltage swell, voltage with harmonics, transients and flicker at power system frequency are tried to classify. Multi-resolution analysis (MRA) technique of DWT and Parseval's theorem are employed. Then SVM is used for classification stage. High accuracy classification is obtained. But in practice, frequencies of PQD may change. Then proposed method is adopted for PQ signals, which have out of power system frequency, in order to understand if this method is dependent or independent from the frequencies of PQD. When PQD's frequencies are changed, it is seen differences in results of proposed method. Because proposed method depends on the frequency. Frequencies of PQD and pure sine are estimated by using curve fitting approach. If frequencies of PQD are out of power system frequency, frequency of pure sine as a reference is updated according to estimated frequency. Feature vector extraction and classification stage are same with first study. It is seen that proposed method depends on updating frequency of pure sine according to frequencies of generated PQD.

2. Feature Vector Constructing Using WT

Wavelet based techniques are powerful mathematical tools for digital signal processing. Wavelets have varying window size. It is wide for slow frequencies and narrow for fast frequencies. So, optimal time-frequency resolution is obtained [6, 26, 27,28, 29]. WT is applied in two ways as continuous wavelet transform (CWT) and discrete wavelet transform (DWT). Computer analysis is realized by using DWT because DWT takes less time than CWT.

DWT of f(t) signal in jth level is defined in Equ. (1) with both scaling and wavelet function.

$$f(t)=\sum_n a_J(n)\phi(t-n)+\sum_n\sum_{j=0}^{J-1} d_J(n)2^{j/2}\psi\left(2^J t-n\right) \tag{1}$$

Where a_J is J level approximation coefficients, d_J is J level detail coefficients, $\phi(t)$is scale function, $\Psi(t)$is mother wavelet function, J is the highest level of WT and t represents time [30].

3. Feature Extraction Stage

In Parseval's theorem, assuming a discrete signal $f[n]$ is the current that flows through the 1Ω resistance. The consumptive energy of the resistance is given in Equ. (2) by using the spectrum coefficients of the Fourier transform in frequency domain [31].

$$\frac{1}{N}\sum_n |f(n)|^2=\sum_k |a_k|^2 \tag{2}$$

Where N is sampling period and a_k is the spectrum coefficients of the Fourier transform [31, 32].

For applying Parseval's theorem to the DWT, Equ. (2) is used to obtain Equ. (3) that is Parseval's theorem in the DWT application [31].

$$\frac{1}{N}\sum_t |f(t)|^2=\frac{1}{N_J}\sum_k |a_J(k)|^2+\sum_{J=1}^{J}\left(\frac{1}{N_J}\sum_k |d_J(k)|^2\right) \tag{3}$$

Energy of distored signal is obtained by using Equ. (3) [32]. The first term on the right of Equ. (3) denotes energy of approximation coefficients and the second term on the right of Equ. (3) denotes energy of detail coefficients. J shows total resolution level in Equ. (3). The second term giving that energy distribution features of the detail version of distorted signal will be employed to extract the features of power disturbance [31, 32]. The process can be represented mathematically by Equ. (4).

$$P_J=\frac{1}{N_J}\sum_k |d_{j,k}|^2=\frac{\|d_J\|^2}{N_J} \tag{4}$$

where $\|d_J\|$ is the norm of the detail coefficient d_J.

Equ. (4) is normalized by Equ. (5).

$$P_J^D=(P_J)^{1/2} \tag{5}$$

Also, Equ. (6) represents the norm of feature vector.

$$P_{isaret}=\left[P_1^D \quad P_2^D \quad .....P_n^D\right] \tag{6}$$

4. Support Vector Machines

SVM, which is first introduced by Vapnik, is a class of supervised learning algorithms [33]. Pattern recognition problems can be solved by using SVM [34, 35, 36, 37]. Also forecasting, constructing intelligent machines, regression estimation problems and the problems of dependency estimation are some of the SVM application areas [38, 39].

When ANN is compared with SVM, it has some important disadvantages [40, 41]. Firstly, for error function to be minimized has many local minima, this learning process can fail. Secondly, learning algorithm cannot control the complexity of architecture of ANN, therefore this architecture determines the generalization abilities.

SVM was used for classifying data points of linear separable data sets. Also, SVM can be applicable to linear and nonlinear conditions. By using SVM, the separating margin between two classes is tried to be maximum. For linear separable training pairs of two classes, the separating hyperpalne $g(x)$ is given in Equ. 7:

$$g(x)=w^T x+b=0 \tag{7}$$

where w are weights, b is bias, x is input vector and $g(x)$ is output vector. For the distance between two classes is maximum, Equ. 8 is solved.

$$\min\frac{1}{2}w^T w \tag{8}$$

and Equ. 9 is considered for minimizing object function in Equ. 8.

$$d_i\left(w^T x_i+b\right)\geq 1 \tag{9}$$

This problem can be solved by minimizing Lagrange function. Equ. (10) is used for this minimization.

$$J(w,b,\alpha)=\frac{1}{2}w^T w-\sum_{i=1}^{p}\alpha_i\left[d_i\left(w^T x_i+b\right)-1\right] \tag{10}$$

In Equ.10 α is non-zero Lagrange coefficient. If two classes are in nonlinear case, Equ. (8) and Equ. (9) have different forms. New objective function ϕ is given by,

$$\phi(w,\xi)=\frac{1}{2}w^T w+C\sum_{i=1}^{p}\xi_i,\ \xi_i>0 \tag{11}$$

$$d_i\left(w^T x_i+b\right)\geq 1-\xi_i \tag{12}$$

where ξ is slack variable and C is penalty factor. In nonlinear case, SVM maps the input vectors x into a high dimensional space through some nonlinear mapping (φ function) [42, 43].

In recent years, methods named as multi-class SVM, which could classify more than two data set, are proposed. The most widely used classification methods are one-against-one (OAO) and one-against-all (OAA) [44, 45].

In OAO, training method of machine depends on comparing all the classes with each other. Also, in OAA method, each data set is trained by assuming that all the rest of the data set belongs to a data set. For a k-class problem, while OAO method constructs $k*(k-1)/2$ hyperplanes, OAA method constructs k hyperplanes [46].

5. Curve-Fitting Approach For Frequency Estimation

This method is curve fitting approach based on the least squares approach and it needs only six samples in current and voltage [47].

These samples can be selected from rising edge or falling edge of the signal while it is passing through near zero value. Place of taken samples is indicated in Fig. 1.

For estimating the power frequency from the sampled signal, selecting only Group 1 or Group 2 sample is enough. This selection procedure is based on numerical differentiation with its sign and a switch function. Numerical differantiation is given as below by finite difference approximation:

$$diff(y)=\frac{y(k+1)-y(k)}{h} \tag{13}$$

Where $y(k)$ is the normalized input signal, h is the sampling interval and $k=1,2,...,N$. For selecting the successive group members, the switch function is required and defined as below.

switch=1 (default)

IF (switch =1 AND $y(k)$<0 AND sign(diff)=-1) THEN
switch=0
ELSEIF (switch =0 AND $y(k)$>0 AND sign(diff)=1)
switch=1
END

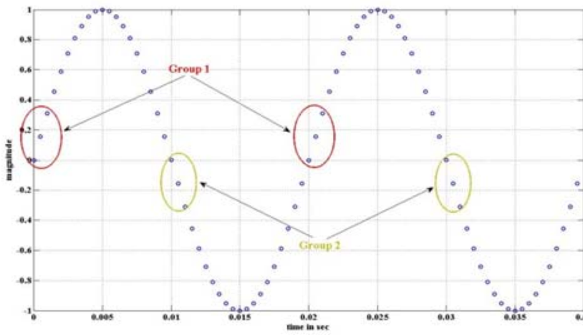

Fig.1. Illustrating of curve fitting approach for frequency estimation [47]

The selected successive samples are formed as matrix according to switch value (0 or 1). For group 1 or 2 two matrices are obtained. Each matrix has 2x3 elements. Time information is in the first row of the matrix, magnitude information of the sampled signal is in the second row. A curve fitting algorithm based on least square approximation is then applied to rows of the matrix and two equations are obtained as given in Equ. (14).

$$C1 = a1 * t + b1 \qquad (14)$$
$$C2 = a2 * t + b2$$

This procedure is shown in Fig. 2.

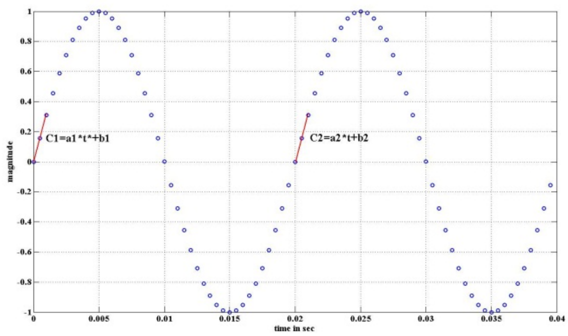

Fig. 2. Obtaining C1 and C2 slopes from selected samples

The time information that makes the value of each C zero is calculated after obtaining $C1$ and $C2$ slopes. Then the power frequency is estimated by using Equ. (15).

$$f = \frac{1}{|ti2| - |ti1|} \qquad (15)$$

In Eq. (15), $ti1$ is the time information for $C1=0$ $(ti1=-b1/a1)$ and $ti2$ is the time information for $C2=0$ $(ti2=-b2/a2)$.

6. Feature Extraction of PQD by Using Energy Method

In order to classify different types of PQD and pure sine which is taken as a reference, voltage swell, voltage sag, voltage with harmonics, transients, flicker are constituted at the zero crossing points of the voltage signal by using MATLAB.

Pure sine and PQD are given in Fig. 3. The sampling frequency is 25.6 kHz. Pure sine and PQD are decomposed by using 12 levels Daubechies-4 discrete wavelet filter. The energy distributions of detail coefficients in Equ. (5) are obtained. Since the examined PQD consist of flicker, of which frequency is between 8-10 Hz, that is distinguished by human eye ideally, 11 level decomposition is sufficient. But in this study 12 level decomposition is proposed for better solution. Because, this decomposition also could analyze lower flicker frequency.

DWT determines high frequency components which are at the beginning and ending of event. Beginning and ending points of voltage with harmonics and transients can be determined by using DWT because these PQD contain high frequency components at the beginning and ending points of these events but types of these disturbances are not decided by using only DWT. DWT failed in determining voltage swell, voltage sag and flicker because these events contain low frequency components. If PQ events, that do not contain high frequency components, occur, in this case analysis must be done by using high grade filters. So processing time will increase. Also, DWT couldn't specify the type of these disturbances. For this reason, disturbances are tried to distinguish each other by examining energy of detail coefficients. In Table 1. frequency band intervals of WT at MRA are seen. Fig. 4. shows energy distribution features of PQD signals and pure sine.

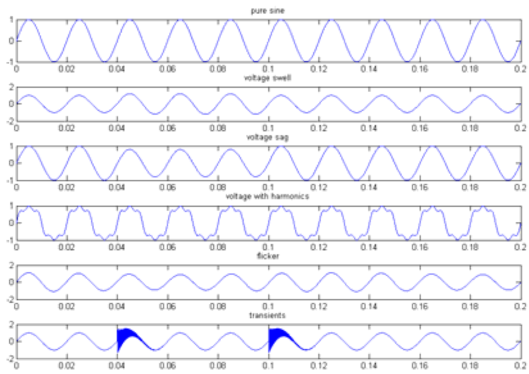

Fig. 3. Waveforms of simulated PQD

Table 1. Frequency band intervals at MRA

Resolution Levels	Frequency Intervals
d1	6400-12800
d2	3200-6400
d3	1600-3200
d4	800-1600
d5	400-800
d6	200-400
d7	100-200
d8	50-100
d9	25-50
d10	12.5-25
d11	6.25-12.5
d12	3.125-6.25
a12	0-3.125

As given in Table 1., $d8$ and $d9$ energy coefficients are important for voltage sag and swell because these disturbances are at 50 Hz power frequency and only their amplitudes change. When energy distribution of voltage sag and swell is compared with energy distribution of pure sine, it can be noticed a decrease in $d8$ and $d9$ coefficients for voltage sag and an increase in $d8$ and $d9$ coefficients for voltage swell. When energy distribution of voltage with 3^{rd} and 5^{th} harmonics is examined, a difference could be seen in 5^{th}, 6^{th} and 7^{th} energy levels. According to Table 1., especially difference in 6^{th} and 7^{th} levels show the presence of 3^{rd} and 5^{th} harmonic components. When energy distribution of transients is examined, a significantly increase in $d1$ and $d2$ coefficients can be seen. These coefficients represent high frequency components. Also, increase in 10^{th} and 11^{th} energy level is seen for flicker.

Until now, generated disturbances for obtaining feature vector are created at the zero crossing points of the voltage signal. In practice, occurrence of disturbances at these points is not guaranteed. So in this paper, disturbances are constituted in eight different points (45^0, 90^0, 135^0, 180^0, 225^0, 270^0, 315^0 and 360^0) which have different characteristics in order to understand if proposed feature extraction method is dependent or independent from the occurrence moment of disturbances. *d8* and *d9* coefficients which are close to 50 Hz power frequency are important for voltage swell and voltage sag. In Fig. 5. and 6. variations of *d8* and *d9* coefficients are given for voltage swell and sag in eight different points, respectively.

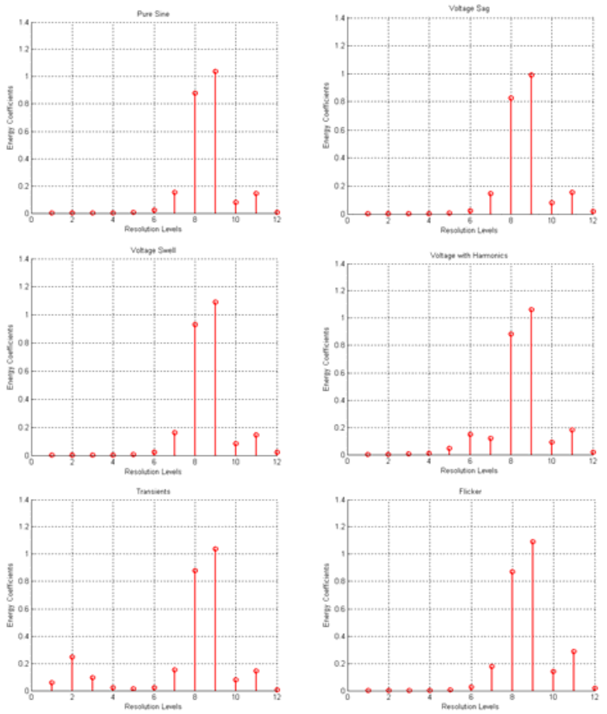

Fig. 4.Energy distribution features of pure sine and PQD

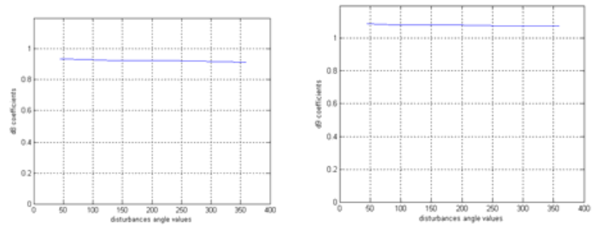

Fig. 5.Variations of d8 and d9 coefficients for voltage swell in eight different points, respectively

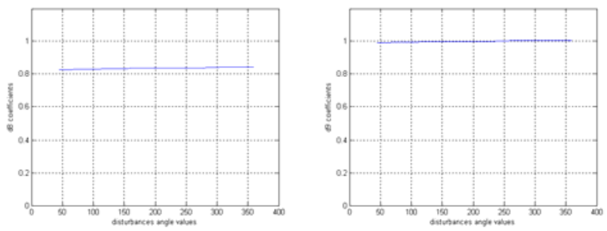

Fig.6. Variations of d8 and d9 coefficients for voltage sag in eight different points, respectively

Variations of *d2* coefficients in eight different points are given in Fig.7 for transients. Since the voltage waveforms consist of harmonics and flicker for all of the sample time, the effects of occurrence moment of these disturbances are not examined.

When voltage swell occurs, *d8* coefficients change between 0.9145-0.9338 with %2.066 variations and *d9* coefficients change between 1.0742-1.0888 with %1.34 variations. Also, while the voltage sag occurs, *d8* coefficients change between 0.8278-0.8447 with %2 variations and *d9* coefficients change between 0.992-1.0054 with %1.33 variations, for transients, *d2* coefficients are fixed to 0.2486. It can be said that this method is independent from occurrence moment of disturbances. For this reason, the proposed method was decided to apply for generating feature vector [48, 49].

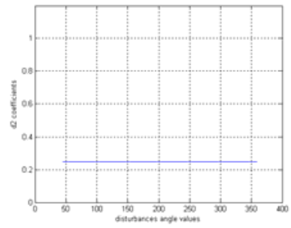

Fig.7. Variations of d2 coefficients for transients in eight different points

7. Classification of PQD by Using SVM

7.1. Classification of PQD at Power System Frequency (50 Hz) by Using SVM

In this section, classification performance of SVM for five PQD at 50 Hz and pure sine is examined.

Lack of data banks for comparing performance of the methods that are used for classification of PQD made studies difficult in this area. Adequate number of data is needed for adapting them to definitions which are defined in standards. Also, these data have to be resembled to the PQD signals which are frequently seen in power systems. In order to reduce this problem, data production approach based on mathematical model is recommended. Mathematical model and control parameters are given to obtain PQD signals which are specified in IEEE 1159 standard in Table 2.

Different scenarios are derived by changing occurrence places, amplitudes and durations of PQD signals. Also by changing frequencies of flicker and transients, data variations are obtained. PQD types, class labels and numbers of PQD based on mathematical model are given in Table 3.

The proposed PQD classification algorithm is given in Fig. 8.

After getting five kinds of PQD data, signals are normalized in Equ. (16).

(16) $$GKB = \frac{GKB}{maks(|GKB[n]|)}$$

where n is number of sample in first period before disturbance. In Equ. (16), PQD signals in different voltage levels are scaled in per unit (pu) [50]. After normalization process, feature vectors of total 258 signals are obtained by getting energies of $d1, d2, ...,d12$ detail coefficients that are obtained by using DWT. When feature vectors of signals which have 512x10 samples are obtained, this value reduced to 12x1 dimensions. So, the data size is reduced to approximately 1/427 ratio. Wavelet functions such as Meyer, Daubechies, Symlet, Coiflet are frequently used for power system analysis. Selection of appropriate wavelet function affects the performance of the classifier. Selection of inappropriate wavelet function causes disturbances in restructured signals. Selection of appropriate wavelet function in wavelet plane is determined with the method which is named as minimum description length. This criterion aims to gain the compromise between the error of signal reconstruction and the number of retained wavelet coefficients. The algorithm permits one to select the suitable wavelet filter [51]. Daubechies-4 wavelet function is widely used in classification of PQD [52, 53, 54].

Table 2. PQD model

PQD Types	Mathematical Model	Control Parameters
Pure Sine	$y(t)=A\sin(wt)$	$A=1(pu)$, $f=50$ Hz
Voltage Sag	$y(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(wt)$	$0.1\leq\alpha\leq 0.9$; $T\leq t_2-t_1\leq 10T$
Voltage Swell	$y(t)=A(1+\alpha(u(t-t_1)-u(t-t_2)))\sin(wt)$	$0.1\leq\alpha\leq 0.8$; $T\leq t_2-t_1 \leq 10\,T$; $t_1<t_2, u(t)=\begin{cases}1, t\geq 0,\\ 0, t<0\end{cases}$
Voltage with Harmonics	$y(t)=A(\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt))$	$0.05\leq\alpha_3\leq 0.3$; $0.05\leq\alpha_5\leq 0.2$
Transients	$y(t)=\sin(wt)+(\alpha\exp(-250bt)\sin(2\pi f_g t))$	$0.5\leq\alpha\leq 4$; $0.3\leq b\leq 50\,ms$; $1000\leq f_g<5000$
Flicker	$y(t)=\sin(2\pi ft)+\alpha\sin(2\pi(f+f_{fl})t)$	$0.1\leq\alpha\leq 0.8$; $8\leq f_{fl}\leq 10$

Table 3. Class labels and numbers of PQD

PQD Type	Class Label	Number of Signal
Voltage Sag	S1	43
Voltage Swell	S2	43
Voltage with Harmonics	S3	43
Transient	S4	43
Flicker	S5	43
Pure Sine	S6	43
Total		258

It is explained that when orthogonal wavelet functions such as Daubechies, Haar, Symlets ve Coiflets are used, there is not statistically significant difference in the classification performance [21]. Daubechies 4 wavelet function is used because of short computational time [21]. For Daubechies-4 wavelet function exhibits a characteristic which is close to the type of constituted disturbances; this wavelet function is commonly used for classifying PQD [50].

Half of constituted data are used for testing and other half of them are used for training. SVM is supervised classification algorithm. Input and output data are given to system together. While extracted feature vector is input of SVM, class labels are output of SVM. Class labels depend on number of class. In training data set, desired output is labeled such as *1, 2, ...,N*. Each number represents one class. So in this study $N=6$.

Also clustering approach shows the ability of distinguishing PQD as a visual. *d2-d9*, *d4-d9* and *d9-d11* feature pairs give best results in classification of five PQD and pure sine. It can be said that these four features (*d2, d4, d9, d11*) are dominant features for classifying PQD signals. Classification of pure sine and five PQD by using (*d2-d9*), (*d4-d9*) and (*d9-d11*) feature pairs are shown in Fig.9.

In Fig. 9. support vectors are shown in circles and C is 0.8. Statistical Pattern Recognition Toolbox for MATLAB (STPRTOOL) is used for simulations. Radial basis function (rbf) is chosen as Kernel function. Tests are repeated for different γ values (width parameter of radial basis function). $\gamma=0.8$ gives best result.

As seen in Table 4., OAO and OAA methods are used for MCM. It is determined that OAO method gives better results than OAA when looking at the training error, test error and NSV. Classification performance results by using SVM are shown in Table 5. It is seen that results have high accuracy and the average performance is 97.905%.

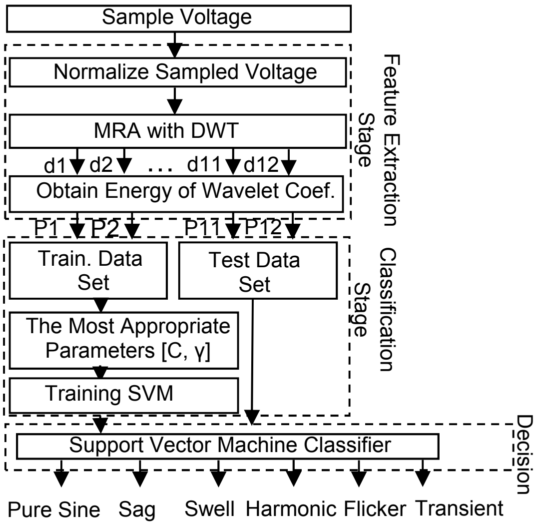

Fig.8. The proposed PQD classification algorithm [55]

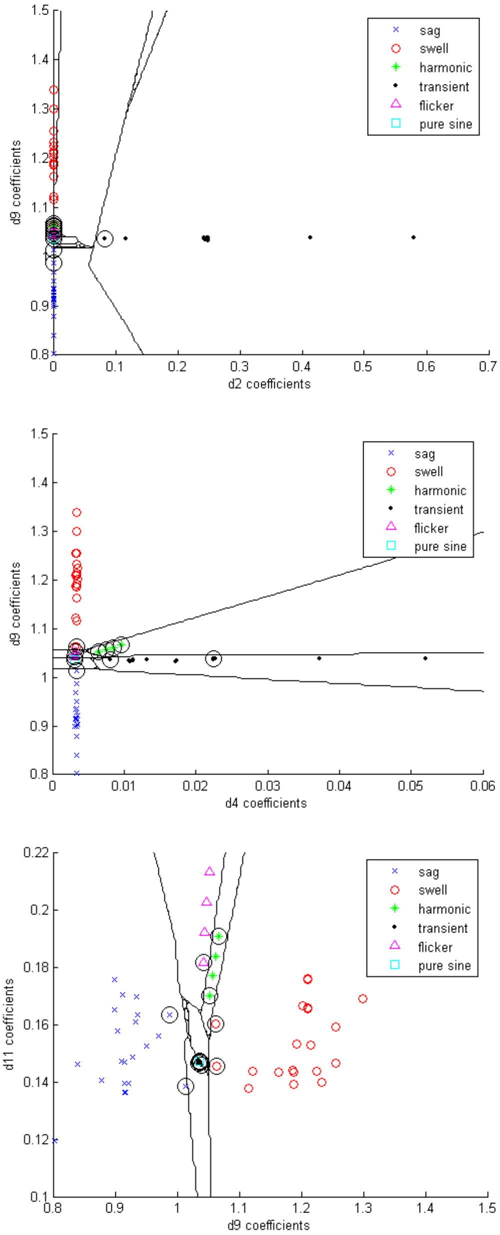

Fig.9.Classification of pure sine and PQD signals using SVM [55]

Table 4. Classification results

Experimental Results			C				
			10	100	1000	10000	Inf
MCM	OAO	NSV	22	13	11	11	11
		Training Error	0,0694	0,0139	0	0	0
		Test Error	0,0278	0,0139	0	0	0
	OAA	NSV	36	26	26	24	27
		Training Error	0,0278	0,0139	0,0139	0	0
		Test Error	0,0139	0,0139	0,0139	0	0

MCM: Multiclass Classification Methods , NSV: Number of Support Vectors

Table 5. Classification performance results by using SVM

Class	S1	S2	S3	S4	S5	S6	Accuracy (%)
S1	234	0	0	0	0	5	97.9
S2	0	223	0	0	0	5	97.8
S3	0	0	264	0	0	0	100
S4	0	0	0	97	0	3	97
S5	0	9	0	0	216	3	94.73
S6	0	0	0	0	0	100	100
Average Performance (%)			97.905				

7.2. Classification of PQD that are out of Power System Frequency (50 Hz) by Using SVM

In this section, SVM' s classification performance of pure sine and PQD such as voltage sag, voltage swell, voltage with harmonics, transients and flicker that are out of power system frequency is examined.

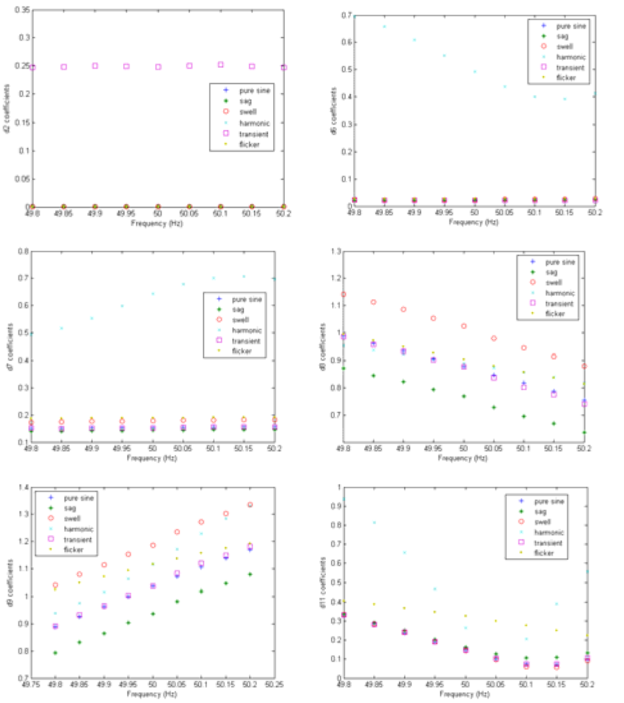

Fig. 10.Variations of d2, d6, d7, d8, d9 and d11 coefficients, in case of pure sine and PQD that are out of 50 Hz.

It is known that power system frequency can deviate from 50 Hz because of incompatibilities between load demand and production. Proposed method depends on the frequency. The change of PQD frequencies causes differences at the result of proposed method. When the frequencies are changed, frequency of pure sine as a reference must be compatible with the system frequency. For this reason, frequencies of PQD have to be estimated periodically to get accurate results. Then frequency of pure sine is updated with frequency of PQD and this feature vector of PQD is given to the classifier.

Wavelet based energy distribution was used as feature vector in the studies that were made so far in the literature. But in these studies, generated PQD signals were created at power system frequency. When frequencies of PQD are changed, performance of method was not examined.

Fig. 10. shows variations of *d2, d6, d7, d8, d9* and *d11* coefficients respectively in case of frequencies of pure sine and PQD signals deviate from 50 Hz. System frequency is controlled around 50 Hertz (Hz) in the range of 49.8-50.2 Hz according to the regulations [56]. So frequencies of signals are assumed to vary between 49.8–50.2 Hz.

In Fig. 10., *d2* coefficients of transients at all frequency values are higher than *d2* coefficients of other disturbances and these coefficients are distinctive feature for transients. *d6* and *d7* coefficients are important for voltage with 3rd and 5th harmonics. In Fig. 10. *d6* and *d7* coefficients of voltage with harmonics at all frequency values are higher than *d6* and *d7* coefficients of other disturbances. *d8* and *d9* coefficients for voltage swell and sag are distinctive information. In Fig. 10. while *d8* coefficients of voltage swell at all frequency values are higher than *d8* coefficients of other disturbances, *d8* coefficients of voltage sag at all frequency values are lower than *d8* coefficients of other disturbances. In Fig. 10. while *d9* coefficients of voltage swell at all frequency values are higher than *d9* coefficients of other disturbances, *d9* coefficients of voltage sag at all frequency values are lower than *d9* coefficients of other disturbances. *d11* coefficients are important for flicker and in Fig. 10. it is seen that *d11* coefficients of flicker at all frequency values are higher than *d11* coefficients of voltage sag, voltage swell, voltage with harmonics and transients.

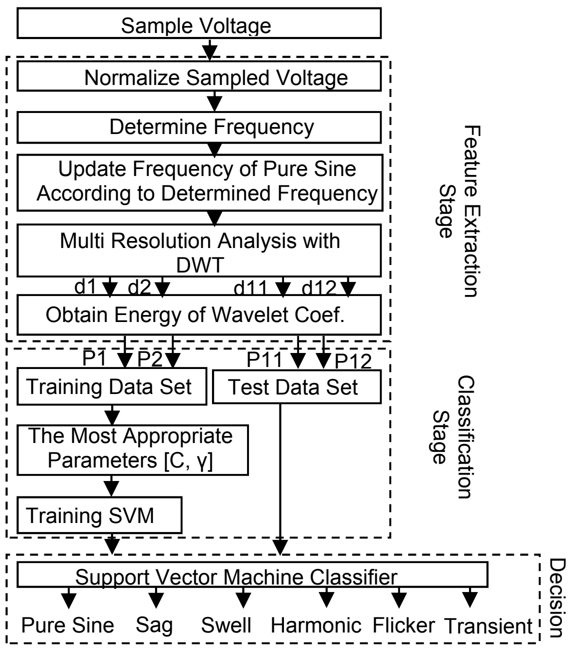

Fig.11. When power system frequency is changed, the proposedPQD classification algorithm [55]

But *d11* coefficients of voltage with harmonics at some frequency values are higher than *d11* coefficients of flicker. Difference between voltage with harmonics and flicker is *d6* and *d7* coefficients of voltage with harmonics at all frequency values are higher than *d6* and *d7* coefficients of flicker.

When power system frequency is changed, proposed PQD classification algorithm is seen in Fig. 11.

Classification performance results are given in Table 6. for the case of PQD with variable frequency around 50 Hz and pure sine with constant frequency at 50 Hz. According to results which are given in Table 6., average performance is %76.11. Especially it is seen that classification performance of voltage with harmonics, transients and pure sine is low.

Classification performance results by using proposed method in this study is given in Table 7. In this case average performance is %91.12. Same generated data are used to get the results which are given in Table 6. and Table 7. By this way a healthy comparison is performed in this study.

Table 6. In case of when frequencies of PQD signals change, frequency of pure sine is not updated and stays constant to 50 Hz

Class	S1	S2	S3	S4	S5	S6	Accuracy(%)
S1	81	0	0	0	4	6	89.01
S2	0	104	0	0	26	0	80
S3	0	12	148	0	35	0	75.89
S4	1	0	0	58	44	0	56.31
S5	0	2	0	0	127	2	96.94
S6	0	0	0	0	17	24	58.53
Average Performance (%)			76.11				

Table 7. In case of when frequencies of PQD signals change, frequency of pure sine is updated with frequency of PQD

Class	S1	S2	S3	S4	S5	S6	Accuracy(%)
S1	82	0	0	0	0	8	91.11
S2	0	120	0	0	0	10	92.3
S3	0	0	184	0	11	0	94.35
S4	0	0	0	86	0	17	83.495
S5	0	1	0	0	112	18	85.49
S6	0	0	0	0	0	100	100
Average Performance (%)			91.12				

9. Conclusion

In this paper, firstly it is tried to classify pure sine and PQD such as voltage sag, voltage swell, voltage with harmonics, transients and flicker at power system frequency. Before classification stage, data is normalized then five PQD and pure sine are decomposed by using 12 levels Daubechies-4 discrete wavelet filter and energy distributions of detail coefficients of PQD and pure sine are obtained. Pure sine is taken as a reference. When looking at variations in feature vector for PQD signals and pure sine, it is seen they are distinguished as visual and also data size is reduced. After obtaining feature vector, powerful classifier SVM is used in classification stage. % 97.905 average performance is obtained.

In literature it is seen to use energy distribution features based on WT as feature vector but when frequencies of PQD are changed, performance of method is not investigated. For this reason performance of method is examined by changing frequencies of PQD in this study. When signals are created, frequencies of signals are assumed to vary between 49.8-50.2 Hz. Therefore, firstly frequencies of signals must be measured. In this study, proposed method uses curve fitting approach for estimating frequency and this method needs only six samples of voltage signals [47]. Then frequency of pure sine is updated with frequency of PQD and then enters the classifier.

Two conditions are discussed in this paper. The first of these conditions is when frequencies of PQD signals change, frequency of pure sine as a reference remains stable at 50 Hz. The second one is when frequencies of PQD signals change, frequency of pure sine is updated with frequencies of PQD. Table 6. and Table 7. are drawn in order to compare between two conditions. To perform healthy comparison, data used in Table 6. and Table 7. Are taken same. Classification performance of voltage sag is %91.11 by using proposed method in this study but if pure sine is fixed to 50 Hz, classification performance decreases to %89.01. Classification performance of voltage swell rises to %92.3 with this method but according to Table 6. this performance is %80. In Table 7. it is seen that while classification performance of voltage with harmonics is %94.35 but in Table 6. it is seen that classification performance of this disturbance is %75.89. It is observed that while classification performance of transient is %83.495 but in Table 6. it is seen that this performance is %56.31. Classification performance is %85.49 for flicker but in Table 6. classification performance is %96.94. Also in this study proposed method distinguishes pure sine with %100 classification performance but it is seen that in Table 6. pure sine is distinguished with % 58.53 classification performance. Also while average performance is %76.11 in first condition but average performance is %91.12 in second condition.

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***Authors**: Dr. Çağrı Arıkan, Yıldız Technical University, Vocational School, Department of Electronics Technology, İstanbul/Turkey, E-mail: carikan@yildiz.edu.tr, Dr. Muammer Özdemir, Ondokuz Mayıs University, Department of Electrical and Electronics Engineering, Samsun/Turkey, E-mail: ozdemirm@omu.edu.tr*