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An Efficient DWT and EWT Feature Extraction Methods for Classification of Real Data PQ Disturbances

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Abstract

Determination and investigation of incidents affecting Power Quality (PQ) is very important for consumers. In this study, estimation of PQ events is obtained to determine the disturbances of PQ by using Empirical Wavelet Transform (EWT) and Discrete Wavelet Transform (DWT) methods and with this estimated parameter. PQ disturbances were examined with Support Vector Machine (SVM), Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) classification methods. Voltage signals (sag, swell, interruption, transient and normal) used in the classification of PQ disturbances were recorded from grid with the aid of a microcontroller based on device designed with a sampling frequency of 6.4 kHz. Classification consequences using Machine Learning Methods show that DWT outperforms over EWT for feature extraction processing and the classification accuracy is tabled. Classification by ANN and ANFIS through the use of conjecture parameters in PQ disturbances based on DWT Method has been recommended.

Key Words

Power Quality, Discrete Wavelet Transform, Empirical Wavelet Transform, Support Vector Machine, Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference System”

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1. INTRODUCTION

PQ Disturbances are non-stationary signals. In literature, in line with the standards, different methods are used to form a feature extract so as to locate the disturbances in the power system. These methods are frequently based on the aim of determining the time-frequency distribution through methods like Fourier Transform (FT), Short-Term Fourier Transform (STFT), S-Transform (ST), Wavelet Transform (WT), Hilbert Huang Transform (HHT) and Gabor Transform (GT). And they also depend on extracting determinant features representing the original sign through energy, entropy and various statistical processes and decreasing the data size.

FT is usually used in specifying the harmonic components in the signal. A window function is used in methods employing STFT, however STFT requires great amount of calculations (Kanirajan & Suresh, 2015). ST is a time-frequency analysis method like STFT and WT. In this method, a frequency domain to change the position of a special window function in the form of a Gaussian is being analysed (Stockwell et al., 2007). WT is used in non-stationary signals and it gives good results, but the performance of management decreases in signals with noise.

HHT has a wide usage in analysis of nonlinear and non-stationary signals. It consists of two main parts: EMD and HT (Zhan et al., 2012). EMD is separated into different frequency components called Intrinsic Mode Function (IMF). Having been separated into components by EMD, these signals can be analysed for their frequency, magnitude and phase's magnitude via Hilbert Transform (Huang et al., 1998). Lifting Based Wavelet Transform (LBWT) used PQ disturbances in the time domain analysis. LBWT method can analyze faster than WT method. (Yilmaz et al., 2007). GT is a developed function of STFT method. It is stated as the time-frequency analysis by getting the FT of the Window Function formed with a time variable to be selected as an entrance signal. GT, is a special form of the STFT that uses the Gaussian Window Function (Cho et al., 2010).

Teager Energy Operator (TEO) is used to analyse and detect the voltage disturbances. TEO-threshold algorithm is to calculate the sudden changes in the signal and therefore determine to PQ disturbances (Subasi et al., 2011).

ANN Systems are used as an effective method in classification problems for PQ disturbances (Gaouda et al., 1999). ANN is used in classification architecture based on complex feature parameters like frequency components, and waveform (Uyar et al., 2008).

As the literature is examined, PQ determination and classification are usually performed in laboratories or by means of computer programs. Data obtained in this way are usually pure and straighter than the real ones. The data used in this study, has been obtained from a real grid with the help of an active circuit having a microcontroller by recording it on an SD card.

In this study, determination for six different classes of PQ disturbances normal signal, sag, swell, transient, interruption and harmonic is fulfilled using real-data. This paper considers the classification of PQ disturbances based on feature extraction DWT and EWT using SVM, ANN and ANFIS.

2. DISCRETE WAVELET TRANSFORM (DWT)

WT is a time-frequency transform method which has recently been also used for analysis and assessment of PQ disturbances (Uyar et al., 2011). WT, as it is in FT, is used for the analysis of stationary and non-stationary signals (Santoso et al., 1996). The greatest feature of WT that separates it from FT is that while only frequency information is acquired in FT, but for the WT, the acquired data consist of sign, frequency and time information (Uyar et al., 2011). Therefore, analysis of systems whose frequency changes over time and their transient analysis can be done sensitively. One of the important properties of WT is that it has wide window width for low-frequencies while having narrow width for high-frequencies. Thus, it is possible to provide the optimum time-frequency resolution on over all frequency ranges (Daubechies, 1990).

WT is examined in two ways namely, continuous WT and DWT. Since Continuous Wavelet Transform (CWT) uses all scales in calculations and it gives many details about the signal calculation of coefficients of wavelets becomes difficult and time-consuming. In DWT, wavelet coefficients are calculated only for discrete time scales rather than all time scales. And thus, analysis can be done in shorter time and more easily. Therefore, DWT is used more often (Bayhan & Yilmaz, 2009).

For a given *f(t)* signal, *K* level DWT, with both wavelet and scaling function, can be defined as (Uyar et al., 2011).

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

Where a_J, is the *J*th scaling coefficient, d_j, *is j*th wavelet coefficient, $\phi(t)$ is scaling function, $\Psi(t)$ *is* wavelet function, *J* represents the highest level of WT and *t* represents time. Scaling function and wavelet function are used to separate the sign in different resolution levels in multi-resolution decomposition. Wavelet function detail coefficients are a_j and scaling function approach coefficients are d_j for the separated signal with WT.

$$a_{j+1}(n)=\sum_{k} h(m-2n)a_j(n) \tag{2}$$

$$d_{j+1}(n)=\sum_{m} g(m-2n)a_j(n) \tag{3}$$

where h denotes coefficients of the low pass filter and g denotes the coefficients of the high pass filter (Sebestian & DSa, 2015).

2.1. PARSEVAL'S THEOREM IN DWT APPLICATION

According to Perseval's Theorem, when the current running over a resistance of 1Ω is considered to be a discrete *f(n)* signal, energy wasted on the resistance in the frequency region equals to the sum of the squares of the spectrum coefficients of FT.

$$\frac{1}{N}\sum_{n}|f(n)|^2=\sum_{k}|c_k|^2 \tag{4}$$

Where, N is the number of samples and c_k denotes the spectrum coefficients of FT. To apply Perseval's Theorem to DWT method, we can obtain the following equation by utilising equation (1) and (4).

$$\frac{1}{N}\sum_{t}|f(t)|^2=\frac{1}{N_J}\sum_{k}|a_J(k)|^2+\sum_{j=1}^{J}\left(\frac{1}{N}\sum_{k}|d_j(k)|^2\right) \tag{5}$$

Therefore, energy of the disturbed signal can be obtained by equation (5) where the first term on the right represents the approximate level of the discrete signal, while the second term states the detail level of the discrete signal this will be used in feature extraction process of the PQ disturbance (Gaing, 2004).

3. EMPRICAL WAVELET TRANSFORM (EWT)

EWT proposed by Jerome Gilles (Gilles, 2013). This method is a time frequency technique to decompose based on information content of the signal using the adaptive wavelet. EWT first detect local maxima of the Fourier spectrum of the signal, then sections the spectrum based on the detected maxima, and lastly generates a corresponding wavelet filter bank. This method works in the fallowing three steps,

1. Determine the frequency components of the applied signal using FFT.
2. The different modes are extracted by obtaining proper segmentation of the Fourier spectrum.
3. Apply scaling and wavelet functions corresponding to each detected segment. Segmentation of the Fourier spectrum is the most important step that provides the adaptability to this technique according to the analysed signal.

The empirical wavelets are defined as band pass filters. Littlewood-Paley and Mayer's wavelets are used as a band pass filters with the empirical wavelets Ψ(w), and the empirical scaling function ϕ(w) can be expressed as follow (Gilles, 2013),

$$\psi_n(w)=\begin{cases}1 & if \quad (1+\gamma)\Omega_n\le|w|\le(1-\gamma)\Omega_{n+1}\\ \cos\left[\frac{\pi}{2}\beta(\gamma,\Omega_{n+1})\right] & if \quad (1-\gamma)\Omega_{n+1}\le|w|\le(1+\gamma)\Omega_{n+1}\\ \sin\left[\frac{\pi}{2}\beta(\gamma,\Omega_n)\right] & if \quad (1-\gamma)\Omega_n\le|w|\le(1+\gamma)\Omega_n\\ 0 & if \quad otherwise\end{cases} \tag{6}$$

and,

$$\phi_1(w)=\begin{cases}1 & if \quad |w|\le(1-\gamma)\Omega_1\\ \cos\left[\frac{\pi}{2}\beta(\gamma,\Omega_1)\right] & if \quad (1-\gamma)\Omega_1\le|w|\le(1+\gamma)\Omega_1\\ 0 & if \quad otherwise\end{cases} \tag{7}$$

The function $\beta(x)$ is an arbitrary $C^k[(0,1)]$ function defined as

$$\beta(x)=\begin{cases}1 & if \quad x\geq 1\\ 0 & if \quad x\leq 0\\ \beta(x)+\beta(1-x)=1 & if \quad \forall x\in[0,1]\end{cases} \tag{8}$$

where $x=\frac{1}{2\gamma\Omega_n}\left(|\Omega|-(1-\gamma)\Omega_n\right)$, where, γ is a parameter to ensure no overlap between two consecutive transition areas

Many functions satisfy these properties, the wide used in the literature is

$$\beta(x)=x^4\left(35-84x+70x^2-20x^3\right) \tag{9}$$

The EWT can be defined for the classic wavelet transform. The detailed coefficients are obtained by the inner product with the empirical scaling function as given below

$$W_x(n,t)=x(t),\psi_n=IFFT\ \ (X(w)\times\psi_n(w)) \tag{10}$$

The approximation coefficients are obtained by the inner product with the scaling function as given below,

$$W_x(1,t)=x(t),\phi_1=IFFT\ \ (X(w)\times\phi_1(w)) \tag{11}$$

Where *X(w)* represents the FFT of the *x(t)* signal.

4. MACHINE LEARNING TOOLS

4.1. Support Vector Machine (SVM)

For data classification and regression issues, SVM is a very efficient method. SVM can be used in many data regression and recognition issues and can be used to the issues of dependency forecasting and estimation of data and building intelligent machines (Xiong et al., 2015).

SVM can prevent the problems of misperception of dimension, local minimum and over learning in the classical technique. Furthermore, it is successfully used in most of the classification issues (Xiong(2) et al., 2015). SVM is used for statistical learning method for the classification of patterns which is based on structural risk minimization technique.

Compared to the other classical techniques, SVM provides better performance like ANN and Bayesian classifier. In addition, for PQ disturbances classification, SVM is an appropriate method (Ray & Kishor, 2014).

According to the training data $(x_1,y_1),\dots,(x_l,y_l)$, $x\in R^M$, $y_i\in\{-1,+1\}$ for two class issue, the decision function of, $\operatorname{sgn}\left(\left(w^T x_i\right)+w_0\right)$ construct by SVM with the maximum margin, in which w_0 represent bias term and w represents vector of the separating hyperplane. 1/‖w‖ formula is the calculation of the distance of the point nearest to the hyperplanes -1 and +1. 2/‖w‖ is the definition of the separating margin (Fig.1) (Naderian & Salemnia, 2015).

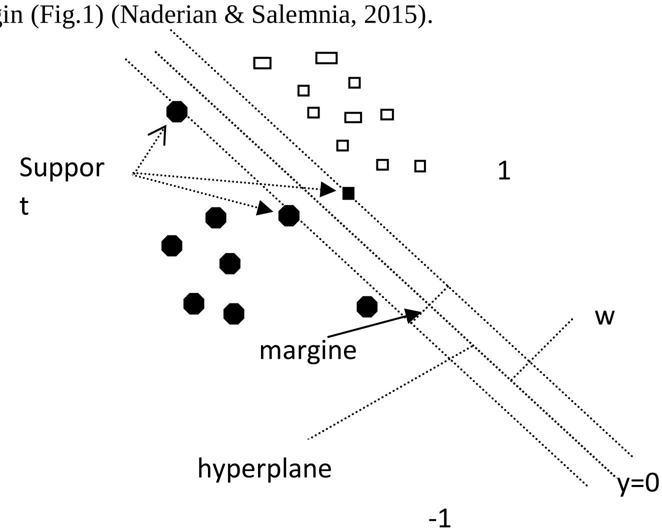


Figure 1. SVM Classification

Besides the linear classification, by using kernel function, SVM can be used in nonlinear classification as well. The nonlinear classification function φ is used for mapping the data x into a high dimensional feature space, in which the linear classification is possible. Thus, the nonlinear function is;

$$f(x) = \mathrm{sgn}\left(\sum_{ij=1}^{m} \alpha_i y_i K(x_i, x_j) + b\right) \tag{12}$$

In which $K(x_i, x_j)$ represent the kernel function $K(x_i, x_j) = \phi(x_i)\ \phi(x_j)$. The functions below are the mostly used kernel function;

a. Linear
b. Sigmoid
c. Polynomial
d. Gaussian Radial Basis Function

Nowadays, for selecting the most suitable kernel function and for setting the kernel function, there is no proper method appropriate for deciding the value of error penalty. Since the most suitable setting of the SVM parameter affects the detection accuracy directly, the proper kernel function and other parameters can be got by using ant colony optimization algorithm (Abdoos et al., 2016).

The PQ disturbances classification is succeed by using of a kernel function like Gaussian Radial Basis function (Naderian & Salemnia, 2015).

4.2. Artificial Neural Network (ANN)

ANNs are information processing units developed by paying attention to the biologic neural system. The most important feature of it is that it can learn from experiences. ANNs have been developed for the aim of automatically fulfilling the abilities of human brain like deriving and forming new information and discovering by means of learning (Hamdy et al., 2013). A neural network is made up of connected cells in layers and the networks connecting these layers (Fig.2).

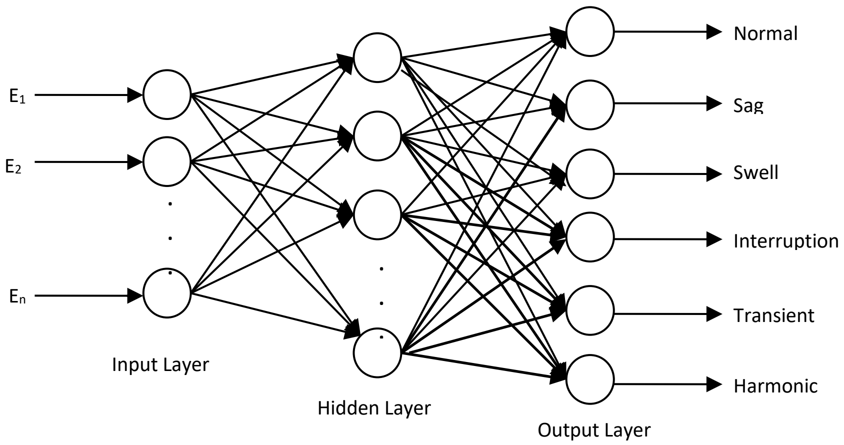


Figure 2. ANN classifier structure.

4.3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is to unify the Fuzzy System(FS) and NN. Offered by S. R. Jang,1993 (Jang, 1993). ANFIS is a hybrid system combination the learning capabilities of NN and inference abilities of fuzzy logic that have the capability to self modify their membership function to achieve a required performance (Lin & Lee, 1991). ANFIS implements a Takagi-Sugeno type learning algorithm, the least squares method and backpropagation algorithm are used together. Sugeno type learning consists of two steps. First step, input values are generated and appropriate result parameters are accepted by least squares method. In the second step, the backpropagation algorithm is used. The parameters are regenerated and the parameters except for the result parameters are replaced. Takagi-Sugeno-type input layer, fuzzification layer, pre-rule layer is the same as Mamdani type. The rules are normalized on the fourth layer. The fifth layer is the function layer, and finally the values from the other nodes in the sixth layer are summed and the output value is calculated (Sumathi & Surekha, 2010)

Figure 3 find out the architecture of the ANFIS of nine for DWT and eleven for EWT inputs and one output.

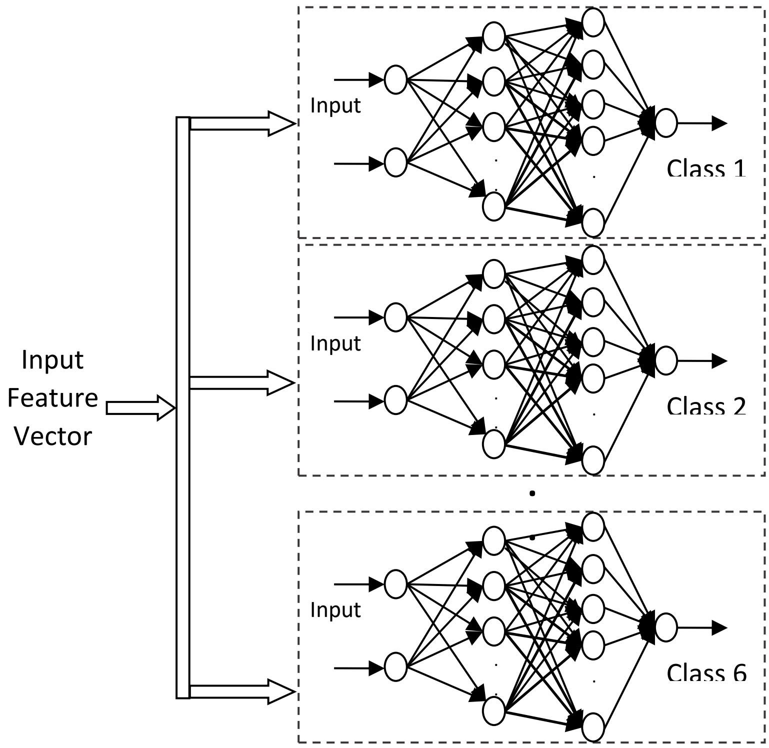


Figure 3. ANFIS classifier structure.

5. FEATURE EXTRACTION AND CLASSIFICATION

5.1. Data Set

This study differs from other studies that data is not produced by computer. Data used in PQ disturbances' Classification were recorded by directly measuring at different companies and at different times. Voltage values have been measured by a grid voltage monitoring device developed on a microcontroller base, and then they were recorded on an SD card. Recorded voltage values have been obtained at a 6,4kHz sampling frequency. Signal has been recorded on to the memory stick so as to include all PQ disturbances in periods of 10. Statistical analyses were carried out with total 1280 data, with 128 data in each of 10 periods.

5.1. FEATURE EXTRACTION

Each Coefficient of WT can be separated from their own energy levels and their frequency period. Ranges of frequency bands in High-Resolution WT Decomposition are given in Table 1.

Decomposition Levels	Frequency Range (Hz)
d1	3200-1600
d2	1600-800
d3	800-400
d4	400-200
d5	200-100
d6	100-50
d7	50-25
d8	25-12,5
d9	12,5-6,25
a9	12,5-6,25

Table 1. Ranges of frequency bands in High-Resolution Decomposition.

WT coefficients can be used to relate the energies obtained by using Perseval's Theorem to every PQ disturbances in voltage signals.

In this study, Haar Function is chosen as the wavelet function. Wavelet Haar made it possible to have less work load and faster analyses. Coefficients for nine levels have been acquired by using WT with Haar Function. Energy levels are obtained through WT Coefficients and Perseval's Theorem.

PQ bozulmaları yüksek freakans içerdiğinden, EWT yönteminde, giriş fonksiyonu üç IMF bileşenine ayrılmıştır. IMF sinyallerinin variance, mean, median, kurtosis ve rms istatistiksel parametreleri hesaplanarak özellik vektörü elde edilmiştir.
In the EWT method, the input function is decomposed into three IMF components, since PQ impairments contain high freakans. The feature vector is obtained by calculating the variance, mean, median, kurtosis and rms statistical parameters of the IMF signals.

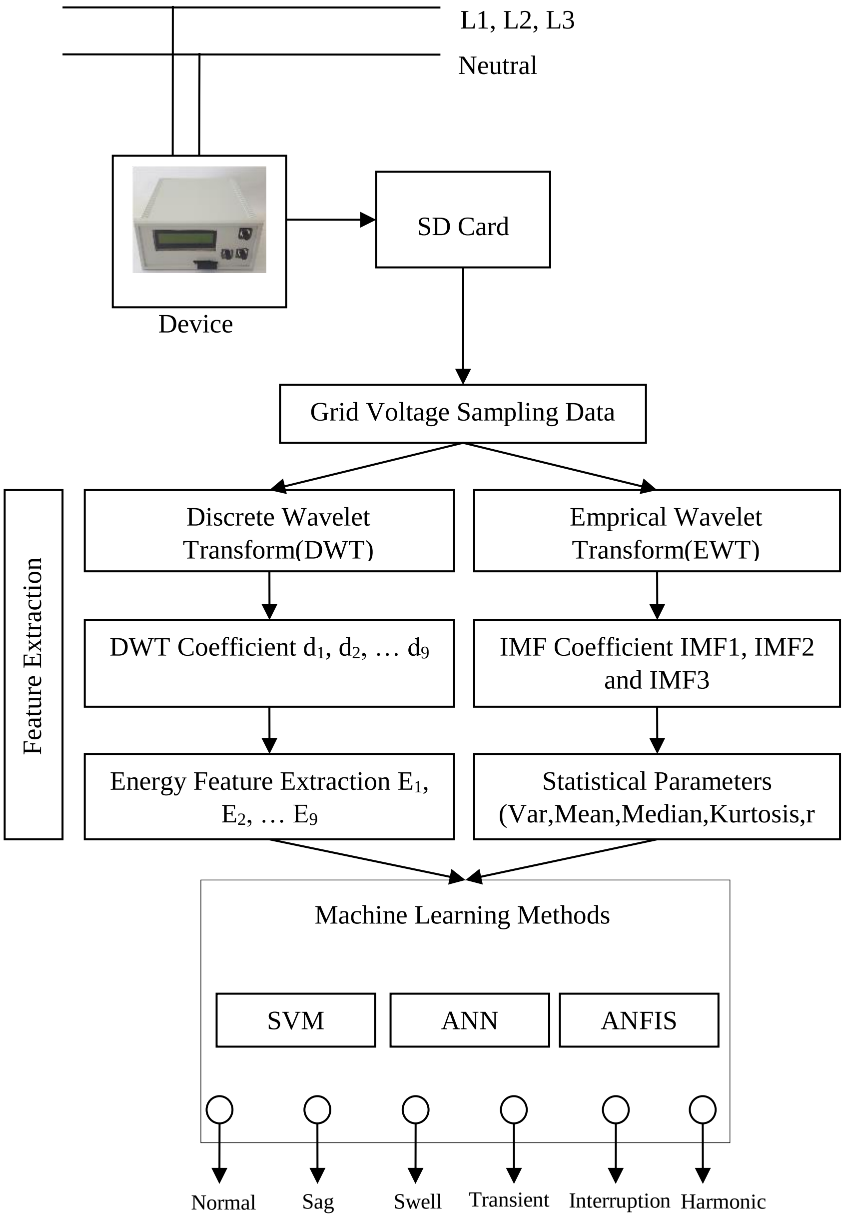


Figure 4. Proposed methodology for the classification of PQ disturbances.

5.2. CLASSIFICATION

PQ disturbance classifications have been applied by using MATLAB Statistical Pattern Recognition Toolbox (Eristi et al., 2010). When the SVM classification method is trained, independent parameters regularise kernel function parameters σ and constant *C* conclude by user. A known method adjustment parameters is to use cross-validation to choose the best parameters from a pre-chosen set (Ekici, 2009). It is shown that SVM gives better outputs, after cross-validation test when the values of σ and *C* are chosen as bigger than respectively to be 0.8 and 100. For this reason, the optimum values are selected as σ = 1 and *C* = 1000 which gives the best outputs. Radial Bases Function (RBF) are selected for kernel function (Ekici, 2009).

In the ANN classification method, nine energy levels calculated by the Parseval Theorem using the DWT coefficients and fifteen parametres of EWT's statistical analysis have been taken as input. A hidden layer with 11 neurons has been used. Output layer has six neurons because of six different PQ disturbances. Classification algorithm that has been developed is shown in Figure 4.

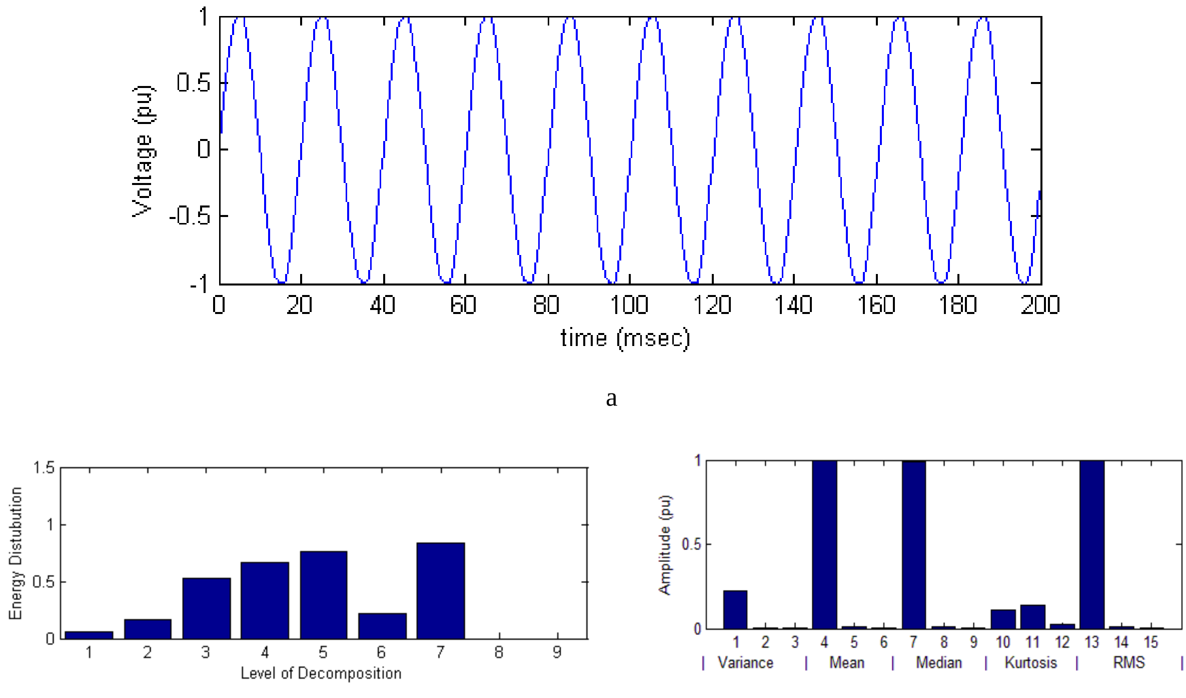
Sugeno type fuzzy model was used for the ANFIS classification method. First, the most suitable parameters are calculated using the least squares method. These parameters were improved by the backward algorithm and the best result parameters were obtained. As shown in Figure 3, the ANFIS architecture used nine inputs for the input vector DWT and fifteen inputs for the EWT. Output layer was classified separately for each PQ disturbances.

In the ANFIS classification method, least square methods and combination of backpropagation are used adjustment the parameters of the membership functions verification the Sugeno type fuzzy system to best follow the given input – output data. Output levels have been determined as six levels PQ disturbances.

6. RESULTS

In this study, two different feature extraction methods (DWT and EWT) have been used. Firstly, With the EWT feature extraction method, three higher IMF components have been calculated. The feature vectors have been obtained by using statistical parameters (Variance, Mean, Median, Kurtosis and rms) in IMF signals. Secondly, the commonly used haar function in the DWT method was chosen. Wavelet Haar made it possible to have less work load and faster analyses. Coefficients for nine levels have been calculated by using Wavelet Transform with Haar Function. Energy levels have been obtained through Perseval's Theorem. These feature vectors have been classified as PQ disturbances using SVM, ANN and ANFIS methods.
In the obtained data, while the x-axis shows time, y-axis is voltage amplitude over per unit. The samples have been recorded for 10 periods of 200 milliseconds with the developed grid monitoring device. Real time PQ disturbances, DWT - Energy levels feature vector and EWT - statistical parametrics feature vector graphs are plotted with the MATLAB software

6.1. NORMAL SIGNAL



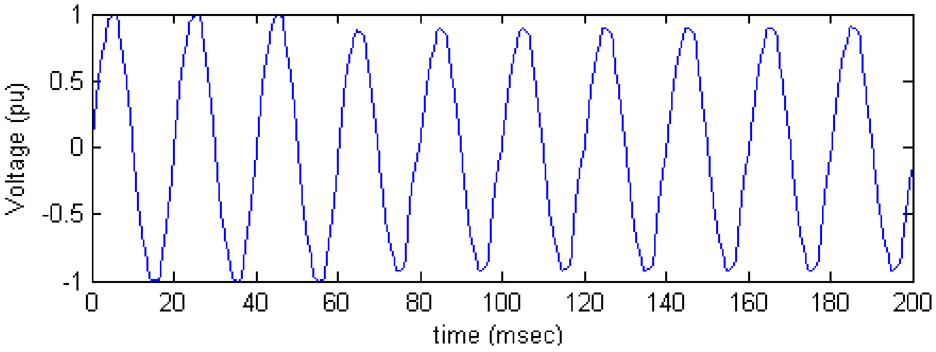
a

b c

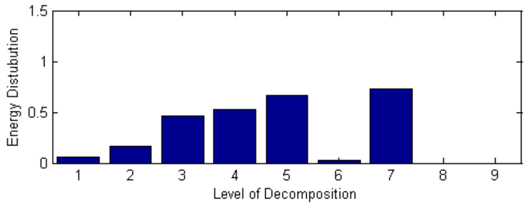
Figure 5. a. Normal signal waveform, b. Energy Distribution for 9 decomposition levels for normal, c. The statistical parameters of EWT.

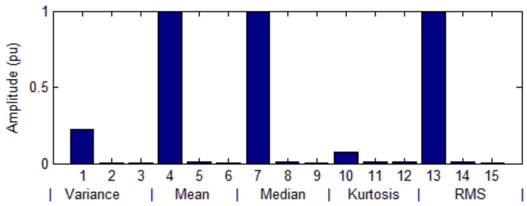
In Figure 5a, normal signals and energy decomposition for normal signals when no PQ disturbances occurrance can be seen. Figure 5b shows the DWT energy levels for the normal signal and Figure 5c shows the distribution of the EWT statistical parameters for the normal signal. Normal signals have been classified as a reference to other PQ disturbances.

6.2. SAG SIGNAL



a



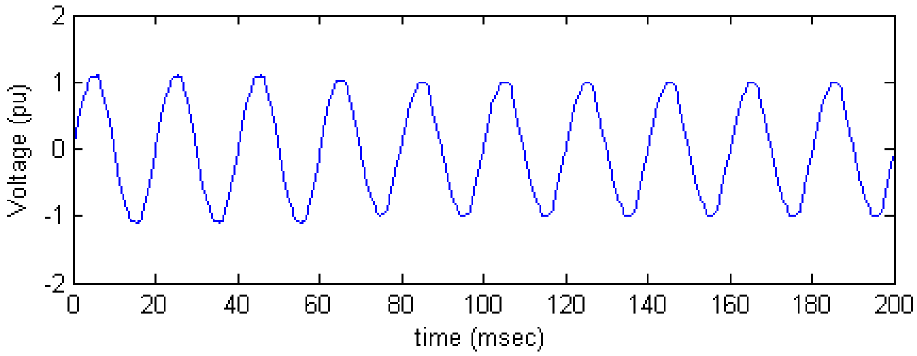


b c

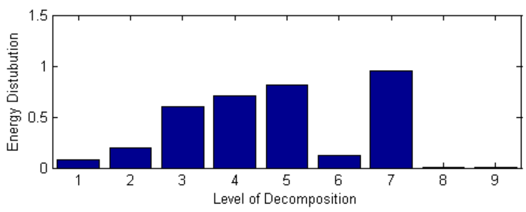
Figure 6. a. Sag signal waveform, b. Energy Distribution for 9 decomposition levels for sag, c. The statistical parameters of EWT.

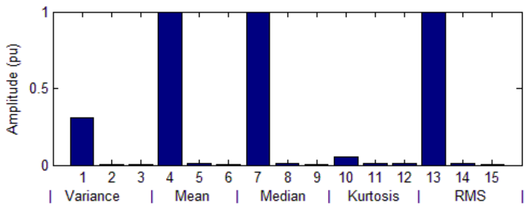
Sag is referred to as short time changes in Power systems where the voltage range is between 10 milliseconds and 1 minute. As a result of a 10% decrease in the amplitude of the voltage a sag occurs (Fig 6a). As a consequence of the the sag in the grid, it is seen that a decrease takes place in P3, P4, P5 ve P7 energy levels when they are compared to the normal levels (Fig. 6b). Variance and Kurtosis statistical methods show that sag disturbance accordance with the normal signals are different levels (Fig.6c).

6.3. SWELL SIGNAL



a



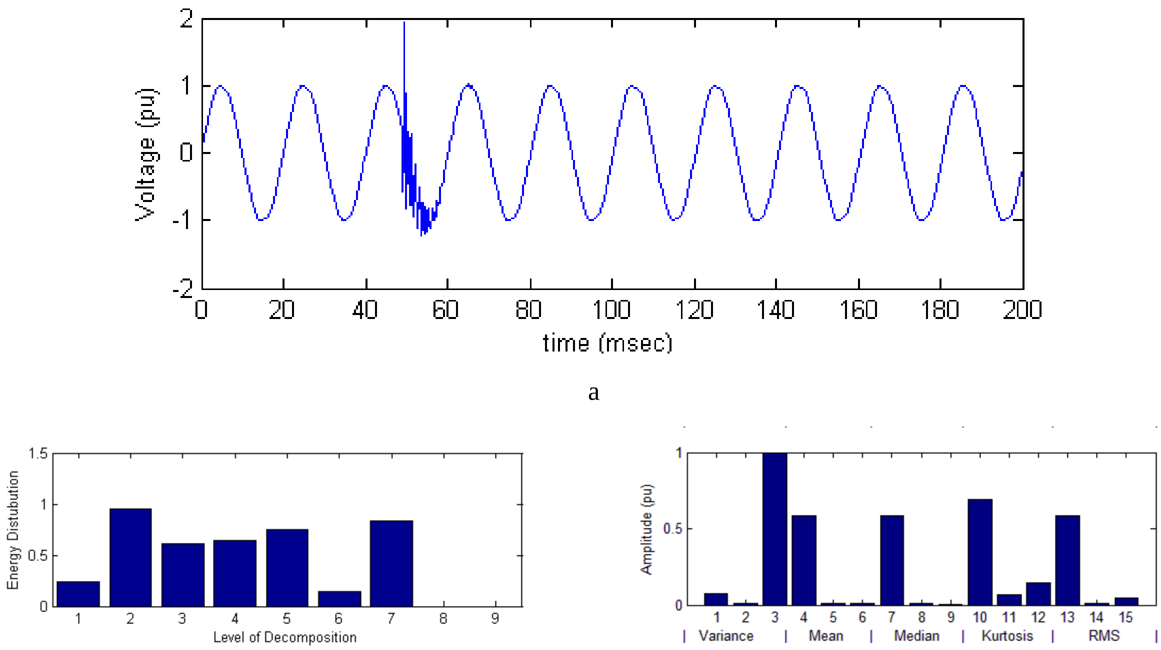


b c

Figure 7. a. Swell signal waveform, b, Energy Distribution for 9 decomposition levels for swell, c. The statistical parameters of EWT.

The SWELL event takes place at a voltage magnitude of 10 milliseconds to 1 minute, with a short 10% increase in the amplitude of the signals(Fig. 7a). As a result of the the swell in the grid, it was seen that increases took place in P3, P4, P5 ve P7 energy levels (Fig 7b). Variance and Kurtosis statistical methods show that transient disturbance accordance with the normal signals have different levels(Fig 7c).

6.4. TRANSIENT SIGNAL



a

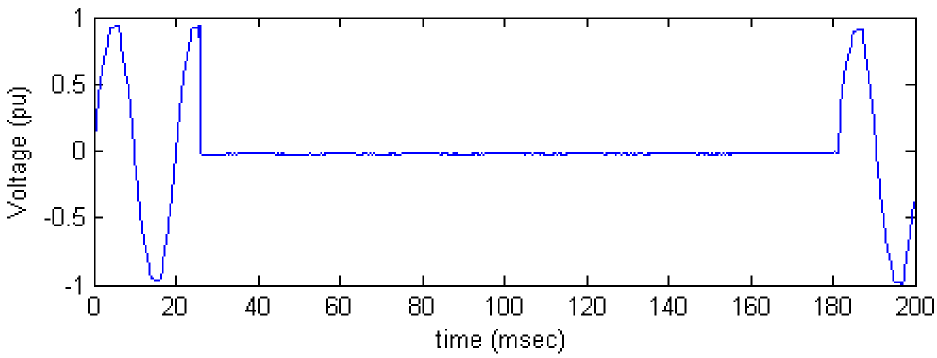
b

c

Figure 8. a. Transient signal waveform, b. Energy Distribution for 9 decomposition levels for transient, c. The statistical parameters of EWT.

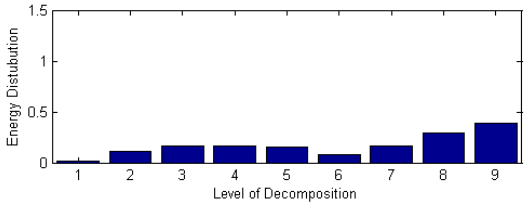
Temporary disturbances like beats can last from 50 nanosecond to 1 millisecond, and they can reach sudden high volltage values (Fig. 8a). Transient, especially occuring in condensator switching and harmonic disturbances. Transient disturbances show a large change in the energy levels P2, P3, P4, P5 and P7 shown in Figure 8b. It is seen in Figure 8b that especially P2 energy rises to high values. Variance, Mean, Median, Kurtosis, and rms statistical methods show that transient disturbance accordance with the normal signals are different levels. Especially L3,L4,L7,L10,L11,L12 and L13 statistical parameters are different values (Fig. 8c).

6.5. INTERRUPTION SIGNAL

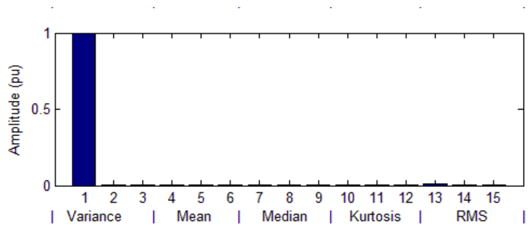


A

Figure 9. a. Interruption signal waveform, b. Energy Distribution for 9 decomposition levels for interruption, c. The statistical parameters of EWT.



b

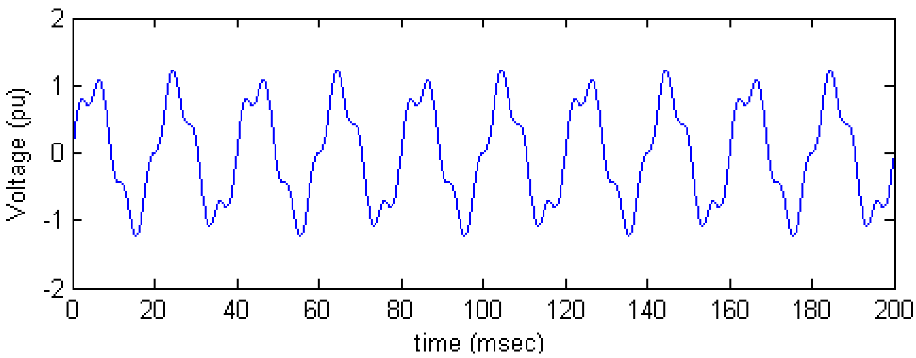


c

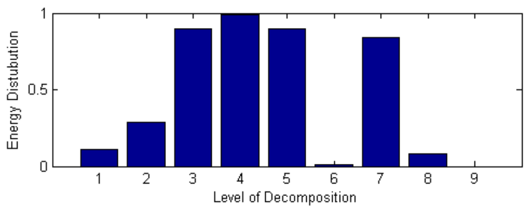
Figure 9.(cont.) a. Interruption signal waveform, b. Energy Distribution for 9 decomposition levels for interruption, c. The statistical parameters of EWT.

Interruption can occur because of power system failures and as a result of malfunctioning of control systems. These interruptions can last from 0,5 period to 1 minute (Fig. 9a). As a result of interruption happening at the grid, values of energy distribution has greatly decreased. Especially L1 variance istatistical parameter different level of normal signal's level (Fig. 9b, 9c).

6.6. HARMONIC SIGNAL



a



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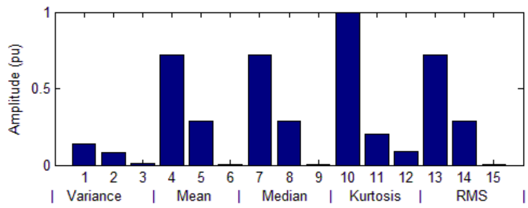

c

Figure 10. a. Harmonic signal waveform, b. Energy Distribution for 9 decomposition levels for harmonic, c. The statistical parameters of EWT.

Harmonics is a destructive effect taking place as an over and over compound of sinusoidal voltage and again has a sinusoidal form. Semi-conductor components can be ranked as one of the most important reasons. Since harmonic PQ disturbances rarely happens on grid voltages, data belonging to these PQ disturbances have been produced by MATLAB (Figure 10a). Analyses has been conducted by producing harmonic signals with changing THD values between 8 and 15. The DWT analyzes showed that the resulting energy levels P3, P4, P5, P7 and P8 differed from the normal signals. (Fig.10b). Variance, Mean, Median, Kurtosis, and rms statistical methods show that harmonic disturbance accordance with the normal signals are different levels. Especially L1,L4,L5,L7,L8,L10,L11,L13 and L14 statistical parameters are different values from normal signal's statistical parameters (Fig. 10c).

Each PQ disturbance have been analysed with nine Level DWT and fiveteen level statistical parametrs of EWT. Six different PQ disturbances, and the frequencies of the acquired results and their amplitudes were all examined according to IEEE standards (IEEE, 1995).

Results obtained through classification method are seen in Table 2 and Table 3. Totally 150 data sets were used for training. 70 data sets were used for testing.

Table 2. Performance Evaluation of different Machine Learning Methods using DWT.

Disturbance	SVM			ANN			ANFIS		
	Total	Correctly Classified	Accuracy (%)	Total	Correctly Classified	Accuracy (%)	Total	Correctly Classified	Accuracy (%)
Normal	20	19	95	20	20	100	20	20	100
Sag	10	10	100	10	10	100	10	10	100
Swell	10	9	90	10	10	100	10	10	100
Transient	10	10	100	10	10	100	10	10	100
Interruption	10	10	100	10	10	100	10	10	100
Harmonic	10	10	100	10	10	100	10	□□	100
Overall Accuracy (%)	97,50			100			100		

Table 3. Performance Evaluation of different Machine Learning Methods using EWT.

Disturbance	SVM			ANN			ANFIS		
	Total	Correctly Classified	Accuracy (%)	Total	Correctly Classified	Accuracy (%)	Total	Correctly Classified	Accuracy (%)
Normal	20	20	100	20	19	95	20	20	100
Sag	10	10	100	10	10	100	10	10	100
Swell	10	9	90	10	10	100	10	9	90
Transient	10	10	100	10	10	100	10	9	90
Interruption	10	10	100	10	10	100	10	9	90
Harmonic	10	10	100	10	10	100	10	□□	100
Overall Accuracy (%)	98,33			99,16			95		

7. CONCLUSION

In this study; two different feature vectors were obtained and classification was done to determine and evaluate the disturbances of PQ. The energy distributions of the coefficients obtained by the DWT method are determined and the first feature vector is calculated. The second feature vector was obtained by calculating the statistical parameters of the IMF components obtained by the EWT method. Although the size of the feature vector obtained by the DWT method is small, it is seen that the ability to distinguish the PQ disturbances signals is quite high. This shows that the feature extraction algorithm is based on reliable basis. In addition, if the feature vector is small in size, it seems that the classifier will reduce the complexity and hence the processing time.

It is seen that DWT - ANN and DWT - ANFIS methods are effective and determinative in classification analysis using real data.

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