Electric Power Components and Systems, 32:407–420, 2004

ISSN: 1532-5008 print/1532-5016 online
DOI: 10.1080/15325000490217443

An Improved Method for Classifying Power Quality Disturbances

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An adaptive neuro-fuzzy inference classifier based on the discrete wavelet transform (DWT) to recognize the type of power quality (PQ) disturbances is presented. The DWT, using the multi-resolution signal decomposition (MSD), can transfer power disturbance characteristics into the time-frequency domain. The energy of the signal decomposed to frequency sub-bands can be used to extract feature parameters for classifying various disturbances. The proposed classifier was designed using four feature parameters that consist of energy concentration level and its mean value, mean energy of the signal, and an auxiliary parameter determined by the rms value and pulse detection. The proposed classifier shows good recognizing efficiency for ten types of PQ events, including one double event disturbance.

Keywords power quality classifier, discrete wavelet transform, signal energy, adaptive neuro-fuzzy inference system

I. Introduction

Power disturbances such as impulses, notches, voltage sags and swells, interruptions, flickers, or harmonic distortion may lead to mal-operation or failure of any sensitive electric facility such as computer-based processes or automatic systems. Power quality (PQ) has become an increasing concern to facility manufacturers, customers, and power utility companies for the past decade [1, 2]. The ultimate goal to deal with PQ issues is to find a proper characteristic from PQ events and to provide a suitable solution to both utilities and users. In order to solve PQ problems, sources and causes related to power disturbances should be specified a priori before any action could be taken. This process includes monitoring power disturbances, analyzing

Manuscript received in final form on 17 January 2003.
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their characteristics, and determining solutions to overcome those problems. Such actions contain detecting, localizing, and classifying different disturbances.

As a general tool for monitoring and analyzing PQ events, the wavelet transform (WT) analysis has been used extensively [3, 4]. Most of the techniques have shown good efficiency in dealing with various power disturbances in both time and frequency domains. In particular, the discrete wavelet transform (DWT) technique, with multi-resolution signal decomposition (MSD), provides some information to detect and localize power disturbances by means of using time-frequency domain [4–6].

In addition to detecting and localizing power disturbances, it is also very important for utilities and customers to classify them by type. There are, however, various difficulties to overcome due to diversities of power disturbances; these come from broad definitions or ambiguous measures for PQ disturbances, so that most approaches cannot provide a common solution to power utility companies, customers, or facility manufacturers. To utilize a reliable classifier, it is essential to choose a feature vector that can indicate and recognize the main characteristics of power disturbances.

Most disturbances are defined and classified in terms of such parameters as magnitude, duration, frequency components, or waveform shape [7]. Typically, a feature vector can be extracted from various disturbance waveforms; for this purpose the DWT can provide a crucial key. Some researchers have extracted features of PQ disturbances to classify their types through the standard deviation [6, 8], while some others have used all the wavelet coefficients decomposed by the MSD as a feature vector [9, 10]. However, the former did not provide any detailed method to classify PQ types automatically and the latter have given a rather complex structure for forming feature parameters which would take more computational burden.

Decomposition coefficients at each scale offer both time and frequency characteristics of power disturbances. Artificial neural network (ANN) fuzzy systems can provide an effective method to cope with such problems [6, 8, 9]. However, the complexity of the classifier structure may depend upon the choice of the feature parameters as well building the ANN system. In general, DWT coefficients demonstrate the energy of its signal in a finite time. Hence, in this research, an adaptive neuro-fuzzy classifier with a simplified feature vector, which is extracted from the signal energy distribution, is proposed to identify the type of PQ event.

II. Wavelet Application in Power Systems

A. PQ Disturbances

There are various indices describing PQ events [1–3, 7, 11], most of which are usually described using waveform characteristics with regard to monitoring, but do not classify PQ events. As a result, some of the indices may be used ambiguously when classifying PQ events through their features. For instance, a harmonic distortion signal with a short-term duration and rms value of about 1.15 per unit (pu) is clearly a voltage swell with harmonics [7]; however, it may be classified as one type or the other, depending on the designer's objective. So far, there has been no PQ classifier available to assess such a double event. On the other hand, if a harmonic distortion is above 10%, it may be identified as a voltage swell or harmonics, even though it is a single event. Therefore, to avoid confusion in differentiating the two, it is important that disturbance characteristics are suitably described for classification.

Power quality disturbances are mainly classified into two categories; steady-state and transient phenomena. Harmonic distortions, voltage flickers, or periodic notches are defined by their characteristics in the steady-state, whereas disturbances like impulses or oscillatory transients are described as transient phenomena during their short-duration. However, voltage variations such as voltage sag, swell, or outage show performances different from the disturbances mentioned above. Finally, to overcome any difficulty that might occur due to the variability of disturbance definitions, it is inevitable that several disturbances should have their indices modified, or their characteristics suitably defined for classification. In this article, the focus is on designing a classifier to recognize up to ten types of power disturbances, as shown in Table 1 [7]. The classified disturbances are divided into four groups. For the simplicity of notation, the tenth disturbance is represented as Group IV. In Table 1, a_m and t_d denote the rms value and duration, respectively.

Voltage variations (Group I) such as sag, swell, and interruption are restricted to short-term events due to a finite classifying window. Typically, harmonic distortion levels can be characterized by the total harmonic distortion (THD) as a measure of the magnitude of harmonics. This shows an entirely different property from those indices in characterizing voltage variations, which sometimes leads to some difficulties in classifying events such as voltage sags, harmonics, and harmonic sag simultaneously. Therefore, it is assumed that harmonic signal has THD of 20 to 40% and rms value of 0.9 to 1.1 pu.

In classifying disturbances like flickers or DC offsets (Group II), the criteria given in the IEEE Standard 1159 are directly used without modifying [7]. Furthermore, if any disturbance signal, such as oscillatory transient, lasts for a short duration and its magnitude is in the ranges of sag or swell, it is firstly assumed that it belongs to the type of voltage variation. In Table 1, Groups II and III indicate typical PQ events that appear in the steady-state and transient conditions, respectively. Moreover, for nine types (Group I–III), only one event may appear within a finite time domain. In practical cases, PQ events may contain two or more characteristics simultaneously. To classify a double event disturbance, one of the ten types is considered as voltage sag with harmonic distortion (Group IV).

B. DWT Applications

The DWT is one useful mathematical tool to decompose disturbance signals in time domain into several scales at different levels of resolution through dilation and translation [12, 13]. In this case, wavelet transform coefficients reveal the time-localizing information about the variation of the disturbance from high- to low-frequency bands. Typically, those coefficients can be used for both detecting/localizing and classifying PQ events. Non-periodic and high-frequency signals from transient disturbance, i.e., impulse or oscillatory transient, can be easily detected and localized in the time-frequency domain. Consequently, observing the DWT coefficients at each scale can pinpoint exactly the occurrence of a power disturbance.

There are many types of DWT in regard to the choice of mother wavelet functions; however, in practical applications, a dyadic transformation of DWT with multi-resolution is usually used for detecting or classifying PQ events. The wavelet

Table 1
Classified PQ events

No.	Categories		Feature descriptions for classifying
1	Group I: Short-term events	Voltage sag	0.1 pu $< a_m <$ 0.9 pu, 0.5 $< t_d <$ 30 cycle
2		Voltage swell	1.1 pu $< a_m <$ 1.8 pu, 0.5 $< t_d <$ 30 cycle
3		Voltage interruption	$a_m <$ 0.1 pu, 0.5 cycle $< t_d <$ 1 sec
4	Group II: Waveform distortion	Harmonics distortion	20–40% THD, 0.9 pu $< a_m <$ 1.1 pu
5		Flicker	0.1–7%, $f <$ 25 Hz
6		DC offset	0–0.1%
7		Notching	Periodic event
8	Group III: Transient	Impulse	One or two overshoots
9		Oscillatory transient	Not short-term events, high frequency
10	Group IV: Double event	Harmonic sag	0.1 pu $< a_m <$ 0.9 pu, 20–40% harmonics

coefficients of the sampled signals, $x(n)$, decomposed by the L-scale MSD, are defined as,

$$d_j(k) = \sum_{n=1}^{N} x(n)h_j(n - 2^j k) \qquad j = 1, 2, \ldots, L \tag{1}$$

$$c_L(k) = \sum_{n=1}^{N} x(n)g_L(n - 2^L k) \tag{2}$$

where $d_j(k)$ is the detailed coefficients at the jth scale, $c_L(k)$ the approximation coefficients at the last scale, L, h_j and g_L denote the impulse responses followed by filtering in the MSD, and N is the number of sampled data in a finite interval. Since the family of dilated wavelets constitutes an orthogonal basis, it is then possible to exactly reconstruct the original signal from its coefficients, as follows [12],

$$x(n) = \sum_{k} \left(\sum_{j=1}^{L} d_j(k)h_j(n - 2^j k) + c_L(k)g_L(n - 2^L k) \right) \tag{3}$$

Using MSD, the disturbance signal can be partitioned into different resolution levels in the time-frequency domain. This result can provide the ability of localizing transient property in the time domain and dividing the total energy of the signal into different frequency bands. Figure 1 illustrates an example of oscillatory transient signal decomposed into ten scales by using a Daubechies mother wavelet, db4. The

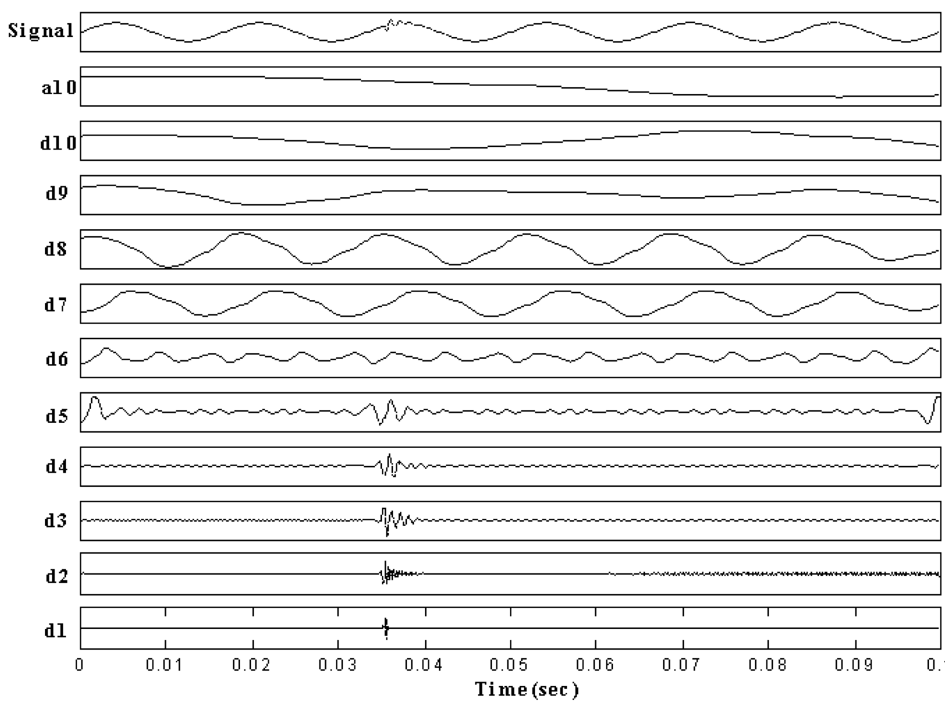


Figure 1. An oscillatory transient.

occurrence of transient event can be detected at the lower scales, $d_1(n)$ to $d_4(n)$. In particular, the first filtered signal, $d_1(n)$, contains the highest frequency components of the signal. This property can be used to detect and localize PQ events such as transients, sharp edges, or jumps in the original power disturbances.

Unlike the oscillatory transient, a harmonic distortion is one of the disturbances defined in the steady-state, Figure 2. Therefore, this event cannot be classified using any variation in the first detail. The main features for such a steady-state signal may appear at the higher scales.

Generally, the detailed signals at lower scales can be used in identifying transient phenomena, but they may not always provide sufficient information to classify PQ events like harmonic distortion or flicker, which belongs in Group II. Therefore, it is required that any distinct characteristics from the disturbances should be found and quantified properly. The signals decomposed by multi-resolution include information such as event occurrence time, frequency properties, and energy distributions. One method to extract a feature vector is to use the energy of the signal because PQ events reflect different distributions at each scale. The mean value of the signal energy for a finite time can be written as,

$$\overline{x} = \frac{1}{N}\sum_{n=1}^{N} x^2(n) \tag{4}$$

From equations (3) and (4) it can be seen that the mean energy of the signal is the sum of mean energy of all scales. Therefore, such an index can be used to extract the different patterns of power disturbances.

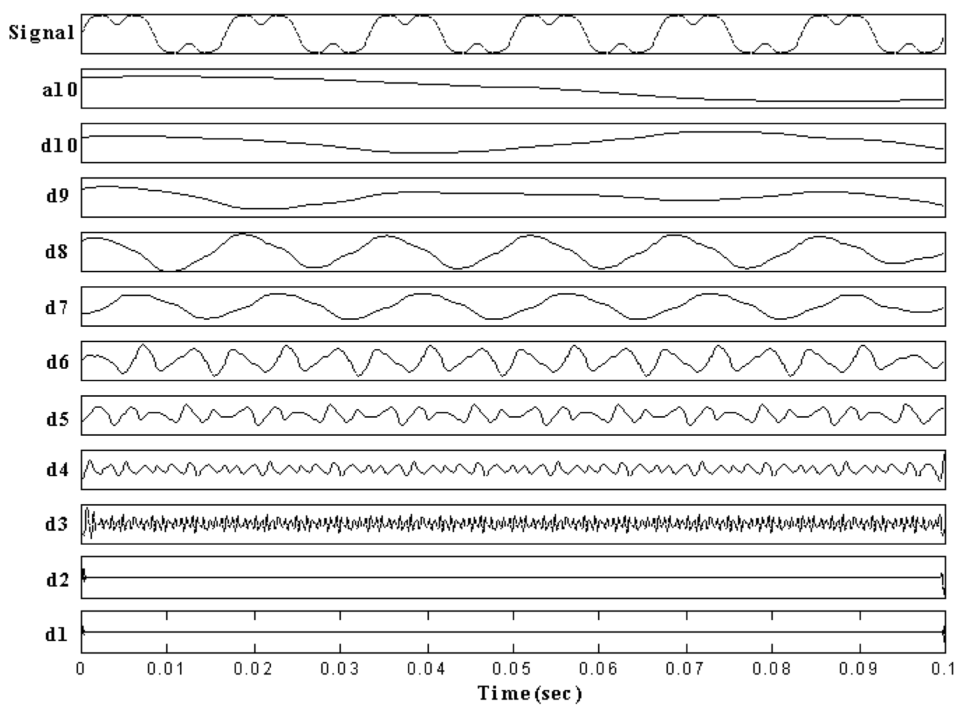


Figure 2. A harmonic distortion.

III. Classifier Design

A. Feature Vector Extraction

Feature parameters that represent the main characteristics of power disturbances can be obtained through examining the general characteristics according to the disturbance type. For this purpose, 400 test samples (40 for each type) are used. The testing disturbance has a sampling frequency, $f_s = 15.36$ kHz and fundamental frequency, $f_o = 60$ Hz. The signals are decomposed by a wavelet function, db4, to ten-scale resolutions in order to determine the feature parameters for each event. In practice, most disturbances in a signal may have short duration, or small energy, compared to the normal waveform of the fundamental frequency signal. Hence, using the disturbance would separate the normal signal from the measured signal, which can directly help to obtain patterns that show disturbance features solely.

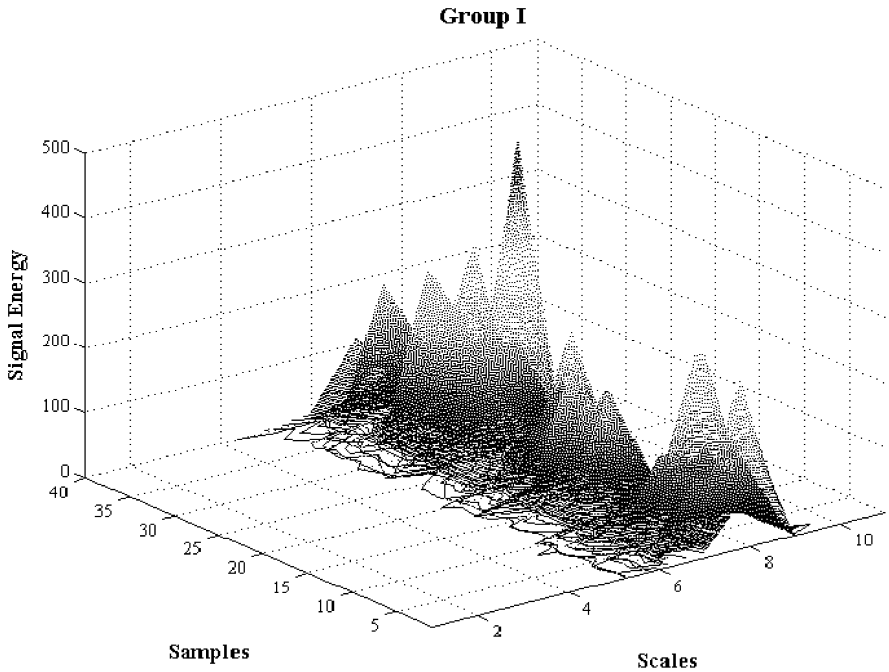
Figure 3 demonstrates the energy distribution analyzed by the MSD for the testing data. Most of the energy for voltage variations (Group I) and flicker (Group II) is concentrated at the eighth scale. Transients (Group III) and periodic notches (Group II) have energy distributions between the first and fourth scales, while harmonic distortion and dc offset show their energy at the sixth and 11$^{\text{th}}$ scales, respectively. In particular, the energy distribution for harmonic sags (Group IV) may not be easily distinguished from results of other types of disturbances, but their energy distributions demonstrate combined properties for both sags and harmonics.

For the MSD of ten scales, the energy at the first scale indicates the highest frequency component in the range 3.84 to 7.68 kHz and it represents time information of any fast transient events. Such a performance gives a crucial point available to distinguish transient events from various disturbances. However, their energy is typically very low compared to the other disturbances.

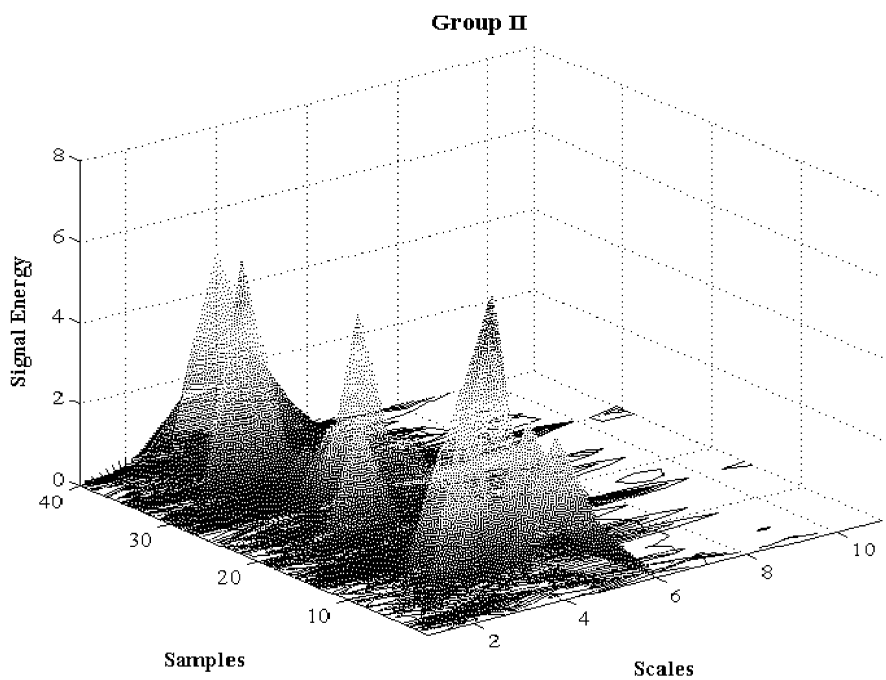
The frequency subband at the eighth scale is 45 to 90 Hz and its central frequency is about 67.5 Hz. Therefore, the signal energy at this scale can show the main property of the fundamental frequency; this implies that any feature vector extracted from the wavelet coefficients at the eighth scale would provide useful information in recognizing large voltage variations. However, it is noted that at this scale the energy levels and their deviations are very large compared to those of other type of disturbances.

General information for pattern extraction can be obtained from Figure 3, although it is easy to use those results directly as feature parameters due to the diversity of energy distributions. One way to overcome this difficulty is to consider the mean energy for all disturbances in the same group, as shown in Figure 4. Since the energy levels and main distribution scales for the four groups are different, it is obvious that any feature vector corresponding to each group can be extracted easier than from Figure 3. However, it may not be easy to distinguish similar PQ events within the same group from energy distributions. Figures 3 and 4 show all information for the ten types of disturbances; however, the more important factor is how to classify ten types from the diversities of energy distributions for all data.

As can be seen in Figures 3 and 4, energy distributions for each type are concentrated on two or three bands (scales), and these shapes—in addition to their energy levels—can help to extract features in classifying disturbance types.

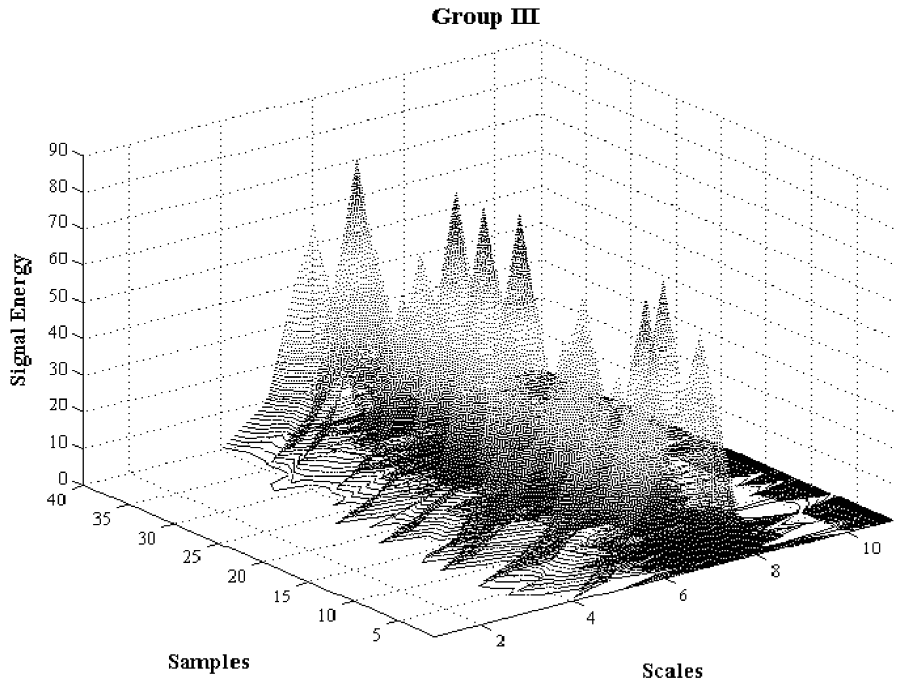


(a)

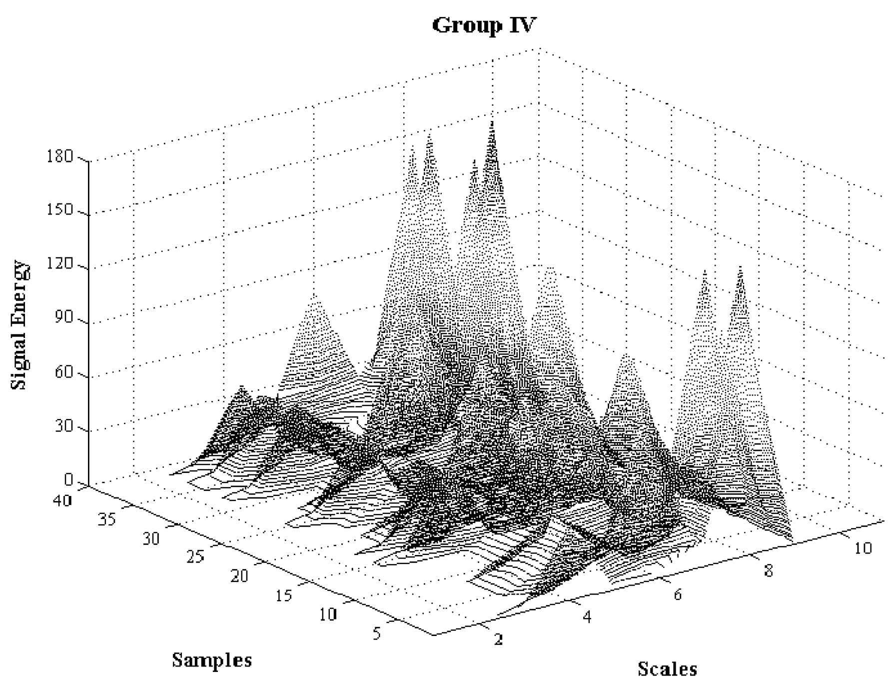


(b)

Figure 3. Energy distribution for testing data: (a) Group I; (b) Group II.



(c)



(d)

Figure 3. Energy distribution for testing data: (c) Group III; (d) Group IV.

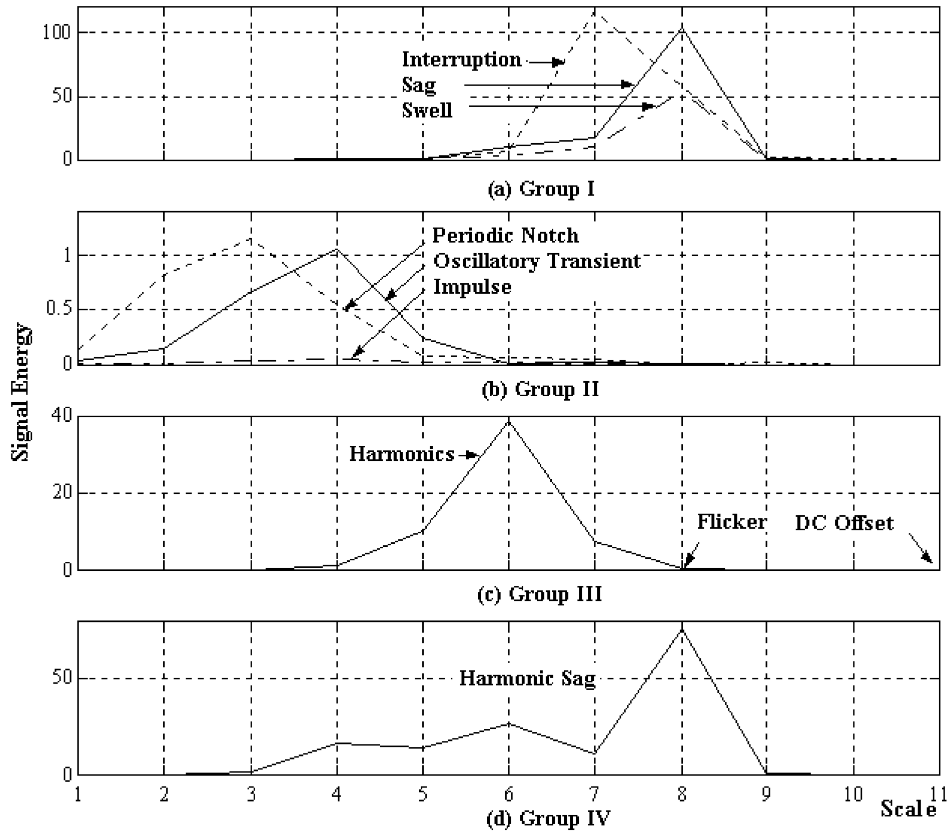


Figure 4. Energy distributions for ten PQ events.

Hence, the main energy concentration position (S_c) and the mean energy (W_a) are introduced as feature parameters defined by,

$$S_c = \frac{\sum_{i=1}^{L+1} w_i s_i}{\sum_{i=1}^{L+1} s_i} \tag{5}$$

$$W_s = \frac{1}{L+1} \sum_{i=1}^{L+1} w_i \tag{6}$$

where w_i is the mean value of energy for all training data at the ith scale, and s_i the scale number. Also, w_{L+1} denotes the mean energy of the approximation coefficients at the scale s_{L+1}.

In spite of using energy concentration and signal mean energy to classify disturbance type, such factors cannot independently represent each feature for the ten types of disturbances. Therefore, any other information available to enhance classifying PQ types should be found. Fortunately, it is easy to use the rms value as a measure to distinguish voltage variations such as sags, swells, or interruptions from other disturbances. In other words, disturbances in Group I can be identified in terms of their rms values and duration.

On the other hand, disturbances such as oscillatory transients, impulses, or notches have lower energy levels compared with other disturbances. It is possible to distinguish these disturbances from higher-energy disturbances by using frequency performances. However, it is not easy to separate whether the signal belongs to impulse, notch, or oscillatory transient from the results, even when taking into account all feature parameters such as rms value, energy concentration, and mean energy. Impulses and notches are usually defined as one shot, or one-cycle waveform distortion. This property can be used to distinguish such disturbances provided that one or two pulses can be detected. In this article, the result obtained by using rms value and pulse detection is also considered an additional feature parameter.

B. Classifier Structure

As discussed above, the types of voltage variations in Group I can be recognized by using rms indices and their duration criteria. A classifier can be designed as a rather simple structure from the fact that voltage variations in Group I can be readily recognized in terms of rms value and duration. Whenever applying the rms value as a classifying index, another difficulty may occur in recognizing harmonic distortions with rms values over 1.1 pu. In the present research, it is assumed that harmonic distortion has THD of 20 to 40% and rms value of 0.9 to 1.1 pu, as given in Table 1.

A classifier schematic is shown in Figure 5. First, the rms value of a disturbed signal is continuously calculated in a fundamental cycle, then the rms level and duration are determined. These results are compared to the criteria for voltage variations, and whether or not the signal belongs to one type of Group I is determined. The mean energy of the original signal is also computed. Next, the fundamental

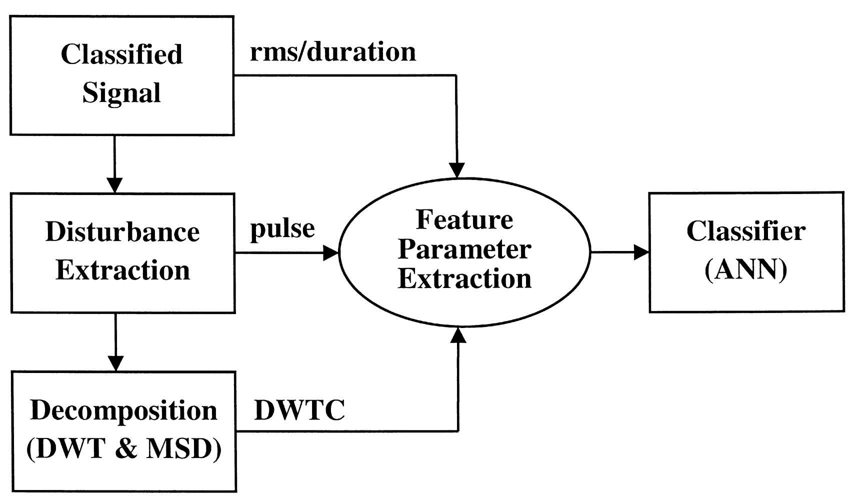


Figure 5. Schematic diagram of the proposed classifier.

frequency signal is removed from the disturbed signal in order to improve recognition efficiency. A suitable method such as FFT, notch filtering, or pulse triggering technique can be used for this purpose [6, 10]. Then, using pulse detection technique to detect the disturbance in one shot or single-cycle signal, it is determined whether the disturbance belongs to oscillatory transient, impulse, or periodic notch.

The disturbance is decomposed to a mother wavelet, db4, with ten resolutions. Such ten-scale decompositions are sufficient to show all significant features in the different frequency bands and all types of disturbances given in Table 1. A de-nosing procedure is carried out at each scale by choosing suitable threshold in order to avoid any influence of signal noise [13]. Based on the ten-scale coefficients, in addition to the approximation coefficients, the energy concentration scale and the mean energy for disturbance are determined using equations (5) and (6).

According to the results obtained, the feature vector is constituted by the following parameters:

- mean energy of original signal
- energy concentration level
- mean energy of disturbance
- auxiliary feature parameter (rms/duration, pulse detection).

This feature vector is then used as input to an ANN classifier, as discussed in Section C below. It should be noted that the proposed classifier has a simplified structure which consists of only four feature parameters in order to recognize ten types of disturbances, including a double event case.

C. Neuro-Fuzzy Classifier

Fuzzy logic systems consist of inputs using linguistic variables and membership functions (MFs) to represent the degree of truth of these inputs. In most fuzzy systems, there is no systematic design process to obtain any optimal property, since MFs and fuzzy rules are usually designed by subjective decisions based on human knowledge and experience. However, adaptive neuro-fuzzy system (ANFS) is one of fuzzy inference systems that have the ability of self-modifying their MFs to achieve a pre-determined desired performance.

Since the ANFS is a class of adaptive networks equivalent to fuzzy inference systems, they utilize the hybrid-learning rule and manage complex decision making or classification in PQ events [6, 8–10, 14]. The shape of a fuzzy MF depends on a set of feature parameters, based on preliminary analysis results through several training data.

A fuzzy inference system with four inputs and one output was designed to automatically classify the ten types of PQ events shown in Table 1. The four inputs are feature parameters extracted from the signal energy of each PQ disturbance, and the output is the type of PQ event to be classified. Twenty-seven MFs for the four inputs, ten MFs for the output, and only ten fuzzy rules were designed to form a classifier, considering four feature parameters obtained through training. All MFs are bell-shaped. The system is a Sugeno type, and a combination of back-propagation and least squares method are used to tune the parameters of input and output MFs.

Table 2
Classified results

No.	Type of disturbance	Training data	Testing data	Subtotal
1	Voltage sag	20/20	19/20	39/40
2	Voltage swell	20/20	20/20	40/40
3	Voltage interruption	20/20	20/20	40/40
4	Harmonic	19/20	19/20	38/40
5	Flicker	20/20	20/20	40/40
6	DC offset	20/20	20/20	40/40
7	Notching	20/20	20/20	40/40
8	Impulse	20/20	19/20	39/40
9	Oscillatory transient	20/20	20/20	40/40
10	Harmonic sag	19/20	18/20	37/40
	Total	198/200	195/200	393/400

IV. Classification Experiments and Results

The designed ANN classifier was examined using another 400 disturbance data set (40 data for each event). Training examples for the ten PQ events are added Gausian white noise of 0.5% (signal-to-noise ratio, 46 dB). Half of the 400 samples were used in training and the rest in testing the performance of the designed classifier. The data was obtained by using the power system simulation package of MATLAB under various operating conditions. In particular, harmonic sag signals are sag voltages combined with harmonic distortion.

Each event signal is classified by six fundamental cycles having 1536 samples. The disturbance signal excluded the fundamental frequency signal from a measured signal and is decomposed by using the DWT with db4 and the ten-scale MSD.

Table 2 lists the training and testing results for the proposed classifier, where the output is approximated to its nearest integer. The recognition rate of training and testing data was 99.0% and 97.5%, respectively, which shows that the feature parameters can sufficiently reflect the main characteristics of the ten types of disturbances. Such recognition efficiency would be expected because the classifying process during testing has imposed several assumptions such as restricting level (harmonics), or using an auxiliary feature vector (rms/duration measurement and pulse detection). However, such considerations are given only to define the types of disturbances clearly, and to improve classifying reliability. It is also noted that the classifier gives good results in classifying a double event disturbance like harmonic sag voltage. The system can provide the possibility of classifying any other multiple event disturbance.

V. Conclusions

An adaptive neuro-fuzzy classifier based on the discrete wavelet transform to recognize the type of power disturbances is presented in this article. The DWT, using multi-resolution signal decomposition, can transfer power disturbance characteristics into the time-frequency domain. The energy of the signal decomposed to each frequency subband can be utilized in extracting feature parameters. By examining the signal energy distribution at each scale, both energy concentration level and mean energy are used to form a feature vector. Furthermore, it was shown that the rms value and the mean energy of disturbance could be used to extract the feature of the parameters effectively. A neuro-fuzzy-based classifier with a simplified structure and only four feature parameters is proposed. Simulation results have also verified that the proposed classifier has good efficiency in recognizing ten types of PQ disturbances with different characteristics. In particular, it is suggested the applicability to classify any double event disturbances like sag voltages with harmonic distortion.

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