2004 IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies (DRPT2004) April 2004 Hong Kong

Automatic Power Quality Recognition System using Wavelet Analysis

H.K. Siu, *Member, IEE* and H.W. Ngan, *SrMember, IEEE*

Abstract—*The quality of electricity has been gaining more emphasis among utilities, service sectors and consumers. They have to maintain the quality by strategic measures in coping with all sort of disturbances generated intrinsically in modern power electronic equipments, large commercial buildings and open power environment. A means of improving electric power quality starts by a systematic identification of the power system disturbances which is posed to be a big challenge. The conventional approach based on Fourier Transform principles has its main drawback of losing the time-domain feature after transformation. Whist the technique of using wavelet transform appears to be more promising with its strength on handling signals on short time intervals for high frequency components and long time intervals for low frequency components. In this paper, an integrated approach, using both Fourier and wavelet transforms, is proposed and it is used to integrate the advantages of both transforms. The wavelet transform is used to extract the required time-domain information from the high frequency components while the Fourier transform is used to provide the accurate measurement from the low frequency components. An automatic power quality recognition system based on the integrated approach is developed. Neural network classifier and rule-based classifier are selected to implement the proposed approach of which its validation is performed via simulated data set.*

Index Terms—**Power Quality, Fourier Transform, Wavelet Transform, Neural Network Classifier and Rule-Based Classifier.**

I. INTRODUCTION

OVER the last two decades, emphasis on quality of electricity has attracted more and more attention to utilities, service sectors and bulk consumers. Quality assurance of electricity supply by itself is a marketable product. The concern of power quality has also deeply founded with users of modern power electronic equipment like those in commercial buildings which is sensitive to power system disturbances and/or those generated by itself.

In order to monitor and control these disturbances, their systematic identification is essential which is posed to be a big challenge. Besides the primary methods based on visual inspection on the disturbance waveform, different monitoring devices, such as disturbance analyzers and harmonic analyzers, are typically used in the industry. These analyzers usually employ techniques based on point-by-point comparison of the rms values of the distorted signal with its corresponding pure signal, and/or transformation of the data into the frequency domain via Fourier transform (FT).

However, the major problem of the traditional analyzing tools based on Fourier transform is that it will not provide sufficient information on the time domain. For non-stationary disturbances such as local transient signal, its location on the time axis will be lost after FT.

One technique emerged to overcome the above mentioned problem is by using wavelet transform (WT) whose strength is on handling signals on short time intervals for high frequency components and long time intervals for low frequency components. By means of the strength, WT is considered suitable for analyzing signals with localized impulses and oscillations particularly for those commonly present in fundamental and low order harmonics.

On the other hand, the FT still has its outstanding and well-proven performance on the measurement of the frequency spectrum of signals. As an integrated approach, the paper proposes to develop an automatic power quality recognition system by combining the advantages on both WT and FT.

II. FOURIER AND WAVELET TRANSFORMS

A. Fourier Transform

The Fourier transform (FT), which breaks down a signal into constituent sinusoids of different frequencies, is perhaps the most well-known and reliable tool in signal analysis for many years. Mathematically, the FT is the sum over all time of signal $x(t)$ multiplied by a complex exponential as below:-

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt \tag{1}$$

For a sampled signal, the discrete Fourier transform with the DFT notation is defined as:-

$$X(k) = \sum_{n=0}^{N-1} x(n) \exp\left(\frac{-j2\pi kn}{N}\right) \tag{2}$$

where $x(n)$ is a sequence of samples from a continuous time signal $x(t)$ taken every t seconds for N samples. If the samples are uniformly spaced, the Fourier matrix can be

0-7803-8237-4/04/$17.00©2004IEEE

factored into a product of just a few sparse matrices and the resulting factors can be applied to a vector in a total of order $N \log(N)$ arithmetic operations. This is the so-called Fast Fourier Transform (FFT).

However, the FT was developed based on assumption that the original time-domain function is periodic in nature. As a result, when dealing with functions with transient components that are localized in time, the FT cannot convey any time information about the transient components. In recent years, new families of orthonormal basis functions called "wavelets" have been discovered and new transforms have been developed to overcome the problem of the FT.

B. Wavelet Transform

Wavelet transform (WT) employs a basis function called the mother wavelet, usually denoted by $\psi(t)$ which has a zero mean with sharp decays in an oscillatory fashion and effectively limited duration. Mathematically, the continuous wavelet transform (CWT) of a given signal $x(t)$ is generally defined as:-

$$CWT\ (a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt \qquad (3)$$

where a is the dilation or scale factor, b is the translation factor, and both variables are continuous

However, derivation of the CWT is quite time-consuming and computationally expensive and hence ineffective in terms of computation time for deriving its information content. As an improvement, the discrete wavelet transform (DWT) is developed by translating and dilating the mother wavelet discretely. The DWT is implemented by replacing a by a_o^m and b by $nb_oa_o^m$ in (3) and applying summation over the sample space as shown in the following:-

$$DWT\ (m,n) = \frac{1}{\sqrt[m]{a_o}} \sum_k x(k) \psi\left(\frac{k - nb_o a_o^m}{a_o^m}\right) \qquad (4)$$

where n represents the translation step and m represents the scaling step and is known as the level number. If $a_o=2$ and $b_0=1$, then the transform is known as the dyadic orthonormal wavelet transform leading to an important technique called the multi-resolution signal decomposition (MSD) which will further be explained in the next section.

By using another basic function, namely scaling function $\phi(t)$, a signal can be decomposed into two signals, i.e. the smoothed version with approximation coefficients $c(k)$ and the detailed version with detailed coefficients $d(k)$ as follows:-

$$x(t) = \sum_{k \in Z} c(k) \phi_{(j,k)}(t) + \sum_{k \in Z} d(k) \psi_{(j,k)}(t) \qquad (5)$$

provided that each scaling and wavelet function shall have an orthogonal basis as illustrated below :

$$\phi(t) = \sum_{k \in Z} a_k \phi(2t-k) \qquad (6a)$$

$$\psi(t) = \sum_{k \in Z} (-1)^k a_{k+1} \phi(2t-k) \qquad (6b)$$

$$\phi_{(j,k)}(t) = 2^{-j/2} \phi(2^{-j} t - k); j,k \in Z \qquad (7a)$$

$$\psi_{(j,k)}(t) = 2^{-j/2} \psi(2^{-j} t - k); j,k \in Z \qquad (7b)$$

$$\sum_{k \in Z} a_{2k} = 1 \qquad (8a)$$

$$\sum_{k \in Z} a_{2k+1} = 1 \qquad (8b)$$

$$\sum_{k \in Z} a_k a_{k+2l} = 0 \ \ for\ l \neq 0 \qquad (8c)$$

$$\sum_{k \in Z} \overline{a_k} a_k = 2 \qquad (8d)$$

where j denotes scale or resolution index, k denotes translation location index, and a_k are the scaling coefficients. Equations (8) list out the set of scaling conditions which must be satisfied before a set of a_k can be qualified as scaling coefficients.

III. Detection of Power Quality Disturbances

A. Multi-resolution Signal Decomposition

The multi-resolution signal decomposition (MSD) technique enables a signal $x(t)$ to be decomposed into a hierarchical set of scaling functions $\phi_{(j,k)}(t)$ or $\phi_l(t)$ with its approximation coefficients $c(l)$, and shifted and dilated version of wavelet functions $\psi_{(j,k)}(t)$ with its detail coefficients $d(j,k)$ by decomposing the approximation coefficients at each level to get further approximation and detailed coefficients (see Fig. 1).

$$x(t) = \sum_{l \in Z} c(l) \phi_l(t) + \sum_{j=0}^{J-1} \sum_{k \in Z} d(j,k) \psi_{(j,k)}(t) \qquad (9)$$

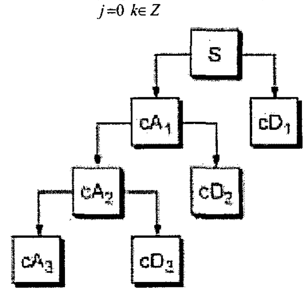


Fig. 1. MSD algorithm

In order to obtain the approximation and detail coefficients for each basis, we can take an inner product as given by

$$c(l) = \langle \phi_l | x \rangle = \int x(t) \phi_l(t) dt \qquad (10a)$$

$$d(j,k) = \langle \psi_{j,k} | x \rangle = \int x(t) \psi_{(j,k)}(t) dt \qquad (10b)$$

In power quality (PQ) disturbance signals, many disturbances contain sharp edges, transitions and jumps. As proposed by many authors, like Gaouda [1], we can use the MSD technique to discriminate the sharp edges, transitions and jumps contained in the detailed version from the smoothed version such that they can be analyzed separately. A typical example, a 6-level MSD of a distorted signal with transient and harmonics, is shown in Fig. 2.

For other different PQ problems, e.g. impulse, voltage sag, voltage swell, interruption, harmonics and transient, etc., the results of applying MSD technique are quite promising as illustrated in Fig. 3.

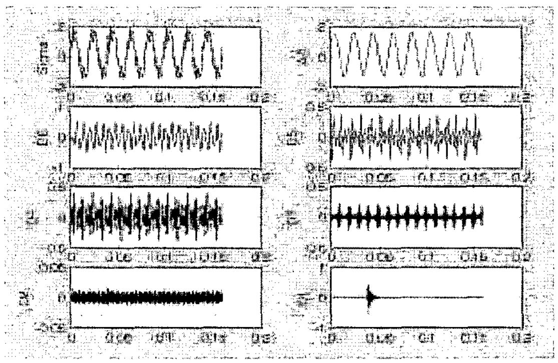
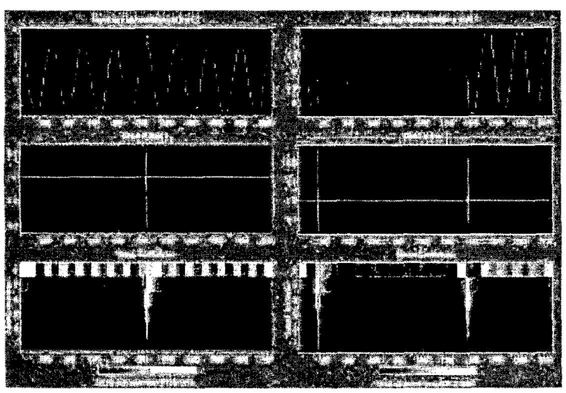
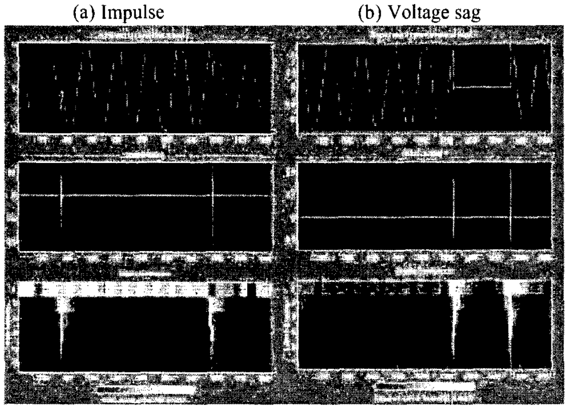


Fig. 2. 6-level MSD of a distorted signal with transient & harmonics

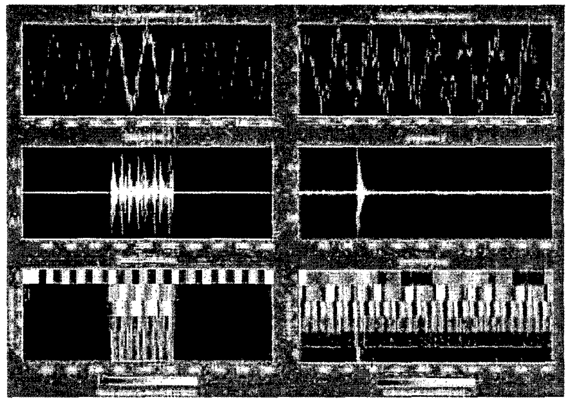


(a) Impulse (b) Voltage sag



(c) Voltage swell (d) Interruption

Fig. 3. Results of applying MSD to different PQ problems



(e) Harmonics (f) Transient and harmonics

Fig. 3. (cont.) Results of applying MSD to different PQ problems

B. Integrated Approach

In order to obtain more information of the distorted signals for further analysis, such as trending analysis and rectification of the PQ problem, etc., the rms measurement of the distorted signals are required as defined below:-

$$V_{rms} = \sqrt{\frac{1}{T}\int_0^T V^2 dt} \tag{11}$$

According to Parseval's theorem, if any function $x(t)$ can be presented as a series expansion by using a combination of the scaling functions and wavelets which form an orthonormal basis as shown in (9). Then

$$\int |x(t)|^2 dt = \sum_{l \in Z} |c(l)|^2 + \sum_{j=0}^{J-1} \sum_{k \in Z} |d(j,k)|^2 \tag{12}$$

Therefore, the energy of the distorted signal can be partitioned in terms of the approximation coefficients and the detail coefficients at different resolution levels. Then the rms measurement of the distorted signal can be derived as follows:-

$$V_{rms} = \sqrt{\frac{1}{T}\sum_{l \in Z} c(l)^2 + \frac{1}{T}\sum_{j=0}^{J-1}\sum_{k \in Z} d(j,k)^2} \tag{13}$$

However, the decomposed waveform after MSD will provide non-uniform frequency bands that are in octave order. Hence, the MSD is not suitable to measure the rms values of individual harmonic components. Although Hamid, Kawasaki and Mardiana [5] proposed to use the wavelet packet transform (WPT) algorithm, which is a direct extension from the MSD algorithm to a full binary tree by decomposing both the detail and approximation coefficients to produce further coefficients, to overcome this limitation, errors still exist due to the roll-off characteristics of the selected wavelets.

Therefore, an integrated approach using both the DWT and FFT algorithms is proposed in this paper for resolving the problem. In which, the distorted signal will first be decomposed into two signals, i.e. detailed and smoothed/approximated versions, by using the DWT algorithm. The required time information such as the duration of the disturbance can now be extracted from the detailed version. The smoothed or approximated version will then be undergone the FFT algorithm in order to obtain the frequency spectrum of the distorted signal. This integrated approach is illustrated in Fig. 4.

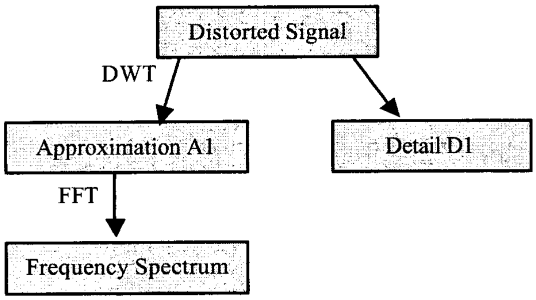
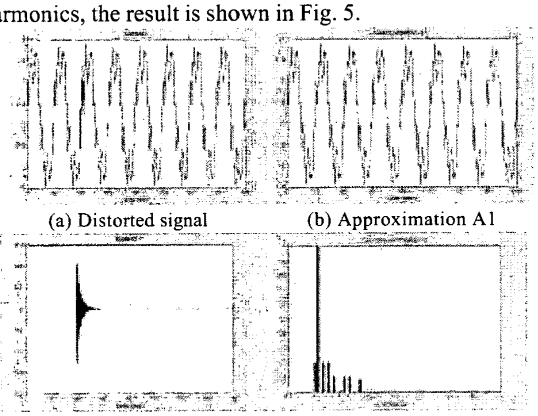


Fig. 4. Integrated approach by using both DWT & FFT algorithms

With the same distorted signal containing transient and harmonics, the result is shown in Fig. 5.



(a) Distorted signal (b) Approximation A1

(c) Detail D1 (d) Frequency spectrum

Fig. 5. Example of using integrated approach

IV. AUTOMATIC POWER QUALITY RECOGNITION SYSTEM

In application, an automatic PQ recognition system is developed based on the proposed integrated approach. Although application of wavelet analysis for recognizing PQ disturbances has been addressed on a number of cases, like Gaouda [1], Negnevitsky [2] and Santoso [3-4], the proposed automatic PQ recognition system carries unique features such as it can be used for both detection and rms measurement for the PQ disturbances at the same time.

A. Proposed Classification Procedures

According to the integrated approach, the proposed classification procedures are listed as follows:-

Step 1 – The input signal is firstly decomposed into the detail coefficients (cD1) and the approximation coefficients (cA1) by using DWT.

Step 2 – The approximation coefficients (cA1) is transformed to frequency domain by using FFT.

Step 3 – Based on the result obtained after using FFT, the following features can be determined:-

i) DC component (V_{dc})
ii) Rms value of fundamental component (V_1)
iii) Total harmonic distortion (*THD*) ratio (*thd*)
iv) Change of fundamental frequency (ΔF)

Step 4 – Then the detail coefficients (cD1) will be de-noised by applying threshold.

Step 5 – Based on the time information about the disturbances extracted from the de-noised detail coefficients (cD1), the frequency spectrums before and after the transition can be measured via FFT and then the following features due to the presence of disturbance can be determined:-

i) Change of rms value of fundamental component (Δv_1)
ii) Disturbance duration (Δt)
iii) Change of DC component (Δv_{dc})
iv) Change of THD ratio (Δthd)

Step 6 – The features obtained in Steps 3 and 5 will be passed to the classifier in order to identify the nature of the disturbance.

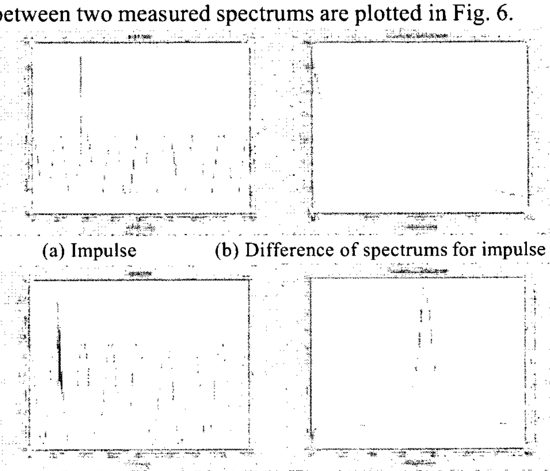
In this paper, two classifiers called rule-based classifier and neural network classifier will be employed to implement the automatic PQ recognition system.

B. Rule-Based Classifier

Basically, the PQ disturbances can be divided into two categories, i.e. short duration variations and long duration variations. Referring to the features measured in Step 3, the following long duration variations can be easily identified.

i) Harmonics (*if* $thd > threshold$)
ii) DC offset (*if* $V_{dc} > threshold$)
iii) Frequency variation (*if* $abs(\Delta F) > threshold$)

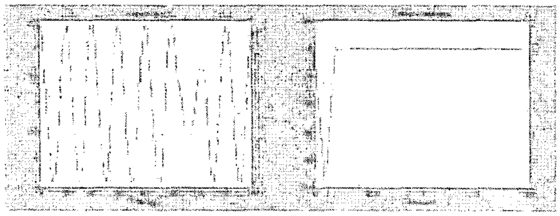
In order to classify the short duration variations, the characteristics of the disturbances are investigated via measuring and comparing the frequency spectrums before and after the transition of the disturbance. The differences between two measured spectrums are plotted in Fig. 6.



(a) Impulse (b) Difference of spectrums for impulse

(c) Transient (d) Difference of spectrums for transient

Fig. 6. Characteristics of short duration variations



(e) Voltage sag (f) Difference of spectrums for sag

Fig. 6. (cont.) Characteristics of short duration variations

From Fig. 6, the characteristics of the differences between two measured spectrums for different disturbances are observed and summarized in Table I.

TABLE I

SUMMARY OF CHARACTERISTICS OF SHORT DURATION VARIATIONS

TYPE OF DISTURBANCES	CHANGE OF V_{DC}	CHANGE OF V_1	CHANGE OF THD
IMPULSIVE TRANSIENT	√	√	√
OSCILLATORY TRANSIENT			√
VOLTAGE SAG, SWELL & INTERRUPTION		√	

According to results shown in Table I and the IEEE Std. 1159 [7], the features extracted from Step 5 can be used to classify the short duration variations as follows:-

i) Impulse *(if Δv_{dc} > threshold)*
ii) Transient *(if Δthd > threshold)*
iii) Voltage sag *(if $-90\% < \Delta v_1 < -10\%$)*
iv) Voltage swell *(if $10\% < \Delta v_1 < 80\%$)*
v) Interruption *(if $\Delta v_1 < -90\%$)*

Based on the above classification criteria, a rule-based classifier can be constructed to identify the disturbances.

C. Neural Network Classifier

Pattern recognition techniques are basically divided into two types, i.e. parametric approach and non-parametric approach. The previous rule-based classifier obviously belongs to the former type. However, the parametric approach usually requires a prior statistical assumption which is not precisely known in many situations and the set of example data is not sufficiently large. Similar to the rule-based classifier, the thresholds for different classification criteria should be well defined based on the prior statistical assumption before the classifier can perform the job satisfactorily. Therefore, a non-parametric approach such as neural network classifier can be considered as an alternative proposal.

As there are 8 features extracted in Steps 3 and 5, and 8 types of disturbances to be detected as listed in Table II, a two-layer perceptron neural network (see Fig. 7) with 8 input neurons and 8 output neurons is adapted to implement the classification.

TABLE II

INPUTS AND OUTPUTS OF NEURAL NETWORK CLASSIFIER

INPUT FEATURES	TYPE OF DISTURBANCES TO BE DETECTED (OUTPUTS)
V_{DC}	IMPULSIVE TRANSIENT
V_1	OSCILLATORY TRANSIENT
THD	VOLTAGE SAG
ΔF	VOLTAGE SWELL
ΔV_1	INTERRUPTION
$\Delta \tau$	HARMONICS
ΔV_{DC}	DC OFFSET
ΔTHD	FREQUENCY VARIATION

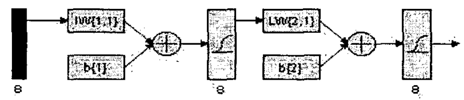


Fig. 7. Two-layer perceptron neural network classifier

D. Training and Verification

In order to train the neural network classifier and verify the rule-based operation, a set of simulated disturbance waveforms is generated as proposed by Liao [6] as listed in Table III. After passed the input features extracted from the generated waveforms and the target outputs to the neural network classifier, the training result is plotted in Fig. 8. Referring to the training result, the error of the neural network classifier has dropped to 6.932×10^{-15} just after 31 epochs.

TABLE III

SIMULATED WAVEFORMS GENERATED FOR TRAINING & VERIFICATION

TYPE OF DISTURBANCES	NOISE LEVEL	NO. OF WAVEFORMS
(A) PURE SIGNAL	0%, 2%, 5%	3
(B) IMPULSIVE TRANSIENT	0%, 2%, 5%	3
(C) OSCILLATORY TRANSIENT	0%, 2%, 5%	3
(D) VOLTAGE SAG	0%, 2%, 5%	3
(E) VOLTAGE SWELL	0%, 2%, 5%	3
(F) INTERRUPTION	0%, 2%, 5%	3
(G) HARMONICS	0%, 2%, 5%	3
(H) DC OFFSET	0%, 2%, 5%	3
(I) FREQUENCY VARIATION	0%, 2%, 5%	3
COMBINATION OF (B)+(G)+(H)+(I)	2%	3
COMBINATION OF (C)+(G)+(H)+(I)	2%	3
COMBINATION OF (D)+(G)+(H)+(I)	2%	3
COMBINATION OF (E)+(G)+(H)+(I)	2%	3
COMBINATION OF (F)+(B)+(C)+(G)	2%	3
	TOTAL :	42

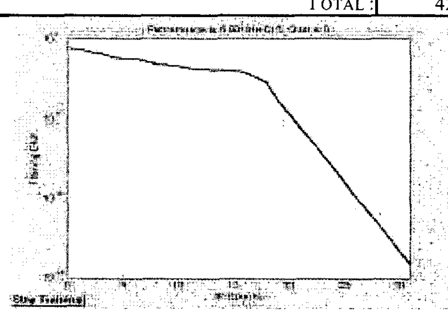


Fig. 8. Plot of error of neural network classifier

At the same time, the simulated waveforms are passed to the rule-based classifier for verification. After adjusting the thresholds, the rule-based classifier could recognize all the disturbances contained in the simulated waveforms. Therefore, the performance of the neural network classifier and the rule-based classifier are quite satisfactory.

V. CONCLUSION

In short, the automatic PQ recognition system is developed by using the proposed integrated approach, i.e. by using DWT and FFT. It can perform both the extraction of the required time information and the rms measurement of the distorted signal. The performance of the two proposed classifiers, namely rule-based classifier and neural network classifier, are also demonstrated and verified by a set of simulated disturbance waveforms. Although the test result of the proposed automatic PQ recognition system is quite promising, the real-life PQ disturbance data will not be as simple as those simulated waveforms and the size of sampled waveforms is hard to be sufficiently large. Therefore, further adjustment and modification is required before this proposed automatic PQ recognition system can be applied in real-life situation.

VI. ACKNOWLEDGMENT

The authors gratefully acknowledge the contributions of Prof. David Zhang and Prof. K.P. Wong for their expert advices and guidance.

VII. REFERENCES

[1] A.M. Gaouda, M.M.A. Salama, M.K.Sultan and A.Y. Chikhani, "Power Quality Detection and Classification Using Wavelet-Multiresolution Signal Decomposition," *IEEE Trans. On Power Delivery*, Vol. 14, No. 4, Oct. 1999, pp. 1469-1476.

[2] Jiansheng Huang, Michael Negnevitsky and D. Thong Nguyen, "A Neural-Fuzzy Classifier for Recognition of Power Quality Disturbances," *IEEE Trans. On Power Delivery*, Vol. 17, No. 2, Apr. 2002, pp. 609-616.

[3] Surya Santoso, Edward J. Powers, W.Mack Grady and Antony C. Parsons, "Power Quality Disturbance Waveform Recognition Using Wavelet-Based Neural Classifier – Part 1: Theoretical Foundation," *IEEE Trans. On Power Delivery*, Vol. 15, No. 1, Jan. 2000, pp. 222-228.

[4] Surya Santoso, Edward J. Powers, W.Mack Grady and Antony C. Parsons, "Power Quality Disturbance Waveform Recognition Using Wavelet-Based Neural Classifier – Part 2: Application," *IEEE Trans. On Power Delivery*, Vol. 15, No. 1, Jan. 2000, pp. 229-235.

[5] Effrina Yanti Hamid, Zen-Ichiro Kawasaki and Redy Mardiana, "Wavelet Packet Transform for Rms and Power Measurements" in *2001 IEEE Power Engineering Society Summer Meeting*, 15-19 Jul. 2001, pp. 1243-1245, Vol. 2.

[6] M. Kezunovic and Y. Liao, "A novel method for equipment sensitivity study during power quality events", in *Proceedings of IEEE Power Engineering Society Winter Meeting*, Singapore, January 2000, pp. 230-235.

[7] *IEEE Recommended Practices for Monitoring Electric Power Quality*, IEEE Standard 1159-1995, 1995.

VIII. BIOGRAPHIES

Ir. H.K. Siu received his B.Eng in 1988 and M.Sc in 1995 from the Hong Kong Polytechnic University and the University of Hong Kong respectively. After graduated from the Hong Kong Polytechnic University, he joined the Electrical and Mechanical Services Department, HKSAR, as an Engineer Trainee and then continued as an Assistant Building Services Engineer. Since 1994, he was promoted to Building Services Engineer, and now, he mainly works for the E&M maintenance of Government buildings. He is also pursuing the study of EngD course offered by the Hong Kong Polytechnic University, and his research topic is about the detection of power quality disturbances and its application on the maintenance of commercial buildings.

Dr. H.W. Ngan received his M.Sc in 1979, MBA in 1985 and PhD in 1993 from the University of Aston in Birmingham, University of Hong Kong and University of Strathclyde respectively. He is now with the Hong Kong Polytechnic University as the Associate Professor in the Department of Electrical Engineering. His current research interests include Power Market Reform, Power System Analysis, FACTS system control strategies, Energy Policy and Planning.