Real-Time Power Quality Disturbances Classification Using Hybrid Method Based on S-Transform and Dynamics

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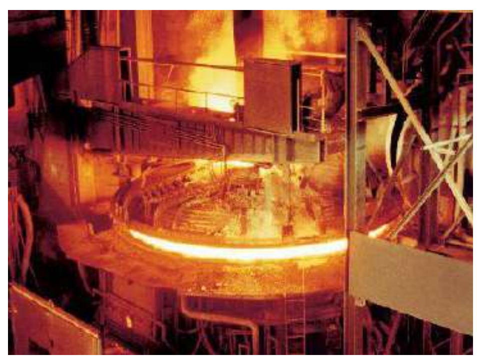
Power Quality Problems

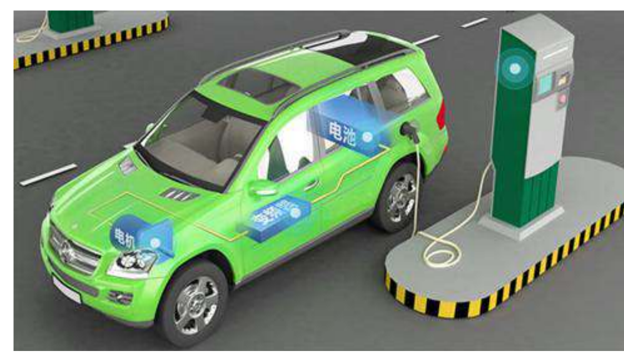
New energies are widely used

Diverse nonlinear loads

intermediate frequency furnace

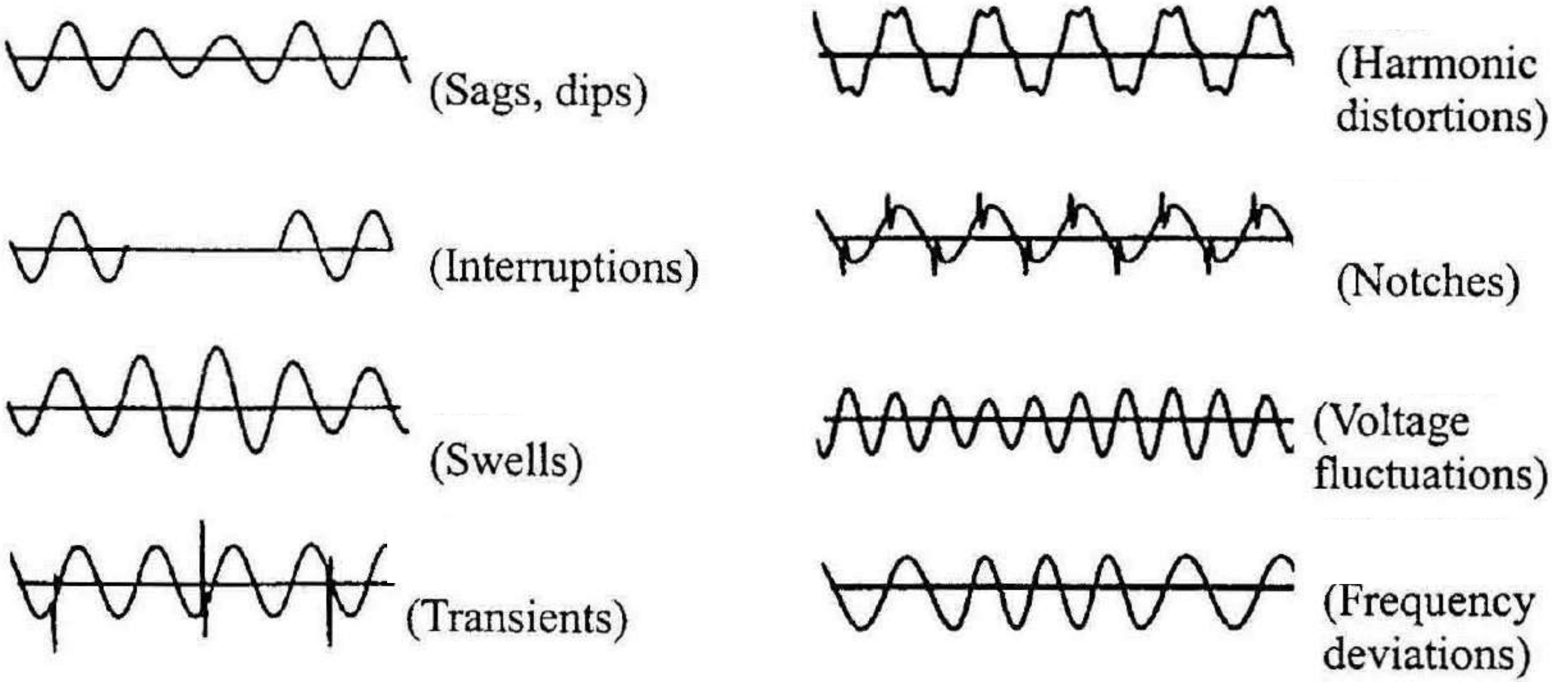


electric arc furnace



charging pile

Power Quality Events



How to classify PQDs

- How to realize Power Quality Disturbances Classification with real time?
- Accurate: better than other methods
- Quick: meet the real time requirements

ABSTRACT

- This paper proposes a real-time power quality disturbances (PQDs) classification by using a hybrid method (HM) based on S-transform (ST) and dynamics (Dyn).
- Classification accuracy and run time are distinctly improved.
- The HM uses Dyn to identify the location of the signal components in the frequency spectrum yielded by Fourier transform, and uses inverse Fourier transform to only some of the signal components. Then features from Fourier transform, ST,and Dyn are selected,
- A decision tree is used to classify the types of PQD.
- In order to reduce the influence of Heisenberg's uncertainty, we proposed that different signal components are windowed by different Gaussian windows, which brings better adaption and flexibility.
- Simulation and test show that the run time of the application has been greatly reduced with satisfactory classification accuracy.

Introduction

- *PQDs classification steps*

1.Feature extraction

2.Categorization

Traditional Method-Feature extraction

- *Wavelet Transform-WT or Wavelet Pocket Transform-WPT*

  Wavelet features extraction relies on the number of decomposed level and wavelet basis. The frequency amplitude could not be counted.This disadvantage always perplexes the classifier。

- *S-transform (ST)*

  ST has a high tolerance of noise and guarantees satisfactory accuracy on classification. The main disadvantage of ST is heavy computation burden.

- *Kalman filter (KF)*

  KF-based approaches depend wholly on the model of state and measurement matrixes. Any mismatch of signal and filter model will bring errors.

Traditional Method-Classifier

- Artificial neural network (ANN)

  ANN can be trained online and refreshed by each new sample.

- support vector machine (SVM)

  SVM has a strong learning process and proved useful when the sample group is small.

- fuzzy logic (FL) and decision tree (DT)

  FL and DT do not need training and rely on rules.

- Problem

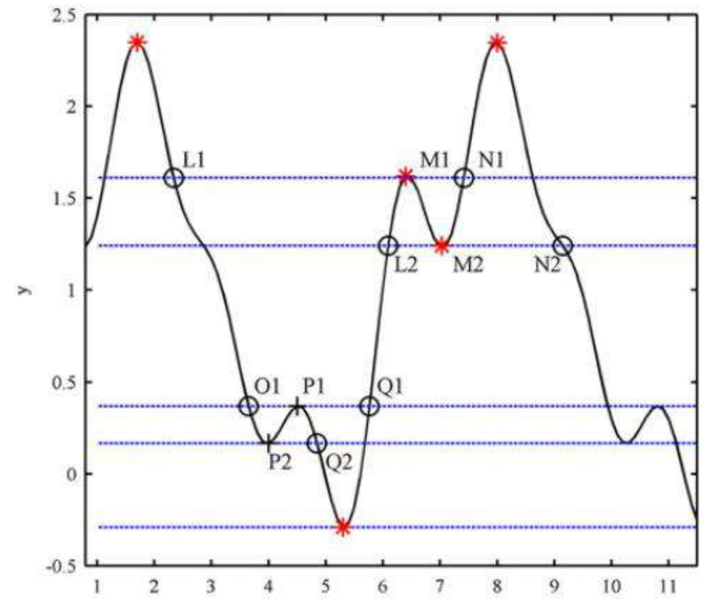
  Most of reported literatures can hardly be employed for real-time application and even many of them are only discussed in simulations.

The hybrid method

- Dynamics+ST
- It makes use of Dyn to reduce the run time of ST significantly and extracts five distinctive features with satisfactory classification accuracy.
- In the consideration of different uses, DT is adopted as the classifier for better compatibility.
- This paper investigates 8 single PQDs and 2 complex PQDs including:
- harmonic, flicker, sag, interruption, swell, spike, multiple notch, oscillation, sag plus harmonic, and swell plus harmonic

Dynamics (Dyn)

- Dynamics (Dyn) was firstly introduced by Grimaud in1992. It is employed to find the extreme points in a sequence under noises. The algorithm is easy and with low computation burden.



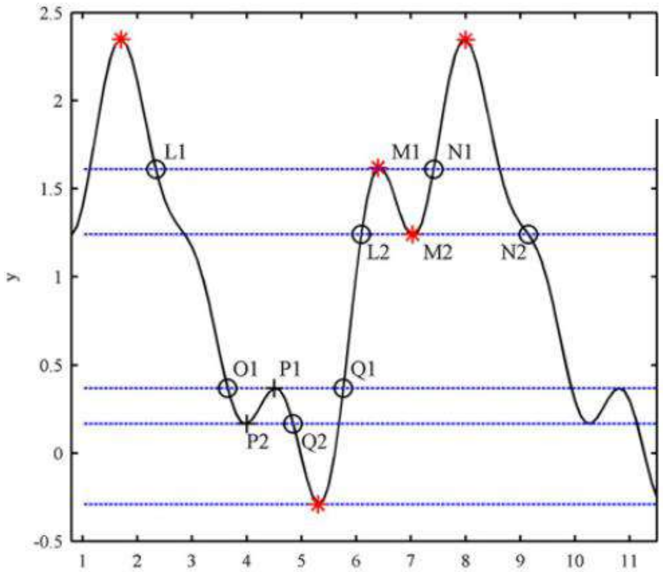
1) Brief review of dynamics:

Define a path $P(m, n)$, where m and n are the endpoints of P, Dyn of the path is the difference of top point and button point of the path. Then the Dyn is

$$\text{Dyn}[P(m, n)] = \{S_{\text{up}}(|h_{\text{alt}}(p_i) - h_{\text{alt}}(p_j)|)\} \qquad (1)$$

where S_{up} is the supremum, p_i and p_j are the highest point and lowest point, respectively, in path P, and $h_{alt}(.)$ is the altitude of the point.

Dynamics (Dyn)



Example: noise elimination by using Dyn.

A path y = f (x) is shown in Fig. 1. M1 and P1 are two of maximal points:

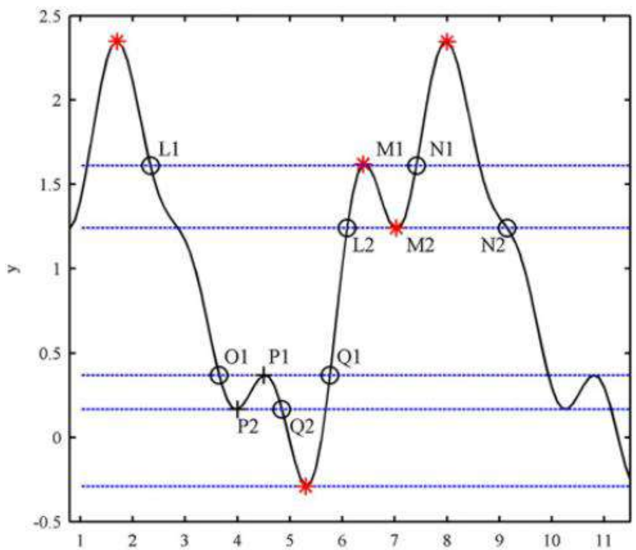
Dynmax(M1) = Dyn(M1, N1)

Dynmax(P1) = Dyn(O1, P1).

If Dyn(O1, P1) < Inf <Dyn(M1, N1), point M1 will be marked by Dyn and point P1 will be labeled with noise and eliminated.

where Inf is the infimum.

Dynamics (Dyn)



In Fig. 1, M2 and P2 are two minimal points:

Dynmin(M2) = Dyn(L2, M2)

Dynmin(P2) = Dyn(P2, Q2).

If Dyn(P2, Q2) < Inf <Dyn(L2, M2), point P2 will be deemed as noise.

Then all the points indicated by Dyn are marked with red stars.

S-Transform

- 2) *Brief review of S-transform:*

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t)\omega(\tau - t, f)\exp(-2\pi i f t)dt$$

$$\omega(\tau - t, f) = \frac{|f|}{\sqrt{2\pi}} \exp\left[\frac{-f^2(\tau - t)^2}{2}\right]$$

$\omega(\tau - t, f)$ ------Gaussian window

Time-frequency analysis method;

Good resolution .

$x(t) \rightarrow x(kT)$

$$X\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=0}^{N-1} x(kT) \cdot \exp\left(\frac{-i2\pi nk}{N}\right)$$ DFT

Discrete form of S transform

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} X\left[\frac{m+n}{NT}\right] \cdot \exp\left(\frac{-2\pi^2 m^2}{n^2}\right) \cdot \exp\left(\frac{i2\pi mj}{N}\right) \quad , \quad n = 1, 2, \ldots N-1$$

$$S[jT, 0] = \frac{1}{N}\sum_{m=0}^{N-1} x\left[\frac{m}{NT}\right] \quad , \quad n = 0$$

S-Transform

- The process of ST can be generally divided into four steps.
  Step 1: Use fast Fourier transform (FFT) to the input signal and obtain the spectrum *H*(*m*) where *m* is the frequency sample index.
  Step 2: Shift *H*(*m*) with *n*.
  Step 3: Compute the FFT of Gaussian window

$$G(m,n) = \exp\left[-a\left(\frac{2\pi^2 m^2}{n^2}\right)\right]$$

  where *a* is the parameter to tune the shape of Gaussian window.

- Step 4: Multiply each *H*(*m* + *n*) with the corresponding *G*(*m, n*) and use IFFT to the result. Then the discrete ST is obtained as

$$S\left[\frac{n}{NT}, jT\right] = \sum_{m=0}^{N-1} H\left(\frac{m+n}{NT}\right) G(m,n) e^{i2\pi mj/N}$$

- where, N point number, T is sampling interval

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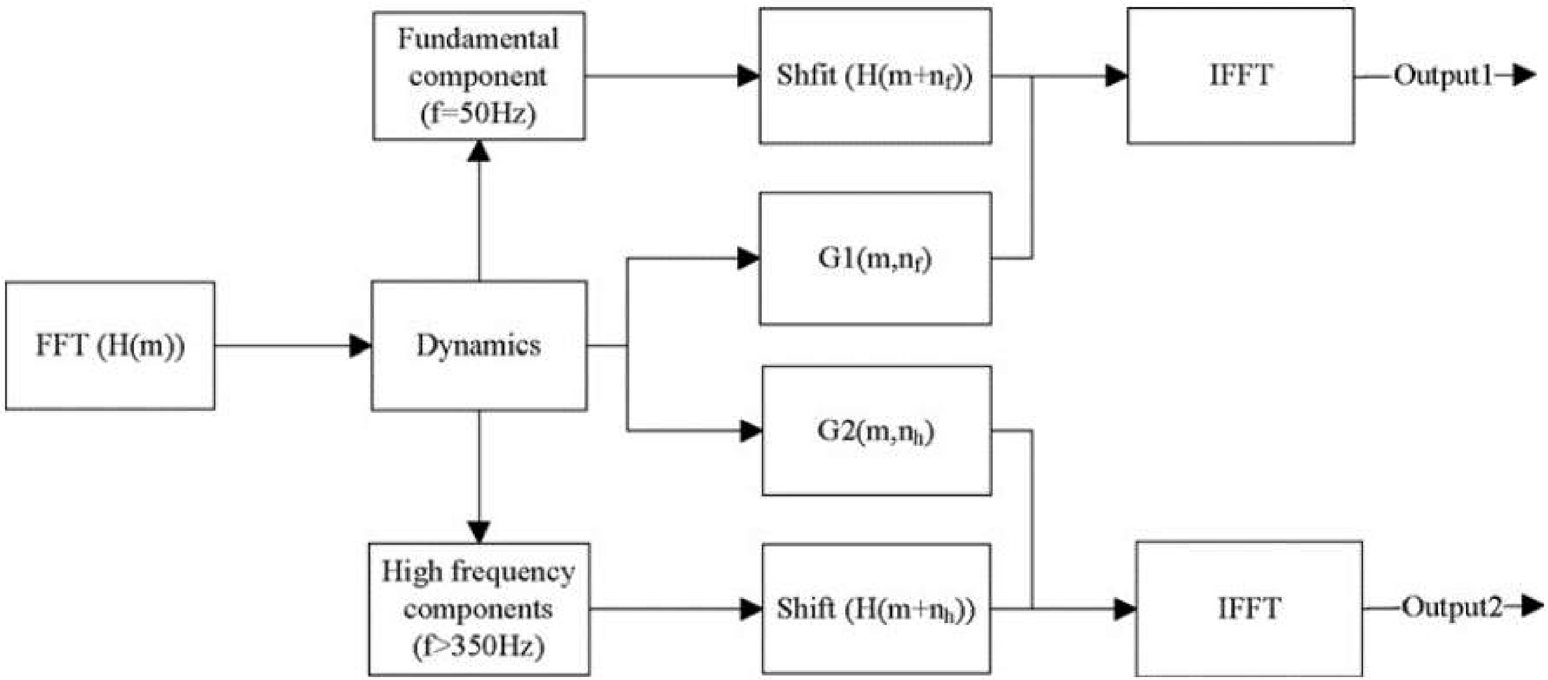
The hybrid method

- In ST, it should be noted that each $H(m+n)$ has its own Gaussian window.
- The main computation burden of ST is that every $H(m + n)$ is used in steps 3 and 4.
- Most of frequency samples yielded by FFT are 0 or just noises which have few information of the signal.
- Hence, the key to reduce run time is to find the location of frequency samples which are not 0 and noises in the spectrum.
- By using Dyn, the interested frequency samples are selected from 0 and noises in the spectrum and only some of them are used in steps 3 and 4.
-

The hybrid method

- Gaussian window plays an important role in ST.
- In low frequency band, high time resolution is expected for fast response of waveform changes.
- In high frequency band, high frequency resolution is expected for good tolerance of noises and influence from other frequency components.
- According to Heisenberg's uncertainty, time and frequency resolution can not increase at the same time. From (4), better time resolution comes with $a < 1$, while better frequency resolution comes with $a > 1$.
- In this paper, we used G1($a < 1$) and G2($a > 1$) to address low frequency components ($f \le 350$ Hz) and high frequency ones ($f > 350$ Hz), respectively.
- By many experiments, G1($a = 0.8$) and G2($a = 10$) give good performances.

The hybrid method



The hybrid method

- Step 1: Use FFT to the input signal and obtain the spectrum $H(m)$;
  Step 2: Use $\text{Dyn}_{\max}$ to identify the location of signal components in $H(m)$;
  Step 3: Shift $H(m)$ with the n_f and n_h which are the fundamental frequency index and high frequency indexes, respectively;
  Step 4: Compute the FFT of Gaussian windows

$$G1(m, n_f) = \exp\left[-a\left(\frac{2\pi^2 m^2}{n_f^2}\right)\right] \tag{6}$$

$$G2(m, n_h) = \exp\left[-a\left(\frac{2\pi^2 m^2}{n_h^2}\right)\right] \tag{7}$$

  Step 5: Use IFFT to $H(m + n_f)G1(m, n_f)$ and $H(m + n_h)G2(m, n_h)$.

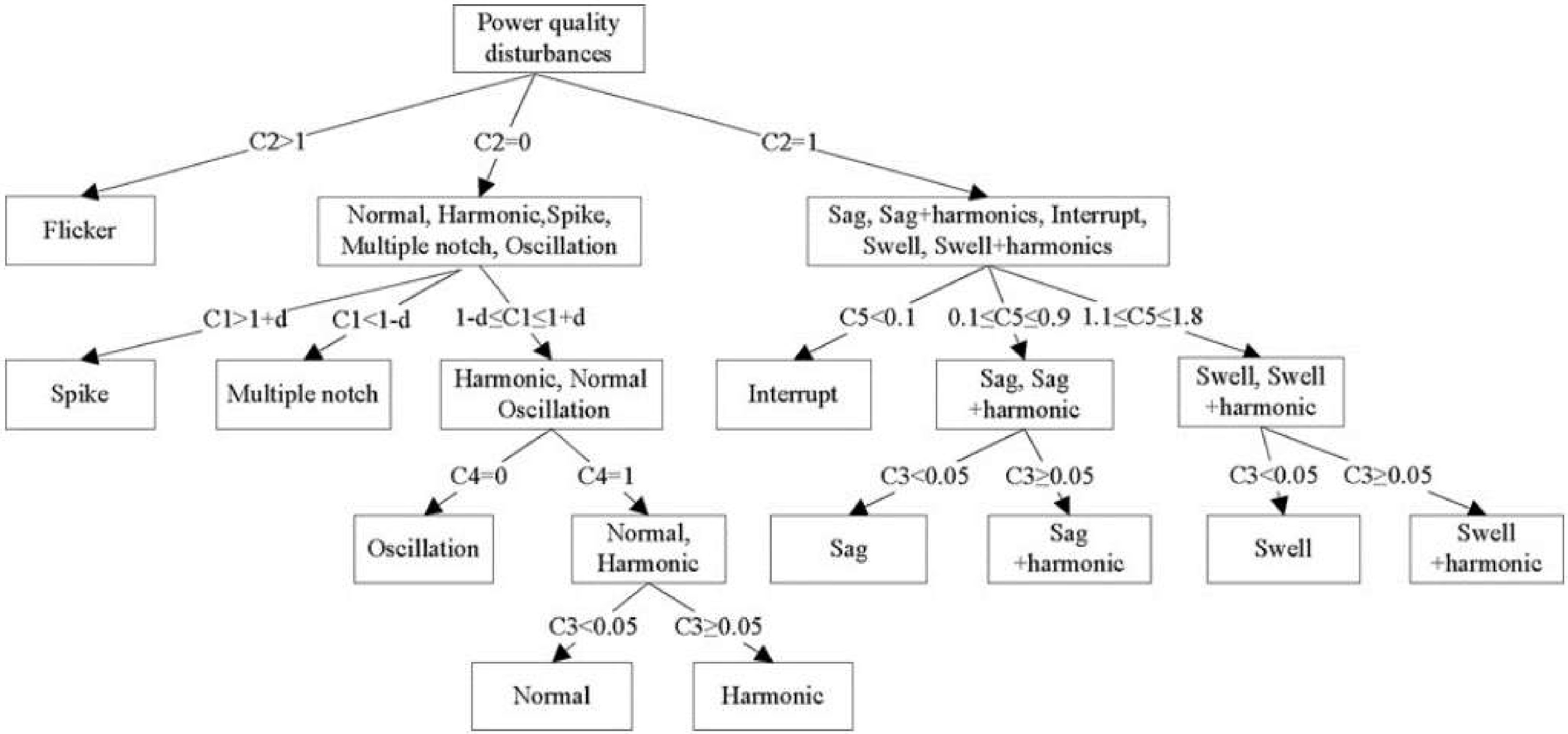
  Then the result of HM is obtained as

$$S_{\text{hybrid}} = H\left(\frac{m + n_f}{NT}\right) G1(m, n_f) e^{i2\pi mj/N} + H\left(\frac{m + n_h}{NT}\right) G2(m, n_h) e^{i2\pi mj/N}. \tag{8}$$

Features Extraction

- *B. Features Extraction and Rules for Decision Tree*

  Five distinctive features are selected in this paper.



B. Features Extraction

- *C*1: The mean value of fundamental amplitude. Parameter *d* is the threshold of noise tolerance. *C*1 is used to differentiate spike and multiple notch from noise.
- *C*2: The sum number of Dynmax and Dynmin of fundamental curve. It can be used to recognize flicker.
- C3: Total harmonic distortion (THD). The THD is obtained by FFT. Each harmonic peak is indicated by

$$\mathrm{THD} = \sqrt{\sum_{n=2}^{11} \left(\frac{A_n}{A_1}\right)^2}$$

  If THD $> 5\%$, C3 = 1 else, C3 = 0.
- C4: C4 is used to identify oscillation.The number of Dynmax of high frequency component curves. If there is one Dyn in one of the curves, C4 is 1, else C4 is 0.
- C5: The amplitude of the point indicated by C2, when C2 is 1. If $0.1 < C5 < 0.9$, then it is sag; if $0 < C5 < 0.1$, then it is interrupt; if $1.1 < C5 < 1.8$, then it is swell. .

Rules for Decision Tree

- we proposed a common use of PQDs classification.
- The rules of DT are presented in Table I. Every node of the tree needs only one feature rather than a group of features.
-

TABLE I

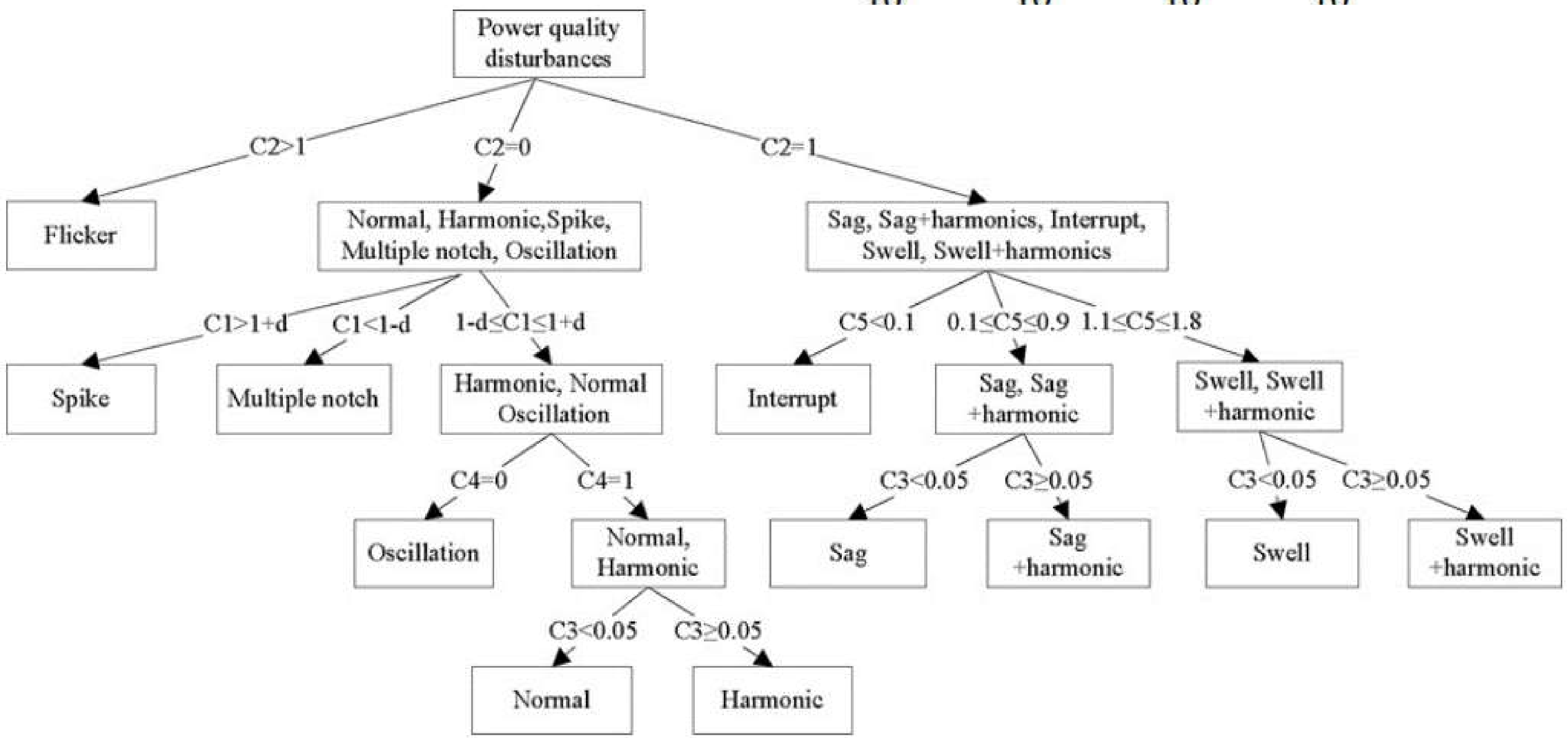
RULES OF DECISION TREE

Power quality disturbances	Feature value				
	$C1$	$C2$	$C3$	$C4$	$C5$
Normal	$(\geq 1-d)$ and $(\leq 1+d)$	0	0	0	Not use
Harmonic	$(\geq 1-d)$ and $(\leq 1+d)$	0	1	0	Not use
Flicker	Not use	>1	Not use	Not use	Not use
Sag	<1	1	0	Not use	$(\geq 0.1)\&(\leq 0.9)$
Interrupt	<1	1	Not use	Not use	(<0.1)
Swell	>1	1	0	Not use	(≥ 1.1) and (≤ 1.8)
Oscillation	$(\geq 1-d)$ and $(\leq 1+d)$	0	Not use	1	Not use
Spike	$>1+d$	0	Not use	Not use	Not use
Swell + harmonic	>1	1	1	Not use	(≥ 1.1) and (≤ 1.8)
Multiple notch	$<1-d$	0	Not use	Not use	Not use
Sag + harmonic	<1	1	1	Not use	(≥ 0.1) and (≤ 0.9)

Rules for Decision Tree

- 4 times (normal, harmonic)
- 3 times(sag, swell, sag plus harmonic, swell plus harmonic, oscillation),
- 2 times(spike, multiple notch, interrupt),
- 1 time(flicker).
- The average comparing times is:

$$E = 4 \times \frac{2}{10} + 3 \times \frac{5}{10} + 2 \times \frac{3}{10} + 1 \times \frac{1}{10} = 3.0.$$



Simulations

- The formulas of simulated signals are mainly referred from:
- C. Lee and Y. Shen, "Optimal feature selection for power quality disturbances classification," *IEEE Trans. Power Del.*, vol. 26, no. 4,pp. 1250–1257, Oct. 2011.

- Signal contaminated with 30 dB noise.
- Dynmax is used in Fourier spectrum, fundamental curve and high frequency component curves.
- Dynmin is used in fundamental curve.
- The noise threshold *d* is 0.005 by many experiments.
- Run time of ST mainly depends on the number of IFFT. Thus, the efficiency of HM can be evaluated by this number.
- The sample rate is 5 kHz and the length of all simulated signals is ten cycles (0.2 s), which means one time ST needs 500 IFFTs.

Simulations

- Figs. (a) are the signals.
- Figs. (b) are the fundamental curves.
- Figs. (c) are the spectrum of the signals yielded by FFT.
- Figs. (d) are the high frequency component curves.
- All points indicated by Dyn are marked with red stars.
- Run time of HM in this group of simulations compared to the one of ST is shown in Table II by assuming the run time of ST is 1 s. It can be seen that the run time has been reduced greatly. In a certain length of signal, higher sample rate brings higher efficiency of HM.

TABLE II

RUNTIME OF THE HYBRID METHOD BY ASSUMING THAT THE RUNTIME OF S-TRANSFORM IS 1 S

Power quality disturbances	Runtime (s)	Power quality disturbances	Runtime (s)	Power quality disturbances	Runtime (s)	Average
Normal	1/500	Multiple notch	1/500	Sag	1/500	1.27/500
Harmonic	3/500	Sag + harmonic	1/500	Interrupt	1/500	
Flicker	1/500	Spike	1/500	Swell	1/500	
Oscillation	2/500	Swell + harmonic	1/500	None	None	

Simulations

- Flicker signal and its features

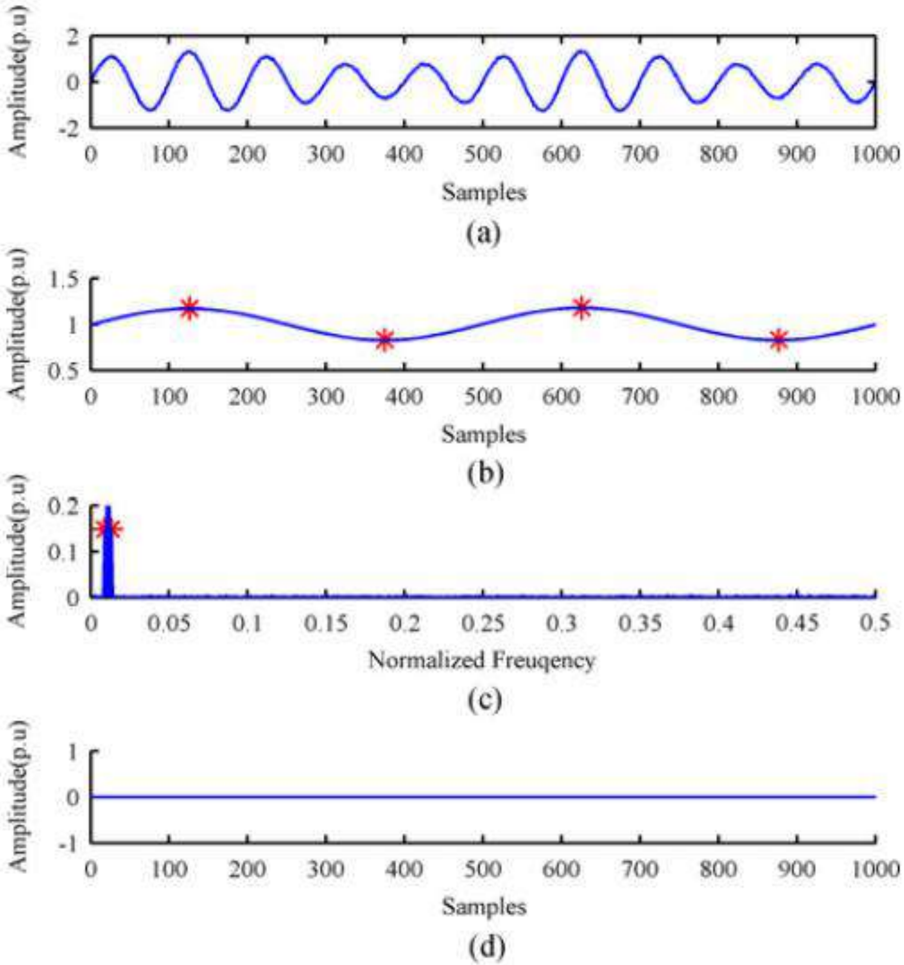


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations

- Oscillation signal and its features

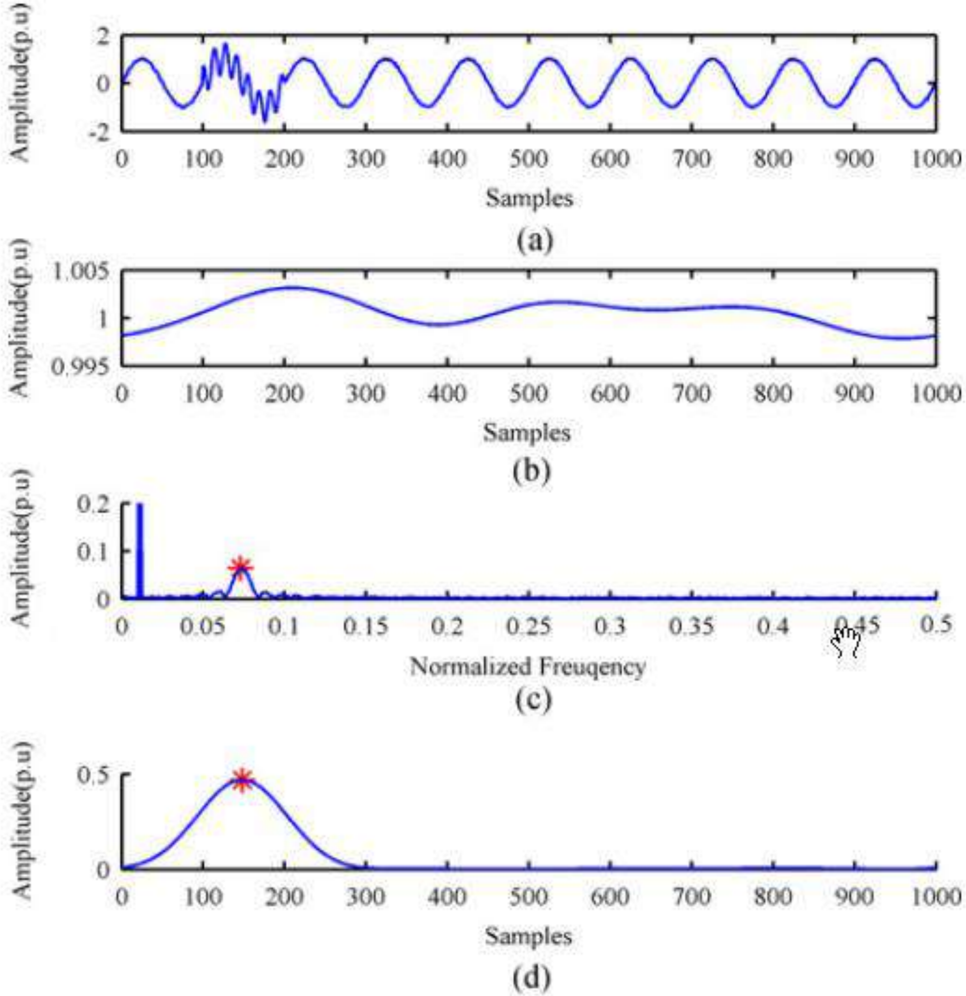


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations

- Multiple notch signal and its features

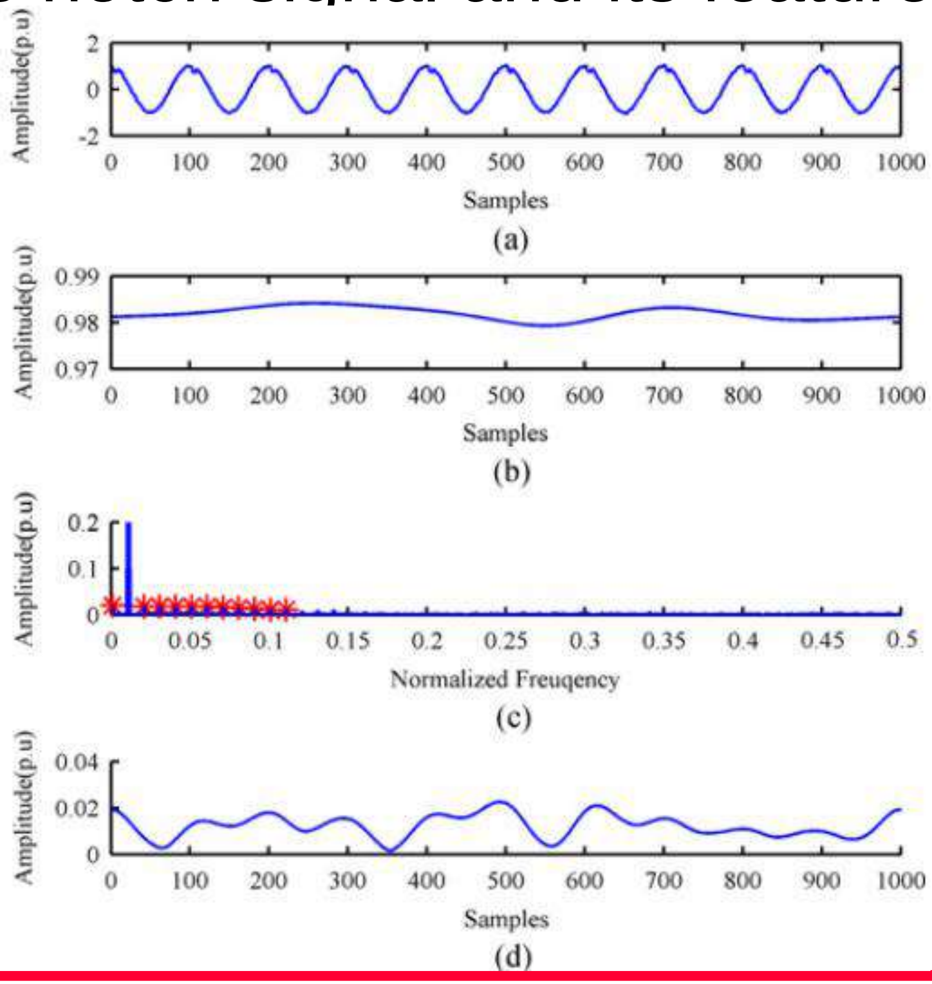


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations

- Sag + harmonic signal and its features

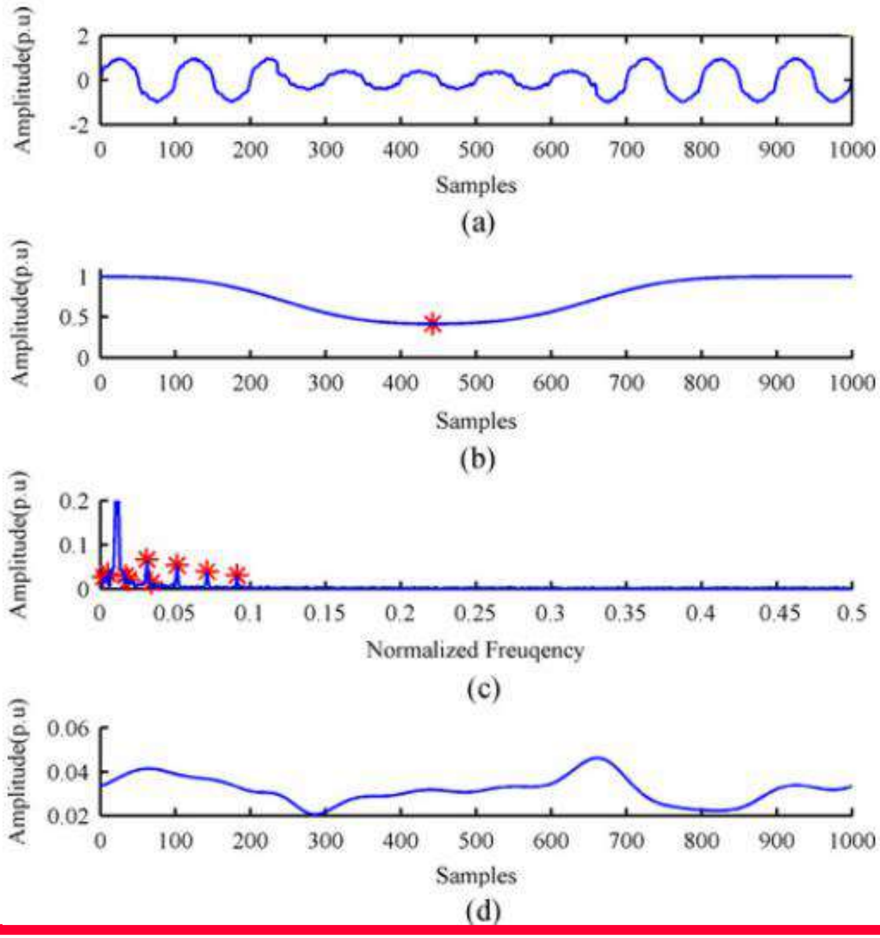


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations

- Spike signal and its features

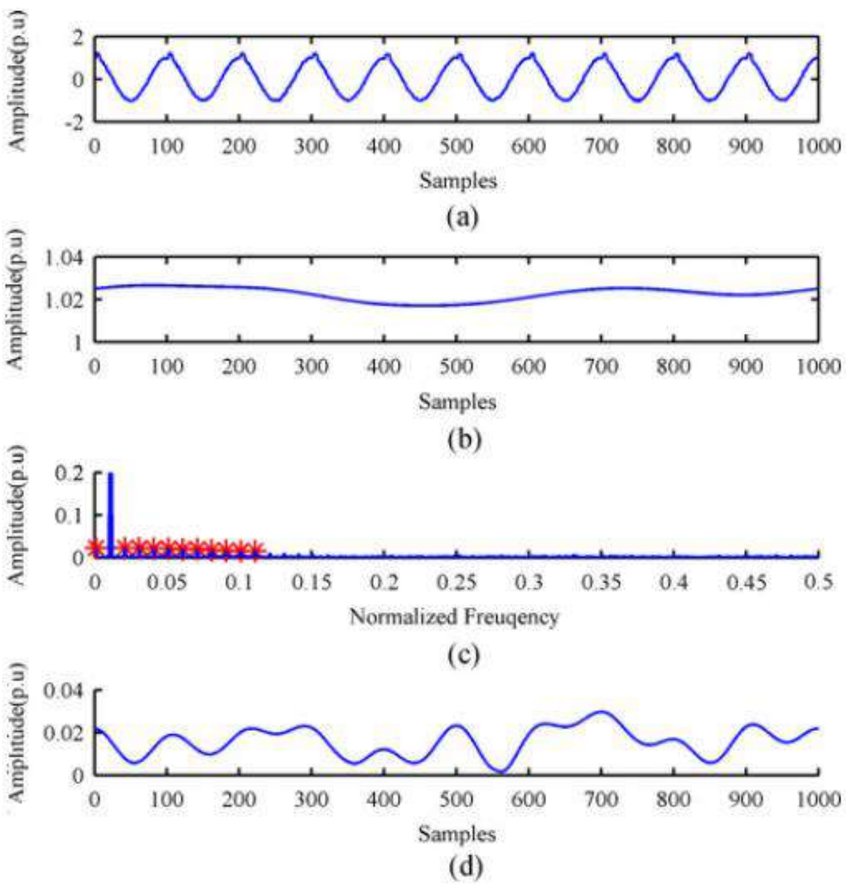


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations

- Swell + harmonic signal and its features

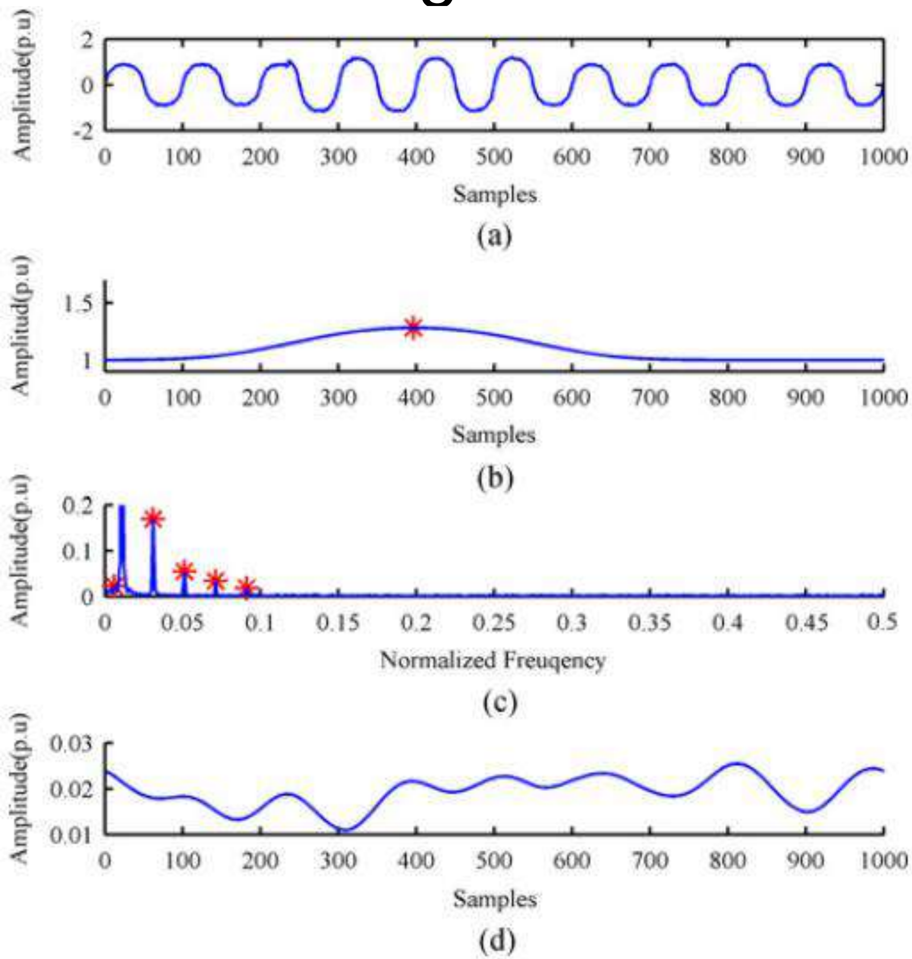


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations

- Sag signal and its features

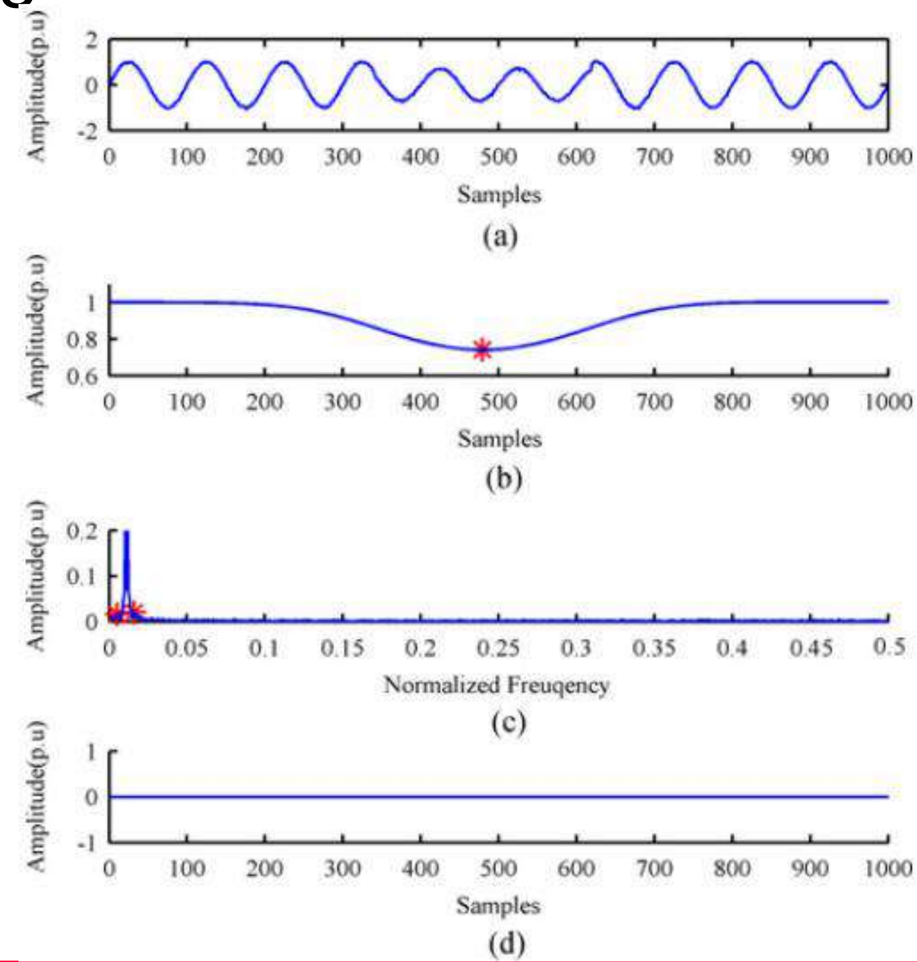


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations

- Swell signal and its features

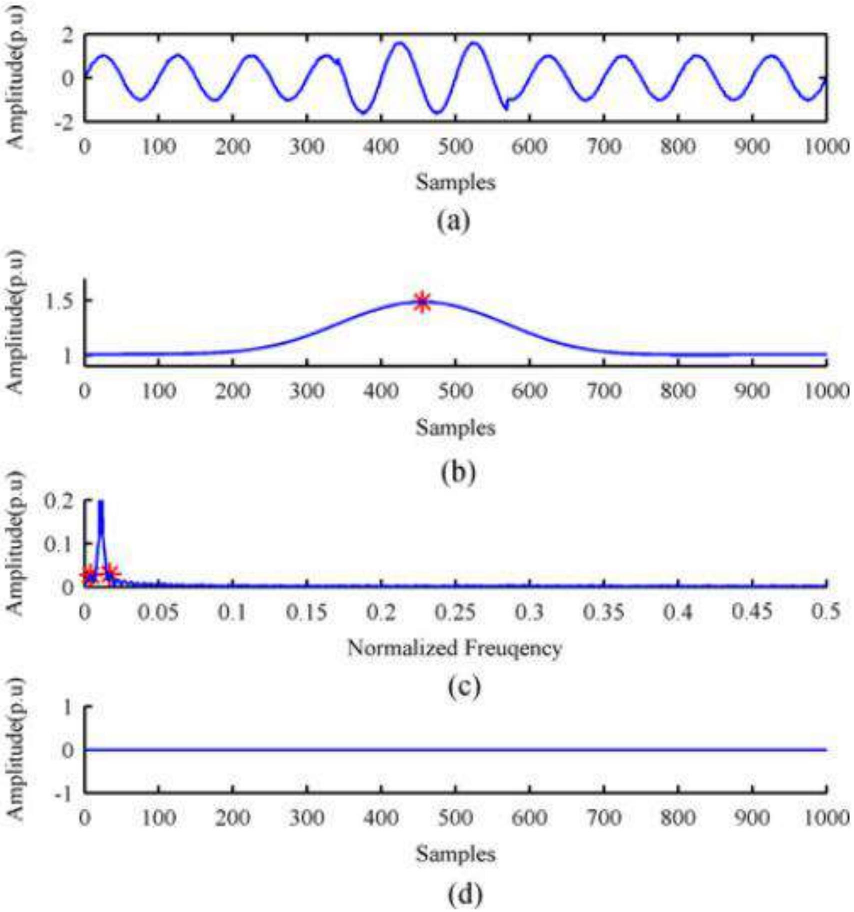


Fig. (a) is the signal.

Fig. (b) is the fundamental curve.

Fig. (c) is the spectrum of the signal yielded by FFT.

Fig. (d) is the high frequency component curve.

Simulations--HM versus M1and M2

- we generated randomly 100 signals of each type of PQDs which are contaminated with 40, 30, and 20 dB noise, respectively. Since HM is based on ST and has real time ability, two related methods are adopted to make comparisons: method in M1

  (*M*1) F. Zhao and R. Yang, "Power quality disturbance recognition using S transform," *IEEE Trans. Power Del.*, vol. 22, no. 2, pp. 944–207, Apr.2007

- and method in *M*2.

  (M2) M. Zhang, K. Li, and Y. Hu, "A real time classification method for power quality disturbances," Electr. Power Syst. Res., vol. 81, no. 1, pp. 660–666, 2011

The classification results of HM, M1, and M2 are presented in Table III.

HM versus M2

TABLE III

PERFORMANCE ON CLASSIFICATION ACCURACY

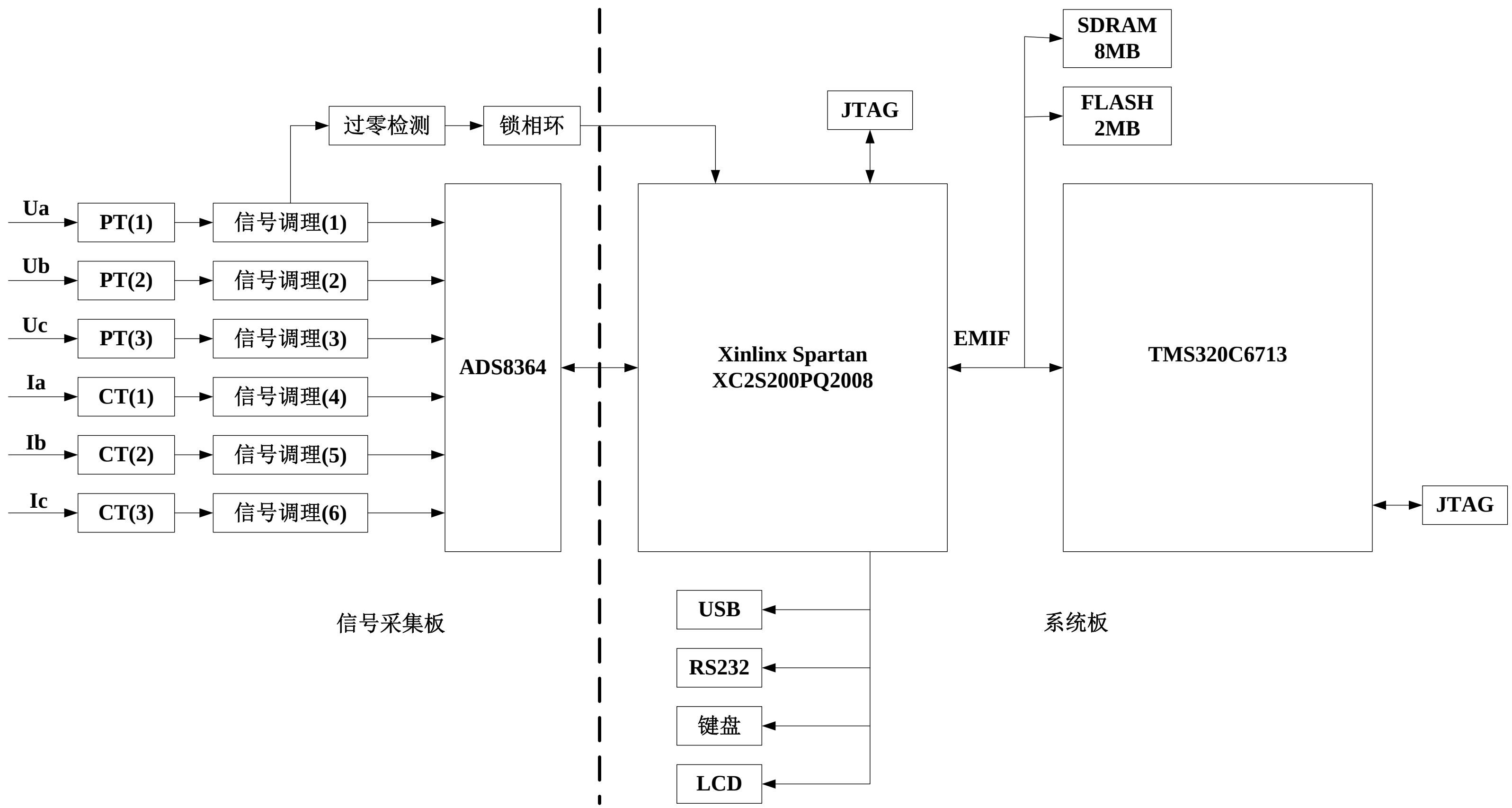
Power quality disturbances	Noise level								
	40 dB			30 dB			20 dB		
	HM	$M1$	$M2$	HM	$M1$	$M2$	HM	$M1$	$M2$
Normal	100	100	100	100	100	100	96	97	99
Harmonic	100	100	100	99	98	99	97	94	97
Flicker	98	—	96	96	—	96	91	—	92
Sag	100	99	99	99	99	95	95	93	89
Interrupt	98	97	95	96	92	86	85	82	81
Swell	100	98	99	98	97	96	97	95	92
Oscillation	100	100	92	99	98	90	97	97	89
Spike	99	99	84	97	99	83	94	96	78
Swell + harmonic	99	99	98	98	98	96	97	96	93
Multiple notch	99	100	85	98	99	82	94	95	78
Sag + harmonic	99	98	97	97	96	95	95	93	94
Mean classification accuracy	99.27	99.00	95.00	97.91	97.60	92.55	94.36	93.80	89.27

Experiment

- A hardware platform is introduced to run HM.
- Laboratory experiments are designed to evaluate the run time and test the correctness of HM by using real standard signals.
- Field signal analyses are also presented to evaluate the performance of HM in industry application,

System Structure

- Hardware system structure



Laboratory Experiments

- Fluke 6100A is used as a standard signal source
- The personal computer is adopted to debug the routine and display the results in Code Composer Studio.
- The length of tested signals is ten cycles (0.2 s). From Fig. 3 and Table II, flicker takes the shortest run time while harmonic takes the longest one among the PQDs.

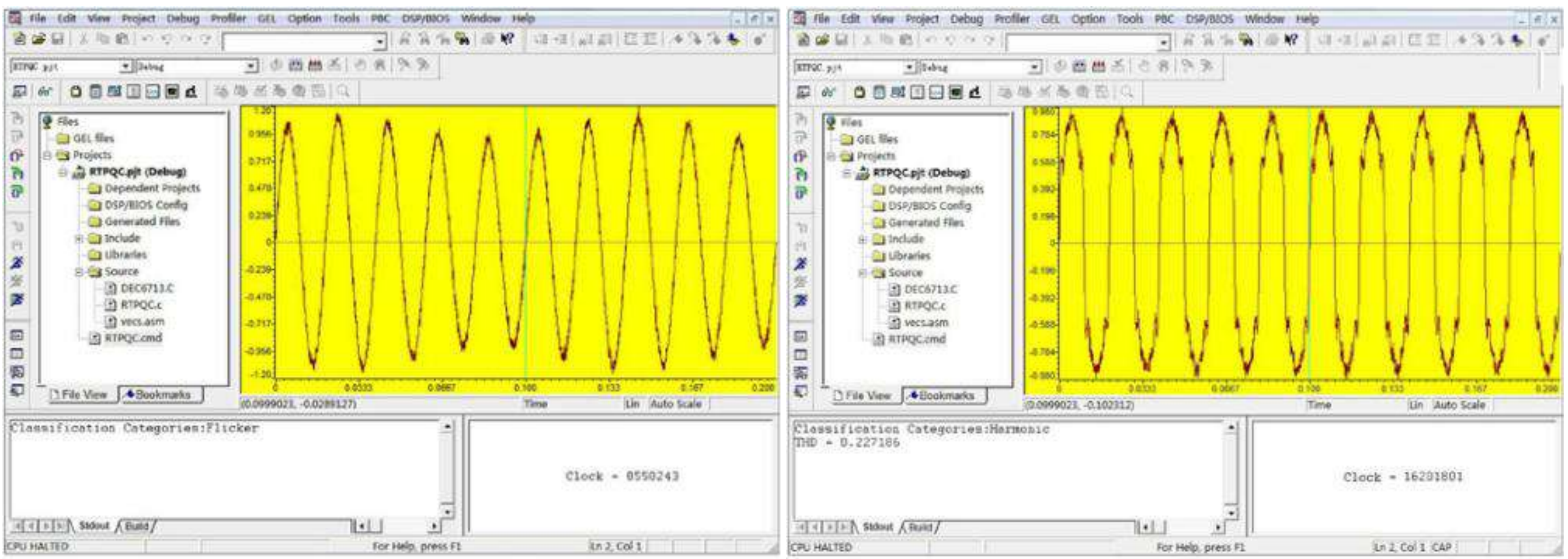
TABLE II

RUNTIME OF THE HYBRID METHOD BY ASSUMING THAT THE RUNTIME OF S-TRANSFORM IS 1 S

Power quality disturbances	Runtime (s)	Power quality disturbances	Runtime (s)	Power quality disturbances	Runtime (s)	Average
Normal	1/500	Multiple notch	1/500	Sag	1/500	1.27/500
Harmonic	3/500	Sag + harmonic	1/500	Interrupt	1/500	
Flicker	1/500	Spike	1/500	Swell	1/500	
Oscillation	2/500	Swell + harmonic	1/500	None	None	

Laboratory Experiments

- (a) Test performance of flicker on DSP.
- (b) Test performance of harmonic on DSP



(a) (b)

Flicker:run time 0.038 s

Harmonic:run time 0.072 s

Thank you　!