THE S-TRANSFORM-BASED DECISION TREE SYSTEM FOR THE CLASSIFICATION OF POWER QUALITY DISTURBANCES

Dinh Thanh Viet[1*], Nguyen Huu Hieu[1], Ngo Minh Khoa[2]**

[1] *The University of Danang, University of Science and Technology; [*]dtviet@ac.udn.vn; [**]huuhieu019@yahoo.com*
[2]*Quynhon University; nmkhoaqnu@gmail.com*

Abstract - In this paper, a new method for the classification of various types of power quality (PQ) disturbances has been presented. In the proposed method, five features which represent the distinctive characteristics of PQ disturbances and reduce the data size are extracted from the PQ disturbances with the use of the S-Transform (ST). Then decision tree (DT) algorithm is applied to classify the nine types of PQ disturbances. The disturbance signals which are generated via Matlab/Simulink are used to evaluate the performance of the proposed method. According to the obtained results, the proposed method classifies various types of PQ disturbances with a high accuracy.

Key words - S-transform; decision tree; power quality disturbances; classification.

1. Introduction

Nowadays, PQ has become a very important subject to both electric utilities and their customers. A lot of modern electric appliances are equipped with power electronics devices utilizing the microprocessor/microcontroller. These appliances introduce various types of PQ problems and moreover, they are very sensitive to the PQ problems. Besides, there has been a significant increase in embedded generation and renewable energy sources which create PQ disturbances, such as voltage variations, flicker and waveform distortions. This requires a system which has the ability to detect and classify the different PQ disturbances.

There are many traditional methods for the analysis of PQ disturbances. The standard method used in the PQ meters for obtaining the supply voltage magnitude is the RMS method, which is simple and easy to implement. In [1], the authors utilize RMS and fast Fourier transform (FFT) to indentify five features of disturbance signals. However, the RMS method does not provide frequency information of the monitored signals. A simple way to analyze any signal is using discrete Fourier transform (DFT) [1]. The DFT is a frequency domain technique which estimates the individual harmonic components and it is suitable for stationary signals only. To overcome the DFT disadvantages, STFT [2] maps a signal into a two- dimension function of time and frequency. The STFT extracts time and frequency information; however, its disadvantage is that size of window is fixed for all frequencies, so there is low resolution for high frequencies and it is useful in providing information for signals that are stationary.

The alternative algorithm of STFT is wavelet transform (WT) which is more suitable for processing non-stationary signals. The multi-resolution analysis allows variations in a time and frequency plane. The idea is to increase the time resolution at a higher frequency and frequency resolution at a lower frequency. In recent years, the WT is widely used in the signal processing of the PQ disturbances. Researchers [3]-[5] have utilized WT to extract the features for PQ disturbance signals. However, the disadvantages of WT are its degraded performance under noisy conditions, the selection of mother wavelet and the level of decomposition has to be proper based on disturbances [2]. In order to improve the performance of WT, an alternative technique called the ST was developed. The ST is an extension to WT which is very analogous to the FT. Furthermore, the ST has been derived from continuous wavelet transform (CWT) by choosing a specific mother wavelet and multiplying a phase correction factor. Thus, the ST has been interpreted as a phase-corrected CWT [6], [7]. The ST has an advantage in that it provides multiresolution analysis while retaining the absolute phase of each frequency. This led to its application for the detection and interpretation of non-stationary signals. Further, the ST provides frequency contours which clearly localize the signals at a higher noise level. One of the advantages over WT of ST is to avoid the requirement of testing various families of wavelets to identify the best one for a better classification. In [8-13] the ST has been used to extract features from PQ disturbances.

A variety of methods based on the features extracted from the signal processing techniques has been adopted for the classification of PQ disturbances. The authors in [3], [8], [11], [12], [14] have utilized neural network to classify the types of PQ disturbances. Similar to neural network, DT approach has found applications in classifying types of PQ disturbances [1], [7].

In this paper, a new method for classifying various types of PQ disturbances has been proposed. The ST is used in order to extract the distinctive features of PQ disturbances. Five features which represent the distinctive characteristics of PQ disturbances and reduce the data size are extracted from the PQ disturbances by using the ST. Then the DT algorithm is used to classify the nine types of PQ disturbances.

2. Methodology Background

2.1. S-transform

The ST was originally defined with a Gaussian window whose standard deviation is scaled to be equal to one wavelength of the complex Fourier spectrum. The original expression of ST presented in [6], [7] is

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-i2\pi ft} dt \qquad (1)$$

The normalizing factor of $|f|/\sqrt{2\pi}$ in (1) ensures that, when integrated over all τ, S(τ,f) converges to X(f), the FT of x(t):

$$\int_{-\infty}^{\infty} S(\tau, f) = \int_{-\infty}^{\infty} x(t) e^{-i2\pi f} dt = X(f) \qquad (2)$$

It is clear from (2) that x(t) can be obtained from S(τ,f). Therefore, the ST is invertible. Let x[kT], k=0, 1,..., N-1 denote a discrete time series, corresponding to x(t), with a time sampling interval of T. The DFT is given by (3)

$$X\left[\frac{n}{NT}\right]=\frac{1}{N}\sum_{k=0}^{N-1}x[kT]e^{-\frac{i2\pi nk}{N}} \tag{3}$$

Where n = 0, 1,..., N-1. In the discrete case, the ST is the projection of the vector defined by the time series x[kT] onto a spanning set of vectors. The spanning vectors are not orthogonal, and the elements of the ST are not independent. Each basis vector (of the FT) is divided into N localized vectors by an element-by-element product with N shifted Gaussians, so that the sum of these N localized vectors is the original basis vector.

Letting f → n /NT and τ → jT, the discrete version of the ST is given in [2] as follows:

$$S\left[jT,\frac{n}{NT}\right]=\sum_{m=0}^{N-1}X\left[\frac{m+n}{NT}\right]e^{-\frac{2\pi^2m^2}{n^2}}e^{i\frac{2\pi mj}{N}} \tag{4}$$

And for the n=0 voice is equal to the constant defined as (5):

$$S\left[jT,0\right]=\frac{1}{N}\sum_{m=0}^{N-1}x\left[\frac{m}{NT}\right] \tag{5}$$

Where j, m and n = 0, 1,..., N-1. Equation (5) puts the constant average of the time series into the zero frequency voice, thus assuring accuracy of the inverse for the general time series.

The output of the ST is a kxn matrix called S-matrix whose rows pertain to frequency and columns to time. Each element of the S-matrix is a complex value. The ST-amplitude (STA) used to analyze PQ disturbances is obtained as:

$$STA(kT,f)=\left|S\left[kT,n/NT\right]\right| \tag{6}$$

Using Matlab/Simulink software to all the signals of nine PQ disturbance types including normal voltage, voltage sag, swell, interruption, flicker, oscillatory transient, harmonic, sag with harmonic and swell with harmonic. In this work, sampling frequency of 3.2 kHz, which is equal to 64 points/cycle, is selected. Fifteen power frequency cycles which contain the disturbance are used for a total 960 points. The power system fundamental frequency is 50 Hz. Figs 1-9a show the waveforms of sampling normal voltage and PQ disturbance signals.

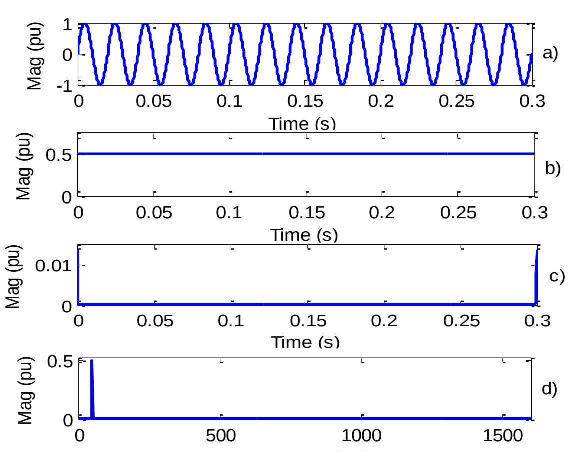

Figure 1. *Normal voltage waveform and its features*

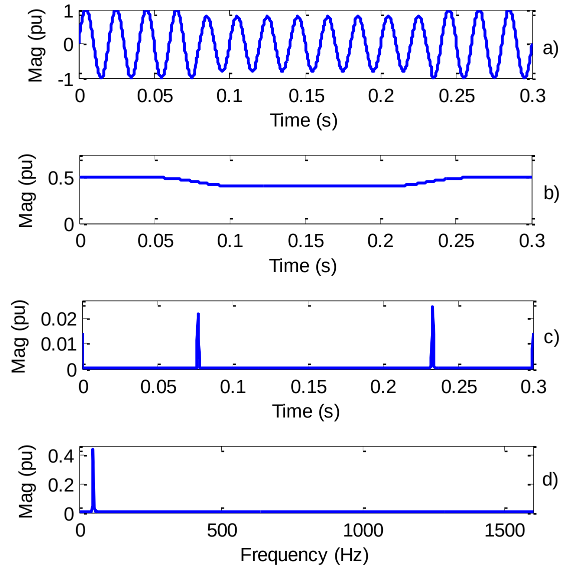

Figure 2. *Voltage sag waveform and its features*

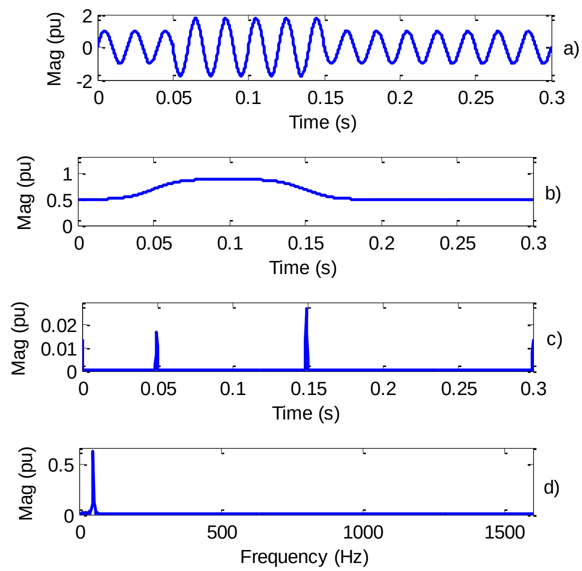

Figure 3. *Voltage swell waveform and its features*

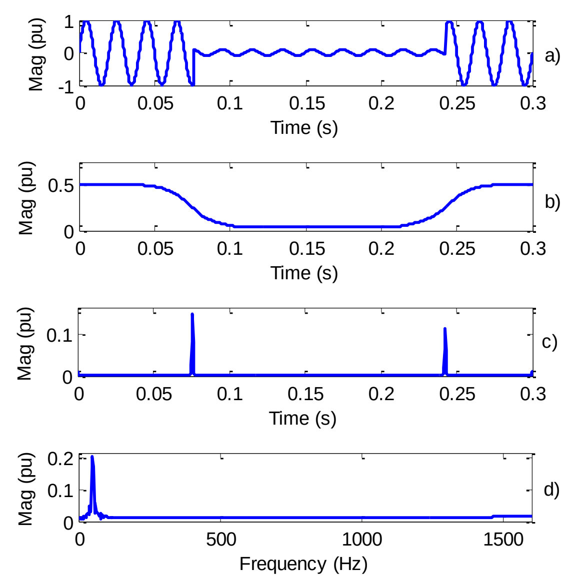

Figure 4. *Voltage interruption waveform and its features*

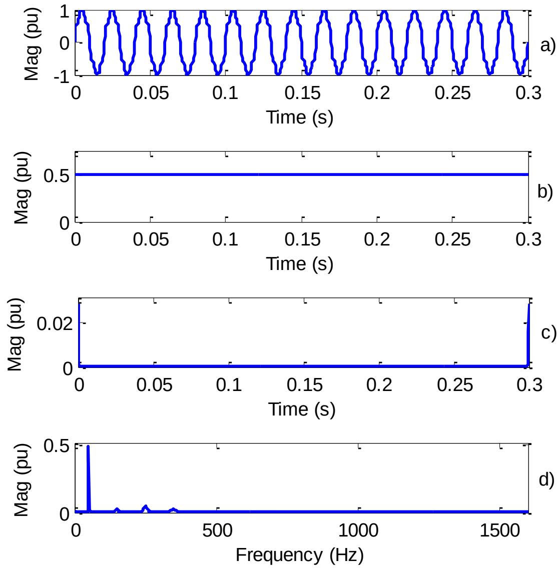

Figure 5. *Voltage harmonic waveform and its features*

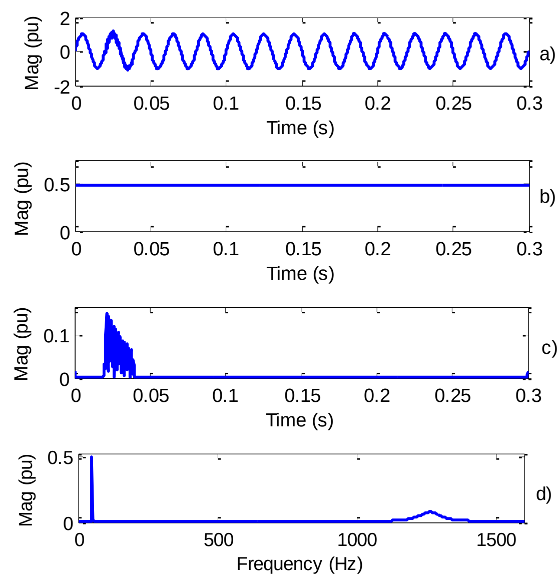

Figure 6. *Oscillatary transient waveform and its features*

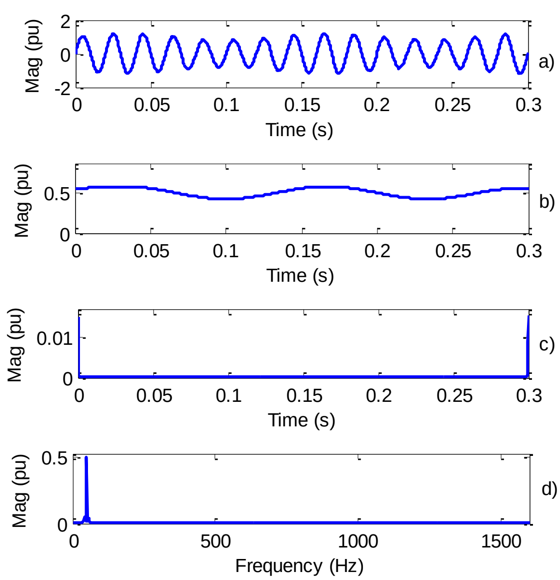

Figure 7. *Voltage flicker waveform and its features*

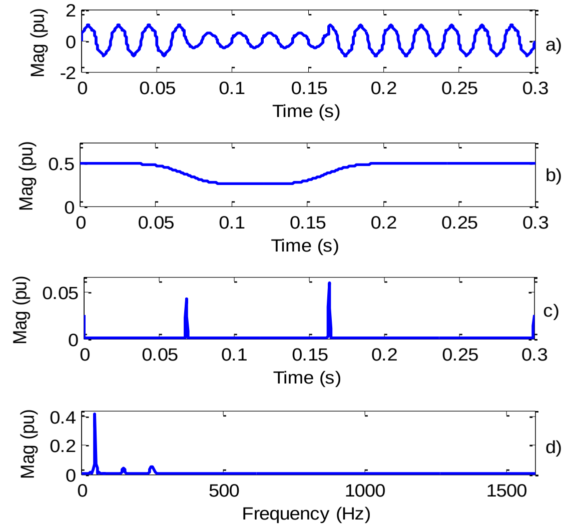

Figure 8. *Voltage sag - harmonic waveform and its features*

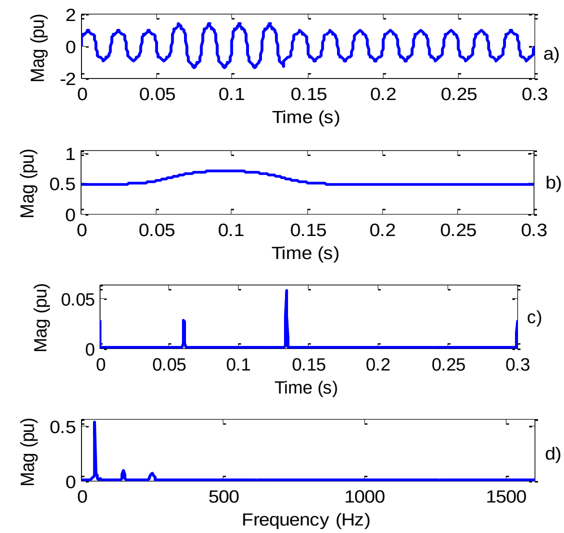

Figure 9. *Voltage swell - harmonic waveform and its features*

There are many plots of time-frequency, time-amplitude and amplitude-frequency which are determined from STA matrix. In this paper, some of them are presented as follows:

+ *The time – maximum amplitude plot – TvA* (Figs 1-9b), which is maximum amplitude versus time by searching columns of STA matrix at every frequency:

$$TvA = \max\left(STA\right) \quad (7)$$

+ The time – amplitude of maximum frequency plot – TvHFA (Figs 1-9c), which is the last row of STA matrix.

+ *The frequency – maximum amplitude – FvA* (Figs 1-9d), which is maximum amplitude versus frequency by searching rows of STA matrix at every time:

$$FvA = \max\left(STA'\right) \quad (8)$$

Where STA' is the transpose matrix of STA matrix.

2.2. Features extraction

The performance of PQ disturbance classification depends on their features. There are variety features of disturbance signals which are extracted by using signal processing methods. In this paper, the five features which are extracted from ST have been proposed. They are defined and determined as follows.

F1: It presents existence of high frequency component of the oscillatory transient. For the three-phase power system, the most common harmonics are 5, 7 and 11th harmonics, for the oscillatory transient mainly includes the high frequency component [1]. Therefore F1 is used to classify oscillatory transient with other disturbances. If there is a peak in the proximity of the high frequency (fn≥650 Hz) on FvA plots (Figs 1-9d), then F1=1, otherwise F1=0.

F2: It distinguishes between stationary and non-stationary signals. If number of peaks on TvHFA plots (Figs 1-9c) greater than or equal to 2, then F2=1. If there is no peak, then F2=0. Thus, if F2=0 then signal is the stationary signal (normal, harmonic, flicker). If F2=1 then signal is the non-stationary signal (sag, swell, interruption, sag with harmonic, swell with harmonic, oscillatory transient). Morever, F2 is used to identify the start time t_s (s) or k*s* (sample) and the end time t_e (s) or k_e (sample) which is corresponding to the peaks on TvHFA plots (Figs 1-9c) of non-stationary signals.

F3: It presents the voltage amplitude oscillation around the average value. F3 is determined on TvA plots (Figs 1-9b) as follows:

$$num_{zeros} = root\left(TvA - mean\left(TvA\right)\right) \tag{9}$$

Where mean(.) returns the the mean value of the argument, root(.) returns the number of roots of the argument. From TvA plots (Figs 1-9b), numzeros is greater than 2 for the flicker signal and numzeros is smaller than 2 for the other disturbances. Therefore, F3 is used to distinguish the flicker signal from the other ones, if numzeros>3, then F3=1, else F3=0.

F4: It presents existence of harmonics in the disturbance signal. F4 is determined by using FvA plot (Figs 1-9d) and the total harmonic distortion (THDV) factor:

$$THD_V = \frac{\sqrt{\sum_{n=2}^{N} V_n^2}}{V_1} \tag{10}$$

Where V_1 is voltage, corresponding to the fundamental frequency amplitude (50 Hz); N is the number of points in the DFT.

F4 is identified by the following rule, if THDV≤0.05 [1] then F4=0, otherwise F4=1. So F4=1 if the signal is voltage harmonic, sag with harmonic or swell with harmonic, F4=0 for other signals.

F5: It is RMS of signal at time that is internal period of voltage sag, swell or interruption.

- The time is between k_s (sample) and k_e (sample) of non-stationary signal.

$$k_i = k_s + round\left(\frac{k_e - k_s}{2}\right) \tag{11}$$

Where round(.) returns the nearest integer of the argument.

- Using half-cycle RMS method at the time k_i (sample) of sampling signal, which is shown as follows:

$$V_{rms} = \sqrt{\frac{1}{32}\sum_{k=k_i-16}^{k_i+15} x^2\left(kT\right)} \tag{12}$$

- F5 is difined as follows:

$$F_5 = \sqrt{2}V_{rms} \tag{13}$$

Using F5 to distinguish between with/without voltage sag, swell and interruption signals through rules as follows: if 0.1≤F5≤0.9 then the signal is the sag signal; if 1.1≤F5≤1.8 then the signal is the swell signal; else if F5≤0.1 then the signal is the interruption signal.

According to the above description and the PQ disturbances definition, the feature values of nine types of PQ disturbances are shown in Table 1, which can be the rules of identifying PQ disturbance type.

2.3. Decision tree algorithm

The decision tree [1] (DT) is a powerful and popular tool for classification and prediction. It represents rules, which can be understood by humans and used in knowledge system such as database. According to Table 1, the DT for classification of PQ disturbances is achieved, shown in Fig 10. Using the DT, the above nine types of PQ disturbances can be classified.

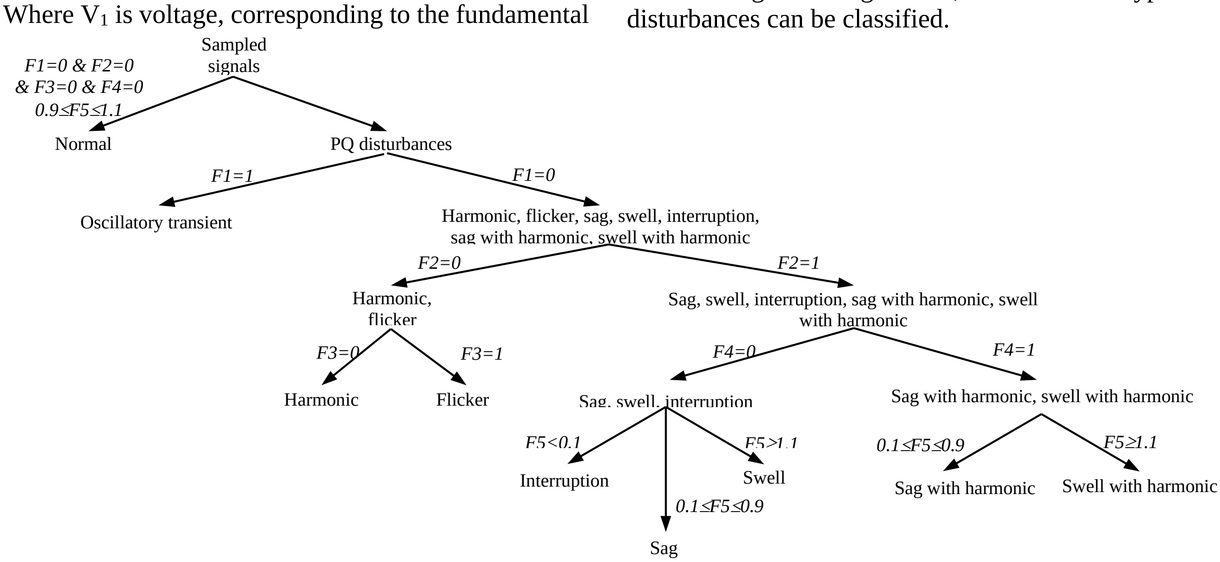

Figure 10. *Decision tree of PQ disturbances classification*

Table 1. *PQ Disturbance Feature Values*

Type of voltage signals	The values of features				
	F1	***F2***	***F3***	***F4***	***F5***
Normal	0	0	0	0	(≥0.9)&(≤1.1)
Sag	0	1	-	0	(≥0.1)&(≤0.9)
Interruption	0	1	-	0	≤0.1
Swell	0	1	-	0	(≥1.1)&(≤1.8)
Harmonic	0	0	0	1	-
Flicker	0	0	1	-	-
Oscillatory transient	1	1	-	-	-
Sag with harmonic	0	1	-	1	(≥0.1)&(≤0.9)
Swell with harmonic	0	1	-	1	(≥1.1)&(≤1.8)

Note "-" not use

3. Results and Discussion

3.1. Case studies

In order to generate disturbances on a power system, the IEEE 13-bus test feeder shown in Fig 11 is used for the generation of PQ events. The load and line data of the test system are presented in [14]. The Matlab/Simulink is applied to model the feeder, simulate the PQ events and generate the PQ disturbance signals. For the case studies, two following events are assumed to happen in the feeder.

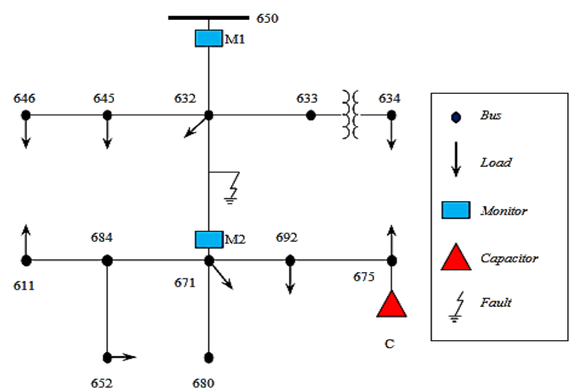

Figure 11. *Diagram of IEEE 13-bus test feeder*

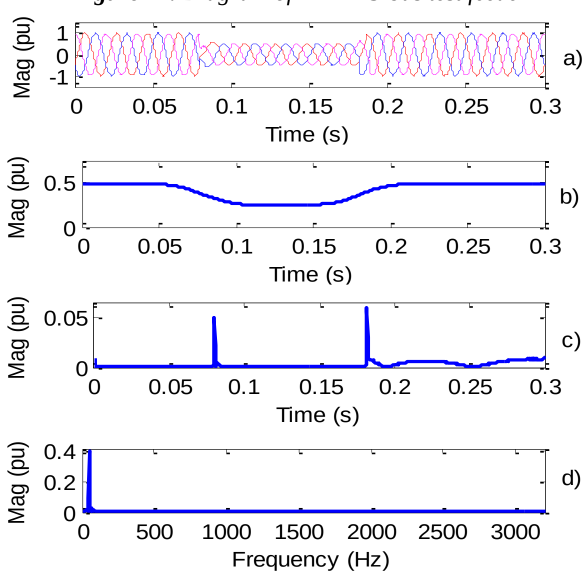

Figure 12. *Voltage at M1 in case 1; (a) three-phase voltage waveforms; (b) TvA; (c) TvHFA; (d) FvA plot*

Case 1: three phase fault at center of Line 632-671, the three phase voltage waveforms and the feature plots at monitor M1 are shown in Fig 12, respectively. The proposed method is applied to classify the disturbances. According to the results obtained by the proposed method, the voltage signal at monitor M1 belong voltage sag.

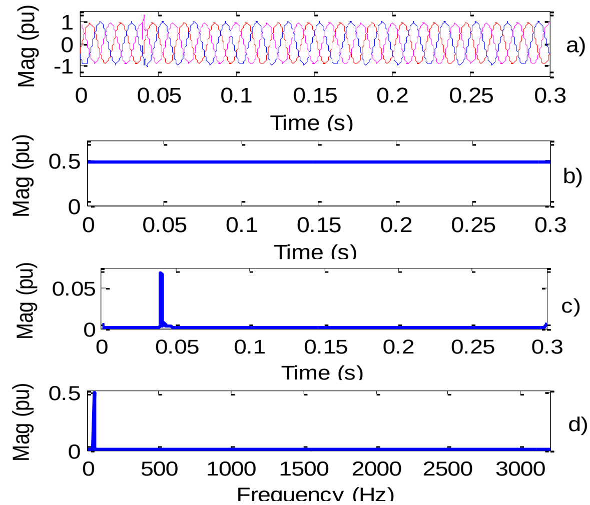

Figure 13. *Voltage at M2 in case 2; (a) three-phase voltage waveforms; (b) TvA; (c) TvHFA; (d) FvA plot*

Case 2: the capacitor at 675 is connected to the network, the three phase voltage waveforms and the feature plots at monitor M2 are shown in Fig 13. The proposed method is also applied to classify the disturbance. As result, the voltage signal at monitor M2 belongs to oscillatory transient type.

3.2. Performance evaluation

In order to evaluate the performance of the proposed method, Matlab/Simulink software is used to generate other nine hundred disturbance waveforms of PQ disturbances, except the waveforms considered in Section 2, with different parameters such as magnitude percentages, durations and instants on waveform according to the signal models [8]. Then the ST is used to extract the five features given in Section 2.2 are calculated. The features, which include F1, F2, F3, F4, F5 are as the input vector of the DT. Finally the DT structure shown in Fig 10 is used to classify the various types of PQ disturbances. The performance result of the proposed method is given in Table 2.

Table 2. *Classification Results of PQ Disturbances*

Type of voltage signal	Classification result			
	Total samples	***Correct samples***	***Incorrect samples***	***Accuracy***
Normal	100	100	0	100%
Sag	100	100	0	100%
Interruption	100	98	2	98%
Swell	100	100	0	100%
Harmonic	100	100	0	100%
Flicker	100	100	0	100%
Oscillatory transient	100	100	0	100%
Sag with harmonic	100	100	0	100%
Swell with armonic	100	100	0	100%
Total	**900**	**898**	**2**	**99.78%**

As shown in Table 2, the S-transform-based decision tree method which is proposed in this paper has the classification result with high accuracy (99.78%). From Table 2, although the average accuracy is high but there are also some mistakes in classification of the voltage interruption signal (98%), because the magnitude percentages of interruption and sag signals are sometimes similar.

4. Conclusion

In this paper, a new pattern recognition approach has been developed in order to classify the types of PQ disturbances. For this purpose, the ST is applied to extract the five distinctive features of disturbance signals. Finally, a DT algorithm has been obtained for classifying the types of PQ disturbance including normal voltage, voltage sag, swell, interruption, flicker, oscillatory transient, harmonic, sag with harmonic and swell with harmonic. According to the above results, the classification accuracy of the proposed method is high enough. Moreover, the DT algorithm is based on a simple rule set with a structure IF … THEN. Thus the proposed method reduces memory space, improves computing speed and can response to the automatic PQ disturbance classification in a real-time analysis.

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