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Wavelet Transform for Classification of Voltage Sag Causes using Probabilistic Neural Network

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Abstract

This paper presents an algorithm to detect and classify voltage sag causes based on Wavelet Transform (WT) and Probabilistic Neural Network (PNN). A technique is required which is capable of extracting both time-frequency information to identify the causes which contribute to power quality disturbances. Wavelet transform based on multiresolution analysis is used to extract the features from the disturbance signal. The detailed coefficients of wavelet transform of first three levels of each disturbance are used as inputs to PNN for identification of voltage sag causes. Three voltage sag causes are taken for classification (i) Three phase short circuit (ii) Starting of induction motor and (iii) Three phase transformer energization. Simulation results show that wavelet transform combined with probabilistic neural network can effectively detect and classify the voltage sag causes.

Keywords: Power quality, probabilistic neural network, voltage sag causes, wavelet transform.

Introduction

The issue of power quality has become important in recent years to utilities and customers owing to the increasing usage of modern power electronic devices that are very sensitive to voltage disturbances. To mitigate the power quality disturbances, one has to know about the sources of power system disturbances or the actual causes behind them. This requires a system which is able to analyze data and classify the different power system disturbances, so that a lot of time is saved if done automatically. Voltage sag is one of the most disturbing power quality problems. The voltage sags are mostly due to short circuit fault, starting of induction motor or due to transformer energizing. A simple way to analyze any signal is by Fourier Transform

(FT) [1]. Fourier transform is a frequency domain technique which would estimate the individual harmonic components and is applied for stationary signals only. Short Time Fourier Transform (STFT) is proposed [2-3] which maps a signal into a two dimensional function of time and frequency. The STFT extracts time and frequency information, the disadvantage is that the size of the window is fixed for all frequencies. The wavelet transform (WT) [4-6] represents a windowing technique with variable regions to overcome the deficiency. It provides a unified methodology to characterize power quality events by decomposing the signal into time and frequency resolution. So wavelet function is localized both in time and frequency [7], yielding wavelet coefficients at different scales.

This paper is organized into six sections, section II gives introduction to wavelet transform and section III presents three voltage sag causes and various features extracted from the detailed coefficients at each level of wavelet transform. Section IV explains the probabilistic neural network classification of voltage sag causes. Section V gives the results and discussion about the methodology. Section VI gives the conclusions of the work.

Wavelet Transform

The wavelet analysis block transforms the distorted signal into different time-frequency scales. The first main characteristic in wavelet transform is the multiresolution technique that it decomposes the original signal into several other signals with different levels (scales) of resolution. From these decomposed signals, the original time-domain signal can be recovered without losing any information. The wavelet analysis transforms the distorted signal into different time-frequency scales. The wavelet transform uses the wavelet function and scaling function to perform simultaneously the multiresolution analysis (MRA) for decomposition and reconstruction of the measured signal. The wavelet function generates the detailed version (high-frequency components) of the decomposed signal and the scaling function generates the approximated version (low-frequency components) of the decomposed signal. The wavelet transform is a well-suited tool for analyzing high-frequency transients in the presence of low-frequency components such as non-stationary and non-periodic wideband signals. For a signal x(t),the continuous wavelet transform(CWT) is defined as

$$CWT_{\psi}x(a,b) = W_x(a,b) = \int_{-\infty}^{\infty} |x(t)| \psi^*_{a,b}(t)dt, \tag{1}$$

Where

$$\psi^*_{a,b} |a|^{-1/2} \psi\left(\frac{t-b}{a}\right) \tag{2}$$

Ψ(t) is the base function or the mother wavelet, the asterisk denotes a complex conjugate.

Since the transformation is achieved by dilating and translating the mother wavelet continuously, it generates substantial redundant information. Therefore, instead of continuous dilation and translation, the mother wavelet maybe dilated and translated discretely by selecting $a = a_o^m$ and $b = nb_o a_o^m$, where a_o and b_o are fixed constants with $a_o > 1$, $b_o > 0$, m,n € Z, and Z is the set of positive integers. Then, the discretized mother wavelet becomes

$$\psi_{m,n}(t) = \alpha_0^{-m/2} \psi\left(\frac{t - nb_0 a_o^m}{a_o^m}\right) \tag{3}$$

and the corresponding discrete wavelet transform(DWT) is given by

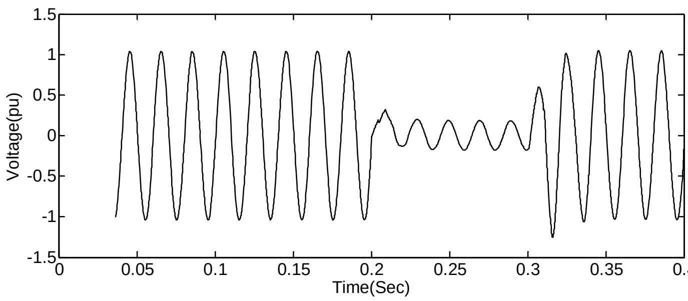
$$DWT_{\psi} x(m,n) = \int_{-\infty}^{\infty} |x(t)| \psi_{m,n}^{*}(t) dt, \tag{4}$$

Using the discrete wavelet transformation power quality problems can be classified easily. The detailed coefficients will generate severe variation at the start point and end points of the disturbance. From this we can calculate the fault occurrence time.

Voltage Sag Causes and Feature Extraction

Fault – Induced Voltage Sag (Rectangular)

Faults are either symmetrical (three phase or three phase-to ground fault) or non-symmetrical (single phase or double phase or double phase-to-ground faults). Depending on the type of fault the magnitudes of the voltage sag of each phase are equal or unequal. Here symmetrical fault is considered as it is balanced voltage sag. The characteristics of such sags are (1) Immediate recovery of voltage (2) The change in the phase angle and (3) No harmonic distortion. A three phase short circuit is applied on a 11kV power system network for different values of fault resistance (R_f) are simulated. The duration of fault applied and time of application are varied. The disturbance is referred as C1 Fig 1. (a), shows waveform of the voltage sag due three phase short circuit (magnitude (pu)), (b)-(f), corresponding waveforms of the detail coefficients at level 5.



(a)

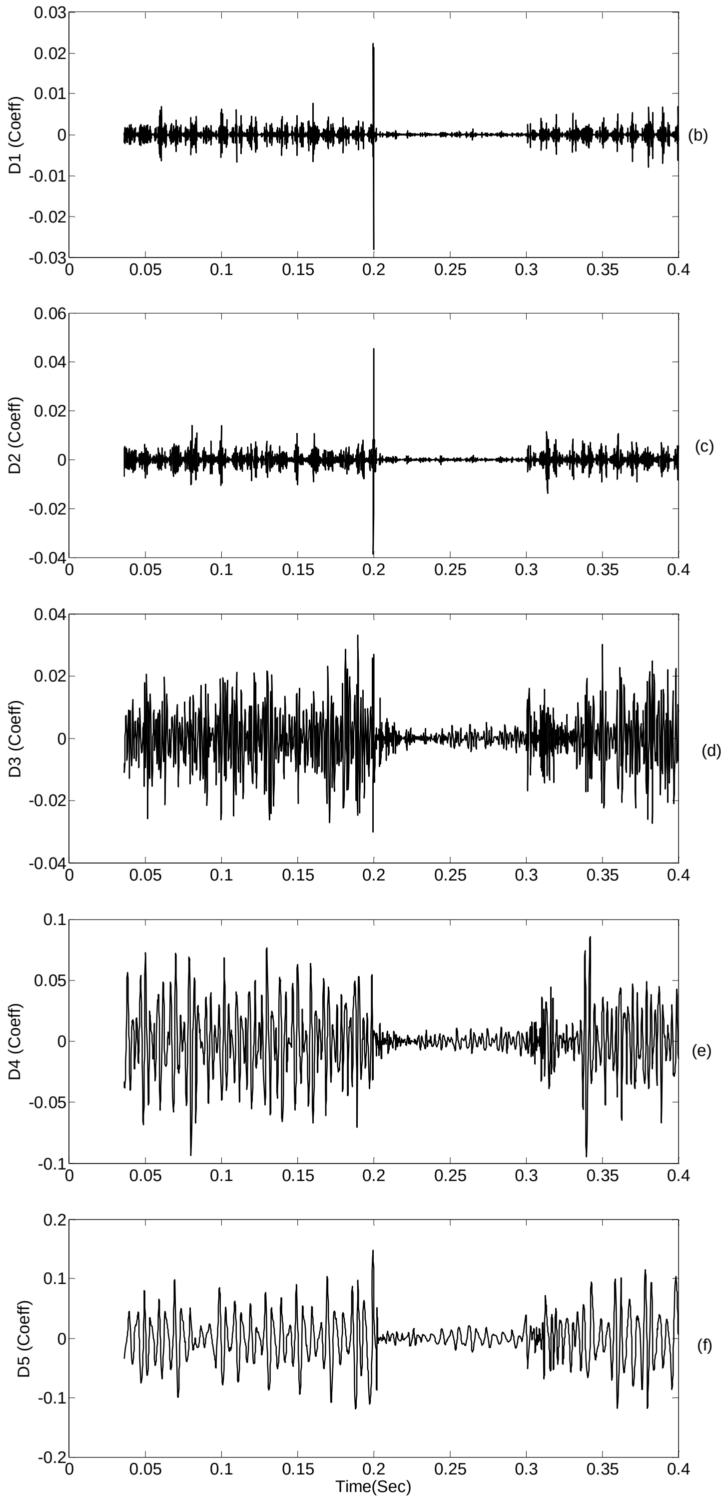
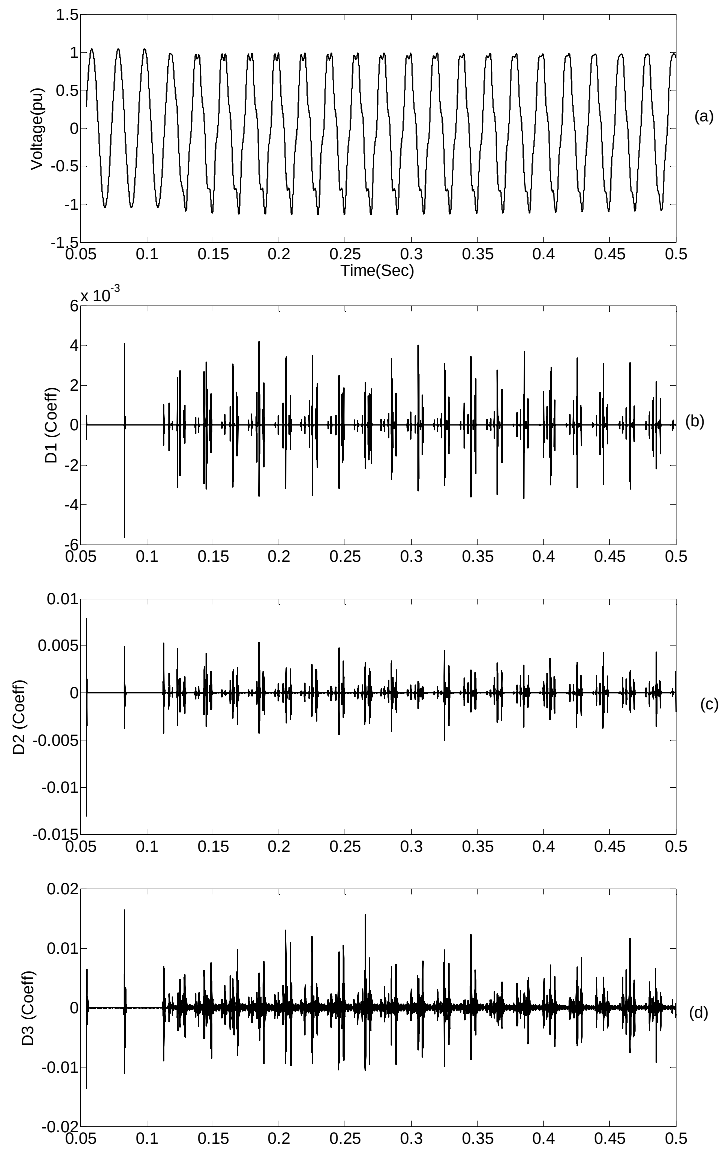


Figure 1: (a) Voltage sag due to three phase short circuit (Rf=10 Ω), (b)-(f) detail coefficients of level 5.

Voltage sag due to Transformer Energization (Non-Rectangular)

The voltage sag caused by transformer energization presents different RMS magnitude. It causes non-rectangular voltage sags and temporary harmonic distortion. The characteristics of such sags are (1) Unbalanced sag in all three phases (2) Shallow voltage sag (3)Gradual recovery of voltage (4) No phase angle shift (5) Harmonic distortions. In this case a 500kV power system consisting of a 500/315kV two winding transformer is energized for simulating the waveforms. The point on wave for energizing the transformer is varied. The simulations are carried out for star/delta, star/star, and delta/star connections. The disturbance is referred as C2. Fig 2. (a) Shows the voltage sag waveform due to transformer energization, (b)-(f) corresponding waveforms of the detail coefficients at level 5.



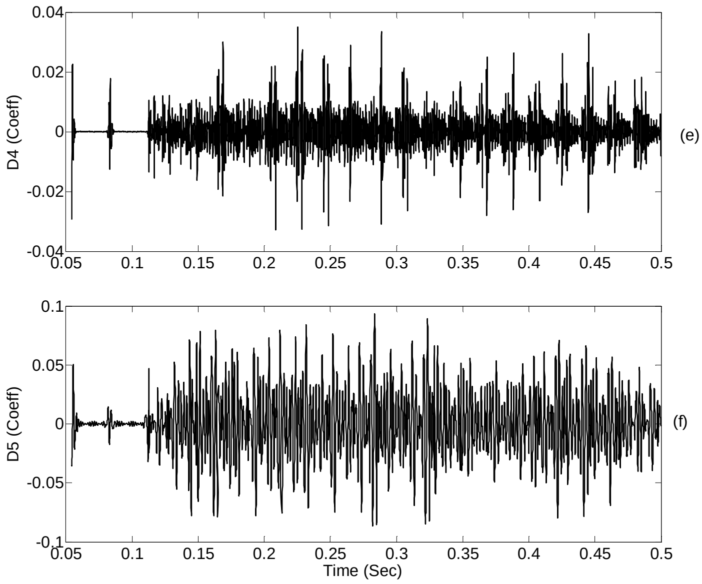
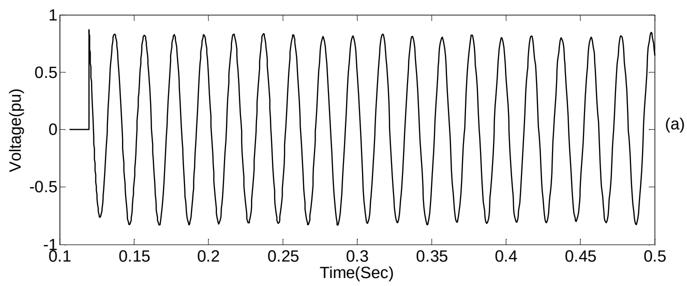


Figure 2: (a) Voltage sag due to transformer energization (b)-(f) detail coefficients of level 5.

Voltage Sag due to Induction Motor Starting (Non-Rectangular)

During starting, motors draw approximately five times their full-load running current, and at a very low power factor. This starting current causes shallow voltage sags. The characteristics of such sags are (1) Balanced sag in all three phases (2) Shallow voltage sag (3) Gradual recovery of voltage (4) No phase angle shift (5) No harmonic distortions. In this case a 400V power system network with the following 5.4, 10, 20, 50,100,150HP rating of the induction motor are considered. The disturbance is referred as C3. Fig 3.(a) shows the voltage sag waveform due starting of induction motor, (b)-(f) corresponding waveforms of the detail coefficients at level 5.

All the power quality disturbances are generated using MATLAB/SIMULINK software.



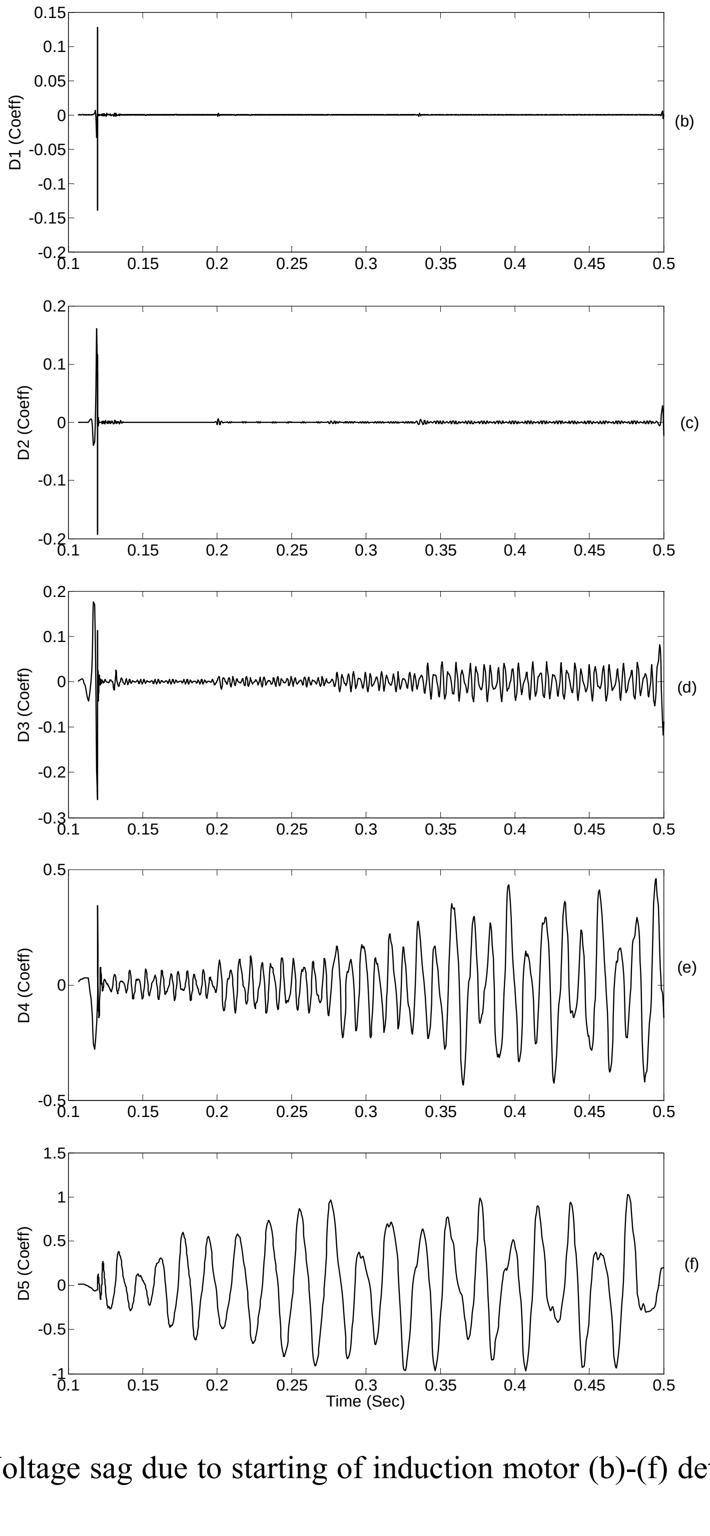


Figure 3: (a) Voltage sag due to starting of induction motor (b)-(f) detail coefficients of level 5.

Feature exaction is a pre-processing operation that transforms a pattern from its original form to a new form suitable for further processing like classification of events. Features of the disturbance signal are extracted from the detailed coefficients by applying the wavelet transform. The first three detailed coefficients (D1, D2, and D3) are considered for the feature extraction. The reason for choosing first three is that most of the frequency content lies in first three modes of oscillations. The following three features are (1) Energy distribution, (2) Standard deviation of the amplitude and (3) Standard deviation of the phase. Thus, we have nine features from the three coefficients for each disturbance.

Probabilistic Neural Network for Classification of Voltage sag Causes

The probabilistic neural network [8] (PNN) is a supervised neural network that is widely used in the area of pattern recognition. The fact that PNNs offer a way to interpret the network's structure in terms of probability density functions (PDF) is an important merit of this type of networks. The standard training procedure for PNNs requires a single pass over all the patterns of the training set. This characteristic renders PNNs faster to train suitable for classification of power quality events. The architecture of PNN is composed of radial basis layer and competitive layer as shown in Fig 4.

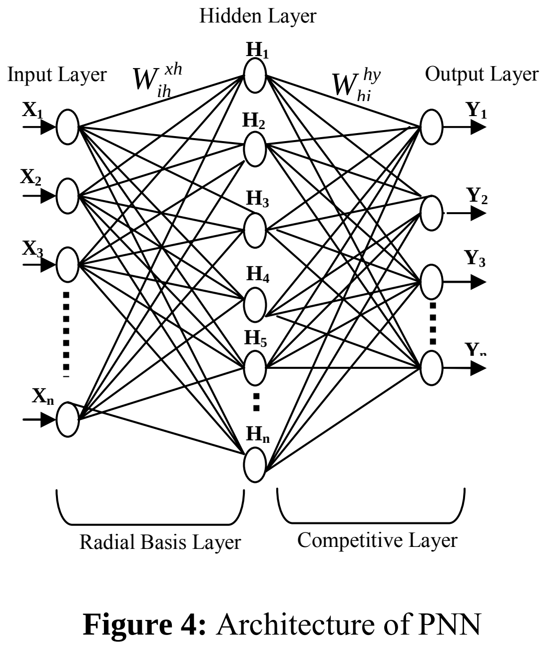


Figure 4: Architecture of PNN

For a classification application, the training data is classified according to their distribution values of probabilistic density function. A simple PDF is given by

$$f_k(x) = \frac{1}{N_k} \sum_{j=1}^{N_k} \exp\left(-\frac{\left\| X - X_{kj} \right\|}{2\sigma^2} \right) \qquad (5)$$

Modifying and applying (11) to the output vector H of the hidden layer in the PNN is given by

$$H_h = \exp\left(\frac{-\sum_i (X_i - W_{ih}^{xh})^2}{2\sigma^2}\right) \qquad (6)$$

where i number of input layers; h number of hidden layers; j number of output layers; k number of training examples; N number of classifications (clusters); σ smoothing parameter (standard deviation); X input vector; $\|X - X_{kj}\|$ Euclidean distance between the vectors X and X_{kj}; W_{ih}^{xh} connection weight between the input layer X and the hidden layer H; W_{hj}^{hy} connection weight between the hidden layer H and the output layer Y; Fig 5 shows the block diagram for classification of voltage sag causes using PNN.

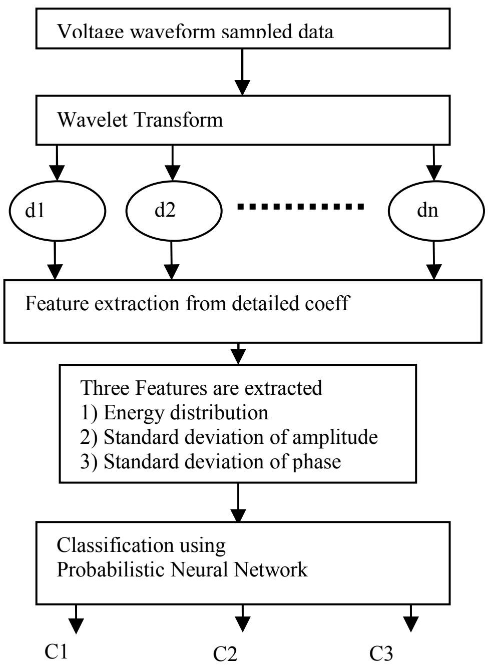


Figure 5: Block diagram for classification of voltage sag causes.

Results and Discussion

Three voltage sag causes are taken for case study. Simulations are performed to generate about 195 signals, 45 data set are used for training the PNN classifier and 150 are used for testing. A classification result using the method is shown in Table I. When PNN is trained, the spread factor is tuned by trial and error method to 0.1, which has given better results. In case of C2 sag classification, out of 50 patterns, 12 patterns are misclassified as C3 and C3 sag 11 are misclassified as C1 resulting to

76% and 78% accuracy of sag classification. The overall accuracy of PNN is calculated by taking average of diagonal elements of Table I and it is found to be 84.67%.

Table 1: Classification Accuracy of PNN

Wavelet Transform	C1	C2	C3	Classification efficiency (%)	Overall efficiency
C1	50	0	0	100	84.67%
C2	0	38	12	76.0	
C3	11	0	39	78.0	

Conclusions
In this paper PNN classification based on the wavelet transform is proposed to classify the voltage sag causes. Wavelet transform is utilized to construct the feature vector based on the multiresolution analysis method. These feature vectors are then applied to a PNN system for training and testing. Three voltage sag causes are taken into consideration in this paper. Simulation results show that can wavelet transform can detect and effectively classify the voltage sag causes.

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