Wavelet Transform and ANNs for Detection and Classification of Power Signal Disturbances

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ABSTRACT

This article proposes WT (Wavelet Transform) and an ANN (Artificial Neural Network) based approach for detection and classification of EPQDs (Electrical Power Quality Disturbances). A modified WT known as ST (Stockwell Transform) is suggested for feature extraction and PNN (Probabilistic Neural Network) for pattern classification.

The ST possesses outstanding time-frequency resolution characteristics and its phase correction techniques determine the phase of the WT to the zero time point. The feature vectors for the input of PNN are extracted using ST technique and these obtained features are discrete, logical, and unaffected to noisy data of distorted signals.

The data of the models required to develop the distorted EPQ (Electrical Power Quality) signals, is obtained within the ranges specified by IEEE 1159-1995 in its literatures.

The features vectors including noisy time varying data during steady state or transient condition and extracted using the ST, are trained through PNN for pattern classification. Their simulation results demonstrate that the proposed methodology is successful and can classify EPQDs even under a noisy environment very efficiently with an average classification accuracy of 96%.

Key Words: **Detection and Classification, Electrical Power Quality Disturbances, Feature Extraction, Stockwell Transform, Probabilistic Artificial Neural Networks.**

1. INTRODUCTION

1.1 Electrical Power Quality

EPQ is a very interesting cross-disciplinary topic, including power engineering, power electronics with digital signal processing, software engineering, and networking. EPQ is defined as any power problem manifested in voltage, current, or frequency deviations that result in failure or misoperation of customer equipment and system itself. The EPQ of power supplies is growing to be a major concern of electricity users. Poor power quality may result in malfunctions, instabilities, short life time, and so on. The causes of poor power quality are the growing popularity of power electronics and other sensitive non-linear loads. The power supplies for

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information technology equipment along with high efficiency lighting, rectifiers, inverters, choppers and adjustable frequency devices are considered the main sources of PQDs. These PQDs are produced from the suppliers or by the users load and they may cause malfunctioning of the equipment [1-4].

1.2 Literature Review

To improve the EPQ of the power system supply, the PQDs should be detected and classified precisely so that correct mitigation measures could be applied. This requires monitoring, recognition and classification of disturbances that is often an inconvenient task involving a broad range of disturbance categories from low-frequency dc offsets to high-frequency transients. In the literature, various methods based on WT, FL (Fuzzy Logic), NN (Neural Network) and GA (Genetic Algorithm) have been proposed and implemented for PQ recognition and classification. [6].

In [7-11] different approaches based on WT and wavelet packet for EPQDs recognition are presented. The combination of FFT (Fourier Transform) and FL is introduced for classification of PQDs in [12]. In [13-14] new techniques based on fuzzy reasoning with WT have been suggested. A rule-based technique with a wavelet packet-based hidden Markov model for recognition and classification of PQDs is presented in [15].

ANN detection schemes are carried out in [16]. In [17-18] hybrid schemes combined with NNs as classifier and WT for feature extractions are suggested. For identifying and classifying PQDs, neural-fuzzy technique is utilized with the decomposition procedure of WT in [19-22]. Application of ANN combined with GA in power quality signals disturbances classification is suggested in [23].

From this survey it is favored to extract signal features by advanced analytical tools, replace of signal time domain values for adaptation of AI (Artificial Intelligence) tools, because of improved efficiency. Thus, monitoring EPQ has become essential for fast recognition and correction of EPQ problems. The survey of DSP (Digital Signal Processing) techniques for EPQDs analysis suggests the different methods like: Park's Vector Approach, Kalman filters and most popular time-frequency analysis methods such as FT, STFT (Short Time Fourier Transform), WT, and ST. The conventional methodologies for monitoring EPQ are expensive and incompetent. In literature over the years, a variety of techniques for automatic detection and classification of EPQDs like voltage swell, sag, harmonics, notch, flicker and transients employ DSP techniques with electrical power systems knowledge and AI.

As PQDs are non-stationary signal, so time-frequency tools such as WT are more practical than FFT that maps signal to frequency domain, without any time information.

FT determines the time-averaged spectral components of a signal which does not provide the changes of magnitude, frequency and phase difference with time. Hence, the time-frequency information of the signals can easily be analyzed with advanced techniques of STFT, WT and ST.

As PQDs are non-stationary signal, and the frequency content varies with time. Due to the limitation of affixed window width, and fixed resolution over time frequency, STFT can not distinguish the signal characteristics properly [24-26]. This has been proved in [26] that WT is incapable of identifying the accurate results when noise is present in the signal.

1.2.1 Proposal

It is also suggested [24-25] that the if wavelet transformation does not extract the essential frequency components from the signal then the efficiency and accuracy of the classification of that signal with the help of AI will be badly affected. Time-scale plot in the absence of phase difference produced by wavelet transformation is a tedious job to be understood [27-28]. From this detailed discussion the combined approach of STFT and WT will be more suitable for this tiresome analysis of EPQDs which vary with time. ST is the combination of STFT and WT and performs multiresolution time-frequency analysis. Therefore, this paper suggests the application of ST which is the finest candidate for such EPQ signal problems.

2. STOCKWELL TRANSFORM AND FEATURE EXTRACTION

2.1 Stockwell Transform

Advanced DSP techniques of WT and its modification known as ST are nowadays utilized for extracting feature vectors methodology from the sampled time data. This can be done obtaining the data by simulation or by field test. The ST creates a time-frequency illustration and combines a frequency dependent resolution and the localization of the imaginary and real spectra. As ST is modified form of FFT, hence in the case of noisy data of non-stationary disturbances the ST provides prototypes that directly resemble the types of disturbances, this ST technique provides the simplest procedure for the classification, which not possible in case of WT. The ST has come up to provide inversely proportional to frequency and inconsistent window, which facilitate to capture of both low and high frequency disturbances of electrical supply network [29-30].

The SM (Stockwell Matrix) can be represented in a time-frequency domain like the WT. The SM known as the output from the ST (N by M matrix) whose N rows relate to frequency and columns relate to the time index and each element of the SM possesses the complex values [29-30].

In [31] it suggested that ST is used to identify EPQDs by visual inspection and from the SM, the STA (Stockwell Transform Amplitude) matrix is calculated by finding the absolute value of each element of the SM as:

$$STA = abs(ST) \tag{1}$$

From Equation (1) the frequency-amplitude, time-frequency and time-amplitude can easily be plotted and these plots can provide the valuable information of localization, detection, and visual classification of EPQDs.

The features after normalization will be introduced to PNN network for training purposes. These features will be obtained from ST.

ST gives the information both in the amplitude spectrum and phase of the signal. In order to exploit the information enclosed in phase of the CWT, it is essential to adjust the phase of mother wavelet. The CWT, W(α,d), of a function h(t) is expressed as:

$$W(\alpha, d) = \int_{-\infty}^{\infty} h(t) w(d, t-\alpha) dt \tag{2}$$

Where W(α,d) is a scaled replica of fundamental mother wavelet; the dilation decides the width of the wavelet and this controls the resolution and the ST is achieved by multiplying the CWT with a phase factor.

$$S(\alpha,f) = e^{j2\pi ft} W(d,\alpha) \tag{3}$$

And its mother wavelet is assumed as:

$$w(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\left(\frac{t^2 f^2}{2}\right)} e^{-j2\pi ft} \tag{4}$$

In Equation (2), where d is dilation factor or scale parameter which is inversely proportional to frequency f.

Equation (4) in final form of continuous ST becomes as [27]:

$$S(\alpha, f) = \int_{-\infty}^{\infty} h(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\alpha-t)^2 f^2}{2}} e^{-j2\pi ft} dt \tag{5}$$

Width of Gaussian window is as:

$$\sigma(f) = T = \frac{1}{|f|} \tag{6}$$

ST is the illustration of local spectra, time average spectrum or can be calculated directly from averaging local spectra through inverse ST and becomes as [27]:

$$h(t)\int_{-\infty}^{\infty}\left\{\int_{-\alpha}^{\alpha} S(\alpha, f)d\alpha\right\}e^{j2\pi ft}df \tag{7}$$

2.2 Feature Extraction

Taking the advantage of FFT with convolution theorem, ST calculates the data very quickly and localizes the phase spectrum and amplitude spectrum simultaneously and efficiently.

It is clear from the literature that ST possesses better applicability than WT. Feature extraction is prepared by applying standard statistical techniques onto the contours of the SM as well as directly on the SM. These features have been found to be useful for detection, classification of relevant parameters of the signals. The power network signal is normalized (1) with respect to a base value, which is the normal value without any disturbance. In this proposal the features of SD (Standard Deviation), energy of the signal are considered as: (i) Standard deviations of maximum magnitudes of each column and row of SM, with phase contour. (ii) Energy of the data set including equivalent to maximum magnitude of each column of the SM.

These features are found to be well well-matched to discriminate the twelve (12) types EPQDs detection and classification techniques very accurately.

3 . DATA GENERATION AND SIMULATION

3.1 Data Generation of EPQDs

In this proposal pure sinusoidal wave with following eight EPQDs are considered to detect, and classify the signal of electrical power system networks.

1. Normal or Pure sine wave
2. Momentary Interruption.
3. Oscillatory transient (Low frequency).
4. Instantaneous voltage sag
5. Instantaneous voltage swell
6. Harmonics
7. Voltage notch
8. Voltage spike (Impulse transient)
9. Voltage flicker

The equations for the above PQDs signals are available in [32] and the parameters are varied within the ranges specified by the IEEE 1159 [5]. The signal under a noisy environment is generated by adding uniformly distributed Gaussian noise of 30db with the original signal. This 30dB SNR value is considered equivalent to a peak noise magnitude which is about 3.5% of the voltage signal [30].

Considering the best computational efficient analysis, original distorted signals are generated with 8 cycles, and each cycle is represented by 64 points, hence total corresponding 512 points are considered using MATLAB 7.13, Simulink 7.8, and Wavelet Toolbox 4.8 versions respectively.

3.2 Results and Discussion

The simulation results with the application of ST shown below provide the important information of the disturbed signals. Form Figs. 1-9; visualization inspections clearly indicate the types of EPQDs with the help of time-frequency contours technique of ST.

Figs. 1-9 show nine (09) diffeent types of EPQDs signals (with eight cycles at 0.16 seconds) with their TFC (Time Frequency Contours), ST maximuim amplitude with time index and ST amplitude spectrum.

In Fig. 1(a-d), (a) shows sine signal wave, (b) TFC, (c) ST maximuim amplitude and time index and (d) ST amplitude spectrum.

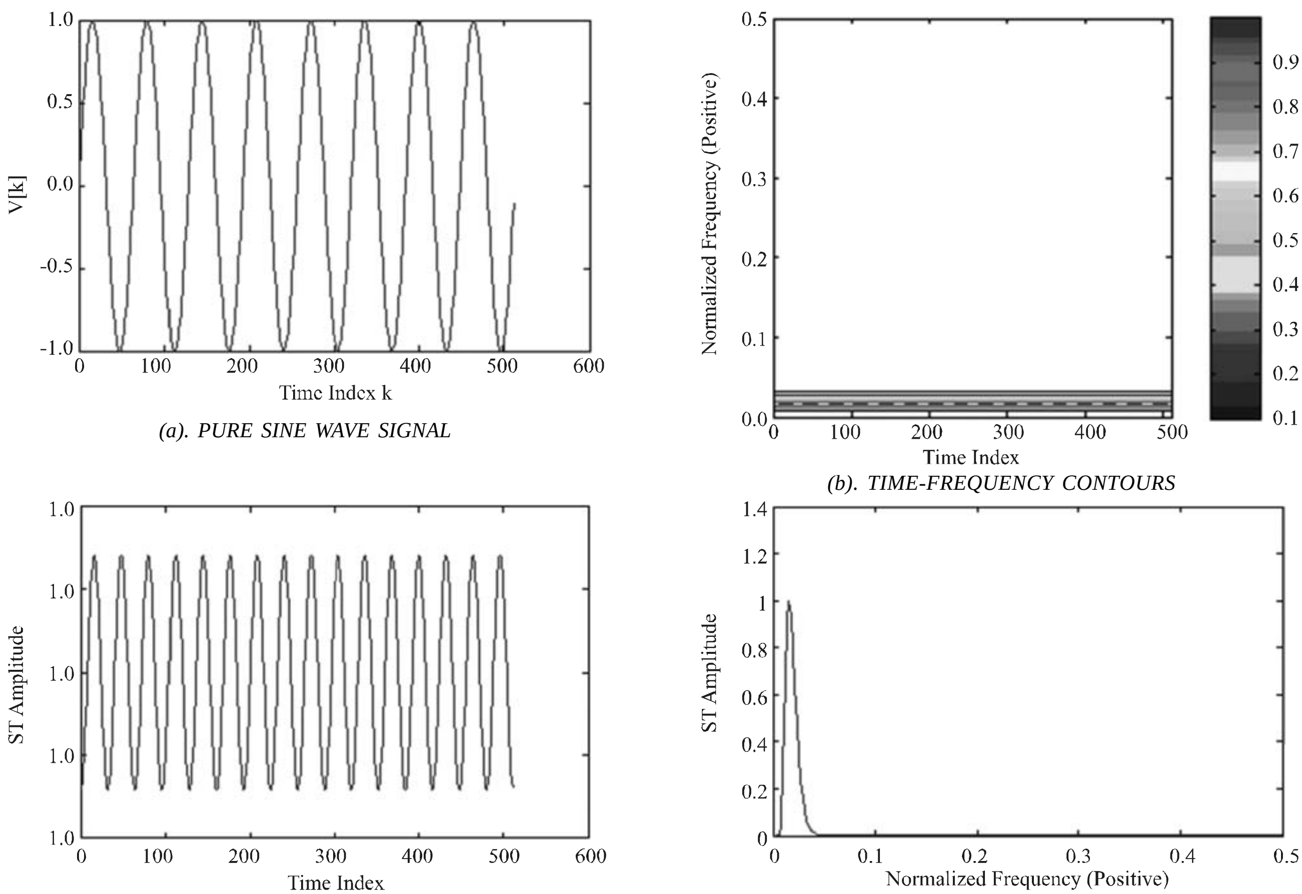
The TFC always provides the hint for the identification or recognition of the types of EPQDs. The TFC in the simulation result of Fig. 1(b) is staright line because the signal is pure sine wave without any disturbanesc.

Fig. 2(a-d) show momentary interruption distortion of the signal with the ST visualization information. The voltage drop of interruption and its exact intervals of starting and finishing in time-frequency domain are shown accurately in Fig. 2(b).

Fig. 3(a-d) shows the lower frequency oscillatory transient and its ST feature waveforms, with TFC, ST maximum amplitude/index and amplitude spectrum. According to the Shannon's Theorem, highest frequency is considered in case of oscillatory transient in Fig. 4.

The Figs. 4-9 show instantaneous sag, swell, harmonics, voltage notch, spike and flicker signals of EPQDs respectively with their changes indicated in their contours representations. It can easily be observed with the visual analysis, the colors of bars and the plots of contour representations play very important part in the visualization analysis of the signal disturbances. In Fig. 9(b) magnitude variation is observed which is resembled which looks like a voltage flicker distortion in time domain.

Figs. 4(b) and 5(b) show the decrease and increase in magnitudes of EPQ signals exactly as in case of sag and swell signals of time-domain. Fig. 6(d) obviously gives an idea of 03 peaks, i.e. EPQD of power system harmonic signal.



(a). PURE SINE WAVE SIGNAL

(b). TIME-FREQUENCY CONTOURS

(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX

(d). STOCKWELL-TRANSFORM AMPLITUDE SPECTRUM

FIG. 1. PURE SINE WAVE AND S-TRANSFORM FEATURE WAVEFORMS

4. APPLICATION OF PNN FOR THE CLASSIFICATION OF EPQDS

The PNN is based on the probabilistic model known as Bayesian classifiers which is used in the basic principle operation of PNN. The Bayesian classifiers PNN model is known as an important among the supervised learning networks possesses the distinct features from those of other networks in the learning processes like [33]:

1. PNN is always applied with probabilistic model, such as Bayesian classifiers.

2. If it is given the sufficient time to train the PNN is guaranteed to converge to a Bayesian classifier.

3. The laborious work of selecting or setting the initial weights of the network is not needed.

4. Hence, there is no affiliation between learning and recalling processes.

5. For the modification of the weights of the network, the tedious process of checking the difference between target vector and the inference vector is not required.

The values of probabilistic density function decide the training paradigms. The first layer computes detachments from the input vector to the training input vectors, when

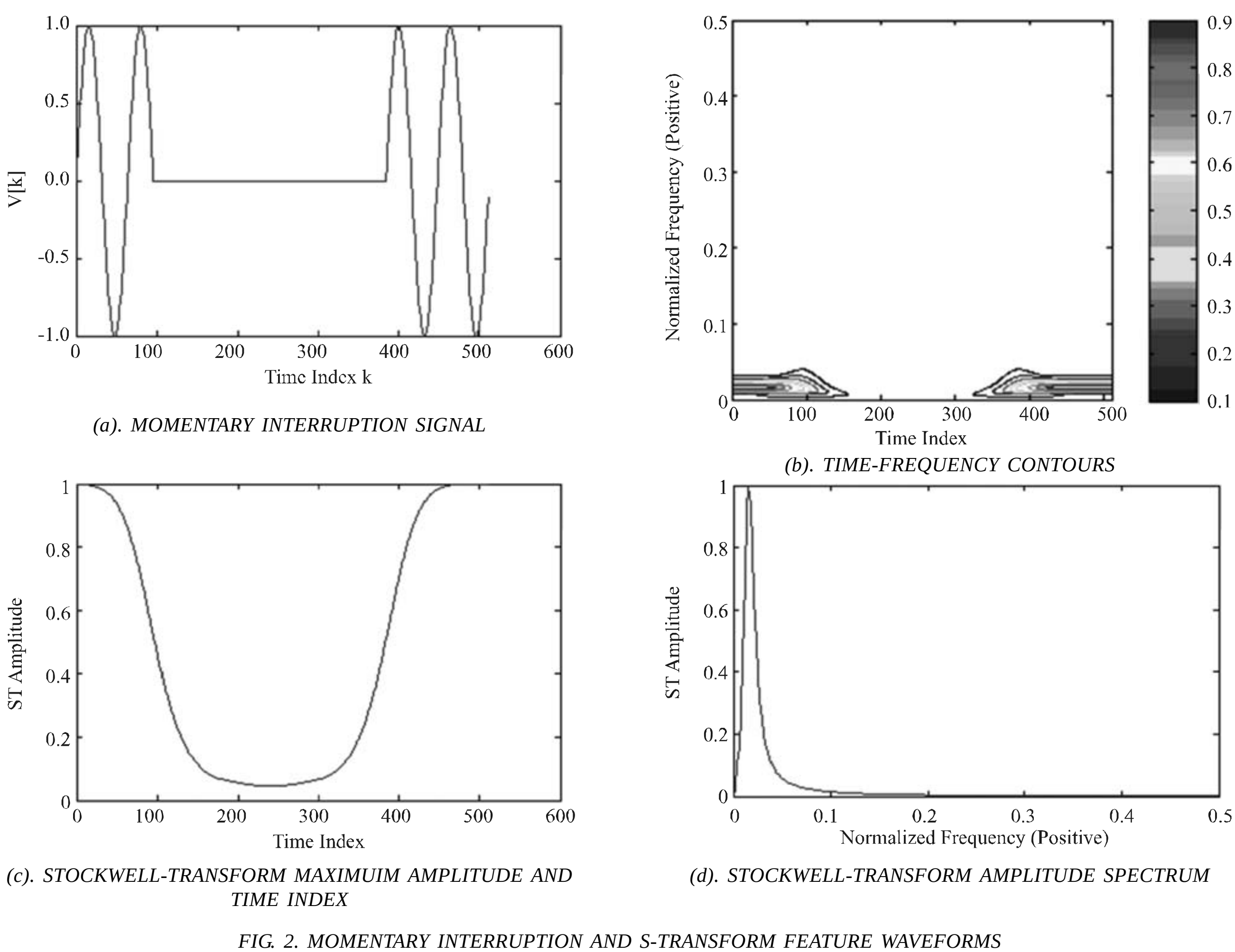


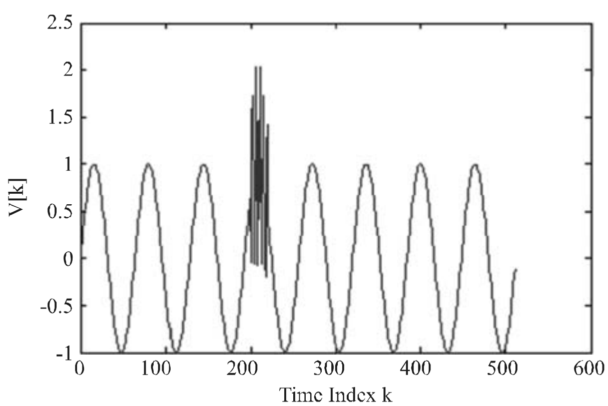
FIG. 2. MOMENTARY INTERRUPTION AND S-TRANSFORM FEATURE WAVEFORMS

an input is presented. This process produces a closure vector between the input vector and a training input. The second layer for each class adjoins all these contributions. In this way a vector of probabilities (as output) is created and eventually, an accurate transfer function at the output of the second layer is selected from the utmost of these probabilities [34-36].

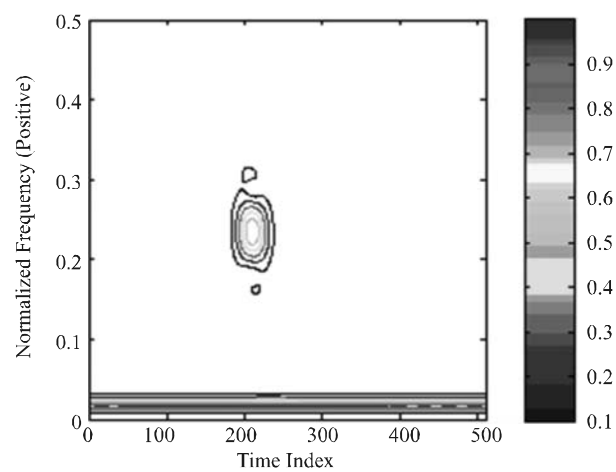
Due to these diverse properties, the learning speed of the PNN model is very fast and makes it the most suitable in real time applications of the fault diagnosis and classification of power signals analysis.

Nine types of different EPQ disturbances are considered as:

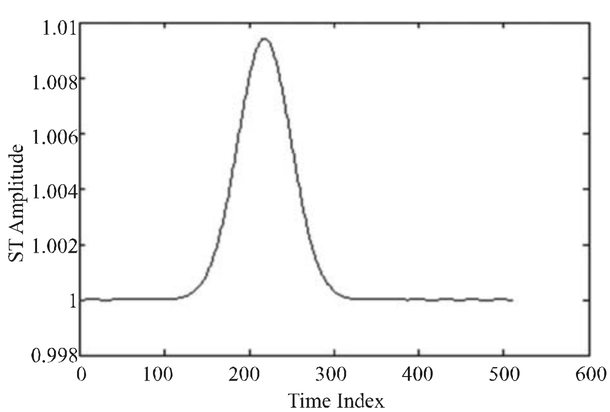
C_1	Normal or Pure sine wave
C_2	Momentary Interruption
C_3	Oscillatory transient (Low frequency)
C_4	Instantaneous voltage sag
C_5	Instantaneous voltage swell
C_6	Harmonics
C_7	Voltage notch
C_8	Voltage spike (Impulse transient)
C_9	Voltage flicker



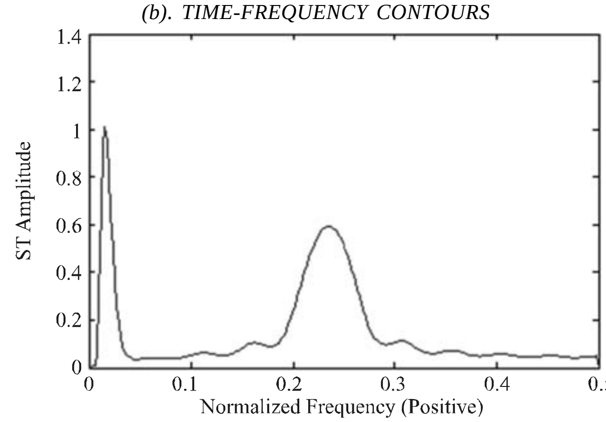
(a). OSCILLATORY TRANSIENT SIGNAL



(b). TIME-FREQUENCY CONTOURS



(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX



(d). STOCKWELL-TRANSFORM AMPLITUDE SPECTRUM

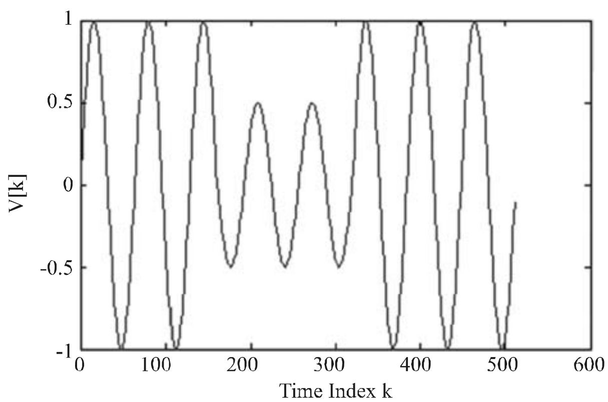
FIG. 3. OSCILLATORY TRANSIENT (LOW FREQUENCY) AND STOCKWELL-TRANSFORM FEATURE WAVEFORMS

Form Sections 3.1 and 3.2, the feature extractions obtained from the ST technique provide the four-dimensional feature sets (03 of SD and 01 of the energy of transformed signal) for training and testing. These vectors provide distinctive knowledge of EPQ signals within minimum data amount required as input for training of PNN as automatically classifier of EPQDs signal.

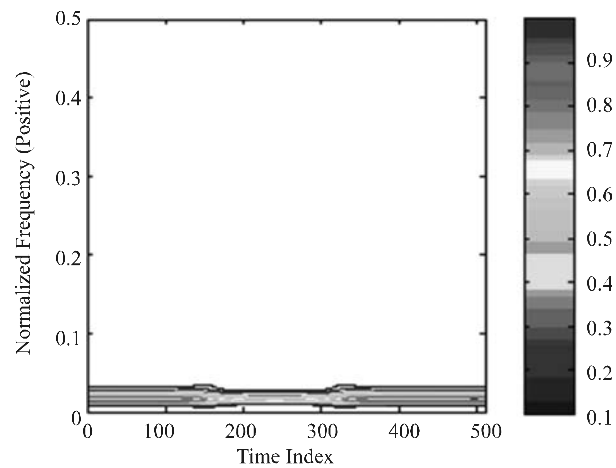
The target output of the PNN is a 09 element vector. For each event only one of the elements will be 1. For C_1 it will [1 0 0 0 0 0 0 0 0], C_2=[0 1 0 0 0 0 0 0 0], C_3=[0 0 1 0 0 0 0 0 0] and for C_9=[0 0 0 0 0 0 0 0 1].

The evaluations performance of developed model of PNN, with its classification results during testing are shown in Table 1.

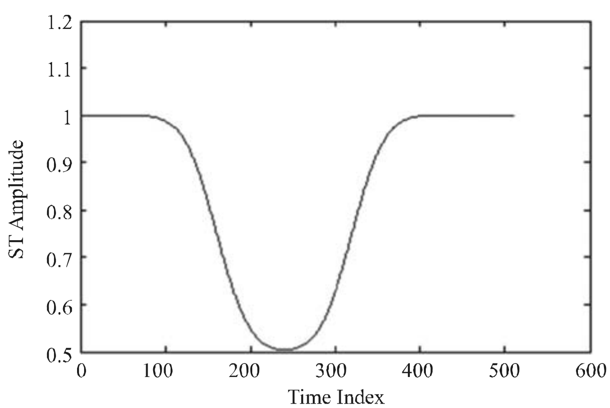
PNN produces a two-layer network, where first layer has radbas neurons, and computes its weighted inputs with dist and its net input with net product (netprod). Whereas second layer has compet neurons, and computes its weighted input with dot product (dotprod) and its net inputs with net sum (netsum). Only the first layer has biases. The PNN is two layer networks. The error goal is set at 0.00001 with 1.1 spread constant. Then input layer of PNN contains 36 neurons (9*4=36) neurons/nodes with radbas transfer function and only 9 neuron/node with purelin transfer functions in output layer are required. This process of training takes only 2 seconds and the networks are trained by using OLS (Orthogonal Least Squares) algorithm. Fig. 10 shows nine types of EPQDs



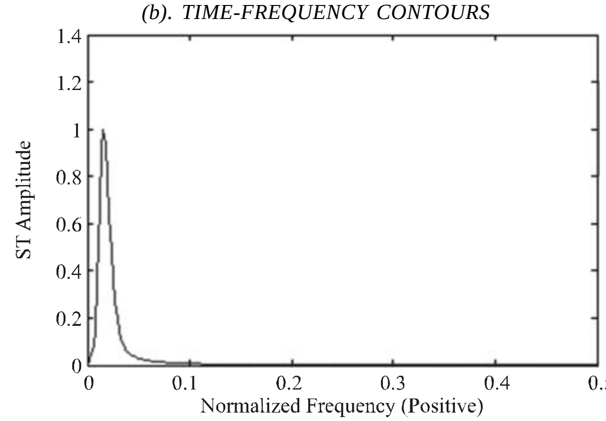
(a). VOLTAGE SAG SIGNAL



(b). TIME-FREQUENCY CONTOURS



(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX



(d). STOCKWELL-TRANSFORM AMPLITUDE SPECTRUM

FIG. 4. INSTANTANEOUS VOLTAGE SAG AND ITS FEATURE WAVEFORMS

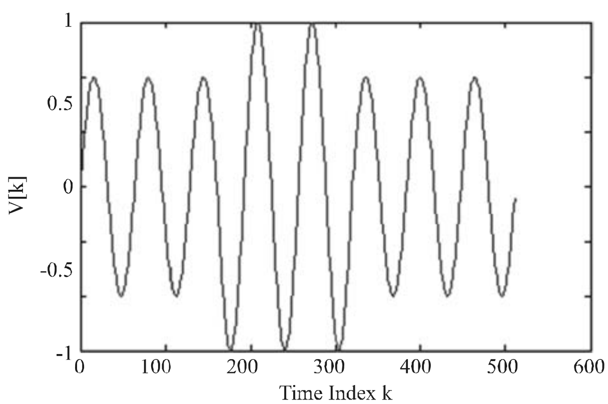
with four-dimensional feature sets (03 of SD and 01 of the energy of transformed signal) are introduced as input for training and out put of PNN classifier are the types of EPQDs.

The overall accuracy of correct classification is the ratio of correctly classified power quality disturbances to that of the total number of EPQDs. The overall classification accuracy of PNN is 93.11% when 50 samples were tested and 96.55% when 100 samples were investigated. It proves that the best classification accuracy can be further improved by training the PNN by higher number of PQDs.

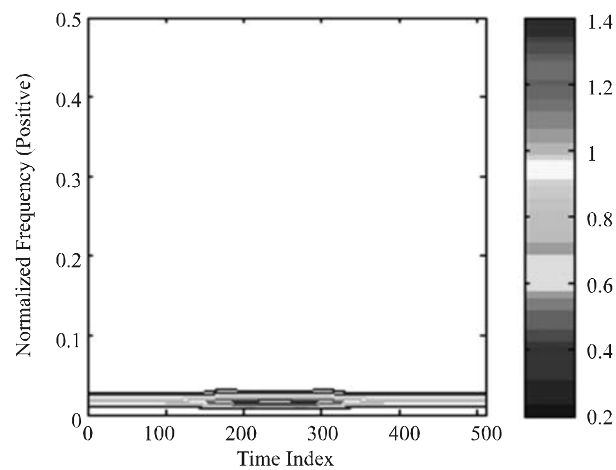
The PNN is simple in training because it requires less learning time, number of epochs, and less time to classify a particular input data during testing. This has been also verified that with suggested four extracted features obtained from ST are sufficient for a PNN to classify the different types of EPQDs.

In First Case: Total 450 samples of 09 types of PQDs are tested, out of those 419 are identified accurately with about 93.11%.

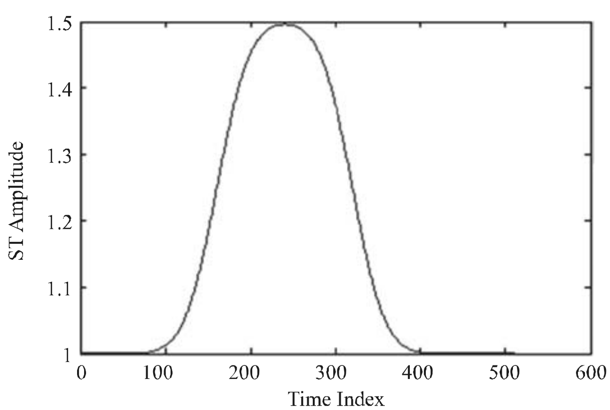
In Second Case: Total 900 samples of 09 types of EPQDs are tested, out of those 869 are identified accurately with about 96.55%.



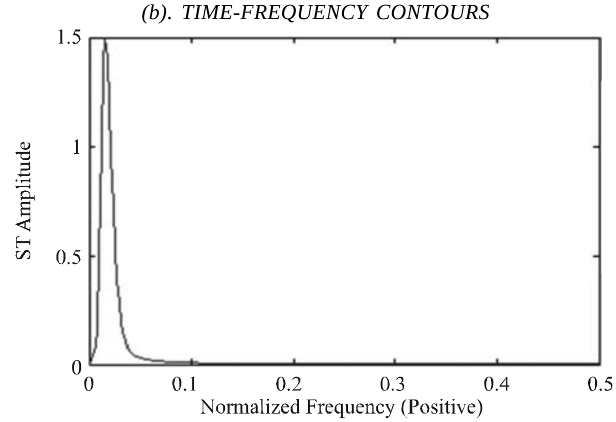
(a). VOLTAGE SWELL SIGNAL



(b). TIME-FREQUENCY CONTOURS

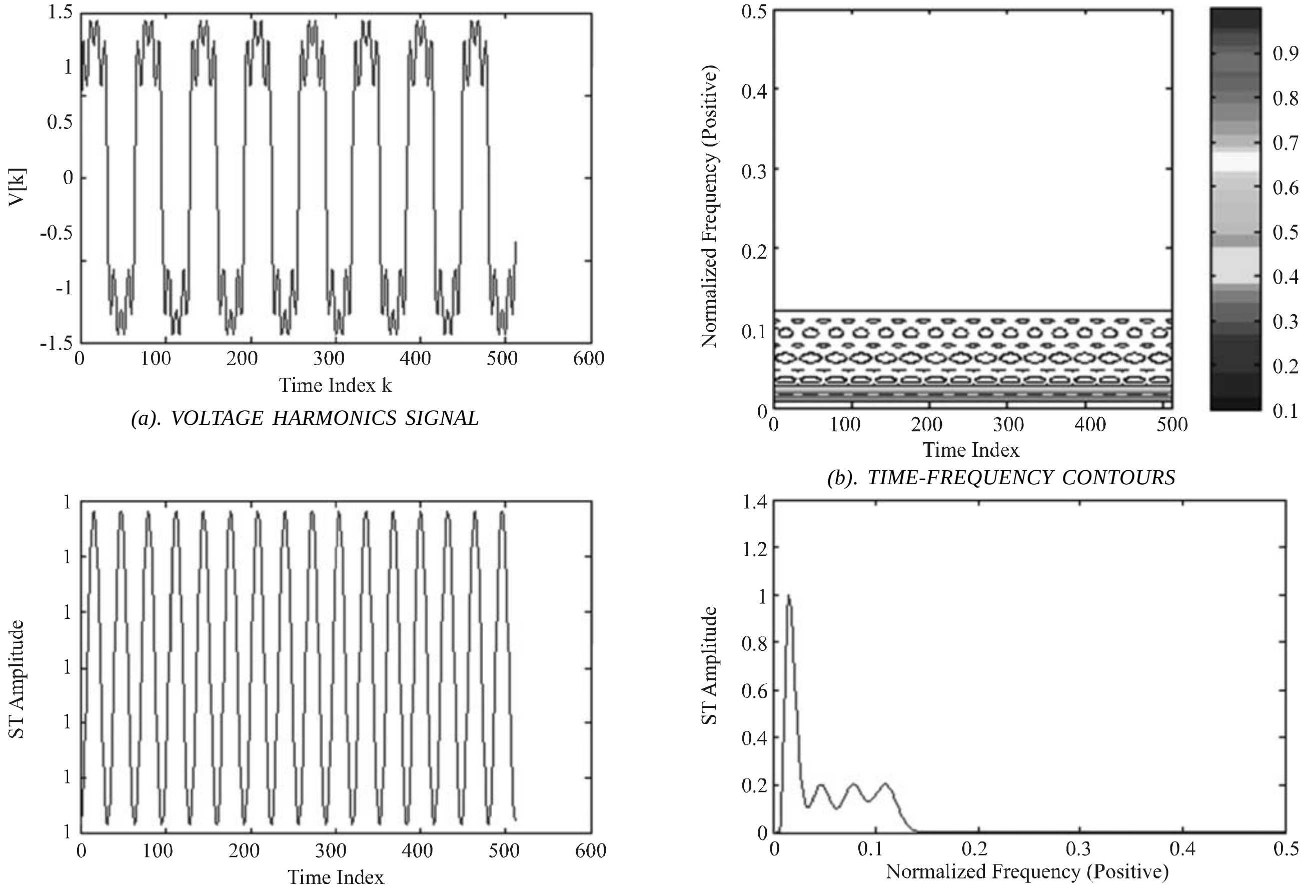


(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX



(d). STOCKWELL-TRANSFORM AMPLITUDE SPECTRUM

FIG. 5. INSTANTANEOUS VOLTAGE SWELL AND ITS FEATURE WAVEFORMS



(a). VOLTAGE HARMONICS SIGNAL

(b). TIME-FREQUENCY CONTOURS

(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX

(d). STOCKWELL-TRANSFORM AMPLITUDE SPECTRUM

FIG. 6. VOLTAGE HARMONICS AND ITS FEATURE WAVEFORMS

5. CONCLUSIONS

In this research work, we have suggested a simple method to detect and classify the types of EPQDs correctly. The features of EPQDs signals have been extracted with the help of ST and PNN as classifier. Due to the lower level of decomposition, useful information is obtained for classification. The proposed technique of modified ST NN classifier along with the statistical computation has improved the classification accurateness. This methodology shows low sensitivity to noise level and simulation results with low error rate confirms this capability.

The proposed methodology shows a high accuracy in the classification of the EPQDs i.e. 93.11% for lower number samples and 96.55% for higher number of samples, which can be enhanced by training PNN classifier with more number of samples of PQDs signals.

PNN has proven to be more time efficient and learns more quickly which makes it more suitable for an online EPQDs classifier. For a future work, this technique can be applied for hybrid EPQDs.

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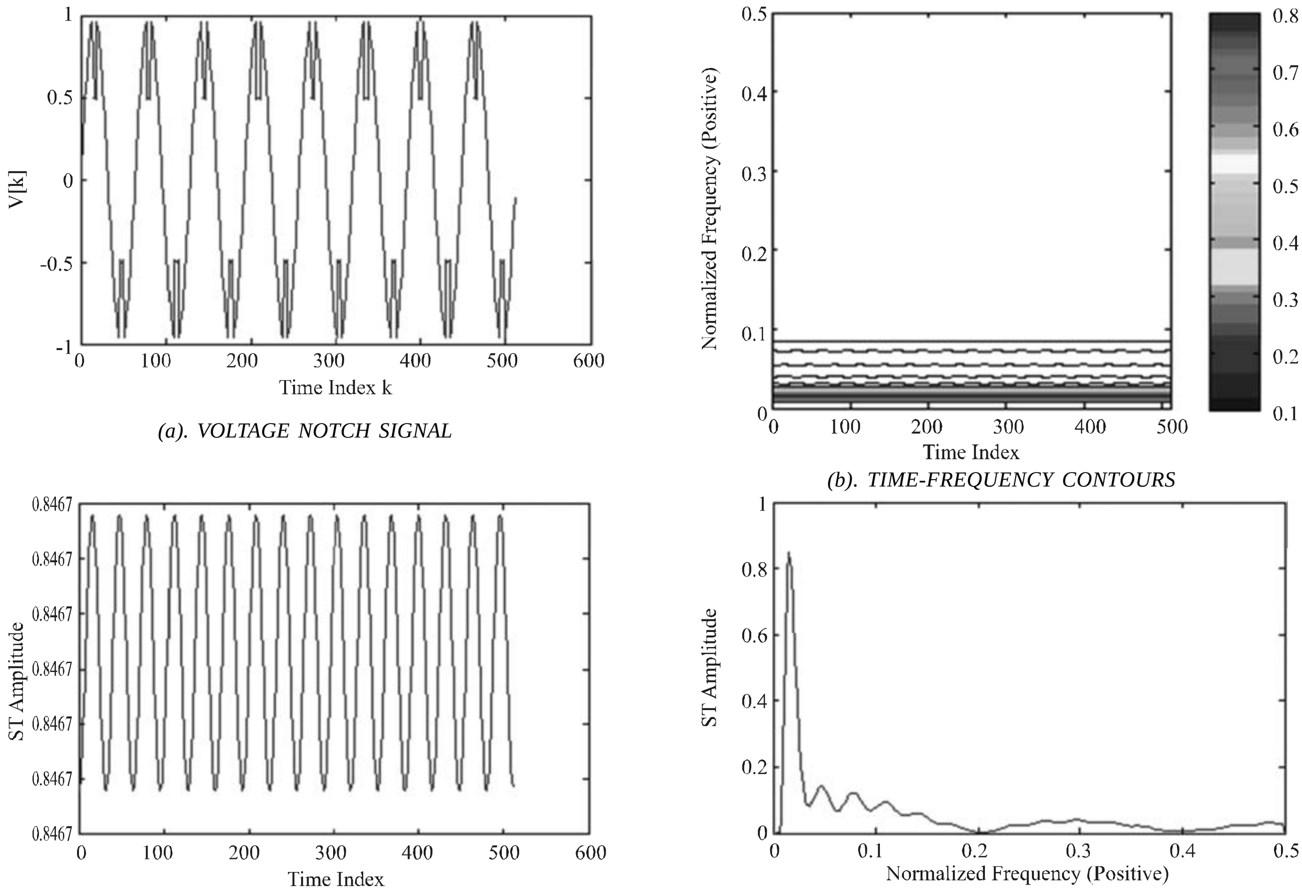

(a). VOLTAGE NOTCH SIGNAL

(b). TIME-FREQUENCY CONTOURS

(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX

(d) STOCKWELL-TRANSFORM AMPLITUDE SPECTRUM

FIG. 7. VOLTAGE NOTCH AND ITS FEATURE WAVEFORMS

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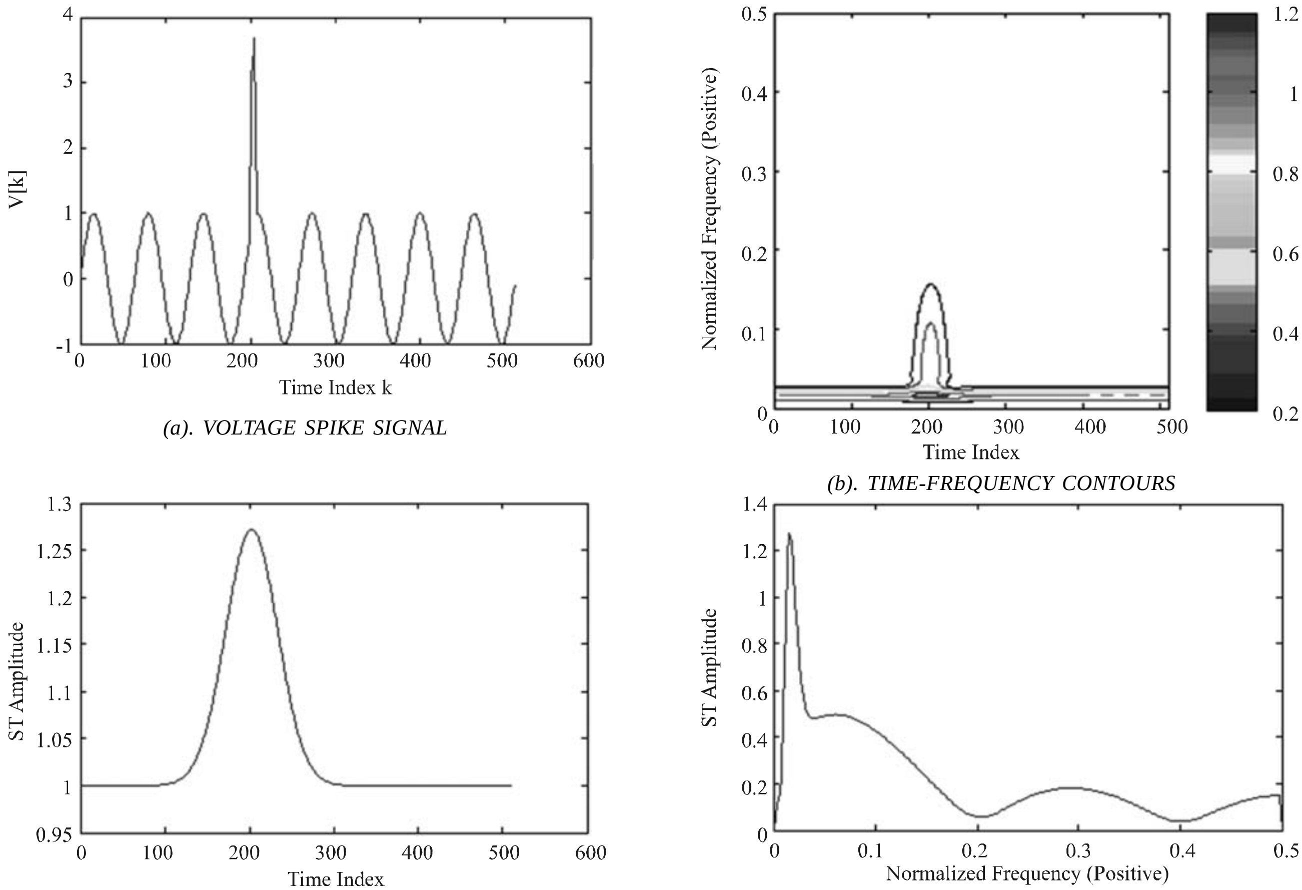

(a). VOLTAGE SPIKE SIGNAL

(b). TIME-FREQUENCY CONTOURS

(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX

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FIG. 8. VOLTAGE SPIKE AND ITS FEATURE WAVEFORMS

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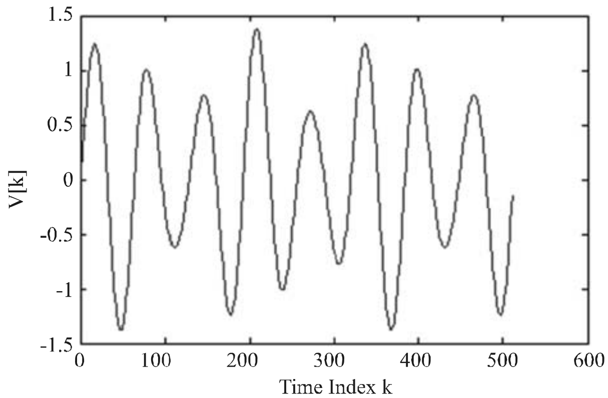
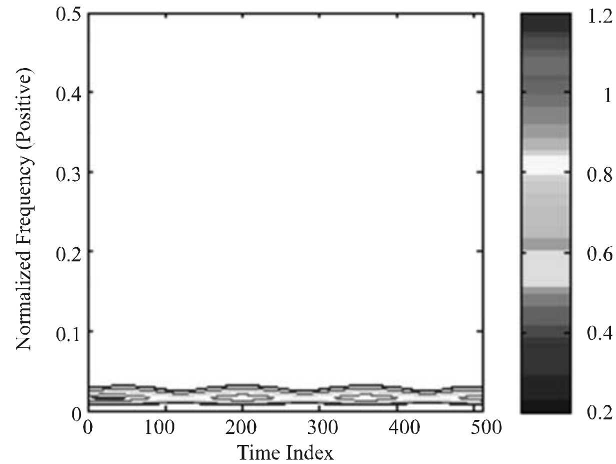
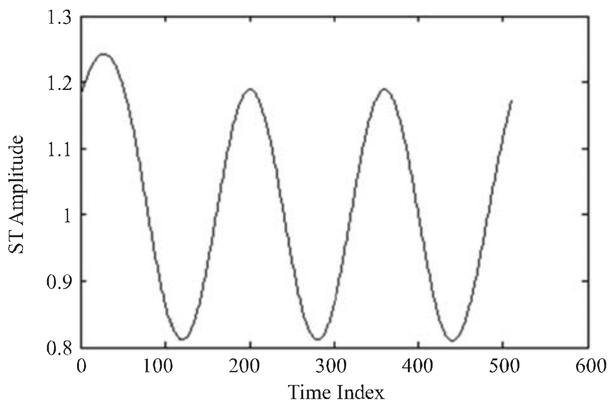


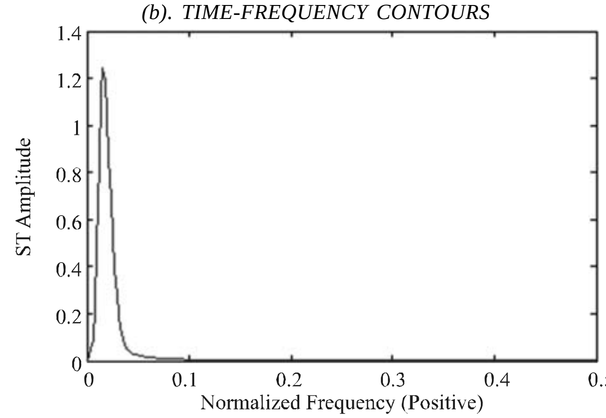
(a). VOLTAGE FLICKER SIGNAL



(b). TIME-FREQUENCY CONTOURS



(c). STOCKWELL-TRANSFORM MAXIMUIM AMPLITUDE AND TIME INDEX



(d). STOCKWELL-TRANSFORM AMPLITUDE SPECTRUM

FIG. 9. VOLTAGE FLICKER AND ITS FEATURE WAVEFORMS

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TABLE 1. SHOWS CLASSIFICATION RESULTS AFTER DEVELOPING PNN WITH 50 AND 100 SAMPLES OF EPQDS SIGNALS

EPQDs	Samples	Identified	Unidentified	EPQDs	Samples	Identified	Unidentified
C_1	50	50	0	C_1	100	100	0
C_2	50	44	06	C_2	100	89	11
C_3	50	50	0	C_3	100	100	0
C_4	50	39	11	C_4	100	93	07
C_5	50	50	0	C_5	100	100	0
C_6	50	50	0	C_6	100	100	0
C_7	50	50	0	C_7	100	100	0
C_8	50	50	0	C_8	100	100	0
C_9	50	36	14	C_9	100	87	13
09	450	419	21	09	900	869	31
Overall Accuracy 93.11%				Overall Accuracy 96.55%			

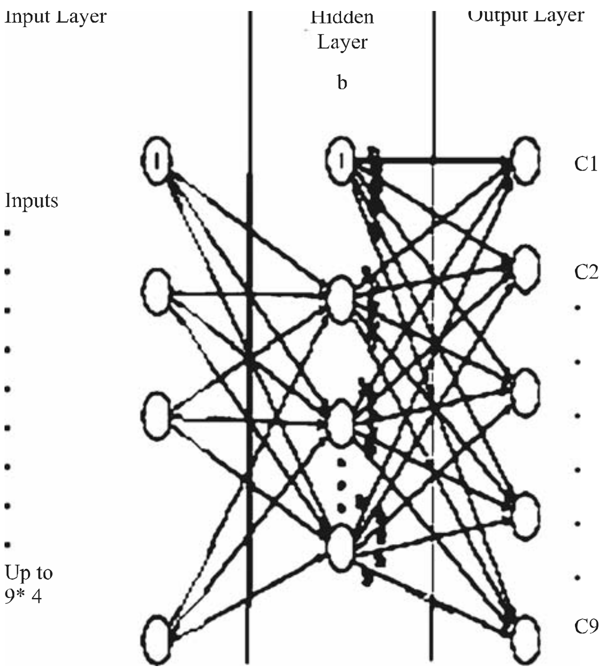

FIG. 10. PROBABILISTIC NEURAL NETWORKS MODEL FOR EPQDS CLASSIFICATION

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