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Recognition of Multiple PQ Issues using Modified EMD and Neural Network Classifier

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Abstract: This paper presents a new framework based on modified EMD method for detection of single and multiple PQ issues. In modified EMD, DWT precedes traditional EMD process. This scheme makes EMD better by eliminating the mode mixing problem. This is a two step algorithm; in the first step, input PQ signal is decomposed in low and high frequency components using DWT. In the second stage, the low frequency component is further processed with EMD technique to get IMFs. Eight features are extracted from IMFs of low frequency component. Unlike low frequency component, features are directly extracted from the high frequency component. All these features form feature vector which is fed to PNN classifier for classification of PQ issues. For comparative analysis of performance of PNN, results are compared with SVM classifier. Moreover, performance of proposed methodology is also validated with noisy PQ signals. PNN has outperformed SVM for both noiseless and noisy PQ signals.

Keywords: Empirical Mode Decomposition, Neural Network, Power Quality, Wavelet Transform.

Nomenclature

PQ	Power Quality
EMD	Empirical Mode Decomposition
IMF	Intrinsic Mode Function
DWT	Discrete Wavelet Transform
PQD	Power Quality Disturbance
FFT	Fast Fourier Transform
STFT	Short-Time Fourier Transform
CWT	Continuous Wavelet Transform
DWPT	Discrete Wavelet Packet Transform
PNN	Probabilistic Neural Network
SVM	Support Vector Machine
PLL	Phase Locked Loop
ICA	Independent Component Analysis
HHT	Hilbert Huang Transform
WT	Wavelet Transform

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1 Introduction

CONCERN towards PQ has become the sine-qua-non for the industrial, domestic and commercial domains. In today's world, proliferation in the application of nonlinear loads like fluorescent lamps with electronic ballasts, switched mode power supplies, solid state control devices, power converters etc. has drawn more attention towards PQ. All these nonlinear loads, capacitor switching banks, short-circuit faults, starting of large machines, and renewable energy integration with grid cause PQ disturbances [1]. PQD is any distortion in the standard voltage and current. PQ limits are given by the international standards, for instance, IEC-61000, IEEE-1159 and EN50160 to keep PQ parameters within acceptable limits. PQ disturbances like sag, swell, harmonics, transient, flickers, interruption etc., pose risk to the life and efficiency of end user equipments like computers, TV, refrigerators, highly sensitive control equipments, tubelights, microwaves etc. and also cause interference to communication lines. Prior detection and continuous monitoring are necessary to mitigate the aftermaths of PQ disturbances [2].

Profuse attempts have been undertaken for the analysis of these disturbances. The most primary technique used in PQ analysis is Fast Fourier Transform but it is unsuccessful in case of non-stationary transient signal. To overcome the limitation of FFT, STFT and WT started being used. There are many variants of WT, being employed by the researchers like CWT, DWT, DWPT and many others [3-5]. In [6], authors have implemented DWPT using polyphase-decomposition based wavelet filters on Xilinx Artix-7 field-programming gate array AC701 board for estimation of power system harmonics. This hardware design facilitates reduction in computational requirements and memory resources. To deal with problem of spectral leakage in WT, authors [7] utilized modified WT, i.e., generalized empirical wavelet transform for estimation of PQ indices like instantaneous values of fundamental amplitude, root mean square, frequency variation, THD, form factor, normalized distortion energy index, and K-factor. Another variant of WT, i.e., Tunable-Q wavelet transform has been applied by Karthik Thirumala et al. [8] for accurate decomposition of signal into different components among which one is fundamental and others are harmonic components. Authors have tuned the wavelet depending upon the inter-harmonics present near fundamental frequency for better analysis of both single and combined disturbances.

Suhail Khokhar et al. [9] have proposed DWT for feature extraction from sixteen PQD signals. They have optimized the features using Ant Bee Colony optimization before feeding them to PNN whose spread constant has also been optimized using the same technique. DWT-PNN based method has been also tested on the noise-ridden signals having Gaussian noise of 20 dB, 30 dB and 40 dB. In [10] also, authors implemented DWT using Daubechies family filter banks for better feature extraction from PQDs. They have determined the unique adaptive threshold for the decomposed PQDs depending upon their value of energy and entropy. The intersection of thresholds and curves of decomposed PQD signals has provided the automatic segmentation of PQ signals. DWT using modified wavelets called fraclets have also been proposed by some authors to further improve wavelet decomposition results for having correct classification of PQ disturbances [11, 12].

Like other techniques, WT have their own limitations like time-frequency uncertainty relation, caution needed while choosing the mother wavelet, interference terms, border distortion, energy leakage etc. Another technique used by the researchers for time-frequency analysis of PQDs is S-transform. M. V. Reddy and Ranjana Sodhi [13] have improved the usability of S-transform for PQ assessment by designing its rule-base using statistical entropy measure for selecting the suitable window. Twelve features have been computed from magnitude and phase values of ST matrix; these features have been fed to AdaBoost classifier using decision stump also. Authors have improved the performance of the classifier by using adaptable initial weights to avoid over-fitting of the classifier. Offering more robustness and less computational complexity, double resolution S-transform has been implemented by J. Li et al. in a digital signal processor for effective feature analysis of PQDs with the help of reduced instruction set of processor [14]. Features provided by double resolution S-transform have been accurately classified into PQ issues by directed acyclic graphs-SVM.

Raj Kumar et al. [15] have opted a different strategy for detection of PQ issues, namely, transients, flickers, interruption, sag, harmonics, swell, spikes and notch. They have implemented the method based on symmetrical components of PQD signals on a digital signal processor, i.e., dSPACE 1104. PLL has been used to generate two other ideal phases to have symmetrical components of all three phases whose positive and negative sequence components have been used for identification of PQ issues. ICA is used to statistically decompose a multivariate signal into independent components. In [16], authors have applied single-channel ICA for detection of transient. This method has been compared with other methods used for transient detection, e.g., average fundamental waveform analysis, notch and high-pass filters, cycle-by-cycle difference etc.

Many analysis works have been carried out depending upon the threshold values without the use of classifiers. For instance, in [17], authors present a modified potential function based technique to detect the PQ disturbances having short duration, e.g., sag, swell and transient. This technique computes a diffusion matrix having threshold values, as per the proposed algorithm which is used for fast real-time tracking and detection. PQ events have been successfully classified by using the concept of neural networks in different forms. Manjeevan Seera et al. [18] have developed PQ analysis model by modifying the basic concepts of fuzzy min–max clustering neural network. Voltage harmonics and total harmonic distortion have been extracted from all three phases of acquired PQD signals. Fuzzy min-max clustering network have been applied upon those features due to their individual capabilities of online learning and prediction explanation respectively. This method can have setback due to increasing complexity while learning due to increase in number of clusters. Another neural network based approach using conjugate gradient back-propagation algorithm has been adopted by Chetan B. Khadse et al. [19] for detection and classification of sag and swell in LabVIEW. This technique recognizes PQ events from their odd and even harmonic components extracted using FFT.

Another main technique for time-frequency localization of PQ events is Hilbert-Huang Transform which comprises of EMD and then Hilbert spectral analysis. Many researchers have relied upon EMD for decomposition of PQD signals to have effective feature extraction. Since, EMD has certain drawbacks like envelope undershoot or overshoot due to the cubic spline interpolation, negative effects at the boundary and the mode mixing [20]; noise-assisted ensemble EMD has been proposed but it also lacks somewhere due to drastic increase in computational burden. Therefore, David Camarena-Martinez et al. [20] have fused the down-sampling stage and spline-cubic interpolation to the standard EMD process to have more adequate IMF extraction and less computational burden. This method extracts the first IMF as the fundamental component and rest information that is mainly of PQDs lies in other IMFs. This technique facilitates elimination of overshoots, undershoots and mode mixing problem with fundamental component of PQD.

To address the limitations of traditional EMD, for instance, intermittence, mode-mixing, and undesirable IMFs, authors have proposed new framework utilizing modified EMD in this work. Ideally, every IMF should have one single oscillatory mode or frequency component. But, as PQD signal has numerous harmonics and time-varying amplitude and frequency, there are chances that each IMF computed by EMD has multiple frequency components. Hence, to ward off this improper decomposition of PQD signal, a pre-processing stage has been introduced before the process of EMD. That pre-processing stage is DWT in this paper. The combination of DWT and EMD is named as modified EMD. Modified EMD has been applied on eleven PQ signals, simulated by parametric equations, i.e., normal, swell, sag, flicker, interruption, harmonics, swell with harmonics, sag with flicker, sag with harmonics, swell with flicker and interruption with harmonics. DWT has been used to split PQ signal into two narrow bands, i.e., low frequency and high frequency components. Only low frequency components are further treated with EMD since main frequency components of PQ signal reside in low frequency region. Eight statistical features such as mean, root mean square, standard deviation, variance, skewness, kurtosis, energy and entropy have been further calculated from the obtained IMFs. The same features have been computed from the high frequency component of PQ signal to also utilize the high frequency information of PQ signal. These features have been used as the characteristics of PQ issues and employed in the training of PNN for automatic classification of PQ issues. PNN has been adopted in this work on account of its faster training procedure and has been also proved superior to SVM for classification of single and multiple PQ issues.

Rest of the paper is organized as follows: Section 2 contains proposed methodology for the classification of PQ issues. Section 3 briefs theoretical background of DWT, modified EMD, and PNN classifier, and Section 4 presents results and discussion followed by conclusion of the proposed technique with the future directions in Section 5.

2 Proposed Methodology

Detection and classification of PQ issues (sag, swell, flicker, interruption, harmonics, sag with harmonics, swell with harmonics, sag with flicker, swell with flicker and interruption with harmonics) have been illustrated in this section. The proposed technique considers the analysis of both single and multiple PQ issues. Single PQ issues include sag, swell, flicker, interruption and harmonics; whereas multiple PQ issues are sag with harmonics, swell with harmonics, sag with flicker, swell with flicker and interruption with harmonics. This method is based mainly on the application of modified EMD and PNN. The block diagram of the proposed methodology is presented in Fig. 1. Different steps of block diagram have been discussed as follows.

2.1 Simulation of PQ Issues

Proposed methodology starts with simulation of PQ input signal which undergoes the detection and classification process. Input signals with PQ issues are generated in MATLAB by varying the parameters of parametric equations as per IEEE-1159 standard. The parametric equations used for simulating PQ issues considered in this work are given in Table 1. Both single and multiple PQ issues such as sag, swell, flicker, interruption, harmonics, sag with harmonics, swell with harmonics, sag with flicker, swell with flicker and interruption with harmonics, have been simulated in this work.

2.2 Signal Decomposition using Modified EMD

This stage explains the application of signal processing technique for transforming the signal into a form which contains significant recognizable information to characterize PQ issue. For this purpose, modified EMD is proposed in this work. Modified EMD presents application of DWT on input

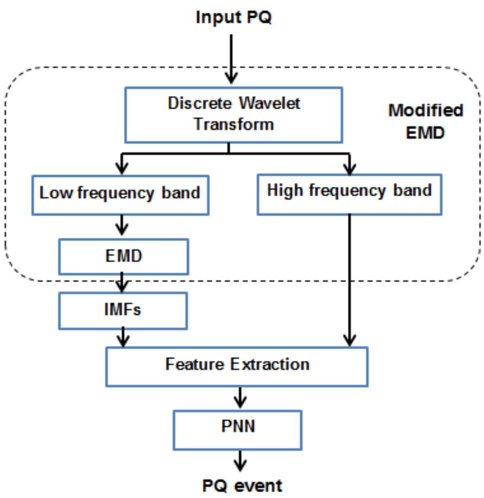

Fig. 1 Proposed methodology for detection and classification of PQ issues.

PQ signal first and then EMD of resultant low frequency signal. For applying DWT, db4 wavelet is used which divides signal into low frequency and high frequency components. EMD is then applied only on low frequency signal and produces IMFs from the low frequency part of PQ issue. All these IMFs now obtained have single oscillatory modes, thus overcoming the problem of mode-mixing.

2.3 Feature Extraction

Feature extraction implies the process of transforming the signal into a set of features. Signal obtained after EMD is too big to be dealt with, so, it is transformed into set of features which represents its characteristic information. Eight statistical features such as mean, root mean square (RMS), standard deviation, variance, skewness, kurtosis, energy and entropy, are calculated from IMFs having useful signal information. These features have also been extracted from the high frequency component of PQ signal to extract the signal information hidden in high frequency component. These features are introduced in Table 2 with their labels. In PQ analysis, feature extraction is a prominent step. More the features are relevant; more is the classification accuracy for PQ issues.

Table 1 Parametric equations used for PQ issues generation.

PQ Issue	Class	Parametric Equation	Parameters
Normal signal	C1	$s(t)=A_m\sin(wt)$	$A_m=1pu, w=2\pi*50$
Voltage Sag	C2	$s(t)=A_m\left(1-\beta\left(u(t-t_1)-u(t-t_2)\right)\right)\sin(wt)$	$0.1\le\beta\le0.9;$ $T\le t_2-t_1\le9T$
Voltage Swell	C3	$s(t)=A_m\left(1+\beta\left(u(t-t_1)-u(t-t_2)\right)\right)\sin(wt)$	$0.1\le\beta\le0.8;$ $T\le t_2-t_1\le9T$
Interruption	C4	$s(t)=A_m\left(1-\beta\left(u(t-t_1)-u(t-t_2)\right)\right)\sin(wt)$	$0.9\le\beta\le1;$ $T\le t_2-t_1\le9T$
Harmonics	C5	$s(t)=A_m\left(\beta_1\sin(wt)+\beta_3\sin(3wt)+\beta_5\sin(5wt)\right)$	$0.05\le\beta_3,\beta_5\le0.15;$ $\sum\beta_i^2=1$
Flicker	C6	$s(t)=A_m\left[1+\beta_1\sin(\beta_2 wt)\right]\sin(wt)$	$0.1\le\beta_1\le0.2;$ $5\le\beta_2\le20Hz$
Sag with Harmonics	C7	$s(t)=A_m\left(1-\beta\left(u(t-t_1)-u(t-t_2)\right)\right)\left(\beta_1\sin(wt)+\beta_3\sin(3wt)+\beta_5\sin(5wt)\right)$	$0.1\le\beta\le0.9;$ $T\le t_2-t_1\le9T;$ $0.05\le\beta_3,\ \beta_5\le0.15;$ $\sum\beta_i^2=1$
Swell with Harmonics	C8	$s(t)=A_m\left(1+\beta\left(u(t-t_1)-u(t-t_2)\right)\right)\left(\beta_1\sin(wt)+\beta_3\sin(3wt)+\beta_5\sin(5wt)\right)$	$0.1\le\beta\le0.8;$ $T\le t_2-t_1\le9T;$ $0.05\le\beta_3,\beta_5\le0.15;$ $\sum\beta_i^2=1$
Interruption with Harmonics	C9	$s(t)=A_m\left(1-\beta\left(u(t-t_1)-u(t-t_2)\right)\right)\left(\beta_1\sin(wt)+\beta_3\sin(3wt)+\beta_5\sin(5wt)\right)$	$0.9\le\beta\le1;$ $T\le t_2-t_1\le9T;$ $0.05\le\beta_3,\beta_5\le0.15;$ $\sum\beta_i^2=1$
Sag with Flicker	C10	$s(t)=A_m\left[1+\beta_1\sin(\beta_2 wt)\right]\sin(wt)\left(1-\beta\left(u(t-t_1)-u(t-t_2)\right)\right)$	$0.1\le\beta\le0.9;$ $T\le t_2-t_1\le9T;$ $0.1\le\beta_1\le0.2;$ $5\le\beta_2\le20Hz$
Swell with Flicker	C11	$s(t)=A_m\left[1+\beta_1\sin(\beta_2 wt)\right]\sin(wt)\left(1+\beta\left(u(t-t_1)-u(t-t_2)\right)\right)$	$0.1\le\beta\le0.8;$ $T\le t_2-t_1\le9T;$ $0.1\le\beta_1\le0.2;$ $5\le\beta_2\le20Hz$

Table 2 Characteristic features of PQ signal.

Feature Label	Features	Expression	Feature Label	Features	Expression
F1	Mean	$\mu = \frac{1}{N}\sum X$	F5	Skewness	$X_{\text{skew}} = \frac{1}{N}\sum\left(\frac{X-\mu}{X_{\text{rms}}}\right)^3$
F2	RMS	$X_{\text{rms}} = \sqrt{\frac{1}{N}\sum X^2}$	F6	Kurtosis	$X_{\text{kurt}} = \frac{1}{N}\sum\left(\frac{X-\mu}{X_{\text{rms}}}\right)^4$
F3	Standard Deviation	$\sigma = \sqrt{\frac{\sum(X-\mu)^2}{N}}$	F7	Energy	$X_{\text{energy}} = \sum_N \lvert X\rvert^2$
F4	Variance	$\sigma^2 = \frac{\sum(X-\mu)^2}{N}$	F8	Entropy	$X_{\text{entropy}} = \sum X \log(X)$

2.4 Classification of PQ Issues

Features have been extracted from all the samples of PQ signals to form the corresponding feature vector. The feature vectors of randomly selected PQ issue samples are used for training of PNN. PNN is a feed forward neural network based on the Bayesian network. The spread constant is adjusted by hit and trial method in order to achieve maximum classification accuracy. PNN gets trained with all the feature vectors in one go facilitating fast response. Trained PNN has been employed for the automatic classification of PQ issues. Test samples are randomly selected for testing of trained classifier.

3 Theoretical Background

3.1 Discrete Wavelet Transform

Discrete wavelet transform (DWT) is one of the most prominently used tool for time-frequency localization of the signal. DWT has been adopted instead of CWT due to the redundancy present in continuous wavelet transform [23]. DWT utilizes the analysis filter-bank to split the signal into approximation and detail information of the signal. Coarse (or approximation) information of the signal is present in low frequency components and detail information of the signal is present in high frequency components. The analysis filter bank for DWT is presented in Fig. 2. DWT of a signal is represented mathematically as below in (1) [24]:

$$DWT(p,n) = \frac{1}{\sqrt{s^p}}\sum_k i(n)\psi\left(\frac{n-kbs^p}{s^p}\right) \tag{1}$$

where $i(n)$ represents the discrete version of $i(t)$, the continuous PQ signal; s and b are constant real values and p and n are the integers. $\psi(n)$, the wavelet function is the mother wavelet that is used to extract signal information at different scaling level, s and translation level, bs^p. Here, p decides the resolution level of the decomposition. There are many mother wavelets used in DWT, e.g., Daubechies, Morlet, Haar, Mexican etc. In this work, 'db4', a member of Daubechies wavelet family has been utilized as the wavelet function. 'db4' wavelet has low-pass, $h[n]$ and high-pass filter coefficients, $g[n]$ as given in equation (2).

$$\begin{bmatrix} h[n] \\ g[n] \end{bmatrix} = \begin{bmatrix} \frac{1+\sqrt{3}}{4} & \frac{3+\sqrt{3}}{4} & \frac{3-\sqrt{3}}{4} & \frac{1-\sqrt{3}}{4} \\ \frac{1-\sqrt{3}}{4} & \frac{-3+\sqrt{3}}{4} & \frac{3+\sqrt{3}}{4} & \frac{-1-\sqrt{3}}{4} \end{bmatrix} \tag{2}$$

DWT utilizes the principle of multiresolution analysis (MRA) to decompose signal under analysis to different resolution levels. Approximation signal obtained from first level decomposition is further decomposed to have approximation and detail coefficients at second level, as per Mallat's algorithm. This process is continued till the signal gets splitted into desired frequency bands. Though, DWT provides time-frequency information of signal simultaneously, but it is limited by Heisenberg uncertainty [21]. Moreover, choice of mother wavelet is also a task to be done carefully which demands prior knowledge of signal. Hence, DWT has not been relied upon by authors as the single and only technique for PQ analysis.

3.2 Modified Empirical Mode Decomposition

Modified empirical mode decomposition is only the preferment of traditional EMD as the only difference between EMD and modified EMD is the pre-processing stage in modified EMD before application of EMD. Pre-processing stage includes application of DWT on PQ signal. The genesis of modified EMD lies in the shortcomings of traditional EMD like mode mixing and intermittence according to Gibbs phenomenon [25]. Sometimes, EMD decomposes the signal into intrinsic mode functions (IMFs) which are not having single oscillatory modes, representing frequency mixing in IMFs. This situation doesn't allow the proper representation of the signal into mono-components. Hence, modified EMD has been adopted which proposes application of DWT to decompose PQ signal into narrow bands, prior to the application of EMD for IMF generation. EMD of the

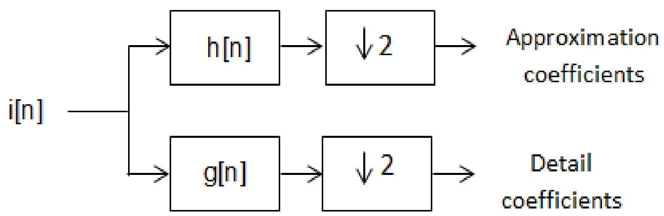

Fig. 2 DWT analysis filter bank.

narrow band signals results into IMFs having only single oscillatory modes.

EMD is the process that deals with both non-stationary and nonlinear signal and provides adaptive time-frequency localization. The concept of EMD is similar to wavelet transform which decomposes the signal in higher and lower frequency band. In EMD, the first IMF having the highest frequency is followed by other IMFs having decreasing frequency components. The basis of empirical mode decomposition is the sifting process in which mean of upper and lower envelope of the signal is repetitively subtracted from the original signal [26]. This sifting process extracts the highest frequency component from the signal in the repetitive manner.

An oscillating signal is called as an intrinsic mode function if it satisfies following two conditions [25]:

i. Number of extrema and zero crossing must be equal or vary by one only.
ii. The mean of envelope which is defined by local maxima and local minima is zero.

The process of EMD is progressed as per the flowchart presented in Fig. 3.

i. Calculate maxima and minima of the signal and apply cubic spline to get upper and lower envelope.
ii. Calculate mean $m(t)$ of the envelopes and subtract it from input signal $i(t)$, define it as in (3):

$$d_1(t) = i(t) - m(t) \tag{3}$$

iii. Check whether $d_1(t)$ satisfies two conditions of IMF, if yes then $d_1(t)$ is first IMF otherwise repeat steps i-iii by considering $d_1(t)$ as input signal and define the next component as in (4):

$$d_{11}(t) = d_1(t) - m_1(t) \tag{4}$$

iv. The process of sifting is replicated j times until first IMF $d_{1j}(t)$ is obtained and residue is calculated as per (5):

$$r_1(t) = i(t) - d_{1j}(t) \tag{5}$$

v. Consider $r_1(t)$ as input and repeat steps i-iv to get second IMF.

This algorithm is executed g times to get g IMFs. If $r_g(t)$ is monotonic, then no further decomposition is possible and the process is stopped here.

After this process, the original signal $i(t)$ can be represented by (6),

$$i(t) = r_g(t) + \sum_{k=1}^{g} IMF_k(t) \tag{6}$$

In this way, g IMFs are extracted from the original input signal $i(t)$. These IMFs are used for analysis of PQ signals, as these IMFs depict the varying amplitude and frequency of non-stationary PQ signals. EMD also offers freedom from Heisenberg uncertainty thus facilitating better time-frequency representation.

3.3 Probabilistic Neural Network Classifier

There are many variants of classifiers based on neural network, for instance, artificial neural network, back propagation neural network, multi-layer perceptron, deep neural network and PNN. D. F. Specht proposed probabilistic neural network in the early 1990s, which was a feed forward neural network based on Bayesian network [27]. PNN comprises of four layers of neurons which are input layer, pattern layer, summation layer and output layer. The architecture of PNN is presented in Fig. 4. Feature vector is presented at the input layer and neurons in pattern layer computes the distance of feature vector from training patterns according to Gaussian function. The summation unit simply sums the input from the pattern units that corresponds to the category from which the training pattern is selected. Summation layer contains as much neurons as the number of classes of training patterns. At the end, output layer uses the principle of maximum a posteriori to produce the final class to which feature vector belongs.

The classification process of PNN can be described as a two class problem. Let the state of a variable δ be either δ_A or δ_B . Decision of whether it is δ_A or δ_B, depends on the set of measurements captured by p-dimensional vector [25],

$$Y^t = [Y_1, Y_2, Y_3, \ldots, Y_j, \ldots, Y_p] \tag{7}$$

then Bayes decision rule becomes as (8) and (9),

$$d(Y)=\delta_A \quad \text{if} \quad h_A I_A f_A(Y) > h_B I_B f_B(Y) \tag{8}$$

$$d(Y)=\delta_B \quad \text{if} \quad h_B I_B f_B(Y) > h_A I_A f_A(Y) \tag{9}$$

where $f_A(Y)$ and $f_B(Y)$ gives probability density function for categories A and B respectively, I_A and I_B are loss function of decisions, h_A is prior probability of having pattern of category A and h_B is prior probability of having pattern of category B. Thus, the boundary between the regions given by Bayes decision, is represented as in (10),

$$f_A(Y)=Kf_B(Y) \quad \text{where} \quad K=\frac{h_B I_B}{h_A I_A} \tag{10}$$

One of the various advantages of PNN is that it does not require any weight initialization. Addition or removal of training patterns is very easy in PNNs as addition and removal of training samples just demands addition or removal of neurons of pattern layer, hence minimal efforts are required for retraining PNN, if needed [28]. PNN is much faster and accurate than multilayer perceptron networks. The higher learning speed of PNN makes it suitable for signal classification and fault diagnosis problems. In this work, PNN classifier has been relied upon for the classification of PQ issues due to its capability of being trained by all the features in one go only. High dimensional feature set obtained from modified EMD is used for the training and testing of PNN in this work.

4 Results and Discussions

The proposed methodology has been validated in this section with the experimental results and discussions. The results of various stages from PQ issue generation to classification have been discussed below.

4.1 PQ Signal Generation

The proposed methodology has been investigated by using 100 patterns of each desired PQ issue. These issues are simulated by using MATLAB software expressions given in Table 1 [21,22]. The controlling parameters in these equations are illustrated in the same table. For the harmonic issue, fundamental component and the two other harmonic components are required. In this study, 3rd and 5th harmonic components are used.

4.2 Detection of PQ Issues

Synthetic signals used for the analysis of PQ issues are obtained from the mathematical equations in MATLAB. Normally, a signal consists of multiple oscillatory components which represent its physical properties. If these components are extracted from the signal, then the interpretation of the signal becomes much easier. Hence for extracting the information from these signals, modified EMD is applied. As PQ signals have multiple oscillatory modes, therefore, DWT has been first applied on PQ signal using 'db4' wavelet. The lower frequency narrow band obtained from wavelet decomposition has been used as the input for EMD rather than the original PQ signal. On applying EMD, IMF components and residue (last IMF) are obtained. In this work, five single and multiple PQ issues each, along with normal signal have been worked upon. Results of three single and two multiple PQ disturbances, i.e., sag, swell, flicker, sag with harmonics, and swell with harmonics are presented in this subsection.

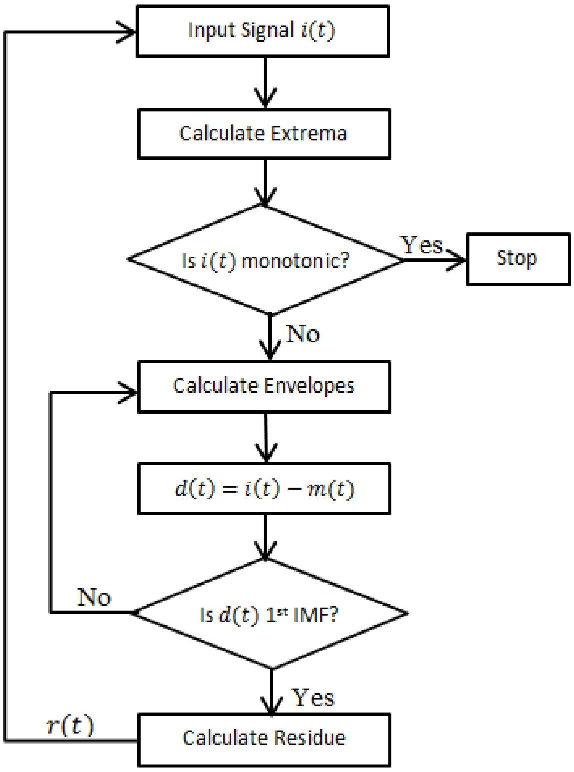

Fig. 3 Flowchart of EMD.

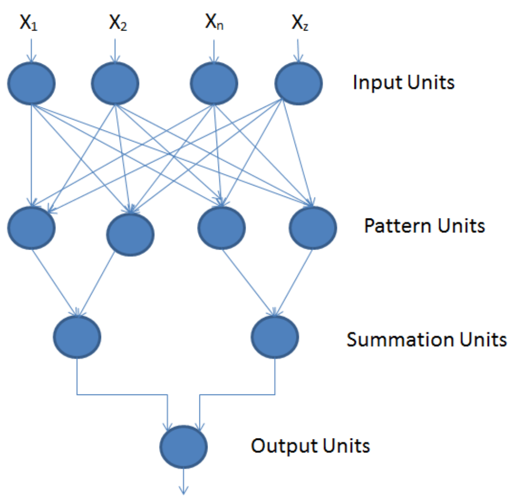

Fig. 4 Basic structure for classification of patterns into categories.

Three single PQ issues are here discussed, which are sag, swell and flicker. All these issues are shown in Fig. 5. Sag is dip in the voltage or current for a short duration, as shown in Fig. 5(a) which represents PQ signal with voltage sag of amplitude 0.7 p.u. Voltage sag signal has been decomposed using wavelet 'db4'. The approximation and detail coefficients of the voltage sag signal have been shown in Fig. 6 corresponding to low frequency and high frequency bands. Among these narrow bands obtained from wavelet decomposition, low frequency part is selected for further empirical mode decomposition to analyse the primary frequency components of PQ signal. IMF components for low frequency component

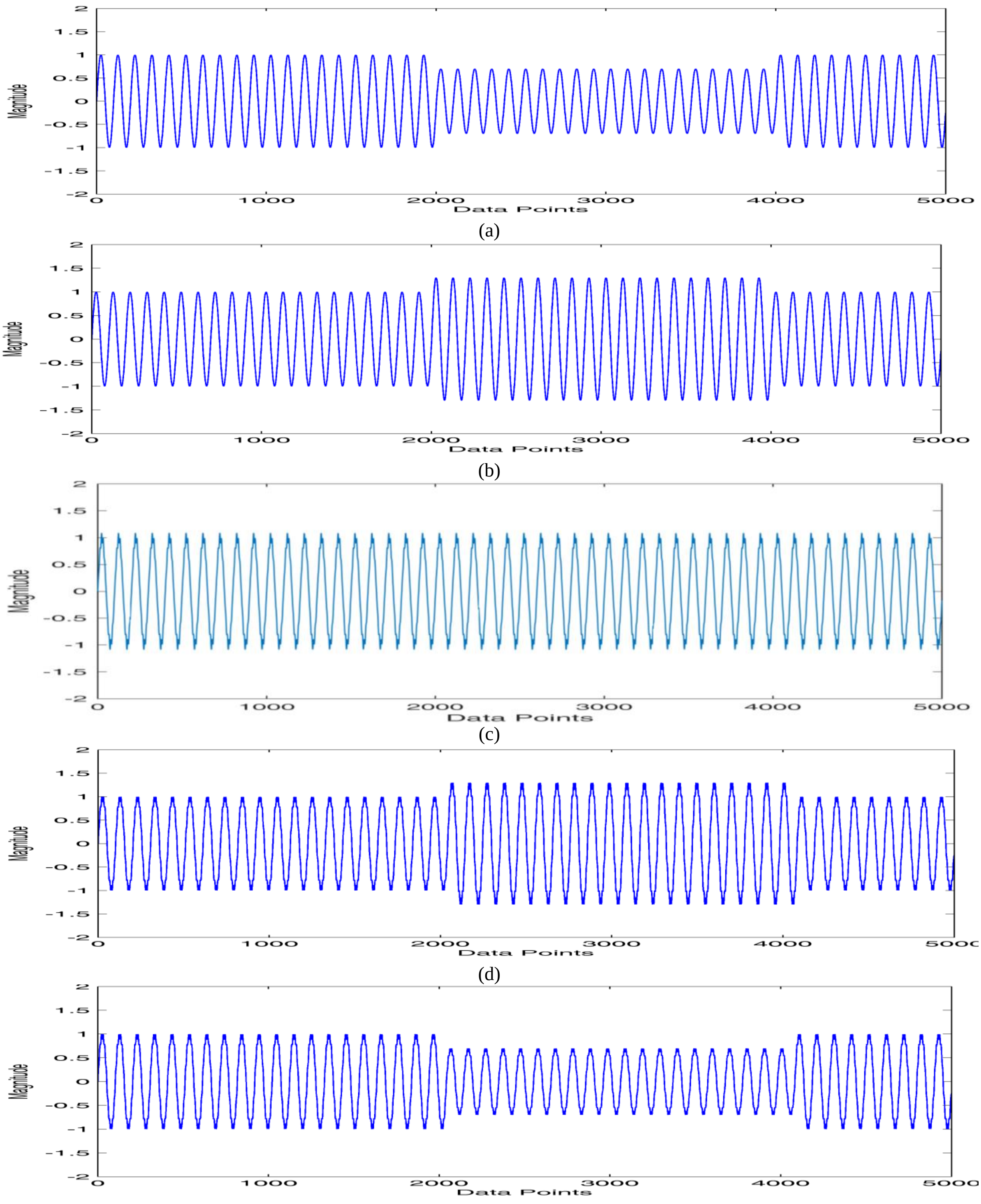

Fig. 5 Power quality signals a) sag, b) swell, c) flicker, d) swell with harmonics and e) sag with harmonics.

are depicted in Fig. 7.

The portion specified by A in Fig. 7, represents the presence of sag in signal and B represents the posterior event. First IMF preserves the frequency and phase of signal, and the little change is observed during the occurrence and termination of sag. During the voltage sag, the voltage amplitude becomes 0.7 p.u. First IMF component contains the highest frequency information. It is clearly visible from the Fig. 7 that the frequency content gets reduced from first IMF component to last IMF component. The last component (fifth IMF) obtained from EMD process is known as residue. After residue, no mono-component is derived. Residue contains no important information about the signal. Hence, only (N-1) IMFs, i.e., four in the case of voltage sag signal, are useful for extracting the time-frequency information of PQ signal; N is the number of mono-components obtained from EMD of sag signal and N^{th} mono-component is treated as residue.

For getting significant information about PQ issue in compact form, eight features mentioned in Table 2 have been computed from first four IMFs. There is also some remnant information of PQ issue in the high frequency component obtained from DWT. So, both components are used to provide various characteristic features of the signal. The same features have also been calculated from high frequency component of PQ signal. The feature vector formed is presented in Fig. 8. In this way, forty features have been computed for the voltage sag. These features form a feature vector as shown in Fig. 8, which has been used to train PNN for voltage sag. Next single disturbance presented is voltage swell.

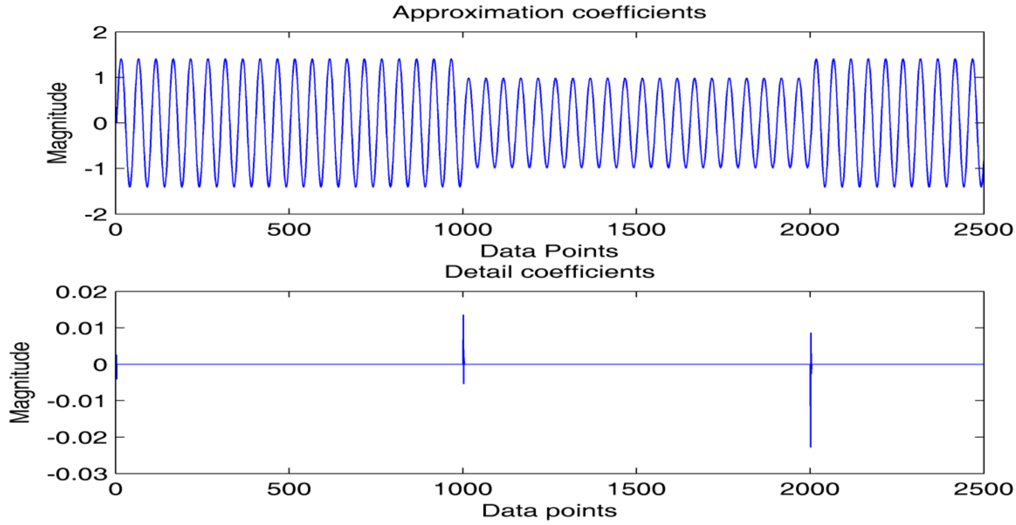

Fig. 6 Low and high frequency components of voltage sag.

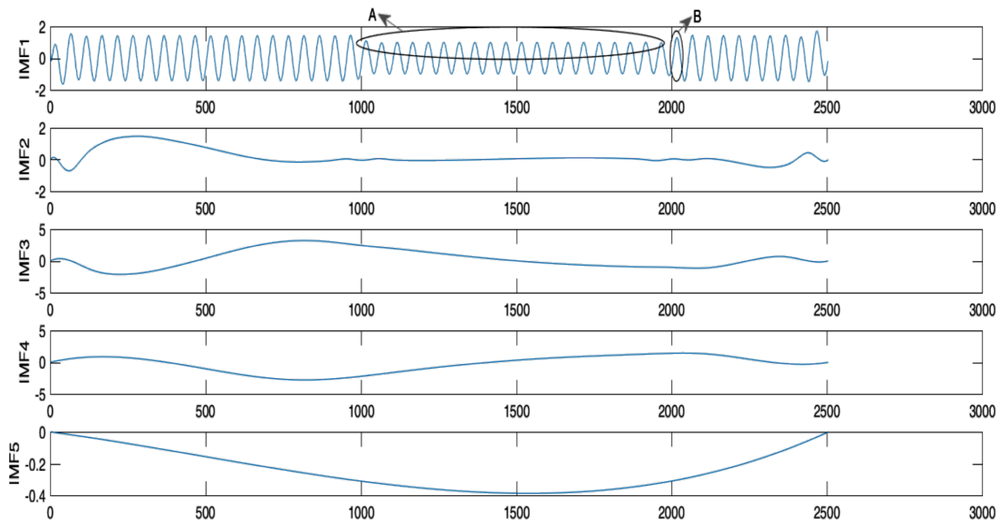

Fig. 7 IMF components and residue of low frequency component of voltage sag.

Voltage swell signal of amplitude 1.3 has been generated as presented in Fig. 5(b). DWT has been applied on the swell signal using wavelet 'db4'. The resultant low frequency and high frequency decomposed bands of the swell signal are represented by the approximation and detail coefficients, Fig. 9. Then, IMFs have been extracted from this low frequency component as given in Fig. 10.

EMD of low frequency band of swell signal has generated seven mono-components among which seventh mono-component is treated as residue. Like sag signal, same features have been computed from first four IMFs and from the higher frequency component of the swell signal.

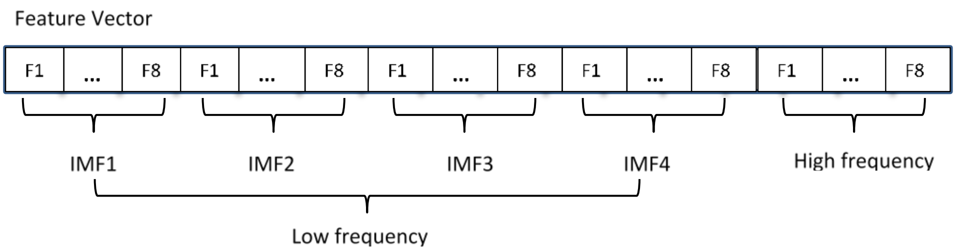

Fig. 8 Feature vector formed for voltage sag.

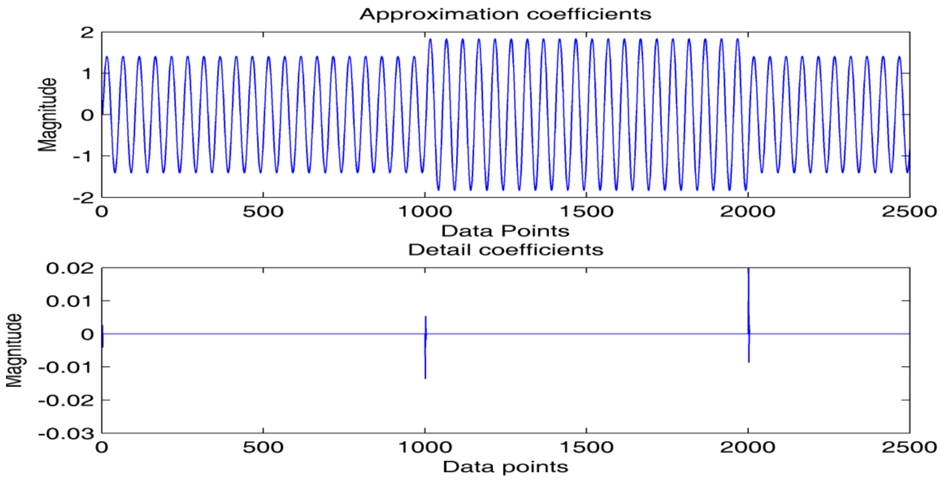

Fig. 9 Low and high frequency components of voltage swell.

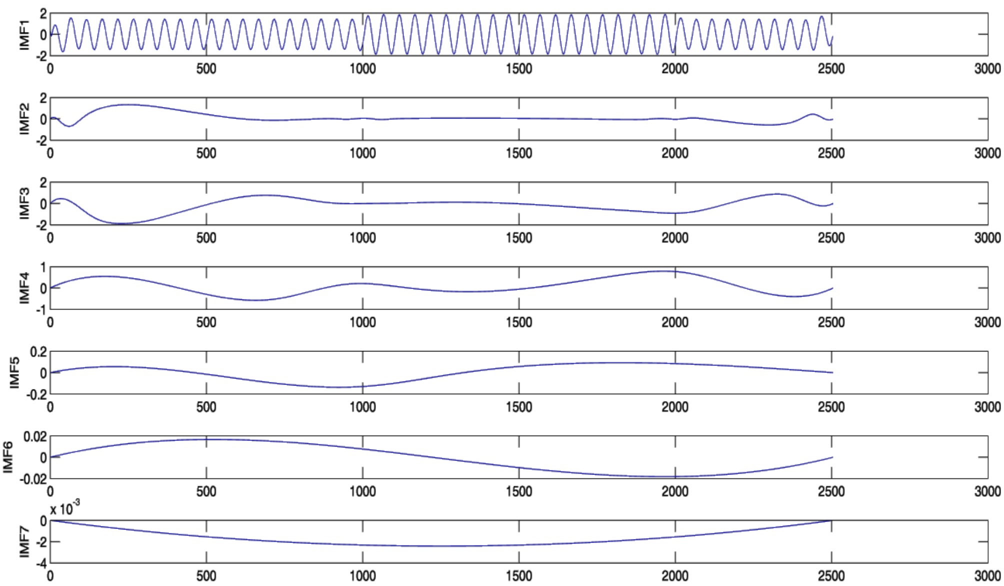

Fig. 10 IMF components and residue of low frequency component of voltage swell.

All these features collectively form the feature vector representing the unique swell signal for training the classifier.

Third single PQ issue is flicker which is the distortion in the magnitude, waveform and frequency of the voltage signal, as shown in Fig. 5(c). Flicker signal is decomposed into low frequency and high frequency bands using wavelet 'db4' which results into approximation and detail coefficients plotted in Fig. 11. The low frequency signal is further decomposed into IMFs using EMD as shown in Fig. 12. Flicker signal has six IMF other than one residue. Characteristic features have been extracted from first four IMFs and also from the high frequency band of the flicker signal to tap the high frequency information of flicker signal.

Multiple PQ issues represent the occurrence of more than one PQ disturbance simultaneously. Five multiple PQ disturbances, namely, sag with harmonics, swell with harmonics, interruption with harmonics, sag with flicker and swell with flicker have been worked upon according to the proposed technique of modified EMD. Sag with harmonics and swell with harmonics have been discussed here. Fig. 5(d) depicts PQ signal having harmonics of third and fifth order with swell. This PQ signal is first decomposed using wavelet 'db4' upto first level and the decomposed signals are shown in Fig. 13.

EMD has been carried out for the lower frequency band. Resultant IMF components for swell with harmonics are presented in Fig. 14. The first IMF component contains the highest frequency information and the last IMF, i.e., seventh IMF contains lowest frequency due to the subtraction of local mean from the signal during various iterations. The last component obtained from EMD process (residue) has no inherent information. The frequency content is very much high in first IMF. In similar fashion, characteristic features have been extracted from first four IMFs of low frequency component and from high frequency component of PQ signal.

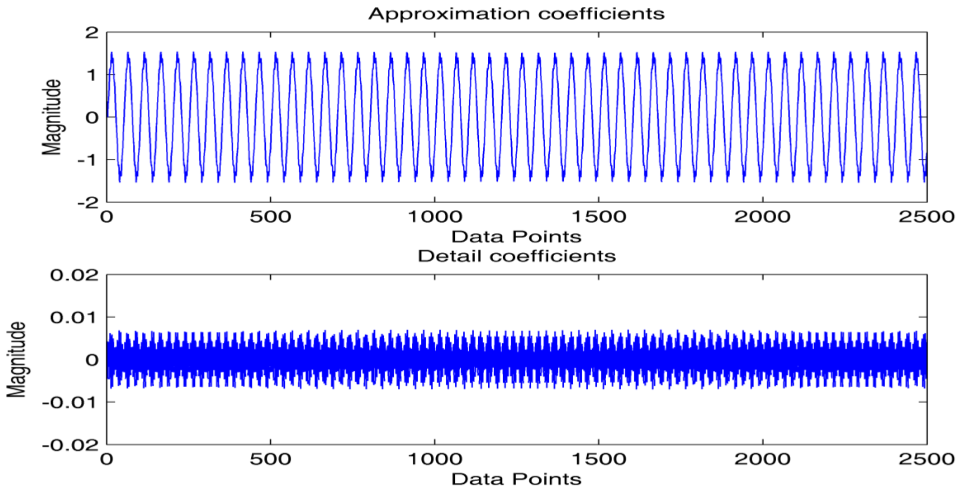

Fig. 11 Low and high frequency components of voltage flicker.

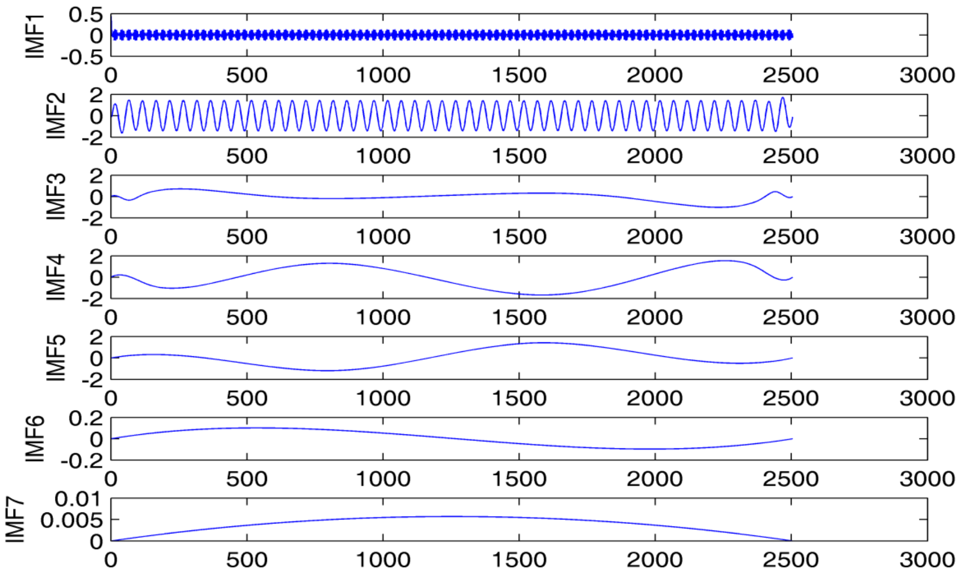

Fig. 12 IMF components and residue of low frequency component of voltage flicker.

Sag with harmonics is another major PQ issue that is simulated as in Fig. 5(e). Harmonics of third and fifth order occurs simultaneously with sag. ‘db4’ wavelet has been used for decomposing PQ signal into low and high frequency bands to further apply EMD on low frequency band. Fig. 15 presents the approximation and detail coefficients of PQ signal showing the low and high frequency component of PQ signal respectively. EMD of low frequency band of sag with harmonics signal has generated seven IMFs and one residue, that does not signify any information about the PQ issue. Characteristic features have been computed from first four IMFs (as more significant information lies in initial IMFs of the PQ signal), given in Fig. 16, and the high frequency band of PQ signal.

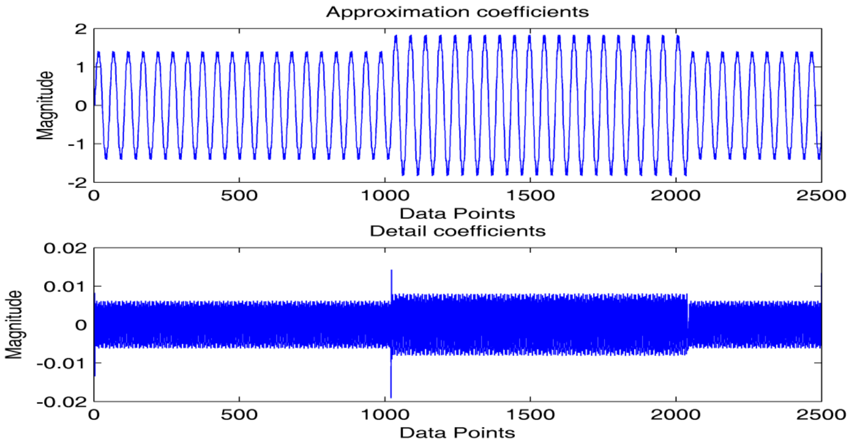

Fig. 13 Low frequency and high frequency components of swell with harmonics.

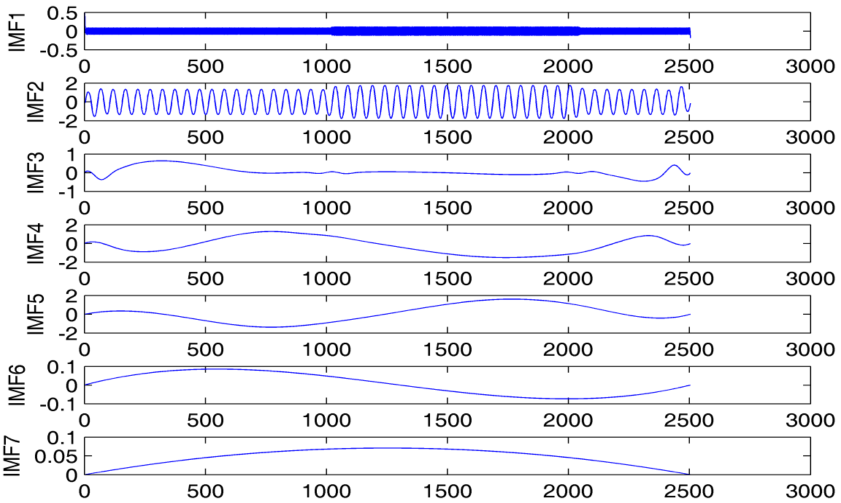

Fig. 14 IMF components and residue of low frequency component of voltage swell with harmonics.

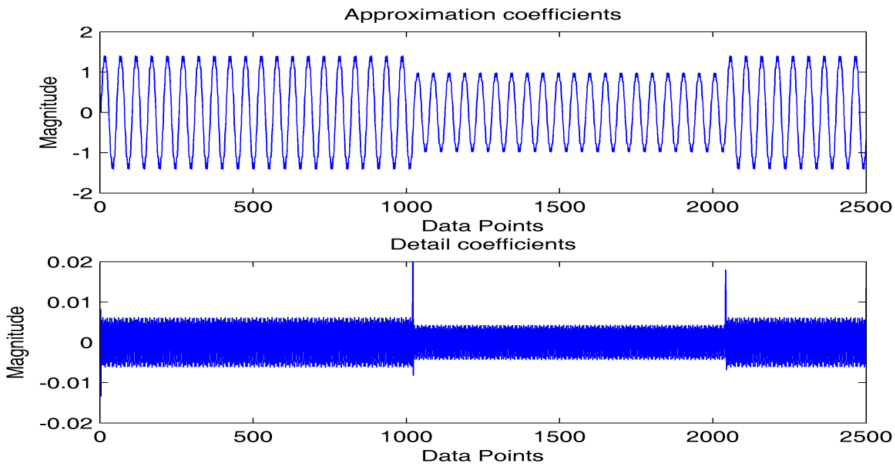

Fig. 15 Low frequency and high frequency components of sag with harmonics.

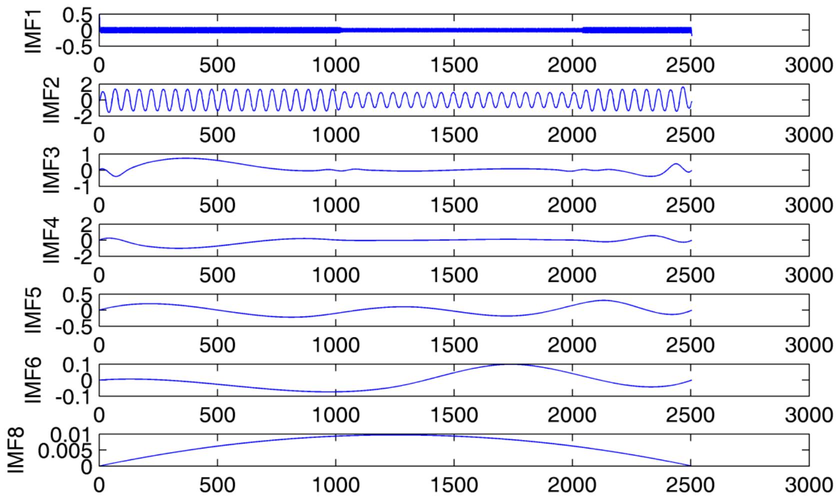

Fig. 16 IMF components and residue of low frequency component of voltage sag with harmonics.

Feature vector has been formed corresponding to all the samples of PQ issues. These feature vectors have been used for training PNN for classification of both single and multiple PQ issues.

4.3 Classification of PQ Issues using PNN

PNN classifier is proposed for classification of single and multiple PQ issues. For classification, eleven classes for ten different PQ issues and normal signal are defined and these classes are such that C1 represents normal, C2 represents sag, C3 represents swell, C4 represents interruption, C5 represents harmonics, C6 represents flicker, C7 represents sag with harmonics, C8 represents swell with harmonics, C9 represents interruption with harmonics, C10 represents sag with flicker and C11 represents swell with flicker. Feature vectors obtained for some randomly selected disturbance samples corresponding to each PQ issue have been utilized for training PNN. Spread constant of PNN has been selected randomly to achieve good classification accuracy. Classification performance of trained PNN has been evaluated by using randomly selected 50% samples of PQ issues as the test samples.

The classification accuracy of PNN corresponding to all PQ issues has been presented in Table 3. The effectiveness of proposed classifier has been investigated for noisy PQ signals also. For this purpose, uniform Gaussian noise has been added to PQ signals at different SNR level. The classification accuracy for PQ signals having SNR of 20 dB, 30 dB and 40 dB has been presented in Table 3. The classification performance of PNN has been compared with that of support vector machine (SVM) using Gaussian kernel. SVM has also been used for the classification of all PQ issues, in both the cases, i.e., noiseless and noisy PQ signals. Though, both PNN and SVM are based on Gaussian function; in the case of PQ issue classification, PNN outperforms SVM in this work due to high-dimensional set of features. SVM has shown average 97.58% accuracy in recognition of noiseless PQ signals. PNN has resulted into average accuracy of 99.64% for noiseless PQ signals. As the SNR of PQ signal decreases, recognition accuracy decreases for both the classifiers. SVM and PNN give 91.09% and 93.25% accuracy respectively for SNR of 20 dB.

The classification accuracy obtained with the proposed work has been compared with some state-of-the-art techniques in the same field of PQ issues recognition in Table 4. Table 4 illustrates the classification accuracy of other established techniques compared with our proposed technique particularly for noiseless PQ signals. These results focus on the better performance of the proposed technique for the classification of PQ issues.

5 Conclusions

This paper presents the application of modified EMD for the analysis of single and multiple PQ issues which are nonlinear and non-stationary. Various types of single and multiple PQ issues such as sag, swell, interruption, harmonics, flicker, sag with harmonics, swell with harmonics, interruption with harmonics, sag with flicker and swell with flicker have been considered in this work for automatic classification. For the detection of these PQ issues, a signal processing technique, modified EMD has been proposed which has DWT preceding traditional EMD. DWT has been applied on PQ signal to split the signal into low and high frequency components. EMD of low frequency component has been carried out producing certain IMFs which represents the oscillatory modes of PQ signal. To extract distinctive information from IMFs, eight characteristic features are extracted from first four IMFs. High frequency component has also been used for the feature extraction. These extracted features are used to train PNN classifier and further test the classification performance of PNN classifier into eleven classes of PQ issues including normal voltage signal.

PNN has remarkably performed the classification of PQ signals even with varying levels of noise. The performance of proposed method is compared with SVM classifier; the results of PNN highlight the outperformance of PNN over SVM.

The current study has tried to implement a signal decomposition technique (EMD) for the detection of PQ anomalies and a neural network for their classification of PQ anomalies. Further, the work can be extended by using optimization techniques for having more suitable features for the classification process. The proposed method is in the process of being tested on the real time PQ issues caused by different faults in the power system.

Table 3 Performance comparison of PNN and SVM under different SNR.

Issue Class	PQ Issue	SVM				PNN			
		Noiseless	40 dB	30 dB	20 dB	Noiseless	40 dB	30 dB	20 dB
C1	Normal	100	97.7	96.4	91.2	100	97.8	97.5	92.2
C2	Sag	99.1	98.4	97.3	90.6	99.9	98.6	96.6	94.2
C3	Swell	99.2	98.1	96.3	90.1	99.8	98.5	97.3	95.1
C4	Interruption	99.8	96.7	95.4	91.1	99.9	97.1	96.9	93.5
C5	Harmonics	97.5	96.1	95.2	90.1	99.8	96.8	95.7	92.4
C6	Flicker	97.2	96.4	94.1	91.5	99.9	97.6	95.5	93.8
C7	Sag with Harmonics	96.9	95.8	93.2	91.3	99.7	97.4	95.1	92.9
C8	Swell with Harmonics	96.2	95.1	93.1	90.4	99.6	96.4	94.8	92.5
C9	Interruptions with Harmonics	96.9	95.8	94.2	92.7	98.8	96.9	95.1	93.9
C10	Sag with Flicker	95.4	94.8	93.2	91.7	99.2	95.9	94.7	92.5
C11	Swell with Flicker	95.2	94.7	92.2	91.3	99.4	95.2	93.1	92.8
Average Accuracy		97.58	96.33	94.60	91.09	99.64	97.11	95.66	93.25

Table 4 PQ issue classification performance of other state-of-the-art techniques.

Ref.	Feature Extraction	Classifier	No. of PQ issue	Classification Accuracy (%)
[30]	S-Transform	MPNN	6	96.17
		SVM	6	97.67
[31]	Wavelet Packet Transform	SVM	8	98.33
[8]	Tunable-Q Wavelet Transform	Dual Multiclass SVM	14	98.78
[29]	Hilbert Huang Transform	PNN	1	98.63
Proposed method	DWT and EMD	PNN	11	99.64

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